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

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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

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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.

F

$\mathbf{E}[\cdot]$	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

$\boldsymbol{\alpha}$	Set of penalty values explored in simulations.
$\boldsymbol{\pi}$	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.
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.

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 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.

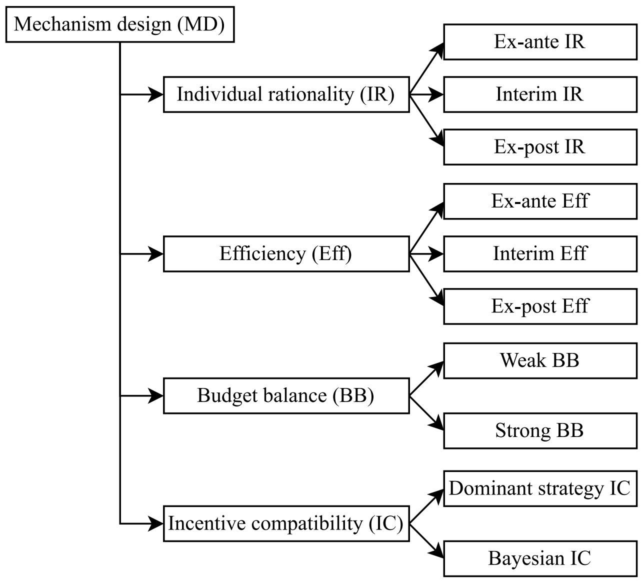


Fig. 1. Main concepts of mechanism design.

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]:

$$C(e_n) < C(e'_n) \tag{1}$$

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]:

$$e_n = \hat{e}_n. \tag{2}$$

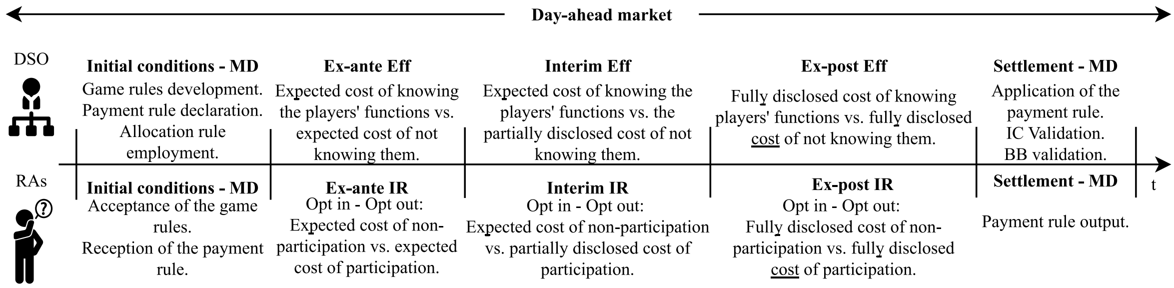


Fig. 2. Mechanism design phases over time.

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):

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

where $\mathcal{T}$ is the period of charge, π_t^0 is a flattened electricity price, and e_t^{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):

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

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

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

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

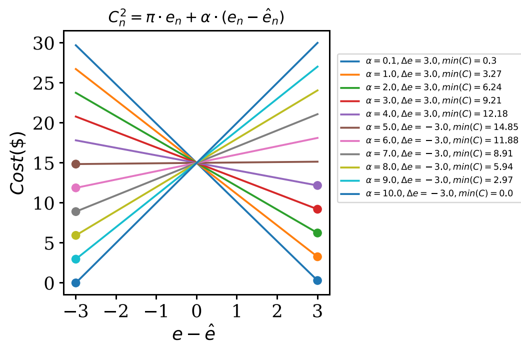
This study employs two complementary approaches to visually represent the outputs of the PRs discussed in Table 2. The first approach introduces a simplified example, free from any optimization framework, to illustrate the strategic behaviour of RAs under the application of the PRs outlined in Table 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 ($\alpha = \{0.1, 1, 2, \dots, 10\}$).

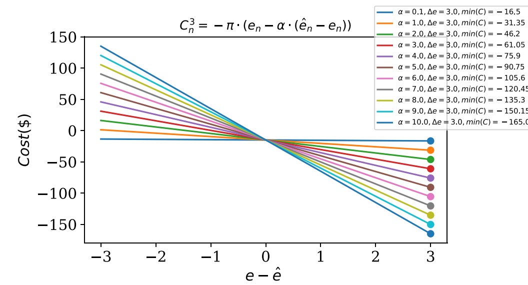
From Figs. 3(a) and 3(b), each dot represents the RA's minimum cost for each penalty value explored. Notably, the minimum cost is achieved when the RA deviates from their actual consumption, i.e., $e \neq \hat{e}$, irrespective of the penalty value α chosen by the DSO. For C^3, it is evident that a strategic 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

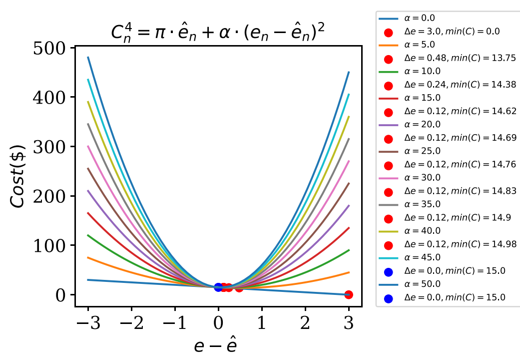
This section evaluates the IR and Eff in the *ex-ante phase*, and the IC and BB in the *settlement phase*, within a one-shot market architecture.



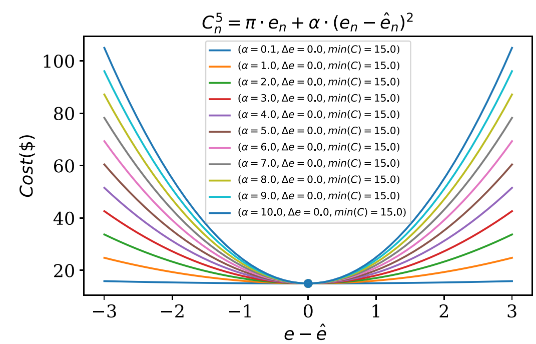
(a) A simple visualization of the minimum cost achieved by a strategic residential agent when the DSO employs C^2 by using example 2. Notice that the residential agent plays strategically by misreporting its electricity consumption plan, i.e., $e \neq \hat{e}$.



(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 $\mathbf{E}[\cdot]$. 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 ($\hat{\mathbf{e}}^0$) from RAs based on their response to a flattened initial price $\boldsymbol{\pi}^0$ and penalty value $\boldsymbol{\alpha}^0$. 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 $\boldsymbol{\pi}^*$ and a final penalty value $\boldsymbol{\alpha}^*$ with RAs to disclose the reported consumption plan to these signals ($\hat{\mathbf{e}}^*$). 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:

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

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

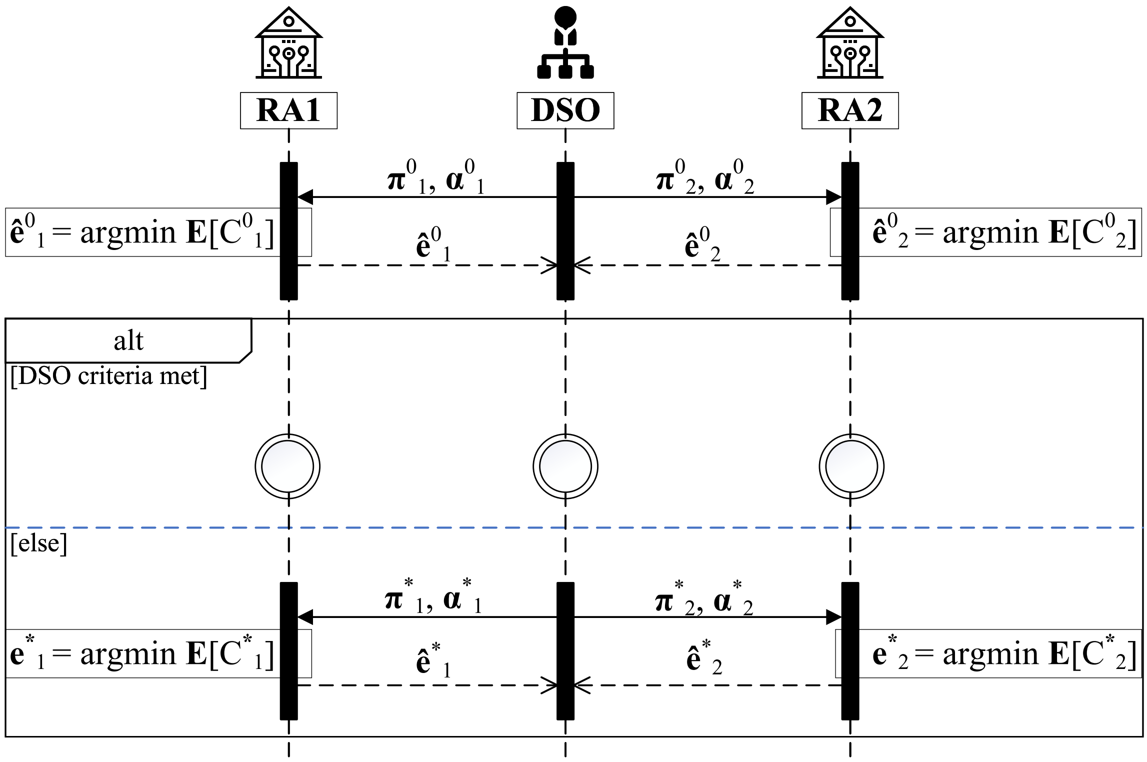


Fig. 4. UML diagram representing the information exchange between a DSO and two RAs during the negotiation at an *ex-ante phase*.

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

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

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 $\gamma_n\cdot(T^i_{SP,t}-T^i_{in,t})^2$ transforms the temperature (°C) units to cost related to Dollars ($). Then, the term γ_n has the units ($/°C^2) [43]. The set of prices is $\boldsymbol{\pi} \in \{\pi_t^0, \pi_t^*\}$, where the flattened initial price is set in $\pi_t^0 = 7.3$¢\$/kWh taken from [44], while the dynamic electricity price π_t^* used is taken from [45]. The penalty set is $\boldsymbol{\alpha} \in \{\alpha^0,\alpha^*\}$, where for the sake of simplicity the penalty values explored under both the flattened and the dynamic price are the same, i.e., $\alpha^0 = \alpha^* = \{5, 10, 100\}$ ¢\$/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:

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

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

$$+C\cdot T_{ext,n,t}, \tag{9c}$$

$$T_{in,n,t} \le \max_{T_{SP,n,t}}(T_{SP,n,t}), \tag{9d}$$

$$T_{in,n,t} \ge \min_{T_{SP,n,t}}(T_{SP,n,t}), \tag{9e}$$

$$T_{in,n,t} = T_{SP,n,t}, \tag{9f}$$

$$0 \le \hat{e}_{n,t} \le \zeta. \tag{9g}$$

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 $f_t(\cdot)$ 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).

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

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 $f_t(\cdot)$.

Table 3
Simulation results - ex-ante IR.

$\mathbf{E}[C[\cdot]]$	RA	α		
		5	10	100
$\mathbf{E}[C_n^2[\mathbf{e}_n^0\|\boldsymbol{\pi}^0]]$	RA1	−25.54	−61.66	−712.07
	RA2	−26.59	−63.33	−733.05
$\mathbf{E}[C_n^2[\mathbf{e}_n^*\|\boldsymbol{\pi}^*]]$	RA1	−27.39	−63.38	−712.82
	RA2	−28.10	−64.70	−733.97
$\mathbf{E}[C_n^3[\mathbf{e}_n^0\|\boldsymbol{\pi}^0]]$	RA1	−78.52	−143.98	−1323.60
	RA2	−68.05	−124.87	−1150.93
$\mathbf{E}[C_n^3[\mathbf{e}_n^*\|\boldsymbol{\pi}^*]]$	RA1	−71.82	−132.06	−1217.92
	RA2	−61.60	−114.17	−1063.32
$\mathbf{E}[C_n^4[\mathbf{e}_n^0\|\boldsymbol{\pi}^0]]$	RA1	7.13	9.01	13.86
	RA2	6.44	8.43	13.31
$\mathbf{E}[C_n^4[\mathbf{e}_n^*\|\boldsymbol{\pi}^*]]$	RA1	6.05	7.53	11.92
	RA2	5.73	7.27	11.70
$\mathbf{E}[C_n^5[\mathbf{e}_n^0\|\boldsymbol{\pi}^0]]$	RA1	10.76	10.93	14.05
	RA2	10.18	10.35	13.50
$\mathbf{E}[C_n^5[\mathbf{e}_n^*\|\boldsymbol{\pi}^*]]$	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 ($\pi_t^* \underset{\sim}{\propto} \hat{e}_{n,t}$) as follows in (11) [30,45].

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

where λ is the fixed cost of operating a power grid [30] set in 2.24 ¢ $ / kWh, and $\hat{e}^i_{agg,t} = \sum_{n\in\mathcal{N}} \hat{e}^i_{n,t}$ 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).

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

where $C(\hat{\mathbf{e}}^{0,*}|\boldsymbol{\pi}^{0,*}) = \sum_{n=1}^{N=2}\mathbf{E}[C_n[\cdot]]$ 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 $\boldsymbol{\pi}$, the penalty $\boldsymbol{\alpha}$, and the thermal comfort $\boldsymbol{\gamma}$ 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]

$$SW = U_{DSO} + U_n - C_{DSO} - C_n \tag{13}$$

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

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

$$C_{DSO} = \lambda\cdot\mathbf{E}\left[\sum_{t=1}^{T}\sum_{n=1}^{N}\left[e^2_{n,t}\right]\right], \tag{16}$$

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

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).

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

[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.

$PoA(\mathbf{E}[C[\cdot]])$	α		
	5	10	100
$PoA(\mathbf{E}[C^2[\mathbf{e}^0\|\pi^0]])$	−3.43	−8.22	−95.07
$PoA(\mathbf{E}[C^2[\mathbf{e}^*\|\pi^*]])$	−3.65	−8.43	−95.18
$PoA(\mathbf{E}[C^3[\mathbf{e}^0\|\pi^0]])$	−9.64	−17.69	−162.79
$PoA(\mathbf{E}[C^3[\mathbf{e}^*\|\pi^*]])$	−8.77	−16.20	−150.07
$PoA(\mathbf{E}[C^4[\mathbf{e}^0\|\pi^0]])$	0.89	1.15	1.79
$PoA(\mathbf{E}[C^4[\mathbf{e}^*\|\pi^*]])$	0.77	0.97	1.55
$PoA(\mathbf{E}[C^5[\mathbf{e}^0\|\pi^0]])$	1.38	1.40	1.81
$PoA(\mathbf{E}[C^5[\mathbf{e}^*\|\pi^*]])$	1.14	1.16	1.57

Table 5
Simulation results - PoD.

$PoD(\mathbf{E}[C[\cdot]])$	α		
	5	10	100
$PoD(\mathbf{E}[C^2[\mathbf{e}^0\|\pi^0]])$	−0.40	−0.17	−0.02
$PoD(\mathbf{E}[C^2[\mathbf{e}^*\|\pi^*]])$	−0.31	−0.14	−0.02
$PoD(\mathbf{E}[C^3[\mathbf{e}^0\|\pi^0]])$	−0.14	−0.08	−0.01
$PoD(\mathbf{E}[C^3[\mathbf{e}^*\|\pi^*]])$	−0.13	−0.07	−0.01
$PoD(\mathbf{E}[C^4[\mathbf{e}^0\|\pi^0]])$	1.51	1.22	1.01
$PoD(\mathbf{E}[C^4[\mathbf{e}^*\|\pi^*]])$	1.47	1.19	1.01
$PoD(\mathbf{E}[C^5[\mathbf{e}^0\|\pi^0]])$	1.00	1.00	1.00
$PoD(\mathbf{E}[C^5[\mathbf{e}^*\|\pi^*]])$	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 straightforwardly 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).

$$PoD(\mathcal{G}) = \frac{\mathbf{E}\left[C(\mathbf{e}^{0,*}|\boldsymbol{\pi}^{0,*})\right]}{\mathbf{E}\left[C(\hat{\mathbf{e}}^{0,*}|\boldsymbol{\pi}^{0,*})\right]}. \tag{19}$$

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., $\mathbf{e} = \hat{\mathbf{e}}$. 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 ($(\mathbf{e}^*, \hat{\mathbf{e}}^*) = \arg\min_{\mathbf{e},\hat{\mathbf{e}}} \mathbf{E}[C^i(\mathbf{e}, \hat{\mathbf{e}}|\boldsymbol{\pi}, \boldsymbol{\alpha})]$, 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 $\hat{\mathbf{e}}$ 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., $\hat{\mathbf{e}} = 0$ 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 $\hat{\mathbf{e}}$ converges closer to the actual electricity consumption $\mathbf{e}$ 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 ($\mathbf{e} = \hat{\mathbf{e}}$), thereby satisfying the IC condition outlined in Eq. (2) for each penalty value explored $\boldsymbol{\alpha}$.

4.2. Mechanism design assessment - settlement phase

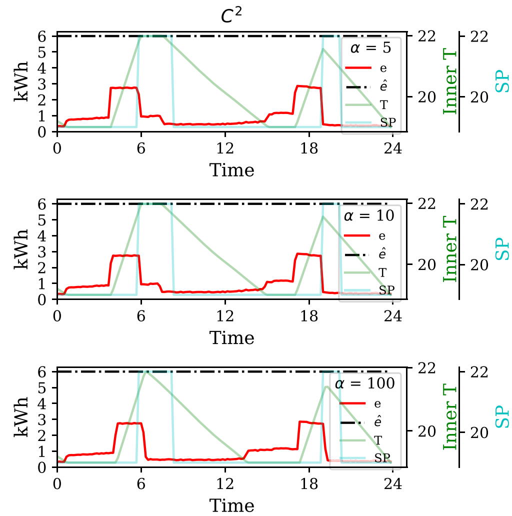
In Section 4.1, the concepts of IR and Eff have already been addressed from an *ex-ante* perspective by applying the MD phases depicted in Fig. 2. Moreover, by following the time-analysis guidance provided by Fig. 2, the concepts of IC and BB could be analysed in the *settlement phase* from the mechanism 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).

$$\underset{\mathbf{e}}{\text{minimize}} \quad C_n^5, \ \forall n \in \mathcal{N} \tag{20a}$$

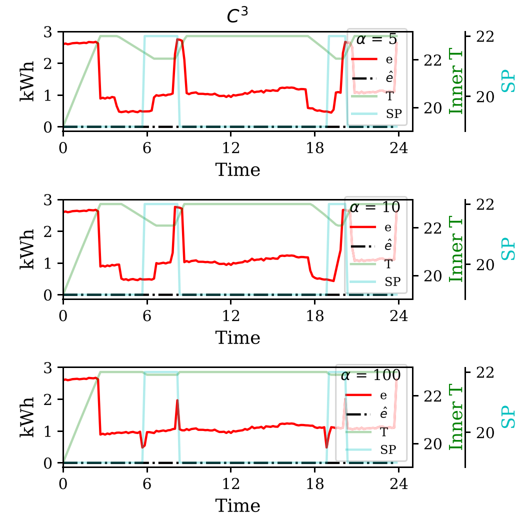
$$\text{subject to} \quad (9c), (9d), (9e), (9f), (9g) \tag{20b}$$

From the optimization (20a) subject to (20b), notice that the RAs are fully interested in minimizing its cost based on the consumption reported ($\hat{\mathbf{e}}$) to the DSO. In this regard, notice that $\hat{\mathbf{e}}$ 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.

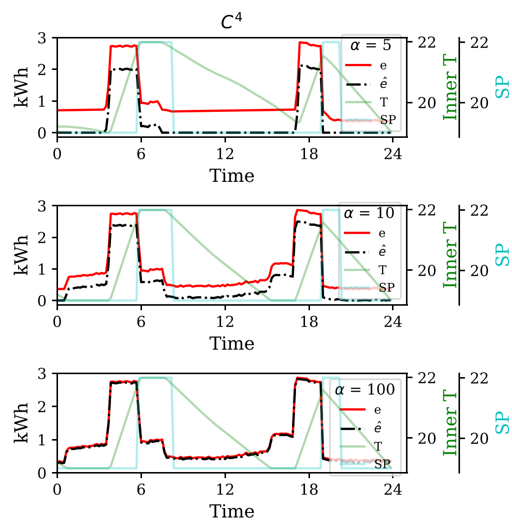
From Figs. 6 and 7, notice that the distribution of the expected cost of each RA always captured the current cost, a coherent result of employing stochastic programming. Moreover, RA pays more generally when uncertainty is disclosed (current cost) than expected cost because it represents deviations from the plan $\hat{\mathbf{e}}$. 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.



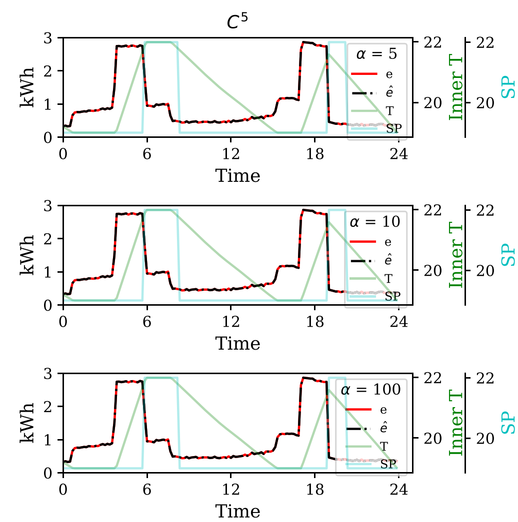
(a) Optimization problem output by employing C^2 in example 3.



(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.

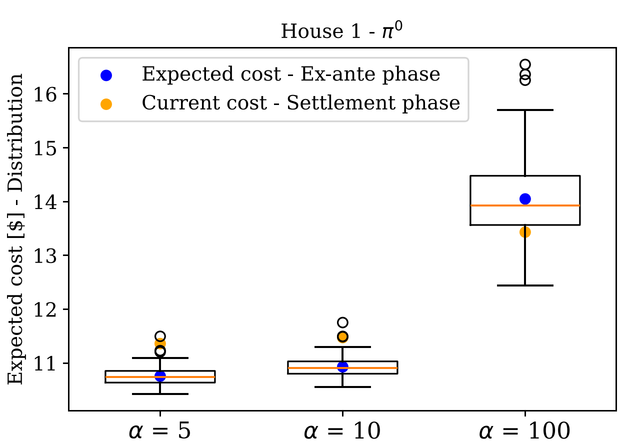


Fig. 6. The expected, the distribution, and the current cost of House 1 (RA 1) by employing C^5 and π_t^0.

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).

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

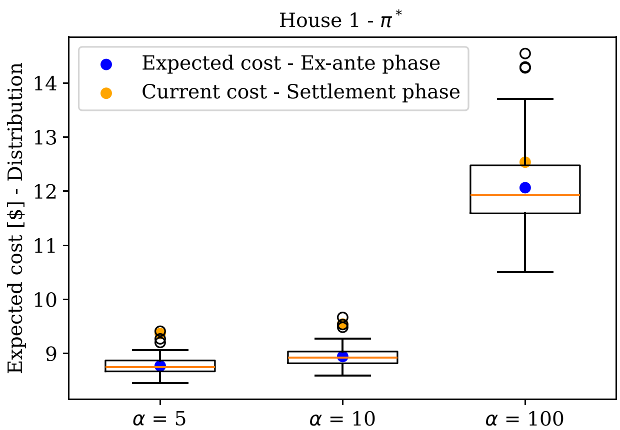


Fig. 7. Expected distribution and current cost of House 1 by employing C^5 and π_t^*.

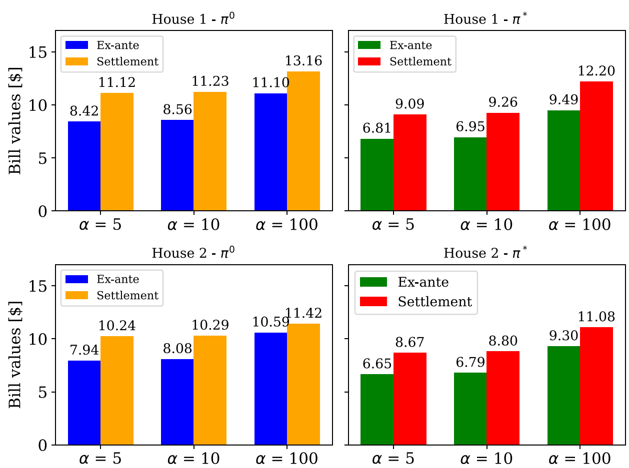


Fig. 8. Payment rule results by employing a flattened π_t^0 and a dynamic π_t^* electricity price.

From Eq. (21), notice that $\hat{e}_{n,t} = argmin_{e,\hat{\mathbf{e}}}\ \mathbf{E}[C_n^5]$ (*argmin* of Eq. (9a)) for the *ex-ante phase*, while $e_{n,t} = argmin_{\mathbf{e}}\ [C_n^5]$ (*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.

$\boldsymbol{\pi}$	$\boldsymbol{\alpha}$		
	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.

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

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 $(\boldsymbol{\pi}, \boldsymbol{\alpha})$ 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 $\hat{\mathbf{e}} < \mathbf{e}$, $\hat{\mathbf{e}} = \mathbf{e}$, and $\hat{\mathbf{e}} > \mathbf{e}$ 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., $\mathbf{e} = \hat{\mathbf{e}}$. 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.

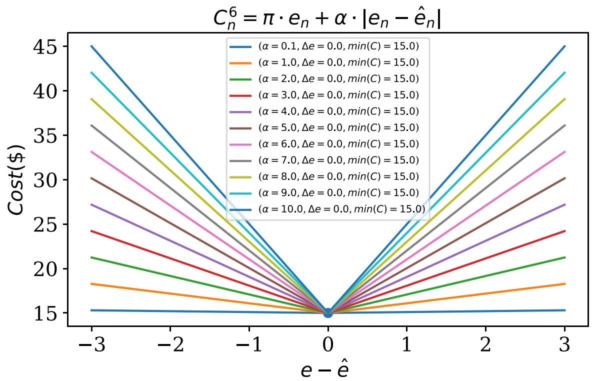


Fig. 9. Graphical visualization of C^6 by using Example 2.

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.

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