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L'INCERTITUDE DES AGENTS RÉSIDENTIELS DANS UN CONTEXTE DE
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DOCTORAT EN GÉNIE ÉLECTRIQUE

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ALEJANDRO PARRADO DUQUE

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UNIVERSITÉ DU QUÉBEC À TROIS-RIVIÈRES

DOCTORAT EN GÉNIE ÉLECTRIQUE (Ph.D.)

Direction de recherche :

Prof. Kodjo Agbossou Université du Québec à Trois-Rivières.	Directeur de recherche
--	------------------------

Prof. Sousso Kelouwani Université du Québec à Trois-Rivières.	Codirecteur de recherche
--	--------------------------

Jury d'évaluation

Prof. Alben Cárdenas Université du Québec à Trois-Rivières.	Président du jury
--	-------------------

Prof. Antoine Lesage-Landry Polytechnique Montréal.	Évaluateur externe
--	--------------------

Prof. Iván Serna Universidad Industrial de Santander.	Évaluateur externe
--	--------------------

Prof. Kodjo Agbossou Université du Québec à Trois-Rivières.	Directeur de recherche
--	------------------------

Prof. Sousso Kelouwani Université du Québec à Trois-Rivières.	Codirecteur de recherche
--	--------------------------

Résumé

La numérisation des systèmes électriques permet aux clients résidentiels de fournir activement à la prestation de services de réseau, tels que la réponse à la demande, au sein d'un cadre d'énergie transactionnelle. Dans ce contexte, des agents logiciels autonomes négocient au nom des utilisateurs et des gestionnaires de réseau afin d'optimiser la fiabilité et l'efficacité économique. Cependant, comme ces agents sont intelligents et rationnels — c'est-à-dire qu'ils priorisent stratégiquement l'intérêt économique des représentés — ils constituent un risque pour le déploiement et la pérennité du programme transactionnel : la manipulation de l'information pour maximiser les gains financiers individuels.

Du point de vue d'une entité centralisée qui gère le réseau électrique, le déploiement d'un système d'énergie transactionnelle dans un environnement entièrement numérisé pose plusieurs défis informationnels, tels que le passage à l'échelle, le traitement des données, les goulots d'étranglement des réseaux de communication et la protection de la vie privée des clients. Pour cette raison, cette thèse adopte une approche distribuée en déployant des agrégateurs (ou coordonnateurs) et des agents résidentiels.

En plus des défis susmentionnés, la fiabilité de l'information dans les mécanismes de négociation constitue un autre défi informationnel fondamental dans un environnement entièrement numérisé. Le mécanisme de négociation employé par le gestionnaire du marché pour compenser les marchés d'électricité à terme est vulnérable à des effets indésirables en raison du comportement stratégique des agents résidentiels. Ce comportement stratégique implique une manipulation potentielle de l'information échangée lors d'une négociation si les agents résidentiels détectent la possibilité d'accroître leurs gains financiers. À cet égard, sans un mécanisme robuste contre les stratégies (« strategy-proof »), un tel comportement peut entraîner des inefficacités, des

déséquilibres budgétaires et des écarts énergétiques par rapport aux accords du marché à terme ; ces résultats indésirables compromettent la faisabilité financière du programme d'énergie transactionnelle et la fiabilité du réseau électrique.

Cette thèse présente un mécanisme résistant aux stratégies, conçu pour empêcher l'injection de fausses informations par les agents résidentiels dans un contexte de négociation sur un marché d'électricité à terme. Le mécanisme proposé fonctionne dans des conditions d'information incomplète, imparfaite et asymétrique, tout en préservant les données privées des clients. Les résultats théoriques et de simulation démontrent que le mécanisme proposé atteint un équilibre en stratégies dominantes, ce qui le rend compatible avec les incitations. Par conséquent, ce mécanisme incite les agents résidentiels à fournir des informations véridiques tout au long du processus de négociation, leur permettant de réaliser des réductions de la facture d'électricité en exploitant leur flexibilité, en harmonie avec les objectifs de l'agrégateur ou du coordinateur.

Abstract

Digitalization of electricity systems enables residential customers to actively participate by providing grid services, such as demand response, within a transactive energy framework. In this landscape, autonomous software agents negotiate on behalf of users and grid operators to optimize the grid and economic efficiency. However, because these agents are intelligent and rational—meaning they strategically prioritize the economic interests of those represented—they introduce a significant risk: the manipulation of information to maximize individual financial gain.

From the perspective of a centralized entity that manages the power grid, deploying a transactive energy system in a fully digitalized environment poses several information challenges, such as scalability, data handling, communication network bottlenecks, and customer privacy preservation. For these reasons, this thesis adopts a distributed approach by deploying aggregators (or coordinators) and residential agents.

In addition to the above challenges, information trustworthiness in negotiation mechanisms arises as another fundamental information challenge in a fully digitalized environment. The negotiation mechanism employed by the market leader (e.g., aggregator, coordinator, or grid manager) to clear day-ahead electricity markets is vulnerable to undesirable outcomes due to the strategic behavior of residential agents. The strategic behavior of these residential agents implies the potential manipulation of information exchanged during a negotiation if they detect the possibility of increasing their financial gains. In this regard, without a strategy-proof mechanism, such strategic behavior can lead to inefficiencies, budget imbalances, and energy deviations from day-ahead market agreements; these undesired outcomes jeopardize the financial feasibility of the transactive energy program and compromise power grid reliability.

For this reason, this thesis presents a truthfulness-oriented, strategy-proof mechanism, designed to prevent the injection of false information in a negotiation setup for a day-ahead electricity market, by residential agents. The proposed mechanism operates under conditions of incomplete, imperfect, and asymmetric information, while preserving customer privacy. Theoretical and simulation results demonstrate that the proposed strategy-proof mechanism reaches a dominant-strategy equilibrium, i.e., an incentive-compatible mechanism. Therefore, the proposed incentive compatibility mechanism leads residential agents to report truthful information throughout the negotiation process, enabling them to perceive electricity bill reductions by exploiting their flexibility in alignment with the aggregator/coordinator's goals.

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When John Von Neumann was asking about why Bulgarians were recognised as Marcians, his answer was on the way of pushing your own limits because of the surrounding difficulties they experienced, emphasising that hard situations are an open door to becoming a more aware and prepared person (due to the First World War). Regarding what concerns me, I'm pretty sure that I'm far from being a Marcian, but I am also pretty sure that I'm far from where I began my own journey.

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List of Acronyms

Notation	Description
BB	Budget balance.
DR	Demand response.
Eff	Efficiency.
IC	Incentive compatibility.
IR	Individual rationality.
MD	Mechanism design.
PoA	Price of Anarchy.
RA	Residential agents.
TE	Transactive energy.
CAPEX	Capital expenditures.
OPEX	Operational expenditures.
BESS	Battery energy storage system.
EV	Electric vehicle.
DSO	Distribution System Operator.
VCG	Vickrey–Clarke–Groves.
DERs	Distributed energy resources.

Nomenclature

Functions

$\mathbb{E}[\cdot]$ Expected value.

$\zeta[\cdot]$ Probability density function of the aggregated reported consumption.

$J[\cdot]$ RAs cost function.

$PR[\cdot]$ Payment rule.

Indices

$*$ Index of negotiation conditions - dynamic price.

$-n$ Index of RA other than n .

0 Index of initial conditions.

n Index of RAs.

t Index of time-step.

Z Index of Monte Carlo scenarios.

Mathematical symbols

$\therefore$ Therefore.

$\propto$ Directly proportional to.
 $\sim$

Parameters

α_n Penalty price vector.

π_n Electricity price vector.

γ Thermal discomfort.

λ Quadratic power grid parameter.

A, B, C Weighted state-space temperature model parameters.

T_{ext} Outdoor temperature.

T_{SP} Inner dwelling temperature set-point.

$\mathbf{r}$ Uncertainty vector.

p Probability of moving iteration by iteration.

Sets

α Set of penalty values explored in simulations.

π Set of electricity prices explored in simulations.

Γ Set of time horizon.

$\mathcal{N}$ Set of RAs.

Ψ Set of iterations

Variables

$\hat{\mathbf{e}}$ RA energy to report.

$\mathbf{e}$ RA energy to import.

$\mathbf{e}_{fix}$ Fix load energy - stochastic - uncontrollable load.

$\mathbf{e}_{var}$ RA heating energy - controllable load.

$\mathbf{T}_{in}$ Inner dwelling temperature.

Chapter 1 - Introduction

Electricity accounts for approximately one-fifth of global final energy consumption and is expected to expand its share as electrification progresses across all sectors [1, 2]. The buildings sector—responsible for nearly 30% of total final energy use [3] and 60% of global electricity demand growth between 2023 and 2024 [4]—is the second largest energy-consuming sector after industry [5]. Within buildings, space heating remains the dominant end use, representing nearly three-quarters of total energy consumption [6]. For instance, in Canada, buildings account for approximately 40% of national final energy use, with electricity providing more than 60% of this demand [6]. In Quebec, electricity is even more predominant, supplying approximately 77% of residential energy needs, of which heating space alone accounts for nearly 60%, and water heating 7% [7]. The significance of the residential sector in Quebec is further emphasized by Hydro-Quebec, which reported that residential customers accounted for the largest share of electricity consumption in 2024 (38%), followed by large industrial (31%), commercial and institutional (27%), and other customers (4%) [8]. These facts underscore the central role of the residential sector in achieving decarbonization targets and justify the increasing attention given to flexible demand strategies and energy efficiency measures, such as those outlined in Hydro-Quebec's 2035 Action Plan [9].

Given the growing electrification and centrality of residential demand in power systems, the interaction between consumers and the grid is becoming increasingly dynamic and complex [10]. Households are no longer passive energy users but potential active participants capable of providing flexibility, storage, and demand response through intelligent devices and distributed resources [11]. This evolving role positions the residential sector as a key enabler of decentralized coordination mechanisms, paving the way for new market structures—such as transactive energy frameworks—that facilitate

negotiations and value exchange between grid actors [12, 13].

Aside from the transition from fossil fuel to renewable-based energy sources to meet current energy demand, the energy transition also entails: i) the electrification of end uses, ii) the integration of modern AI-driven loads, and iii) the full digitalization of the electric power sector [4]. This latter transformation is driving an accelerated paradigm shift across all levels of the energy systems, reshaping how grid services—such as flexibility—are discovered, valued, and transacted at the grid edge [14]. To enable this transformation, software agents—autonomous decision-makers acting on behalf of market participants—play a central role by unlocking demand-side flexibility through granular price and coordination signals, without compromising privacy or local autonomy [15].

In transactive energy (TE) systems, such agents could opt for participating in day-ahead interactions that steer aggregate load profiles toward system objectives while improving customer bills [16]. Operationally, TE programs must reconcile three realities [17]. First, customers' flexibility is heterogeneous and shaped by comfort, technology ownership (e.g., heating systems), and uncertainty; second, coordinating the consumption profiles of customers must be achieved with minimal disclosure of types (private information) to protect privacy and maintain scalability; third, market participants are strategic agents [18]. These realities motivate a coordinator–residential agent (RA) architecture in which a coordinator, acting on behalf of the utility, proposes dynamic price and penalty signals to flatten the energy consumption, and RAs respond with consumption plans by assessing features such as their possibility of cheating in the negotiation, comfort, and device constraints [19, 20]. The interaction between the coordinator and the RAs in the TE system is modeled as a leader–follower (Stackelberg) game with bounded rationality, implemented through a contract split into four phases when RAs can weigh their

participation before the negotiation phase starts: *Enrollment*, *Coordination*, *Execution*, and *Settlement*. Otherwise, the classical *ex-ante*, *interim*, and *ex-post* phases of mechanism design are enough to explain the mechanism’s outputs [21]. These phases are relevant in the thesis to the structure of signals, decisions, and players’ accountability over time.

Within this architecture, there are two canonical clearing market approaches [22]. One-shot framework exchanges a single round of signals and reports; it provides reduced communication overhead and clear settlement logic. However, they tend to sacrifice efficiency at the expense of avoiding disclosing the customer’s private information. Iterative designs allow multi-round feedback, improving stability and optimality under mild convergence conditions while preserving decentralized information [23]. Iterative bidding and decentralized market-coupling mechanisms offer relevant precedents [24]: they can converge to efficient outcomes with limited information exchange and robustness to certain strategic deviations—properties that are especially valuable when RAs keep their information private and share only their electricity consumption plans.

Yet, minimal information exchange is not enough. In any negotiation in which RAs can freely choose to report a true or false consumption plan in a day-ahead electricity market, strategic misreporting becomes a first-order design concern. Although the coordinator is responsible for designing a strategy-proof mechanism from the negotiation phase, the potential manipulation of the consumption plan by each RA could be assessed only in the *settlement* phase. This fact elevates mechanism design from an optional lens to a central design discipline in this application.

1.1 Problem statement

Day-ahead electricity markets, a particular type of forward market, play a key role in power system operation [16]. They enable utilities to plan system operations based on demand and supply forecasts, ensuring reliability through day-to-day energy scheduling.

In a TE setting, utilities and customers are equipped with agents that negotiate day-ahead transactions. Customers participate in a negotiation with the coordinator, seeking agreements that best serve their interests [17].

However, beyond the technological challenges of deploying agents on the customer side, and beyond the inherent uncertainty of weather and human behavior, residential agents with sufficient rationality and intelligence may behave strategically: they can attempt to manipulate the negotiation mechanism for their own economic benefit [25]. If misreporting occurs, the coordinator may design an operational plan based on an inaccurate demand plan, jeopardizing the system's technical reliability and the TE system's long-term financial viability [26].

Therefore, this thesis addresses the prevention of strategic manipulation in TE systems by employing the concept of incentive compatibility from mechanism design. Therefore, the market leader (the coordinator) designs a negotiation mechanism to conduct RAs to assess the benefits of misreporting a consumption plan rather than truthfully reporting it. At the same time, the coordinator must ensure that participation remains attractive while assessing the mechanism's budget and the efficiency results compared to a naive (benevolent) mechanism [27].

This thesis then addresses the following main problems:

- A discrepancy exists between the coordinator's goals and the strategic actions of residential agents, who may misreport their information in day-ahead markets to game the mechanism for individual gain. This discrepancy results in inefficiencies, budget imbalances, and deviations from the intended consumption schedules.
- Without privacy-preserving communication frameworks, customers may be reluctant to share the information the market leader needs, undermining participation and diminishing the overall effectiveness of TE programs.
- Current coordination mechanisms do not yield incentive-compatible designs that both secure participation while assessing budget balance and efficiency, which in turn results in the absence of stable equilibria or negotiation outcomes that are economically viable.

1.2 Objectives and contributions

This thesis aims to develop a mechanism that avoids the negative effects of strategic residential agents in a day-ahead electricity market within a transactive energy context. This main objective leads to the formulation of the following three specific objectives:

1. Develop a TE system between a coordinator (leader) and residential agents (followers) to assess the mechanism design concepts. This development involves modeling their roles, capabilities, and interactions while considering demand-side uncertainty to clear a day-ahead electricity market.
2. Formulate an incentive-compatible mechanism in the TE system to discourage misreporting of information during negotiation while keeping an agent's interaction.
3. Evaluate the incentive-compatible mechanism in both one-shot and iterative electricity market architectures, assessing its effect on individual rationality, budget

balance, and efficiency.

This thesis advances the state of the art by analyzing and mitigating strategic behavior in TE systems involving residential agents, while rigorously preserving customer privacy. The TE framework developed in this work systematically evaluates individual rationality, budget balance, and efficiency under an incentive-compatible mechanism. To achieve this, the work builds on concepts from mechanism design and game theory, including:

- Modeling of a TE system as a Stackelberg game with a one-leader–multiple-followers structure, incorporating demand-side uncertainty and its impact on the coordinator’s decision policies.
- Formulation of a paired price-penalty coordination policy designed to align residential agent behavior with grid objectives. This policy incentivizes truthful reporting and reduces peak energy consumption while strictly preserving customers’ privacy.
- Theoretical characterization of the TE system, establishing the sufficient conditions under which truthful reporting constitutes the dominant strategy for residential agents.

1.3 Methodology

This section presents the methodological framework developed to address the objectives of this thesis. The approach integrates concepts from TE systems, mechanism design, game theory, and electricity markets, as presented in Fig. 1.1. Together, these elements provide the theoretical and practical foundation for analyzing and mitigating RAs’ strategic behavior in a negotiation environment.

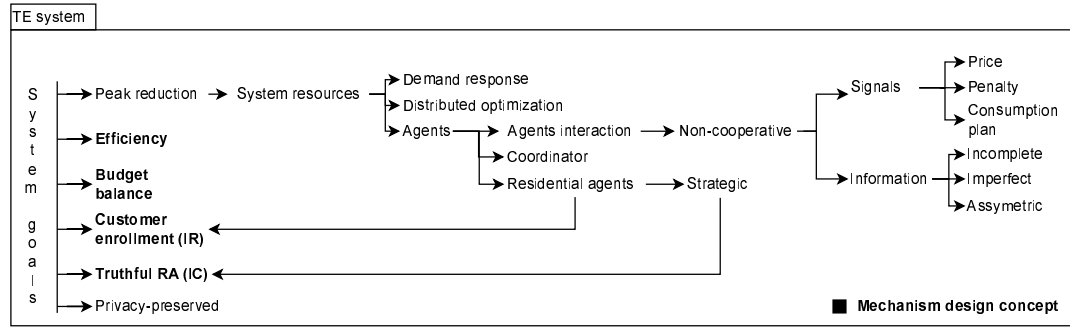


Figure 1.1 An overview of the key concepts in the methodology of this thesis.

1.3.1 Software agents

Software agents are central to this study, as the coordinator and residential agents use them to conduct negotiations in the TE context of this thesis. Following the definition by [16], an agent is: “a computer system situated in some environment and capable of autonomous action in this environment to meet its delegated objectives.”

Software agents are classified according to their architecture and capabilities [16]. In the former, they may be purely reactive, model-based, goal-based, utility-based (with perfect or bounded rationality), learning, or hybrid. In this work, the residential agents are considered hybrid entities combining model-based, goal-based, and bounded-rational, utility-driven behaviors. This representation is appropriate because the proposed mechanism is designed to discourage strategic manipulation by rational and intelligent residential agents, which are modeled using stochastic convex optimization to incorporate their heating load preferences and their willingness to sacrifice thermal comfort in their software.

From a capabilities perspective, key dimensions include autonomy, reactivity, pro-activeness, social ability, adaptability, and planning horizon [16]. From these, the

capabilities that best fit with those considered in this thesis are autonomy, pro-activeness, social ability, and planning horizon. These characteristics allow RAs to act independently, interact with the coordinator, and plan their energy use strategically over time.

1.3.2 Mechanism design

Mechanism design—“the art of designing the rules of a game to achieve a specific desired outcome” [21]—provides the conceptual basis for handling strategic behavior. Four key principles underpin this framework:

- Individual rationality (IR): agents participate only if the cost of joining a program is lower than the cost of not participating;
- Efficiency (EFF): evaluates the economic performance of the mechanism relative to the social welfare optimum;
- Budget balance (BB): assesses whether revenues cover costs, implying no external subsidies are required;
- Incentive compatibility (IC): ensures that agents find it optimal to report truthfully rather than manipulate information.

In practice, no mechanism can satisfy all four principles simultaneously. Two impossibility results are particularly relevant: the Green–Laffont (Hurwicz) Theorem and the Myerson–Satterthwaite Theorem [21, 28]. The first states that achieving *ex-post* efficiency and weak budget balance is impossible while maintaining dominant-strategy IC. The second demonstrates that no mechanism simultaneously achieves *ex-post* efficiency, weak budget balance, and *interim* IR under Bayesian IC.

Given these impossibility results, the IC mechanism proposed in this thesis does not simultaneously satisfy all four fundamental properties of mechanism design. Instead, by

ensuring IC within a TE system, this thesis evaluates how such a mechanism influences the remaining desirable properties—efficiency, budget balance, and individual rationality. This evaluation provides a quantitative understanding of the trade-offs that arise when prioritizing IC in the design of practical TE negotiation architectures.

Moreover, this thesis reframes the canonical mechanism design phases (*ex-ante*, *interim*, *ex-post*) into four intuitive phases of the negotiation process:

1. Enrollment: RAs decide whether to participate in the negotiation.
2. Coordination: participating RAs and the coordinator interact through price–penalty signals.
3. Execution: RAs act once uncertainty (e.g., demand realization) is revealed.
4. Settlement: The coordinator enforces agreements in the coordination phase, and no further negotiation, e.g., reconciliation, exists.

This phase-based structure ensures that theoretical properties can be evaluated at appropriate stages of the negotiation.

1.3.3 Game theory

Game theory provides the mathematical framework for modeling negotiations in which entities—here, the coordinator and RAs—interact strategically [29]. Two broad categories of games are relevant: cooperative games, where agents exchange all necessary information to achieve a socially optimal outcome, and noncooperative games, where agents prioritize their objectives, often under limited or asymmetric information conditions [30].

Because RAs aim to preserve privacy and limit the disclosure of their private types (e.g.,

preferences), this thesis adopts a noncooperative framework, specifically a Stackelberg game, where the coordinator acts as the leader and the RAs as the followers [31]. The information environment further characterizes the game, as follows:

- Incomplete: RAs do not communicate and thus lack knowledge of others' private types;
- Imperfect: agents cannot fully observe the decisions of others during negotiation;
- Asymmetric: the coordinator and RAs have access to different information sets.

This formulation reflects the practical constraints of TE negotiations and aligns with the methodological focus on strategic, privacy-preserving interactions [21, 32].

1.3.4 Transactive energy and electricity markets

The digitalization of electricity systems is transforming customers from passive consumers into active participants capable of providing services to the grid [14]. TE frameworks enable this interaction by allowing customers and utilities to negotiate mutually beneficial agreements.

Electricity markets can be categorized along architecture and structure [16]. Market architecture includes submarkets, types, and linkages. Among the many submarkets (energy, ancillary services, capacity, forward, futures, etc.), this thesis focuses on forward energy markets, specifically day-ahead, which schedule daily consumption in advance. Within market types, two dominate: bilateral (direct search, bulletin board, brokered) and mediated (dealer, exchange, pool). The negotiation environment adopted in this thesis is a special case of a brokered market with a decentralized negotiation structure. Both explicit (daily enrollment agreements) and implicit (shared use of distribution assets) are relevant regarding linkages.

On the other hand, market structure considers sectors (wholesale, retail, transmission) and entities (generators, retailers, operators, aggregators, consumers, etc.). The setting of this thesis corresponds to a deregulated retail market involving non-profit aggregators (the coordinator) and small consumers (residential customers).

This characterization situates the negotiation environment in an electricity market context, ensuring that the theoretical contributions are consistent with practical market arrangements.

1.3.5 Stochastic convex programming

The analysis of the best-response decisions the RAs make in the negotiation phase, in the presence of uncertainty and the price policy adopted by the market leader, has been conducted using backward induction [30]. Moreover, the cost functions and the payment rules considered in this thesis are compact, convex, and continuous [33]. These properties were fundamental to determining whether the proposed mechanism reached a dominant-strategy equilibrium and to ensuring a global optimum solution [21, 30, 33].

The Monte Carlo method, specifically the Sample Average Approximation (SAA), was employed throughout the thesis to solve the stochastic optimization problems in the *enrollment* and *coordination* phases [34]. In this approach, the expected value of the objective function under uncertainty, i.e., $\mathbb{E}[J_n(\mathbf{e}, \hat{\mathbf{e}}, \mathbf{r})]$ for each RA, is replaced by the sample average estimator over a generated set of N independent and identically distributed scenarios. By simulating a wide range of possible outcomes, the SAA method offers a reliable, computationally tractable approximation of complex uncertainties, improving decision-making precision for both the RAs and the coordinator [35].

1.3.6 Methodology summary

The methodology integrates five core conceptual pillars: software agents, mechanism design, game theory, transactive energy, and electricity markets. Together, these elements provide the required structure to address the central challenge of this thesis: designing a mechanism that prevents strategic misreporting by residential agents in day-ahead negotiations while preserving customer privacy. The interplay of these concepts supports the achievement of the research objectives by:

- Modeling an agent's strategic behavior,
- Embedding mechanism design principles to counteract strategic manipulation,
- Framing negotiations within a noncooperative, Stackelberg game, and
- Situating the analysis in the operational and institutional setting of TE and electricity markets.

This thesis develops an IC-based coordination mechanism through this methodological foundation and evaluates core concepts such as individual rationality, budget balance, and efficiency.

1.4 Assumptions

Although this thesis embraces several concepts and theories already grounded in the literature, such as electricity markets, stochastic convex programming, mechanism design, and game theory, the following related topics are out of the scope and, therefore, were considered as assumptions:

- All game players, i.e., the coordinator and customers, are equipped with agent-based technology. Neither the CAPEX nor the OPEX for this deployment

was covered. The agents implemented on the customer's side are therefore referred to as residential agents in this document.

- A bidirectional communication channel is established between the coordinator and RAs. However, there's no communication between the RAs themselves. The proposed mechanism's effects on latency and communication failures haven't been explored.
- Residential agents do not share their private information (types) with the coordinator, such as comfort indoor temperatures. They just share their consumption plan for the day-ahead consumption period. In the context of this thesis, the global negotiation framework is characterized by an exchange of signals between a coordinator and multiple followers during the *negotiation* phase. At the outset of the negotiation, the coordinator sends both an initial electricity price signal and a penalty price signal to each RA to initiate the negotiation. Subsequently, each RA incorporates these negotiation signals into its own optimization problem and returns a corresponding consumption plan. The signal exchange process during the *negotiation* phase depends on the underlying market architecture and may be realized as either a one-shot interaction or an iterative negotiation procedure.
- Agents are both bounded rational and intelligent, grounded on the utility-based approach employed in this thesis.
- Any form of bribery or collusion was not analyzed. In this regard, no RA was prioritized by the coordinator, and all of them performed negotiations following the same rules. Additionally, the lack of communication channels between the RAs prevents their collusion.
- Since the IC mechanism proposed in this thesis incorporates penalization for deviations from the negotiated consumption plan, and stochasticity is embedded

in each agent’s decision-making process, some deviations may arise from inherent uncertainty rather than intentional misreporting. This thesis does not address compensation or corrective measures for such uncertainty-induced deviations.

1.5 Manuscript structure

After the introductory chapter, which includes the problem statement and motivation, contributions, methodology, and assumptions of this thesis, Chapter 2 presents the state of the art, providing a comprehensive review of the most relevant literature and the latest research contributions in the field of incentive compatibility.

Chapter 3 presents the main contribution of this thesis in the form of papers as output of the aforementioned research. In this chapter, an incentive-compatible mechanism is introduced to address strategic agents in both one-shot and iterative market architectures. Moreover, the proposed mechanism formally assesses relevant mechanism design concepts, such as individual rationality, budget balance, and efficiency.

Chapter 4 is dedicated to highlighting the main contributions of this work, as well as its limitations. New challenges, opportunities, and future directions are highlighted to incentivize research in the field of mechanism design and its applications in the artificial intelligence era. Finally, chapter 5 presents the conclusions of this thesis.

Chapter 2 - State-of-the-art

This chapter reviews the current state of research relevant to incentive compatibility as the guiding principle. The chapter begins by examining attitudes and self-enforcing policies, then introduces the main concepts of mechanism design and their temporal assessment. Foundational IC mechanisms, such as the Vickrey–Clarke–Groves (VCG) and Kelly mechanisms, as well as recent research on incentive compatibility, are reviewed, and their limitations when applied to TE are explored. Customer enrollment in demand response programs is also presented, along with the barriers to customer engagement and the aggregator’s role. Finally, a contrast between centralized and distributed approaches is highlighted.

2.1 Attitudes and self-enforcing policies

Cooperative attitudes can foster efficient agreements in idealized scenarios [18]. However, robust market design requires the assumption of strategic behavior, in which agents are presumed to act in their own self-interest. This assumption accounts for the risk of agents misreporting information or free-riding, posing a challenge to collective efficiency that the proposed mechanism must address [36]. When RAs interact with a coordinator in DR programs, assuming benevolent behavior is risky. If RAs misreport their baseline consumption to maximize rewards, the program may collapse economically and technically, jeopardizing system reliability.

Self-enforcing policies have been proposed to mitigate these risks. These policies align private incentives with truthful behavior, often through carefully designed reward–penalty schemes [26]. In this context, the primary objectives of these self-enforcing policies are i) to elicit reliable consumption reports from RAs, ii) to enable the coordinator to determine incentive-compatible remuneration schemes while accurately anticipating

the system's operational costs, and iii) to impose penalties for deviations from agreed schedules. Collectively, these objectives aim to reduce reserve requirements and enhance transparency in the determination of settlement prices. [32].

2.2 Mechanism design

Mechanism design (MD) is a branch of economics and game theory concerned with creating rules of interaction that lead self-interested agents toward outcomes aligned with social objectives [21]. In contrast to classical game theory, where the game's structure is given and the analyst studies equilibrium outcomes, MD reverses the problem: it asks how the "rules of the game" should be crafted to elicit desirable outcomes even in the presence of private information and strategic behavior.

Four canonical properties underpin MD [29]: individual rationality, in which an agent participates only if the expected payoff from joining is greater than the payoff from opting out. IR ensures that customers prefer engaging in TE programs rather than consuming electricity independently in the markets. A mechanism is efficient if it maximizes social welfare. In energy systems, efficiency implies minimizing total system costs while maintaining reliability. The coordinator assesses a TE program's budget balance based on the mechanism's revenues and payments. Weak budget balance requires that total payments are non-negative (i.e., the mechanism does not run a deficit), whereas strong budget balance requires an exact balance without surplus or deficit. Lastly, incentive compatibility requires that truth-telling is a dominant strategy. In practice, this means customers have no incentive to misreport expected consumption or flexibility. This taxonomic framework is illustrated in Fig. 2.1.

MD properties are typically assessed across three information phases [21]:

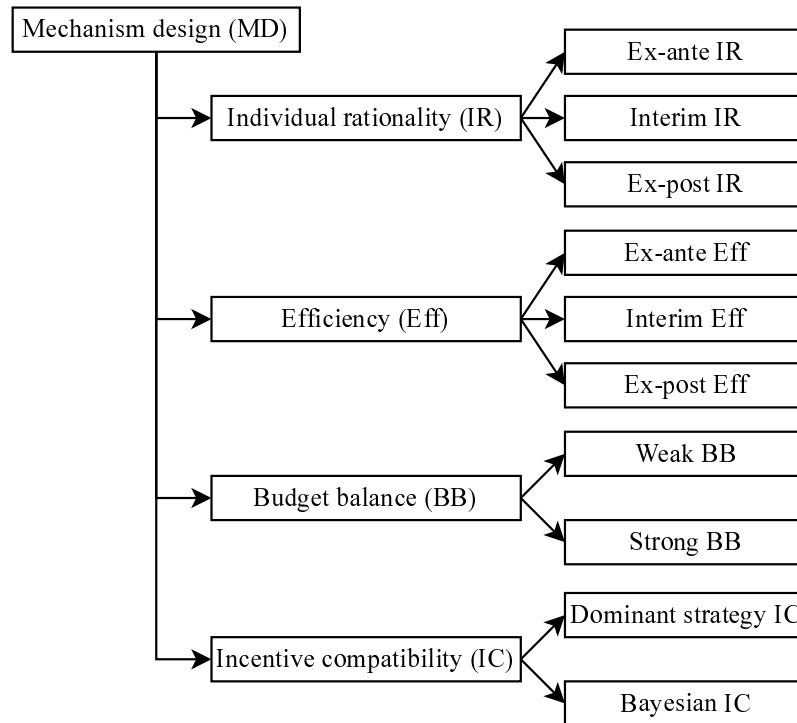


Figure 2.1 Main concepts of mechanism design.

- Ex-ante: Decisions are evaluated before uncertainty is revealed, based on expected outcomes.
- Interim: Partial information is revealed (e.g., own type known but not others).
- Ex-post: Outcomes are assessed after all uncertainty has materialized.

This thesis reformulates these as enrollment, coordination, execution, and settlement phases to align with the practical stages of customer engagement in TE systems.

Mechanism design has been used in electricity markets to structure auctions for generation capacity, transmission rights, and demand response. Traditional applications, however, assume centralized markets with large, rational players. The transition toward distributed and customer-centric TE requires adapting MD principles to settings with small, heterogeneous residential customers, private and uncertain information about preferences and flexibility, limited communication or computational capabilities, and the

need for scalable solutions [22].

Thus, while MD provides the theoretical foundation, practical TE implementations must simplify or approximate canonical mechanisms, often through budget penalties, contracts, or hybrid schemes.

2.3 The concept of incentive compatibility

IC is essential for discouraging strategic misreporting. A mechanism is IC if an agent's cost of truth-telling is lower than the cost of misreporting, as expressed in Eq. (2.1) [21, 37]:

$$C(\hat{e}_n) < C(\hat{e}'_n) \quad (2.1)$$

Since RAs must freely report their expected consumption, the challenge lies in designing mechanisms that make truth-telling optimal for self-interested agents. Hard constraints such as $e_n = \hat{e}_n$ are infeasible; instead, elicitation schemes that internalize penalties or rewards are required [25].

2.4 Customers enrollment

The literature often assumes customers voluntarily participate in DR programs if they see lower bills. Nevertheless, real-world trials demonstrate lower engagement due to comfort preferences, limited energy literacy, limited automation, and concerns about transparency [38, 39]. As a result, many DR programs have been discontinued [40]. Empirical evidence suggests that voluntary “opt-in” schemes generate higher responsiveness than mandatory enrollment, but engagement remains modest [41]. Additional barriers include:

- Lack of enabling technologies (e.g., smart home systems) [42].
- Poorly designed dynamic tariffs [11].
- Low trust in coordinators and unclear benefit distribution [43].
- Demographic heterogeneity influences willingness to shift loads [44].

Overcoming these barriers requires automated decision-making tools to guide customers in negotiating flexibility, a need that remains unmet mainly [10, 13].

2.5 Foundational incentive compatible mechanisms

Two classical IC allocation mechanisms are the Vickrey–Clarke–Groves (VCG) auction and the Kelly mechanism. Both aim to allocate a divisible good (such as energy) among agents, but they differ in their features [32].

VCG Mechanism – In a VCG auction, agents report their valuation functions and constraints (not just a signal) to solve an optimization problem in a centralized way, and the mechanism chooses the efficient allocation that maximizes total value. Each agent's payment is based on the harm it imposes on others (the Clarke pivot rule), which makes truth-telling a dominant strategy (strategy-proof). VCG guarantees allocative efficiency and dominant-strategy incentive compatibility – leading participants to have no incentive to misreport. However, although VCG is not budget-balanced [45], i.e., the total payments collected from demand may not equal total payments to supply, leading to deficits or surpluses, it also requires eliciting complete utility functions, which are infeasible for practical participants. As utility functions should be elicited from customers and collected by the coordinator, the VCG mechanism also has a scalability drawback, given its exponential complexity that increases with the number of participants and their respective constraints.

On the other hand, the Kelly mechanism is a decentralized approach where each agent submits a single bid, a scalar “willingness to pay”, and resources are allocated proportionally subject to network constraints [32]. Priorly when implemented in a very large network, so customers find it difficult to estimate its effect on the price and instead work with a kind of price-taker agent rather than a price-maker-revealing under the sole condition of being implemented in a very large network, so customers find it difficult enough to estimate their effect on the price, and then work with a kind of price-taker agent instead of price-makers. The price-taking regime (agents assume their bid doesn’t affect prices) leads to an equilibrium with at least 75% of the social optimum. In fact, in many networks, a Nash equilibrium may not even exist; if it does, efficiency can collapse to an arbitrarily low level. Hence, without additional incentives or constraints, Kelly-type schemes allow gaming.

Importantly, both VCG and Kelly are fundamentally allocation mechanisms – they are designed to allocate a fixed divisible good optimally or fairly. While guaranteeing specific IC properties, they may not align with TE requirements [32]. For instance, these mechanisms entail the coordinator directly allocating electricity consumption to customers rather than allowing them to freely determine their electricity consumption, resembling a form of direct load control, and the Kelly mechanism is grounded in bids of price-and-consumption. These mechanisms are therefore typically applied to auctions, and their implementation in electricity markets remains within the aforementioned limitations.

2.6 Recent literature about incentive compatibility

The following subsections present recent literature contributions, including but not limited to variants of VCG, dynamic penalties, or hybrid schemes to address IC in TE settings. These contributions are categorized in this work as penalty-based approaches in

TE systems, mechanisms based on VCG and variants, TE frameworks, game-theoretic and dynamic incentive mechanisms, and others.

2.6.1 Penalty-Based Approaches

Some studies have explored penalty mechanisms to discourage deviations from agreed consumption plans. [46] proposed a price–penalty scheme to incentivize load flexibility during specific time windows. While effectively reducing peak demand, the mechanism lacked strategy-proofness, allowing customers to misreport baselines for economic gain. Similarly, [47, 48] introduced penalty functions for day-ahead markets but did not formally address IC, IR, Eff, or BB, nor did they consider strategic agent behavior.

2.6.2 Mechanisms Based on VCG and Variants

The Vickrey–Clarke–Groves (VCG) mechanism remains a benchmark for achieving IC. However, its practical application faces challenges such as budget imbalance and privacy concerns. [49] developed a scaled VCG variant to mitigate budget deficits. Although this approach improved BB, it relied on the unrealistic assumption that no agent holds significant market power, overlooking the possibility of strategic manipulation in real-world settings. More recently, [50] introduced a privacy-preserving VCG modification that maintained IC and IR but sacrificed efficiency and did not resolve the inherent BB issue.

2.6.3 Transactive Energy Frameworks

TE-based mechanisms have also been investigated for distributed coordination. [51] developed a framework for allocating cooperative surplus in combined cooling, heating, and power systems, ensuring IC, IR, and cost recovery. However, the mechanism required extensive sharing of private information, raising privacy concerns. [52]

proposed a two-phase optimization for coordinating consumption and generation profiles, incorporating IR and weak BB while promoting fairness. Nevertheless, IC and efficiency were not guaranteed, leaving the mechanism vulnerable to strategic exploitation.

2.6.4 Game-Theoretic and Dynamic Incentive Mechanisms

Dynamic and game-theoretic approaches have emerged as alternatives to static designs. [53] introduced a three-layer mechanism involving system operators, flexibility service providers, and user agents to manage smart appliance loads. While innovative, the study did not explicitly address IC. [54] proposed a dynamic incentive mechanism to elicit private information and ensure time-consistent rewards. Although [54] partially considered IC, efficiency, and BB were not analyzed, and no penalties were imposed for deviations. Similarly, [55] presented a task-allocation mechanism satisfying IC and IR but requiring full type disclosure, which compromises privacy and omits Eff and BB considerations.

2.6.5 Recent Advances and Open Challenges

Recent works have begun to integrate IC into TE-specific contexts. [56] formulated a bilevel optimization model for electric vehicle (EV) charging coordination, incorporating behavioral aspects of participation. However, IC, BB, and Eff were not addressed, and no penalty scheme was included. [57] introduced a dominant-strategy, non-bankrupting equilibrium concept that satisfies IC, IR, and Eff but assumes agents know the full probability distribution of others' types—a strong informational requirement.

2.6.6 Synthesis and Research Gap

Table 2-1 summarizes representative works from the past five years, classifying them by market architecture, clearing methods, incentive schemes, knowledge, information, and

Table 2-1 State of the art.

Ref.		[46]	[53]	[49]	[47]	[48]	[51]	[58]	[54]	[52]	[56]	[50]	[55]	[57]	[19]	[20]	This work
Year		2020	2020	2021	2021	2021	2021	2022	2022	2023	2024	2024	2024	2024	2024	2025	2025
Market architecture	Submarket	Day-ahead	✓	✓	X	✓	✓	✓	X	X	✓	✓	X	X	✓	✓	✓
		Spot	X	X	X	X	X	X	✓	X	X	✓	✓	X	X	X	X
		Real-time	X	X	✓	X	X	X	✓	X	X	X	X	X	X	X	X
	Market control	Centralised	X	X	✓	X	X	X	X	X	X	✓	X	✓	X	X	X
		Distributed	✓	✓	X	✓	X	✓	X	X	X	✓	X	✓	X	✓	✓
Market clearing method	One-shot	✓	X	✓	X	X	X	X	✓	X	✓	✓	X	✓	X	✓	X
	Iterative	X	✓	X	✓	✓	✓	✓	X	✓	X	X	✓	X	✓	X	✓
Incentive-based	Reward	✓	✓	✓	X	X	✓	X	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Penalty	✓	X	✓	✓	✓	X	✓	X	X	X	✓	X	✓	✓	✓	✓
Knowledge	Common	X	X	-	X	X	✓	X	X	X	X	X	X	X	X	X	X
	Mutual	✓	✓	-	✓	✓	X	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Information	Complete	X	X	-	X	X	✓	X	X	X	X	✓	X	X	X	X	X
	Incomplete	✓	✓	-	✓	✓	X	✓	✓	✓	✓	X	✓	✓	✓	✓	✓
	Symmetric	X	X	✓	X	X	✓	X	X	X	X	X	X	X	X	X	X
	Asymmetric	✓	✓	X	✓	✓	X	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Perfect	X	X	✓	X	X	✓	X	X	X	X	X	X	X	X	X	X
	Imperfect	✓	✓	X	✓	✓	X	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mechanism design concepts	IR	Ex-ante	X	X	X	X	X	✓	✓	✓	✓	X	✓	✓	✓	✓	✓
		Interim	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
		Ex-post	X	✓	✓	X	X	X	X	X	X	✓	X	X	X	X	X
	Eff	Ex-ante	X	X	X	X	X	✓	X	X	X	X	X	✓	X	✓	✓
		Interim	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
		Ex-post	X	✓	✓	X	X	X	X	X	X	✓	X	X	X	X	X
	BB	Weak	X	✓	✓	X	✓	X	X	✓	X	X	X	X	✓	✓	✓
		Strong	✓	✓	X	X	X	✓	X	X	X	X	X	X	X	X	X
	IC		X	✓	✓	X	X	✓	X	✓	X	X	✓	✓	✓	✓	✓

satisfaction of MD properties.

Overall, the literature reveals three persistent gaps:

- 1. Dynamic IC under Privacy Constraints:** Most mechanisms either assume full type disclosure or operate in one-shot settings, limiting their applicability in iterative, privacy-preserving TE environments.
- 2. Comprehensive Property Assessment:** Few studies jointly evaluate IC, IR, BB, and Eff across all negotiation phases, particularly under uncertainty.
- 3. Penalty Design and Strategic Robustness:** While penalties are widely used, systematic methods for tuning them to ensure IC without compromising participation or efficiency remain underexplored.

Addressing these gaps motivates the present work, which develops and evaluates an iterative, privacy-preserving mechanism that enforces IC while assessing IR, BB, and Eff in a TE context.

2.7 Distributed and centralized approaches

Traditional power systems rely on centralized generation dispatch and fixed pricing [16, 22]. In contrast, TE embraces distributed, deregulated architectures. Studies and roadmaps highlight that future grids require flexible coordination between centralized and distributed elements. The GridWise TE roadmap notes that technologies supporting centralized control and distributed optimization are key to success, and that transactive systems are one that provides this flexibility [12]. Distributed optimization implies that every market player make decisions based on its private information, beliefs, and valuations, and interact in an environment with other agents [24].

Distributed approaches allow user satisfaction, user-oriented flexibility, and finer demand–supply balance, while centralized systems offer economies of scale but less adaptability. For example, a hybrid design might use central day-ahead market clearing for bulk resources, while local peer-to-peer or aggregator-led markets manage neighborhood flexibility. Several works show multi-agent market designs (e.g., Stackelberg games among microgrids) or multi-layer market structures as promising for modern grids [24]. Distributed/deregulated TE models can better integrate residential DERs and adapt to uncertainty, whereas purely centralized models may not scale or fully capture prosumers’ incentives.

Chapter 3 - Article-based statement of the results

The achievement of the main objective in this work involves the performance of several tasks orientated to formulate a negotiation environment, the role programming of the game players, i.e., agents interacting in the negotiation environment, the definition and backward analysis of the payment rule, the conditions to satisfy the IC property, as well as the framework to assess the IR, EFF, and BB concepts. The progress of the thesis methodology was reported in three papers, specifically:

1. The first paper, titled "*Is it worthwhile to participate in transactive energy? A decision-making model for empowering residential customers*" was published in *The Electricity Journal*, ELSEVIER, on November 12, 2024. This work demonstrated a sufficient condition for an IC mechanism in an iterative negotiation, based on the relationship between the penalty for deviations from an agreement (α) and the power grid cost parameter (λ). Moreover, this work explored the effect of penalty values on customers' IR conditions. Section 3.1, "The effect of a penalty mechanism on the willingness of residential agents to participate in a TE program", presents these findings.
2. The second paper, titled "*Penalty mechanism in transactive energy: A mechanism design approach for day-ahead markets*" was published *Energy Strategy Reviews*, ELSEVIER, on April 25, 2025. This work explored payment rules (PR) employed in the literature from an IC perspective. In addition, it presented the adverse effect of non-strategic-proof mechanisms by quantifying the outputs for the IR, EFF, and BB conditions. Section 3.2, "The effect of strategy behavior on the performance of the TE program", presents these findings.
3. The third paper, titled "*A Reward-Penalty Mechanism to Prevent Strategic-Agents*

Behaviour in an Iterative Negotiation Framework: A Transactive Energy Context" is under revision in the journal *Energy Economics*, ELSEVIER. This work formally demonstrated that the proposed mechanism reaches a dominant strategy equilibrium, thereby ensuring the IC property, in an iterative game case study. Coordination goals were achieved, while customers reduced their electricity bill compared to a non-coordination participation scenario. Section 3.3, "Preventing strategic behavior of residential agents in an iterative negotiation framework based on the analysis of RAs strategies", presents these findings.

3.1 The effect of a penalty mechanism on the willingness of residential agents to participate in a TE program

3.1.1 Background and motivation

The paper addresses a central question for TE systems: can residential customers and a coordinator (aggregator/utility) benefit from coordinated, day-ahead participation when agents are strategic and information is private? It situates TE within the broader digitalization of power systems, where software agents act on behalf of users to respond to price and coordination signals. Prior work often assumes benevolent behavior or complete information, leaving programs vulnerable to gaming (e.g., false plans/baselines), low enrollment, and privacy concerns. To bridge this gap, the paper adopts mechanism design as the guiding framework, focusing on two MD properties: incentive compatibility (IC) and individual rationality (IR), and maps them onto a practical, four-phase TE contract: Enrollment, Coordination, Execution, Settlement. This paper also performs a cost-benefit analysis for the coordinator and the customers. The key design challenge of this paper was to create a strategy-proof payment rule (PR) that makes it strictly more costly to misreport than to be truthful, while keeping information exchange minimal (RAs share only plans,

not private types). The study also recognizes real-world uncertainty (weather, load).

3.1.2 Methodology

The TE interaction is modeled as a Stackelberg game (coordinator, the leader; RAs, the followers) with minimal information exchange. The contract has four phases:

- Enrollment – The coordinator publishes a flat reference price and a set of candidate penalty values (α); each RA runs a convex stochastic program to decide whether to enroll (ex-ante IR check).
- Coordination – For enrolled RAs, the coordinator iteratively updates prices using a cost-sharing rule based on aggregated planned consumption; RAs update plans by solving convex programs with a proximal term to ensure convergence and stability [23].
- Execution – Uncertainty realizes (actual loads/temperatures), yielding actual consumption and deviations from the individual reported consumption plan.
- Settlement – Bills are computed via a payment rule that charges (i) actual energy at the settled price plus (ii) a symmetric quadratic penalty on deviations between actual and reported plans. If strategic-misreporting behavior was prevented, customers experienced a penalization cost for deviations associated with uncertainty. Theoretical first-order conditions and parameter relations (notably, $\alpha \gg \lambda$, where λ parameterizes the price generator) establish truth-telling as a dominant strategy equilibrium. Moreover, the truth-telling customer strategy led them to reduce their bills regarding a non-participation scenario. Therefore, the IC mechanism proposed also satisfies the IR conditions.

The RA model accounts for imported energy costs, thermal discomfort (quadratic

around the temperature set point), battery degradation, and deviation penalties. Dynamics include a simple thermal state-space model and battery energy storage constraints (state-of-charge and power limits). On the other hand, the coordinator model updates prices based on the expected aggregate plan; only plans are observed, preserving privacy.

The simulation setup is grounded in 20 residential customers, 10-minute resolution, 100 Monte Carlo -Sample Average Approximation (SAA) scenarios, winter load statistics, BESS capacity 2.5 kWh, flat price from a utility report [59], and dynamic prices from prior TE co-simulation work [60]. Penalties explored: $\alpha = \{47, 50, 53, 57, 60, 63, 66\}$ were carefully selected based on the RA's decisions to voluntarily opt out of the negotiations.

3.1.3 Outcomes

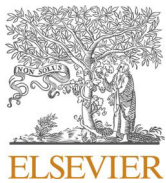
The study demonstrates that participation in a TE program can be economically attractive for residential customers and the coordinator, provided the mechanism is carefully designed to ensure truthful reporting and fairness. Through simulations involving 20 residential agents equipped with thermal loads and battery storage, the authors show that the proposed mechanism—based on a price–penalty structure—effectively discourages misreporting of consumption plans. The theoretical proof of incentive compatibility is validated numerically: once the quadratic penalty for deviations is applied and billing is based on actual consumption rather than reported values, agents have no economic incentive to submit false plans. This result holds even under uncertainty with a non-zero mean, confirming the robustness of the design.

The analysis also reveals necessary trade-offs. Enrollment decisions are susceptible to the penalty parameter: low penalties encourage full participation, while excessively high penalties deter customers from joining the coordination phase. Although the effect

of the penalty mechanism in the IR condition was demonstrated in Figure 2, “Enrollment decisions by RAs 1, 5, and 11 based on the penalty value α_n ”, this finding underscores the need to carefully calibrate penalties to balance participation incentives with the deterrence of strategic behavior. During the coordination phase, customers who opt in generally achieve lower expected electricity costs than a flat-price baseline, benefiting from dynamic pricing and optimized scheduling. However, the study notes that these expected savings can diminish during execution if actual consumption deviates significantly from the agreed plan, as penalties for deviations increase costs. This fact reinforces the importance of accurate forecasting and adherence to planned consumption.

From the coordinator’s perspective, profitability depends on both the level of participation and the flexibility offered by customers. The simulations indicate that profits peak at intermediate penalty values, where enough customers enroll to provide meaningful flexibility without being discouraged by excessive risk. Nonetheless, the coordinator’s realized profits in the settlement phase are consistently lower than those projected during coordination, primarily due to uncertainty and the quadratic cost structure. Despite this, the mechanism generally achieves positive revenues, demonstrating practical feasibility. The results confirm that a privacy-preserving, penalty-based mechanism can align individual incentives with system objectives, ensuring truthful reporting and improving economic outcomes.

3.1.4 Paper 1



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 à Trois-Rivières, 3351, boulevard des Forges, Trois-Rivières, Québec G8Z 4M3, Canada

^b Department of Mechanical Engineering, Hydrogen Research Institute, Laboratoire d'innovation et de recherche en énergie intelligente, Université du Québec à Trois-Rivières, 3351, boulevard des Forges, Trois-Rivières, 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

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ABSTRACT

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: alejandroparrado@uqtr.ca (A. Parrado-Duque).

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

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 (Eguarte 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
(Tsao usoglou 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; meanwhile the 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 $\mathcal{N} = \{1, 2, \dots, N\}$ of RAs powered by a distribution transformer. Also, consider a finite set of one coordinator $\mathcal{C} = \{1\}$ who is fully interested in coordinating the day-ahead energy consumption of the RAs over the entire consumption horizon $\Gamma = \{1, 2, \dots, T\}$ 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 $\mathbf{e}_n = (e_{n,1}, e_{n,2}, \dots, e_{n,T})$ 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 $\mathbf{e} = (\mathbf{e}_1, \mathbf{e}_2, \dots, \mathbf{e}_N)$ represent the energy consumption profile of all RAs in the coordination scheme. Let denote the set of pairs $\mathbf{s}_n = \{(\pi_{n,1}, \alpha_{n,1}), (\pi_{n,2}, \alpha_{n,2}), \dots, (\pi_{n,T}, \alpha_{n,T})\}$ 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 $\mathbf{s} = (\mathbf{s}_1, \mathbf{s}_2, \dots, \mathbf{s}_N)$ 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 $\mathcal{G} = \{\mathcal{N}, \mathcal{M}, \mathcal{C}, \{\mathcal{E}_n\}_{n \in \mathcal{N}}, \{\mathcal{J}_n\}_{n \in \mathcal{N}}, \{\mathcal{J}_n\}_{n \in \mathcal{N}}\}$, where:

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

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.

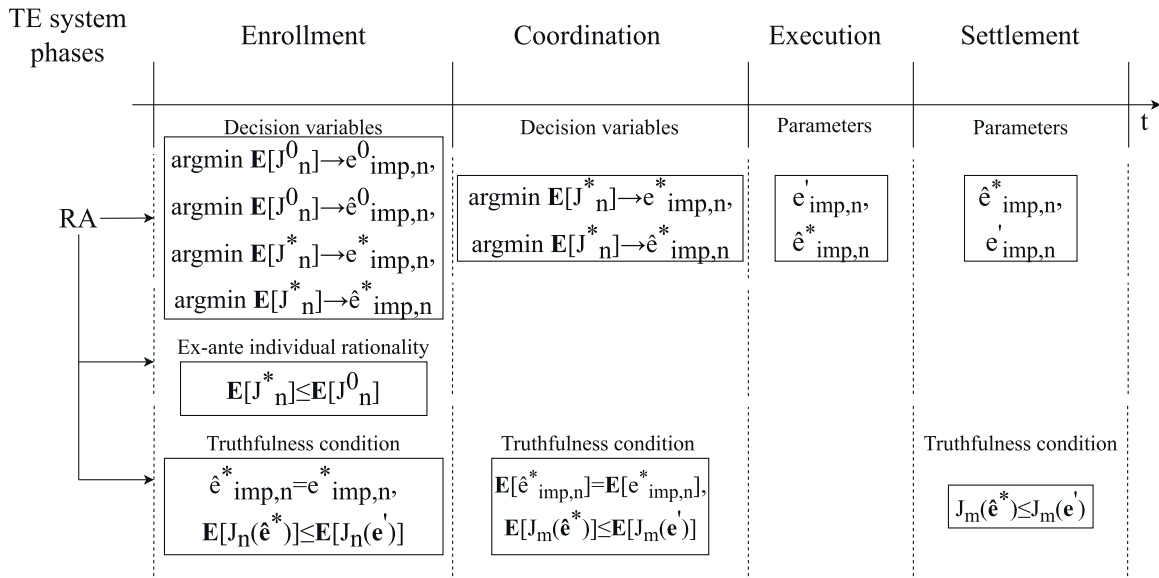


Fig. 1. Contract phases in the TE system from a mechanism design perspective.

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 $\mathcal{M} \subseteq \mathcal{N}$.
- 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 $\mathcal{M}$.
 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 $\mathcal{N}$ of customers decide whether to enroll in day-ahead coordination. In the second phase, enrolled customers $\mathcal{M}$ 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).

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

where $\mathbb{E}[\cdot]$ 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), $\bar{T}_{SP,n,t}$ is the temperature set-point in $^\circ C$, $\bar{T}_{in,n,t}$ 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 $\mathbb{E}[LOI(e, r)]$ 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 ($\hat{e}$) 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).

$$\mathbb{E}[e_{imp,n,t}] = \mathbb{E}[e_{var,n,t} + e_{fix,n,t} + e_{cha,n,t} - e_{dis,n,t}]. \quad (2)$$

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).

$$\bar{T}_{in,n,t} = A \cdot \bar{T}_{in,n,t-1} + B \cdot e_{var,n,t} + C \cdot \bar{T}_{ext,t} \quad (3)$$

$$\min_{\bar{T}_{SP,n,t}} (\bar{T}_{SP,n,t}) \leq \bar{T}_{in,n,t} \leq \max_{\bar{T}_{SP,n,t}} (\bar{T}_{SP,n,t}) + \theta \quad (4)$$

$$\bar{T}_{in,n,t=0} = \bar{T}_{in,n,t=T} \quad (5)$$

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 $n \in \mathcal{N}$ is limited by the battery capacity as expressed in Eq. (6)-(10) (Banfield et al., 2021).

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

$$SOC_{n,t} \leq SOC_{n,t} \leq \overline{SOC}_{n,t} \quad (7)$$

$$SOC_{n,t=0} = SOC_{n,t=T} \quad (8)$$

$$\underline{p}_{cha,n,t} \leq p_{cha,n,t} \leq \overline{p}_{cha,n,t} \quad (9)$$

$$\underline{p}_{dis,n,t} \leq p_{dis,n,t} \leq \overline{p}_{dis,n,t} \quad (10)$$

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.

$$\text{minimize}_{e \in \mathcal{E}} \mathbb{E}[J_n(e)] \quad (11a)$$

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

Therefore, for each RA n , the feasible consumption profile set is expressed in Eq. (12).

$$\mathcal{E}_n = \{e_n | (2) - (10)\} \quad (12)$$

Correspondingly, the feasible set of consumption profile of all RAs in their Enrollment phase is $\mathcal{E} = \{(e_1, e_2, \dots, e_N) | e_n \in \mathcal{E}_n, \forall n \in \mathcal{N}\}$.

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.

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

where $\mathbb{E}[J(e_n^*)]$ is the expected participation cost of each RA $\mathcal{N}$ coordinating their individual electricity consumption, and $\mathbb{E}[J(e_n^0)]$ 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 $\mathcal{M} \subseteq \mathcal{N}$ 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 $\mathcal{M}$ 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 $\mathcal{M} \in \mathcal{N}$, 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).

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

subject to (2) – (10), $\forall t \in \Gamma, \forall m \in \mathcal{M}, \forall i \in \Psi$, (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). $\tau = 3 \cdot (|\mathcal{M}| - 1) \cdot \lambda$ is a regularization parameter of the proximal algorithm, $|\mathcal{M}|$ is the length of the subset $\mathcal{M}$, λ is a DSO technical parameter associated to the energy distribution cost (Tsaousoglou et al., 2020) defined as $\lambda = \sum_{t \in \Gamma} [\pi_t^0 \cdot \sum_{n \in \mathcal{N}} (\hat{e}_{imp,n,t}^0)] / \sum_{t \in \Gamma} \sum_{n \in \mathcal{N}} (\hat{e}_{imp,n,t}^0 \cdot \hat{e}_{imp,n,t}^0)$, and $\hat{e}_{imp}^i - \hat{e}_{imp}^{i-1}$ 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).

$$\mathcal{E}_m = \{e_m | (2) - (10)\} \quad (15)$$

Correspondingly, the feasible set of consumption profile of all RAs in their Coordination phase is $\mathcal{E} = \{(e_1, e_2, \dots, e_M) | e_m \in \mathcal{E}_m, \forall m \in \mathcal{M}\}$.

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 ($\mathbf{E}[J_n(e^0)]$), ii) a possible dynamic electricity price (π^*) to allow them to compute their expected participation cost ($\mathbf{E}[J_n(e^*)]$) they could face by participation, and iii) a set of penalty values α_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 ($\mathbf{E}[J_n(e^*)]$).

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 (π^*) 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 α_n are derived from simulations to discover the discourage-responsiveness participation of RAs based on their expected participation cost ($\mathbf{E}[J_n(e^*)]$). 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):

$$C_{m,t}^i = \frac{\hat{e}_{m,t}^i}{\hat{e}_{agg,t}^i} \cdot C^i(\hat{e}_{agg,t}^i), \quad (16)$$

where $C_{m,t}^i$ is the individual electricity cost of coordinated RAs subset $m \in \mathcal{M} : \mathcal{M} \subseteq \mathcal{N}$ at time $t \in \Gamma$ and at iteration $i \in \Psi$, $\hat{e}_{agg,t}^i = \sum_{m \in \mathcal{M}} \hat{e}_{m,t}^i$ is the aggregated electricity consumption at time $t \in \Gamma$ and at iteration $i \in \Psi$ reported by RAs' subset $\mathcal{M}$, and $C^i(\hat{e}_{agg,t}^i)$ 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).

$$C_{m,t}^i = \frac{\hat{e}_{m,t}^i}{\hat{e}_{agg,t}^i} \cdot \lambda \cdot (\hat{e}_{agg,t}^i)^2 \quad (17)$$

$$C_{m,t}^i := \underbrace{\hat{e}_{m,t}^i \cdot \lambda \cdot \hat{e}_{agg,t}^i}_{\text{Price}} \quad (18)$$

$$\pi_t^{i+1} = \lambda \cdot \hat{e}_{agg,t}^i. \quad (19)$$

where $\lambda = \sum_{t \in \Gamma} (\pi_t^0 \cdot \hat{e}_{agg,t}^0 / (\hat{e}_{agg,t}^0)^2)$ is a regularization parameter, and $(\hat{e}_{agg,t}^0)$ 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 $C_{m,t}^i$.

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).

$$\mathbf{E}[\pi_t^{i+1}] = \lambda \cdot \mathbf{E}[\hat{e}_{agg,t}^i]. \quad (20)$$

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

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).

$$PR_n(e_{imp,n,t}^*) \leq PR_n(\hat{e}_{imp,n,t}). \quad (21)$$

where PR_n is the individual payment rule, $e_{imp,n,t}^*$ is the true optimal consumption plan of each customer, and $\hat{e}_{imp,n,t}$ is any consumption report that could be different from the true plan. Truthful information reported by agents is crucial for enhancing the economic efficiency of a system and reducing the computational burden on the coordinator side (Kuijpers, 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).

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

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

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).

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

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

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

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

$$\mathcal{S}_c = \{\pi_n, \alpha_n | (19)\} \quad (26)$$

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

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

$$\mathcal{S}_c = \{\pi_m, \alpha_m | (20)\} \quad (27)$$

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

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

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

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).

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

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 $\frac{\partial PR_n^*}{\partial e_{imp,n,t}^*} = 0$ 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).

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

From Eq. (29), notice that a rational RA should be entirely motivated to report the true consumption plan to the coordinator ($\mathbf{e}^* = \hat{\mathbf{e}}^*$) instead of reporting any other fake consumption plan ($\hat{\mathbf{e}}$). 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:

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

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):

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

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

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):

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

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

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. $\square$

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:

$$PR_n^*(\mathbf{e}^*, \hat{\mathbf{e}}^*) = \sum_{t=1}^T \left[e_{imp,n,t}^* \cdot \pi_{n,t}^* + \alpha_{n,t}^* \cdot [e_{var,n,t} + (e_{fix,n,t} + r_{n,t}) + e_{cha,n,t} - e_{dis,n,t} - (e_{var,n,t} + e_{fix,n,t} + e_{cha,n,t} - e_{dis,n,t})]^2 \right], \forall n \in \mathcal{N}, \quad (36)$$

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

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. $\square$

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):

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

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

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

$$\text{Condition} \Rightarrow \lambda > 0, \quad \alpha_{n,t} > 0, \text{ and } \alpha_{n,t} \gg \lambda, \quad (40)$$

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

$$\Rightarrow \hat{e}_{imp,n,t}^* = e_{imp,n,t}^*, \quad \forall n \in \mathcal{N}, \quad \forall t \in \Gamma. \quad (42)$$

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. $\square$

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 $(\mu_{f,n,t}, \sigma_{f,n,t}^2)$ as the mean and variance, respectively, as follows in Eq. (43).

$$e_{fix,n,t} = f(\mu_{f,n,t}, \sigma_{f,n,t}^2) \quad (43)$$

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 $(\mu_{g,t}, \sigma_{g,t}^2)$ as the mean and variance, respectively, as follows.

$$\mathbf{E}[\mathbf{e}_{agg,t}^i] = \mathbf{E}[\mathbf{e}_{agg,t}^i + \zeta_t] : \zeta_t \sim g(\mu_{g,t}, \sigma_{g,t}^2). \quad (44)$$

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_t^0) 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 $\alpha_n = \{47, 50, 53, 57, 60, 63, 66\}$, 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_t^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

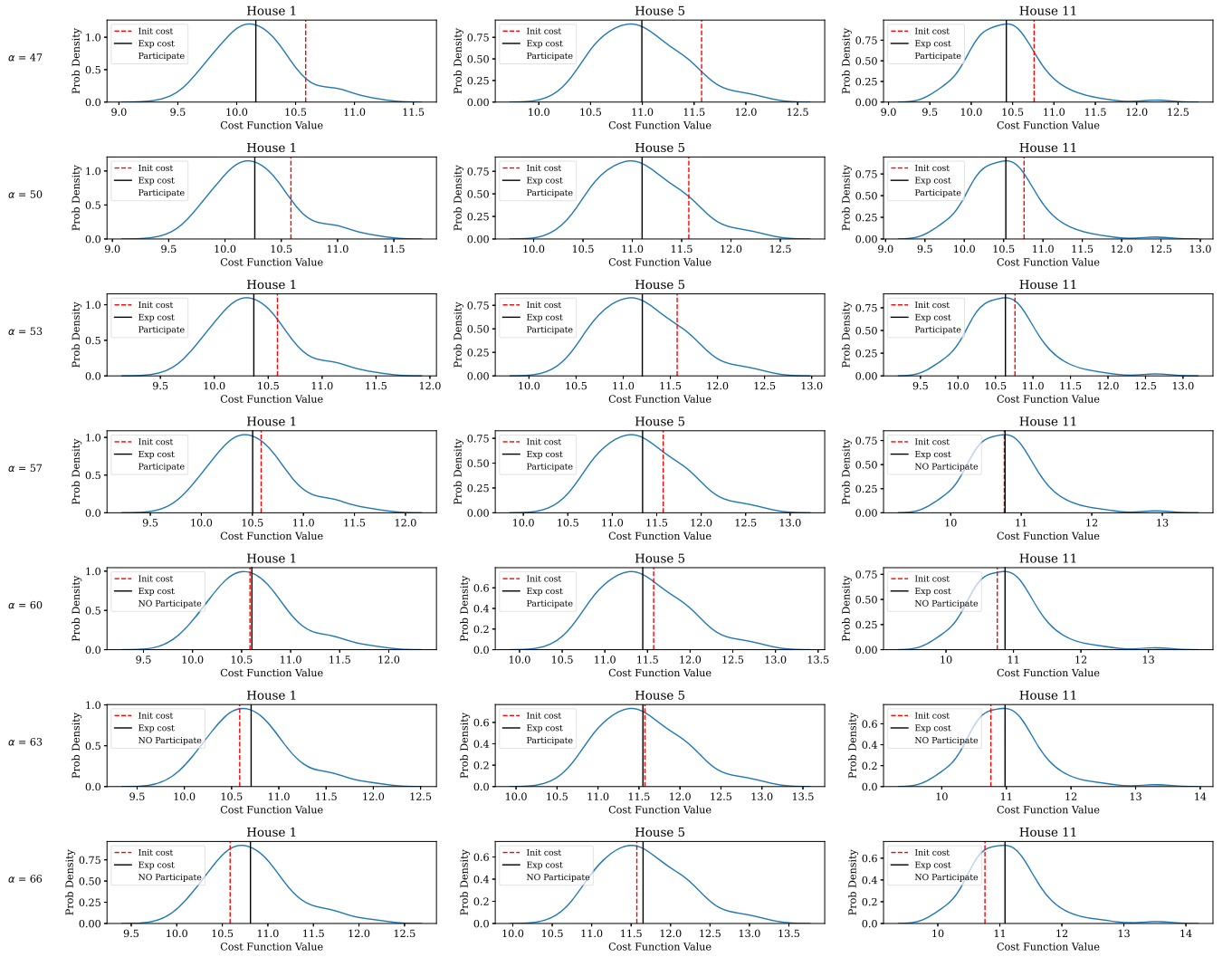
Fig. 2. Enrollment decisions by RAs 1, 5, and 11 based on the penalty value α_n .

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 $\mathcal{N}$ 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 ($\pi^0 = 7.3\text{¢/kWh}$) and a small penalty value for deviations ($\alpha = 1$) to ensure a truthful consumption base ($\hat{e}_{imp,n,t}^0$) reported by each RA. The

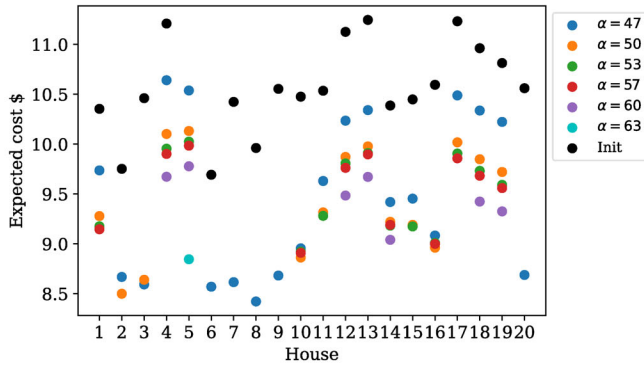


Fig. 3. Expected customers' electricity cost in the Coordination phase.

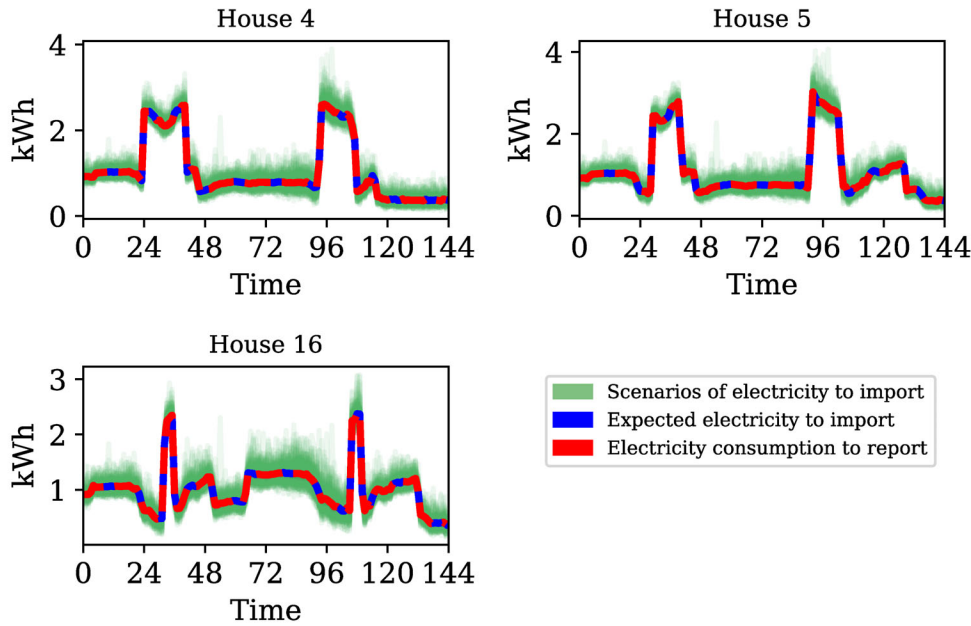


Fig. 4. Validating the truthful report of agents on the mechanism proposed.

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

From Fig. 2¹, 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 α_n shared by the coordinator. For example, RA one decides to participate for penalty values up to fifty-seven ($\alpha = 57$) but rejects participation for values of sixty or higher ($\alpha \leq 60$). Conversely, RA five participates in all explored penalty values except sixty-six ($\alpha = 66$). 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 $\mathcal{H} \subseteq \mathcal{N}$ that

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

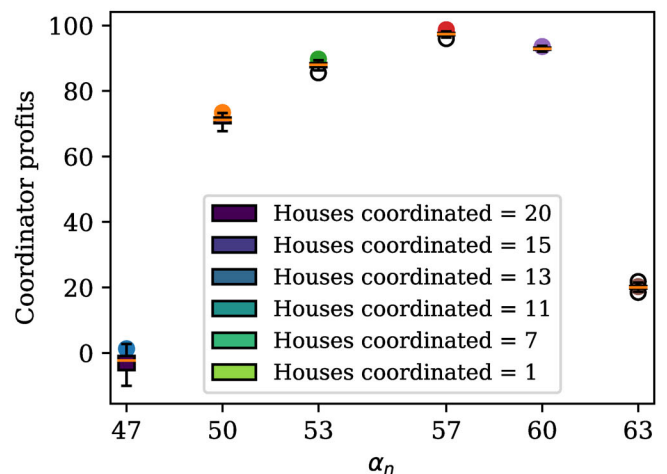


Fig. 5. Expected coordinator profits in the Coordination phase.

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

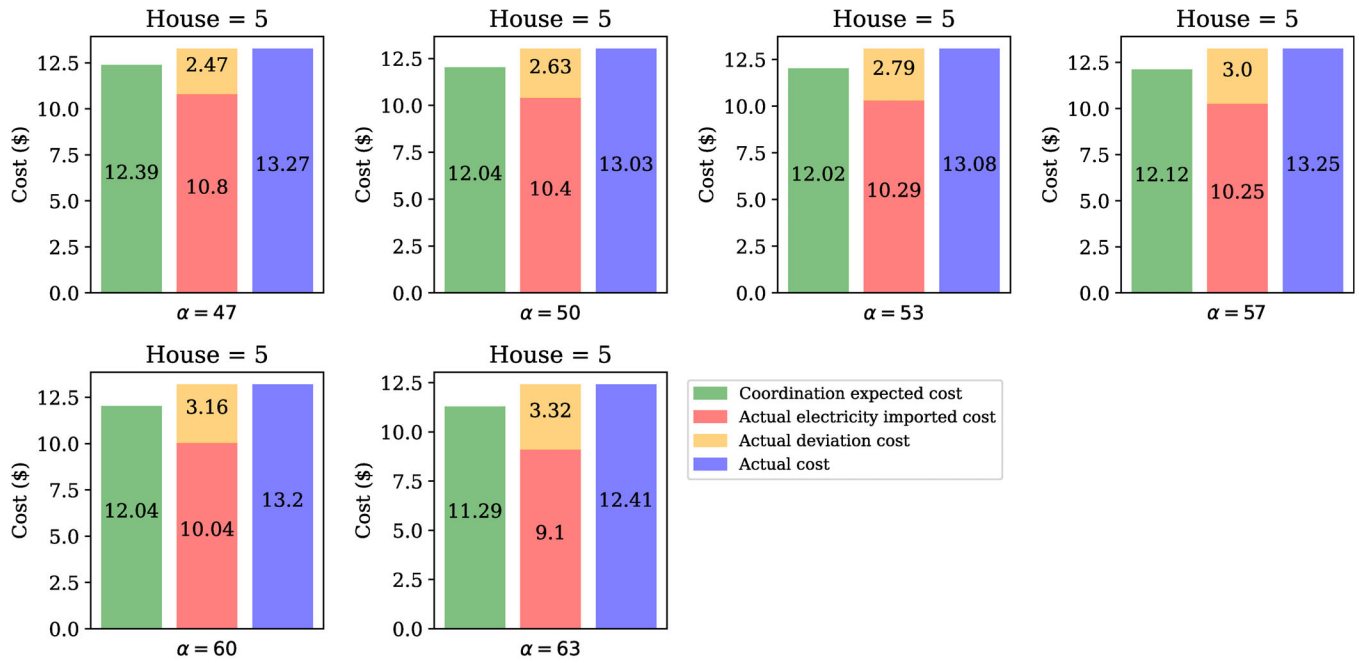


Fig. 6. Total and individual cost by α_n for customer five.

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 ($\mathcal{M} \subseteq \mathcal{N}$). To visually depict this phenomenon, Fig. 5 illustrates the coordinator's profit variations, depending upon the subset of RAs $\mathcal{M} \in \mathcal{N}$ and the penalty value α_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 (α_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	1	2	3	4	5	6	7	8	9	10	House	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	

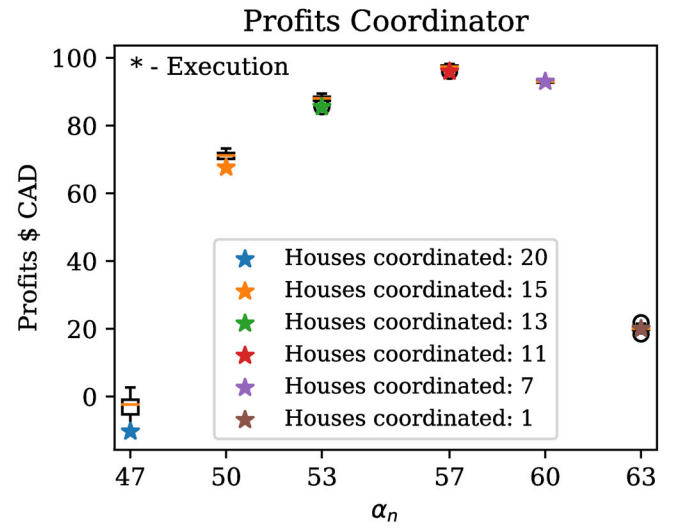


Fig. 7. Coordinator profits - Execution phase.

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. **Souso 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.

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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., Algaonkar, 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., Mees, 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>.
- Eguarte, 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-Aghaie, 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., Verbić, 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., Sirola, 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., Ardane, 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., Ardane, 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 à Trois-Rivières, 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 Rivières (UQTR), Trois-Rivières, QC, Canada, in 2013 and 2018, respectively. His research interests include statistical and machine learning methods with applications to energy management in the residential sector, distributed optimization, multiagent control, smart grid technologies, intelligent energy planning, smart energy storage, and load monitoring.

Kodjo Agbossou: (Senior Member, IEEE) received 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 à Trois-Rivières (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.

Souso 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 à Trois-Rivières (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 Bolívar (UTB). He is currently engaged as a PhD student at Université du Québec à Trois-Rivières, 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.

3.1.5 Clarifications of 3.1

- Formulation (1) in the previous paper was an editorial mistake at the time of publication. The corrected formulation is as follows:

$$\mathbf{E}[J_n(e)] = \mathbf{E} \left[\sum_{t=1}^T \left(\underbrace{e_{imp,n,t} \cdot \pi_{n,t}}_{\text{Cost of electricity imports}} + \underbrace{\gamma_n \cdot (\tilde{T}_{SP,n,t} - \tilde{T}_{in,n,t})^2}_{\text{Cost of thermal discomfort}} + \underbrace{(e_{dis,n,t} + e_{cha,n,t}) \cdot C_{bat,n,t}}_{\text{Cost of battery operation}} \right) \right] + \underbrace{\mathbf{E} \left[\sum_{t=1}^T (\text{LOI}(e, r)) \right]}_{\text{Penalty mechanism}} \quad (3.1)$$

- Formulation (4) in the previous paper was an editorial mistake at the time of publication. Given that $\tilde{T}_{SP,n,t}$ is a set-point vector predefined by the customer according to their temperature preferences, and $\tilde{T}_{in,n,t}$ is the inner dwelling temperature optimization variable for each customer (which is directly related to the heating consumption load), the corrected formulation is as follows:

$$\min(\tilde{T}_{SP,n,t}) \leq \tilde{T}_{in,n,t} \leq \max(\tilde{T}_{SP,n,t}) + \vartheta \quad (3.2)$$

3.2 The effect of strategy behavior on the performance of the TE program

3.2.1 Background

The paper addresses a critical challenge in TE systems: ensuring truthful information exchange between RAs and a DSO in day-ahead electricity markets in a one-shot market architecture. TE frameworks leverage distributed flexibility by enabling customers to negotiate energy consumption plans with the utility. However, strategic agents can exploit

weaknesses in negotiation mechanisms by misreporting expected consumption, leading to economic inefficiencies, budget imbalances, and even operational risks for the grid.

The paper applies mechanism design theory to address this issue, focusing on creating rules that align individual incentives with socially desirable outcomes. Four key properties guide this design: IC, ensuring truth-telling is optimal; IR, guaranteeing participation benefits; Eff, approximating social welfare; and BB, avoiding external subsidies.

The study situates its contribution in the context of one-shot negotiation mechanisms for day-ahead TE programs. Unlike iterative schemes, one-shot designs involve a single exchange of signals, reducing communication overhead but still keeping the risk of strategic misreporting. The paper proposes a penalty-based approach to discourage deviations from agreed plans and evaluates its performance across different mechanism design phases: ex-ante, interim, and settlement. This work is motivated by the need for privacy-preserving, computationally feasible solutions that can operate under uncertainty while remaining economically viable.

3.2.2 Methodology

The proposed mechanism is structured as a one-shot negotiation game between a DSO (leader) and multiple RAs (followers). The DSO announces a dynamic price and a penalty policy, and each RA decides on its day-ahead consumption plan. The interaction is modeled as a Stackelberg game under incomplete and asymmetric information: RAs know their own preferences and constraints but not those of others. At the same time, the DSO lacks complete visibility into private types.

The core innovation lies in the payment rule (PR), which determines the final bill for each RA. Five candidate PRs are analyzed, ranging from simple linear pricing to

quadratic penalty-based schemes. The IC property is tested by examining whether truthful reporting minimizes the RA's expected cost under each PR. Theoretical and simulation analysis show that only the PR combining actual energy charges with a quadratic penalty on deviations satisfies IC without requiring extreme penalty values.

This paper employed a stochastic optimization model for RAs to validate these findings, incorporating energy costs, thermal comfort, and penalties for deviations from a plan. Uncertainty in demand is modeled using probability distributions and solved via SAA simulation. The DSO's pricing strategy is based on a cost-sharing model that updates prices according to aggregate reported consumption. The assessment focuses on three phases: ex-ante IR and efficiency (using price of anarchy and price of deception), settlement-phase IC and BB, and the impact of penalty magnitude on participation and fairness.

3.2.3 Outcomes

The analysis reveals that the most commonly used payment rules fail to ensure IC, allowing agents to reduce costs by misreporting consumption. Linear penalties or billing based on reported rather than actual consumption create strong incentives for manipulation. In contrast, the proposed quadratic penalty rule, combined with billing on actual energy use, makes truthful reporting the dominant strategy, even under uncertainty. This result is confirmed both analytically and through simulation.

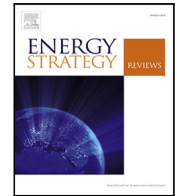
The study also examines the trade-offs between IC and other mechanism properties. While the quadratic penalty rule achieves IC and IR, its impact on budget balance depends on penalty calibration. Low penalties encourage participation but may lead to budget deficits, whereas excessively high penalties deter enrollment, reducing flexibility

and efficiency. The simulations show that dynamic pricing combined with moderate penalties can improve economic efficiency compared to flat pricing, but strong BB remains challenging without additional redistribution mechanisms.

From a customer perspective, participation is generally beneficial under realistic penalty values, satisfying ex-ante IR. However, deviations from planned consumption in the execution phase can significantly increase costs, reinforcing the importance of accurate forecasting and adherence. The mechanism's performance under uncertainty demonstrates its robustness: expected costs align closely with actual costs, and the distribution of outcomes confirms that penalties effectively discourage strategic misreporting.

The paper concludes that a well-designed penalty-based mechanism can achieve strategy-proofness in one-shot TE negotiations while preserving privacy and limiting complexity.

3.2.4 Paper 2



Penalty mechanism in transactive energy: A mechanism design approach for day-ahead markets

Alejandro Parrado-Duque ^a, Nilson Henao ^a, Sousso Kelouwani ^b, Kodjo Agbossou ^a,
Juan C. Oviedo-Cepeda ^c

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

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

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

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ABSTRACT

Ensuring incentive compatibility mechanisms to enforce market obligations is crucial in deploying a transactive energy system. While previous studies have reported adopting penalty mechanisms for market compliance, these studies did not generally analyse the incentive compatibility property of mechanism design. Neglecting this mechanism design property can lead to inefficient market outcomes and economic losses for system operators. This paper analyses self-enforcing policies to verify whether they comply with the incentive compatibility property in a one-shot market architecture. Additionally, it provides a comprehensive introduction to the phases of mechanism design – *ex-ante*, *interim*, and *ex-post* – and their relationship with key design principles: individual rationality, efficiency, budget balance, and incentive compatibility, highlighting expected outcomes at each phase. A case study demonstrates how a strategy-proof mechanism significantly influences individual rationality, efficiency, and budget balance, offering practical insights for improving decision-making frameworks in electricity markets. Moreover, the findings reveal that adopting a non-strategy-proof mechanism undermines the long-term viability of transactive energy systems. This work provides actionable recommendations for system operators and policymakers on implementing mechanisms that prevent strategic behaviour from agents.

1. Introduction

Adopting penalty mechanisms in transactions is key to preventing intended gaming of the system by agents who must forecast and report their expected consumption for a specific period in advance in transactive energy markets [1,2].

Example 1. Suppose a distribution system operator (DSO) implements a demand response (DR) program for a group of customers who agree to the contractual terms set by the DSO. Among these terms, customers must adopt an agent-based technology to make decisions on their behalf and to respond to signals in advance (e.g., incentives) by reducing or shifting energy consumption during specified events.

Given that residential agents (RAs) are intelligent and rational machines making a decision based on logic (e.g., an optimization problem) [3], how can the DSO be confident about the energy shifting

or energy curtailment they committed to in the transaction? In fact, could RAs report false information to the DSO to benefit the customers they represent in the transaction? [4].

Without going far beyond technical capabilities, designing a mechanism that ensures a share of truthful information among transactive participants is a major key challenge that DSOs face in transactive markets [5]. Given that RAs operate as logical decision-making machines, it is imperative for the DSO to develop a well-structured MD to safeguard the interests of transactive agents. The DSO must prioritize formulating a mechanism where RAs report a truthful representation of their expected consumption [4].

Since each RA is a powerful computing machine, the mechanism designed by the DSO must create proper incentives for the RAs to report truthful information. While the direct imposition of truthfulness as a constraint on their optimization problem is straightforward, employing

* Corresponding author.

E-mail addresses: alejandroparrado@uqtr.ca (A. Parrado-Duque), nilson.henao@uqtr.ca (N. Henao), sousso.kelouwani@uqtr.ca (S. Kelouwani), kodjo.agbossou@uqtr.ca (K. Agbossou), oviedocepeda.juancarlos@ireq.ca (J.C. Oviedo-Cepeda).

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Nomenclature**A**

BB	Budget balance.
DR	Demand response.
DSO	Distribution system operator.
Eff	Efficiency.
IC	Incentive compatibility.
IR	Individual rationality.
MD	Mechanism design.
PoA	Price of Anarchy.
PoD	Price of Deception.
PoS	Price of Stability.
PR	Payment rule.
RAs	Residential agents.
TE	Transactive energy.
VCG	Vickrey–Clarke–Groves.

C

$J[\cdot]$	RAs cost function.
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F

$E[\cdot]$	Expected value.
$f[\cdot]$	Probability density function of the fix load.

I

*	Index of negotiation conditions - dynamic price.
0	Index of initial conditions - flat price.
n	Index of RAs.
t	Index of time-step.
W	Index of Monte Carlo scenarios.

P

α	Penalty value.
γ	Thermal discomfort.
λ	Quadratic DSO cost.
π	Electricity price vector.
ζ	Maximum allowable individual electricity consumption.
A, B, C	Weighted state-space temperature model parameters.
T_{ext}	Outdoor temperature.
T_{SP}	Inner dwelling temperature set-point.

S

α	Set of penalty values explored in simulations.
π	Set of electricity prices explored in simulations.
$\mathcal{N}$	Set of RAs engaged in the TE system.
$\mathcal{T}$	Set of time horizon.

V

$\hat{e}$	RA energy to report.
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e	RA energy to import.
e_{fix}	Fix load energy - stochastic - uncontrollable load.
e_{var}	RA heating energy - controllable load.
T_{in}	Inner dwelling temperature.

information and identify that false information outweighs the benefits, thereby prioritizing truthfulness in its reporting [7].

1.1. Attitudes and self-enforcing policies

Agents' benevolent attitudes require the complete trust of agents in an environment where they interact [4]. Ideally, if the notion of cheating were entirely absent, mutual trust would facilitate cooperative behaviour among agents, potentially leading to improved, or even optimal, social outcomes [8].

However, the individual interests of agents interacting with peers in an environment (being free-riders by nature) complicates attaining mutually beneficial agreements, even having the power of game theory in our hands [9]. If individual interest exists, even employing benevolent authorities that try to coordinate players' actions is useless when intending to handle fair play among agents [9]. Let us consider again [Example 1](#). If the DSO assumes RAs have a benevolent attitude, the former will conceive a mechanism to deploy a DR program by trusting the reduction consumption report of RAs. However, RAs may identify an opportunity to maximize their benefit by exploiting the rewards offered through the DR program. Consequently, the DSO may face a situation where the program fails economically and technically, eventually discontinuing the DR program. This scenario converges into a social trap [8], or the tragedy of the commons, affecting not just the profits of customers over time but also the profits of the DSO and jeopardizing the power grid operation.

In response to these challenges, self-enforcing policies have emerged as a promising approach to achieving trust in agent transactions [1]. In fact, DSOs interested in deploying reward-based programs should prioritize the design of such policies [9]. The primary goal of self-enforcing policies should be to incentivize RAs to provide accurate information. For instance, by ensuring a true report from RAs, the DSO could be confident about the energy to dispatch. The second goal of these policies should facilitate the determination of rewards for each RA participant and assess the potential profits for a given period. The last goal is to establish mechanisms to penalize RAs for any deviations from the agreed-upon plan while reducing the need to dispatch energy reserves for reliability, providing a transparent pricing structure for any units of energy deviated [10].

1.2. Mechanism design

Thus far, the paper has focused on pursuing truthfulness through self-enforcing policies, like penalty mechanisms. This fundamental notion aligns with the broader framework of mechanism design (MD), often described as "the art of designing the rules of a game to achieve a specific desired outcome" [11]. Within the realm of mechanism design, the concept of truthfulness in agents' interactions is referred to as incentive compatibility (IC), constituting one of the principal concerns alongside individual rationality (IR), efficiency (Eff), and budget balance (BB). IR and Eff encompass three subcategories: *ex-ante*, *interim*, and *ex-post*, while BB is typically subdivided into weak and strong variants. In contrast, IC is commonly segmented into dominant strategy incentive compatibility and Bayesian incentive compatibility, contingent upon the structural characteristics of the game. This taxonomical framework is illustrated in [Fig. 1](#).

a utilitarian framework can create an environment where it is in the RAs' best interest to be truthful [6]. Under this framework, each RA must be able to compute the cost of reporting both true and false

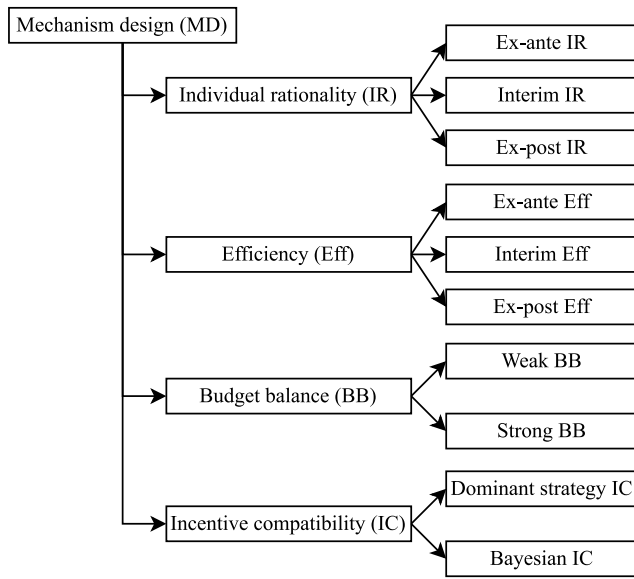


Fig. 1. Main concepts of mechanism design.

Using [Example 1](#) as a reference to elucidate each concept from the preceding [Fig. 1](#), both *ex-ante* and *interim* IR consider expectations over all the scenarios a customer could perform in a specific contract time window (e.g., daily) responding to the signals in advance. *Ex-post* IR deals with the actual cost a customer perceives once the uncertainty is disclosed, i.e., at the end of the contract (e.g., daily). An RA will only participate in a program if the economic benefits surpass the cost of flexibility. From an economic perspective, Eff is a major concern for the DSO. It must ensure that the optimal solution derived from the market clearing method closely aligns with the Social Welfare solution. In a comprehensive view of the problem, the DSO may also aim to guarantee efficiency across the three categories: *ex-ante*, *interim*, and *ex-post*. Conversely, a mechanism is deemed to exhibit strong BB iff (if and only if) the DSO disburses all the money it collects from and to the RAs via rewards, thereby neither making a profit nor incurring a loss. If the mechanism yields a profit but never a loss, then it exhibits weak BB. Lastly, a Dominant strategy IC and a Bayesian IC differ based on whether the RAs can (Bayesian) or cannot (Dominant strategy) introduce in their optimization problem the expectation of the strategies that other participants might choose to employ through transactions, a concept related to the completeness of information.

A critical question arises at this point: how do the concepts of MD manifest throughout the application timeline of a mechanism? [Fig. 2](#) illustrates the evolution of each MD concept over time. The process begins with the DSO formulating a mechanism to negotiate electricity market services with RAs in the *initial conditions* phase. The phases of *ex-ante*, *interim*, and *ex-post* are particularly significant, as a mechanism designer may focus on achieving specific objectives within only one phase. For instance, a DSO might design a mechanism to ensure that all RAs participate in a negotiation within a day-ahead electricity market, thereby satisfying *ex-ante* IR. However, the mechanism might not necessarily guarantee that, during execution (when uncertainties influencing electricity consumption come into play), the cost of opting in is lower than the cost of opting out—meaning *ex-post* IR might not be satisfied. Also, notice that a similar reasoning applies to the efficiency concept. Finally, the mechanism concludes with the *settlement phase*, during which the DSO applies the payment rules (PRs) for the RAs. It is not until this stage that the DSO could evaluate whether the mechanism successfully satisfies the broader objectives of IC and BB.

Moreover, as illustrated in [Fig. 2](#), the *ex-ante* and *interim* phases for both Eff and IR primarily depend on the expected value. In contrast,

IC and BB are assessed based on the realization of variables, i.e., using actual (current) values. This observation introduces the concept of uncertainty into the discussion, with its progression through time explained as follows: uncertainty remains undisclosed in the *ex-ante* phase, becomes partially revealed during the *interim* phase, and is fully resolved in the *ex-post* phase.

Referring to the proposition by [\[11\]](#), it is asserted that *ex-ante* Eff holds greater strength than *interim* Eff, while this latter surpasses *ex-post* Eff. Consequently, ensuring *ex-ante* Eff suffices to guarantee both *interim* and *ex-post* Eff. Similarly, concerning IR, *ex-post* IR exhibits a higher degree of rigour than *interim* IR, and this latter outweighs *ex-ante* IR. Furthermore, ensuring *ex-post* IR establishes sufficient conditions for asserting both *interim* and *ex-ante* IR.

Another critical question that inherently emerges in the study of MD: how do these concepts interact to achieve an optimal mechanism? Or, is there a mechanism that satisfies all four main concerns associated with MD simultaneously: IR, Eff, BB, and IC? Here, two pivotal impossibility theorems come into play: The Green-Laffont (Hurwicz) Theorem and the Myerson-Satterthwaite Theorem [\[11,12\]](#). The former suggests that achieving *ex-post* Eff and weakly BB while ensuring a Dominant strategy IC is impossible. The latter stated that there is not a mechanism that complies with *ex-post* Eff, weakly BB, and *interim* IR while ensuring Bayesian IC.

1.3. Organization

Section 2 presents the state-of-the-art related to IC, the existing limitations of proposed mechanisms, and the contributions of this work. Section 3 explores cost functions to encourage customers to report truthful information. Section 4 presents the potential negative effects of deceptive behaviour on RAs, as well as the performance of individual rationality and efficiency at the *ex-ante* phase, and incentive compatibility and budget balance at the *settlement phase*. Section 5 discusses a non-differentiable approach to reach an IC mechanism. Finally, Section 6 presents conclusions, limitations of this work, and future work.

2. Related works and contributions

This section introduces the concept of incentive compatibility from a theoretical perspective, the limitations of two well-known mechanisms, the Vickrey–Clarke–Groves and Kelly mechanisms, the state-of-the-art with the last relevant literature published in the field of MD, and the contributions of this work.

2.1. The concept of incentive compatibility

Incentive compatibility (IC) emerges as a fundamental concept in mechanism design to mitigate dishonest behaviour in agents' transactions. A mechanism is considered IC if the cost associated with telling the truth (e_n) is lower than the cost associated with lying (e'_n), as expressed in Eq. (1) [\[7,11\]](#):

$$C(e_n) < C(e'_n) \quad (1)$$

Eq. (1) ensures that agents have a clear incentive to provide truthful information rather than deception [\[7\]](#). In the context of TE markets, IC plays a crucial role in fostering trust among participants, thereby enabling decentralized or distributed market approaches instead of centralized markets, which the latter implies a computational burden [\[4\]](#). Since all agents should be free to select their expected consumption in a certain period ahead, IC requires the creation of a fully free optimization variable related to the consumption that an agent will report, let us say $\hat{e}$. Ideally, the DSO would impose a hard constraint in the optimization problem of RAs to enforce truthful reporting, as follows in Eq. (2) [\[6\]](#):

$$e_n = \hat{e}_n. \quad (2)$$

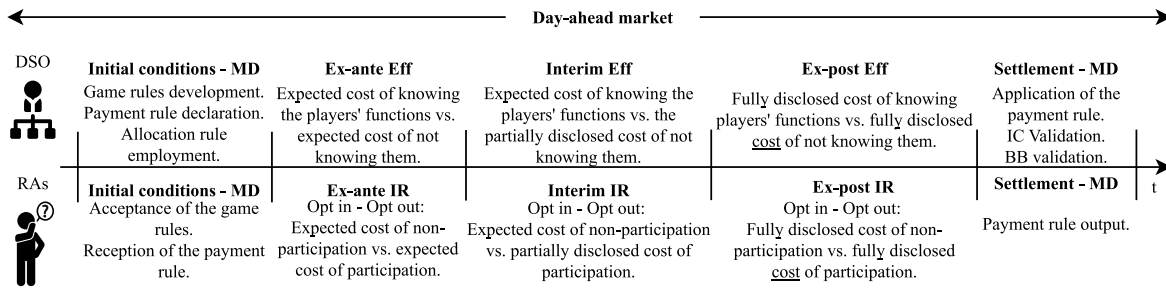


Fig. 2. Mechanism design phases over time.

However, as highlighted by [6], the DSO cannot rely on benevolent attitudes from potentially self-interested RAs. Instead, DSOs should look for elicitation mechanisms to get truthful information from RAs by applying the concept of IC.

2.2. Limitations of the Vickrey–Clarke–Groves and the Kelly mechanisms

Two well-known IC mechanisms in the literature are the Vickrey–Clarke–Groves (VCG) and the Kelly mechanisms. Despite their theoretical appeal, these mechanisms encounter significant challenges when applied to the electricity sector, primarily due to the scale of operations involved in managing a power grid [10].

The VCG mechanism aims to allocate goods, such as electricity consumption, among customers at specific prices. Both electricity allocation and electricity prices are optimization variables in a VCG mechanism. To do so, the DSO demands each customer's utility function and constraints (not just a signal) to solve an optimization problem in a centralized way. Notice that in this mechanism, instead of the DSO receiving bids from the customers, it would receive utility functions, condense all of them in just one optimization formulation, and solve the problem. However, this method has three drawbacks. Firstly, this method requires a computational burden on the DSO because the problem is solved centrally [10]. Secondly, centralized optimization requires RAs to disclose their entire private information, particularly their utility functions [10]. This fact raises privacy concerns and can be computationally expensive for the DSO to manage [13] in large power systems. Lastly, the mechanism entails the DSO directly allocating electricity consumption to customers rather than allowing them to freely determine their electricity consumption, resembling a form of direct load control.

On the other hand, the Kelly mechanism allows the DSO to request bids from the RAs instead of utility functions while solving the false-name bids issue raised in the VCG mechanism [10]. These bids represent the amounts that users are willing to pay for electricity for a certain period ahead. Once the DSO receives the RAs' bids, it solves an optimization problem to allocate electricity consumption, similar to the VCG mechanism. Since this mechanism is IC under certain conditions, it also has its own limitations. First, solving a centralized optimization problem imposes a significant computational burden on the DSO side [10]. Second, asking customers how much they are willing to pay for electricity is uncommon and not straightforward in the electricity sector. Finally, like the VCG mechanism, the Kelly mechanism results in a form of direct load control. This mechanism is IC for larger networks when RAs find it impossible to estimate their individual effect on the electricity price set by the DSO (price-maker agents). However, in smaller networks, RAs can play strategically, become aware of their influence on electricity prices, and then maximize their profits by gaming the system [10].

2.3. State-of-the-art

In [14,15], the authors claimed to have designed an IC mechanism for a DR program. However, intelligent and rational agents could exploit the mechanism by over-reporting their consumption to reduce costs, making it non-strategy-proof. Additionally, this work avoided the impact of stochasticity on the IC mechanism, and the metrics of IR, Eff, and BB were not analysed. In [1,2], the authors proposed solutions to address the challenges of implementing penalty mechanisms in transactive energy (TE) markets. However, their work did not provide an overview of mechanism design (MD), omitting key MD concepts in their analysis. Authors in [16] introduced a modified scaled VCG mechanism for a power market of linear-quadratic-Gaussian agents to address the BB limitation of the original VCG mechanism. Nevertheless, the proposed mechanism inherits the VCG mechanism's limitations, failing to ensure IC in the presence of stochasticity, and authors claimed to resolve the impossibility theorems previously mentioned by meeting the IR, Eff, and BB requirements, provided that no agent is too negligible or too powerful, maintaining a power balance. In [17], the authors proposed an incentivized market model (an IC mechanism) for real-time operations under moral hazard in dynamic power grids. Although the model included an IR constraint from the customer side, it did not analyse the mechanism's effects on Eff and BB. Additionally, the mechanism raises privacy concerns since it requires sharing customers' private information with the DSO and among them. Authors in [18] presented a mechanism for a two-stage repeated stochastic game to model player behaviour in electricity markets. The two stages are based on the VCG mechanism, carrying the previously discussed limitations. Strategic agents could misreport information in the first stage to gain benefits in the second stage (i.e., the interplay between day-ahead and real-time markets). Moreover, BB was neither considered nor assessed in the mechanism. Finally, in [19], the authors proposed an IR and IC mechanism for task allocation between a leader and autonomous agents. However, this mechanism aims to elicit all agents' private information indirectly based on rewards, thus limiting customers' privacy. Furthermore, this study did not address Eff and BB.

To provide a comprehensive comparison between this work and the state of the art, Table 1 presents a detailed analysis of carefully selected papers published over the past five years that explore the application of mechanism design in electricity markets. The comparison considers several key aspects to highlight differences and advancements. Firstly, the papers are categorized based on the clearing price-quantity method, distinguishing between one-shot and iterative processes for market clearing. Regarding market architecture, the classification includes sub-markets commonly used in electricity trading, such as day-ahead, spot, and real-time markets. Additionally, the control structure employed in each study is classified into three types: centralized, decentralized, and distributed. While decentralized systems may not necessarily pursue a shared objective, distributed approaches typically act toward a common goal defined by a coordinating entity [20]. Another crucial aspect analysed is the type of incentive mechanism employed, differentiating between rewards and penalties. Reward-based approaches

Table 1
Related works on mechanism design applied to electricity markets.

Work	Year	Clearing method		Market architecture						Incentive-based		Mechanism design assessment			
				Submarkets			Market control								
		One-shot	Iterative	Day-ahead	Spot	Real-time	Centralized	Decentralized	Distributed	Reward	Penalty	IR	Eff	BB	IC
[1]	2019	✓	X	✓	X	X	X	X	✓	X	✓	X	X	X	X
[2]	2019	✓	X	✓	X	✓	X	X	✓	X	✓	X	X	X	X
[21]	2020	✓	X	✓	X	X	X	X	✓	✓	✓	✓	X	✓	X
[22]	2020	X	✓	✓	X	X	X	X	✓	✓	X	✓	✓	X	✓
[16]	2021	✓	X	X	X	✓	✓	X	X	✓	✓	✓	✓	X	✓
[23]	2021	X	✓	✓	X	X	X	X	✓	X	✓	X	X	X	X
[24]	2021	X	✓	✓	X	✓	X	✓	X	X	✓	X	X	✓	X
[25]	2021	X	✓	✓	X	✓	X	X	✓	✓	X	✓	X	X	✓
[26]	2022	X	✓	X	✓	X	X	✓	X	X	✓	✓	✓	✓	X
[17]	2022	✓	X	X	X	✓	X	✓	X	✓	X	✓	X	X	✓
[27]	2023	X	✓	✓	X	X	X	✓	X	✓	X	✓	X	✓	X
[28]	2024	✓	X	✓	X	X	X	X	✓	✓	X	✓	X	X	X
[29]	2024	✓	X	X	✓	X	✓	X	X	✓	✓	✓	✓	X	✓
[19]	2024	X	✓	X	✓	X	X	✓	X	✓	X	✓	X	X	✓
[18]	2024	✓	X	✓	X	✓	✓	X	X	✓	✓	✓	X	X	✓
[30]	2024	X	✓	✓	X	X	X	✓	X	X	✓	✓	X	X	✓
This work	2025	✓	X	✓	X	X	X	X	✓	✓	✓	✓	✓	✓	✓

typically provide economic benefits *ex-post* to agents who exhibit desired behaviour, while penalty-based mechanisms can be applied at any phase of the mechanism timeline—*ex-ante*, *interim*, or *ex-post*, as illustrated in Fig. 2. Notably, some reported works employ a hybrid approach, combining incentives at different phases to achieve better outcomes. Finally, Table 1 evaluates whether each study addresses the four main principles of mechanism design: individual rationality (IR), efficiency (Eff), budget balance (BB), and incentive compatibility (IC). This structured comparison not only underscores the unique contributions of existing research but also contextualizes the advancements and practical relevance of the mechanisms proposed in this paper.

2.4. Contributions

Although several works have made significant progress in the field of MD, several limitations still need to be addressed, particularly concerning IC. The literature highlights issues such as the need for RAs to share their private information completely, raising privacy concerns. Additionally, many proposed solutions rely on centralized decision-making instead of distributed or decentralized approaches (where RAs could also make decisions), which increases computational burdens and raises privacy concerns. Furthermore, there is a lack of comprehensive quantification of the adverse effects caused by strategic agents in a one-shot market architecture in each concept of mechanism design, i.e., individual rationality, efficiency, budget balance, and incentive compatibility. Finally, previous studies have not thoroughly examined the effects of ensuring an IC mechanism on individual *ex-ante* IR, *ex-ante* Eff, and BB within specific MD phases.

In this regard, This work proposes a distributed market control with a DSO that employs a penalty mechanism to discourage strategic misreporting of energy consumption plans from RAs during negotiations for a day-ahead period, i.e., ensuring an incentive-compatible mechanism. The mechanism proposed in this work requires just the planned consumption signal from RAs instead of all the types (private information from the customers), requiring minimal information. Then, The DSO aims to implement a TE system to negotiate the conditions of a DR program with RAs, designing a mechanism primarily focused on achieving the IC property while assessing IR and Eff in an *ex-ante* phase, as well as BB in the *settlement* phase. The contributions are then enlisted as follows:

- This work provides a comprehensive analysis of the proposed mechanism's effectiveness by explicitly evaluating individual rationality and efficiency in the *ex-ante* phase and budget balance along with incentive compatibility in the *settlement* phase. This phase-specific approach ensures a more granular understanding of the mechanism's performance over time.

- This work introduces the design of a transactive energy mechanism in a one-shot market architecture. The mechanism ensures incentive compatibility by requiring agents to share only minimal information signals (e.g., electricity price or planned consumption) while maintaining their privacy.
- This work explicitly focuses on designing an incentive-compatible mechanism that discourages strategic manipulation of electricity consumption plans by agents. Employing individual rationality, efficiency, and budget balance metrics quantifies the adverse effects of strategic behaviour, offering valuable insights for mitigating undesirable market outcomes.

3. Cost functions, payment rules, and penalty policies

Consider a single DSO that supplies electricity to a close set of customers $\mathcal{N} = \{1, 2, 3, \dots, n\}$. Consider a typical scenario where the DSO charges the customer for any unit of energy they demand from the power grid at a specific flattened price. Then, the payment rule that the DSO typically charges to each customer C_n is as follows in Eq. (3):

$$C_n = \sum_{\forall t \in \mathcal{T}} \pi_t^0 \cdot e_{t,n}^{act}, \quad \forall n \in \mathcal{N}. \quad (3)$$

where $\mathcal{T}$ is the period of charge, π_t^0 is a flattened electricity price, and $e_{t,n}^{act}$ is the actual electricity consumption of customer n . As noticed, the DSO will charge each customer for their actual consumption by employing Eq. (3). No negotiation for a future consumption period was considered in Eq. (3).

Now, let us revisit Example 1 with complementary conditions. Suppose the DSO develops a DR program to reduce the peak-energy periods in a day-ahead market. Customers are equipped with a free agent-based technology that enables bidirectional communication. Furthermore, the DSO incentivizes customers by employing a dynamic electricity price (π_t^*) to encourage consumption at a reduced price during non-peak periods. To change their consumption patterns, customers must express their willingness to forego some comfort $g(\cdot)$ (e.g., thermal or entertainment comfort) to save money and earn the rewards offered by the DSO. Suppose each RA adopts the same optimization problem as stated in Eq. (4a) subject to constraints Eqs. (4b)–(4c):

$$\underset{e \in \mathcal{E}}{\text{minimize}} \quad f(e) = \sum_{\forall t \in \mathcal{T}} \pi_t^* \cdot e_{t,n} + g(e_{t,n}) \quad (4a)$$

$$\text{subject to} \quad p(e) \leq 0, \quad \forall t \in \mathcal{T}, \forall n \in \mathcal{N}, \quad (4b)$$

$$h(e) = 0, \quad \forall t \in \mathcal{T}, \forall n \in \mathcal{N}. \quad (4c)$$

where $e \in \mathbb{R}^m$ is the optimization variable, $f : \mathbb{R}^m \rightarrow \mathbb{R}$ is a convex objective function, $p : \mathbb{R}^m \rightarrow \mathbb{R}$ is a convex inequality constraint function, and $h : \mathbb{R}^m \rightarrow \mathbb{R}$ is an affine equality constraint function.

Table 2
Determining the IC property of five self-enforcing policies.

Payment rules	References	IC			Proof	Explanation
		Yes	No	Depend		
$C^1 = \pi \cdot e$	[31–37]		✓		–	A penalty function is not included. Then, the RA does not perceive any penalty for electricity deviation from an agreement.
$C^2 = \pi \cdot e + \alpha \cdot (e - \hat{e})$	[21]		✓		$\frac{\partial C^2}{\partial \hat{e}} = 0 \rightarrow \alpha = 0$	A linear penalty function is included. However, notice that the result of derivation does not satisfy Eq. (2).
$C^3 = -\pi \cdot (e - \alpha \cdot (\hat{e} - e))$	[1,2,23,24]		✓		$\frac{\partial C^3}{\partial \hat{e}} = 0 \rightarrow \pi \cdot \alpha = 0$	A linear penalty function is included. However, this PR implies that the RA does not perceive a penalty for reporting false information and does not satisfy Eq. (2).
$C^4 = \pi \cdot \hat{e} + \alpha \cdot (e - \hat{e})^2$	[38–41]			✓	$\frac{\partial C^4}{\partial \hat{e}} = 0 \rightarrow \hat{e} = \pi / (2 \cdot \alpha) + e$	A quadratic penalty function is included, and the linear function is modified. However, the term $\pi / (2 \cdot \alpha)$ must tend to zero to satisfy the Eq. (2).
$C^5 = \pi \cdot e + \alpha \cdot (e - \hat{e})^2$	This work	✓			$\frac{\partial C^5}{\partial \hat{e}} = 0 \rightarrow \hat{e} = e$	A quadratic penalty function is included. Notice that the RA will be charged with their actual consumption (linear term in the PR) instead of their consumption to report. Since this PR satisfies the Eq. (2), this PR ensures IC.

Building upon the discussion of cost functions, payment rules, and penalty policies, it is essential to explore how these mechanisms can be optimized to encourage truthful reporting and efficient participation by RAs. Mechanism design provides a powerful framework for this purpose, employing self-enforcing policies to incentivize agents to disclose accurate information within negotiation environments [9]. These policies, called payment rules in mechanism design jargon, serve as crucial instruments for electricity markets.

By adopting these self-enforcing policies, the DSO mitigates the risks of transaction failures and encourages an environment where customers are motivated to report truthful information. In this approach, the DSO must develop and implement policies that make it costly for RAs to provide false information, thereby ensuring the disclosure of accurate data. The DSO must have confidence in adopting an IC mechanism, as discussed in Section 2.1, which is essential to maintain the integrity and efficiency of transactional programs. For this reason, this work explores five payment rules in Table 2 to determine theoretically whether adopting these self-enforcing policies satisfies the IC condition expressed in Eq. (2).

Table 2 shows that C^1 is not a suitable PR for adoption by any DSO in a TE market. This fact is a consequence of the absence of a penalty for non-obligation fulfillment contracts from the RAs. While C^1 might be appropriate in scenarios where benevolent and trustful RAs are ensured, its use could jeopardize power grid operations due to the strategic behaviour of rational and intelligent RAs during a transactional framework. Similarly, adopting a linear PR, as seen in C^2 , is not recommended. In such cases, agents quickly realize that under-reporting their consumption can minimize their cost function, unsatisfying the IC conditions outlined in Eq. (2). Moreover, C^3 also fails to satisfy the IC condition Eq. (2), as RAs may under-report their electricity consumption to minimize their cost. On the other hand, the quadratic penalty function in C^4 , while symmetric, cannot ensure compliance with Eq. (2) for any penalty value α . Then, the report of truthful information becomes solely dependent on the relationship between the price and the penalty pair for C^4 . Notably, if the term $\pi / (2 \cdot \alpha)$ tends zero, the IC condition Eq. (2) is met. This condition is achieved when the penalty value α significantly exceeds the electricity price π , i.e., $\alpha \approx \infty$. Lastly, the DSO must charge each RA based on their actual electricity consumption (e) rather than the reported consumption ($\hat{e}$), as presented in C^5 . The penalty function should be quadratic and symmetric to penalize over and under-reported consumption. Therefore, among the five PRs explored in Table 2, only C^5 satisfies the IC condition Eq. (2).

This study employs two complementary approaches to visually represent the outputs of the PRs discussed in Table 2. The first approach

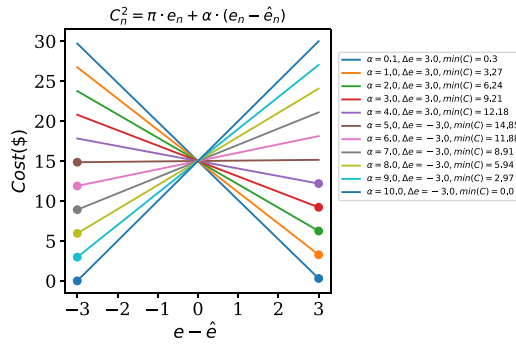
introduces a simplified example, free from any optimization framework, to illustrate the strategic behaviour of RAs under the application of the PRs outlined in Table 2. This example serves as an accessible entry point for understanding the influence of these payment rules on agent behaviour. The second approach involves the development of an optimization problem tailored for a residential customer, incorporating the PRs to create a more realistic and practical scenario. This optimization-based analysis validates the IC findings in Table 2 and provides a deeper understanding of their implications in a real-world context. The simplified example is presented below in Example 2, while the optimization problem is detailed in Section 4. The latter approach requires a formal optimization formulation and the consideration of the MD phases outlined in Fig. 2, providing a comprehensive evaluation of the PRs within the context of the mechanism's application.

Example 2. Suppose an RA demands three units of energy ($e = 3$), and the DSO's price is five cents per unit ($\pi = 5$). The RA aims to determine the optimal consumption to report to the DSO. With the freedom to choose the reported consumption ($\hat{e}$), the RA explores fifty values ranging from zero to six. Additionally, the DSO explores eleven penalty values ranging from 0.1 to 10 ($\alpha = \{0.1, 1, 2, \dots, 10\}$).

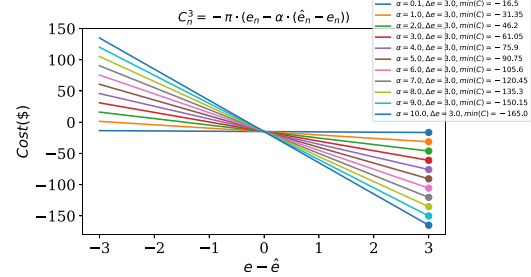
From Figs. 3(a) and 3(b), each dot represents the RA's minimum cost for each penalty value explored. Notably, the minimum cost is achieved when the RA deviates from their actual consumption, i.e., $e \neq \hat{e}$, irrespective of the penalty value α chosen by the DSO. For C^3 , it is evident that a strategic agent may perceive negative costs (or profits) for misreporting electricity consumption to the DSO. Therefore, along with the findings of Table 2, the PR C^3 is not a suitable candidate to be adopted for the mechanism designer. In Fig. 3(c), the RA could reduce their electricity cost by reporting false information, as indicated by the red dots. However, as the price-penalty rate increases (e.g., $\alpha = 45$ or $\alpha = 50$), the RA becomes less inclined to misreport information, thereby satisfying the IC condition outlined in Eq. (2). Although this fact validates the IC classification as *depend* made in Table 2, further effects of this large penalty values requirement over IR, Eff, and BB are explored in the forthcoming sections. Finally, from Fig. 3(d), it is possible to verify that the PR is well structured to prevent deceptive behaviour regardless of any penalty value α , i.e., RA reports true information, even for small penalty values (e.g., $\alpha = 0.1$). Furthermore, only C^5 is strategic-proof from the five PRs explored, and the IC condition presented in Table 2 is visually validated.

4. Mechanism design assessment

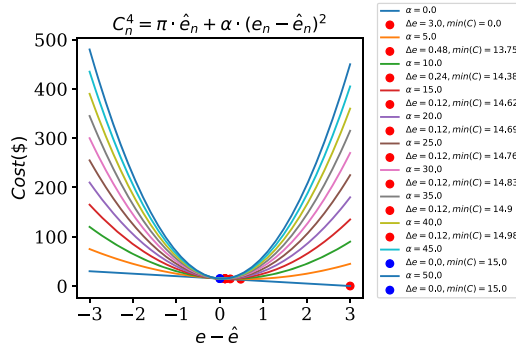
This section evaluates the IR and Eff in the *ex-ante* phase, and the IC and BB in the *settlement* phase, within a one-shot market architecture.



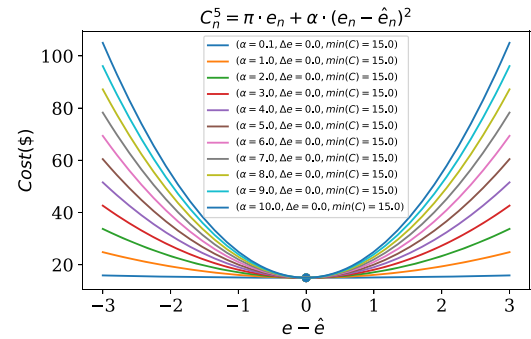
(a) A simple visualization of the minimum cost achieved by a strategic residential agent when the DSO employs C^2 by using example 2. Notice that the residential agent plays strategically by misreporting its electricity consumption plan, i.e., $e \neq \hat{e}$.



(b) A simple visualization of the minimum cost achieved by a strategic residential agent when the DSO employs C^3 by using example 2. Notice that the residential agent plays strategically by misreporting its electricity consumption plan, i.e., $e \neq \hat{e}$.



(c) A simple visualization of the minimum cost achieved by a strategic residential agent when the DSO employs C^4 by using example 2. Notice that the residential agent plays strategically by misreporting its electricity consumption plan, i.e., $e \neq \hat{e}$.



(d) A simple visualization of the minimum cost achieved by a strategic residential agent when the DSO employs C^5 by using example 2. Notice the residential agent could not play strategically by misreporting its electricity consumption plan, i.e., $e = \hat{e}$.

Fig. 3. Graphical visualization of the cost effect of the payment rules explored in Table 2 by using Example 2.

The payment rules defined in Table 2 form the basis for this assessment. As illustrated in Fig. 2, analysing IR and Eff in the *ex-ante* phase is crucial for both the DSO and the RAs. For the DSO, understanding these metrics informs the decision to implement a dynamic pricing strategy to incentivize consumption pattern changes and evaluate the economic efficiency of the price-penalty pair. For the RAs, these metrics help estimate the expected reward for participating in the DR program based on their economic rationality. In the *settlement* phase, the DSO focuses on verifying if the proposed mechanism adheres to the IC property, ensuring that customers incur higher costs for deviations from their plans and whether any economic profit or loss arises from the revelation of uncertainty during the plan's execution by the RAs, i.e., budget balance condition.

4.1. Ex-ante phase

This work considers a simple game with a DSO who aims to coordinate two RAs $\mathcal{N} = \{1, 2\}$, $\forall n \in \mathcal{N}$ for a day-ahead period at each time-slot $t \in \mathcal{T}$, as captured by the UML diagram in Fig. 4.

Fig. 4 illustrates the adoption of stochastic optimization on the RA side through the use of the expected value operator $E[\cdot]$. This stochastic framework introduces the effect of uncertainty in the decision-making process of each RA, offering a more realistic and robust foundation for the results presented in this study case [42]. From Fig. 4, notice that there is no exchange of information between the RAs. Instead, the information flows from the DSO to each RA individually. A one-shot negotiation approach was implemented between the DSO and RAs as

part of the IC mechanism design. Firstly, the DSO captures the initial electricity consumption reported ($\hat{e}^0$) from RAs based on their response to a flattened initial price π^0 and penalty value α^0 . Notice that the consumption reported by RAs could not be truthful. Moreover, the DSO decides whether the negotiation moves to the next step based on any criteria (e.g., dispatch). If so, the DSO shares a dynamic final price π^* and a final penalty value α^* with RAs to disclose the reported consumption plan to these signals ($\hat{e}^*$). No further negotiation is performed because of a one-shot negotiation approach.

4.1.1. A stochastic optimization formulation of the payment rules

Since RAs are intelligent and rational machines, they would adopt the payment rules provided in Table 2 as cost functions in their optimization program. An additional thermal discomfort term was also considered to get a price-response elasticity from the customer side (i.e., $g(\cdot)$ term in Eq. (4a)) [35,43]. Notice that the thermal discomfort term is convex in all its space [43]. In this regard, customers sacrifice thermal comfort to shift their consumption patterns regarding a price-incentive signal provided by the DSO, as follows:

$$C_n^2 = \sum_{t=1}^T \left[\pi \cdot e_{n,t} + \gamma_n \cdot (T_{SP,n,t} - T_{in,n,t})^2 + \alpha \cdot (e_{n,t} - \hat{e}_{n,t}) \right], \forall n \in \mathcal{N}, \forall t \in \mathcal{T}. \quad (5)$$

$$C_n^3 = \sum_{t=1}^T \left[\pi \cdot (e_{n,t} - \alpha \cdot \hat{e}_{n,t}) + \gamma_n \cdot (T_{SP,n,t} - T_{in,n,t})^2 \right], \quad (6)$$

$\forall n \in \mathcal{N}, \forall t \in \mathcal{T}.$

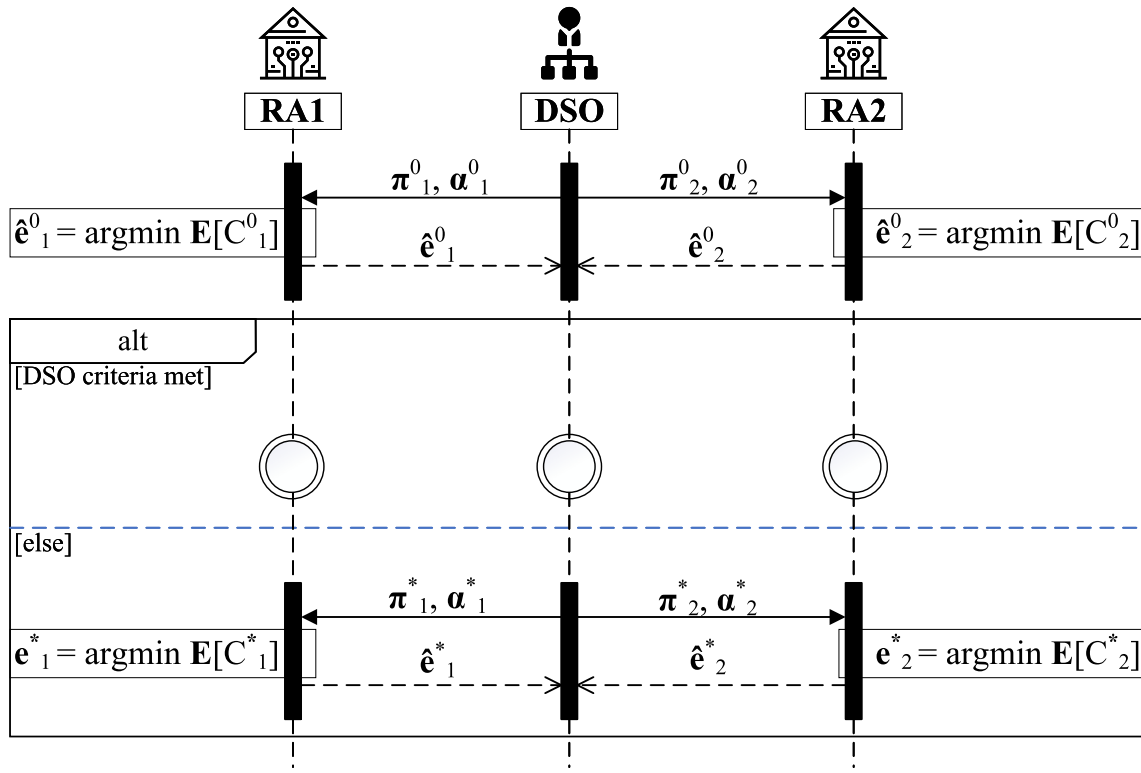


Fig. 4. UML diagram representing the information exchange between a DSO and two RAs during the negotiation at an *ex-ante* phase.

$$C_n^4 = \sum_{t=1}^T \left[\pi \cdot \hat{e}_{n,t} + \gamma_n \cdot (T_{SP,n,t} - T_{in,n,t})^2 + \alpha \cdot (e_{n,t} - \hat{e}_{n,t})^2 \right], \forall n \in \mathcal{N}, \forall t \in \mathcal{T}. \quad (7)$$

$$C_n^5 = \sum_{t=1}^T \left[\pi \cdot e_{n,t} + \gamma_n \cdot (T_{SP,n,t} - T_{in,n,t})^2 + \alpha \cdot (e_{n,t} - \hat{e}_{n,t})^2 \right], \forall n \in \mathcal{N}, \forall t \in \mathcal{T}. \quad (8)$$

where π_t is the set of electricity prices explored $\pi_t \in \{\pi_t^0, \pi_t^*\}$, $e_{n,t}$ is the optimization variable related to the individual electricity consumption to import composed by the heating system $e_{var,n,t}$ (controllable load) and the fixed load $e_{fix,n,t}$ (uncontrollable load). Notice that the uncertainty source considered in this work is the fixed load $e_{fix,n,t}$ following a time-dependent distribution $f(\mu_{n,t}, \sigma_{n,t})$ of historical data [30]. $\hat{e}_{n,t}$ is the optimization variable related to the individual electricity consumption to report, γ_n is a parameter selected by each customer to weight the thermal comfort significance against the electricity consumption cost, $T_{SP,n,t}$ is the temperature of preference (set-points) predefined by each customer, and $T_{in,t}$ is the inner dwelling temperature of each customer. The term $\gamma_n \cdot (T_{SP,n,t}^i - T_{in,t}^i)^2$ transforms the temperature ($^{\circ}\text{C}$) units to cost related to Dollars (\$). Then, the term γ_n has the units ($\$/^{\circ}\text{C}^2$) [43]. The set of prices is $\pi \in \{\pi_t^0, \pi_t^*\}$, where the flattened initial price is set in $\pi_t^0 = 7.3\text{¢}/\text{kWh}$ taken from [44], while the dynamic electricity price π_t^* used is taken from [45]. The penalty set is $\alpha \in \{\alpha^0, \alpha^*\}$, where for the sake of simplicity the penalty values explored under both the flattened and the dynamic price are the same, i.e., $\alpha^0 = \alpha^* = \{5, 10, 100\} \text{ ¢}/\text{kWh}^2$.

All RAs are equipped with an agent-based technology that adopts the same stochastic optimization program as defined in Eqs. (9a)–(9g) as follows:

$$\text{minimize}_{e, \hat{e}} \quad \mathbf{E}[C_n^2], \mathbf{E}[C_n^3], \mathbf{E}[C_n^4], \mathbf{E}[C_n^5], \forall n \in \mathcal{N} \quad (9a)$$

$$\text{subject to} \quad T_{in,n,t} = A \cdot T_{in,n,t-1} + B \cdot e_{var,n,t} \quad (9b)$$

$$+ C \cdot T_{ext,n,t}, \quad (9c)$$

$$T_{in,n,t} \leq \max(T_{SP,n,t}), \quad (9d)$$

$$T_{in,n,t} \geq \min(T_{SP,n,t}), \quad (9e)$$

$$T_{in,n,t} = T_{SP,n,t}, \quad (9f)$$

$$0 \leq \hat{e}_{n,t} \leq \zeta. \quad (9g)$$

where $\mathbf{E}[\cdot]$ is the expected value. In the optimization formulation (9a)–(9g), constraint (9c) is a space state-model to consider the dynamics of the inner dwelling temperature ($T_{in,n,t}$) based on the previous temperature reading ($T_{in,n,t-1}$), the baseboard heating consumption ($e_{var,n,t}$), and the outside environment temperature ($T_{ext,n,t}$) [46]; constraints (9d) and (9e) are the inner dwelling temperature limits based on the set-point of each customer; constraint (9f) ensures that the initial and final dwelling temperature remain equal [46]; finally, constraint (9g) ensures that the reported electricity consumption ($\hat{e}$) remains bounded, then obtaining a closed optimization problem [47]. This constraint is crucial for solving C^2 , particularly when RAs choose to over-report electricity consumption, as depicted in Fig. 5(a).

As mentioned earlier, the source of uncertainty adopted in this work comes from the uncontrollable load e_{fix} . The uncertainty was modelled by using real consumption data of two houses measured during a three-month winter period [48]. A probability density function $f_i(\cdot)$ with parameters $(\mu_{f,n,t}, \sigma_{f,n,t})$ as the mean and variance, respectively, modelled the uncertainty by using the well-known tool named Prophet [49] as follows in Eq. (10).

$$e_{fix,n,t} = f(\mu_{n,t}, \sigma_{n,t}) \quad (10)$$

The Monte Carlo method was employed in this work to solve the convex stochastic program [42]. One hundred scenarios ($W = 100$) were generated for each house by sampling from the probability density function $f_i(\cdot)$.

Table 3
Simulation results - ex-ante IR.

E[C[·]]	RA	α		
		5	10	100
E[C _n ² (e _n ⁰ π^0)]	RA1	-25.54	-61.66	-712.07
	RA2	-26.59	-63.33	-733.05
E[C _n ² (e _n [*] π^*)]	RA1	-27.39	-63.38	-712.82
	RA2	-28.10	-64.70	-733.97
E[C _n ³ (e _n ⁰ π^0)]	RA1	-78.52	-143.98	-1323.60
	RA2	-68.05	-124.87	-1150.93
E[C _n ³ (e _n [*] π^*)]	RA1	-71.82	-132.06	-1217.92
	RA2	-61.60	-114.17	-1063.32
E[C _n ⁴ (e _n ⁰ π^0)]	RA1	7.13	9.01	13.86
	RA2	6.44	8.43	13.31
E[C _n ⁴ (e _n [*] π^*)]	RA1	6.05	7.53	11.92
	RA2	5.73	7.27	11.70
E[C _n ⁵ (e _n ⁰ π^0)]	RA1	10.76	10.93	14.05
	RA2	10.18	10.35	13.50
E[C _n ⁵ (e _n [*] π^*)]	RA1	8.77	8.94	12.06
	RA2	8.51	8.69	11.84

4.1.2. Influence of strategic-agents in the mechanism

Since this work employs the dynamic electricity price from [45], the way RAs could play strategically arises from the relationship between the price and the reported electricity consumption plan ($\pi_t^* \propto \hat{e}_{n,t}$) as follows in (11) [30,45].

$$\pi_t^* = \lambda \cdot \hat{e}_{agg,t}. \quad (11)$$

where λ is the fixed cost of operating a power grid [30] set in 2.24 ¢ \$ / kWh, and $\hat{e}_{agg,t}^i = \sum_{n \in \mathcal{N}} \hat{e}_{n,t}^i$ is the aggregated electricity consumption at time $t \in \mathcal{T}$. Hence, intelligent agents could infer this price-reported-consumption relationship and, therefore, under-report their consumption plan to reach the minimum possible price that economically benefits them. In this regard, the DSO should devise an IC mechanism to avoid negative effects on the TE system by strategic agents. Additional influences that strategic-agents could perform in a negotiation have been reported in [30].

4.1.3. Ex-ante IR

A rational agent engages in a transaction when perceiving an economic benefit. To facilitate this decision-making process, the DSO shares with the RAs a flattened price (π_t^0) and a dynamic price (π_t^*) as presented in Fig. 4. Each RA independently evaluates the output of these options to decide their participation, as presented in Fig. 2 in the *ex-ante phase*: an RA will opt in if the comparison yields a positive economic benefit and opt out otherwise.

Using the results presented in Table 2 and Fig. 3(d), the DSO can conclude that the expected cost outcomes for each RA under the payment rule C_n^5 are strategy-proof, effectively preventing deceptive behaviour by RAs. As a result, the true expected costs for each RA, depicted in Table 3, are achieved when the DSO employs C^5 , alongside either a flattened or dynamic electricity price (π^0, π^*) and at varying penalty values (α). Furthermore, dynamic pricing in this scenario reduces expected costs for each RA compared to flattened pricing. This cost reduction is due to the price-elasticity relation of each customer, where RAs adjust their consumption behaviour – by sacrificing thermal comfort – to lower their electricity costs. Consequently, as illustrated in Fig. 2, the individual rationality condition is satisfied, encouraging RAs to actively participate in the TE program.

In contrast, Table 3 highlights significant issues with the first two payment policies, C_n^2 and C_n^3 , as they allow RAs to achieve negative costs, i.e., gain utility by gaming the system. These issues arise because RAs misreport their information, manipulating the mechanism to increase profitability. Moreover, the higher the penalty value α , the greater the utilities perceived by the RAs. Even when the DSO

applies larger penalty values without properly designing the penalty policy, RAs continue to exploit the mechanism, gaining profits while participating in the system. Although the penalty policy under C_n^4 prevents RAs from achieving negative costs (utility), it still allows them to reduce their costs by misreporting information. Rational RAs are, therefore, incentivized to participate in transactions with the DSO while continuing to game the system.

Since gaming the system and individual rationality results are captured in Table 3 supported with findings already presented in Table 2 and Fig. 3(d), *ex-ante* inefficiencies of the negotiation mechanism are captured in the following Section 4.1.4 by employing the Price of Anarchy and Price of Deception metrics.

4.1.4. Ex-ante eff

The Price of Anarchy (PoA) and the Price of Stability (PoS) are widely recognized metrics used to evaluate the efficiency of a mechanism that attains an equilibrium [12]. These metrics provide a comparative analysis against an ideal scenario where all participating agents collaborate towards a common goal. In games where multiple equilibria exist, the PoA measures the worst-case efficiency, while the PoS offers insight into the best-case efficiency. Conversely, when games have a single equilibrium, the values of PoA and PoS coincide. Given that the optimization model utilized in this study converges to a single equilibrium [10,13,47,50], the mathematical formulations for PoA and PoS are identical, as represented in Eq. (12).

$$PoA(G) = PoS(G) = \frac{\mathbf{E}[C(\hat{e}^{0,*}|\pi^{0,*})]}{\mathbf{E}[OPT]} \quad (12)$$

where $C(\hat{e}^{0,*}|\pi^{0,*}) = \sum_{n=1}^{N=2} \mathbf{E}[C_n[\cdot]]$ is the sum of the individual cost of each RA. From Eq. (12), notice that the PoA is consistently greater than or equal to one due to the affectation of the parameters like the price π , the penalty α , and the thermal comfort γ on the equilibrium points of the game [51–53]. Furthermore, it is noteworthy that as the PoA approaches one, the outcome converges closer to the socially optimal outcome (OPT), indicating higher efficiency. The DSO then devises a SW formulation to capture the OPT solution. This fact implies that all private information RAs hold is transferred to the DSO, facilitating the computation of the OPT outcome in a centralized manner [54,55]. The SW formulation is depicted in Eq. (13).¹

$$SW = U_{DSO} + U_n - C_{DSO} - C_n \quad (13)$$

$$U_{DSO} = \sum_{n=1}^N \left[\mathbf{E} \left[\sum_{t=1}^T \left[\pi \cdot e_{n,t} + \alpha \cdot (e_{n,t} - \hat{e}_{n,t})^2 \right] \right] \right], \quad (14)$$

$$U_n = - \sum_{n=1}^N \left[\mathbf{E} \left[\sum_{t=1}^T \left[\gamma_n \cdot (T_{SP,n,t} - T_{in,n,t})^2 \right] \right] \right], \quad (15)$$

$$C_{DSO} = \lambda \cdot \mathbf{E} \left[\sum_{t=1}^T \sum_{n=1}^N \left[e_{n,t}^2 \right] \right], \quad (16)$$

$$C_n = \sum_{n=1}^N \left[\mathbf{E} \left[\sum_{t=1}^T \left[\pi \cdot e_{n,t} + \alpha \cdot (e_{n,t} - \hat{e}_{n,t})^2 \right] \right] \right]. \quad (17)$$

From Eq. (13), notice that the DSO utility (U_{DSO}) is equal to the cost perceived by the customers (C_n), resulting in their cancellation. Consequently, the SW function that the DSO seeks to maximize is reformulated as depicted in Eq. (18).

$$SW = U_n - C_n, \\ SW = - \sum_{n=1}^N \left[\mathbf{E} \left[\sum_{t=1}^T \left[\gamma_n \cdot (T_{SP,n,t} - T_{in,n,t})^2 \right] \right] \right] - \lambda \cdot \mathbf{E} \left[\sum_{t=1}^T \sum_{n=1}^N \left[e_{n,t}^2 \right] \right]. \quad (18)$$

¹ We employed C^5 in Eq. (13) for illustrative purposes. However, all payment rules, C^2 , C^3 , C^4 , and C^5 were used to get the results of Table 4.

Table 4
Simulation results - ex-ante Eff - PoA.

PoA(E[C ⁱ ·])	α		
	5	10	100
PoA(E[C ² (e ⁰ π^0)])	-3.43	-8.22	-95.07
PoA(E[C ² (e* π^*)])	-3.65	-8.43	-95.18
PoA(E[C ³ (e ⁰ π^0)])	-9.64	-17.69	-162.79
PoA(E[C ³ (e* π^*)])	-8.77	-16.20	-150.07
PoA(E[C ⁴ (e ⁰ π^0)])	0.89	1.15	1.79
PoA(E[C ⁴ (e* π^*)])	0.77	0.97	1.55
PoA(E[C ⁵ (e ⁰ π^0)])	1.38	1.40	1.81
PoA(E[C ⁵ (e* π^*)])	1.14	1.16	1.57

Table 5
Simulation results - PoD.

PoD(E[C ⁱ ·])	α		
	5	10	100
PoD(E[C ² (e ⁰ π^0)])	-0.40	-0.17	-0.02
PoD(E[C ² (e* π^*)])	-0.31	-0.14	-0.02
PoD(E[C ³ (e ⁰ π^0)])	-0.14	-0.08	-0.01
PoD(E[C ³ (e* π^*)])	-0.13	-0.07	-0.01
PoD(E[C ⁴ (e ⁰ π^0)])	1.51	1.22	1.01
PoD(E[C ⁴ (e* π^*)])	1.47	1.19	1.01
PoD(E[C ⁵ (e ⁰ π^0)])	1.00	1.00	1.00
PoD(E[C ⁵ (e* π^*)])	1.00	1.00	1.00

Table 4 reveals that PoA not only exhibits negative values for the cases C^2 and C^3 , but it is also less than one for some alpha-cases in the RAs' cost function C^4 . This finding suggests two key points: (i) RAs identify and exploit vulnerabilities in the mechanism when the DSO applies the payment rules C^2 , C^3 , and C^4 , and (ii) PoA is not a suitable metric to capture inefficiencies when a mechanism is not strategy-proof. Conversely, with implementing the payment rule C^5 , PoA consistently exceeds one across all three analysed alpha scenarios. Moreover, it is straightforward to conclude that the DSO achieves a higher system efficiency by using a dynamic price π_t^* instead of a flattened price π_t^0 . This finding aligns with the observations in Fig. 3(d), where RAs lack incentives to exploit the system for their benefit, and therefore, the system efficiency results, presented in Table 4 are consistent. Therefore, the PoA value for C^5 in Table 4 indicates the mechanism is close to the efficiency in the *ex-ante* phase.

To address the limitation of the PoA, authors in [56] proposed the Price of Deception (PoD) as a metric specifically designed to assess the effect of agents' strategic behaviour on mechanisms' outcomes as follows in Eq. (19).

$$PoD(G) = \frac{E[C(e^{0,*} | \pi^{0,*})]}{E[C(\hat{e}^{0,*} | \pi^{0,*})]}. \quad (19)$$

Similarly to the PoA, the PoD is greater than or equal to one ($PoD \geq 1$) from a cost perspective in mechanism design. A PoD value of one signifies that the optimal strategy for an agent is to report its true consumption plan, i.e., $e = \hat{e}$. The further the PoD value deviates from one, the more significant the negative effect exercised by the deceptive RAs on the mechanism designed by the DSO. Results associated with the PoD are presented in Table 5.

As seen in Table 5, the PoD metric fails to effectively capture the impact of negative cost (i.e., profits) resulting from RAs misreporting their consumption plans in the cost functions C^2 and C^3 . When examining the results for C^4 , the PoD values suggest that as the penalty value α increases, the PoD approaches one, thereby annulling the effect of false information reported by the RAs. This observation aligns with the explanation in Table 2, indicating that the ratio π/α must approach zero (i.e., α must be significantly larger than π , i.e., $\alpha \approx \infty$) to satisfy the IC condition depicted Eq. (2). Finally, for the payment rule C^5 , PoD consistently equals one for each electricity price and penalty value. This fact indicates that the cost policy effectively neutralizes RAs' deceptive behaviour, regardless of the penalty value α . In this scenario, truthful reporting then becomes the optimal strategy for RAs.

4.1.5. Ex-ante IC - RAs perspective

Based on Fig. 2, IC could be just analysed in the *settlement* phase. However, results associated with the IC concept could also be examined from an RA's perspective in the *ex-ante* phase in a simulation environment. It is possible to analyse the IC property by accessing all the private information RAs processes during the *ex-ante* phase. In this regard, the expected true and report consumption ($(e^*, \hat{e}^*) = \arg \min_{e, \hat{e}} E[C^i(e, \hat{e} | \pi, \alpha)]$, where $i = 2, 3, 4, 5$.) outputs associated with employing each cost function in Eq. (9a) are graphically analysed in Figs. 5(a)–5(d) as follows.

Fig. 5(a) shows that RAs tend to misreport $\hat{e}$ by employing C^2 by setting it as high as possible (i.e., $\zeta = 8$) to minimize their electricity costs, regardless of the penalty values explored. Instead of over-reporting the electricity consumption as depicted in Fig. 5(a), by adopting C^3 , the RA under-reported their electricity consumption by setting it to zero, i.e., $\hat{e} = 0$ as depicted in Fig. 5(b). This false information reported by the RA maximized its thermal comfort and minimized its electricity cost by perceiving a negative cost (profit), i.e., an economically rational decision. In Fig. 5(c), it is observed that as the penalty value increases, the reported consumption $\hat{e}$ converges closer to the actual electricity consumption e demanded by the RA subject to the payment rule C^4 . These results are coherent with findings previously discussed, such as those presented in Table 2 and Fig. 3(c). However, it is crucial to note that excessively high penalty values, such as one hundred, may deter customer enrolment in the TE program due to the perception of exorbitant penalties relative to the electricity price. Finally, Fig. 5(d) clearly demonstrates that RAs do not stand to benefit from misreporting electricity consumption. Instead, the optimal strategy for RAs is to report their actual electricity consumption ($e = \hat{e}$), thereby satisfying the IC condition outlined in Eq. (2) for each penalty value explored α .

4.2. Mechanism design assessment - settlement phase

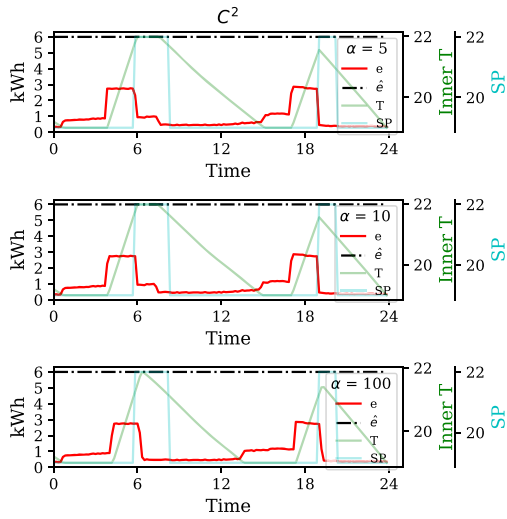
In Section 4.1, the concepts of IR and Eff have already been addressed from an *ex-ante* perspective by applying the MD phases depicted in Fig. 2. Moreover, by following the time-analysis guidance provided by Fig. 2, the concepts of IC and BB could be analysed in the *settlement* phase from the mechanism designer's point of view. The plan must be executed to perform the analysis in the *settlement* phase. This fact implies that RAs must make decisions based on uncertainty revelation. For simplicity's sake, this subsection presents the analysis of just C^5 since the other cost functions do not perform through IC as depicted in Figs. 5(a)–5(c).

$$\min_{\hat{e}} C_n^5, \forall n \in \mathcal{N} \quad (20a)$$

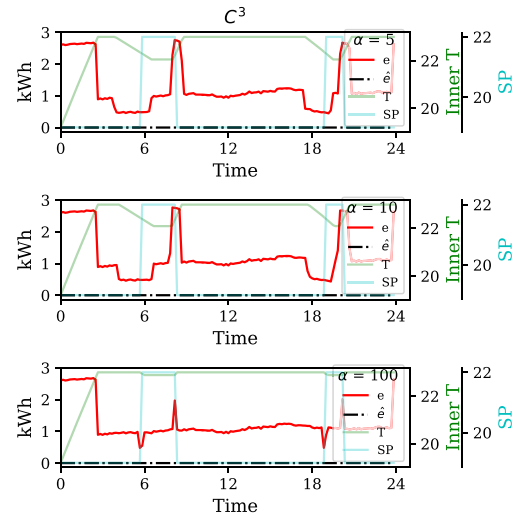
$$\text{subject to } (9c), (9d), (9e), (9f), (9g) \quad (20b)$$

From the optimization (20a) subject to (20b), notice that the RAs are fully interested in minimizing its cost based on the consumption reported ($\hat{e}$) to the DSO. In this regard, notice that $\hat{e}$ is a parameter instead of a decision variable as in the *ex-ante* phase. Any deviation from that reported consumption will incur a higher electricity cost for the customer. The uncertainty revelation was taken as one sample of the distribution considered in the *ex-ante* phase. Results associated with the expected, and current cost, as well as the distribution cost are depicted in Figs. 6 and 7 for one customer (House 1) subject to a flattened and a dynamic electricity price, respectively.

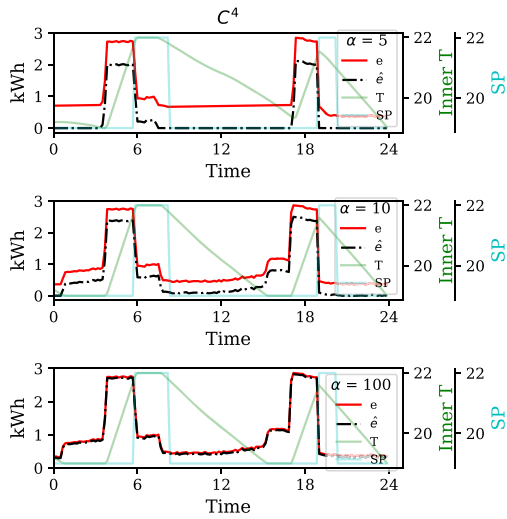
From Figs. 6 and 7, notice that the distribution of the expected cost of each RA always captured the current cost, a coherent result of employing stochastic programming. Moreover, RA pays more generally when uncertainty is disclosed (current cost) than expected cost because it represents deviations from the plan $\hat{e}$. IC is ensured by adopting C^5 in the programming of each RA, even in the case of Fig. 6 for $\alpha = 100$ where the current cost is lower than the expected cost but effectively captured by the distribution of the expected cost. This reduction in the current cost compared to the expected cost is attributed to the customer's greater sacrifice of thermal comfort during the plan's execution.



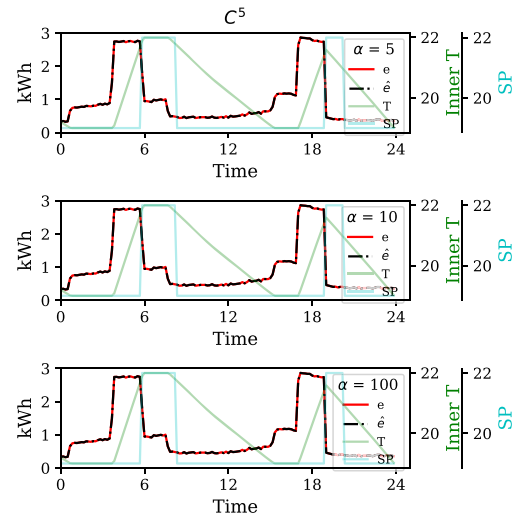
(a) Optimization problem output by employing C^2 in example 3.



(b) Optimization problem output by employing C^3 in example 3.



(c) Optimization problem output by employing C^4 in example 3.



(d) Optimization problem output by employing C^5 in example 3.

Fig. 5. Optimization outputs by employing π_t^0 in Eqs. (9a)–(9g) - RA 1.

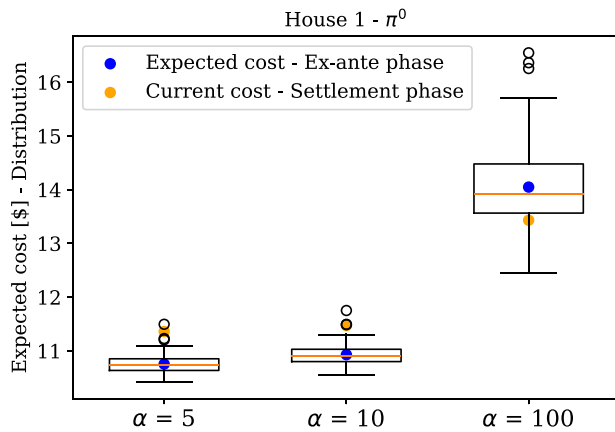


Fig. 6. The expected, the distribution, and the current cost of House 1 (RA 1) by employing C^5 and π_t^0 .

Notice that in a real-world scenario and under the implementation of an IC mechanism, the best an agent can do when facing uncertainty is to report its expected consumption value. Stochastic optimization does not exist to predict an event with perfect accuracy but to manage uncertainty's effect on decision-making.

4.2.1. IC - DSO perspective

This work has presented cost results, considering the cost of importing electricity, the cost of deviation from a plan, and the cost of thermal discomfort for each residential agent (RA). However, the latest is a utility-based approach oriented to analysing game outputs'. Instead, the payment rule indicates the money perceived by the DSO from customers, i.e., the DSO charges each customer for the electricity imported and the penalty for the square of any unit of electricity deviated from a plan, not thermal customer discomfort. In this regard, the payment rule (PR) for each RA who adopts C^5 in the *ex-ante* and *settlement* phases are presented in Eq. (21).

$$PR_n(C_n^5) = \sum_{t=1}^T \left[\pi \cdot e_{n,t} + \alpha \cdot (e_{n,t} - \hat{e}_{n,t})^2 \right] \quad (21)$$

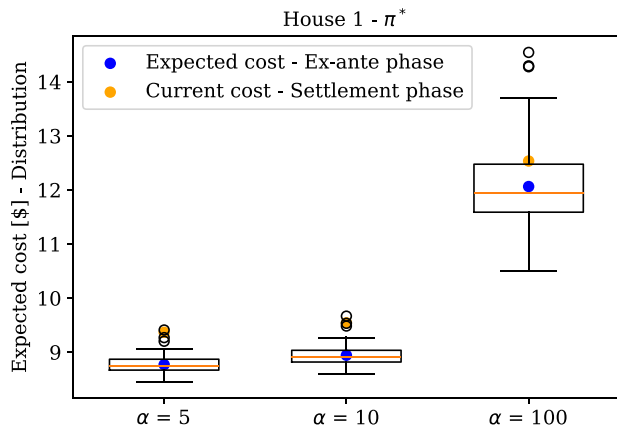


Fig. 7. Expected distribution and current cost of House 1 by employing C^5 and π_t^* .

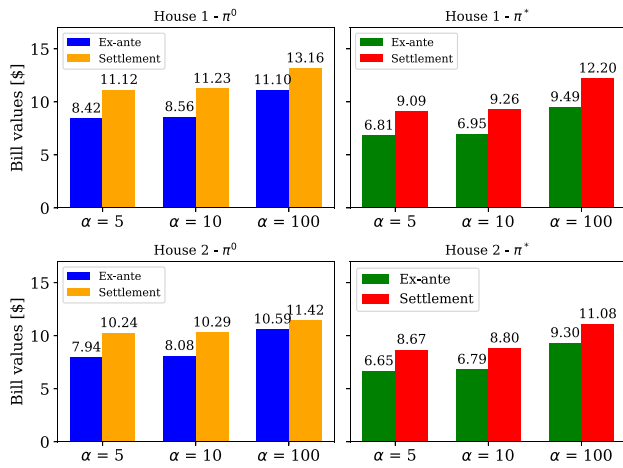


Fig. 8. Payment rule results by employing a flattened π_t^0 and a dynamic π_t^* electricity price.

From Eq. (21), notice that $\hat{e}_{n,t} = \arg\min_{e \in \hat{e}} \mathbf{E}[C_n^5]$ (argmin of Eq. (9a)) for the *ex-ante* phase, while $e_{n,t} = \arg\min_e [C_n^5]$ (argmin of Eq. (20a)) for the *settlement* phase. Results associated with the PR of each customer at each phase are then depicted in Fig. 8.

From Fig. 8, it is possible to conclude that a dynamic electricity price (π_t^*) effectively reduced the electricity cost for both customers, in comparison with a flattened electricity price (π_t^0). In this sense, customers perceive benefits for participating in the negotiation mechanism with the DSO, satisfying the *ex-post* individual rationality condition. On the other hand, any deviation from the agreement plan in the *ex-ante* phase incurred in an increased electricity cost in the *settlement* phase, satisfying the IC condition expressed in Eq. (1). Indeed, this mechanism is strategy-proof because the agents did not perceive any benefit by consumption misreport' as depicted in Fig. 3(d).

4.2.2. BB - DSO perspective

The budget balance (BB) condition implies that the DSO neither incurs profit nor sustains losses. A strong BB is achieved when the total revenue collected from customers equals zero, denoted as $\sum_{n \in \mathcal{N}} U_n = 0$. Conversely, a weak BB signifies that the DSO does not allocate the entire collected revenue back to users, resulting in a positive utility, expressed as $\sum_{n \in \mathcal{N}} U_n > 0$ [11].

As indicated in Fig. 2, the validation of BB could be conducted in the *settlement* phase. In this context, verifying the BB condition involves aggregating the payment rule and considering the DSO's cost of producing

Table 6

Budget balance results for $PR(C^5)$ and for each price and penalty value considered in this work - Settlement phase.

π	α		
	5	10	100
π_t^0	0.13	0.37	3.55
π_t^*	-3.73	-3.34	2.00

the energy demanded by customers as specified in Eq. (16). Furthermore, Eq. (22) presents the BB condition while Table 6 condenses its associated result.

$$\underbrace{\sum_{n=1}^N \sum_{t=1}^T \left[\pi \cdot e_{n,t} + \alpha \cdot (e_{n,t} - \hat{e}_{n,t})^2 \right]}_{\text{Aggregated PR}} - \underbrace{\lambda \cdot \sum_{t=1}^T \sum_{n=1}^N \left[e_{n,t}^2 \right]}_{C_{DSO} \text{ in Eq.(16)}} = 0 \quad (22)$$

Table 6 shows that the DSO perceives profits when using a flattened electricity price (π_t^0) for all penalty values. This fact arises due to the absence of a redistribution payment rule during the *settlement* phase, resulting in a weak BB in the mechanism. Conversely, BB is not ensured with a dynamic electricity price (π_t^*) for penalty values $\alpha = 5$ and $\alpha = 10$, as the DSO incurs economic losses (i.e., the cost of supplying demand exceeds the revenue collected from customers). However, a weak BB is achieved in the mechanism with a penalty value of $\alpha = 100$. Since a dynamic electricity price encourages customers to adjust their consumption patterns, the DSO's economic losses highlight the potential need for a redistribution payment rule in the *settlement* phase as soon as a dynamic price emerges as a DR alternative by the DSO.

5. Discussion: a non-differentiable cost function

The preceding analysis focused on differentiable cost functions to ascertain whether they lead to IC mechanisms. Notably, only the symmetric functions, namely C^4 and C^5 , which penalize deviations from a plan quadratically, demonstrate a tendency to induce truthful reporting by RAs, contingent upon factors such as the ratio between electricity prices and penalty (π, α) for C^4 . However, a pertinent question arises: what if the DSO employs an absolute value function to penalize deviations? Unlike the previous cost functions, this function is non-differentiable across its domain, presenting a novel analytical challenge. To illustrate, consider the graphical representation of C^6 in Fig. 9. In this context, examining scenarios where $\hat{e} < e$, $\hat{e} = e$, and $\hat{e} > e$ can elucidate whether the function satisfies the IC property. Furthermore, utilizing the IC cost perspective outlined in Eq. (1) provides further insight.

As depicted in Fig. 9, the minimum cost for RAs is achieved when Eq. (2) is met, i.e., $e = \hat{e}$. Remarkably, the ratio between penalty and electricity prices does not alter the fulfilment of Eq. (2). This behaviour mirrors that observed in the analysis of C^5 (Fig. 3(d)). Consequently, C^6 emerges as a mechanism that promotes truthful behaviour among agents. Then, the policymakers should decide whether to apply a more severe punishment for each unit of energy deviated - quadratic penalty function- or a less severe one by employing an absolute value function.

6. Conclusions and policy implications

6.1. Conclusions

This study presents a comprehensive benchmark of cost functions essential for retailers in the electricity market, ensuring the exchange of trustworthy information from customers while performing transactions.

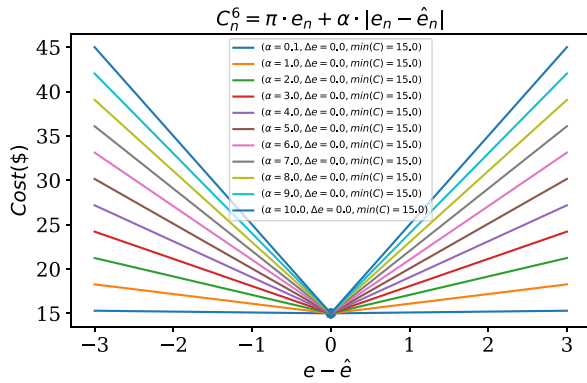


Fig. 9. Graphical visualization of C^6 by using Example 2.

Building upon the insights provided by the main Ref. [1], which highlighted the complexities faced by DSOs in implementing penalty mechanisms in TE markets, this work complements the existing literature by offering an insightful benchmark of cost functions for retailers to explore and implement in TE markets, ensuring the IC property of mechanism design while assessing its effect over efficiency, individual rationality, and budget balance. Furthermore, our findings underscore the risks associated with deploying a TE system, particularly concerning the assumption of benevolent attitudes from residential agents. Instead, DSOs must remain vigilant of these risks and consider adopting self-enforcing policies as a more suitable approach to ensure a truthful exchange of information while incentivizing customer participation in the TE system. By implementing such policies, DSOs can foster a secure and truthful environment where agents interact confidently, ultimately enhancing the efficacy and reliability of TE markets.

6.2. Limitations and future research

This study has a few limitations that open avenues for future research. While this work evaluates specific payment rules from the literature to analyse the incentive compatibility (IC) property of mechanism design (MD), future studies could investigate additional cost functions, payment rules, or contract structures that also satisfy the IC requirements in transactive energy (TE) markets. Additionally, the increasing adoption of distributed energy resources (DERs) by customers – such as photovoltaic systems, electric vehicles, and energy storage – and the expanding range of grid services these technologies can provide in TE markets introduce new challenges for ensuring strategy-proof mechanisms. These developments suggest the need for more robust MD approaches to guarantee truthful information exchange from RAs, thereby ensuring long-term participation and the program's sustainability.

Another key area for exploration involves addressing additional sources of uncertainty that could lead to electricity deviations during the execution of a plan. Factors such as changes in weather conditions, fluctuations in wholesale, intra-day, or real-time market variables, and unforeseen events could affect the individual rationality condition of participants and potentially lead to budget imbalances affecting the DSO economic performance. For example, unexpected changes in weather forecasts might increase electricity costs for RAs, negatively influencing their engagement in negotiations and undermining the economic performance of TE systems.

Regarding limitations to apply the theoretical findings of this study to a real-world case study requires widespread customer adoption of agent-based technologies capable of making decisions on their behalf at each phase of the mechanism's application, as illustrated in Fig. 2. However, as noted in [30], there is currently significant resistance to adopting such technologies among end-users. Without agent-based

systems, customers would need to decide their electricity consumption plans daily manually—a task impractical given the complexity of processing large amounts of information, such as weather forecasts and their effect on energy consumption. Policymakers should prioritize efforts to promote customers adopting agent-based technologies for energy-related applications.

Finally, another technological challenge concerns the need for reliable communication channels between agent-based systems and DSOs to facilitate uninterrupted participation in transactions. To address this, future research could explore the feasibility of deploying offline TE programs that ensure the agent makes decisions even without some communication between agents. Such programs could provide a more resilient framework for transactive energy systems.

CRediT authorship contribution statement

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

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Kodjo Agbossou reports financial support was provided by Natural Sciences and Engineering Research Council of Canada. Kodjo Agbossou reports a relationship with Natural Sciences and Engineering Research Council of Canada that includes: funding grants. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The authors do not have permission to share data.

References

- [1] R. Ghorani, M. Fotuhi-Firuzabad, M. Moeini-Aghtaie, Main challenges of implementing penalty mechanisms in transactive electricity markets, *IEEE Trans. Power Syst.* 34 (5) (2019) 3954–3956, <http://dx.doi.org/10.1109/TPWRS.2019.2908587>, URL <https://ieeexplore.ieee.org/document/8678451/>.
- [2] R. Ghorani, H. Farzin, M. Fotuhi-Firuzabad, F. Wang, Market design for integration of renewables into transactive energy systems, *IET Renew. Power Gener.* 13 (14) (2019) 2502–2511, <http://dx.doi.org/10.1049/iet-rpg.2019.0551>, URL <https://onlinelibrary.wiley.com/doi/10.1049/iet-rpg.2019.0551>.
- [3] F. Lopes, H. Coelho, Electricity markets with increasing levels of renewable generation: Structure, operation, agent-based simulation, and emerging designs, in: *Studies in Systems, Decision and Control*, vol. 144, Springer International Publishing, 2018, <http://dx.doi.org/10.1007/978-3-319-74263-2>, URL <http://link.springer.com/10.1007/978-3-319-74263-2>.
- [4] B. Kuipers, Trust and cooperation, *Front. Robot. AI* 9 (April) (2022) 1–18, <http://dx.doi.org/10.3389/frobt.2022.676767>.
- [5] M. Müller, Belief-independence and (robust) strategy-proofness, *Theory and Decision* 96 (3) (2024) 443–461, <http://dx.doi.org/10.1007/s11238-023-09955-7>, URL <https://link.springer.com/10.1007/s11238-023-09955-7>.

- [6] I.V. Chremos, A.A. Malikopoulos, Mechanism design theory in control engineering: A tutorial and overview of applications in communication, power grid, transportation, and security systems, *IEEE Control. Syst.* 44 (1) (2024) 20–45, <http://dx.doi.org/10.1109/MCS.2023.3329919>, URL <https://ieeexplore.ieee.org/document/10384599/>.
- [7] J. Watson, *Strategy*, W. W. Norton and Company, 2013.
- [8] F. Satoshi, Prescription for social dilemmas: Psychology for urban, transportation, and environmental problems, *Prescription for Social Dilemmas: Psychology for Urban, Transportation, and Environmental Problems*, Springer Japan, 2017, pp. 1–215, <http://dx.doi.org/10.1007/978-4-431-55618-3>.
- [9] L. Fisher, *Rock, Paper, Scissors: Game Theory in Everyday Life*, Basic Books, 2008.
- [10] E. Parilina, P. Viswanadha Reddy, G. Zaccour, Handbook of dynamic game theory, in: *A Course of Noncooperative and Cooperative Games Played over Event Trees*, vol. 51, Springer International Publishing, 2018, <http://dx.doi.org/10.1007/978-3-319-44374-4>, URL <http://link.springer.com/10.1007/978-3-319-44374-4>.
- [11] L. Jain, X. Wu, *Game Theoretic Problems in Network Economics and Mechanism Design Solutions*, Springer London, London, 2009, <http://dx.doi.org/10.1007/978-1-84800-938-7>, URL <https://link.springer.com/10.1007/978-1-84800-938-7>.
- [12] Y. Shoham, K. Leyton-Brown, Multiagent systems, *Multiagent Systems: Algorithmic, Game-Theoretic, and Logical Foundations*, Cambridge University Press, 2008, <http://dx.doi.org/10.1017/CBO9780511811654>.
- [13] L. Nespoli, M. Salani, V. Medici, A rational decentralized generalized Nash equilibrium seeking for energy markets, in: *2018 International Conference on Smart Energy Systems and Technologies, SEST, IEEE*, 2018, pp. 1–6, <http://dx.doi.org/10.1109/SEST.2018.8495809>, URL <https://ieeexplore.ieee.org/document/8495809/>.
- [14] Y. Chen, W.S. Lin, F. Han, Y.-H. Yang, Z. Safar, K.J.R. Liu, A cheat-proof game theoretic demand response scheme for smart grids, in: *2012 IEEE International Conference on Communications, ICC, IEEE*, 2012, pp. 3362–3366, <http://dx.doi.org/10.1109/ICC.2012.6364397>, URL <http://ieeexplore.ieee.org/document/6364397/>.
- [15] Y. Chen, W.S. Lin, F. Han, Y.-H. Yang, Z. Safar, K.J.R. Liu, Incentive compatible demand response games for distributed load prediction in smart grids, *APSIPA Trans. Signal Inf. Process.* 3 (1) (2014) 1–13, <http://dx.doi.org/10.1017/ATSIP.2014.8>, URL <http://www.nowpublishers.com/article/Details/SIP-021>.
- [16] K. Ma, P.R. Kumar, Incentive compatibility in stochastic dynamic systems, *IEEE Trans. Autom. Control* 66 (2) (2021) 651–666, <http://dx.doi.org/10.1109/TAC.2020.2987802>, URL <https://ieeexplore.ieee.org/document/9068413/>.
- [17] Y. Wasa, K. Hirata, K. Uchida, A contract theory approach to dynamic incentive mechanism and control synthesis for moral hazard in power grids, *IEEE Trans. Control Syst. Technol.* 30 (5) (2022) 2072–2083, <http://dx.doi.org/10.1109/TCST.2021.3130922>, URL <https://ieeexplore.ieee.org/document/9644928/>.
- [18] B. Satchidanandan, M.A. Dahleh, Incentive compatibility in two-stage repeated stochastic games, *IEEE Trans. Control. Netw. Syst.* 11 (1) (2024) 295–306, <http://dx.doi.org/10.1109/TCNS.2023.3280861>, URL <https://ieeexplore.ieee.org/document/10138437/>.
- [19] M. Montazeri, H. Kebriaei, B.N. Araabi, A tractable truthful profit maximization mechanism design with autonomous agents, *IEEE Trans. Autom. Control PP* (iii) (2024) 1–6, <http://dx.doi.org/10.1109/TAC.2024.3360335>, URL <https://ieeexplore.ieee.org/document/10416648/>.
- [20] F. Etedadi Aliabadi, K. Agbossou, S. Kelouwani, N. Henao, S.S. Hosseini, Coordination of smart home energy management systems in neighborhood areas: A systematic review, *IEEE Access* 9 (2021) 36417–36443, <http://dx.doi.org/10.1109/ACCESS.2021.3061995>, URL <https://ieeexplore.ieee.org/document/9363112/>.
- [21] S.M. Ghorashi, M. Rastegar, S. Senemmar, A.R. Seifi, Optimal design of reward-penalty demand response programs in smart power grids, *Sustain. Cities Soc.* 60 (May) (2020) 102150, <http://dx.doi.org/10.1016/j.scs.2020.102150>.
- [22] G. Tsaousoglou, K. Steriotis, N. Efthymiopoulos, P. Makris, E. Varvarigos, Truthful, practical and privacy-aware demand response in the smart grid via a distributed and optimal mechanism, *IEEE Trans. Smart Grid* 11 (4) (2020) 3119–3130, <http://dx.doi.org/10.1109/TSG.2020.2965221>, URL <https://ieeexplore.ieee.org/document/8954657/>.
- [23] B. Dulipala, S. Debbarma, Energy scheduling model considering penalty mechanism in transactive energy markets: A hybrid approach, *Int. J. Electr. Power Energy Syst.* 129 (June 2020) (2021) 106742, <http://dx.doi.org/10.1016/j.ijepes.2020.106742>.
- [24] J.B. Dulipala, S. Debbarma, Decision-making model with reduced risk of penalties in transactive energy markets, *Electr. Power Syst. Res.* 199 (May) (2021) 107371, <http://dx.doi.org/10.1016/j.epsr.2021.107371>.
- [25] Y. Yao, C. Gao, K. Lai, T. Chen, J. Yang, An incentive-compatible distributed integrated energy market mechanism design with adaptive robust approach, *Appl. Energy* 282 (2021) 116155, <http://dx.doi.org/10.1016/j.apenergy.2020.116155>, URL <https://linkinghub.elsevier.com/retrieve/pii/S0306261920315609>.
- [26] W. Zhong, K. Xie, Y. Liu, S. Xie, L. Xie, Nash mechanisms for market design based on distribution locational marginal prices, *IEEE Trans. Power Syst.* 37 (6) (2022) 4297–4309, <http://dx.doi.org/10.1109/TPWRS.2022.3152517>.
- [27] M.D. de Souza Dutra, N. Alguacil, Fairness of prosumers' incentives in residential demand response: A practical decentralized optimization approach, *Int. J. Electr. Power Energy Syst.* 148 (December 2022) (2023) 109015, <http://dx.doi.org/10.1016/j.ijepes.2023.109015>, <https://linkinghub.elsevier.com/retrieve/pii/S0142061523000728>.
- [28] K. Zhang, Y. Xu, H. Sun, Bilevel optimal coordination of active distribution network and charging stations considering EV drivers' willingness, *Appl. Energy* 360 (2024) 122790, <http://dx.doi.org/10.1016/j.apenergy.2024.122790>, URL <https://linkinghub.elsevier.com/retrieve/pii/S0306261924001739>.
- [29] M. Hoseinpour, M. Hoseinpour, M. Haghighifam, M.R. Haghighifam, Privacy-preserving and approximately truthful local electricity markets: A differentially private VCG mechanism, *IEEE Trans. Smart Grid* 15 (2) (2024) 1991–2003, <http://dx.doi.org/10.1109/TSG.2023.3301174>.
- [30] A. Parrado-Duque, N. Henao, K. Agbossou, S. Kelouwani, J.C. Oviedo-Cepeda, J. Domínguez-Jiménez, Is it worthwhile to participate in transactive energy? A decision-making model for empowering residential customers, *Electr. J.* 37 (7–10) (2024) 107447, <http://dx.doi.org/10.1016/J.TEJ.2024.107447>, URL <https://linkinghub.elsevier.com/retrieve/pii/S1040619024000824>.
- [31] S.S. Binyamin, S.A. Ben Slama, B. Zafar, Artificial intelligence-powered energy community management for developing renewable energy systems in smart homes, *Energy Strat. Rev.* 51 (January) (2024) 101288, <http://dx.doi.org/10.1016/j.esr.2023.101288>, <https://linkinghub.elsevier.com/retrieve/pii/S2211467X23002389>.
- [32] D. Cserssik, Simulation-based estimation of the economic benefits implied by coordinated balancing capacity procurement and deployment in a day-ahead market model, *Energy Strat. Rev.* 50 (October) (2023) 101248, <http://dx.doi.org/10.1016/j.esr.2023.101248>, <https://linkinghub.elsevier.com/retrieve/pii/S2211467X23001980>.
- [33] A. Kumar, A.R. Singh, R.S. Kumar, Y. Deng, X. He, R. Bansal, P. Kumar, R. Naidoo, An effective energy management system for intensified grid-connected microgrids, *Energy Strat. Rev.* 50 (September) (2023) 101222, <http://dx.doi.org/10.1016/j.esr.2023.101222>, <https://linkinghub.elsevier.com/retrieve/pii/S2211467X23001724>.
- [34] J. Stute, M. Kühnbauch, Dynamic pricing and the flexible consumer – Investigating grid and financial implications: A case study for Germany, *Energy Strat. Rev.* 45 (December 2022) (2023) 100987, <http://dx.doi.org/10.1016/j.esr.2022.100987>, <https://linkinghub.elsevier.com/retrieve/pii/S2211467X2200181X>.
- [35] J. Domínguez-Jiménez, N. Henao, K. Agbossou, A. Parrado, J. Campillo, S.H. Nagarsheth, A stochastic approach to integrating electrical thermal storage in distributed demand response for nordic communities with wind power generation, *IEEE Open J. Ind. Appl.* 4 (April) (2023) 121–138, <http://dx.doi.org/10.1109/OJIA.2023.3264651>, URL <https://ieeexplore.ieee.org/document/10093061/>.
- [36] J. Domínguez, A. Parrado-Duque, O.D. Montoya, N. Henao, J. Campillo, K. Agbossou, Techno-economic feasibility of a trust and grid-aware coordination scheme, in: *2023 IEEE Texas Power and Energy Conference, TPEC, IEEE*, 2023, pp. 1–5, <http://dx.doi.org/10.1109/TPEC56611.2023.10078675>, URL <https://ieeexplore.ieee.org/document/10078675/>.
- [37] M. Sarfati, M.R. Hesamzadeh, P. Holmberg, Production efficiency of nodal and zonal pricing in imperfectly competitive electricity markets, *Energy Strat. Rev.* 24 (August 2018) (2019) 193–206, <http://dx.doi.org/10.1016/j.esr.2019.02.004>, <https://linkinghub.elsevier.com/retrieve/pii/S2211467X19300203>.
- [38] M. Haji Bashi, G. Yousefi, H. Gharagozloo, H. Khazraj, C. Leth Bak, F. Fariada Silva, A Comparative Study on the Bidding Behaviour of Pay as Bid and Uniform Price Electricity Market Players, in: *2018 IEEE International Conference on Environment and Electrical Engineering and 2018 IEEE Industrial and Commercial Power Systems Europe, IEEEIC/ICPS Europe, IEEE*, 2018, pp. 1–6, <http://dx.doi.org/10.1109/IEEEIC.2018.8493776>, URL <https://ieeexplore.ieee.org/document/8493776/>.
- [39] N. Mazzi, J. Kazempour, P. Pinson, Price-taker offering strategy in electricity pay-as-bid markets, *IEEE Trans. Power Syst.* 33 (2) (2018) 2175–2183, <http://dx.doi.org/10.1109/TPWRS.2017.2737322>.
- [40] A.G. Vlachos, P.N. Biskas, Demand response in a real-time balancing market clearing with pay-as-bid pricing, *IEEE Trans. Smart Grid* 4 (4) (2013) 1966–1975, <http://dx.doi.org/10.1109/TSG.2013.2256805>, URL <http://ieeexplore.ieee.org/document/6520964/>.
- [41] Q. Liu, X. Fang, C. Bai, X. Fang, Modeling and analysis of generator's strategic bidding under marginal pricing and pay-as-bid pricing methods, in: *2022 5th International Conference on Energy, Electrical and Power Engineering, CEEPE, IEEE*, 2022, pp. 982–988, <http://dx.doi.org/10.1109/CEEPE55110.2022.9783351>, URL <https://ieeexplore.ieee.org/document/9783351/>.
- [42] A. Ali, J.Z. Kolter, S. Diamond, S. Boyd, Disciplined convex stochastic programming: A new framework for stochastic optimization, *UAI 2015*, in: *Uncertainty in Artificial Intelligence - Proceedings of the 31st Conference*, vol. 1, (3) 2015, pp. 62–71.
- [43] R. Cheng, L. Tesfatsion, Z. Wang, A consensus-based transactive energy design for unbalanced distribution networks, *IEEE Trans. Power Syst.* (2022) 1, <http://dx.doi.org/10.1109/TPWRS.2022.3158900>, URL <https://ieeexplore.ieee.org/document/9735416/>.
- [44] Hydro-Quebec, *Annual Report 2022*, Tech. rep., Hydro-Quebec, 2022.

- [45] R. Arnedo, N. Henao, K. Agbossou, J.C. Oviedo-Cepeda, J.A. Dominguez, D. Toquica, OpenATE: A distributed co-simulation engine for transactive energy systems, in: 2023 IEEE 11th International Conference on Smart Energy Grid Engineering, SEGE, IEEE, 2023, pp. 188–193, <http://dx.doi.org/10.1109/SEGE59172.2023.10274534>, URL <https://ieeexplore.ieee.org/document/10274534/>.
- [46] L. Rueda, K. Agbossou, N. Henao, S. Kelouwani, J.C. Oviedo-Cepeda, B. Le Lostec, S. Sansregret, M. Fournier, Online unsupervised occupancy anticipation system applied to residential heat load management, IEEE Access 9 (2021) 109806–109821, <http://dx.doi.org/10.1109/ACCESS.2021.3098631>, URL <https://ieeexplore.ieee.org/document/9491101/>.
- [47] J. Qin, Y. Wan, F. Li, Y. Kang, W. Fu, Distributed economic operation in smart grid: Model-based and model-free perspectives, in: Studies in Systems, Decision and Control, vol. 455, Springer Nature Singapore, Singapore, 2023, <http://dx.doi.org/10.1007/978-981-19-8594-2>, URL <https://link.springer.com/10.1007/978-981-19-8594-2>.
- [48] J.A. Dominguez, K. Agbossou, N. Henao, S.H. Nagarsheth, J. Campillo, L. Rueda, Distributed stochastic energy coordination for residential prosumers: Framework and implementation, Sustain. Energy, Grids Networks 38 (2024) 101324, <http://dx.doi.org/10.1016/j.segan.2024.101324>, URL <https://linkinghub.elsevier.com/retrieve/pii/S2352467724000535>.
- [49] S.J. Taylor, B. Letham, Forecasting at scale, 2017, <http://dx.doi.org/10.7287/peerj.preprints.3190v2>, PeerJ Preprints.
- [50] P. Jacquot, O. Beaude, S. Gaubert, N. Oudjane, Analysis and implementation of an hourly billing mechanism for demand response management, IEEE Trans. Smart Grid 10 (4) (2019) 4265–4278, <http://dx.doi.org/10.1109/TSG.2018.2855041>, URL <https://ieeexplore.ieee.org/document/8410042/>.
- [51] P. Jacquot, O. Beaude, S. Gaubert, Demand response in the smart grid: The impact of consumers temporal preferences, in: 2017 IEEE International Conference on Smart Grid Communications, SmartGridComm, IEEE, 2017, pp. 540–545, <http://dx.doi.org/10.1109/SmartGridComm.2017.8340690>, URL <http://ieeexplore.ieee.org/document/8340690/>.
- [52] X. Wang, N. Xiao, L. Xie, E. Frazzoli, D. Rus, Analysis of price of anarchy in heterogeneous price-sensitive populations, in: 53rd IEEE Conference on Decision and Control, IEEE, 2014, pp. 6478–6483, <http://dx.doi.org/10.1109/CDC.2014.7040405>, URL <http://ieeexplore.ieee.org/document/7040405/>.
- [53] X. Wang, N. Xiao, L. Xie, E. Frazzoli, Analysis of price of total anarchy in congestion games via smoothness arguments, IEEE Trans. Control. Netw. Syst. 4 (4) (2017) 876–885, <http://dx.doi.org/10.1109/TCNS.2016.2592678>, URL <http://ieeexplore.ieee.org/document/7515192/>.
- [54] H. Ming, J. Meng, C. Gao, M. Song, T. Chen, D.-H. Choi, Efficiency improvement of decentralized incentive-based demand response: Social welfare analysis and market mechanism design, Appl. Energy 331 (2023) 120317, <http://dx.doi.org/10.1016/j.apenergy.2022.120317>, URL <https://linkinghub.elsevier.com/retrieve/pii/S0306261922015744>.
- [55] J. Hussain, Q. Huang, J. Li, Z. Zhang, F. Hussain, S.A. Ahmed, K. Manzoor, Optimization of social welfare in P2P community microgrid with efficient decentralized energy management and communication-efficient power trading, J. Energy Storage 81 (2024) 110458, <http://dx.doi.org/10.1016/j.est.2024.110458>, URL <https://linkinghub.elsevier.com/retrieve/pii/S2352152X24000434>.
- [56] J.P. Bailey, The Price of Deception in Social Choice (Ph.D. thesis), Georgia Institute of Technology, 2017, URL <http://hdl.handle.net/1853/59189>.

3.2.5 Clarifications of 3.2

- An editorial mistake was made in the explanation text of Equation (11), where the units for the fixed power grid cost λ is $\text{¢ } \$/kWh^2$.

3.3 Preventing strategic behavior of residential agents in an iterative negotiation framework based on the analysis of RAs strategies

3.3.1 Background

One-shot negotiation mechanisms can be practical when the coordinator has sufficient energy reserves to manage demand spikes, as they minimize computational and communication overhead. However, these mechanisms often sacrifice efficiency and flexibility in an incomplete, asymmetric, and imperfect information context. In contrast, iterative clearing approaches allow multiple rounds of interaction, enabling the coordinator to refine price and penalty signals until convergence, thereby improving system performance and fairness.

Despite these advantages, iterative frameworks introduce new challenges. In a day-ahead market setting, RAs may behave strategically, exploiting the negotiation process to maximize their individual benefits. Such behavior typically involves misreporting planned consumption at one or more iterations to influence future price signals or reduce penalties. This opportunistic conduct can undermine the mechanism's objectives, leading to inefficiencies and jeopardizing grid reliability.

To address this issue, this work analyzes RA strategies within an iterative negotiation framework and demonstrates that the proposed mechanism achieves a dominant strategy equilibrium, ensuring IC. Under this design, truthful reporting becomes the most

advantageous strategy for each RA at every iteration, regardless of the actions of other participants.

3.3.2 Methodology

The proposed mechanism is modeled as an iterative Stackelberg game between a coordinator (leader) and multiple RAs (followers). The coordinator solves an upper-level stochastic optimization problem to determine dynamic prices (rewards) and penalties for deviations. At the same time, each RA solves a lower-level optimization problem to update its consumption plan. This process repeats until convergence or a stopping criterion is met.

The information structure is incomplete, imperfect, and asymmetric: RAs retain their private types (preferences, constraints) and do not communicate with each other, while the coordinator observes only aggregated plans. Communication occurs exclusively between the coordinator and each RA through bidirectional signals.

The study evaluates RA behavior under different reporting strategies to assess strategic robustness. Two baseline scenarios are considered: (i) all agents report truthfully, and (ii) misreport. Additionally, a cross-strategy analysis examines mixed behaviors. The payment rule—which combines actual energy charges with penalties for deviations from reported plans—is central to this analysis. Finally, the performance of the coordination mechanism is compared against a non-coordinated baseline to quantify system-level benefits.

3.3.3 Outcomes

The analysis confirms that, under the proposed payment rule, the cost of misreporting at any iteration exceeds the cost of truthful reporting, even if the negotiation terminates immediately after the deviation. This result holds independently of other agents' actions, establishing truth-telling as a dominant strategy and validating the IC property. Moreover,

Eq. (3) develops the condition for satisfying the IR condition in terms of the penalty vector (α), i.e., ensuring that customers opt to enroll in the negotiation.

Beyond strategic robustness, the mechanism delivers tangible operational benefits. Coordinated participation significantly reduces peak demand compared to the non-coordination scenario, improving grid stability. Although RAs incur comfort sacrifices to adjust their consumption, they experience lower electricity bills relative to the baseline, creating a win-win outcome for both customers and the coordinator. Furthermore, the study suggests that, under certain conditions, the mechanism can reach the social welfare optimum. However, achieving long-term sustainability may require additional measures, such as subsidies or redistribution schemes, to maintain budget balance without discouraging participation.

3.3.4 Paper 3

Highlights

A Reward-Penalty Mechanism to Prevent Strategic-Agents Behaviour in an Iterative Negotiation Framework: A Transactive Energy Context

Alejandro Parrado-Duque, Sousso Kelouwani, Kodjo Agbossou, Nilson Henao, Juan C. Oviedo-Cepeda, Juan Domínguez-Jiménez

- Agents may exploit an iterative negotiation framework for their benefit.
- The coordinator designs a strategy-proof mechanism for an iterative negotiation.
- Residential agents opt in based on their individual rationality condition.
- The mechanism's efficiency depends on the likelihood of moving to the next iteration.

A Reward-Penalty Mechanism to Prevent Strategic-Agents Behaviour in an Iterative Negotiation Framework: A Transactive Energy Context

Alejandro Parrado-Duque^{a,*}, Souso Kelouwani^b, Kodjo Agbossou^a, Nilson Henao^a, Juan C. Oviedo-Cepeda^c, Juan Domínguez-Jiménez^a

^aDepartment of Electrical and Computer Engineering, Hydrogen Research Institute, Laboratoire d'innovation et de recherche en énergie intelligente, Université du Québec à Trois-Rivières, 3351, boulevard des Forges, Trois-Rivières, G8Z 4M3, Québec, Canada

^bDepartment of Mechanical Engineering, Hydrogen Research Institute, Laboratoire d'innovation et de recherche en énergie intelligente, Université du Québec à Trois-Rivières, 3351, boulevard des Forges, Trois-Rivières, G8Z 4M3, Québec, Canada

^cHydro-Québec, 75, boulevard René-Lévesque Ouest, Montréal, H2Z 1A4, Québec, Canada

Abstract

The day-ahead electricity market is crucial for planning the operation of a power grid's assets in advance. However, this market currently faces the challenge of strategic behaviour by residential agents, a feature enabled by the deployment of transactive energy systems at the residential level. In an iterative negotiation approach, strategic agents may exploit weaknesses in the mechanism by reporting false information to maximize financial gains, thereby compromising the program's long-term sustainability. This paper proposes a distributed privacy-preserving mechanism that prevents strategic residential agents from reporting false consumption plans in a day-ahead electricity market. The mechanism comprises three phases: (i) a negotiation phase, modelled as a convex bilevel stochastic optimization problem, where residential agents and a coordinator iteratively agree on electricity prices, penalties for deviations, and individualized consumption plan; (ii) an execution phase, where residential agents optimize their real-time consumptions based on disclosed uncertainties; and (iii) a settlement phase, where the coordinator charges the customers with an electricity bill by applying the formal payment rule reported before the negotiation starts. Theoretical analysis demonstrates that truthful reporting constitutes a dominant strategy at every iteration, yielding a strategy-proof mechanism. Simulation results validate the mechanism's effectiveness, showing a 19.1% reduction in peak energy consumption and a decrease in average electricity prices from 8.05¢ to 4.03¢/kWh, satisfying individual rationality for participants. While the mechanism satisfies incentive compatibility, ex-ante efficiency, and IR, it exhibits a budget imbalance. This fact suggests that long-term financial viability requires external subsidies or complementary market strategies.

Keywords: Day-ahead market, Game theory, Incentive compatibility, Mechanism Design, Reward-Penalty mechanism, Stochastic programming, Transactive energy.

Nomenclature

Acronyms

BB Budget balance.

DR Demand response.

Eff Efficiency.

IC Incentive compatibility.

IR Individual rationality.

MD Mechanism design.

OPT Optimal social outcome.

RA Residential agent.

TE Transactive energy.

Functions

PR Payment rule.

Indices

i Index of iterations.

n Index of residential agents (RAs).

t Index of time-step in vector variables.

Parameters

T_{ext} Outdoor temperature vector.

$T_{SP,n}$ Inner dwelling temperature set-point vector for RA n .

γ_n Thermal discomfort valuation for RA n .

λ Grid cost parameter.

ρ_{coord} Grid cost weight.

*Corresponding author.

Email address: alejandro.parrado@uqtr.ca (Alejandro Parrado-Duque)

τ	Proximal decomposition parameter.
τ_{coord}	Price iteration weight.
A_n, B_n, C_n	Weighted state-space temperature model parameters for RA n .
T	Market horizon.
p	Probability of stopping the game at the current iteration.
Sets	
$\mathcal{N}$	Set of RAs.
Variables	
$\alpha_{n,i}$	Penalty value for RA n at iteration i .
$\hat{e}_{n,i}$	Reported energy demand vector for RA n at iteration i .
π_i	Electricity price vector at iteration i .
ζ_n	Reported consumption error for RA n .
$e_{fix,n,i}$	Fixed demand vector for RA n at iteration i .
$e_{n,i}$	Energy demand vector for RA n at iteration i .
$e_{var,n,i}$	Controllable demand vector for RA n at iteration i .
r_n	Demand error vector for RA n .
$T_{n,i}$	Inner dwelling temperature for RA n at iteration i .
OPT	Optimal social outcome
PoA	Price of Anarchy.
PoS	Price of Stability.

1. Introduction

Latest advances in agent technology are advancing the digitalisation of the electricity sector [1]. Agents are autonomous machines that make decisions on behalf of their users according to their particular interests [2]. In the electricity sector, these agents enable consumers to participate actively in energy and power markets, facilitating demand-side management for the system operators [3]. Agents can participate in forward, real-time, and/or spot markets to provide different grid services [4]. Thus, they may help alleviate the substantial grid stress growth driven by the energy transition, a worldwide concern [5].

The energy transition has driven a growing trend in electricity demand as energy use is electrified [5]. In this context, agent coordinators become fundamental for providing precise incentives to modulate demand patterns and shift consumption peaks [6]. This work explores a coordinating strategy to shape the power profiles of residential agents (RAs) in a day-ahead electricity market. The objective is to design a mechanism to negotiate the RAs' consumption plan, taking into account their interests (a selfish attribute), bounded rationality, and intelligence

[7]. The interaction between a coordinator and RAs employs price and penalty signals. Indeed, it is modeled as a game, with the coordinator as the leader and the RAs as the followers.

A clear-cut option for the coordinator agent is to request all RAs' private information to find the consumption plan that reduces peak demand while ensuring energy sales. A more workable option is to send incentives, via the electricity price, to modulate the aggregated power profile while the customer's information remains private [8]. The interaction mechanism depends on the type and amount of information exchanged by the participants, as this determines whether one-shot or iterative algorithms should be employed to clear the market. One-shot implies a single signal from the coordinator and just one feedback from the RAs [9]. Conversely, an iterative algorithm comprises several rounds where agents exchange different signals until reaching an agreement [10]. This work focuses on an iterative algorithm for clearing the day-ahead market while preserving customers' data privacy. In this regard, RAs keep their types private and share only their day-ahead consumption plan with the coordinator, who tries to shape it at each round.

The minimal information exchange of the RAs is not the sole challenge the coordinator agent must address. RAs are strategic, which naturally seek to exploit a negotiation mechanism's weakness to obtain better self-outcomes without considering social consequences, i.e., their only interest is to minimize their costs. Previous works considered such a condition for one-shot game interactions [9]. However, dealing with strategic agents remains an open challenge for coordinators in iterative electricity markets.

Therefore, the coordinator must solve some fundamental questions that arise in the iterative game. First, can any or all RAs share false information with the coordinator during the negotiation or at any round of the iterative algorithm? How can a coordinator be confident about the veracity of the information shared by RAs? Is it possible to prevent the strategic behaviour of RAs? In this regard, the coordinator must design a strategy-proof mechanism in which RAs find it costly to report false information; thus, they prefer to share truthful information over iterations. This strategic-proof feature is called incentive compatibility (IC) in the field of mechanism design [11].

In addition to the truthfulness-IC condition, the coordinator must design a mechanism that makes RAs' participation in the negotiation financially attractive. RAs will not participate otherwise, given the mechanism's individual-rationality (IR) condition. Besides, the resulting agreement should achieve an efficient level while also balancing revenues and costs. These complementary properties are economic efficiency (Eff) and budget balance (BB), respectively [12].

As a remark, IC and BB are typically assessed in the settlement phase of the agreements, whereas IR and Eff can be considered at any phase (*ex-ante*, *interim*, *ex-post*, or *settlement*) [9]. This distinction is relevant because the market leader must analyze the effects of followers' strategies on the metrics of the mechanism design concepts at each applicable phase.

Another relevant distinction lies between the *ex-post* and *settlement* phases. In the former, the coordinator could offer contract changes, such as compensation or rewards. In the latter,

the coordinator bills each RA based on the agreed payment rule (PR). The PR is one of the relevant parameters for the RAs to formulate consumption strategies.

1.1. State of the art

Relevant literature from the last five years was associated with the scope of this work in Table 1. These works have been classified based on market architecture (submarket: day-ahead, spot, or real-time, and market control: centralised, decentralised, or distributed), market clearing method (one-shot or iterative), incentive-based (reward and/or penalty based), knowledge (common or mutual), information (complete or incomplete, symmetric or asymmetric, and perfect or imperfect), and the mechanism design concepts assessment (individual rationality and efficiency in an *ex-ante*, *interim*, or *ex-post* phase, budget balance: weak or strong, and incentive compatibility).

For the sake of clarification, submarkets differ in temporal granularity [2]: the day-ahead market requires decisions for the next twenty-four hours; the spot market (also called intraday) typically involves scheduling five to fifteen minutes in advance; and the real-time market operates on a much shorter timescale, usually seconds to one minute ahead. In the case of market controls [13], a centralised control implies a single entity makes decisions on behalf of all participants; a decentralised control shares a common objective with all participants and coordinates among them to achieve it; and in a distributed control, each agent acts independently to pursue its goals, reaching consensus through negotiations. For market-clearing methods [10], one-shot decisions are made in a single round based on available information, while iterative decisions evolve over multiple rounds, depending on the information shared and the computational capacity of the coordinating entity. Incentive-based rewards and/or penalty mechanisms depend on how the coordinator encourages residential agents to adopt a specific consumption behaviour [14]. Common knowledge implies that all agents know a fact, and they know that all others know it, *ad infinitum*; by contrast, mutual knowledge means all agents know the fact, but it is not necessarily known that others know it (or that they know that others know, and so on) [12]. Information is complete when every market participant (in this context, the coordinator and the RAs) has unrestricted access to the full set of information possessed by all other participants; otherwise, it is incomplete [12]. Information is symmetric if all market participants access the same information; otherwise, it is asymmetric [15]. Information is perfect if any market participant can access the decisions of the others at any stage of the negotiation; otherwise, it is imperfect [15]. Finally, the concepts of mechanism design, IR, Eff, BB, and IC, and the phases *ex-ante*, *interim*, and *ex-post* have already been introduced.

In [16], a distribution company determines a price-penalty pair for calling load flexibility from customers, encouraging them to reduce their consumption during a specific time-period event; however, this work did not design a strategy-proof mechanism, and customers could manipulate it to their benefit by misreporting their consumption baselines. In [17], a three-layer mechanism is modelled that involves a system operator, a flexibility service provider, and user agents to control a flexibility

smart appliance load from the latter; however, the work lacks an assessment of IR for any negotiation phase and BB. In [18], a variant of the Vickrey–Clarke–Groves mechanism is proposed to solve the classical issue in this method of the deficit in the budget balance by implementing a scaled factor; however, the primary assumption about no strategic agents with too negligible or too dominant power on the negotiation misrepresents the real-world conditions, where intelligent agents could infer enough information to manipulate the mechanism of a negotiation. In [19, 20], the authors proposed a function to penalise market deviations in a day-ahead market; however, the mechanism did not deal with strategic agents, and the IC, IR, Eff, and BB conditions were not demonstrated. In [21], a transactive energy framework was proposed to allocate a cooperative surplus of a combined cooling, heating, and power system while social welfare maximisation, IR, cost recovery, and IC are ensured; however, the mechanism requires an exchange of private information among participants, and therefore, their private information is compromised. In [22], a bid-submission of price and power generation/consumption mechanism from customers is proposed to ensure IR, Eff, and strong BB; however, IC is not ensured, and the submission of bids from customers is not a typical practice in the electricity markets since it requires a considerable level of automation and regulation of agents. In [23], a dynamic incentive mechanism is proposed in an incentivised market for eliciting private information from agents, and a solution to a time-consistency reward design problem is demonstrated; however, the efficiency and budget balance were not addressed in the formulation, nor is a penalty charged to customers for deviations from market obligations. In [24], a two-phase optimisation framework is proposed to coordinate customers' consumption/generation profiles via incentives; although the work considered the concepts of IR, weak BB, and fairness, IC and Eff were not covered, and strategic agents may exploit the mechanism. In [25], a bilevel optimisation problem was formulated to coordinate the charge of electric vehicles (EVs), while the participation willingness of EV drivers was modelled from a psychological perspective; however, the concepts of Eff, BB, and IC were not addressed in the paper, nor a penalty for deviations from a consumption plan. In [26], a variation of a VCG mechanism was proposed in an electricity market to deal with the privacy concerns of customers while reaching a near-optimal solution; although the mechanism proposed kept the accomplishment of IC and IR, the efficiency property was sacrificed, and the natural budget imbalance of the VCG mechanism was not addressed. In [27], a task publisher agent heads a mechanism to elicit customers' private information while aiming to satisfy the IR and IC mechanism properties; however, the mechanism requires full customer type disclosure, and the effects on Eff and BB were not assessed. In [28], the authors introduce a dominant-strategy, non-bankrupting equilibrium concept while reducing the informational and computational burden on agents. This is accomplished by reducing the complexity of processing data derived from the behavior of other market participants. Although the IR, Eff, and IC properties were addressed in the proposed framework, the mechanism still requires agents to possess full

Table 1: State of the art.

Ref.			[16]	[17]	[18]	[19]	[20]	[21]	[22]	[23]	[24]	[25]	[26]	[27]	[28]	[4]	[9]	This work
Year			2020	2020	2021	2021	2021	2021	2022	2022	2023	2024	2024	2024	2024	2024	2025	2025
Market architecture	Submarket	Day-ahead	✓	✓	X	✓	✓	✓	X	X	✓	✓	X	X	✓	✓	✓	✓
		Spot	X	X	X	X	X	X	✓	X	X	X	✓	✓	X	X	X	X
		Real-time	X	X	✓	X	X	X	✓	X	X	X	X	X	X	X	X	X
	Market control	Centralised	X	X	✓	X	X	X	X	X	X	X	✓	X	✓	X	X	X
		Decentralised	X	X	X	X	✓	X	✓	✓	✓	X	X	✓	X	X	X	X
		Distributed	✓	✓	X	✓	X	✓	X	X	X	✓	X	✓	X	✓	✓	✓
Market clearing method	One-shot		✓	X	✓	X	X	X	X	✓	X	✓	✓	✓	X	✓	X	✓
	Iterative		X	✓	X	✓	✓	✓	✓	X	✓	X	X	✓	X	✓	X	✓
Incentive-based	Reward		✓	✓	✓	X	X	✓	X	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Penalty		✓	X	✓	✓	✓	✓	X	✓	X	X	✓	X	✓	✓	✓	✓
Knowledge	Common		X	X	-	X	X	✓	X	X	X	X	X	X	X	X	X	X
	Mutual		✓	✓	-	✓	✓	X	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Information	Complete		X	X	-	X	X	✓	X	X	X	X	✓	X	X	X	X	X
	Incomplete		✓	✓	-	✓	✓	X	✓	✓	✓	✓	X	✓	✓	✓	✓	✓
	Symmetric		X	X	✓	X	X	✓	X	X	X	X	X	X	X	X	X	X
	Asymmetric		✓	✓	X	✓	✓	X	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Perfect		X	X	✓	X	X	✓	X	X	X	X	X	X	X	X	X	X
	Imperfect		✓	✓	X	✓	✓	X	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mechanism design concepts	IR	Ex-ante	X	X	X	X	X	✓	✓	✓	✓	✓	X	✓	✓	✓	✓	✓
		Interim	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
		Ex-post	X	✓	✓	X	X	X	X	X	X	X	✓	X	X	X	X	X
	Eff	Ex-ante	X	X	X	X	X	X	✓	X	X	X	X	X	✓	X	✓	✓
		Interim	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
		Ex-post	X	✓	✓	X	X	X	X	X	X	X	✓	X	X	X	X	X
	BB	Weak	X	✓	✓	X	✓	X	X	X	✓	X	X	X	X	✓	✓	✓
		Strong	✓	✓	X	X	X	X	✓	X	X	X	X	X	X	X	X	X
	IC		X	✓	✓	X	X	✓	X	✓	X	X	✓	✓	✓	✓	✓	✓

knowledge of the entire probability distribution over the types of other agents, which is impractical, and the BB property was not assessed and declared as an avenue for future research.

In [4], a coordination mechanism based on incentive-penalty was proposed to encourage customers to participate in a TE program; since the work explored a methodology to select penalty values based on the IR concept while ensuring the IC property, the mechanism's efficiency was not assessed, nor was the probability of strategic agents' behaviour through iterations studied. In [9], a one-shot negotiation mechanism for a TE program was proposed to assess the IR, EFF, BB, and IC concepts; however, the agent's strategic manipulation across iterations, as well as an optimal penalty policy, were not addressed.

Recent advancements have further integrated evolutionary game theory with deep reinforcement learning to capture the bounded rationality and adaptive behaviors of market participants [29]. For instance, the deployment of evolutionary smart contracts and multi-stage negotiations has demonstrated significant efficiency gains by incorporating behavioral factors such as loss aversion and adaptive contract windows [30]. Furthermore, the diffusion of strategies across networked agents has been shown to be predominantly governed by compensation and penalty signals [31]. While these behavioral models provide a descriptive analysis of market evolution, this work provides a prescriptive mechanism design approach to ensure that truthful reporting remains the dominant strategy equilibrium, regardless of agent learning dynamics.

1.2. Contributions and Organization

As presented from the existing literature, there is a tendency to propose negotiation mechanisms to address at least one of the main mechanism design concepts. However, despite the well-documented interdependencies between these concepts, contemporary studies often neglect a holistic evaluation of how a

proposed mechanism performs across all relevant dimensions.

Inherent uncertainties could cause deviations from market obligations in a day-ahead market. However, these deviations could also be deliberately and strategically induced by rational, intelligent agents who misreport information during the *ex-ante* (negotiation) phase. Such strategic manipulation of the negotiation process can generate economic inefficiencies, budget imbalances, and, eventually, the termination of the TE program. This outcome can be interpreted as a form of the tragedy of the commons, in which potential future customers' savings are sacrificed by the program's discontinuation.

Accordingly, the primary contributions of this paper focus on the design of a strategy-proof mechanism within an iterative negotiation framework, which can be summarised as follows:

- This work designs a symmetric penalty policy, alongside the pay-as-consumed formulation in the payment rule, that prevents the strategic behaviour of residential agents during iterative negotiations. This milestone is achieved within a Stackelberg game—characterized by a single market leader (the coordinator) and multiple followers (residential agents)—ensuring that truthful reporting remains the dominant strategy.
- This work proposes a feasible region of the penalty variable based on the conditions of incentive compatibility and individual rationality.
- This work assesses the effects of a mechanism that ensures both the incentive compatibility and individual rationality conditions on efficiency and budget balance.

The rest of the paper is organised as follows: Section 2 presents the problem formulation, including the game model and the market phases. Section 3 presents the coordination phase by considering the mathematical formulation from the

coordinator and the RA side. Section 4 presents the mathematical formulation for dealing with strategic agents in an iterative game. Section 5 introduces the scenarios and assumptions considered in this paper. Section 6 presents the simulation results. Finally, Section 7 presents the conclusions of this work and recommends future work.

2. Problem formulation

The considered energy market is cleared day-ahead with incomplete information as the RAs keep their types private. The coordinator agent (the market leader) implements an iterative algorithm to shape the aggregated demand profile, requiring only the RAs' consumption plan at each iteration. Such interaction between the coordinator and the RAs occurs in an *ex-ante* phase; notably, this framework does not consider RAs' interactions or coalition formation among RAs. As rational and strategic actors, RAs seek weaknesses in a mechanism whenever possible to increase their benefit. In this regard, RAs could strategically manipulate the shared consumption plan with the coordinator to influence the negotiation outcomes in their own benefit. The coordinator must thus prevent potential manipulation of RAs by designing an IC, i.e., a strategy-proof mechanism, that makes RAs perceive the greatest benefit from reporting a truthful consumption plan. That is, the RAs recognise communicating real intentions as the optimal strategy.

2.1. Game model

Here, $\mathcal{N}$ represents the set of RAs that a single coordinator handles, indexed by n . Each RA is selfish and tries to minimise its cost based on the price and penalty signals shared by the coordinator at each iteration of the negotiation phase. This electricity market configures a Stackelberg game in which the coordinator acts as the leader and the RAs as followers [4]. The price (π_i), and the consumption report ($\hat{e}_{n,i}$) signals at each iteration i are time-indexed vectors of the size of the market period T . Along with the price, the coordinator shares with the RAs the penalty values (α_i) for the market period to price the deviations from the reported consumption plan. It also informs the probability (p) of passing to the next negotiation iteration. The game information is incomplete since neither the coordinator nor the RAs shares all their data. From the customer side, let denote the vector $\mathbf{e}_{n,i} = [e_{i,n,1}, e_{i,n,2}, \dots, e_{i,n,T}]$ as the true (private) energy consumption plan of customer $n \in \mathcal{N}$ at iteration i .

A key element of the market mechanism is the impossibility of RAs to communicate, so they cannot form coalitions. Thus, possible strategies are to communicate the true consumption plan, i.e., $\mathbf{e}_{i,n} = \hat{\mathbf{e}}_{i,n}$, or to lie, seeking a benefit in cost or comfort. The game builds on the axioms of recall, knowledge, rationality, and corruption rules presented in [4]. Besides, the following game rules are adopted:

- The moves between the coordinator and the RAs are sequential, but the RAs act in parallel to respond to the coordinator.

- The coordinator determines the interaction stop criteria based on the probability p .
- Each RA makes a consumption decision plan based on individual optimisation.
- Participants value their comfort/cost through mathematical models.
- All RAs are enrolled and participate in the market-clearing process.

2.2. Market Phases

The considered market phases are coordination (*ex-ante*), execution (*interim*), and settlement. In the coordination, agents interact day-ahead to agree on coordination signals (prices and penalties for deviation), and consumption plans for the whole market period. The coordinator broadcast the electricity rates, penalties for deviations, and the probability of stopping the negotiation. The RAs, as followers, consider the price and penalty vectors and the probability of stopping the negotiation, and optimise their payoff function to determine the consumption plan to report.

During execution, there is no communication between the agents. Instead, the RAs' uncertainty is disclosed, and they adjust their consumption to avoid penalties while maintaining comfort. Finally, during the settlement phase, the coordinator bills customers based on the agreed coordination signals and actual consumption.

As mentioned, this work contrasts the PR from the cost function. The former corresponds to the billing policy that charges customers for electricity consumption and for deviations from the reported plan. On the other hand, the cost function includes the PR and the valuation of customers' comfort/discomfort. Indeed, the PR is applied by the coordinator during the settlement phase, while the RAs use the cost function to make decisions in the negotiation and execution phases. Equation (1) presents the PR formulation for the iteration i for each RA $n \in \mathcal{N}$.

$$PR_{n,i} = \pi_i \cdot (\mathbf{e}_{n,i} + \mathbf{r}_n) + \alpha_{n,i} \cdot (\mathbf{e}_{n,i} + \mathbf{r}_n - \hat{\mathbf{e}}_{n,i})^{\circ 2} \quad (1)$$

where $(\mathbf{e}_{i,n} + \mathbf{r}_n)$ corresponds to the real electricity consumption of each RA $n \in \mathcal{N}$. Here, $\circ$ denotes the Hadamard power, and $\cdot$ is the standard inner product on a Euclidean vector space. Note that $\mathbf{r}_n$ is a stochastic variable since RAs may not fully regulate energy consumption. It represents uncontrollable deviations from the true private energy plan $\mathbf{e}_{i,n}$. If the customer is committed to consume as reported, i.e., $(\mathbf{e}_{i,n} = \hat{\mathbf{e}}_{i,n})$, it will only pay penalties for deviations $\mathbf{r}_n$.

3. Coordination phase

Mechanism design addresses the limited information constraint in non-cooperative games. In contrast to cooperative games, in which participants share their types, RAs keep their utility functions private. Then, the coordinated goals of reducing electricity provision cost require iterative interactions to

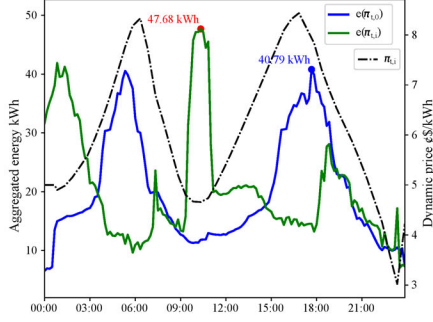


Figure 1: Rebound peak due to a dynamic pricing mechanism.

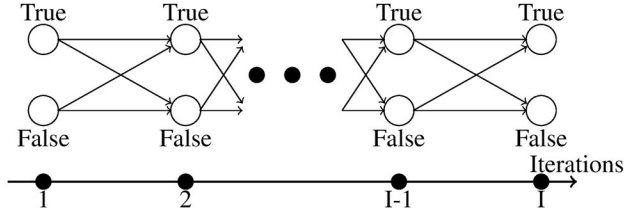


Figure 2: Decision sequence for the RAs in the iterative game.

discover sufficient information. On each iteration, the RAs exchange consumption plans with the game leader or coordinator until convergence criteria are met.

Coordination of consumption plans is crucial to prevent rebound peaks in demand response programs. Fig. 1 illustrates a situation where non-coordinated dynamic prices create an undesirable peak event by shifting demand. The dynamic price follows the peaks of the initial consumption plan to disincentivise consumption, but it motivates all shiftable loads to consume around 9:00 and 12:00. This is a worse scenario for the coordinator, since the resulting peak demand is higher than in the original consumption plan. This situation reveals the need for more sophisticated coordination strategies in the presented context of non-cooperative games.

The coordination phase (*ex-ante*) comprises negotiations between the coordinator and the RAs to agree on a day-ahead consumption plan. The negotiation responds to a bilevel stochastic optimisation problem. At the upper level, the coordinator optimises the prices and penalties (π_i, α_i) . Subsequently, the RAs optimise their consumption report $\hat{e}_{n,i}$ in the lower level. Fig. 2 presents the possibilities for the RAs at each iteration, either they can report the true consumption plan or risk its payoff by communicating false information.

3.1. Coordinator Modelling

The coordinator aims to flatten the aggregated demand profile by leveraging RAs' flexibility. It considers the price of the power grid operation (λ) and a proximal decomposition for the electricity rates. Equation (2) presents the complete objective function for the coordinator.

$$\min_{\pi_i} \mathbb{E} \left[\tau_{coord} \|\pi_i - \pi_{i-1}\|_2^2 + \rho_{coord} \|\pi_i - \lambda \sum_{n \in \mathcal{N}} (\hat{e}_{n,i-1} + \zeta_n)\|_2^2 \right] \quad (2)$$

The electricity provision cost depends on the aggregated demand and the parameter λ [17]. τ_{coord} is the proximal decomposition parameter and ρ_{coord} is a weighing parameter to balance the coordinator objectives.

The resulting π_i is sent to the RAs to optimise their consumption plan. Furthermore, the coordinator agent employs the price from the final agreement iteration to bill the customers according to the payment rule. There are no price modifications (i.e., updated negotiations) during execution or settlement.

In the iterative game, p is the probability of stopping at the current iteration. It is useful for computing an upper bound on the penalty factor under the IR condition. Indeed, the effect of α on the payment rule should not surpass the opportunity cost of not participating in the mechanism. Equation (3) states the necessary condition that makes customers opt for enrolling. Moreover, the IR condition is looking to be satisfied by the penalty value term as presented in Eq. (3), in the sense of controlling the risk perception of penalties by inherent deviations in a day-ahead electricity market.

$$\sum_{t=1}^T \alpha_{n,i,t} \text{Var}[r_{n,t}] < \pi_0 \cdot e_{n,0} - \pi_i \cdot e_{n,i} \quad (3)$$

where π_0 and $e_{n,0}$ are both the electricity price and consumption of each customer under the uncoordinated (initial) conditions.

3.2. Residential Agents Model

For the sake of simplicity, it is assumed that all RAs solve the same problem of controlling a single-zone space heater. Each RA should decide on the consumption $e_{n,i}$ and the report $\hat{e}_{n,i}$ plan. Considering the relationships among these variables at each market phase is valuable for depicting RA decisions. In the negotiation phase, RAs perform stochastic optimisation to report an electricity consumption plan, considering the best decisions they can make at execution time. At the execution phase, the uncertainty is disclosed, and RAs optimise their actual consumption based on the agreed reported values. The objective function comprises three terms: the payment rule, the cost of thermal discomfort, and the proximal decomposition coordination. The payment rule can be decomposed into the cost of electricity imports and the cost of plan deviations [4].

$$\min_{e_{n,i}} \mathbb{E} \left[\min_{e_{n,i}} \sum_{t=1}^T \left(\underbrace{\pi_{i,t}(e_{n,i,t} + r_{n,t})}_{\text{Cost of electricity imports}} + \underbrace{\gamma_n (T_{SP,n,t} - T_{n,i,t})^2}_{\text{Cost of thermal discomfort}} \right) + \underbrace{\alpha_{n,i,t} (e_{n,i,t} + r_{n,t} - \hat{e}_{n,i,t})^2}_{\text{Cost of plan deviations}} + \underbrace{\frac{\tau}{2} (e_{n,i,t} - e_{n,i-1,t})^2}_{\text{Coordination algorithm}} \right] \quad (4)$$

Subject to:

$$T_{n,i,t+1} = A(T_{n,i,t}) + B(e_{var,n,i,t}) + C(T_{ext,t}) \quad (5)$$

$$e_{n,i,t} + r_{n,t} = e_{var,n,i,t} + e_{fix,n,i,t} \quad \forall i, t \quad (6)$$

$$\min(T_{SP,n,t}) \leq T_{n,i,t} \leq \max(T_{SP,n,t}) \quad \forall i, t \quad (7)$$

$$T_{n,i,0} = T_{n,i,T} \quad \forall i \quad (8)$$

$$\hat{e}_{n,i,t}, e_{n,i,t} \geq 0 \quad \forall i, t \quad (9)$$

Notice that $\hat{e}_{n,i}$ is a parameter in the execution phase. Here, γ_n is an individual parameter that weight the thermal discomfort in $\$/^\circ C^2$ [32]. $T_{SP,n,t}$ is the temperature set-point in $^\circ C$, independent and private for each RA $n \in \mathcal{N}$. $T_{n,i,t}$ is the indoor temperature in $^\circ C$. τ is a regularization parameter of the proximal algorithm [33]. Finally, the fixed load $e_{fix,n,i,t}$ corresponds to the part of the demand that is not price-responsive, while $e_{var,n,i,t}$ is the control variable for the space heater.

In the coordination phase, RAs are free to report consumption within the time window allowed by the coordinator at each iteration i . The coordinator communicates the probability of stopping at iteration i to the RAs so they can compute their strategy.

4. Dealing with strategic agents in the iterative-game

In the execution phase, RAs adjust their actual energy consumption, $e_{n,i}$, based on the previously reported plan, $\hat{e}_{n,i}$, and the realization of the stochastic uncertainty, r_n . Consequently, the optimal execution strategy is formulated as a function of the reported plan at the iteration where the game ends. During the coordination phase, the agent evaluates the expected value of its cost function to anticipate optimal real-time actions. The expected value of the error term shall be zero, i.e., $\mathbb{E}[r_{n,t}] = 0 \quad \forall i, t$, therefore, the RAs minimise this expected value with respect to the reported plan. This optimization yields the optimal reporting strategy for $\hat{e}_{n,i}$, as characterized by Eq. (10).

$$(\hat{e}_{n,i,t} - e_{n,i,t}) = \frac{1}{2\alpha_{n,i,t}} \left((1-p) \frac{\partial \pi_{i+1,t}}{\partial \hat{e}_{n,i,t}} e_{n,i+1,t} + \pi_{n,i,t} + \tau(e_{n,i,t} - e_{n,i-1,t}) \right) \quad (10)$$

4.1. Incentive compatibility conditions

IC implies that reporting untruthful information costs more than reporting the actual consumption plan. In other words, the optimal strategy makes the difference between $e_{n,i}$ and $\hat{e}_{n,i}$ zero. In Eq. (10), there is a sole possibility in which reporting truthful information is the less expensive strategy, which is when $\alpha_{n,i,t}$ takes a very high value. Even when the probability of stopping p is one and the influence of $\hat{e}_{n,i,t}$ over $\pi_{n,i+1,t}$, there is still chance to lie depending on the ratio between $\pi_{n,i,t}$ and $\alpha_{n,i,t}$. The last term of Eq. (10) depends on the difference between consecutive iterations, which tends to zero as the algorithm converges.

4.2. RAs' influence on the price mechanism.

A strategic RA acts based on the amount of information it holds about the mechanism and the influence it could exert to exploit it. In this regard, given that the coordinator communicates the $PR_{n,i}$ to each RA before every iteration and there is no modification in the *ex-post* phase, the sole opportunity RAs could find to cheat the game is at the coordination phase. They could map the tendency of the prices from Eq. (2) to the rule presented in Eq. (11).

$$\pi_{i,t} = \frac{\rho_{coord} \lambda \sum_{n=1}^N (\hat{e}_{n,i-1,t} + \text{Var}[\zeta_n]) + \tau_{coord} \pi_{i-1}}{\tau_{coord} + \rho_{coord}}. \quad (11)$$

Notice that the difference in consecutive prices tends to zero as the algorithm converges. Thus, the price tends to the Eq. (12) in the long run.

$$\pi_{i,t} = \lambda \sum_{n=1}^N (\hat{e}_{n,i-1,t} + \text{Var}[\zeta_n]). \quad (12)$$

It is worth highlighting from Eq. (12) that each RA $n \in \mathcal{N}$ could influence the price of the next iteration i by misreporting consumption at iteration $i-1$. As the price becomes proportional to consumption, it is minimum when reporting zero consumption, i.e., $\hat{e}_{n,i-1} = 0$, assuming RAs' strategies are independent, and assuming that RAs could no energy injection to the grid, as stated in Eq. (9).

To establish strategy-proofness across all feasible reports, consider any strategy $\hat{e}_{n,i} = k e_{n,i}$, where $k \in [0, 1]$. Because the RA's expected cost function in Eq. (4) is convex with respect to the reported plan $\hat{e}$, the potential benefit from price manipulation is strictly weighed against the quadratic penalty for plan deviations. Subsection 4.3 demonstrates that truthful reporting ($k = 1$) dominates the extreme misreporting case ($k = 0$), given that the convexity of the cost function ensures that $k = 1$ is the global minimizer [34]. Consequently, the mechanism is robust against any intermediate misreporting level, as any $k < 1$ would result in a higher expected cost due to the quadratic growth of the penalty term relative to the linear reduction in price.

4.3. Dominant strategy equilibrium.

Let's denote C_n as the expected incremental cost incurred by each RA for applying the $PR_{n,i}$ to consider the reporting strategies. The cost depends on the probability of stopping the iterative game, as presented in Eq. (13).

$$C_n(\hat{e}_{n,i}) = p \mathbb{E}[PR_{n,i} | \hat{e}_{n,i}] + p(1-p) \mathbb{E}[PR_{n,i+1} | \hat{e}_{n,i}] \quad (13)$$

From Eq. (13), notice that p represents the probability that the negotiation stops at iteration i . Consequently, the domain of p is $(0, 1]$. The value $p = 0$ is excluded because the negotiation process cannot continue indefinitely in terms of iterations — it will eventually stop according to one of two stopping criteria: a random termination event or convergence. The goal is to prove that RAs minimise C by reporting actual consumption rather than trying to reduce the price in the next iteration, according

to (12). In this context, Eq. (14) presents the necessary IC condition to be satisfied for all RAs.

$$C_n(\hat{\mathbf{e}}_{n,i} = \mathbf{e}_{n,i}) < C_n(\hat{\mathbf{e}}_{n,i} = \mathbf{0}) \quad \forall n. \quad (14)$$

First, let us develop the cost when customers submit a truthful consumption report (left-hand side of inequality Eq. (14)) as follows in Eq. (15).

$$C_n(\hat{\mathbf{e}}_{n,i} = \mathbf{e}_{n,i}) = p(\pi_i \cdot \mathbf{e}_{n,i} + \alpha_{n,i} \cdot \text{diag}(\mathbf{Var}[\mathbf{r}_n])) + p(1-p)(\pi_{i+1} \cdot \mathbf{e}_{n,i+1} + \alpha_{n,i+1} \cdot \text{diag}(\mathbf{Var}[\mathbf{r}_n])) \quad (15)$$

Next, Eq. (16) develops the right-hand side of inequality Eq. (14), when all RAs try to reduce the price by reporting zero electricity consumption at iteration i .

$$C_n(\hat{\mathbf{e}}_{n,i} = \mathbf{0}) = p(\pi_i \cdot \mathbf{e}_{n,i} + \alpha_{n,i} \cdot (\mathbf{e}_{n,i}^{\circ 2} + \text{diag}(\mathbf{Var}[\mathbf{r}_n]))) + p(1-p) \left(\left(\lambda \sum_{n=1}^N \text{Var}[\zeta_n] \right) \mathbf{1} \cdot \mathbf{e}_{n,i+1} + \alpha_{n,i+1} \cdot \text{diag}(\mathbf{Var}[\mathbf{r}_n]) \right) \quad (16)$$

The RA assumes a quadratic cost related to the real consumption amplified by the penalty vector α , if it decides to cheat, and the negotiation stops. Finally, the inequality is developed by replacing the expected cost values to obtain Eq. (17).

$$(1-p)(\pi_{i+1} \cdot \mathbf{e}_{n,i+1}) < \alpha_{n,i} \cdot \mathbf{e}_{n,i}^{\circ 2} + (1-p) \left(\lambda \sum_{n=1}^N \text{Var}[\zeta_n] \right) \mathbf{1} \cdot \mathbf{e} \quad (17)$$

From Eq. (17), note that the right-hand side of the inequality grows quadratically while the left-hand side is linear. Consequently, there is a value of $\alpha_{n,i}$ that holds the inequality, and makes reporting zero consumption a more expensive strategy, as long as $\alpha_{n,i} > \pi_{i+1}$. Under these conditions, the quadratic cost of the penalty for plan deviations outweighs the marginal gain from price manipulation, ensuring that reporting the true consumption plan, $\hat{\mathbf{e}}_{n,i} = \mathbf{e}_{n,i}$, becomes a dominant strategy for each RA $n \in \mathcal{N}$.

5. Simulations-Based Scenarios Set-Up

This methodology employs the Monte Carlo -Sample Average Approximation (SAA) method [35] -to solve the stochastic programs formulated for the RAs and the coordinator. The technique generates a large set of representative scenarios to estimate the expected values within the stochastic programming framework. By simulating a wide range of probable outcomes, the SAA method provides a robust approximation of complex uncertainties, thereby enhancing the decision-making precision for both the RAs and the coordinator [34].

The simulation-based scenarios consider the following global assumptions: a single transformer powers a group of

customers. The power grid's topology has not been considered. The number of customers are twenty, i.e., $\mathcal{N} = \{1, 2, 3, \dots, N = 20\}$. The optimisation time horizon is set to one day, with a time step of ten minutes, i.e., $T = 144$. The variance of $\mathbf{r}_n$ was modelled using the open-source tool Prophet [36] with historical data from real houses in Quebec. The Monte Carlo scenarios tested were one thousand. The coordinator is a benevolent entity that the DSO deploys. The coordinator optimisation provides the same price vector to the RAs, but an individual penalty vector. The initial electricity price is $\pi_{0,t} = 8.05\text{¢}/kWh \forall t$, obtained from [37]. The initial penalty vector for deviations is $\alpha_{n,0,t} = 10\text{¢}/kWh^2 \forall n, t$. The customers are selfish agents, fully enrolled in the DR program. The value of the coordinator parameters are: $\lambda = 0.35$, $\tau_{coord} = 0.5$, $\rho_{coord} = 0.1$. The values of the RAs parameters are: $\tau = 10.65$, $A = 0.998$, $B = 0.002$, $C = 0.128$. The coordinator sets the probability of moving to the next iteration as zero-dot-five, i.e., $1 - p = 0.5$ in the coordination phase. The stopping probability p serves as the coordination weight in the agents' expected cost function, directly influencing their strategic risk perception. This work adopts $p = 0.5$ as a neutral design point that prevents RAs from probabilistically discounting current penalties in favor of future price manipulation, thereby stabilizing the mechanism's strategy-proofness during iterative negotiation.

This work compares uncoordinated and coordinated scenarios. In the uncoordinated case, RAs' inelastic consumption responds to a flat initial electricity price $\pi_{0,t}$. In the coordinated case, RAs' optimal scheduled electricity consumption is determined by the coordinator's dynamic price-penalty vectors. Comparing electricity bills under both scenarios evaluates individual rationality and participation incentives. Simulations assess the mechanism's budget balance outcomes. The code uses Python's CVXPY for convex optimization and Embedded Conic Solver (ECOS) as the solver [38, 39]. Numerical simulations run on an Intel(R) Core(TM) i7-10700T processor at 2.00 GHz and 32 GB RAM.

6. Simulation Results.

This section presents the results of applying the reward-penalty mechanism to customers participating in the TE mechanism. Section 6.1 shows the simulation results for the *negotiation phase*, including an analysis of algorithm convergence, the performance of DR in shaping electricity consumption patterns, and the computation of both EFF and IR metrics in the *ex-ante* phase. Section 6.4 focuses on the results by applying the PR declared by the coordinator in the contract based on the negotiation outcomes and customers' actual electricity consumption. It also presents results related to *ex-post* IR from the customer perspective, evidence of IC, and the mechanism's economic performance, computed from the coordinator's perspective using the BB metric.

6.1. Negotiation phase - ex-ante results.

This section presents the stochastic optimisation outcomes for the RAs in the uncoordinated and coordinated scenarios, as

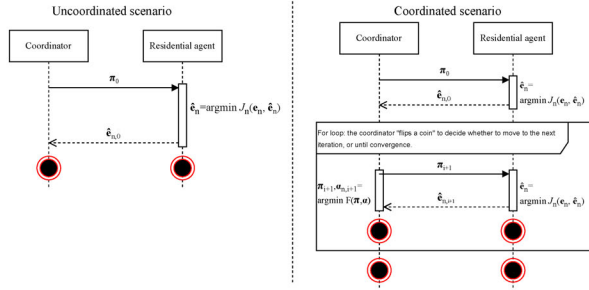


Figure 3: Difference between the uncoordinated and the coordinated scenarios.

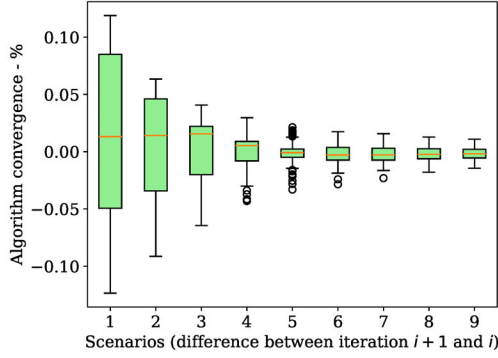


Figure 4: Algorithm convergence in the negotiation phase.

well as the coordinator stochastic optimisation outputs for the coordinated scenarios. This comparison demonstrates the effectiveness of the coordination mechanism proposed for both the coordinator and the customers. Notice that the coordinator did not play a role in the uncoordinated scenario since customers are not supposed to be enrolled in the TE program, as depicted in Fig. 3.

From Fig. 3, the coordinator provides a flat electricity price to the RAs in the uncoordinated case, and no penalties are imposed for deviations from the reported consumption plan. As a result, no negotiation process takes place. In contrast, the coordinated scenario involves an iterative bargaining process, where progression to the next iteration is determined probabilistically based on a likelihood value defined by the coordinator. Notice that this likelihood influences the penalty value the coordinator shares with the RAs at each iteration, as depicted in Eq. (17).

6.1.1. Algorithm convergence.

Fig. 4 shows that the algorithm converges effectively, yielding optimal solutions within the proposed mechanism. The difference in aggregated energy consumption between consecutive iterations diminishes progressively, with the solution stabilising after iteration five. This convergence indicates that the mechanism successfully reaches the socially optimal outcome (OPT), enabled by the proximal decomposition algorithm [33].

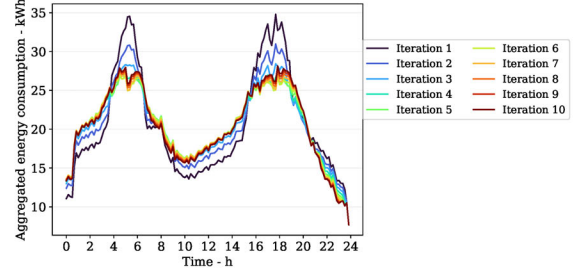


Figure 5: Aggregated electricity consumption through iterations of the negotiation process.

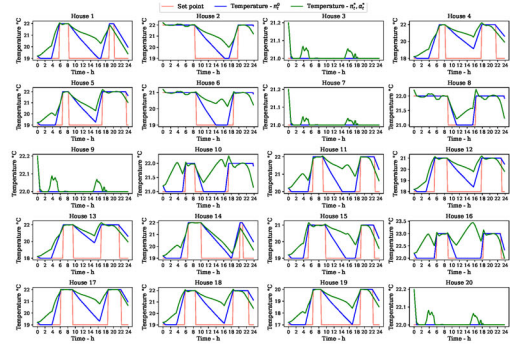


Figure 6: Individual inner dwelling house temperature. A comparison between the set-point, the temperature in the uncoordinated scenario, and the temperature at the last iteration of the coordinated scenario.

6.1.2. Iterative electricity consumption results

The RAs adjust customers' electricity consumption patterns based on their thermal preferences, comfort flexibility, and the reward-penalty signals provided by the coordinator, as stated in Eq. (4). Figure 5 illustrates the evolution of the aggregated electricity consumption across iterations, resulting from the negotiation process shown in Fig. 3.

From Fig. 5, the peak energy consumption decreased by 19.1% when comparing the initial and the final iteration results. Thus, the coordinator effectively leveraged customers' thermal load flexibility by encouraging the RAs to adjust their electricity consumption patterns in response to the price-penalty vectors. Figure 6 depicts the customer's inner dwelling temperature for the uncoordinated and coordinated scenarios, and the customer's set-point.

Figure 6 shows that the difference between the thermostat set point and the indoor temperature across all analysed scenarios drives the utility discomfort cost. In this context, the RAs reduce billing costs by allowing deviations from thermal comfort, achieved by adjusting their electricity consumption patterns. These shifts in consumption behaviour result in the aggregated energy profile observed in Fig. 5.

6.2. Ex-ante efficiency.

Economic efficiency is a fundamental concept in mechanism design. In this work, economic efficiency during the ex-ante phase is evaluated using the Price of Anarchy (PoA)

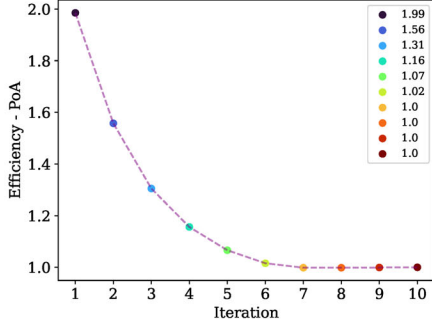


Figure 7: The ex-ante efficiency of the mechanism captured by the Price of Anarchy metric.

[15, 40, 41, 42]. Equation (18) formalises the PoA metric: the larger the PoA , the greater the inefficiency of the mechanism; conversely, a PoA closer to one indicates a more economically efficient outcome.

$$PoA = PoS = \frac{\mathbf{E} \left[\sum_{n=1}^N \left(PR_{n,i} + \gamma_n \|T_{SP,n} - T_{n,i}\|_2^2 \right) \right]}{\mathbf{E}[OPT]} \quad (18)$$

From (18), the numerator corresponds to the sum of the individual customers' cost, and the denominator is the OPT. The PoA for each customer response at iteration i is depicted in Fig. 7.

As presented in Fig. 7, the value of the PoA depends on the bi-level optimization outcomes at each iteration $i \in \Psi$. Given the mechanism's design, the coordinator assigns a likelihood of 0.5 ($p = 0.5$) of progressing through iterations. This probabilistic stopping criterion implies that the coordinator may terminate the negotiation at any stage, potentially sacrificing economic efficiency in exchange for ensuring a strategic-proof mechanism.

This trade-off directly reflects the implications of the Green-Laffont (or Hurwicz) impossibility theorem [12, 43], which asserts that no mechanism can simultaneously satisfy the four fundamental properties: IR, EFF, BB, and IC. In this work, prioritizing IC and IR via a strictly convex cost function ensures that truthful reporting is the unique dominant-strategy equilibrium for all agents. Consequently, because the set of equilibria collapses to this single point, the Price of Anarchy and the Price of Stability are equivalent ($PoA = PoS$). Thus, while the theorem predicts an efficiency loss ($PoA > 1$) in early iterations, the equilibrium's uniqueness provides a stable, predictable characterization of efficiency throughout the negotiation process.

6.3. Ex-ante individual rationality.

Rational RAs adjusted their electricity consumption patterns based on the price-penalty pair signals received from the coordinator to leverage the opportunities of reducing their electricity bill, as presented in 5. Their IR leads them to opt in if participating in the *coordination phase* could result in a reduced electricity bill for their uncoordinated expected outputs; otherwise, they opt out. In this regard, their willingness to participate in

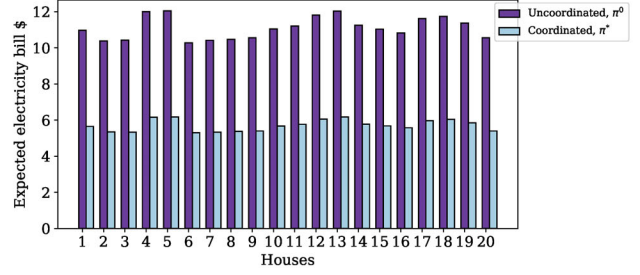


Figure 8: Ex-ante individual rationality of the mechanism's participants captured by their expected electricity bill in both the uncoordinated (flat price, π_0) and the coordinated (dynamic price, π_i) scenario.

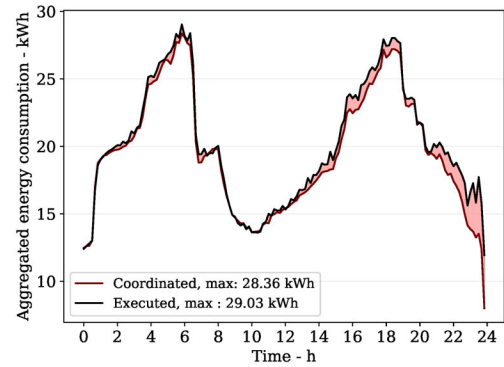


Figure 9: Comparison of the real and the coordinated aggregated electricity consumption.

the TE program to coordinate day-ahead electricity consumption can be compared by computing their expected cost in the uncoordinated and coordinated scenarios, as shown in 8.

The results depicted in Fig. 8 demonstrate that the expected electricity bill in the coordinated scenario is lower than in the uncoordinated pair scenario, and therefore, in financial terms, all the customers opt in. Furthermore, the *ex-ante* IR property is successfully achieved in this work.

6.4. Settlement phase

The *settlement phase* results build upon the outputs of the coordination and execution phases, as presented in Eq. (1). In the coordinated scenario, the electricity consumption initially reported by the RAs may be adjusted in response to the realisation of uncertainty, based on their comfort-cost trade-offs, as formulated in the RAs' objective functions in Eq. (4).

Figure 9 shows the deviation between the coordinated consumption plan and the actual electricity consumption, represented by the filled area. In this scenario, customers tend to slightly increase their aggregated electricity consumption to compensate for the impact of uncertainty on their cost-comfort trade-off. Accordingly, the coordinator compares each customer's reported consumption plan with their usage at every time step t , according to the PR declared in Eq. (1).

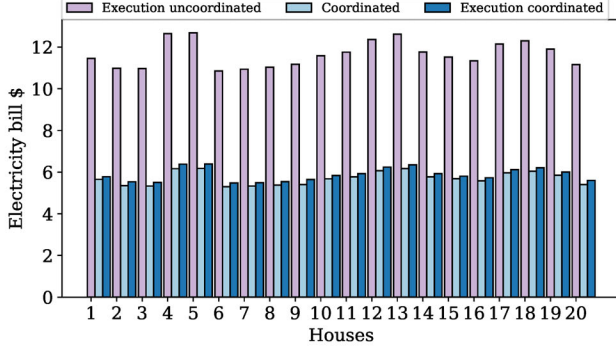


Figure 10: Individual electricity bill by comparing the execution of the uncoordinated scenario, the coordinated scenario, and the execution of the coordinated scenario.

6.4.1. Ex-Post Analysis of Individual Rationality and Incentive Compatibility

This section provides the comparison of three scenarios from the perspective of the customers: i) the executed scenario if all customers decide not to be enrolled in the *coordination phase*, ii) the coordinated scenario referring to customers expectations to be charged as output of the *coordination phase* (also presented in Fig. 8), and iii) the current cost each customer experienced by their real electricity consumption based on the application of the PR presented in Eq. (1).

Fig. 10 shows that customers save money by participating in the TE program, despite the penalty policy applied for deviations from the planned electricity consumption. This conclusion is drawn by comparing the uncoordinated execution bars with the coordinated execution bars. Although the mechanism was not originally designed to guarantee *ex-post* IR, the results demonstrate that this property can be achieved under the price-penalty conditions agreed upon during the *coordination phase*. Besides, comparing the results of the execution-coordinated and coordinated scenarios in Fig. 10, it is evident that customers experienced a higher cost in the former than in the latter. This fact gives the coordinator, at the end of the day, clues about the achievement of the IC property of the mechanism, and therefore, no RAs' strategic behaviour, if it existed, had a positive payoff for the customers.

6.4.2. Budget balance results

The BB property could naturally be assessed at the end of the negotiation period. In this case, considering the revenue, i.e., money collection by supplying the customers based on the PR in Eq. (1) minus the cost of operating the power grid. Conceptually, a strong budget balance occurs when revenue exactly covers operating costs, resulting in a BB value of zero. A positive BB indicates a weak budget balance, meaning the coordinator retains a surplus by not fully redistributing the collected revenue to users. Conversely, a negative BB implies a deficit, necessitating external subsidies to cover costs [9]. The BB is computed according to Eq. (19).



Figure 11: Budget balance results in executing uncoordinated and coordinated scenarios.

$$BB = \underbrace{\sum_{n=1}^N \sum_{t=1}^T [\pi_{i,t}(e_{n,i,t} + r_{n,t}) + \alpha_{i,n,t}(e_{n,i,t} + r_{n,t} - \hat{e}_{n,i,t})^2]}_{\text{Revenue}} - \underbrace{\lambda \sum_{t=1}^T \sum_{n=1}^N [(e_{n,i,t} + r_{n,t})^2]}_{\text{Cost of power grid operation}} \quad (19)$$

The BB results for this mechanism are depicted in Fig. 11 for both the uncoordinated and the coordinated scenarios.

From Fig. 11, notice that executing both the uncoordinated and coordinated scenarios leads to a BB deficit, implying that the customers require subsidies to be supplied. Despite a cost reduction of the power grid operation of 14.37% by comparing the execution uncoordinated with the execution coordinated scenarios (mainly driven by the reduction of the peak power consumption and the filled valley consumption depicted in Fig. 5), the depth of the deficit is significantly different in both cases: the deficit is 3.2% in the execution of the uncoordinated scenario, while it is 43% in the execution of the coordinated scenario. This phenomenon occurs due to a reduction in the electricity price between both scenarios (comparison of average prices in the uncoordinated scenario $\pi_{0,t} = 8.05\text{¢/kWh } \forall t$ and the coordinated scenario $\frac{1}{T} \sum_{t=1}^T \pi_{i,t} = 4.03\text{¢/kWh}$), although a rise in the total aggregated electricity consumption of 0.5% in the coordinated regarding the uncoordinated scenario. It is also important to highlight from Fig. 9 that deviations from the plan were not considerable, and therefore, the penalty component in the PR was not enough to balance the budget. However, exogenous factors were outside the scope of this work and could eventually lead to budgetary compensation. For instance, the energy reduction achieved through the RAs' coordination (depicted in Fig. 5) could be allocated to another market, such as an inter-regional or international market, enabling potentially profitable scenarios for the DSO.

7. Discussion

Inherent uncertainties continuously challenge the alignment between electricity generation and demand in forward elec-

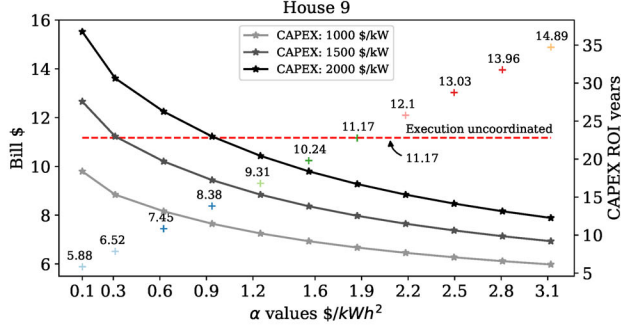


Figure 12: Effect of different penalty values α in the IR condition and the ROI of BESS for three different CAPEX.

tricity markets. In this context, the penalty policy significantly influences customers' risk perception, as uncertainty inevitably affects their costs. Customers are penalised for deviations from their reported consumption plans, but may choose to mitigate them by deploying battery energy storage systems (BESS). However, BESS adoption involves capital costs and ongoing operation and maintenance costs, which must be carefully weighed. For BESS deployment to be economically viable within the proposed mechanism, the expected penalty cost from consumption deviations must exceed the total cost of ownership, including capital expenditure and operation and maintenance expenses.

Notice that in the equilibrium point, i.e., truthful consumption plan reported by the customer $e_{n,i} = \hat{e}_{n,i}$, each customer should pay the penalty corresponding to the realisation of the uncertainty variable r_n . This implies that the penalty term for deviations from a consumption plan is at the mercy of the performance of the forecast model of each RA: how much it can predict the consumption pattern of the customer one day ahead, considering working days, weekends, events, weather, etc. Based on the individual cost of deviation obtained from simulations in Section 6, customer number nine incurred the largest payment for deviations from the plan that day, amounting to 5.66 ¢.

Assuming that every day the customer experiences the same penalisation cost, and considering a CAPEX of 1000 CAD/kW for a BESS with 2 hours of autonomy [44], it would take 48 years for the customer to compensate only the CAPEX of a BESS. On the other hand, if the coordinator raises the penalty value, the BESS could become viable, but the IR is affected, i.e., the customer's willingness to participate in the TE is diminished, as presented in Fig. 12, based on the results obtained from simulations.

From Fig. 12, notice that a penalty for deviations of 1.9 \$/kWh² would be enough not to satisfy the IR condition, and therefore, rational RAs would opt out of the TE program. However, notice from Fig. 12 that, for customer nine, the larger the penalty values, the lower the BESS CAPEX return on investment (ROI). These assessments must then be performed by the coordinator and the customers. The former could be interested in encouraging customers to adopt BESS to fulfil their day-

ahead market obligations and to require the grid services this technology could provide to the power grid, especially when BESS are integrated with grid-forming converters. The latter could be interested in adopting BESS technology to increase their flexibility and autonomy, enable local integration of renewable power, and provide grid services to the coordinator.

8. Conclusion

This work introduced a privacy-preserving mechanism to promote active customer participation in a transactive energy (TE) program. The interaction between the coordinator and residential customers was modelled as a Stackelberg game under incomplete, imperfect, and asymmetric information conditions, capturing realistic limitations in information availability. A convex bilevel stochastic optimisation framework was developed to support this interaction, enabling an iterative negotiation process in which agents determine day-ahead electricity consumption plans. Through theoretical analysis and simulation-based validation, the mechanism effectively prevented manipulation by strategic, rational, and intelligent agents within an iterative negotiation framework. By providing price-incentive signals, the mechanism successfully encouraged customers to coordinate their electricity consumption in a day-ahead market setting.

The proposed mechanism was originally designed to satisfy IR in the *ex-ante* phase. However, simulation results revealed that customers could also experience monetary savings in the *ex-post* phase. These savings depend on the truthful reporting of consumption plans and the accuracy of their forecasting models in managing uncertainty. This work also highlights the trade-offs involved in mechanism design, particularly through the lens of the Green-Laffont (or Hurwicz) impossibility theorem [12, 43], which asserts that it is generally impossible to satisfy all desirable properties—namely, incentive compatibility (IC), economic efficiency (EFF), budget balance (BB), and individual rationality (IR)—simultaneously. In this case, achieving an incentive-compatible mechanism required compromising on efficiency and budget balance. Finally, although the coordination of RAs led to more efficient electricity use, it resulted in a budget deficit due to lower electricity prices and limited penalty revenue. This fact suggests that the mechanism may require financial support through subsidies or complementary energy markets (e.g., inter-regional or ancillary services markets) to recover operational costs and fully maintain long-term sustainability.

Moreover, the current coordinator objective function utilises proximal decomposition to manage demand peaks, future iterations of this work could implicitly incorporate explicit network capacity limits and voltage constraints. Integrating the proposed strategy-proof mechanism with a distribution-level Optimal Power Flow would further enhance its practical relevance in highly constrained power systems.

While this study assumes homogeneous state-space parameters for the RAs to ensure the replicability of the simulation environment, it is important to underscore that the mechanism's strategy-proofness is grounded in the exogenous structure of

the PR. Because the IC property is independent of agents' internal thermal characteristics, the theoretical results on dominant strategies remain valid for heterogeneous populations with varying building physics and occupancy patterns.

Future research may consider the design of a mechanism to counter free-model agents and their strategic learning over time. Moreover, a potential area of interest for future research is investigating how large consumers, such as those in the commercial and industrial sectors, might manipulate electricity markets by misreporting information during negotiations. Moreover, avenues of research could also examine the effects of strategic manipulation across different electricity markets, such as spot, intra-day, or real-time markets.

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References

- [1] B. Kuipers, Trust and Cooperation, *Frontiers in Robotics and AI* 9 (April) (2022) 1–18. doi:10.3389/frobt.2022.676767.
- [2] F. Lopes, H. Coelho, Electricity Markets with Increasing Levels of Renewable Generation: Structure, Operation, Agent-based Simulation, and Emerging Designs, Vol. 144 of *Studies in Systems, Decision and Control*, Springer International Publishing, 2018. doi:10.1007/978-3-319-74263-2. URL <http://link.springer.com/10.1007/978-3-319-74263-2>
- [3] IRENA, Innovation landscape brief: Aggregators, Tech. rep., International Renewable Energy Agency, Abu Dhabi (2019). doi:10.1016/b978-1-84334-144-4.50003-3.
- [4] A. Parrado-Duque, N. Henao, K. Agbossou, S. Kelouwani, J. C. Oviedo-Cepeda, J. Domínguez-Jiménez, Is it worthwhile to participate in transactive energy? A decision-making model for empowering residential customers, *The Electricity Journal* 37 (7-10) (2024) 107447. doi:10.1016/J.TEJ.2024.107447. URL <https://linkinghub.elsevier.com/retrieve/pii/S1040619024000824>
- [5] IEA, Global Energy Review 2025, Tech. rep., IEA (3 2025). URL www.iea.org
- [6] X. Nie, S. A. Mansouri, A. Rezaee Jordehi, M. Tostado-Véliz, A two-stage optimal mechanism for managing energy and ancillary services markets in renewable-based transmission and distribution networks by participating electric vehicle and demand response aggregators, *International Journal of Electrical Power & Energy Systems* 158 (2024) 109917. doi:10.1016/j.ijepes.2024.109917. URL <https://linkinghub.elsevier.com/retrieve/pii/S0142061524001388>
- [7] I. V. Chremos, A. A. Malikopoulos, Mechanism Design Theory in Control Engineering: A Tutorial and Overview of Applications in Communication, Power Grid, Transportation, and Security Systems, *IEEE Control Systems* 44 (1) (2024) 20–45. doi:10.1109/MCS.2023.3329919. URL <https://ieeexplore.ieee.org/document/10384599/>
- [8] P. Zhang, S. A. Mansouri, A. Rezaee Jordehi, M. Tostado-Véliz, Y. Z. Alharthi, M. Safaraliev, An ADMM-enabled robust optimization framework for self-healing scheduling of smart grids integrated with smart prosumers, *Applied Energy* 363 (2024) 123067. doi:10.1016/j.apenergy.2024.123067. URL <https://linkinghub.elsevier.com/retrieve/pii/S0306261924004501>
- [9] A. Parrado-Duque, N. Henao, S. Kelouwani, K. Agbossou, J. C. Oviedo-Cepeda, Penalty mechanism in transactive energy: A mechanism design approach for day-ahead markets, *Energy Strategy Reviews* 59 (5 2025). doi:10.1016/j.esr.2025.101712.
- [10] T. Tanaka, F. Farokhi, C. Langbort, Faithful implementations of distributed algorithms and control laws, *IEEE Transactions on Control of Network Systems* 4 (2) (2017) 191–201. doi:10.1109/TCNS.2015.2489318.
- [11] K. Abedrabboh, L. Al-Fagih, Applications of mechanism design in market-based demand-side management: A review, *Renewable and Sustainable Energy Reviews* 171 (2023) 113016. doi:10.1016/j.rser.2022.113016. URL <https://linkinghub.elsevier.com/retrieve/pii/S1364032122008978>
- [12] L. Jain, X. Wu, Game Theoretic Problems in Network Economics and Mechanism Design Solutions, Springer London, London, 2009. doi:10.1007/978-1-84800-938-7. URL <https://link.springer.com/10.1007/978-1-84800-938-7>
- [13] F. Etedadi Aliabadi, K. Agbossou, S. Kelouwani, N. Henao, S. S. Hosseini, Coordination of Smart Home Energy Management Systems in Neighborhood Areas: A Systematic Review, *IEEE Access* 9 (2021) 36417–36443. doi:10.1109/ACCESS.2021.3061995. URL <https://ieeexplore.ieee.org/document/9363112/>
- [14] D. Balliet, L. B. Mulder, P. A. Van Lange, Reward, punishment, and cooperation: A meta-analysis, *Psychological Bulletin* 137 (4) (2011) 594–615. doi:10.1037/a0023489.

- [15] E. Parilina, P. Viswanadha Reddy, G. Zaccour, Handbook of Dynamic Game Theory, Vol. 51, Springer International Publishing, 2018. doi:10.1007/978-3-319-44374-4.
URL <http://link.springer.com/10.1007/978-3-319-44374-4>
- [16] S. M. Ghorashi, M. Rastegar, S. Senemmar, A. R. Seifi, Optimal design of reward-penalty demand response programs in smart power grids, Sustainable Cities and Society 60 (May) (2020) 102150. doi:10.1016/j.scs.2020.102150.
URL <https://doi.org/10.1016/j.scs.2020.102150>
- [17] G. Tsaousoglou, K. Steriotis, N. Efthymiopoulos, P. Makris, E. Varvarigos, Truthful, Practical and Privacy-Aware Demand Response in the Smart Grid via a Distributed and Optimal Mechanism, IEEE Transactions on Smart Grid 11 (4) (2020) 3119–3130. doi:10.1109/TSG.2020.2965221.
URL <https://ieeexplore.ieee.org/document/8954657/>
- [18] K. Ma, P. R. Kumar, Incentive Compatibility in Stochastic Dynamic Systems, IEEE Transactions on Automatic Control 66 (2) (2021) 651–666. doi:10.1109/TAC.2020.2987802.
URL <https://ieeexplore.ieee.org/document/9068413/>
- [19] B. Dulipala, S. Debbarma, Energy scheduling model considering penalty mechanism in transactive energy markets: A hybrid approach, International Journal of Electrical Power & Energy Systems 129 (June 2020) (2021) 106742. doi:10.1016/j.ijepes.2020.106742.
- [20] J. B. Dulipala, S. Debbarma, Decision-making model with reduced risk of penalties in transactive energy markets, Electric Power Systems Research 199 (May) (2021) 107371. doi:10.1016/j.epsr.2021.107371.
- [21] Y. Yao, C. Gao, K. Lai, T. Chen, J. Yang, An incentive-compatible distributed integrated energy market mechanism design with adaptive robust approach, Applied Energy 282 (2021) 116155. doi:10.1016/j.apenergy.2020.116155.
URL <https://linkinghub.elsevier.com/retrieve/pii/S0306261920315609>
- [22] W. Zhong, K. Xie, Y. Liu, S. Xie, L. Xie, Nash Mechanisms for Market Design Based on Distribution Locational Marginal Prices, IEEE Transactions on Power Systems 37 (6) (2022) 4297–4309. doi:10.1109/TPWRS.2022.3152517.
- [23] Y. Wasa, K. Hirata, K. Uchida, A Contract Theory Approach to Dynamic Incentive Mechanism and Control Synthesis for Moral Hazard in Power Grids, IEEE Transactions on Control Systems Technology 30 (5) (2022) 2072–2083. doi:10.1109/TCST.2021.3130922.
URL <https://ieeexplore.ieee.org/document/9644928/>
- [24] M. D. de Souza Dutra, N. Alguacil, Fairness of prosumers' incentives in residential demand response: A practical decentralized optimization approach, International Journal of Electrical Power & Energy Systems 148 (December 2022) (2023) 109015. doi:10.1016/j.ijepes.2023.109015.
URL <https://doi.org/10.1016/j.ijepes.2023.109015>
<https://linkinghub.elsevier.com/retrieve/pii/S0142061523000728>
- [25] K. Zhang, Y. Xu, H. Sun, Bilevel optimal coordination of active distribution network and charging stations considering EV drivers' willingness, Applied Energy 360 (2024) 122790. doi:10.1016/j.apenergy.2024.122790.
URL <https://linkinghub.elsevier.com/retrieve/pii/S0306261924001739>
- [26] M. Hoseinpour, M. Hoseinpour, M. Haghifam, M. R. Haghifam, Privacy-Preserving and Approximately Truthful Local Electricity Markets: A Differentially Private VCG Mechanism, IEEE Transactions on Smart Grid 15 (2) (2024) 1991–2003. doi:10.1109/TSG.2023.3301174.
- [27] M. Montazeri, H. Kebriaei, B. N. Araabi, A Tractable Truthful Profit Maximization Mechanism Design with Autonomous Agents, IEEE Transactions on Automatic Control PP (iii) (2024) 1–6. doi:10.1109/TAC.2024.3360335.
URL <https://ieeexplore.ieee.org/document/10416648/>
- [28] B. Satchidanandan, M. A. Dahleh, Incentive Compatibility in Two-Stage Repeated Stochastic Games, IEEE Transactions on Control of Network Systems 11 (1) (2024) 295–306. doi:10.1109/TCNS.2023.3280861.
URL <https://ieeexplore.ieee.org/document/10138437/>
- [29] L. Cheng, P. Huang, M. Zhang, R. Yang, Y. Wang, Optimizing Electricity Markets Through Game-Theoretical Methods: Strategic and Policy Implications for Power Purchasing and Generation Enterprises (2 2025). doi:10.3390/math13030373.
- [30] L. Cheng, M. Zhang, K. Wang, M. Yuan, Z. Liu, J. Wang, K. Zhang, P. Huang, Evolutionary smart contracts for virtual power plant trading: integrating prospect theory and multi-stage negotiation in cross-regional energy markets, International Journal of Electrical Power and Energy Systems 173 (12 2025). doi:10.1016/j.ijepes.2025.111453.
- [31] L. Cheng, P. Peng, W. Lu, P. Huang, Y. Chen, Study of Flexibility Transformation in Thermal Power Enterprises under Multi-Factor Drivers: Application of Complex-Network Evolutionary Game Theory, Mathematics 12 (16) (8 2024). doi:10.3390/math12162537.

- [32] R. Cheng, L. Tesfatsion, Z. Wang, A Consensus-Based Transactive Energy Design for Unbalanced Distribution Networks, *IEEE Transactions on Power Systems* (2022) 1–1doi:10.1109/TPWRS.2022.3158900.
URL <https://ieeexplore.ieee.org/document/9735416/>
- [33] N. Parikh, Proximal Algorithms, *Foundations and Trends in Optimization* 1 (3) (2014) 127–239. doi:10.1561/2400000003.
- [34] A. Ali, J. Z. Kolter, S. Diamond, S. Boyd, Disciplined convex stochastic programming: A new framework for stochastic optimization, *Uncertainty in Artificial Intelligence - Proceedings of the 31st Conference, UAI 2015* 1 (3) (2015) 62–71.
- [35] M. C. Fu, *Handbook of Simulation Optimization*, Vol. 216 of International Series in Operations Research & Management Science, Springer New York, New York, NY, 2015. doi:10.1007/978-1-4939-1384-8.
URL <https://link.springer.com/10.1007/978-1-4939-1384-8>
- [36] S. J. Taylor, B. Letham, *Forecasting at Scale*, *PeerJ Preprints* (2017). doi:10.7287/peerj.preprints.3190v2.
URL <https://doi.org/10.7287/peerj.preprints.3190v2>
- [37] Hydro-Québec, *Hydro-Québec – Annual Report 2024*, Tech. rep., Hydro-Québec (2024).
- [38] A. Agrawal, R. Verschuere, S. Diamond, S. Boyd, A rewriting system for convex optimization problems, *Journal of Control and Decision* 5 (1) (2018) 42–60. doi:10.1080/23307706.2017.1397554.
- [39] S. Diamond, S. Boyd, CVXPY: A Python-Embedded Modeling Language for Convex Optimization, *Journal of Machine Learning Research* 17 (83) (2016) 1–5.
URL <http://arxiv.org/abs/1603.00943>
- [40] L. Nespoli, M. Salani, V. Medici, A rational decentralized generalized Nash equilibrium seeking for energy markets, in: *2018 International Conference on Smart Energy Systems and Technologies (SEST)*, IEEE, 2018, pp. 1–6. doi:10.1109/SEST.2018.8495809.
URL <https://ieeexplore.ieee.org/document/8495809/>
- [41] P. Jacquot, O. Beaude, S. Gaubert, N. Oudjane, Analysis and Implementation of an Hourly Billing Mechanism for Demand Response Management, *IEEE Transactions on Smart Grid* 10 (4) (2019) 4265–4278. doi:10.1109/TSG.2018.2855041.
URL <https://ieeexplore.ieee.org/document/8410042/>
- [42] J. Qin, Y. Wan, F. Li, Y. Kang, W. Fu, Distributed Economic Operation in Smart Grid: Model-Based and

Model-Free Perspectives, Vol. 455 of Studies in Systems, Decision and Control, Springer Nature Singapore, Singapore, 2023. doi:10.1007/978-981-19-8594-2.
URL <https://link.springer.com/10.1007/978-981-19-8594-2>

- [43] Y. Shoham, K. Leyton-Brown, *Multiagent Systems*, Cambridge University Press, 2008. doi:10.1017/CBO9780511811654.

- [44] NREL, *Utility-Scale Battery Storage* (6 2025).
URL <https://atb.nrel.gov/electricity/2024/utility-scale-battery-storage>

Appendix A. Sufficient Conditions for a Non-Empty Penalty Feasible Region

To ensure a strategy-proof and individually rational mechanism, there must exist a penalty vector $\alpha_{n,i}$ that simultaneously satisfies the IC and IR conditions. From the analysis in Section 4, the IC condition dictates a strict lower bound for the penalty variable at each time step t , as follows:

$$\alpha_{n,i,t} > \pi_{i,t} \quad \forall t \in T \quad (\text{A.1})$$

Conversely, the IR condition formulated in Eq. (3) imposes an aggregated upper limit on the penalty vector to ensure the residential agent’s expected cost does not exceed their uncoordinated baseline.

$$\sum_{t=1}^T \alpha_{n,i,t} \text{Var}[r_{n,t}] < \pi_0 \cdot e_{n,0} - \pi_i \cdot e_{n,i} \quad (\text{A.2})$$

To guarantee a non-degenerate feasible interval for $\alpha_{n,i,t}$, we evaluate the boundary case where the penalty approaches its theoretical infimum, $\alpha_{n,i,t} \rightarrow \pi_{i,t}$. Substituting this lower bound into the IR constraint yields the formal sufficient condition for existence:

$$\sum_{t=1}^T \pi_{i,t} \text{Var}[r_{n,t}] < \pi_0 \cdot e_{n,0} - \pi_i \cdot e_{n,i} \quad (\text{A.3})$$

As long as the total expected cost savings strictly exceed the sum of the products of the dynamic clearing price and the prediction variance across the market horizon, the feasible region is non-empty. This guarantees that a penalty value $\alpha_{n,i,t}$ can be selected that satisfies both strategy-proofness and the agent’s willingness to participate.

In practice, the coordinator fulfills this condition through the iterative proximal algorithm, which shapes the demand profile to significantly reduce the dynamic price $\pi_{i,t}$ relative to the baseline π_0 . As demonstrated by the simulation results in Section 6, the mechanism achieved an approximate 50% reduction in average clearing prices. This substantial increase in the right-hand side of the inequality in Eq. (A.3) provides a robust buffer, ensuring the sufficient condition holds even under configurations with high forecast uncertainty $\text{Var}[r_{n,t}]$.

3.3.5 Complementary analysis.

The analysis of the IC property in the mechanism proposed in Section 3.3.4 has so far focused on the electricity costs customers perceive during the negotiation and execution phases. The proposed mechanism adopted this electricity-cost approach to protect the customer's private information. This privacy-preservation approach inherently limits the observability of the coordinator/DSO's capabilities for verifying each customer's private information and decision criteria in a TE system.

This subsection demonstrates that the IC property is preserved in the mechanism in a utility analysis, i.e., the mechanism proposed is strategy-proof.

A utility-based approach.

By reformulating a cost-based to a utility-based analysis, the definition of IC is therefore depicted in (3.3).

$$\begin{aligned}
 U_n(\hat{e}_{n,i} = e_{n,i}) &> U_n(\hat{e}_{n,i} = \mathbf{0}) \quad \forall n, \\
 &\text{or,} \\
 C_n(\hat{e}_{n,i} = e_{n,i}) &< C_n(\hat{e}_{n,i} = \mathbf{0}) \quad \forall n.
 \end{aligned} \tag{3.3}$$

Where the left-hand side of inequality Eq. (3.3) is the utility/cost of RA n by a truthful report, while the right-hand side of inequality Eq. (3.3) is the utility/cost of RA n by a cheating report strategy. A dominant equilibrium strategy is reached if the inequality condition in Eq. (3.3) is satisfied. In this regard, Eq. (13) of the Third paper is modified to adopt a utility-based approach instead of a payment rule approach, as follows in Eq. (3.4).

$$C_n(\hat{e}_{n,i}) = p\mathbb{E}[C_{n,i}|\hat{e}_{n,i}] + p(1-p)\mathbb{E}[C_{n,i+1}|\hat{e}_{n,i}] \quad (3.4)$$

When customers submit a truthful report, the iterative cost is developed in Eq. (3.5).

$$\begin{aligned} C_n(\hat{\mathbf{e}}_{n,i} = \mathbf{e}_{n,i}) &= p(\boldsymbol{\pi}_i \cdot \mathbf{e}_{n,i} + \boldsymbol{\alpha}_{n,i} \cdot \text{diag}(\text{Var}[\mathbf{r}_n]) + \mathbf{D}_{n,i}) \\ &+ p(1-p)(\boldsymbol{\pi}_{i+1} \cdot \mathbf{e}_{n,i+1} + \boldsymbol{\alpha}_{n,i+1} \cdot \text{diag}(\text{Var}[\mathbf{r}_n]) + \mathbf{D}_{n,i+1}) \end{aligned} \quad (3.5)$$

Where $\mathbf{D}_n$ is the discomfort cost of customer n . On the other hand, if customers adopt the strategy of submitting a zero consumption plan at iteration i , the iterative cost is developed in Eq. (3.6).

$$\begin{aligned} C_n(\hat{\mathbf{e}}_{n,i} = \mathbf{0}) &= p(\boldsymbol{\pi}_i \cdot \mathbf{e}_{n,i} + \boldsymbol{\alpha}_{n,i} \cdot (\mathbf{e}_{n,i}^2 + \text{diag}(\text{Var}[\mathbf{r}_n]) + \max(\mathbf{D}_{n,i}))) \\ &+ p(1-p) \left(\left(\lambda \sum_{n=1}^N \text{Var}[\zeta_n] \right) \mathbf{1} \cdot \mathbf{e}_{n,i+1} \right. \\ &\left. + \boldsymbol{\alpha}_{n,i+1} \cdot \text{diag}(\text{Var}[\mathbf{r}_n]) + \min(\mathbf{D}_{n,i+1}) \right) \end{aligned} \quad (3.6)$$

Finally, the inequality in Eq. (3.4) is developed by replacing the expected cost values to obtain Eq. (3.7).

$$\begin{aligned} &\mathbf{D}_{n,i} + (1-p)(\boldsymbol{\pi}_{i+1} \cdot \mathbf{e}_{n,i+1} + \mathbf{D}_{n,i+1}) < \\ &\boldsymbol{\alpha}_{n,i} \cdot \mathbf{e}_{n,i}^2 + \max(\mathbf{D}_{n,i}) + (1-p) \left(\lambda \sum_{n=1}^N \text{Var}[\zeta_n] \right) \mathbf{1} \cdot \mathbf{e} + (1-p) \min(\mathbf{D}_{n,i+1}) \end{aligned} \quad (3.7)$$

In a truthful scenario, it is supposed that flexible customers coordinated their actions with the coordinator's goals. In this regard, they would sacrifice comfort while the negotiation moves through iterations. Therefore $D_{n,i+1} > D_{n,i}$. On the contrary, in an untruthful scenario, customers might face the risk of being hardly penalized not just in the electricity cost component, i.e., $\alpha_{n,i} \cdot e_{n,i}^2$ but also in the comfort component (to minimize their bill), i.e., $\max(\mathbf{D}_{n,i})$. Customers can reach a minimal comfort cost, i.e., $\min(\mathbf{D}_{n,i+1})$, if the iterative negotiation stops at iteration $i+1$ when they opt for a cheating strategy at iteration i . Therefore, intuitively, the discomfort inequalities could be formulated as follows in (3.8).

$$\max(\mathbf{D}_{n,i}) > \mathbf{D}_{n,i+1} > \mathbf{D}_{n,i} > \min(\mathbf{D}_{n,i}) \quad (3.8)$$

By employing the discomfort inequalities expressed in Eq. (3.8) into the inequality depicted in Eq. (3.7), it is possible to conclude that the right-hand side of inequality Eq. (3.7) outweighs the left-hand side, even in the analysis of the discomfort term. Furthermore, the relationship between the penalty and the price, i.e., $\alpha_{n,i,t} > \pi_{i,t}$, (alongside the random stop negotiation criteria) remains as a crucial condition for ensuring that $\hat{e}_{n,i} = e_{n,i}$ is a dominant strategy.

Chapter 4 - Discussion and Future Research Directions

This chapter discusses the main limitations of the present thesis and outlines promising directions for future research. These limitations are grouped into three categories: (i) the RA model, (ii) the electricity market architecture, and (iii) the coordinator model. Each category highlights the assumptions made in this thesis, their implications, and opportunities for extending the research.

4.1 Residential agent model

4.1.1 Agent type

This thesis considered strategic RAs capable of optimizing their decisions under bounded rationality but did not incorporate learning or evolutionary behavior [61]. Consequently, agents could not adapt their strategies over time or infer patterns in the coordinator's actions, such as predicting stopping conditions in iterative negotiations. In real-world TE systems, where artificial intelligence and reinforcement learning are increasingly prevalent, agents may develop sophisticated strategies to exploit weaknesses in the mechanism.

Future research should investigate learning-based strategic agents, such as those employing reinforcement learning or belief-based models, to assess the robustness of IC mechanisms under adaptive behavior. This extension would provide valuable insights into the long-term sustainability of TE programs in environments where agents continuously evolve.

4.1.2 Agent thermal model

The RA thermal dynamics were modeled using a linear state-space representation, a widely adopted simplification in the literature [62]. While this approach offers computational tractability and reasonable accuracy, it does not fully capture nonlinearities or the influence of exogenous factors such as occupancy patterns, solar gains, or specific appliance usage.

Future work could integrate nonlinear thermal models or data-driven approaches (e.g., machine learning-based predictors) to improve accuracy. This enhancement enables more realistic simulations and a more accurate assessment of comfort–cost trade-offs in coordination mechanisms.

4.1.3 Behavioral features

The current RA model omits behavioral aspects such as appliance usage preferences, lifestyle patterns, and willingness to compromise comfort [44]. These factors significantly influence flexibility potential and participation decisions.

Incorporating behavioral economics and human-in-the-loop modeling into RA optimization could improve the realism of TE simulations [63]. For example, integrating probabilistic models of appliance scheduling or preference-based utility functions would enable a richer analysis of participation incentives and fairness.

4.2 Coordinator model

The coordinator in this thesis operated under limited information, observing only aggregated plans and applying a payment rule to enforce IC. While this design preserves privacy, it restricts the coordinator’s ability to incorporate system-level objectives such as

fairness.

Future research could explore hybrid information structures, where partial or anonymized data sharing enables improved optimization without compromising privacy. Another promising direction is the integration of redistribution mechanisms or budget-balancing transfers to address the inherent trade-off between IC and BB. Finally, incorporating uncertainty-aware pricing strategies and risk-based incentives could improve resilience to forecast errors and enhance economic viability.

4.3 Electricity market model

This thesis focused on a day-ahead market as the negotiation environment. While this choice aligns with current TE implementations, modern electricity systems increasingly involve multi-market interactions, including real-time, ancillary services, and capacity markets. Limiting the analysis to a single market overlooks potential strategic behaviors that emerge when agents participate across multiple time frames.

Future research should investigate market-coupling scenarios in which RAs interact across day-ahead and real-time markets. Such studies could reveal whether agents adopt mixed strategies—e.g., misreporting in one market while behaving truthfully in another—and how these behaviors affect IC, IR, BB, and EFF.

Moreover, while the proposed mechanism ensures that agents are penalized in the settlement phase, it does not currently include an ex post reconciliation phase to buffer against purely stochastic deviations. This design choice aligns to provide robust price signals for grid services, ensuring that flexibility is both reliable and verifiable. Empirical evidence from this study indicates that even under uncertainty, participation remains 'individually rational' as costs remain below uncoordinated levels.

However, incorporating 'safe-provisions' or dead-band reconciliation could further enhance participant acceptance, especially for agents with lower technological control over their loads. Future iterations of this protocol could explore hybrid settlement schemes that distinguish between intentional strategic manipulation and unavoidable forecast errors, thereby balancing system-wide stability with individual fairness.

4.4 Broader Research Opportunities

Beyond the specific limitations discussed, several broader avenues emerge:

- **Fairness and Equity:** evaluating how IC mechanisms impact customer segments and designing fairness-aware payment rules.
- **Scalability and Computation:** a hierarchical decomposition approach could be used to ensure the protocol's scalability as the number of participants grows. By clustering agents into smaller sub-grids or coordination zones, the system can maintain fast convergence rates and reduce communication latency.
- **Integration with Distributed Energy Resources (DERs):** extending the framework to include DERs such as electric vehicles and photovoltaic systems, and evaluating the set of strategies the prosumers could opt for misreporting in negotiations.
- **Empirical validation:** assessing the IC mechanism proposed in this thesis in real-world contexts characterized by heterogeneous human behavior and uncontrolled conditions is essential to rigorously test the theoretical solution.

4.5 Summary

The sensitivity analysis of the proposed mechanism highlights the critical interplay between the penalty parameter (α) and the grid cost factor (λ), which together ensure strategy-proofness while maintaining the individual rationality of residential agents.

By examining these parameters, the study demonstrates that while higher penalties effectively deter information misreporting, they must be carefully calibrated to avoid discouraging agent participation, which would otherwise diminish the coordinator's profitability and the system's overall flexibility. Despite these insights, the current work omitted considerations of hardware-level constraints such as communication latency, device-specific degradation costs, and the impact of pure forecast uncertainty versus intentional strategic behavior. Consequently, future research should transition toward modeling agents with reinforcement learning capabilities to test the mechanism's resilience against evolving strategies. Expanding the framework to include multi-market interactions—such as simultaneous participation in energy and ancillary services—and assessing its scalability within the commercial and industrial sectors will be essential for validating its robustness in complex, real-world energy ecosystems.

Chapter 5 - Conclusions

This thesis addresses a fundamental challenge in deploying transactive energy (TE) systems: designing negotiation mechanisms that prevent strategic misreporting by residential agents (RAs) while preserving privacy and ensuring economic viability. The research was motivated by the growing complexity of electricity markets under the energy transition, where distributed flexibility and active consumer participation are essential for maintaining grid reliability and affordability. Within this context, the work focused on designing and evaluating an incentive-compatible (IC) mechanism for day-ahead coordination, grounded in mechanism design theory and implemented through one-shot and iterative negotiation frameworks.

The contributions of this thesis are threefold. First, it formalized a TE interaction model as a Stackelberg game under incomplete, imperfect, and asymmetric information, capturing the strategic nature of RAs and the privacy constraints inherent to decentralized coordination. Second, it proposed a payment rule combining dynamic pricing with a quadratic penalty for deviations, theoretically proving that truthful reporting constitutes a dominant strategy at every iteration of the negotiation process. The adoption of this payment rule ensures that the IC property does not require full-type disclosure, reconciling strategic robustness with privacy preservation. Third, the performance of the mechanism was assessed by considering key economic properties—individual rationality, budget balance, and efficiency—through extensive simulations under uncertainty. The findings demonstrate that coordinated participation reduces peak demand and customer costs relative to non-coordination scenarios, while maintaining positive revenues for the coordinator under realistic penalty settings and uncertainty.

Beyond these achievements, the thesis highlights necessary trade-offs and open

challenges. While the proposed mechanism successfully enforces IC and IR, achieving strong BB and full efficiency remains elusive, particularly under uncertainty and heterogeneous participation. The analysis also reveals the sensitivity of enrollment decisions to the penalty policy, underscoring the need for adaptive approaches that balance deterrence of strategic behavior with customer engagement.

Looking forward, this research opens several promising directions. Future work should explore learning-based strategic agents, multi-market interactions, fairness-aware mechanisms, and the integration of distributed energy resources such as electric vehicles and storage aggregators. Addressing these challenges will be critical for scaling TE programs from controlled pilots to real-world deployments, ensuring that economic efficiency, equity, and trustworthiness underpin the operation of future smart grids.

In summary, this thesis demonstrates that mechanism design principles can be effectively applied in demand response setups to align individual incentives with system objectives, paving the way for more resilient, transparent, and economically sustainable electricity markets.

Bibliographie

- [1] IRENA, “World Energy Transitions Outlook 2024: 1.5°C pathway,” International Renewable Energy Agency, Abu Dhabi, Tech. Rep., 2024. [Online]. Available: www.irena.org
- [2] iea, “World Energy Outlook 2024,” International Energy Agency, Tech. Rep., 2024. [Online]. Available: www.iea.org/terms
- [3] IRENA, “World energy transitions outlook 2023 : 1.5°C pathway,” International Renewable Energy Agency, Abu Dhabi, Tech. Rep., 2023.
- [4] IEA, “Global Energy Review 2025,” IEA, Tech. Rep., 3 2025. [Online]. Available: www.iea.org
- [5] REN21, “Renewables Global Status Report,” REN21, Tech. Rep., 2025.
- [6] —, “Renewables in buildings,” REN21, Tech. Rep., 2025.
- [7] J. Whitmore and P. Pineau, “État de l’énergie au Québec,” Chaire de gestion du secteur de l’énergie - HEC Montréal, Montreal, Tech. Rep., 2025.
- [8] Hydro-Québec, “Hydro-Québec – Annual Report 2024,” Hydro-Québec, Tech. Rep., 2024.
- [9] —, “Action Plan 2035 – Towards a Decarbonized and Prosperous Québec,” Hydro-Québec, Tech. Rep., 2023. [Online]. Available: www.hydroquebec.com/about/
- [10] N. Rossetto, “Beyond Individual Active Customers: Citizen and Renewable Energy Communities in the European Union,” *IEEE Power and Energy Magazine*, vol. 21, no. 4, pp. 36–44, 7 2023. [Online]. Available: <https://ieeexplore.ieee.org/document/10158968/>
- [11] J. Loffredo, “Consumer empowerment: Lessons from the European Union [In my view],” *IEEE Power and Energy Magazine*, vol. 21, no. 4, pp. 98–100, 7 2023. [Online]. Available: <https://ieeexplore.ieee.org/document/10158966/>
- [12] The GridWise Architecture Council, “GridWise Transactive Energy Framework,” The GridWise Architecture Council, Tech. Rep., 2019.
- [13] P. Rodilla, P. Mastropietro, and P. Brito-Pereira, “The Challenge of Integrating Demand Response in Capacity Remuneration Mechanisms: Providing a Comprehensive Theoretical Framework,” *IEEE Power and*

- Energy Magazine*, vol. 21, no. 4, pp. 64–71, 7 2023. [Online]. Available: <https://ieeexplore.ieee.org/document/10158940/>
- [14] IEA, “Unlocking Smart Grid Opportunities in Emerging Markets and Developing Economies,” International Energy Agency, Tech. Rep., 2024. [Online]. Available: www.iea.org/t&c/
- [15] D. Toquica, K. Agbossou, N. Henao, R. Malhamé, S. Kelouwani, and F. Amara, “Prevision and planning for residential agents in a transactive energy environment,” *Smart Energy*, vol. 2, p. 100019, 5 2021. [Online]. Available: <https://linkinghub.elsevier.com/retrieve/pii/S2666955221000198>
- [16] F. Lopes and H. Coelho, *Electricity Markets with Increasing Levels of Renewable Generation: Structure, Operation, Agent-based Simulation, and Emerging Designs*, ser. Studies in Systems, Decision and Control. Springer International Publishing, 2018, vol. 144. [Online]. Available: <http://link.springer.com/10.1007/978-3-319-74263-2>
- [17] S. C. Doumen, D. S. Boff, S. E. Widergren, and J. K. Kok, “Taming the wild edge of smart grid – Lessons from transactive energy market deployments,” *Electricity Journal*, vol. 36, no. 2-3, 3 2023.
- [18] B. Kuipers, “Trust and Cooperation,” *Frontiers in Robotics and AI*, vol. 9, no. April, pp. 1–18, 4 2022.
- [19] A. Parrado-Duque, N. Henao, K. Agbossou, S. Kelouwani, J. C. Oviedo-Cepeda, and J. Domínguez-Jiménez, “Is it worthwhile to participate in transactive energy? A decision-making model for empowering residential customers,” *The Electricity Journal*, vol. 37, no. 7-10, p. 107447, 8 2024. [Online]. Available: <https://linkinghub.elsevier.com/retrieve/pii/S1040619024000824>
- [20] A. Parrado-Duque, N. Henao, S. Kelouwani, K. Agbossou, and J. C. Oviedo-Cepeda, “Penalty mechanism in transactive energy: A mechanism design approach for day-ahead markets,” *Energy Strategy Reviews*, vol. 59, 5 2025.
- [21] L. Jain and X. Wu, *Game Theoretic Problems in Network Economics and Mechanism Design Solutions*. London: Springer London, 2009. [Online]. Available: <https://link.springer.com/10.1007/978-1-84800-938-7>
- [22] T. Tanaka, F. Farokhi, and C. Langbort, “Faithful implementations of distributed algorithms and control laws,” *IEEE Transactions on Control of Network Systems*, vol. 4, no. 2, pp. 191–201, 2017.
- [23] N. Parikh, “Proximal Algorithms,” *Foundations and Trends in Optimization*, vol. 1,

no. 3, pp. 127–239, 2014.

- [24] F. Etedadi Aliabadi, K. Agbossou, S. Kelouwani, N. Henao, and S. S. Hosseini, “Coordination of Smart Home Energy Management Systems in Neighborhood Areas: A Systematic Review,” *IEEE Access*, vol. 9, pp. 36 417–36 443, 2021. [Online]. Available: <https://ieeexplore.ieee.org/document/9363112/>
- [25] I. V. Chremos and A. A. Malikopoulos, “Mechanism Design Theory in Control Engineering: A Tutorial and Overview of Applications in Communication, Power Grid, Transportation, and Security Systems,” *IEEE Control Systems*, vol. 44, no. 1, pp. 20–45, 2 2024. [Online]. Available: <https://ieeexplore.ieee.org/document/10384599/>
- [26] R. Ghorani, M. Fotuhi-Firuzabad, and M. Moeini-Aghaie, “Main Challenges of Implementing Penalty Mechanisms in Transactive Electricity Markets,” *IEEE Transactions on Power Systems*, vol. 34, no. 5, pp. 3954–3956, 9 2019. [Online]. Available: <https://ieeexplore.ieee.org/document/8678451/>
- [27] K. Abedrabboh and L. Al-Fagih, “Applications of mechanism design in market-based demand-side management: A review,” *Renewable and Sustainable Energy Reviews*, vol. 171, p. 113016, 1 2023. [Online]. Available: <https://linkinghub.elsevier.com/retrieve/pii/S1364032122008978>
- [28] Y. Shoham and K. Leyton-Brown, *Multiagent Systems*. Cambridge University Press, 12 2008.
- [29] Y. Narahari, *Game Theory and Mechanism Design*, ser. IISc Lecture Notes Series. World Scientific, 5 2014, vol. 4, no. 1.
- [30] T. Fujiwara-Greve, *Non-Cooperative Game Theory*, ser. Monographs in Mathematical Economics. Tokyo: Springer Japan, 2015, vol. 1.
- [31] V. Ungureanu, *Pareto-Nash-Stackelberg Game and Control Theory*, ser. Smart Innovation, Systems and Technologies. Springer Cham, 2018, vol. 89. [Online]. Available: <http://link.springer.com/10.1007/978-3-319-75151-1>
- [32] E. Parilina, P. Viswanadha Reddy, and G. Zaccour, *Handbook of Dynamic Game Theory*. Springer International Publishing, 2018, vol. 51. [Online]. Available: <http://link.springer.com/10.1007/978-3-319-44374-4>
- [33] A. Agrawal, R. Verschueren, S. Diamond, and S. Boyd, “A rewriting system for convex optimization problems,” *Journal of Control and Decision*, vol. 5, no. 1, pp. 42–60, 1 2018.

- [34] M. C. Fu, *Handbook of Simulation Optimization*, ser. International Series in Operations Research & Management Science. New York, NY: Springer New York, 2015, vol. 216. [Online]. Available: <https://link.springer.com/10.1007/978-1-4939-1384-8>
- [35] A. Ali, J. Z. Kolter, S. Diamond, and S. Boyd, “Disciplined convex stochastic programming: A new framework for stochastic optimization,” *Uncertainty in Artificial Intelligence - Proceedings of the 31st Conference, UAI 2015*, vol. 1, no. 3, pp. 62–71, 2015.
- [36] L. Fisher, *Rock, Paper, Scissors: Game Theory in Everyday Life*. Basic Books, 2008.
- [37] J. Watson, *Strategy*. W. W. Norton and Company, 2013.
- [38] B. Parrish, R. Gross, and P. Heptonstall, “On demand: Can demand response live up to expectations in managing electricity systems?” *Energy Research and Social Science*, vol. 51, no. May 2018, pp. 107–118, 2019. [Online]. Available: <https://doi.org/10.1016/j.erss.2018.11.018>
- [39] D. Sloot, N. Lehmann, and A. Ardone, “Explaining and promoting participation in demand response programs: The role of rational and moral motivations among German energy consumers,” *Energy Research and Social Science*, vol. 84, no. May 2021, p. 102431, 2022. [Online]. Available: <https://doi.org/10.1016/j.erss.2021.102431>
- [40] S. Thomas, “Allowing British Electricity Consumers to Choose Their Supplier: Was it Worth It?” *IEEE Power and Energy Magazine*, vol. 21, no. 4, pp. 18–25, 7 2023. [Online]. Available: <https://ieeexplore.ieee.org/document/10158967/>
- [41] E. Beckstedde and L. Meeus, “From “Fit and Forget” to “Flex or Regret” in Distribution Grids: Dealing With Congestion in European Distribution Grids,” *IEEE Power and Energy Magazine*, vol. 21, no. 4, pp. 45–52, 7 2023. [Online]. Available: <https://ieeexplore.ieee.org/document/10158972/>
- [42] H. Yazdani, M. Doostizadeh, and F. Aminifar, “Unlocking the value of flexibility of behind-the-meter prosumers: An overview of mechanisms to esteemed trends,” *Electricity Journal*, vol. 35, no. 5, 6 2022.
- [43] B. Parrish, P. Heptonstall, R. Gross, and B. K. Sovacool, “A systematic review of motivations, enablers and barriers for consumer engagement with residential demand response,” *Energy Policy*, vol. 138, no. December 2019, p. 111221, 2020. [Online]. Available: <https://doi.org/10.1016/j.enpol.2019.111221>

- [44] P. H. Li, I. Keppo, M. Xenitidou, and M. Kamargianni, "Investigating UK consumers' heterogeneous engagement in demand-side response," *Energy Efficiency*, vol. 13, no. 4, pp. 621–648, 2020.
- [45] L. Exizidis, J. Kazempour, A. Papakonstantinou, P. Pinson, Z. De Greve, and F. Vallee, "Incentive-Compatibility in a Two-Stage Stochastic Electricity Market With High Wind Power Penetration," *IEEE Transactions on Power Systems*, vol. 34, no. 4, pp. 2846–2858, 7 2019.
- [46] S. M. Ghorashi, M. Rastegar, S. Senemmar, and A. R. Seifi, "Optimal design of reward-penalty demand response programs in smart power grids," *Sustainable Cities and Society*, vol. 60, no. May, p. 102150, 2020. [Online]. Available: <https://doi.org/10.1016/j.scs.2020.102150>
- [47] B. Dulipala and S. Debbarma, "Energy scheduling model considering penalty mechanism in transactive energy markets: A hybrid approach," *International Journal of Electrical Power & Energy Systems*, vol. 129, no. June 2020, p. 106742, 7 2021.
- [48] J. B. Dulipala and S. Debbarma, "Decision-making model with reduced risk of penalties in transactive energy markets," *Electric Power Systems Research*, vol. 199, no. May, p. 107371, 10 2021.
- [49] K. Ma and P. R. Kumar, "Incentive Compatibility in Stochastic Dynamic Systems," *IEEE Transactions on Automatic Control*, vol. 66, no. 2, pp. 651–666, 2 2021. [Online]. Available: <https://ieeexplore.ieee.org/document/9068413/>
- [50] M. Hoseinpour, M. Hoseinpour, M. Haghifam, and M. R. Haghifam, "Privacy-Preserving and Approximately Truthful Local Electricity Markets: A Differentially Private VCG Mechanism," *IEEE Transactions on Smart Grid*, vol. 15, no. 2, pp. 1991–2003, 3 2024.
- [51] Y. Yao, C. Gao, K. Lai, T. Chen, and J. Yang, "An incentive-compatible distributed integrated energy market mechanism design with adaptive robust approach," *Applied Energy*, vol. 282, p. 116155, 1 2021. [Online]. Available: <https://linkinghub.elsevier.com/retrieve/pii/S0306261920315609>
- [52] M. D. de Souza Dutra and N. Alguacil, "Fairness of prosumers' incentives in residential demand response: A practical decentralized optimization approach," *International Journal of Electrical Power & Energy Systems*, vol. 148, no. December 2022, p. 109015, 6 2023. [Online]. Available: <https://doi.org/10.1016/j.ijepes.2023.109015><https://linkinghub.elsevier.com/retrieve/pii/S0142061523000728>
- [53] G. Tsousoglou, K. Steriotis, N. Efthymiopoulos, P. Makris, and E. Varvarigos,

- “Truthful, Practical and Privacy-Aware Demand Response in the Smart Grid via a Distributed and Optimal Mechanism,” *IEEE Transactions on Smart Grid*, vol. 11, no. 4, pp. 3119–3130, 7 2020. [Online]. Available: <https://ieeexplore.ieee.org/document/8954657/>
- [54] Y. Wasa, K. Hirata, and K. Uchida, “A Contract Theory Approach to Dynamic Incentive Mechanism and Control Synthesis for Moral Hazard in Power Grids,” *IEEE Transactions on Control Systems Technology*, vol. 30, no. 5, pp. 2072–2083, 9 2022. [Online]. Available: <https://ieeexplore.ieee.org/document/9644928/>
- [55] M. Montazeri, H. Kebriaei, and B. N. Araabi, “A Tractable Truthful Profit Maximization Mechanism Design with Autonomous Agents,” *IEEE Transactions on Automatic Control*, vol. PP, no. iii, pp. 1–6, 2024. [Online]. Available: <https://ieeexplore.ieee.org/document/10416648/>
- [56] K. Zhang, Y. Xu, and H. Sun, “Bilevel optimal coordination of active distribution network and charging stations considering EV drivers’ willingness,” *Applied Energy*, vol. 360, p. 122790, 4 2024. [Online]. Available: <https://linkinghub.elsevier.com/retrieve/pii/S0306261924001739>
- [57] B. Satchidanandan and M. A. Dahleh, “Incentive Compatibility in Two-Stage Repeated Stochastic Games,” *IEEE Transactions on Control of Network Systems*, vol. 11, no. 1, pp. 295–306, 3 2024. [Online]. Available: <https://ieeexplore.ieee.org/document/10138437/>
- [58] W. Zhong, K. Xie, Y. Liu, S. Xie, and L. Xie, “Nash Mechanisms for Market Design Based on Distribution Locational Marginal Prices,” *IEEE Transactions on Power Systems*, vol. 37, no. 6, pp. 4297–4309, 11 2022.
- [59] Hydro-Quebec, “Annual Report 2022,” Hydro-Quebec, Tech. Rep., 2022.
- [60] R. Arnedo, N. Henao, K. Agbossou, J. C. Oviedo-Cepeda, J. A. Dominguez, and D. Toquica, “OpenATE: A Distributed Co-simulation Engine for Transactive Energy Systems,” in *2023 IEEE 11th International Conference on Smart Energy Grid Engineering (SEGE)*. IEEE, 8 2023, pp. 188–193. [Online]. Available: <https://ieeexplore.ieee.org/document/10274534/>
- [61] S. L. Choi, R. Jain, P. Emami, K. Wadsack, F. Ding, H. Sun, K. Gruchalla, J. Hong, H. Zhang, X. Zhu, and B. Kroposki, “eGridGPT: Trustworthy AI in the Control Room,” National Renewable Energy Laboratory, Tech. Rep., 2024. [Online]. Available: <https://www.nrel.gov/docs/fy24osti/87440.pdf>
- [62] L. Rueda, K. Agbossou, N. Henao, S. Kelouwani, J. C. Oviedo-Cepeda,

- B. Le Lostec, S. Sansregret, and M. Fournier, "Online Unsupervised Occupancy Anticipation System Applied to Residential Heat Load Management," *IEEE Access*, vol. 9, pp. 109 806–109 821, 2021. [Online]. Available: <https://ieeexplore.ieee.org/document/9491101/>
- [63] D. Toquica, K. Agbossou, R. Malhame, N. Henao, S. Kelouwani, and M. Fournier, "A Recommender System for Predictive Control of Heating Systems in Economic Demand Response Programs," *IEEE Open Journal of Industry Applications*, vol. 3, pp. 79–89, 2022.

Appendix A - Résumé

A.1 Introduction

L'électricité représente environ un cinquième de la consommation finale d'énergie dans le monde et devrait accroître sa part à mesure que l'électrification progresse dans tous les secteurs [1, 2]. Le secteur du bâtiment — responsable d'environ 30 % de la consommation énergétique finale totale [3] et de 60 % de la croissance mondiale de la demande d'électricité entre 2023 et 2024 [4] — constitue le deuxième secteur le plus énergivore après l'industrie [5]. À l'intérieur du secteur du bâtiment, le chauffage des locaux demeure l'usage final dominant, représentant près des trois quarts de la consommation totale d'énergie [6].

Au Canada, par exemple, les bâtiments représentent environ 40 % de la consommation énergétique finale nationale, l'électricité assurant plus de 60 % de cette demande [6]. Au Québec, l'électricité est encore plus prédominante : elle fournit environ 77 % des besoins énergétiques résidentiels, dont le chauffage des locaux représente à lui seul près de 60 %, et le chauffage de l'eau environ 7 % [7]. L'importance du secteur résidentiel au Québec est d'ailleurs soulignée par Hydro-Québec, qui a rapporté qu'en 2024, les clients résidentiels représentaient la plus grande part de la consommation d'électricité (38 %), suivis des grands clients industriels (31 %), des clients commerciaux et institutionnels (27 %), et d'autres clients (4 %) [8]. Ces faits mettent en évidence le rôle central du secteur résidentiel dans l'atteinte des objectifs de décarbonation et justifient l'attention croissante portée aux stratégies de flexibilité de la demande et aux mesures d'efficacité énergétique, telles que celles énoncées dans le Plan d'action 2035 d'Hydro-Québec [9].

Compte tenu de l'électrification croissante et de la centralité de la demande résidentielle

dans les systèmes électriques, l'interaction entre les consommateurs et le réseau devient de plus en plus dynamique et complexe [10]. Les ménages ne sont plus de simples utilisateurs passifs d'énergie, mais des acteurs potentiellement actifs capables de fournir de la flexibilité, du stockage et des services de réponse à la demande grâce à des dispositifs intelligents et des ressources distribuées [11]. Ce rôle évolutif positionne le secteur résidentiel comme un élément clé dans la mise en place de mécanismes de coordination décentralisés, ouvrant la voie à de nouvelles structures de marché — telles que les cadres d'énergie transactionnelle — qui facilitent les négociations et les échanges de valeur entre les acteurs du réseau [12, 13].

Outre la transition des combustibles fossiles vers des sources d'énergie renouvelables pour répondre à la demande actuelle, la transition énergétique implique également : i) l'électrification des usages finaux, ii) l'intégration de charges modernes pilotées par l'intelligence artificielle, et iii) la numérisation complète du secteur électrique [4]. Cette dernière transformation entraîne un changement de paradigme accéléré à tous les niveaux des systèmes énergétiques, redéfinissant la manière dont les services au réseau — tels que la flexibilité — sont identifiés, valorisés et échangés à la périphérie du réseau [14].

Pour permettre cette transformation, les agents logiciels — décideurs autonomes agissant au nom des participants au marché — jouent un rôle central en libérant la flexibilité du côté de la demande à travers des signaux de prix et de coordination fins, sans compromettre la confidentialité ni l'autonomie locale [15].

Dans les systèmes d'énergie transactionnelle (TE), ces agents peuvent choisir de participer à des interactions « day-ahead » (au jour-le-lendemain) qui orientent les profils de charge agrégés vers les objectifs du système tout en améliorant les factures des clients [16]. Sur le plan opérationnel, les programmes TE doivent concilier trois réalités [17]. Premièrement,

la flexibilité des clients est hétérogène et influencée par leur confort, leur équipement technologique (par ex. les systèmes de chauffage) et l'incertitude ; deuxièmement, la coordination des profils de consommation doit être réalisée avec une divulgation minimale d'informations privées afin de préserver la confidentialité et la scalabilité ; troisièmement, les participants au marché sont des agents stratégiques [18] : les logiciels tenteront d'exploiter toute faille dans les règles d'un contrat.

Ces réalités motivent une architecture *coordinateur-agent résidentiel (AR)* dans laquelle un coordinateur, agissant au nom de la compagnie d'électricité, propose des signaux dynamiques de prix et de pénalité afin d'aplanir la consommation d'énergie, tandis que les AR répondent avec des plans de consommation en évaluant des éléments tels que la possibilité de tricher lors de la négociation, le confort et les contraintes de leurs dispositifs [19, 20]. L'interaction entre le coordinateur et les AR dans le système TE est modélisée comme un jeu de Stackelberg, avec rationalité bornée, mis en œuvre au travers d'un contrat structuré en quatre phases : *Inscription, Coordination, Exécution et Règlement*, permettant de structurer les signaux, les décisions et la responsabilité dans le temps.

Dans cette architecture, deux approches canoniques de marché existent [22]. Le cadre *one-shot* (à un seul échange) implique un seul tour de signaux et de rapports ; il offre une charge de communication réduite et une logique de règlement claire, mais sacrifie une partie de l'efficacité afin d'éviter la divulgation d'informations privées. Les conceptions itératives, quant à elles, permettent des rétroactions multi-cycles, améliorant la stabilité et l'optimalité sous certaines conditions de convergence tout en préservant la nature décentralisée de l'information [23]. Les mécanismes d'enchères itératives et de couplage de marché décentralisé offrent des précédents pertinents [24] : ils peuvent converger vers des résultats efficaces avec un échange d'informations limité et une robustesse face à certaines déviations

stratégiques — des propriétés particulièrement précieuses lorsque les AR conservent leurs informations privées et ne partagent que leur plan de consommation.

Cependant, un échange minimal d'informations ne suffit pas. Dans toute négociation où les AR peuvent choisir librement de rapporter un plan de consommation vrai ou faux sur le marché « day-ahead », la manipulation stratégique devient un enjeu de conception de premier ordre. Ce constat élève la conception de mécanismes (*mechanism design*) d'un simple cadre théorique à une discipline centrale pour cette application.

A.2 Problématique

Les marchés de l'électricité « day-ahead », une forme particulière de marché à terme, jouent un rôle clé dans l'exploitation des systèmes électriques [16]. Ils permettent aux compagnies d'électricité de planifier l'exploitation du système en fonction des prévisions de la demande et de l'offre, assurant ainsi la fiabilité grâce à une planification énergétique quotidienne.

Dans un cadre TE, les compagnies d'électricité et les clients sont équipés d'agents capables de négocier des transactions à l'avance. Les clients participent à une négociation avec le coordinateur, cherchant à établir des accords qui servent au mieux leurs intérêts [17].

Cependant, au-delà des défis technologiques liés au déploiement des agents chez les clients, et au-delà de l'incertitude inhérente aux conditions météorologiques et au comportement humain, les agents résidentiels dotés d'une rationalité et d'une intelligence suffisantes peuvent adopter un comportement stratégique : ils peuvent tenter de manipuler le mécanisme de négociation à leur avantage économique [25]. Si un tel comportement de fausse déclaration

se produit, le coordinateur risque d'élaborer un plan opérationnel fondé sur une demande inexacte, compromettant la fiabilité technique du système et la viabilité financière à long terme du programme TE [26].

Ainsi, cette thèse vise à prévenir la manipulation stratégique dans les systèmes TE en appliquant le concept de compatibilité incitative (*incentive compatibility*) issu de la conception de mécanismes. L'objectif du coordinateur est de concevoir un mécanisme dans lequel, lors de la négociation, les agents trouvent plus coûteux de mentir sur leur plan de consommation que de le déclarer de manière véridique. En même temps, le coordinateur doit s'assurer que la participation reste attrayante, tout en évaluant l'équilibre budgétaire du mécanisme et son efficacité par rapport à un mécanisme naïf (bénévole) [27].

Cette thèse aborde donc les problèmes principaux suivants :

- Une divergence existe entre les objectifs du coordonnateur et les actions stratégiques des agents résidentiels, qui peuvent fournir des informations erronées sur les marchés journaliers afin de manipuler le mécanisme à leur avantage individuel. Cet écart entraîne des inefficacités, des déséquilibres budgétaires et des écarts par rapport aux programmes de consommation prévus.
- En l'absence de cadres de communication qui préserveraient les données privées, les clients peuvent être réticents à partager les informations dont le leader du marché a besoin, ce qui compromet la participation et diminue l'efficacité globale des programmes d'énergie transactionnelle.
- Les mécanismes de coordination actuels ne permettent pas de concevoir des systèmes compatibles avec les incitations qui garantissent à la fois la participation et l'équilibre budgétaire ainsi que l'efficacité ; cela se traduit par une absence d'équilibres stables ou de résultats de négociation économiquement viables.

A.3 Objectifs et contributions

Cette thèse vise à développer un mécanisme capable d'éviter les effets négatifs du comportement stratégique des agents résidentiels dans un marché de l'électricité « day-ahead » au sein d'un cadre d'énergie transactionnelle (TE). Cet objectif principal conduit à la formulation des trois objectifs spécifiques suivants :

1. Développer un système TE entre un coordinateur (leader) et des agents résidentiels (suiveurs) afin d'évaluer les concepts de la conception de mécanismes. Ce développement comprend la modélisation de leurs rôles, de leurs capacités et de leurs interactions, tout en tenant compte de l'incertitude du côté de la demande, pour le règlement d'un marché de l'électricité « day-ahead ».
2. Formuler un mécanisme compatible avec les incitations au sein du système TE, afin de décourager la fausse déclaration d'information lors de la négociation tout en maintenant l'interaction des agents.
3. Évaluer le mécanisme compatible avec les incitations dans des architectures de marché à un seul échange (*one-shot*) et itératives, en analysant ses effets sur la rationalité individuelle, l'équilibre budgétaire et l'efficacité.

Cette thèse fait progresser l'état de l'art en abordant le comportement stratégique dans les systèmes TE comportant des agents résidentiels, tout en préservant la confidentialité des clients. Le cadre TE développé dans ce travail évalue de manière systématique la rationalité individuelle, l'équilibre budgétaire et l'efficacité sous un mécanisme compatible avec les incitations. Pour atteindre cet objectif, ce travail s'appuie sur des concepts issus de la conception de mécanismes et de la théorie des jeux, notamment :

— La modélisation d'un système TE comme un jeu de Stackelberg comportant une

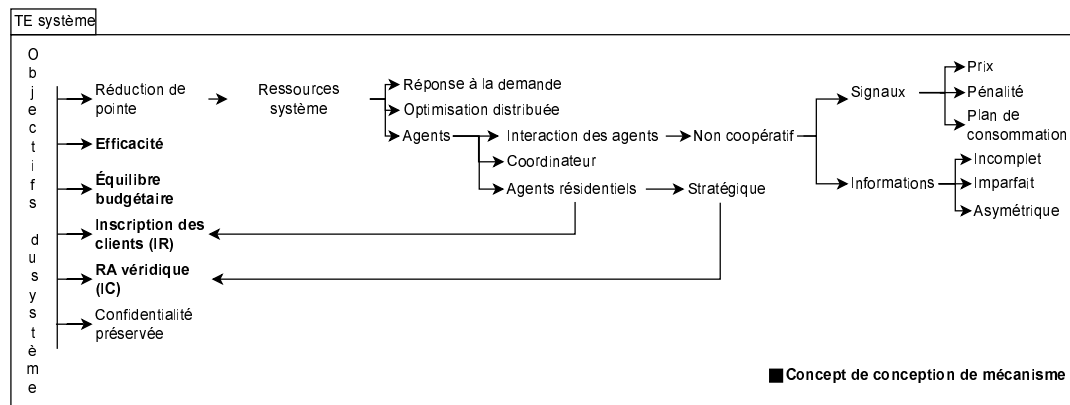


FIGURE A.1 – Synthèse des concepts clés de la méthodologie de cette thèse.

structure à un leader et plusieurs suiveurs, intégrant l’incertitude du côté de la demande et son impact sur les politiques de décision du coordinateur.

- La conception d’une politique de coordination basée sur un couple prix–pénalité, qui aligne les actions des agents résidentiels sur les objectifs du coordinateur — en favorisant la déclaration véridique des agents dans un contexte de négociation, tout en préservant leur confidentialité et en coordonnant leurs actions pour réduire la consommation de pointe.
- La formulation d’un mécanisme TE avec une caractérisation théorique des conditions suffisantes sous lesquelles la déclaration véridique constitue la stratégie dominante pour les agents résidentiels dans le cadre proposé.

A.4 Méthodologie

Cette section présente le cadre méthodologique développé pour atteindre les objectifs de cette thèse. L’approche proposée intègre des concepts issus de la conception de mécanismes, de la théorie des jeux et des systèmes d’énergie transactionnelle (TE), en les inscrivant dans le contexte opérationnel des marchés de l’électricité, comme illustré à la Fig. A.1.

La méthodologie repose sur la modélisation des interactions entre un coordinateur (ou agrégateur) et un ensemble d’agents résidentiels représentant les clients finaux. Ces interactions se déroulent dans un environnement numérique entièrement distribué, où les agents logiciels agissent de manière autonome, intelligente et stratégique pour défendre leurs intérêts économiques respectifs.

A.4.1 Cadre général de modélisation

Le cadre proposé est fondé sur une structure hiérarchique de type *Stackelberg*, dans laquelle le coordinateur agit comme leader, tandis que les agents résidentiels jouent le rôle de suiveurs. Le coordinateur définit les signaux économiques — tels que les prix et les pénalités — afin d’inciter les agents à ajuster leur consommation ou leur flexibilité. En retour, les agents résidentiels réagissent de manière rationnelle en optimisant leur bien-être individuel selon les signaux reçus.

Cette structure permet d’analyser le comportement stratégique des agents dans un marché de l’électricité « day-ahead », où les informations sont incomplètes, imparfaites et asymétriques. Le coordinateur ne connaît pas les préférences réelles ni la flexibilité disponible de chaque agent, ce qui ouvre la possibilité de manipulation stratégique dans les déclarations.

A.4.2 Conception de mécanismes et compatibilité avec les incitations

Le développement du mécanisme s’appuie sur la théorie de la conception de mécanismes, dont l’objectif est de concevoir des règles du jeu garantissant que la stratégie optimale pour chaque agent est de déclarer la vérité, indépendamment de l’information privée des autres participants. Dans ce cadre, le mécanisme proposé vise à assurer :

- la **véridicité** (*truthfulness*) : les agents sont incités à révéler leurs informations réelles ;
- la **rationalité individuelle** : chaque agent obtient un gain non négatif en participant au mécanisme ;
- l'**équilibre budgétaire** : les flux financiers entre le coordinateur et les agents demeurent équilibrés ;
- l'**efficacité allocative** : les ressources énergétiques flexibles sont utilisées de manière optimale.

Le mécanisme est formulé de manière à prévenir l'injection d'informations fausses tout en respectant la confidentialité des données des clients. Pour cela, il repose sur une politique de coordination basée sur un couple prix-pénalité, qui ajuste les incitations en fonction de la déclaration et du comportement observé des agents.

A.4.3 Environnement numérique et agents logiciels

L'intégration du mécanisme dans un environnement TE numérisé implique l'utilisation d'agents logiciels capables de négocier de manière autonome. Ces agents, dotés de capacités de perception, de décision et d'apprentissage, représentent les intérêts économiques de leurs propriétaires (coordinateur ou clients résidentiels).

Dans un contexte de marché distribué, ces agents interagissent via une plateforme de négociation, où les transactions énergétiques — telles que la réduction de charge ou la fourniture de flexibilité — sont évaluées, négociées et réglées. Cette approche favorise la décentralisation des décisions et la scalabilité du système, tout en limitant les besoins de communication centralisée et en préservant la confidentialité des utilisateurs.

A.4.4 Approche d'évaluation et simulations

La validation du mécanisme proposé repose sur des simulations menées à partir d'un ensemble de 20 modèles de clients résidentiels, inspirés de la collaboration avec Hydro-Québec. Ces simulations permettent d'analyser la robustesse du mécanisme sous différentes conditions d'information et de comportement stratégique, ainsi que son impact sur la performance économique et la fiabilité du système électrique.

Les indicateurs de performance considérés incluent la véracité des déclarations, l'efficacité du marché, la stabilité budgétaire et la réduction des écarts énergétiques entre les prévisions « day-ahead » et les réalisations effectives.

A.4.5 Programmation stochastique convexe

L'analyse de la décision de meilleure réponse effectuée par les agents résidentiels (AR) lors de la phase de négociation, en présence d'incertitude et sous la politique de prix adoptée par le leader du marché, a été réalisée en recourant au concept d'induction à rebours [30]. De plus, les fonctions de coût et les règles de paiement considérées dans cette thèse sont compactes, convexes et continues [33]. Ces propriétés ont été fondamentales pour déterminer si le mécanisme proposé atteignait un équilibre en stratégies dominantes et pour garantir une solution d'optimum global [21, 30, 33].

A.4.6 Résumé

En résumé, la méthodologie proposée combine la théorie des jeux, la conception de mécanismes et la modélisation multi-agents pour concevoir un mécanisme TE véridique et distribué. Ce cadre méthodologique permet d'analyser le comportement stratégique des agents résidentiels dans un environnement d'information asymétrique, d'évaluer la

compatibilité avec les incitations et de garantir une coordination efficace entre les acteurs du marché.

A.5 Description de résultats publiés

L'atteinte de l'objectif principal de cette recherche a nécessité la réalisation de plusieurs tâches visant à formuler un environnement de négociation, à définir le rôle et la programmation des joueurs du jeu, c'est-à-dire les agents interagissant dans cet environnement, ainsi qu'à établir et analyser rétrospectivement la règle de paiement. Ces tâches incluent également la définition des conditions nécessaires pour satisfaire la propriété de compatibilité avec les incitations (IC), ainsi que le développement d'un cadre d'évaluation des concepts de rationalité individuelle (IR), d'efficacité allocative (EFF) et d'équilibre budgétaire (BB).

L'avancement de la méthodologie de la thèse a été documenté à travers trois articles scientifiques, présentés comme suit :

1. Le premier article, intitulé « *Is it worthwhile to participate in transactive energy? A decision-making model for empowering residential customers* », a été publié dans *The Electricity Journal* (ELSEVIER) le 12 novembre 2024. Ce travail a démontré une condition suffisante pour garantir un mécanisme compatible avec les incitations dans un cadre de négociation itératif, fondée sur la relation entre la pénalité appliquée aux écarts par rapport à un accord (α) et le paramètre de coût du réseau électrique (λ). En outre, il a exploré l'effet des valeurs de pénalité sur la condition de rationalité individuelle (IR) des clients. Les résultats correspondants sont présentés dans la Section A.5.1, « *L'effet d'un mécanisme de pénalité sur la volonté des agents résidentiels de participer à un programme TE* ».
2. Le deuxième article, intitulé « *Penalty mechanism in transactive energy: A mechanism*

design approach for day-ahead markets », a été publié dans *Energy Strategy Reviews* (ELSEVIER) le 25 avril 2025. Ce travail a examiné les règles de paiement (*Payment Rules, PR*) utilisées dans la littérature sous l'angle de la compatibilité avec les incitations. Il a également mis en évidence les effets négatifs des mécanismes non véridiques en quantifiant leurs impacts sur les conditions IR, EFF et BB. Ces résultats sont présentés dans la Section A.5.2, « *L'effet du comportement stratégique sur la performance du programme TE* ».

3. Le troisième article, intitulé « *A Reward-Penalty Mechanism to Prevent Strategic-Agents Behaviour in an Iterative Negotiation Framework: A Transactive Energy Context* », est actuellement en révision dans la revue *Energy Economics* (ELSEVIER). Ce travail a démontré formellement que le mécanisme proposé atteint un équilibre en stratégie dominante, c'est-à-dire qu'il assure la propriété de compatibilité avec les incitations (IC), pour un cas d'étude basé sur un jeu itératif. Les objectifs de coordination ont été atteints, tout en permettant aux clients de réduire leur facture d'électricité par rapport à un scénario sans coordination. Les résultats correspondants sont présentés dans la Section A.5.3, « *Prévenir le comportement stratégique des agents résidentiels dans un cadre de négociation itératif fondé sur l'analyse des stratégies des agents* ».

A.5.1 Effet d'un mécanisme de pénalité sur la volonté des agents résidentiels de participer à un programme d'énergie transactionnelle

Contexte et motivation

Cet article aborde une question centrale pour les systèmes d'énergie transactionnelle (TE) : les clients résidentiels et le coordinateur (agrégateur ou service public) peuvent-ils bénéficier d'une participation coordonnée sur le marché *day-ahead*, lorsque les agents

sont stratégiques et que l'information est privée ? Il situe la TE dans le cadre plus large de la numérisation des systèmes électriques, où des agents logiciels agissent au nom des utilisateurs pour répondre aux signaux de prix et de coordination. Les travaux antérieurs supposent souvent un comportement bienveillant ou une information complète, rendant les programmes vulnérables à des manipulations stratégiques (p. ex. faux plans ou fausses lignes de base), à un faible taux d'adhésion et à des préoccupations liées à la confidentialité des données.

Pour combler cette lacune, l'article adopte la conception de mécanismes (*mechanism design*) comme cadre analytique principal, en se concentrant sur deux propriétés clés : la compatibilité avec les incitations (IC) et la rationalité individuelle (IR). Ces concepts sont appliqués à un contrat TE pratique à quatre phases : inscription, coordination, exécution et règlement. L'étude effectue également une analyse coûts-bénéfices pour le coordinateur et les clients.

Le principal défi de conception de cet article consiste à élaborer une règle de paiement (*Payment Rule, PR*) robuste, rendant le mensonge plus coûteux que la véracité, tout en limitant au minimum les échanges d'informations (les agents résidentiels ne partagent que leurs plans, et non leurs types privés). L'étude prend également en compte l'incertitude réelle (conditions météorologiques, charges électriques).

Méthodologie

L'interaction TE est modélisée comme un jeu de Stackelberg — le coordinateur agissant en tant que leader, et les agents résidentiels (AR) en tant que suiveurs — avec un échange d'informations minimal. Le contrat se déroule en quatre phases :

— **Inscription** – Le coordinateur publie un prix de référence fixe et un ensemble de

valeurs de pénalité candidates (α). Chaque AR exécute un programme stochastique convexe (basé sur des scénarios Monte Carlo) pour décider de participer ou non (vérification *ex-ante* de la condition IR).

- **Coordination** – Pour les AR inscrits, le coordinateur met à jour de manière itérative les prix selon une règle de partage des coûts fondée sur la consommation planifiée agrégée. Les AR ajustent leurs plans en résolvant des programmes convexes avec un terme proximal pour assurer la stabilité et la convergence.
- **Exécution** – L’incertitude se réalise (charges et températures réelles), produisant une consommation effective et des écarts par rapport au plan de consommation déclaré.
- **Règlement** – Les factures sont calculées selon une règle de paiement combinant (i) la consommation réelle facturée au prix final et (ii) une pénalité quadratique symétrique sur l’écart entre la consommation réelle et celle déclarée. Lorsque le comportement stratégique est évité, les clients subissent une pénalisation liée aux écarts dus à l’incertitude, et non à une fausse déclaration. Les conditions du premier ordre et les relations paramétriques (notamment $\alpha \gg \lambda$, où λ paramètre le générateur de prix) établissent la véracité comme équilibre en stratégie dominante. De plus, la stratégie véridique conduit les clients à réduire leur facture par rapport à un scénario sans participation, démontrant ainsi que le mécanisme IC proposé satisfait également la condition IR.

Le modèle d’AR considère les coûts d’énergie importée, l’inconfort thermique (fonction quadratique autour du point de consigne de température), la dégradation de la batterie et les pénalités de déviation. Les dynamiques incluent un modèle thermique linéaire d’état et des contraintes de stockage d’énergie (état de charge et limites de puissance). Du côté du coordinateur, le modèle prend en compte la mise à jour des prix à partir des plans

agrégés attendus ; seuls les plans sont observés, garantissant ainsi la préservation de la confidentialité.

Le cadre de simulation repose sur 20 clients résidentiels, une résolution de 10 minutes, 100 scénarios Monte Carlo, des profils de charge hivernaux, une capacité de stockage BESS de 2,5 kWh, un prix fixe tiré d'un rapport de service public [59], et des prix dynamiques issus de travaux antérieurs de co-simulation TE [60]. Les pénalités explorées, $\alpha = \{47, 50, 53, 57, 60, 63, 66\}$, ont été sélectionnées en fonction des décisions des AR de se retirer volontairement des négociations.

Résultats

L'étude démontre que la participation à un programme TE peut être économiquement avantageuse pour les clients résidentiels comme pour le coordinateur, à condition que le mécanisme soit soigneusement conçu pour garantir la véracité et l'équité. Les simulations menées sur 20 agents résidentiels équipés de charges thermiques et de systèmes de stockage montrent que le mécanisme proposé — fondé sur une structure prix-pénalité — décourage efficacement la manipulation stratégique des plans de consommation. La démonstration théorique de la compatibilité avec les incitations est confirmée numériquement : dès que la pénalité quadratique est appliquée et que la facturation repose sur la consommation réelle plutôt que déclarée, les agents n'ont aucun intérêt économique à soumettre de faux plans. Ce résultat reste valide même en présence d'incertitude à moyenne non nulle, confirmant la robustesse du mécanisme.

L'analyse révèle également des compromis nécessaires. Les décisions d'inscription dépendent du paramètre de pénalité : des pénalités faibles encouragent une participation complète, tandis que des pénalités trop élevées dissuadent les clients de rejoindre la phase

de coordination. Ce constat souligne l'importance d'un calibrage précis pour équilibrer incitation à la participation et dissuasion du comportement stratégique. Pendant la phase de coordination, les clients participants obtiennent en général des coûts d'électricité attendus inférieurs à ceux d'un tarif fixe, profitant d'une tarification dynamique et d'une planification optimisée. Toutefois, ces économies prévues peuvent diminuer en phase d'exécution lorsque la consommation réelle s'écarte sensiblement du plan convenu, car les pénalités pour déviation augmentent les coûts — d'où l'importance d'une prévision précise et d'un suivi rigoureux.

Du point de vue du coordinateur, la rentabilité dépend à la fois du niveau de participation et du degré de flexibilité offert par les clients. Les simulations indiquent que les profits culminent pour des valeurs intermédiaires de pénalité, où la participation reste suffisante pour garantir une flexibilité utile sans décourager les clients par un risque excessif. Néanmoins, les bénéfices réalisés en phase de règlement demeurent systématiquement inférieurs aux projections faites en coordination, en raison de l'incertitude et de la structure quadratique des coûts. Malgré cela, le mécanisme génère généralement des revenus positifs, ce qui démontre sa faisabilité pratique. Les résultats confirment qu'un mécanisme fondé sur la pénalisation et préservant la confidentialité peut aligner les incitations individuelles sur les objectifs du système, assurer la véracité des déclarations et améliorer les performances économiques.

A.5.2 L'effet du comportement stratégique sur la performance du programme d'Énergie transactionnelle (TE)

Contexte

Cet article aborde un défi crucial dans les systèmes d'Énergie transactionnelle (TE) : garantir un échange d'informations véridiques entre les agents résidentiels (RAs) et le gestionnaire du réseau de distribution (DSO) dans les marchés d'électricité à l'avance d'un jour, dans une architecture de marché à coup unique. Les cadres TE exploitent la flexibilité distribuée en permettant aux clients de négocier leurs plans de consommation d'énergie avec la compagnie d'électricité. Cependant, des agents stratégiques peuvent exploiter les faiblesses des mécanismes de négociation en déclarant de manière erronée leur consommation prévue, entraînant des inefficacités économiques, des déséquilibres budgétaires, voire des risques opérationnels pour le réseau.

L'article adopte la théorie de la conception de mécanismes pour traiter cette problématique, en cherchant à créer des règles alignant les incitations individuelles avec les résultats socialement désirables. Quatre propriétés clés guident cette conception : (i) la compatibilité incitative (IC), garantissant que dire la vérité est la stratégie optimale ; (ii) la rationalité individuelle (IR), assurant que la participation est bénéfique ; (iii) l'efficacité (Eff), visant à approcher le bien-être social ; et (iv) l'équilibre budgétaire (BB), évitant les subventions externes.

L'étude situe sa contribution dans le contexte des mécanismes de négociation à coup unique pour les programmes TE à l'avance d'un jour. Contrairement aux schémas itératifs, les conceptions à coup unique impliquent un seul échange de signaux, réduisant ainsi la charge de communication tout en conservant le risque de déclarations stratégiques.

L'article propose une approche fondée sur des pénalités pour décourager les écarts par rapport aux plans convenus et évalue sa performance à travers différentes phases de conception de mécanismes : ex-ante, intermédiaire et de règlement. Ce travail est motivé par la nécessité de solutions respectueuses de la vie privée, computationnellement viables et capables d'opérer sous incertitude tout en maintenant la viabilité économique.

Méthodologie

Le mécanisme proposé est structuré comme un jeu de négociation à coup unique entre un DSO (leader) et plusieurs RAs (suiveurs). Le DSO annonce un prix dynamique et une politique de pénalité, et chaque RA décide de son plan de consommation d'énergie pour le lendemain. L'interaction est modélisée comme un jeu de Stackelberg sous information incomplète et asymétrique : les RAs connaissent leurs propres préférences et contraintes, mais pas celles des autres, tandis que le DSO n'a pas une visibilité complète sur les types privés.

L'innovation principale réside dans la règle de paiement (PR), qui détermine la facture finale de chaque RA. Cinq PR candidates sont analysées, allant de la tarification linéaire simple à des schémas quadratiques basés sur des pénalités. La propriété IC est testée en examinant si la déclaration véridique minimise le coût espéré du RA sous chaque PR. L'analyse théorique et les simulations montrent que seule la PR combinant la facturation de l'énergie réelle avec une pénalité quadratique sur les écarts satisfait la condition IC sans exiger de valeurs de pénalité extrêmes.

Pour valider ces résultats, l'article emploie un modèle d'optimisation stochastique pour les RAs, intégrant les coûts énergétiques, le confort thermique et les pénalités liées aux écarts par rapport au plan. L'incertitude de la demande est modélisée à l'aide de distributions

de probabilité et résolue par simulation de Monte Carlo. La stratégie tarifaire du DSO repose sur un modèle de partage de coûts qui ajuste les prix selon la consommation agrégée déclarée. L'évaluation se concentre sur trois phases : (i) la rationalité individuelle et l'efficacité ex-ante (via le prix de l'anarchie et le prix de la tromperie) ; (ii) la compatibilité incitative et l'équilibre budgétaire à la phase de règlement ; et (iii) l'impact de l'ampleur de la pénalité sur la participation et l'équité.

Résultats

L'analyse révèle que les règles de paiement les plus couramment utilisées ne garantissent pas la compatibilité incitative, permettant ainsi aux agents de réduire leurs coûts en déclarant de manière stratégique leur consommation. Les pénalités linéaires ou la facturation basée sur les valeurs déclarées plutôt que sur les valeurs réelles créent de fortes incitations à la manipulation. En revanche, la règle de pénalité quadratique proposée, combinée à une facturation selon l'énergie réellement consommée, rend la déclaration véridique la stratégie dominante, même en présence d'incertitude. Ce résultat est confirmé à la fois analytiquement et par simulation.

L'étude examine également les compromis entre IC et les autres propriétés du mécanisme. Bien que la règle de pénalité quadratique atteigne les conditions IC et IR, son impact sur l'équilibre budgétaire dépend du calibrage de la pénalité. Des pénalités faibles favorisent la participation mais peuvent entraîner des déficits budgétaires, tandis que des pénalités trop élevées découragent l'inscription, réduisant ainsi la flexibilité et l'efficacité. Les simulations montrent que la tarification dynamique combinée à des pénalités modérées peut améliorer l'efficacité économique par rapport à la tarification fixe, bien qu'un équilibre budgétaire strict reste difficile à atteindre sans mécanismes de redistribution additionnels.

Du point de vue du client, la participation est généralement avantageuse pour des valeurs de pénalité réalistes, satisfaisant ainsi la rationalité individuelle ex-ante. Toutefois, les écarts de consommation lors de la phase d'exécution peuvent augmenter significativement les coûts, soulignant l'importance de prévisions précises et du respect des plans. Les performances du mécanisme sous incertitude démontrent sa robustesse : les coûts espérés sont proches des coûts réels, et la distribution des résultats confirme que les pénalités découragent efficacement les comportements stratégiques.

L'article conclut qu'un mécanisme bien conçu, basé sur des pénalités, peut atteindre la résistance stratégique (ou stratégie-proofness) dans les négociations TE à coup unique tout en préservant la confidentialité et en limitant la complexité.

A.5.3 Prévenir le comportement stratégique des agents résidentiels dans un cadre de négociation itératif basé sur l'analyse des stratégies des RAs

Contexte

Les mécanismes de négociation à coup unique peuvent être pratiques lorsque le coordinateur dispose de réserves d'énergie suffisantes pour gérer les pointes de demande, car ils minimisent les charges computationnelles et de communication. Cependant, ces mécanismes sacrifient souvent l'efficacité et la flexibilité dans un contexte d'information incomplète, asymétrique et imparfaite. À l'inverse, les approches de compensation itérative permettent plusieurs tours d'interaction, offrant au coordinateur la possibilité d'ajuster progressivement les signaux de prix et de pénalité jusqu'à convergence, améliorant ainsi la performance et l'équité du système.

Malgré ces avantages, les cadres itératifs introduisent de nouveaux défis. Dans un marché à l'avance d'un jour, les RAs peuvent adopter un comportement stratégique, exploitant le processus de négociation pour maximiser leurs bénéfices individuels. Un tel comportement implique généralement de fausses déclarations des plans de consommation à une ou plusieurs itérations afin d'influencer les signaux de prix futurs ou de réduire les pénalités. Cette conduite opportuniste peut compromettre les objectifs du mécanisme, entraîner des inefficacités et mettre en péril la fiabilité du réseau.

Pour remédier à ce problème, ce travail analyse les stratégies des RAs dans un cadre de négociation itératif et démontre que le mécanisme proposé atteint un équilibre en stratégie dominante, garantissant la compatibilité incitative (IC). Dans cette conception, la déclaration véridique devient la stratégie la plus avantageuse pour chaque RA à chaque itération, indépendamment des actions des autres participants.

Méthodologie

Le mécanisme proposé est modélisé comme un jeu de Stackelberg itératif entre un coordinateur (leader) et plusieurs RAs (suiveurs). Le coordinateur résout un problème d'optimisation stochastique de niveau supérieur afin de déterminer des prix dynamiques (récompenses) et des pénalités pour les écarts. En parallèle, chaque RA répond en résolvant un problème d'optimisation de niveau inférieur pour mettre à jour son plan de consommation. Ce processus se répète jusqu'à convergence ou jusqu'à ce qu'un critère d'arrêt soit atteint.

La structure de l'information est incomplète, imparfaite et asymétrique : les RAs conservent leurs types privés (préférences, contraintes) et ne communiquent pas entre eux, tandis que le coordinateur n'observe que les plans agrégés. La communication s'effectue exclusivement entre le coordinateur et chaque RA via des signaux bidirectionnels.

L'étude évalue le comportement des RAs sous différentes stratégies de déclaration afin d'évaluer la robustesse stratégique. Deux scénarios de référence sont considérés : (i) tous les agents déclarent de manière véridique, et (ii) tous les agents trichent. De plus, une analyse croisée des stratégies examine des comportements mixtes. La règle de paiement — combinant la facturation de l'énergie réelle avec des pénalités pour les écarts par rapport aux plans déclarés — constitue le cœur de cette analyse. Enfin, la performance du mécanisme de coordination est comparée à un scénario de non-coordination afin de quantifier les bénéfices à l'échelle du système.

Résultats

L'analyse confirme que, sous la règle de paiement proposée, le coût d'une fausse déclaration à toute itération est supérieur au coût associé à une déclaration véridique, même si la négociation se termine immédiatement après la déviation. Ce résultat tient indépendamment des actions des autres agents, établissant la véracité comme stratégie dominante et validant la propriété de compatibilité incitative.

Au-delà de la robustesse stratégique, le mécanisme procure des avantages opérationnels tangibles. La participation coordonnée réduit significativement la demande de pointe par rapport au scénario sans coordination, améliorant ainsi la stabilité du réseau. Bien que les RAs subissent une légère perte de confort pour ajuster leur consommation, ils bénéficient de factures d'électricité plus faibles que dans le scénario de référence, créant ainsi une situation gagnant-gagnant pour les clients et le coordinateur. En outre, l'étude suggère que, sous certaines conditions, le mécanisme peut atteindre l'optimum de bien-être social. Cependant, la durabilité à long terme pourrait nécessiter des mesures additionnelles, telles que des subventions ou des mécanismes de redistribution, afin de maintenir l'équilibre budgétaire sans décourager la participation.

A.5.4 Analyse complémentaire

L'analyse de la propriété de compatibilité incitative (IC) dans le mécanisme proposé dans cette thèse s'est jusqu'à présent concentrée sur le coût de l'électricité perçu par les clients durant les phases de négociation et d'exécution. Cette approche fondée sur le coût de l'électricité a été adoptée par le mécanisme afin de préserver les informations privées des clients. Cette approche de préservation de la confidentialité conduit intrinsèquement à une observabilité limitée de la part du coordinateur ou du DSO, restreignant ainsi sa capacité à vérifier les informations privées et les critères décisionnels de chaque client dans un système d'énergie transactionnel (TE).

Bien qu'une analyse fondée sur l'utilité ait été théoriquement omise dans le cadre de cette recherche pour les raisons mentionnées ci-dessus, cette sous-section vise à démontrer que la propriété IC est préservée dans le mécanisme même sous une analyse basée sur l'utilité, c'est-à-dire que le mécanisme proposé est *strategy-proof* (à l'épreuve des stratégies).

Une approche basée sur l'utilité

En reformulant une analyse basée sur le coût en une analyse basée sur l'utilité, la définition de la propriété IC est alors représentée par l'équation (A.1).

$$\begin{aligned}
 U_n(\hat{e}_{n,i} = e_{n,i}) &> U_n(\hat{e}_{n,i} = \mathbf{0}) \quad \forall n, \\
 &\text{ou,} \\
 C_n(\hat{e}_{n,i} = e_{n,i}) &< C_n(\hat{e}_{n,i} = \mathbf{0}) \quad \forall n.
 \end{aligned}
 \tag{A.1}$$

Où le côté gauche de l'inégalité (3.3) correspond à l'utilité (ou au coût) de l'agent

résidentiel (RA) n lorsqu'il rapporte fidèlement ses informations, tandis que le côté droit correspond à l'utilité (ou au coût) du même RA lorsqu'il adopte une stratégie de fausse déclaration. Un équilibre en stratégie dominante est atteint si la condition d'inégalité de l'équation (A.1) est satisfaite. À cet égard, l'équation (13) du troisième article est modifiée pour adopter une approche basée sur l'utilité plutôt qu'une approche basée sur la règle de paiement, comme indiqué à l'équation (A.2).

$$C_n(\hat{e}_{n,i}) = p\mathbb{E}[C_{n,i}|\hat{e}_{n,i}] + p(1-p)\mathbb{E}[C_{n,i+1}|\hat{e}_{n,i}] \quad (\text{A.2})$$

Lorsque les clients soumettent un rapport véridique, le coût itératif se développe comme indiqué à l'équation (A.3).

$$\begin{aligned} C_n(\hat{e}_{n,i} = e_{n,i}) &= p(\pi_i \cdot e_{n,i} + \alpha_{n,i} \cdot \text{diag}(\text{Var}[\mathbf{r}_n]) + \mathbf{D}_{n,i}) \\ &+ p(1-p)(\pi_{i+1} \cdot e_{n,i+1} + \alpha_{n,i+1} \cdot \text{diag}(\text{Var}[\mathbf{r}_n]) + \mathbf{D}_{n,i+1}) \end{aligned} \quad (\text{A.3})$$

Où $\mathbf{D}_n$ représente le coût de l'inconfort du client n . En revanche, si les clients adoptent la stratégie consistant à soumettre un plan de consommation nul à l'itération i , le coût itératif est formulé comme dans l'équation (A.4).

$$\begin{aligned} C_n(\hat{e}_{n,i} = 0) &= p(\pi_i \cdot e_{n,i} + \alpha_{n,i} \cdot (e_{n,i}^2 + \text{diag}(\text{Var}[\mathbf{r}_n]) + \max(\mathbf{D}_{n,i}))) \\ &+ p(1-p) \left(\left(\lambda \sum_{n=1}^N \text{Var}[\zeta_n] \right) \mathbf{1} \cdot e_{n,i+1} \right. \\ &\left. + \alpha_{n,i+1} \cdot \text{diag}(\text{Var}[\mathbf{r}_n]) + \min(\mathbf{D}_{n,i+1}) \right) \end{aligned} \quad (\text{A.4})$$

Enfin, l'inégalité de l'équation (3.4) est développée en remplaçant les valeurs de coût espérées, ce qui conduit à l'équation (A.5).

$$\begin{aligned} & \mathbf{D}_{n,i} + (1-p)(\pi_{i+1} \cdot e_{n,i+1} + \mathbf{D}_{n,i+1}) < \\ & \alpha_{n,i} \cdot e_{n,i}^2 + \max(\mathbf{D}_{n,i}) + (1-p) \left(\lambda \sum_{n=1}^N \text{Var}[\zeta_n] \right) \mathbf{1} \cdot e + (1-p) \min(\mathbf{D}_{n,i+1}) \end{aligned} \quad (\text{A.5})$$

Dans un scénario véridique, il est supposé que les clients flexibles coordonnent leurs actions avec les objectifs du coordinateur. À cet égard, ils acceptent de sacrifier leur confort à mesure que la négociation progresse au fil des itérations. Ainsi, $D_{n,i+1} > D_{n,i}$. À l'inverse, dans un scénario non véridique, les clients risquent d'être fortement pénalisés, non seulement sur le coût de l'électricité, c'est-à-dire $\alpha_{n,i} \cdot e_{n,i}^2$, mais également sur le composant de confort (afin de minimiser leur facture), soit $\max(\mathbf{D}_{n,i})$. Les clients peuvent atteindre un coût minimal d'inconfort, c'est-à-dire $\min(\mathbf{D}_{n,i+1})$, si la négociation itérative s'arrête à l'itération $i+1$ lorsqu'ils adoptent une stratégie de triche à l'itération i . Intuitivement, les inégalités de confort peuvent donc être formulées comme dans l'équation (A.6).

$$\max(\mathbf{D}_{n,i}) > \mathbf{D}_{n,i+1} > \mathbf{D}_{n,i} > \min(\mathbf{D}_{n,i}) \quad (\text{A.6})$$

En appliquant les inégalités de confort exprimées dans l'équation (A.6) à l'inégalité représentée dans l'équation (A.5), il est possible de conclure que le côté droit de l'inégalité (A.5) dépasse le côté gauche, même dans l'analyse du terme d'inconfort. De plus, la relation entre la pénalité et le prix, soit $\alpha_{n,i,t} > \pi_{i,t}$ (conjointement avec le critère d'arrêt aléatoire de la négociation), demeure une condition cruciale pour garantir que $\hat{e}_{n,i} = e_{n,i}$

constitue une stratégie dominante.