

UNIVERSITÉ DU QUÉBEC À TROIS-RIVIÈRES

MODÉLISATION DES COMMUNAUTÉS ÉNERGÉTIQUES BASÉE SUR LA  
COSIMULATION ET METHODES POUR LEUR GESTION OPTIMALE DISTRIBUÉE  
AVEC ÉNERGIE RENOUVELABLE ET STOCKAGE THERMIQUE SOUS  
INCERTITUDE

THÈSE PRÉSENTÉE  
COMME EXIGENCE PARTIELLE DU  
DOCTORAT EN GÉNIE ÉLECTRIQUE

PAR  
JUAN ANTONIO DOMÍNGUEZ JIMÉNEZ

NOVEMBRE 2025

Université du Québec à Trois-Rivières

Service de la bibliothèque

Avertissement

L'auteur de ce mémoire ou de cette thèse a autorisé l'Université du Québec à Trois-Rivières à diffuser, à des fins non lucratives, une copie de son mémoire ou de sa thèse.

Cette diffusion n'entraîne pas une renonciation de la part de l'auteur à ses droits de propriété intellectuelle, incluant le droit d'auteur, sur ce mémoire ou cette thèse. Notamment, la reproduction ou la publication de la totalité ou d'une partie importante de ce mémoire ou de cette thèse requiert son autorisation.

## UNIVERSITÉ DU QUÉBEC À TROIS-RIVIÈRES

## DOCTORAT EN GÉNIE ÉLECTRIQUE (Ph.D)

**Direction de recherche :**

---

Prof. Kodjo Agbossou	Directeur de recherche
----------------------	------------------------

---

Prof. Javier Campillo	Codirecteur de recherche
-----------------------	--------------------------

**Jury d'évaluation**

---

Kodjo Agbossou	Directeur de recherche
----------------	------------------------

---

Javier Campillo	Codirecteur de recherche
-----------------	--------------------------

---

Loïc Boulon	Président du jury
-------------	-------------------

---

Frédéric Domingue	Membre interne
-------------------	----------------

---

Louis Gosselin	Évaluateur externe
----------------	--------------------

Thèse soutenue le 09 juillet 2025

## Résumé

La libéralisation progressive des marchés de l'énergie et l'émergence des échanges locaux transforment profondément la manière dont les ressources sont gérées et échangées au niveau communautaire. Dans ce contexte en pleine évolution, la montée en importance des communautés énergétiques appelle des approches innovantes capables de coordonner efficacement les ressources énergétiques distribuées tout en garantissant des solutions optimales et robustes. Les mécanismes traditionnels de gestion de l'énergie reposent souvent sur des architectures centralisées et intrusives, qui négligent la variabilité stochastique et l'hétérogénéité des préférences des utilisateurs. Afin de surmonter ces limites, cette thèse propose une approche distribuée pour l'analyse opérationnelle des systèmes énergétiques communautaires fonctionnant sous information imparfaite. L'approche combine l'optimisation convexe stochastique, la théorie des jeux et la co-simulation avancée afin de capturer l'interaction entre la dynamique physique et les processus décisionnels dans un marché local composé d'un coordonnateur et plusieurs prosummateurs résidentiels équipés d'accumulateurs thermiques locaux et de plinthes électriques chauffantes. Une bibliothèque Modelica dédiée a été conçue pour représenter avec précision la dynamique thermo-électrique d'une unité réelle d'un ATL commercial, permettant un couplage fidèle entre le comportement physique et les stratégies de contrôle. Les préoccupations des utilisateurs liées aux erreurs de prévision en conditions hivernales extrêmes sont explicitement intégrées grâce à une formulation stochastique sensible au risque, permettant aux prosummateurs de se prémunir de manière optimale contre l'incertitude. Ensuite, une plateforme cyber-physique a été mise en œuvre pour tester et déployer le mécanisme de coordination proposé, en utilisant exclusivement des outils open-source, du matériel commercial à faible coût et des données réelles du Québec. Les résultats démontrent que la coordination stochastique distribuée permet de réduire

significativement la demande de pointe, de favoriser l'intégration des énergies renouvelables et de diminuer les coûts systémiques, tout en préservant l'autonomie des utilisateurs, en garantissant la confidentialité des données et en renforçant la résilience face aux risques hivernaux.

## **Abstract**

The ongoing liberalization of energy markets and the rise of local energy exchanges are reshaping how resources are managed and traded at the community level. Within this context, the growing relevance of energy communities calls for innovative approaches to coordinate distributed energy resources efficiently while providing optimal and robust solutions. Traditional energy management mechanisms often rely on centralized and intrusive architectures, which tend to overlook stochastic variability and the heterogeneity of user preferences. To address these limitations, this thesis advances a distributed framework for the operational analysis of community-based energy systems operating under imperfect information. The approach combines stochastic convex optimization, game theory, and advanced co-simulation to capture the interplay between the physical dynamics and decision-making processes of a local market composed by a coordinator and several residential prosumers equipped with electric thermal storage units and baseboard heaters. A dedicated Modelica library was developed to represent the thermo-electrical dynamics of a real electric thermal storage room unit, enabling accurate coupling between physical behavior and control strategies. Users concerns about forecasting errors under extreme subzero conditions are explicitly incorporated through a risk-aware stochastic formulation that allows prosumers to optimally hedge against uncertainty. A cyber-physical platform was implemented to test and deploy the proposed coordination mechanism using fully open-source software and low-cost commercial hardware, along with real data from Quebec. The results demonstrate that distributed stochastic coordination can significantly reduce peak demand, enhance renewable integration, and lower system-level costs all while preserving user autonomy, ensuring data privacy, and strengthening resilience against winter-related risks.

## Acknowledgement

I would like to sincerely thank my research advisor, Prof. Kodjo Agbossou, a member of the Department of Electrical and Computer Engineering at UQTR and Director of the Laboratoire d'Innovation et de Recherche en Énergie Intelligente (LIREI), for guiding me with this project, for the quality of his supervision, and for his advice, support, and encouragement. I would also like to thank my co-advisor, Prof. Javier Campillo, former Deputy Minister of Energy of Colombia, for his help, his scientific support, and for giving me the opportunity to contribute to nation-building by applying the knowledge I gained during my doctoral journey to the formulation of public energy policy in Colombia.

I would like to express my special gratitude to Dr. Nilson Henao, research agent at LIREI, for his technical support, his dedication in the development of this research project, and for always guiding me towards the optimal path to accomplish the project's objectives. He made me realize that research becomes truly meaningful when coupled with innovation. I would also like to thank Dr. Luis Rueda, Dr. Fatima Amara and Dr. Juan Carlos Oviedo, researchers at the Hydro-Québec's Laboratoire de Technologies de l'Énergie (LTE), for their scientific contributions and for the time they devoted to our discussions, meetings, and document revisions. Their support allowed me to better understand algorithms and rapid deployment methods, which I had the opportunity to implement at LTE.

This work would not have been possible without the help of various institutes and organizations who, through their financial or technical support, recognized my work and placed their trust in me including the Hydro-Québec's LTE, the Natural Sciences and Engineering Research Council of Canada (NSERC), the Institut de Recherche sur l'Hydrogène (IRH) and the Fondation de l'UQTR.

***A Dios,***

*Solamente agradecimientos, por siempre darme la sabiduría y serenidad por haber tomado las decisiones acertadas, y por rodearme de las personas adecuadas que hicieron de este proceso algo llevadero.*

***A mi esposa,***

*Me acompañaste durante todo el proceso, fuiste mi motor y mis ojos cuando no tenía lucidez para tomar las decisiones. Conociste todas mis facetas, las buenas y las no tan buenas, y aún así, me elegiste a diario. Por eso y por infinitamente más, mil gracias.*

***A mi familia***

*Gracias, por el constante apoyo, sostén, y acompañamiento. A ustedes les debo todo, especialmente por siempre confiar y creer en mí. Cada uno de los esfuerzos realizados durante este proceso tuvieron el nombre de mi madre, de mi padre, mis hermanos y mis sobrinos. Cada uno de los sacrificios asociados a este proceso, tuvieron sentido para brindar a mis futuros hijos y sobrinos el privilegio de poder elegir.*

***A mis amigos y colegas***

*Se convirtieron en la familia que Dios puso en mi camino. Gracias por hacer menos complejo mi proceso de formación estando lejos de casa.*

## Table of contents

Résumé .....	iii
Abstract .....	v
Table of contents .....	viii
List of tables .....	xiv
List of figures .....	xv
Nomenclature .....	xxi
Chapter 1 - Introduction .....	1
1.1 General context .....	1
1.2 Energy transition perspectives for Nordic communities .....	6
1.3 Motivation .....	8
1.4 Problem statement .....	13
1.5 Objectives .....	15
1.6 Contributions .....	16
1.7 Publications .....	17
1.7.1 Journal Articles .....	17
1.7.2 Peer-reviewed Conference Articles .....	17
1.8 Outline of the dissertation .....	18
1.9 Assumptions .....	19
Chapter 2 - State-of-the-art .....	21

2.1	Modelling aspects - Building thermal dynamics meet electric thermal storage	25
2.1.1	Energy communities	25
2.1.2	Building's thermal dynamics	27
2.1.3	Thermal energy storage	29
2.2	Distributed energy management with imperfect information	36
2.2.1	Uncertainty Propagation	36
2.2.2	Uncertainty Representation	38
2.2.3	Distributed energy management	40
2.2.4	Distributed optimization methods	42
2.2.5	Optimization approaches depending on information's nature	48
2.3	Risk-preferences join distributed demand response	56
Chapter 3 - Article-based statement of the results		62
3.1	Modelling through distributed cosimulation	62
3.1.1	Background	63
3.1.2	Methodology	63
3.1.3	Outcomes	66
3.2	Distributed energy management	86
3.2.1	Background	86
3.2.2	Methodology	88
3.2.3	Outcomes	89
3.3	Risk-aware optimal scheduling	106
3.3.1	Background	106
3.3.2	Methodology	108
3.3.3	Outcomes	108

Chapter 4 - Discussions and limitations .....	129
Chapter 5 - Conclusions .....	135
5.1 Summary of works .....	135
5.1.1 Cosimulation framework .....	135
5.1.2 Distributed energy management under imperfect information .....	136
5.1.3 Robust energy planning .....	137
5.2 Challenges .....	138
5.2.1 Refining Demand-Side Risk Strategies : Joint Chance Constraints and Robust Methods .....	138
5.2.2 Welfare Analysis Under Network Parameter Uncertainty .....	139
5.2.3 Complexity of thermal storage operating in forced convection operating mode .....	140
5.3 Recommendations .....	140
5.3.1 Towards Complex Models and Standardized Interfaces .....	140
5.3.2 Long-term energy planning and fairness .....	141
5.3.3 Network Modeling Extensions for Energy Community Assessment	143
5.3.4 Coalition-Based Approaches to Distributed Energy Management ..	144
5.3.5 Governance and Financial Sustainability in Energy Community Implementation .....	145
5.3.6 Bridging Simulation and Reality : Hardware Constraints in Energy Community Deployment .....	146
5.3.7 Decoupling electricity-thermal domains through district heating and cooling applications .....	146
Annex A - Version en Français .....	158

A.1	Contexte général .....	158
A.2	Perspectives de transition pour les communautés nordiques .....	161
A.3	Motivation .....	163
A.4	Problématique de thèse .....	165
A.5	Objectifs .....	166
A.6	Contributions .....	167
A.7	Etat de l’art .....	167
A.8	Description des résultats publiés .....	169
A.9	Modellisation .....	169
A.9.1	Contexte .....	169
A.9.2	Méthodologie .....	169
A.9.3	Résultats .....	170
A.10	Gestion de l’énergie distribuée avec informationv imparfaite .....	171
A.10.1	Contexte .....	171
A.10.2	Méthodologie .....	172
A.10.3	Résultats .....	172
A.11	Planification énergétique robuste .....	173
A.11.1	Contexte .....	173
A.11.2	Méthodologie .....	173
A.11.3	Résultats .....	174
A.12	Discussions .....	174
A.12.1	Limitations .....	177
A.13	Conclusions .....	178

A.14	Résumé des travaux .....	178
A.14.1	Cadre de cosimulation .....	178
A.14.2	Gestion distribuée de l'énergie sous information imparfaite .....	179
A.14.3	Planification énergétique robuste .....	179
A.15	Limitations et défis .....	180
A.15.1	Affinement des stratégies de gestion des risques côté demande :	
	Contraintes de chance conjointes et méthodes robustes .....	180
A.15.2	Analyse du bien-être sous incertitude des paramètres du réseau .....	181
A.15.3	Complexité du stockage thermique fonctionnant en mode de convection forcée .....	182
A.16	Recommandations .....	182
A.16.1	Vers des modèles complexes et des interfaces standardisées .....	182
A.16.2	Planification à long terme de l'énergie et équité .....	183
A.16.3	Analyses avancées et performance sur le long terme .....	183
A.16.4	Extensions de modélisation du réseau pour l'évaluation des communautés énergétiques .....	184
A.16.5	Approches coopératives pour la gestion distribuée de l'énergie ....	184
A.16.6	Gouvernance et durabilité financière des communautés énergétiques .....	185
A.16.7	Écart simulationréalité et contraintes matérielles .....	186
A.16.8	Dissociation électricitéthermique via des réseaux de chauffage et de refroidissement urbains .....	186
Annex B -	Extended Modelling .....	187
B.1	Modeling and sizing of renewable and flexible resources .....	187
B.2	Forecast error modeling .....	189

B.3	Modelica ETS Library .....	191
B.4	Building model .....	194
B.5	Cosimulation framework .....	197
B.6	Flowcharts .....	201

## **List of tables**

Table 2-1	Existing papers focusing on electric thermal storage .....	35
Table 2-2	Comparison of decision-making approaches. ....	54
Table 2-3	Related works on risk-aware energy coordination strategies with energy communities .....	61
Table B.1	Main features of building models .....	196
Table B.2	Input parameters to simulate the heating demand of the buildings. ..	197

## List of figures

Figure 1.1	Average annual investment in fuel supply by type and scenario, 2013-2050 [1] .....	2
Figure 1.2	Temporal variation of wind speed (left) and temperature (right) for the winter of 2023, based on original data retrieved via a Tomorrow.io client. ....	12
Figure 1.3	Detailed variation of wind speed (left) and temperature (right) over a specific period in February 2023, using original forecast data obtained through a Tomorrow.io client. ....	12
Figure 2.1	Timeline at a glance of the topics this thesis addresses. ....	22
Figure 2.2	Timeline for ETS-related studies .....	22
Figure 2.3	Timeline for stochastic demand response with distributed algorithms	24
Figure 2.4	Conceptual framework of an energy community : stakeholders, resources, business models, and optimization approaches .....	27
Figure 2.5	Main fronts of building thermal dynamics in research. ....	28
Figure 2.6	Classification of thermal energy storage methods based on storage mechanisms. ....	30
Figure 2.7	Thermal energy storage status and innovation in the building sector (adapted from [2]) .....	32
Figure 2.8	Key aspects of Electric Thermal Storage Systems .....	33
Figure 2.9	Electric thermal storage (ETS) operation under dynamic pricing : (A) Charging during low-cost periods and (B) Discharging during high-cost periods. ....	34

Figure 2.10	Principal factors introducing uncertainty in smartgrids. ....	37
Figure 2.11	Two-stage uncertainty propagation : fixed first stage, fluctuating second stage. ....	37
Figure 2.12	Different uncertainty representations : (A) probability density, (B) distribution ambiguity, (C) elliptical, and (D) polyhedral robust sets.	41
Figure 2.13	Comparison of energy management strategies. Illustration of (A) centralized, (B) distributed, and (C) decentralized energy management approaches. ....	43
Figure 2.14	Main optimization methods regarding distributed energy management in literature. ....	48
Figure 2.15	An overview of formulations for optimization problems under uncertainty by managing it through the (A) objective function and (B) the set of restrictions ....	50
Figure 3.1	FMU approach for cosimulation ....	64
Figure 3.2	Visual representation of methods to manage the first objective .....	65
Figure 3.3	Temperature of bricks of ETS when installed in different buildings	66
Figure 3.4	Visual representation of methods to manage the second objective ...	87
Figure 3.5	Visual representation of methods to manage the third objective .....	107
Figure 3.6	Risk-awareness impact over the average grid cost .....	108
Figure 5.1	Execution of the distributed stochastic coordination program over two months in winter 2023. (A) First 5 days, and (B) The whole winter period .....	142
Figure A.1	Investissement annuel moyen dans l’approvisionnement en combustible par type et scénario, 2013-2050 .....	159

Figure A.2	Aperçu chronologique des thèmes abordés dans cette thèse. ....	168
Figure A.3	Approche FMU pour la cosimulation .....	170
Figure B.1	Standard deviation of the (A) outdoor temperature, (B) wind speed, (C) relative humidity, and (D) solar DNI .....	190
Figure B.2	Standard deviation of the (A) PV power temperature, (B) Wind turbine power .....	190
Figure B.3	Thermal zones distribution for the different building setups modeled	196
Figure B.4	Co-simulation framework integrating Modelica (thermal battery) and EnergyPlus (building) FMUs via PyFMI. ....	199
Figure B.5	Spatial versatility of Electric Thermal Storage deployment. ....	199
Figure B.6	Flowchart to perform energy coordination with the modelled thermo-energetic environment .....	202
Figure B.7	Flowchart to perform distributed stochastic energy coordination ...	203
Figure B.8	Flowchart to implement distributed computing with stochastic energy coordination .....	204
Figure B.9	Unified model language diagram to elucidate the procedure to perform energy coordination involving multiple customers .....	205
Figure B.10	Flowchart to determine chance constraints equivalents .....	206
Figure B.11	Flowchart to perform distributed computing with risk-aware energy coordination .....	207
Figure B.12	Diagramme de flux pour effectuer une coordination énergétique stochastique distribuée .....	208
Figure B.13	Organigramme pour déterminer les équivalents de contraintes aléatoires .....	209

Figure B.14 Organigramme pour effectuer un calcul distribué avec une coordination énergétique tenant compte des risques .....	210
Figure B.15 Organigramme pour effectuer la coordination énergétique avec l'environnement thermoénergétique modélisé .....	211

## List of Acronyms

- APS** Announced pledges scenario
- ADMM** Alternating direction method of multipliers
- CCP** Chance constrained programming
- COP** Coefficient of performance
- CCHP** Combined cooling, heating and power
- CVAR** Conditional value-at-risk
- DEM** Distributed energy management
- DER** Distributed energy resource
- DRO** Distributionally robust optimization
- EBH** Electric baseboard heater
- EC** Energy community
- ETS** Electric thermal storage
- FMU** Functional mock-up unit
- GP** Gaussian processes
- HEMS** Home energy management system
- HVAC** Heating, Ventilation, and Air Conditioning
- IEA** International Energy Agency
- IGDT** Information gap decision theory
- LCOE** Levelized Cost of Energy
- NZE** Net zero emissions
- NSL** Non-shiftable loads
- PDF** Probability density function

**PCM** Phase change materials

**RO** Robust optimization

**RSI** Thermal resistance

**SP** Stochastic programming

**STEPS** Stated policies scenario

**TCL** Thermostatically controllable loads

**TES** Thermal energy storage

**VAR** Value-at-risk

**VPP** Virtual power plant

**WF** Weather forecast

## Nomenclature

### Parameters

$\alpha$	Risk aversion coefficient
$\varepsilon$	Chance constraint tolerance
$\rho, \lambda$	Regularization or penalty parameter
$\rho_m$	Density of storage material [kg/m <sup>3</sup> ]
$C_{core}$	ETS Specific heat capacity [J/kg·K]
$A_s$	ETS Heat transfer surface area [m <sup>2</sup> ]
$V_s$	ETS Volume of storage unit [m <sup>3</sup> ]
$\eta_{ch}, \eta_{dis}$	Charging / discharging efficiency
$\Delta k$	Time-step
$\xi$	Random phenomenon (e.g., forecast error)
$x^{comfort}$	Indoor temperature setpoint [°C]
$x^{min}, x^{max}$	Minimum / maximum admissible indoor temperature [°C]
$C_{building}$	Thermal capacitance of the building [kJ/K]
$T_{amb}$	Ambient temperature [°C]
$p^{ETS}$	Rated charging power of ETS [kW]
$\pi_k$	Electricity tariff [CAD/kWh]
$\gamma$	User's price elasticity
$\mu$	Expected value (mean) of stochastic variable
$\sigma$	Standard deviation of stochastic variable
$\Sigma_\xi$	Covariance matrix of forecast errors
$RSI$	Thermal resistance

## Sets

$\mathcal{I}$	Set of iterations
$\mathcal{N}$	Set of scenarios
$\mathcal{H}$	Set of time slots
$\mathcal{R}$	Set of residential prosumers
$\Omega$	Sample space of uncertainty realizations

## Decision and State Variables

$f^F(x)$	First stage -fixed decisions
$f^S(x, y, \zeta)$	Second stage -fluctuating decisions
$h(x), g(x)$	System constraints
$f(x), g(x)$	Optimization objective functions
$x, y, u$	Generic decision variables
$X_k$	System state at time-slot $k$
$u_k$	Customer control variable (consumption decision) [kWh]
$P_k^{PV}$	Power generated by photovoltaic system at time-slot $k$ [kW]
$P_k^{wind}$	Power generated by wind turbine at time-slot $k$ [kW]
$P_k^{ETS}$	Electrical power supplied to the ETS unit at time-slot $k$ [kW]
$E_k^{ETS}$	Stored thermal energy in the ETS unit at time-slot $k$ [kWh]
$E_k^{bat}$	Energy stored in the battery (if applicable) at time-slot $k$ [kWh]
$ES_k^{ETS}$	State of charge of the ETS unit at time-slot $k$
$X_{in,k}, T_{out,k}$	Indoor and outdoor temperature at time-slot $k$ [°C]
$T_{ETS,k}$	Core temperature of the thermal storage unit at time-slot $k$ [°C]

$Q_k^{ETS}$	Heat released by the ETS to the indoor space at time-slot $k$ [kWh]
$Q_{loss,k}^{ETS}$	Heat losses at time-slot $k$ [kWh]
$Q_{solar,k}$	Solar heat gains at time-slot $k$ [kWh]
$L_\rho$	Augmented Lagrangian function
$w_k$	Random realization of weather variables (temperature, irradiance, wind)

### Constants and Statistical Symbols

$\mathbb{E}[\cdot]$	Expected value operator
$\mathbb{P}[\cdot]$	Probability of an event
$\text{VaR}_\alpha$	Value-at-Risk at confidence $\alpha$
$\phi(\cdot)$	Probability density function (PDF)

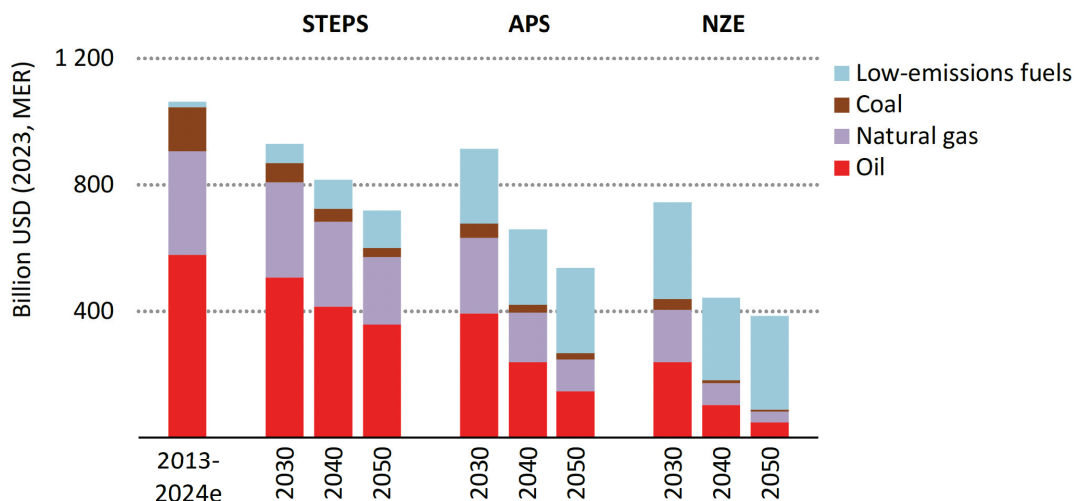
# Chapter 1 - Introduction

## 1.1 General context

The world faces numerous environmental challenges that require an energy transition towards more sustainable production and efficient consumption [3]. In this regard, the window to reach net-zero emissions by 2050 is rapidly closing, but there is still time for the world to get on track through prompt actions. The energy transition has accelerated in recent years, with the pace of clean technology deployment and capital investment surging to record levels [1]. To provide a more comprehensive analysis, the International Energy Agency (IEA) establishes three scenarios : the Stated Policies Scenario (STEPS), the Announced Pledges Scenario (APS), and the Net Zero Emissions (NZE) scenario.

As indicated in Figure 1.1, reaching the ZNE and APS scenarios (the most ambitious) requires significant investment. Investment in the power sector is expected to increase by nearly 70% by 2035 in the STEPS, with the most significant increases in electricity grids and renewables. The annual investment in fossil fuels falls from USD 1 trillion to USD 650 billion in the STEPS scenario by 2050 and drops to USD 90 billion in the NZE case. Low-emissions fuels pave the way for diversification, and in the APS and NZE Scenarios, they become essential components of the clean energy economy.

Over the last few years, energy investments have experienced a boost, increasing from USD 2.2 trillion to USD 2.8 trillion. Almost all of the increase has been directed towards clean energy and infrastructure, which now accounts for USD 1.8 trillion compared with USD 1 trillion for fossil fuels [1]. All these investments are required to cover the projected significant increase in electricity demand in sectors ranging from industry and buildings to transportation. The largest electricity consumers today are the building and industrial sectors, which combined account for over 90% of global electricity consumption. HVAC,



IEA. CC BY 4.0.

Figure 1.1 Average annual investment in fuel supply by type and scenario, 2013-2050 [1]

appliances, and cooking represent the majority of consumption in buildings, and electricity demand is expected to increase in all of these areas. On the industrial side, the trend is similar, as industrial output increases, driven by policies aimed at reducing emissions that encourage the electrification of industrial equipment. Lastly, transportation is a substantial contributor to the forecasted demand growth, resulting from the significant penetration of electric cars.

To cope with such increased demand projections, the world has embarked on deploying mainly renewable energy sources to mitigate climate impact. Despite the massive potential in deploying large-scale projects to achieve the projected scenarios rapidly, many countries around the globe are facing situations associated with environmental permitting that are postponing the project's date of commissioning. As the world runs out of time to reach ambitious climate goals, decision-makers must look beyond large-scale initiatives, as exemplified by the case of distributed generation. Distributed energy resources (DERs) offer multiple benefits to consumers, support decarbonization, and improve resilience. A

large share of today's grids were designed for the 20th-century operational mode, when the share of DERs was small. Nowadays, with a growing portion of electricity being generated by variable renewable sources, greater system flexibility is needed to balance supply and demand consistently. All the above fosters strategies that empower end-users as key actors in the energy transition, rather than passive consumers detached from daily electricity market dynamics. Modern power grids comprise numerous participants with diverse interests and technical constraints, each with dissimilar and sometimes conflicting objectives. This leads to the need to develop technological instruments, update regulatory frameworks, and establish new energy market structures [4].

Consistently, the energy community (EC) concept appears in the landscape to address such situations. By definition, ECs refer to organizations whose members are intensely involved in implementing rational energy use measures and introducing renewable energy sources in production and consumption for multiple purposes [5]. Equally important is the fact that with the momentum experienced by distributed generation worldwide, ECs can contribute to meeting energy transition needs by decentralizing conventional management schemes, facilitating active demand-side participation [6], and increasing electricity access in remote areas.

Experiences from developed and some developing countries suggest that residential customers can modify their usual consumption patterns to experience economic savings through tariff adjustments. The success of these schemes is highly correlated with power systems that have adopted renewable energy into their mix, fostering competitive prices [7]. Nonetheless, renewable sources are inherently intermittent and therefore, such uncertainties propagate across the power grid. The literature addresses this issue primarily through storage technologies [8, 9]. Energy storage is classified into four main classes, primarily based

on the physical properties of materials : electrochemical (batteries), mechanical (pumped hydro, compressed air), chemical (hydrogen), and thermal storage. While batteries provide rapid response times and are suitable for short-term power balancing, their scalability, lifespan, environmental impacts, and waste management remain concerns. Mechanical storage solutions require specific geographical conditions, including permitting issues, which limit their widespread adoption. Hydrogen storage, despite its elevated energy density, involves substantial conversion losses that minimize overall efficiency.

In contrast, thermal energy storage (TES) provides a cost-competitive and scalable alternative. This technology is particularly relevant given that a large share of global energy consumption is devoted to heating and cooling applications [10, 11]. Unlike other storage technologies, TES does not face waste management issues. Moreover, it represents a mature and cost-effective solution, outperforming its counterparts in technical, economic, and environmental aspects [12, 13]. TES can harness surplus renewable power to store heat for later use, hence enhancing energy efficiency and grid stability. Its high energy density and versatility for both short- and long-duration applications help to address seasonality effects, delivering economic benefits in both summer and winter. Consequently, TES can play a pivotal role in supporting decarbonization across residential, commercial, and industrial sectors. In this context, the concept of energy communities equipped with thermal storage emerges as a promising strategy to tackle multiple challenges of the energy transition.

Nowadays, energy communities experience challenges in i) mechanisms that ensure sustainability, ii) well-defined regulatory frameworks, and iii) prior consultation procedures, among others [14]. Along similar lines, there is a vast potential research niche to be occupied in energy communities' optimal operation for short-term energy planning tasks. Operating them not only implies complex models for decision-making and uncertainty

management but also designing strategies that facilitate energy actors to anticipate potential risks before embarking into these projects.

This thesis contributes to the literature by advancing stochastic and risk-aware methodologies that facilitate the distributed and optimal operation of energy communities integrating thermal storage systems. The proposed framework addresses three major challenges : (i) the rigorous characterization and modelling of thermal and energy requirements ; (ii) the coordination of distributed resources under demand-side uncertainties at the prosumer level; and (iii) the design of robust energy planning strategies capable of anticipating and mitigating operational risks in day-ahead applications. Taken together, these developments enhance both individual economic outcomes and the collective efficiency and resilience of the overall energy system, hence bridging the gap between theoretical formulations and practical deployment in real-world community settings.

Building upon the global context described above, it becomes essential to assess how renewable integration and thermal energy storage strategies perform under real-world operating conditions. While the preceding context outlined the general framework of the energy transition and the emergence of energy communities as enablers of decentralization and flexibility, the following section focuses on their application in cold and remote regions, where weather and geographical constraints challenge energy systems. In this regard, Northern Quebec –particularly the communities located in Nunavik –serves as a representative case study due to its extreme weather conditions, remoteness, and high dependency on fossil fuels. However, the mechanisms and methodologies proposed in this thesis are not limited to this region, they are conceived to be transferable and scalable to other contexts facing similar issues of isolation, intermittency, and heating-dominated demand, providing insights for broader implementation of renewable-based community

energy systems.

## **1.2 Energy transition perspectives for Nordic communities**

The vast majority of Canada's 300 remote communities rely on fossil-fuels to cope with essential needs regarding electricity. Particularly, remote communities in Northern Quebec, such as those in Nunavik, rely almost exclusively on diesel for electricity and, additionally, they exploit heavy fuel oil to meet residential heating demand [15]. This strong dependence on fossil fuels results in a local significant environmental footprint. The average environmental impact is approximately 514 kg of CO per customer-month, mainly associated with heating demand during severe winters [16]. Households are typically equipped with fuel-oil furnaces or boilers, and isolated diesel power plants primarily generate electricity [17].

Since Nunavik is not connected to the main provincial transmission system, each community satisfies its individual demand needs through local energy cooperatives while Hydro-Québec runs the diesel power generator. As a result, to alleviate the high cost of living, energy is subsidized in this region through the Gasoline Subsidy Program, which significantly reduces the cost of electricity and heating oil for residents. The cost of heating oil in Nunavik is 2.22 \$/L before subsidy and 1.554 \$/L after subsidy [18].

Instead, in Northern Quebec, the energy-related money flows between stakeholders and local organizations are unique and very unlikely to change in the short term. In contrast, in some other remote areas in Canada, the price of the electricity can increase up to eight times higher than in urban centers. This disparity reinforces social inequities and energy insecurity, while limiting the effectiveness of price signals as incentives for demand response or energy efficiency strategies [16].

Furthermore, building codes in these communities differ markedly from conventional dwellings regarding materials, preferences, and energy use. They are typically built with high-insulation envelopes and materials adapted to withstand extreme cold, which sets them apart from standard constructions [19]. Tenants in Nunavik show an extreme preference for thermal comfort and temperature stability, often maintaining high indoor temperatures and opening windows even during cold periods to improve air freshness rather than save energy [19]. This behavior is a clear reflect of cultural and psychological priorities for well-being and stable warmth over energy conservation, as documented in Cavalerie [20] through field measurements and occupant interviews in Quaqtq. All that said, plus the increasing demand as a result of population growth and the subsequent adverse environmental impact of fuel oil to meet residential heating needs calls for new approaches, for instance renewable sources to provide clean, locally-generated and reliable energy in these communities [15].

Consequently, as renewable projects are a potential tool to reduce carbon footprint, households in that region are becoming increasingly aware of renewables, yet perceptions are shaped by concerns over reliability and comfort [21]. While there is interest in solar or wind, residents often remain cautious about unfamiliar technologies in harsh climates. Households may experience skepticism toward untested technologies in extreme subzero climates to cover familiar heating systems. These perceptions suggest that successful integration of renewables must be accompanied by strong community engagement, clear communication of benefits, and technical solutions that directly address reliability and comfort [22].

In contrast, this thesis does not attempt to replicate the today system but instead explores a prospective transition scenario. In this scenario, renewable energy technologies such as wind and photovoltaic systems are combined with electric thermal storage

and complemented by diesel as backup. The introduction of distributed resources and management strategies opens new opportunities for demand-side flexibility and information exchange and paves the way for deploying energy communities with local markets.

This framing highlights that this thesis should be understood as a transition-oriented analysis, not as a representation of the current energy situation in Nunavik. By contrasting the current reality with a potential future scenario integrating renewables, thermal storage, and electric heating systems, the study provides insights into the technical aspects that would enable a community-driven energy transition in Northern Quebec.

### **1.3 Motivation**

Climate change is exerting increasing pressure on multiple sectors worldwide, demanding prompt and efficient actions to decarbonize national economies. Although the large-scale deployment of renewable generation has substantially increased global electricity supply, it also requires robust transmission infrastructure, often delayed by environmental approval processes and public opposition. Consequently, decentralized strategies have emerged as complementary pathways to accelerate the energy transition. Among these, the massive deployment of energy communities (ECs) has gained particular attention, as it embraces distributed energy resources (DERs) through people-centred initiatives that empower end-users to become active participants in the transition process.

The growing relevance of ECs is not only a technological or social phenomenon but also a natural outcome of electricity market liberalization. The gradual unbundling of vertically integrated utilities and the introduction of competition and third-party access in power markets have enabled the participation of new actors, including prosumers and local cooperatives. Liberalization thus provided the institutional foundation for ECs by promoting

non-discriminatory access to networks, supplier choice, and the valuation of local generation according to temporal and spatial price signals. In this sense, energy communities can be understood as a social and technological extension of market liberalization, translating the principles of efficiency and competition into local-scale governance and collaboration.

Incorporating renewable energy sources into energy communities provides economic incentives to end-customers while fostering local sustainability. However, the variable nature of these sources introduces uncertainty that must be properly anticipated. One effective way to mitigate such intermittency is through energy storage. Thermal energy storage (TES), particularly electric thermal storage (ETS), offers significant cost advantages compared to lithium-ion batteries, despite the latter's substantial price reductions over the past fifteen years. With a levelized cost of storage ranging from 0.1 to 25 USD/kWh, TES technologies remain considerably more economical than lithium batteries, typically around 125 USD/kWh, representing roughly one-quarter of their cost [2]. This wide cost range reflects the heterogeneity of TES technologies: mature sensible storage options such as water tanks or solid-state systems achieve costs as low as 0.1 – 1 USD/kWh due to their simplicity, scalability, and long lifetimes, whereas emerging latent (phase-change materials, ice, salt hydrates) and thermochemical systems remain more expensive up to 25 USD/kWh owing to higher material costs, integration challenges, and limited commercial deployment.

This pronounced cost differential positions thermal storage as a promising option for energy communities seeking cost-effective and flexible solutions capable of enhancing self-consumption, supporting renewable integration, and reducing dependency on the central grid.

It makes sense, especially in Nordic regions such as Quebec, where heating and cooling needs stand for around 60-70% of electricity consumption [23], and having reduced upfront

costs on thermal batteries may allow customers to experience economic savings in the presence of dynamic tariffs . To address short-term optimal energy planning, home energy management systems (HEMS) can assist customers by guaranteeing economic savings and preserving utilities. However, uncertainty created by renewables can still compromise both objectives if not appropriately addressed in decision-making systems.

One could extrapolate such an impact over a whole neighborhood, where several HEMS are deployed to represent every customer's interest. That may imply the following difficulties :

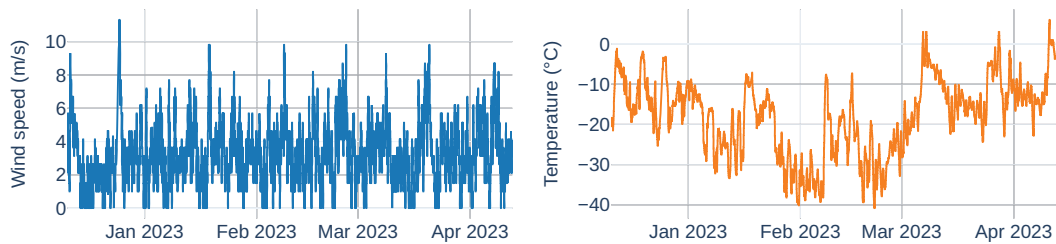
- **Lack of coordination and communication among end-users** : the limited information-sharing mechanisms can evoke selfish behaviors, and thus, collaboration among users gets affected, and the system's overall energy efficiency is reduced.
- **Supply and demand-side uncertainties** : on the one hand, weather fluctuations affect the accuracy of renewable power forecasts. On the other hand, users' consumption patterns are not strictly unpredictable but mostly stochastic and can be forecasted to some extent using historical data and probabilistic models. Nonetheless, short-term deviations driven by behavioral or contextual factors justify treating demand as uncertain and motivate adequate design of stochastic approaches.
- **Heterogeneous user preferences** : Each tenant has different preferences. Some may prioritize economic savings, while others prioritize comfort. Hence, it becomes challenging to develop a unified decision-making system.

Despite the above-listed aspects, many researchers adopt centralized dispatch as they have reduced complexity but do not have redundancy schemes. On the contrary, distributed layouts represent the trend worldwide and have an elevated complexity since decision-making is transferred to the demand side by splitting a unique problem into

multiple little ones. The Complexity increases when the strategy should address : i) no information exchanges between participants (selfish behaviors), ii) imperfect information on renewable power expected generation (created by weather forecasting errors) and non-controllable loads (created by customers' habits), iii) heterogeneous preferences. Besides, information on real-life projects that deploy ETS assets into icy climates is limited, and the possibility of building robust thermo-energetic frameworks to provide scenario generation is reduced. Under all these challenges, building a framework that enables researchers to succeed in having friendly power demand profiles and validation infrastructure to evaluate algorithms' performance under imperfect information represents the primary motivation of this thesis.

These situations become worse in real-world applications in extreme environments. For instance, the province of Quebec experiences harsh access conditions, and the northern part exhibits a significant dependency on fossil fuels, which shapes energy planning tasks. For these setups, deploying energy management schemes incorporating thermal storage and renewable assets can reduce the adverse effects of using diesel generators. Adopting such technologies and setups within a community energy framework can foster the shift towards resilient energy systems.

With that motivation, the proposed methods in this thesis are evaluated in the province of Quebec, Canada. Figures 1.2 and 1.3 illustrate accurate data of typical conditions during winter 2023 for the outdoor temperature and wind speed. By incorporating energy communities sustainably via distributed methods, thermal storage assets, and renewable power, phasing out fossil fuels can be fostered at a significantly prompt pace.



and temperature (right) for the winter of 2023.

Figure 1.2 Temporal variation of wind speed (left) and temperature (right) for the winter of 2023, based on original data retrieved via a Tomorrow.io client.

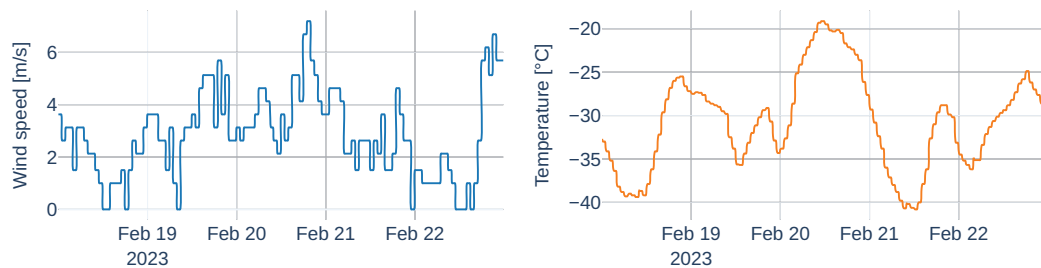


Figure 1.3 Detailed variation of wind speed (left) and temperature (right) over a specific period in February 2023, using original forecast data obtained through a Tomorrow.io client.

#### 1.4 Problem statement

In Quebec, the operating cost of off-grid electricity networks is about 20 times higher than that of the main network. These off-grid networks are mainly located in remote northern regions and are generally powered by diesel power plants. In addition, using electricity for space or water heating is discouraged and indirectly penalized in such territories. Consequently, building owners cope with heating needs with individual oil boilers (mazut) during intense cold periods, leading to a significant carbon footprint issue.

The current imminent energy transition claims for ECs. These communities leverage solar photovoltaic and wind energy as competitive carriers, replacing conventional power resources. Nevertheless, renewables' intermittent and unpredictable nature raises significant challenges for the continuity and stability of the energy supply to buildings, especially during harsh winter periods when power demand increases to cover heating needs. Storage means such as batteries should be deployed to guarantee the balance between consumption and production. However, electrochemical technologies remain expensive to meet high storage requirements. ETS is a competitive solution, exhibiting lower capital investments. Indeed, lessons learned from already deployed projects suggest that thermal storage can bring about 20 to 40% of economic savings and facilitate renewable integration, depending on customer preferences. While initiatives deploying such assets exist, their main drawback is that they perform direct load control [24], violating customers' privacy and centralizing the decision-making tasks by discouraging the transition towards sustainable energy communities [25–27].

To address that main problem, the following specific problems need to be harnessed :

- **Lack of low-detail information of ETS-related projects** : Building owners who adopt ETS can benefit from economic savings by taking advantage of

dynamic pricing benefits. However, modelling building thermal dynamics in the presence of ETS can be challenging due to non-linear phenomena. Currently, only manufacturers' data is accessible, and existing ETS models rely on approximations of electric batteries that do not have the same operational constraints as ETS units. Although existing building simulators allow for the characterization of energy consumption, they do not capture the interaction with complex HVAC systems like ETS. Additionally, unpredictable weather behaviour further complicates modelling, making it difficult to predict how an ETS-equipped building will respond to varying weather conditions. In summary, while ETS offers economic benefits, its practical implementation and modelling present considerable challenges.

- **Distributed decision-making under imperfect information** : Today's autonomous grids can leverage the benefits of resource coordination. That is a family of methods that encourage participants to properly align their strategies to pursue a given global objective (cost sharing) and is often addressed through distributed optimization algorithms. Nevertheless, the stochastic nature of weather forecasting errors and renewable energy sources introduces uncertainty into the optimization process, which, when coupled with the potential for cost overruns and customers' discomfort, poses a significant risk to the effective operation of these algorithms.
- **Risk-aware demand-side decisions for distributed resources coordination** : Conventional resource coordination algorithms allow exploiting demand response's salient features to experience demand and supply-side benefits. However, when customers integrated with renewable generators and ETS units have concerns about the weather forecasts and the subsequent renewable production availability, the imported energy to cope with heating needs could substantially increase due to conservative (risk-aware) behaviours. Not knowing such a fact can increase the

autonomous grid's running cost. Introducing risk-aware decisions to cover space heating becomes crucial as it provides grid operators with meaningful information about the possible worst scenario for the demand side. However, adopting this approach requires thorough mathematical modelling as the decision-making problem becomes NP-Hard.

### **1.5 Objectives**

This research is undermined by the following main objective : To design a framework that enables grasping energy community needs by proposing a distributed strategy to intelligently encourage residential customers to participate in a local energy market. That main objective needs to solve the following three specific objectives :

1. To model and characterize the thermo-energetic environment of the autonomous network. This objective includes developing simulation tools, co-simulation and statistical and stochastic models to characterize production and consumption and their dependence on environmental factors specific to remote regions.
2. To design a distributed energy management strategy capable of performing predictive control at a one-day horizon for each building. These controllers will have access to weather forecast data and signals from the network operator. Models of the local action environment (building resources) will be built using machine learning algorithms without human intervention.
3. To reduce the impact of stochastic renewable power and weather forecasting errors at the customer level by proposing a robust distributed energy management strategy. Given customers' concerns about renewable power and weather forecasting, this strategy allows the community coordinator to compute the amount of power to be dispatched, given diverse aggregated demand profiles.

## 1.6 Contributions

Achieving the proposed objectives have lead to three main contributions :

- **Contribution I : Proposal for Characterizing Thermo-Energetic Environments for Communities with Advanced Setups.** Building a framework that entails characteristics of communities during severe winters. This framework comprises state-of-the-art modelling tools that enable studying the complex interactions between building thermal dynamics and electric thermal storage units.
- **Contribution II. Advancements in Distributed Optimal Energy Planning via Stochastic Optimization in Communities Highly Penetrated with Renewable Power and Thermal Storage :** Proposing a distributed stochastic energy management encompassing an energy coordination strategy for remote territories with distributed ETS units and renewable sources. Such a strategy exploits game-theoretic methods to model the interaction between a local coordinator and the energy community inhabitants.
- **Contribution III. Anticipating Undesired Demand-side Effects in Communities Operated Distributedly via Chance Constrained Predictive Control.** Designing a robust control mechanism for reliability-aware optimal scheduling of distributed ETS units. This mechanism enables risk-aware decisions to cover space heating needs in the presence of stochastic renewable production at the customer level. Besides, it lets the grid operators know about situations that may arise due to customers' concerns about local energy imbalances created by weather forecasting errors.

## 1.7 Publications

### 1.7.1 Journal Articles

- **J1** : Domínguez-Jiménez, J., Henao, N., Agbossou, K., Parrado, A., Campillo, J., & Nagarsheth, S. H. (2023). A stochastic approach to integrating electrical thermal storage in distributed demand response for nordic communities with wind power generation. *IEEE Open Journal of Industry Applications*, 4, 121-138. **Top 3 of Best 2023 Publications in IEEE Open Journal of Industry Applications Award.**
- **J2** : Dominguez, J. A., Agbossou, K., Henao, N., Nagarsheth, S. H., Campillo, J., & Rueda, L. (2024). Distributed stochastic energy coordination for residential prosumers : Framework and implementation. *Sustainable Energy, Grids and Networks*, 38, 101324.
- **J3** : Dominguez, J. A., Henao, N., Parrado, A., Agbossou, K., Campillo, J., & Rueda, L. (2025). Risk-aware distributed chance constrained energy coordination in energy communities. *Energy*, 134778.

### 1.7.2 Peer-reviewed Conference Articles

- **C1** : Dominguez, J. A., Rueda, L., Henao, N., Agbossou, K., & Campillo, J. (2022, October). Distributed co-simulation for smart homes energy management in the presence of electrical thermal storage. In *IECON 2022 48th Annual Conference of the IEEE Industrial Electronics Society* (pp. 1-6). IEEE.
- **C2** : Dominguez, J. A., Parrado-Duque, A., Montoya, O. D., Henao, N., Campillo, J., & Agbossou, K. (2023, February). Techno-economic feasibility of a trust and grid-aware coordination scheme. In *2023 IEEE Texas Power and Energy Conference (TPEC)* (pp. 1-5). IEEE.

- **C3** : Dominguez, J. A., Sabir, S., Henao, N., Agbossou, K., Oviedo-Cepeda, J. C., & Campillo, J. (2024, November). ORFLEX : Open Platform for Rapid Testing and Deploying Local Flexibility Markets. In IECON 2024-50th Annual Conference of the IEEE Industrial Electronics Society (pp. 1-6). IEEE.
- **C4** : Ramirez, C. E. D., Nagarsheth, S. H., Henao, N., Ramirez, J. P. D., Agbossou, K., & Jimenez, J. A. D. (2024, November). Optimal Sizing and Operation of Electric Thermal Storage Systems for the Multi-zone Residential Apartment Building. In IECON 2024-50th Annual Conference of the IEEE Industrial Electronics Society (pp. 1-6). IEEE.

## 1.8 Outline of the dissertation

This thesis is composed of five chapters structured as follows :

- **Chapter 1** : This chapter describes the context, motivation and thesis problem. Also, in this chapter, the contributions and objectives are clearly defined.
- **Chapter 2** : State-of-the-art is presented, starting with a brief introduction before the literature review. Literature advances were summarized for each of the sub-problems to be managed.
- **Chapter 3** : This chapter presents the articles dedicated to each objective in three main sections. Initially, it summarizes the modelling aspects to characterize the thermo-energetic environment of the energy community adequately. As a result, a Modelica model for ETS combined with a distributed cosimulation approach was developed. Next, distributed demand-side management with imperfect information was modelled while evaluating economic and technical feasibility. Finally, a risk-aware approach to anticipate non-desired scenarios related to thermal discomfort is proposed utilizing probabilistic constraints and propagating the risk

from the customer's optimal trajectory towards the resulting electricity price and the community's aggregated power consumption.

- **Chapter 4** : An in-depth discussion is presented to analyze the exhibited results from the previous chapter. A discussion of new opportunities and challenges that can be investigated regarding further research subjects is emphasized to generate optimized price policies.
- **Chapter 5** : Presents conclusions and recommendations. A synthesis of the work performed is presented, ending with recommendations that will allow future improvement of the proposed methods.

### **1.9 Assumptions**

1. The ETS self-discharge feature was set as a defined rate in a given period from similar studies. Furthermore, an extra thermal resistance element was introduced to calibrate the model in terms of thermal inertia so that it would be close to real data.
2. Parameters such as the density, heat transfer coefficient and thermal conductivity were assumed to be invariant in time. As for heat distribution, it was assumed to be uniform.
3. Building models do not represent the conventional jacked floor of Nordic housing code.
4. The heat transfer coefficient of electric thermal storage room units is taken equal to that of the electric baseboards in predictive control tasks.
5. There is willingness of community members to adopt electrified heating systems, and to pay for the respective capital and operative expenses that the proposed transition implies.
6. Building thermal dynamics react linearly to external perturbations from climate

conditions. The constructed building models did not consider uncertainties from human-behaviors such as occupancy profiles and opening/closing windows.

7. Community members reveal their best and most accurate responses and are supposed to be rational agents. This thesis did not address aspects about mechanism design.
8. There are no means to share information between customers during the energy coordination game.

## Chapter 2 - State-of-the-art

The notion of energy communities arises primarily to bridge energy gaps and empower end-customers. This concept originated in Denmark during the 1970s, when Danish communities formed community-owned wind energy projects. These cooperatives pooled local resources to install wind turbines, marking one of the first large-scale implementations of community-owned renewable energy. Other similar initiatives took place in Germany, the Netherlands and the United States. However, at that time, small-scale deployment of renewable energy projects faced high upfront costs, and advances in power electronics had not yet occurred.

However, this new century has brought numerous advances in power electronics and materials science, which have enabled renewable energy sources, primarily solar photovoltaics and wind power, to experience substantial momentum. Then, the cost of such technologies decreased rapidly, and that trend is expected to continue in the upcoming years. Nowadays, implementing mature renewable projects is possible even at residential scales, which are characterised by higher capital expenses compared to utility-scale projects. These numbers can increase by at least twice (x2) in difficult-to-reach territories. Figure 2.1 provides a big picture of the timeline for the topics listed above.

The above context paves the way for stating that remote areas represent a huge potential for implementing power communities. That is because it is necessary to increase energy efficiency by reducing their dependence on fossil fuels. Such territories rely on dirty fuels to meet their essential heating needs. During winter, extreme subzero temperatures occur, and in Quebec, covering these needs accounts for approximately 80% of the total residential consumption. Additionally, the grid operator discourages the use of electricity to meet essential needs through tariffs, and building owners opt for dirty heating oils to keep their

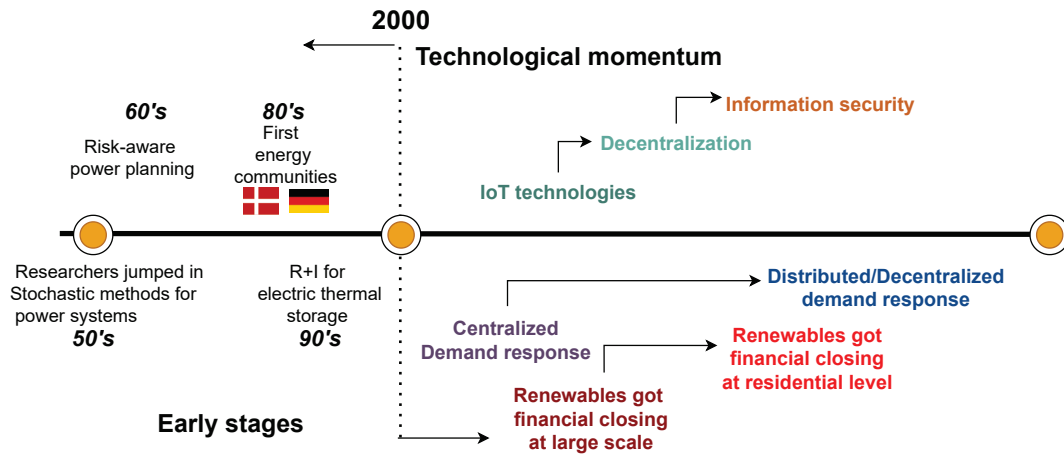


Figure 2.1 Timeline at a glance of the topics this thesis addresses.

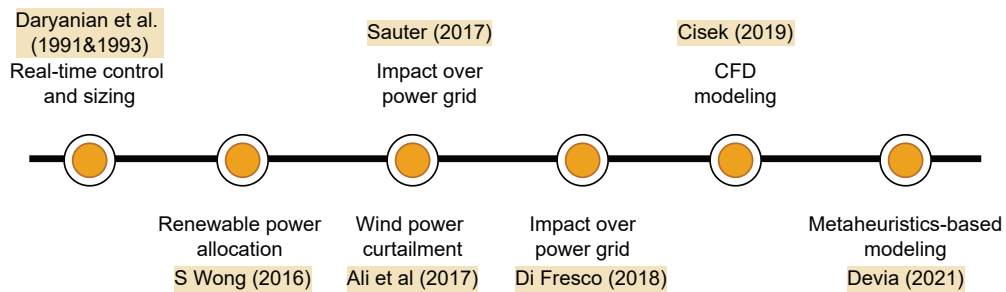


Figure 2.2 Timeline for ETS-related studies

dwelling warm.

Researchers have conducted studies to address the challenges that represent the typical operation of communities located in distant territories with harsh climate conditions. Previous studies have proposed mature technologies that rely on underground resources to meet space and water heating needs [15, 16]. Their high coefficient of performance, which is reflected in reduced operational expenses, is a significant advantage. However, district heating infrastructures are characterised by tremendous upfront costs, representing a major barrier to their deployment.

To overcome that limitation, other technologies, specialized to be portable and economically affordable became available. That is the case of electric thermal storage (ETS), a technology that appeared in the energy sector by the end of the 20th century. ETS have been the subject of study for multiple topics, including : real-time control and optimal sizing [28], renewable power allocation [29], mitigating wind power curtailment and enhancing demand response programs [24,30], and modelling (gray and white-box) [31,32]. Accordingly, Figure 2.2 illustrates how the literature has progressed on that topic.

As ETS will be incorporated into buildings in a distributed manner within low-voltage power grids, the coordination procedure for these assets is crucial to avoid creating adverse effects on the stability of the grids. Accordingly, with the momentum gained from distributed technologies, research has progressed into coordination algorithms that address the behaviour of individuals who act selfishly within a community. That can be seen in the second part of this storytelling.

Now, having a good understanding of how energy communities have experienced enhancements over time, and the way other storage technologies, such as ETS, have penetrated the market and advanced in literature during the last decades, it is time to discuss the pertinence of energy management strategies, uncertainty handling approaches and how such a concept fits into this thesis.

Over the last 20 years, distributed strategies have experienced significant momentum in several domains, including communications, information security, and energy, among others. The world is rushing, and the vast amount of information has motivated researchers and innovators to explore different ways to transition from centralized/monolithic layouts to distributed counterparts. Energy-wise, managing distributed resources presents multiple challenges at the primary, secondary, and tertiary levels. While both deal with inertia,

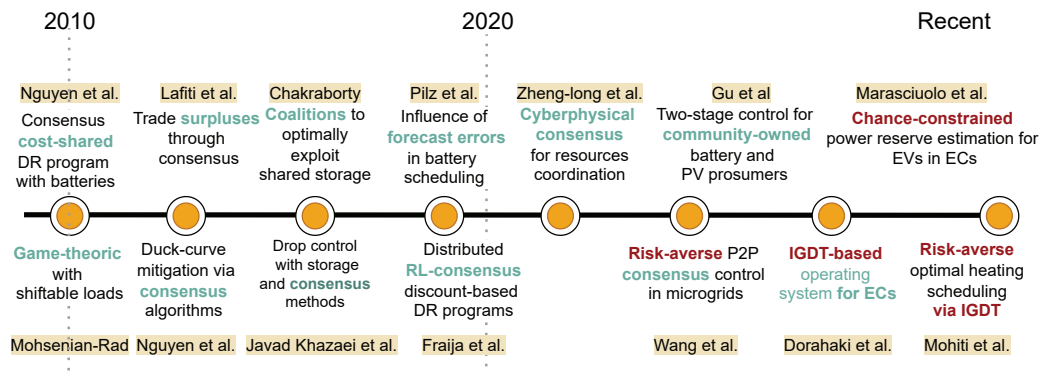


Figure 2.3 Timeline for stochastic demand response with distributed algorithms

short-circuit, frequency stability, and voltage control, the latter is responsible for optimally scheduling energy in time, utilizing available technologies. Accordingly, tertiary control optimizes power flow, using data from physical circuits, load and weather forecasts, and electricity markets.

However, when decisions are made individually, it is necessary to employ different mathematical approaches to address the opposing interests of participants in a demand response program. The literature suggests consensus algorithms as a means to manage large problems by effectively employing distributed optimization. Some of the most relevant works during the past fifteen (15) years are illustrated in Figure 2.3. These studies demonstrate not only the application of consensus algorithms in optimal energy management but also the growing interest among researchers in stochastic approaches to anticipate undesirable effects resulting from supply and demand-side uncertainties.

Although previous studies have made efforts to address random phenomena related to power grids, conventional approaches that average the realizations of the random variable in a specific objective do not always satisfy the decision-making requirements for robust energy planning. Although the concept of robustness appeared in the 1950s, its application

in power grids was not until some years later. Robust approaches enable performing worst-case analysis, which is highly beneficial for power grids. With the aid of thorough methods, conventional robust optimization has now given rise to other trends, such as distributionally robust optimization and chance-constrained optimization, which reduce the over-conservatism of the original methods.

Finally, to provide a detailed description of each component that comprises the main problem of this thesis, it was split into three sub-problems, which are listed in the following subsections. First, building integrated with ETS units and the way thermal dynamics can be modelled, given limitations to gather accurate data. Nevertheless, modelling aspects imply low-detail information to make synthetic data valuable. Afterwards, managing multiple buildings in a distributed manner can be challenging, as every building owner will have access to forecast services, and in the presence of renewable power, uncertainties will impact the strategy. To address that, it is necessary to adopt stochastic methods that show the best option for demand forecasting with imperfect information. Finally, when risk preferences are incorporated into the strategy, stochastic Monte Carlo methods become limited. To manage that, other decision-making that can better grasp customers' needs must be implemented. Mainly, because often risk terms in optimization problems account for non-convex, non-differentiable equations that compromise the problem's convexity.

## **2.1 Modelling aspects - Building thermal dynamics meet electric thermal storage**

### *2.1.1 Energy communities*

The growing energy demand and the transition towards renewable energy sources require efficient models for local energy generation and consumption. Accordingly, energy Communities allow for the sharing and management of locally produced renewable

energy, increasing self-sufficiency and reducing pressure on the grid. Developing energy communities involve many dimensions, including energy, water usage, computer science, social perspectives, and economics, among others [33].

One of the significant contributions of energy communities is the ability to introduce advanced mathematical models to predict energy production and consumption. Such models manage distributed energy resources, including photovoltaic systems, storage, wind turbines, heating, ventilation, cooling, and conditioning systems. The proper incorporation of mathematical models can help community members to optimally schedule their appliances, reducing their overall cost and maximising individual welfare. Figure 2.4 provides a structured overview of energy communities, highlighting key elements such as stakeholders, energy flows, modelling techniques, business models, and optimization strategies. It categorises resources into controllable and non-controllable assets, includes decision-making methods, and integrates data-driven approaches to enhance energy management.

Energy communities represent an approach to decentralize energy generation, distribution, and consumption, fostering sustainability and active participation from multiple stakeholders, including citizens, local governments, investors, and energy system actors. The implementation of these communities requires robust modeling, which encompasses building models, energy flow analysis, and data-driven approaches for demand forecasting, leveraging artificial intelligence and historical consumption patterns. Regarding resources, they can be classified as controllable (such as energy storage, electric vehicle charging, and HVAC systems) and non-controllable (such as photovoltaic panels and wind turbines), which influence overall grid optimization. From a business model perspective, energy communities can operate under local energy markets, third-party sponsorship, community

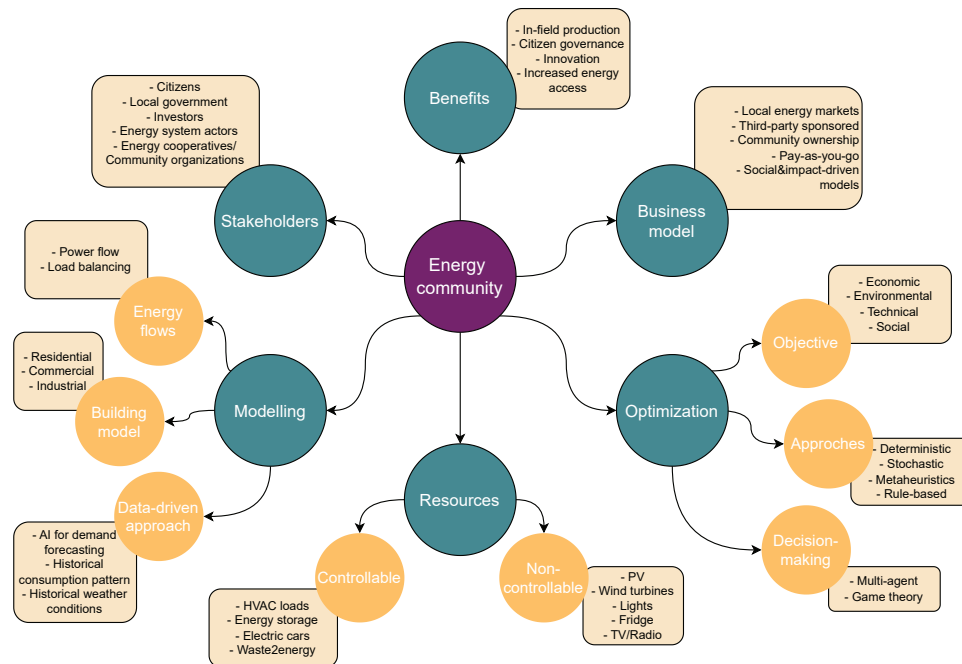


Figure 2.4 Conceptual framework of an energy community : stakeholders, resources, business models, and optimization approaches

ownership, and pay-as-you-go schemes, including social and impact-driven models. Optimization in these systems pursues economic, environmental, technical, and social objectives, employing deterministic, stochastic, metaheuristic, and rule-based approaches. Lastly, decision-making within energy communities relies on multi-agent models and game theory to coordinate interactions among prosumers, grid operators, and other actors, ensuring efficient and fair energy management.

### 2.1.2 Building's thermal dynamics

Building energy management to meet thermal needs has been a mature research subject for several decades. Regardless of the sector, including residential, commercial or industrial, a large share of daily processes requires heating/cooling loads to provide some goods or to guarantee occupants' thermal comfort. Although there may be challenges and opportunities

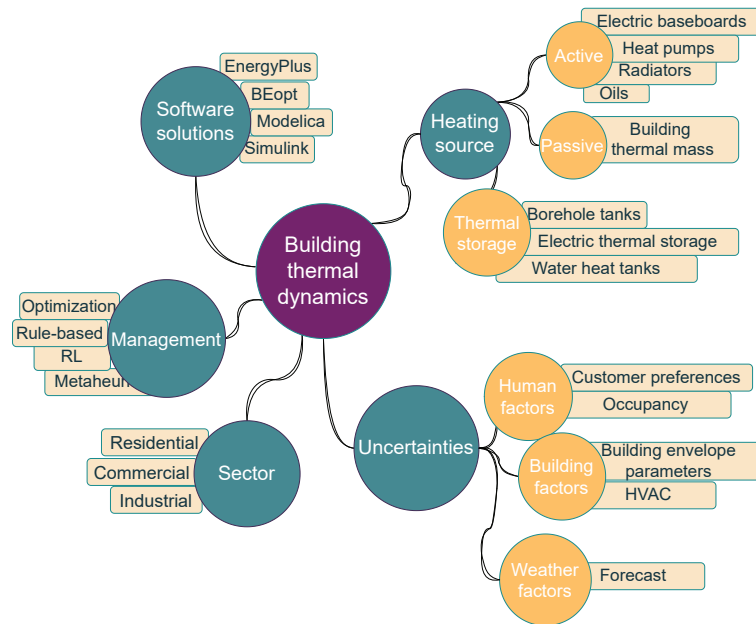


Figure 2.5 Main fronts of building thermal dynamics in research.

in the industrial and commercial sectors, the scope is limited to the residential sector, given the significant importance of the heating load during winter.

As depicted in Figure 2.5, building thermal dynamics encompass multiple research fronts, including management methods, heating vectors, uncertainties, and the sector of interest. First, software solutions appear in the landscape as a solution to provide advanced models that facilitate scenario generation and study cases. In this regard, tools such as EnergyPlus, BEopt, and Modelica are at the forefront of the current state-of-the-art in the literature [34, 35]. These rely on advanced mathematical methods and algorithms that provide a great understanding of building thermal dynamics, considering weather conditions and other factors. Additionally, literature reports demand-side management strategies to meet thermal loads using rule-based control and optimisation methods (see Section 2.2). These can be deployed at various levels, including residential, commercial, and industrial. Next, heating sources can be divided into two main segments : active and passive. Besides,

thermal storage has mainly been exploited to cope with heating needs. In this regard, the literature reports a large number of papers that utilise combined cooling, heating, and power (CCHP), as well as heat pumps and radiators through district heating [36]. While heat pumps outperform all their counterparts in terms of the coefficient of performance (COP), they entail high capital expenses for underground piping infrastructure, which limits their adoption. Subsequently, building thermal dynamics are not exempt from uncertainties that can come from human factors (customer preferences, occupancy profiles), weather conditions (forecast errors), and the physics of the system itself (envelope parameters and HVAC systems).

### *2.1.3 Thermal energy storage*

Thermal Energy Storage plays a fundamental role in the energy transition, particularly for meeting residential heating needs efficiently and sustainably. Despite the growing demand for more efficient heating solutions, significant challenges persist regarding the widespread implementation of advanced TES technologies. Economic, technical, and regulatory constraints often limit the adoption of innovative systems, particularly in the residential sector where property owners tend to prioritize solutions with reduced initial costs and proven technologies.

Thermal Energy Storage plays a fundamental role in the energy transition, particularly for meeting residential heating needs efficiently and sustainably. Despite the growing demand for more efficient heating solutions, significant challenges persist regarding the widespread implementation of advanced TES technologies. Economic, technical, and regulatory constraints often limit the adoption of innovative systems, particularly in the residential sector, where property owners tend to prioritise solutions with reduced initial costs and proven technologies.

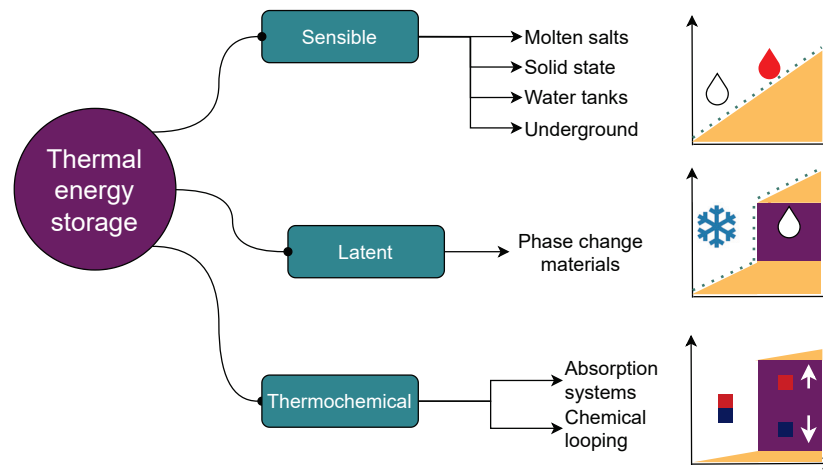


Figure 2.6 Classification of thermal energy storage methods based on storage mechanisms.

The classification of thermal storage systems is primarily based on the physical or chemical mechanisms they employ to store energy, each with distinctive characteristics that determine their suitability for specific applications. Figure 2.6 presents a classification of thermal energy storage (TES) into three main categories based on their storage mechanisms: Sensible heat storage (top) relies on increasing the temperature of a storage medium, such as molten salts, solid-state materials, water tanks, or underground reservoirs. The associated diagram illustrates a linear temperature rise as heat is stored. Latent heat storage (middle) uses phase change materials (PCMs) that absorb/release heat during phase transitions (e.g., solid-liquid). The diagram shows a constant-temperature plateau, representing the phase change process. Thermochemical storage (bottom) stores energy through chemical reactions such as absorption systems and chemical looping. The diagram depicts the reversible nature of chemical energy storage and release.

Nevertheless, the feasibility of thermal storage relies on the scalability of the application in which it is needed. As shown in Figure 2.7, sensible heat-based systems

currently dominate the residential market due to their simplicity, technological maturity, and cost-effectiveness. Nevertheless, emerging latent heat and thermochemical storage technologies present considerable potential for future applications, offering greater energy density and long-term storage capabilities that could significantly transform the energy landscape of the building sector.

Currently, 46% of the global installed TES capacity to cope with heating needs is tailored for buildings, as noted in [2]. Figure 2.7 states that the most suitable application to cover heating needs in residential buildings is sensible thermal storage. While latent and thermochemical solutions represent potential options for the future, they currently remain demonstration/prototype projects that have not yet achieved financial closure. Within this context, residential applications often require a large share of building owners to opt for water-based heating sources, given their maturity and cost competitiveness.

Thermal storage is divided mainly into three separate categories : multiple manners, as indicated in Figure 2.6. Sensible heat storage stores energy based on temperature changes of a material. It represents the simpler design, and since it is difficult to maintain a constant temperature, its main uses are for short-term applications. Latent heat storage stores energy based on the absorption or release of heat during a material's phase change. Thermochemical heat storage, in contrast, stores energy based on chemical reactions and sorption systems, and can be used for inter-seasonal energy storage.

Among the various solutions for sensible heat storage, Electric Thermal Storage (ETS) has emerged as a particularly viable solution for specific geographic and economic contexts. ETS systems represent an intersection between traditional heating methods and modern demand-side management schemes, offering significant advantages, especially in regions where other options present substantial implementation barriers. While sensible water-based

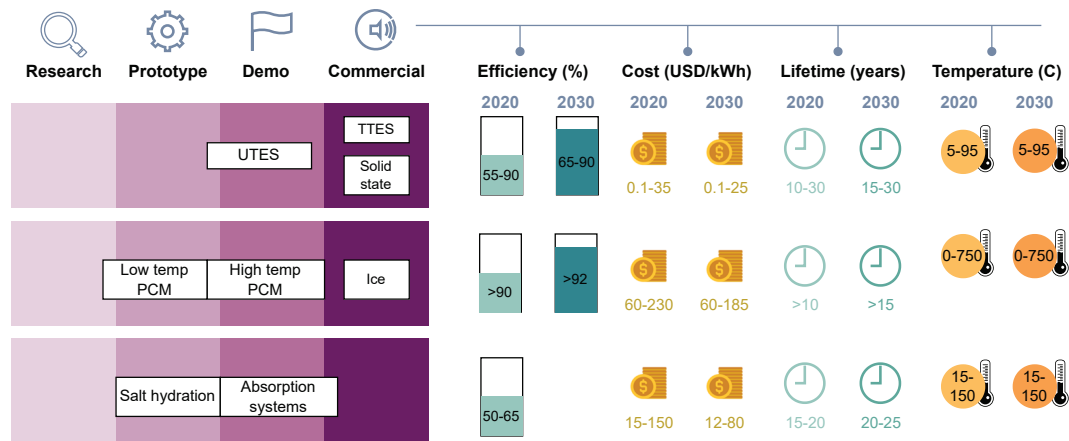


Figure 2.7 Thermal energy storage status and innovation in the building sector (adapted from [2])

storage remains predominant in accessible urban environments, ETS provides an interesting alternative for areas where conventional heating infrastructure faces logistical or financial obstacles. This technology leverages the electrical grid's flexibility to store thermal energy during advantageous periods, effectively decoupling the time of energy generation from consumption while maintaining reliable heating capacity for residential applications.

Furthermore, electric thermal storage represents a cost-effective solution that facilitates the integration of renewable energy sources, not only bringing economic benefits to building owners but also reducing initial capital expenditure compared to district heating systems. Nevertheless, two principal barriers emerge concerning ETS implementation : i) accurate mathematical modeling of system behavior and ii) effective integration within demand response frameworks. The former challenge has been extensively investigated in previous research [29,37]. Similarly, substantial contributions regarding the latter challenge can be found in the literature [24, 30, 38].

ETS systems exhibit diversity in their configurations. They are primarily differentiated by the composition of the storage medium, their spatial placement within structures, and the

methodologies used for electrical-to-thermal energy conversion. Storage media typically comprise either liquid or solid materials, each offering distinct thermodynamic properties. With respect to placement, ETS units may be installed directly within the heated living space or centrally positioned (e.g., in basement areas) to provide thermal distribution throughout the dwelling. The conversion process from electrical to thermal energy can be accomplished via two principal mechanisms : heating elements (resistive rods) or through heat pump technology. The latter offers a superior coefficient of performance, albeit at a higher initial investment. Figure 2.9 illustrates a global picture of research topics regarding ETS systems.

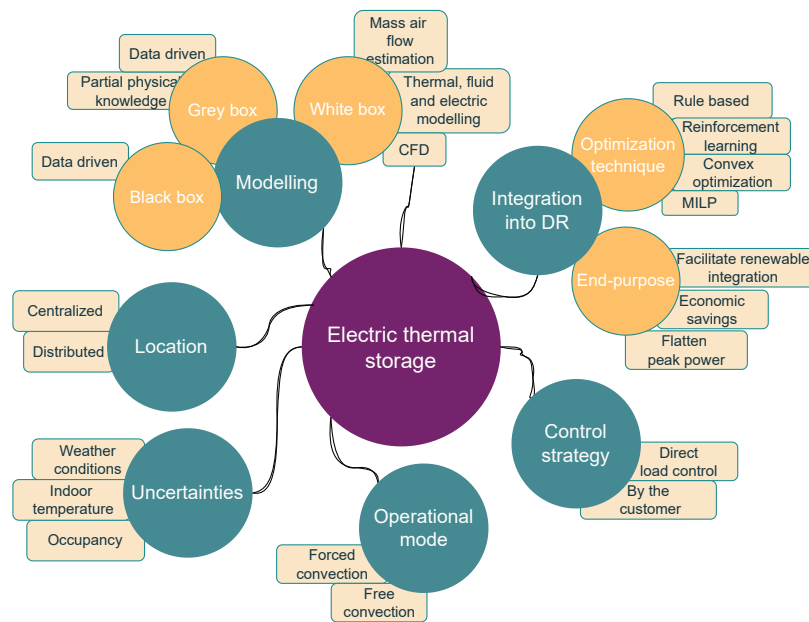


Figure 2.8 Key aspects of Electric Thermal Storage Systems

In this thesis, brick-core thermal storage systems are analyzed. They convert electrical energy into heat using heating rods placed between high-density bricks, where thermal energy is stored. The bricks are enclosed in an insulated box to minimize self-discharge. The heat can be pulled off from the system either passively or actively : if a controlled

fan is present, air is blown through channels in the bricks, enabling forced convection. Conversely, if there is no fan, the system operates under free convection. Typically, ETS systems are charged during off-peak hours when electricity prices are lower. Figure 2.9 illustrates this concept. They are commercially available at different scales for residential buildings, differing mainly in their maximum electric power and thermal storage size. Typical systems vary in size from 1.32 to 10.8 kW and 13.5 to 40 kWh.

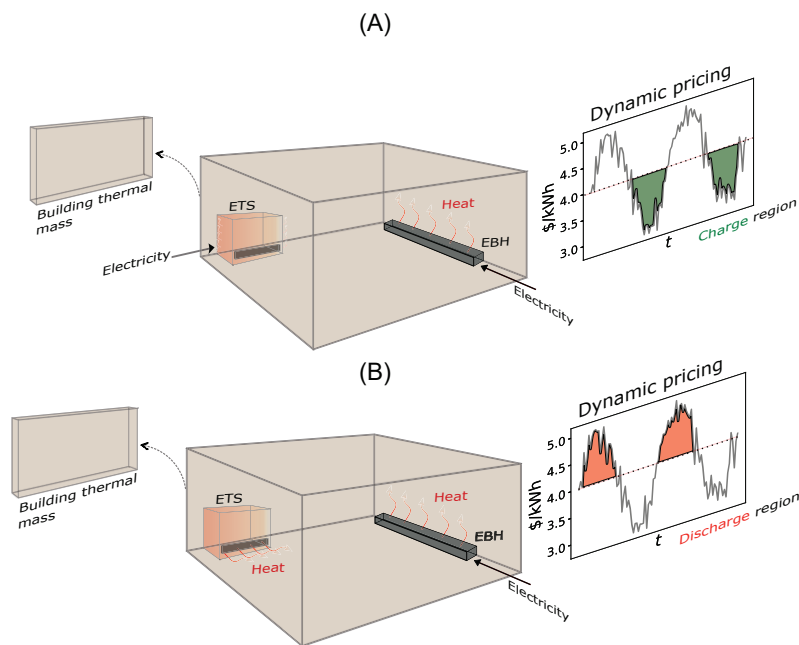


Figure 2.9 Electric thermal storage (ETS) operation under dynamic pricing : (A) Charging during low-cost periods and (B) Discharging during high-cost periods.

Currently, the number of papers on this topic is limited especially when it comes to detailed models that accurately represent the complex thermal dynamics of such units. Grey-box models have been proposed [31] using meta-heuristic methods to compute an RC equivalent, one representing the charge and the other representing the discharge procedure. However, that model is only feasible for a particular system ; therefore, parameter estimation

should be done for every device in the market. Other approaches introduced cyber-physical models but do not reveal detailed information about how every heat component was estimated [39]. Other works adopt linear models that [24] consider self-discharge terms, but still rely on black-box models, which do not accurately reflect the complex phenomena that ETS units experience.

The main drawback with real-world data studies is that they provide a static *current* picture; therefore, their use is limited to a very narrow set of scenarios. To gain a better understanding of the ETS units' performance, it is necessary to utilise flexible tools that can be quickly modified. As stated by [40], this flexibility can only be achieved by models. Accordingly, this thesis proposes a Modelica-based ETS model.

Table 2-1 Existing papers focusing on electric thermal storage

Ref	ETS model	Building model	Co-simulation	Physics-based controller	Research Domain	End-purpose
[24]	Grey-box	Grey-box	x	x	Optimal control	Evaluating the potential of ETS and wind power to meet isolated grid's electric supply needs
[29]	black-box	x	x	x	Optimal control	Introducing customer behavior characteristics in the optimal scheduling of ETS for reduced wind power curtailment
[39]	Grey-box	x	x	x	Optimal control	Reducing wind power curtailment with ETS surpluses for auxiliary thermal network
[41]	black-box	x	x	x	Optimal control	Evaluating the impact of ETS on distribution grids
[42]	black-box	Grey-box	x	x	Optimal control	Incentive-based distributed mechanism through an ETS-enabled demand response program
<b>This</b>	Modelica	EnergyPlus	✓	✓	Modeling	To model residential building's thermal dynamics in the presence of ETS

Although Modelica models exhibit excellent performance, they are insufficient on their own, as interaction with a building model is required to evaluate the impact on the building's thermal dynamics. This issue is often addressed through cosimulation methods. Accordingly, many papers exist that employ these methods [43–50]. However, none of these have addressed the interaction between building and ETS units. Accordingly, this thesis employs co-simulation methods to enable such interaction. This leads to a solid co-simulation framework that adequately characterizes the buildings' thermal dynamics in the presence of ETS.

## **2.2 Distributed energy management with imperfect information**

Several papers have conducted efforts in introducing diverse intermittent phenomena into decision-making process, particularly on renewable power availability [51–55], user occupancy [56–58], load profiles [59–61], among others. Figure 2.12 summarizes the possibilities in which uncertainty is often introduced in decision-making procedures.

### *2.2.1 Uncertainty Propagation*

The impact of fluctuations in the random variables propagates through the system, influencing all terms that depend on the uncertain parameters. For instance, Eqns. (2.1)(2.2) illustrate a classical two-stage optimization problem. In this formulation,  $\xi$  denotes a random variable,  $f^F(x)$  represents the first-stage decisions made prior to the realization of uncertainty, and  $f^S(x)$  corresponds to the second-stage (recourse) decisions that adjust in response to the revealed value of  $\xi$ .

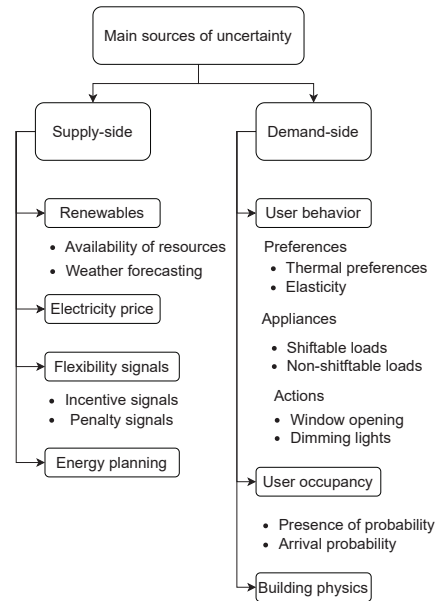


Figure 2.10 Principal factors introducing uncertainty in smartgrids.

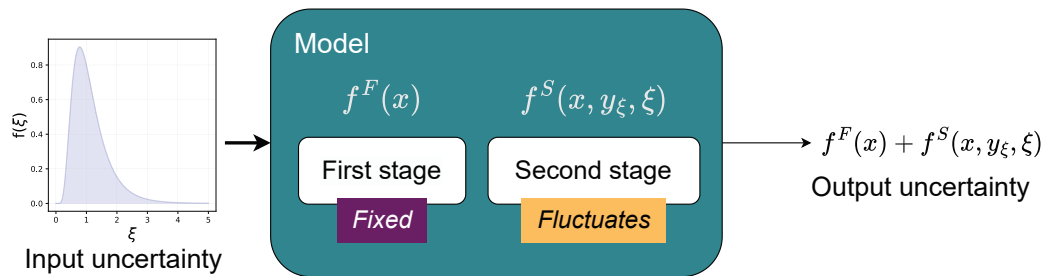


Figure 2.11 Two-stage uncertainty propagation : fixed first stage, fluctuating second stage.

$$\min_{x, y_{\xi}} f^F(x) + f^S(x, y_{\xi}, \xi) \quad (2.1)$$

s.t.

$$h_F(x) = 0, \quad g_F(x) \leq 0, \quad (2.2)$$

The impacts of variations in the uncertain parameter  $\xi$  propagate through the model,

influencing both the second-stage cost  $f^S(x, y, \xi)$  and, in some cases, the system constraints. For instance, system operators must maintain power balance when renewable generation fluctuates, which may require producing more or less power, thereby affecting the overall system cost. Additionally, variations in renewable generation can induce changes in power flows and voltage magnitudes, potentially leading to constraint violations. Consequently, understanding these effects is challenging, as it requires accounting for multiple sources of uncertainty and their combined influence. To better analyze how uncertainty propagates through the system, it is useful to distinguish between input uncertainty and output uncertainty. The former corresponds to the non-controllable source of variability,  $\xi$ , while the latter is associated with the responses of the system, such as  $f^F(x)$  and  $f^S(x, y, \xi)$ . Figure 2.11 provides a visual representation of this relationship. Estimating input uncertainty  $\xi$  is typically more straightforward, as it can often be characterized using historical data or probabilistic forecasting methods. However, even with perfect forecasts for each uncertainty source, determining how multiple sources of uncertainty interact and jointly propagate through the model can be complex. This challenge is further exacerbated in systems governed by non-linear and non-convex equality constraints, such as the AC power flow equations. Therefore, when selecting an uncertainty representation, researchers must consider methods that adequately capture both input and output uncertainties to ensure reliable decision-making under uncertainty.

### *2.2.2 Uncertainty Representation*

The appropriate selection of an uncertainty representation is often constrained by the limited availability of detailed real-world data describing the random variable. When determining which representation to employ, it is essential to consider : i) the information available about the probability distribution of the random variable, ii) the conditions under

which data can be accessed, and iii) the expected quantity and quality of data that can be collected. Addressing these aspects helps guide the choice of an uncertainty representation, as the answers may point toward different modeling approaches depending on the data characteristics and uncertainty structure. Figure 2.12 illustrates a two-dimensional uncertainty distribution along with several common representation methods, which are further discussed below.

**Probability distribution :** In some cases, it is feasible to directly handle the probability distribution of the random variable. Depending on the nature of the uncertainty, the problem may retain a linear structure, allowing quantities to be expressed as weighted linear combinations of the random parameters. In practice, researchers sometimes address uncertainty by substituting it with their best estimate commonly referred to as the certainty equivalent problem. In such cases, the random variable is replaced by its expected value (mean) or, less frequently, by its mode.

Aside, other approaches assume perfect information, in which it is presumed that the realization of the random variable is known in advance. This replaces the uncertain parameters with their actual outcomes, providing the best possible (yet idealized) solution. Although unrealistic in real-world contexts, this practice is highly valuable as a benchmark, offering insights into the upper performance bound of the system under complete information.

**Ambiguity sets :** In many practical situations, only partial knowledge of the probability distribution of the random variable is available either because the true distribution is unknown or because it is computationally intractable to handle directly. To address this challenge, a common approach is to identify a family of plausible distributions that the uncertain parameter may belong to. This family is commonly referred to as an ambiguity set.

A distributionally robust representation of uncertainty accounts for all possible distributions within this ambiguity set, therefore ensuring that the solution remains feasible and performs well under distributional ambiguity. The literature distinguishes between moment-based and metric-based ambiguity sets. Both can be constructed using empirical data, which makes this approach inherently data-driven and suitable for real-world applications where full probabilistic information is unavailable.

**Geometrical sets :** In some cases, it may be impossible to estimate the probability distribution of the random variable. In such situations, the researcher may instead aim to guarantee that the solution remains feasible across a specified range of possible realizations. Here, the random variable is defined as any realization within a given uncertainty set. Common representations of uncertainty sets include ellipsoidal, box-constrained, and more general polyhedral sets, which are often constructed using data-driven techniques [62]. The uncertainty set can be designed to represent either (i) all plausible realizations of the random variable, hence capturing the bounded support of its probability distribution, or (ii) only those realizations against which the decision-maker wishes to safeguard the solution. It is important to note that a larger uncertainty set – encompassing a broader range of realizations – typically results in a more conservative, robust and subsequently more expensive solution.

### *2.2.3 Distributed energy management*

Energy management can be performed in centralized, distributed, or decentralized architectures, as illustrated in Figure 2.13. Distributed energy management has been extensively studied over the past decades using a wide range of optimization techniques. Among these, consensus optimization stands out as one of the most effective approaches to decompose large and complex problems into smaller, tractable subproblems [63]. In

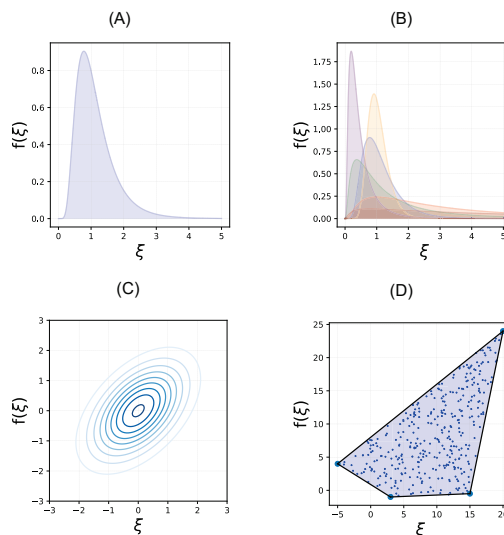


Figure 2.12 Different uncertainty representations : (A) probability density, (B) distribution ambiguity, (C) elliptical, and (D) polyhedral robust sets.

essence, the objective is to coordinate the solution of a global optimization problem among multiple agents, nodes, or processors, while minimizing communication overhead and ensuring convergence to a consistent global optimum.

Figure 2.13 illustrates the main paradigms of energy management explored in the literature. In Figure 2.13A, the grid operator directly controls household energy consumption through a Centralized Energy Management System (CEMS). The operator transmits a control signal  $u_k$  to each household, meaning that consumption decisions are imposed unidirectionally. In this configuration, users have limited control over their appliances, as the utility optimizes heating device operation to ensure grid stability. In Figure 2.13B, energy management is conducted by a top-entity –such as a community coordinator– who formulates a price policy and broadcasts it to households. Consumption decisions remain individual but depend on the price signals provided by the coordinator.

Each building is equipped with a Home Energy Management System (HEMS) that adjusts its heating appliances in response to the price trajectory  $\pi_k$  and the optimal trajectory  $u_k$ . This configuration allows for greater user flexibility, although some dependence on the coordinator persists. Eventually, Figure 2.13C represents a fully decentralized architecture, where no central authority coordinates energy consumption. Instead, households make autonomous decisions based on local interactions with their neighbors. Each home operates its own HEMS, which exchanges price information and consumption decisions with others, forming a fully collaborative network. This approach maximizes user autonomy and enables highly flexible behaviors, though it also requires consensus mechanisms and stability management to prevent grid imbalances.

A key challenge in implementing distributed and decentralized energy management lies in ensuring that control strategies remain non-intrusive, i.e., they do not require excessive data sharing or central intervention. Unlike traditional centralized schemes that impose direct control over household devices, these architectures aim to preserve user autonomy while still achieving global efficiency. Privacy preservation, communication overhead, and computational scalability are major factors influencing their feasibility. Consequently, the development of algorithms that minimize private data exchange while maintaining reliable and efficient coordination among agents remains a central research focus.

#### *2.2.4 Distributed optimization methods*

**Proximal algorithm :** Proximal methods offer a rough framework for regularized problems with penalties that are tailored to a specific problem application. Such customized penalties facilitate solving the problem iteratively. A simple interpretation to grasp proximal decomposition methods is that regularization that goes away in the limit. In each iteration we can solve the regularized problem :

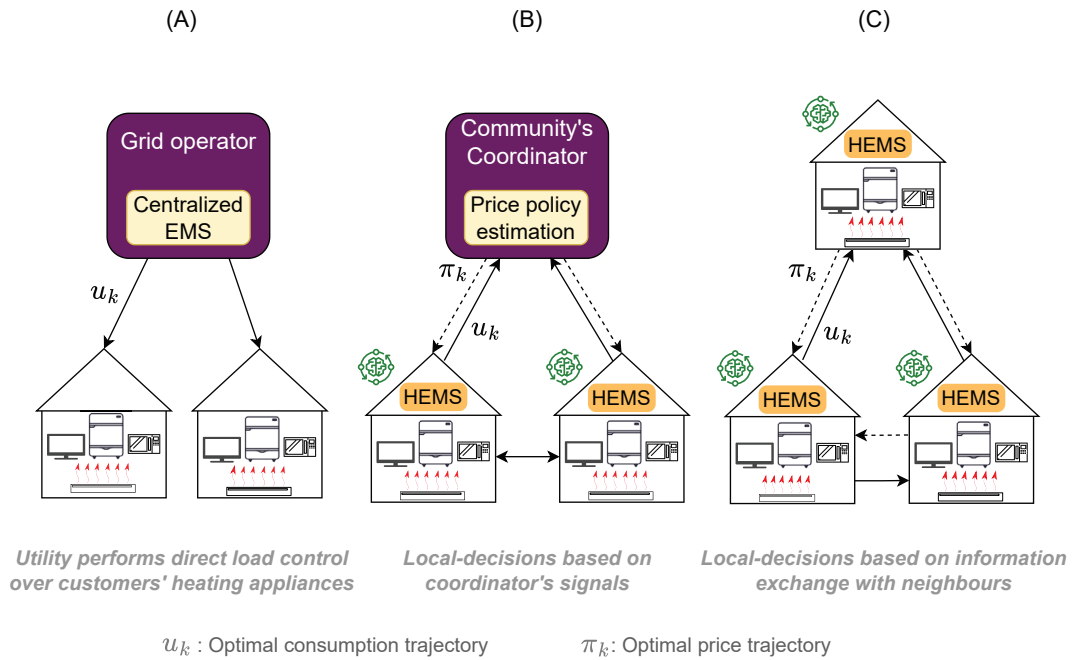


Figure 2.13 Comparison of energy management strategies. Illustration of (A) centralized, (B) distributed, and (C) decentralized energy management approaches.

$$\text{Minimize } f(x) + \frac{1}{2} \lambda \|x - x^r\|_2^2 \quad (2.3)$$

where  $r$  is the iteration index and  $\lambda$  is a regularization parameter. The second term can be interpreted as quadratic regularization centered at the previous iterate  $x^r$ ; in other words, it is a damping term that encourages  $x^{r+1}$  not to be very far from  $x^r$ .

**ADMM** : The alternating direction method of multipliers (ADMM), also known as Douglas-Rachford splitting, and can be understood as an augmented Lagrangian. Let's write the problem of minimizing  $f(x) + g(x)$  as

---

**Algorithm 1** Proximal Decomposition
 

---

- 1 : **Input** : Initial point  $x^0$ , step size  $\lambda > 0$ , tolerance  $\varepsilon$
  - 2 : **Initialize** : Set iteration counter  $r = 0$
  - 3 : **Repeat until convergence** :
  - 4 :   Solve the proximal subproblems in parallel :
  - 5 :    $x_i^{r+1} = \arg \min_{x_i} \left( f_i(x_i) + \frac{\lambda}{2} \|x_i - x^r\|^2 \right), \quad \forall i$
  - 6 :   Compute the consensus update :
  - 7 :    $x^{r+1} = \frac{1}{N} \sum_{i=1}^N x_i^{r+1}$
  - 8 :   Update iteration counter  $r = r + 1$ .
  - 9 : **End Repeat**
  - 10 : **Output** : Optimal solution  $x^* = 0$
- 

$$\text{Minimize } f(x) + g(z) \tag{2.4}$$

$$\text{Subject to } Ax + Bz = c \tag{2.5}$$

The augmented Lagrangian associated is :

$$L_\rho(x, z, y) = f(x) + g(z) + y^T (Ax + Bz - c) + \frac{\rho}{2} \|Ax + Bz - C\|_2^2 \tag{2.6}$$

which is called consensus form. Here, the variable has been split into two variables  $x$  and  $z$ , and we have added the consensus constraint that they must agree. This is evidently equivalent to minimizing  $f + g$ .  $\rho > 0$  is a parameter and  $y \in Rn$  is a dual variable associated with a consensus constraint. This is the usual Lagrangian augmented with an additional quadratic. So the ADMM can then be expressed as :

$$x^{r+1} := \operatorname{argmin}_x L_\rho(x, z^r, y^r) \quad (2.7)$$

$$z^{r+1} := \operatorname{argmin}_z L_\rho(x^{r+1}, z, y^r) \quad (2.8)$$

$$y^{r+1} := y^r + \rho(Ax^{r+1} + Bz^{r+1} - c) \quad (2.9)$$

In each of the  $x$  and  $z$  steps,  $L_\rho$  is minimized over the variable, using the most recent value of the other primal variable and the dual variable. The dual variable is the (scaled) running sum of the consensus errors. The advantage of the ADMM is that the objective terms (which can both include constraints, since they can take on infinite values) are handled completely separately, and indeed, the functions are accessed only through their proximal operators. Algorithm (2) summarizes the whole procedure.

---

**Algorithm 2** Alternating Direction Method of Multipliers (ADMM)

---

- 1 : **Input** : Initial values  $x^0, z^0, y^0$ , parameter  $\rho > 0$ , tolerance  $\varepsilon$
  - 2 : **Initialize** : Set iteration counter  $r = 0$
  - 3 : **Repeat until convergence** :
  - 4 :   Solve the  $x$ -update :
  - 5 :      $x^{r+1} = \operatorname{argmin}_x (f(x) + \frac{\rho}{2} \|Ax + Bz^r - c + y^r/\rho\|^2)$
  - 6 :   Solve the  $z$ -update :
  - 7 :      $z^{r+1} = \operatorname{argmin}_z (g(z) + \frac{\rho}{2} \|Ax^{r+1} + Bz - c + y^r/\rho\|^2)$
  - 8 :   Update the dual variable :
  - 9 :      $y^{r+1} = y^r + \rho(Ax^{r+1} + Bz^{r+1} - c)$
  - 10 :   Update iteration counter  $r = r + 1$ .
  - 11 : **End Repeat**
  - 12 : **Output** : Optimal solution  $(x^*, z^*, y^*) = 0$
- 

**Bender's decomposition** : It is a technique that allows solving very large linear programming problems that have a block structure, a common in stochastic programming where the uncertainty is usually represented with scenarios. With the Benders decomposition, the variables of the original problem are divided into two subsets so

that a master problem (first-stage decisions) is solved over the first set of variables, and the values for the second set of variables are determined in a slave (second stage) subproblem for a given first-stage solution. If the subproblem states that the first-stage decisions are infeasible, then *Benders cuts* are transferred to the master problem, which is then re-solved until no cuts can be generated. That is why this method is also called "row generation". Let's consider the general optimization problem :

$$\text{Minimize } f(x,y) \tag{2.10}$$

$$\text{Subject to } g(x,y) \leq 0, \tag{2.11}$$

$$x \in X, \quad y \in Y, \tag{2.12}$$

where  $x$  represents the complicating variables, typically integer or discrete, and  $y$  represents the continuous variables. Benders' decomposition reformulates this as a two-stage process, solving a master problem for  $x$  and a subproblem for  $y$  given a fixed  $x$ . Algorithm (3) summarizes the whole procedure.

---

### Algorithm 3 Benders' Decomposition

---

- 1 : **Input** : Initial master problem with relaxed constraints
  - 2 : **Initialize** : Set iteration counter  $r = 0$ , select an initial feasible  $x^r$
  - 3 : **Repeat until convergence** :
  - 4 :   Solve the **Subproblem** given  $x^r$  to obtain  $y^r$  and dual variables.
  - 5 :   If the subproblem is infeasible, generate a feasibility cut and add it to the master problem.
  - 6 :   If the subproblem is feasible, compute the optimality cut and add it to the master problem.
  - 7 :   Solve the **Master Problem** to obtain new  $x^{r+1}$ .
  - 8 :   Update iteration counter  $r = r + 1$ .
  - 9 : **End Repeat**
  - 10 : **Output** : Optimal solution  $(x^*, y^*) = 0$
-

**Distributed Newton's Method :** Newton's method is a second-order optimization algorithm that uses Hessian information to achieve quadratic convergence near an optimum. In distributed settings, solving Newton's method efficiently requires partitioning computations across multiple nodes while preserving the curvature information of the function being optimized. The general form of a constrained optimization problem is given by

$$\text{Minimize } f(x) \tag{2.13}$$

$$\text{Subject to } h(x) = 0, \quad g(x) \leq 0 \tag{2.14}$$

where  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  is a twice-differentiable objective function,  $h(x)$  represents equality constraints, and  $g(x)$  represents inequality constraints. The Newton step is derived from the second-order Taylor expansion of the Lagrangian function

$$L(x, \lambda, \nu) = f(x) + \lambda^T h(x) + \nu^T g(x), \tag{2.15}$$

where  $\lambda$  and  $\nu$  are the dual variables associated with the constraints. The Newton direction  $\Delta x$  is obtained by solving the linearized KKT system.

In a distributed setting, computing the Newton step efficiently requires parallelizing the evaluation of the Hessian and gradient while solving the linear system in a decentralized manner. A common approach is to use decentralized consensus algorithms to approximate the Newton direction without forming the full Hessian explicitly. The distributed Newton method can then be summarized as follows by Algorithm 4 :

---

**Algorithm 4** Distributed Newtons Method
 

---

- 1 : **Input** : Initial point  $x^0$ , tolerance  $\varepsilon$
  - 2 : **Repeat until convergence** :
  - 3 :   Compute  $\nabla f(x^r)$  and  $\nabla^2 f(x^r)$  in parallel across nodes.
  - 4 :   Solve the linearized system for  $\Delta x^r$  using a distributed solver.
  - 5 :   Perform backtracking line search to determine step size  $\alpha$ .
  - 6 :   Update the primal variable :  $x^{r+1} = x^r + \alpha \Delta x^r$ .
  - 7 : **End Repeat**
  - 8 : **Output** : Optimal solution  $x^* = 0$
- 

### 2.2.5 Optimization approaches depending on information's nature

By recognizing that this thesis employs uniquely model-based approaches, it is necessary to define the possible ways to manage problems depending whether imperfect information exist or not. Accordingly, this section aims to introduce the main approaches to solve situations in which uncertainty meets the panorama. That is summarized in Figure 2.14.

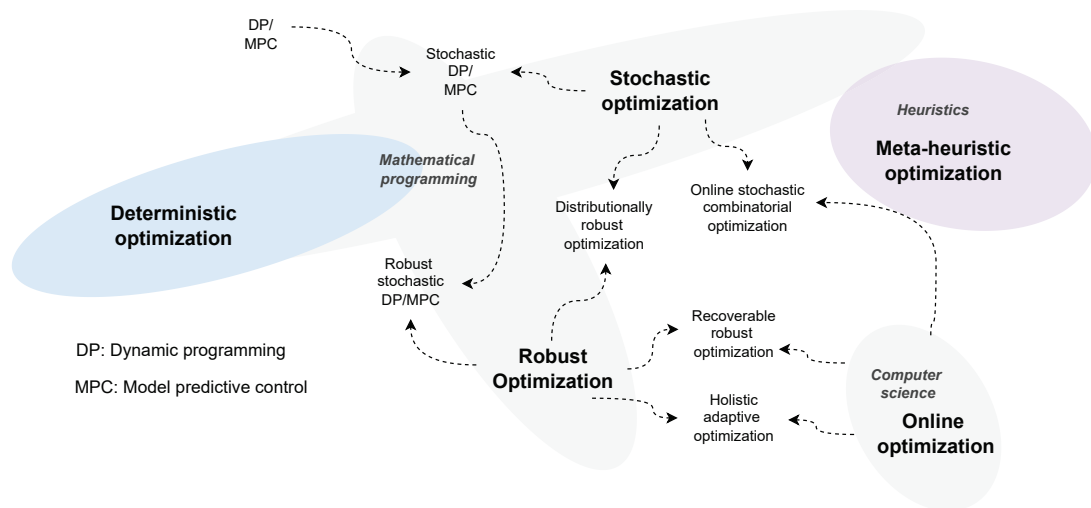


Figure 2.14 Main optimization methods regarding distributed energy management in literature.

**Deterministic optimization :** A mathematical formulation for a deterministic problem can be represented as :

$$\text{Minimize } f(\mathbf{x}) \quad (2.16)$$

$$\text{s.t} \quad (2.17)$$

$$g_i(\mathbf{x}) \leq 0, \quad i = 1, 2, \dots, m,$$

$$h_j(\mathbf{x}) = 0, \quad j = 1, 2, \dots, n. \quad (2.18)$$

$$\mathbf{x} \in \mathcal{X}. \quad (2.19)$$

where  $x$  is a decision variable,  $g_i$  is a function that depends on  $x$ , and  $h_j$  is a set of constraints the system must satisfy.

**Stochastic optimization :** When uncertainties meet the system, it is necessary to address them in a proper manner. In this regard, the mathematical problem below encompasses a convex optimization that minimizes the expected value of a cost function :

$$\text{Minimize } \mathbb{E}_{\xi \sim F_x(X)} [f(\mathbf{x}, \xi)] \quad (2.20)$$

st.

$$g_i(\mathbf{x}, \xi) \leq 0, \quad i = 1, 2, \dots, m, \quad (2.21)$$

$$h_j(\mathbf{x}, \xi) = 0, \quad j = 1, 2, \dots, n, \quad (2.22)$$

$$\mathbf{x} \in \mathcal{X}. \quad (2.23)$$

where  $x$  is a decision variable,  $g_i$  is a function that depends on  $x$ , and  $h_j$  is a set of

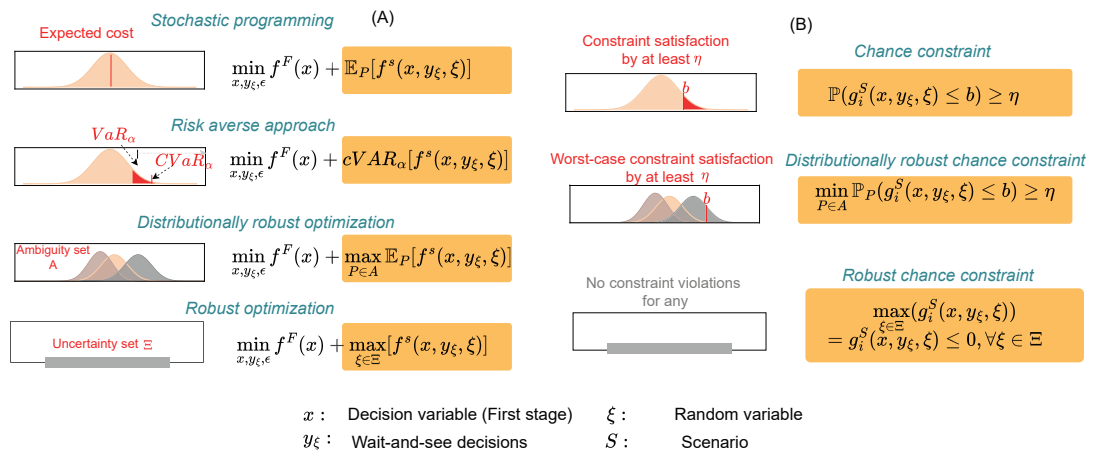


Figure 2.15 An overview of formulations for optimization problems under uncertainty by managing it through the (A) objective function and (B) the set of restrictions

constraints the system must satisfy.  $\xi$  is a random variable that suits a function  $F_x(X)$  with a given PDF. This problem can be solved through the realization of the random variable via multiple scenarios which can have or not the same probability of occurrence.

**Robust optimization :** Robust decisions are required when the system is under uncertainties and decisions must anticipate challenging scenarios. However, the difficulty when implementing this approach is not only mathematical but also about pertinency, to properly establish whether it is in fact important to have reliable decisions as the operational system cost will increase. Figure 2.15 summarizes optimization approaches when the notion of *risk* joins decision-making theory. It is evident that the risk aversion can be handled from the objective (see Fig. 2.15A) or constraints (see Fig. 2.15B) viewpoint.

**Worst-case optimization :** It represents the most used approach as it does not depends on probability functions to estimate the uncertainty boundaries in the problem. Indeed, such boundaries are user-defined and have geometrical representations. The canonical representation of a robust optimization problem in a convex setting is given by :

$$\text{Minimize } f(\mathbf{x}) \quad (2.24)$$

s.t.

$$g_i(\mathbf{x}, \mathbf{u}) \leq 0, \quad \forall \mathbf{u} \in \mathcal{U}, \quad i = 1, 2, \dots, m, \quad (2.25)$$

$$h_j(\mathbf{x}, \mathbf{u}) = 0, \quad \forall \mathbf{u} \in \mathcal{U}, \quad j = 1, 2, \dots, n, \quad (2.26)$$

$$\mathbf{x} \in \mathcal{X}. \quad (2.27)$$

where  $\mathbf{u} = \{ u : Au \leq b \}$  is the linear uncertainty set, defined by a set of linear inequalities  $Au \leq b$ , representing all possible values of the uncertain parameters  $u \in \mathbf{u}$ .  $x$  is the decision variable in a feasible set  $\mathcal{X}$ , and  $\xi$  represents uncertain parameters in an uncertainty set  $\mathcal{U}$ .

The uncertainty set  $\mathcal{U} \subset \mathbb{R}^m$  defines all possible realizations of  $\xi$ . Common examples include :

- Box uncertainty :

$$\mathcal{U} = \{ \xi : \|\xi\|_\infty \leq b \} \quad (2.28)$$

- Ellipsoidal uncertainty

$$\mathcal{U} = \{ \xi : \|\xi\|_2 \leq b \} \quad (2.29)$$

- Polyhedral uncertainty

$$\mathcal{U} = \{ \xi : A\xi \leq b \} \quad (2.30)$$

**CVAR-constrained approach :** When risk-aware decisions are mandatory and the risk concern needs to be handled from the objective function, then the CVAR operator could be employed. The following mathematical formulation can explain such a system.

Given a random loss function  $L(x, \xi)$  where  $x$  represents the decision variable and  $\xi$  represents uncertain parameters, CVaR optimization aims to minimize the  $\alpha$ -CVaR of the loss :

$$\text{Minimize } f^F(x) + \beta \text{cVaR}_\alpha[f^S(x, y, \xi)] \quad (2.31)$$

s.t.

$$g_i(\mathbf{x}, \xi) \leq 0, \quad i = 1, 2, \dots, m, \quad (2.32)$$

$$h_j(\mathbf{x}, \xi) = 0, \quad j = 1, 2, \dots, n, \quad (2.33)$$

$$\mathbf{x} \in \mathcal{X}, \quad (2.34)$$

$$\xi = \max(0, \mathbb{E}[f(x)] - VaR). \quad (2.35)$$

where  $\alpha \in (0, 1)$  is the confidence level, typically close to 1 (e.g., 0.95 or 0.99).  $\beta$  is an user-defined weight to model risk aversion and the CVaR can be defined as :

$$\text{CVaR}_\alpha(L(x, \xi)) = \min_{VaR \in \mathbb{R}} \left\{ VaR + \frac{1}{1 - \alpha} \mathbb{E} \left[ (f^F(x, \xi) - VaR)_+ \right] \right\} \quad (2.36)$$

where Value-at-Risk (VaR) acts as an auxiliary variable at confidence level  $\alpha$ , and  $(z)_+ = \max(z, 0)$  denotes the positive part of  $z$ .

Thus, the CVaR term can be reformulated linearly as :

$$VaR + \frac{1}{1 - \alpha} \sum_s \omega_s \xi \quad (2.37)$$

here  $\omega$  are probabilities of scenarios  $s$ . This formulation captures the objective to minimize the expected loss in the tail of the loss distribution beyond the VaR level.

**Chance-constrained approach :** When risk-aware decisions are mandatory i.e. decisions under a given level of accomplishment of a particular constraint, then chance-constraints must be employed. The following mathematical formulation can explain such a system :

$$\text{Minimize } f(\mathbf{x}) \quad (2.38)$$

s.t.

$$\mathbb{P}\{g_i(\mathbf{x}, \xi) \leq 0\} \geq 1 - \varepsilon_i, \quad i = 1, 2, \dots, m$$

$$h_j(\mathbf{x}) = 0, \quad j = 1, 2, \dots, n \quad (2.39)$$

$$\mathbf{x} \in \mathcal{X} \quad (2.40)$$

$$\xi \sim F_x(X) \quad (2.41)$$

here, there exists a probabilistic constraint, where  $1 - \varepsilon$  is an allowed violation. This sort of problems are characterized for its high conservatism level and their complexity as they represent NP-hard and non-differentiable problems.

While each of the listed methods has its own set of advantages and disadvantages, convex optimization methods stand for a wide-adopted approach in the distributed energy management landscape. This obeys mainly to the fact that it provides strong theoretical guarantees and efficiency. Accordingly, literature shows that the way the problem is formulated depends largely on the information's nature i.e. perfect (deterministic) or imperfect (stochastic).

Table 2-2 Comparison of decision-making approaches.

Method	Pros	Cons
Rule-based	Avoid complex modelling tasks - Easy to program - Easy to implement	- Requires a high expertise on the system's behavior - Needs to be updated continuously - Often non-optimal
Meta-heuristics	- Provides a vast variety of search process - Can easily model non-convex and non-linear phenomena	- Do not guarantee global optimum - Difficult to be adapted to new situations - Tuning complexity - Computationally intensive
Convex optimization	- Converge to the global optimum - Efficiency- Mathematical rigor	- Limited applicability - Sensible to model assumptions
Dynamic programming	- Converge to the global optimum - Versatility - Efficiency- Mathematical rigor	- Computationally intensive for high-dimensional state or decision spaces - Assumes optimal substructure

Literature reports many works in distributed energy management (DEM) for multiple purposes. A large share of them exploit demand flexibility through demand response with controllable loads and storage assets. Many researchers exploit salient features of thermostatically controllable loads (TCL) and electric batteries as resources for customers to participate in demand response programs [64–66]. In these strategies, local coordinators and demand aggregators have been widely accepted [67–69]. They provide aggregation load as a main service and coordinate residential customers from incentive signals [70, 71]. They establish mechanisms (mostly cost-sharing-based) to coordinate customers' decision-making procedures to provide affordable electricity rates and utilities for the distributed system operator [63, 72–74].

Deterministic approaches are a great go-to option when the target is to get a good grasp on technologies' performance in a fast manner. While they can provide unique and optimal global solutions, these require for perfect information on systems' perturbations, which is unfeasible in real life. On the other hand, stochastic approaches rely on

mathematical programming and handle real-life uncertain phenomena through different methods, including scenario-based and robust optimization. A vast amount of existing works have shown the ability of this sort of technique to show great performance under imperfect information [75–81]. Scenario-based approaches have the advantage of providing efficient solutions, but relying on historical data to build distributions; their implementation can be compromised in large-scale problems. However, other approaches such as distributionally robust optimization [59, 77, 82] and chance constraint should be considered when the notion of risk/reliability is a matter [62, 83]. Nevertheless, RO's main drawback is to model the ambiguity set that describes the uncertain phenomena and that solutions can fall into over-conservative scenarios with very low odds of occurring.

Even though many papers exist in distributed stochastic energy management (DSEM), numbers get reduced when ETS and RES appear all together in the context of remote ECs. Regarding ETS, efforts have been made by literature in thorough research, including ETS for demand response [24], facilitating the integration of RES [29], and reducing renewables' curtailment [38]. However, a lack of works exists that propose accurate models that enable scenario generation of buildings integrated with ETS room units. Having this can facilitate the creation of simpler models to be exploited by optimal control techniques.

Concerning DSEM, existing works have adopted widely game-theoretical methods. These are able to encompass uncertainties from load, electricity price, and renewable generation. Existing papers proposed resources coordination and cooperation approaches to address that problem. The main difference is that coordination provides common benefits by maximizing individual welfare, and cooperation requires sharing information across the customers to accomplish the same goal [72]. Besides, they have shown that incorporating BES, DWHs, and EHPs distributedly can bring about meaningful benefits such as economic

savings and reduced grid's operational cost [63]. However, DSEM with customers integrated with ETS room units and RES literature remains infant. It is not clear yet what can be the possible impacts created by weather forecasting and, subsequently, renewable generation on power grids with high penetration of ETS units. Ignoring such impacts may compromise the grid's stability and customers' payments and utilities. In this regard, top-level entities such as coordinators must be able to anticipate critical scenarios due to customers' concerns about having enough heat stored in ETS through green power.

### 2.3 Risk-preferences join distributed demand response

Risk management in power grids involves identifying, assessing, and mitigating potential threats and uncertainties to ensure the reliable and sustainable operation. Planning and operating tasks of such systems require for mechanisms that address risky situations that may arise from multiple fronts including i) resource availability, ii) equipment reliability, iii) financial, iv) maintenance, among others. Below is listed a brief description of each :

- **Resource availability** : Since these systems are high penetrated by renewable generators, then effective risk management should be harnessed by assessing the local resource availability and implementing backup or power reserve to address fluctuations.
- **Equipment reliability** : autonomous off-grid systems use specific technologies such as solar panels, batteries, and inverters. Ensuring the reliability of these components is crucial for system performance. Risk management includes selecting quality equipment, regular maintenance, and having contingency plans for equipment failures.
- **Forecasting** : Demand and weather conditions forecast combined represent pivotal elements regarding the optimal dispatch in remote autonomous grids. Given

the adverse climate conditions in winter, risk-aware operators must anticipate demand-side risk as a consequence of weather forecasting errors.

- **Financial** : remote off-grid projects require significant upfront investment. Financial risks include cost overruns, changes in currency exchange rates, and the availability of funding. Risk management strategies involve thorough financial planning, budget monitoring, and considering financial instruments to hedge against currency fluctuations.
- **Maintenance** : the current context imply autonomous grids located in remote areas, making regular maintenance challenging. Operational and maintenance risks include the availability of skilled personnel, access to spare parts, and the impact of weather conditions. Risk management includes establishing maintenance schedules, training local personnel, and having spare parts on-site.

To date, there exist a vast amount of papers exist on risk-aware optimal scheduling for energy management systems. That includes various advanced methods to analyse stochastic phenomena depending on particular aspects properly. For instance, stochastic programming is a suitable option in a risk-neutral process, and when historical data is available [75–81]. Conversely, when any knowledge of the probability distribution of random variables is available and seeks the optimal solution in the worst-case scenario, then robust optimization (RO) and the information decision gap theory (IGDT) stand for suitable methods [59, 77, 82]. When partial distribution information is known, such as mean and variance of the stochastic phenomena, and constraints are satisfied with a certain probability, chance-constraint programming (CCP) is a suitable approach [62, 83, 84].

In SP approaches, the computational complexity increases exponentially with the number of data samples, making them inapplicable to large-scale systems as the expected value

requires tremendous numbers of scenarios to ensure the feasibility of the solution. On the other hand, robust approaches deal with the worst-case, thus providing too conservative policies. With CCP, these problems can be overcome since some uncertain constraints are defined based on a risk/reliability level, and for this value, the optimization problem can be solved by finding tractable deterministic equivalents. In CCP, the larger the reliability level, the larger the stability of the system but also the cost. The main advantage of CCP is that employing deterministic equivalents facilitates solving nonlinear in the presence of uncertainty. Researchers have adopted different metrics to perform risk-aware decision-making such as : the value-at-risk (VAR), the conditional value at risk (cVAR).

While the VAR has been criticized in literature as a risk metric for not satisfying the sub-additivity property, its practicality and ease of use make it a convenient choice in CCP. This because its simplicity and its ability to represent a probabilistic constraint on the downside risk of a portfolio or system. The cVaR on the other side, is also used in CCP but its implementation is more complex as it involves integrating over the tail of the distribution, which can be computationally more demanding than VaR.

Several works have employed CCP in the landscape of stochastic energy management for multiple applications. Regarding optimal energy management, Wang et al. [83] used CCP to optimally schedule EVs and electricity-heat flexible load through demand response under renewable uncertainties. They performed a risk assessment regarding the power reserve. Their results have estimated power reserve depending on risk levels, indicating that lower risk implies more conservatism and, thus, larger operational expenses. Although they have shown cost and GHG emissions reductions, the soundness of the strategy may increase by adopting game-theoretical methods to model the interaction with other entities such as demand aggregators, retailers, and even proactive customers.

Aghdam et al. [85] carried out stochastic optimal scheduling of multi-microgrid systems considering emissions. They have considered wind, PV and load uncertainties to satisfy the security constraint at a given reliability level. Nevertheless, the authors did not consider microgrids' privacy as they solved the problem in a centralized manner. Additionally, they can not guarantee the global optimum as they have formulated the dispatch problem as a nonlinear problem. Yurtseven et al. [86] CCP-based stochastic optimal power flow (OPF) for hybrid ac/dc grid to handle demand-side and renewable uncertainties. They have recast conventional OPF constraints through their deterministic equivalents regarding bus voltage, line currents, and converter voltage, among others. Consistent with similar works, their results suggest that risk-averse grid operators will experience larger operational costs. However, while hosting capacity increases with the level of risk taken, the profit gained by taking a higher risk drastically decreases after 90% of the chance-constraint limit for the study case. Also, with the increase in the penetration level, the difference between expected costs of different chance constraint limits increases. The author's approach may have considered incorporating storage technologies to evaluate the trade-off between their sizing and the amount of uncertainty they may absorb. Additionally, a comprehensive comparison against a deterministic baseline would provide great insights on the cost of elevated decision-maker's conservatism levels.

Efforts have been performed in reliability-aware battery sizing. For instance, Huo et al. [87] employed CCP for reliability-aware battery sizing method for island microgrid. CCP was useful to the battery state-of-charge to avoid sizing the energy storage to accommodate extreme uncertainties and avoid uneconomic investment. Although they employed thorough methods to estimate the battery size, considering how the grid operator may remunerate batteries' owners to provide flexibility and how the combined interaction with other energy carriers can affect the strategy may enhance the thoroughness of the manuscript.

Similarly, Sadeghiana et al. [88] performed efficient battery sizing employing CCP approach considering market price uncertainty in a virtual power plant (VPP). They performed risk assessment in a long-term period, prioritizing the concept of conditional value at risk (cVAR) over the VAR. Their main findings suggest that with a smaller risk with optimal ESS allocation in the VPP, the overall cost of VPP increases. In addition, a lower risk of planning in the VPP results in a lower capacity of ESS. However, they have only evaluated market price uncertainties and not demand-side uncertainties. Considering this will surely shape the optimal scheduling of batteries in VPPs.

Only electric batteries have been contemplated for risk-aware stochastic energy management in all the reviewed studies. However, unlike ETS, these assets do not face the same challenges regarding the limited degrees of freedom in the discharge power. In recent years, numerical analysis and white-box modelling have been a hot research spot regarding ETS [32,89–91]. Another application has been optimal scheduling and power flow methods to facilitate renewable integration, reduce diesel consumption, reduce renewable and load curtailment, and evaluate its impact on distribution networks. However, existing studies that address coordinated optimal scheduling of ETS distributedly rarely consider the impact of customers' concerns about the inherent stochastic nature of renewable power as a consequence of weather forecasting errors. The comparison of the proposed work with other similar published works is shown in Table 2-3.

Accordingly, this thesis addresses risk-aware demand-side resource coordination for residential prosumers equipped with solar-PV generation and ETS units. We have modeled two demand-side potential issues that may appear due to weather forecasting errors : the violation of indoor temperature boundaries and renewable availability.

Table 2-3 Related works on risk-aware energy coordination strategies with energy communities

Ref	Uncertainty source	Controllable load	Storage asset	Energy game	Uncertainty modeling	Optimal ETS scheduling	Risk assessment	Risk metric	Powerflow	Goal
[24]	-		ETS	-	-	✓	-	-	✓	Highlight benefits of integrating ETS to reduce operating costs, load curtailment, and electric batteries.
[29]	-		ETS	-	-	✓	-	-	✓	Evaluating potential of ETS and wind power to meet isolated grid's electric supply needs
[39]	-		ETS	-	-	✓	-	-	✓	Introducing customer behavior characteristics in optimal scheduling of ETS for reduced wind power curtailment.
[41]	-		ETS	-	-	✓	-	-	✓	Reducing wind power curtailment with ETS surpluses for auxiliary thermal network regulation with scheduling deviation thresholds
[38]	-		ETS	-	-	✓	-	-	✓	Evaluating impact of smart electric storage heating on distribution grid
[92]	RG D	EV	-	✓	✓	-	✓	cVar	-	Operation of commercial district integrated energy system considering dynamic integrated demand response
[93]	EP RG EVD	EV	-	✓	✓	-	✓	cVar Var	-	Developing regret-based stochastic bi-level framework for optimal decision making of DR aggregator for energy purchase from short term electricity market and wind generation
[94]	RG	CHP	BAT	-	✓	-	✓	cVar		Optimal planning of integrated energy system with uncertain wind power
[95]	RG	CHP	-	-	✓	-	✓	cVar		Real-time control for energy-hub coordinated prosumer community under cooperative perspective
<b>This</b>	WF RG NSL	EB	ETS	✓	✓	✓	✓	Var	✓	Performing distributed resource coordination addressing demand-side risk-aware decisions given uncertain weather forecast and renewable availability for residential prosumers.

## Chapter 3 - Article-based statement of the results

The examination of the intended objectives is presented within the articles in this section. Notwithstanding the previous discussions, every article details the contribution, the approach, and the prior art regarding the proposed objective. Accordingly, the mathematical methods and experimental procedures to achieve the ambitions are described. Subsequently, the evaluations and results are reported to demonstrate the efficiency of the developed frameworks in every manuscript.

### 3.1 Modelling through distributed cosimulation

*« This section directly addresses the first objective of the research. Below the reader can find the methodology adopted, and the way customers interact with a top-entity that dispatch conventional generation along with renewable power. Detailed aspects on the models orchestrations for building and thermal storage is presented. Besides, an energy coordination strategy with uncertainties in customers' utility is adopted. The content of this chapter is related to the following paper : »*

**Domínguez-Jiménez, J.,** Henao, N., Agbossou, K., Parrado, A., Campillo, J., & Nagarsheth, S. H. (2023). A stochastic approach to integrating electrical thermal storage in distributed demand response for Nordic communities with wind power generation. *IEEE Open Journal of Industry Applications*, 4, 121-138.

**Top 3 of Best 2023 Publications in IEEE Open Journal of Industry Applications Award.**

### *3.1.1 Background*

Effective energy management strategies to cope with essential needs during cold climates requires a well-defined framework with sound methods that underlie potential results. Considering the multifaceted environment and all the domains implied that need to be addressed, optimal energy management is not only the crucial factor. Indeed, when information is scarce, models are required to get a good grasp on such a convergence of domains that results into complex environments. Therefore, the investigation into accurate modelling tools has been the origin of the following studies. The relevance of such an analyses lie in the limited number of approaches that enable getting a great understanding on technologies such as electric thermal storage and their interaction with optimal decision-making solutions that aim to reduce operational costs. The integration of ETS units into HEMS has revealed the necessity of algorithms that allow for coordinating smart loads at the customer level with reduced information exchange. Hence, a fully open-source model for ETS through object-oriented modelling and an efficient distributed energy coordination approach is the backbone of the provided analyses. This foundation has led to developing a framework capable of generating the synthetic data of buildings integrated with ETS, for which real data is reduced.

### *3.1.2 Methodology*

When operational information on energy projects is scarce, models have been a wide adopted approach to bridge that gap. Particularly, energy projects for regions that suffer severe winters are characterized to have a strong dependency with weather conditions. While literature reports several approaches for energy consumption modeling in buildings, the situation is not similar regarding ETS assets. In this regard, we modelled energy consumption for buildings using EnergyPlus. Additionally, since collecting accurate data

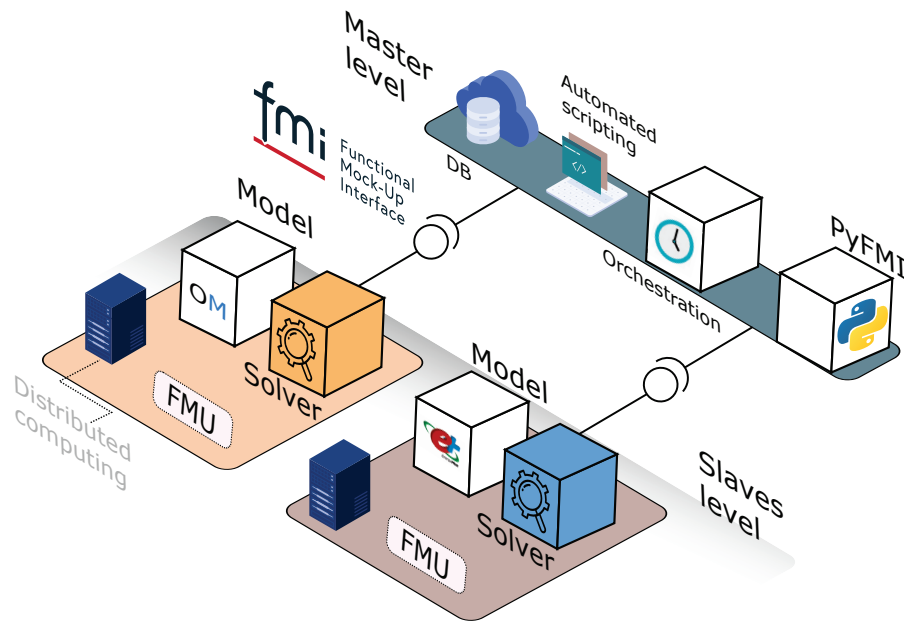


Figure 3.1 FMU approach for cosimulation

from ETS-related projects can be tough, we developed a framework to build Modelica equivalents for ETS units. Modelica is an object-oriented, equation-based, and acausal solution to have accurate models that involve several domains. The ETS Modelica model was built exclusively from manufacturer's information and validated with accurate collected data in our realistic infrastructure.

Once we built both models separately, they were connected throughout the FMI protocol by having PyFMI as a master tool, and packaging the built models into FMUs (EnergyPlus and Modelica) to act as slave in the cosimulation procedure. Figure 3.1 condenses this procedure. Afterwards, synthetic data is available and ready to build practical space-state models to perform optimal control task by employing HEMS. These were built with least-square regression methods. Eventually, it is required to define supply and demand-side features along with weather forecast error modelling to perform distributed energy management through energy coordination, as indicated in Figure B.6. The horizon

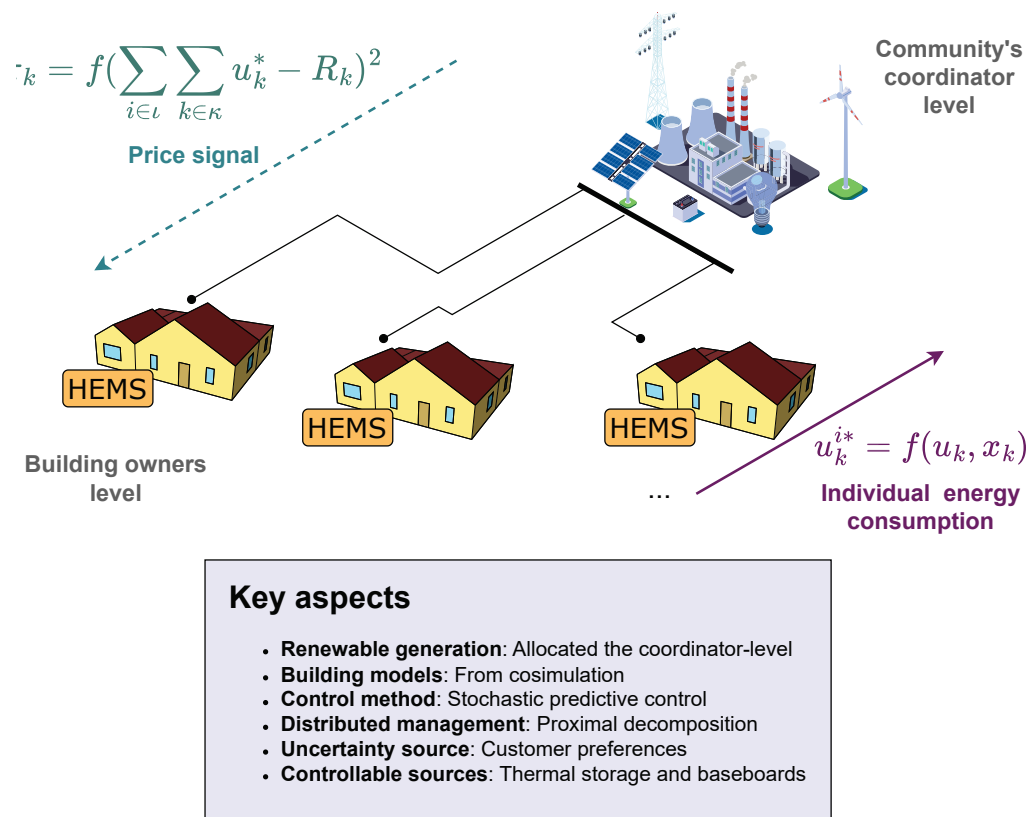


Figure 3.2 Visual representation of methods to manage the first objective

control was set to 24 hours (which is typical of day-ahead markets), during the coldest day of winter 2023.

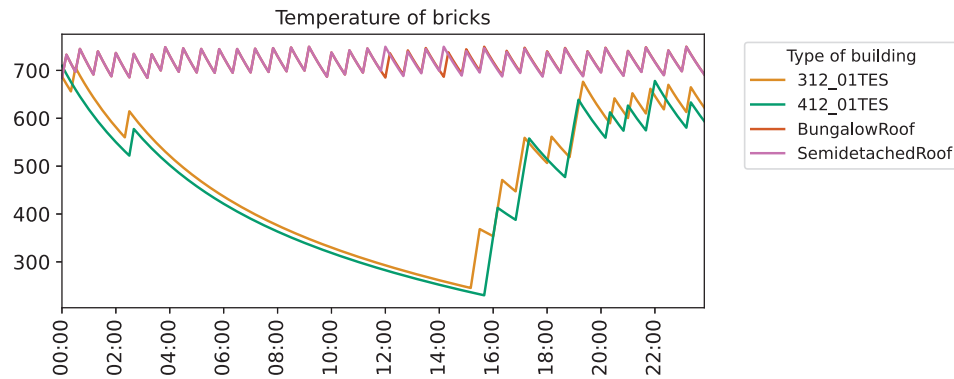


Figure 3.3 Temperature of bricks of ETS when installed in different buildings

### 3.1.3 Outcomes

The study of modelling essential elements and the exercise of coordinating distributed resources with randomness at the supply level have brought about the followings remarks.

- The thermo-energetic environment of buildings with multiple thermal zones incorporated with ETS was successfully built. The framework allowed to allocate ETS units into diverse thermal zones to perform sound energy analysis.
- Weather forecast from solar irradiation, relative humidity, outdoor temperature, wind speed, wind direction, along with its inherent uncertain errors were modelled during one (1) year in a particular region in Quebec.
- The proposed Modelica model exhibited errors up to 5% in free and forced convection scenarios.
- ETS can bring about significant cost reductions depending on the customers' ability to keep thermal comfort.
- Distributed management enabled customers to reach comfort levels while reducing

operational costs.

- The game's leader was able to address stochasticity from wind power through scenario based approach and grid's operational cost was reduced significantly by transferring renewable power availability throughout the price signal (efficient market hypothesis).
- Extensive simulations were performed to evaluate the impact of having gradually increased participation of customers with thermal storage assets. It has revealed that the individual welfare of participants does not necessarily increase as a result of this exercise.
- The strategy's effectiveness revealed the ability to reduce the peak-to-average ratio by over 45% even with imperfect information from wind power generation.

It is worth mentioning that different cases go beyond the scope of the developed framework. For instance, HEMS with non-linearities introduced by forced convection scenarios created by window opening for instance. Furthermore, in our analysis, customer's price elasticity was modulated in such a way that during conventional peak periods, customer wanted to maintain their comfort needs while during working hours the indoor temperature was not a concern and demand-side flexibility could be exploited.

# A Stochastic Approach to Integrating Electrical Thermal Storage in Distributed Demand Response for Nordic Communities With Wind Power Generation

JUAN DOMÍNGUEZ-JIMÉNEZ <sup>1,2</sup> (Graduate Student Member, IEEE), NILSON HENAO <sup>1</sup>,  
KODJO AGBOSSOU <sup>1</sup> (Senior Member, IEEE), ALEJANDRO PARRADO <sup>1</sup>, JAVIER CAMPILLO <sup>2</sup>,  
AND SHAIVAL H. NAGARSHETH <sup>1</sup>

<sup>1</sup>Laboratoire d'innovation et de recherche en énergie intelligente (LIREI), Institut de recherche sur l'hydrogène (IRH), Université du Québec à Trois-Rivières, Trois-Rivières, QC G9A 1R8, Canada

<sup>2</sup>Facultad de Ingeniería, Universidad Tecnológica de Bolívar, Cartagena de Indias 131001, Colombia

CORRESPONDING AUTHOR: JUAN DOMÍNGUEZ-JIMÉNEZ (juan.antonio.dominguez.jimenez@uqtr.ca)

**ABSTRACT** Demand response and distributed energy storage play a crucial role in improving the efficiency and reliability of electric grids. This article describes a strategy for optimally integrating distributed energy storage units within a forward market to address space heating demand under a Stackelberg game in isolated microgrids. The proposed strategy performs distributed management in an offline fashion through proximal decomposition methods. It leverages stochastic programming to consider user flexibility degree and wind power generation uncertainties. Also, flexibility for demand response is realized through electric thermal storage (ETS). The performance of the proposed strategy is evaluated via simulation studies carried out through a case study in Kuujuaq, Quebec. Ten residential agents compose the demand side, each with flexibility levels and economic preferences. The simulation results show that adapting ETS results in economic savings for the customers. Those benefits increased in the presence of wind power, from 25% to 40% on average. Likewise, coordinated strategies led the coordinator to obtain reduced operational costs and peak-to-average ratio by over 35% and 56%, respectively. The proposed approach reveals that optimal coordination of ETS in the presence of dynamic tariffs can reduce diesel consumption, maximize renewable production and reduce grid stress.

**INDEX TERMS** Electric thermal storage (ETS), distributed demand response (DR), stochastic programming, microgrids, co-simulation.

## NOMENCLATURE

### Abbreviations

BES	Battery energy storage.
CHP	Combined heat and power.
COP	Coefficient of performance.
DCP	Disciplined convex programming.
DHW	Domestic water heater.
DR	Demand response.
EB	Electric baseboard.
EH	Electric heater.

EHP	Electric heat pump.
ETS	Electric thermal storage.
FMUs	Functional mock-up units.
GB	Gas boiler.
HEMS	Home energy management systems.
MPC	Model predictive control.
OCP	Optimal control problem.
PAR	Peak-to-average ratio.
RA	Residential agent.
TCL	Thermostatically controlled load.
TOU	Time of use.

WT Wind turbine.

### Functions

$\mathbf{E}[\cdot]$  Expected value.  
Residential agent's cost.  
Utility's payoff cost.  
 $J[\cdot]$  Residential agent's payoff function.  
 $\text{PAR}[\cdot]$  Peak-to-Average ratio.  
Proximal operator.  
Residential agent's utility.

### Indices

$i$  Index of iteration.  
 $j$  Scenario index.  
 $k$  Time slot index.  
 $r$  Customer index.  
 $z$  Thermal zone.

### Parameters

$\alpha$  User's elasticity.  
 $\Delta_W$  Wind speed under uncertainty.  
 $\hat{\gamma}_k^i$  User's elasticity under uncertainty.  
 $\mu_{\text{in}}$  Rated electrical consumption of the heating system.  
 $\pi$  Electricity price.  
 $k$  Wind power.  
 $\sigma_k$  Standard deviation of the forecast error.  
 $\tau$  Regularization parameter.  
 $a, b, c$  Diesel generator parameters.  
 $H$  Houses.  
 $T_k^{\text{Out}}$  Outdoor temperature.  
 $T_{\text{pref}}$  Comfort temperature.  
 $u_{\text{max}}^{\text{EB}}$  EB's maximal rated power consumption.  
 $u_{\text{max}}^{\text{ETS}}$  ETS' maximal rated power consumption.

### Sets

$C$  Set of residential agents.  
 $k$  Set of time-slots.  
 $N$  Set of scenarios.

### Variables

$\pi^i$  Electricity price at iteration  $i$ .  
 $B_k$  Billing tarif.f.  
 $L_k$  Aggregated demand.  
 $P_k^{\text{Ch}}$  ETS Charging power.  
 $P_k^{\text{Th}}$  ETS thermal discharging power.  
 $\text{PAR}$  Peak-to-average ratio.  
 $\text{SOC}_k$  ETS State-of-the-charge.  
 $T_k^z$  Thermal zone  $z$  indoor temperature at time slot  $k$ .  
 $u_{\text{EB}}$  Electrical baseboard electricity consumption.  
 $u_k^*$  User's optimal trajectory.  
 $u_k^{\text{ETS, ch}}$  ETS electrical charging power.  
 $u_k^{\text{ETS, dsch}}$  ETS thermal discharging power.

## I. INTRODUCTION

### A. BACKGROUND AND MOTIVATION

In 2021, global electricity demand experienced the most significant increase since the recovery from the financial crisis in 2010 [1]. The last year represented a critical period that has created rebound effects in energy demand pushing electricity prices. Besides, renewable sources increased significantly, but electricity generation from fossil fuels reached record levels [2]. Although renewables are set to fulfill increases in global electricity, this trend boils down to plain emissions from electricity generation. Therefore, the power sector plays a critical role in the decarbonization of economies worldwide.

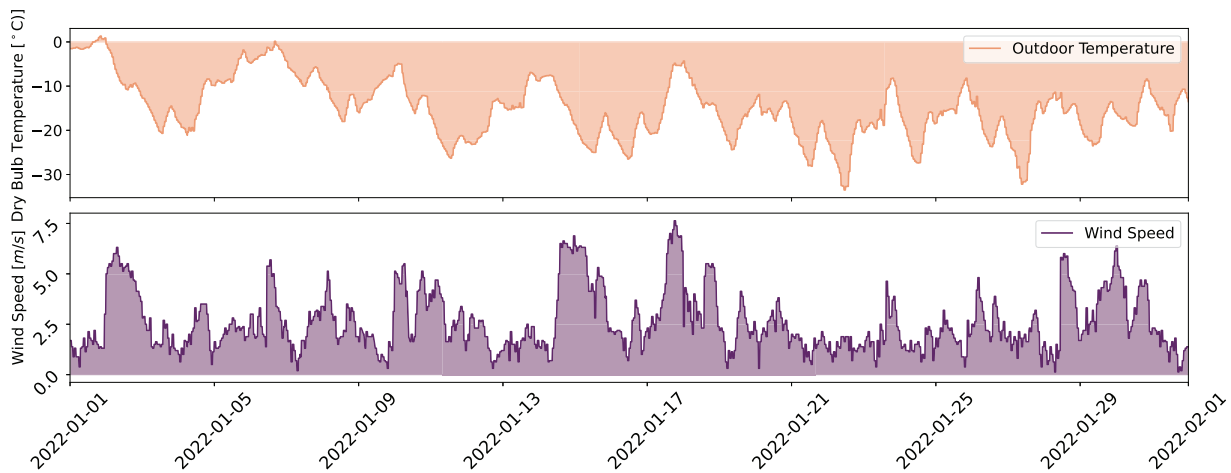
Distributed energy resources and demand response (DR) programs drive the increased performance experienced by smart grids over the last decade [3]. The migration from passive to active electrical networks allows users to participate actively in DR programs [4]. Such programs enable dynamic pricing tariffs that encourage customers to reduce electricity bills. The literature have adopted game-theory and multi-agent systems to model the interaction between end-users and utilities [5], [6], [7], [8]. In this regard, many papers suggest thermostatically controlled loads (TCLs) and lithium batteries to alleviate grid stress by filling valleys and shaving peaks. These have gained significant momentum since lithium production prices experienced a sustained decrease in the last decade [9].

During the last decade, tremendous efforts have been performed on district heating systems, including combined heat and power (CHP) and distributed heat pumps, since they represent the most efficient solution to:

- 1) increase demand flexibility;
- 2) facilitate DR;
- 3) reduce the running cost of power grids [10], [11], [12], [13].

Although they promote energy efficiency and grid stability, they do not make sense for every context. Scenarios that behave: inadequate customer density (lack of aggregated thermal load), limited interest from stakeholders (due to extensive payback periods), hard-to-reach geographical conditions (increased transportation and deployment costs), and low public budget stand for critical cases in which they can be an impractical solution. Therefore, the necessity of technologies that could overcome the last-mentioned limitations arises.

In this light, electric thermal storage (ETS) brings similar advantages to lithium batteries. In fact, ETS exhibit lower purchasing prices than the latter. Although having a unique purpose (space heating), such a technology is a flexible asset for customers [14]. ETS facilitates the integration of renewable production and may reduce the need for additional capacity of dispatchable generators. Previous studies have consistently shown the ability of ETS to reduce customer payments and energy costs, flatten the power curve, maximize renewable generation, and provide a cost-effective solution for DR programs [15], [16], [17], [18], [19]. All these studies have considered deterministic and centralized approaches. The utilization of deterministic methods considers complete



**FIGURE 1.** Weather conditions during Winter in 2022 in Kuujuaq.

information modeling, which is not a feasible scenario due to inherent outdoor temperature and user preference uncertainties. Subsequently, real-world circumstances make a stochastic approach to ETS scheduling inevitable. Centralized systems, in turn, are highly invasive, have no fault tolerance, and exhibit poor performance at a large scale. Very few attempts handle uncertainties in distributed management contexts with ETS assets at the customer-level.

Microgrids allocated in remote regions experience harsh conditions, especially during winter. In such regions, the heating load represents the higher electricity consumption (by over 70%) and is the primary driver of peak periods. Nordic remote communities are characterized by their extensive dependence on fossil fuels and often experience higher electricity prices compared to urban scenarios. Furthermore, economic and technical reasons impose many challenges for hard-to-reach communities that often rely on diesel consumption. Canada has around 280 isolated microgrids, most located in the northern regions, characterized by a significant heating demand in winter. Fig. 1 illustrates a typical day in Kuujuaq, a northern community allocated in Nunavik, Quebec. The average outdoor temperature is  $-25^{\circ}\text{C}$  and fluctuates between  $-8^{\circ}\text{C}$  and  $-35^{\circ}\text{C}$ . The wind blows constantly; hence, introducing wind turbines is a potential opportunity. These communities face high fuel and electricity costs compared to urban scenarios in Canada. Unlike the rest of Quebec, inhabitants of such regions are penalized after the first 40 kWh during a weekly contract. In case household demand exceeds 40 kWh, they are penalized for charging eight times the conventional rate. Hence, building owners take a conservative behavior to avoid paying expensive electricity bills. Consequently, the required heating demand is supplied mainly by wood pellets, fuel oil, gas, and electricity. Hence, the need for efficient energy management strategies arises to reduce such a dependency and provide affordable electricity prices. A potential solution is a strategy that exploits the salient features of ETS to reach a reduced peak-to-average ratio (PAR) combined to maximize renewable production. The optimal scheduling of distributed

ETS units can enhance the power grid performance through increased flexibility on the demand side. Such a strategy can provide the following benefits:

- 1) reduced power losses;
- 2) lower electricity bills;
- 3) reduced greenhouse gas emissions.

This stands as a primary motivation for this article.

## B. RELATED WORKS

Demand flexibility is possible from controllable loads and storage assets. An optimal combination of them could reduce grid stress and bring economic savings. Many researchers exploit TCLs and lithium batteries as potential customer resources to participate in DR programs [20], [21], [22]. On the other hand, utilities manage the integration of any flexibility vector through aggregators, which have been widely accepted in the literature and real-life projects [23], [24], [25]. They provide aggregation load as the main service and coordinate residential customers from incentive signals. Despite DERs offering advantages for DR purposes, an uncoordinated integration of these may result in adverse effects [26]. To solve this problem, the literature has adopted demand aggregators/retailers responsible for residential or neighborhood coordination [27], [28].

Such coordination is performed mainly in the following three ways: centralized, decentralized, and distributed. Etedadi et al. [26] review these three concepts' main advantages and disadvantages. In centralized schemes, utilities control households' electric appliances, and residential users send information about power and preferences via smart meters. This architecture has proved cost-effective in applications including residential [29], [30] and electric vehicles [31]. However, this architecture has multiple drawbacks: it is highly invasive, fragile to faults, and implies a huge computational burden for large-scale applications. On the other hand, decentralized and distributed architectures split large problems into subproblems, mainly to reduce complexity. The distributed architecture shares a common constraint amongst the house

**TABLE 1 Literature Classification Based on Techniques to Model Uncertainty**

Ref	Unc. Modelling	Flexibility vector	Management strategy				Uncertainty Source						
			Cent.	Dec.	Dist.	Environment	Heat Demand	Elec. Demand	Elec. Price	Occ.	User's Pref.	Price Elasticity	
[60]	Two Stage RO	CHP, EHP, EH, WT, BES	✓			Solar, Text		✓	✓	✓			
[45]	Two Stage SP	GSHP, GB, WT	✓			Solar		✓	✓				
[61]	SP	WT	✓			Solar, Text							
[48]	Risk Averse	WT	✓			Solar, Wind, Text		✓					
[46]	Scenario based	DHW	✓			Solar							
[49]	Two Stage SP	EHP, WT	✓					✓	✓	✓	✓		
[62]	Scenario based	WT, BAT	✓					✓					
[50]	Robust	CS, WT	✓						✓				Ref.:
[51]	Scenario based	WT	✓			Wind		✓	✓				
[63]	Scenario based	EHP, WT	✓			Solar							
[64]	Stochastic MPC	EHP	✓					✓					
[65]	Scenario based	WT		✓		Solar		✓	✓				
[66]	Deterministic	EPH, EH			✓								
[67]	Deterministic	EH, GSHP, GB, WT		✓									
[68]	Deterministic				✓								
[69]	Stochastic MPC	EH		✓	✓						✓		
[70]	Two Stage SP	EHP		✓		Solar							
[47]	Scenario based	EHP	✓			Solar, Wind, Text		✓	✓				
[71]	Scenario based	EHP, WT	✓				✓						
This approach	Scenario based	ETS, WT			✓	Wind		✓	✓				✓

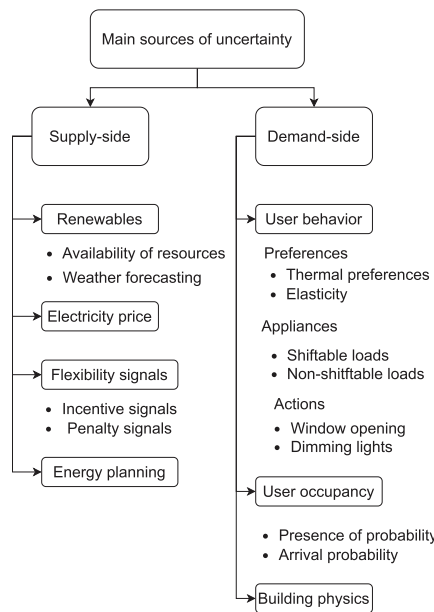
Reference, Unc.: Uncertainty, Cent.: Centralized, Dec.:Decentralized, Dist.:Distributed, Elec.:Electricity, Occ.:Occupants, Pref.: Preference

agents. In DR programs, local home energy management systems (HEMS) are often exploited to schedule smart electric appliances. HEMS aims to reduce electricity bills and consider the information of users’ preferences. The scheduled power profiles (computed by residential agents) are shared with the utility/aggregator via smart meters [32]. Afterwards, the utility broadcasts a price signal to residential users according to the received aggregated consumption [33].

The literature has adopted game-theoretical approaches to control the interaction between utilities, and customers [34], [35], [36]. Stackelberg games have been widely adopted by the literature; they model scenarios encompassing one leader and multiple followers. In the residential domain, customers are modeled as rational and price-aware agents aiming to maximize a specific utility, such as thermal comfort. An aggregator establishes a price policy according to the set of strategies from residential agents. Utilities establish goals including: flattening the power curve [37], [38], reducing fossil-fuel consumption [39], maximizing renewable production [40], [41], among others. Mediawathe and Chaturika [42] proposed an incentive-compatible energy trading strategy for neighborhood area networks with shared energy storage. Their results showed reductions up to 45% of peak demand at the maximum

adoption of energy storage assets. Similarly, through game theory, Tang et al. [43] handled power management at the building cluster level. Findings of this work state that storage units allow for a reduction by over 50% on aggregated peak demand and electricity cost. A significant problem in game-based approaches is how to distribute incentives. That motivated researchers to propose an approach to estimate them reasonably for optimal energy storage integration using an absolute option game [44].

While deterministic approaches allow an excellent grasp of decision-making at utility and user levels, they provide a static picture of uncertain parameters in real-life scenarios. Consequently, unpredictable events caused by uncertainties impose challenges on the daily operations of smart grids. Table 1 classifies studies by the technique used to model uncertainties and their respective sources, the flexibility vector, and the control strategy. Stochastic optimization, i.e., two-stage [45], [46], [47], two-stage robust [47], scenario-based [48], [49], [50], [51], are well-adopted methods to tackle uncertainty. Regarding flexibility, many papers focused on CHP, heat pumps, and borehole tanks. They drew special attention because of their ability to reduce grid stress and their significant coefficient of performance. A group of studies modeled fluctuations



**FIGURE 2.** Principal factors introducing uncertainty in smartgrids.

in electricity demand and price, while another group of researchers considered uncertainty from occupancy and thermal user preferences. Most of these approaches rely on centralized approaches, which is a primary drawback.

Martinez and colleagues reviewed the primary uncertainty sources on the demand side [52]. They highlighted that electricity demand is primarily affected by fluctuations related to thermal-economical preferences and occupancy. Such preferences are often affected by users' elasticity, duration of DR events, and human behaviors, i.e., opening/closing windows, turning ON/OFF lights, and cooking [53]. DR initiatives with renewable assets, usually for utilities, consider uncertainties from electricity demand and weather forecasting that affects renewable production directly [54]. For customers, such programs tend to model fluctuations over the only information the utility provides to them, the electricity price. Fig. 2 summarizes the main sources that affect demand side management.

Although user occupancy-related uncertainties can cause a significant impact on energy consumption at the residential level [55], such approaches often rely on Markovian models in the context of control strategies. Their main drawback is their dependence on every state and its corresponding observed object. Alternatively, uncertainties associated with user preferences can be introduced in cost functions through weighted terms. These terms can capture information about users' ability to pay for guaranteed thermal comfort, representing their degree of flexibility. The latter plays a crucial role in iterative-wised bilevel strategies, where users do not reveal their objectives.

Researchers have dedicated efforts regarding ETS for multiple purposes, including reduced diesel consumption, frequency regulation, renewable power maximization, and demand side management [56], [57], [58]. Unfortunately, only

a few researchers have considered the impact of uncertainties. Wong and Pinard in [14] elaborated a study to evaluate the opportunities of ETS combined with wind power in electric grids. Similarly, Sauther et al. [58] outlined a study to assess the impact of ETS in low-voltage distribution networks in northern communities' isolated microgrids. Their strategy achieved meaningful reductions in operating costs (by over 23%) when integrating ETS. In [18], authors developed a tool that enables feasibility evaluation of a DR program by ETS. Unlike other approaches, they considered electricity prices and power imbalance uncertainties through Monte Carlo simulations. The main remark of this article is that the benefits of participating in the program are not enough, even if users are willing to adopt ETS units. Hence, the utility must pass to the asset owner at least 50% of the load reduction remuneration to achieve payback in 15 years.

Kilkki et al. [59] introduced an optimized control of price-based DR with electric storage space heating. Here, a Stackelberg game underlies transactions between customers and the retailer, where multiple pricing mechanisms were considered, including spot price, time-of-use, optimized price, and optimized price with discount. However, the authors did not evaluate the effects of uncertainties in their approach.

Flexibility in multienergy communities with electrical and thermal storage: A stochastic, robust approach for multiservice DR.

In North America, space and water heating loads are fulfilled mainly by electrical heating systems. Over the last decade, ETS units have experienced a significant market uptake. Table 2 describes data of 13 projects in Canada and the United States. Here, information is summarized regarding the range of rebates and rate discounts used and the ways to control the ETS. Most initiatives have two goals: shifting demand away from peak hours and facilitating the integration of renewables. In some cases, it was the only way to enable customer time of use (TOU) rates. Investors offer incentives for either rebates or rate discounts to encourage people to participate. A weakness of these initiatives is that most are centralized architectures, which face multiple difficulties nowadays with leading trends about decentralization and the Internet of Things.

Regardless of the final purposes, when it comes to ETS, literature-reported papers mainly focused on deterministic optimization problems. Researchers made few attempts at stochastic approaches considering uncertainties. Despite [18] considering uncertainty for estimating the feasibility of an ETS-based DR, the authors did not model rational residential agents, which aim to reduce electricity bills or maximize individual welfare. In this regard, uncertainties affect the user's strategy and the aggregated demand profile, which directly alters the benefits of participating in a DR program.

### C. CONTRIBUTIONS AND ORGANIZATION

The studies on optimal stochastic integration of ETS in DR programs in microgrids are limited to date. Although the

**TABLE 2** ETS-Based Projects Conducted in Canada and United States

Project	Communication topology	Amount of people participating	Incentive	Presence of renewables	Controllable heating systems	Pros	Cons	Objective
PowerShift Atlantic	Centralized			Wind	ETS, DHW		- Utility have to control the timing of electricity use - Installation was not covered	Implement TOU rates for residential users
Nova Scotia Power	Centralized		- 50% of reduction on TOU rates		ETS room units (9 kW)		- Utility have to control the timing of electricity use	Shift demand away from peak hour and renewables integration
New Brunswick Power	Centralized	100 (2013)		Wind	ETS room units		- Utility have to control the timing of electricity use	
City of Summerside, PEI	Centralized		- 10% discount for installation - 33% of reduction of electricity rate for 8 years. - 50% of reduction on TOU rates				- Utility have to control the timing of electricity use	
Minnesota - Connexus energy cooperative and great river energy	Centralized			Wind	ETS room units		- Utility have to control the timing of electricity use	Load-shifting
Concord Light	Centralized		- 50 USD per installed kW - 100 USD per installed kW - 58% of reduction on TOU rate regarding the standard one.		ETS room units, ASHP		- Utility have to control the timing of electricity use	Meet the heating load with ETS as backup system
Bedford rural electric Co-op	Centralized		- 75 USD per installed kW - 58% of reduction on TOU rates - 25% of installation cost.		ETS, DHW		- Utility have to control the timing of electricity use	
South Kentucky rural electric cooperative	Centralized		- 40% discount from residential electricity rate.		ETS room units		- Utility have to control the timing of electricity use	

literature has reported the facilities that ETS brings about enhanced renewable integration and reduced operational costs, the knowledge is scarce about:

- 1) the optimal management of ETS in a distributed fashion;
- 2) changes in ETS-related decision-making processes as a consequence of uncertainties at the customer and supplier level;
- 3) customer behavior toward an increasing share of purchased ETS;
- 4) cost-effectiveness for customers.

Furthermore, in microgrids, the inherent fluctuations created by renewable sources, combined with altered consumption as a result of changes in the level of flexibility, impose severe challenges in the operation of the power system. Also, real-life projects exploiting ETS are characterized by utilities controlling the ETS units in order to maximize renewable production, which makes such approaches highly invasive. Although several studies have modeled renewable production with inherent uncertainty, few approaches have considered uncertainty on users' elasticity, representing a potential flexibility factor on the demand side. Hence, we propose a strategy to close these gaps by exploiting stochastic programming methods encompassing appropriate uncertainty modeling concerning renewable production and users' flexibility. The mechanism performs distributed DR by exploiting salient features of HEMS. The proposed strategy is based on a forward market and a Stackelberg game, including a local coordinator and a set of ten residential agents. The main contributions of this article are as follows.

- 1) Optimal stochastic integration of ETS assets in the presence of wind power is effectuated on a small microgrid in the context of a DR program. The proposed approach allows exploring the potential of ETS and wind to meet an isolated grid's electric supply needs. Besides, uncertainties from different sources are accounted for through stochastic programming.
- 2) Modeling and characterizing the thermo-energetic environment of a particular hard-to-reach Nordic community. It exploits the development of simulation tools,

cosimulation as well as statistical and stochastic models to characterize production and consumption and their dependence on environmental factors specific to remote regions.

- 3) A hierarchical Stackelberg game between the coordinator and a set of residential customers is proposed for managing information exchange to establish a contract within a forward market. Therefore, the interests of each participant can reach an equilibrium value, and a nested distributed DR strategy is achieved.
- 4) A market-efficient hypothesis is adopted, in which all information is reflected in the price. Hence, instead of centralized control, an optimal control mechanism at the customer level (decentralized) is effectuated by propagating the wind power availability toward the electricity price.

The rest of this article is organized as follows. Section II covers the methodology adopted in the article, including modeling, game description, and optimization problem. Section III presents the simulation results of the proposed strategy, while its discussions are embedded in Section IV. Finally, Section V concludes this article.

## II. METHODOLOGY

This section explains the proposed strategy to exploit the potential of wind power and ETS to flatten the power curve of a set of residential customers. The proposed strategy considers that the coordinator belongs to the utility and is profit neutral. Also, customers are connected to a single bus bar. Fig. 3 presents a sequential diagram of the methodology. First, the physical modeling for ETS and house is achieved. Second, distributed cosimulation is exploited to enable the interaction between ETS and the house model. Details for the last mentioned stages can be found in a previous work [72]. As a result, each house provides a historical energy consumption in the presence of an ETS room unit. Subsequently, a learning stage is effectuated to build a linear model to be controlled by exploiting a model predictive control (MPC) controller.

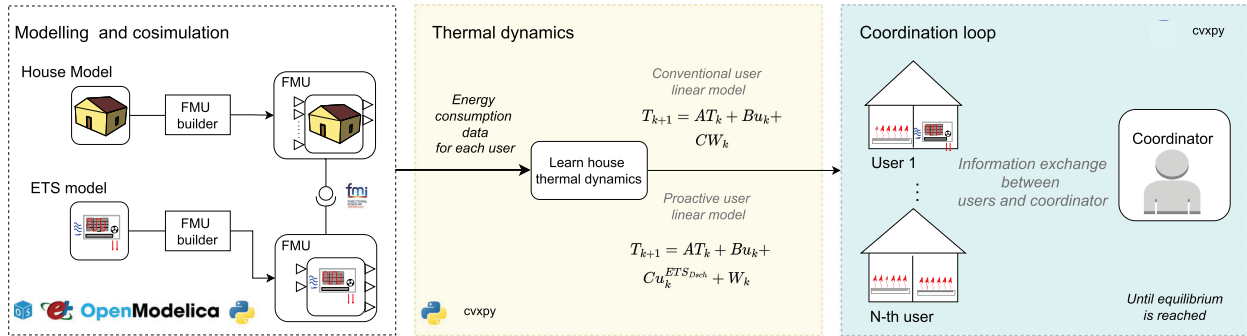


FIGURE 3. Overview representation of the proposed methodology.

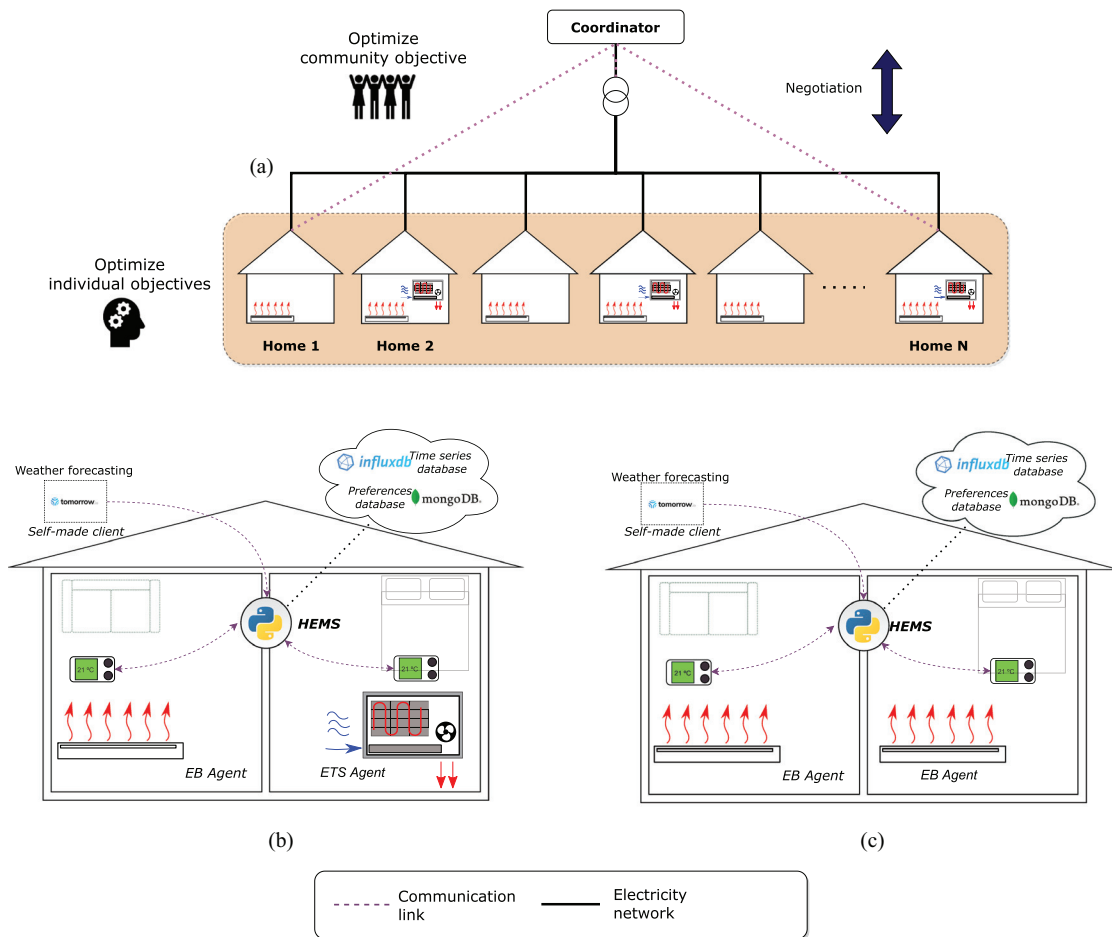


FIGURE 4. (a) Stackelberg game between leader and followers with distributed DR. (b) Local HEMS for a proactive user. (c) Local HEMS for a traditional user.

This procedure is repeated for every customer. Eventually, a coordination loop starts with the set of residential agents.

Fig. 4 provides a unified picture of the proposed strategy. Fig. 4(a) presents the sequential game between the set of residential agents and the coordinator, where they exchange price and power consumption data within a multistage game. Fig. 4(b) and (c) shows local HEMS for proactive and traditional users; each has different preferences and flexibility

levels. A proximal decomposition algorithm is used to enable distributed DR. At the utility level, the coordinator is responsible for reducing diesel consumption and providing an electricity price in terms of the availability of wind production. This work considers the following.

- 1) Residential agents are willing and have the economic means to purchase ETS units.
- 2) Constraints free electric network.

**TABLE 3** Main Characteristics of Modeled Houses

Dwelling characteristics	
Location	Kuujuuaq
Housing type	Twin Semi-detached
Approximated total surface	90 $m^2$
Occupation	2 adults / 2 children
Space heating systems	Baseboard heaters/ETS

- 3) ETS units discharge is modeled by forced convection with fixed blower power consumption.
- 4) Since the strategy is within a forward market for short-term optimal planning, upfront cost for ETS are not included.

### A. MODELING

Real-world data from hard-to-reach communities in the energy landscape is often limited. Therefore, the need to exploit advanced energy modeling tools arises to capture valuable information about consumers' energy consumption patterns. In this light, we exploit a stack of open-source tools and languages, including EnergyPlus, OpenStudio, and Modelica, to generate information about households' energy consumption with heating systems composed of electric baseboards and ETS units. More details can be found in [72].

The house models are developed with OpenStudio and Energyplus; the ETS model is coded in Modelica. Both were encapsulated as functional mock-up units to enable distributed cosimulation. They exchange information under the FMI protocol, a well-accepted research method that enables distributed cosimulation. The house leads the interaction, providing the internal temperature to the ETS. Then, given a power consumption profile and the provided temperature, the ETS releases a certain amount of heat  $Q$  previously stored in the zone. Additionally, time orchestration is needed since each model has its own solver, and they have different time resolutions. Table 3 summarizes the characteristics of a typical house in the targeted community. Here, the set point for each thermal zone act as an input, while the power consumption and internal temperature of each thermal zone act as the model's outputs.

A self-developed ETS modelica model that suits the commercial STEFFES 2102 unit is utilized with maximum input power of 3.6 kW and a storage capacity of 13.2 kWh. The models' inputs are the power consumption, the internal room temperature, and the operational status (charging, discharging, or self-discharging). The outputs of the ETS are the energy consumption, the storage capacity, and the heat  $Q$  delivered to the room.

### B. GAME DESCRIPTION

Noncooperative games exploit the inclusion of multiple decision-making agents, each of which attempts to maximize its own benefits. The Stackelberg game is a noncooperative game model and has a hierarchical structure. The leader has

proactive features and sets its strategy first; then, the follower gives the optimal trajectory according to the leader's strategy. Afterwards, the follower passes the strategy to the leader. However, due to incomplete information issues, multiple iterations are needed to reach the system's optimal value and game equilibrium. The hierarchical Stackelberg game including a coordinator and a set of residential customers is constructed as follows.

- 1) Participants: Two set of agents with autonomous and controllable capabilities (i) a coordinator and (ii) residential agents act as the participants of the game.
- 2) Strategies: During the game, the utility sets the sale price; then, customers estimate their optimal consumption using MPC. The equilibrium point is the optimal strategy of the game, and the game leader cannot obtain higher operating income by unilaterally changing the electricity price strategy. At the same time, the followers cannot obtain higher profits by adjusting their strategy.
- 3) Utility functions: While the coordinator tries to reduce the microgrid's running cost, the customers will maximize their comfort objectives.

### C. UNCERTAINTY MODELING

#### 1) USER'S PRICE-ELASTICITY

Usually, conventional approaches consider vertical fluctuations in the electricity price value, which cause severe impacts on residential agents' strategies since their flexibility relies largely on price signals in a DR program. According to Martinez [52], proper introduction of uncertainty arising from time-related features of flexibility signals underline the future need for smart controllers; nevertheless, very little attention has been paid to users' price elasticity uncertainties.

Particularly, flexibility event duration is usually experienced from the consumers' perspective; for instance, during a setback event, i.e., modifying set-point preferences when the user is absent [73], [74]. Often, this value is assumed to be time-varying; however, real-life cases may differ significantly. Other than variations in set-point, there are numerous factors, which can affect the ability of customers to pay for their comfort, including the following.

- 1) Presence of substitute goods: Substitute good is defined as a product that satisfies the same need, even if it is not similar. Therefore, the elasticity is expected to be more significant in the presence of substitutes. For instance, in this work, the demand becomes more elastic in the presence of ETS room units as substitutes.
- 2) Price of goods concerning the consumer's income: The higher the price, the more elastic the demand, since it implies a higher cost. On the other hand, lower price constitutes inelastic demand. Furthermore, taking into consideration the consumer's income is also evident. For instance, higher income consumers are less sensitive to price, i.e., their demands tend to be inelastic.
- 3) Degree of necessity: An increase in the necessity of the good lowers the elasticity (inelastic demand). On the

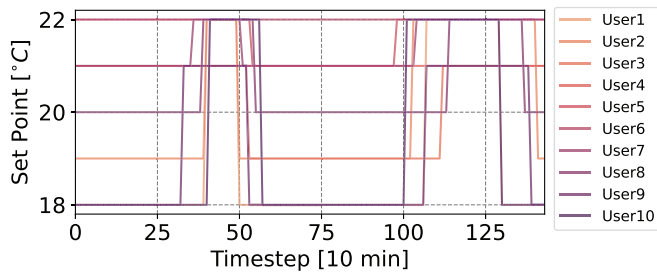


FIGURE 5. Residential agents' thermal preferences.

other hand, if the good is not essential, the demand is more elastic.

- 4) Time horizon: Generally, demand is more inelastic in short-term periods. Specifically, if the price of a good suddenly rises, consumers may not have time to react. Instead, in the long run, consumers adapt their consumption habits, which makes the demand more elastic.

This article adopts a time-variant approach to introduce unpredictable changes in users' decisions. In order to introduce uncertainties on the demand side, we introduce hourly fluctuations over  $\alpha$ , representing the flexibility level of customers, depending on their deterministic elasticity level mentioned above. Therefore, additive uncertainty is embedded in each user with different variances as

$$\hat{\gamma}_k^r = \alpha_k^r + \Gamma_k^r \quad (1)$$

where  $\Gamma_k^i \sim \mathcal{N}(0, \delta)$  is the price-elasticity for user  $r$ . While high values of  $\hat{\gamma}_k^i$  depict inelastic customers, low values represent flexible users aiming to reduce electricity bills rather than guaranteeing their comfort preferences. Elastic users exhibit higher variances, while inelastic customers show lower variances. Different variance values are considered to create heterogeneity on the demand side.

#### D. FOLLOWER PROBLEM: RESIDENTIAL HEATING DEMAND

Residential agents are decision-makers who perform actions according to their preferences. In this work, preferences represent the comfort needs and the flexibility of the consumer to pay for the latter. Fig. 5 illustrates user's preferences. Each customer performs MPC given the price established by the coordinator. The resulting strategy for each agent follows disciplined convex optimization rules and, therefore, an optimal trajectory. The proposed approach models two types of consumers.

- 1) The *Traditional*—conventional consumers who depend on electrical heaters to satisfy their needs.
- 2) The *Proactive*—conscious consumers interested in reducing their electricity bills by introducing thermal storage assets.

#### 1) THERMAL PREFERENCES

Controllable loads are subject to the preferences and the set-points of each customer. Such preferences can be modeled as normal logarithmic distributions [75] with zero mean ( $\mu =$

0), standard deviation one ( $\sigma = 1$ ), and scaled by the terms  $\omega_k$  and  $\rho_k$  as

$$\alpha_k^r = \omega + \rho_k \cdot \text{lognorm}(\mu, \sigma). \quad (2)$$

In (2), higher values of  $\alpha_k^r$  represents inelastic users, i.e., low flexibility to sacrifice its thermal comfort, and it is assumed as  $\omega = 3$  while  $\rho = 1$ . Furthermore, the set-points of the heating system defined for each customer follow the preferences previously defined in (2) as presented in Fig. 5.

#### 2) THERMAL DYNAMICS

A linear model based on the EnergyPlus modeling is used to estimate the thermal dynamics of the house in each thermal zone. The state-space model for a residence with two thermal zones for a *traditional* and a *proactive* user can be represented as

$$\begin{bmatrix} T_{k+1}^1 \\ T_{k+1}^2 \end{bmatrix} = A \begin{bmatrix} T_k^1 \\ T_k^2 \end{bmatrix} + B \begin{bmatrix} u_k^{EB_1} \\ u_k^{EB_2} \end{bmatrix} + D \begin{bmatrix} T_k^{Out} \end{bmatrix} \quad (3a)$$

$$\begin{bmatrix} T_{k+1}^1 \\ T_{k+1}^2 \end{bmatrix} = A \begin{bmatrix} T_k^1 \\ T_k^2 \end{bmatrix} + B \begin{bmatrix} u_k^{EB_1} \\ u_k^{EB_2} \end{bmatrix} + C \begin{bmatrix} u_k^{ETS_{Dsch}} \\ 0 \end{bmatrix} + D \begin{bmatrix} T_k^{Out} \end{bmatrix} \quad (3b)$$

where  $T_k$  is the internal temperature,  $T_k^{Out}$  is the outside temperature.  $k$  is the time step.  $u_k^{EB}$  and  $u_k^{ETS_{Dsch}}$  models power consumption for EB and thermal forced discharge for the ETS.  $A$ ,  $B$ , and  $C$ ,  $D$ ,  $E$  are coefficient matrices that are computed by minimizing the sum-of-squares loss function between (3a) and (3b) and the actual measured output over a set of historical data.

#### 3) UTILITY FUNCTION

To maximize the individual welfare of the customers, a multiobjective cost function is proposed to perform the optimization process. The first term of the cost function guarantees the occupants' comfort, the second one minimizes the customer's payments for any type of dynamic tariff and the third one the operational cost for proactive users. The objective is to maximize the individual welfare as the difference between the utility  $U_k$  that the user perceives from consuming energy, and the cost  $C_k$  that it has to pay in return, and the cost of running an ETS unit (Proactive users). A mathematical formulation of the optimal control problem takes the form

$$\max_{J_u} \mathbb{E}_{\xi \sim F} [J(T_k^{in}, \mathbf{u}, \gamma_k)] \approx 1/N \sum_{k=1}^T -U_k - C_k - C_k^M \quad (4a)$$

$$\text{s.t } T_{k+1}^{in} = f(T_k^{in}, u_k^{EB}, u_k^{ETS_{Ch}}, u_k^{ETS_{Dsch}}) \quad (4b)$$

$$T_k^{in} \in [T_{min}^{in}, T_{max}^{in}] \quad (4c)$$

$$u_k^{EB} \in [0, u_{max}^{EB}] \quad (4d)$$

$$u_k^{ETS_{Ch}} \in [0, u_{max}^{ETS_{Ch}}] \quad (4e)$$

$$u_k^{ETS_{Dsch}} \in [0, P_{max}^{ETS_{Dsch}}] \quad (4f)$$

$$x_0 = \text{Initial State} \quad (4g)$$

$$u_0 = \text{Initial State} \quad (4h)$$

$$\text{SOC}_{k+1} = \text{SOC}_k + (u_k^{\text{ETS}_{\text{Ch}}} - u_k^{\text{ETS}_{\text{Dsch}}}) \Delta_k \quad (4i)$$

where

$$U_k = \gamma_k (T_k^C - T_k)^2 \quad (5)$$

$$C_k = \pi_k u_k \quad (6)$$

$$C_k^M = (u_k^{\text{ETS}_{\text{Ch}}} - u_k^{\text{ETS}_{\text{Dsch}}}) \Delta_k \cdot C_k^b \quad (7)$$

$$C_k^b = \frac{I}{2\eta (\overline{\text{ES}} - \underline{\text{ES}})}. \quad (8)$$

The term  $N$  is the number of scenarios,  $U_k$  is the comfort objective,  $C_k$  stands for the cost term, and  $C_k^M$  is the operating cost of running an ETS unit. Note that if the user is traditional,  $C_k^M$  equals zero.  $C_k^b$  is a parameter, where  $\eta$  is the total rated cycles of the ETS unit,  $I$  is the upfront cost to purchase an ETS, and  $\text{ES}$  is a parameter meaning a desired amount of energy stored in kWh. The denominator is multiplied by two (2) since a cycle is assumed to be the ETS charging to  $\overline{\text{ES}}$  and discharging to  $\underline{\text{ES}}$ . These two were set to 80 and 20, respectively.

Particularly, this formulation assumes that the residential agents' decision has a risk-neutral attitude as it implies that potential losses are equally offset by potential gains, always considering that the average value maximizes the expected value.

A key consideration in solving the stochastic optimal control problem is the propagation of the mean and variance of the random variable making the objective function stochastic. The problem is subject to several constraints:  $T_{\min}$  and  $T_{\max}$  are the possible allowed temperature interval in the rooms of the house (user-defined),  $u_{\max}^{\text{ETS}}$  and  $u_{\max}^{\text{EB}}$  are the maximum output power of the ETS for each thermal zone,  $x_0$  and  $u_0$  are the initial conditions of each thermal zone regarding the indoor temperature and the energy consumption of controllable loads.  $\Delta_k$  is a ratio to obtain the energy amount per time slot  $k$ .  $\text{SOC}_{k+1}$  is the current energy stored,  $\text{SOC}_k$  is the immediate previous energy stored,  $u_k^{\text{ETS}_{\text{Ch}}}$  is the ETS power consumption, and  $u_k^{\text{ETS}_{\text{Dsch}}}$  is the heat delivered to the room.

### E. LEADER PROBLEM: MINIMIZING ENERGY COST

Energy cost model is an incremental cost function that represents the cost of generating a unit of electricity by the energy source at each hour. Widely used quadratic cost (for a diesel generator) functions fit such criteria, i.e.,

$$C_k(L_k) = a_k L_k^2 + b_k L_k + c_k \quad (9)$$

where  $a_k$ ,  $b_k$ , and  $c_k$  are  $> 0$  at each hour.  $L_k$  represents sum of all sets of best strategies  $[u_1^{k*}, u_2^{k*}, \dots, u_n^{k*}]$ . The term  $u_n^{k*}$  denotes the best strategy of the  $n$ th user. The cost function adopted is strictly convex and represents an artificial cost tariff

employed by the utility to perform proper demand control. For instance, Hydro Quebec adopts a convex price model in the form of a two-step piece-wise linear function to encourage users inhabiting remote areas to consume more conservatively. Such a function can be smoothed by a quadratic cost, which is more suitable for optimization purposes.

In the presence of renewable production  $R_k$ , (9) becomes stochastic due to the inherent variability of renewable sources. We set  $b_k$  and  $c_k$  to zero for simplicity, and (9) is recast as

$$\mathbb{E}(C_k) \approx \frac{1}{N} a_k \sum_{k=1}^T (L_k - R_k)^2. \quad (10)$$

Additionally, residential customers are charged depending on their own energy consumption, according to the following billing tariff:

$$B_k \approx \sum_{r=1}^C \sum_{k=1}^T \mathbb{E}(C_k) u_k^r. \quad (11)$$

In this way, the expected billings reflect the user's total daily energy consumption and relate it to the total expected energy cost of the system. Furthermore, economic savings for the coordinator and residential agents were estimated as the initial cost without DR versus the resulting final cost at the game's latest iteration in the proposed strategy.

### F. DISTRIBUTED OPTIMIZATION (PROXIMAL DECOMPOSITION)

In practice, sequential updating to ensure convergence of algorithms can become a difficult task. Therefore, distributed algorithms, such as proximal decomposition [14], [76], [77], are preferable to overcome such issues. It allows users to update their strategies simultaneously without sharing information with their neighbors. As mentioned in Section II, the problem is modeled hierarchically employing a Stackelberg game. At customer level, each follower maximizes its own convex local cost function, with a total amount of discrete-time slots. Meanwhile, the leader aggregates the strategies and establishes a new price depending on wind power availability to encourage customers to coordinate their actions while balancing power demand and power supply.

An additional term in the consumers' payoff function has been designed to ensure the algorithm's convergence under tender conditions and the coordination between users. This term is intended to penalize large variations between successive iterations in the decomposed optimization process [12]. Consequently, the final form of the consumer's payoff function can be written as

$$\min_{u_k^1, \dots, u_k^r} \mathbf{J} + \frac{\tau}{2} \left\| u_k^{r,i} - u_k^{r,i-1} \right\| \quad (12)$$

where  $i$  and  $r$  stand for the iteration and user index, respectively,  $\tau$  is a regularization parameter. The latter has been

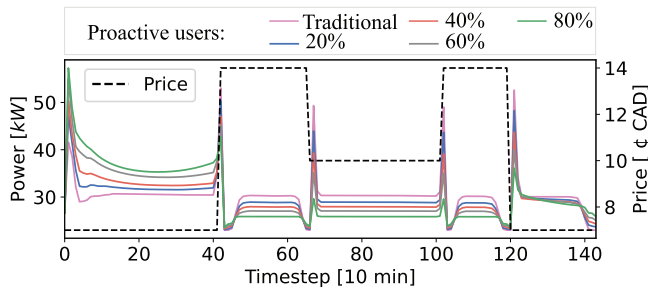


FIGURE 6. Impact of several uncoordinated thermal storage units.

chosen according to [77]

$$\tau \geq 4(N-1)\lambda. \quad (13)$$

The value of  $\lambda$  has been calculated and used as the initial average price. The algorithm's convergence has been modeled as the situation where there are no significant variations in the aggregated profile between two iterations. This convergence criterion is defined as [31]

$$\|L_k^i - L_k^{i-1}\|_2 / \|L_k^i\|_2 \leq 10^{-2}. \quad (14)$$

### G. COORDINATION

The conventional and individual DR of multiple agents may decrease the grid reliability and the economic benefits for both utilities and consumers. RAs are fully autonomous and will always try to maximize their welfare. Hence, if given the same signal price, they simultaneously schedule their loads during off-peak hours, resulting in Prisoner's dilemma. That is reflected as 'rebound peaks' during low pricing periods.

Fig. 6 demonstrates the effect of uncoordinated thermal storage units on energy. Here, it is evident how each agent performs actions to maximize its welfare, acting selfishly. Comprehensively, the flexibility vectors connected uncoordinatedly may cause undesirable effects on low-voltage distribution networks. Hence, harmonious coordination on the demand side is needed to solve the rebound peak issues and improve the reliability of distribution electricity networks. Consequently, utilities warrant sharing a mechanism with residential agents that encourages them to actively coordinate to reduce power peaks (utility benefit) and their electricity bills (consumer benefit).

### III. SIMULATION RESULTS

In this article, the case study considered for simulation results consists of a group of ten (10) residential consumers in Kuujuaq, a northern hard-to-reach community in Quebec. This region faces extreme subzero temperatures during winter. The microgrid is a single transformer powering a group of customers, the capacity of the transformer is enough to meet the demand without creating overcharging scenarios, and a large diesel generator is considered along with centralized wind power stands for energy carriers to power the community. The

dwellings have the features listed in Table 3. Customers are fully autonomous agents that can modify their consumption patterns given an incentive signal from the coordinator. In particular, we use the term *adoption* for purchasing an ETS to cover heating needs for one of the two thermal zones.

Following is the list of preferences of each user.

- 1) H1:  $TC = 22, \alpha = 8.07$ .
- 2) H2:  $TC = 21, \alpha = 3.54$ .
- 3) H3:  $TC = 21, \alpha = 3.58$ .
- 4) H4:  $TC = 22, \alpha = 3.34$ .
- 5) H5:  $TC = 22, \alpha = 5.37$ .
- 6) H6:  $TC = 22, \alpha = 8.07$ .
- 7) H7:  $TC = 21, \alpha = 3.54$ .
- 8) H8:  $TC = 21, \alpha = 3.58$ .
- 9) H9:  $TC = 22, \alpha = 3.34$ .
- 10) H10:  $TC = 22, \alpha = 5.37$ .

The performance of the proposed strategy is tested with different rates of proactive users in 24 h with a time resolution equal to 10 min. To calculate the energy cost, we set  $b_k = c_k = 0$  in the quadratic cost function (9) and estimated  $a_k = 0.9$  cents/kWh<sup>2</sup>, which remains constant throughout the day. The performance is evaluated through PAR, i.e., calculated as  $PAR = (\max(L_k)T)/L_k$ .

User strategies are based on convex optimization problems where the objective is a sum of convex functions. The disciplined convex programming method is utilized to solve them through the Python-embedded modeling language for convex optimization [78]. Besides, we use the ECOS solver suitable for solving massive convex cone programs to calculate the optimal solution.

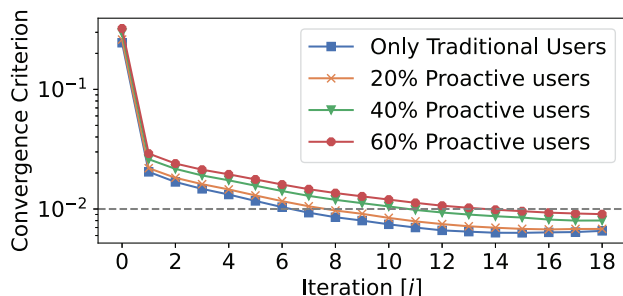
### A. OVERALL PERFORMANCE

This case study describes how residential agents participate actively under a price-based strategy proposed by a local coordinator. From the coordinator, DS-3000's vertical-axis wind turbines represent nondispatchable resources. This wind turbine has an output power of 3 kW based on the manufacturer's information. On the demand side, EBs and ETS account for controllable loads. Also, incomplete information is considered with fluctuations in users' flexibility and wind power forecasting. Proactive households possess one ETS room unit with 3.6 kW input power and a capacity of 13.2 kWh. To estimate operational costs, we consider the asset service life of 15 years and capital expenses of 2500 CAD. In addition, it was considered that the customers are ETS owners and the maximum power of electric baseboards was 2 kW. We set the initial and final state-of-the-charge to 20% of their capacity. Note that all users have the same model of ETS installed.

Fig. 7 demonstrates the algorithm convergence for variations in ETS penetration over the first 20 iterations. It is observed that the convergence is reached after 10 to 13 iterations depending on the level of ETS adoption on the demand side. Notably, higher ETS adoption values result in the slowest convergence compared with lower ETS penetration levels.

**TABLE 4** PAR and Aggregated Cost Comparison

Metric	Uncertainty Case	Uncoordinated	Coordinated					
			Share of proactive users (%)					
			0	20	40	60	80	100
PAR	Demand	3.5	2.51	2.17	2.02	1.71	1.68	1.53
	Demand + Wind Power	3.5	2.52	2.37	2.23	2.15	1.96	1.89
Agg. cost	Demand	106.71	75.46	72.95	70.69	68.63	67.9	67.3
	Demand + Wind Power	101.13	64.37	61.15	59.23	57.50	57.10	56.9

**FIGURE 7.** Convergence of algorithm with termination criterion.

That is due to an increase in the overall degrees of freedom of the problem, which increases the iterations to reach the defined convergence criterion.

### B. COMPARISON BETWEEN DIFFERENT PERCENTAGES OF PROACTIVE USERS

The effectiveness of increasing the proactive users through the proposed strategy is tested. Here, one user is considered proactive by installing an ETS room unit that covers heating needs for one of the two thermal zones. Table 4 condenses results obtained for two parameters, including the PAR and aggregated energy cost at each level of ETS adoption. Besides, it summarizes results with and without wind production. Results show PAR reduction of up to 56% is achieved when all customers decided to purchase an ETS unit; ETS adoption reduced the PAR with and without wind production. Nevertheless, the former results lower when wind power is absent.

Fig. 8 compares multiple aggregate loads as a result of the sum of the user's optimal strategies. That includes uncertainty from the user's flexibility without wind power production. Also, it contains information about the resulting average electricity prices for each level of ETS adoption. We observed that as the share of proactive users increased, the power curve was more flattened, filling valleys, and reducing peaks. Besides, the proposed strategy furnishes reductions in average grid price per kWh up to 26% (from 10 cents/kWh to 7.4 cents/kWh). Fig. 9 illustrates wind power production case and their uncertainties. The demand curve is flattened as in the previous case. Fig. 10 shows the resulting electricity price and some users' storage decisions by hourly blocks. Proactive

users charged their ETS at low prices and released such power during peaks.

### C. BENEFIT ANALYSIS

The cost-effectiveness of the proposed mechanism for customers and utility is also analyzed. Fig. 11 describes the distribution of expected benefits for residential users with and without wind power generation. The results show that the proposed program brings economic savings, and the expected benefits increase substantially in the presence of wind power.

Figs. 11–13 provide a picture of the evolution of user expected benefits with different rates of proactive users. When all users are willing to purchase an ETS unit, payments reduce significantly. Also, users with more degrees of freedom (proactive) and higher flexibility obtain higher savings. However, as ETS adoption increases, users' benefits increase differently [14]. Note that traditional users (except users 8 and 9) obtain benefits close to 10%, less than proactive users. Proactive users differ in economic savings because they exhibit different user preferences and flexibility. That may affect payments for the rest of the customers.

From the utility viewpoint, Table 4 shows how proactive users can substantially reduce energy costs due to uncertainties from demand and wind power. Fig. 14 depicts an example of the expected average cumulative expense with and without wind power generation at 40% and 60% of proactive users.

### IV. DISCUSSION

Strategies for optimal integration of energy storage assets in distribution systems have gained significant momentum. That includes the courtesy of migration from passive to active networks, embedding renewables, growth of particular sectors (industrial, commercial and residential), and the changes in consumers' consumption patterns, among others. Users have become more active on the demand side since utilities encourage them to purchase flexible loads to participate in DR programs. Even though literature has addressed the optimal integration of distributed energy storage resources, a large share relies on fully deterministic approaches, which are very far from real-life scenarios and may provide biased results. DR programs, including electric batteries, such as those proposed in [77] and [31], although based on complete information, reported meaningful reductions in the aggregated

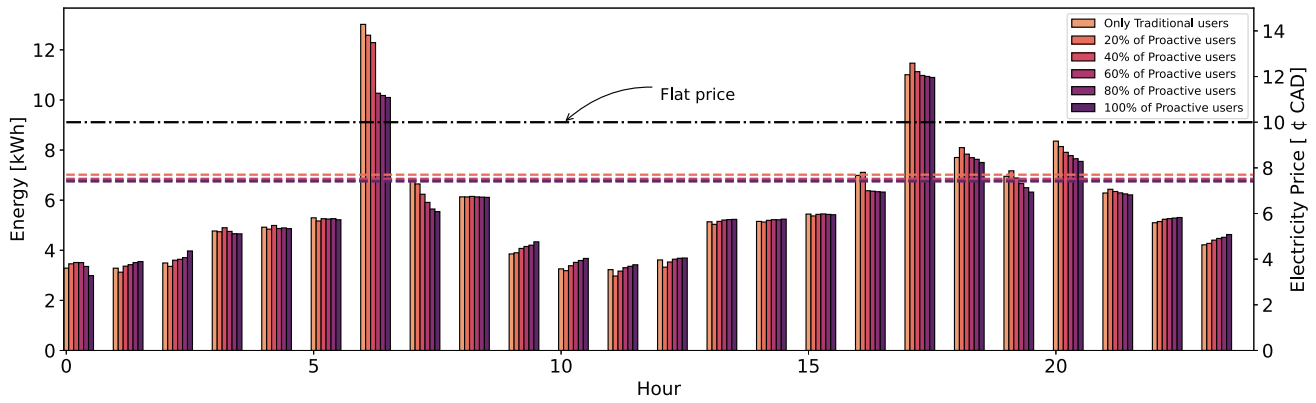


FIGURE 8. Coordinated aggregate hourly per-slot energy blocks with stochastic demand for each level of ETS adoption (No wind power).

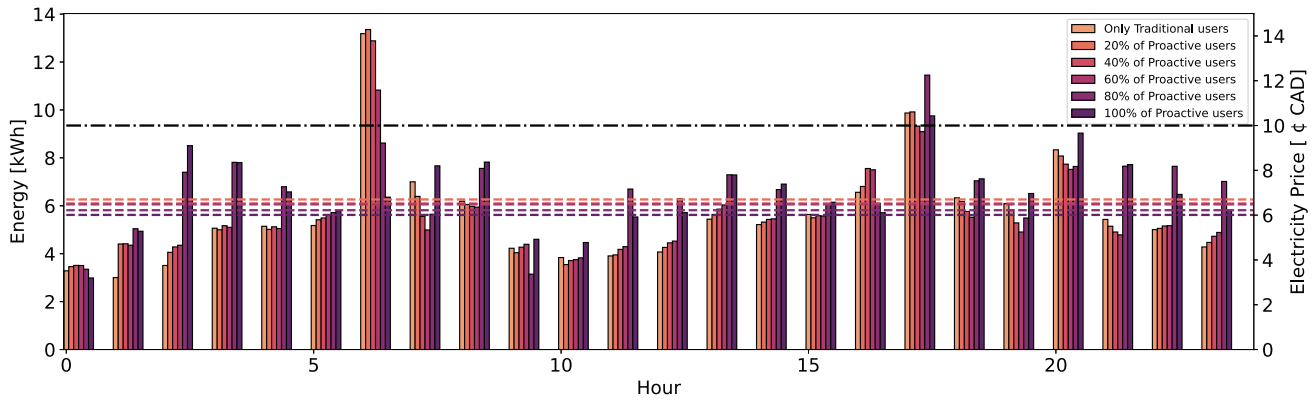


FIGURE 9. Coordinated aggregate hourly per-slot energy blocks with stochastic demand and electricity price for each level of ETS adoption (with wind power).

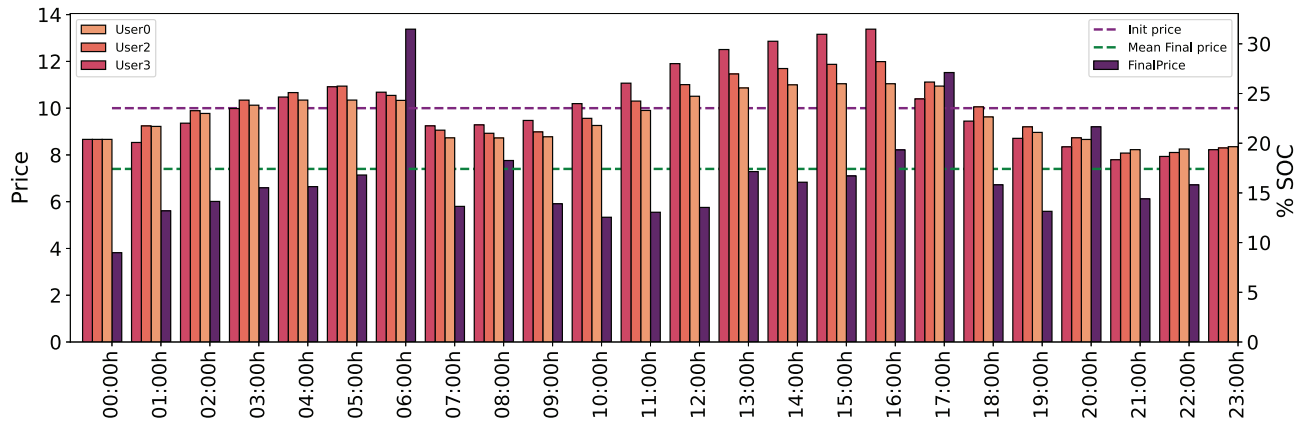
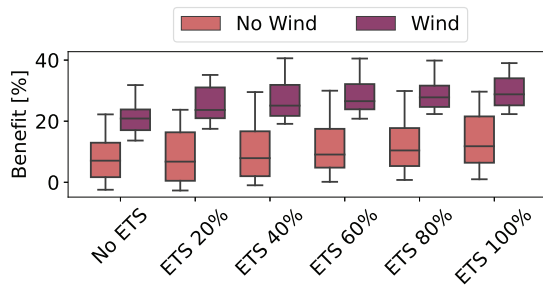


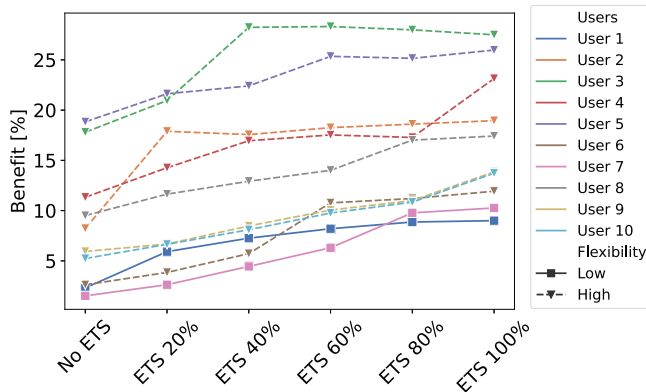
FIGURE 10. Aggregate per-slot prices and SOC for 100% for a subset of proactive agents.

energy cost, the PAR. Simulations from [77] showed that 24% of active users on the demand side create a reduction in the PAR equivalent to 17.1%. Similarly, in [31], their findings showed that full adoption of electric batteries on the demand side substantially reduces the PAR, passing from 1.8797 to 1.3427 (40% improvement). Regarding economic benefits for users, both approaches agreed that customers obtained benefits depending on the amount of energy they contributed to the whole energy volume, as they rely on a distributed approach.

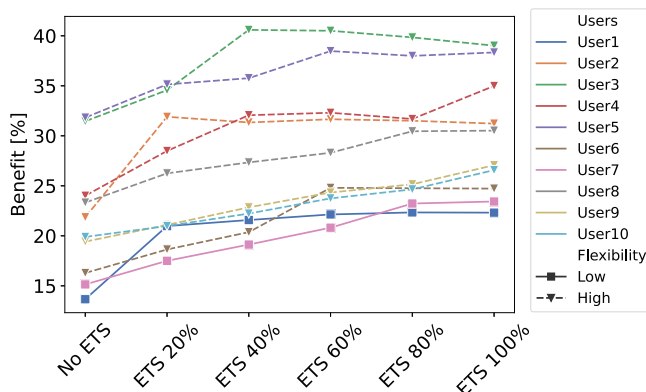
On the other hand, the proposed strategy demonstrated a 26% of PAR reduction and 56% of PAR reduction when ETS penetrates all the housings. That is a significant achievement in comparison to the work in the literature. A similar approach [79] considered variable generation costs; however, it relies on complete information meaning that weather forecasting was perfect. Eventually, consistent with prior findings, our approach showed comparable benefits for utilities and customers without complete information (i.e., encompassing



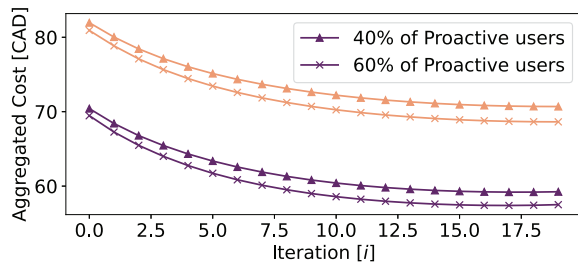
**FIGURE 11.** Comparison of distribution for expected daily benefits for users across different cases with and without wind power.



**FIGURE 12.** Expected economic daily benefits for users across different cases.



**FIGURE 13.** Expected economic daily benefits for users across different cases with wind power.



**FIGURE 14.** Average cumulative expense over the period of analysis for two subsets of active users, at each iteration, with and without wind power.

the stochasticity from wind power generation and user flexibility). That shows the superiority of the proposed strategy in comparison to others.

As the increased adoption of ETS led to reduced individual electricity bills, the proactive users putting substantial effort than traditional ones should receive a higher incentive. Consumers could receive such incentives as i) discount rates, ii) rebates, or iii) reduction in electricity prices during specific periods. Besides, a gradual increase in acceptance of ETS units on the demand side does not necessarily provide a constant marginal reduction in the PAR nor constant marginal increases in individual electricity bills. A particular case of user 2 showed in Figs. 13 and 12 concurs, where the transition from 60% to 80% of ETS adoption resulted in a loss of incentive of about 1.5%. That is consistent with real-life cases [80], which clarifies some thoughts about dynamic pricing work in a winter-peaking climate in a particular case of Hydro-Quebec. Under the “rate flex” tariffs (critical-peak pricing), some users paid more than they would have at their regular rate in winter conditions.

The results demonstrated that substantial reductions in PAR could be achieved by adopting ETS on the demand side. As ETS units on the demand side belong to customers with specific thermal preferences and elasticity, savings for the utility (regarding PAR reduction) may sometimes not fall sustainably. Hence, in addition to a willingness to purchase an ETS unit, exploiting the potential of the flexibility vector is essential to shift the demand for lower pricing periods.

The proposed strategy demonstrated outstanding performance in reaching equilibrium under uncertainties from users’ flexibility and wind power regardless of the nature of user preferences (dynamic or constant set-points). Eventually, the proposed strategy could be adapted for communities integrated with solar-PV and natural gas. However, it will modify the resulting energy cost as multiple carriers appear in the landscape. Consequently, customers’ decisions can also be affected, as the price policy depends on aggregated consumption.

Though techniques, such as robust optimization (RO) and the information gap decision theory (IGDT), could be exploited to address similar problems; however, the former is pertinent to exploit when probabilities can be tough to model [81]. Additionally, it may not fit all demand-side management strategies since it is based on the worst-case, often leading to overconservative solutions. Similarly, IGDT, a nonprobabilistic optimization technique, has shown a significant ability to model uncertainties and reduce risks in daily operations of smart grids [82], [83], [84]. Here, optimal decisions are made without any assumptions for the probability of uncertainties. Nevertheless, the proposed strategy utilizes historical data, enabling the characterization of the probability distribution of essential variables over time. Furthermore, the proposed approach is scalable as the strategy performs distributed optimization with the proximal decomposition method. This algorithm exhibits a linear complexity,

meaning that its convergence time is proportional to the number of iterations needed to clear the market.

## V. CONCLUSION

In this article, a practical approach utilizing the leader-follower Stackelberg game and cosimulation methods to explore the potential of ETS in the presence of wind power generation to meet a microgrid's electric supply needs is presented. Notably, a day-ahead problem is formulated whereby each active user on the demand side minimizes the payoff function autonomously to cover their energy needs. The proposed strategy relies on distributed optimization by utilizing the proximal decomposition method, which permits computing the best strategies for each user without violating the user's privacy. Stochastic programming is leveraged to consider uncertainties from renewables and users' preferences. Simulation studies were carried out over ten RAs of a northern community in Quebec, possessing different flexibility. Simulation results depict that partial adoption of ETS units creates different benefit rates for users depending on their degree of flexibility. This active participation of users in the proposed strategy provided them with economic savings. Besides, utilities significantly reduced the energy costs in wind power generation. The simulation results also indicated that the proposed strategy flattened the demand curve, reducing the need for diesel fuel and expensive peaking power plants. In the future, studies should consider prosumers and local energy markets to empower coalitions among customers rather than relying solely on utility negotiations. Furthermore, a hardware implementation pilot would be interesting to create a hybrid framework by controlling both simulated and real houses.

## ACKNOWLEDGMENT

The authors would like to thank the Laboratoire d'innovation et de recherche en énergie intelligente (LIREI) and the Natural Sciences and Engineering Research Council of Canada.

## REFERENCES

- [1] IEA, "Energy storage," 2020. [Online]. Available: <https://www.iea.org/reports/energy-storage>
- [2] IEA, "World energy outlook 2021," IEA, Paris, France, Tech. Rep., 2021.
- [3] C. Rahmann and R. Alvarez, "The role of smart grids in the low carbon emission problem," in *Planning and Operation of Active Distribution Networks: Technical, Social and Environmental Aspects*. Cham, Switzerland: Springer, 2022, pp. 455–485.
- [4] J. Campillo, E. Dahlquist, F. Wallin, and I. Vassileva, "Is real-time electricity pricing suitable for residential users without demand-side management?," *Energy*, vol. 109, pp. 310–325, Aug. 2016. [Online]. Available: <https://linkinghub.elsevier.com/retrieve/pii/S0360544216305187>
- [5] M. Pilz and L. Al-Fagih, "Recent advances in local energy trading in the smart grid based on game-theoretic approaches," *IEEE Trans. Smart Grid*, vol. 10, no. 2, pp. 1363–1371, Mar. 2019.
- [6] X. Dong, X. Li, and S. Cheng, "Energy management optimization of microgrid cluster based on multi-agent-system and hierarchical Stackelberg game theory," *IEEE Access*, vol. 8, pp. 206183–206197, 2020.
- [7] P. Kiran, K. R. M. V. Chandrakala, and T. N. P. Nambiar, "Multi-agent based systems on micro grid—A review," in *Proc. Int. Conf. Intell. Comput. Control*, 2017, pp. 1–6.
- [8] M. Eslahi-Kelozazi and F.-A. Parand, "Game theoretic approaches in modeling and solving smart grid issues," in *Proc. 2nd Int. Conf. Knowl.-Based Eng. Innov.*, 2015, pp. 1019–1024.
- [9] IEA, *Global Energy Review 2021*, Paris, France, 2021.
- [10] M. H. Nazari, M. Bagheri-Sanjareh, and S. H. Hosseini, "A new method for energy management of residential microgrid for sizing electrical and thermal storage systems," *Sustain. Cities Soc.*, vol. 76, 2022, Art. no. 103482.
- [11] S. Zheng, X. Jin, G. Huang, and A. C. Lai, "Coordination of commercial prosumers with distributed demand-side flexibility in energy sharing and management system," *Energy*, vol. 248, 2022, Art. no. 123634.
- [12] J. Wei, Y. Zhang, J. Wang, L. Wu, P. Zhao, and Z. Jiang, "Decentralized demand management based on alternating direction method of multipliers algorithm for industrial park with CHP units and thermal storage," *J. Modern Power Syst. Clean Energy*, vol. 10, no. 1, pp. 120–130, 2022.
- [13] G. Ferro, M. Robba, R. Haider, and A. M. Annaswamy, "A distributed optimization based architecture for management of interconnected energy hubs," *IEEE Trans. Control Netw. Syst.*, vol. 9, no. 4, pp. 1704–1716, Dec. 2022.
- [14] S. Wong and J.-P. Pinar, "Opportunities for smart electric thermal storage on electric grids with renewable energy," *IEEE Trans. Smart Grid*, vol. 8, no. 2, pp. 1014–1022, Mar. 2017.
- [15] B. V. Solanki, P. S. Sauter, C. A. Canizares, K. Bhattacharya, and S. Hohmann, "Electric thermal storage system impact on northern communities' microgrids," 2017. [Online]. Available: <https://publikationen.bibliothek.kit.edu/1000073509>
- [16] N. T. Janssen, R. A. Peterson, and R. W. Wies, "Generalized heat flow model of a forced air electric thermal storage heater core," *J. Thermal Sci. Eng. Appl.*, vol. 9, no. 4, Dec. 2017, Art. no. 041008. [Online]. Available: <https://asmedigitalcollection.asme.org/thermalscienceapplication/article/doi/10.1115/1.4036366/392609/Generalized-Heat-Flow-Model-of-a-Forced-Air>
- [17] W. Devia, K. Agbossou, and A. Cardenas, "An evolutionary approach to modeling and control of space heating and thermal storage systems," *Energy Buildings*, vol. 234, Mar. 2021, Art. no. 110674. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0378778820334605>
- [18] Z. Broka, K. Baltputnis, A. Sauhats, L. Sadovica, and G. Junghans, "Stochastic model for profitability evaluation of demand response by electric thermal storage," in *Proc. IEEE 59th Int. Sci. Conf. Power Elect. Eng. Riga Tech. Univ.*, 2018, pp. 1–6. [Online]. Available: <https://ieeexplore.ieee.org/document/8659837/>
- [19] Z. Broka, J. Kozadajevs, A. Sauhats, D. P. Finn, and W. J. Turner, "Modelling residential heat demand supplied by a local smart electric thermal storage system," in *Proc. 57th Int. Sci. Conf. Power Elect. Eng. Riga Tech. Univ.*, 2016, pp. 1–8.
- [20] M. J. M. Al Essa, "Home energy management of thermostatically controlled loads and photovoltaic-battery systems," *Energy*, vol. 176, pp. 742–752, Jun. 2019. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0360544219306656>
- [21] A. Martín-Crespo, S. Saludes-Rodil, and E. Baeyens, "Flexibility management with virtual batteries of thermostatically controlled loads: Real-time control system and potential in Spain," *Energies*, vol. 14, no. 6, Jan. 2021, Art. no. 1711. [Online]. Available: <https://www.mdpi.com/1996-1073/14/6/1711>
- [22] G. Liu, Y. Tao, L. Xu, Z. Chen, J. Qiu, and S. Lai, "Coordinated management of aggregated electric vehicles and thermostatically controlled loads in hierarchical energy systems," *Int. J. Elect. Power Energy Syst.*, vol. 131, Oct. 2021, Art. no. 107090. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S014206152100329X>
- [23] A. M. Carreiro, H. M. Jorge, and C. H. Antunes, "Energy management systems aggregators: A literature survey," *Renewable Sustain. Energy Rev.*, vol. 73, pp. 1160–1172, Jun. 2017. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S1364032117301776>
- [24] L. Gkatzikis, I. Koutsopoulos, and T. Salonidis, "The role of aggregators in smart grid demand response markets," *IEEE J. Sel. Areas Commun.*, vol. 31, no. 7, pp. 1247–1257, Jul. 2013.
- [25] K. Bruninx, H. Pandžić, H. Le Cadre, and E. Delarue, "On the interaction between aggregators, electricity markets and residential demand response providers," *IEEE Trans. Power Syst.*, vol. 35, no. 2, pp. 840–853, Mar. 2020.
- [26] F. Etedadi Aliabadi, K. Agbossou, S. Kelouwani, N. Henao, and S. S. Hosseini, "Coordination of smart home energy management systems in neighborhood areas: A systematic review," *IEEE Access*, vol. 9, pp. 36417–36443, 2021.

- [27] R. Gulati, F. Wohlgezogen, and P. Zhelyazkov, "The two facets of collaboration: Cooperation and coordination in strategic alliances," *Acad. Manage. Ann.*, vol. 6, no. 1, pp. 531–583, 2012.
- [28] M. Hu, F. Xiao, and S. Wang, "Neighborhood-level coordination and negotiation techniques for managing demand-side flexibility in residential microgrids," *Renewable Sustain. Energy Rev.*, vol. 135, 2021, Art. no. 110248.
- [29] T. Logenthiran, D. Srinivasan, and T. Z. Shun, "Demand side management in smart grid using heuristic optimization," *IEEE Trans. Smart Grid*, vol. 3, no. 3, pp. 1244–1252, Sep. 2012.
- [30] G. Niro, D. Salles, M. V. Alcantara, and L. C. da Silva, "Large-scale control of domestic refrigerators for demand peak reduction in distribution systems," *Electric Power Syst. Res.*, vol. 100, pp. 34–42, 2013.
- [31] T. L. Nguyen et al., "Agent based distributed control of islanded microgrid-real-time cyber-physical implementation," in *Proc. IEEE PES Innov. Smart Grid Technol. Conf. Europe*, 2017, pp. 1–6.
- [32] B. Celik, R. Roche, D. Bouquain, and A. Miraoui, "Decentralized neighborhood energy management with coordinated smart home energy sharing," *IEEE Trans. Smart Grid*, vol. 9, no. 6, pp. 6387–6397, Nov. 2018.
- [33] Z. Wang et al., "Decentralized energy management system for networked microgrids in grid-connected and islanded modes," *IEEE Trans. Smart Grid*, vol. 7, no. 2, pp. 1097–1105, Mar. 2016.
- [34] Z. Wang, L. Wang, A. I. Dounis, and R. Yang, "Multi-agent control system with information fusion based comfort model for smart buildings," *Appl. Energy*, vol. 99, pp. 247–254, Nov. 2012. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0306261912003686>
- [35] F. Bünnig, R. Sangi, and D. Müller, "A modelica library for the agent-based control of building energy systems," *Appl. Energy*, vol. 193, pp. 52–59, May 2017. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0306261917300612>
- [36] T. Rajeev and S. Ashok, "Dynamic load-shifting program based on a cloud computing framework to support the integration of renewable energy sources," *Appl. Energy*, vol. 146, pp. 141–149, May 2015. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0306261915001877>
- [37] A. Fraija, K. Agbossou, N. Henao, and S. Kelouwani, "Peak-to-average ratio analysis of a load aggregator for incentive-based demand response," in *Proc. IEEE 29th Int. Symp. Ind. Electron.*, 2020, pp. 953–958.
- [38] M. A. A. Abdalla, W. Min, and O. A. A. Mohammed, "Two-stage energy management strategy of EV and PV integrated smart home to minimize electricity cost and flatten power load profile," *Energies*, vol. 13, no. 23, 2020, Art. no. 6387.
- [39] E. I. C. Zebra, H. J. van der Windt, G. Nhumaio, and A. P. Faaaj, "A review of hybrid renewable energy systems in mini-grids for off-grid electrification in developing countries," *Renewable Sustain. Energy Rev.*, vol. 144, 2021, Art. no. 111036.
- [40] J. Kitson et al., "Modelling of an expandable, reconfigurable, renewable DC microgrid for off-grid communities," *Energy*, vol. 160, pp. 142–153, 2018.
- [41] Y.-Y. Hong, W.-C. Chang, Y.-R. Chang, Y.-D. Lee, and D.-C. Ouyang, "Optimal sizing of renewable energy generations in a community microgrid using Markov model," *Energy*, vol. 135, pp. 68–74, 2017.
- [42] C. P. Mediawathe, M. Shaw, S. Halgamuge, D. B. Smith, and P. Scott, "An incentive-compatible energy trading framework for neighborhood area networks with shared energy storage," *IEEE Trans. Sustain. Energy*, vol. 11, no. 1, pp. 467–476, Jan. 2020.
- [43] R. Tang, H. Li, and S. Wang, "A game theory-based decentralized control strategy for power demand management of building cluster using thermal mass and energy storage," *Appl. Energy*, vol. 242, pp. 809–820, May 2019. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0306261919305616>
- [44] Y. Zeng and W. Chen, "The socially optimal energy storage incentives for microgrid: A real option game-theoretic approach," *Sci. Total Environ.*, vol. 710, Mar. 2020, Art. no. 136199. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0048969719361959>
- [45] G. Mavromatidis, K. Orehoung, and J. Carmeliet, "Design of distributed energy systems under uncertainty: A two-stage stochastic programming approach," *Appl. Energy*, vol. 222, pp. 932–950, 2018.
- [46] H. Huuki, S. Karhinen, H. Böök, A. V. Lindfors, M. Kopsakangas-Savolainen, and R. Svento, "Utilizing the flexibility of distributed thermal storage in solar power forecast error cost minimization," *J. Energy Storage*, vol. 28, 2020, Art. no. 101202.
- [47] D. Testi, L. Urbanucci, C. Giola, E. Schito, and P. Conti, "Stochastic optimal integration of decentralized heat pumps in a smart thermal and electric micro-grid," *Energy Convers. Manage.*, vol. 210, 2020, Art. no. 112734.
- [48] Z. Li, Y. Xu, X. Feng, and Q. Wu, "Optimal stochastic deployment of heterogeneous energy storage in a residential multienergy microgrid with demand-side management," *IEEE Trans. Ind. Informat.*, vol. 17, no. 2, pp. 991–1004, Feb. 2021.
- [49] N. Good, E. Karangelos, A. Navarro-Espinosa, and P. Mancarella, "Optimization under uncertainty of thermal storage-based flexible demand response with quantification of residential users' discomfort," *IEEE Trans. Smart Grid*, vol. 6, no. 5, pp. 2333–2342, Sep. 2015.
- [50] A. Najafi-Ghalelou, S. Nojavan, K. Zare, and B. Mohammadi-Ivatloo, "Robust scheduling of thermal, cooling and electrical hub energy system under market price uncertainty," *Appl. Thermal Eng.*, vol. 149, pp. 862–880, 2019.
- [51] S. Pazouki, M.-R. Haghifam, and A. Moser, "Uncertainty modeling in optimal operation of energy hub in presence of wind, storage and demand response," *Int. J. Elect. Power Energy Syst.*, vol. 61, pp. 335–345, 2014.
- [52] S. Martinez, M. Vellei, and J. Le Dréau, "Demand-side flexibility in a residential district: What are the main sources of uncertainty?," *Energy Buildings*, vol. 255, 2022, Art. no. 111595.
- [53] L. Rueda, K. Agbossou, A. Cardenas, N. Henao, and S. Kelouwani, "A comprehensive review of approaches to building occupancy detection," *Building Environ.*, vol. 180, Aug. 2020, Art. no. 106966. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0360132320303255>
- [54] M. Pourbehzadi, T. Niknam, J. Aghaei, G. Mokryani, M. Shafie-khah, and J. P. Catalão, "Optimal operation of hybrid AC/DC microgrids under uncertainty of renewable energy resources: A comprehensive review," *Int. J. Elect. Power Energy Syst.*, vol. 109, pp. 139–159, 2019.
- [55] L. Rueda et al., "Online unsupervised occupancy anticipation system applied to residential heat load management," *IEEE Access*, vol. 9, pp. 109806–109821, 2021.
- [56] N. T. Janssen, R. A. Peterson, and R. W. Wies, "Improved frequency regulation on hybrid wind-diesel microgrids using self-sensing electric thermal storage devices," in *Proc. Australas. Univ. Power Eng. Conf.*, 2014, pp. 1–6.
- [57] N. T. Janssen, R. W. Wies, and R. A. Peterson, "Frequency regulation by distributed secondary loads on islanded wind-powered microgrids," *IEEE Trans. Sustain. Energy*, vol. 7, no. 3, pp. 1028–1035, Jul. 2016.
- [58] P. S. Sauter, B. V. Solanki, C. A. Cañizares, K. Bhattacharya, and S. Hohmann, "Electric thermal storage system impact on northern communities' microgrids," *IEEE Trans. Smart Grid*, vol. 10, no. 1, pp. 852–863, Jan. 2019.
- [59] O. Kilkki, A. Alahäivälä, and I. Seilonen, "Optimized control of price-based demand response with electric storage space heating," *IEEE Trans. Ind. Informat.*, vol. 11, no. 1, pp. 281–288, Feb. 2015.
- [60] N. Good and P. Mancarella, "Flexibility in multi-energy communities with electrical and thermal storage: A stochastic, robust approach for multi-service demand response," *IEEE Trans. Smart Grid*, vol. 10, no. 1, pp. 503–513, Jan. 2019.
- [61] E. Ahmadi, Y. Noorollahi, B. Mohammadi-Ivatloo, and A. Anvari-Moghaddam, "Stochastic operation of a solar-powered smart home: Capturing thermal load uncertainties," *Sustainability*, vol. 12, no. 12, 2020, Art. no. 5089.
- [62] H. Mehrjerdi and E. Rakhshani, "Optimal operation of hybrid electrical and thermal energy storage systems under uncertain loading condition," *Appl. Thermal Eng.*, vol. 160, 2019, Art. no. 114094.
- [63] H. Kalantar-Neyestanaki and M. Soltani, "Uncertainty-cognizant model predictive control for energy management of residential buildings with pvt and thermal energy storage," 2022, *arXiv:2201.08909*.
- [64] K. Sasaki, H. Aki, and T. Ikegami, "Application of model predictive control to grid flexibility provision by distributed energy resources in residential dwellings under uncertainty," *Energy*, vol. 239, 2022, Art. no. 122183.

- [65] S. E. Ahmadi, D. Sadeghi, M. Marzband, A. Abusorrah, and K. Sedraoui, "Decentralized bi-level stochastic optimization approach for multi-agent multi-energy networked micro-grids with multi-energy storage technologies," *Energy*, vol. 245, 2022, Art. no. 123223.
- [66] M. Diekerhof, S. Schwarz, and A. Monti, "Distributed optimization for electro-thermal heating units," in *Proc. IEEE PES Innov. Smart Grid Technol. Conf. Europe*, 2016, pp. 1–6.
- [67] T. Dengiz and P. Jochem, "Decentralized optimization approaches for using the load flexibility of electric heating devices," *Energy*, vol. 193, 2020, Art. no. 116651.
- [68] L. Zheng, B. Zhou, Y. Cao, S. W. Or, Y. Li, and K. W. Chan, "Hierarchical distributed multi-energy demand response for coordinated operation of building clusters," *Appl. Energy*, vol. 308, 2022, Art. no. 118362.
- [69] M. Latif and A. Nasir, "Decentralized stochastic control for building energy and comfort management," *J. Building Eng.*, vol. 24, 2019, Art. no. 100739.
- [70] H. Schwarz, V. Bertsch, and W. Fichtner, "Two-stage stochastic, large-scale optimization of a decentralized energy system: A case study focusing on solar PV, heat pumps and storage in a residential quarter," *OR Spectr.*, vol. 40, no. 1, pp. 265–310, 2018.
- [71] Z. You, M. Zade, B. Kumaran Nalini, and P. Tzscheuschler, "Flexibility estimation of residential heat pumps under heat demand uncertainty," *Energies*, vol. 14, no. 18, 2021, Art. no. 5709.
- [72] J. Dominguez, L. Rueda, N. Henao, K. Agbossou, and J. Campillo, "Distributed co-simulation for smart homes energy management in the presence of electrical thermal storage," in *Proc. IEEE 48th Annu. Conf. Ind. Electron. Soc.*, 2022, pp. 1–6.
- [73] D. Toquica, K. Agbossou, N. Henao, R. Malhamé, S. Kelouwani, and F. Amara, "Prevision and planning for residential agents in a transactive energy environment," *Smart Energy*, vol. 2, 2021, Art. no. 100019.
- [74] L. Rueda, S. Sansregret, B. Le Lostec, K. Agbossou, N. Henao, and S. Kelouwani, "A probabilistic model to predict household occupancy profiles for home energy management applications," *IEEE Access*, vol. 9, pp. 38187–38201, 2021.
- [75] N. Henao, M. Fournier, and S. Kelouwani, "Characterizing smart thermostats operation in residential zoned heating systems and its impact on energy saving metrics," in *Proc. 10th Conf. IBPSA-Canada*, 2018, pp. 17–25.
- [76] H. K. Nguyen, J. B. Song, and Z. Han, "Distributed demand side management with energy storage in smart grid," *IEEE Trans. Parallel Distrib. Syst.*, vol. 26, no. 12, pp. 3346–3357, Dec. 2015.
- [77] I. Atzeni, L. G. Ordonez, G. Scutari, D. P. Palomar, and J. R. Fonollosa, "Demand-side management via distributed energy generation and storage optimization," *IEEE Trans. Smart Grid*, vol. 4, no. 2, pp. 866–876, Jun. 2013. [Online]. Available: <https://ieeexplore.ieee.org/document/6297498/>
- [78] S. Diamond and S. Boyd, "CVXPY: A python-embedded modeling language for convex optimization," *J. Mach. Learn. Res.*, vol. 1, pp. 320–331, Apr. 2016.
- [79] A.-H. Mohsenian-Rad, V. W. S. Wong, J. Jatskevich, R. Schober, and A. Leon-Garcia, "Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid," *IEEE Trans. Smart Grid*, vol. 1, no. 3, pp. 320–331, Dec. 2010. [Online]. Available: <https://ieeexplore.ieee.org/document/5628271/>
- [80] F. Pelletier and A. Faruqi, "Does dynamic pricing work in a winter-peaking climate? A case study of Hydro Quebec," *Electricity J.*, vol. 35, no. 2, Mar. 2022, Art. no. 107080. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S1040619022000069>
- [81] H. Bakker, F. Dunke, and S. Nickel, "A structuring review on multi-stage optimization under uncertainty: Aligning concepts from theory and practice," *Omega*, vol. 96, 2020, Art. no. 102080.
- [82] S. E. Hosseini, M. Najafi, A. Akhavein, and M. Shahparasti, "Day-ahead scheduling for economic dispatch of combined heat and power with uncertain demand response," *IEEE Access*, vol. 10, pp. 42441–42458, 2022.
- [83] A. Najafi et al., "Uncertainty-based models for optimal management of energy hubs considering demand response," *Energies*, vol. 12, no. 8, 2019, Art. no. 1413.
- [84] S. Nojavan, H. Ghesmati, and K. Zare, "Robust optimal offering strategy of large consumer using IGDT considering demand response programs," *Electric Power Syst. Res.*, vol. 130, pp. 46–58, 2016.



**JUAN DOMÍNGUEZ-JIMÉNEZ** (Graduate Student Member, IEEE) received the double B.S. degrees in electronics and electric engineering and the master's degree in engineering from the Universidad Tecnológica de Bolívar (UTB), Cartagena, Colombia, in 2016 and 2019, respectively. He is currently working toward the Ph.D. degree in electric and informatics engineering with the Smart Energy Research and Innovation Laboratory, Université du Québec à Trois-Rivières, Trois-Rivières, QC, Canada.

His research interests include distributed stochastic optimization, hierarchical smart energy management strategies, energy markets, physical modeling of electric thermal storage systems, and multiagent systems.



**NILSON HENAO** received the B.S. degree in electronics engineering from the Universidad de los Llanos, Villavicencio, Colombia, in 2010 and the M.Sc. and Ph.D. degrees in electrical engineering from the University of Quebec at Trois Rivières (UQTR), Trois-Rivières, QC, Canada, in 2013 and 2018, respectively.

His research interests include statistical and machine learning methods with applications to energy management in the residential sector, distributed optimization, multiagent control, smart grid technologies, intelligent energy planning, smart energy storage, and load monitoring.



**KODJO AGBOSSOU** (Senior Member, IEEE) received the B.S., M.S., and Ph.D. degrees in electronic measurements from the Université de Nancy I, Nancy, France, in 1987, 1989, and 1992, respectively.

He was a Postdoctoral Researcher with the Electrical Engineering Department, Université du Québec à Trois-Rivières (UQTR), Trois-Rivières, QC, Canada, from 1993 to 1994, and a Lecturer with the Electrical Engineering Department from 1997 to 1998. He was the Director of graduate studies in Electrical Engineering with UQTR from 2002 to 2004. He was the Head of the Department of Electrical and Computer Engineering, UQTR, from 2007 to 2011. He was the Head of the Engineering School, UQTR, from 2011 to 2017. He is currently the Hydro-Québec Research Chairholder on Transactive Management of Power and Energy in the Residential Sector and the Chair of the Smart Energy Research and Innovation Laboratory, UQTR, where he is a member of the Hydrogen Research Institute and Research Group "GREI." He is the author of more than 325 publications. He has four patents and two pending patents. His current research interests include the areas of renewable energy, the use of hydrogen, home demand side management (HDSM), integration of energy production, storage and electrical energy generation systems, the connection of electric vehicles to the grid, and control and measurements.

Dr. Agbossou has been the Sub-Committee Chair on home and building energy management of the Smart Grid Technical Committee, IEEE Industrial Electronics Society (IES), since 2015.



**ALEJANDRO PARRADO-DUQUE** received the B.S. and master's degrees in Electric Engineering from the Universidad Industrial de Santander, Bucaramanga, Colombia, in 2018 and 2020, respectively. He is currently working toward the Ph.D. degree in electrical engineering with the Smart Energy Research and Innovation Laboratory, Université du Québec à Trois-Rivières, QC, Canada.

His research interests include distributed energy resources, advanced metering infrastructure, power quality, the resilience of energy systems, energy markets, and transactional energy.



**JAVIER CAMPILLO** received the M.Sc. degree in energy engineering from Mälardalen University, Vasteras, Sweden, in 2003 and the Ph.D. degree in energy and environment engineering from Mälardalen University in 2008.

He was an Electronic Engineer in 2016. He is currently an Associate Professor in electrical engineering with the Engineering faculty, Universidad Tecnológica de Bolívar, Cartagena, Colombia, and the General Director of the Colombian Institute for Planning and Promotion of Energy Solutions for

Non-Interconnected Zones (IPSE). His research interests include microgrids, power electronics, renewable energy and energy storage.



**SHAIVAL HEMANT NAGARSHETH** received the B.E. degree in instrumentation and control engineering from Gujarat Technological University, Ahmedabad, India, with Gold Medal in 2014, and the M.Tech. degree from Nirma University, Ahmedabad, India, with Gold Medal in 2016 and the Ph.D. degree in electrical engineering from the Sardar Vallabhbhai National Institute of Technology (NIT Surat), Surat, India, in 2021.

He is currently a Postdoctoral Research Fellow with the Smart Energy Research and Innovation

Laboratory, Université du Québec à Trois-Rivières (UQTR), Trois-Rivières, QC, Canada. His current research interest encompasses the Control and Estimation of Energy Systems, including Home and Building Energy Management of Smart Grids.

Dr. Nagarsheth was the recipient of the European Embedded Control Institute (EECI) Overseas Grant for 2019-IGSC held at Automatic Control Laboratory, ETH Zürich, Zürich, Switzerland and the IFAC-Young Author Support (YAS) award for two papers at the 2020 IFAC World Congress, Germany.

### 3.2 Distributed energy management

« *This section elucidates the methodology adopted to address the second research objective. By incorporating uncertainties from weather forecast and non-shiftable appliances, the proposal can operate an energy community distributedly. Compared to the first paper, this approach managed power flow aspects to validate the technical feasibility of the solution. Besides, building thermal models were constructed from accurate data in Quebec. Eventually, the proposal was validated through a realistic infrastructure to bridge gaps from in-field implementations. The methodology and implementation details are based on the following paper :* »

**Dominguez, J. A.**, Agbossou, K., Henao, N., Nagarsheth, S. H., Campillo, J., & Rueda, L. (2024). Distributed stochastic energy coordination for residential prosumers : Framework and implementation. *Sustainable Energy, Grids and Networks*, 38, 101324.

#### 3.2.1 Background

During the fulfillment of the first objective, the framework was built and tested with uncertainties from weather forecast and its impact was evaluated through centralized wind power at the supply level. Besides, distributed HEMS were incorporated at the customer level with thermal storage units. To attack the second objective, our analysis allocates renewable power units at the customer level, therefore they are no more passive but active customers that can exploit in-situ generation for self-generation purposes i.e. prosumers. When it comes to price-driven strategies, that approach is often avoided by researchers as the odds of having undesired effects at the supply level are elevated as the incentive

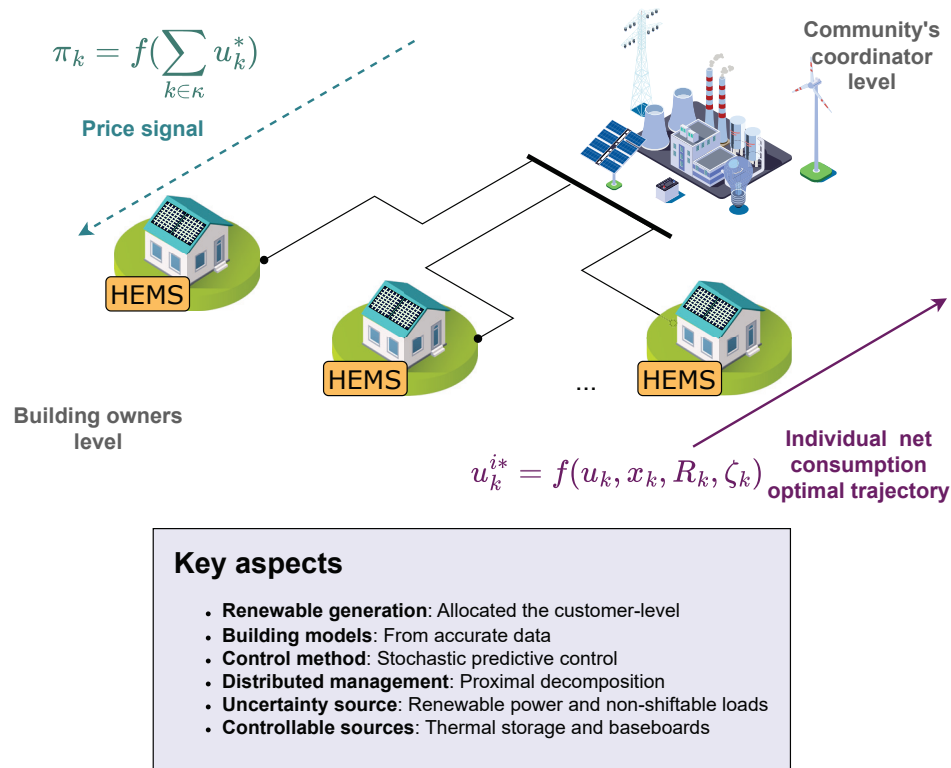


Figure 3.4 Visual representation of methods to manage the second objective

signal is a complete function of participants' preferences. In addition, our analysis in incorporates realistic data about multi-zone indoor temperature and energy consumption from non controllable loads data to design accurate building models. That enabled reducing the opportunity cost created by randomness introduced by the already modeled weather forecasting errors and the novel uncertainty from non-controllable load consumption. Additionally, the strategy's operational performance was tested technically to evaluate the impacts over the grid through test feeders. Eventually, evaluating this sort of approaches in real-life can be challenging as it implies not only large capital expenses but also large physical infrastructure and robust communication layouts. Figure 3.4 provides a visual

representation of the complete approach.

### *3.2.2 Methodology*

To address the second objective, we have exploited stochastic programming was adopted to manage demand-side uncertainties created by weather forecasting errors and non-shiftable loads. Since human intervention is supposed to be reduced, we have employed machine learning and convex optimization algorithms to grasp customer preferences and perform optimal power scheduling tasks. The strategy relies on a non-cooperative framework that exploits decomposition algorithms to perform distributed energy management. Figure B.7 summarizes the whole procedure.

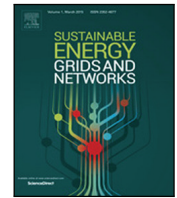
It is worth mentioning that, building models were built from real-life data of fifteen houses in Quebec. The houses are equipped with electric baseboards heaters, thermostats with PID-based temperature control, and several non-shiftable appliances. The maximum power of the electric baseboard heaters for each house is 10 kW. Among other features, buildings' occupancy varied between 1 and 6 occupants, areas ranging from 1,568 to 4,020 sq.ft., and 2 to 5 rooms per dwelling. More details can be found in [42].

In addition, to validate such results, and recognizing that performing accurate test imply large expenses, we have built a cyber-physical infrastructure. That adopted distributed computing approach to reduce the simulation time given the requirements on the demand-side. The infrastructure deploy automated agents able to i) retrieve their historic energy consumption and thermal preferences, ii) estimate the equivalent RC building model, iii) gather weather data to model forecast error, iv) collect price signals, v) execute optimal decision-making and iv) exchange information with the community coordinator. Figure B.8 illustrates a flowchart that condensates the procedure.

### 3.2.3 Outcomes

The study of modelling essential elements and the exercise of coordinating distributed resources with demand-side uncertainties provided the subsequent remarks :

- Accurate building models with realistic occupant behavior and thermal preferences, and non-controllable consumption.
- Addressing uncertainties associated to non-controllable loads during decision-making process to reduce thermal discomfort effects.
- The strategy was able to demonstrate convergence under demand-side uncertainties.
- The strategy's technical feasibility showed salient results regarding peak shaving and enhanced voltage profiles in radial test feeders.
- The cyber-physical infrastructure built employed open-source tools and enabled experiencing reducing the computational burden by over 60%.
- The individuals' welfare was contrasted against the deterministic baseline to show that the system can be close but never be equal or better than decision-making under perfect information scenarios i.e. no forecast errors.



## Distributed stochastic energy coordination for residential prosumers: Framework and implementation

Juan A. Dominguez <sup>a,\*</sup>, Kodjo Agbossou <sup>a</sup>, Nilson Henao <sup>a</sup>, Shaival H. Nagarsheth <sup>a</sup>, Javier Campillo <sup>c,d</sup>, Luis Rueda <sup>b</sup>

<sup>a</sup> Institut de recherche sur l'hydrogène, Université du Québec à Trois-Rivières, Trois-Rivières, G9A 5H7, Quebec, Canada

<sup>b</sup> Laboratoire des Technologies de l'Énergie, Institut de Recherche Hydro-Québec, Shawinigan, G9N 0C5, Quebec, Canada

<sup>c</sup> Universidad Tecnológica de Bolívar, Cartagena, 130001, Bolívar, Colombia

<sup>d</sup> Institute for Planning and Promotion of Energy Solutions for Non-Interconnected Areas, Bogota, 110131, Colombia

### ARTICLE INFO

#### Keywords:

Demand response  
Stochastic programming  
Electric thermal storage  
Predictive control  
Internet of things  
Cyber-physical infrastructure  
Solar photovoltaics

### ABSTRACT

This paper addresses the problem of energy coordination among customers in a local energy market to meet heating needs. Accordingly, this paper proposes a demand response framework for the energy coordination of multiple residential prosumers in a hierarchical coordination game-theoretic scenario. That consists of a benevolent coordinator and multiple residential prosumers integrated with solar PV under demand uncertainties as a consequence of forecasting errors in weather data and non-shiftable load. The coordinator and customers are considered to be a leader and various followers, respectively. The coordinator employs a cost-shared strategy to reduce peak demand. Customers maximize individual welfare by employing stochastic programming through demand flexibility realized via electric baseboard heaters and electric thermal storage. Subsequently, the proposed strategy is implemented through a cyber-physical infrastructure incorporating a distributed computing platform with embedded systems and extensive simulations using accurate weather and real-life energy consumption data. A comparative analysis is performed using a deterministic baseline with perfect information, i.e. no forecasting errors. In addition, the proposed mechanism is tested on an adapted CIGRE low-voltage benchmark system. Simulation results demonstrate the techno-economical feasibility of the proposed solution in uncertain environments. Furthermore, they recommend practical strategies for short-term planning of grids highly penetrated by renewables and intelligent devices by increasing their flexibility and leveraging salient features of cyber-physical systems.

### 1. Introduction

In the past decade, traditional top-down, one-way energy transmission from large generation stations has evolved into a more sophisticated and complex system to integrate intermittent renewable energy sources and distributed energy resources connected at different network points. Such distributed generation scheme aids in decarbonizing the energy supply mix, which is currently dominated by fossil fuel sources, accounting for almost 63% of the global share [1]. Given their significant consumption, commercial buildings have drawn particular attention regarding energy conversion, storage, and distribution. However, residential buildings have gained significant interest during the last five years, given the imminent transition towards a more sustainable power grid, in which customers have an active role in daily operations. The sustained cost reduction of solar-PV and electric batteries' operational costs has enabled their adoption at the customer

level. Hence, conventional customers have become prosumers, representing entities able to consume and produce energy. This facilitates the integration of distributed energy resources (DER) into existing electric power systems.

Modern prosumers can exploit controllable loads, energy storage assets, and renewable production to store electricity during low-price hours to use during peak hours given price or incentive signals. This may help reduce the network's stress while providing reduced electricity bills [2,3]. Additionally, smart technologies have increased flexibility [4,5] in demand response (DR) programs for the residential sector. This sector represents a significant share in many countries, and modifying its consumption patterns may improve the system's operation. Many DR programs exist to meet adequate inelastic needs, such as space and water heating. Some of these programmes integrate energy storage systems to shift the demand without compromising user

\* Corresponding author.

E-mail address: [JUAN.ANTONIO.DOMINGUEZ.JIMENEZ@UQTR.CA](mailto:JUAN.ANTONIO.DOMINGUEZ.JIMENEZ@UQTR.CA) (J.A. Dominguez).

<https://doi.org/10.1016/j.segan.2024.101324>

Received 16 October 2023; Received in revised form 22 December 2023; Accepted 12 February 2024

Available online 17 February 2024

2352-4677/© 2024 Elsevier Ltd. All rights reserved.

comfort [6,7]. In this regard, thermal storage is a potential solution since it can exploit either building inner thermal mass (passive storage) or ceramic bricks to store the energy in the form of heat (active storage) to increase flexibility.

Electric thermal storage (ETS) systems have been used for decades for efficient electricity use by enabling the management of charging electric power and thermal heat output. They exhibit similar features as electric batteries since they store energy (thermal energy converted from electric energy) during off-peak hours and release it depending on the thermal demand [8,9]. ETS systems can become a significant source of flexibility in many regions [10], especially areas experiencing harsh winters, such as Nordic communities. Such opportunity has stimulated researchers and local governments to develop efficient strategies to accelerate the adoption of ETS-based DR programs [8,11–14]. Studies suggest that such programmes allow for better integration of renewable sources, which may increase customers' interest in passing from conventional consumer roles to prosumers. However, encouraging customers through the economic advantages of flexibility with ETS systems and proposing efficient ETS management strategies at the residential level in the presence of uncertain renewable power, weather forecasting errors and non-shiftable loads is necessary.

To address these problems, proposing a cost-effective distributed energy management strategy incorporating multiple flexibility factors and active prosumers is suitable. However, it represents a challenging issue since distributed energy management, with customers integrated with highly electrified heating systems (i.e. ETS + electric baseboard heater (EBH)) and solar PV production, imply:

- Proper stochastic optimal control mechanisms to reduce the odds of providing inadequate charging scheduling for ETS units with uncertain PV power, thus, reducing the risks of creating thermal discomfort.
- Heterogeneous charging/discharging profiles since each customer has a different valuation of comfort.
- The need to coordinate customers' decisions to avoid falling into the prisoner's dilemma, i.e. all users charging ETS systems during off-peak periods, thus creating rebound peaks.
- Efficient validation infrastructures to evaluate the strategy's cost-effectiveness and the communication delays associated with the task to be executed by automated agents in real-life scenarios.

### 1.1. Related works

It is desirable to focus the DR programs on real-life scenarios accounting for limited information due to the highly uncertain environments created by renewables, customer preferences, and weather forecasting. In this context, the convenience of DR programs involving the customers in negotiations with utilities to convey the electricity price has been explored in the literature. Indeed, hierarchical distributed energy management strategies enable customers to be represented by automated agents that aid them in discovering more intelligent consumption strategies. Previous findings on applying this strategy for residential energy management are listed in Table 1. Here, classification depends on the technique to model uncertainties and their respective sources, the flexibility vector, the control strategy and cyber-physical implementations.

Furthermore, hierarchical distributed energy management involves DERs coordination. A comprehensive review on this topic was presented in [15]. The authors reported a systematic taxonomy of categories for coordination to address different issues in three layers: Agency — splits the problem into direct/indirect control over the appliances. Information — deals with how the information is shared. It bifurcated the indirect control into mediated, bilateral and implicit coordination. Game — encompasses the concepts of competitive or cooperative games. Accordingly, our approach does not consider any

coalition between prosumers (non-cooperative), the utility has no control over prosumer assets, and individual information is not shared; it suits an indirect control with mediated coordination and mediated competition. Indeed, that sort of strategy is also named a coordination game [15–17].

Multiple researchers worked on deterministic approaches, representing infeasible utopian scenarios. They adopted competitive Stackelberg games putting substantial effort in (i) fair distribution of team gains [18], (ii) cost-effective techno-economic DR programs [19,20], and (iii) establishing novel cost functions modelling prosumers injecting stored energy back to the grid [21]. Other studies adopted cooperative games, modelling customer's coalitions via information sharing to improve self-sufficiency for prosumers [22,23], and reduce economic savings [24]. Nevertheless, these approaches are based on non-realistic-scenarios-representing a critical drawback.

Some studies have explored realistic scenarios and have adopted different strategies to incorporate uncertainties from diverse sources. For instance, Pilz et al. [25] modelled forecasting errors for prosumers integrated with electric storage. Their results highlight the influence of the forecasting error on the game's outcome. Nevertheless, the authors assumed that forecasting errors followed the same dynamics of supply/demand, which may not always be the case as the error stems from multiple time-related features. Lv et al. [26] employed robust optimization with a rolling horizon to introduce uncertainties from solar irradiation, outdoor temperature, renewable power and loads. Likewise, Zheng et al. [27] utilized rolling horizon optimization to model uncertain non-shiftable loads and renewable power for multi-energy coordination of buildings. However, their objective function consists only of the operational costs associated with consuming energy; hence, enough understanding of the customer's utility related to comfort is not incorporated.

On the other hand, some researchers [28,29] worked on optimal load management for multizone buildings by incorporating customer comfort in their objective functions coupled with HVAC systems and electric storage in the presence of renewable power. Rezaei et al. in [30] managed multiple prosumers minimizing their electricity bills while guaranteeing comfort under uncertain PV production. Nevertheless, they neither considered uncertain non-shiftable loads nor weather forecasting errors. Similar works are reported accounting for uncertain charging/discharging electric power of aggregated EVs with the notion of receding horizon [31]. Those studies have proved the ability of Stackelberg games to guarantee convergence and avoid falling into the so-called prisoner's dilemma since all the consumers behave similarly (e.g., charging storage assets simultaneously during off-peak periods). Especially the adaptation of storage assets necessitates planning and coordination as heterogeneity arises with preference differences in charging/discharging patterns between the customers [32–34]. Besides, most approaches reported a reduction in customers' electricity bills, but very few optimized for the same time customers' utilities. On the other hand, the negotiations occurring during Stackelberg-based games also need to model the effect of uncertainties in the coordination process and update the players' decisions accordingly. Additionally, the grid status evaluation after the DR program's accomplishment incorporating the imperfect against perfect information scenarios is scarcely available.

Electric batteries combined with renewable sources provide substantial economic benefits while respecting operational constraints under stochasticity stemming from (i) weather forecasting, (ii) EV charging/discharging patterns, and (iii) incentive signals, among others. Particularly, ETS units have drawn interest as it performs similarly to electric batteries but at a reduced price. Few works (e.g., [8–14,35–37]) simulate the salient features of ETS in power grids at the residential level. The optimization models have been developed to reduce the overall costs (e.g., electricity tariff cost) under various constraints. Niu et al. [38] adopted passive thermal storage, i.e. building thermal mass for similar purposes.

**Table 1**  
Findings of previous similar efficient energy management strategies.

Ref	Study field	Imperfect Information	Distributed Optimization	Storage	Renewable carrier	Uncertainty Sources	Uncertainty modelling	Uncertainty in building thermal dynamics	Coordination strategy	Energy Management	Cyber physical implementation
[22]	Cooperative DR	x	x	x	PV	x	x	x	✓	Distributed	x
[18]	Non-cooperative DR	x	ADMM	x	x	x	x	x	✓	Distributed	x
[19]	Non-cooperative DR	x	Proximal decomposition	x	x	x	x	x	✓	Distributed	x
[42]	Cooperative DR	x	NST-PAC	DH	NSpec	x	x	x	✓	Decentralized	x
[24]	ADMM	x	ADMM	TES	x	x	–	x	✓	Decentralized	x
[23]	Cooperative energy hubs	x	Nash bargaining game	TES	x	x	CO	x	✓	Distributed	x
[21]	Stackelberg Non-cooperative DR	x	Iterative Entropic Algorithm	EES	x	x	x	x	✓	Distributed	x
[27]	Non-cooperative DR	✓	ADMM	x	x	Weather forecasting, NSL	Rolling optimization	x	✓	Distributed	x
[25]	Non-cooperative DR	✓	x	EES	PV	Weather forecasting error	Dynamic programming	x	✓	Distributed	x
[32]	Bi-Level EMS Coordination	✓	x	TES	x	Wind power	x	x	✓	Distributed	x
[26]	Maximize demand-side flexibility	✓	x	TES	PV	Renewable, Outdoor temperature	Rolling optimization	x	✓	Centralized	x
[43]	Stackelberg Stochastic EV Scheduling	✓	Decomposition methods	EES	x	Demand	Robust optimization	x	✓	Distributed	x
[44]	Stackelberg Non-cooperative DR	✓	x	EES	PV, WT	Renewable	Chance constraint	x	✓	Centralized	x
[45]	Stackelberg Non-cooperative DR	✓	Bisection-based	EES, TES	PV	Renewable, NSL	Stochastic programming	x	x	Distributed	x
[30]	Stackelberg Non-cooperative DR	✓	ADMM	EES	PV	Renewable, NSL	Stochastic programming	x	x	Distributed	x
Our approach	Non-cooperative DR	✓	Proximal decomposition	ETS	PV	Renewables NSL, Weather Forecasting	Stochastic programming	✓	✓	Distributed	✓

The reported literature in ETS suggests that this technology significantly reduces operating costs and enables better integration of intermittent renewable sources. Although electric batteries and ETS units as storage assets bring flexibility, but also introduce complexity for optimal control problems. While electric battery discharging rates only modify the remaining energy storage, ETS discharging affects the thermal dynamics of the building, which results in a more complex model. Consequently, comprehensive analysis is still required to characterize better uncertainties rather than setting it as a share of the actual variable.

While most of the works in this domain are related to cybersecurity and blockchain distributed applications (DApps) [39,40], some initiatives about co-simulation-based framework approaches. For instance, the Pacific North West Laboratory (PNL) launched the Transactive Energy Simulation Platform (TESP), incorporating many tools to test and deploy co-simulation-based scenarios for transactive energy systems. Besides, the Open Platform for Energy Networks (OPEN) [41] framework combines distributed energy resource modelling (e.g. for PV generation sources, battery energy storage systems, electric vehicles), energy market modelling, power flow simulation and multi-period optimization for scheduling flexible energy resources.

Even though the outbreak of energy-related platforms, there is still a gap between co-simulation-based results and real-life deployments. More studies need to be aware of building cyber-physical infrastructure validation relying on state-of-the-technique tools for testing and deploying their strategies. Developing advanced validation infrastructures is the cornerstone to better understand the system's performance under near real-life challenging environments. That can give insights into possible limitations associated with communication delays, interoperability, and viability. In this way, even if there may exist a difference between the outcome of the strategy and the execution in real-life, these will obey mostly model-related errors and inherent uncertainties in the environment. Specifically, this can ensure that software-oriented solutions can be deployed in challenging scenarios.

### 1.2. Contributions

This paper aims to address the challenges mentioned above through a distributed stochastic energy management framework that models smart prosumers capable of optimally scheduling hybrid heating systems in the presence of solar-PV. A coordination game is adopted to handle information exchange between a coordinator and a set of customers. The coordinator is responsible for providing the incentive signal, and the customers compute their best strategy given the latter. Customers participating have solar-PV generation and ETS systems as the primary flexibility vector for space heating needs. Furthermore, real-world data is used to characterize weather forecasting to estimate renewable production at the customer level. The proposal exploits stochastic programming to reduce the adverse effects of the demand-side uncertainties associated with non-shiftable loads, weather forecasting errors, and subsequent renewable production. The main contributions of this study can be summarized as follows:

- A framework encompassing a coordination game with a local energy market. It facilitates developing and testing smart local energy system management applications by providing an extensible object-oriented platform for integrated modelling, control and simulation.
- A stochastic optimal controller for customers integrated with solar-PV and highly electrified heating systems is proposed. The controller maximizes individual welfare, guaranteeing thermal comfort while considering the energy to pay in return. Besides, the controller includes the ETS operational costs and a regularization term via proximal decomposition, which ensures convergence.
- A distributed computing platform to deploy, test and validate comprehensive simulations and reduce the gap from real-life deployments. It provides reproducible, reliable and verifiable results. This infrastructure allows estimating the computational requirement of automated agents in real-life implementations.

The rest of the paper is organized as follows: Section 2 describes the problem statement. Section 3 covers the mathematical modelling of non-shiftable loads, PV production and weather forecasting errors and the energy coordination game along with the leader's and followers' problems. Section 4 presents the software components through object-oriented programming and the cyber-physical infrastructure used for the real-life deployment of the proposed strategy. Then, Section 5 and VI contain the results and discussions of the paper. Finally, the conclusions are in Section 7.

## 2. Problem statement

In remote Nordic communities of Canada, off-grid systems supply electricity, exhibiting a heavy reliance on fossil fuels for daily energy needs. This leads to significantly higher electricity prices compared to urban areas. These regions also endure harsh winters with average outdoor temperatures below -35 degrees Celsius on average. Particularly, in Quebec, real-life lessons of off-grid systems suggest that it is more efficient and cheaper to heat rooms and water with fuel than with electricity [46]. Consequently, to cope with the high electricity costs, building owners have opted to use low-quality heavy fuel oil (Mazout) for space heating, posing a significant carbon footprint problem. Furthermore, a transition towards covering space heating needs by means of electric baseboards (as in urban areas) will increase their electricity bills and create tremendous issues in power grids as the heating load accounts for about 62% of the yearly household energy consumption [47].

Nordic territories have become pivotal for deploying renewable energy projects and cost-effective technologies, such as ETS, to reduce diesel dependency. Introducing renewables can have positive effects, including GHG emissions reduction, energy self-sufficiency, community building and empowerment, as well as energy savings. Nevertheless, when intermittent renewable sources join power grids at high penetration levels, the complexity of optimal scheduling tasks increases due to imperfect information scenarios created by uncertainties. Meanwhile, ETS units offer a promising solution for demand-flexibility purposes but require careful coordination to prevent undesirable effects on the power grid, like rebound peaks.

The theme of this paper is to present a mechanism able to perform coordinated optimal stochastic scheduling for the heating load of customers integrated with EBH, ETS and solar-PV via a coordination game in a distributed manner to address the aforementioned situation. The manuscript comprehensively compares decision-making procedures under imperfect information given a perfect (deterministic) baseline. This analysis is performed for (i) customer utility and payment, (ii) the aggregated demand profile, and (iii) the voltage profile. Given the significant investments and multiple barriers to deploying this proposal, the proposed approach is validated and tested through an open-source-based distributed computing platform.

To address the problem mentioned above, the theoretical and practical development in this paper encompasses the following: (i) development of a framework to manage and coordinate the prosumers in game theoretic mechanisms (ii) Stochastic modelling for HEMS including the weather forecast, non-shiftable load and solar PV production (iii) hardware validation via cyber-physical implementation utilizing feasible infrastructure and open-source software.

## 3. Framework & modelling

This section explains the proposed framework and modelling devised to implement and validate the distributed stochastic energy management strategy of the paper. The proposed framework relies on several open-source tools to handle the distributed energy coordination game to provide optimal energy management strategies for multiple residential prosumers equipped with ETS units. Fig. 1 illustrates the interaction mechanism between the coordinator (leader) and customers

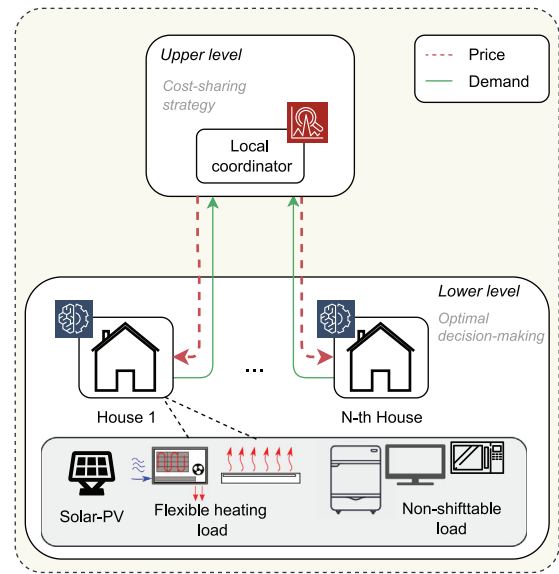


Fig. 1. The description of the energy coordination procedure.

(followers), where all customers are integrated with the solar-PV generation, non-shiftable loads, and flexible heating load comprised of EBH and ETS.

A leader-follower interaction enables the interaction mechanism. The coordinator (leader) leads the interaction by establishing an incentive signal. Afterwards, customers, acting as followers, compute their best consumption strategies based on stochastic convex optimization methods. A more detailed explanation on the structure of the framework through object-oriented programming is presented in Section 4.

### 3.1. Stochastic modelling

#### 3.1.1. Non-shiftable loads

During winter days, power consumption data of major individual appliances from 9 houses in Quebec has been collected. Correspondingly, semi-synthetic data generation models have been employed to simulate several daily and weekly load profiles, which allows the creation of stochastic profiles for the non-shiftable loads, see Fig. 2. We have adopted the well-known Prophet Python module [48] by setting the confidence interval to 95% and weekly seasonality.

#### 3.1.2. Weather forecasting errors

We modelled the solar irradiation, relative humidity and outdoor temperature forecasting errors to reduce the impacts of their inherent uncertainty on the proposed strategy. To accomplish this, 'Tomorrow.io', an open-source framework, is utilized to get actual forecasting weather data through a self-made client coded in Python. Afterwards, the forecasting errors for every 15 min during Winter 2023 were estimated. The prediction records correspond to the Kuujuaq community during 2022. Perturbations related to the relative humidity  $\Delta_k^H$ , the outdoor temperature  $\Delta_k^T$ , and the solar irradiation  $\Delta_k^I$  are modelled as:

$$\Delta_k^I \sim \mathcal{N}(0, \sigma_k^I), \Delta_k^H \sim \mathcal{N}(0, \sigma_k^H), \Delta_k^T \sim \mathcal{N}(0, \sigma_k^T), \quad (1)$$

where  $\Delta_k^T$ ,  $\Delta_k^I$ , and  $\Delta_k^H$  represents a zero-centred Gaussian noise for each variable;  $\sigma$  deals with the standard deviation of the prediction error of each variable. The standard deviation of the prediction error in Eq. (1) was modelled for each hour in each prediction horizon of  $h = 1$  to  $h = 24$ . Since the forecasting is done hourly, a query to the client was made every 15 min. Hence, forecasting data for

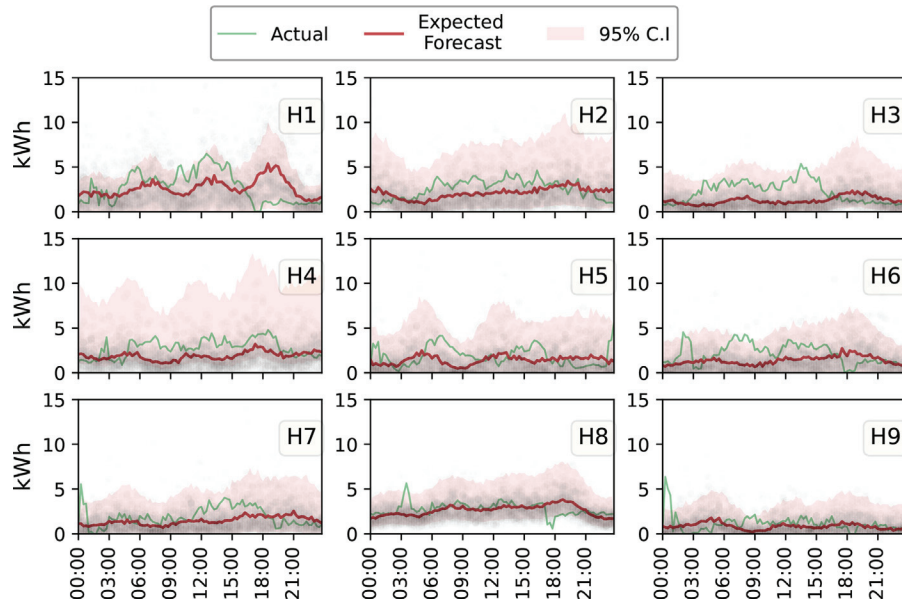


Fig. 2. Uncertain non-shiftable loads for all the customers.

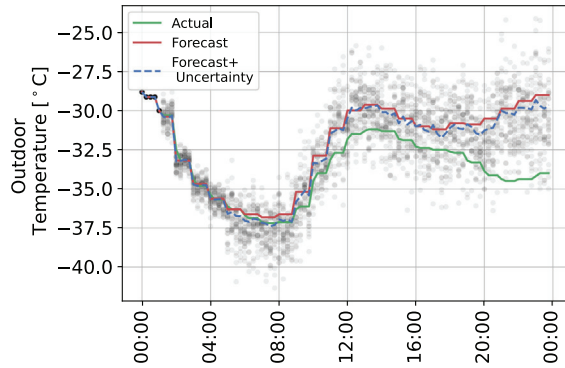


Fig. 3. Uncertain weather forecasting on the outdoor temperature (grey dots: samples drawn from PDF of the outdoor temperature forecast error).

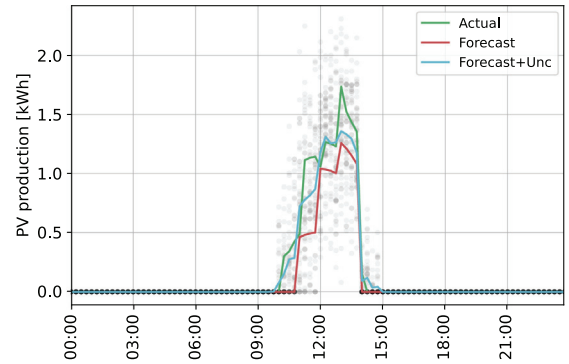


Fig. 4. Uncertain solar-PV production for a particular customer (grey dots: samples drawn from PDF of the photovoltaic production forecast error).

every 15 min throughout the day was collected, which guaranteed that the error propagation was achieved by considering the hour of the day. We introduced additive uncertainty propagation for the outdoor temperature and relative humidity based on:

$$\hat{T}_k = T_k + \Delta_k^T, \hat{H}_k = H_k + \Delta_k^H, \quad (2)$$

where  $I_k$ ,  $T_k$ , and  $H_k$  denotes the actual measurements of these variables. Eventually, we adopted multiplicative uncertainty propagation for the solar irradiation as follows:

$$\hat{I}_k = I_k e^{\xi_k^I}, \quad (3)$$

where  $\xi_k^I$  corresponds to the following ratio:

$$\xi_k^I = \log\left(\frac{\hat{I}_k}{I_k}\right). \quad (4)$$

Fig. 3 illustrates an example of the actual outdoor temperature with the ordinary forecast, an enhanced version with its inherent uncertain error.

### 3.1.3. Solar-PV production

We combined the outcome of the weather forecasting errors with the PVLlib module, coded in Python, to model the uncertain renewable production at the customer level. We have extended the approach

presented in Section 3.1.2 for the wind speed, the global, the diffuse horizontal and the direct horizontal irradiation. The system was modelled given geographical and technical characteristics such as the location of the Kuujuaq community and a number of inverters, among others. Solar-PV penetration levels varied from 30% to 50% of the maximum households' demand. Fig. 4 illustrates an instance of renewable power production for one customer with the ordinary forecast provided by Tomorrow.io and an enhanced version with its inherent uncertain error.

### 3.2. Energy coordination game

In this section, we focus on analysing the day-ahead optimization problem in the framework of the coordination game. Once the forward contract between the coordinator and the residential prosumers is deployed, the parties will agree on the price and demand for future delivery. In this case, the only good trade is active energy, and the agreements will be made the day ahead for a 24 h supply. Subsequently, the coordinator sends a vector with the proposed price and waits for the residential agents to respond with their consumption strategy. Such configuration leads to a Stackelberg game where the coordinator initially leads the interaction, presenting its strategy. On the other side, the residential customers, as followers, formulate their strategies considering the price signal from the aggregator under uncertain weather

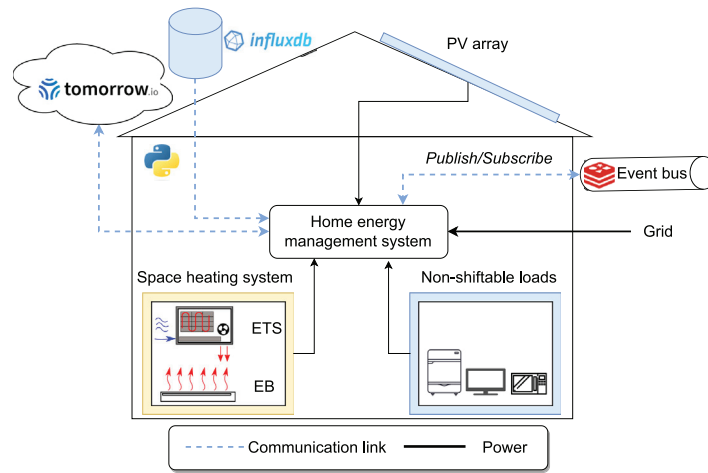


Fig. 5. Structure of HEMS integrated with solar PV and hybrid controllable heating system.

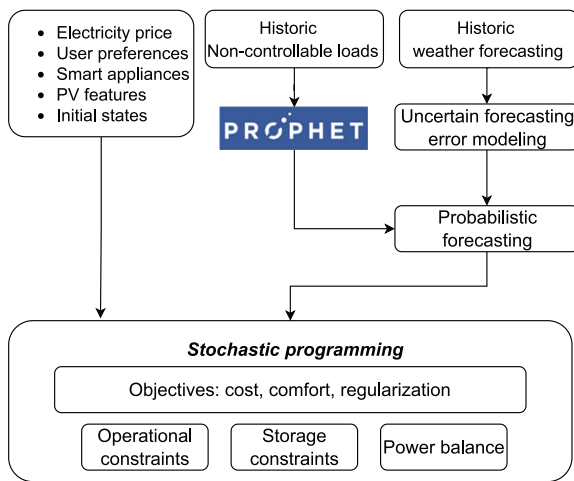


Fig. 6. Schematic overview of the HEMS for a residential user.

forecasting errors, non-shiftable loads and solar-PV generation. Note that reconciliation procedures related to deviations from the forward contract (after the market period) are out of the scope of this paper. The following subsections present the problem formulations for the leader and the follower agents.

### 3.2.1. Follower problem

Follower (residential agents) incorporate a home energy management system (HEMS) equipped with a hybrid heating system comprised of EBH and an ETS system, non-shiftable loads, among others, as indicated in Fig. 5. The HEMS is responsible for scheduling the heating load optimally in the presence of uncertain solar-PV production and uncertain non-shiftable appliances. This entity consumes a self-coded weather forecasting client. Besides, the HEMS publishes report data to a time series database (InfluxDB) and interacts with the leader via an event bus (Redis). Subsequently, Fig. 6 describes a schematic overview to address the optimization problem.

The optimization problem for the residential agent is formulated in Eq. (5). The objective is to maximize individual welfare. That is modelled as the stochastic difference between the utility,  $U_k$ , the user perceives from importing energy and the cost,  $C_k$ , it must pay for in each  $s$  scenario.

$$\max_{u_{imp}^r, \dots, u_{imp,T}^r} \mathbb{E}[J] \approx \frac{1}{N} \sum_{s=1}^N \sum_{k=1}^T U_{k,s}^r - C_{k,s}^r, \quad (5)$$

where

$$U_k^r = -\alpha_k^r (x_k^r - x_{c,k}^r)^2, \quad (6a)$$

$$C_k^r = C_{imp,k}^r + C_{ETS,k}^r. \quad (6b)$$

Here,  $U_k$  is the utility function (Eq. (6a)) that depends largely on  $\alpha_k^r$ , a weighting parameter representing the user's  $r$  price elasticity. Also, it depends on  $x_{c,k}^r$  and  $x_k^r$ , which are the customer's comfort temperature and the actual indoor temperature. On the other hand, the cost term (Eq. (6b)),  $C_k^r$ , is composed of two affine functions that represent the amount of energy the customer is importing  $C_{imp,k}^r$  and the ETS running cost  $C_{ETS,k}^r$ , explained by Eqs. (7) and (9). The cost of importing energy depends on  $\pi_k$  and  $u_{imp,k}^r$ , which are the electricity price and the amount of importing energy from the grid for the customer  $r$ , respectively. The latter comprises  $u_{EBH,k}^r$  and  $u_{ETS,k}^r$  which are the load of EBH and ETS respectively. Besides it considers two uncertain inputs, including the non-shiftable load  $u_{NSL,k}^r$  and the solar-PV production  $u_{PV,k}^r$ .

$$C_{imp,k}^r = \pi_k u_{imp,k}^r, \quad (7)$$

where

$$u_{imp,k}^r = u_{EBH,k}^r + u_{ETS,k}^r + u_{NSL,k}^r - u_{PV,k}^r. \quad (8)$$

Eq. (9), is composed of the ETS operational cost  $C_k^b$ , and the charging/discharging decisions on the ETS ( $u_{ETS,k}^r, Q_{ETS,k}^r$ ).  $\eta$  is the total rated cycles of the ETS unit,  $IC$  is the economic investment, and  $ES$  is a parameter depicting desired amount of energy stored in  $kWh$ . The denominator is multiplied by two since a cycle is assumed to be the ETS charging up to  $\overline{ES}$  and discharging towards  $\underline{ES}$ . These two were set to 80 and 20, respectively. With the parameters listed in Table 2, the  $C_k^b$  estimated is 0.0561 CAD. This value will provide enough understanding to the controller to know the proper timing to absorb daily uncertainties with the ETS unit.

$$C_{ETS,k}^r = (u_{ETS,k}^r + Q_{ETS,k}^r) C_k^b, \quad (9)$$

$$C_k^b = \frac{IC}{2\eta(\overline{ES} - \underline{ES})}. \quad (10)$$

Regarding house thermal dynamics, real-life scenarios require white models entailing complex non-linear phenomena, which increases the complexity significantly for optimal control. Hence, researchers have developed simpler models using machine learning techniques to create intuitive discrete linear thermal models [7]. In this case, the following linear model is considered:

$$x_{k+1}^r = A x_k^r + B u_{EBH,k}^r + C Q_{ETS,k}^r + D \hat{W}_k. \quad (11)$$

**Table 2**

ETS parameters.	
Parameter	Value
Investment cost	1800 CAD
Lifespan years	20 years
Power consumption	3.6 kW
Energy capacity	13.2 kWh
Rated cycles/year	120

The model of the thermal dynamics (Eq. (11)) is linear and requires environmental variables, including the outdoor temperature, the solar irradiation and the relative humidity, as the customers are connected to a weather forecast service. In this regard,  $\hat{W}_k$  stands for a vector  $[\hat{I}_k, \hat{T}_k, \hat{H}_k]$  comprising the expected value on the forecasting with the respective uncertain error, as detailed in Section 3.1. The terms  $A$ ,  $B$ , and  $C$ ,  $D$ ,  $E$  are coefficient matrices computed by minimizing the sum-of-squares loss function between Eq. (11) and the actual measured output over a historical data set. The limits for  $x_k$  ( $x_{\min}, x_{\max}$ ) are set equal for all customers.  $u_{EBH,k}$  models power consumption for EBH and  $Q_{ETS,k}$  is the heating energy as a consequence of the heat at the outlet of the ETS room unit. For this case, we considered a static ETS unit, indicating that it can only operate in free convection.

Finally, the problem is subject to the below-listed constraints. Constraint (12a) models the thermal dynamics, (12b) is the power balance, (12c) is the ETS energy stored  $ES_k^r$ . (12d)–(12f) limits the EBH and ETS units in electric and thermal consumption.

$$s.t. : x_{k+1}^r = g^r(x_k^r, u_{EBH,k}^r, Q_{ETS,k}^r, \hat{W}_k) \quad (12a)$$

$$u_{imp,k}^r = u_{EBH,k}^r + u_{ETS,k}^r + u_{NSL,k}^r - u_{PV,k}^r \quad (12b)$$

$$ES_{k+1}^r = ES_k^r + \eta^c u_{ETS,k}^r - \frac{1}{\eta^d} Q_{ETS,k}^r \quad (12c)$$

$$0 \leq u_{EBH,k}^r \leq u_{\max} \quad \forall r, k \quad (12d)$$

$$0 \leq u_{ETS,k}^r \leq u_{ETS}^{\max} \quad \forall r, k \quad (12e)$$

$$0 \leq Q_{ETS,k}^r \leq Q_{\max} \quad \forall r, k \quad (12f)$$

$$x_{\min} \leq x_k^r \leq x_{\max} \quad \forall r, k \quad (12g)$$

### 3.2.2. Leader problem: minimizing energy cost

The energy cost model is an incremental cost function that represents the cost of generating a unit of electricity by the energy source at each hour. A widely used quadratic cost (for diesel generator) function fits such criteria, i.e.

$$C_k(L_k) = a_k L_k^2 + b_k L_k + c_k, \quad (13)$$

where  $a_k, b_k$  and  $c_k$  are  $> 0$  at each hour.  $L_k$  represents sum of all sets of best strategies  $[u_{imp,k}^{1*}, u_{imp,k}^{2*}, \dots, u_{imp,k}^{r*}]$ . The term  $u_{imp,k}^{r*}$  denotes the best strategy of the  $r$ th user. The cost function adopted is strictly convex and represents the utility's artificial cost tariff to perform proper demand control.

Accordingly, utilities adopt electricity dynamic rates [49] to encourage customers to consume more conservatively during peak periods in winter.

Such a function can be smoothen out by a quadratic cost, which is more suitable for optimization. Furthermore, the total energy cost of the system over  $T$  time slots corresponds to:

$$C_k^{\text{total}} = \sum_{k=1}^T C_k. \quad (14)$$

Eventually, each customer is charged proportionally to its energy consumption, i.e.

$$\Gamma^r = \frac{u_{imp,k}^r}{L_k}, \quad (15)$$

where  $\Gamma^r$  stands for the user  $r$ 's is the proportion of its energy demand against the total aggregated demand. Subsequently, the user  $r$ 's payment is proportional to the total aggregated demand:

$$UP^r = \Gamma^r C_k^{\text{total}}. \quad (16)$$

### 3.2.3. Distributed optimization (Proximal decomposition)

In practice, sequential updating to ensure the convergence of algorithms can become a difficult task. Therefore, distributed algorithms such as proximal decomposition [50,51] are preferable to overcome such issues. It allows users to update their strategies simultaneously without sharing information with their neighbours. As mentioned previously, the problem is modelled hierarchically employing a coordination game, as no coalitions exist among customers, hence no information sharing regarding power or preferences is allowed. At the customer level, each follower maximizes its own convex local cost function with a total amount of discrete-time slots.

#### Algorithm 1: Market clearing

**input** :  $\{a_k, b_k, c_k\} \quad \forall k, \{\alpha_k^r, g_k^r, x_{c,k}^r\} \quad \forall k, x_{\min}, x_{\max}, u_{\max}, u_{ETS}^{\max}, Q_{\max}$ .

**output**:  $u_{imp,k}^{r*}, x_k^{r*} \quad \forall r, k$

**begin**

The coordinator sets an initial value of  $\pi_k \forall k$ ;

**while** the error between successive iterations is higher than  $\epsilon$

**do**

The coordinator sends  $\pi_k \forall k$  to all customers.

**for Each customer do**

-instantiates its DERs

-query the weather forecasting service

-calculate the weather forecasting error

distributions

-calculate the stochastic non-shiftable loads profiles

-calculate the stochastic PV production

-solve the local stochastic optimization problem (Eq. (5)).

**end**

The customer returns their best consumption strategy

$u_{imp,k}^r \forall k, r$  ;

The coordinator recalculates  $C_k^{\text{total}} \forall k$  for the next iteration. ;

The customer signs the forward contract according to the latest values of  $\{u_{imp,k}^r, \pi_k\} \forall k$

**end**

**end**

Meanwhile, the leader aggregates the strategies and establishes a new price encourage to customers to coordinate their actions while balancing power demand and supply. An additional term in the consumers' payoff function has been designed to ensure the algorithm's convergence under tender conditions and the coordination between users. This term penalizes large variations between successive iterations in the decomposed optimization process [50]. Consequently, the final form of the consumer's payoff function can be written as

$$\max_{u_{imp,1}^r, \dots, u_{imp,T}^r} \mathbb{E}[J] \approx \frac{1}{N} \sum_{s=1}^N \sum_{k=1}^T U_{k,s}^r - C_{k,s}^r + \tau \sum_{k=1}^T (u_{imp_k}^{r,i} - u_{imp_k}^{r,i-1})^2, \quad (17)$$

where  $i$  stands for the iteration index. The term  $\tau$  in the latter half of Eq. (17) is given by

$$\tau \geq 4(NC - 1)\lambda, \quad (18)$$

where  $\lambda$  has been calculated and used as the initial average price and  $NC$  is the number of prosumers participating in the strategy.

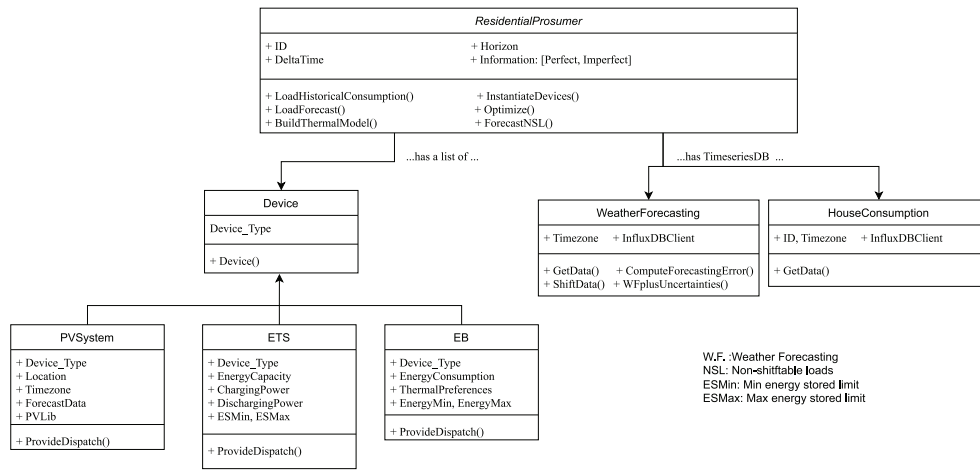


Fig. 7. UML diagram of the Residential prosumers class with its methods and attributes.

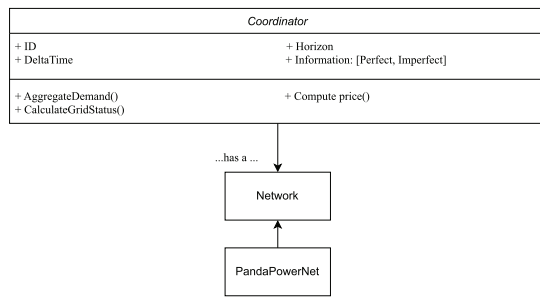


Fig. 8. UML diagram of the Coordinator class with its methods and attributes.

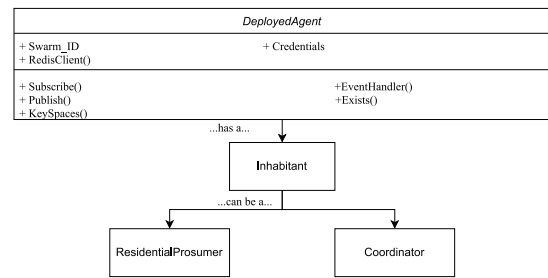


Fig. 9. UML diagram of the DeployedAgent class with its methods and attributes.

The algorithm converges when the relative error of aggregated profile between successive iterations is lower than a predefined threshold  $\epsilon$  [52], i.e.

$$\|u_{imp,k}^{r,i} - u_{imp,k}^{r,i-1}\|_2 / \|u_{imp,k}^{r,i}\|_2 \leq 10^{-2}. \quad (19)$$

Algorithm 1 presents the perfect market clearing procedure.

#### 4. Implementation

This section explains the software-related components and the cyber-physical infrastructure devised to implement and validate the distributed stochastic energy management strategy of the paper.

##### 4.1. Object-oriented modelling

Residential prosumer models are coded in Python, a widely used programming language for open-source scientific computing. That enables easy integration with a range of third-party open-source packages. It is coded utilizing object-oriented programming, providing modularity, code reuse and extensibility. The software components are divided into three major segments: ResidentialProsumer, Coordinator and the DeployedAgent. Figs. 7–9 shows a universal modelling language (UML) class diagram of each, respectively. Additionally, Fig. 10 provides a visual representation of the ResidentialProsumer and Coordinator, and how the DeployedAgent can host each of them by switching on the desired entity. Note that the information inside dark and light boxes represent the classes that each entity inherits and the methods it can perform, respectively.

The ResidentialProsumer class has the category of information (perfect, imperfect) as the primary attribute to handle deterministic or stochastic cases, respectively. Besides, a random ID, the horizon

control, and the desired timesteps are required attributes of this class. This entity can consume InfluxDB time series databases through the WeatherForecasting and HouseConsumption classes. On the one hand, the first deals with weather forecasting information, the required data processing, and the ability to compute forecasting errors and their probability density functions (PDFs). This class provides weather forecasting data depending on the information nature. On the other hand, the second handles the historical energy consumption and thermal preferences data related to real houses in Québec, Canada.

Methods LoadHistoricalConsumption and LoadForecast consume the classes mentioned above. Subsequently, a linear model is built utilizing the BuildThermalModel for predictive control tasks from the acquired historical data about energy consumption and the building thermal dynamics. Afterwards, the available devices are instantiated through InstantiateDevices. The customer may own a PVSystem, an ETS, and an EB as controllable assets.

Suppose the information nature is set to Imperfect (stochastic case); then, the ForecastNSL method provides stochastic profiles for non-shiftable loads based on each customer’s historical data.

The entity Coordinator employs AggregateDemand to aggregate the strategies provided by all residential prosumers and ComputePrice to estimate the optimal price policy through a sharing the energy cost strategy following the problem listed in Section 3.2.2. Additionally, it evaluates the grid status CalculateGridStatus leveraging outstanding features of the PandaPower Python module.

The entity DeployedAgent enables interaction with hardware devices. It requires network identification SwarmID and secret credentials to consume a RedisClient. It hosts an inhabitant that could be a Coordinator or a ResidentialProsumer. Coordinator and residential prosumer modules have been encapsulated as Docker containers to facilitate testing, deploying tasks, and communicating with other

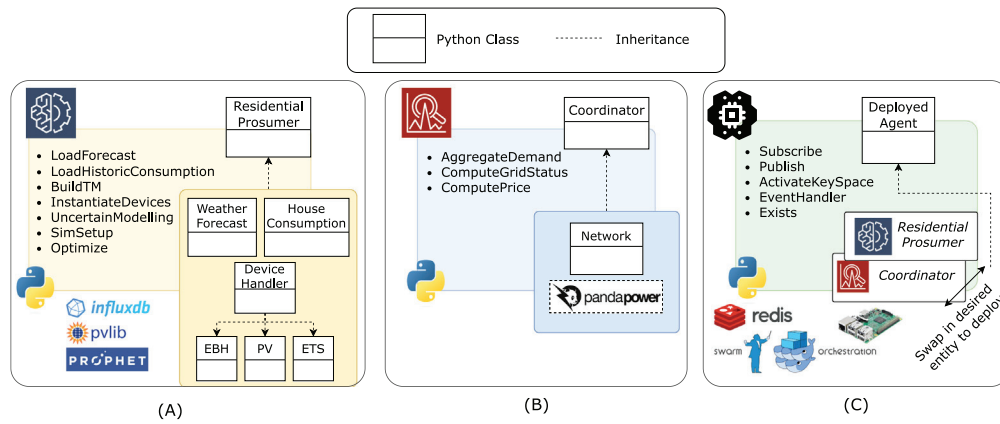


Fig. 10. The visual representation of each entity: (A) residential prosumer, (B) coordinator and (C) deployed entity.

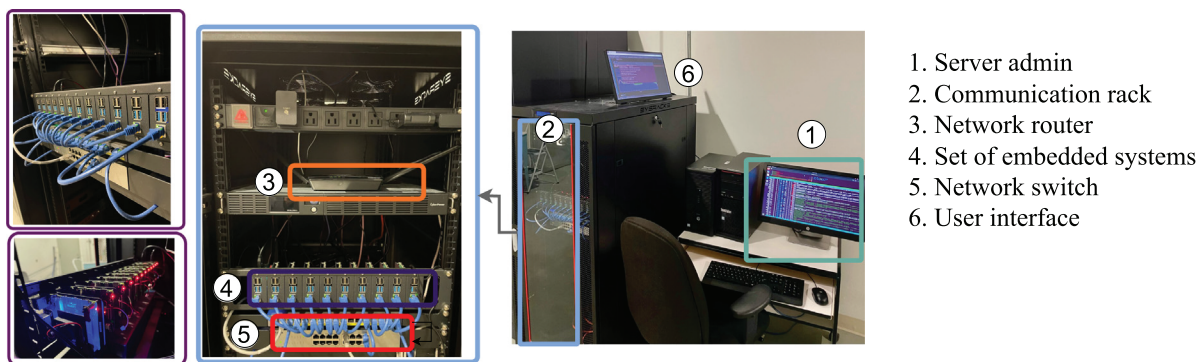


Fig. 11. The infrastructure and its components.

players using event-oriented solutions under the Publish/Subscribe notation. Afterwards, containers are deployed as services over a distributed computing platform using Docker Swarm.

#### 4.2. Cyber-physical infrastructure

We implement the distributed algorithm on a self-developed and flexible open-source cyber-physical infrastructure. It is designed to integrate multiple entities to simulate residential agents with high levels of detail and speed. Fig. 11 displays all the components of the cyber-physical infrastructure, named OpenATE. The infrastructure comprises a set of hardware devices for different purposes, including management (server admin), communications (router and switch) and real-life interfaces (embedded systems) and a visual interface. The infrastructure is a distributed control software platform that exhibits multiple salient features, including flexibility, scalability, and cost-effectiveness. One of the main characteristics is that it enables deploying and operating energy-related projects through IoT devices. This facility can be extrapolated to many applications since it is deployable from low-cost computing resources, readily communicate with and gather data from a wide range of building and home systems, and physical devices such as EBH, ETS and other smart appliances. Eventually, it consists of a state-of-the-art stack of tools to build a cost-effective distributed computing cluster. The system was built to leverage low-cost IoT devices (Raspberry Pi 4B) with salient features to enable the autonomous operation of residential agents. The computing cluster has 266.01 GB of total memory and 75 CPU.

Fig. 12 illustrates how these modules interact regarding the energy management strategy given the Algorithm 1. In a nutshell, it illustrates the way residential agents (inhabiting embedded devices) interact with

a shared event bus. Besides, it contains stateful services that exploits continuous integration and continuous delivery (CI/CD) along with version control (Git) technologies. Furthermore, the solution leverages virtual extensible LAN (VXLANs) features.

The real-life deployment of the proposed solution relies on Docker Swarm to provide redundancy and automatic workload balancing for multiple workers and a manager node. The latter is a critical component responsible for managing the swarm and storing the swarm state. Besides, it accomplishes functions such as organizing and scheduling container tasks given particular commands. Such commands are transmitted to an *EventBus* that is a communication broker, enabling operating under the wide-adopted Publish/Subscribe architecture. Consequently, each worker subscribed to the *EventBus* is enabled to interact with the coordinator, as illustrated in Figs. 12A and 12C.

The workers act as fully independent entities that will perform some actions given certain commands. To handle this, first, the *Residential-Prosumer* module was tested, exhibiting robustness and reproducibility, and afterwards was encapsulated in a Python Package (NordicEMS) to facilitate deployment tasks. Next, the *Smart-Client* Python Package was built to inherit all the methods and attributes of *NordicEMS*, As illustrated in Fig. 12B. It acts as a middleware entity translating the incoming commands in the *EventBus*, providing reactive features to the residential agent.

#### 5. Results

To evaluate the proposed distributed energy management strategy, real data from 9 single-family detached dwellings located in the Quebec region has been exploited. These data were exploited to obtain the thermal model and qualitative insights into the power consumption

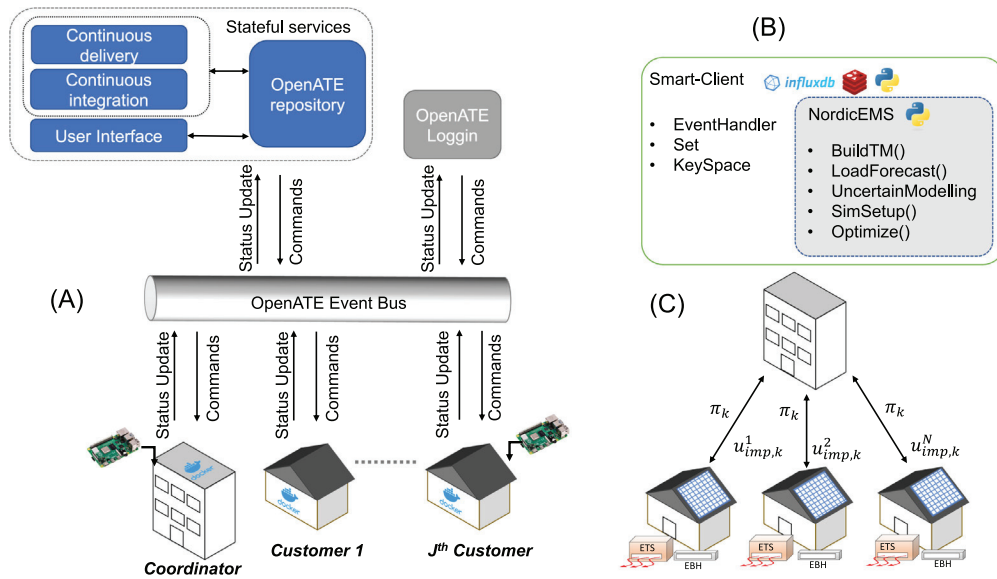


Fig. 12. (A) OpenATE core architecture (B) Main features of each Python self-coded module to perform distributed stochastic MPC. (C) Coordination game illustration with customers having different flexibility vectors.

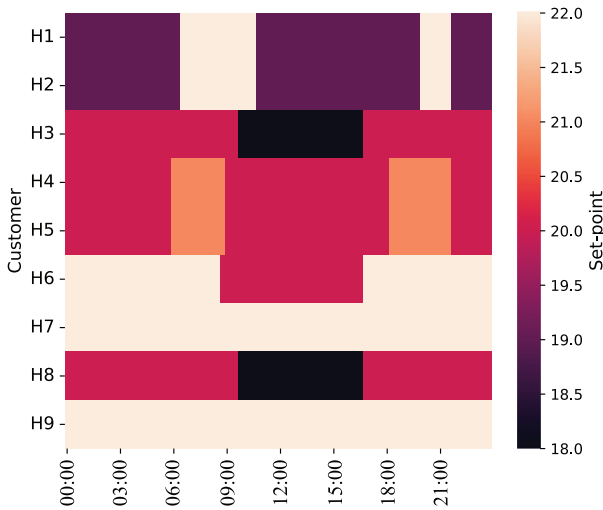


Fig. 13. The residential customers' thermal preferences.

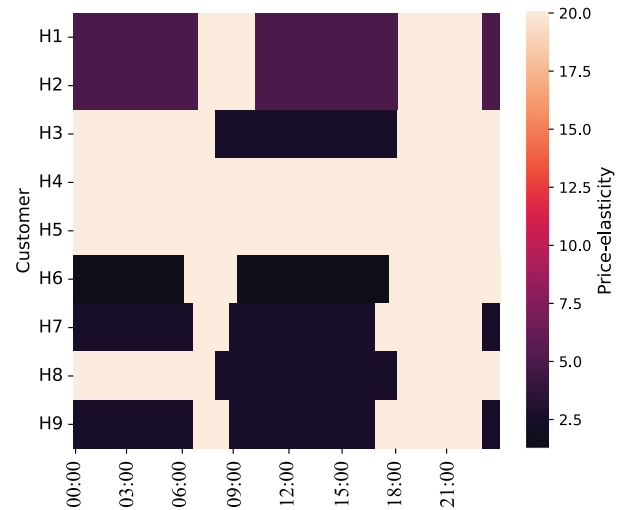


Fig. 14. The residential customers' price-elasticities ( $\alpha_k$ ).

pattern for each building. The data acquisition system measured and collected indoor and outdoor temperatures, electric baseboard heaters' power consumption, and other loads' consumption for winter. Detailed information on these houses can be found in [53]. Moreover, Canada has around 300 remote communities, from which 70% of them rely on diesel to fulfil their needs. To focus on northern Quebec's community Kuujuaq for testing the proposed method, we have deployed a weather forecast client over the Kuujuaq community. That provides a realistic picture as it enables performing statistic and stochastic models that characterize harsh weather environments and, consequently, renewable production specific to the target remote community. We modelled nine residential customers, having installed both and fed their data into the system. To perform stochastic analysis,  $N$  was fixed at 100. This setup is challenging as it implies heterogeneity, e.g. in diverse individual demand, ETS charging/discharging patterns, user preferences, and stochasticity associated with each customer's renewable production and non-shiftable loads.

Figs. 13 and 14 illustrates how customer differ regarding thermal preferences and price-elasticities ( $\alpha_k$ ) across the day. This value models

the comfort-level in each time-slot. When the customer is interested in respecting its comfort temperature set-point, then it becomes elevated. Conversely, when the consumer opts for the economic mode, the magnitude of  $\alpha_k$  gets reduced. Thus, the mechanism freely changes the internal temperature while respecting the constraints. These values were set for simulation purposes to create scenarios comprising elastic and inelastic customers. Furthermore, the residential customers differ in their flexibility degree to sacrifice thermal comfort and ETS charging/discharging patterns. Since the former represents the customer's elasticity, the study considers the same heating system handled by different users to see the changes in consumption.

### 5.1. Elapsed time by task for automated customers

We evaluated the performance of the prototype built for distributed computing with the proposed distributed DR mechanism. From Table 3, we can state that the group of automated agents with the embedded hardware can handle the following tasks (i) setting environment parameters, (ii) learning the house's thermal dynamics, (iii) modelling

**Table 3**  
Statistics of the automated agents' hardware execution time depending on the task.

Task	Time [s]			
	Mean	Std	Min	Max
Stochastic control	8.59	2.56	6.87	9.62
Deterministic control	4.72	0.65	4.12	5.92
Build TM Simulation setup	4.80	2.81	2.65	11.46
Load historic	0.25	0.01	0.23	0.29
Uncertainty modelling	0.003	0.0001	0.0003	0.0004
	82.71	12.72	73.79	103.14

uncertainties and (iv) performing optimal control with perfect (deterministic) and imperfect (stochastic) information scenarios. The latter entails cases with uncertainties in non-shiftable loads, solar-PV production and weather forecasting variables that affect the building's thermal dynamics.

These results suggest that an automated residential agent lasts about 4.72 seconds to provide optimal scheduling of their appliances with a Utopian deterministic approach. In turn, the stochastic case imposes a meaningful increase in the runtime, passing to 8.59 s on average. Notably, such time is comparable to the required time to model the uncertainties of the time-series databases to obtain historical consumption and weather forecasting data. This data is exploited afterwards to create probability distributions during the winter to properly characterize weather forecasting errors, renewable solar production, and non-shiftable demand. On the other hand, on average, automated customers can build their thermal models in 4.8 s. As a result of this analysis, the framework is robust enough to be deployed in a real-life distributed computing environment. Database services, however, still suffer from communication delays. Furthermore, stochastic scenarios relying on historical data to build probability distributions may impose a significant computational burden on low-cost hardware devices.

Eventually, we measured the computational cost of our strategy in two cases: centralized and distributed (with our distributed computing platform). The main difference between these two is that the first solves every customer problem sequentially while the other solves all of them in parallel. As a result, our system can reduce the computational burden by over 42%, passing from 75 s to 37 s to reach market equilibrium.

Since the parties participating in the game considered do not reveal their intentions and best response functions, iterations are needed to agree on the amount of energy consumption and the electricity price. Fig. 15 demonstrates the algorithm convergence. It is evident that the algorithm converged after reaching 10 iterations. The equilibrium was reached at that time, and hence the market clearing price was established. Consequently, none of the parties should move unidirectionally as their objectives have been fulfilled. When evaluating the system between the infeasible deterministic and stochastic scenarios, no significant impact was evidenced on the algorithm convergence. However, as detailed in Table 3, the runtime increased substantially.

### 5.2. Market-clearing

All the customers exchange their information regarding individual power consumption strategies with the local coordinator, given the price signal. Also, the customers are supposed to be willing to participate actively with the local coordinator in the game. Subsequently, when the market is cleared, the resulting pricing tariff is achieved, illustrated in Fig. 16. Consequently, the participation of customers in

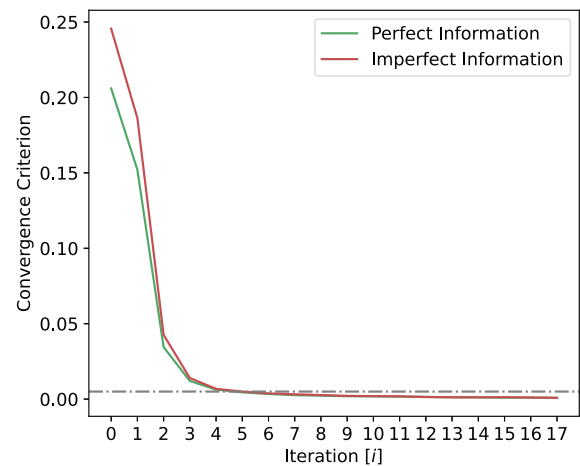


Fig. 15. Convergence criterion.

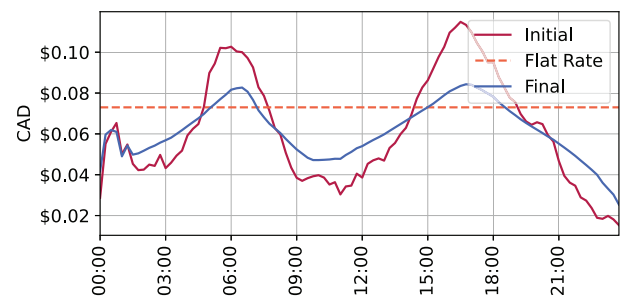


Fig. 16. Comparison between the initial flat rate vs the resulting market-clearing price.

the programme fetches them economic benefits. Fig. 16 shows that the final price remains below the initial flat price (7.3 cents/kWh) by over 80% of the day, indicating some critical hours exceeding the flat rate. However, such periods motivate the customers to exploit their ETS units during the rest of the day to avoid increases in their electricity bills. Nevertheless, as indicated in Section 3.2.1, the cost of running the ETS unit is about 5.6 cents/kWh, indicating that when the price signal is over the concerned value, leveraging ETS storage capacity becomes economically feasible.

### 5.3. Mechanism performance

From the decision theory's viewpoint, stochastic programming encompasses imperfect information through scenarios as the outcome of random events. Hence, the performance of our proposed stochastic strategy is compared to the results of a deterministic model with perfect information [54]. The deterministic approach considers no uncertainties in weather forecasting, non-shiftable load, and PV production forecasting, representing an infeasible solution. Hence, the deterministic approach is the proper baseline for evaluating the stochastic technique's performance, which models uncertain phenomena.

#### 5.3.1. Expected customer economic savings

The cost-effectiveness of the proposed mechanism for customers and the coordinator is also analysed. Fig. 17 describes the resulting customer payments under three cases: (i) deterministic, (ii) stochastic and (iii) without DR. The results show that the proposed programme brings economic savings under demand-uncertainties. Moreover, Figs. 18 and 19 illustrate how a particular customer exploited its heating system and compared it with the unfeasible case. As customers differ in their utilities' valuation, economic savings differ. As an outcome, the programme resulted in monetary savings ranging from 3% to 12%, being the more

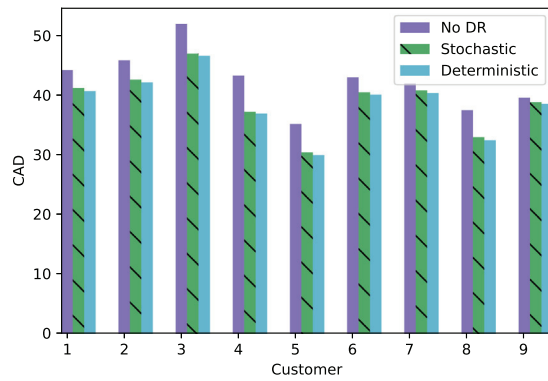


Fig. 17. Benchmark on the total cost for each agent with perfect, imperfect information and without DR cases.

elastic customers who have received more benefits, and conversely, the inelastic ones received fewer profits. Besides, note that our proposed strategy is close to the perfect deterministic case and better than not participating in the proposed DR program.

Furthermore, the uncertain behaviour of weather forecasting (outdoor temperature, solar irradiation and relative humidity), solar production and non-shiftable loads impacted optimal decisions for the hybrid heating system and, consequently, the indoor temperature. We evaluated the efficacy of the proposed mechanism under uncertainty. The closeness of the indoor temperature to the perfect one is evident in Fig. 20. However, the grey area in Fig. 20 depicts the difference indicating that each customer's impact on the discomfort term differs. That is attributed to the model entailing the thermal dynamics of each household, which varies in vector  $D$  (Eq. (11)), describing the weight of considering weather forecasted variables. Physically, it can be attributed to multiple reasons, including different isolation materials, thick external walls, the number of windows, and the area, creating different values of thermal resistances on the built RC models for the same weather conditions.

### 5.3.2. Expected coordinator economic savings

From the coordinator's viewpoint, substantial reductions in energy costs were achieved under demand-uncertainties. Fig. 21 illustrates an example of the obtained PAR with perfect and imperfect information and the case without DR. A cost reduction of over 12% was achieved with imperfect information, while the perfect scenario provided cost reductions of 14%. Similarly, the PAR was reduced by over 26% compared to the utopian deterministic case, while our controller with imperfect information provided a PAR reduction of 24%.

### 5.3.3. Technical evaluation

An adapted version of the CIGRE Low-voltage network benchmark [55] is utilized to perform the technical evaluation, as shown in Fig. 22. The ability to model radial networks, often found in remote communities in real-life scenarios, where customers depend on a single feeder and the voltage is significantly affected by distant loads caused by diesel generators, warrants its use. The original version had three sectors, including residential, industrial and commercial. Since this work focuses on the residential sector, we have considered only the residential sector. The adapted version includes prosumers integrated with solar-PV and DERs such as ETS and EBH. Solar-PV penetration varied from 30%–50% of the maximum households' demand, indicating that distributed renewable generation was for self-consumption purposes for every customer. The system contains a diesel generator exhibiting a power capacity of 0.5MW, allowing the evaluation of the potential positive effects of implementing our strategy in a real existing Northern community microgrid. The size of the diesel generator was based on

the maximum peak demand without the strategy (No DR case), which accounts for approximately 360 kW, as indicated in Fig. 21.

The well-adopted Pandapower module (coded in Python) is exploited to compute power flow and estimate the voltage per unit across the nodes. Figs. 23 and 24 illustrate the voltage profile during each peak, respectively. These peaks correspond to the morning and afternoon time, given the customer preferences (Fig. 13). It can be observed that in both cases, the resulting operational profile was enhanced. However, certain nodes violate the lower 0.95 pu phase voltage limit slightly. That can be solved by applying closed-loop strategies, such as receding horizon control [41], which allow the system to gain knowledge by updating the leader and follower strategies at each interval once the stochastic variables are revealed [56]. However, it goes beyond the scope of this paper.

## 6. Discussions

Recently, the coordination of HEMSs integrating multiple DERs in distribution systems has become a research hot spot. Such approaches accelerate the migration from passive to active networks, embedding renewables, growth of particular sectors (industrial, commercial and residential), and the changes in consumers' consumption patterns, among others. As a result, residential customers are becoming game changers since their decisions can significantly impact the efficiency of demand response programmes.

However, deploying distributed automated agents to make decisions for residential customers involves multiple challenges. Few works are aware of building scalable platforms to deploy, test and evaluate their algorithms. The attempts in this regard are mainly in blockchain to empower decentralized management energy systems [39,40] by incorporating notions before real-life deployments. For instance, estimating the computational burden imposed by communication-related tasks for residential customers may overcome the ones related to estimating the optimal strategies to handle controllable loads using stochastic control.

The effectiveness of distributed energy management strategies worldwide provides multiple benefits for utilities and residential, commercial, and institutional sectors. Nevertheless, the situation for remote communities is quite different as there are still limited initiatives to provide economic incentives to building owners, as powering communities with fossil fuels substantially increases the electricity price. Based on the results of this work, deploying this strategy can provide meaningful PAR reductions and, subsequently, the number of litres of diesel to run the generator.

Authors in [57] performed a dynamic game approach for DR purposes with multiple active customers integrated with electric batteries and solar PV production, considering weather forecasting errors uncertainties. They evaluated the robustness of such a mechanism by performing simulations over a year and assessing the PAR's distribution. Their findings showed that full adoption of electric batteries on the demand side substantially reduces the PAR and guarantees economic savings for the worst-case scenario.

The authors reported PAR reductions by over 35% when all customers adopted electric batteries, and bill reductions up to 11% on average. However, instead of actually performing demand forecasting, they fixed the error as a share of the demand/supply, which may provide biased results. On the other hand, their optimization problem is limited only to reducing operational costs, without considering any customers' utility objective. Conversely, the proposed work exploits an off-the-shelf commercial weather forecasting solution, facing real-life challenges that rise consequently when it comes to scheduling highly electrified heating systems with uncertain local renewable generation and non-shiftable loads. Besides, this paper provided optimal charging scheduling of multiple hybrid heating systems, including thermal storage units affecting the house's thermal dynamics. Additionally, this work models the forecasting errors on solar irradiation, outdoor temperature, and relative humidity. With all the aforementioned, our

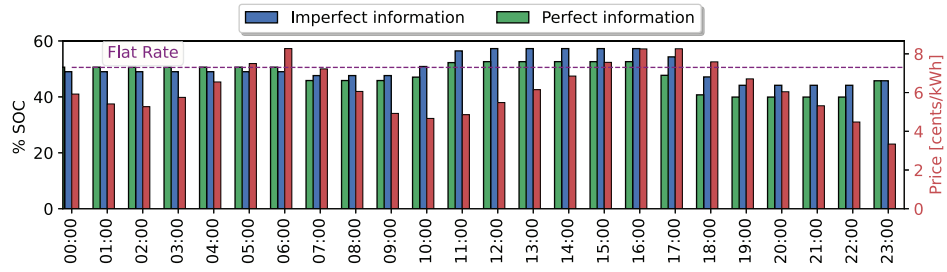


Fig. 18. Customer H1's ETS usage under the agreed rate.

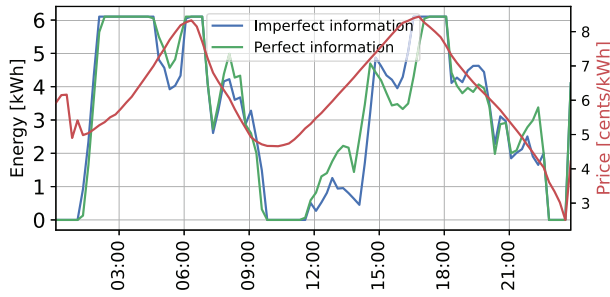


Fig. 19. Customer H1's electric baseboard usage under the agreed rate.

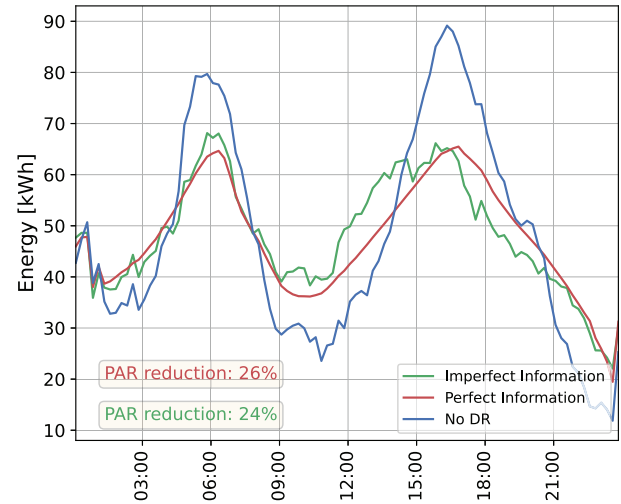


Fig. 21. Benchmark on the resulting PAR with perfect, imperfect information, and without DR cases.

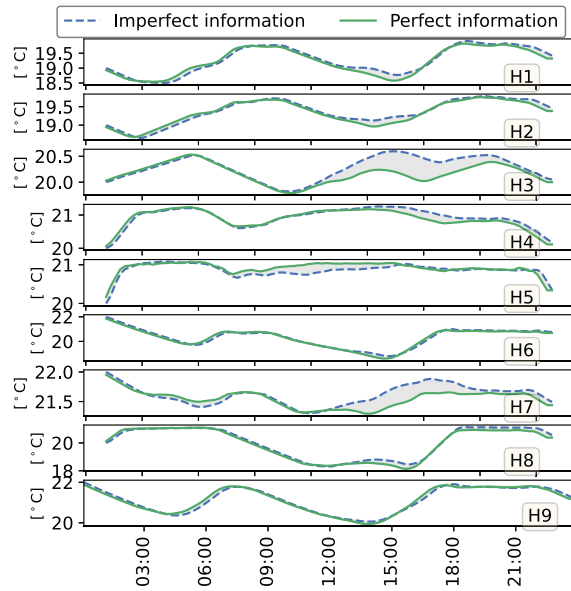


Fig. 20. Impact created on customers' discomfort under perfect and imperfect information cases.

strategy is able to bring significant PAR and electricity bills reduction (by over 24% and 12%, respectively) with the stochastic scenario. Note that these results obey high values of  $\alpha_k$ , which represent the customers' price elasticity, as indicated in Fig. 14. Such values are comparable in magnitude to the electricity price, and consequently, the customers experience inelastic behaviours as they have a high valuation on their thermal comfort.

The proposed approach exhibited a great techno-economic performance for coordinating DERs distributedly under diverse stochastic phenomena. Besides, by adopting open-source and state-of-the-art solutions, this work provides meaningful insights regarding realistic deployments of modern DR programs, including sound mathematical methods underlying optimal controllers and scalable hardware

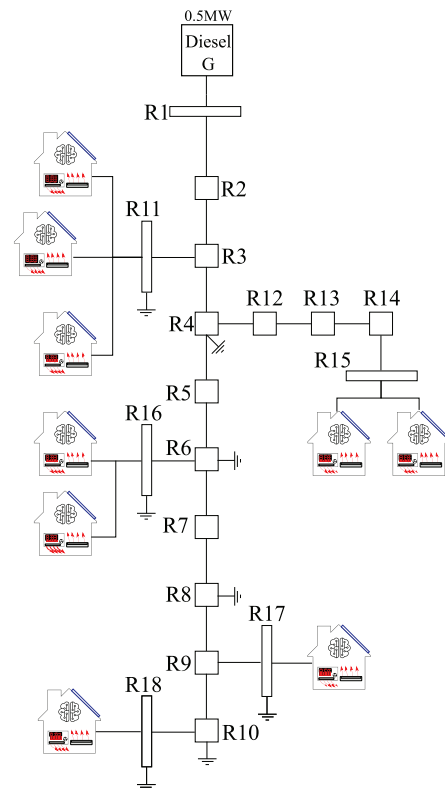


Fig. 22. Modified CIGRE LV system with smart households integrated PV systems, ETS and EBH.

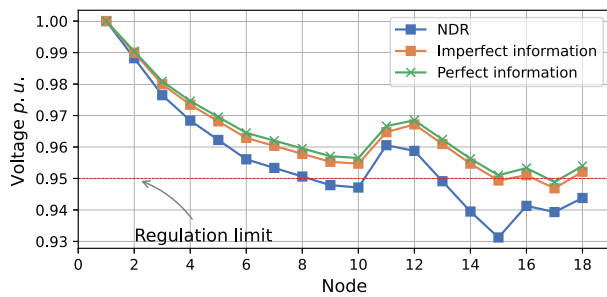


Fig. 23. Three-phase voltage magnitudes during the am peak.

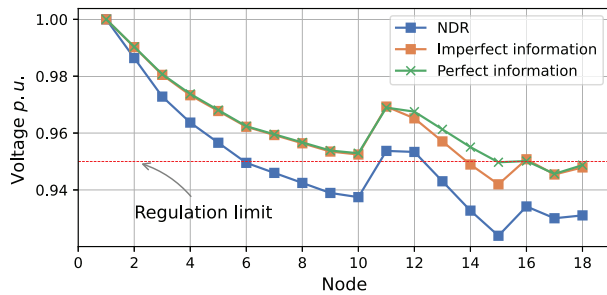


Fig. 24. Three-phase voltage magnitudes during the pm peak.

infrastructures and mechanisms enabling machine-to-machine communications. Nevertheless, there exist situations that can compromise the effectiveness of the proposed methods. First, although the implementation stage relies completely on commercial and open-source solutions to perform distributed computing, the security layer that could prevent malicious entities from creating cyber-physical attacks is still missing. Such an issue can be harnessed by adopting solutions such as blockchain algorithms. Second, while the proposed approach can provide a great estimation of the expected day-ahead load profile with imperfect information, there exist some notions that the proposal cannot handle currently, such as risk-aware decisions. Given the extreme sub-zero climate conditions, building owners may have concerns about weather forecasting errors, as these represent the perturbation when scheduling the heating load. A critical situation could appear when all customers decide to provide robust scheduling for the worst-case scenario, i.e. forecasting errors accumulate over time. As stated in Nagpal et al. [58], it may result in a tightened thermal comfort zone, increasing the lower comfort temperature and, hence, the resulting individual power consumption. Subsequently, when aggregating all the consumption profiles, an increased power consumption appears. Eventually, robust approaches often experience very low odds of occurring; however, grid operators in remote communities must have an estimation of the highest peak power to address power reserve issues properly.

## 7. Conclusions

In this paper, we have used a coordination game approach to investigate the problem of stochastic energy consumption scheduling between a benevolent coordinator and a set of customers under demand uncertainty. The proposed distributed energy management exploits a demand response framework with an energy cost-shared strategy, an incentive-compatible mechanism that encourages consumers to participate. The stochastic optimal controller of the paper maximizes individuals' welfare through thermal comfort and optimal utilization of the ETS. Simulations were performed to test the efficacy of the proposed approach on a cyber-physical computing testbed with embedded IoT devices and weather data of Kuujuaq, Québec. The comparative

simulations showed robustness to handle asynchronous communications by adopting an event-oriented approach and a complete stack of open-source tools. Under the stochastic scenario, the proposed strategy showed great ability to improve aggregated profile's PAR and provided economic savings by coordinating customers' strategies. Furthermore, the technical feasibility of the proposed strategy was tested and validated by adapting the CIGRE low-voltage benchmark system, highlighting the benefits of coordinating customer decisions regarding the enhanced resulting operational voltage profile. The results demonstrated the real-life feasibility of the proposed distributed energy management strategy in a community with embedded renewable energy sources. Future works should consider multi-stage stochastic programming to update customers' decisions and reduce the adverse effects of demand uncertainties. Besides, a cooperative game approach could be implemented to exploit renewable exceeds and create energy trading between customers. In order to overcome challenging scenarios that may compromise the cost-effectiveness of the strategy, future developments must adopt risk-aware decision-making by anticipating undesired demand-side effects due to customers' concerns on weather forecasting errors that could affect building thermal dynamics and, subsequently, the resulting aggregated load profile.

## CRedit authorship contribution statement

**Juan A. Dominguez:** Conceptualization, Investigation, Methodology, Software, Writing – original draft. **Kodjo Agbossou:** Funding acquisition, Supervision. **Nilson Henao:** Conceptualization, Validation. **Shaival H. Nagarsheth:** Writing – review & editing. **Javier Campillo:** Supervision. **Luis Rueda:** Investigation, Validation.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

The authors do not have permission to share data.

## Acknowledgements

This work was supported in part by the Laboratoire des technologies de l'énergie (LTE) d'Hydro-Québec, Canada, the Natural Science and Engineering Research Council of Canada and the Foundation of UQTR, Canada.

## References

- [1] I.E. Agency, *World Energy Outlook 2019*, Tech. rep., 2019, p. 11.
- [2] A. Artoni, N.J. Hewitt, F. Polonara, Domestic demand-side management (DSM): Role of heat pumps and thermal energy storage (TES) systems, *Appl. Therm. Eng.* 51 (1) (2013) 155–165, <http://dx.doi.org/10.1016/j.applthermaleng.2012.09.023>, URL <https://www.sciencedirect.com/science/article/pii/S1359431112006357>.
- [3] F. Plaum, R. Ahmadihangar, A. Rosin, J. Kilter, Aggregated demand-side energy flexibility: A comprehensive review on characterization, forecasting and market prospects, *Energy Rep.* 8 (2022) 9344–9362, <http://dx.doi.org/10.1016/j.egy.2022.07.038>, URL <https://linkinghub.elsevier.com/retrieve/pii/S2352484722012999>.
- [4] H. Shayeghi, E. Shahryari, M. Moradzadeh, P. Siano, A survey on microgrid energy management considering flexible energy sources, *Energies* 12 (11) (2019) 2156, <http://dx.doi.org/10.3390/en12112156>, URL <https://www.mdpi.com/1996-1073/12/11/2156>.
- [5] P. Siano, Demand response and smart grids—A survey, *Renew. Sustain. Energy Rev.* 30 (2014) 461–478, <http://dx.doi.org/10.1016/j.rser.2013.10.022>, URL <https://www.sciencedirect.com/science/article/pii/S1364032113007211>.
- [6] L. Rueda, K. Agbossou, A. Cardenas, N. Henao, S. Kelouwani, A comprehensive review of approaches to building occupancy detection, *Build. Environ.* 180 (2020) 106966, <http://dx.doi.org/10.1016/j.buildenv.2020.106966>, URL <https://www.sciencedirect.com/science/article/pii/S0360132320303255>.

- [7] N. Henao, M. Fournier, S. Kelouwani, T. De, Characterizing smart thermostats operation in residential zoned heating systems and its impact on energy saving metrics, *Electrical and Computer Engineering of Université du Québec Trois-Rivières, Canada. Institut de Recherche d'Hydro-Québec, Canada*, 2018.
- [8] P.S. Sauter, B.V. Solanki, C.A. Cañizares, K. Bhattacharya, S. Hohmann, Electric thermal storage system impact on northern communities' microgrids, *IEEE Trans. Smart Grid* 10 (1) (2019) 852–863, <http://dx.doi.org/10.1109/TSG.2017.2754239>, h.
- [9] W. Devia, K. Agbossou, A. Cardenas, An evolutionary approach to modeling and control of space heating and thermal storage systems, *Energy Build.* 234 (2021) 110674, <http://dx.doi.org/10.1016/j.enbuild.2020.110674>, URL <https://www.sciencedirect.com/science/article/pii/S0378778820334605>.
- [10] L. Petrichenko, Z. Broka, A. Sauhats, Impact of smart electric thermal storage on distribution grid, in: 2017 IEEE International Conference on Environment and Electrical Engineering and 2017 IEEE Industrial and Commercial Power Systems Europe, EEEIC / I CPS Europe, 2017, pp. 1–6, <http://dx.doi.org/10.1109/EEEIC.2017.7977625>.
- [11] J.A. Dominguez, L. Rueda, N. Henao, K. Agbossou, J. Campillo, Distributed Co-simulation for smart homes energy management in the presence of electrical thermal storage, in: IECON 2022 – 48th Annual Conference of the IEEE Industrial Electronics Society, 2022, pp. 1–6, <http://dx.doi.org/10.1109/IECON49645.2022.9969092>, ISSN: 2577-1647.
- [12] O. Kilkki, A. Alahäivälä, I. Seilonen, Optimized control of price-based demand response with electric storage space heating, *IEEE Trans. Ind. Inform.* 11 (1) (2014) 281–288.
- [13] N.T. Janssen, R.A. Peterson, R.W. Wies, Generalized heat flow model of a forced air electric thermal storage heater core, *J. Thermal Sci. Eng. Appl.* 9 (4) (2017) 041008, <http://dx.doi.org/10.1115/1.4036366>, URL <https://asmedigitalcollection.asme.org/thermalscienceapplication/article/doi/10.1115/1.4036366/392609/Generalized-Heat-Flow-Model-of-a-Forced-Air>.
- [14] S. Wong, J.-P. Pinard, Opportunities for smart electric thermal storage on electric grids with renewable energy, *IEEE Trans. Smart Grid* 8 (2) (2017) 1014–1022, <http://dx.doi.org/10.1109/TSG.2016.2526636>.
- [15] F. Charbonnier, T. Morstyn, M.D. McCulloch, Coordination of resources at the edge of the electricity grid: Systematic review and taxonomy, *Appl. Energy* 318 (2022) 119188, <http://dx.doi.org/10.1016/j.apenergy.2022.119188>, URL <https://www.sciencedirect.com/science/article/pii/S030626192200558X>.
- [16] W. Saad, Z. Han, H.V. Poor, T. Basar, Game-theoretic methods for the smart grid: An overview of microgrid systems, demand-side management, and smart grid communications, *IEEE Signal Process. Mag.* 29 (5) (2012) 86–105.
- [17] G. Li, Q. Li, Y. Liu, H. Liu, W. Song, R. Ding, A cooperative Stackelberg game based energy management considering price discrimination and risk assessment, *Int. J. Electr. Power Energy Syst.* 135 (2022) 107461.
- [18] F. Etedadi, S. Kelouwani, K. Agbossou, N. Henao, F. Laurencelle, Consensus and sharing based distributed coordination of home energy management systems with demand response enabled baseboard heaters, *Appl. Energy* 336 (2023) 120833.
- [19] M.K. Mishra, K. Murari, S.K. Parida, Demand-side management and its impact on utility and consumers through a game theoretic approach, *Int. J. Electr. Power Energy Syst.* 140 (2022) 107995, <http://dx.doi.org/10.1016/j.ijepes.2022.107995>, URL <https://www.sciencedirect.com/science/article/pii/S0142061522000412>.
- [20] X. Dong, X. Li, S. Cheng, Energy management optimization of microgrid cluster based on multi-agent-system and hierarchical Stackelberg game theory, *IEEE Access* 8 (2020) 206183–206197, <http://dx.doi.org/10.1109/ACCESS.2020.3037676>.
- [21] H.M. Soliman, A. Leon-Garcia, Game-theoretic demand-side management with storage devices for the future smart grid, *IEEE Trans. Smart Grid* 5 (3) (2014) 1475–1485.
- [22] S. Zheng, X. Jin, G. Huang, A.C. Lai, Coordination of commercial prosumers with distributed demand-side flexibility in energy sharing and management system, *Energy* 248 (2022) 123634.
- [23] S. Fan, Z. Li, J. Wang, L. Piao, Q. Ai, Cooperative economic scheduling for multiple energy hubs: A bargaining game theoretic perspective, *IEEE Access* 6 (2018) 27777–27789.
- [24] J. Wei, Y. Zhang, J. Wang, L. Wu, P. Zhao, Z. Jiang, Decentralized demand management based on alternating direction method of multipliers algorithm for industrial park with CHP units and thermal storage, *J. Mod. Power Syst. Clean Energy* 10 (1) (2022) 120–130.
- [25] M. Pilz, L. Al-Fagih, A dynamic game approach for demand-side management: scheduling energy storage with forecasting errors, *Dynam. Games Appl.* 10 (4) (2020) 897–929.
- [26] C. Lv, H. Yu, P. Li, C. Wang, X. Xu, S. Li, J. Wu, Model predictive control based robust scheduling of community integrated energy system with operational flexibility, *Appl. Energy* 243 (2019) 250–265, <http://dx.doi.org/10.1016/j.apenergy.2019.03.205>, URL <https://www.sciencedirect.com/science/article/pii/S0306261919306257>.
- [27] L. Zheng, B. Zhou, Y. Cao, S.W. Or, Y. Li, K.W. Chan, Hierarchical distributed multi-energy demand response for coordinated operation of building clusters, *Appl. Energy* 308 (2022) 118362.
- [28] X. Wang, Y. Liu, L. Xu, J. Liu, H. Sun, A chance-constrained stochastic model predictive control for building integrated with renewable resources, *Electr. Power Syst. Res.* 184 (2020) 106348, <http://dx.doi.org/10.1016/j.epr.2020.106348>, URL <https://www.sciencedirect.com/science/article/pii/S0378779620301541>.
- [29] E. Bilyik, A. Kahraman, A predictive control strategy for optimal management of peak load, thermal comfort, energy storage and renewables in multi-zone buildings, *J. Build. Eng.* 25 (2019) 100826, <http://dx.doi.org/10.1016/j.job.2019.100826>, URL <https://www.sciencedirect.com/science/article/pii/S2352710219302165>.
- [30] E. Rezaei, H. Dagdougui, M. Rezaei, Distributed stochastic model predictive control for peak load limiting in networked microgrids with building thermal dynamics, *IEEE Trans. Smart Grid* 13 (3) (2022) 2038–2049, <http://dx.doi.org/10.1109/TSG.2022.3159365>, Conference Name: IEEE Transactions on Smart Grid.
- [31] F. Guo, C. Wen, J. Mao, Y.-D. Song, Distributed economic dispatch for smart grids with random wind power, *IEEE Trans. Smart Grid* 7 (3) (2016) 1572–1583, <http://dx.doi.org/10.1109/TSG.2015.2434831>, Conference Name: IEEE Transactions on Smart Grid.
- [32] Z. Dong, X. Zhang, G. Strbac, Evaluation of benefits through coordinated control of numerous thermal energy storage in highly electrified heat systems, *Energy* 237 (2021) 121600, <http://dx.doi.org/10.1016/j.energy.2021.121600>, URL <https://www.sciencedirect.com/science/article/pii/S036054422101848X>.
- [33] M. Hu, F. Xiao, S. Wang, Neighborhood-level coordination and negotiation techniques for managing demand-side flexibility in residential microgrids, *Renew. Sustain. Energy Rev.* 135 (2021) 110248, <http://dx.doi.org/10.1016/j.rser.2020.110248>, URL <https://www.sciencedirect.com/science/article/pii/S1364032120305372>.
- [34] S. Zheng, X. Jin, G. Huang, A.C. Lai, Coordination of commercial prosumers with distributed demand-side flexibility in energy sharing and management system, *Energy* 248 (2022) 123634, <http://dx.doi.org/10.1016/j.energy.2022.123634>, URL <https://www.sciencedirect.com/science/article/pii/S0360544222005370>.
- [35] B.V. Solanki, P.S. Sauter, C.A. Canizares, K. Bhattacharya, S. Hohmann, Electric thermal storage system impact on northern communities' microgrids, 2017, URL <https://publikationen.bibliothek.kit.edu/1000073509>.
- [36] Z. Broka, K. Baltputnis, A. Sauhats, L. Sadovica, G. Junghans, Stochastic model for profitability evaluation of demand response by electric thermal storage, in: 2018 IEEE 59th International Scientific Conference on Power and Electrical Engineering of Riga Technical University, RTUCon, IEEE, Riga, Latvia, 2018, pp. 1–6, <http://dx.doi.org/10.1109/RTUCon.2018.8659837>, URL <https://ieeexplore.ieee.org/document/8659837/>.
- [37] F.E. Aliabadi, K. Agbossou, N. Henao, S. Kelouwani, F. Laurencelle, Distributed residential demand response using building mass and electric thermal storage system, in: 2022 IEEE 10th International Conference on Smart Energy Grid Engineering, SEGE, IEEE, 2022, pp. 19–25.
- [38] J. Niu, Z. Tian, Y. Lu, H. Zhao, Flexible dispatch of a building energy system using building thermal storage and battery energy storage, *Appl. Energy* 243 (2019) 274–287, <http://dx.doi.org/10.1016/j.apenergy.2019.03.187>, URL <https://www.sciencedirect.com/science/article/pii/S030626191930604X>.
- [39] Q. Yang, H. Wang, Blockchain-empowered socially optimal transactive energy system: Framework and implementation, *IEEE Trans. Ind. Inform.* 17 (5) (2021) 3122–3132, <http://dx.doi.org/10.1109/TII.2020.3027577>, Conference Name: IEEE Trans. Ind. Inform..
- [40] H.R. Bokkissam, S. Singh, R.M. Acharya, M.P. Selvan, Blockchain-based peer-to-peer transactive energy system for community microgrid with demand response management, *CSEE J. Power Energy Syst.* 8 (1) (2022) 198–211, <http://dx.doi.org/10.17775/CSEEJPES.2020.06660>.
- [41] T. Morstyn, K.A. Collett, A. Vijay, M. Deakin, S. Wheeler, S.M. Bhagavathy, F. Fele, M.D. McCulloch, OPEN: An open-source platform for developing smart local energy system applications, *Appl. Energy* 275 (2020) 115397.
- [42] G. Ferro, M. Robba, R. Haider, A.M. Annaswamy, A distributed optimization based architecture for management of interconnected energy hubs, *IEEE Trans. Control Netw. Syst.* (2022).
- [43] H. Yang, X. Xie, A.V. Vasilakos, Noncooperative and cooperative optimization of electric vehicle charging under demand uncertainty: A robust stackelberg game, *IEEE Trans. Veh. Technol.* 65 (3) (2016) 1043–1058, <http://dx.doi.org/10.1109/TVT.2015.2490280>, Conference Name: IEEE Transactions on Vehicular Technology.
- [44] Y. Li, C. Wang, G. Li, C. Chen, Optimal scheduling of integrated demand response-enabled integrated energy systems with uncertain renewable generations: A Stackelberg game approach, *Energy Convers. Manage.* 235 (2021) 113996, <http://dx.doi.org/10.1016/j.enconman.2021.113996>, URL <https://www.sciencedirect.com/science/article/pii/S0196890421001722>.
- [45] J. Tan, Y. Li, X. Zhang, W. Pan, W. Ruan, Operation of a commercial district integrated energy system considering dynamic integrated demand response: A Stackelberg game approach, *Energy* 274 (2023) 126888, <http://dx.doi.org/10.1016/j.energy.2023.126888>, URL <https://www.sciencedirect.com/science/article/pii/S0360544223002827>.
- [46] HydroQuebec, in: HydroQuebec (Ed.), Rate for Residential and Agricultural Customers Served by an Off-Grid System North of the 53rd Parallel (Domestic Rate), URL <https://www.hydroquebec.com/residential/customer-space/rates/rate-dn.html>.

- [47] Natural Resources Canada, Energy Fact Book 2020–2021, Tech. rep, 2020, URL <https://natural-resources.canada.ca/>.
- [48] S.J. Taylor, B. Letham, Forecasting at Scale, *Amer. Statist.* 72 (1) (2018) 37–45, <http://dx.doi.org/10.1080/00031305.2017.1380080>, Publisher: Taylor & Francis, eprint: DOI: 10.1080/00031305.2017.1380080.
- [49] F. Pelletier, A. Faruqi, Does dynamic pricing work in a winter-peaking climate? a case study of hydro quebec, *Electric. J.* 35 (2) (2022) 107080.
- [50] H.K. Nguyen, J.B. Song, Z. Han, Distributed demand side management with energy storage in smart grid, *IEEE Trans. Parallel Distrib. Syst.* 26 (12) (2015) 3346–3357, <http://dx.doi.org/10.1109/TPDS.2014.2372781>, Conference Name: IEEE Transactions on Parallel and Distributed Systems.
- [51] I. Atzeni, L.G. Ordonez, G. Scutari, D.P. Palomar, J.R. Fonollosa, Demand-side management via distributed energy generation and storage optimization, *IEEE Trans. Smart Grid* 4 (2) (2013) 866–876, <http://dx.doi.org/10.1109/TSG.2012.2206060>, URL <https://ieeexplore.ieee.org/document/6297498/>.
- [52] T.L. Nguyen, Q.-T. Tran, R. Caire, C. Gavriluta, Van Hoa Nguyen, Agent based distributed control of islanded microgrid — Real-time cyber-physical implementation, in: 2017 IEEE PES Innovative Smart Grid Technologies Conference Europe, ISGT-Europe, IEEE, Torino, 2017, pp. 1–6, <http://dx.doi.org/10.1109/ISGTEurope.2017.8260275>, URL <https://ieeexplore.ieee.org/document/8260275/>.
- [53] F. Etedadi, S. Kelouwani, K. Agbossou, N. Henao, F. Laurencelle, Consensus and sharing based distributed coordination of home energy management systems with demand response enabled baseboard heaters, *Appl. Energy* 336 (2023) 120833, <http://dx.doi.org/10.1016/j.apenergy.2023.120833>, URL <https://www.sciencedirect.com/science/article/pii/S0306261923001976>.
- [54] H. Bakker, F. Dunke, S. Nickel, A structuring review on multi-stage optimization under uncertainty: Aligning concepts from theory and practice, *Omega* 96 (2020) 102080.
- [55] S. Barsali, et al., Benchmark systems for network integration of renewable and distributed energy resources, 2014.
- [56] D. Mak, D.-H. Choi, Smart home energy management in unbalanced active distribution networks considering reactive power dispatch and voltage control, *IEEE Access* 7 (2019) 149711–149723, <http://dx.doi.org/10.1109/ACCESS.2019.2947238>, URL <https://ieeexplore.ieee.org/document/8867871/>.
- [57] M. Pilz, L. Al-Fagih, Recent advances in local energy trading in the smart grid based on game-theoretic approaches, *IEEE Trans. Smart Grid* 10 (2) (2019) 1363–1371, <http://dx.doi.org/10.1109/TSG.2017.2764275>.
- [58] H. Nagpal, I.-I. Avramidis, F. Capitanescu, P. Heiselberg, Optimal energy management in smart sustainable buildings – A chance-constrained model predictive control approach, *Energy Build.* 248 (2021) 111163, <http://dx.doi.org/10.1016/j.enbuild.2021.111163>, URL <https://linkinghub.elsevier.com/retrieve/pii/S0378778821004473>.

### 3.3 Risk-aware optimal scheduling

« *This section showcases how the third research objective was achieved. By explicitly incorporating demand-side concerns associated with weather forecast errors, the proposed framework enables customers to adopt risk-aware predictive strategies in their local decision-making systems. Such an approach becomes crucial in distributed energy systems, where controllability decreases as a greater share of community members actively participates. Under these circumstances characterized by a high penetration of small-scale renewable generation and the presence of thermostatically controllable loads customers are now able to express their perceived discomfort related to thermal deviations caused by non-shiftable consumption and renewable uncertainties. The methodology presented herein builds upon the following paper : »*

**Dominguez, J. A.**, Henao, N., Parrado, A., Agbossou, K., Campillo, J., & Rueda, L. (2025). Risk-aware distributed chance constrained energy coordination in energy communities. *Energy*, 134778.

#### 3.3.1 Background

Risk perception in energy communities managed in a distributed fashion has been the third key element that has drawn our interest. Particularly, the focal point of our analysis is the introduction of customers concern's on forecasting errors for both technical and mathematical reasons. Technically, it is difficult to estimate how much power reserve must be sized to cope with extra needs as a result of demand-side risk aversion to loss thermal comfort. Ignoring the previous matters may result into unnecessary oversized energy systems that are often non affordable and non-efficient. Mathematically,

incorporating risk perception or reliability notions imply probabilistic constraints that involve non-differential, non-linear and non-convex approaches. In this regard, estimating deterministic mathematical equivalents for those complex scenarios is a matter that elevates the system's complexity. Therefore, a risk-averse distributed energy management scheme optimization is proposed. Besides, extensive simulations were carried out with an upgraded infrastructure to assess the impact of customers concerns on forecasting errors and also to evaluate the strategy's scalability. Figure 3.5 summarizes all the above listed.

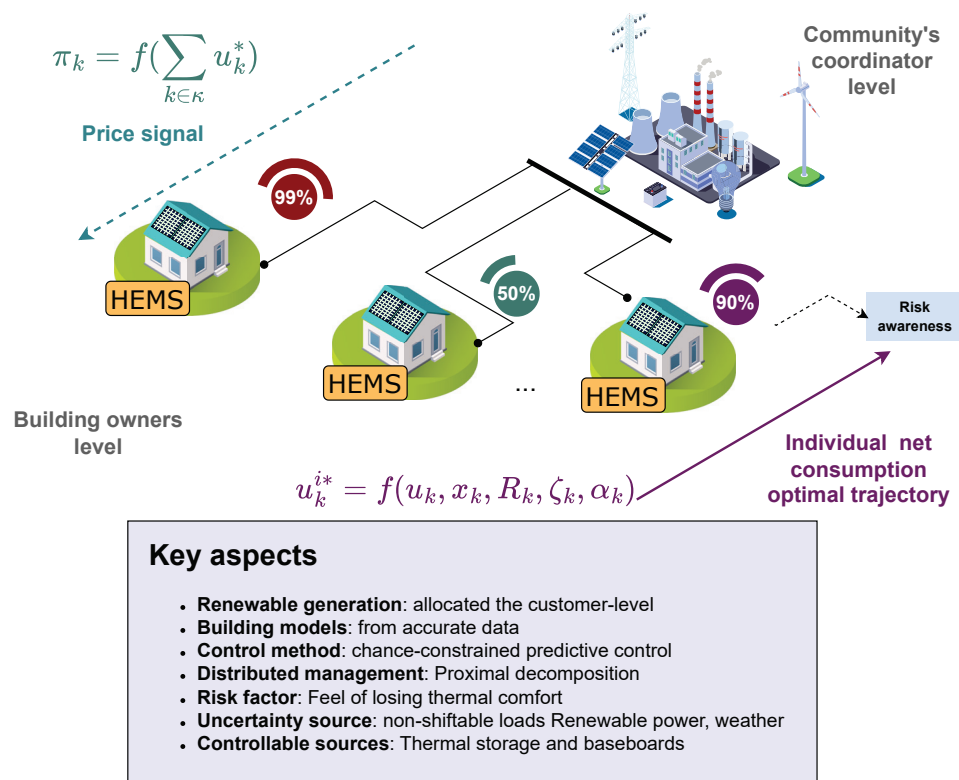


Figure 3.5 Visual representation of methods to manage the third objective

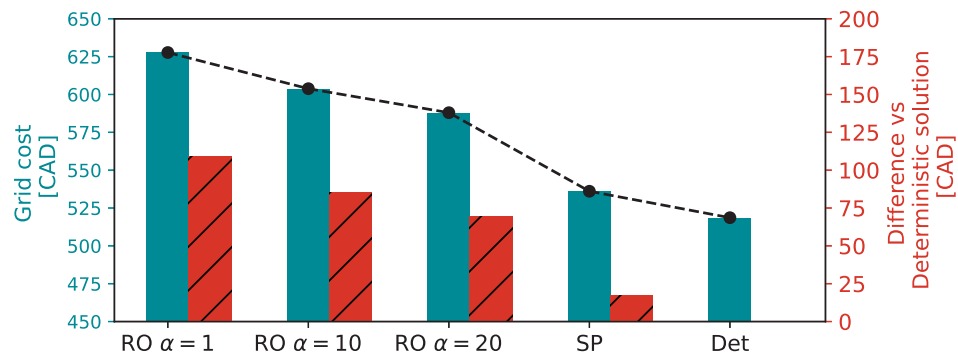


Figure 3.6 Risk-awareness impact over the average grid cost

### 3.3.2 Methodology

The theme of the third objective is to propose robust mechanism that enables introducing customers' risk perception to cover space heating needs as a result of forecasting errors on renewable production. To accomplish that, we have adopted individual chance constraints to model the customers' concerns to deviate out from the comfort zone. By having full knowledge on forecasting errors' PDF, it was possible to estimate deterministic equivalents that incorporates cumulative forecast errors from weather conditions and renewable production. At this point, risk-aware optimal control was possible and uncertainties from non-shiftable loads was also introduced via stochastic programming. Figure B.10 illustrates a flowchart to perform risk-aware distributed optimal coordination and to estimate deterministic equivalents. Similarly, Figure B.11 elucidates how to deploy our strategy into an upgraded cyber-physical infrastructure that enabled increasing gradually the number of participants by experiencing the salient features provided by Kubernetes and other tools.

### 3.3.3 Outcomes

The study of modelling demand-side concerns along with coordinating distributed resources provided the subsequent remarks :

- Deterministic equivalents were computed through individual chance constraints to incorporate risk-notion into optimal decision-making while balancing cost and utility terms.
- Having reliable system operations as a result of demand-side concerns increase the operational cost by over 22 %, as indicated in Figure 3.6.
- Chance constrained thermal comfort when incorporated into the problem with accumulated forecasting errors can anticipate potential issues that may appear as a result of weather-related uncertainties.
- Extensive simulations through realistic cyber-physical infrastructure validated the scalability of the proposal by increasing participants on the demand-side while at the same time reducing computational efforts.
- The proposed approach provide meaningful insights to estimate the required extra power and therefore sizing backup units and reduce unnecessary capital expenses.
- Low value-at-risk and cumulative forecasting errors significantly impact the expected aggregated profile, creating potential power congestion situations.
- Different simulations were carried out at different risk levels to evaluate the economic and technical impacts.



# Risk-aware distributed chance constrained energy coordination in energy communities

Juan A. Dominguez <sup>a</sup>, Nilson Henao <sup>a</sup>, Alejandro Parrado <sup>a</sup>, Kodjo Agbossou <sup>a</sup>, Javier Campillo <sup>c</sup>, Luis Rueda <sup>b</sup>

<sup>a</sup> Institut de recherche sur l'hydrogène, Université du Québec à Trois-Rivières, Trois-Rivières, G9A 5H7, Quebec, Canada

<sup>b</sup> Laboratoire des Technologies de l'Énergie, Institut de Recherche Hydro-Québec, Shawinigan, G9N 0C5, Quebec, Canada

<sup>c</sup> Ministry of Mines and Energy, Bogota, 130001, Colombia

## ARTICLE INFO

### Keywords:

Risk-aversion  
Chance constraints  
Distributed control  
Energy communities  
Electric thermal storage

## ABSTRACT

The concept of energy communities is drawing particular attention, given their potential to bridge energy gaps by fostering energy transition through community-led initiatives. Although the literature offers well-established business models that ensure long-term sustainability, several improvement opportunities exist to manage demand-side risks that could jeopardize the program's effectiveness. Accordingly, this paper proposes to evaluate potential customer hazards given end-users' concerns about thermal discomfort given uncertainty sources in weather forecasting and subsequent renewable production. The strategy employs a distributed energy coordination framework for residential prosumers within a hierarchical control structure governed by a benevolent coordinator. Prosumers maximize their welfare using a stochastic chance-constrained programming approach, while the coordinator minimizes planned grid costs through a cost-sharing approach. Each customer is integrated with electric thermal storage and renewable power. Extensive simulations were performed with accurate energy consumption and weather forecast data in the province of Quebec. Results demonstrate that demand-side risk-aversion preferences can significantly impact the expected aggregated demand profile, creating power congestion situations. The price of robustness as a consequence of anticipating forecasting errors ranged from 9.06 to 15.15% compared to the optimal solution with perfect information. Eventually, the proposal was validated through a cyber-physical infrastructure meeting scalability requirements.

## 1. Introduction

During the last decade, the energy sector worldwide has put significant efforts into achieving climate goals. One of the most ambitious strategies is to build thousands kilometers of transmission lines to incorporate large-scale renewable power projects [1]. Nevertheless, high-voltage transmission projects can take a decade, given environmental permits and other issues [2]. Distributed generation represents a key solution for enhancing energy efficiency while mitigating these delays [3]. Indeed, the global distributed generation market size was valued at USD 256.2 billion in 2021, and it is projected to reach USD 650.07 billion by 2030, growing at a compound annual growth rate of 10.9% during the forecast period (2022–2030) [3].

Distributed generation, combined with the continued cost reductions in mature technologies such as solar photovoltaic and wind power, has been a critical enabler in fostering energy transition mechanisms in industrial, commercial, and residential sectors [4]. While the industrial and commercial sectors have historically been involved in

transitioning from fossil fuels to green power grids, the residential sector is still embracing renewable power efficiently. Accordingly, energy communities (ECs) appear in the energy landscape, with citizen engagement emerging as a central focus in accelerating clean energy transitions. ECs are characterized by having members intensely involved in planning and implementing measures for the rational use of energy and introducing renewable energy sources in the production, consumption, and supply of electricity, thermal, mechanical energy or fuels [5]. Their implementation depends strongly on their sustainability in time, which is why, during the last few years, literature has put meaningful efforts into business models. Traditional self-consumption and place-based communities currently lead the group of business models [6].

Although long-term analysis shows that sustainability is possible thanks to well-established business models, many concerns need to be addressed operationally to guarantee the project's cost-effectiveness, including governance, regulatory and energy optimization [7]. Regarding the latter, home energy management systems (HEMS) provide a

\* Corresponding author.

E-mail address: [juan.antonio.dominguez.jimenez@uqtr.ca](mailto:juan.antonio.dominguez.jimenez@uqtr.ca) (J.A. Dominguez).

<b>Nomenclature</b>	
<b>Abbreviations</b>	
ADMM	Alternating direction method of multipliers
CCP	Chance constrained programming
CFD	Cumulative density function
CVAR	Conditional value at risk
DER	Distributed energy resource
DR	Demand response
DRCC	Distributionally robust chance constraint
DRO	Distributionally robust optimization
EBH	Electric Baseboard Heater
EC	Energy community
EES	Electric Energy Storage
ETS	Electric Thermal Storage
HEMS	Home Energy Management Systems
IGDT	Information gap decision theory
P2P	Peer to peer
PAR	Peak-to-Average Ratio
PL	Power limit
POPC	Probability of power congestion
PoR	Price of robustness
PV	Photovoltaics
RO	Robust optimization
SCCP	Stochastic chance constrained programming
SOC	State-of-the-charge
VAR	Value at risk
VPP	Virtual power plant
WT	Wind Turbine
<b>Functions</b>	
$\mathbb{P}$	Probability
$C^{Det}$	Cost of the deterministic solution
$C^R$	Cost of the risk averse solution
$C_{r,k}^{ETS}$	Cost of operating the thermal storage unit
$C_{r,k}^{imp}$	Prosumer's electricity bill
$J$	Individual welfare function
$U_{r,k}$	Prosumer's utility function
<b>Indices</b>	
$i$	Index for iteration
$j$	Index for scenarios
$k$	Index for time slots
$r$	Index for participants
<b>Parameters</b>	
$\eta^c$	ETS Charging efficiency
$\hat{t}$	Reversal time
$\overline{ES}_k$	Maximal allowed ETS heat stored
$\rho_k$	Thermal discharge rate under free convection
$\Sigma_k$	Covariance matrix of the uncertain vector $W_k$
$\underline{ES}_k$	Minimal allowed ETS heat stored

$C^{total}$	Cost of the grid
$C_k^b$	Cost of the energy stored in form of heat
$IC$	CAPEX of the ETS
$NP$	Number of prosumers
$W_k$	Vector of weather conditions
$\alpha_k$	User's price elasticity
$\eta$	Risk-aversion parameter
$\gamma_k$	Probability density function of the weather forecast error
$\pi_k$	Electricity price
$\sigma_k$	Standard deviation of the forecast error
$\tau$	Regularization parameter
$A, B, C$	Building state equation matrices
$a, b, c$	Diesel generator parameters
$u_{EBH}^{max}$	EBH's maximal rated power consumption
$u_{ETS}^{max}$	ETS' maximal rated power consumption
$x^{max}$	Maximal indoor temperature
$x^{min}$	Minimal indoor temperature
$x_{r,k}^c$	Comfort temperature of the $r$ 'th user
<b>Sets</b>	
$I$	Set of iterations
$J$	Set of scenarios
$\mathcal{K}$	Set of time-slots
$\mathcal{R}$	Set of prosumers
<b>Variables</b>	
$ES_k$	Energy stored in the ETS
$u_{r,k}^{EBH}$	Electrical baseboard electricity consumption
$u_{r,k}^{ETS}$	ETS electrical charging power
$u_{r,k}^{imp}$	User's imported energy consumption
$u_{r,k}^{REBH}$	Renewable power to be used by EBH
$u_{r,k}^{RETS}$	Renewable power to be used by ETS
$x_k$	Building's indoor temperature

great solution to optimally allocate renewable power and schedule controllable appliances while guaranteeing cost reductions and satisfying utilities [8]. That, combined with the outbreak of decentralizing energy

markets, suggests that HEMS can facilitate community members to meet one of the most important goals of ECs: the commitment of community members in energy production and consumption, enhancing efficiency, grid resilience, and cost savings. In the presence of renewable power, ECs may face challenges related to demand-side uncertainties created by forecasting errors, including (i) power imbalances, (ii) inefficient resource allocation, and (iii) customer dissatisfaction, among others. Forecasting errors can lead to imbalances between energy generation and consumption, jeopardizing grid stability. To address this, Huo et al. [9] utilized advanced optimization methods to balance grid reliability and operational costs effectively. Likewise, Yan et al. [10] introduced an approach to optimally estimate power reserves, compensating for unpredictable discrepancies and maintaining grid stability. Effective resource allocation is critical for energy efficiency in ECs. Pilz et al. [11] demonstrated that optimal scheduling of battery storage can enhance the peak-to-average ratio (PAR) by over 10% utilizing game theory. Nevertheless, improper management of shared resources can lead to participants feeling unmet heating or cooling needs, causing disengagement from demand-side programs. To address this, Vellei and Le Dreau [12] developed a method to predict dissatisfaction levels caused by transient indoor temperature changes during demand response calls. On the other hand, energy storage systems play a crucial role in mitigating dissatisfaction by improving grid flexibility and decoupling heating and electricity demand. Wang et al. [13] remarked that thermal energy

assets enhance energy efficiency and reduce undesired effects on DR participants. Testi et al. [14] consistently emphasized that leveraging heat pumps to switch between electrical and thermal loads increases system flexibility. This approach enhances operational strategies and brings about economic, technical, and environmental benefits.

On top of the above mentioned, energy requirements of ECs depend strongly on climate conditions, given the large share of energy consumption tailored to cope with heating or cooling demand [15]. For instance, in Quebec, HVAC energy consumption accounts for 70%–80% of the total energy consumption [16]. That region experiences situations in winter as a large share of heating systems are primarily powered by electricity. Hence, deploying an EC under these conditions implies different considerations. Literature and real-life projects suggest incorporating electric thermal storage (ETS) units at the customer level [17]. These systems can assist in covering heating needs through affordable investments compared to lithium batteries while leveraging benefits from dynamic rates. ETS stores heat in high-density ceramic bricks during on-peak periods and release it during off-peak events to satisfy customer thermal comfort [18].

Three main challenges may arise when deploying an EC under the conditions mentioned above. First, the intermittent nature of renewable sources and weather forecasts pose significant challenges due to imperfect information in distributed management strategies [19]. Second, ETS units that operate in free convection allow modulating charging power but not discharging power. That creates a significant concern as heating power, i.e. the discharge power, cannot be considered as a decision variable as it depends on multiple variables, including the indoor temperature, the outdoor temperature, and occupation, among others, thus reducing the degrees of flexibility of the HEMS [20]. Furthermore, when ETS systems are charged utilizing renewable power, their optimal power planning is no longer deterministic but stochastic. Third, having distributed demand-side strategies creates room for multiple situations as the decision-making tasks are transferred to customers. Therefore, EC coordinators should be able to adequately anticipate potential adverse events that can compromise the grid's cost-effectiveness. One potential risk in such schemes is that customers may experience a fear of losing thermal comfort during severe cold periods [21]. Thermal comfort depends strongly on building thermal dynamics, which is affected directly by weather prediction and the subsequent renewable power availability. As a result, building owners may experience risk aversion due to forecasting errors resulting in conservative consumption patterns that could jeopardize the power grid by increasing the odds of power congestion, reduced power quality, and vast ramping conditions. Addressing these issues represents the primary motivation of this study.

## 2. Related works

Literature reports substantial efforts in ECs; most of the research papers are on the domain of business models [6]. Numbers are high regarding demand-side management strategies that encompass uncertainties from multiple domains. However, these approaches only enable modeling risk-neutral decisions, as they rely on maximizing/minimizing the expected value of cost functions. These approaches often employ stochastic programming for reducing operational cost [40], minimizing CO<sub>2</sub> emissions [41], or maximizing grid reliability [42], among others.

Nevertheless, few attempts have been made regarding approaches that can effectively incorporate demand-side concerns related to thermal comfort considering weather forecast errors along with renewable power generation. Table 1 summarizes similar works. Mohiti et al. [22] introduced a risk-averse energy management system for optimal heat and power scheduling in ECs encompassing uncertainties from photovoltaic power and load forecasting by employing the Information gap decision theory (IGDT). They adjusted indoor and hot water temperatures to meet robustness criteria. Likewise, Yi et al. [23] proposed a distributed optimal operation of a hybrid PV-battery system considering

renewable and load uncertainties. They adopted chance-constrained optimization to address concerns about power imbalances. Galheou et al. [24] proposed a risk-constrained scheduling of energy hubs through stochastic p-robust optimization. The energy hub is composed of thermal and battery storage. Authors incorporated risk-aversion to CO<sub>2</sub> emissions in their management strategy. Dolanyi et al. [25] formulated a CVAR-based optimal bidding and scheduling problem through stochastic programming. They have exploited shared battery storage by transferring forecasting concerns to state-of-the-charge (SOC) boundaries and encompassing uncertainties from market imbalances and load forecast errors. However, they solved the problem in a centralized fashion. Liu et al. [43] performed an IGDT-based optimal control over an energy community with underground thermal storage. They have encompassed risk aversion to power imbalances due to load and PV power uncertainties. Wang et al. [13] introduced a CVAR-based stochastic collaborative optimization model for microgrids through consensus optimization. They have performed stochastic demand-side resource coordination, including thermal and battery storage.

Liang et al. in [27] proposed a CVAR-constrained optimal dispatch for VPPs with correlated demand response by tackling uncertainties from renewables and electricity price. Nevertheless, authors compared the expected cost of their stochastic approach against the deterministic baseline which is not a reasonable as random variables were not realized yet. Tostado-Veliz et al. in [28] elaborated a research on a risk-aware platform that entails diverse DERs in energy communities with a P2P market. Although they proposed a distributed clearing markets without central entities, they have addressed uncertainty through robust techniques and box-based sets which depends strongly on experts' knowledge on physical phenomena and so results could be highly biased. Wang et al. in [29] introduced an optimal scheduling strategy for VPPs with distributed resources and generation user-side based on distributionally robust optimization. By incorporating their approach, aggregation benefits were significantly increased. Even though they have encompassed variability from electricity prices, they managed the problem centrally by assuming that selfish demand-side interests do not exist. Zhong et al. in [30] carried out a Stackelberg-based framework for energy hubs through distributionally robust optimization. Their approach exhibits great performance in maximizing profits and power reserve cost. Li et al. in [31] adopted an ADMM-based P2P framework to trade interconnected microgrids. They encompassed uncertainty from load consumption and renewable power. Etedadi et al. [32] elaborated an study to coordinate distributedly HEMS through a reward-sharing and incentive-compatible mechanism are proposed to distribute economic benefits among participants. Authors employed an ADMM-based energy coordination. Although the research showed outstanding features regarding efficient gain allocation and peak power reduction, they did not incorporate risk aversion metrics into their local decision making systems. Yang et al. in [33] proposed a risk-constrained power scheduling for energy hubs with renewables, demand response, and electric vehicles through the slime mold algorithm and CVAR to manage the uncertainties from renewable generation and load demands. However, competitive interest were not modeled and decision-making was made centrally.

Similarly, Najafi and Livani [36] developed a probabilistic constraint-based framework to address uncertainties in demand response and volt/var optimization using Gaussian models. They modeled renewable power forecast errors with non-Gaussian distributions. While their approach demonstrated technical feasibility in two test feeders, it was not validated on a realistic infrastructure that could expose potential model limitations for accurate implementation. Esfahani et al. [37] proposed a distributed co-optimization framework for energy scheduling, frequency regulation, and voltage support, leveraging data-driven distributionally robust optimization. Their findings regarding uncertainty management align with prior literature, showing that the total revenue of VPPs and individual prosumers decreases as risk-aversion increases, impacting energy arbitrage, frequency regulation, and voltage

**Table 1**  
Similar works in risk-averse management for energy communities.

Ref	Storage	Energy coord.	Forecasting errors	Risk factor		Risk management strategy/Risk metric	Distributed computing	Validation
				Supply	Demand			
Mohiti et al. [22]	EES	x	Load, PV power	x	x	x	x	x
Yin [23]	EES	x	Load	Power imbalance	x	CCP/VAR	x	x
Ghaleou et al. [24]	EES TES	x	x	CO2 emissions	x	Stochastic p-Robust	x	x
Dolanyi et al. [25]	EES	x	Load, Market imbalances	x	SOC boundaries	SCCP	x	x
Liu et al. [26]	TES	x	Load, PV power	Power imbalance	x	IGDT	x	x
Wang et al. [13]	EES TES	✓	Load	x	CO2 emissions	SCCP/cVAR	x	x
Liang et al. [27]	EES TES	x	Wind power, Electricity price		x	SP/CVAR	x	x
Tostado-Veliz et al. [28]	EES	✓	Wind power	x	x	RO	x	x
Wang et al. [29]	EES	x	Electricity price	Market bidding	x	DRO/CVAR	x	x
Zhong et al. [30]	EES	✓	Renewable power			DRO/CVAR	x	x
Li et al. [31]	EES	✓	Load, Renewable power	Power imbalance	x	DRO/	x	x
Etedadi et al. [32]	x	✓	x	x		x	x	x
Yang et al. [33]	x	x	x	Power imbalance		RO/CVAR	x	x
Javed et al. [34]	x	x	x	x	x	x	x	✓
Cruz et al. [35]	x	x	x	x	x	x	✓	✓
Najafi and Livani [36]	EES	x	Renewable power	Voltage regulation	x	DRO	x	x
Esfahani et al. [37]	x	✓	Renewable power	x	Power imbalance	DRO	x	x
Mianei et al. [38]	EES	x	Load and Renewable power	Power imbalance	x	CCP/VAR	x	x
Yang et al. [39]	x		Load and weather	x	Load deviations	DRCC	x	x
This	TES	✓	Load, Renewable power Weather	Probability of power congestion	Renewable power availability Thermal comfort boundaries	SCCP/VAR	✓	✓

support. Mianaei et al. [38] introduced a robust approach for scheduling combined cooling, heating, and power in microgrids with demand response. They addressed forecast errors in renewable generation and power consumption to model risk aversion over the security constraint. Cao et al. [44] presented a joint chance-constrained green energy management strategy for microgrids with multiple energy carriers. Using distributionally robust optimization, the authors incorporated risk preferences within each microgrid. However, their solution did not employ a distributed approach, a fact that compromises users' information privacy. Their results demonstrated that the strategy effectively balances carbon emissions between robust and deterministic optimization dimensions. Finally, Yang et al. [39] proposed a carbon-aware strategy for managing thermostatically controlled loads using a distributionally robust chance-constrained approach. Their block coordinate descent-based algorithm reduced conservatism by addressing load forecasting

errors, promoting decarbonization in the building sector. Other works in risk-aware strategies for optimal operation of ECs and microgrids include battery sizing, contract sustainability, and benefit allocation for aggregators and virtual power plants. Accordingly, Sadeghian et al. in [45] advanced the literature on battery sizing by demonstrating that risk-constrained storage allocation strategies in VPPs can reliably schedule power. Their approach considers uncertainties in investment and electricity markets by considering metrics like the loss of load expectation and energy non-served. Toquica et al. [46] assessed the risks associated with forward contracts in Transactive Energy Systems (TES). By leveraging accurate data and forecasting services, their findings revealed that demand-side uncertainties significantly affect contracts' conditional value at risk (CVAR), highlighting the importance of predictive accuracy in maintaining contract sustainability. Nguyen et al. [47] employed a CVAR-constrained approach to

maximize profits for microgrid aggregators participating in forward contracts. Similarly, Vahedipour et al. [48] extended this concept by using a CVAR-constrained strategy to optimize the economic benefits of demand response (DR) providers. Their approach enhanced reserve services while increasing the profitability of VPPs. Building on these efforts, researchers have aimed to enhance VPP operations by addressing uncertainties in renewable generation, demand, and market prices. For instance, Yang et al. [33] demonstrated that CVAR-constrained methods can reduce operational costs by up to 12.65% and CO<sub>2</sub> emissions by 15.43%, offering a robust framework for addressing risks. Additionally, Syrri et al. [49] proposed a risk-constrained DR approach tailored for capacity release in distribution networks. Their findings indicate that contracting fewer DR customers than those indicated by deterministic models can maintain reliability, paving the way for probabilistic planning in DR programs.

Unlike other works, Gu et al. [50] have performed additional efforts to validate in practice a data-driven stochastic energy sharing optimization and implementation for community energy storage and PV prosumers. Cruz et al. [35] also contributed research in this regard, by designing a testbed with low-cost embedded hardware for DR purposes in a smart community integrated with renewables. They have provided insights about communication delays for aggregators to schedule optimally consumers' appliances. Likewise, Javed et al. in [34] proposed an EMS through low-cost IoT technologies. They addressed security, low-latency communication, and demand response to balance energy demands, reduce costs in human-centric energy solutions. However, they did not perform energy coordination strategy nor managed uncertainties.

While research is pushing hard regarding strategies that embrace risk preferences at the supply and demand level, most of these need to consider risk preferences during decision-making tasks in communities experiencing harsh winters with high penetration of renewable power and distributed thermal storage. In this regard, space heating stands for an essential commodity to satisfy thermal comfort, and building owners may experience risk-aversion to weather forecast accuracy and the subsequent intermittent renewable power availability. Furthermore, a large share of similar works depend on sequential decision-making frameworks that enable understanding algorithms and evaluating the system's overall performance. But, these systems do not reflect the complexities and difficulties faced in real-life deployments. Additionally, none of them have validated their results in realistic infrastructures that enable anticipating possible critical problems that may appear when implementing these solutions in real-life.

### 2.1. Contributions

This paper extends the existing literature by proposing a risk-aware distributed demand response strategy for energy communities with community members integrated with solar PV, wind turbines and thermal storage assets. The strategy entails demand-side risk related to not meeting building's heating needs as a result of to weather forecasting errors and renewable power availability. These risks are incorporated along with stochastic modeling of non-shiftable load consumption through HEMS distributedly by employing an SCCP approach. The strategy also includes a novel controller for ETS that considers physical constraints regarding thermal discharge, relying on accurate data collected in a realistic laboratory. The main contributions are summarized as follows:

- Introducing a risk-aware distributed resources coordination framework facilitates extensive simulations to analyze critical situations that may arise in the operation of ECs as a result of demand-side risks. That allows for estimating the impact of customers' concerns on weather forecasting and renewable ability in the power grid.

- Proposing a novel ETS controller. The proposed mathematical model uses the charging electric input as the control variable and the remaining stored energy as the state variable. The thermal discharge depends only on the stored energy and thus reduces the model's complexity by approaching more real-life scenarios considering the physical constraints of actual systems.
- Bridging the gap between theoretical and real-life deployments by testing and evaluating the strategy's performance over a realistic infrastructure. That allows for performing scalable simulations and It provides reproducible, reliable and verifiable results by decreasing substantially the computational burden. That is composed of a set of complete open-source tools which enable anticipating situations that automated agents may face in realistic situations.

## 3. Stochastic modeling

The proposed strategy encompasses stochastic phenomena related to (i) weather forecast errors, (ii) renewable production and (iii) non-shiftable loads.

### 3.1. Weather forecast and non-shiftable loads

Accurate data from weather forecasting data and non-shiftable loads were retrieved for the analysis in this paper. Tomorrow.io, an open-source framework, is utilized to get actual forecasting weather data through a self-made client coded in Python. We have modeled forecasting errors of relative humidity, outdoor temperature, wind speed, and solar irradiation and built corresponding probability density functions. Besides, power consumption data of major individual appliances from 11 houses in Quebec has been collected. Correspondingly, semi-synthetic data generation models have been employed to simulate several daily and weekly load profiles, which allows the creation of stochastic profiles for non-shiftable loads. We have adopted the well-known Prophet Python module [51] by setting the confidence interval to 95% and weekly seasonality. More details can be found in [52].

### 3.2. Renewable production

We combined the outcome of the weather forecasting errors with the PVlib module, coded in Python, and a self-coded wind turbine model to model the uncertain renewable production at the customer level. Each renewable generator was exploited with the actual and forecasted weather data every day during 2023.

$$\gamma_k^{PV} \sim \mathcal{N}(0, \sigma_k^{PV}), \forall k \in \mathcal{K} \quad (1a)$$

$$\gamma_k^{WT} \sim \mathcal{N}(0, \sigma_k^{WT}), \forall k \in \mathcal{K} \quad (1b)$$

$$\gamma_k^R \sim \mathcal{N}(0, \sigma_k^{WT} + \sigma_k^{PV}), \forall k \in \mathcal{K} \quad (1c)$$

Eqs. (1a)–(1c) entail zero-centered Gaussian noise for each variable; and  $\sigma$  models the standard deviation of the prediction error of each renewable generator. Fig. 1A and B illustrate the evolution of the standard deviation forecasted production for each generator as a share of the installed capacity. The system was modeled given geographical and technical characteristics such as the geographic location, the number of inverters, peak capacity, among others. Renewable penetration was set to 80% of penetration of the maximum households' demand, and each renewable generator's contribution was set to 50% of this value.

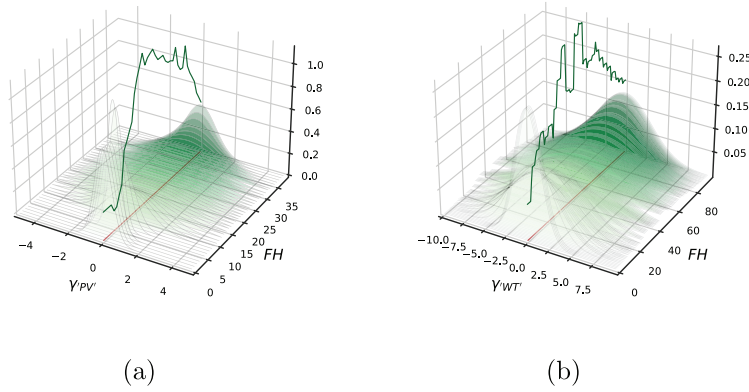


Fig. 1. Forecasting error std. in time of (a) solar photovoltaic and (b) wind power production.

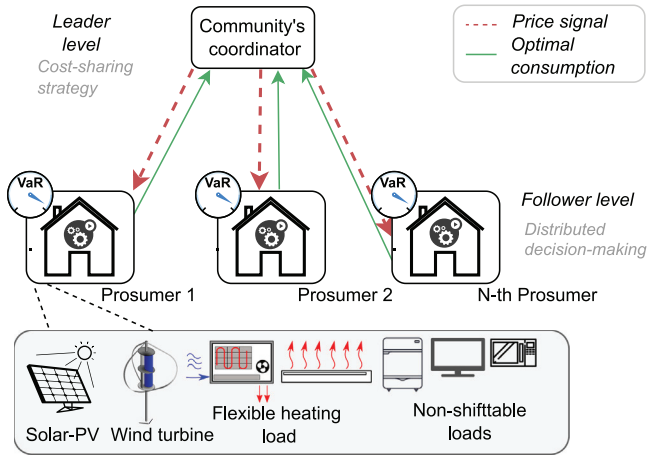


Fig. 2. The description of the risk-aware stochastic energy coordination strategy.

#### 4. Energy coordination game

This section focuses on analyzing the day-ahead optimization problem in the framework of the energy coordination game. Fig. 2 provides a visual representation of the proposal. Once a forward contract between the community's coordinator and the community members is deployed, the parties will agree on the price and demand for future delivery. The only good trade is active energy, and the agreements will be made the day ahead for a 24-h supply. Subsequently, the community's coordinator sends a vector with the proposed price and waits for the participants to respond with their best consumption strategy. Such configuration leads to a Stackelberg game where the coordinator initially leads the interaction, presenting its strategy. Subsequently, the community members, as followers, formulate their strategies considering the price signal from the coordinator under several demand-side uncertainties including weather forecast errors, non-shiftable loads consumption and renewable generation (solar and wind power). Eventually, the energy coordination strategy is solved in a distributed fashion, through decomposition methods in order to guarantee information privacy, and the strategy is implemented and validated through a cyber-physical structure.

##### 4.1. Community's coordinator problem

The coordinator is an entity that represents the interests of the whole community by maximizing social welfare. By sharing the system's cost with the community members, this entity encourages members to participate in efficient energy use and promote sustainability.

In this case, the entity is benevolent, indicating that the exercise of its activity is not reimbursed. The main goal of the coordinator is to minimize the grid's operational cost through a quadratic cost as follows:

$$C(L_k) = a_k L_k^2 + b_k L_k + c_k, \quad \forall k \in \mathcal{K} \quad (2a)$$

$$L_k = \sum_{r \in \mathcal{R}} u_{r,k}^{imp}, \quad \forall k \in \mathcal{K} \quad (2b)$$

where  $a_k$  is  $>0$  and  $b_k$  and  $c_k$  are set to zero for simplicity at each  $k$  time step.  $L_k$ , on the other hand, represents the sum of best strategies over the set  $\mathcal{R}$  of prosumers. Such a function can be smoothed out by a quadratic cost, which is more suitable for optimization purposes. Then, the total energy cost of the system over  $T$  time slots corresponds to:

$$C_{total} = \sum_{k \in \mathcal{K}} C(L_k) \quad (3)$$

Besides, in order to effectively compute billings for prosumers' payments, the community's coordinator exploits an hourly proportional billing strategy [53]. The cost is divided across consumers at each time period, according to the load they asked at that moment. Consequently, each user pays the real cost of its demand, especially in peak periods. The bill of the  $r$ th user,  $BU_r$ , is computed as:

$$BU_r = \sum_{k \in \mathcal{K}} \frac{u_{r,k}^{imp}}{\sum_{r' \in \mathcal{R}} u_{r',k}^{imp}} C_{total} \quad (4)$$

By substituting  $C_{total}$  in Eq. (4), it can be deduced then that the billing is a composition of the energy imported by user  $r$  and the corresponding electricity price  $\pi_k$ . The latter is then formulated as:

$$\pi_k = a_k L_k, \quad \forall k \in \mathcal{K} \quad (5)$$

This indicates that the electricity price in this strategy is proportional to the aggregated consumption.

##### 4.2. Prosumer problem

Community members act as followers. They utilize a HEMS with a hybrid heating system comprised of EBH and an ETS system, non-shiftable loads, wind turbines and solar PV production as indicated in Fig. 3. The HEMS is responsible for scheduling the heating load optimally in the presence of user-defined preferences about thermo-economic preferences and also risk aversion on renewable production and weather forecast services. Followers consume a self-developed microservice that relies on a time-series database service and APIs to provide forecasting errors described in Section 3. The whole decision-making was coded in a Python package, exploiting the salient features of object-oriented programming. The HEMS exhibits a reduced human intervention as the community member only needs to provide the

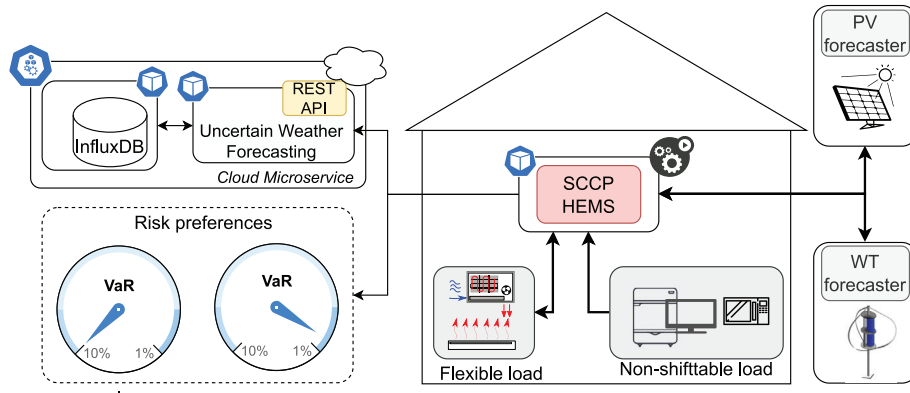


Fig. 3. Block diagram of the risk-aware of HEMS for residential prosumers.

thermal set-point and the willingness to pay for its comfort. The rest of the tasks, including weather forecasting, modeling forecasting errors, optimal control, interacting with the coordinator, among others are fully automated through a complete stack of tools listed in Section 5. Below is a detailed description of each optimal decision-making system, including the deterministic and risk-aware approaches.

#### 4.2.1. Deterministic approach

The optimization problem for the residential prosumer is formulated in Eq. (6). The objective is to reduce user discomfort while reducing power capacity costs. That is modeled as the difference between the utility,  $U_k$ , the user perceives from guaranteeing its comfort and the operational cost,  $C_k$ .

$$\max_{u_r^{imp}} J = \sum_{k \in \mathcal{K}} U_{r,k} - C_{r,k}, \quad \forall r \in \mathcal{R} \quad (6)$$

$$s.t. : x_{r,k+1} = A_r x_{r,k} + B_r [u_{r,k}^{EBH} + \rho ES_{r,k}] + C_r W_k, \quad \forall k \in \mathcal{K}, \forall r \in \mathcal{R} \quad (7a)$$

$$u_{r,k}^{imp} = u_{r,k}^{EBH} + u_{r,k}^{ETS} + u_{r,k}^{NSL} - u_{r,k}^R, \quad \forall k \in \mathcal{K}, \forall r \in \mathcal{R} \quad (7b)$$

$$u_{r,k}^R = u_{r,k}^{R_{ETS}} + u_{r,k}^{R_{EBH}}, \quad \forall k \in \mathcal{K}, \forall r \in \mathcal{R} \quad (7c)$$

$$ES_{j,k+1} = ES_{r,k} + \eta^c u_{r,k}^{ETS} - \rho ES_{r,k}, \quad \forall k \in \mathcal{K}, \forall r \in \mathcal{R} \quad (7d)$$

$$0 \leq u_{r,k}^{EBH} \leq u_{EBH}^{max}, \quad \forall k \in \mathcal{K}, \forall r \in \mathcal{R} \quad (7e)$$

$$0 \leq u_{r,k}^{ETS} + u_{r,k}^{R_{ETS}} \leq u_{ETS}^{max}, \quad \forall k \in \mathcal{K}, \forall r \in \mathcal{R} \quad (7f)$$

$$x_r^{min} \leq x_{r,k} \leq x_r^{max}, \quad \forall k \in \mathcal{K}, \forall r \in \mathcal{R} \quad (7g)$$

where

$$U_{r,k} = -\alpha_{r,k} (x_{r,k} - x_{r,k}^c)^2, \quad \forall k \in \mathcal{K}, \forall r \in \mathcal{R} \quad (8a)$$

$$C_{r,k} = C_{r,k}^{imp} + C_{j,k}^{ETS}, \quad \forall k \in \mathcal{K}, \forall r \in \mathcal{R} \quad (8b)$$

$$C_{r,k}^{imp} = \pi_k u_{imp,k}^r, \quad \forall k \in \mathcal{K}, \forall r \in \mathcal{R} \quad (9a)$$

where,  $U_k$  is the utility function Eq. (8a) that depends largely on  $\eta_k^c$ , a weighting parameter representing the user's  $r$  price elasticity. Also, it depends on  $x_{r,k}^c$  and  $x_{r,k}$ , which are the customer's comfort temperature and the actual indoor temperature. On the other hand, the cost term Eq. (8b), is composed of two affine functions that represent

the amount of energy the customer is importing  $C_{r,k}^{imp}$  and the ETS running cost  $C_{r,k}^{ETS}$ , explained by Eqs. (10a) and (10b). The cost of importing energy depends on  $\pi_k$  and  $u_{imp,k}^r$ , which are the electricity price and the amount of imported energy from the grid for the customer  $r$ , respectively. The latter comprises two uncertain inputs, including the non-shiftable load  $u_{r,k}^{NSL}$  and the renewable production  $u_{r,k}^R$ . Besides,  $x_{r,k+1}$  encompasses the building thermal dynamics. The model was built through linear methods to estimate coefficients  $A$ ,  $B$ , and  $C$  using accurate data.  $B$  models the heating transfer coefficient from EBH and ETS.  $C$  allows modeling the impact of weather conditions (the outdoor temperature, the solar irradiation and the relative humidity) over the thermal dynamics since the customers are connected to a weather forecast service.

The problem is subject to the listed constraints (7a)–(7g). Constraint (7a) models the building's thermal dynamics, (7b) is the power balance, (7d) is the ETS energy stored in form of heat  $ES_{r,k}^r$ , (7c) is the renewable power constraint, indicating that all the renewable production is tailored for space heating purposes as it drives power consumption in severe cold climate conditions. Note that in (7d) only charging power is a decision variable, and the discharge is performed free-convection, depending on the energy stored scaled by  $\rho$ , a learning coefficient estimated through accurate data that models the rate of discharge of the device. Besides, constraints (7e)–(7f) limit the EBH and ETS units in electric and thermal consumption. The limits for  $x_{r,k}$  ( $x_r^{min}$ ,  $x_r^{max}$ ) are set equal for all customers.

$$C_{j,k}^{ETS} = (u_{r,k}^{ETS} + \rho ES_{r,k}) C_k^b, \quad \forall k \in \mathcal{K}, \forall r \in \mathcal{R} \quad (10a)$$

$$C_k^b = \frac{IC}{2\beta(\overline{ES}_k - \underline{ES}_k)}, \quad \forall k \in \mathcal{K} \quad (10b)$$

Constraint (10a), models the ETS operational cost  $C_{j,k}^{ETS}$ , including the energy cost of the device  $C_k^b$ , and the charging/discharging decisions on the ETS.  $\beta$  is the total rated cycles of the ETS unit,  $IC$  is the economic investment,  $\overline{ES}$  and  $\underline{ES}$  are parameters the maximum and minimum desired energy stored. Detailed information on this can be found in [52]

#### 4.2.2. Risk-aware stochastic approach

The deterministic approach does not account for uncertainties in weather forecasts and non-shiftable load consumption. As the thermal dynamics, energy imported, and the ETS state-of-the-charge depend on both random phenomena, then they all become stochastic. Hence, to include uncertainty in probabilistic terms, a SCCP approach is proposed. This approach enables creating deterministic equivalents for constraints (7g) and (7c), that will further be affected by uncertainty of weather forecast errors in building's thermal dynamics and customer concerns on renewable production. As a result, Eq. (6) is recast as follows:

$$\max_{u_r^{imp}} \mathbb{E}[J] \approx \frac{1}{N} \sum_{j \in \mathcal{J}} \sum_{k \in \mathcal{K}} U_{r,k} - C_{r,k}, \quad \forall r \in \mathcal{R} \quad (11)$$

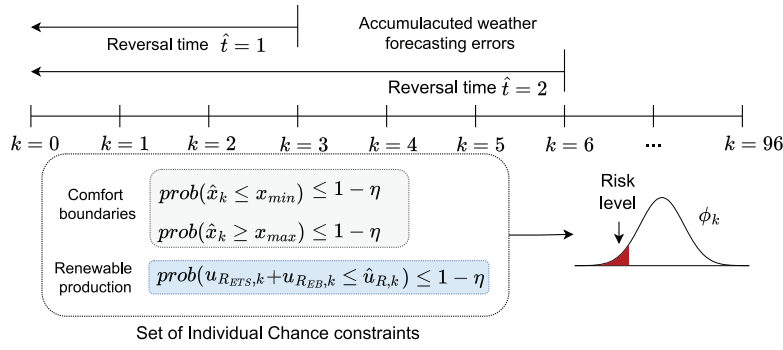


Fig. 4. The strategy to represent risk-aware user comfort preferences.

$$s.t. : x_{r,k+1} = A^r x_{r,k} + B^r [u_{r,k}^{EBH} + \rho ES_k^r] + C^r W_k, \quad \forall k \in \mathcal{K}, \forall r \in \mathcal{R} \quad (12a)$$

$$u_{imp,k}^r = u_{r,k}^{EBH} + u_{r,k}^{ETS} + u_{r,k}^{NSL} - u_{r,k}^R, \quad \forall k \in \mathcal{K}, \forall r \in \mathcal{R} \quad (12b)$$

$$ES_{j,k+1} = ES_{r,k} + \eta^c (u_{r,k}^{ETS} + u_{r,k}^{RETS}) - ES_{r,k}, \quad \forall k \in \mathcal{K}, \forall r \in \mathcal{R} \quad (12c)$$

$$0 \leq u_{r,k}^{ETS} + u_{r,k}^{RETS} \leq u_{ETS}^{max}, \quad \forall k \in \mathcal{K}, \forall r \in \mathcal{R} \quad (12d)$$

$$0 \leq u_{r,k}^{EBH} + u_{r,k}^{REBH} \leq u_{max}, \quad \forall k \in \mathcal{K}, \forall r \in \mathcal{R} \quad (12e)$$

$$\mathbb{P}[u_{r,k}^{RETS} + u_{r,k}^{REBH} \leq u_{r,k}^R + \zeta_k] \leq 1 - \eta, \quad \forall k \in \mathcal{K}, \forall r \in \mathcal{R} \quad (12f)$$

$$\mathbb{P}[x_{r,k} + \gamma_k \leq x^{min}] \leq 1 - \eta, \quad \forall k \in \mathcal{K}, \forall r \in \mathcal{R} \quad (12g)$$

$$\mathbb{P}[x_{r,k} + \gamma_k \geq x^{max}] \leq 1 - \eta, \quad \forall k \in \mathcal{K}, \forall r \in \mathcal{R} \quad (12h)$$

where  $1-\eta$  is the value-at-risk (VaR), which shapes every constraint and decision variable in the resulting problem. The VaR was set constant over the whole horizon control. Given the uncertainty on non-shiftable loads, Eq. (12b) is now stochastic and is passed towards the objective as an active restriction. Nevertheless, as the aim of this approach is introducing risk-preferences, hence, Eqs. (7c) and (7g) are reformulated into Eqs. (12g)–(12h) and Eq. (12f) respectively. However, that set of equations are not tractable due to the random nature of the uncertainties. Therefore, constraints can be reformulated analytically into equivalent deterministic constraints as described in Section 4.3 (see Fig. 4).

#### 4.3. Deterministic equivalent calculation

Optimal decision-making under risk preferences face the challenge of accounting for various possible outcomes. Nevertheless, handling all these outcomes directly can be computationally intense and complex. The concept of the deterministic equivalent allows simplifying the problem (11) by converting it into a format that can be analyzed in a straightforward manner. That ensures the optimization problem can still be formulated as a convex problem. Probabilistic constraints often involve satisfying that a specific condition is accomplished at a certain confidence level. To recast chance constraints into deterministic equivalents, the probabilistic component is eliminated, usually by leveraging knowledge of the distribution of the random variable. The following mathematical procedure can help to grasp better the last mentioned:

$$\mathbb{P}(g(x, \zeta) \leq b) \leq 1 - \eta \quad (13)$$

Eq. (13) represents a chance constraint, where  $\mathbb{P}$  is the probability function,  $x$  is a decision variable,  $\zeta$  is a random variable and  $b$  is a known parameter;  $g(x, \zeta) \leq b$  is the constraint function dependent on decision variables and the uncertain phenomenon, and  $1 - \eta$  represents the allowable probability of violation. Eq. (13) can be recast in terms of the cumulative distribution function  $\phi_\zeta$ :

$$\phi_\zeta(h(x)) \leq 1 - \eta \quad (14)$$

where  $h(x)$  is a mathematical expression that depends on the type of probability distribution. Note that in this paper, the random variables were modeled using Gaussian distributions. Then, solving Eq. (14) for  $h(x)$ , the deterministic equivalent results in:

$$h(x) \leq \phi^{-1}(1 - \eta) \quad (15)$$

This mathematical expression depends on decision variables and random parameters, usually the mean and standard deviation for Gaussian distributed errors. The following subsections describe the estimation of deterministic equivalents for renewable power allocation and thermal comfort boundaries.

##### 4.3.1. Renewable power availability

Since the whole renewable production is tailored to cope with space heating needs, it is necessary to encompass the inherent uncertainty associated with. In this regard, Eqs. (16a)–(16e) describe the procedure to recast the original probabilistic renewable allocation constraint in Eq. (12f) by its deterministic equivalent given a  $\eta$  reliability level. Eq. (16b) solves the probabilistic constraint for  $\Delta_k^R$ , the renewable power forecasting error. Subsequently, Eq. (16b) is recast in Eq. (16c) given the fact that a random variable with known cumulative distribution function exists [54]. Eventually, Eq. (16e) represents the deterministic equivalent of the renewable power availability to cover heating needs. This result is interpreted as a reduced renewable power perception by customers given the negative presence of the inverse CDF term in terms of the  $\Sigma_\zeta$  covariance matrix. Consequently, customers may adopt conservative behaviors as more power need to be imported from the grid to effectively cope with heating needs under critical sub-zero temperatures.

$$\mathbb{P}(u_{r,k}^{RETS} + u_{r,k}^{REBH} \leq u_{r,k}^R + \zeta_k) \leq 1 - \eta, \quad \forall k \in \mathcal{K}, \forall r \in \mathcal{R} \quad (16a)$$

$$\mathbb{P}(\zeta_k \geq u_{r,k}^{RETS} + u_{r,k}^{REBH} - u_{r,k}^R) \leq 1 - \eta, \quad \forall k \in \mathcal{K}, \forall r \in \mathcal{R} \quad (16b)$$

$$1 - \phi_k \left( \frac{\mu_k^\zeta - [u_{r,k}^{RETS} + u_{r,k}^{REBH} - u_{r,k}^R]}{\sigma_k^\zeta} \right) \leq 1 - \eta, \quad \forall k \in \mathcal{K}, \forall r \in \mathcal{R} \quad (16c)$$

$$u_{r,k}^R \geq u_{r,k}^{RETS} + u_{r,k}^{REBH} + \phi_k^{-1}(\eta) \sigma_k^\zeta, \quad \forall k \in \mathcal{K}, \forall r \in \mathcal{R} \quad (16d)$$

$$u_{r,k}^{RETS} + u_{r,k}^{REBH} = u_{r,k}^R - \phi_k^{-1}(\eta) \|(\Sigma_k^\zeta)^{1/2}\|_2, \quad \forall k \in \mathcal{K}, \forall r \in \mathcal{R} \quad (16e)$$

#### 4.3.2. Thermal comfort limits

Thermal dynamics are affected by weather forecast errors. To introduce them, Eqs. (17a)–(17d) and (18a)–(18d) depict the procedure require to recast the bottom and top thermal limits probabilistic chance constraints into deterministic equivalents at certain risk aversion preference. Eq. (17b) solves the inequality for  $\gamma_k$ , the random vector that encompasses the outdoor temperature, solar irradiation and relative humidity forecast. Besides,  $\gamma_k$  is weighted by  $C$  in order to model the equivalent effect of the weather forecast error over the indoor temperature. Given that PDFs are known, then the latter can be recast as shown in Eq. (17c), where  $\phi$  is the CDF and  $\phi^{-1}$  its corresponding inverse of each weather variable forecast error. Then, Eq. (17d) models the resulting deterministic equivalent for the bottom thermal comfort. The same procedure was employed to compute the top thermal comfort limit, resulting in the deterministic equivalent shown in Eq. (18d).

$$\mathbb{P}(x_{r,k} + \gamma_k \leq x^{\min}) \leq 1 - \eta, \quad \forall k \in \mathcal{K}, \forall r \in \mathcal{R} \quad (17a)$$

$$\mathbb{P}(\gamma_k \leq x^{\min} - x_{r,k}) \leq 1 - \eta, \quad \forall k \in \mathcal{K}, \forall r \in \mathcal{R} \quad (17b)$$

$$\phi\left(\frac{\mu_k^\gamma - (x^{\min} - x_{r,k})}{\sigma_k^\gamma}\right) \leq 1 - \eta, \quad \forall k \in \mathcal{K}, \forall r \in \mathcal{R} \quad (17c)$$

$$x_{r,k} \geq x^{\min} + \phi_k^{-1}(1 - \eta) \sum_{k=i}^k \|(\Sigma_k^\gamma)^{1/2}\|_2, \quad \forall k \in \mathcal{K}, \forall r \in \mathcal{R} \quad (17d)$$

Regarding the bottom thermal limit, the interior part of the inverse CDF term,  $\phi^{-1}$ , tends to be zero. Conversely, the upper thermal limit, the interior part of the inverse CDF term,  $\phi^{-1}$ , tends to one. As a result, the system increases conservatism level by reducing the operational thermal limits region due to the standard deviation of the cumulative weather forecasting errors. Unlike renewable power availability, the reversal time  $\hat{t}$  term was introduced in the resulting deterministic equivalent to accommodate weather forecasting errors while guaranteeing feasible solutions [9]. That value was fixed to 3 h to avoid over conservative solutions.

$$\mathbb{P}(x_{r,k} + \gamma_k \geq x^{\max}) \leq 1 - \eta, \quad \forall k \in \mathcal{K}, \forall r \in \mathcal{R} \quad (18a)$$

$$\mathbb{P}(\gamma_k \geq x^{\max} - x_{r,k}) \leq 1 - \eta, \quad \forall k \in \mathcal{K}, \forall r \in \mathcal{R} \quad (18b)$$

$$1 - \phi\left(\frac{\mu_k^\gamma - (x^{\max} - x_{r,k})}{\sigma_k^\gamma}\right) \leq 1 - \eta, \quad \forall k \in \mathcal{K}, \forall r \in \mathcal{R} \quad (18c)$$

$$x_{r,k} \leq x^{\max} + \phi_k^{-1}(\eta) \sum_{k=i}^k \|(\Sigma_k^\gamma)^{1/2}\|_2, \quad \forall k \in \mathcal{K}, \forall r \in \mathcal{R} \quad (18d)$$

#### 4.4. Distributed optimization

The game is solved iteratively as customers are aware to not share their preferences. Accordingly, the proximal algorithm was adopted as it enables prosumers to update their strategy simultaneously without sharing information with other participants. Besides, it assists in guaranteeing the strategy's convergence [55,56]. The problem is modeled hierarchically employing a risk-aware stochastic coordination game and no coalitions are allowed among customers.

The Eq. (11) with the deterministic equivalents computed in Section 4.3 is now a convex optimization problem that is solved by using Disciplined Convex Programming (DCP) rules. Accordingly, each prosumer solve its own convex local cost function and the leader aggregates the strategies and establishes a new electricity rate to motivate customers to coordinate their actions. An additional term in the consumers' welfare function is included to ensure convergence under tender conditions. This term penalizes large variations between successive iterations in the decomposed optimization process [32]. Consequently, the final form of the consumer's payoff function can be written as

$$\text{Eq. (11)} + \frac{\tau}{2} \sum_{k \in \mathcal{K}} (u_{r,k,i}^{\text{imp}} - u_{r,k,i-1}^{\text{imp}})^2, \quad \forall r \in \mathcal{R}, \forall i \in I, \forall j \in J \quad (19)$$

where  $i$  stands for the iteration index. The term  $\tau$  in the latter half of Eq. (19) is given by

$$\tau \geq 4(NP - 1)\lambda, \quad (20)$$

where  $\lambda$  has been calculated and used as the initial average price and  $NP$  is the number of prosumers participating in the strategy. Algorithm 1 condenses the iterative procedure to clear the market. The algorithm converges when the relative error of the aggregated profile between successive iterations is lower than a predefined threshold  $\epsilon$  [57], i.e.

$$\|u_{r,k,i}^{\text{imp}} - u_{r,k,i-1}^{\text{imp}}\|_2 / \|u_{r,k,i}^{\text{imp}}\|_2 \leq 10^{-2}, \quad \forall k \in \mathcal{K}, \forall r \in \mathcal{R}, \forall i \in I \quad (21)$$

The optimal solution is obtained by solving the Eq. (19) by means of the Splitting Conic Solver (SCS) which is suitable for large-scale problems through the Python-embedded modeling language for convex optimization, CVXPY.

---

**Algorithm 1:** Distributed optimization algorithm for the energy community.

---

**input :**  $\{a_k, b_k, c_k\} \quad \forall k \in \mathcal{K},$   
 $\{\alpha_{r,k}, x_{r,k}^c, A_r, B_r, C_r\} \quad \forall k \in \mathcal{K}, \forall r \in \mathcal{R},$   
 $x^{\min}, x^{\max}, u_{EBH}^{\max}, u_{ETS}^{\max}, \eta, \rho.$   
**output:**  $u_{r,k,i}^{\text{imp}}, x_{r,k,i} \quad \forall k \in \mathcal{K}, \forall i \in I$

**begin**

The coordinator sets an initial value of  $\pi_k^0 \forall k \in \mathcal{K};$

**while** the error between successive iterations is higher than  $\epsilon$

**do**

The coordinator sends  $\pi_k^i$  to all customers.

**for** Each prosumer **do**

-instantiates its DERs

-query the weather forecasting service

-compute the weather forecasting error distributions

-retrieve the stochastic non-shiftable loads profiles

-estimate the stochastic renewable production

- solve the local risk-averse optimization problem (Eq. (11)).

**end**

The customer returns their best consumption strategy

$u_{r,k}^{\text{imp}} \forall k, r;$

The coordinator recalculates  $\pi_k$  for the next iteration.;

The customer signs the forward contract according to the latest values of  $\{u_{r,k,i}^{\text{imp}}, \pi_{k,i}\}$

**end**

**end**

---

## 5. Cyber-physical infrastructure

The proposed algorithm was tested and evaluated over a scalable open-source cyber-physical infrastructure. It was built to integrate multiple entities to behave as digital entities representing customers' interests with high levels of detail and speed. Figs. 5 and 6 displays all the components of the infrastructure along with the stack of tools exploited and the physical prototype.

Hardware-wise, the prototype comprises several embedded systems (acting as the edge layer), a local server for administration purposes as well as a router and a switch to enable communications. On the software side, the prototype leverages salient features of observability, database services, rapid testing and delivery, and the flexibility of self-coded Python packages to set customers' preferences. Infrastructure management was possible by exploiting Kubernetes and Helm. The infrastructure has seven Raspberry Pi 4B+ (RPi), each acting as a

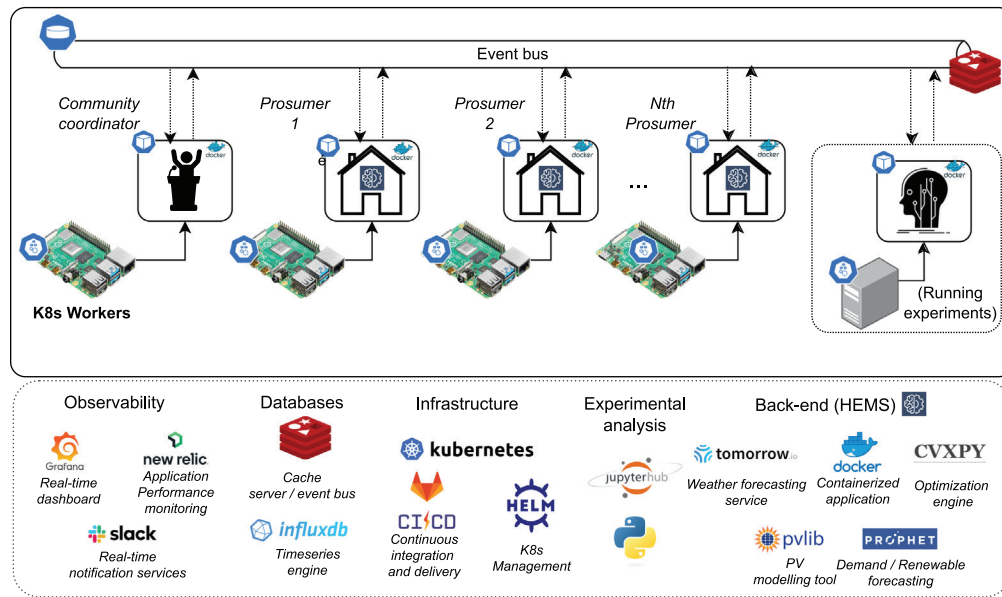


Fig. 5. Description of the cyber-physical infrastructure for validation purposes.

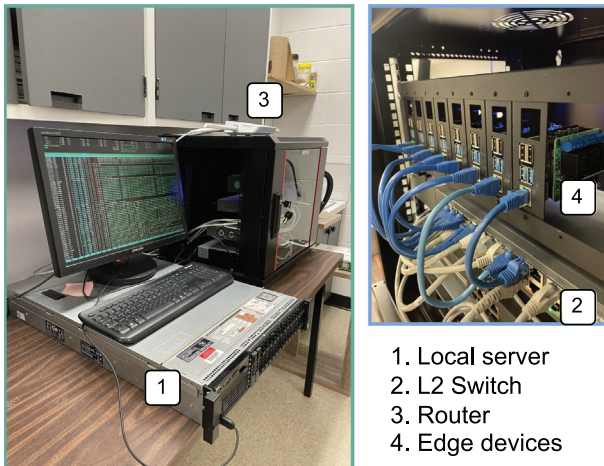


Fig. 6. Hardware setup for algorithm implementation.

worker node. The system has a total of 48 GB RAM memory for distributed computing and 252 GB for data analysis. Each RPi counts with a quad-core ARM Cortex-A53 CPU, a 16 GB trans-flash card, and 8 GB DDR2 SDRAM. The infrastructure also contains a layer three (L3) switch and an internet trunk line.

### 6. Data description

This section introduces an overview of the data employed in this paper. It includes the sources used and the relevant variables that embodies the analysis. The data in this paper includes accurate weather forecast, energy consumption (heating and non-shiftable loads) and indoor temperature of residential buildings in Quebec. Such information was the necessary input to build linear models through least square regression [15]. Table 2 provides an instance of parameters for ten (10) building thermal models exploited in this study. Weather forecast data was retrieved during two years in Quebec through a self-coded client using Tomorrow.io. Then, forecasting errors were estimated to address the impact of demand-side uncertainties of weather conditions and the subsequent renewable power to be introduced into the proposed risk-constrained distributed power scheduling. Regarding ETS

Table 2  
Building thermal models of ten prosumers.

Prosumer	Parameter				
	A	B	C <sub>1</sub>	C <sub>2</sub>	C <sub>3</sub>
1	0.998	0.014969	0.001158	0.000016	0.00019042
2	0.998	0.015580	0.002091	0.000014	0.00015961
3	0.997	0.008515	0.001160	0.000061	0.00033255
4	0.998	0.013508	0.000804	0.000033	0.00035082
5	0.995	0.033347	0.003737	0.000039	0.00068790
6	0.983	0.063049	0.005713	0.000079	0.00248747
7	0.992	0.035895	0.004762	0.000079	0.00103393
8	0.998	0.012722	0.001386	0.000040	0.00016971
9	0.994	0.061797	0.005845	0.000026	0.00033961
10	0.993	0.026186	0.003143	0.000034	0.00083368

control, accurate data were collected to model physics features in the realistic setup shown in Fig. 7. Besides, Fig. 8 explains the deployment architecture exploited to perform experiments with low-cost hardware and open-source technologies. Experiments were conducted during two months in winter 2023. The ETS unit under analysis operated in free convection, indicating that thermal discharge cannot be controlled directly and depends strictly on the remaining energy stored and environment conditions. Experiments were conducted during two months. The conducted experiments indicated that the thermal discharge measured every 15 min,  $\rho$ , during free-convection is around 0.25 kWh, which represents around 3% of the maximum heat capacity. The ETS distributed at the prosumer level had a capacity of 20 kWh and a maximum charging power of 9 kW.

### 7. Results

The case study considered for simulation results consists of a set of residential prosumers in Quebec. To accomplish that, accurate weather forecast data was retrieved along with its inherent uncertainties associated to forecasting errors following methods listed in Section 3.1. Building thermal models were built based on accurate energy consumption data from Quebec [52]. In a previous research, the data acquisition system measured and collected indoor and outdoor temperatures, EBH's power consumption, and non-shiftable loads' consumption for winter. Detailed information on these houses can be found in [32]. The targeted region faces extreme sub-zero temperatures during winter

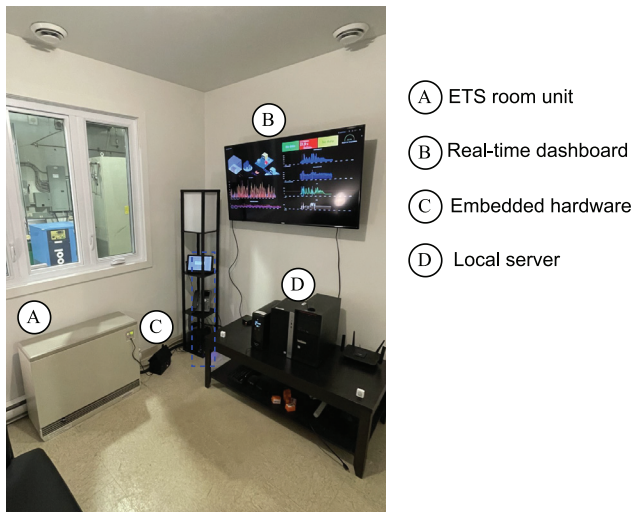


Fig. 7. A picture of the realistic setup to model ETS dynamics.

(see Fig. 9). Community members are modeled as autonomous agents who can modify their consumption patterns depending on risk and thermo-economic preferences, and the given incentive signal from the community’s coordinator. Both enroll in a contract within a forward market, which relies on the market clearing electricity price computed through the Algorithm 1. The number of scenarios  $N$  was fixed at 100 to incorporate uncertainties from non-shiftable loads’ consumption. Furthermore, local decision-making for community members follows a time-discrete nature, where the planning horizon (24 h) is divided into uniform time slots of 15 min each. Fig. 10 illustrates the expected values for weather forecasting and renewable generation with its inherent uncertainty for the analyzed period.

Demand-side price elasticities were set in order to exploit demand flexibility’s potential while respecting comfort and privacy. To provide realistic results, these values were determined according to the comfort preferences in the Quebec residential sector, presented in the basis of a previous study for characterizing smart thermostats operation in Quebec. [58]. Fig. 11 illustrates an instance on 10 customers price elasticities. Besides, as customers are not willing to reveal their preferences, the energy coordination game was solved through iterations employing decomposition methods. This setup is challenging and it represents a realistic approach as it implies demand-side heterogeneity, e.g. in diverse individual demand, ETS charging patterns, thermal preferences, and stochasticity associated with each customer’s renewable production, non-shiftable loads and risk-aversion. The EC business model is assumed to be self-consumption, indicating that selling energy exceeds as well as peer-to-peer transactions are not modeled. Eventually, convergence was reached around 10 iterations in all cases

### 7.1. Risk-assessment

Extensive simulations were carried out varying risk aversion and reversal time to assess their collective impact on the load profile upon the algorithm’s convergence. The outcomes are detailed in Table 3 regarding the PAR reduction achieved, the resulting peak demand and the probability of power congestion (POPC) for each parameter set. The latter is estimated through Eq. (22) depending on the power limit  $PL$ . In this case, a 75 kVA low-voltage distribution transformer is assumed to supply the community’s needs.

$$POPC = \frac{\sum_{k \in \mathcal{K}} \varphi_k}{T}, \quad (22)$$

where

$$\varphi_k = \begin{cases} 1, & \text{if } \varphi_k \geq PL, \quad \forall k \in \mathcal{K} \\ 0, & \text{if otherwise} \end{cases} \quad (23)$$

Fig. 12 the thermal comfort boundaries for a particular prosumer for different risk-aversion preferences and number of hours for accumulated forecasting errors. Roughly, it indicates a direct relationship between the  $RT$  and risk parameter over the comfort limits. Furthermore, as shown in Eqs. (12g) and (12h), the probabilistic comfort boundaries consider the  $C$  vector that models the impact of weather conditions on the building’s thermal dynamics [21]. Fig. 13 shows another example to grasp such an issue better. Although both prosumers have equal risk aversion preferences and reversal time, the building thermal models have different  $C$  vectors and, thus, heterogeneous physical properties. Hence, climate conditions impact each prosumer differently. Then, the resulting comfort boundaries can vary under the same risk-aversion and cumulative forecasting setups.

Subsequently, Figs. 14 and 15 describe the aggregated load profiles once the algorithm converged for each of the combinations listed in Table 3. In scenarios where customers display significant flexibility—willingness to compromise on comfort, the impact of accumulating forecasting errors through  $\hat{t}$  on the strategy’s ability to reduce the PAR is markedly pronounced. Specifically, a setting of VaR at 1% and  $\hat{t}$  at 3 h represents the most adverse scenario, leading to a severe alteration on the PAR reduction, passing from 71.10% to 34.10% and creating a peak demand of 21.10 kWh, which leads to a POPC of 39.58%.

Continuing, when we adjusted customers to react in an inelastic manner. The results showed that scenarios when flexibility is scarce across different risk-aversion and cumulative forecasting error combinations generally show lower reductions in PAR compared to high flexibility scenarios. With respect to low risk cases, the reduction in PAR ranges from 22.19% to 26.69% across different reversal times. This suggests that even within low flexibility scenarios, lower risk aversion tend to result in slightly higher reductions in PAR. For the remaining cases, the reductions in PAR remain relatively consistent across different reversal times, with values ranging from 22.19% to 27.80%, indicating an insignificant variation in PAR reduction. Nevertheless, it is evident that when customers become inelastic, the resulting demand profile exhibits a larger variance than in any case with high flexibility capabilities. Different to very flexible cases, this study case showcased that regardless of the risk aversion and reversal time preferences, the system will always face an overload situation around 31.51%. Note that comparing two study cases, the system experiences the same POPC under the same risk-aversion and reversal time set-up. That may suggest that even when customers have a large willingness to sacrifice their comfort and the decision-making mechanism meets risk preferences, it can lead to similar challenging situations on the power grid. Such setups alter similar ETS charging profiles, as illustrated in Fig. 18. It can be seen how customers increase the ETS usage in low flexibility cases, as their valuation on comfort increases. Additionally, higher reversal times imply an increase in power consumption.

Likewise, as the market clearing price depends on the aggregated profile, it is necessary to evaluate whether the study cases performed could or could not impact the electricity price. Figs. 16 and 17 illustrate for all the combinations listed in Table 3, the impact of demand-side risks over the price with flexible and inflexible customers, respectively. For  $\hat{t} = 1$ , variations over the risk level do not affect the clearing price regardless of the flexibility degree. However, when the reversal time increases to  $\hat{t} = 1$  and  $\hat{t} = 3$ , the impact on the clearing price is significant. Combined increases of  $\hat{t}$  and risk aversion result in higher odds of surpassing the initial rate at some periods during the day. Besides, when community members react with inelastic preferences, the market clearing price is significantly more volatile than the counterpart of flexible behaviors. This finding is consistent with the PAR reductions reported previously i.e. high and low willingness to experience discomfort implies substantial improvement on the aggregated profile.

On the customers’ utility side, Figs. 20 and 19 illustrate an instance of two customers’ utilities acting in an elastic and inelastic manner, respectively. Consistent with the analysis previously done for the aggregated profiles, it can be seen that when comparing the customers’

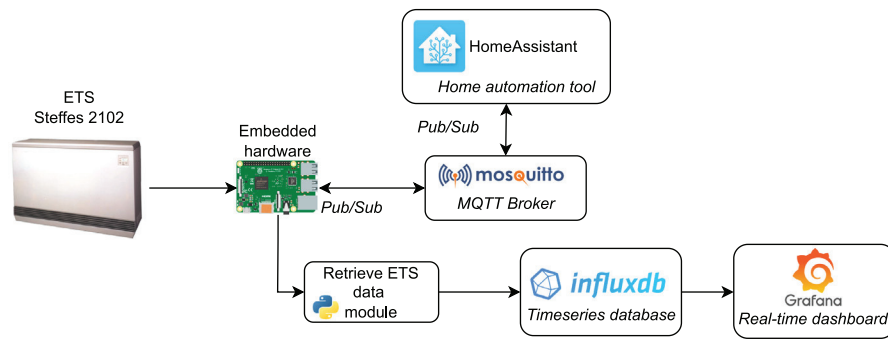


Fig. 8. Realistic architecture for retrieving ETS accurate data.

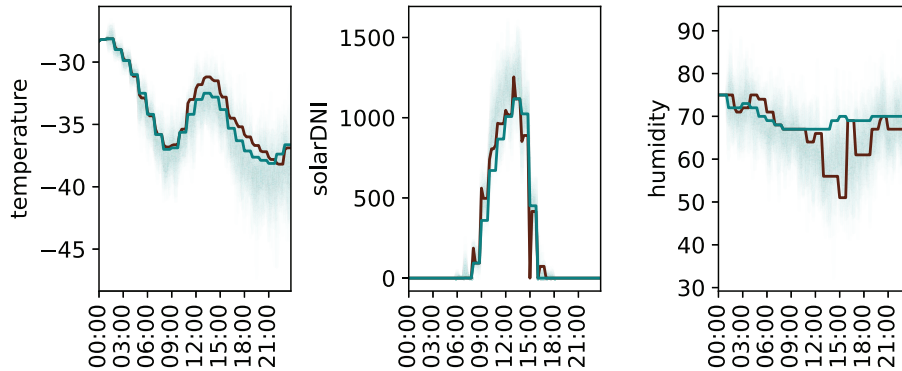


Fig. 9. Expected value of weather forecasting and its comparison against the deterministic baseline.

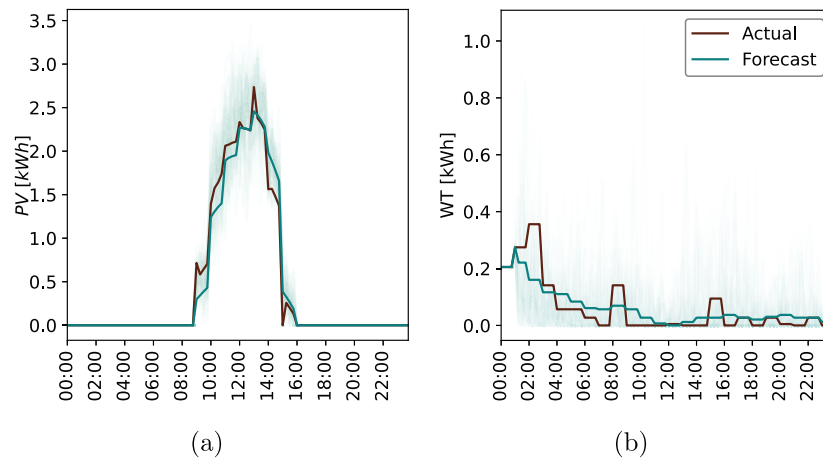


Fig. 10. Forecasting of (a) PV and (b) WT production for a particular prosumer.

utilities under risk preferences, degree of flexibility and cumulative forecasting errors, the trend is maintained. That means that indoor temperature increases with elevated risk-aversion and large hours to accommodate forecast errors and vice versa. As previously mentioned, once weather forecasting errors are accumulated, the system becomes more conservative and increases the heating consumption in order to anticipate future situations that may happen as a result of non-controllable phenomena. Consequently, the indoor temperature will increase.

### 7.2. Price of robustness

The price of Robustness (PoR) metric is selected to evaluate the impact of modifying risk-aversion and reversal time parameters over the grid's cost. Such a metric is widely used to measure the trade-off

between optimality and robustness [59]. Eq. (24) quantifies the cost of performing robust decisions compared with the optimal solution having perfect information on the uncertainty parameters.

$$PoR = \frac{C^R - C^{Det}}{C^{Det}} \quad (24)$$

Based on results in Table 3, an analysis of variance was performed with the PoR obtained for each combination to assess the influence of the risk-aversion parameter, the reversal time and the flexibility degree over the PoR. For all the factors considered,  $p$ -values under 0.05 were obtained, indicating that they all significantly affect the PoR. It can be evidenced that having inelastic community members, for instance, can increase the PoR by around 14.90, 14.50 and 12.94% for the highest to lower risk-aversion preferences, respectively. That can be comparable with the scenarios with elastic demand, which exhibits 11.71, 11.07 and 10.30% of overrun cost created by the established robustness

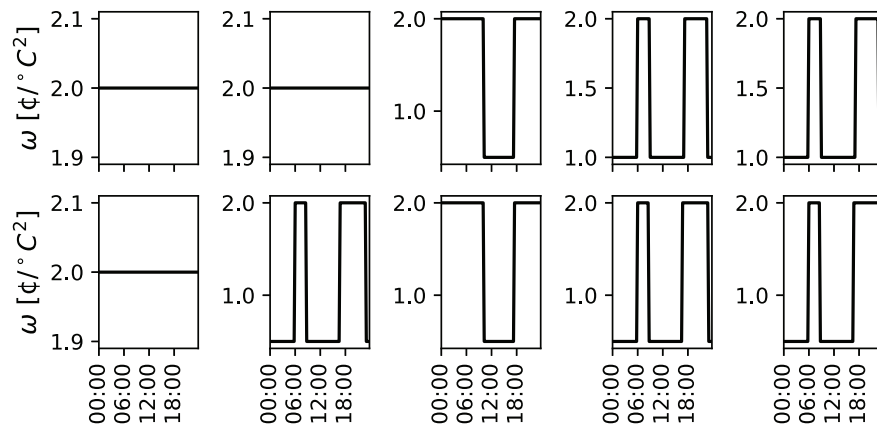


Fig. 11. Prosumers' price elasticities.

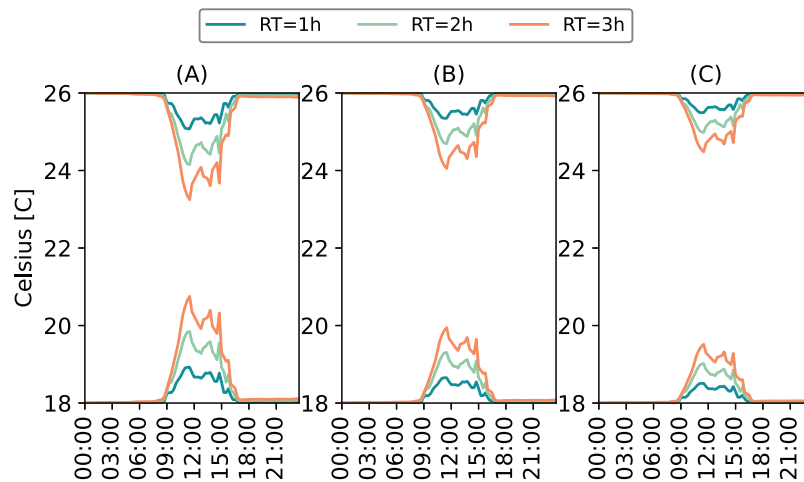


Fig. 12. Thermal comfort boundaries for a particular community member experiencing different risk-aversion preferences (A) 1% (B) 5% and (C) 10%.

**Table 3**  
Summary of results obtained for risk analysis.

Flexibility degree	Risk user preferences		PAR		Reduction [%]	Peak demand [kWh]	POPC [%]	PoR [%]
	VaR	Reversal time	Initial	Final				
High	1%	1 h	1.762	1.01	71.10	14.99	0	12.32
	5%	1 h	1.756	1.052	70.39	14.94	0	9.51
	10%	1 h	1.752	1.052	70	14.91	0	9.09
	1%	2 h	1.781	1.172	60.90	16.86	0	12.26
	5%	2 h	1.779	1.058	72.10	15.07	0	11.90
	10%	2 h	1.779	1.058	72.10	15.07	0	9.06
	1%	3 h	1.724	1.383	34.10	21.10	39.58	12.21
	5%	3 h	1.757	1.194	56.3	17.18	0	12.12
	10%	3 h	1.785	1.088	69.70	15.50	0	10.81
Low	1%	1 h	1.481	1.258	22.30	21.31	30.20	15.15
	5%	1 h	1.482	1.260	22.19	21.28	30.20	13.69
	10%	1 h	1.483	1.260	22.30	21.26	30.20	10.01
	1%	2 h	1.494	1.227	26.69	20.62	27.08	15.06
	5%	2 h	1.482	1.260	22.19	21.28	30.20	15.06
	10%	2 h	1.482	1.260	22.19	21.28	30.20	13.38
	1%	3 h	1.540	1.318	22.19	21.65	39.58	15.01
	5%	3 h	1.450	1.221	27.80	20.43	23.95	15.01
	10%	3 h	1.485	1.254	23.10	21.14	30.20	14.69

criteria. Regarding the risk level, the average PoR is 13.31, 12.79 and 11.62% for high to low-risk-aversion setups, respectively. Eventually, concerning the impact of reversal time, the average PoR is 13.66, 12.87 and 11.17% for reversal time of one, two and three hours, respectively.

These findings suggest that the cost of robust solutions, under the mentioned conditions, may experience a direct relationship between the grid's operational cost and risk-aversion preferences, reversal time and community members' willingness to provide flexibility.

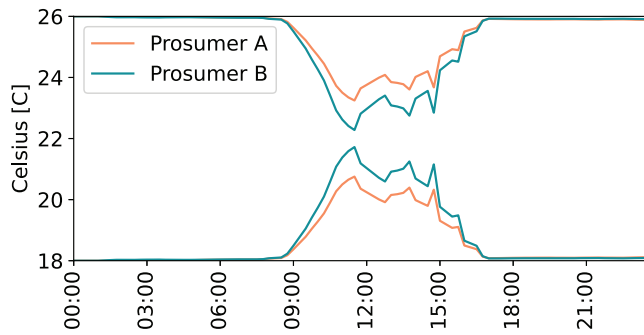


Fig. 13. Comparison of thermal comfort boundaries for two community members with the same preferences about risk aversion and cumulative forecasting errors.

Table 4

Elapsed time to reach algorithm's convergence.

Number of users	Energy coordination Elapsed time [s]	
	Distributed fashion	Centralized fashion
10	59.61	237.6
30	78.58	324.36
60	148.20	599.54

### 7.3. Scalability assessment

Multiple study cases were carried out while increasing the number of participants to validate the scalability of the approach. These experiments assessed the strategy's scalability and provided insights into resource utilization, including CPU and RAM demands.

The computational effort imposed over the platform was measured to report insights on the algorithm's complexity. Table 4 illustrates the elapsed time regarding agents' programmed tasks as the number of customers increases from ten (10) to sixty (60). It can be evidenced that the higher the number of customers, the higher the computational time required to solve the problem. However, in each case, compared to solving the problem in a centralized (sequential) fashion, the proposal outperforms centralized/sequential computing by over four times (x4) regarding the required time the algorithm takes to converge. Furthermore, Table 5 shows the mean, minimum and maximum elapsed time in seconds for each automated task carried out by the prosumers. Retrieving historic energy consumption requires significantly less time than gathering historical weather forecasts. The reason why it occurs is because the latter database is quite larger than the former. Regarding risk-aware optimal decision-making, the time required is significantly larger than both mentioned. In all the cases, as long as the number of participants increases, so does the elapsed time to complete the task. Eventually, Fig. 21 summarizes the main results obtained on the aggregated profile after the scalability test. The results obtained before and after the risk-aware energy coordination can be seen. Even with an increasing number of community members, the strategy exhibits salient features to reduce the peak-to-average ratio while still providing economic benefits to participants.

## 8. Discussion

Energy communities have become a hot spot for research during the last years. These involve multiple challenges and opportunities in many domains, including optimal operation and control, social strategies for guaranteeing a program's sustainability, and community empowerment. However, diverse situations may arise in northern regions with tremendous sub-zero temperatures in winter, and building owners need to cope with heating needs with high reliability. Accordingly, adopting robust strategies is required to assist these communities in incorporating risk-aware strategies that enable tenants to manifest their concerns

due to external uncertain phenomena such as weather forecasting and intermittent renewable production.

In this regard, the results presented in Section 7 have provided meaningful insights into the relationship between reversal time, risk aversion levels, and user willingness to reduce consumption. Indeed, we have identified that user flexibility is crucial in enhancing the aggregated demand profile. However, risk-averse preferences combined with cumulative forecast errors reduced the strategy's performance regarding the PAR and increased the probability of congestion and the grid's expected operating cost. The results have revealed that even in scenarios with community members willing to modify their consumption patterns, in the presence of risk aversion and reversal time, the probability of congestion can be comparable to scenarios with an inelastic demand.

Several studies have introduced risk preferences through stochastic chance constrained optimization for ECs. Dolanyi et al. [25] modeled concerns on load and market imbalance errors and these were transferred to battery's SOC boundaries. The system's overall cost increased proportionally to the risk-level factor modifying the CVAR. Yin et al. [23] evaluated the impact of uncertainties for different battery sizes while manifesting risk-aversion to power mismatches. Subsequently, the total income decreased as long as the reliability level increase, since the operator sell less power to electricity and reserve more power for local use to reduce risks brought by uncertainties. Wang [13] optimized battery and thermal storage by incorporating risk-aversion to CO2 emissions through energy coordination. These systems tried to trade-off between risk preferences and grid cost.

Even though multiple efforts have been push into risk-aversion strategies to coordinating distributed energy resources, previous works did not validated their results nor implemented distributed computing nor combined risk aversion towards combined renewable production and perception on losing thermal comfort. Also, compared with other works, this paper tested the strategy with progressive increase on the demand-side while guaranteeing strategy's stability under challenging situations with asynchronous communications, diverse risk and thermo-economic preferences and thus heterogeneous energy consumption patterns. Nevertheless, the amount of imported power is substantially increased as a result of community members' risk-aversion to do not meet their heating needs. This can lead to having increased odds of renewable curtailment as thermal storage has been previously committed to keep buildings warm along time. However, intra-day power dispatch strategies can easily overcome that issue by optimally allocating current resource's availability. Additionally, a limitation of this work is that the price of robustness is estimated concerning a quadratic cost function, which may contain only some of the information associated with operating distribution lines in congestion situations and may not follow linear behaviors. Also, our approach modeled ETS units only operating with natural discharge, allowing substantial opportunities to model forced convection cases that imply non-convex and non-linear optimization problems.

Other works addressed risk preferences by adopting primarily IGDT as a non-probabilistic method. Mohiti et al. in [22,60] proposed strategies for optimal heat and power scheduling in ECs by employing risk aversion metrics and accurate data with real-time studies with TES on an actual EC at Chalmers University. Perhaps their validated results with realistic infrastructures and great abilities to model risk aversion to CO2 emissions and power imbalances the methods underlying these studies present biased results as the uncertainty modeling is non-probabilistic and depends strongly on the knowledge authors had on unpredictable uncertain phenomena.

Accordingly, few works validated their approaches in real life through low-cost infrastructures, except Javed et al. [34] and Cruz et al. [35]. Javed et al. employed hardware setups for local cloud and edge-based DR optimization experiments involving heating appliances. Their implementation reduced time, human effort, and human dependencies while ensuring cybersecurity, interoperability, scalability,

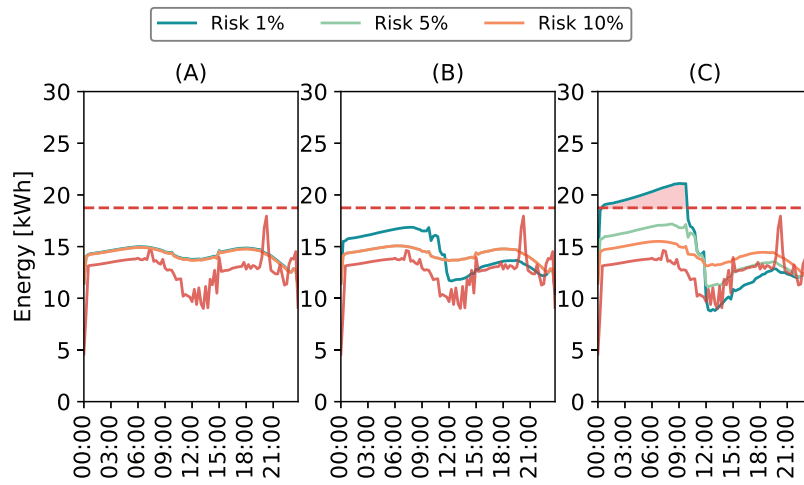


Fig. 14. Aggregated resulting profile for high flexible demand with diverse risk preferences and reversal time (A) 1 h (B) 2 h and (C) 3 h.

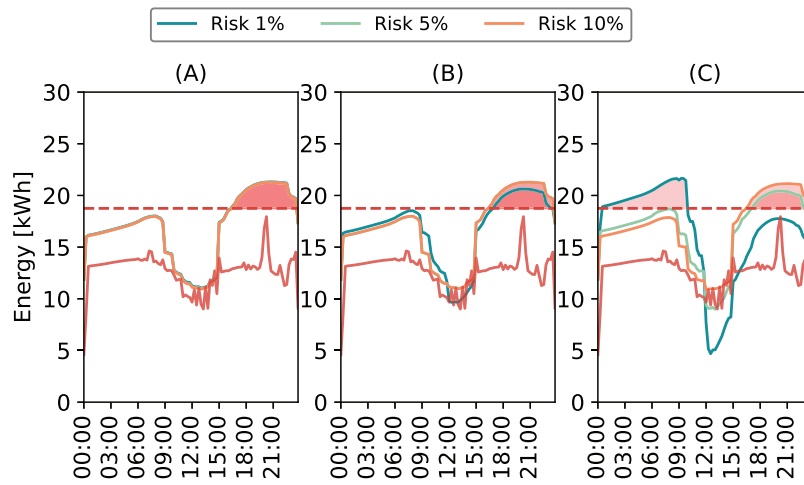


Fig. 15. Aggregated resulting profile for low flexible demand with diverse risk preferences and reversal time (A) 1 h (B) 2 h and (C) 3 h.

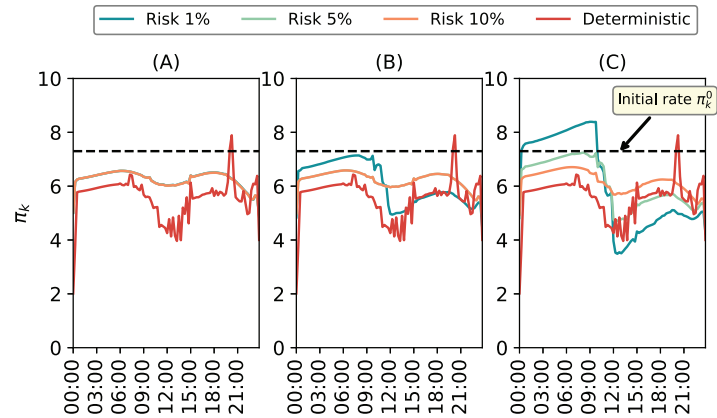


Fig. 16. Market clearing price  $\pi_k$  for high flexible demand under different combinations of risk preferences reversal times. (A) 1 h, (B) 2 h, and (C) 3 h.

Table 5

Statistics of the automated agents' hardware execution time in seconds depending on the task.

Number of users	Agent tasks elapsed time [s]		
	Risk-aware HEMS	Retrieve weather forecast	Loadhistoric energy consumption
10	18.90 [16.60, 21.03]	76.70 [72.09, 81.30]	0.44 [0.37, 0.57]
30	27.26 [26.02, 29.68]	104.68 [107.46, 114.74]	0.60 [0.47, 0.80]
60	29.36 [26.54, 30.96]	109.68 [107.46, 114.74]	0.61 [0.49, 0.82]

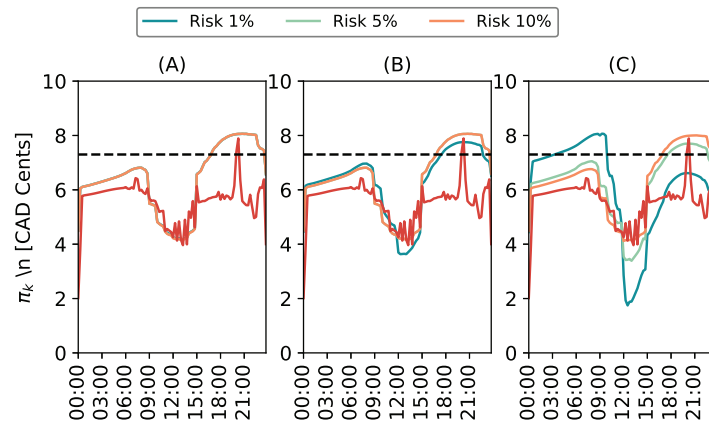


Fig. 17. Market clearing price  $\pi_k$  for inflexible demand under different combinations of risk preferences reversal times. (A) 1 h, (B) 2 h, and (C) 3 h.

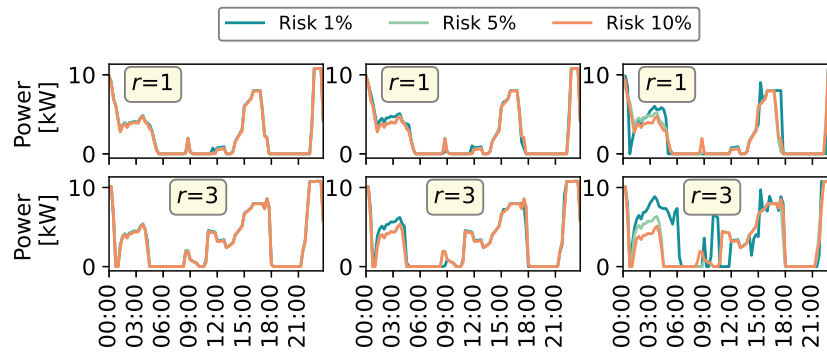


Fig. 18. ETS charging profile for two different flexible customers  $r \in \mathcal{R}$ . RT: (A) 1 h, (B) 2 h and (C) 3 h.

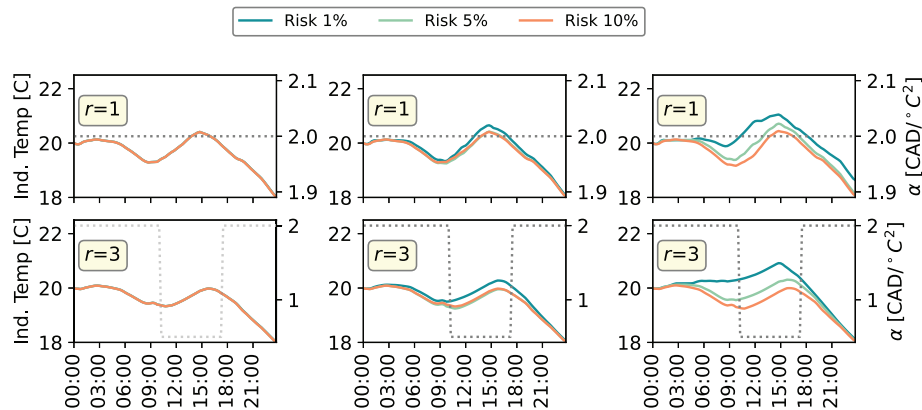


Fig. 19. Indoor temperature profiles for two flexible customers  $r \in \mathcal{R}$  experiencing different reversal time and risk preferences. (A) RT 1 h (B) 2 h and (C) 3 h.

dynamism, and flexibility. Cruz et al. on the other hand, developed a testbed within a cooperative DR framework. Using IoT equipment, their infrastructure exhibited feasible communication overheads while scheduling a small consumer with four appliances.

But there is need meaningful efforts to build scalable platforms to deploy, test and evaluate their algorithms to provide insights on how deploying systems that could anticipate real-life implementations. In this regard, compared to other approaches, this work was the only one to implement a cyber-physical infrastructure through open-source tools and to prove system’s scalability by measuring the computational burden imposed by multiple tasks of automated agents in high uncertain environments.

On top of the above mentioned, to make this or similar strategies a reality, regulatory and legal frameworks should be more flexible, as

the existing conditions do not adequately support energy communities [61]. Having complex grid access rules, a lack of clear policies inside the community, and restrictive permitting processes can compromise the development and growth of energy communities. Besides, capital expenses to establish them can be high, and securing funding can be challenging, especially for small communities that cannot leverage large-scale economic benefits. Government subsidies are often necessary to reduce these barriers.

This research, however, is subject to several limitations including:

- Electric thermal storage was modeled only in free-convection operational mode. The provided mathematical model could represent the thermal dynamics of the asset. However, there is still room for more accurate models considering forced convection events and their impact on the indoor temperature. Furthermore,

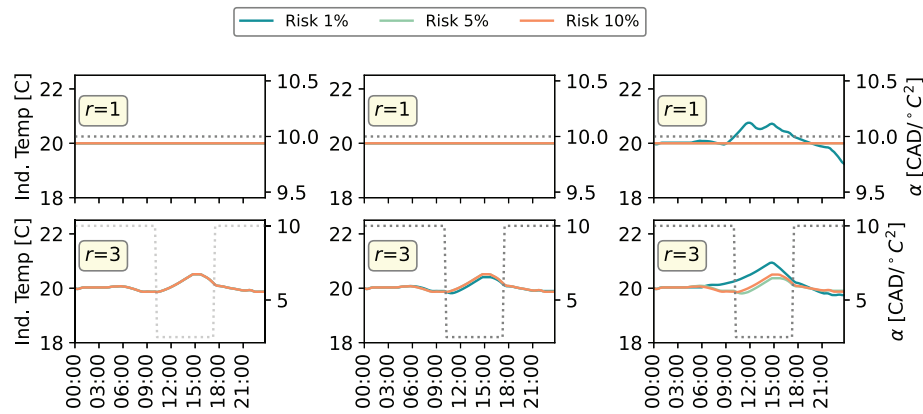


Fig. 20. Indoor temperature profiles for two inflexible customers  $r \in \mathcal{R}$  experiencing different reversal time and risk preferences. (A) RT 1 h (B) 2 h and (C) 3 h.

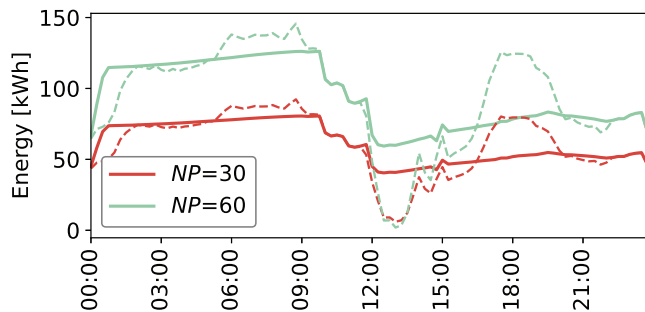


Fig. 21. Aggregated profiles for large-scale simulations with 30 and 60 customers under risk-aversion at 1% before (dashed) and after (solid) implementing the strategy.

having observability about the state variable, i.e. the temperature of the bricks, could provide the means for deeper analyses.

- Although weather forecast errors were adequately addressed by exploiting accurate data, this study does not account for uncertainties related to building physical properties, occupation and other phenomena such as windows opening that may considerably impact energy consumption. Lower-detail information enhances energy planning efficiency and minimizes user discomfort; hence, incorporating these factors could provide a more comprehensive analysis.
- The reported results were drawn using a cyber-physical infrastructure that enabled large-scale simulations with consistent performance. However, this setup represents a controlled environment and does not account for challenges and unpredictable phenomena that may arise under real-world conditions.
- The deterministic equivalent procedure described in Section 4.3 is tailored for Gaussian distributions. For scenarios involving random variables that follow other types of distributions, additional adaptations would be required, and the results may vary depending on the characteristics of those distributions.
- Since this paper does not consider mechanism design aspects, concepts such as individual rationality and incentive compatibility were not considered within the prosumers' decision-making process. This fact implies that the coordinator did not adopt a strategy to prevent strategic behaviors of prosumers (gaming the system) throughout the iterations performed in the coordination process that could lead to undesired scenarios.

## 9. Conclusions

In this paper, we introduced a framework for demand-side risk analysis tailored to emerging energy communities. That was made

using a hierarchical stochastic coordination approach with one leader and multiple followers. Community members were incentivized to participate in the program through affordable price signals provided by the leader. Stochastic chance-constrained methods form the foundation of the optimal controller each prosumer owns. It maximizes individuals' welfare by ensuring thermal comfort, reducing costs, and modeling risk preferences by incorporating renewable production and electric thermal storage assets. Results from extensive simulations with different set-ups for risk-aversion preferences, degree of flexibility and cumulative forecasting errors showed that customers' concerns about weather forecasting errors and subsequent renewable production could significantly increase the aggregated energy profile. Furthermore, the price of robustness of the proposed strategy ranged from 9 to 15%, as a result of anticipating forecasting errors by employing risk-aware decision-making. Even though the strategy can reduce the PAR, the system's stability is compromised when customers are unwilling to sacrifice their comfort, boosting the probability of power congestion up to 32% on average. Indeed, high-risk aversion with high reversal time values and flexible demand can lead to power congestion. The proposed distributed energy management strategy is feasible in a community with embedded renewable energy sources.

Future works should consider multi-stage stochastic programming to update customers' decisions according to real-time weather data. Besides, further developments should consider evaluating the proposed strategy over other business models that enable selling renewable production exceeds and also modeling possible local coalitions that may have shared storage assets. Furthermore, evaluating a more precise estimation of the price of robustness that considers accurately technical cost associated with congestion situations should also be addressed. Eventually, it is necessary to model ETS units operating in forced convection to evaluate the impact of risk-aware decisions over the strategy's performance to have more comprehensive comparative analysis.

## CRedit authorship contribution statement

**Juan A. Dominguez:** Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Nilson Henao:** Validation, Conceptualization. **Alejandro Parrado:** Formal analysis, Conceptualization. **Kodjo Agbossou:** Supervision. **Javier Campillo:** Supervision, Investigation. **Luis Rueda:** Visualization, Supervision.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Acknowledgments

This work was supported in part by the Laboratoire des technologies de l'énergie (LTE) d'Hydro-Quebec, the Natural Science and Engineering Research Council of Canada and the Foundation of UQTR, Canada.

## Data availability

The authors do not have permission to share data.

## References

- [1] Lew D, Bakke J, Bloom A, Brown P, Caspary J, Clack C, Miller N, Orths A, Silverstein A, Simonelli J, Zavadil R. Transmission planning for 100% clean electricity: Enabling clean, affordable, and reliable electricity. *IEEE Power Energy Mag* 2021;19(6):56–66. <http://dx.doi.org/10.1109/MPE.2021.3104127>, URL <https://ieeexplore.ieee.org/abstract/document/9579029>. Conference Name: IEEE Power and Energy Magazine.
- [2] International Energy Agency. Electricity grids and secure energy transitions: Enhancing the foundations of resilient, sustainable and affordable power systems. OECD; 2023. <http://dx.doi.org/10.1787/455dd4fb-en>, URL [https://www.oecd-ilibrary.org/energy/electricity-grids-and-secure-energy-transitions\\_455dd4fb-en](https://www.oecd-ilibrary.org/energy/electricity-grids-and-secure-energy-transitions_455dd4fb-en).
- [3] World energy outlook 2024 – analysis. 2024, URL <https://www.iea.org/reports/world-energy-outlook-2024>.
- [4] Agency IE. Energy efficiency 2023. *Energy Effic* 2023.
- [5] Lowitzsch J, Hoicka CE, van Tulder FJ. Renewable energy communities under the 2019 European clean energy package – governance model for the energy clusters of the future? *Renew Sustain Energy Rev* 2020;122:109489. <http://dx.doi.org/10.1016/j.rser.2019.109489>, URL <https://www.sciencedirect.com/science/article/pii/S1364032119306975>.
- [6] F.G. Reis I, Gonçalves I, A.R. Lopes M, Henggeler Antunes C. Business models for energy communities: A review of key issues and trends. *Renew Sustain Energy Rev* 2021;144:111013. <http://dx.doi.org/10.1016/j.rser.2021.111013>, URL <https://www.sciencedirect.com/science/article/pii/S1364032121003038>.
- [7] Gjorgievski VZ, Cundeva S, Georgiou GE. Social arrangements, technical designs and impacts of energy communities: A review. *Renew Energy* 2021;169:1138–56. <http://dx.doi.org/10.1016/j.renene.2021.01.078>, URL <https://www.sciencedirect.com/science/article/pii/S0960148121000859>.
- [8] Etedadi Aliabadi F, Agbossou K, Kelouwani S, Henao N, Hosseini SS. Coordination of smart home energy management systems in neighborhood areas: A systematic review. *IEEE Access* 2021;9:36417–43. <http://dx.doi.org/10.1109/ACCESS.2021.3061995>.
- [9] Huo D, Santos M, Sarantakos I, Resch M, Wade N, Greenwood D. A reliability-aware chance-constrained battery sizing method for island microgrid. *Energy* 2022;251:123978. <http://dx.doi.org/10.1016/j.energy.2022.123978>, URL <https://www.sciencedirect.com/science/article/pii/S0360544222008817>.
- [10] Yan X, Abbas D, Francois B. Uncertainty analysis for day ahead power reserve quantification in an urban microgrid including PV generators. *Renew Energy* 2017;106:288–97. <http://dx.doi.org/10.1016/j.renene.2017.01.022>, URL <https://linkinghub.elsevier.com/retrieve/pii/S0960148117300228>.
- [11] Pilz M, Al-Fagih L. A dynamic game approach for demand-side management: Scheduling energy storage with forecasting errors. *Dyn Games Appl* 2020;10(4):897–929. <http://dx.doi.org/10.1007/s13235-019-00309-z>.
- [12] Vellei M, Le Dréau J. A novel model for evaluating dynamic thermal comfort under demand response events. *Build Environ* 2019;160:106215. <http://dx.doi.org/10.1016/j.buildenv.2019.106215>, URL <https://www.sciencedirect.com/science/article/pii/S0360132319304251>.
- [13] Wang X, Liu Y, Xu L, Liu J, Sun H. A chance-constrained stochastic model predictive control for building integrated with renewable resources. *Electr Power Syst Res* 2020;184:106348. <http://dx.doi.org/10.1016/j.epsr.2020.106348>, URL <https://www.sciencedirect.com/science/article/pii/S0378779620301541>.
- [14] Testi D, Urbanucci L, Giola C, Schito E, Conti P. Stochastic optimal integration of decentralized heat pumps in a smart thermal and electric microgrid. *Energy Convers Manage* 2020;210:112734. <http://dx.doi.org/10.1016/j.enconman.2020.112734>, URL <https://www.sciencedirect.com/science/article/pii/S0196890420302727>.
- [15] Toquica D, Agbossou K, Henao N, Malhamé R, Kelouwani S, Amara F. Prediction and planning for residential agents in a transactive energy environment. *Smart Energy* 2021;2:100019. <http://dx.doi.org/10.1016/j.segy.2021.100019>, URL <https://www.sciencedirect.com/science/article/pii/S2666955221000198>.
- [16] Fraija A, Agbossou K, Henao N, Kelouwani S. Peak-to-average ratio analysis of a load aggregator for incentive-based demand response. In: 2020 IEEE 29th international symposium on industrial electronics. ISIE, 2020, p. 953–8. <http://dx.doi.org/10.1109/ISIE45063.2020.9152474>, ISSN: 2163-5145.
- [17] Sauter PS, Solanki BV, Cañizares CA, Bhattacharya K, Hohmann S. Electric thermal storage system impact on northern communities' microgrids. *IEEE Trans Smart Grid* 2019;10(1):852–63. <http://dx.doi.org/10.1109/TSG.2017.2754239>, h.
- [18] Dominguez JA, Rueda L, Henao N, Agbossou K, Campillo J. Distributed co-simulation for smart homes energy management in the presence of electrical thermal storage. In: IECON 2022 – 48th annual conference of the IEEE industrial electronics society. 2022, p. 1–6. <http://dx.doi.org/10.1109/IECON49645.2022.9969092>, ISSN: 2577-1647.
- [19] Mavromatidis G, Orehoung K, Carmeliet J. A review of uncertainty characterisation approaches for the optimal design of distributed energy systems. *Renew Sustain Energy Rev* 2018;88:258–77. <http://dx.doi.org/10.1016/j.rser.2018.02.021>, URL <https://www.sciencedirect.com/science/article/pii/S1364032118300510>.
- [20] Beaudin M, Zareipour H. Home energy management systems: A review of modelling and complexity. *Renew Sustain Energy Rev* 2015;45:318–35. <http://dx.doi.org/10.1016/j.rser.2015.01.046>, URL <https://www.sciencedirect.com/science/article/pii/S1364032115000568>.
- [21] Nagpal H, Avramidis I-I, Capitanescu F, Heiselberg P. Optimal energy management in smart sustainable buildings – a chance-constrained model predictive control approach. *Energy Build* 2021;248:111163. <http://dx.doi.org/10.1016/j.enbuild.2021.111163>, URL <https://linkinghub.elsevier.com/retrieve/pii/S0378778821004473>.
- [22] Mohiti M, Mazidi M, Steen D, Tuan LA. A risk-averse energy management system for optimal heat and power scheduling in local energy communities. In: 2022 IEEE international conference on environment and electrical engineering and 2022 IEEE industrial and commercial power systems europe. EEEIC / ICPS Europe, 2022, p. 1–6. <http://dx.doi.org/10.1109/EEEIC/ICPSEurope54979.2022.9854642>, URL <https://ieeexplore.ieee.org/document/9854642>.
- [23] Yin H, Wang Y, Wu G, Liu Y, Chen Y, Liu J. Distributed optimal operation of PV-storage-load micro-grid considering renewable and load uncertainties. *J Energy Storage* 2024;86:111168. <http://dx.doi.org/10.1016/j.est.2024.111168>, URL <https://www.sciencedirect.com/science/article/pii/S2352152X24007527>.
- [24] Najafi-Ghalelou A, Khorasany M, Razzaghi R. Risk-constrained scheduling of energy hubs: A stochastic p-robust optimization approach. *IEEE Syst J* 2022;16(4):5787–98. <http://dx.doi.org/10.1109/JSYST.2022.3143517>, URL [https://ieeexplore.ieee.org/abstract/document/9707899?casa\\_token=9lBysVDGwAkAAAAA:Cj\\_Bm\\_7kO2-5P7raREtZtNyTNH7Wo\\_Kqc-URAK2uXVvabZFYWzP9Ys6WFXmqlnb-2sjkPFRQ](https://ieeexplore.ieee.org/abstract/document/9707899?casa_token=9lBysVDGwAkAAAAA:Cj_Bm_7kO2-5P7raREtZtNyTNH7Wo_Kqc-URAK2uXVvabZFYWzP9Ys6WFXmqlnb-2sjkPFRQ). Conference Name: IEEE Systems Journal.
- [25] Dolanyi M, Bruninx K, Toubeau J-F, Delarue E. Risk-based constraints for the optimal operation of an energy community. *IEEE Trans Smart Grid* 2022;13(6):4551–61. <http://dx.doi.org/10.1109/TSG.2022.3185310>, URL <https://ieeexplore.ieee.org/document/9803201>. Conference Name: IEEE Transactions on Smart Grid.
- [26] Liu C, Xu W, Li A, Sun D, Huo H. Analysis and optimization of load matching in photovoltaic systems for zero energy buildings in different climate zones of China. *J Clean Prod* 2019;238:117914. <http://dx.doi.org/10.1016/j.jclepro.2019.117914>, URL <https://linkinghub.elsevier.com/retrieve/pii/S0959652619327842>.
- [27] Liang Z, Alsafaseh Q, Jin T, Pourbabak H, Su W. Risk-constrained optimal energy management for virtual power plants considering correlated demand response. *IEEE Trans Smart Grid* 2019;10(2):1577–87. <http://dx.doi.org/10.1109/TSG.2017.2773039>, URL <https://ieeexplore.ieee.org/document/8105838/>.
- [28] Tostado-Véliz M, Mansouri SA, Rezaee Jordehi A, Habeeb SA, Jurado F. A risk-aware P2P platform involving distributed generators, energy communities and storage assets. *J Energy Storage* 2024;100:113606. <http://dx.doi.org/10.1016/j.est.2024.113606>, URL <https://linkinghub.elsevier.com/retrieve/pii/S2352152X2403192X>.
- [29] Wang Y, Huang W, Chen H, Yu Z, Hu L, Huang Y. Optimal scheduling strategy for virtual power plants with aggregated user-side distributed energy storage and photovoltaics based on CVaR-distributionally robust optimization. *J Energy Storage* 2024;86:110770. <http://dx.doi.org/10.1016/j.est.2024.110770>, URL <https://linkinghub.elsevier.com/retrieve/pii/S2352152X24003542>.
- [30] Zhong J, Zhao Y, Li Y, Yan M, Peng Y, Cai Y, Cao Y. Synergistic operation framework for the energy hub merging stochastic distributionally robust chance-constrained optimization and Stackelberg game. *IEEE Trans Smart Grid* 2024. <http://dx.doi.org/10.1109/TSG.2024.3454341>, 1–1. URL <https://ieeexplore.ieee.org/document/10666779/>.
- [31] Li J, Khodayar ME, Wang J, Zhou B. Data-driven distributionally robust co-optimization of P2P energy trading and network operation for interconnected microgrids. *IEEE Trans Smart Grid* 2021;12(6):5172–84. <http://dx.doi.org/10.1109/TSG.2021.3095509>, URL <https://ieeexplore.ieee.org/document/9477425/>.
- [32] Etedadi F, Kelouwani S, Agbossou K, Henao N, Laurencelle F. Consensus and sharing based distributed coordination of home energy management systems with demand response enabled baseboard heaters. *Appl Energy* 2023;336:120833. <http://dx.doi.org/10.1016/j.apenergy.2023.120833>, URL <https://www.sciencedirect.com/science/article/pii/S0306261923001976>.
- [33] Yang C, Wu Z, Li X, Fars A. Risk-constrained stochastic scheduling for energy hub: Integrating renewables, demand response, and electric vehicles. *Energy* 2024;288:129680. <http://dx.doi.org/10.1016/j.energy.2023.129680>, URL <https://www.sciencedirect.com/science/article/pii/S0360544223030748>.

- [34] Javed S, Tripathy A, Deventer Jv, Mokayed H, Paniagua C, Delsing J. An approach towards demand response optimization at the edge in smart energy systems using local clouds. *Smart Energy* 2023;12:100123. <http://dx.doi.org/10.1016/j.segy.2023.100123>, URL <https://www.sciencedirect.com/science/article/pii/S2666955223000308>.
- [35] Cruz C, Palomar E, Bravo I, Gardel A. Cooperative demand response framework for a smart community targeting renewables: Testbed implementation and performance evaluation. *Energies* 2020;13(11):2910. <http://dx.doi.org/10.3390/en13112910>, URL <https://www.mdpi.com/1996-1073/13/11/2910>. Number: 11 Publisher: Multidisciplinary Digital Publishing Institute.
- [36] Najafi S, Livani H. Chance-constrained co-optimization of demand response and Volt/Var under Gaussian mixture model uncertainty. *Renew Energy Focus* 2025;53:100674. <http://dx.doi.org/10.1016/j.ref.2024.100674>, URL <https://www.sciencedirect.com/science/article/pii/S1755008424001388>.
- [37] Esfahani M, Alizadeh A, Amjady N, Kamwa I. A distributed VPP-integrated co-optimization framework for energy scheduling, frequency regulation, and voltage support using data-driven distributionally robust optimization with Wasserstein metric. *Appl Energy* 2024;361:122883. <http://dx.doi.org/10.1016/j.apenergy.2024.122883>, URL <https://www.sciencedirect.com/science/article/pii/S0306261924002666>.
- [38] Mianaei PK, Aliahmadi M, Faghri S, Ensaf M, Ghasemi A, Abdoos AA. Chance-constrained programming for optimal scheduling of combined cooling, heating, and power-based microgrid coupled with flexible technologies. *Sustain Cities Soc* 2022;77:103502. <http://dx.doi.org/10.1016/j.scs.2021.103502>, URL <https://www.sciencedirect.com/science/article/pii/S221067072100768X>.
- [39] Yang Y, Shi J, Wang D, Wu C, Han Z. Carbon-aware scheduling of thermostatically controlled loads: A bilevel DRCC approach. *IEEE Trans Smart Grid* 2025. <http://dx.doi.org/10.1109/TSG.2024.3525134>, 1–1. URL <https://ieeexplore.ieee.org/abstract/document/10820107>. Conference Name: IEEE Transactions on Smart Grid.
- [40] Ji H, Wang H, Yang J, Feng J, Yang Y, Okoye MO. Optimal schedule of solid electric thermal storage considering consumer behavior characteristics in combined electricity and heat networks. *Energy* 2021;234:121237. <http://dx.doi.org/10.1016/j.energy.2021.121237>, URL <https://www.sciencedirect.com/science/article/pii/S0360544221014857>.
- [41] de Lima TD, Tabares A, Bañol Arias N, Franco JF. Investment & generation costs vs CO2 emissions in the distribution system expansion planning: A multi-objective stochastic programming approach. *Int J Electr Power Energy Syst* 2021;131:106925. <http://dx.doi.org/10.1016/j.ijepes.2021.106925>, URL <https://www.sciencedirect.com/science/article/pii/S0142061521001654>.
- [42] Peker M, Kocaman AS, Kara BY. A two-stage stochastic programming approach for reliability constrained power system expansion planning. *Int J Electr Power Energy Syst* 2018;103:458–69. <http://dx.doi.org/10.1016/j.ijepes.2018.06.013>, URL <https://www.sciencedirect.com/science/article/pii/S0142061517333823>.
- [43] Liu J, Yu H, Ji H, Zhao K, Lv C, Li P. Optimal operation strategy of a community integrated energy system constrained by the seasonal balance of ground source heat pumps. *Sustainability* 2020;12(11):4627. <http://dx.doi.org/10.3390/su12114627>, URL <https://www.mdpi.com/2071-1050/12/11/4627>. Number: 11 Publisher: Multidisciplinary Digital Publishing Institute.
- [44] Cao Z, Li Z, Yang C. Credible joint chance-constrained low-carbon energy management for multi-energy microgrids. *Appl Energy* 2025;377:124390. <http://dx.doi.org/10.1016/j.apenergy.2024.124390>, URL <https://www.sciencedirect.com/science/article/pii/S0306261924017732>.
- [45] Sadeghian O, Oshnoei A, Khezri R, Muyeen S. Risk-constrained stochastic optimal allocation of energy storage system in virtual power plants. *J Energy Storage* 2020;31:101732. <http://dx.doi.org/10.1016/j.est.2020.101732>, URL <https://www.sciencedirect.com/science/article/pii/S2352152X20315693>.
- [46] Toquica D, Amara F, Malhamé R, Agbossou K, Henao N, Oviedo JC, Rueda L. Risk analysis of transactive energy retail markets. *IEEE Trans Ind Appl* 2023. URL <https://ieeexplore.ieee.org/abstract/document/10296018/>. Publisher: IEEE.
- [47] Nguyen DT, Le LB. Risk-constrained profit maximization for microgrid aggregators with demand response. *IEEE Trans Smart Grid* 2015;6(1):135–46. <http://dx.doi.org/10.1109/TSG.2014.2346024>, URL <https://ieeexplore.ieee.org/document/6887330>. Conference Name: IEEE Transactions on Smart Grid.
- [48] Vahedipour-Dahraie M, Rashidzadeh-Kermani H, Anvari-Moghaddam A, Siano P. Risk-averse probabilistic framework for scheduling of virtual power plants considering demand response and uncertainties. *Int J Electr Power Energy Syst* 2020;121:106126. <http://dx.doi.org/10.1016/j.ijepes.2020.106126>, URL <https://www.sciencedirect.com/science/article/pii/S0142061519341122>.
- [49] Syrri ALA, Mancarella P. Reliability and risk assessment of post-contingency demand response in smart distribution networks. *Sustain Energy Grids Netw* 2016;7:1–12. <http://dx.doi.org/10.1016/j.segan.2016.04.002>, URL <https://www.sciencedirect.com/science/article/pii/S2352467716300030>.
- [50] Gu B, Mao C, Wang D, Liu B, Fan H, Fang R, Sang Z. A data-driven stochastic energy sharing optimization and implementation for community energy storage and PV prosumers. *Sustain Energy Grids Netw* 2023;34:101051. <http://dx.doi.org/10.1016/j.segan.2023.101051>, URL <https://www.sciencedirect.com/science/article/pii/S2352467723000590>.
- [51] Taylor SJ, Letham B. Forecasting at Scale. *Amer Statist* 2018;72(1):37–45. <http://dx.doi.org/10.1080/00031305.2017.1380080>, Publisher: Taylor & Francis eprint: <https://doi.org/10.1080/00031305.2017.1380080>.
- [52] Dominguez JA, Agbossou K, Henao N, Nagarsheth SH, Campillo J, Rueda L. Distributed stochastic energy coordination for residential prosumers: Framework and implementation. *Sustain Energy Grids Netw* 2024;38:101324. <http://dx.doi.org/10.1016/j.segan.2024.101324>, URL <https://www.sciencedirect.com/science/article/pii/S2352467724000535>.
- [53] Jacquot P, Beaudet O, Gaubert S, Oudjane N. Demand side management in the smart grid: An efficiency and fairness tradeoff. In: 2017 IEEE PES innovative smart grid technologies conference europe. ISGT-Europe, Torino, Italy: IEEE; 2017, p. 1–6. <http://dx.doi.org/10.1109/ISGTEurope.2017.8260265>, URL <http://ieeexplore.ieee.org/document/8260265/>.
- [54] Aghdam FH, Taghizadegan Kalantari N, Mohammadi-Ivatloo B. A stochastic optimal scheduling of multi-microgrid systems considering emissions: A chance constrained model. *J Clean Prod* 2020;275:122965. <http://dx.doi.org/10.1016/j.jclepro.2020.122965>, URL <https://www.sciencedirect.com/science/article/pii/S0959652620330109>.
- [55] Nguyen HK, Song JB, Han Z. Distributed demand side management with energy storage in smart grid. *IEEE Trans Parallel Distrib Syst* 2015;26(12):3346–57. <http://dx.doi.org/10.1109/TPDS.2014.2372781>, Conference Name: IEEE Transactions on Parallel and Distributed Systems.
- [56] Atzeni I, Ordóñez LG, Scutari G, Palomar DP, Fonollosa JR. Demand-side management via distributed energy generation and storage optimization. *IEEE Trans Smart Grid* 2013;4(2):866–76. <http://dx.doi.org/10.1109/TSG.2012.2206060>, URL <https://ieeexplore.ieee.org/document/6297498/>.
- [57] Nguyen TL, Tran Q-T, Caire R, Gavriluta C, Van Hoa Nguyen. Agent based distributed control of islanded microgrid — Real-time cyber-physical implementation. In: 2017 IEEE PES innovative smart grid technologies conference europe. ISGT-Europe, Torino: IEEE; 2017, p. 1–6. <http://dx.doi.org/10.1109/ISGTEurope.2017.8260275>, URL <https://ieeexplore.ieee.org/document/8260275/>.
- [58] Henao NF, Fournier M, Kelouani S. Characterizing smart thermostats operation in residential zoned heating systems and its impact on energy saving metrics. 2018.
- [59] Bertsimas D, Sim M. The price of robustness. *Oper Res* 2004;52(1):35–53. <http://dx.doi.org/10.1287/opre.1030.0065>, URL <https://pubsonline.informs.org/doi/abs/10.1287/opre.1030.0065>. Publisher: INFORMS.
- [60] Mohiti M, Mazidi M, Oggioni N, Steen D, Tuan LA. An IGDT-based energy management system for local energy communities considering phase-change thermal energy storage. *IEEE Trans Ind Appl* 2024;1–11. <http://dx.doi.org/10.1109/TIA.2024.3359126>, URL <https://ieeexplore.ieee.org/document/10415531>. Conference Name: IEEE Transactions on Industry Applications.
- [61] Bashi MH, De Tommasi L, Le Cam A, Relação LS, Lyons P, Mundó J, Pandelieva-Dimova I, Schapp H, Loth-Babut K, Egger C, et al. A review and mapping exercise of energy community regulatory challenges in European member states based on a survey of collective energy actors. *Renew Sustain Energy Rev* 2023;172:113055.

## Chapter 4 - Discussions and limitations

This thesis has addressed integrating energy communities within distribution networks from a multidimensional perspective, combining advanced modelling techniques to characterize the community's environment, stochastic optimization models, and implementation testbeds. The attached papers have explored various aspects of the problem, from modelling strategies to assessing techno-economic impacts before and after implementing the proposed demand-side control strategy.

The results indicate that adequately integrating energy communities through cost-effective methods into the grid can enhance energy efficiency and reduce participants' electricity bills (Paper 1 and Paper 2). According to previous studies [96], it was found that demand flexibility and distributed generation can effectively address forecasting errors by employing well-defined mechanisms based on game theory concepts and convex optimization principles. In this regard, our findings extend this perspective by demonstrating that the strategy is suitable for realistic implementations after validating simulations using state-of-the-art distributed computing tools (Paper 2 and Paper 3).

Besides, this thesis considered no information sharing across customers, as it stands for the most potential implementation layout in real-life, where customers are not interested in others' behaviors and information privacy plays a crucial role. In fact, avoiding information exchange across participants reflects both technical and social realities : (i) from a technical standpoint, minimizing data disclosure reduces the risk of privacy breaches and aligns with regulatory frameworks that increasingly emphasize data protection in the energy sector ; (ii) from a social standpoint, customers often value autonomy and are reticent to reveal their preference, since it could expose sensitive information about their routines or financial conditions ; and (iii) from a practical standpoint, designing distributed optimization

methods that operate under privacy-preserving conditions ensures higher acceptance and adoption by end-users, making the proposed strategy closer to real-world deployment. This consideration highlights that effective coordination can still be achieved without explicit peer-to-peer information exchange, provided that robust mathematical mechanisms and distributed computing tools are employed.

Afterwards, this thesis addressed validated the results through realistic infrastructures and off-the-shelf solutions. The validation tests were designed to highlight the ability of the proposed strategy to perform well in a distributed manner. Moreover, unlike previously published coordination methods in the demand-response literature, using different stochastic methods to provide metrics on how close the decision-making process is to the perfect deterministic baseline allows for a more intuitive understanding of our results' performance (Paper 2). The experiments conducted allowed us to observe the consistency of algorithm convergence in the presence of imperfect information. Indeed, stochastic programming and chance constraints highlighted the importance of adequately modelling forecast errors from weather conditions, renewable generation, and non-shiftable loads (Paper 2 and Paper 3). Furthermore, careful estimation of benefits for the coordinator and community members revealed that an increased number of participants does not necessarily negatively impact the individual welfare of some participants (Paper 1).

Compared to recent works in the literature [24, 31], this thesis provides a more comprehensive view by leveraging distributed cosimulation advantages, allowing for a more realistic characterization of the thermo-energetic and economic community environment when real-life data is scarce (Paper 1). However, a significant limitation must be acknowledged. While the proposed framework was able to account for free and forced convection operational modes of ETS units, the computed linear building model is

not capable of capturing non-linear phenomena that introduce uncertainty into the building thermal state equation, such as window opening and closing during winter. Beyond this limitation, the modelling of ETS assets opens up several promising research niches. First, the integration of ETS units with district heating or district thermal networks creates opportunities to explore hybrid coordination schemes, where centralized infrastructures and distributed storage interact to enhance flexibility and resilience at the community scale. Second, studying larger ETS devices operated in centralized configurations along with boilers and other HVAC systems may represent a niche to evaluate the techno-economic potential of ETS in residential and commercial applications. Last but not least important, the adoption of ETS technologies must also be contextualized within regional market structures. For instance, in Quebec, where electricity is managed through flat pricing schemes and there is limited regulatory momentum towards adopting dynamic tariffs, ETS deployment may not appear financially attractive to end-users. In such cases, valuable lessons can be drawn from provinces like British Columbia and Yukon, where rebate and discount programs have been successfully implemented to reduce the upfront cost of ETS devices and to incentivize their adoption without imposing additional financial burdens on households. This thesis demonstrated that such incentive-based adoption strategies can coexist with decentralized coordination mechanisms with the DSO not controlling directly individual behind-the-meter ETS units. Instead, the proposed privacy-preserving distributed optimization framework ensures that ETS flexibility can be effectively mobilized while maintaining customer autonomy and trust. This creates a promising pathway where regulatory incentives, economic feasibility, and thorough distributed control tools align to make ETS a scalable and socially acceptable solution in real-life energy communities.

Concerning distributed stochastic coordination, few works in the literature have dedicated attention to providing a well-established framework that can be further tested

with different weather conditions by swapping in alternative datasets to build the respective building thermal model (Paper 2). Although similar works [97,98] have addressed stochastic distributed control in energy communities with thermal storage and renewable assets, modular solutions integrating software and hardware domains remain scarce. For risk analysis, related studies [99–101] have made progress in robust energy planning to anticipate undesired effects in short-term control horizons. However, this thesis extends the literature by estimating the price of robustness for both coordinators and community members, providing a broader perspective on the efforts required by each energy actor when anticipating forecasting errors based on user-dependent risk preferences.

The Stackelberg formulation used in this thesis provided a robust way to capture hierarchical interactions between coordinators and households, but real-world communities may not always conform to strict leader-follower dynamics. This opens the door to alternative game-theoretic approaches, such as bargaining models, or auction-based mechanisms, which could offer different setups of fairness and competition. Exploring such methodological diversification would make distributed coordination more adaptable to contexts where central coordinators are absent or where peer-to-peer governance models are preferred. At the same time, the technological scope of this thesis, centered on ETS and PV systems, should be understood as one piece of a much broader energy ecosystem. Communities often rely on diverse portfolios of DERs including biogas, small scale hydro, heat pumps, and hybrid storage solutions. Integrating these resources could significantly reshape coordination outcomes, with ETS flexibility becoming particularly valuable when complemented by assets that provide both electrical and thermal services. Besides, by quantifying the price of robustness, this thesis exposes an often-overlooked dimension of distributed coordination : the asymmetric distribution of costs when addressing uncertainty. While coordinators may bear higher computational and strategic burdens, households

experience heterogeneous impacts depending on their individual risk preferences, raising critical equity questions. Should robustness costs be centralized, distributed evenly, subsidized by local governments, or shared proportionally among actors? Answering this challenge requires not only technical optimization but also regulatory frameworks that encompass fairness, accountability, and social acceptance into the design of future energy communities.

Ultimately, the findings of this thesis have significant implications, as they encompass the entire procedure, from modelling and advanced methods for cost-effective energy planning under uncertainties to implementation. From a practical perspective, the results inform regulators and companies about optimal strategies to promote the adoption of energy communities. From a theoretical standpoint, this research suggests that current energy optimization models should incorporate more accurate building models and comprehensive information on the power grid state to achieve enhanced prediction accuracy and welfare estimation.

While the proposed framework successfully addresses multiple dimensions of distributed coordination, modelling accuracy, implementation, several limitations must be acknowledged to contextualize the scope and applicability of the findings. It is worth mentioning that such constraints do not undermine the contributions of this work; instead, they elucidate crucial aspects that deserve further exploration to refine the proposed approaches. The following limitations summarize essential assumptions, methodological simplifications, and contextual boundaries that shaped the outcomes of this research and that future studies could address to extend its relevance across different technical, economic, and social contexts.

- Renewable power OPEX was not modelled : perhaps this parameter could account for

a large share of the total cost of the project in difficult-to-reach areas -in some cases, these may be more expensive to run than diesel generators-, it was not considered. Furthermore, the introduction of such a consideration will not affect at all the convexity of the problem, as it is just about introducing an affine transformation to the objective function.

- System inability to detect free-riders : although numerical and implementation exercises revealed the ability of the system to reduce the overall grid cost, with limited information sharing among customers, the mechanism has a major limitation associated with customers that may experience economic savings with inelastic preferences. This is a typical market failure that could be solved by measuring the lack of individual effort and failure to meet commitments through the optimal benefit allocation combined with ensuring incentive compatibility.
- Lack of just standpoint on the transition perspective : while economic development and life quality is likely to happen with electrification of the demand, that might not be the case for indigenous communities. This is a major concern that this work did not address, but it is recognized as a pivotal aspect that could be modeled to provide a just perspective into the decision making strategy that entails the customers willingness to purchase demand-response enabled appliances such as electric heating systems. The notion of such an humanistic point of view can provide a more realistic sense to the scenarios generated.

## **Chapter 5 - Conclusions**

This thesis has focused on investigating optimal decision-making methods to operate distributed energy communities with imperfect information. By extensively exploring these multi-domain systems, three main problems have been determined for further improvements. This research has attempted to define these problems and other significant matters of operating aspects of energy communities that have yet to be deeply addressed.

Subsequently, three main issues of modelling aspects, distributed energy management strategies under imperfect information and incorporating demand-side risks have been examined, leading to this essay's suggestions. These suggestions account for the cosimulation framework for synthetic data generation, the distributed decision-making strategy, and the risk modelling for robust energy planning. The proposed approaches have been detailed in three studies (articles), each providing the following conclusions.

### **5.1 Summary of works**

#### *5.1.1 Cosimulation framework*

In the first study, the problem of the lack of proficient data for ETS-integrated buildings in cold regions, particularly Kuujuaq, has been focused on. Accordingly, a synthetic data generation tool has been developed. Generally, this tool exploits the operation schedules and thermo-electric characteristics of ETS room units located in a house to create the electric and thermal power profiles for which no actual data exists. Results have shown that the proposed approach can effectively model ETS' main features during free and forced convection cases while incorporating it with robust building models throughout cosimulation methods. As discussed, the proposed framework exhibited errors under 5 % for free and forced convection scenarios. Besides, the first research study also thoroughly

studied methods to address centralized wind power generation for the optimal operation of several customers with ETS units. We have adopted the proposed cosimulation framework to create building models that optimization tools could grasp using machine learning methods. Then, distributed energy management was possible thanks to deploying HEMS and decomposition methods. Comprehensive simulations were performed to increase the share of proactive customers (willing to purchase an ETS unit), and results showed that the individual's welfare could be affected. Similarly, the benefits of wind power were assessed by revealing sustained increases in economic savings for customers and reduced grid operating costs as ETS and wind power share increased. Future studies can focus on online optimization while incorporating the developed framework to improve demand forecast accuracy.

### *5.1.2 Distributed energy management under imperfect information*

In this second analysis, we have addressed the issue of managing several prosumers with ETS units in a distributed fashion with no information between them. Unlike the first study, this one considered accurate energy data to construct building models, thus creating more realistic results. While decomposition methods were also utilized, uncertainty from non-shiftable loads was tackled by maximizing individuals' welfare through stochastic programming methods. The strategy showed convergence and salient abilities to flatten the demand profile. Furthermore, while the proposed strategy exhibited economic feasibility by satisfying individuals' rationality, technical viability was not guaranteed. Accordingly, the outcome of the energy game was passed through a low-voltage test feeder. The results showed the strategy's ability to enhance the operational voltage profile by showcasing the precision of the methodology through a comparison with a deterministic baseline. Eventually, this study validated the proposed strategy in a distributed computing cluster

with a complete stack of open-source tools. This infrastructure allowed for estimating the computational requirement of automated agents in real-life implementations. Further studies could experience the benefits of distributed computing and evaluate similar strategies at a large scale to evaluate the impact of imperfect information created by distributed generation through energy communities.

### *5.1.3 Robust energy planning*

In the third research, the inadequacy of distributed energy management strategies to incorporate customers' concerns on the weather forecast and the subsequent renewable production to cope with heating needs have become the primary motivation to contribute a practical risk-aware strategy while grasping ETS realistic operating modes over predictive control methods. By extending the framework presented in the second research, this study successfully modelled customers' fear of loss of thermal comfort as a result of forecasting errors. To accomplish that, extensive analyses were performed by utilizing chance-constrained optimization methods. Results showed that cumulative forecasting errors and risk-aversion parameters significantly impact the aggregated profile even after reaching the game's convergence. As a result, a reliable grid operation is possible with 22 % of overrun costs. One of the main remarks of this research was that power congestion may appear with odds by up to 37 %. To perform all study cases, the existing distributed computing was overhauled with state-of-the-art tools to bring automated prosumer features, including load balancing, self-healing, and prompt setup. Future studies should adopt joint chance constraints and incorporate other energy resources, including heat pumps and electric batteries, to evaluate their ability to encompass the described customers' concerns.

Accordingly, the above conclusion finalizes the extensive analyses provided in this study to examine the concept of distributed energy management with renewable power and

thermal storage from different standpoints. Even though all the propositions, the future of this concept highly depends on regulatory issues and the community's ability to grasp operating power grids highly penetrated by digitization that could guarantee sustainability. The massive realization of these strategies depends not only on the customers' willingness to adopt clean energy but also on governmental interests, as bringing clean energy to hard-to-reach areas is often economically not feasible, leading to providing subsidies to make it affordable. Nevertheless, the fundamentals of the proposed approaches, which concern the desires of customers and system operators, should be considered in future short-term energy analyses and implementations that are favored for mass production.

## **5.2 Challenges**

### *5.2.1 Refining Demand-Side Risk Strategies : Joint Chance Constraints and Robust Methods*

Although the proposed strategy addressed demand-side risk-awareness via individual chance constraints, this was performed with assumptions that warrant further discussion. This thesis assumed that each deterministic equivalent constraint satisfies a specified probability at each time slot. However, such an assumption may not hold in realistic implementations, as probabilistic constraints were modeled on the tenant's thermal comfort, which exhibits Markovian properties, indicating that the current state of the system depends at least on the previous state. In this regard, a potential solution to address that issue is computing deterministic equivalents with joint chance constraints that satisfies multiple constraints under uncertainty simultaneously. This methodology suits better the interdependent nature of thermal comfort parameters across consecutive time periods, hence, enhancing the robustness of the risk-aware optimization framework.

We recognize that further studies are still required to build joint probability density

functions that could provide more realistic insights, for instance, having joint distributions for cloud and solar conditions, temperature and wind speed, and the whole combinations possible in such a way that the further short-term energy planning could experience the benefits of having more sound probabilistic analysis.

The integration of distributionally robust optimization (DRO) presents a particularly promising opportunity in this context. Unlike conventional stochastic programming approaches that assume perfect knowledge of probability distributions, it relies on distribution uncertainty by optimizing for the worst-case distribution within an defined ambiguity set. This approach can be useful when the underlying distribution change over time given occupant behaviors or climate conditions. By incorporating DRO techniques, the optimization strategy can guarantee performance even when the knowledge on the probability distributions is partial, thereby providing a more reliable basis for decision-making under the complex uncertainties inherent in building power control.

### *5.2.2 Welfare Analysis Under Network Parameter Uncertainty*

Demand-side management initiatives lead to increased utilities, and its estimation depends mostly on the difference between amount of energy sold times the price of the electricity before and after executing the program. However, it only represents the economic benefit and does not reflect the total impact on the individual's welfare. Accordingly, the truth welfare must be computed, and it stands for the difference between the utility perceived and the respective cost ( $W = \sum_{k \in \mathcal{K}} U_k - C_k$ ). Computing the cost of the strategy,  $C_k$  over the power grid is a complex exercise that requires knowing in detail the system's parameters at the distribution level including lines impedance and network topology. In many practical scenarios, these parameters are either unknown or only partially available, introducing significant uncertainty in cost estimation. This lack of information complicates

the assessment of reduced costs associated with improving the Peak-to-Average Ratio (PAR), as the distribution network's response to demand-side interventions is not fully predictable.

### *5.2.3 Complexity of thermal storage operating in forced convection operating mode*

Electric thermal storage assets, in real-life can operate in free or forced convection. These modes differ, roughly in the presence of a fan that actively extracts air from the core bricks through forced convection. Even though this increases heat transfer efficiency and provides controllability over discharge periods, it also additions complexity to the decision-making system. In addition, the state equation of the ETS is coupled with the state equation of the building, since the heat released by the unit directly influences the buildings temperature dynamics. This interaction implies some inter-dependencies where the thermal response of the building affects the optimal operation of the ETS, and vice versa. As a consequence, the optimal control of the ETS operation should consider not only its internal dynamics but also the thermal behavior of the building. This coupling further increases the computational complexity often requiring mixed-integer programming (MILP) approaches. These methods can grasp the forced convection mode while still maintaining computational tractability. But, they may involve significantly longer computation times.

## **5.3 Recommendations**

### *5.3.1 Towards Complex Models and Standardized Interfaces*

The proposed approach exploited cosimulation models (EnergyPlus + Modelica) to generate synthetic data for buildings and thermal storage systems. That make sense for environments when accurate data is scarce. Furthermore, incorporating these models into decision-making convex systems is a complex task. Then. we processed our results

through least squares regression to build equivalent linear models. Although this approach adequately allowed for scenario generation and model development for optimal power scheduling, significant research gaps remain. Specifically, there is an imminent need to propose methodologies that join white-box models with non-linear and non-convex phenomena, aiming to increase the accuracy of demand forecasting capabilities. Further research may include scalability issues when it comes to implementing complex models in realistic environments, especially, for larger neighbors. Besides, propagating uncertainties through multi-domain models presents another significant challenge, as forecast errors can affect thermal, electrical and control dimensions. Additionally, huge efforts are required to standardize communication protocols and to integrate these complex models with existing building energy management systems through commercial energy market platforms.

### *5.3.2 Long-term energy planning and fairness*

This thesis integrated stochasticity from weather conditions and the subsequent renewable power and from customers' price elasticity in the proposed energy management strategy. This technique enabled the evaluation of the impact of imperfect information scenarios over utilities, cost and welfare terms. All energy analyses reported in the published papers were performed within a prediction horizon of 24 hours. Nevertheless, the strategy was also evaluated over a period of 2 months during the winter 2023, to evaluate the potential benefits in a long run and possible correlations in time between variables. Figure 5.1A effectively quantifies the energy optimization achieved through the implementation of the proposed demand management approach, with notable efficiency gains observed during the coldest temperature periods where heating demands typically surge. However, as it is not clear within this horizon control, simulations were extended for about two months, and Figure 5.1(B) summarizes the results. Here, the reveals a direct correlation between

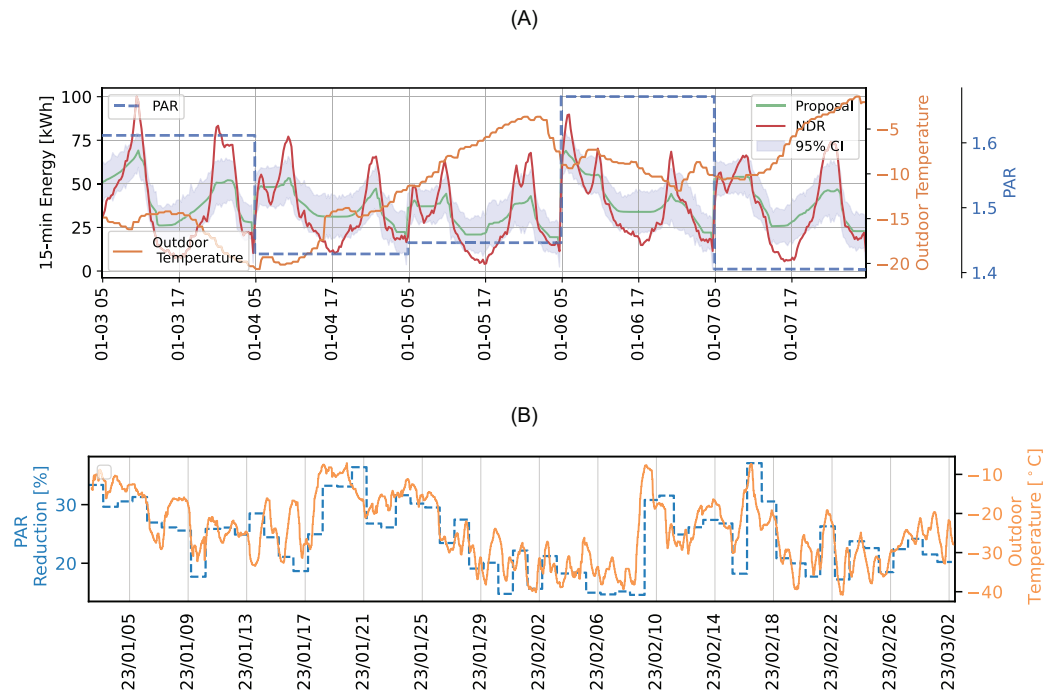


Figure 5.1 Execution of the distributed stochastic coordination program over two months in winter 2023. (A) First 5 days, and (B) The whole winter period

these variables, with PAR reduction values fluctuating between 15-35% throughout the period. The data demonstrates that energy demand management effectiveness (measured by PAR reduction) improves during relatively warmer periods and decreases during colder intervals. Notably, the highest PAR reduction values (30-35%) correspond with significant temperature variations rather than specific absolute temperatures, while the period from late January to early February exhibits minimums in both variables. These findings suggest that the distributed stochastic coordination program dynamically responds to outdoor temperature fluctuations, adjusting its optimization strategy accordingly.

However, more advanced analyses can be performed for longer periods, in which the proposal's performance could be evaluated not only in winter but also in summer. This could

provide more comprehensive scenarios that allow researchers conclude on the possible negative impacts given uncertainties and the importance of thermostatically controllable loads. Besides, techno-economic analyses to evaluate energy indexes and key performance metrics to assess project's sustainability can be unlocked. On the other hand, this thesis assessed power flow analyses solely within the CIGRE low-voltage distribution network, revealing a significant research gap for more comprehensive power grid stability analyses. Future research should examine the impact of this proposal on larger power systems to generate insights regarding non-participating citizens. Such analyses would reveal insights on how electricity tariffs might absorb these effects, with important implications for fairness and equity across all energy system stakeholders. This broader perspective would address critical questions about the distributional impacts of energy communities and ensure that benefits are not achieved at the expense of non-participants in a wider energy ecosystem.

### *5.3.3 Network Modeling Extensions for Energy Community Assessment*

The proposed solution exploited the well-known Pandapower framework to evaluate technically the feasibility of the proposed energy coordination strategy. Simulations were performed over the low-voltage CIGRE test feeder, considering only the residential sector. However, further studies can be performed with a more realistic test feeder by addressing not only tertiary control issues but also attacking primary and secondary control issues. To manage that, future initiatives could incorporate transmission-level circuit equivalents, understanding the need of localized power to anticipate properly the potential loss of inertia and short-circuit capacity due to the huge penetration of energy communities in power systems. Furthermore, modelling scenarios with unbalanced power grids at low voltage can provide insights into how energy coordination strategies with imperfect information could alleviate such situations.

The proposed framework could be extended to include resilience metrics, evaluating how energy communities could respond to extreme events and contribute to network restoration. Eventually, the integration of other energy vectors including natural gas, biomass, hydrogen, green methen and others, represents an important frontier, allowing for more comprehensive optimization across different energy domains while revealing additional technical constraints that must be incorporated into future modeling efforts.

#### *5.3.4 Coalition-Based Approaches to Distributed Energy Management*

Coordinating distributed energy resources is a task that can be done through cooperative and non-cooperative approaches. Our approach modelled the latter case, representing a challenging scenario since customers do not share information and behave selfishly, which is very close to many real-life cases in distributed generation. Nevertheless, when customers are willing to conform coalitions by enabling information sharing between them, other algorithms and considerations are required. Future research could adopt other decentralized algorithms, that could split a large problem into small pieces by explicitly having a shared goal in each participant's objective. Afterwards, as stated by Etedadi *et al.* in [42] it is required to distribute the gains of the systems across all the customers via some mechanisms such as the Shapley value.

Additionally, cooperative frameworks stand for an outstanding research niche in demand-side flexibility aggregation and coordinated community members' responses. Accordingly, multi-agent systems emerge as a powerful solution as individuals maintain autonomy while contributing to collective objectives through bargaining strategies. Privacy-preserving computation techniques are essential in these contexts to build trust at the community level by sharing only necessary information. That could facilitate the adoption of information security platforms to provide transparency. There is huge potential

for implementations where secure transactions between coalition members occur, potentially enabling peer-to-peer energy trading within the cooperative framework. Future initiatives may entail coalition formation mechanisms that respond to grid conditions over a period, creating resilient power control strategies that could maximize social welfare while ensuring a reliable operation.

### *5.3.5 Governance and Financial Sustainability in Energy Community Implementation*

Legal certainty and a well-established regulatory framework could reduce risk for potential investors and facilitate implementation procedures on energy communities. As it goes beyond the scope of this research, future works must evaluate the regulatory and legal suitability of this approach into current regulatory frameworks. In real-life, multiple challenges could emerge when implementing energy communities at large scale, including : i) sustainability, ii) risk management, and iii) fiscal spending. Sustainability issues may arise when funding comes from public resources that subsidize capital expenses due to households' inability to pay for the required equipment. Additionally, fully community-led programs could increase the probability of patrimonial detriment when prior capacity building programs are limited so that communities can manage not only operational expenses but also retail commitments with the wholesale market. The latter can create increased fiscal spending, as governmental entities would need to intervene and allocate public funds to prevent the transfer of market inefficiencies to end customers.

Legal frameworks are mandatory to clarify ownership structures, liability distribution, and governance pipelines within energy communities. Regulatory sandboxes could bring about fully controlled environments in order to test innovative business models without fully committing to permanent regulatory changes. Furthermore, potential tensions between existing regulations and new models that can be addressed by means of transition

mechanisms. The development of performance metrics and monitoring protocols can track the effectiveness of regulatory interventions. Finally, special attention should be given to education and awareness programs for regulatory entities and local authorities, enhancing their capacity to evaluate and support energy community initiatives within their existing policy frameworks.

#### *5.3.6 Bridging Simulation and Reality : Hardware Constraints in Energy Community Deployment*

Unlike other studies, this research validated the proposed distributed resource coordination using a realistic infrastructure developed with open-source tools. We performed multiple simulations utilizing distributed computing features on low-cost embedded hardware. Although this thesis successfully modeled scenarios with 80 demand-side participants, we encountered technical limitations in the edge devices' capabilities to handle the computational burden of hosting multiple residential customer agents. Consequently, there exists a significant research and innovation opportunity to evaluate this strategy under real-life conditions to properly understand community needs. These requirements may vary substantially in hard-to-reach territories, which typically require prior consultation procedures and entail higher capital and operational expenses.

#### *5.3.7 Decoupling electricity-thermal domains through district heating and cooling applications*

This thesis focused on a particular thermal storage technology such as ETS because it stands out as a cost-competitive technology, facilitates renewable power integration, and offers easy maintenance and transportation. Nevertheless, its LCOE could be higher than the exhibited by district heating and cooling applications. This is related to the fact that ETS units do not provide any benefit during summer, as the need in that moment is for

space cooling.

On the other hand, district heating and cooling systems are also a cost-competitive solution, with the largest coefficient of performance in thermal domain. They integrate multiple heat sources and providing both heating and cooling services overcoming seasonality issues. One of the main advantages of district heating is that it can be powered from a large number of energy vectors including renewable power, geothermal, biomass, and also energy excess for industry. Even though they experience substantial upfront costs, future research should explore distributed stochastic control for communities equipped with district heating systems to evaluate the cost-competitiveness against fully distributed ETS layouts.

## References

- [1] IEA, “World Energy Outlook 2024,” Tech. Rep., 2024.
- [2] IRENA, “Innovation outlook : Thermal energy storage,” Tech. Rep., 2021.
- [3] IEA, “Global Energy Review 2021,” p. 36, 2021.
- [4] International Energy Agency, *Renewable Energy Market Update : Outlook for 2020 and 2021*. OECD, Jun. 2020. [Online]. Available : [https://www.oecd-ilibrary.org/energy/renewable-energy-market-update\\_afbc8c1d-en](https://www.oecd-ilibrary.org/energy/renewable-energy-market-update_afbc8c1d-en)
- [5] J. Lowitzsch, C. E. Hoicka, and F. J. van Tulder, “Renewable energy communities under the 2019 European Clean Energy Package Governance model for the energy clusters of the future?” *Renewable and Sustainable Energy Reviews*, vol. 122, p. 109489, Apr. 2020. [Online]. Available : <https://www.sciencedirect.com/science/article/pii/S1364032119306975>
- [6] L. Wang, J. Lin, H. Dong, Y. Wang, and M. Zeng, “Demand response comprehensive incentive mechanism-based multi-time scale optimization scheduling for park integrated energy system,” *Energy*, vol. 270, p. 126893, May 2023. [Online]. Available : <https://www.sciencedirect.com/science/article/pii/S0360544223002876>
- [7] Z. Hu, J.-h. Kim, J. Wang, and J. Byrne, “Review of dynamic pricing programs in the U.S. and Europe : Status quo and policy recommendations,” *Renewable and Sustainable Energy Reviews*, vol. 42, pp. 743–751, Feb. 2015. [Online]. Available : <https://www.sciencedirect.com/science/article/pii/S1364032114009034>
- [8] A. Arteconi, N. J. Hewitt, and F. Polonara, “Domestic demand-side management (DSM) : Role of heat pumps and thermal energy storage (TES) systems,” *Applied Thermal Engineering*, vol. 51, no. 1, pp. 155–165, Mar. 2013. [Online]. Available : <https://www.sciencedirect.com/science/article/pii/S1359431112006357>
- [9] I. Atzeni, L. G. Ordonez, G. Scutari, D. P. Palomar, and J. R. Fonollosa, “Demand-Side Management via Distributed Energy Generation and Storage Optimization,” *IEEE Transactions on Smart Grid*, vol. 4, no. 2, pp. 866–876, Jun. 2013. [Online]. Available : <https://ieeexplore.ieee.org/document/6297498/>
- [10] Z. Ge, Y. Li, D. Li, Z. Sun, Y. Jin, C. Liu, C. Li, G. Leng, and Y. Ding, “Thermal energy storage : Challenges and the role of particle technology,” *Particuology*, vol. 15, pp. 2–8, Aug. 2014. [Online]. Available : <https://www.sciencedirect.com/science/article/pii/S1674200114000571>
- [11] J. Heier, C. Bales, and V. Martin, “Combining thermal energy storage with buildings a review,” *Renewable and Sustainable Energy Reviews*, vol. 42, pp. 1305–1325, Feb. 2015. [Online]. Available : <https://www.sciencedirect.com/science/article/pii/S1364032114009629>
- [12] J. Niu, Z. Tian, Y. Lu, and H. Zhao, “Flexible dispatch of a building energy system using building thermal storage and battery energy storage,” *Applied Energy*, vol. 243, pp. 274–287, Jun. 2019. [Online]. Available : <https://www.sciencedirect.com/science/article/pii/S030626191930604X>

- [13] F. Desai, J. Sunku Prasad, P. Muthukumar, and M. M. Rahman, “Thermochemical energy storage system for cooling and process heating applications : A review,” *Energy Conversion and Management*, vol. 229, p. 113617, Feb. 2021. [Online]. Available : <https://www.sciencedirect.com/science/article/pii/S0196890420311456>
- [14] E. Barabino, D. Fioriti, E. Guerrazzi, I. Mariuzzo, D. Poli, M. Raugi, E. Razaeei, E. Schito, and D. Thomopoulos, “Energy Communities : A review on trends, energy system modelling, business models, and optimisation objectives,” *Sustainable Energy, Grids and Networks*, vol. 36, p. 101187, Dec. 2023. [Online]. Available : <https://linkinghub.elsevier.com/retrieve/pii/S2352467723001959>
- [15] E. Gunawan, “Alternative heating systems for northern remote communities : Techno-economic analysis of ground-source heat pumps in kuujuaq, nunavik, canada,” *Reykjavik University*, 2019.
- [16] D. Moreno, J. Raymond, and L. Gosselin, “Techno-economic analysis of hybrid solar-assisted geothermal and biomass heating systems in remote subarctic communities (nunavik, canada),” *Energy*, vol. 313, p. 133898, 2024.
- [17] C. Yan, D. Rousse, and M. Glaus, “Multi-criteria decision analysis ranking alternative heating systems for remote communities in nunavik,” *Journal of cleaner production*, vol. 208, pp. 1488–1497, 2019.
- [18] R. de l’énergie du Québec, “Prix mensuel du mazout régions administratives, 2023,” Document PDF, 2023, disponible en ligne : <https://www.regie-energie.qc.ca/storage/app/media/consommateurs/informations-pratiques/prix-petrole/Tableaux/region-administrative/mazout/mensuel/mazout2023.pdf>.
- [19] A. Cavalerie, D. Dumas, and L. Gosselin, “Indoor comfort management and energy consumption in Arctic buildings : Occupant perceptions in an indigenous community of Canada,” *Building and Environment*, vol. 253, p. 111300, Apr. 2024. [Online]. Available : <https://www.sciencedirect.com/science/article/pii/S0360132324001422>
- [20] A. Cavalerie, “Étude et prédiction du comportement d’ouverture des fenêtres dans des bâtiments résidentiels au nunavik, québec : une approche quantitative et qualitative,” 2024.
- [21] A. Cuerrier, N. D. Brunet, J. Gérin-Lajoie, A. Downing, and E. Lévesque, “The Study of Inuit Knowledge of Climate Change in Nunavik, Quebec : A Mixed Methods Approach,” *Human Ecology*, vol. 43, no. 3, pp. 379–394, Jun. 2015. [Online]. Available : <https://doi.org/10.1007/s10745-015-9750-4>
- [22] D. Dumas and L. Gosselin, “Preliminary Analysis of the Electricity Consumption of Residential Units in Nunavik (Quebec, Canada),” in *Proceedings of the 5th International Conference on Building Energy and Environment*, L. L. Wang, H. Ge, Z. J. Zhai, D. Qi, M. Ouf, C. Sun, and D. Wang, Eds. Singapore : Springer Nature, 2023, pp. 1171–1179.
- [23] Hydro-Québec, “Breakdown of a households electricity use,” <https://www.hydroquebec.com/residential/customer-space/electricity-use/>

- electricity-consumption-by-use.html, 2025, webpage consulted for electricity consumption breakdown by use in Quebec households.
- [24] P. S. Sauter, B. V. Solanki, C. A. Cañizares, K. Bhattacharya, and S. Hohmann, “Electric Thermal Storage System Impact on Northern Communities Microgrids,” *IEEE Transactions on Smart Grid*, vol. 10, no. 1, pp. 852–863, Jan. 2019, h.
- [25] Canada and Natural Resources Canada, *Towards renewable energy integration in remote communities : a summary of electric reliability considerations.*, 2018, oCLC : 1086318740. [Online]. Available : [http://epe.lac-bac.gc.ca/100/201/301/weekly\\_acquisitions\\_list-ef/2019/19-06/publications.gc.ca/collections/collection\\_2019/rncan-nrcan/M134-52-2018-eng.pdf](http://epe.lac-bac.gc.ca/100/201/301/weekly_acquisitions_list-ef/2019/19-06/publications.gc.ca/collections/collection_2019/rncan-nrcan/M134-52-2018-eng.pdf)
- [26] A. Prieur, “Remote Northern Microgrids in Canada,” p. 16.
- [27] C. Vitello, “The future of energy in remote communities - ReNew Canada,” section : Feature. [Online]. Available : <https://www.renewcanada.net/feature/the-future-of-energy-in-remote-communities>
- [28] B. Daryanian and R. E. Bohn, “Sizing of electric thermal storage under real time pricing,” *IEEE Transactions on Power Systems*, vol. 8, no. 1, pp. 35–43, 1993.
- [29] S. Wong and J.-P. Pinard, “Opportunities for Smart Electric Thermal Storage on Electric Grids With Renewable Energy,” *IEEE Transactions on Smart Grid*, vol. 8, no. 2, pp. 1014–1022, Mar. 2017.
- [30] Z. Broka, K. Baltputnis, A. Sauhats, L. Sadovica, and G. Junghans, “Stochastic Model for Profitability Evaluation of Demand Response by Electric Thermal Storage,” in *2018 IEEE 59th International Scientific Conference on Power and Electrical Engineering of Riga Technical University (RTUCON)*. Riga, Latvia : IEEE, Nov. 2018, pp. 1–6. [Online]. Available : <https://ieeexplore.ieee.org/document/8659837/>
- [31] W. Devia, K. Agbossou, and A. Cardenas, “An evolutionary approach to modeling and control of space heating and thermal storage systems,” *Energy and Buildings*, vol. 234, p. 110674, Mar. 2021. [Online]. Available : <https://linkinghub.elsevier.com/retrieve/pii/S0378778820334605>
- [32] P. Cisek and D. Taler, “Numerical analysis and performance assessment of the Thermal Energy Storage unit aimed to be utilized in Smart Electric Thermal Storage (SETS),” *Energy*, vol. 173, pp. 755–771, Apr. 2019. [Online]. Available : <https://www.sciencedirect.com/science/article/pii/S0360544219302919>
- [33] I. F.G. Reis, I. Gonçalves, M. A.R. Lopes, and C. Henggeler Antunes, “Business models for energy communities : A review of key issues and trends,” *Renewable and Sustainable Energy Reviews*, vol. 144, p. 111013, Jul. 2021. [Online]. Available : <https://www.sciencedirect.com/science/article/pii/S1364032121003038>
- [34] F. Büning, R. Sangi, and D. Müller, “A Modelica library for the agent-based control of building energy systems,” *Applied Energy*, vol. 193, pp. 52–59, May 2017. [Online]. Available : <https://www.sciencedirect.com/science/article/pii/S0306261917300612>

- [35] D. Mazzeo, N. Matera, C. Cornaro, G. Oliveti, P. Romagnoni, and L. De Santoli, "EnergyPlus, IDA ICE and TRNSYS predictive simulation accuracy for building thermal behaviour evaluation by using an experimental campaign in solar test boxes with and without a PCM module," *Energy and Buildings*, vol. 212, p. 109812, Apr. 2020. [Online]. Available : <https://www.sciencedirect.com/science/article/pii/S0378778819324521>
- [36] A. Lake, B. Rezaie, and S. Beyerlein, "Review of district heating and cooling systems for a sustainable future," *Renewable and Sustainable Energy Reviews*, vol. 67, pp. 417–425, Jan. 2017. [Online]. Available : <https://www.sciencedirect.com/science/article/pii/S1364032116305585>
- [37] G. Xu, X. Hu, Z. Liao, C. Xu, C. Yang, and Z. Deng, "Experimental and Numerical Study of an Electrical Thermal Storage Device for Space Heating," *Energies*, vol. 11, no. 9, p. 2180, Sep. 2018, number : 9 Publisher : Multidisciplinary Digital Publishing Institute. [Online]. Available : <https://www.mdpi.com/1996-1073/11/9/2180>
- [38] L. Petrichenko, Z. Broka, and A. Sauhats, "Impact of smart electric thermal storage on distribution grid," in *2017 IEEE International Conference on Environment and Electrical Engineering and 2017 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I CPS Europe)*, Jun. 2017, pp. 1–6.
- [39] H. Ji, H. Wang, J. Yang, J. Feng, Y. Yang, and M. O. Okoye, "Optimal schedule of solid electric thermal storage considering consumer behavior characteristics in combined electricity and heat networks," *Energy*, vol. 234, p. 121237, Nov. 2021. [Online]. Available : <https://www.sciencedirect.com/science/article/pii/S0360544221014857>
- [40] N. Daina, A. Sivakumar, and J. W. Polak, "Modelling electric vehicles use : a survey on the methods," *Renewable and Sustainable Energy Reviews*, vol. 68, pp. 447–460, Feb. 2017. [Online]. Available : <https://www.sciencedirect.com/science/article/pii/S1364032116306566>
- [41] H. Ji, L. Sun, and J. Li, "Security Assessment and Preventive Control of Combined Electricity and Heat Systems with Distributed Electric Thermal Storage."
- [42] F. Etedadi, S. Kelouwani, K. Agbossou, N. Henao, and F. Laurencelle, "Consensus and sharing based distributed coordination of home energy management systems with demand response enabled baseboard heaters," *Applied Energy*, vol. 336, p. 120833, Apr. 2023. [Online]. Available : <https://www.sciencedirect.com/science/article/pii/S0306261923001976>
- [43] A. Nicolai and A. Paepcke, *Co-Simulation between detailed building energy performance simulation and Modelica HVAC component models*, Jul. 2017, pages : 72.
- [44] Y. Kwak, J.-H. Huh, and C. Jang, "Development of a model predictive control framework through real-time building energy management system data," *Applied Energy*, vol. 155, pp. 1–13, Oct. 2015. [Online]. Available : <https://www.sciencedirect.com/science/article/pii/S0306261915007291>

- [45] T. Hong, H. Sun, Y. Chen, S. C. Taylor-Lange, and D. Yan, "An occupant behavior modeling tool for co-simulation," *Energy and Buildings*, vol. 117, pp. 272–281, Apr. 2016. [Online]. Available : <https://www.sciencedirect.com/science/article/pii/S0378778815303480>
- [46] D. Cutler, T. Kwasnik, S. Balamurugan, T. Elgindy, S. Swaminathan, J. Maguire, and D. Christensen, "Co-simulation of transactive energy markets : A framework for market testing and evaluation," *International Journal of Electrical Power & Energy Systems*, vol. 128, p. 106664, 2021.
- [47] A. Awad, P. Bazan, and R. German, "A house appliances-level co-simulation framework for smart grid applications," in *Systems Modeling : Methodologies and Tools*. Springer, 2019, pp. 303–317.
- [48] D. Gusain, M. Cvetković, and P. Palensky, "Simplifying multi-energy system co-simulations using energysim," *SoftwareX*, vol. 18, p. 101021, 2022.
- [49] N. Erdogan, S. Kucuksari, and U. Cali, "Co-simulation of optimal evse and techno-economic system design models for electrified fleets," *IEEE Access*, vol. 10, pp. 18 988–18 997, 2022.
- [50] A. Summers, C. Goes, D. Calzada, N. Jacobs, S. Hossain-McKenzie, and Z. Mao, "Towards cyber-physical special protection schemes : Design and development of a co-simulation testbed leveraging sceptre," in *2022 IEEE Power and Energy Conference at Illinois (PECI)*. IEEE, 2022, pp. 1–7.
- [51] Y. Zhang, L. Fu, W. Zhu, X. Bao, and C. Liu, "Robust model predictive control for optimal energy management of island microgrids with uncertainties," *Energy*, vol. 164, pp. 1229–1241, Dec. 2018. [Online]. Available : <https://www.sciencedirect.com/science/article/pii/S0360544218317365>
- [52] Z. Shi, H. Liang, S. Huang, and V. Dinavahi, "Distributionally Robust Chance-Constrained Energy Management for Islanded Microgrids," *IEEE Transactions on Smart Grid*, vol. 10, no. 2, pp. 2234–2244, Mar. 2019.
- [53] P. Scarabaggio, S. Grammatico, R. Carli, and M. Dotoli, "Distributed Demand Side Management With Stochastic Wind Power Forecasting," *IEEE Transactions on Control Systems Technology*, vol. 30, no. 1, pp. 97–112, Jan. 2022, conference Name : IEEE Transactions on Control Systems Technology.
- [54] L. Ni, F. Wen, W. Liu, J. Meng, G. Lin, and S. Dang, "Congestion management with demand response considering uncertainties of distributed generation outputs and market prices," *Journal of Modern Power Systems and Clean Energy*, vol. 5, no. 1, pp. 66–78, Jan. 2017. [Online]. Available : <http://link.springer.com/10.1007/s40565-016-0257-9>
- [55] A. Narayan and K. Ponnambalam, "Risk-averse stochastic programming approach for microgrid planning under uncertainty," *Renewable Energy*, vol. 101, pp. 399–408, Feb. 2017. [Online]. Available : <https://www.sciencedirect.com/science/article/pii/S0960148116307741>

- [56] L. Rueda, K. Agbossou, N. Henao, S. Kelouwani, J. C. Oviedo-Cepeda, B. Le Lostec, S. Sansregret, and M. Fournier, "Online Unsupervised Occupancy Anticipation System Applied to Residential Heat Load Management," *IEEE Access*, vol. 9, pp. 109 806–109 821, 2021.
- [57] L. Rueda, S. Sansregret, B. Le Lostec, K. Agbossou, N. Henao, and S. Kelouwani, "A Probabilistic Model to Predict Household Occupancy Profiles for Home Energy Management Applications," *IEEE Access*, vol. 9, pp. 38 187–38 201, 2021, conference Name : IEEE Access.
- [58] M. Hu and F. Xiao, "Quantifying uncertainty in the aggregate energy flexibility of high-rise residential building clusters considering stochastic occupancy and occupant behavior," *Energy*, vol. 194, p. 116838, Mar. 2020. [Online]. Available : <https://www.sciencedirect.com/science/article/pii/S0360544219325332>
- [59] M. Movahedpour, M. J. Kiani, M. Zadehbagheri, and S. Mohammadi, "Microgrids Operation by Considering Demand Response and Supply Programs in the Presence of IGDT-Based Reverse Risk," *IEEE Access*, vol. 10, pp. 48 681–48 700, 2022, conference Name : IEEE Access.
- [60] L. Zheng, B. Zhou, Y. Cao, S. Wing Or, Y. Li, and K. Wing Chan, "Hierarchical distributed multi-energy demand response for coordinated operation of building clusters," *Applied Energy*, vol. 308, p. 118362, Feb. 2022. [Online]. Available : <https://www.sciencedirect.com/science/article/pii/S0306261921016068>
- [61] X. Yan, D. Abbes, and B. Francois, "Uncertainty analysis for day ahead power reserve quantification in an urban microgrid including PV generators," *Renewable Energy*, vol. 106, pp. 288–297, Jun. 2017. [Online]. Available : <https://linkinghub.elsevier.com/retrieve/pii/S0960148117300228>
- [62] L. Roald, F. Oldewurtel, B. Van Parys, and G. Andersson, "Security Constrained Optimal Power Flow with Distributionally Robust Chance Constraints," arXiv, Tech. Rep. arXiv:1508.06061, Aug. 2015, arXiv:1508.06061 [math] type : article. [Online]. Available : <http://arxiv.org/abs/1508.06061>
- [63] T. L. Nguyen, Q.-T. Tran, R. Caire, C. Gavriluta, and Van Hoa Nguyen, "Agent based distributed control of islanded microgrid Real-time cyber-physical implementation," in *2017 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe)*. Torino : IEEE, Sep. 2017, pp. 1–6. [Online]. Available : <https://ieeexplore.ieee.org/document/8260275/>
- [64] M. J. M. Al Essa, "Home energy management of thermostatically controlled loads and photovoltaic-battery systems," *Energy*, vol. 176, pp. 742–752, Jun. 2019. [Online]. Available : <https://www.sciencedirect.com/science/article/pii/S0360544219306656>
- [65] A. Martín-Crespo, S. Saludes-Rodil, and E. Baeyens, "Flexibility Management with Virtual Batteries of Thermostatically Controlled Loads : Real-Time Control System and Potential in Spain," *Energies*, vol. 14, no. 6, p. 1711, Jan. 2021, number :

- 6 Publisher : Multidisciplinary Digital Publishing Institute. [Online]. Available : <https://www.mdpi.com/1996-1073/14/6/1711>
- [66] G. Liu, Y. Tao, L. Xu, Z. Chen, J. Qiu, and S. Lai, “Coordinated management of aggregated electric vehicles and thermostatically controlled loads in hierarchical energy systems,” *International Journal of Electrical Power & Energy Systems*, vol. 131, p. 107090, Oct. 2021. [Online]. Available : <https://www.sciencedirect.com/science/article/pii/S014206152100329X>
- [67] A. M. Carreiro, H. M. Jorge, and C. H. Antunes, “Energy management systems aggregators : A literature survey,” *Renewable and Sustainable Energy Reviews*, vol. 73, pp. 1160–1172, Jun. 2017. [Online]. Available : <https://www.sciencedirect.com/science/article/pii/S1364032117301776>
- [68] L. Gkatzikis, I. Koutsopoulos, and T. Salonidis, “The Role of Aggregators in Smart Grid Demand Response Markets,” *IEEE Journal on Selected Areas in Communications*, vol. 31, no. 7, pp. 1247–1257, Jul. 2013.
- [69] K. Bruninx, H. Pandi, H. Le Cadre, and E. Delarue, “On the Interaction Between Aggregators, Electricity Markets and Residential Demand Response Providers,” *IEEE Transactions on Power Systems*, vol. 35, no. 2, pp. 840–853, Mar. 2020.
- [70] R. Gulati, F. Wohlgezogen, and P. Zhelyazkov, “The two facets of collaboration : Cooperation and coordination in strategic alliances,” *Academy of Management Annals*, vol. 6, no. 1, pp. 531–583, 2012.
- [71] M. Hu, F. Xiao, and S. Wang, “Neighborhood-level coordination and negotiation techniques for managing demand-side flexibility in residential microgrids,” *Renewable and Sustainable Energy Reviews*, vol. 135, p. 110248, 2021.
- [72] F. Etedadi Aliabadi, K. Agbossou, S. Kelouwani, N. Henao, and S. S. Hosseini, “Coordination of Smart Home Energy Management Systems in Neighborhood Areas : A Systematic Review,” *IEEE Access*, vol. 9, pp. 36 417–36 443, 2021.
- [73] H. K. Nguyen, J. B. Song, and Z. Han, “Distributed Demand Side Management with Energy Storage in Smart Grid,” *IEEE Transactions on Parallel and Distributed Systems*, vol. 26, no. 12, pp. 3346–3357, Dec. 2015, conference Name : IEEE Transactions on Parallel and Distributed Systems.
- [74] C. Wu, H. Mohsenian-Rad, J. Huang, and A. Y. Wang, “Demand side management for Wind Power Integration in microgrid using dynamic potential game theory,” in *2011 IEEE GLOBECOM Workshops (GC Wkshps)*, Dec. 2011, pp. 1199–1204, iSSN : 2166-0077.
- [75] G. Mavromatidis, K. Orehounig, and J. Carmeliet, “Design of distributed energy systems under uncertainty : A two-stage stochastic programming approach,” *Applied energy*, vol. 222, pp. 932–950, 2018.
- [76] H. Huuki, S. Karhinen, H. Böök, A. V. Lindfors, M. Kopsakangas-Savolainen, and R. Svento, “Utilizing the flexibility of distributed thermal storage in solar power forecast error cost minimization,” *Journal of Energy Storage*, vol. 28, p. 101202, 2020.

- [77] D. Testi, L. Urbanucci, C. Giola, E. Schito, and P. Conti, "Stochastic optimal integration of decentralized heat pumps in a smart thermal and electric micro-grid," *Energy Conversion and Management*, vol. 210, p. 112734, 2020.
- [78] Z. Li, Y. Xu, X. Feng, and Q. Wu, "Optimal stochastic deployment of heterogeneous energy storage in a residential multienergy microgrid with demand-side management," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 2, pp. 991–1004, 2020.
- [79] N. Good, E. Karangelos, A. Navarro-Espinosa, and P. Mancarella, "Optimization under uncertainty of thermal storage-based flexible demand response with quantification of residential users discomfort," *IEEE Transactions on Smart Grid*, vol. 6, no. 5, pp. 2333–2342, 2015.
- [80] A. Najafi-Ghalelou, S. Nojavan, K. Zare, and B. Mohammadi-Ivatloo, "Robust scheduling of thermal, cooling and electrical hub energy system under market price uncertainty," *Applied Thermal Engineering*, vol. 149, pp. 862–880, 2019.
- [81] S. Pazouki, M.-R. Haghifam, and A. Moser, "Uncertainty modeling in optimal operation of energy hub in presence of wind, storage and demand response," *International Journal of Electrical Power & Energy Systems*, vol. 61, pp. 335–345, 2014.
- [82] M. Tostado-Véliz, S. Kamel, F. Aymen, A. Rezaee Jordehi, and F. Jurado, "A Stochastic-IGDT model for energy management in isolated microgrids considering failures and demand response," *Applied Energy*, vol. 317, p. 119162, Jul. 2022. [Online]. Available : <https://www.sciencedirect.com/science/article/pii/S0306261922005347>
- [83] X. Wang, Y. Liu, L. Xu, J. Liu, and H. Sun, "A chance-constrained stochastic model predictive control for building integrated with renewable resources," *Electric Power Systems Research*, vol. 184, p. 106348, Jul. 2020. [Online]. Available : <https://www.sciencedirect.com/science/article/pii/S0378779620301541>
- [84] C. Shang and F. You, "Distributionally robust optimization for planning and scheduling under uncertainty," *Computers & Chemical Engineering*, vol. 110, pp. 53–68, Feb. 2018. [Online]. Available : <https://www.sciencedirect.com/science/article/pii/S009813541730426X>
- [85] F. H. Aghdam, N. Taghizadegan Kalantari, and B. Mohammadi-Ivatloo, "A stochastic optimal scheduling of multi-microgrid systems considering emissions : A chance constrained model," *Journal of Cleaner Production*, vol. 275, p. 122965, Dec. 2020. [Online]. Available : <https://www.sciencedirect.com/science/article/pii/S0959652620330109>
- [86] K. Yurtseven and H. Ergun, "Stochastic Optimal Power Flow For Hybrid AC/DC Grids Using General Polynomial Chaos."
- [87] D. Huo, M. Santos, I. Sarantakos, M. Resch, N. Wade, and D. Greenwood, "A reliability-aware chance-constrained battery sizing method for island

- microgrid,” *Energy*, vol. 251, p. 123978, Jul. 2022. [Online]. Available : <https://www.sciencedirect.com/science/article/pii/S0360544222008817>
- [88] O. Sadeghian, A. Oshnoei, R. Khezri, and S. Muyeen, “Risk-constrained stochastic optimal allocation of energy storage system in virtual power plants,” *Journal of Energy Storage*, vol. 31, p. 101732, Oct. 2020. [Online]. Available : <https://www.sciencedirect.com/science/article/pii/S2352152X20315693>
- [89] J. A. Dominguez, L. Rueda, N. Henao, K. Agbossou, and J. Campillo, “Distributed Co-simulation for Smart Homes Energy Management in the Presence of Electrical Thermal Storage,” in *IECON 2022 48th Annual Conference of the IEEE Industrial Electronics Society*, Oct. 2022, pp. 1–6, iSSN : 2577-1647.
- [90] X. Pan, M. Yuan, G. Xu, X. Hu, Z. Liao, and C. Xu, “Structure and Operation Optimization of a Form-Stable Carbonate/Ceramic-Based Electric Thermal Storage Device for Space Heating,” *Energies*, vol. 16, no. 11, p. 4506, Jan. 2023, number : 11 Publisher : Multidisciplinary Digital Publishing Institute. [Online]. Available : <https://www.mdpi.com/1996-1073/16/11/4506>
- [91] B.-E. Bayandelger, Y. Ueda, and A. Adiyabat, “Experimental Investigation and Energy Performance Simulation of Mongolian Ger with ETS Heater and Solar PV in Ulaanbaatar City,” *Energies*, vol. 13, no. 21, p. 5840, Jan. 2020, number : 21 Publisher : Multidisciplinary Digital Publishing Institute. [Online]. Available : <https://www.mdpi.com/1996-1073/13/21/5840>
- [92] J. Tan, Y. Li, X. Zhang, W. Pan, and W. Ruan, “Operation of a commercial district integrated energy system considering dynamic integrated demand response : A Stackelberg game approach,” *Energy*, vol. 274, p. 126888, Jul. 2023. [Online]. Available : <https://www.sciencedirect.com/science/article/pii/S0360544223002827>
- [93] H. Rashidzadeh-Kermani, M. Vahedipour-Dahraie, M. Shafie-Khah, and P. Siano, “A Regret-Based Stochastic Bi-Level Framework for Scheduling of DR Aggregator Under Uncertainties,” *IEEE Transactions on Smart Grid*, vol. 11, no. 4, pp. 3171–3184, Jul. 2020, conference Name : IEEE Transactions on Smart Grid. [Online]. Available : <https://ieeexplore.ieee.org/document/8966941>
- [94] H. Li, Z. Wang, T. Hong, and M. A. Piette, “Energy flexibility of residential buildings : A systematic review of characterization and quantification methods and applications,” *Advances in Applied Energy*, vol. 3, p. 100054, Aug. 2021. [Online]. Available : <https://linkinghub.elsevier.com/retrieve/pii/S2666792421000469>
- [95] L. Ma, N. Liu, J. Zhang, and L. Wang, “Real-Time Rolling Horizon Energy Management for the Energy-Hub-Coordinated Prosumer Community From a Cooperative Perspective,” *IEEE Transactions on Power Systems*, vol. 34, no. 2, pp. 1227–1242, Mar. 2019, conference Name : IEEE Transactions on Power Systems. [Online]. Available : <https://ieeexplore.ieee.org/document/8501599>
- [96] M. Pilz and L. Al-Fagih, “A Dynamic Game Approach for Demand-Side Management : Scheduling Energy Storage with Forecasting Errors,” *Dynamic*

- Games and Applications*, vol. 10, no. 4, pp. 897–929, Dec. 2020. [Online]. Available : <https://doi.org/10.1007/s13235-019-00309-z>
- [97] E. Rezaei, H. Dagdougui, and M. Rezaei, “Distributed Stochastic Model Predictive Control for Peak Load Limiting in Networked Microgrids With Building Thermal Dynamics,” *IEEE Transactions on Smart Grid*, vol. 13, no. 3, pp. 2038–2049, May 2022, conference Name : IEEE Transactions on Smart Grid.
- [98] Z. Dong, X. Zhang, and G. Strbac, “Evaluation of benefits through coordinated control of numerous thermal energy storage in highly electrified heat systems,” *Energy*, vol. 237, p. 121600, Dec. 2021. [Online]. Available : <https://www.sciencedirect.com/science/article/pii/S036054422101848X>
- [99] M. Mohiti, M. Mazidi, N. Oggioni, D. Steen, and L. A. Tuan, “An IGDT-Based Energy Management System for Local Energy Communities Considering Phase-Change Thermal Energy Storage,” *IEEE Transactions on Industry Applications*, pp. 1–11, 2024, conference Name : IEEE Transactions on Industry Applications. [Online]. Available : <https://ieeexplore.ieee.org/document/10415531>
- [100] M. Mohiti, M. Mazidi, D. Steen, and L. A. Tuan, “A Risk-Averse Energy Management System for Optimal Heat and Power Scheduling in Local Energy Communities,” in *2022 IEEE International Conference on Environment and Electrical Engineering and 2022 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe)*, Jun. 2022, pp. 1–6. [Online]. Available : <https://ieeexplore.ieee.org/document/9854642>
- [101] M. Dolanyi, K. Bruninx, J.-F. Toubreau, and E. Delarue, “Risk-Based Constraints for the Optimal Operation of an Energy Community,” *IEEE Transactions on Smart Grid*, vol. 13, no. 6, pp. 4551–4561, Nov. 2022, conference Name : IEEE Transactions on Smart Grid. [Online]. Available : <https://ieeexplore.ieee.org/document/9803201>
- [102] N. Mercer, P. Parker, A. Hudson, and D. Martin, “Off-grid energy sustainability in nunatakavut, labrador : Centering inuit voices on heat insecurity in diesel-powered communities,” *Energy Research & Social Science*, vol. 62, p. 101382, 2020.
- [103] Société d’habitation du Québec, *Construction d’habitations au Nunavik : Guide de bonnes pratiques*, 2nd ed. Québec, Canada : Société d’habitation du Québec, 2018, deuxième édition, version en ligne. Dépôt légal Bibliothèque et Archives nationales du Québec, 2018. [Online]. Available : <http://www.habitation.gouv.qc.ca>
- [104] C. national de recherches du Canada, *Code de construction du Québec : Chapitre I, Bâtiment / National Building Code of Canada 2015 (modifié)*. Ottawa, ON, Canada : Conseil national de recherches du Canada, 2022, Édition modifiée pour le Québec. [Online]. Available : <https://nrc-publications.canada.ca/eng/view/object/?id=bf4d8bef-e7d9-438c-b077-55423410a7d6>

## Appendix A - Version en Français

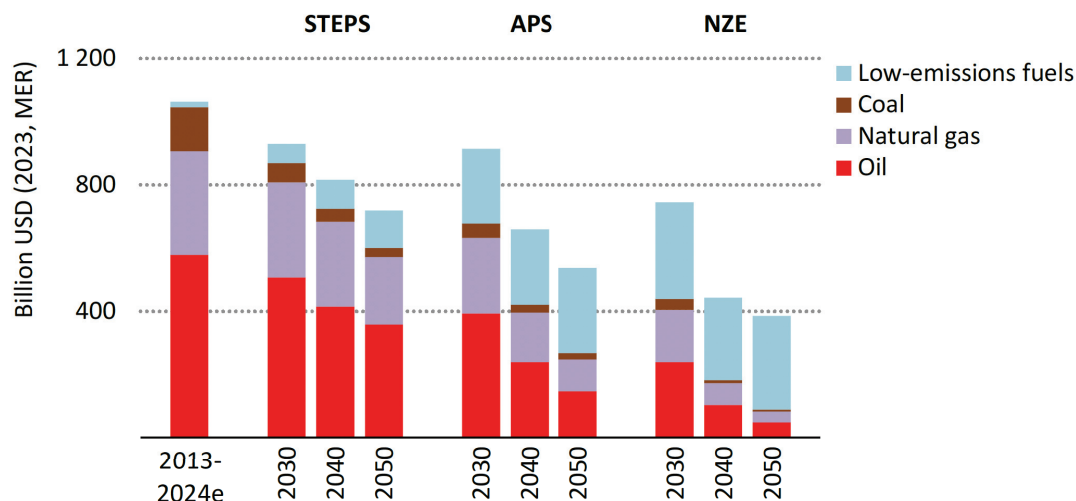
### A.1 Contexte général

Le monde est confronté à de nombreux défis environnementaux qui nécessitent une transition énergétique vers une production plus durable et une consommation plus efficace [3]. À cet égard, la fenêtre pour atteindre des émissions nettes nulles d'ici 2050 se referme rapidement, mais il reste encore du temps pour remettre le monde sur la bonne voie grâce à des actions rapides. La transition énergétique s'est accélérée au cours des dernières années, le rythme du déploiement des technologies propres et des investissements en capital atteignant des niveaux record [1]. À titre d'exemple, l'Agence internationale de l'énergie (AIE) établit trois scénarios : le scénario des politiques déclarées (STEPS), le scénario des engagements annoncés (APS) et le scénario des émissions nettes nulles (NZE).

Comme l'indique la Figure 1.1, atteindre les scénarios NZE et APS (les plus ambitieux) nécessite des investissements énormes. Les investissements dans le secteur de l'électricité devraient augmenter aux alentours de 70% d'ici 2035 dans le scénario STEPS, les hausses les plus importantes étant observées dans les réseaux électriques et les énergies renouvelables. L'investissement annuel dans les combustibles fossiles diminue, passant de 1 000 milliards de dollars à 650 milliards de dollars dans le scénario STEPS à 2050, et chute à 90 milliards de dollars dans le scénario NZE. Les combustibles à faibles émissions ouvrent la voie à la diversification ; dans les scénarios APS et NZE, ils jouent un rôle fondamental dans l'économie de l'énergie propre.

Au cours des dernières années, les investissements énergétiques ont augmenté progressivement, passant de 2,2 billions à 2,8 billions de dollars. Presque toute cette augmentation a été dirigée vers les énergies propres et les infrastructures, représentant désormais 1,8 billion de dollars contre seulement 1 billion pour les combustibles fossiles [1]. Tous ces investissements sont nécessaires pour répondre à la forte augmentation prévue de la demande d'électricité dans les secteurs allant de l'industrie et du bâtiment aux transports. Les plus grands consommateurs d'électricité aujourd'hui sont les secteurs du bâtiment et de l'industrie, qui totalisent à eux deux plus de 90% de la consommation mondiale. Le chauffage, la ventilation et la climatisation, les appareils électroménagers représentent la majeure partie de la consommation dans les bâtiments, et la demande d'électricité devrait augmenter dans tous ces domaines. Du côté industriel, la tendance est similaire : la production croît sous l'effet des politiques de réduction des émissions qui favorisent l'électrification des équipements. Pareillement, le secteur des transports contribue de manière importante à la croissance prévue de la demande, en raison de la forte adoption des véhicules électriques.

Pour faire face à de telles projections d'augmentation de la demande, le monde s'est engagé dans un déploiement massif de sources d'énergie renouvelables afin d'atténuer



IEA. CC BY 4.0.

FIGURE A.1 – Investissement annuel moyen dans l’approvisionnement en combustible par type et scénario, 2013-2050

l’impact climatique. Malgré le potentiel considérable qu’offrent les projets de grande échelle pour atteindre rapidement les scénarios projetés, de nombreux pays à travers le monde sont confrontés à des retards liés aux procédures d’autorisation environnementale, ce qui repousse la date de mise en service de ces projets. Alors que le temps presse pour atteindre les objectifs climatiques ambitieux, les décideurs doivent regarder au-delà des seules initiatives à grande échelle, comme l’illustre le cas de la production décentralisée. Les ressources énergétiques distribuées (RED) offrent de multiples avantages aux consommateurs, soutiennent la décarbonation et améliorent la résilience. Une grande partie des réseaux actuels a été conçue pour le mode de fonctionnement du 20<sup>ème</sup> siècle, à une époque où l’adoption des DER était minuscule. À date, alors qu’une proportion croissante de l’électricité provient de sources renouvelables variables, une plus grande flexibilité du système est nécessaire pour équilibrer en permanence l’offre et la demande.

Tout cela favorise le besoin de stratégies centrées sur les citoyens, dans lesquelles les consommateurs finaux jouent un rôle crucial, contrairement aux situations actuelles où ils ne participent aux opérations quotidiennes du marché de l’électricité. Les réseaux électriques modernes rassemblent de nombreux acteurs aux intérêts et contraintes techniques variés, poursuivant des objectifs souvent divergents, et parfois contradictoires. Cela crée la nécessité de développer de nouveaux instruments technologiques, de mettre à jour les cadres réglementaires et d’établir de nouvelles structures de marché de l’énergie [4].

Dans cette optique, le concept de communauté énergétique (CE) émerge pour répondre à ces enjeux. Par définition, les CE sont des organisations dont les membres s’impliquent activement dans la mise en de mesures d’utilisation rationnelle de l’énergie et l’introduction

de sources d'énergie renouvelables dans la production et la consommation à diverses fins [5]. Grâce à l'essor mondial de la production décentralisée, les CEs peuvent contribuer à répondre aux besoins de la transition énergétique en décentralisant les mécanismes de gestion conventionnels, en facilitant la participation active de la demande [6], ainsi qu'en améliorant l'accès à l'électricité dans les zones éloignées.

Les expériences des pays développés et de certains pays en développement montrent que les consommateurs résidentiels peuvent modifier leurs habitudes de consommation en présence d'un prix dynamique [7]. Le succès de ce genre de mécanismes est fortement lié aux systèmes ayant énergies renouvelables, ce qui encourage ainsi des prix compétitifs. Cependant, les sources renouvelables étant par nature intermittentes, ces incertitudes se propagent à travers le réseau électrique. La littérature aborde principalement cette problématique à travers les technologies de stockage [8, 9]. Le stockage d'énergie se classe en quatre grandes catégories selon les propriétés physiques des matériaux : électrochimique (batteries), mécanique (pompage hydraulique, air comprimé), chimique (hydrogène) et thermique. Les batteries offrent des temps de réponse rapides et conviennent à court terme, mais leur durée de vie, leurs impacts environnementaux et la gestion de leurs déchets demeurent problématiques. En outre, le stockage mécanique exige des conditions géographiques spécifiques et sont soumises à diverses contraintes, ce qui limite leur adoption à grande échelle. Au niveau du stockage d'hydrogène, bien qu'il présente une densité énergétique élevée, il implique d'importantes pertes de conversion donc réduisant considérablement l'efficacité globale.

En revanche, le stockage d'énergie thermique (SET) devient une alternative compétitive, portable, entre autres atouts. Cette technologie porte une importance particulière, car une grande partie de la consommation énergétique mondiale est consacrée aux applications de chauffage et de refroidissement [10, 11]. Contrairement à d'autres formes de stockage, le SET ne présente pas de problèmes liés à la gestion des déchets. En plus, il s'agit d'une solution mature et rentable, surpassant ses homologues sur les domaines technique, économique et environnemental [12, 13]. Le SET permet de profiter les excédents d'électricité renouvelable pour stocker la chaleur en vue d'une utilisation ultérieure, améliorant ainsi l'efficacité énergétique et la stabilité du réseau. Sa forte densité énergétique et sa versatilité pour des applications permettent d'atténuer les effets de saisonnalité, générant des atouts économiques tant en été qu'en hiver. Par conséquent, le TES peut jouer un rôle essentiel dans la réduction de l'empreinte carbone des plusieurs secteurs. Dans ce contexte, le concept de communautés énergétiques équipées de stockage thermique émerge comme une stratégie prometteuse pour relever de multiples défis liés à la transition énergétique.

En contrepartie, les communautés énergétiques sont confrontées à plusieurs défis, notamment i) le manque de mécanismes assurant leur durabilité, ii) des cadres réglementaires appropriés, et iii) la consultation préalable, entre autres [14]. Cependant, en ce qui concerne l'exploitation optimale des communautés énergétiques pour des tâches de planification

énergétique à court terme, c'est un terrain étant toujours peu exploré. Leur fonctionnement implique non seulement des modèles complexes de prise de décision et de gestion de l'incertitude, mais aussi la conception de stratégies permettant aux acteurs énergétiques d'anticiper les risques avant d'investir du capital.

Cette thèse contribue à la littérature en développant des méthodes stochastiques permettant l'optimisation distribuée de communautés énergétiques intégrant le stockage thermique. Les méthodes proposées traitent des difficultés liées à i) la caractérisation et la modélisation appropriées des besoins énergétiques, ii) la coordination des ressources distribuées en présence d'incertitudes, et iii) la planification énergétique robuste afin d'anticiper les risques potentiels. L'ensemble de ces approches vise à optimiser les bénéfices économiques individuels et la performance collective du système.

Alors que le contexte précédent a présenté le cadre général de la transition énergétique et l'émergence des communautés énergétiques comme vecteurs de décentralisation et de flexibilité, la section suivante se concentre sur leur application dans les régions froides et isolées, où les contraintes climatiques et géographiques mettent les systèmes énergétiques à l'épreuve. À cet égard, le Nord du Québec constitue une étude de cas représentative en raison de ses conditions climatiques extrêmes, de son isolement et de sa forte dépendance aux combustibles fossiles. Par contre, les mécanismes et méthodologies proposés dans cette thèse ne se limitent pas à cette région : ils sont conçus pour être transférables et évolutifs à d'autres contextes confrontés à des problématiques similaires d'intermittence et de demande dominée par le chauffage, offrant ainsi des perspectives pour une mise en oeuvre élargie de systèmes énergétiques communautaires fondés sur les énergies renouvelables.

## **A.2 Perspectives de transition pour les communautés nordiques**

La grande majorité des 300 communautés éloignées du Canada dépendent encore des combustibles fossiles pour couvrir leurs besoins essentiels. En particulier, les communautés isolées du Nord du Québec, telles que celles du Nunavik, reposent presque exclusivement sur le diesel pour la production d'électricité et utilisent, en complément, du mazout pour répondre à la demande de chauffage résidentiel. Cette forte dépendance aux combustibles fossiles entraîne une empreinte environnementale très élevée - chaque citoyen y contribue environ 514 kg de CO<sub>2</sub> par mois, principalement attribuable à la demande de chauffage durant les hivers rigoureux [16]. Les bâtiments sont généralement équipés de fournaies ou de chaudières au mazout, tandis que l'électricité est produite principalement par des génératrices diesel [17].

Comme le Nunavik n'est pas raccordé au réseau provincial de transport d'électricité, chaque communauté satisfait ses besoins énergétiques à l'aide de coopératives locales

d'énergie, tandis qu'Hydro-Québec exploite les génératrices diesel. En conséquence, afin d'atténuer l'essor du coût de la vie, l'énergie est subventionnée dans cette région par le programme de subvention du carburant, qui réduit considérablement le coût de l'électricité et du mazout pour les résidents - aux alentours de 2,22 \$/L avant subvention et de 1,554 \$/L après subvention [18].

D'un autre côté, dans le Nord du Québec, les flux monétaires liés à l'énergie entre les parties prenantes et les organisations locales sont uniques et très peu susceptibles de dévoluer à court terme. En revanche, dans d'autres régions éloignées du Canada, le prix de l'électricité peut atteindre jusqu'à huit fois celui observé dans les centres urbains [102]. Cette disparité renforce les inégalités sociales et l'insécurité énergétique, tout en limitant l'efficacité des signaux de prix comme incitations à la réponse à la demande ou aux stratégies d'efficacité énergétique [16].

Par ailleurs, les normes de construction dans ces régions diffèrent fortement de celles des bâtiments conventionnelles en ce qui concerne les matériaux, les préférences et l'usage de l'énergie. Les constructions sont généralement conçues avec des enveloppes à forte isolation thermique et des matériaux adaptés aux conditions climatiques extrêmes, ce qui les distingue des constructions standards [19]. À titre d'exemple, les occupants du Nunavik manifestent une préférence marquée pour le confort thermique et la stabilité de la température intérieure, maintenant souvent des températures élevées et ouvrant les fenêtres même durant les périodes froides afin d'améliorer la qualité de l'air plutôt que d'économiser l'énergie. Ce comportement traduit clairement des priorités culturelles et psychologiques en faveur du bien-être et de la chaleur stable plutôt que de la conservation énergétique, comme l'ont constaté Cavalier et al. [20] à travers des mesures sur le terrain et des entretiens avec des occupants à Quaqtaq. Cela dit, la croissance démographique et la demande énergétique croissante en plus de l'impact environnemental du mazout utilisé pour le chauffage, appellent de nouvelles approches, notamment le recours à des sources d'énergie renouvelable pour fournir une énergie propre, locale et fiable à ces communautés [15].

Dans cette perspective, bien que les projets d'énergie renouvelable constituent un outil potentiel pour réduire l'empreinte carbone, les ménages de cette région deviennent progressivement plus conscients de leurs atouts, toujours en exprimant des préoccupations liées à la fiabilité et au confort [21]. Si l'intérêt pour les panneaux solaires ou les éoliennes se manifeste, les habitants demeurent encore prudents face à ces technologies dans des conditions climatiques extrêmes. Les ménages peuvent exprimer un certain scepticisme à l'égard de technologies non éprouvées dans des climats polaires, en particulier lorsqu'il s'agit de remplacer des systèmes de chauffage conventionnels. Ces perceptions montrent que la réussite de l'intégration des sources renouvelables doit se baser pas seulement sur un dialogue communautaire qui exprime de façon claire des bénéfices mais encore sur des solutions techniques répondant directement aux enjeux de fiabilité et de confort [22].

Toutefois, cette thèse ne cherche surtout pas à reproduire le système énergétique actuel, mais à explorer un scénario prospectif de transition. Dans ce scénario, les technologies d'énergie renouvelable sont combinées au stockage d'énergie thermique et complétées par le diesel en tant que backup. L'introduction de REDs avec des stratégies de gestion ouvre de nouvelles possibilités de flexibilité du côté de la demande et d'échanges d'informations, préparant ainsi la voie au déploiement de communautés énergétiques locales dotées de marchés intégrés. Cela dit, cette thèse doit être comprise comme une analyse orientée vers la transition, et non comme une représentation de la situation énergétique actuelle au Nunavik. En opposant la réalité présente à un scénario futur potentiel intégrant les énergies renouvelables, le stockage thermique et les systèmes de chauffage électrique, cette thèse offre un éclairage technique sur les leviers nécessaires à la mise en d'une transition énergétique communautaire dans le Nord du Québec. Cependant, les enseignements et méthodologies proposés ne se limitent pas à cette région : ils peuvent également être déployés à toute autre zone présentant une forte dépendance aux charges thermiques électriques et un potentiel renouvelable significatif.

### A.3 Motivation

Le changement climatique impose une décarbonation rapide des économies, mais le déploiement massif des énergies renouvelables reste freiné par les contraintes d'infrastructure et d'approbation environnementale. Dans ce contexte, des stratégies décentralisées ont émergé comme des voies complémentaires pour accélérer la transition énergétique. Parmi elles, les communautés énergétiques (CE) suscitent un intérêt croissant, car elles intègrent les ressources énergétiques distribuées (DER) au sein d'initiatives centrées sur les citoyens, permettant aux consommateurs de devenir des acteurs actifs du processus de transition. Issues de la libéralisation des marchés de l'électricité, les CE traduisent les principes d'efficacité et de concurrence en modèles locaux de gouvernance et de coopération [2]. L'intégration des sources d'énergie renouvelable dans ces communautés offre des incitations économiques et favorise la durabilité locale, mais leur variabilité exige de recourir à des technologies de stockage. Le STE, et plus particulièrement le stockage thermique électrique, se distingue par ses avantages économiques notables par rapport aux batteries au lithium-ion, avec un coût nivelé du stockage compris entre 0,1 et 25 USD/kWh, contre environ 125 USD/kWh pour les batteries [2]. Cette large fourchette reflète la diversité technologique du STE : les systèmes matures à stockage sensible (réservoirs d'eau, matériaux solides) atteignent des coûts bas grâce à leur simplicité et leur longévité, tandis que les options latentes ou thermochimiques demeurent plus coûteuses. Ce différentiel de coût positionne le TES comme une solution flexible et rentable pour accroître l'autoconsommation, soutenir l'intégration des énergies renouvelables et réduire la dépendance au réseau. Cette approche s'avère particulièrement pertinente dans les régions nordiques comme le Québec, où les besoins de chauffage et de climatisation représentent environ 60 à 70% de la consommation d'électricité [23], et où la réduction des coûts initiaux liés aux batteries thermiques

pourrait permettre aux consommateurs de réaliser des économies sous des régimes tarifaires dynamiques.

Pour répondre aux besoins de planification énergétique optimale à court terme, les systèmes de gestion de l'énergie domestique (HEMS) peuvent assister les utilisateurs en assurant des économies financières tout en maintenant la fiabilité de l'alimentation énergétique. Cependant, l'incertitude associée à la production d'énergie renouvelable peut compromettre ces deux objectifs si elle n'est pas adéquatement prise en compte dans les processus de décision. On peut extrapoler cet effet à l'échelle d'un quartier, où plusieurs HEMS sont déployés pour représenter les intérêts de chaque utilisateur. Cela engendre plusieurs difficultés :

- **Manque de coordination et de communication entre les utilisateurs finaux :** l'absence de mécanismes de partage d'information peut engendrer des comportements égoïstes, affectant ainsi la collaboration entre les utilisateurs et réduisant l'efficacité énergétique globale du système.
- **Incertitudes liées à l'offre et à la demande :** d'une part, les fluctuations météorologiques affectent la précision des prévisions de production renouvelable ; d'autre part, les profils de consommation des utilisateurs, bien que partiellement prévisibles à partir de données historiques et de modèles probabilistes, demeurent stochastiques. Les écarts de court terme liés à des facteurs comportementaux ou contextuels justifient donc de traiter la demande comme incertaine et motivent la conception de modèles stochastiques adaptés.
- **Hétérogénéité des préférences des utilisateurs :** chaque occupant possède des priorités différentes. Certains privilégient les économies financières, tandis que d'autres recherchent avant tout le confort. Il devient dès lors difficile de concevoir un système de décision unifié.

Malgré ces défis, de nombreux chercheurs privilégient toujours une approche centralisée bien qu'elle ne permette pas d'intégrer des mécanismes de redondance. À l'inverse, les architectures distribuées, de plus en plus répandues à l'échelle mondiale, se caractérisent par une complexité accrue, car une grande partie de la prise de décision est transférée vers la demande, en divisant un problème unique en plusieurs sous-problèmes. Par contre, il faut tenir compte les suivants enjeux : (i) l'absence d'échange d'information entre les participants (comportements égoïstes), (ii) une information imparfaite sur la production renouvelable (erreurs de prévision météorologique) et sur les charges non contrôlables (habitudes des utilisateurs), et (iii) des préférences hétérogènes. De plus, les informations issues de projets réels intégrant des ATL dans des climats froids demeurent limitées, ce qui restreint les possibilités de construire des cadres thermo-énergétiques robustes pour la génération de scénarios. Face à ces défis, le développement d'une approche permettant d'obtenir des profils de demande plus harmonieux et une infrastructure expérimentale pour évaluer les algorithmes de décision en conditions d'information imparfaite constitue la motivation principale de cette thèse.

Ces difficultés sont encore plus marquées dans les environnements extrêmes. Par exemple, la province de Québec connaît des conditions d'accès difficiles, et sa région nordique dépend fortement des combustibles fossiles, ce qui influence la planification énergétique. Dans ces contextes, le déploiement de schémas de gestion énergétique intégrant le stockage thermique et les ressources renouvelables peut réduire les effets néfastes liés à l'utilisation de générateurs diesel. L'adoption de telles technologies au sein d'un scénario communautaire d'énergie peut favoriser la transition vers des systèmes énergétiques plus résilients.

## A.4 Problématique de thèse

Au Québec, le coût d'exploitation des réseaux électriques hors réseau est près de vingt fois supérieur à celui du réseau principal. Ces systèmes, situés dans des régions nordiques isolées et alimentés principalement par des centrales au diesel, découragent l'utilisation de l'électricité pour le chauffage, obligeant ainsi les propriétaires de bâtiments à recourir à des chaudières individuelles au mazout, ce qui accroît considérablement les émissions de carbone.

Dans ce contexte, la transition énergétique en cours appelle au déploiement de communautés énergétiques (CE) intégrant des ressources solaires et éoliennes comme alternatives compétitives aux combustibles fossiles. Cependant, la variabilité et l'imprévisibilité des énergies renouvelables compromettent la continuité et la fiabilité de l'approvisionnement énergétique, en particulier durant les hivers rigoureux où la demande de chauffage atteint son maximum. Bien que les batteries puissent assurer l'équilibre entre production et consommation, leur coût élevé limite leur adoption à grande échelle. Le stockage thermique électrique apparaît alors comme une solution économiquement compétitive, nécessitant un investissement initial plus faible et permettant de réaliser entre 20 et 40 % d'économies tout en facilitant l'intégration des énergies renouvelables [24]. Cependant, les initiatives actuelles reposent souvent sur un contrôle direct de la charge, ce qui compromet la vie privée des utilisateurs et recentralise la prise de décision, freinant ainsi la transition vers des communautés énergétiques véritablement décentralisées [25–27].

Pour résoudre ce problème principal, il faut quand même souligner les défis ci-dessous :

- Manque d'informations détaillées sur les projets qui intègrent des ATL : Les données existantes proviennent principalement des fabricants, et les modèles actuels assimilent souvent ATL à des batteries électriques, sans tenir compte des phénomènes thermiques non linéaires ni des interactions complexes avec les systèmes CVC (chauffage, ventilation, climatisation). De plus, la variabilité météorologique rend difficile la prédiction du comportement des bâtiments équipés des ATL.
- Prise de décision distribuée sous information imparfaite : Les méthodes de coordination décentralisée sont sensibles aux erreurs stochastiques de prévision météorologique et

à la variabilité des sources renouvelables, ce qui accroît l'incertitude opérationnelle, les coûts et l'inconfort des utilisateurs.

- Décisions côté demande tenant compte du risque : Le comportement prudent (aversion au risque) des consommateurs, en situation d'incertitude sur la production renouvelable disponible, peut conduire à des stratégies de chauffage conservatrices et à une augmentation des importations d'énergie. L'intégration de méthodes d'optimisation stochastique sensible au risque devient essentielle pour anticiper les pires scénarios, bien qu'elle entraîne une complexité computationnelle élevée (NP-difficile).

## A.5 Objectifs

Cette recherche s'articule autour de l'objectif principal suivant : concevoir une approche permettant de comprendre les besoins des communautés énergétiques, en proposant une stratégie distribuée visant à encourager efficacement les consommateurs résidentiels à participer à un marché local de l'énergie.

1. Modéliser et caractériser l'environnement thermoénergétique du réseau autonome. Cet objectif comprend le développement d'outils de simulation, de co-simulation et de modèles statistiques et stochastiques pour caractériser la production et la consommation et leur dépendance aux facteurs environnementaux spécifiques aux régions éloignées.
2. Concevoir une stratégie de gestion énergétique distribuée capable d'effectuer un contrôle prédictif à un horizon d'un jour pour chaque bâtiment. Ces contrôleurs auront accès aux données de prévisions météorologiques et aux signaux de l'opérateur du réseau. Des modèles de l'environnement d'action local (ressources du bâtiment) seront construits à l'aide d'algorithmes d'apprentissage automatique sans intervention humaine.
3. Réduire l'impact des erreurs stochastiques de prévision de l'énergie renouvelable et de la météo au niveau du client en proposant une stratégie robuste de gestion de l'énergie distribuée. Compte tenu des préoccupations des clients concernant l'énergie renouvelable et les prévisions météorologiques, cette stratégie permet au coordinateur communautaire de calculer la quantité d'énergie à distribuer, compte tenu de divers profils de demande agrégée.

## A.6 Contributions

La réalisation des objectifs proposés a conduit à trois contributions principales :

- **Contribution I : Caractériser des environnements thermo-énergétiques pour les communautés avec des configurations avancées.** Construire un cadre qui implique les caractéristiques des communautés pendant les hivers rigoureux. Ce cadre comprend des outils de modélisation de pointe qui permettent d'étudier les interactions complexes entre la dynamique thermique des bâtiments et les unités de stockage thermique électrique.
- **Contribution II. Faire du progrès dans la planification énergétique optimale distribuée via l'optimisation stochastique dans les communautés fortement pénétrées par l'énergie renouvelable et le stockage thermique :** Proposition d'une gestion stochastique distribuée de l'énergie englobant une stratégie de coordination énergétique pour les territoires éloignés avec ATL distribuées et des sources renouvelables. Une telle stratégie exploite des méthodes de théorie des jeux pour modéliser l'interaction entre un coordinateur local et les habitants de la communauté énergétique.

## A.7 Etat de l'art

La notion de communautés énergétiques a émergé principalement pour combler les lacunes énergétiques et autonomiser les consommateurs finaux. Ce concept trouve son origine au Danemark dans les années 1970, lorsque des communautés danoises ont mis en place des projets éoliens appartenant à la collectivité. Ces coopératives ont mutualisé leurs ressources locales pour installer des éoliennes, marquant ainsi l'une des premières mises en oeuvre à grande échelle d'un projet appartenant à la communauté. Des initiatives similaires ont vu le jour en Allemagne, aux Pays-Bas et aux États-Unis. Toutefois, à cette époque, le déploiement à petite échelle de ce genre de projets faisait face à des coûts initiaux élevés et à l'absence de progrès significatifs en électronique de puissance.

Les avancées en électronique de puissance et en science des matériaux ont permis un essor considérable des énergies renouvelables, notamment du photovoltaïque et de l'éolien, dont les coûts continuent de diminuer. Ces progrès rendent désormais possibles des projets à l'échelle résidentielle, bien que les investissements restent au moins deux fois plus élevés dans les régions difficiles d'accès (Figure A.2). Les zones isolées représentent ainsi un fort potentiel pour les communautés énergétiques, où l'objectif est de réduire la dépendance aux combustibles fossiles utilisés pour le chauffage des espaces et de l'eau, couvrant environ 80% de la consommation résidentielle totale au Québec. Cependant, les tarifs appliqués à l'électricité incitent encore les ménages à recourir au mazout. Face à ce contexte, diverses études ont proposé des solutions pour les territoires froids et éloignés, notamment les

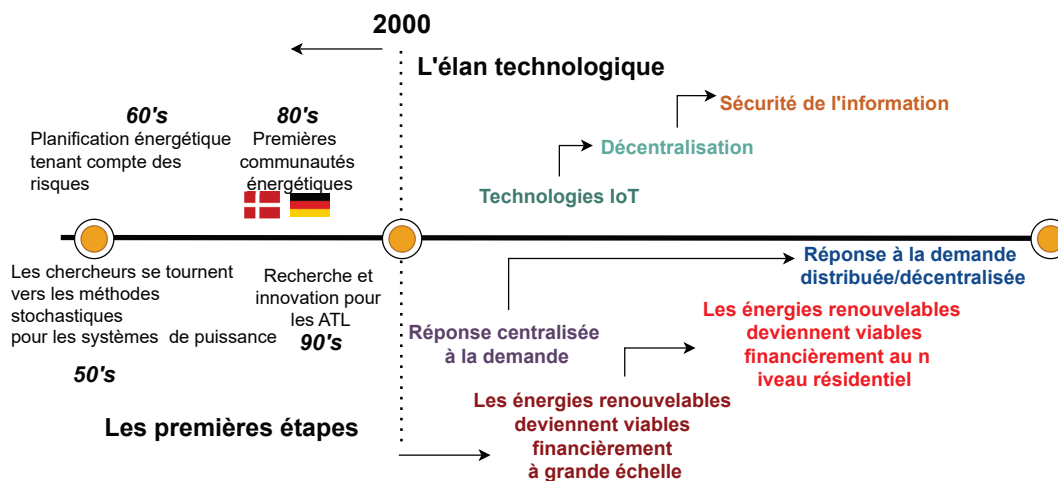


FIGURE A.2 – Aperçu chronologique des thèmes abordés dans cette thèse.

systèmes géothermiques à haut coefficient de performance, mais leur coût d'investissement élevé limite leur déploiement. Les accumulateurs thermiques locaux (ATL) apparaissent alors comme une alternative portable et économique, étudiée pour le contrôle en temps réel, le dimensionnement optimal [28], l'intégration des renouvelables [29], la gestion de la réponse à la demande [24, 30] et la modélisation [31, 32]. Dans ce contexte, la recherche actuelle s'intéresse beaucoup à l'intégration des ATL dans les bâtiments raccordés aux réseaux basse tension et aux défis de leur coordination pour éviter les impacts négatifs sur la stabilité du réseau. Dans cette même ligne, l'essor des stratégies distribuées dans les domaines de l'énergie, des communications et de la cybersécurité a transformé la gestion des ressources énergétiques. Dans les réseaux électriques, le contrôle tertiaire vise l'optimisation du flux d'énergie en intégrant les prévisions météorologiques ainsi que celle de la demande, mais la prise de décision décentralisée exige des outils mathématiques adaptés pour gérer les conflits d'intérêts et les incertitudes. Les algorithmes de consensus sont alors utilisés pour résoudre ces problèmes de manière distribuée, tandis que les approches stochastiques permettent d'anticiper les effets de la variabilité côté offre et côté demande.

Toutefois, les méthodes classiques, basées sur des moyennes statistiques, ne fournissent les éléments nécessaires permettant une planification robuste. Ces approches, apparues dans les années 1950, permettent une analyse du pire cas, essentielle pour les systèmes électriques. Ces méthodes ont évolué vers des formulations plus avancées, telles que l'optimisation robuste distributionnelle et l'optimisation sous contraintes de chance, qui réduisent le conservatisme des modèles traditionnels. Enfin, cette thèse aborde trois sous-problèmes : la modélisation thermique des bâtiments équipés d'ATL avec données limitées, la gestion distribuée des bâtiments sous incertitude à l'aide de méthodes stochastiques,

et l'intégration de préférences de risque dans la planification, nécessitant des outils de décision adaptés pour traiter la non-convexité et la non-différentiabilité des fonctions de risque.

## **A.8 Description des résultats publiés**

L'examen des objectifs visés est présenté dans les articles de cette section. Nonobstant les discussions précédentes, chaque article détaille la contribution, l'approche et l'état de la technique concernant l'objectif proposé. En conséquence, les méthodes mathématiques et les procédures expérimentales pour atteindre les ambitions sont décrites. Par la suite, les évaluations et les résultats sont rapportés pour démontrer l'efficacité des cadres développés dans chaque manuscrit. Les sections suivantes proposent les articles.

## **A.9 Modélisation**

### **A.9.1 Contexte**

La gestion efficace de l'énergie dans les climats froids requiert un cadre rigoureux fondé sur des méthodes robustes et des modèles précis. En raison de la complexité multidisciplinaire du problème et du manque de données disponibles, il est essentiel de disposer d'outils de modélisation capables de représenter fidèlement les interactions entre technologies et stratégies décisionnelles. Les recherches menées se concentrent ainsi sur le stockage thermique électrique et son intégration dans les systèmes de gestion énergétique domestique, soulignant la nécessité d'algorithmes de coordination décentralisée avec un échange d'informations minimal. Dans ce contexte, le développement d'un modèle open source basé sur la modélisation orientée objet et d'une approche de coordination énergétique distribuée constitue la base de l'approche proposée, permettant la génération de données synthétiques pour les bâtiments équipés d'ATL lorsque les données réelles sont limitées.

### **A.9.2 Méthodologie**

Vu que les informations opérationnelles sur les projets énergétiques régionaux sont limitées, la modélisation constitue une approche essentielle pour combler ces lacunes, en particulier dans les régions exposées à des hivers rigoureux où la performance énergétique dépend fortement des conditions météorologiques. Alors que la littérature offre plusieurs méthodes pour modéliser la consommation énergétique des bâtiments, peu d'études abordent les accumulateurs thermiques locaux (ATL). Pour pallier ce manque, la consommation des bâtiments a été modélisée sous EnergyPlus, tandis qu'une librairie dédiée a été conçue pour générer un modèle basé sur le langage Modelica pour les ATL. Ce dernier, orienté objet et basé sur des équations acausales, permet une représentation précise des phénomènes multi-domaines. Le modèle Modelica a été construit à partir des données fabricants et validé

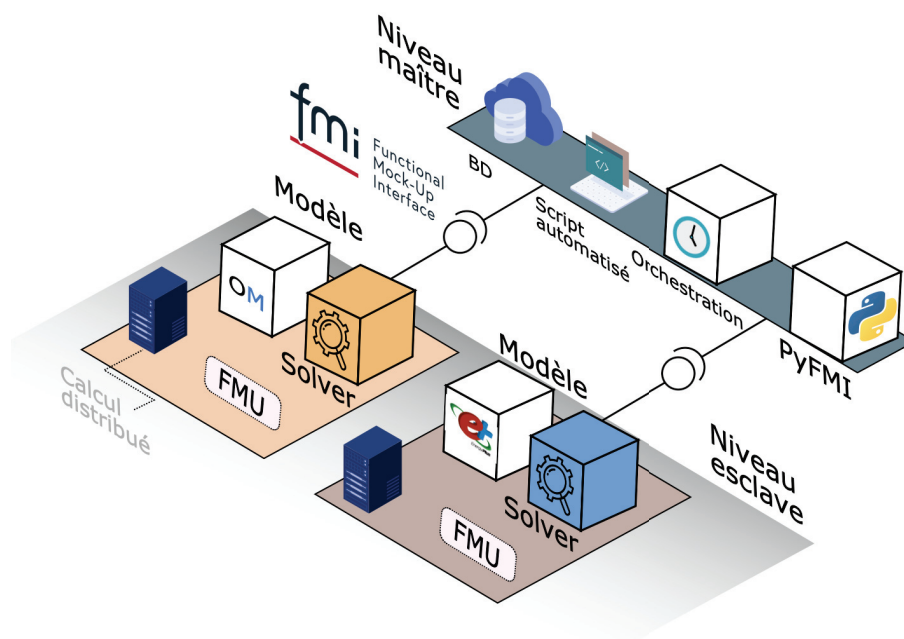


FIGURE A.3 – Approche FMU pour la cosimulation

à l'aide de mesures expérimentales, a ensuite été couplé à EnergyPlus via le protocole FMI, en utilisant PyFMI comme outil maître et en intégrant les deux modèles dans des FMU pour la co-simulation (Figure A.3).

Cette approche a permis de générer des données synthétiques destinées à la construction de modèles d'espace d'état simplifiés, utilisés pour le contrôle optimal via HEMS à l'aide de méthodes de régression aux moindres carrés. Enfin, la définition des caractéristiques d'offre et de demande, ainsi que la modélisation des erreurs de prévision météorologique, ont permis de réaliser une gestion distribuée de l'énergie fondée sur la coordination énergétique (voir Figure B.15).

### A.9.3 Résultats

#### Synthèse des résultats

L'étude sur la modélisation thermoénergétique des bâtiments et la coordination distribuée des ressources sous incertitude a conduit aux remarques suivantes :

- Un environnement thermoénergétique multi-zones intégrant des accumulateurs thermiques locaux (ATL) a été construit avec succès, permettant une analyse énergétique complète.
- Les prévisions météorologiques (irradiation, humidité, température, vent) et leurs

- erreurs ont été modélisées sur un an pour une région du Québec.
- Le modèle Modelica proposé a montré une erreur inférieure à 5 % dans les scénarios de convection libre et forcée.
  - L'intégration d'ATL permet des économies de coûts importantes selon la tolérance des clients au confort thermique.
  - La gestion distribuée améliore simultanément le confort thermique et réduit les coûts d'exploitation du réseau.
  - Le leader du jeu a traité la stochasticité de la production éolienne via une approche par scénarios, réduisant les coûts du réseau grâce au signal de prix.
  - Les experiments montrent qu'une participation accrue des clients équipés d'ATL n'améliore pas toujours le bien-être individuel.
  - La stratégie proposée a réduit le rapport pic/moyenne de plus de 45 % malgré des informations imparfaites sur la production éolienne.

Il convient de mentionner que différents situations dépassent la portée de l'approche développé. Par exemple, les HEMS avec des non-linéarités introduites par des scénarios de convection forcée créés par l'ouverture des fenêtres par exemple. De plus, dans notre analyse, l'élasticité des prix du client a été modulée de telle manière que pendant les périodes de pointe conventionnelles, le client souhaitait maintenir ses besoins de confort tandis que pendant les heures de travail, la température intérieure n'était pas un problème et la flexibilité du côté de la demande pouvait être exploitée.

## **A.10 Gestion de l'énergie distribuée avec informationv imparfaite**

### **A.10.1 Contexte**

Pendant la réalisation du premier objectif, le cadre de simulation a été construit et testé en considérant les incertitudes météorologiques, dont l'impact a été évalué à travers l'intégration de l'énergie éolienne centralisée au niveau de l'opérateur du réseau. Des HEMS distribués ont également été déployés chez les consommateurs, intégrant des unités de accumulateurs thermiques locaux. Pour le deuxième objectif, l'analyse a alloué des renouvelables au niveau du client, transformant ainsi les utilisateurs en prosommateurs capables d'exploiter leur propre production. Contrairement aux approches classiques fondées sur les signaux de prix souvent évitées en raison de leurs risques sur l'offre, cette fois ci, la méthodologie tient compte des préférences individuelles tout en intégrant des données réelles sur la température intérieure et la consommation des charges non contrôlables, afin de construire des modèles de bâtiments précis. Cette approche a permis de réduire le coût d'opportunité associé aux erreurs de prévision et à l'incertitude de la demande, tout en validant la robustesse opérationnelle de la stratégie à travers des tests réalisés sur des un test-feeder IEEE. Toutefois, la mise en oeuvre réelle de telles solutions

demeure complexe, nécessitant d'importants investissements, et puis un banc d'essai a été conçu avec une infrastructures physique étendue et des systèmes de communication fiables afin de réduire l'écart entre la vie réelle et la simulation.

### **A.10.2 Méthodologie**

Pour répondre au deuxième objectif, nous avons exploité la programmation stochastique adoptée pour gérer les incertitudes du côté de la demande créées par les erreurs de prévision météorologique et les charges non déplaçables. Étant donné que l'intervention humaine est censée être réduite, nous avons utilisé des algorithmes d'apprentissage automatique et d'optimisation convexe pour saisir les préférences des clients et effectuer des tâches de planification à court terme optimales. La stratégie repose sur un jeu non coopératif qui exploite des algorithmes de décomposition pour effectuer une gestion distribuée de l'énergie. La Figure B.12 résume la procédure.

De plus, pour valider ces résultats, et reconnaissant que la réalisation de tests précis implique des dépenses importantes, nous avons construit une infrastructure cyber-physique. Cette approche informatique distribuée a été adoptée pour réduire le temps de simulation compte tenu des exigences du côté de la demande, en profitant les atouts du calcul distribué. L'infrastructure déploie des agents automatisés capables de i) récupérer leur consommation énergétique historique et leurs préférences thermiques, ii) estimer le modèle de bâtiment RC équivalent, iii) collecter des données météorologiques pour modéliser l'erreur de prévision, iv) collecter des signaux de prix, v) exécuter une prise de décision optimale et iv) échanger des informations avec le coordinateur de la communauté. La figure B.12 illustre un organigramme qui condense la procédure.

### **A.10.3 Résultats**

L'étude de la modélisation des éléments essentiels et l'exercice de coordination des ressources distribuées avec les incertitudes du côté de la demande ont fourni les remarques suivantes :

- Modèles de bâtiments basés sur données réels avec un comportement réaliste des occupants et des préférences thermiques, et une consommation non contrôlable.
- Prise en compte des incertitudes associées aux charges non contrôlables lors du processus de prise de décision pour réduire les effets de l'inconfort thermique.
- La stratégie a pu démontrer convergence sous les incertitudes du côté de la demande.
- La faisabilité technique de la stratégie a montré des résultats marquants concernant l'écrêtement des pics et les profils de tension améliorés dans un test feeder IEEE largement utilisé.
- L'infrastructure cyber-physique construite a utilisé des outils open source et a permis de réduire la charge de calcul de plus de 60%.

- Le bien-être des individus a été comparé à la ligne de base déterministe pour montrer que le système peut être proche mais jamais égal ou meilleur que la prise de décision dans des scénarios d'information parfaite, c'est-à-dire sans erreur de prévision.

## **A.11 Planification énergétique robuste**

### **A.11.1 Contexte**

La perception du risque dans les communautés énergétiques gérées de manière distribuée a été le troisième élément clé qui a retenu notre attention. En particulier, le point central de cette analyse est l'introduction des préoccupations des clients concernant les erreurs de prévision pour des raisons à la fois techniques et mathématiques. Techniquement, il est difficile d'estimer la quantité de réserve de puissance à dimensionner pour faire face aux besoins supplémentaires résultant de l'aversion au risque du côté de la demande pour la perte de confort thermique. Ignorer les questions précédentes peut entraîner des systèmes énergétiques surdimensionnés inutiles qui sont souvent inabordables et non efficaces. Mathématiquement, l'intégration des notions de perception du risque ou de fiabilité implique des contraintes probabilistes qui impliquent des approches non différentielles, non linéaires et non convexes. À cet égard, l'estimation d'équivalents mathématiques déterministes pour ces scénarios complexes est une question peut réduire la complexité du système. Par conséquent, une optimisation qui intègre les préoccupations des consommateurs, également d'une façon distribuée est proposée. En outre, des simulations approfondies ont été réalisées avec une infrastructure de calcul physique améliorée pour évaluer l'impact des préoccupations des clients sur les erreurs de prévision et également pour évaluer l'évolutivité de la stratégie.

### **A.11.2 Méthodologie**

Le thème du troisième objectif est de proposer un mécanisme robuste qui permet d'introduire la perception du risque des clients pour couvrir les besoins de chauffage des locaux en raison d'erreurs de prévision sur la production renouvelable. Pour y parvenir, nous avons adopté des contraintes de hasard individuelles pour modéliser les préoccupations des clients de s'écarter de la zone de confort. En ayant une connaissance complète de la distribution des erreurs de prévision, il a été possible d'estimer des équivalents déterministes qui intègrent les erreurs de prévision cumulatives des conditions météorologiques et de la production renouvelable. Ensuite, un contrôle optimal en tenant compte des risques était possible et les incertitudes liées aux charges non déplaçables ont également été introduites via la programmation stochastique. Les figures B.14 et B.13 illustrent un organigramme permettant d'effectuer une coordination optimale distribuée tenant compte des risques et d'estimer les équivalents déterministes. Enfin, la figure B.14 illustre comment déployer notre stratégie dans une infrastructure cyber-physique améliorée qui a permis d'augmenter

progressivement le nombre de participants en expérimentant les fonctionnalités saillantes fournies par Kubernetes et d'autres outils.

### A.11.3 Résultats

L'étude de la modélisation des risques du côté de la demande ainsi que de la coordination des ressources distribuées a fourni les remarques suivantes :

- Des équivalents déterministes ont été calculés à l'aide de contraintes de hasard individuelles pour intégrer la notion de risque dans la prise de décision optimale tout en équilibrant les termes de coût et d'utilité.
- Le fait d'avoir des opérations système fiables en raison des préoccupations côté demande augmente le coût opérationnel de plus de 22 %.
- Le confort thermique limité par le hasard, lorsqu'il est intégré au problème avec des erreurs de prévision accumulées, peut anticiper les problèmes potentiels qui peuvent apparaître en raison d'incertitudes liées aux conditions météorologiques.
- Des simulations approfondies via une infrastructure cyber-physique réaliste ont validé la performance de la proposition en augmentant les participants du côté de la demande tout en réduisant les efforts de calcul.
- L'approche proposée fournit des informations utiles pour estimer la puissance supplémentaire requise et donc dimensionner les unités de secours et réduire les dépenses d'investissement inutiles.
- La faible valeur à risque et les erreurs de prévision cumulatives ont un impact significatif sur le profil agrégé attendu, créant des situations potentielles de congestion électrique.
- Différentes simulations ont été réalisées à différents niveaux de risque pour évaluer les impacts économiques et techniques.

## A.12 Discussions

*Ce chapitre est consacré à l'analyse des résultats obtenus à partir des méthodes proposées et détaillées dans le chapitre précédent.*

Cette thèse a abordé l'intégration des communautés énergétiques au sein des réseaux de distribution selon une perspective multidimensionnelle, combinant des techniques de modélisation avancées pour caractériser l'environnement communautaire, des modèles d'optimisation stochastique et des bancs d'essai d'implémentation. Les articles associés ont exploré divers aspects du problème, depuis les stratégies de modélisation jusqu'à l'évaluation des impacts technico-économiques avant et après la mise en oeuvre de la stratégie de contrôle de la demande proposée.

Les résultats indiquent qu'une intégration adéquate des communautés énergétiques

dans le réseau, via des méthodes économiquement efficaces, peut améliorer l'efficacité énergétique et maximiser le bien-être des participants (Article 1 et Article 2). Conformément à des travaux antérieurs [96], il a été démontré que la flexibilité de la demande et la production distribuée peuvent compenser efficacement les erreurs de prévision lorsqu'elles sont gérées à l'aide de mécanismes bien définis basés sur la théorie des jeux et les principes de l'optimisation convexe. À cet égard, les résultats de cette thèse prolongent une perspective en montrant que la stratégie proposée est applicable dans des conditions réalistes, après validation par des simulations utilisant des outils informatiques distribués de pointe (Article 2 et Article 3).

En outre, cette thèse n'a pas considéré le partage d'information entre les clients, reflétant ainsi la configuration la plus plausible en conditions réelles, où les utilisateurs ne sont pas intéressés par le comportement des autres et où la confidentialité des données joue un rôle essentiel. En effet, éviter les échanges d'informations entre participants traduit à la fois des réalités techniques et sociales : (i) d'un point de vue technique, la minimisation de la divulgation de données réduit les risques de violation de la vie privée et s'aligne sur les cadres réglementaires qui renforcent la protection des données dans le secteur énergétique ; (ii) d'un point de vue social, les consommateurs valorisent l'autonomie et se peuvent se montrer réticents à partager leurs préférences, susceptibles de révéler des informations sensibles sur leurs habitudes ou leur situation financière ; (iii) d'un point de vue pratique, concevoir des méthodes d'optimisation distribuées fonctionnant dans des conditions de préservation de la confidentialité favorise leur acceptation et leur adoption par les utilisateurs finaux, rendant la stratégie proposée plus proche d'une mise en réelle. Cette approche montre qu'une coordination efficace peut être atteinte sans échange explicite d'informations entre consommateurs, le tout en utilisant des mécanismes mathématiques robustes et des outils de calcul distribué adaptés.

Par la suite, cette thèse a validé les résultats à travers des infrastructures réalistes et des solutions disponibles sur le marché. Les tests de validation ont mis en évidence la capacité de la stratégie proposée à fonctionner efficacement de manière distribuée. De plus, contrairement aux méthodes de coordination publiées précédemment dans la littérature sur la réponse à la demande, l'usage de différentes méthodes stochastiques a permis d'établir des métriques quantifiant la proximité du processus décisionnel avec la référence déterministe parfaite, offrant ainsi une compréhension plus intuitive de la performance des résultats (Article 2). Les expériences menées ont permis d'observer la cohérence de la convergence algorithmique en présence d'informations imparfaite. En effet, la programmation stochastique et les contraintes de chance ont mis en évidence l'importance d'une modélisation adéquate des erreurs de prévision liées aux conditions météorologiques, à la production renouvelable et aux charges non modulables (Article 2 et Article 3). Par ailleurs, l'évaluation des bénéfices pour le coordinateur et les membres de la communauté a montré qu'une participation active des consommateurs ne détériore pas nécessairement le bien-être individuel de certains participants (Article 1).

Comparée aux travaux récents de la littérature [24, 31], cette thèse propose une vision plus complète grâce à l'exploitation des avantages de la *co-simulation distribuée*, permettant une caractérisation plus réaliste de l'environnement thermo-énergétique et économique communautaire lorsque les données réelles sont limitées (Article 1). Cependant, une limitation majeure doit être reconnue : bien que le cadre développé prenne en compte les régimes de convection libre et forcée des ATL, le modèle linéaire du bâtiment ne capture pas les phénomènes non linéaires qui introduisent de l'incertitude dans l'état thermique du bâtiment, tels que l'ouverture et la fermeture des fenêtres en hiver.

Au-delà de cette limitation, la modélisation des équipements ETS ouvre plusieurs perspectives de recherche prometteuses. Premièrement, l'intégration des ATL aux réseaux de chauffage ou de stockage thermique urbains crée des opportunités pour explorer des schémas de coordination hybrides, où des infrastructures centralisées et des stockages distribués interagissent pour renforcer la flexibilité et la résilience à l'échelle communautaire. Deuxièmement, l'étude des ATL de plus grande capacité, opérant dans des configurations centralisées avec chaudières et systèmes HVAC, pourrait permettre d'évaluer le potentiel technico-économique de ces technologies pour les applications résidentielles et commerciales. Enfin, l'adoption des ATL doit être contextualisée selon les structures de marché régionales. Par exemple, au Québec, où l'électricité est facturée à tarif fixe et où l'adoption de tarifs dynamiques demeure limitée, le déploiement des ATL peut sembler peu attractif financièrement pour les utilisateurs. Cependant, des enseignements précieux peuvent être tirés de provinces comme la Colombie-Britannique et le Yukon, où des programmes de subventions et de rabais ont été mis en avec succès pour réduire les coûts initiaux et encourager leur adoption sans alourdir les charges financières des ménages. Cette thèse a démontré que ces stratégies d'adoption fondées sur des incitations peuvent coexister avec des mécanismes de coordination décentralisée, le distributeur ne contrôlant pas directement les ATL situées derrière le compteur. Le cadre d'optimisation distribué et respectueux de la vie privée proposé assure que la flexibilité des ATL peut être efficacement mobilisée tout en préservant l'autonomie et la confiance des clients. Cela ouvre une voie prometteuse où les incitations réglementaires, la viabilité économique et les outils de contrôle distribués convergent pour faire des ATL une solution extensible et socialement acceptable dans les communautés énergétiques réelles.

En ce qui concerne la coordination stochastique distribuée, peu de travaux de la littérature ont proposé un cadre méthodologique solide pouvant être testé sous diverses conditions météorologiques en utilisant des ensembles de données hétérogènes pour construire le modèle thermique correspondant (Article 2). Bien que des études similaires [97, 98] aient abordé le contrôle distribué stochastique dans les communautés énergétiques intégrant stockage thermique et ressources renouvelables, les solutions modulaires reliant les domaines logiciel et matériel demeurent rares. Concernant l'analyse du risque, des travaux récents [99–101] ont contribué à la planification énergétique robuste à court terme pour anticiper les effets indésirables. Cette thèse va plus loin en estimant le *prix de la*

*robustesse* pour les coordinateurs et les membres de la communauté, offrant ainsi une vision plus large des efforts requis par chaque acteur énergétique afin d’anticiper les erreurs de prévision selon leurs préférences de risque.

La formulation de Stackelberg utilisée dans cette thèse a permis de représenter efficacement les interactions hiérarchiques entre coordinateurs et ménages. Toutefois, les communautés réelles ne suivent pas toujours des dynamiques strictes de type leadersuiveur. Cela ouvre la voie à d’autres approches de la théorie des jeux, telles que les modèles de négociation ou les mécanismes d’enchères, offrant de nouvelles configurations d’équité et de concurrence. De plus, la portée technologique de cette thèse, centrée sur les systèmes ATL et renouvelables, doit être comprise comme une composante d’un écosystème énergétique plus large. Les communautés reposent souvent sur des portefeuilles diversifiés de ressources distribuées, par exemple, biogaz, petite hydraulique, pompes à chaleur, solutions hybrides de stockage. L’intégration de ces vecteurs pourrait profondément transformer les résultats de coordination, et pareillement, la flexibilité des ATL reste précieuse lorsqu’elle est complétée par des ressources offrant à la fois des services électriques et thermiques. Par ailleurs, en quantifiant le prix de la robustesse, cette thèse met en lumière une dimension souvent négligée de la coordination distribuée : la distribution asymétrique des coûts face à l’incertitude. Alors que les coordinateurs supportent une charge computationnelle et stratégique plus élevée, les ménages subissent des impacts hétérogènes selon leurs préférences individuelles en matière de risque, soulevant ainsi des questions d’équité. Faut-il centraliser, mutualiser ou subventionner ces coûts de robustesse ? Répondre à ce défi suppose non seulement des outils d’optimisation adaptés, mais aussi des cadres réglementaires intégrant les principes de justice, de responsabilité et d’acceptabilité sociale dans la conception des futures communautés énergétiques.

Pour clore, les conclusions de cette thèse ont des implications importantes, couvrant l’ensemble du processus de la modélisation et des méthodes avancées de planification énergétique sous incertitude à leur mise en . D’un point de vue pratique, les résultats fournissent aux régulateurs et aux entreprises des stratégies optimales pour promouvoir l’adoption des communautés énergétiques. Sur le plan théorique, cette recherche suggère que les modèles actuels d’optimisation énergétique devraient intégrer des modèles de bâtiment plus précis et des informations plus complètes sur l’état du réseau électrique afin d’améliorer la précision des prévisions et l’évaluation du bien-être social.

### **A.12.1 Limitations**

- Les coûts d’exploitation des sources renouvelables n’ont pas été modélisés : bien que ce paramètre puisse représenter une part importante du coût total dans les zones difficiles d’accès parfois même supérieure à celle des générateurs diesel, il n’a pas été pris en compte. Toutefois, son inclusion n’affecterait pas la convexité du problème, car il s’agirait simplement d’introduire une transformation affine dans la

fonction objectif.

- Incapacité du système à détecter les «free-riders» : bien que les expériences numériques et pratiques aient montré la capacité du système à réduire les coûts globaux du réseau avec un partage limité d'informations entre les clients, une limite majeure subsiste concernant les utilisateurs pouvant réaliser des économies tout en ayant des préférences inélastiques. Il s'agit d'une défaillance de marché classique, qui pourrait être atténuée par une évaluation de l'effort individuel et le respect des engagements à travers une allocation optimale des bénéfices garantissant la compatibilité des incitations.
- Manque de perspective juste sur la transition : si le développement économique et l'amélioration de la qualité de vie accompagnent généralement l'électrification de la demande, cela n'est pas nécessairement le cas pour les communautés autochtones. Cet aspect, bien que non abordé ici, constitue un enjeu majeur qui pourrait être modélisé pour offrir une perspective équitable dans les stratégies de décision, notamment concernant la volonté des ménages d'adopter des équipements de chauffage électriques compatibles avec la réponse à la demande. Intégrer une telle dimension humaniste offrirait une vision plus réaliste des scénarios générés.

## A.13 Conclusions

Cette thèse s'est concentrée sur l'étude des méthodes de prise de décision optimales pour l'exploitation des communautés énergétiques distribuées en présence de l'information imparfaite. En explorant de manière approfondie ces systèmes multi-domaines, trois problèmes principaux ont été identifiés pour de futures améliorations. Cette recherche a tenté de définir ces problèmes ainsi que d'autres aspects significatifs du fonctionnement des communautés énergétiques qui n'ont pas encore été largement abordés.

Par la suite, trois principales questions ont été étudiées : les aspects de modélisation, la gestion distribuée de l'énergie sous information imparfaite et l'intégration des risques liés à la demande. Ces investigations ont conduit aux propositions suivantes : un cadre de cosimulation pour la génération de données synthétiques, une stratégie à deux niveaux de prise de décision distribuée et une modélisation des risques pour une planification énergétique robuste. Les approches proposées ont été détaillées dans trois études (articles), chacune apportant les conclusions suivantes.

## A.14 Résumé des travaux

### A.14.1 Cadre de cosimulation

Dans la première étude, le manque de données précises pour les bâtiments intégrant des ATL dans les régions froides, en particulier au Québec, a été traité par le développement

d'un outil de génération de données synthétiques. Cet outil exploite les caractéristiques thermo-électriques des ATL installés dans une maison afin de créer des profils de puissance électrique et thermique en l'absence de données réelles. Les résultats montrent que l'approche proposée reproduit fidèlement les principales caractéristiques des ATL en convection libre et forcée, tout en s'intégrant à des modèles de bâtiments robustes via la co-simulation. Le cadre affiche des erreurs inférieures à 5% pour les deux régimes de convection. En outre, l'intégration d'une production éolienne centralisée a été explorée pour optimiser l'exploitation des clients équipés avec ATL. Ce cadre de co-simulation a ensuite servi à bâtir des modèles de bâtiments exploitables par des outils d'optimisation (méthodes d'apprentissage automatique), permettant une gestion distribuée de l'énergie grâce au déploiement de HEMS et à des méthodes de décomposition. Les simulations montrent que l'augmentation du nombre de clients proactifs (prêts à acquérir un ATL) peut affecter le bien-être individuel, tout en révélant des gains économiques soutenus pour les clients et une réduction des coûts d'exploitation du réseau grâce à l'apport renouvelable. Perspectives. Les travaux futurs pourront cibler l'optimisation en ligne en intégrant le cadre développé pour améliorer la précision des prévisions de demande, ainsi que la création d'une bibliothèque Modelica dédiée à l'ATL Steffes 2102 (composants paramétrables, documentation et exemples de co-simulation), afin de faciliter la reproductibilité et le transfert vers des cas d'étude réels.

#### **A.14.2 Gestion distribuée de l'énergie sous information imparfaite**

Dans cette seconde étude, la gestion distribuée de plusieurs prosummateurs équipés des ATL a été examinée sans échange d'informations entre eux. Contrairement à la première analyse, celle-ci s'est appuyée sur des données énergétiques réelles, produisant des résultats plus représentatifs. Les méthodes de décomposition ont de nouveau été utilisées, cette fois en intégrant l'incertitude des charges non déplaçables par la programmation stochastique, maximisant ainsi le bien-être individuel. La stratégie proposée a démontré sa convergence et sa capacité à lisser la demande. Cependant, bien que sa faisabilité économique soit confirmée, la viabilité technique a été évaluée par simulation sur un réseau basse tension IEEE, révélant une performance pas loin de la référence déterministe. Enfin, la stratégie a été validée sur un cluster de calcul distribué exploitant une pile complète d'outils open source, permettant d'estimer les exigences informatiques des agents automatisés et d'envisager des implémentations à plus grande échelle pour étudier l'impact de l'information imparfaite issue de la génération distribuée dans les communautés énergétiques.

#### **A.14.3 Planification énergétique robuste**

Dans cette troisième étude, l'insuffisance des stratégies de gestion distribuée de l'énergie pour prendre en compte les préoccupations des clients concernant les prévisions météorologiques et la production renouvelable a motivé la mise en place d'une stratégie de gestion des risques plus efficace. En étendant le cadre présenté dans la seconde étude, cette recherche a

modélisé la crainte des clients de perdre leur confort thermique en raison des erreurs de prévision.

Pour ce faire, des analyses approfondies ont été réalisées à l'aide de méthodes d'optimisation sous contraintes probabilistes. Les résultats ont montré que les erreurs de prévision cumulées et les paramètres d'aversion au risque ont un impact significatif sur le profil énergétique global (aux alentours du 22%), même après convergence.

En conséquence, une exploitation fiable du réseau est possible avec un surcoût de 22 %. Une des principales observations de cette étude est que des congestions de puissance peuvent apparaître avec une probabilité allant jusqu'à 37 %. Pour mener toutes ces analyses, l'infrastructure informatique distribuée existante a été améliorée avec des outils de pointe, permettant d'automatiser les fonctionnalités des prosommateurs, y compris l'équilibrage des charges, l'auto-réparation et une configuration rapide. Les recherches futures devraient envisager l'adoption de contraintes de chance conjointes et l'intégration d'autres ressources énergétiques, comme les pompes à chaleur et les batteries électriques, afin d'évaluer leur capacité à répondre aux préoccupations des clients.

Ainsi, la conclusion ci-dessus finalise les analyses approfondies menées dans cette étude pour examiner le concept de gestion décentralisée de l'énergie avec des sources renouvelables et du stockage thermique sous différents angles. Malgré toutes les propositions avancées, l'avenir de ce concept dépend fortement des enjeux réglementaires et de la capacité des communautés à comprendre l'exploitation des réseaux électriques fortement numérisés, ce qui pourrait garantir la durabilité. La mise en œuvre massive de ces stratégies dépend non seulement de la volonté des consommateurs d'adopter les énergies propres, mais aussi des intérêts gouvernementaux, car l'apport d'énergie propre dans les zones difficiles d'accès est souvent économiquement non viable, nécessitant ainsi des subventions pour la rendre abordable. Néanmoins, les fondements des approches proposées, qui prennent en compte les attentes des consommateurs et des opérateurs de systèmes, devraient être intégrés dans les futures analyses énergétiques à court terme et dans les mises en œuvre favorisées pour la production de masse.

## **A.15 Limitations et défis**

### **A.15.1 Affinement des stratégies de gestion des risques côté demande : Contraintes de chance conjointes et méthodes robustes**

Bien que la stratégie proposée ait abordé la gestion des risques côté demande via des contraintes de chance individuelles, elle repose sur des hypothèses qui nécessitent une discussion approfondie. Cette thèse suppose que chaque contrainte déterministe équivalente satisfait une probabilité spécifiée à chaque instant. Cependant, une telle hypothèse peut ne pas être valide dans des implémentations réalistes, car les contraintes probabilistes ont été

modélisées en fonction du confort thermique des locataires, qui présente des propriétés markoviennes, indiquant que l'état actuel du système dépend au moins de l'état précédent. À cet égard, une solution potentielle pour traiter ce problème consiste à calculer des équivalents déterministes avec des contraintes de chance conjointes qui satisfont plusieurs contraintes sous incertitude simultanément. Cette méthodologie est mieux adaptée à la nature interdépendante des paramètres de confort thermique sur des périodes consécutives, renforçant ainsi la robustesse du cadre d'optimisation basé sur la gestion des risques.

Nous reconnaissons que des études supplémentaires sont nécessaires pour établir des fonctions de densité de probabilité conjointe permettant d'obtenir des perspectives plus réalistes, comme la prise en compte conjointe des conditions nuageuses et solaires, de la température et de la vitesse du vent, ainsi que de toutes les combinaisons possibles, afin que la planification énergétique à court terme puisse bénéficier d'analyses probabilistes plus solides.

L'intégration de l'optimisation robuste distributionnelle (DRO) présente une opportunité particulièrement prometteuse dans ce contexte. Contrairement aux approches classiques de programmation stochastique qui supposent une connaissance parfaite des distributions de probabilité, l'optimisation distributionnelle robuste repose sur l'incertitude de la distribution en optimisant pour le pire cas dans un ensemble d'ambiguïtés défini. Cette approche peut être utile lorsque la distribution sous-jacente change au fil du temps en raison du comportement des occupants ou des conditions climatiques. En incorporant des techniques DRO, la stratégie d'optimisation peut garantir des performances même en présence d'une connaissance partielle des distributions de probabilité, offrant ainsi une base plus fiable pour la prise de décision dans un environnement incertain inhérent à la gestion de l'énergie dans les bâtiments.

### **A.15.2 Analyse du bien-être sous incertitude des paramètres du réseau**

Les initiatives de gestion côté demande entraînent une augmentation des utilités, dont l'estimation repose principalement sur la différence entre la quantité d'énergie vendue multipliée par le prix de l'électricité avant et après l'exécution du programme. Cependant, cette évaluation ne représente que le bénéfice économique et ne reflète pas l'impact total sur le bien-être individuel. Ainsi, le véritable bien-être doit être calculé en considérant la différence entre l'utilité perçue et le coût associé ( $W = \sum_{k \in \mathcal{K}} U_k - C_k$ ). Le calcul du coût de la stratégie,  $C_k$ , sur le réseau électrique est un exercice complexe nécessitant une connaissance détaillée des paramètres du système au niveau de la distribution, y compris l'impédance des lignes et la topologie du réseau, entre autres. Dans de nombreux scénarios pratiques, ces paramètres sont soit inconnus, soit seulement partiellement disponibles, ce qui introduit une incertitude significative dans l'estimation des coûts. Ce manque d'information complique l'évaluation des coûts réduits liés à l'amélioration du ratio pic/moyenne (PAR), car la réponse du réseau de distribution aux interventions côté demande n'est pas entièrement

prévisible.

### **A.15.3 Complexité du stockage thermique fonctionnant en mode de convection forcée**

Les dispositifs de stockage thermique électrique, dans la réalité, peuvent fonctionner en convection libre ou forcée. Ces modes diffèrent essentiellement par la présence d'un ventilateur qui extrait activement l'air des briques centrales par convection forcée. Bien que cela augmente l'efficacité du transfert de chaleur et permette un meilleur contrôle des périodes de déchargement, cela ajoute également une complexité supplémentaire au système de prise de décision. De plus, l'équation d'état des ATL est couplée à l'équation d'état du bâtiment, puisque la chaleur libérée par l'unité influence directement la dynamique thermique du bâtiment. Cette interaction implique des interdépendances où la réponse thermique du bâtiment affecte l'exploitation optimale du stockage thermique, et inversement. En conséquence, le contrôle optimal de l'exploitation du stockage thermique doit tenir compte non seulement de sa dynamique interne, mais aussi du comportement thermique du bâtiment. Ce couplage augmente encore la complexité computationnelle, nécessitant souvent des approches de programmation en nombres entiers mixtes (MILP). Ces méthodes peuvent modéliser le mode de convection forcée tout en maintenant une faisabilité computationnelle, mais elles peuvent impliquer des temps de calcul considérablement plus longs.

## **A.16 Recommandations**

### **A.16.1 Vers des modèles complexes et des interfaces standardisées**

L'approche proposée a exploité des modèles de co-simulation (EnergyPlus + Modelica) pour générer des données synthétiques pour les bâtiments et les systèmes de stockage thermique. Cela est pertinent dans des environnements où les données précises sont rares. Cependant, l'intégration de ces modèles dans des systèmes de décision convexes est une tâche complexe. Ainsi, nous avons traité nos résultats par régression aux moindres carrés pour construire des modèles linéaires équivalents. Bien que cette approche ait permis une génération de scénarios et un développement de modèles pour la planification optimale de l'énergie, des lacunes importantes subsistent. Plus précisément, il est urgent de proposer des méthodologies qui associent les modèles "white-box" à des phénomènes non linéaires et non convexes, afin d'améliorer la précision des capacités de prévision de la demande. Les recherches futures pourraient inclure des questions de passage à l'échelle lors de l'implémentation de modèles complexes dans des environnements réalistes, en particulier pour des quartiers plus vastes. En outre, la propagation des incertitudes à travers des modèles multi-domaines constitue un autre défi important, car les erreurs de prévision peuvent affecter les dimensions thermique, électrique et de contrôle. De plus, des efforts considérables sont requis pour standardiser les protocoles de communication et intégrer ces

modèles complexes aux systèmes existants de gestion de l'énergie des bâtiments via des plateformes commerciales du marché de l'énergie.

### **A.16.2 Planification à long terme de l'énergie et équité**

Cette thèse a intégré la stochasticité des conditions météorologiques et de la production électrique renouvelable, ainsi que l'élasticité prix des consommateurs, dans la stratégie de gestion de l'énergie proposée. Cette technique a permis d'évaluer l'impact des scénarios d'information imparfaite sur les coûts et le bien-être. Toutes les analyses énergétiques rapportées dans les articles publiés ont été réalisées sur un horizon de prévision de 24 heures. Cependant, la stratégie a également été évaluée sur une période de deux mois durant l'hiver 2023 afin d'examiner les bénéfices potentiels à long terme et les corrélations temporelles entre variables. La figure 5.1A quantifie efficacement l'optimisation énergétique obtenue grâce à la mise en œuvre de la stratégie de gestion de la demande, avec des gains d'efficacité notables observés lors des périodes les plus froides où la demande de chauffage augmente. Toutefois, comme cela n'est pas clair sur cet horizon de contrôle, les simulations ont été prolongées à environ deux mois, et la figure 5.1(B) résume les résultats. On y observe une corrélation directe entre ces variables, avec des réductions du PAR fluctuant entre 15 et 35% sur toute la période. Les données démontrent que l'efficacité de la gestion de la demande énergétique (mesurée par la réduction du PAR) s'améliore pendant les périodes relativement plus chaudes et diminue lors des périodes plus froides. Notamment, les valeurs les plus élevées de réduction du PAR (30-35%) correspondent à des variations importantes de température plutôt qu'à des températures absolues spécifiques, tandis que la période allant de la fin janvier au début février présente des minimums pour les deux variables. Ces résultats suggèrent que le programme de coordination stochastique distribué réagit dynamiquement aux fluctuations de température extérieure, adaptant ainsi sa stratégie d'optimisation en conséquence.

### **A.16.3 Analyses avancées et performance sur le long terme**

Cependant, des analyses plus avancées peuvent être effectuées sur des périodes plus longues, permettant d'évaluer la performance de la proposition non seulement en hiver mais aussi en été. Cela pourrait fournir des scénarios plus complets permettant aux chercheurs de conclure sur les impacts négatifs potentiels liés aux incertitudes et à l'importance des charges thermiquement contrôlables. En outre, des analyses technico-économiques pourraient être menées pour évaluer les indices énergétiques et les principaux indicateurs de performance afin d'évaluer la durabilité du projet.

D'autre part, cette thèse a évalué les analyses de flux de puissance uniquement au sein du réseau de distribution basse tension CIGRE, révélant un écart de recherche significatif pour des analyses plus complètes de la stabilité du réseau électrique. Les recherches futures devraient examiner l'impact de cette proposition sur des systèmes électriques plus vastes

afin de générer des informations sur les citoyens non participants. De telles analyses fourniraient des informations sur la manière dont les tarifs de l'électricité pourraient absorber ces effets, avec d'importantes implications pour l'équité entre les parties prenantes du système énergétique. Cette perspective élargie permettrait de répondre à des questions essentielles sur les impacts distributifs des communautés énergétiques et de garantir que les bénéfices ne se font pas au détriment des non-participants dans un écosystème énergétique plus large.

#### **A.16.4 Extensions de modélisation du réseau pour l'évaluation des communautés énergétiques**

La solution proposée a exploité le cadre bien connu Pandapower pour évaluer la faisabilité technique de la stratégie de coordination énergétique. Les simulations ont été réalisées sur le réseau test basse tension CIGRE, en ne considérant que le secteur résidentiel. Cependant, des études supplémentaires peuvent être effectuées avec un réseau test plus réaliste en abordant non seulement les problèmes de contrôle tertiaire, mais aussi les questions de contrôle primaire et secondaire. Pour gérer cela, les futures initiatives pourraient incorporer des équivalents de circuits au niveau du transport, en comprenant le besoin de puissance localisée afin d'anticiper correctement la perte potentielle d'inertie et de capacité de court-circuit due à la forte pénétration des communautés énergétiques dans les systèmes électriques. De plus, la modélisation de scénarios avec des réseaux électriques déséquilibrés en basse tension peut fournir des informations sur la manière dont les stratégies de coordination énergétique avec des informations imparfaites pourraient atténuer ces situations.

Le cadre proposé pourrait être étendu pour inclure des métriques de résilience, évaluant comment les communautés énergétiques pourraient répondre à des événements extrêmes et contribuer à la restauration du réseau. Finalement, l'intégration d'autres vecteurs énergétiques, y compris le gaz naturel, la biomasse, l'hydrogène et le méthane vert, représente une frontière importante, permettant une optimisation plus complète à travers différents domaines énergétiques tout en révélant des contraintes techniques supplémentaires qui doivent être intégrées dans les futurs efforts de modélisation.

#### **A.16.5 Approches coopératives pour la gestion distribuée de l'énergie**

La coordination des ressources énergétiques distribuées peut être réalisée par des approches coopératives et non coopératives. Notre approche a modélisé le second cas, représentant un scénario difficile puisque les clients ne partagent pas d'informations et se comportent de manière égoïste, ce qui est très proche de nombreux cas réels en production distribuée. Néanmoins, lorsque les clients sont disposés à former des coalitions en partageant des informations entre eux, d'autres algorithmes et considérations sont nécessaires. Les recherches futures pourraient adopter d'autres algorithmes décentralisés

qui diviseraient un grand problème en petites parties en ayant explicitement un objectif partagé dans chaque fonction d'optimisation des participants. Ensuite, comme mentionné par Etedadi *et al.* dans [42], il est nécessaire de distribuer les gains du système entre tous les clients via la valeur de Shapley.

De plus, les cadres coopératifs constituent un domaine de recherche particulièrement prometteur pour l'agrégation de flexibilité côté demande et la réponse coordonnée des membres d'une communauté. En conséquence, les systèmes multi-agents émergent comme une solution puissante permettant aux individus de maintenir leur autonomie tout en contribuant à des objectifs collectifs grâce à des stratégies de négociation. Les techniques de calcul préservant la confidentialité sont essentielles dans ces contextes afin d'instaurer la confiance au sein de la communauté en ne partageant que les informations nécessaires. Par conséquent, cela facilite l'adoption de plateformes de sécurité de l'information telles que la blockchain pour assurer la transparence. Bien que cela ait été effectué dans l'un des articles de cette thèse, il existe un énorme potentiel pour des implémentations permettant des transactions sécurisées entre les membres d'une coalition, favorisant potentiellement le commerce d'énergie pair-à-pair au sein du cadre coopératif. Les initiatives futures pourraient inclure des mécanismes de formation de coalition qui répondent aux conditions du réseau sur une période donnée, créant des stratégies de contrôle de l'énergie résilientes qui maximisent le bien-être social tout en garantissant l'équité.

### **A.16.6 Gouvernance et durabilité financière des communautés énergétiques**

Une certitude juridique et un cadre réglementaire bien établi pourraient réduire le risque pour les investisseurs potentiels et faciliter les procédures de mise en des communautés énergétiques. Étant donné que cela dépasse le cadre de cette recherche, les travaux futurs doivent évaluer l'adéquation réglementaire et juridique de cette approche aux cadres réglementaires actuels. En pratique, de nombreux défis pourraient émerger lors de la mise en des communautés énergétiques à grande échelle, notamment : i) la durabilité, ii) le risque d'investissement et iii) l'augmentation des dépenses fiscales. Les problèmes de durabilité peuvent surgir lorsque le financement provient de ressources publiques subventionnant les dépenses en capital en raison de l'incapacité des ménages à payer l'équipement nécessaire. De plus, des programmes entièrement dirigés par la communauté peuvent accroître la probabilité d'une détérioration patrimoniale s'il n'existe pas de programmes de renforcement des capacités préalables pour gérer non seulement les responsabilités d'exploitation et de maintenance, mais aussi les engagements commerciaux avec les acteurs de l'énergie.

Les cadres juridiques doivent clarifier les structures de propriété, la répartition des responsabilités et les mécanismes de gouvernance au sein des communautés énergétiques. Les bacs à sable réglementaires pourraient offrir des environnements entièrement contrôlés

pour tester des modèles commerciaux innovants sans s'engager pleinement dans des changements réglementaires permanents. De plus, les tensions potentielles entre les réglementations existantes des services publics et les nouveaux modèles pourraient être abordées par le biais de mécanismes de transition. L'élaboration de métriques de performance et de protocoles de suivi peut permettre de mesurer l'efficacité des interventions réglementaires.

### **A.16.7 Écart simulationréalité et contraintes matérielles**

Contrairement à d'autres études, notre recherche a validé la coordination des ressources distribuées à l'aide d'une infrastructure réaliste développée avec du code open-source. Nous avons effectué plusieurs simulations en utilisant des fonctionnalités de calcul distribué sur du matériel embarqué à faible coût. Bien que cette thèse ait réussi à modéliser des scénarios avec 80 participants côté demande, nous avons rencontré des limitations techniques dans la capacité des dispositifs périphériques à gérer la charge de calcul liée à l'hébergement de plusieurs agents résidentiels. Par conséquent, il existe une opportunité significative d'innovation et de recherche pour évaluer cette stratégie dans des conditions réelles afin de mieux comprendre les besoins des communautés.

### **A.16.8 Dissociation électricitéthermique via des réseaux de chauffage et de refroidissement urbains**

Cette thèse s'est concentrée sur une technologie particulière de stockage thermique, telle que les ATL, car elle représente une solution compétitive en termes de coûts, facilite l'intégration des énergies renouvelables et offre une maintenance ainsi qu'un transport aisés. Néanmoins, son LCOE pourrait être plus élevé que celui des applications de chauffage et de refroidissement urbains. Cela est dû au fait que les unités ETS n'apportent aucun avantage en été, lorsque le besoin principal est le refroidissement des espaces. D'autre part, les systèmes de chauffage et de refroidissement urbains constituent également une solution compétitive en termes de coûts, avec le plus grand coefficient de performance dans le domaine thermique. Ils intègrent plusieurs sources de chaleur et fournissent à la fois des services de chauffage et de refroidissement, permettant ainsi de surmonter les problèmes de saisonnalité. L'un des principaux avantages du chauffage urbain est qu'il peut être alimenté par un grand nombre de vecteurs énergétiques, notamment l'énergie renouvelable, la géothermie, la biomasse, ainsi que les excédents d'énergie industrielle. Bien qu'ils nécessitent des coûts initiaux élevés, les recherches futures devront porter sur le contrôle stochastique distribué pour les communautés équipées de systèmes de chauffage urbain, afin d'évaluer leur compétitivité économique par rapport aux configurations entièrement distribuées en intégrant des ATL.

## Appendix B - Extended Modelling

All the models developed for ETS room units, building thermal dynamics analysis, and the co-simulation framework integrating both components are openly available in a dedicated GitHub repository<sup>1</sup>. This repository includes the functional mock-up units (FMUs), setup files, and all the scripts required to reproduce the experiments. In addition, it provides the necessary configurations to deploy supporting databases such as MongoDB and InfluxDB, which are used for time-series data storage and model parameter tracking. Furthermore, the repository consolidates multiple methodologies for continuous integration and delivery (CI/CD), containerization, and packaging, promoting good software-engineering practices not only for research but also innovation.

### B.1 Modeling and sizing of renewable and flexible resources

Renewable generation and flexible resources were modeled in alignment with each research objective. Together, the studies contributed to building a robust and reproducible framework for distributed coordination under uncertainty, validated through real data and cyberphysical infrastructures. In the first stage, as local communities remained skeptical about the performance of untested technologies under harsh climatic conditions, the sizing strategy adopted a cautious target share of approximately 2025% of the total heating demand to be supplied by wind generation. This level was deemed feasible to replace a significant portion of diesel-based generation while preserving grid reliability and user comfort, as evidenced by the 3540% reductions in operational costs and peak-to-average ratios. For solar photovoltaic (PV) resources, the sizing process was carried out individually for each prosumer, based on their average daily energy consumption. The installed PV capacity

---

1. <https://github.com/jdominguezj>

was set such that the expected energy yield closely matched household demand, avoiding excessive generation and clipping losses. This approach enabled efficient self-consumption while maintaining realistic penetration levels typically between 30% and 50% of each household's peak load, corresponding to 15 kWp of installed capacity. Stochastic irradiance scenarios derived from weather forecasts were then used to assess the adequacy of this sizing under uncertain operating conditions. Finally, the extended framework included the integration of small-scale vertical-axis wind turbines (Hi-VAWT DS-3000W), adopting the same sizing principles. This addition allowed addressing risk aversion to renewable variability, ensuring that both solar and wind resources could be jointly coordinated to enhance reliability and reduce operational risk.

Regarding space heating technologies, this thesis incorporated both Electric Baseboard Heaters (EBH) and Electric Thermal Storage (ETS) room units to account for the diversity of household heating systems and their respective flexibility. EBHs were modeled as direct electric resistance heaters with instantaneous response and no storage capacity, capturing the behavior of users with limited flexibility but high sensitivity to dynamic pricing. Conversely, ETS units were modeled as controllable thermal storage systems characterized by distinct charging and discharging phases and state-of-charge dynamics. Their nominal capacities were selected to cover one at least thermal zone per dwelling, typically between 10-15 kWh of storage, with rated charging powers of 3–4 kW. These devices acted as distributed flexibility assets capable of shifting heating demand to low-price or high-renewable periods. Eventually, this thesis also recognizes that thermal and electrical dynamics differ fundamentally. While the electrical response of heating devices is immediate, the thermal behavior of buildings exhibits inertia, meaning that a temporary reduction in heating power does not cause an abrupt drop in indoor temperature. This characteristic allows ETS units to operate as flexibility buffers, storing thermal energy during low-cost or high-renewable

periods and releasing it gradually without compromising user comfort. By jointly modeling EBHs and ETS, the framework captured both fast-reacting and storage-based flexibility, enabling the coordination mechanisms to balance comfort preservation with cost and emission reductions under stochastic operating conditions.

## **B.2 Forecast error modeling**

In this section, we present the analysis of prediction errors for photovoltaic (PV) and wind power, as well as meteorological variables including temperature, wind speed, humidity, and direct normal irradiance. The forecast data was obtained using a self-coded Tomorrow.io client, where queries were performed every 15 minutes to obtain forecasts up to seven days into the future. The predictions were then compared with historical measurements over the entire winter of 2023 to construct 15-minute error distributions for each variable.

Figure B.1 illustrates the standard deviation of forecast errors for crucial meteorological variables. Regarding Figure B.1(A), the outdoor temperature exhibits a cumulative increase in error deviation throughout the day, then, we can state that prediction uncertainty increases over time. Figure B.1(B) depicts for the wind speed, and it experiences a more consistent error pattern. A similar situation occurs for the relative humidity, condensed in Figure B.1(C). Furthermore, Figure B.1(D) illustrates the solar irradiance, showing that the has the highest variability happens during peak sunlight hours.

Figure B.2 describes the standard deviation of prediction errors in renewable power generation. B.2 (A) shows that PV power has its peak around midday when solar production is highest, indicating greater uncertainty when irradiance levels change suddenly. B.2(B) represents the wind power error, and it fluctuates throughout the day, reflecting the

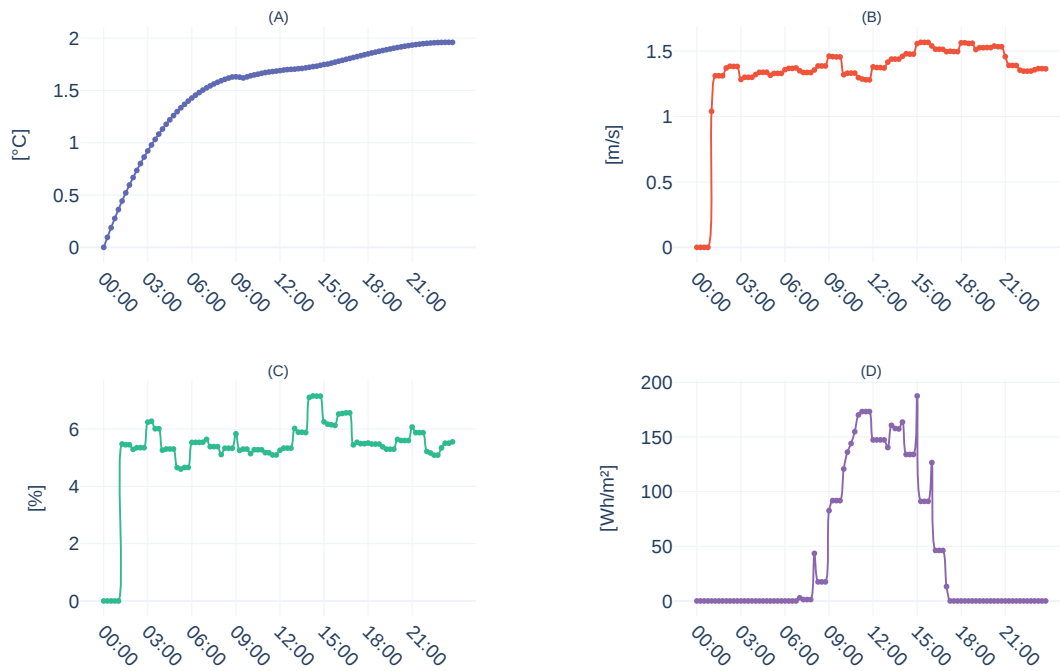


FIGURE B.1 – Standard deviation of the (A) outdoor temperature, (B) wind speed, (C) relative humidity, and (D) solar DNI

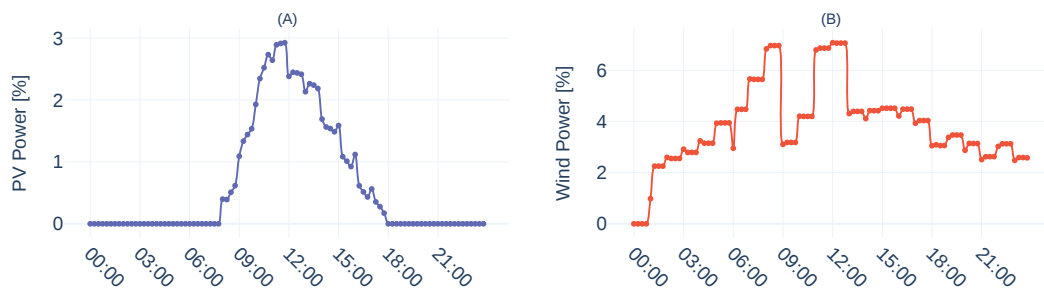


FIGURE B.2 – Standard deviation of the (A) PV power temperature, (B) Wind turbine power

unpredictable nature of wind energy generation.

In summary, these pictures showcase that there is a particular variability related to prediction accuracy depending on the variable and time of day. Some particular errors suit a pattern such as PV errors - peaking during daylight hours-, and others like wind power and humidity, exhibit a non-zero but consistent behavior over time. Grasping these fluctuations is crucial for improving forecasting models and optimizing energy management strategies.

### B.3 Modelica ETS Library

#### Library description

The Modelica library developed in this thesis comprises a thermal storage model that emulate the behavior of ETS room units under distinct heat-transfer regimes : **free convection** and **forced convection**. The library relies on the **Modelica Standard Library** (MSL) components. Both models share a common physical foundation based on lumped-parameter thermal networks, but differ in the way heat is released to the surrounding air.

In the **free-convection** configuration, the heat exchange between the storage core and the room air occurs naturally. This representation is particularly suited for compact, passive ETS installations typically placed in bedrooms or small residential zones where no fans are present. The corresponding model prioritizes simplicity and numerical stability, making it suitable for long-horizon co-simulation and control-oriented studies. Conversely, the **forced-convection** model incorporates an active heat airflow through a convective element. This approach captures the dynamics of fan-assisted ETS units that can modulate their thermal output. The air mass flow rate, represented as a controllable parameter or external input, directly influences the effective heat-transfer coefficient ( $hA$ ), allowing detailed

analysis of transient charging and discharging behavior.

### **(I) Energy conversion and physical abstraction**

This first panel outlines the fundamental energy conversion process that defines an ETS room unit. Electrical power is supplied to a resistive circuit, and the generated heat is then stored within a ceramic block acting as the main thermal reservoir. Then, a control logic determines the on/off operation of the heating element. This schematic highlights the multi-domain nature of the ETS, combining electrical, thermal, and logical components in a unified representation.

### **(II) Internal structure and convection mechanisms**

The second panel focuses on the internal configuration of the ETS core. It consists of several ceramic brick rows (F) that accumulate heat during charging cycles. Thermal exchange with the surrounding air is represented by a convection interface (H), which can operate in both convective modes. A control block (G) manages the transition between both regimes, enabling comparative analysis between passive and fan-assisted heat release. This dual-mode structure reproduces realistic operating conditions found in commercial ETS units, where fan operation depends on temperature and comfort requirements.

### **(III) Co-simulation integration**

The third panel illustrates the ETS model being prepared to be used as a Functional Mock-up Unit (FMU) interacts with an EnergyPlus building model through PyFMI. The building provides the room temperature signal, while the ETS returns its heat output to the zone air. Key outputs include the core temperature, heat flow, electrical power, and the state of charge (SOC). A dedicated Temperature-to-HeatFlowAdaptor ensures consistent

boundary coupling, allowing bidirectional energy exchange. This configuration enables the joint evaluation of building storage interactions under realistic operating schedules and supervisory control strategies.

## Main governing equations

The thermal behavior of the Electric Thermal Storage (ETS) unit is described by a set of lumped energy-balance equations that capture the conversion, accumulation, and release of heat within the ceramic core. These equations form the physical basis of the Modelica implementation, ensuring consistency between the electrical input, stored energy, and thermal output delivered to the room.

**Core energy balance.** The ceramic core acts as a single thermal mass characterized by its effective heat capacity  $C_{\text{core}}$ . The evolution of its temperature is governed by :

$$C_{\text{core}} \dot{T}_{\text{core}} = u(t) P_{\text{heater}} - \dot{Q}_{\text{conv}},$$

where  $u(t)$  is the control signal (PowerTrigger),  $P_{\text{heater}}$  is the rated electrical power, and  $\dot{Q}_{\text{conv}}$  represents the convective heat transfer to the surrounding air.

**Convective heat transfer.** The heat released from the core to the room is modeled as :

$$\dot{Q}_{\text{conv}} = hA (T_{\text{core}} - T_{\text{air}}),$$

where  $hA$  denotes the effective convective coefficient, whose value depends on whether the unit operates under free or forced convection. In the forced mode, a fan increases  $hA$  proportionally to the air mass flow rate, while in free convection, it remains constant and lower.

**Electrical power and stored energy.** The electrical consumption and state of charge of the ETS are obtained from :

$$P_{\text{el}}(t) = u(t) P_{\text{heater}}, \quad E_{\text{stored}}(t) = \int_0^t [u(\tau) P_{\text{heater}} - \dot{Q}_{\text{conv}}(\tau)] d\tau.$$

These expressions link the instantaneous electrical input to the stored and delivered thermal energy, ensuring full energy conservation within the system.

## Integration under FMI

When exported as a Functional Mock-up Unit (FMU), the model interacts with an EnergyPlus building FMU through a master algorithm in PyFMI. The building provides the zone temperature  $T_{\text{air}}(t)$  as input, while the ETS returns  $\dot{Q}_{\text{conv}}$  as an internal heat gain. Supervisory controllers (e.g., rule-based, MPC, or stochastic optimization) can drive the PowerTrigger signal based on energy price forecasts, PV generation, or comfort constraints.

## B.4 Building model

Different building setups were modeled by exploiting EnergyPlus and OpenStudio. While the former stand for the building energy simulation platform to model both energy consumption for heating, cooling, ventilation, lighting and plug and process loads and water use in buildings, the latter was used as an guided user interface (GUI) so that simulation and scenario generation could be carried out in a straightforward manner.

For data generation purposes, three main building setups were used. This was to further show the high flexibility of the proposed approach regarding the possibility of incorporating

thermal storage room units from Modelica.

Tables B.1 and B.2 summarize the main characteristics and input parameters used to simulate the thermal performance and heating demand of the representative buildings considered in this study. A large share of these values were defined according to the provincial construction code [103, 104]. The building envelope was defined using multilayer assemblies consistent with cold-climate construction practices in Northern Québec, where external walls were modeled with four layers, internal walls with a single layer, and double-glazed windows were selected to capture realistic heat-loss behavior. Internal heat transfer between zones was explicitly considered to account for convective and conductive exchanges. Three configurations were examined to represent different building scales and occupancy levels typically found in community and residential infrastructures. The two-zone, three-zone, and four-zone configurations correspond to total conditioned areas of 360, 728, and 1800 squared meters, with 2, 4, and 6 occupants, respectively. These values allow evaluating the influence of floor area and internal gains on overall heating requirements and HVAC system sizing.

As depicted in Tables B.1 and B.2 the thermal envelope was characterized by a wall R-value of 5.5 RSI and a fenestration U-value of 1.9 W/m<sup>2</sup>K, which is inside allowed values in residential envelopes in subarctic environments [103]. Space heating was coped with by electric baseboard heaters and electric thermal storage room units with nominal powers ranging between 3–15 kW and 3.6 kW, respectively. These systems were selected to emulate potential to-be decarbonized heating solutions in off-grid or diesel-based microgrids.

Internal gains included heat exchange with the ground, lighting, electrical equipment, and occupants. Contact isolation (jacked elevated floors) with the ground was not modeled and it is a major limitation of this thesis. Lighting and equipment gains ranged between

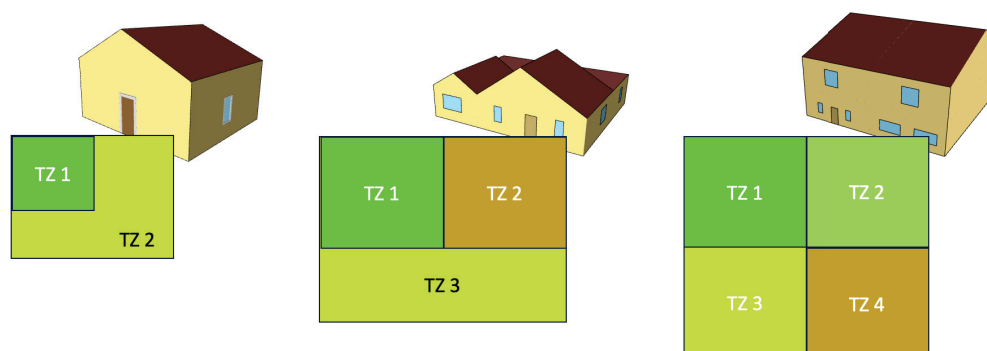


FIGURE B.3 – Thermal zones distribution for the different building setups modeled

900-2700 kJ/h and 4471 – 7776 kJ/h, respectively, depending on building size and occupancy density, while human gains varied from 900 kJ/h in the smallest configuration up to 2200 kJ/h in the largest one. This parametrization ensures that the simulated buildings capture some of the dominant thermal behaviors of Québec dwellings, including the interaction between internal gains, envelope insulation, thereby providing a great baseline for assessing the techno-economic and environmental performance of alternative heating systems.

Table B.1 – Main features of building models

Category	Parameter	Value
Building features	External walls	Four layers
	Internal walls	Single layer
	Windows	Double glazing
	Internal heat transfer	Considered
	Configurations	Two zones, Three zones, Four zones
Configurations Area and occupancy	Two zones	360 m <sup>2</sup> , 2 occupants
	Three zones	728 m <sup>2</sup> , 4 occupants
	Four zones	1800 m <sup>2</sup> , 6 occupants

Table B.2 – Input parameters to simulate the heating demand of the buildings.

Category	Parameter	Value
Thermal Envelope	Wall (R-value)	5.5 RSI
	Fenestration (U-value)	1.9 W/m <sup>2</sup> K
HVAC system	Electric baseboard heaters & Electric thermal storage room units	3–15 kW and 3.6 kW respectively
Internal gains	Contact with ground	Yes
	Lights	900-2700 kJ/h
	Electrical equipment	4471-7776kJ/h
	People	900-2200 kJ/h

## B.5 Cosimulation framework

The simulation environment adopted in this thesis relies on the *Functional Mock-up Interface (FMI)* standard to couple heterogeneous models into a common co-simulation platform. The framework integrates an **ETS model** developed in Modelica and a **building model** implemented in EnergyPlus, both exported as Functional Mock-up Units (FMUs). These FMUs are orchestrated through the **PyFMI library**, which acts as the master algorithm in charge of time coordination, data exchange, and process supervision (Fig. B.4). Plus, Figure B.5 showcases the remarkable versatility of the proposed modeling and co-simulation approach, which enables ETS units to be placed in any thermal zone or location within the simulated environment. Rather than being limited by a predefined layout, the framework allows researchers to instantiate any number of ETS devices and assign them to different zones. This flexibility is inherent to the architecture combining

Modelica's physical modeling with EnergyPlus via PyFMI, and makes it possible to evaluate distributed configurations ranging from single-dwelling applications to large-scale community deployments. Consequently, the approach provides a powerful tool to explore how spatial distribution and user-defined allocation of ETS units influence energy coordination, comfort, and system efficiency.

At the *slave level*, each FMU retains its internal solver :

- The thermal battery FMU, based on Modelica, that comes along with the DASSL solver.
- The building FMU, based on EnergyPlus, which captures detailed thermal dynamics of the envelope and HVAC operation.

At the *master level*, PyFMI provides a flexible scripting interface to manage initialization, communication, and post-processing. The responsibilities of the master include :

- Loading FMUs and checking their integrity.
- Setting initial states and simulation parameters.
- Advancing the simulation by orchestrating timesteps.
- Exchanging outputs between FMUs to ensure bidirectional coupling.
- Handling errors and tolerable numerical inconsistencies.
- Gathering and storing results for further analysis.

The corresponding co-simulation master algorithm is summarized in Algorithm . After loading the FMUs, initial conditions are assigned and the simulation proceeds in discrete timesteps. At each timestep, input values are set for each FMU, all FMUs are advanced simultaneously, and outputs are retrieved. These outputs are then exchanged and re-inserted as inputs, enabling the bidirectional interaction between building and storage models. This iterative process continues until the simulation horizon is reached, after which the results are collected for analysis.

Such an approach ensures numerical consistency and modularity, while leveraging the strengths of different modeling environments : the physical accuracy of EnergyPlus in building thermal dynamics, and the flexibility of Modelica for advanced thermal storage modeling. Moreover, the Python interface facilitates integration with optimization and control algorithms, which are central to this work.

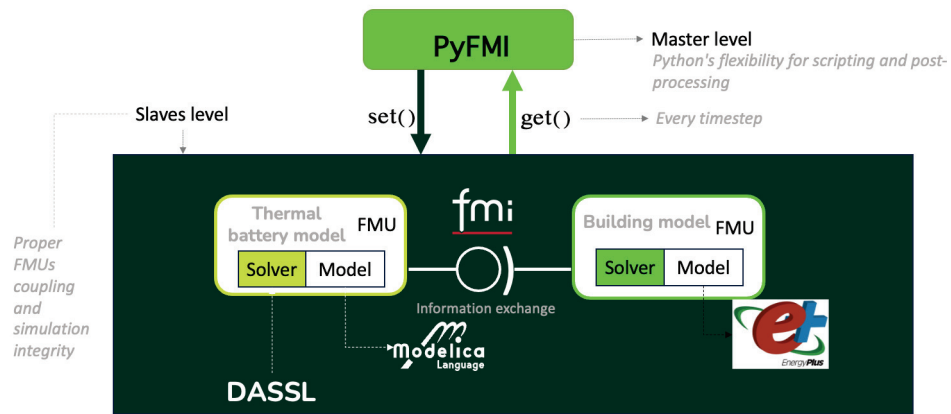


FIGURE B.4 – Co-simulation framework integrating Modelica (thermal battery) and EnergyPlus (building) FMUs via PyFMI.

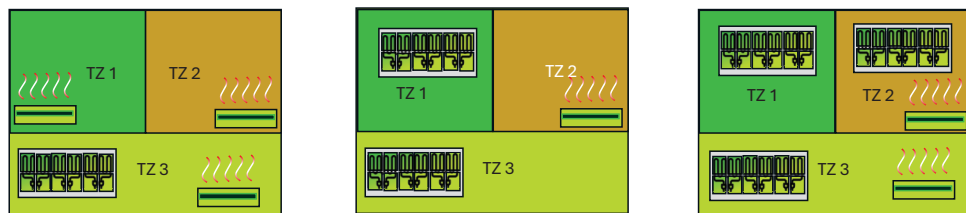


FIGURE B.5 – Spatial versatility of Electric Thermal Storage deployment.

---

**Algorithm** Master Algorithm for Co-simulation using PyFMI

---

```
0: Load FMUs :  $fmu_1 \leftarrow \text{load\_fmu}(\text{"Building.fmu"})$ 
0: Load FMUs :  $fmu_2 \leftarrow \text{load\_fmu}(\text{"ETS.fmu"})$ 
0: Set initial values for all FMUs
0: Initialize all FMUs :  $\text{Building.initialize}(), \text{ETS.initialize}()$ 
0: for  $t = t_0$  to  $t_f$  step  $\Delta t$  do
0:   Set inputs to each FMU :
0:   for all  $fmu_i$  do
0:      $fmu_i.set(inputs, values)$ 
0:   end for
0:   Advance all FMUs one step :
0:   for all  $fmu_i$  do
0:      $fmu_i.do\_step(t, \Delta t)$ 
0:   end for
0:   Get outputs from each FMU :
0:   for all  $fmu_i$  do
0:      $y_i \leftarrow fmu_i.get(outputs)$ 
0:   end for
0:   Exchange outputs as inputs between FMUs
0:    $t \leftarrow t + \Delta t$ 
0: end for
0: Finalize and gather results =0
```

---

## B.6 Flowcharts

This section condenses flowchart diagrams to grasp better the required procedures to execute methodologies related to :

- Flowchart to grasp the sequence to perform energy coordination once characterized the thermo-energetic environment (Figure B.6 (EN) B.15 (FR)).
- Algorithmic development of distributed stochastic energy coordination (Figure B.7 (EN) B.12 (FR)).
- Physical infrastructure deployment and delivery to accomplish with distributed stochastic energy coordination (Figure B.8).
- Sequential procedure to execute distributed energy coordination (Figure B.9).
- Estimating deterministic tractable equivalents for probabilistic constraints (Figure B.10 (EN) B.10 (FR) ).
- Algorithmic development of risk-aware energy coordination (Figure B.11 (EN), B.14 (FR)).

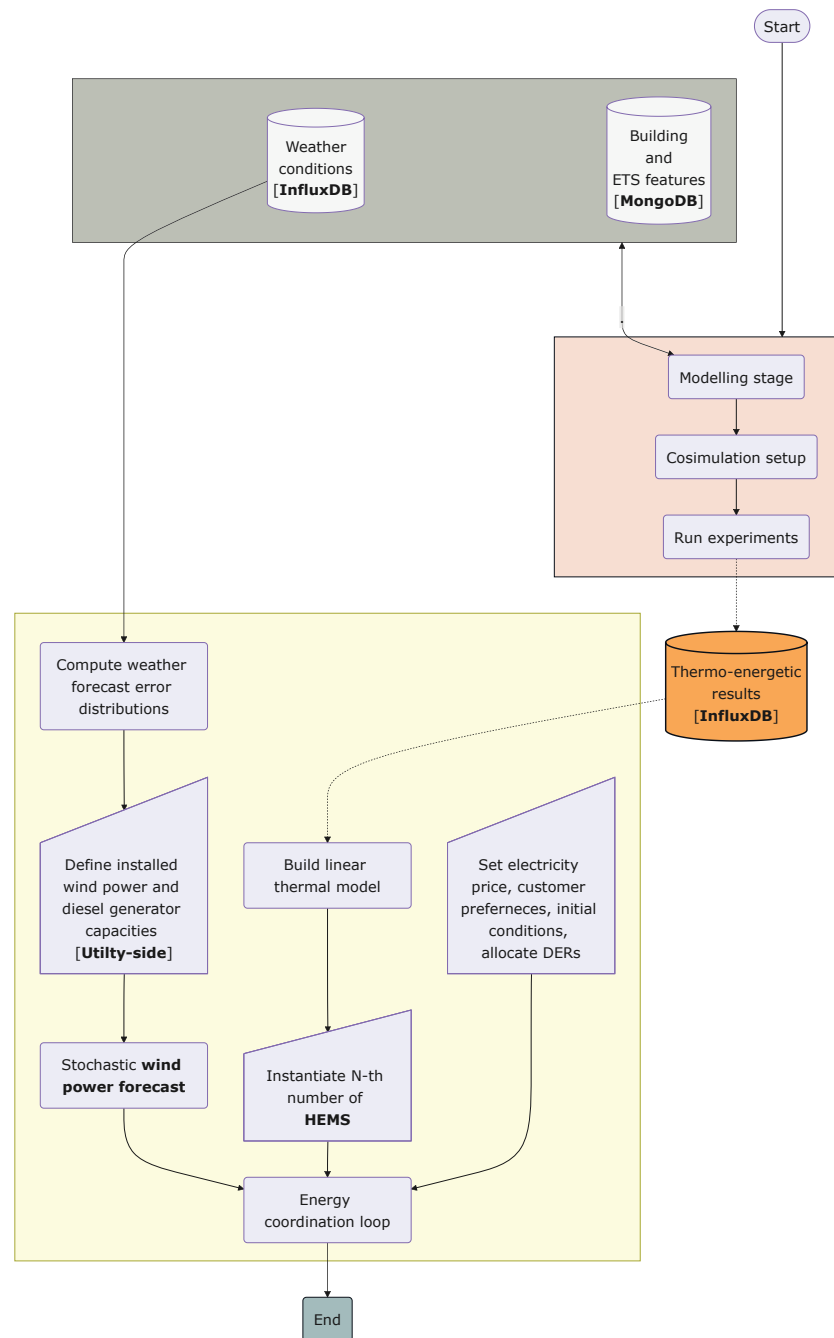


FIGURE B.6 – Flowchart to perform energy coordination with the modelled thermo-energetic environment

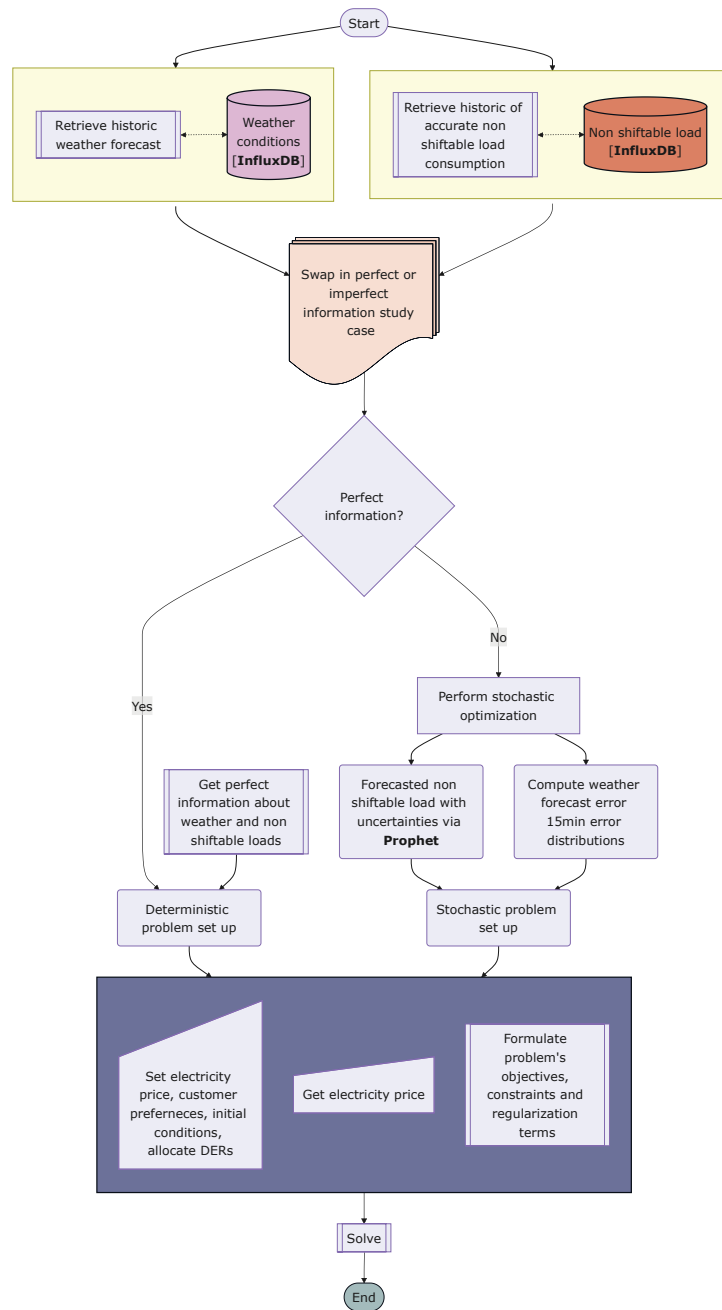


FIGURE B.7 – Flowchart to perform distributed stochastic energy coordination

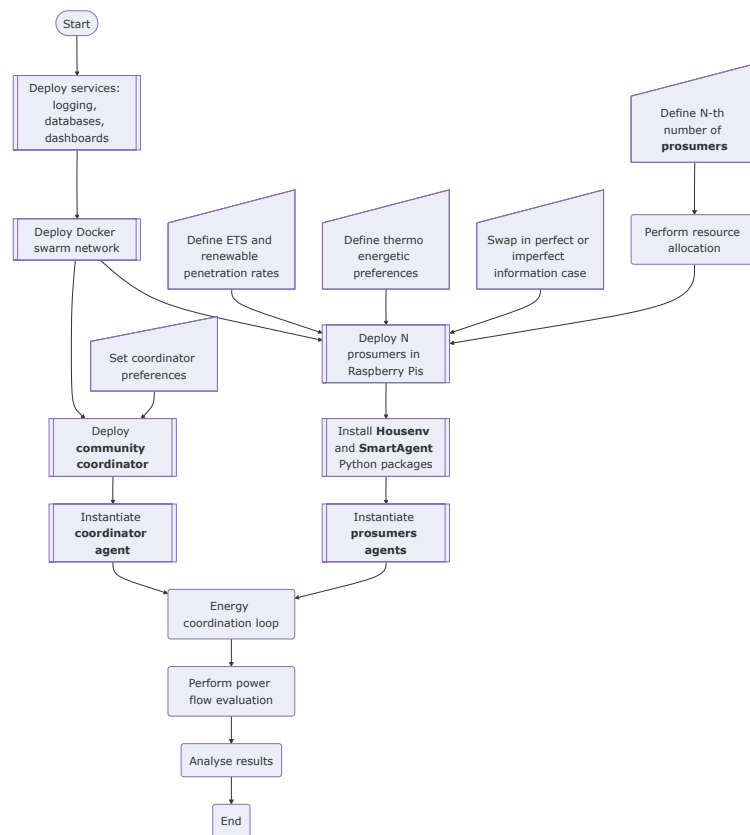


FIGURE B.8 – Flowchart to implement distributed computing with stochastic energy coordination

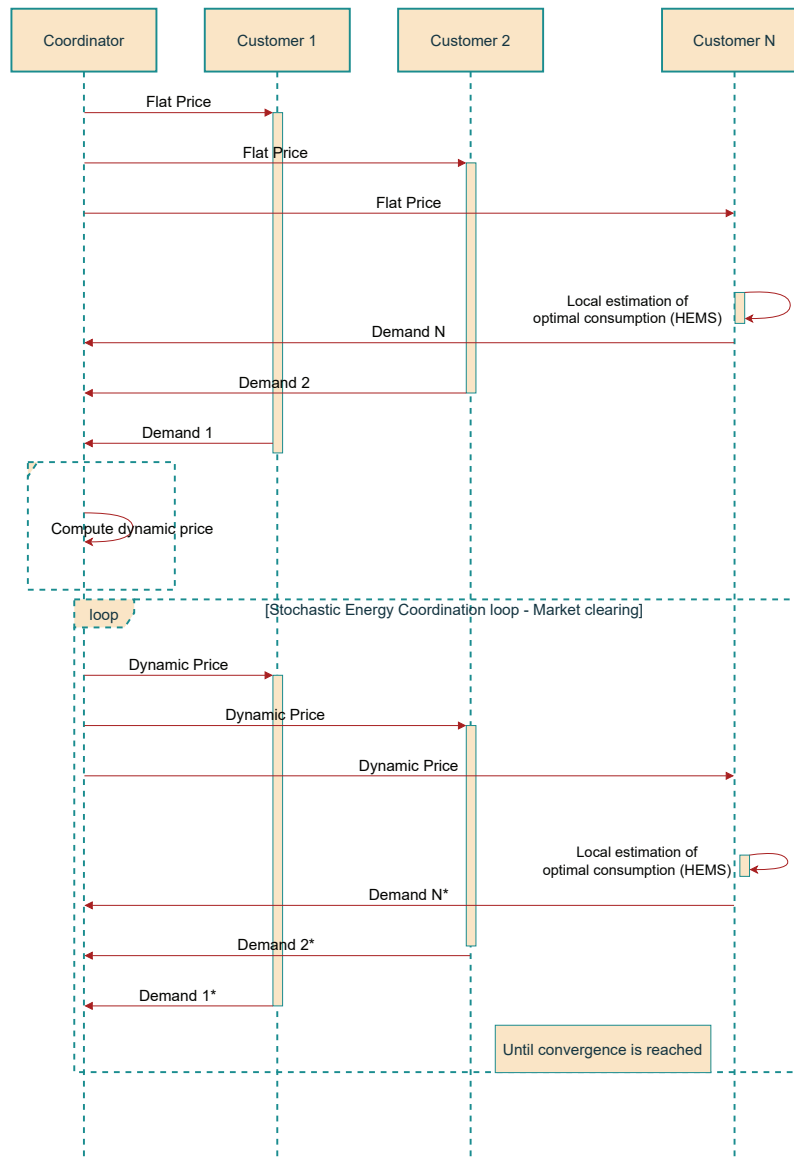


FIGURE B.9 – Unified model language diagram to elucidate the procedure to perform energy coordination involving multiple customers

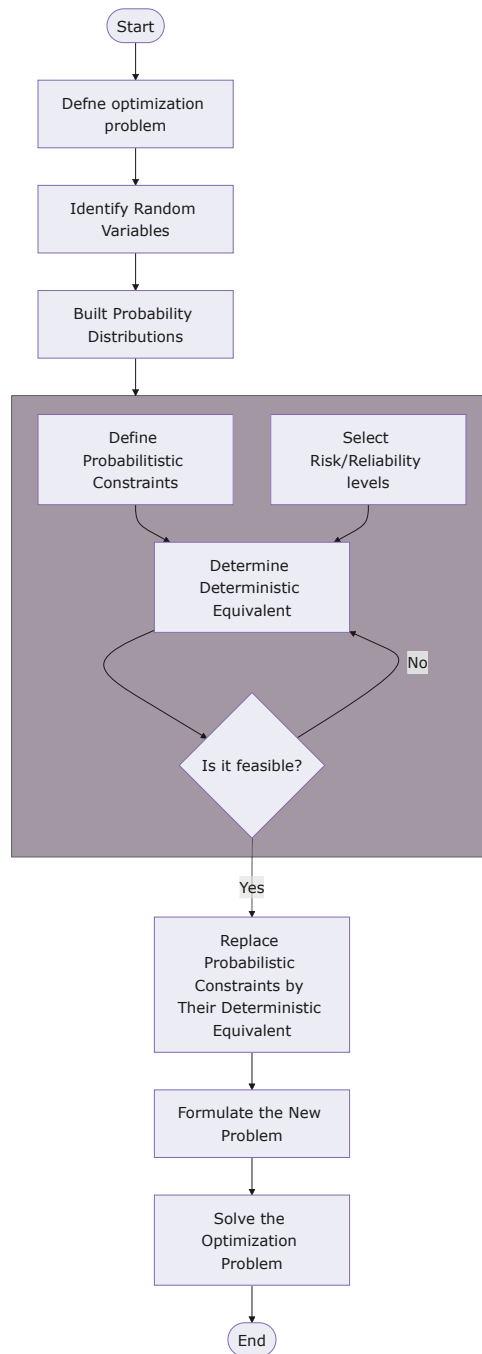


FIGURE B.10 – Flowchart to determine chance constraints equivalents

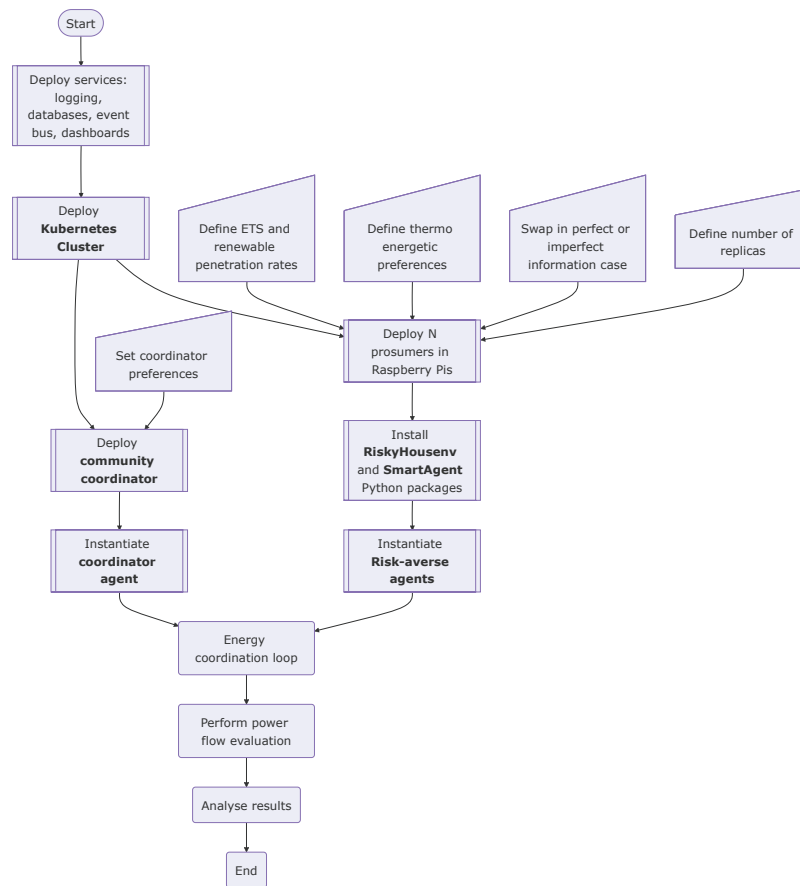


FIGURE B.11 – Flowchart to perform distributed computing with risk-aware energy coordination

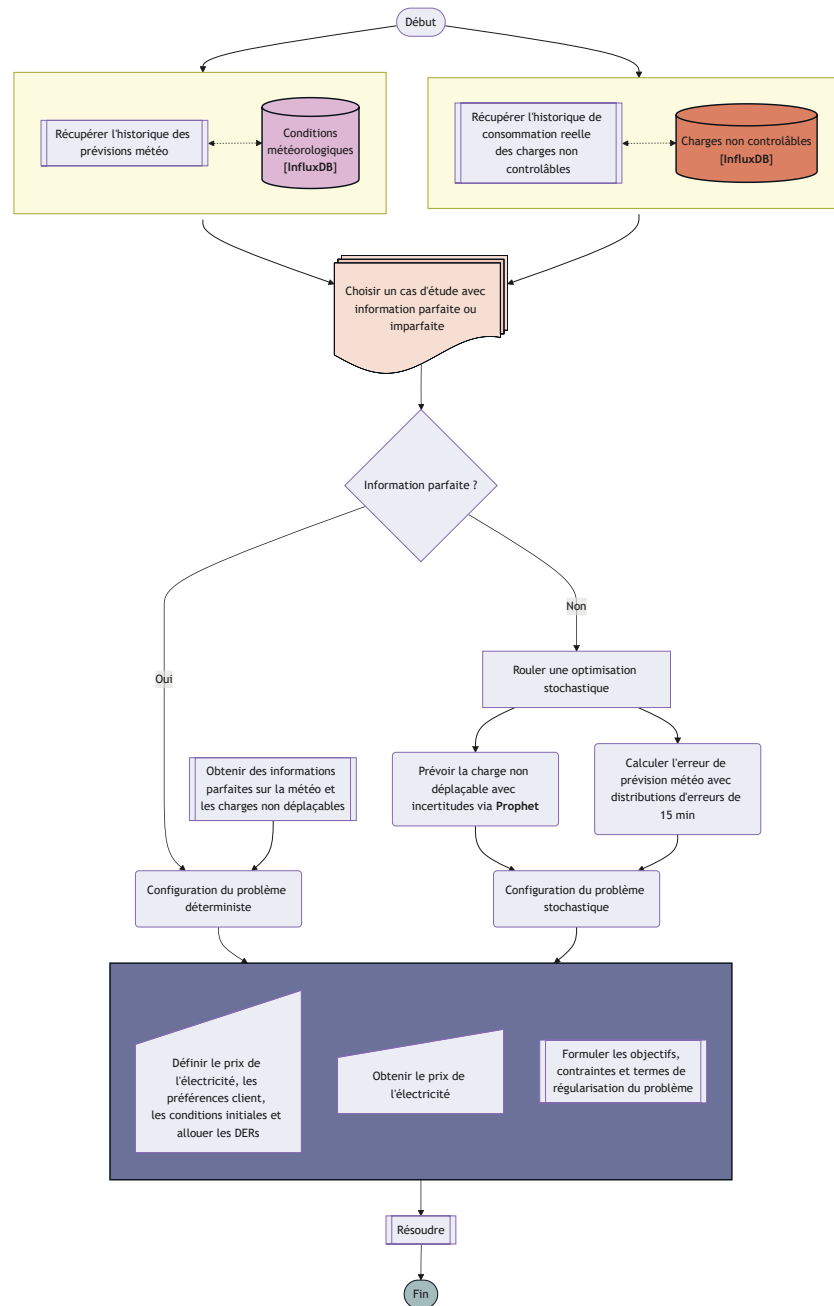


FIGURE B.12 – Diagramme de flux pour effectuer une coordination énergétique stochastique distribuée

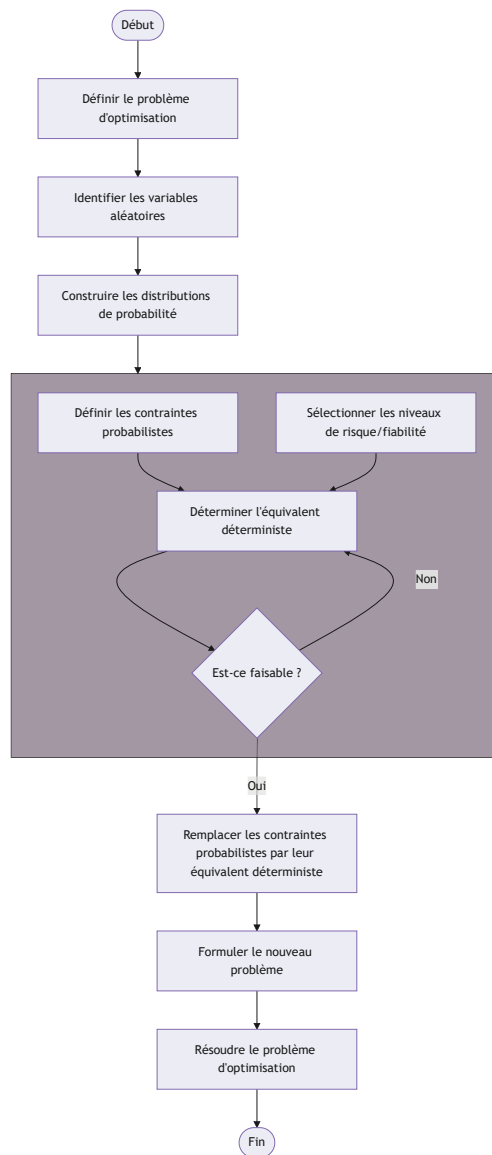


FIGURE B.13 – Organigramme pour déterminer les équivalents de contraintes aléatoires

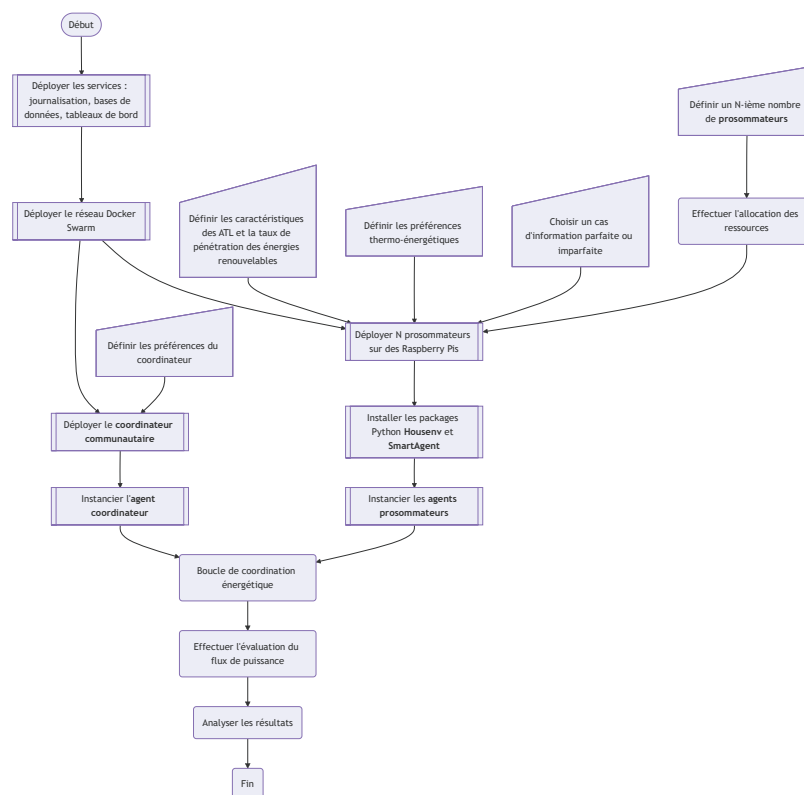


FIGURE B.14 – Organigramme pour effectuer un calcul distribué avec une coordination énergétique tenant compte des risques

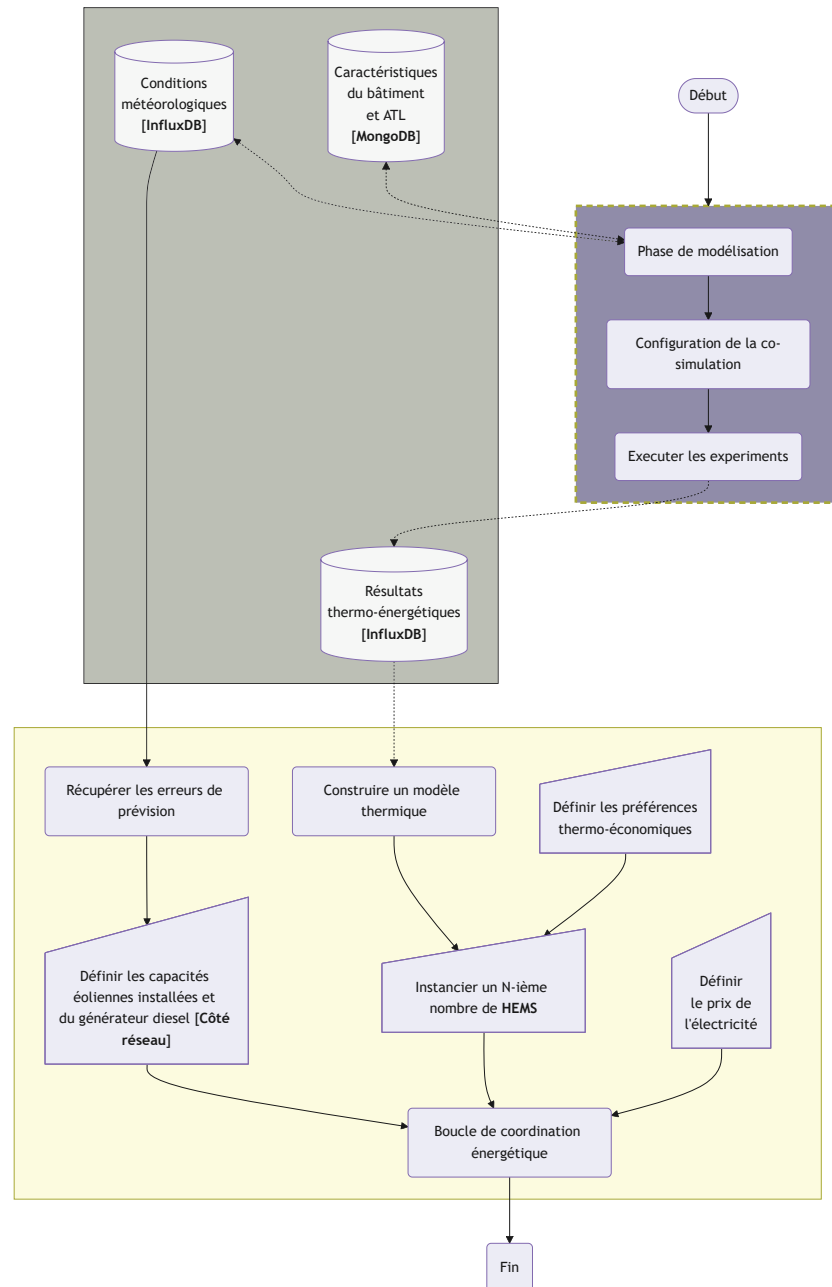


FIGURE B.15 – Organigramme pour effectuer la coordination énergétique avec l'environnement thermoénergétique modélisé