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

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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 Kuujjuaq, 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.
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

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

Sets

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

Variables

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

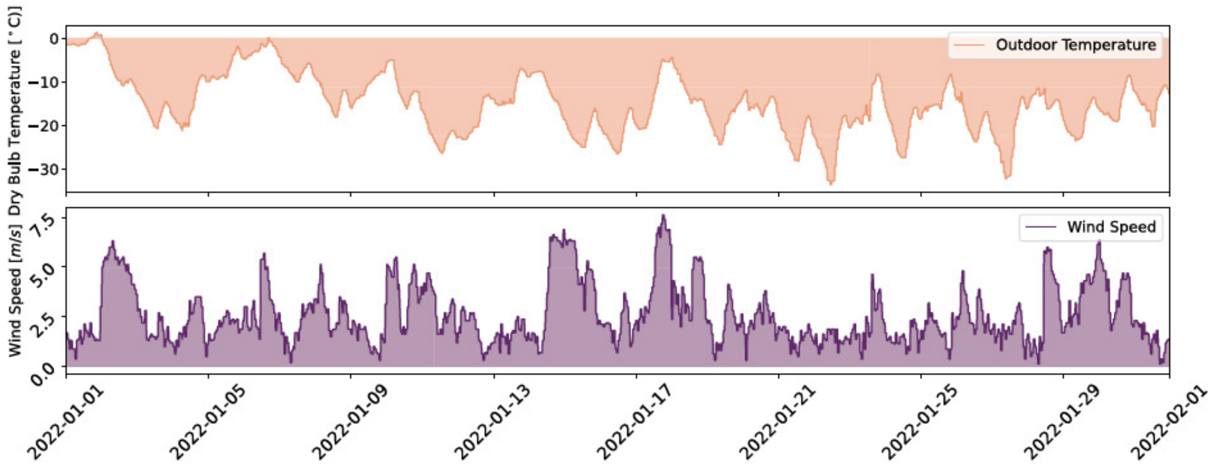

FIGURE 1. Weather conditions during Winter in 2022 in Kuujjuaq.

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 Kuujjuaq, a northern community allocated in Nunavik, Quebec. The average outdoor temperature is $-25\ ^\circ$C and fluctuates between $-8\ ^\circ$C and $-35\ ^\circ$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	✓						✓			
[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		✓	✓			✓

Ref.: 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. Mediwaththe and Chathurika [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

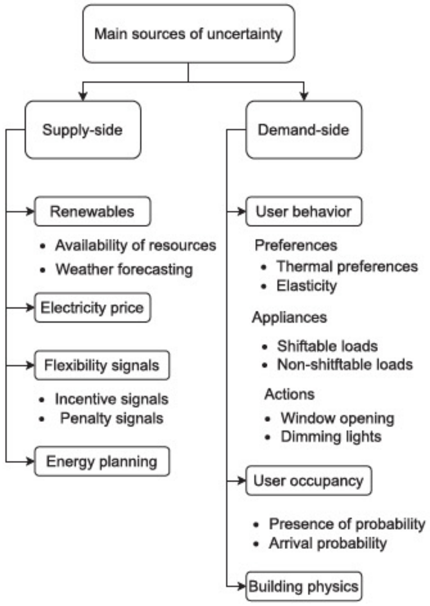

FIGURE 2. Principal factors introducing uncertainty in smartgrids.

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	
Nova Scotia Power	Centralized		- 50% of reduction on TOU rates		ETS room units (9 kW)		- Installation was not covered - Utility have to control the timing of electricity use	Implement TOU rates for residential users
New Brunswick Power	Centralized	100 (2013)		Wind	ETS room units	-	- Utility have to control the timing of electricity use	Shift demand away from peak hour and renewables integration
City of Summerside, PEI	Centralized		- 10% discount for installation - 33% of reduction of electricity rate for 8 years.				- Utility have to control the timing of electricity use	
Minnesota - Connexus energy cooperative and great river energy	Centralized		- 50% of reduction on TOU rates - 50 USD per installed kW	Wind	ETS room units		- Utility have to control the timing of electricity use	Load-shifting
Concord Light	Centralized		- 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		ETS, DHW		- Utility have to control the timing of electricity use	
South Kentucky rural electric cooperative	Centralized		- 25% of installation cost. - 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.

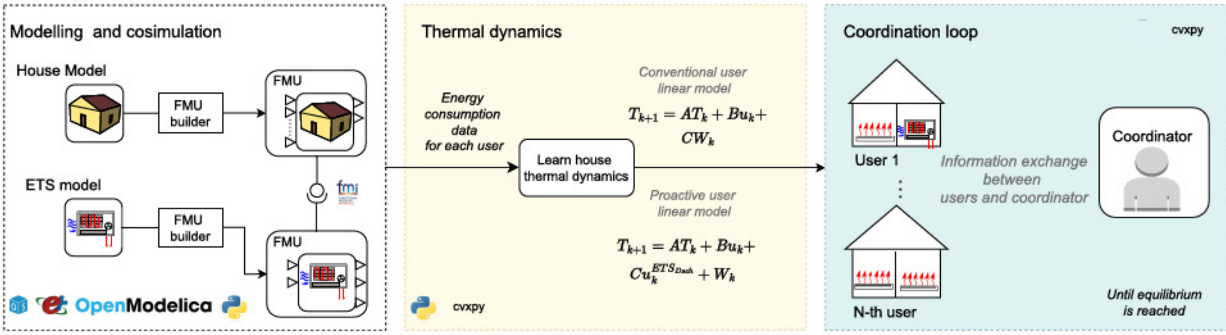

FIGURE 3. Overview representation of the proposed methodology.

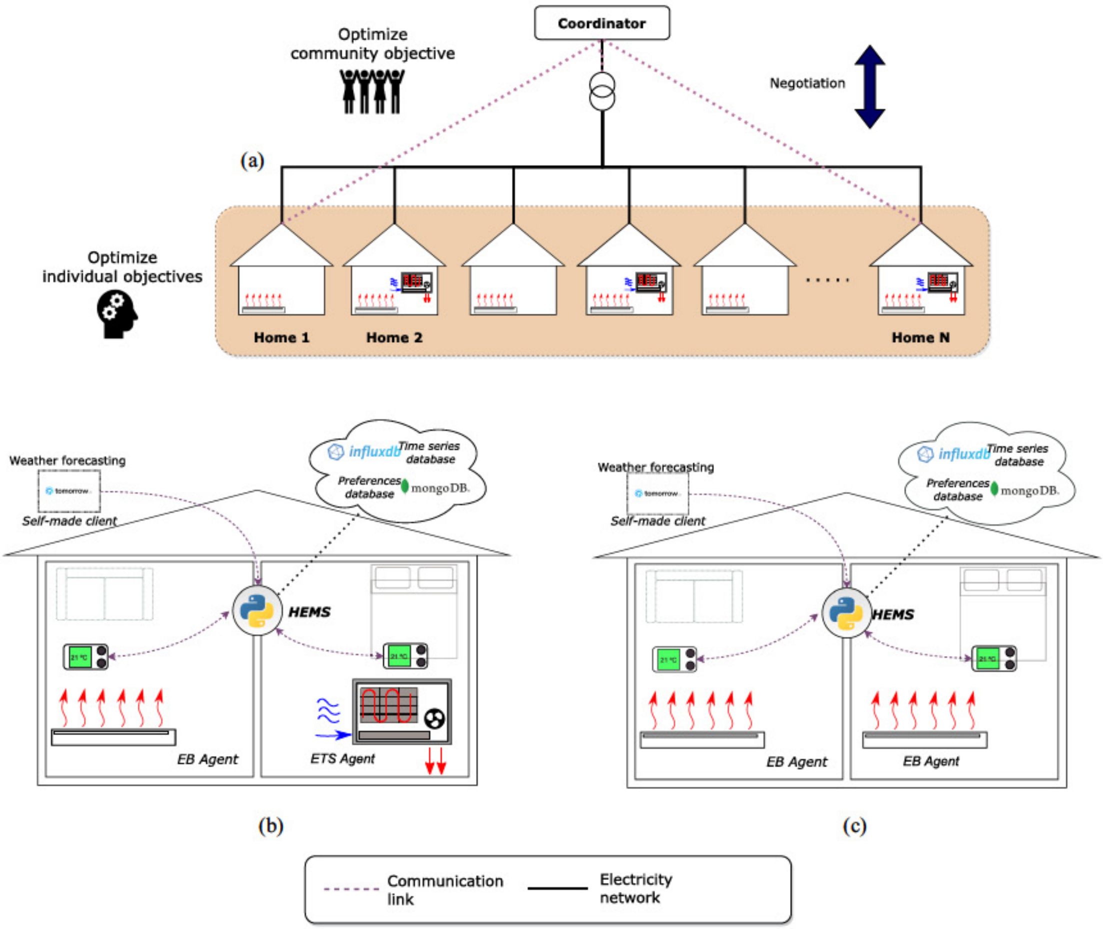

FIGURE 4. (a) Stackelberg game between leader and followers with distributed DR. (b) Local HEMS for a proactive user. (c) Local HEMS for a traditional user.

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	Kuujjuaq
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

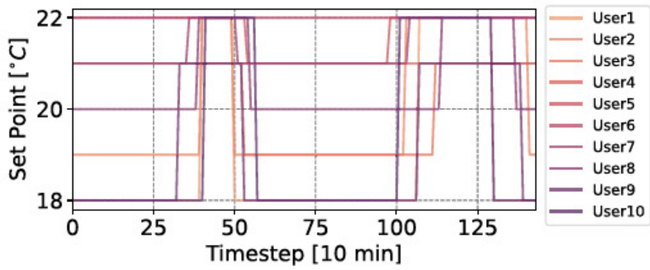

FIGURE 5. Residential agents' thermal preferences.

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 α, 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

$$\hat{\gamma}_k^r = \alpha_k^r + \Gamma_k^r \tag{1}$$

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 ω_k and ρ_k as

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

In (2), higher values of α_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

$$\begin{bmatrix} T_{k+1}^1 \\ T_{k+1}^2 \end{bmatrix} = A \begin{bmatrix} T_k^1 \\ T_k^2 \end{bmatrix} + B \begin{bmatrix} u_k^{\mathrm{EB}_1} \\ u_k^{\mathrm{EB}_2} \end{bmatrix} + D \begin{bmatrix} T_k^{\mathrm{Out}} \end{bmatrix} \tag{3a}$$

$$\begin{bmatrix} T_{k+1}^1 \\ T_{k+1}^2 \end{bmatrix} = A \begin{bmatrix} T_k^1 \\ T_k^2 \end{bmatrix} + B \begin{bmatrix} u_k^{\mathrm{EB}_1} \\ u_k^{\mathrm{EB}_2} \end{bmatrix} + C \begin{bmatrix} u_k^{\mathrm{ETS}_{\mathrm{Dsch}}} \\ 0 \end{bmatrix} + D \begin{bmatrix} T_k^{\mathrm{Out}} \end{bmatrix} \tag{3b}$$

where T_k is the internal temperature, T_k^{Out} is the outside temperature. k is the time step. u_k^{EB} and $u_k^{\mathrm{ETS}_{\mathrm{Dsch}}}$ 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' 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

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

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

$$T_k^{\mathrm{in}} \in [T_{\min}^{\mathrm{in}}, T_{\max}^{\mathrm{in}}] \tag{4c}$$

$$u_k^{\mathrm{EB}} \in [0, u_{\max}^{\mathrm{EB}}] \tag{4d}$$

$$u_k^{\mathrm{ETS}_{\mathrm{Ch}}} \in [0, u_{\max}^{\mathrm{ETS}_{\mathrm{Ch}}}] \tag{4e}$$

$$u_k^{\mathrm{ETS}_{\mathrm{Dsch}}} \in [0, P_{\max}^{\mathrm{ETS}_{\mathrm{Dsch}}}] \tag{4f}$$

$$x_0 = \text{Initial State} \tag{4g}$$

$$u_0 = \text{Initial State} \tag{4h}$$

$$\mathrm{SOC}_{k+1} = \mathrm{SOC}_k + (u_k^{\mathrm{ETS_{Ch}}} - u_k^{\mathrm{ETS_{Dsch}}})\Delta_k \tag{4i}$$

where

$$U_k = \gamma_k (T_k^C - T_k)^2 \tag{5}$$

$$C_k = \pi_k u_k \tag{6}$$

$$C_k^M = \left(u_k^{\mathrm{ETS_{Ch}}} - u_k^{\mathrm{ETS_{Dsch}}}\right)\Delta_k \cdot C_k^b \tag{7}$$

$$C_k^b = \frac{I}{2\eta\left(\overline{\mathrm{ES}} - \underline{\mathrm{ES}}\right)}. \tag{8}$$

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 η is the total rated cycles of the ETS unit, I is the upfront cost to purchase an ETS, and 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 $\overline{\mathrm{ES}}$ and discharging to $\underline{\mathrm{ES}}$. 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), $u_{\max}^{\mathrm{ETS}}$ and $u_{\max}^{\mathrm{EB}}$ 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. Δ_k is a ratio to obtain the energy amount per time slot k. SOC_{k+1} is the current energy stored, SOC_k is the immediate previous energy stored, $u_k^{\mathrm{ETS_{Ch}}}$ is the ETS power consumption, and $u_k^{\mathrm{ETS_{Dsch}}}$ 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.,

$$C_k(L_k) = a_k L_k^2 + b_k L_k + c_k \tag{9}$$

where a_k, b_k, and c_k are > 0 at each hour. L_k represents sum of all sets of best strategies $[u_1^{k*}, u_2^{k*} \ldots, u_n^{k*}]$. The term u_n^{k*} denotes the best strategy of the nth 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

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

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

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

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

$$\min_{u_k^1,\ldots,u_T^r} J + \frac{\tau}{2}\left\| u_k^{r,i} - u_k^{r,i-1} \right\| \tag{12}$$

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

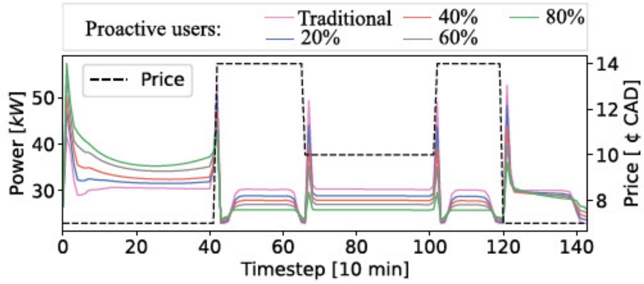

FIGURE 6. Impact of several uncoordinated thermal storage units.

chosen according to [77]

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

The value of λ 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 Kuujjuaq, 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^2, which remains constant throughout the day. The performance is evaluated through PAR, i.e., calculated as $\text{PAR} = (\max(L_k)T)/L_k$.

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

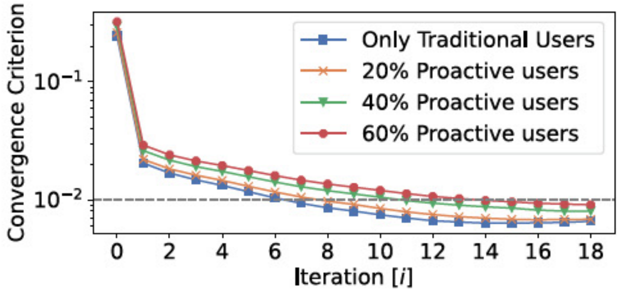

FIGURE 7. Convergence of algorithm with termination criterion.

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

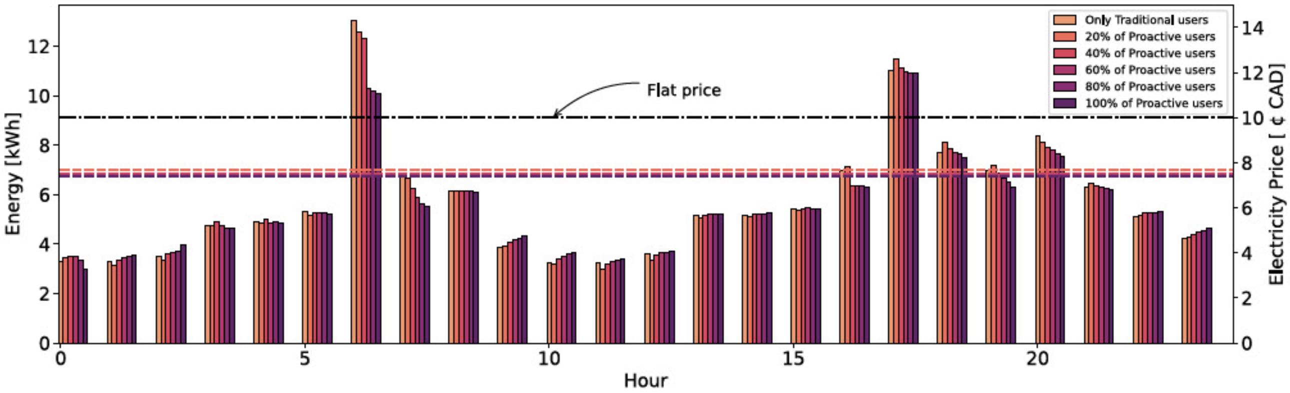

FIGURE 8. Coordinated aggregate hourly per-slot energy blocks with stochastic demand for each level of ETS adoption (No wind power).

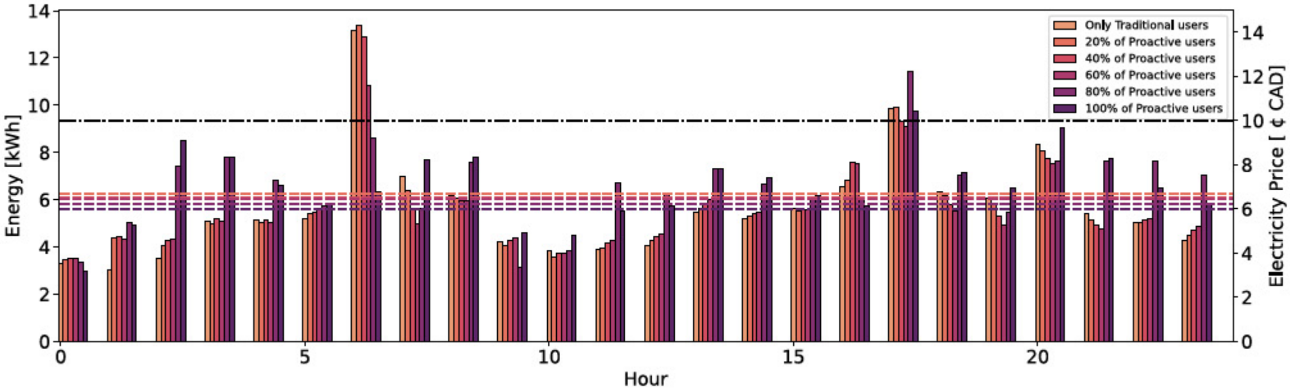

FIGURE 9. Coordinated aggregate hourly per-slot energy blocks with stochastic demand and electricity price for each level of ETS adoption (with wind power).

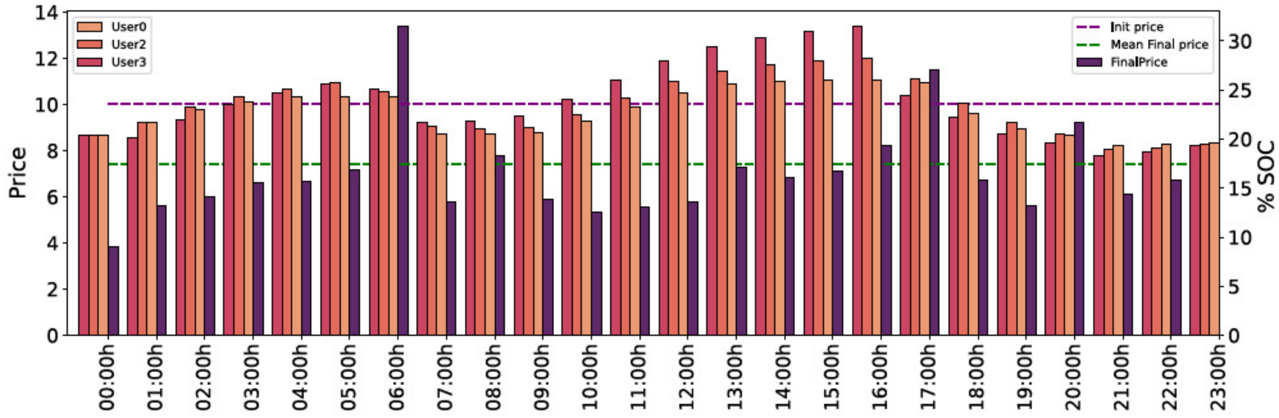

FIGURE 10. Aggregate per-slot prices and SOC for 100% for a subset of proactive agents.

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

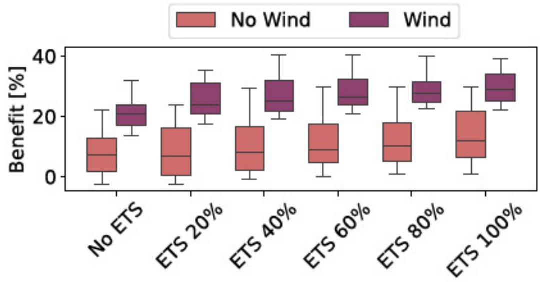

FIGURE 11. Comparison of distribution for expected daily benefits for users across different cases with and without wind power.

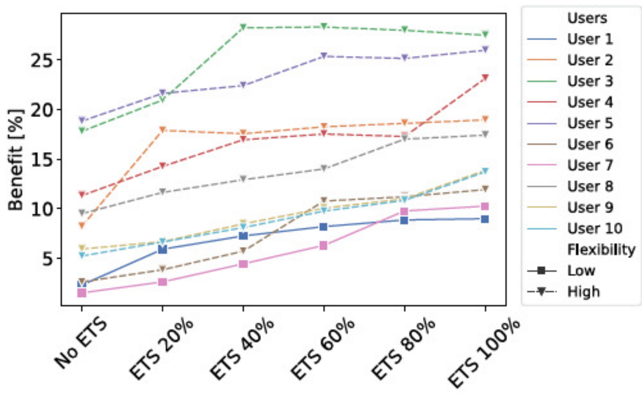

FIGURE 12. Expected economic daily benefits for users across different cases.

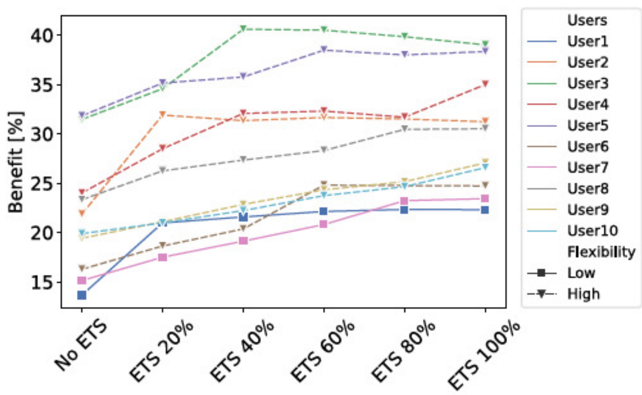

FIGURE 13. Expected economic daily benefits for users across different cases with wind power.

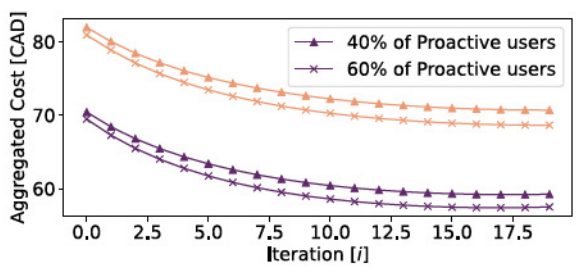

FIGURE 14. Average cumulative expense over the period of analysis for two subsets of active users, at each iteration, with and without wind power.

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 concords, 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.

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