The Electricity Journal 37 (2024) 107447

Contents lists available at ScienceDirect

The Electricity Journal

journal homepage: www.elsevier.com/locate/tej

Is it worthwhile to participate in transactive energy? A decision-making model for empowering residential customers

Alejandro Parrado-Duque [a,*], Nilson Henao [a], Kodjo Agbossou [a], Sousso Kelouwani [b], Juan C. Oviedo-Cepeda [c], Juan Domínguez-Jiménez [a]

[a] Department of Electrical and Computer Engineering, Hydrogen Research Institute, Laboratoire d'innovation et de recherche en énergie intelligente, Université du Québec á Trois-Riviéres, 3351, boulevard des Forges, Trois-Riviéres, Québec G8Z 4M3, Canada

[b] Department of Mechanical Engineering, Hydrogen Research Institute, Laboratoire d'innovation et de recherche en énergie intelligente, Université du Québec á Trois-Riviéres, 3351, boulevard des Forges, Trois-Riviéres, Québec G8Z 4M3, Canada

[c] Laboratoire des Technologies de l'Énergie, Institut de Recherche Hydro-Québec, 600 Av. De La Montagne, Shawinigan, Québec G9N 7N5, Canada

A R T I C L E I N F O

Keywords:
Convex stochastic programming
Day-ahead market
Game theory
Individual rationality
Reward-Penalty mechanism
Transactive energy

A B S T R A C T

The deployment of transactive energy systems hinges on well-defined policies that govern the decisions of transactive agents. Traditionally, upper-level agents, such as distribution system operators, aggregators, or coordinators, assume perpetual acceptance and participation by lower-level agents, like residential customers, in new demand-side programs. This assumption, alongside the presumption of agents' benevolent behavior in a transactional environment, often overlooks the potential for false information in electricity markets, leading to significant economic losses and program failures. To address these challenges, we develop a transactive energy system based on mechanism design, structured around four comprehensive phases: Enrollment, Coordination, Execution, and Settlement. Customers adopt a decision-making model grounded in convex stochastic programming, enabling them to freely choose their daily enrollment in a demand response program and define their willingness to coordinate day-ahead electricity consumption once the Enrollment phase is cleared. The payment rule proposed in this work, which includes a penalty policy for energy deviations, ensures truthful information reporting from residential agents to the coordinator within a negotiation environment. Our results demonstrate that residential agents' enrollment decisions vary according to the penalty values defined by the coordinator. Additionally, the number of customers enrolled in the Coordination phase significantly influences the coordinator's daily profits. The study also highlights how electricity deviations during the Execution phase can increase customers' costs beyond initial expectations, emphasizing the importance of adherence to planned consumption for optimal economic outcomes. This research offers a comprehensive transactive energy system that enhances customer participation through the principle of individual rationality and ensures truthful information reporting among agents based on the incentive compatibility concept in a day-ahead electricity market. Then, is it worthwhile to participate in transactive energy? The short answer is yes, and the reasons are unveiled throughout this paper.

1. Introduction

1.1. Background and Motivation

Digitalization of the electricity sector enables the adoption of key technologies required to successfully deploy transactive energy (TE) systems (The GridWise Architecture Council, 2019). TE, a recent market-based approach, balances supply and demand by leveraging all market participants' resources, including demand-side participation in grid services through demand response mechanisms or behind-the-meter capabilities, when financially viable for both parties (Guerrero et al., 2020; Song et al., 2022). Central to the deployment of TE systems is fostering transactive agents (TAs) by all entities involved. TAs, essentially machines programmed to fulfill specific delegated objectives, are crucial in facilitating communication and interaction among TE participants (Lopes and Coelho, 2018). By adopting TAs, TE systems can effectively orchestrate the exchange of resources and optimize grid operations (Lopes and Coelho, 2018).

Naturally, TAs dispose of levels of intelligence and rationality to

* Corresponding author.
E-mail address: alejandro.parrado@uqtr.ca (A. Parrado-Duque).

https://doi.org/10.1016/j.tej.2024.107447
Received 25 April 2024; Received in revised form 2 October 2024; Accepted 12 November 2024
Available online 19 November 2024

Nomenclature

TE	Transactive energy
TAs	Transactive agents
RAs	Residential agents
IC	Incentive compatibility
IR	Individual rationality
BESS	Battery energy storage system
DG	Distributed generation
DR	Demand response
DSO	Distribution System Operator
DERs	Distributed energy resources
EV	Electric vehicle
ISO	Independent System Operator
$\mathbf{E}[\cdot]$	Expected value
$LOI[\cdot]$	Penalty function
$J[\cdot]$	RAs cost function
$f[\cdot]$	Probability density function of the fixed load
$g[\cdot]$	Probability density function of the aggregated load
$PR[\cdot]$	Payment rule
n	Index of engaged customers in the TE system
m	Index of enrolled customers in the Coordination phase
t	Index of time-step
i	Index of iteration
0	Index of initial conditions
z	Index of Monte Carlo scenarios
*	Index of optimal response
λ	Quadratic energy cost, DSO parameter - $\$/kWh^2$
τ	Proximal algorithm parameter - $\$/kWh^2$
γ	Thermal discomfort parameter - $\$/\circ C^2$
C_{bat}	BESS degradation parameter - $\$/kWh$
α	Penalty value parameter - $\$/kWh^2$
$\widetilde{T}_{SP}$	Temperature set-point - $\circ$
$\mu_{f,n,t}$	Mean of the probability density function of the fixed load
$\sigma^2_{f,n,t}$	Variance of the probability density function of the fixed load
$\mu_{g,t}$	Mean of the probability density function - coordinator side
$\sigma^2_{g,t}$	Variance of the probability density function - coordinator side
Z	Number of Monte Carlo scenarios
$\mathscr{N}$	Set of RAs engaged in the TE system
$\mathscr{M}$	Subset $\mathscr{M} \subseteq \mathscr{N}$ of RAs enrolled in the Coordination phase
$\mathscr{C}$	Set of coordinators
Γ	Set of time horizon
Ψ	Set of iterations
$\boldsymbol{\alpha}$	Set of penalty values explored in simulations
p_{dis}	RA BESS power discharge - kW
p_{cha}	RA BESS power charge - kW
e_{cha}	RA BESS energy charge - kWh
e_{dis}	RA BESS energy discharge - kWh
e_{var}	RA heating energy - kWh
e_{fix}	Fix load energy - stochastic - kWh
e_{imp}	RA energy to import - kWh
$\widehat{e}_{imp}$	RA energy to report - kWh
π	Electricity price - $\$/kWh$
$\widetilde{T}_{in}$	Schedule dwelling temperature - $\circ C$
SOC	BESS state-of-charge

strive for the best possible outcomes while operating in an environment (Lopes and Coelho, 2018). Since agents are inherently selfish, the desired target is always an individual best outcome (Kuipers, 2022).

The agent's role defines the level where the agent will operate in the environment (The GridWise Architecture Council, 2019). This work develops upper- and lower-level TAs called the coordinator and the residential agent (RA). The coordinator represents utility interests, while the RA advocates for customer interests within a distribution system. The capabilities of TAs are governed by the elements that comprise the TE system proposed by the coordinator. For instance, a market architecture, an interaction mechanism, and a set of rules constitute a TE system (Lopes and Coelho, 2018). Based on the adoption of upper- and lower-level entities, this work is conducive to formulating a non-cooperative Stackelberg game to model the TA interaction and empowering RAs in deciding whether to coordinate a day-ahead electricity consumption by adopting a contract.

Since the basis of the interaction between the TAs is given by the elements defined in the TE system (Adeyemi et al., 2020), three issues are expected to be addressed in this paper: i) What steps should a TE system consider to reach an interaction among TAs? ii) What decision-making model could the RAs adopt to decide whether to participate in a TE goal? iii) How to ensure that TAs report truthful information among them? This paper addresses these questions by seeing TE systems as a world that embraces elements to guide TAs to achieve desired goals. As mentioned, a market architecture, an interaction mechanism, and a set of rules constitute TE. These TE elements are structured by the coordinator, who, for this work's aim, formulates: i) a day-ahead electricity market as the market architecture, ii) a non-cooperative game, i.e., the Stackelberg game as the interaction mechanism, and iii) a smart contract as the set of rules of the TE system.

1.2. State-of-the-art

In most cases, the literature assumes that customers will enroll and actively participate in any electricity market where they perceive a reduced electricity bill based on the concept of individual rationality (Sloot et al., 2022). However, such studies often make overly optimistic assumptions about customer engagement in demand response (DR) programs, overlooking factors like comfort preferences, collective and individual understanding of energy-related concepts, and the perceived legitimacy of these programs (Parrish et al., 2019). These factors significantly influence real-world trials, resulting in lower enrollment rates and reduced load-shift responsiveness (Parrish et al., 2019). As a result, technological programs deployed in the electricity sector have demonstrated underperformance, and retailers and Distribution System Operators (DSOs) have withdrawn the programs (Thomas, 2023). For instance, DR programs reported in (Parrish et al., 2019; Sloot et al., 2022) show that forced customer enrollment (opt-out) had a low load responsiveness compared with awareness-decision-based (opt-in) and voluntary participation. In fact, (Beckstedde and Meeus, 2023) mentioned that a potential way to request customers' provision flexibility in short-term contracts is related to voluntary instead of mandatory participation. However, its effect magnitude still needs to be determined.

Technological devices (e.g., home energy management systems) and efficient local electricity markets should be enablers to unlock customer flexibility potential, but their lack of progress (Yazdani et al., 2022; Avramidis et al., 2023) and widespread engagement (Sloot et al., 2023) are current barriers. Lack of information (Carmichael et al., 2021), energy-related knowledge (Lee et al., 2020), the absence of an automatic control heating system (Eguiarte et al., 2022), and a constrained market for participation to provide demand-side flexibility (Loffredo, 2023) are additional barriers customers commonly face. For instance, customers in Norway and Belgium cannot easily understand what dynamic electricity

Table 1
Related works on penalty mechanisms and topics addressed in this work.

Work	Year	Day-ahead	Penalty	DERs				Participation model	Negotiation model	Truthful consumption report	Privacy	Power flow model	Convex optimization
				DR	DG	EV	BESS						
(Ghorani et al., 2019b)	2019	X	✓	X	✓	X	X	X	✓	X	✓	X	X
(Ghorani et al., 2019a)	2019	✓	✓	X	✓	X	X	X	✓	X	✓	✓	✓
(Ghorashi et al., 2020)	2020	✓	✓	✓	X	X	X	X	X	X	✓	✓	X
(Tsaousoglou et al., 2020)	2020	✓	X	✓	X	✓	X	X	✓	✓	✓	X	✓
(Dulipala and Debbarma, 2021a)	2021	✓	✓	X	✓	✓	X	X	✓	X	✓	X	X
(Dulipala and Debbarma, 2021b)	2021	✓	✓	X	✓	X	X	X	✓	X	✓	X	X
(Yao et al., 2021)	2021	✓	X	X	✓	X	X	X	✓	X	X	X	✓
(de Souza Dutra and Alguacil, 2023)	2023	✓	X	✓	✓	✓	X	X	✓	X	✓	X	✓
(Zhang et al., 2024)	2024	✓	X	✓	X	✓	X	X	✓	X	✓	✓	✓
(Ranjbar et al., 2024)	2024	✓	X	✓	✓	X	✓	X	✓	X	✓	✓	X
This work	2024	✓	✓	✓	X	X	✓	✓	✓	✓	✓	X	✓

tariff they choose in their contracts (Loffredo, 2023). Moreover, trust in the DR program (e.g., transparency) is critical in customer technology adoption (Parrish et al., 2020). For instance, participants with access to current price levels and consumption or automation technology tend to be more responsive (+2.5 % and +15 %, respectively) than participants who receive pricing alone (Parrish et al., 2019). Additional socio-demographic characteristics such as age, geographic region, education qualification, household size, and household income play a key role in determining the willingness to load shifting (Li et al., 2020).

Additional efforts in developing a comprehensive decision-making model should take place to engage customers in new technologies since household contribution is fundamental to achieving a fossil-free electricity system (Rossetto, 2023). In fact, an automated customer decision-making model that helps customers determine the flexibility they are willing to negotiate, all given a specific time horizon, has yet to be proposed (Rodilla et al., 2023).

Since passive customers (i.e., traditional customers without a participation in an electricity market) could adopt the agents-based technology to operate in a TE environment on their behalf (Doumen et al., 2023), and since they are free to assess their participation in the electricity market (Thomas, 2023), gaming the system is an actual concern that could eventually limit the potential of market-based flexibility (Beckstedde and Meeus, 2023).

In a TE system, gaming the system could affect the efficient operation of an electricity market because participants could not fulfill their market obligations (Ghorani et al., 2019b). TAs could game the system by identifying a negotiation mechanism's weakness that improves their payoff. One way to cheat the system is by introducing false information (Beckstedde and Meeus, 2023). In this regard, looking for a mechanism where agents are motivated to report truthful information is called incentive compatibility (IC) in the mechanism design theory (Parilina et al., 2018). Since literature has tried to expand the application of this key phenomenon in all sectors, additional efforts must be made to include its implications in TE systems.

For instance, (Ghorani et al., 2019b,a) proposed a penalty function to deal with electricity deviations from an agreed plan in a TE system, but their analysis was not conducted to ensure that prosumers report truthful information to the DSO. (Ghorashi et al., 2020) proposed a penalty for on-peak and off-peak load periods, but their analysis lacked verification of whether the transacted agents' information was true or false. (Dulipala and Debbarma, 2021b,a) adopts the penalty mechanism proposed in (Ghorani et al., 2019b), carrying the concerns already addressed. (Yao et al., 2021) proposed a coalition approach where participants could share energy among themselves, creating a loss of profits for some participants. Despite the authors in (Yao et al., 2021) mention of ensuring truthful report of information from users through an IC mechanism, the IC property was not effectively addressed in the paper. (de Souza Dutra and Alguacil, 2023) proposed a bilevel optimization problem considering the cost of deviating from a desired aggregated consumption defined by the aggregator. However, the aggregator did not verify whether the information reported by RAs was accurate. (Zhang et al., 2024) proposed a demand response (DR) program to manage the integration of electric vehicle (EV) charging stations in active distribution networks. However, their approach did not empower customers with the option to decide their participation, nor did it provide the DSO with a mechanism to verify the accuracy of bids submitted by EV drivers. Finally, (Ranjbar et al., 2024) introduced a transactive energy (TE) system to coordinate prosumers within a distribution network structured across three participant layers: prosumers, DSO, and ISO. While their mechanism demonstrates the reliability benefits of TE by optimizing power flow, it remains vulnerable to inaccurate bids from prosumers in a day-ahead market, potentially leading to economic losses and technical issues.

To condense all this information and provide the reader with an overview of this work's contributions, Table 1 presents a meaningful comparison of related works, including information about the market, penalties addressed, distributed energy resources (DERs) types, participation model, negotiation model, an agent-based program to ensure report of accurate information, and optimization model.

For clarity, the item *participation model* from Table 1 refers to a decision-making model that customers could exploit to assess their participation in a program phase. In this case, this work introduces a comprehensive decision-making model designed to help customers make informed decisions about whether to coordinate their consumption for the day-ahead period. On the other hand, a *negotiation model* entails a two-way interaction where both parties exchange information and mutually decide whether to accept or reject the proposed terms. For instance, if the DSO imposes signals to alter customers' consumption patterns without offering them a choice, the process lacks genuine negotiation and consensus. In contrast, this work aims to empower customers by incorporating a decision-making model in both the Enrollment and Coordination phases. Customers actively decide to participate during the Enrollment phase and reach a consensus on their consumption plans during the Coordination phase.

1.3. Contributions and organization

The contributions of this work are outlined as follows:

- A comprehensive contract with four phases is developed to model the interaction among Transactive Agents (TAs) in a Transactive Energy (TE) system. These four phases are relevant to the customers and the coordinator in understanding their role and their capabilities at each phase of the TE system.
- A decision-making model is provided to empower customers by facilitating their daily decision to participate or refuse in a reward coordination scheme based on the signals proposed in a TE system.
- A mechanism is designed to encourage residential agents to report truthful information to the coordinator in the TE system. This mechanism is intended to prevent the introduction of false information in the information exchange process.

The rest of the paper is organized as follows: Section 2 introduces the methodology employed in this work, considering the system model and problem formulation, the RAs' optimization model in the different contract phases, and the coordinator model. Section 3 presents the parameters of the model employed through the simulations. Section 4 presents the results-based simulation obtained by applying each phase of the contract from the perspective of the coordinator and the RAs. Finally, Section 5 highlights the main findings of this work as conclusions.

2. System model and problem formulation

This work considers the deployment of a coordinator to handle, in a distributed manner, the day-ahead operation of a distribution system. Note that in this paper a distributed approach is preferred to the central operation of a distribution system because the latter may face several challenges in the operation a growing and diversified electricity system (Ranjbar et al., 2024). Given its promising capabilities, the coordinators strategically develop a TE system for a group of residential customers. The coordinator: i) develops the steps and rules of the TE system, and ii) proposes the TE program to the customers; meanwhilethe customers decide on a daily basis whether to participate in the TE system. Regardless of their participation, this work assumes all the customers are equipped with the technology to be part of the program. This TE program is fully interested in developing a decision-making framework to empower active customers to enhance their management system and not just assume that they will suddenly accept the TE rules proposed by the coordinator. Subsequent sections comprehensively describe the TE program's procedural steps and agent guidelines.

Consider a finite set $\mathscr{N} = \{1, 2, \ldots, N\}$ of RAs powered by a distribution transformer. Also, consider a finite set of one coordinator $\mathscr{C} = \{1\}$ who is fully interested in coordinating the day-ahead energy consumption of the RAs over the entire consumption horizon $\Gamma = \{1, 2, \ldots, T\}$ through price and penalty policies. The RAs actively participate in consumption coordination once they accept the enrollment conditions determined by the coordinator. Let denote the vector $\boldsymbol{e}_n = (e_{n,1}, e_{n,2}, \ldots, e_{n,T})$ as the energy consumption profile of customer n over the consumption horizon, where $e_{n,t}$ is the energy consumption of customer n at time slot t. Let $\boldsymbol{e} = (\boldsymbol{e}_1, \boldsymbol{e}_2, \ldots, \boldsymbol{e}_N)$ represent the energy consumption profile of all RAs in the coordination scheme. Let denote the set of pairs $\boldsymbol{s}_n = \{(\pi_{n,1}, \alpha_{n,1}), (\pi_{n,2}, \alpha_{n,2}), \ldots, (\pi_{n,T}, \alpha_{n,T})\}$ as the price (π) and penalty (α) signals formulated by the coordinator over the consumption horizon Γ, where $(\pi_{n,t}, \alpha_{n,t})$ are the price and penalty signals of customer n at time slot t, respectively. Let $\boldsymbol{s} = (\boldsymbol{s}_1, \boldsymbol{s}_2, \ldots, \boldsymbol{s}_N)$ denote the prices and penalties profiles of all RAs in the coordination scheme.

2.1. Non-cooperative game

A non-cooperative game - the Stackelberg game - has been employed in this work to model the negotiation process between the coordinator (the game's leader) and the RAs (the game's followers). While a non-cooperative game is suited for this purpose as it captures situations where players (decision-makers) act independently from their peers within the game, the Stackelberg game is fitted as it allows the coordination of the followers based on the leader's decisions (Fujiwara-Greve, 2015). This game structure is chiefly attributed to the absence of communication channels among the followers, thereby precluding the making of joint decisions. The game model, as well as the game rules, are further presented.

2.1.1. Game model

The game involves the interaction between one single coordinator and several RAs. The game has a minimum exchange of information, i.e., one two-way signal, modeling a typical coordinator with market power. In this setup, the coordinator discloses pricing and penalty signals to the RAs while the RAs perform their optimization problem and report participation signals or scheduled electricity consumption. Therefore, a Stackelberg game is a tuple $\mathscr{G} = \{\mathscr{N}, \mathscr{M}, \mathscr{C}, \{\mathscr{E}_n\}_{n\in\mathscr{N}}, \{\mathscr{S}_n\}_{n\in\mathscr{N}}, \{J_n\}_{n\in\mathscr{N}}\}$, where:

- Players: The total RAs in set $\mathscr{N}$, the coordinated RAs in set $\mathscr{M} \subseteq \mathscr{N}$, and the single coordinator in set $\mathscr{C}$.
- RAs' strategy set: $\mathscr{E}_n \subseteq \mathbb{R}^T$ for each $n \in \mathscr{N}$, is nonempty, compact, and convex.
- Coordinator strategy set: $\mathscr{S}_c \subseteq \mathbb{R}^T$ for each $c \in \mathscr{C}$, is nonempty, compact, and convex.
- RAs' payoff function: $J = (J_1, J_2, \ldots, J_N)$ where $J_n : \mathscr{E} \mapsto \mathbb{R}^T$.

2.1.2. Game global rules

The game model of a Stackelberg game relies on a series of axioms to establish a coherent framework and govern the gameplay among participants (Ungureanu, 2018; Parilina et al., 2018).

- Moves: While RAs' moves are simultaneous, the moves between the coordinator and the RAs are sequential.
- Information: Minimal exchange among participants, with private strategy sets and payoff functions. The game incorporates incomplete, imperfect, and asymmetric information.
- Recall: Players can access their past moves and actions.
- Knowledge: Mutual knowledge arises from the game rules shared, the existing communication between RAs and the coordinator, but the absence of this between the RAs themselves.
- Rationality (bounded): Players optimize their payoff functions within the constraints of their bounded rationality.
- Corruption: The game excludes dishonest practices such as corruption, collusion, and bribery. However, without a truthful mechanism, there is a risk that RAs may exploit the system.
- Payoff: Players determine the value of their payoff functions post-strategy selections.

2.1.3. Game contract phases rules

- Enrollment phase.

- Moves. This phase considers one iteration for a day-ahead planning horizon.
  1. The coordinator sends the set of RAs an approximated price while exploring a set of penalty values within the day-ahead plan coordination.

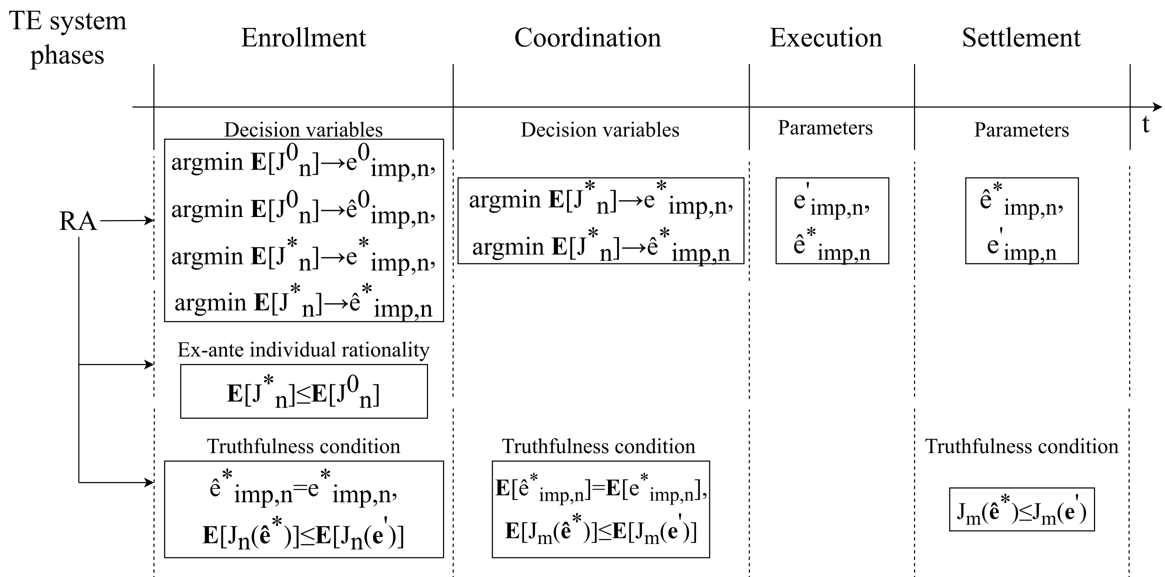

Fig. 1. Contract phases in the TE system from a mechanism design perspective.

   2. The RAs send an approval or rejection participation signal in that day-ahead coordination.
- Payoff.
   1. The coordinator set up the penalty value to charge each customer.
   2. The RAs perform a risk-analysis algorithm to decide whether to participate in the day-ahead coordination mechanism. This action creates the subset $\mathscr{M} \subseteq \mathscr{N}$.

- Coordination phase.

- Moves. This phase considers multiple iterations for a day-ahead planning horizon until convergence.
   1. The coordinator shares prices and penalty signals iteratively with the subset of RAs $\mathscr{M}$.
   2. The RAs share an electricity consumption profile updated to the coordinator based on the prices and penalties received.
- Payoff.
   1. The coordinator performs Eq. (19).
   2. The RAs perform Eq. (14a) s.t. Eq. (14b).

- Execution phase.

- Moves. The uncertainty is revealed, and a simulation is performed to find the actual synthetic RAs' electricity consumption.

- Settlement phase.

- Payoff.
   1. The coordinator charges the customers with the electricity bill considering the negotiation agreements.

2.1.4. TE system contract phases

The contract of the TE system consists of four phases depicted in Fig. 1. In the first phase, set $\mathscr{N}$ of customers decide whether to enroll in day-ahead coordination. In the second phase, enrolled customers $\mathscr{M}$ individually coordinate their consumption profiles. The third phase involves the execution of the consumption plan. In the fourth phase, the coordinator settles agreements with enrolled customers and charges an initial tariff to those who did not coordinate. The process is then infinitely repeated for day-ahead consumption planning. The two first game phases depicted in Fig. 1 involve an optimization problem, while the remaining ones concern the uncertainty realization. The optimization problem for the RAs' Enrollment and Coordination phase is described in the following subsections.

2.2. Residential agents problem formulation

All the RAs are assumed to adopt the same payoff function for simplicity. Each RA is fully interested in minimizing electricity costs by optimizing imported electricity, BESS charge and discharge, and thermal discomfort.

2.2.1. RA - enrollment model

The RAs payoff function involves the cost of importing electricity from the grid, the individual thermal discomfort component, the battery operation cost, and the penalty cost for electricity deviations, as developed in Eq. (1).

$$\mathbf{E}[J_n(\boldsymbol{e})] = \left[\mathbf{E}\left[\sum_{t=1}^{T} \left(\overbrace{e_{imp,n,t}\cdot\pi_{n,t}}^{\text{Cost of electricity imports}} + \overbrace{\gamma_n\cdot\left(\widetilde{T}_{SP,n,t} - \widetilde{T}_{in,n,t}\right)^2}^{\text{Cost of thermal discomfort}} + \underbrace{\left(e_{dis,n,t} + e_{cha,n,t}\right)\cdot C_{bat,n,t}}_{\text{Cost of battery operation}} \overbrace{\gamma_n\cdot\left(\widetilde{T}_{SP,n,t} - \widetilde{T}_{in,n,t}\right)^2}^{\text{Cost of thermal discomfort}} \right) \right] + \underbrace{\mathbf{E}\left[\sum_{t=1}^{T} \left(\mathrm{LOI}(\boldsymbol{e}, \boldsymbol{r})\right) \right]}_{\text{Penalty mechanism}} \right] \tag{1}$$

where $\mathbf{E}[\cdot]$ is the expected value operator, $e_{imp,n,t}$ is the electricity imported from the grid (decision variable) in kWh, $\pi_{n,t}$ is the individual electricity price in $\$/kWh$, γ_n is an individual parameter that weight individually the thermal discomfort in $\$/\circ C^2$ (Cheng et al., 2022), $\widetilde{T}_{SP,n,t}$ is the temperature set-point in $\circ C$, $\widetilde{T}_{in,n,t}$ is the schedule dwelling temperature in $\circ C$, $e_{cha,n,t}$ and $e_{dis,n,t}$ are the charge and discharge electricity from the BESS (battery energy storage system) in kWh, $C_{bat,n,t}$ is a constant parameter that weight the BESS' charging and discharging degradation process (Banfield et al., 2021) in $\$/kWh$, and $\mathbf{E}[LOI(\boldsymbol{e}, r)]$ penalizes the electricity deviations from the reported consumption plan based on an uncertainty parameter r in $\$$.

The $LOI[\cdot]$ function serves two primary purposes. First, it addresses the inherent uncertainties in forward markets, such as the day-ahead market employed in this work. These uncertainties can hinder customers' ability to meet market obligations, leading to economic inefficiencies within the TE system (Ghorani et al., 2019b) and posing operational risks to the distribution network due to energy imbalances (Sharma et al., 2020). Therefore, each RA is assumed to operate a battery energy storage system (BESS), which helps manage individual uncertainty costs. This fact is particularly viable given the dynamic electricity pricing the coordinator employs in the DR program. Second, the coordinator imposes penalties on deviations that are not attributed to inherent uncertainties to counteract the potential for strategic manipulation by intelligent and rational agents, who might report false planned consumption ($\widehat{\mathbf{e}}$) to gain economic advantages. This approach intends to discourage such strategic behavior and maintain the integrity of the TE system.

The energy balance model is considered as follows in Eq. (2) (Banfield et al., 2021).

$$\mathbf{E}\left[e_{imp,n,t}\right] = \mathbf{E}\left[e_{var,n,t} + e_{fix,n,t} + e_{cha,n,t} - e_{dis,n,t}\right]. \tag{2}$$

where $e_{var,n,t}$ represents the heating system variable in kWh, $e_{fix,n,t}$ is the inflexible customer load and the source of customer' uncertainty in kWh, and $e_{cha,n,t}$, $e_{dis,n,t}$ are the battery-related energy variables in kWh. As pointed out, each customer defines its utility function based on the temperature discomfort regarding a thermostat set-point. The thermal discomfort weighted in the customer cost Eq. (1) function is affected by an individual parameter γ_n, representing the customer thermal flexibility (Cheng et al., 2022). The higher the γ_n term, the less flexible the customer is. Each RA employs a state-of-space model to capture the dynamics of the inner dwelling temperature Eq. (3), defines the inner temperature limits Eq. (4), and ensures that the initial and final dwelling house temperature remain equal Eq. (5) (Rueda et al., 2021).

$$\widetilde{T}_{in,n,t} = A\cdot\widetilde{T}_{in,n,t-1} + B\cdot e_{var,n,t} + C\cdot\widetilde{T}_{ext,t} \tag{3}$$

$$\min_{\widetilde{T}_{SP,n,t}}(\widetilde{T}_{SP,n,t}) \leq \widetilde{T}_{in,n,t} \leq \max_{\widetilde{T}_{SP,n,t}}(\widetilde{T}_{SP,n,t}) + \vartheta \tag{4}$$

$$\widetilde{T}_{in,n,t=0} = \widetilde{T}_{in,n,t=T} \tag{5}$$

Moreover, Eq. (1) implies the operation of a BESS from the RA side. As the electricity market considered in this work does not consider energy exports to the grid, the RA could operate a BESS behind the meter to (i) reduce the uncertainties effect over the customer cost function, (ii) reduce the cost function by employing the charge and discharge BESS operation states based on a dynamic electricity price (Srinivasan et al., 2023). Moreover, the power storage level of each BESS unit of each RA $n \in \mathscr{N}$ is limited by the battery capacity as expressed in Eq. (6)-(10) (Banfield et al., 2021).

$$SOC_{n,t} = SOC_{n,t-1} + \left(\eta_{cha}\cdot p_{cha,n,t} - p_{dis,n,t}/\eta_{dis}\right)\cdot\Delta t \tag{6}$$

$$\underline{SOC_{n,t}} \leq SOC_{n,t} \leq \overline{SOC_{n,t}} \tag{7}$$

$$SOC_{n,t=0} = SOC_{n,t=T} \tag{8}$$

$$\underline{p_{cha,n,t}} \leq p_{cha,n,t} \leq \overline{p_{cha,n,t}} \tag{9}$$

$$\underline{p_{dis,n,t}} \leq p_{dis,n,t} \leq \overline{p_{dis,n,t}} \tag{10}$$

where Eq. (6) models the state-of-space modeling relating to the battery state-of-charge (SOC), Eq. (7) represents the battery operational SOC limits, Eq. (8) ensures that the initial and final SOC conditions are equal, and Eq. (9) and Eq. (10) describes the BESS charging and discharging power capacity limits.

The RA performs the optimization problem defined in Eq. (11a) and constraints defined in Eq. (11b) to determine whether to participate in the day-ahead coordination.

$$\text{minimize}_{\boldsymbol{e}\in\mathscr{E}}\mathbf{E}[J_n(\boldsymbol{e})] \tag{11a}$$

$$\text{subject to } (2)-(10), \quad \forall\, t\in\Gamma, \forall\, \boldsymbol{n}\in\mathscr{N} \tag{11b}$$

Therefore, for each RA $\boldsymbol{n}$, the feasible consumption profile set is expressed in Eq. (12).

$$\mathscr{E}_n = \{\boldsymbol{e}_n|(2)-(10)\} \tag{12}$$

Correspondingly, the feasible set of consumption profile of all RAs in their Enrollment phase is $\mathscr{E} = \{(\boldsymbol{e}_1, \boldsymbol{e}_2, \ldots, \boldsymbol{e}_N)|\boldsymbol{e}_n \in \mathscr{E}_n, \forall n \in \mathscr{N}\}$.

RAs determine their enrollment in the day-ahead coordination process by computing the participation condition (Watson, 2013) expressed in Eq. (13). The participation condition assesses the expected payoff between coordination and non-coordination scenarios, as presented in Fig. 1. Notice that RAs compute their participation condition as an individual rationality (IR) requirement, a key concept in mechanism design (Jain and Wu, 2009). Three types of IR - ex-ante, interim, and ex-post - are well identified in the literature (Jain and Wu, 2009). An RA decides to be enrolled in the Coordination phase if the *participation condition* (or *ex-ante*) IR is clearly met; otherwise, it opts not to engage in the coordination process.

$$\mathbf{E}[J(e_n*)] \leq \mathbf{E}[J(e_n^0)]. \tag{13}$$

where $\mathbf{E}[J(e_n{*})]$ is the expected participation cost of each RA $\mathscr{N}$ coordinating their individual electricity consumption, and $\mathbf{E}[J(e_n^0)]$ is the cost of not participation, i.e., the consumption subject to a flattened electricity price. Notably, the RAs do not communicate their consumption in response to the coordinator signals in the Enrollment phase; instead, they respond with an approval or rejection signal to be part of the subset $\mathscr{M} \subseteq \mathscr{N}$ and participate in the Coordination phase.

Once agents decide to be enrolled and the coordinator selects them to participate in the Coordination phase, the RAs cannot withdraw from the contract. Furthermore, the subset $\mathscr{M}$ of RAs must coordinate their expected electricity consumption. However, due to the inherent uncertainty in determining electricity consumption in a day-ahead market, the interim and the ex-post IR cannot be ensured in this work without affecting the truthfulness condition (Yuan et al., 2017).

2.2.2. RA - coordination model

Once the RAs' subset $\mathscr{M} \in \mathscr{N}$, those RAs who decide to coordinate their consumptions, is defined, the RA performs the optimization problem defined in Eq. (14a) and constraints Eq. (14b) to coordinate their day-ahead individual electricity consumption. It is important to emphasize that this coordination process converges gradually through iterative procedures, where an incremental index, denoted as $i \in \Psi$, is introduced to the RA's payoff as follows in Eq. (14b).

$$\text{minimize}_{\boldsymbol{e}\in\mathscr{E}}\mathbf{E}\left[J_m^i(\boldsymbol{e})\right] + \underbrace{\left[\frac{\tau}{2}\cdot\left|\left|e_{imp,m}^i - e_{imp,m}^{i-1}\right|\right|_2^2\right]}_{\text{Proximal algorithm}} \tag{14a}$$

subject to $(2)-(10), \quad \forall t \in \Gamma, \forall m \in \mathscr{M}, \forall \quad i \in \Psi,$ (14b)

where the convergence (Scutari et al., 2014) and a stable solution (Parikh, 2014) are reached by employing the proximal decomposition algorithm (a strongly convex and non-expansive function). $\tau = 3\cdot(|\mathscr{M}|-1)\cdot\lambda$ is a regularization parameter of the proximal algorithm, $|\mathscr{M}|$ is the length of the subset $\mathscr{M}$, λ is a DSO technical parameter associated to the energy distribution cost (Tsaousoglou et al., 2020) defined as $\lambda = \sum_{t\in\Gamma}\left[\pi_t^0\cdot\sum_{n\in\mathscr{N}}\left(\widehat{e}^0_{imp,n,t}\right)\right]/\sum_{t\in\Gamma}\sum_{n\in\mathscr{N}}\left(\widehat{e}^0_{imp,n,t}\cdot\widehat{e}^0_{imp,n,t}\right)$, and $e^i_{imp}-e^{i-1}_{imp}$ indicates the difference among the current and past consumption vectors of the imported load. In this phase, RAs report their consumption to the coordinator until they reach convergence (e_n*).

Therefore, for each RA m, the feasible consumption profile set is expressed in Eq. (15).

$$\mathscr{E}_m = \{\boldsymbol{e}_m|(2)-(10)\} \tag{15}$$

Correspondingly, the feasible set of consumption profile of all RAs in their Coordination phase is $\mathscr{E} = \{(\boldsymbol{e}_1, \boldsymbol{e}_2, \ldots, \boldsymbol{e}_M)|\boldsymbol{e}_m \in \mathscr{E}_m, \forall m \in \mathscr{M}\}$.

2.3. Coordinator model

2.3.1. Coordinator - enrollment phase

In the Enrollment phase, the coordinator provides crucial signals to residential agents (RAs) to facilitate their decision-making regarding participation in the Coordination phase: i) a flattened electricity price (π_t^0) enables RAs to compute their expected no-participation (or initial) cost ($\mathbf{E}[J_n(\boldsymbol{e}^0)]$), ii) a possible dynamic electricity price ($\pi^*{}_t$) to allow them to compute their expected participation cost ($\mathbf{E}[J_n(\boldsymbol{e}*)]$) they could face by participation, and iii) a set of penalty values $\boldsymbol{\alpha}_n$ applied in the penalty policy, which the coordinator charges to participating RAs. These penalty values are used by each RA to compute their expected participation cost ($\mathbf{E}[J_n(\boldsymbol{e}*)]$).

For purposes of this work, the coordinator sets the flattened electricity price based on the annual average electricity price defined in (Hydro-Quebec, 2022). Moreover, the dynamic electricity price ($\pi^*{}_t$) used in the Enrollment phase is sourced from (Arnedo et al., 2023), where coordination prices among twenty RAs over more than twenty days were observed. Finally, the penalty values $\boldsymbol{\alpha}_n$ are derived from simulations to discover the discourage-responsiveness participation of RAs based on their expected participation cost ($\mathbf{E}[J_n(\boldsymbol{e}*)]$). Further considerations are provided in Section 3.

2.3.2. Coordinator - coordination phase

RAs coordinate their electricity consumption by following a coordinator's price and penalty signals. This coordination endeavor hinges on encouraging desired behaviors by manipulating electricity prices, an iterative process until convergence is reached. Notably, the electricity price at the time ($t \in \Gamma$) and at iteration ($i \in \Psi$) is calculated by employing the sharing-the-cost model proposed in (Nguyen et al., 2015). This model aligns with principles of equitable resource allocation by equitably distributing the operational costs incurred within the distribution system, i.e., charging identical electricity tariffs to all customers. The sharing-the-cost model proposed by (Nguyen et al., 2015) in a deterministic environment is as follows in Eq. (16):

$$C^i_{m,t} = \frac{\widehat{\boldsymbol{e}}^i_{m,t}}{\widehat{\boldsymbol{e}}^i_{agg,t}}\cdot C^i(\widehat{\boldsymbol{e}}^i_{agg,t}), \tag{16}$$

where $C^i_{m,t}$ is the individual electricity cost of coordinated RAs subset $m \in \mathscr{M} \therefore \mathscr{M} \subseteq \mathscr{N}$ at time $t \in \Gamma$ and at iteration $i \in \Psi$, $\widehat{\boldsymbol{e}}^i_{agg,t} = \sum_{m\in\mathscr{M}}\widehat{\boldsymbol{e}}^i_{m,t}$ is the aggregated electricity consumption at time $t \in \Gamma$ and at iteration $i \in \Psi$ reported by RAs' subset $\mathscr{M}$, and $C^i(\widehat{\boldsymbol{e}}^i_{agg,t})$ is the aggregated cost of the energy demanded at time $t \in \Gamma$. Assuming the latter as a quadratic cost, the price generator at time $t \in \Gamma$ is found in Eq. (19).

$$C^i_{m,t} = \frac{\widehat{\boldsymbol{e}}^i_{m,t}}{\widehat{\boldsymbol{e}}^i_{agg,t}}\cdot\lambda\cdot\left(\widehat{\boldsymbol{e}}^i_{agg,t}\right)^2 \tag{17}$$

$$C^i_{m,t} := \widehat{\boldsymbol{e}}^i_{m,t}\cdot\underbrace{\lambda\cdot\widehat{\boldsymbol{e}}^i_{agg,t}}_{\text{Price}} \tag{18}$$

$$\pi^{i+1}_t = \lambda\cdot\widehat{\boldsymbol{e}}^i_{agg,t}. \tag{19}$$

where $\lambda = \sum_t^T\left(\pi_t^0\cdot\widehat{e}^0_{agg,t}/\left(\widehat{e}^0_{agg,t}\right)^2\right)$ is a regularization parameter, and $(\widehat{e}^0_{agg,t})$ is the initial aggregated electricity consumption subject to a flattened electricity price (π_t^0). Notice that the coordinator charges all the customers the same electricity price, while their individual electricity consumption complements their cost C^i_m.

This work adapted the sharing-the-cost model proposed by (Nguyen et al., 2015) to introduce the notion of expected aggregated consumption deviations. The expectation value on the coordinator side rises since it could be aware that the customers could unintentionally deviate from the consumption plan due to the inherent uncertainties that appear in a day-ahead market (Lopes and Coelho, 2018). Then, the price generator at time $t \in \Gamma$ of the next iteration $i+1 \in \Psi$ is as follows in Eq. (20).

$$\mathbf{E}\left[\pi^{i+1}_t\right] = \lambda\cdot\mathbf{E}\left[\widehat{\boldsymbol{e}}^i_{agg,t}\right]. \tag{20}$$

where $\mathbf{E}\left[\pi^{i+1}_{m,t}\right]$ is the electricity price that the coordinator charges to all RAs subset $m \in \mathscr{M} \therefore \mathscr{M} \subseteq \mathscr{N}$ at time $t \in \Gamma$ and at iteration $i \in \Psi$, and $\mathbf{E}\left[\widehat{\boldsymbol{e}}^i_{agg,t}\right] = \mathbf{E}\left[\sum_{m\in\mathscr{M}}\widehat{\boldsymbol{e}}^i_{m,t}\right]$ is the expected aggregated electricity consumption at time $t \in \Gamma$ and at iteration $i \in \Psi$ of RAs' subset $\mathscr{M}$.

The current negotiation process employs a price-incentive mechanism, making it susceptible to exploitation by rational and intelligent agents seeking to maximize economic gains. This vulnerability has prompted our research into the philosophy of incentive compatibility (IC) concept, originating from mechanism design and analyzed in game theory (Jain and Wu, 2009). However, achieving IC in time-dependent games is challenging due to the complexity of assessing agents' strategic behavior over time (Parilina et al., 2018). Moreover, additional complexity arises because customers have the freedom to program their decision-making models in their agent-based devices. This work addressed these challenges by formulating a payment rule (PR) that embraces the IC philosophy: the RAs payment must be structured to convey that the cost of deviating from an agreement outweighs the benefits of adhering to it (Watson, 2013; Parilina et al., 2018). Notice that the PR is fixed and cannot be modified once the coordinator shares it in the daily contract. The IC condition is then depicted in Eq. (21).

$$PR_n(e_{imp,n,t}*) \leq PR_n(\widehat{e}_{imp,n,t}). \tag{21}$$

where PR_n is the individual payment rule, $e_{imp,n,t}$* is the true optimal consumption plan of each customer, and $\widehat{e}_{imp,n,t}$ is any consumption report that could be different from the true plan. Thruthful information reported by agents is crucial for enhancing the economic efficiency of a system and reducing the computational burden on the coordinator side (Kuipers, 2022). Conversely, a mechanism lacking this property could pose a significant risk to successfully deploying a TE program, as it may lead to economic inefficiencies attributed to the mechanism's design (Parilina et al., 2018). Furthermore, the coordinator should anticipate RAs could report false information to take advantage of the price-incentive mechanism. Hence, the coordinator designed a penalty policy to prevent misreporting consumption from the RAs by defining it in the payment rule, as follows in Eq. (22).

$$\mathbf{E}\left[\sum_{t=1}^{T}(\mathrm{LOI}(\boldsymbol{e},\boldsymbol{r}))\right]=\mathbf{E}\left[\sum_{t=1}^{T}\alpha_{n,t}\cdot\left(e_{imp,n,t}-\hat{e}_{imp,n,t}\right)^2\right],\ \forall t\in\Gamma,\quad \forall n \in \mathcal{N}. \tag{22}$$

$$\hat{e}_{imp,n,t}\geq 0,\ \forall t\in\Gamma,\ \forall n\in\mathcal{N}. \tag{23}$$

where $\alpha_{n,t}$ is a parameter representing the penalty value for each RA by deviating from the reported plan. Equation (23) implies that RAs are free to select their electricity consumption to be reported, adding a new level of privacy and rationality to them, i.e., RAs can report a true or false consumption, following their bounded rationality. A rational RA then embraces the penalty policy defined by the coordinator in the payment rule. Furthermore, each RA's feasible consumption profile set in the Enrollment phase Eq. (12) is updated to Eq. (24).

$$\mathcal{E}_n=\{\boldsymbol{e}_n|(2)-(10),(23)\}. \tag{24}$$

And the feasible consumption profile set of each RA in the Coordination phase Eq. (15) is updated to Eq. (25).

$$\mathcal{E}_m=\{\boldsymbol{e}_m|(2)-(10),(23)\}. \tag{25}$$

Moreover, the feasible policies profile set of the coordinator in the Enrollment phase is presented in Eq. (26).

$$\mathcal{S}_c=\{\boldsymbol{\pi}_n,\boldsymbol{\alpha}_n|(19)\} \tag{26}$$

Correspondingly, the feasible set of the coordinator policies in the Enrollment phase is: $\mathcal{S}=\{((\boldsymbol{\pi},\ \boldsymbol{\alpha},)_1,(\boldsymbol{\pi},\ \boldsymbol{\alpha},)_2,\ldots,(\boldsymbol{\pi},\ \boldsymbol{\alpha})_N)|(\boldsymbol{\pi},\ \boldsymbol{\alpha})_n\in\mathcal{S}_c,\ \forall n\in\mathcal{N}\}$.

And the feasible policies profile set of the coordinator in the Coordination phase is presented in Eq. (27).

$$\mathcal{S}_c=\{\boldsymbol{\pi}_m,\boldsymbol{\alpha}_m|(20)\} \tag{27}$$

Correspondingly, the feasible set of the coordinator policies in the Coordination phase is: $\mathcal{S}=\{((\boldsymbol{\pi},\ \boldsymbol{\alpha},)_1,(\boldsymbol{\pi},\ \boldsymbol{\alpha},)_2,\ldots,(\boldsymbol{\pi},\ \boldsymbol{\alpha})_M)|(\boldsymbol{\pi},\ \boldsymbol{\alpha})_m\in\mathcal{S}_c,\forall m\in\mathcal{M}\}$.

2.3.3. Truthfulness - analysis

In this framework, while RAs can choose their cost functions, the coordinator's PR, set in the contract, governs the Settlement phase and determines electricity charges and penalties for deviations that customers pay at the end of each day. If the PR meets the IC condition and the mechanism rules are well structured, a rational RA aligns its cost function with the PR as its best strategy, optimizing its consumption plan and maximizing economic benefits. The PR is then elucidated in Eq. (28).

$$PR_n*(\boldsymbol{e}*,\hat{\boldsymbol{e}}*)=\sum_{t=1}^{T}\left[e_{imp,n,t}*\cdot\pi_{n,t}*+\alpha_{n,t}*\cdot\left(e_{imp,n,t}*-\hat{e}_{imp,n,t}*\right)^2\right],\ \forall\ n\in\mathcal{N}. \tag{28}$$

where $e_{imp,n,t}*$ represents the current electricity imported from the grid, and $\hat{e}_{imp,n,t}*$ is the electricity consumption that each RA reports to the coordinator. Then, by verifying $\frac{\partial PR_n*}{\partial\hat{e}_{imp,n,t}*}=0$ and considering that RAs lack access to the price function (a piece of private information held by the coordinator, incomplete information) as well as lack the capacity for learning the price function (i.e., bounded intelligence) (Sreekumar et al., 2023), it is possible to determine that the PR satisfying the condition Eq. (21), as follows in Eq. (29).

$$\frac{\partial PR_n*}{\partial\hat{e}_{imp,n,t}*}=0\rightarrow e_{imp,n,t}*=\hat{e}_{imp,n,t}*,\quad\forall\quad n\in\mathcal{N},\forall\, t\in\Gamma. \tag{29}$$

From Eq. (29), notice that a rational RA should be entirely motivated to report the true consumption plan to the coordinator ($\boldsymbol{e}*=\hat{\boldsymbol{e}}*$) instead of reporting any other fake consumption plan ($\hat{\boldsymbol{e}}'$). Since the mechanism proposed in this work ensures the condition Eq. (21), a dominant strategy equilibrium is achieved in the game proposed (Jain and Wu, 2009; Parilina et al., 2018).

To illustrate how a strategic RA might exploit the system, consider the following scenarios given a strategic RA's behavior. First, let's examine the PR (28) without the penalty function *LOI*, as follows:

$$PR_n*(\boldsymbol{e}*)=\sum_{t=1}^{T}\left[e_{imp,n,t}*\cdot\pi_{n,t}*\right],\ \forall\, t\in\Gamma,\quad\forall\quad n\in\mathcal{N}. \tag{30}$$

Suppose a strategic RA's behavior can disclose the price generator employed by the coordinator expressed in (20). Furthermore, RAs adjust their actions to minimize their cost by knowing their influence over the electricity price, as follows in (32):

$$\pi_{n,t}*\left(\hat{e}'_{agg,t}\right)=\lambda\cdot\hat{e}'_{agg,t},\quad\forall\quad t\in\Gamma, \tag{31}$$

$$PR_n*(\boldsymbol{e}*)=\sum_{t=1}^{T}\left[e_{imp,n,t}*\cdot\lambda\cdot\hat{e}'_{agg,t}\right],\forall\, t\in\Gamma,\quad\forall\quad n\in\mathcal{N}. \tag{32}$$

Strategic agents understand its influence over the price in the negotiation process. Even in a non-cooperative game, the optimal individual reports a rational RA can do, given the absence of a well-structured penalty policy in the PR, is $\hat{e}'_{imp,n,t}=0$, and their bill becomes then as follows in (35):

$$\hat{e}'_{agg,t}=\sum_{\forall n\in\mathcal{N}}\left(\hat{e}'_{imp,n,t}\right)=0,\quad\forall\quad t\in\Gamma, \tag{33}$$

$$PR_n^*(\boldsymbol{e}^*)=\sum_{t=1}^{T}\left[e^*_{imp,n,t}\cdot\lambda\cdot\cancelto{0}{\hat{e}'_{agg,t}}\right],\ \forall\ n\in\mathcal{N}, \tag{34}$$

$$PR_n*(\boldsymbol{e}*)=0,\quad\forall\quad n\in\mathcal{N}.\blacksquare \tag{35}$$

Proof. From (35), notice that a customer does not perceive an electricity bill payment as the RA acted strategically on his behalf by reporting a false consumption ($\hat{e}'_{imp,n,t}$). Furthermore, this PR is neither a feasible solution for the DSO nor an equilibrium point of the game. □

Now, let's consider the PR case (28) (with a quadratic penalty policy) and explore the effect of a truthful consumption report of an RA over the electricity bill by replacing the energy balance expressed in (2) on the PR (28), as follows:

$$PR_n^*(\boldsymbol{e}^*, \hat{\boldsymbol{e}}^*) = \sum_{t=1}^{T} \left[e^*_{imp,n,t} \cdot \pi^*_{n,t} + \alpha^*_{n,t} \cdot \left[\cancel{e_{var,n,t}} + (\cancel{e_{fix,n,t}} + r_{n,t}) + \cancel{e_{cha,n,t}} - \cancel{e_{dis,n,t}} - (\cancel{e_{var,n,t}} + \cancel{e_{fix,n,t}} + \cancel{e_{cha,n,t} - e_{dis,n,t}}) \right]^2 \right], \forall\, n \in \mathcal{N}, \tag{36}$$

$$= \sum_{t=1}^{T} \left[e_{imp,n,t} * \cdot \pi_{n,t} * + \alpha_{n,t} * \cdot (r_{n,t})^2 \right], \forall \quad t \in \Gamma, \forall \quad n \in \mathcal{N}. \blacksquare \tag{37}$$

Proof. Equation (37) indicates that each RA's bill consists of a linear term based on the current energy consumption and a quadratic penalty associated with the uncertainty rather than any deviation from a false consumption plan. Since deviations due to uncertainty are uncontrollable for RAs in this framework, reporting truthful information minimizes their electricity bill. As a result, the proposed mechanism achieves a dominant strategy equilibrium. □

Let's now explore the case with the penalty policy as proposed in (28) and assuming RAs know the price function (20), as follows in (38):

$$PR_n * (\boldsymbol{e}*, \widehat{\boldsymbol{e}}*) = \sum_{t=1}^{T} \left[e_{imp,n,t} * \cdot \lambda \cdot e_{agg,t} * + \alpha_{n,t} * \cdot \left(e_{imp,n,t} * - \widehat{e}_{imp,n,t} * \right)^2 \right], \ \forall\ n \in \mathcal{N}. \tag{38}$$

Then, by verifying $\frac{\partial PR_n *}{\partial \widehat{e}_{imp,n,t} *} = 0$ in (38):

$$\widehat{e}_{imp,n,t} * = e_{imp,n,t} * \cdot \left(1 - \frac{\lambda}{2 \cdot \alpha_{n,t}} \right), \quad \forall \quad n \in \mathcal{N}, \quad \forall \quad t \in \Gamma, \tag{39}$$

$$\text{Condition} \Rightarrow \lambda > 0, \quad \alpha_{n,t} > 0, \text{ and } \alpha_{n,t} \ggg \lambda, \tag{40}$$

$$\text{Therefore} \Rightarrow \hat{e}^*_{imp,n,t} = e^*_{imp,n,t} \cdot \left(1 - \cancel{\frac{\lambda}{2 \cdot \alpha_{n,t}}} \right)^{\approx 0}, \ \forall\, n \in \mathcal{N}, \ \forall\, t \in \Gamma, \tag{41}$$

$$\Rightarrow \widehat{e}_{imp,n,t} * = e_{imp,n,t} *, \quad \forall \quad n \in \mathcal{N}, \quad \forall \quad t \in \Gamma. \blacksquare \tag{42}$$

Proof. Notice that λ should be greater than zero since it is a technical parameter associated with the generation cost (Tsaousoglou et al., 2020), and the penalty values $\alpha_{n,t}$ should also be greater than zero (Eq. (37)). Therefore, a significant enough difference between these values could ensure a truthful exchange of information from RAs to the coordinator and achieve a dominant strategy equilibrium. □

2.4. Uncertainty modelling

2.4.1. RA uncertainty

This work considers the inflexible load (e_{fix}) as the source of uncertainty for each RA, following a probability density function $f(\cdot)$ with parameters $(\mu_{f,n,t},\ \sigma^2_{f,n,t})$ as the mean and variance, respectively, as follows in Eq. (43).

$$e_{fix,n,t} = f(\mu_{f,n,t},\ \sigma^2_{f,n,t}) \tag{43}$$

2.4.2. Coordinator uncertainty

Meanwhile, the coordinator also considers stochasticity in the RAs' consumption report to build a price policy considering uncertainties as presented in Eq. (20). Furthermore, the coordinator stochastic variable ζ is modeled as presented in Eq. (44), following a distribution function $g(\cdot)$ with parameters $(\mu_{g,t},\ \sigma^2_{g,t})$ as the mean and variance, respectively, as follows.

$$\mathbf{E}\left[\boldsymbol{e}^i_{agg,t} \right] = \mathbf{E}[\widehat{e}^i_{agg,t} + \zeta_t] \therefore \zeta \sim g(\mu_{g,t},\ \sigma^2_{g,t}). \tag{44}$$

2.5. Solving the stochastic programming

The methodology utilizes the Monte Carlo method to solve stochastic programming in both residential agents' formulations (Eq. (11a), Eq. (14a)) and the coordinator's counterpart in the price generator (Eq. (19)). This technique generates numerous representative scenarios (denoted as Z) to determine expected values within the stochastic programming framework. The Monte Carlo method robustly approximates complex probabilistic outcomes by simulating various likely scenarios, enhancing precision in decision-making processes for RAs and the coordinator (Ali et al., 2015).

3. Simulations-based scenarios set-up

This work considers that the total set of customers is twenty, i.e., $\mathcal{N} = 20$, all connected by a transformer. Simulations were performed every ten minutes as a time step for coordinating a day-ahead electricity market, i.e., $T = 144$. The conditions agreed upon in the TE phases are updated daily. The initial customer costs were computed by setting the initial electricity price (π^0_t) as 7.30 ₵ $/kWh based on (Hydro-Quebec, 2022). The dynamic electricity price used in the Enrollment phase was considered from (Arnedo et al., 2023). The Enrollment phase selects the group of customers $\mathcal{M} \subseteq \mathcal{N}$ to be part of the coordination process. The penalty values explored were seven $\boldsymbol{\alpha}_n = \{47, 50, 53, 57, 60, 63, 66\}$, which were found through simulations to discourage the participation of RAs in the Coordination phase gradually. The λ value is 0.2981. Given the weak IC condition expressed in (40), the ratio $\lambda/(2\cdot\alpha)$ ranges from 0.0063 to 0.0045, enough to neglect the term in the case of strategic agents in this work. Moreover, the ratio α_n/π^0 ranges from 6.43 up to 9.04 times. Battery degradation cost $C_{bat,n,t}$ has a value of 0.0007 ₵ $/kWh based on (Banfield et al., 2021). Customers respond with a "participation" or "no participation" signal to the coordinator based on each penalty value. The Monte Carlo scenarios tested were one hundred ($Z = 100$). Moreover, the thermal preferences of each RA are defined based on a log-normal distribution with zero mean ($\mu_{pref} = 0$) and one standard distribution $\sigma_{pref} = 1$. This work modeled the uncertainty function of each house based on a Winter database of historical data for three months provided by Hydro-Quebec by employing the forecaster presented in (Taylor and Letham, 2017). The battery capacity of each house is set as 2.5 kWh, starting and finishing daily with ten percent

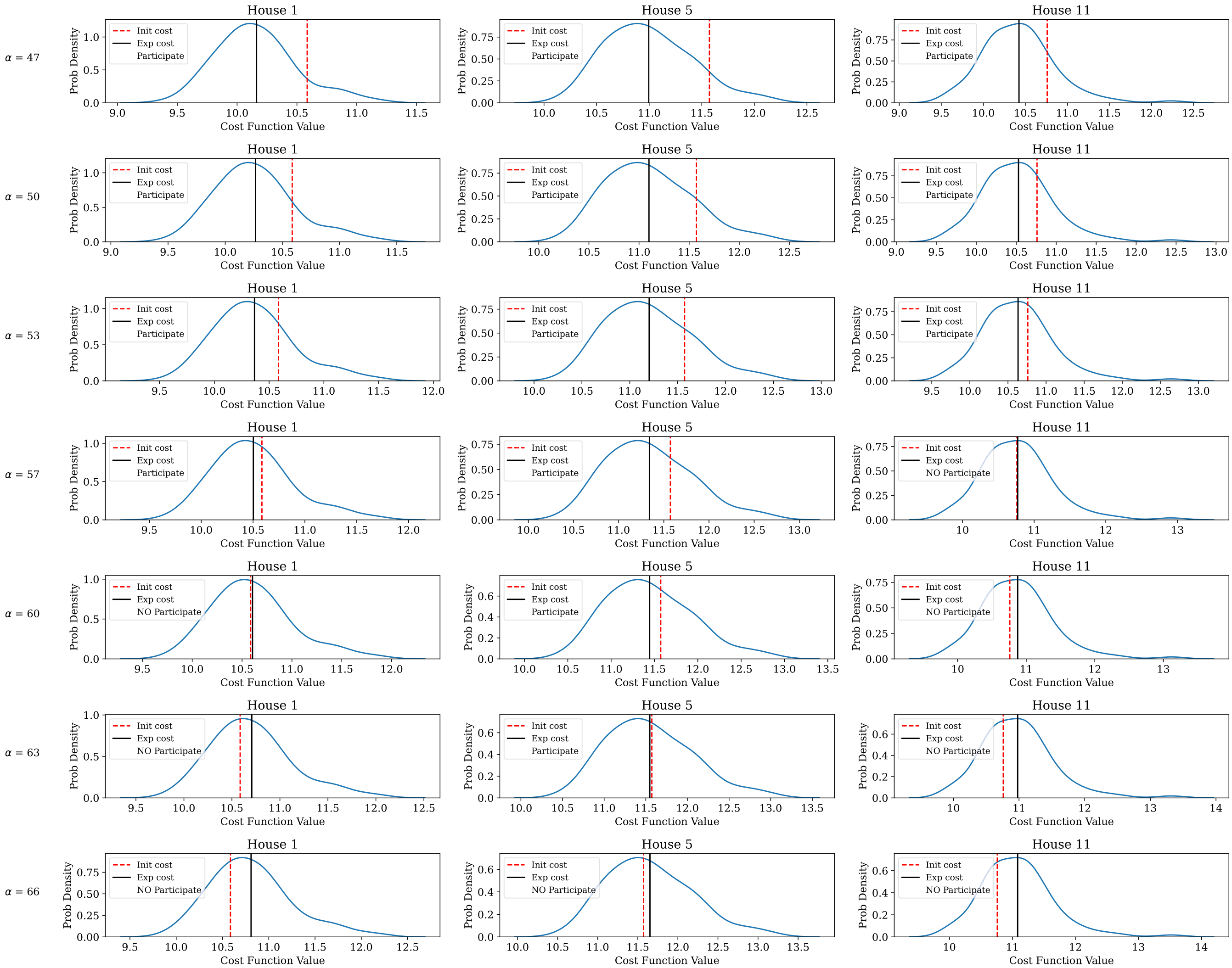

Fig. 2. Enrollment decisions by RAs 1, 5, and 11 based on the penalty value α_n.

Table 2
Number of enrolled RAs by penalty value α_n who decide to participated in the Coordination phase.

α_n	#	House																			
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
47	20	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
50	15	✓	✓	✓	✓	✓					✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	
53	13	✓			✓	✓					✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	
57	11	✓			✓	✓					✓		✓	✓	✓		✓	✓	✓	✓	
60	7				✓	✓							✓	✓	✓				✓	✓	
63	1					✓															
66	0																				

(10 %) of the SOC. RAs lack of a learning stage, leading to a bounded intelligence and rationality. Finally, the code implementation was in Python through the embedded library for modeling language for convex optimization (CVXPY). ECOS (Embedded Conic Solver) was the solver used in this work (Agrawal et al., 2018). The numerical simulations were run on a desktop computer with an Intel(R) Core(TM) i7-10700T processor at 2.00 GHz and 32 GB RAM.

4. Results

This section was segmented to provide the TE phases' results for the coordinator and the RAs.

4.1. Enrollment results

4.1.1. Customers - enrollment phase

The RA optimizes its decision to participate in the day-ahead electricity consumption coordination by evaluating the expected payoff and the disclosed price vector from the coordinator to the set $\mathscr{N}$ of RAs. In Fig. 2, each RA's response is privately analyzed, considering various penalty values explored by the coordinator (as explained in Section 3). The vertical dashed red line in the figure represents the base case scenario, where RAs optimize their consumption with a flat electricity price ($\pi^0 = 7.3$¢/kWh) and a small penalty value for deviations ($\alpha = 1$) to ensure a truthful consumption base ($\hat{e}^0_{imp,n,t}$) reported by each RA. The

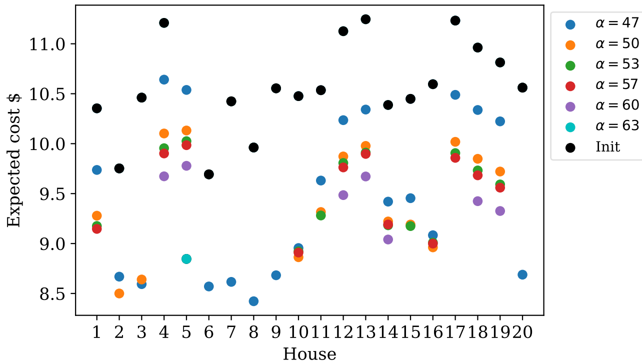

Fig. 3. Expected customers' electricity cost in the Coordination phase.

decide to coordinate their day-ahead electricity consumption.

4.2. Coordination results

4.2.1. Customers - coordination phase

The expected electricity costs for customers during the Coordination phase are shown in Fig. 3. The number of marker points indicates the level of participation in the Coordination phase for each penalty value—more markers signify higher participation, while fewer markers indicate lower participation. For example, customer five consistently participated across all explored penalty values, as seen by the higher number of marker points. In contrast, customers six, seven, eight, and twenty opted out of participation for penalty values above forty-seven, evidenced by only a single blue marker point. For those RAs who opt out of the Coordination phase, their expected costs (based on initial conditions - a flat price) are represented in black as the penalty parameter α increases to sixty-three ($\alpha = 63$). It is important to note that the participation criterion is met when the expected coordination cost is lower than the initial cost, encouraging customers to enroll in the

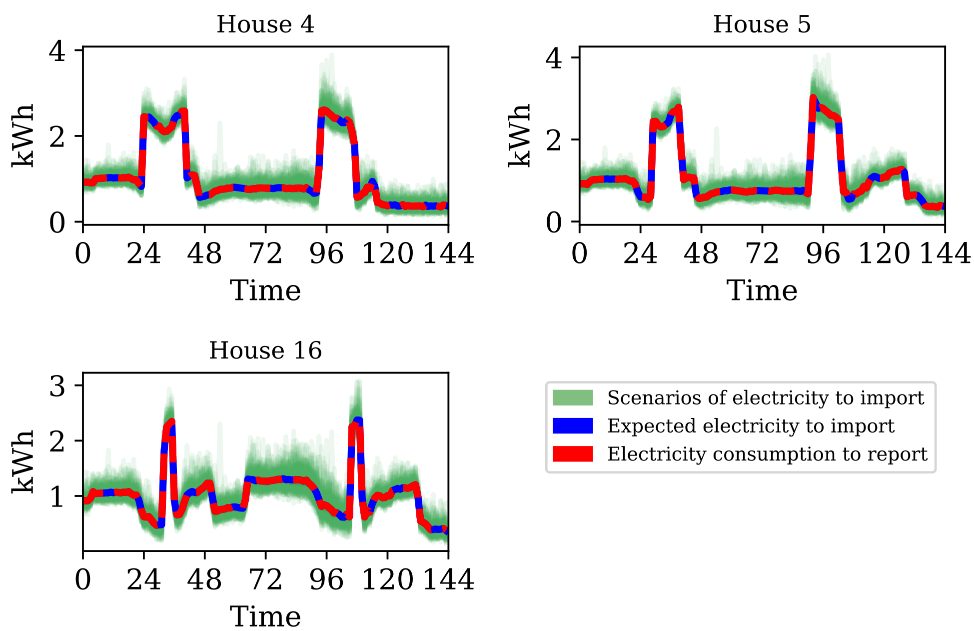

Fig. 4. Validating the truthful report of agents on the mechanism proposed.

black line denotes the expected payoff value considering dynamic tariffs and penalty values $\boldsymbol{\alpha}_n$ shared by the coordinator. These conditions are analyzed to compute the participation condition expressed in Eq. (13) for all RAs.

From Fig. 2[1], notice that the vertical dashed red line represents the base case scenario. Additionally, the vertical black line denotes the expected payoff value obtained by considering a dynamic tariff and penalty values $\boldsymbol{\alpha}_n$ shared by the coordinator. For example, RA one decides to participate for penalty values up to fifty-seven (α = 57) but rejects participation for values of sixty or higher ($\alpha \leq 60$). Conversely, RA five participates in all explored penalty values except sixty-six (α = 66). Finally, RA eleven was the most inflexible among the showed houses, rejecting participation for penalty values equal to or above fifty-seven ($\alpha = 57$).

4.1.2. Coordinator - enrollment phase

The RAs' response to the coordinator has been summarized in Table 2, where the check-mark represents participation, and the numerical symbol (#) represents the number of RAs enrolled by each penalty value assessed. These RAs are then the subset $\mathscr{M} \subseteq \mathscr{N}$ that

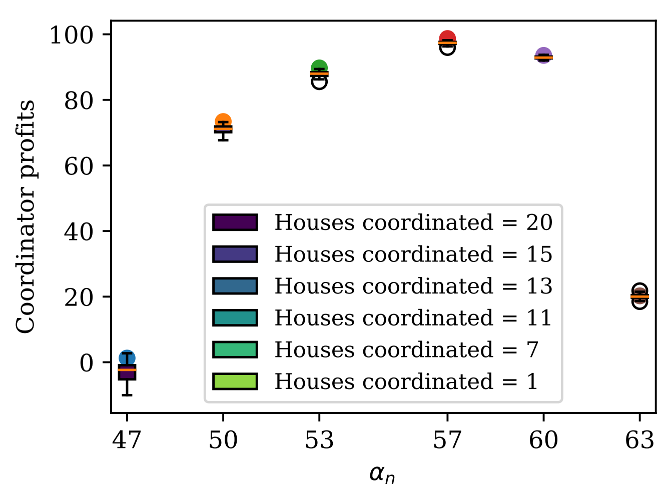

Fig. 5. Expected coordinator profits in the Coordination phase.

[1] Three RAs' responses have been randomly depicted in Fig. 2 since a figure presenting the results for the total RAs is unreadable.

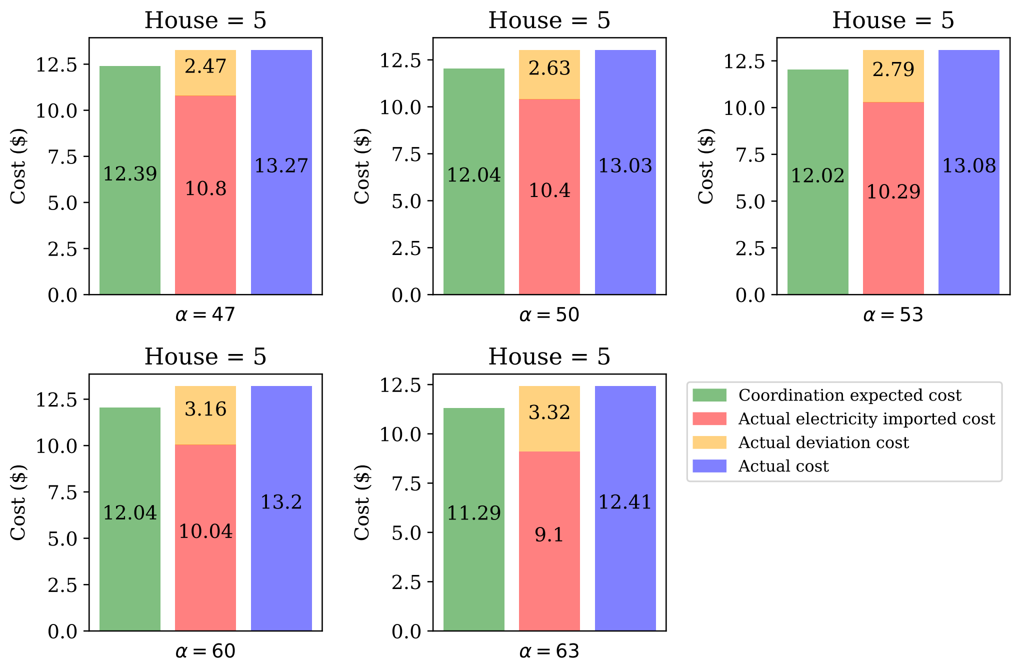

Fig. 6. Total and individual cost by α_n for customer five.

Coordination phase and potentially reduce their electricity bills.

Moreover, to ensure that customers could expect their electricity cost as presented in Fig. 3, the IC property of the mechanism proposed is validated as formally demonstrated in Eq. (29). Consequently, Fig. 4 depicts the null difference between the expected (e) and reported ($\hat{e}$) electricity consumption to be imported by RA, for $\alpha = 47$, validating that the RAs report truthful information.

4.2.2. *Coordinator - coordination phase*

Concurrently, the coordinator experienced fluctuations in profitability, a dynamic attributed to the extent of coordination capacity, characterized by the flexibility offered by the enrolled customers ($\mathscr{M} \subseteq \mathscr{N}$). To visually depict this phenomenon, Fig. 5 illustrates the coordinator's profit variations, depending upon the subset of RAs $\mathscr{M} \in \mathscr{N}$ and the penalty value $\boldsymbol{\alpha}_n$. Notice that the penalty value of fifty-seven ($\alpha = 57$) yielded the most expected profitable scenario for the coordinator. This specific value implies that eleven customers will be actively enrolled in the day-ahead coordination, while the remaining customers will be charged with the base-case scenario (a flattened electricity price and non-penalty value).

4.3. *Execution and settlement results*

The findings related to the Execution and the Settlement phases are integrated into a single section. Notably, in these phases, market participants did not optimize. Instead, the focus shifted towards the effect of uncertainty disclosing on the customers' cost and coordinator profits.

4.3.1. *Customers - execution and settlement phase*

Uncertainty disclosure over the customers' cost was analyzed individually. Based on Fig. 6, the current electricity cost is higher than the expected cost for customer five. This behavior happened since any deviation from the reported consumption induces a deviation cost by the penalty mechanism.

Additionally, Table 3 provides insights into individual customer electricity costs during the Settlement phase. The data highlights variations in individual costs based on customer participation levels from the Enrollment phase for each penalty value ($\boldsymbol{\alpha}_n$). While coordination tends to reduce individual electricity costs, even slight deviations from the agreed plan significantly impact individual RA costs. Therefore, the ability of RAs to adhere to the agreed consumption plan is crucial for cost savings through coordinated consumption, preventing severe penalties and potentially higher costs than non-participation.

4.3.2. *Coordinator - execution and settlement phase*

For the coordinator, actual profits were effectively determined through stochastic programming, considering all scenarios in the Monte Carlo analysis, as illustrated in Figure 7. The results indicate that the expected profits computed at the Coordination phase are consistently higher than the ones confirmed at the Execution phase. This disparity in profitability is primarily influenced by the quadratic cost model applied to electricity consumption, as described in equation Eq. (19), and the fluctuating number of houses participating in the Coordination phase, determined by penalty values. Despite these variations, it is noteworthy that, within the analyzed scenarios, the coordinator consistently achieves positive profits (except for the penalty value $\alpha = 47$), underscoring the effectiveness of the negotiation mechanism employed in this study.

5. Conclusion

This work proposed a TE system employing TAs to facilitate participant decision-making. The interaction among TAs is orchestrated through four smart contract phases: Enrollment, Coordination, Execution, and Settlement. RAs determine their participation in coordinating a day-ahead electricity market, guided by a decision-making model based on convex stochastic programming. This model enables customers to quantify potential daily benefits by assessing the coordinator's price and penalty signals. Moreover, the methodology aids the coordinator in determining the optimal number of houses to coordinate, optimizing day-ahead prices and penalties. The proposed mechanism ensures truthful information exchange among TAs, preventing gaming by RAs. Then, is it worthwhile to participate in transactive energy? The short answer is yes. This paper proposes a framework where both residential customers and a coordinator can achieve economic benefits, making transactive energy an attractive option for the electricity sector. Future research endeavors could delve into the individual strategic behavior of agents, adapting their conditions based on a dynamic time-dependent mechanism to introduce false information into the system (Müller,

Table 3
Individual actual electricity cost - Settlement phase.

alpha	House 1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	Coordinator revenue ($)
47	12.47	11.40	11.33	13.38	13.27	11.30	11.35	11.16	11.42	11.69	12.36	12.97	13.08	12.15	12.19	11.82	13.22	13.07	12.96	11.42	244.01
50	12.17	11.40	11.54	13.00	13.03	9.69	10.22	10.12	10.51	11.76	12.21	12.77	12.87	12.12	12.09	11.86	12.91	12.74	12.62	10.52	236.13
53	12.23	9.49	10.53	13.01	13.08	9.69	10.22	10.12	10.51	11.98	12.34	12.86	12.97	12.24	12.23	12.07	12.96	12.79	12.65	10.52	234.50
57	12.41	9.49	10.53	13.17	13.25	9.69	10.22	10.12	10.51	12.18	10.65	13.03	13.16	12.46	10.43	12.27	13.12	12.95	12.83	10.52	232.98
60	10.47	9.49	10.53	13.09	13.20	9.69	10.22	10.12	10.51	10.58	10.65	12.90	13.09	12.46	10.43	10.46	11.17	12.84	12.74	10.52	225.18
63	10.47	9.49	10.53	11.46	12.41	9.69	10.22	10.12	10.51	10.58	10.65	11.14	11.08	10.49	10.43	10.46	11.17	11.13	10.71	10.52	213.28

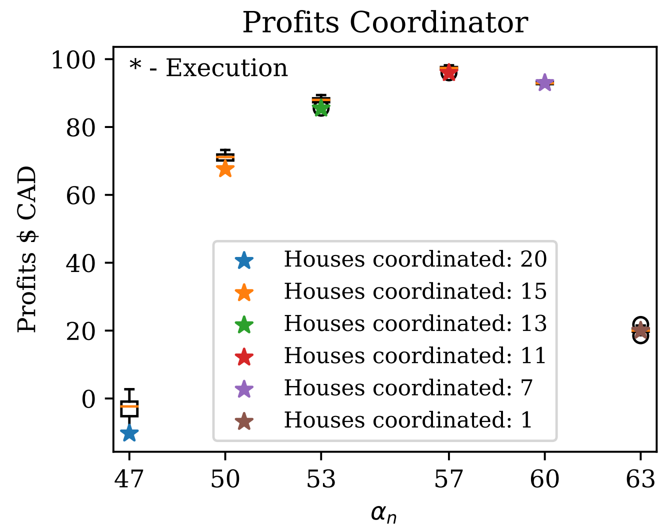

Fig. 7. Coordinator profits - Execution phase.

2024). Furthermore, it is worth noting that the RAs analyzed in this study lack a learning stage, which means they could potentially acquire information about the mechanism over time, thereby compromising the confidentiality of the coordinator's data. Future research may consider free-model agents and their strategic learning over time to create a mechanism against this level of intelligence on agents (Jalving et al., 2023). A potential area of interest for future research relies on investigating how large consumers, such as those in the commercial and industrial sectors, might manipulate electricity markets by misreporting information during negotiations.

Moreover, Future research may explore real-time control integration and mechanisms allowing deceptive behavior. Investigating the impact of uncertainty modeling on reported electricity consumption and its implications for IC properties offers potential avenues for further inquiry. Limitations include dependence on weather and dwelling occupancy forecasts for improved accuracy to minimize electricity deviations. Additionally, an extended study of customer enrollment over varying contract periods is needed to comprehensively assess the proposed methodology's economic effectiveness.

CRediT authorship contribution statement

Alejandro Parrado-Duque: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Nilson Henao:** Writing – review & editing, Validation, Supervision, Project administration. **Juan Oviedo-Cepeda:** Writing – review & editing, Validation, Supervision, Investigation. **Juan Dominguez-Jimenez:** Writing – review & editing, Investigation. **Kodjo Agbossou:** Validation, Supervision, Resources, Project administration, Funding acquisition. **Sousso Kelouwani:** Validation, Supervision, Project administration.

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

The authors would like to thank the Laboratoire des Technologies de l'Énergie d'Hydro-Québec, the Natural Science and Engineering Research Council of Canada, and the Foundation of Université du Québec á Trois-Riviéres.

References

Adeyemi, A., Yan, M., Shahidehpour, M., Bahramirad, S., Paaso, A., 2020. Transactive energy markets for managing energy exchanges in power distribution systems. Electr. J. 33. https://doi.org/10.1016/j.tej.2020.106868.

Agrawal, A., Verschueren, R., Diamond, S., Boyd, S., 2018. A rewriting system for convex optimization problems. J. Control Decis. 5, 42–60. https://doi.org/10.1080/23307706.2017.1397554.

Ali, A., Kolter, J.Z., Diamond, S., Boyd, S., 2015. Disciplined convex stochastic programming: a new framework for stochastic optimization. Uncertain. Artif. Intell. - Proc. 31st Conf., UAI 2015 (1), 62–71.

Arnedo, R., Henao, N., Agbossou, K., Oviedo-Cepeda, J.C., Dominguez, J.A., Toquica, D., 2023.OpenATE: A Distributed Co-simulation Engine for Transactive Energy Systems, In: 2023 IEEE 11th International Conference on Smart Energy Grid Engineering (SEGE), IEEE.188-193.⟨https://ieeexplore.ieee.org/document/10274534/⟩, 10.1109/SEGE59172.2023.10274534.

Avramidis, I.I., Capitanescu, F., Deconinck, G., Nagpal, H., Heiselberg, P., Madureira, A., 2023. From the humble building to the smart sustainable grid: empowering consumers, nurturing bottom-up electricity markets, and building collaborative power systems. IEEE Power Energy Mag. 21, 53–63. https://doi.org/10.1109/MPE.2023.3269538. ⟨https://ieeexplore.ieee.org/document/10158943/⟩.

Banfield, B., Robinson, D.A., Agalgaonkar, A.P., 2021. Distributed MPC of Residential energy storage for voltage regulation and peak shaving along radial distribution feeders. IEEE Trans. Energy Convers. 36, 1413–1424. https://doi.org/10.1109/TEC.2020.3033507. ⟨https://ieeexplore.ieee.org/document/9238425/⟩.

Beckstedde, E., Meeus, L., 2023. From "Fit and Forget" to "Flex or regret" in distribution grids: dealing with congestion in european distribution grids. IEEE Power Energy Mag. 21, 45–52. https://doi.org/10.1109/MPE.2023.3269545. ⟨https://ieeexplore.ieee.org/document/10158972/⟩.

Carmichael, R., Gross, R., Hanna, R., Rhodes, A., Green, T., 2021. The Demand response technology cluster: accelerating UK residential consumer engagement with time-of-use tariffs, electric vehicles and smart meters via digital comparison tools. Renew. Sustain. Energy Rev. 139, 110701. https://doi.org/10.1016/j.rser.2020.110701.

Cheng, R., Tesfatsion, L., Wang, Z., 2022. A consensus-based transactive energy design for unbalanced distribution networks. IEEE Trans. Power Syst. 1. https://doi.org/10.1109/TPWRS.2022.3158900. ⟨https://ieeexplore.ieee.org/document/9735416/⟩.

Doumen, S.C., Boff, D.S., Widergren, S.E., Kok, J.K., 2023. Taming the wild edge of smart grid - Lessons from transactive energy market deployments. Electr. J. 36. https://doi.org/10.1016/j.tej.2023.107253.

Dulipala, B., Debbarma, S., 2021a. Energy scheduling model considering penalty mechanism in transactive energy markets: a hybrid approach. Int. J. Electr. Power Energy Syst. 129, 106742. https://doi.org/10.1016/j.ijepes.2020.106742.

Dulipala, J.B., Debbarma, S., 2021b. Decision-making model with reduced risk of penalties in transactive energy markets. Electr. Power Syst. Res. 199, 107371. https://doi.org/10.1016/j.epsr.2021.107371.

Eguiarte, O., de Agustín-Camacho, P., Garrido-Marijuan, A., Vukovic, M., del Portillo, L., Romero-Amorrortu, A., 2022. Engaging domestic users on demand response for heating cost reduction with a recommendation tool: case study in Belgrade. Energy Rep. 8, 325–331. https://doi.org/10.1016/j.egyr.2022.01.069.

Fujiwara-Greve, T., 2015. Non-Cooperative Game Theory. volume 1 of Monographs in Mathematical Economics. Springer, Japan, Tokyo. https://doi.org/10.1007/978-4-431-55645-9.

Ghorani, R., Farzin, H., Fotuhi-Firuzabad, M., Wang, F., 2019a. Market design for integration of renewables into transactive energy systems. IET Renew. Power Gener. 13, 2502–2511. https://doi.org/10.1049/iet-rpg.2019.0551.

Ghorani, R., Fotuhi-Firuzabad, M., Moeini-Aghtaie, M., 2019b. Main challenges of implementing penalty mechanisms in transactive electricity markets. IEEE Trans. Power Syst. 34, 3954–3956. https://doi.org/10.1109/TPWRS.2019.2908587. ⟨https://ieeexplore.ieee.org/document/8678451/⟩.

Ghorashi, S.M., Rastegar, M., Senemmar, S., Seifi, A.R., 2020. Optimal design of reward-penalty demand response programs in smart power grids. Sustain. Cities Soc. 60, 102150. https://doi.org/10.1016/j.scs.2020.102150.

Guerrero, J., Gebbran, D., Mhanna, S., Chapman, A.C., Verbič, G., 2020. Towards a transactive energy system for integration of distributed energy resources: Home energy management, distributed optimal power flow, and peer-to-peer energy trading. Renew. Sustain. Energy Rev. 132. https://doi.org/10.1016/j.rser.2020.110000. ⟨https://linkinghub.elsevier.com/retrieve/pii/S1364032120302914⟩.

Hydro-Quebec, 2022.Annual Report 2022. Technical Report. Hydro-Quebec.

Jain, L., Wu, X., 2009. Game Theoretic Problems in Network Economics and Mechanism Design Solutions. Springer, London, London. https://doi.org/10.1007/978-1-84800-938-7.

Jalving, J., Ghouse, J., Cortes, N., Gao, X., Knueven, B., Agi, D., Martin, S., Chen, X., Guittet, D., Tumbalam-Gooty, R., Bianchi, L., Beattie, K., Gunter, D., Siirola, J.D., Miller, D.C., Dowling, A.W., 2023. Beyond price taker: Conceptual design and optimization of integrated energy systems using machine learning market surrogates. Appl. Energy 351. https://doi.org/10.1016/j.apenergy.2023.121767.

Kuipers, B., 2022. Trust and cooperation. Front. Robot. AI 9, 1–18. https://doi.org/10.3389/frobt.2022.676767.

Lee, D., Hess, D.J., Neema, H., 2020. The challenges of implementing transactive energy: A comparative analysis of experimental projects. Electr. J. 33. https://doi.org/10.1016/j.tej.2020.106865.

Li, P.H., Keppo, I., Xenitidou, M., Kamargianni, M., 2020. Investigating UK consumers' heterogeneous engagement in demand-side response. Energy Effic. 13, 621–648. https://doi.org/10.1007/s12053-020-09847-7.

Loffredo, J., 2023. Consumer empowerment: lessons from the European Union [In my view]. IEEE Power Energy Mag. 21, 98–100. https://doi.org/10.1109/MPE.2023.3269548. ⟨https://ieeexplore.ieee.org/document/10158966/⟩.

Lopes, F., Coelho, H., 2018. Electricity Markets with Increasing Levels of Renewable Generation: Structure, Operation, Agent-based Simulation, and Emerging Designs. volume 144 of Studies in Systems, Decision and Controls. Springer International Publishing. https://doi.org/10.1007/978-3-319-74263-2.

Müller, M., 2024. Belief-independence and (robust) strategy-proofness. Theory Decis. 96, 443–461. https://doi.org/10.1007/s11238-023-09955-7.

Nguyen, H.K., Song, J.B., Han, Z., 2015. Distributed demand side management with energy storage in smart grid. IEEE Trans. Parallel Distrib. Syst. 26, 3346–3357. https://doi.org/10.1109/TPDS.2014.2372781. ⟨http://ieeexplore.ieee.org/document/6963474/⟩.

Parikh, N., 2014. Prox. Algorithms Found. Trends Optim. 1, 127–239. https://doi.org/10.1561/2400000003.

Parilina, E., ViswanadhaReddy, P., Zaccour, G., 2018. Handbook of Dynamic Game Theory. volume 51. Springer International Publishing. https://doi.org/10.1007/978-3-319-44374-4.

Parrish, B., Gross, R., Heptonstall, P., 2019. On demand: can demand response live up to expectations in managing electricity systems? Energy Res. Soc. Sci. 51, 107–118. https://doi.org/10.1016/j.erss.2018.11.018.

Parrish, B., Heptonstall, P., Gross, R., Sovacool, B.K., 2020. A systematic review of motivations, enablers and barriers for consumer engagement with residential demand response. Energy Policy 138, 111221. https://doi.org/10.1016/j.enpol.2019.111221.

Ranjbar, F.R., Ravadanegh, S.N., Safari, A., 2024. Transactive energy trading in distribution systems via privacy-preserving distributed coordination. Appl. Energy 361. https://doi.org/10.1016/j.apenergy.2024.122823.

Rodilla, P., Mastropietro, P., Brito-Pereira, P., 2023. The challenge of integrating demand response in capacity remuneration mechanisms: providing a comprehensive theoretical framework. IEEE Power Energy Mag. 21, 64–71. https://doi.org/10.1109/MPE.2023.3269551. ⟨https://ieeexplore.ieee.org/document/10158940/⟩.

Rossetto, N., 2023. Beyond individual active customers: citizen and renewable energy communities in the European Union. IEEE Power Energy Mag. 21, 36–44. https://doi.org/10.1109/MPE.2023.3269541. ⟨https://ieeexplore.ieee.org/document/10158968/⟩.

Rueda, L., Agbossou, K., Henao, N., Kelouwani, S., Oviedo-Cepeda, J.C., LeLostec, B., Sansregret, S., Fournier, M., 2021. Online unsupervised occupancy anticipation system applied to residential heat load management. IEEE Access 9, 109806–109821. https://doi.org/10.1109/ACCESS.2021.3098631. ⟨https://ieeexplore.ieee.org/document/9491101/⟩.

Scutari, G., Facchinei, F., Pang, J.S., Palomar, D.P., 2014. Real and complex monotone communication games. IEEE Trans. Inf. Theory 60, 4197–4231. https://doi.org/10.1109/TIT.2014.2317791. ⟨https://ieeexplore.ieee.org/document/6799233/⟩.

Sharma, S., Niazi, K., Verma, K., Rawat, T., 2020. Coordination of different DGs, BESS and demand response for multi-objective optimization of distribution network with special reference to Indian power sector. Int. J. Electr. Power Energy Syst. 121, 106074. https://doi.org/10.1016/j.ijepes.2020.106074. ⟨https://linkinghub.elsevier.com/retrieve/pii/S0142061519327322⟩.

Sloot, D., Lehmann, N., Ardone, A., 2022. Explaining and promoting participation in demand response programs: the role of rational and moral motivations among German energy consumers. Energy Res. Soc. Sci. 84, 102431. https://doi.org/10.1016/j.erss.2021.102431.

Sloot, D., Lehmann, N., Ardone, A., Fichtner, W., 2023. A behavioral science perspective on consumers' engagement with demand response programs. Energy Res. Lett. 4, 1–7. https://doi.org/10.46557/001c.38831.

Song, M., Meng, J., Lin, G., Cai, Y., Gao, C., Chen, T., Xu, H., 2022. Applications of shared economy in smart grids: shared energy storage and transactive energy. Electr. J. 35. https://doi.org/10.1016/j.tej.2022.107128.

de Souza Dutra, M.D., Alguacil, N., 2023. Fairness of prosumers' incentives in residential demand response: a practical decentralized optimization approach. Int. J. Electr. Power Energy Syst. 148, 109015. https://doi.org/10.1016/j.ijepes.2023.109015. ⟨https://linkinghub.elsevier.com/retrieve/pii/S0142061523000728⟩.

Sreekumar, A., Sakthivelu, A., Kiesling, L., 2023. Auction theory and device bidding functions for transactive energy systems: a review. Curr. Sustain. /Renew. Energy Rep. 10, 102–111. https://doi.org/10.1007/s40518-023-00217-2.

Srinivasan, A., Wu, R., Heer, P., Sansavini, G., 2023. Impact of forecast uncertainty and electricity markets on the flexibility provision and economic performance of highly-decarbonized multi-energy systems. Appl. Energy 338. https://doi.org/10.1016/j.apenergy.2023.120825.

Taylor, S., Letham, B., 2017.Forecasting at scale.PeerJ Preprints.

The GridWise Architecture Council, 2019.GridWise Transactive Energy Framework. Technical Report. The GridWise Architecture Council.

Thomas, S., 2023. Allowing British electricity consumers to choose their supplier: was it worth it? IEEE Power Energy Mag. 21, 18–25. https://doi.org/10.1109/MPE.2023.3269543. ⟨https://ieeexplore.ieee.org/document/10158967/⟩.

Tsaousoglou, G., Steriotis, K., Efthymiopoulos, N., Makris, P., Varvarigos, E., 2020. Truthful, practical and privacy-aware demand response in the smart grid via a distributed and optimal mechanism. IEEE Trans. Smart Grid 11, 3119–3130. https://doi.org/10.1109/TSG.2020.2965221. ⟨https://ieeexplore.ieee.org/document/8954657/⟩.

Ungureanu, V., 2018. Pareto-Nash-Stackelberg Game and Control Theory. volume 89 of Smart Innovation, Systems and Technologies. Springer, Cham. https://doi.org/10.1007/978-3-319-75151-1.

Watson, J., 2013. Strategy. W. W. Norton and Company.

Yao, Y., Gao, C., Lai, K., Chen, T., Yang, J., 2021. An incentive-compatible distributed integrated energy market mechanism design with adaptive robust approach. Appl. Energy 282, 116155. https://doi.org/10.1016/j.apenergy.2020.116155. ⟨https://linkinghub.elsevier.com/retrieve/pii/S0306261920315609⟩.

Yazdani, H., Doostizadeh, M., Aminifar, F., 2022. Unlocking the value of flexibility of behind-the-meter prosumers: an overview of mechanisms to esteemed trends. Electr. J. 35. https://doi.org/10.1016/j.tej.2022.107126.

Yuan, G., Hang, C.W., Huhns, M.N., Singh, M.P., 2017.A Mechanism for Cooperative Demand-Side Management, In: 2017 IEEE 37th International Conference on Distributed Computing Systems (ICDCS), IEEE.361-371.⟨http://ieeexplore.ieee.org/document/7979982/⟩, 10.1109/ICDCS.2017.300.

Zhang, K., Xu, Y., Sun, H., 2024. Bilevel optimal coordination of active distribution network and charging stations considering EV drivers' willingness. Appl. Energy 360, 122790. https://doi.org/10.1016/j.apenergy.2024.122790. ⟨https://linkinghub.elsevier.com/retrieve/pii/S0306261924001739⟩.

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 a PhD Candidate in electrical engineering with the Smart Energy Research and Innovation Laboratory, *Université* du Québec á Trois-Riviéres, Canada. His research interests include distributed energy resources, electricity markets, transactive energy, resilience of power grids, power quality, and advanced metering infrastructure.

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 Riviéres (UQTR), Trois-Riviéres, 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 his B.S., M.S., and Ph.D. in electronic measurements from Université de Nancy I, France. He has held various academic positions at Université du Québec á Trois-Riviéres (UQTR), including Director of Graduate Studies, Head of the Electrical and Computer Engineering Department, and Head of the Engineering School. Currently, he is the Hydro-Québec Research Chairholder on Transactive Management of Power and Energy in the Residential Sector and Chair of the Smart Energy Research and Innovation Laboratory at UQTR. He has authored over 325 publications and holds four patents, and his research focuses on renewable energy, hydrogen use, and home demand-side management.

Sousso Kelouwani: (Senior Member, IEEE) received his Ph.D. in robotics systems from Ecole Polytechnique de Montreal in 2011. He is a Full Professor of mechatronics at Université du Québec á Trois-Riviéres (UQTR) and a member of the Hydrogen Research Institute. He holds four patents and has published over 100 scientific articles. He is the Canada Research Chair in energy optimization of intelligent transport systems and the Noovelia Research Chair in intelligent navigation of autonomous industrial vehicles. His research focuses on optimizing energy systems for vehicles, advanced driver assistance, and intelligent vehicle navigation. He has received multiple awards, including the Canada General Governor Gold Medal.

Juan C. Oviedo-Cepeda: obtained his Electrical Engineering degree in 2016 and his Ph.D. degree in 2021 from Universidad Industrial de Santander, Colombia. Since 2021, he has been linked as a researcher in the electric power industry, and he is currently a researcher at Hydro-Québec. His research areas are intelligent grids, automatic demand response, and energy markets, which naturally led him to work actively in Transactive Energy.

Juan Domínguez-Jiménez: is an Electrical Engineer (2016), Master in Engineering (2019) from the Universidad Tecnológica de Bolivar (UTB). He is currently engaged as a PhD student at Université du Quebec á Trois-Riviéres, Canada, and his present research activities are in the area of autonomous grids, thermal energy storage, object-oriented modeling, distributed optimization, and multi-agent systems.