Highlights

A Novel Adaptive Penalty Mechanism for Peer-to-Peer Energy Trading

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- A novel adaptive penalty mechanism is designed for the Peer-to-Peer energy trading.
- Participants are encouraged to compensate for energy deviations to prevent clearing price deviations.
- A three-dimensional penalty is developed to reduce excessive penalty risks for market participants.
- A distributed default clearing algorithm is devised to implement the proposed penalty mechanism.

A Novel Adaptive Penalty Mechanism for Peer-to-Peer Energy Trading

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ABSTRACT

With the rapid development of Distributed Energy Sources (DERs), Peer-to-Peer (P2P) energy trading is regarded as an effective scheme to improve local energy utilization. Nevertheless, unlike wholesale electricity markets of the current grid size, small-scale prosumers and highly unpredictable intermittent DERs account for a significant proportion of P2P markets, leading to an escalation of market uncertainties. To facilitate effective market functionality, penalty mechanisms for unqualified participants are essential, as is typically the case in the wholesale electricity market. However, there has been little discussion of the use of penalty mechanisms in P2P markets. In this context, we propose a novel adaptive penalty mechanism (APM) to drive the defaulting prosumers to fulfill orders. Unlike the traditional two-dimensional (price, quantity) penalty price, APM uses a three-dimensional penalty and introduces deviation percentage factors to reduce the risk of excessive penalty rates. Penalty prices are determined by utilizing the distributed default clearing algorithm to adapt to market conditions, thereby preventing deviations in clearing prices. Case studies are conducted to demonstrate the feasibility and efficiency of the proposed APM in the P2P market. The results indicate that the APM strike an appropriate between cost-effectiveness and regulation, requiring about 20% less reserve capacity than the severe penalty.

1. Introduction

Recently, the adoption of DERs has been increasing due to combat climate change and its impacts. At the same time, advances in information and communication technologies, smart meters, energy management systems (EMSs), and distributed ledger technologies (such as blockchain) have transformed traditional consumers into prosumers [1, 2]. Through the provision of flexible load scheduling, monitoring and sharing of energy usage information, prosumers can participate actively in energy trading as both producers and consumers. Various P2P energy trading tests and projects have been carried out at some countries' distribution end to help users benefit from the installed DER equipment. By these means, the management and optimization of energy resources are expected to be enhanced in the future.

The P2P energy market is a new market scheme that allows network peers to share all or part of their energy surplus and deficits. It provides benefits in terms of prosumer autonomy, market transparency, and competitiveness [3]. Moreover, [4, 5] demonstrates that appropriate P2P markets can provide participants with profit or cost savings and encourage prosumers to remain involved. The market's long-term sustainability depends on the participation of members, and the market mechanism must therefore protect the core interests of members. Given the increasing penetration of renewable energy and the autonomous demand management of producers, energy production and consumption are prone to greater randomness and uncertainty. The market participants at the distribution level are smaller than those at the transmission level, thus making DER and load forecasting more challenging [6]. Besides severely impacting the grid's performance, efficiency, and reliability [7], these uncertainties can also lead to escalating defaults in the market.

The P2P pricing mechanism can be broadly classified into three categories: centralized pricing mechanism, decentralized pricing mechanism, and auction mechanism [8–15]. The centralized pricing mechanism with a centralized transaction process and information sharing manner [11, 12, 15]. However, the computational load associated with P2P sharing may become significant with the growth of DER penetration [16]. Decentralized pricing mechanisms are characterized by decentralized transaction procedures and information exchange [10], with prosumers retaining full control over their decision-making processes when negotiating transaction prices [8, 9]. However, the absence of centralized control results in a heavy communication burden between agents, which inhibits the market's efficiency. Auction mechanisms are usually employed in community market environments. It combines the advantages of centralized and decentralized pricing mechanisms. Communication among participants is centralized and the transaction process is decentralized [13]. Communities cannot directly intervene in market participants' energy imports and exports, but they can indirectly urge prosumers to participate in P2P sharing through appropriate pricing signals [14]. Many studies show that P2P energy trading can facilitate cooperation among prosumers in several ways. However, uncertainty and default problems may lead to the price mechanism generating misleading price signals, thereby reducing market fairness.

Some research efforts have been devoted to address the uncertainties in the P2P market. For example, a novel P2P joint energy and reserve market is proposed in [7], in which a decentralized negotiation pricing mechanism is adopted.

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Nomenclature

DER	Distributed Energy Resource	P2P	Peer-to-Peer
APM	Adaptive Penalty Mechanism	EMS	Energy Management System
ESS	Energy Storage System	DA	Double Auction
ESD	Energy Surplus Deviation	EDD	Energy Deficit Deviation
PCP	Pre-determined Clearing Price	ACP	Actual Clearing Price
OED	Overall Energy Deviation	DP	Deviation Percentage
MDP	Maximum Deviation Percentage		

Renewable energy agencies provide community managers with their uncertainty distributions, which help calculate the total reserves that should be maintained. An auction pricing mechanism-based P2P energy trading model is proposed in [17, 18], to coordinate demand response schemes and potential generation-consumption uncertainties. In general, the uncertainty may cause significant differences between the energy ordered in the market and the actual energy delivered, which would constitute a default. Additionally, prosumers could intentionally violate contracts in order to obtain maximum benefit [19]. However, the impacts of such a default on the market settlement are rarely discussed in the above-mentioned work, nor are measures taken to guarantee the performance of the participants' contracts. Ideally, market operators should encourage participants to fulfill their obligations under the agreement. This will protect the rights and interests of market participants and encourage them to demonstrate their real capacity to produce and consume in the marketplace [20]. To preserve market fairness, it is also important to limit the impact of uncertainty on trading outcomes and to prevent arbitrage opportunities arising from default.

Penalties proved to be effective tools for encouraging participants to perform their contracts. Some electricity markets, such as regional electricity markets in North America, California Independent System Operator (CAISO), Midcontinent Independent System Operator (MISO), and Southwest Power Pool (SPP), adopt penalty schemes to address the undesired power imbalance in the grid [21–23]. For example, the CAISO market adopts penalty prices to enforce constraints, thus ensuring supply equals demand (power balance constraints) or transmission constraints. Research on penalties has also been conducted in some studies. A penalty scheme is proposed in [6], in which a penalty price is set for power rate, regulation mileage and electricity quantity to control the market volatility within an expected limit. In [24] , a real-time decentralized demand-side management system is proposed that forces customers create a uniform load spectrum by penalizing customers who fail to comply with it in their actual consumption. In [25], the authors propose an energy planning model which considers the penalty costs associated with deviations from the energy target to maximize profits. Included in the works [26–28], the penalty costs are presented for wind power plants failing to provide the scheduled power. Additionally, the reserve markets incorporating electric vehicles and the penalties associated with non-compliance with the contract are investigated in [29] [30] [31]. Notably, [30] outlines two penalty mechanisms (inability to cover total reserve capacity and insufficient reserve capacity). In [32] the penalty cost is proposed to reduce the difference between real-time power delivery and day-ahead scheduling, thereby minimizing the potential for fluctuations in power transmission.

These studies show that penalty mechanisms have different goals depending on the application and market environment. However, most of these efforts are aimed at penalizing producers with professional forecasting and energy management abilities, while neglecting prosumers in the emerging P2P market. Additionally, these measures impose a two-dimensional penalty (price and quantity) upon defaulting users and ignore their defaulting magnitude or severity. Considering the high degree of uncertainty associated with the behaviors of prosumers, implementing the traditional penalty mechanism in the energy market will have more negative effects [20]. Moreover, despite the incentive compatibility resulting from the imposition of penalties, participants may experience a reduction in revenue adequacy [7]. Thus, a novel penalty mechanism is required that is compatible with the features of the P2P market.

In response to the problems mentioned above, contributions of this paper include the following:

- A P2P energy market model involves a penalty mechanism is built to explore the default issue. Participants can minimize the costs associated with penalties by self-regulating actively to reduce energy deviations. A discussion is provided on the impacts of the energy deviations and penalties on trading outcomes.

- A novel APM is proposed that adapts to market conditions by updating the penalty factor. The deviation percentage parameter is introduced to reduce participants' excessive penalty risks on the market. With the penalty factor determined by the market operator to minimize overall costs, the clearing price deviations can be prevented by controlling the energy deviation into an acceptable range.

- A distributed default clearing algorithm is presented. By solving the individual optimal energy scheduling for the participants and the penalty decision-making for the market operator separately, the efficiency of the calculation can be guaranteed, and the privacy of participants can be protected as well.

The rest of this paper is organized as follows. Section 2 formulates the P2P energy trading process considering

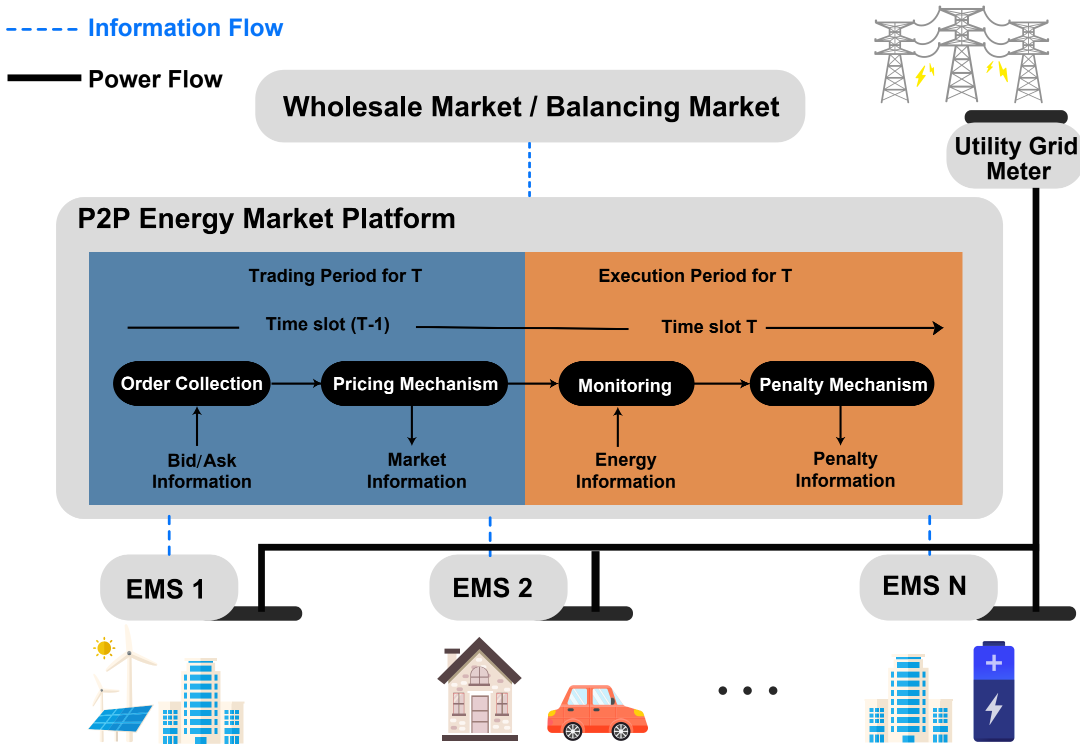


Fig. 1: Framework of P2P energy trading involves a penalty mechanism

the default behaviors and penalty mechanism. Section 3 discusses the impact of default on trading results and the likely undesired consequences of the penalties. Section 4 describes the proposed APM with the distributed default clearing algorithm in detail. Section 5 presents the results and discussions of the case studies. Section 6 concludes this paper.

2. P2P energy trading framework

2.1. P2P energy market framework description

The P2P energy trading structure of the grid-connected microgrid is shown in Fig. 1. Prosumers are connected via bidirectional energy and information flows. The whole community is connected to the utility grid through a network connection. The P2P energy market is an online trading platform that provides a marketplace for energy buyers and sellers while simultaneously serving a regulatory role. Additionally, the P2P energy trading platform will interact with other markets (wholesale and balancing markets) to achieve real-time energy balance. Through this structure, prosumers can trade energy with others to attain local energy self-consumption. Participants in this market can be individual or commercial prosumers (such as shopping malls, small factories, schools, etc.) who have installed generation facilities (such as photovoltaic systems, batteries, and electric vehicles). This paper assumes that participants have installed an energy management system (EMS) and smart meter to optimize facilities' energy scheduling. The smart meter collects each consumer's information, including photovoltaic power production, energy consumption, energy storage system (ESS) status, and energy transactions with other consumers and public grids. Additionally, the smart meter communicates with the EMS for processing energy management. Typical methods contain switching the facility's operating mode, changing its operating hours, and running it via an ESS. With the continuous updating of real-time data available through smart meters, it is possible to monitor each participant's energy usage and therefore detect defaulters [33]. On this point, an agreement must be signed between each prosumer and the market. The following information should be included in the agreement but is not limited to:

- Participants are required to submit their orders to the market with specific price and energy quantity information in advance, subject to the limit specified by the market.
- Participants agree to release data on smart meters; the market can access the information in real-time when anomalies are detected.
- Participants who fail to complete the energy quantity stipulated in the matched order will be charged a penalty according to the amount of deviation.

The P2P market trading cycle refers to a discrete period with a fixed duration throughout the day. During the trading period, both buyers and sellers send individual orders to the market. The market operator collects orders for period T and applies the pricing mechanism to determine the clearing price and settle the trade. During the order execution period, participants will deliver energy following pre-matched orders; however, some participants may fail to deliver. To prevent any significant failure risk caused by increased failure sources, the market operator must detect the defaulting participants as soon as possible to change their consumption/generation. The penalty mechanism determines the allowable range of energy deviation and the corresponding penalty prices in the market. The market detects defaulting participants and sends them penalty signals by continuously monitoring. After receiving a penalty signal, the participant's EMS will manage the energy to reduce fines. Once defaulting participants remain, the market operator will continue to send them penalty signals until the penalty mechanism has been exercised to the full extent.

2.2. The pricing mechanism for the P2P energy market

The Double Auction (DA) is a widely used pricing mechanism in many P2P market studies, such as [34–39]. Discriminatory and uniform k-DA are common auction mechanisms [36]. The transaction prices are determined between each pair of winning buyers and sellers under the discriminatory k-DA. In contrast, a unified k-DA mechanism is designed to make it possible to generate a unified settlement price for all winning participants within a transaction cycle, which is common in competitive wholesale electricity markets. Similarly, the Brooklyn Microgrid project has adopted this method for P2P trading [38]. The price manipulation problem can be prevented by establishing appropriate pricing mechanisms that encourage participants to be honest to avoid using bid price arbitrage [40, 41].

Nevertheless, the bid price is not the only factor affecting market settlement. The energy deviation between the order book and the actual energy delivered/consumed will cause errors in transaction results. The discriminatory DA mechanism is characterized by more transactions, requiring complicated computation procedures to determine different transaction prices [42]. As P2P market participants in a community often exhibit greater randomness, managing defaulting orders will require a more complicated method to calculate and settle the price deviation and energy deviation between different orders. In contrast, the uniform DA pricing mechanism requires less computational complexity, which can better cooperate with the penalty mechanism.

Considering that in a trading time duration t, N participants are involved in the transaction, including NB buyers and NS sellers. The prosumers with energy deficits are referred to as the buyers, set $B = \{j|j = 1, 2, 3..., NB\}$. Accordingly, the prosumers with energy surplus are referred to as the sellers, set $S = \{i|i = 1, 2, 3..., NS\}$. The market platform creates an order book according to the price priority principle. An order match will only be made when the buying price exceeds the selling price. The objective of the market is to pass on the generation costs to consumers reasonably and efficiently, thus maximizing net social welfare [43]:

$$\max \sum_{i=1}^{NS} p_i^{Sell} \cdot Q_i^S - \sum_{j=1}^{NB} p_j^{Buy} \cdot Q_j^b \tag{1}$$

$$\text{s.t.} \quad \sum_{i=1}^{NS} Q_i^S = \sum_{j=1}^{NB} Q_j^b \tag{2}$$

$$p_i^{\text{Sell}} \leq p_j^{Buy} \tag{3}$$

$$\sum_{i=1}^{NS} Q_{i,l}^S + \sum_{j=1}^{NB} Q_{j,l}^b \leq Q_l^{Max} \tag{4}$$

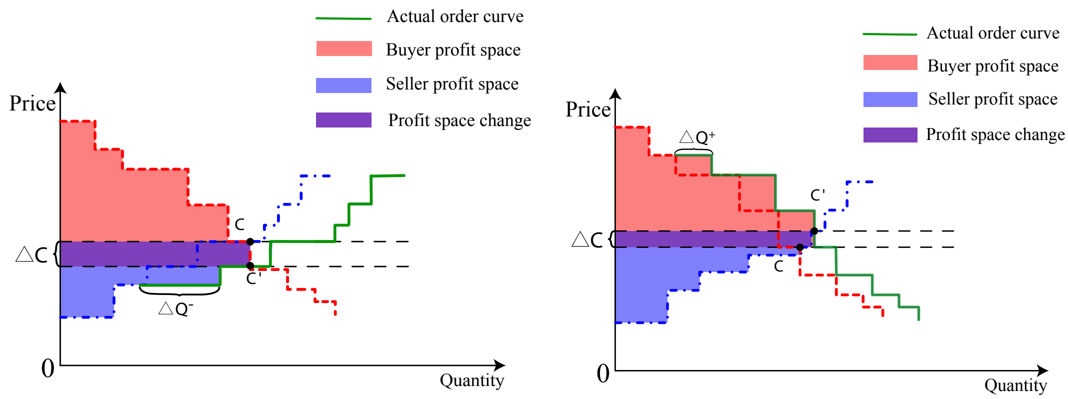
where p_i^{Sell} denotes the bid price of the ith seller, NS is the number of sellers engaging in energy trading; p_j^{Buy} denotes the bid price of the jth buyer, NS is the number of consumers engaging in energy trading. Q_i^s is the energy quantity for seller, Q_j^b is the energy quantity for buyer. Q_l^{Max} is the energy limit of the branch l in the network. The first constraint in Eq. (2) is present to ensure energy balance. The second constraint in Eq. (3) pertains to weakly budget balance for the buyers. Eq. (4) are the physical constraints imposed by the grid.

2.3. Default analysis

It is not uncommon for inaccurate generation predictions and demand-side fluctuations, such as instrument faults, schedule changes, unexpected visitors, and the uncertainties associated with manual operations. For example, for a load prediction made at 15-minute intervals, the possible mean absolute percentage error dispersion ranged between 3% and 250%, with a mean of 57.5%; and the dispersion with a 30-minute prediction and with a 60-minute forecast is 48% and 43.2%, respectively [44]. On the other hand, deviations in net load profiles for providing ancillary services may result in the breach of pre-negotiated residual orders in the P2P energy trading [19]. These situations will inevitably lead to energy deviations between orders and actual consumption/production.

The energy deviation refers to the variation of the measured energy quantity from the specified energy quantity in the order book, as Eq. (5) shows. It can be divided into the Energy Surplus Deviation (ESD), i.e., the actual energy delivered exceeding the ordered energy, and the Energy Deficit Deviation (EDD), i.e., the actual energy delivered is less than the ordered energy. ESD and EDD are expressed as Eqs. (6) and (7), respectively. ESD could result from participants' actual production exceeding the sold quantity or participants' actual consumption being lower than the purchased quantity. EDD could result from the actual energy production being less than the sold quantity or the actual energy consumption exceeding the amount purchased.

$$\Delta Q_{i,t} = Q_{i,t}^{\text{Actual}} - Q_{i,t}^{\text{Order}} \tag{5}$$



(a) (b)

Fig. 2: (a) The impact of ESD on double auction process; (b) The impact of EDD on double auction process

$$\Delta Q^{+}_{i,t} = \begin{cases} Q^{\text{Actual}}_{i,t} - Q^{s}_{i,t}, & \text{when } Q^{\text{Actual}}_{i,t} > Q^{s}_{i,t} \\ Q^{b}_{i,t} - Q^{\text{Actual}}_{i,t}, & \text{when } Q^{\text{Actual}}_{i,t} < Q^{b}_{i,t} \end{cases} \tag{6}$$

$$\Delta Q^{-}_{i,t} = \begin{cases} Q^{S}_{i,t} - Q^{\text{Actual}}_{i,t}, & \text{when } Q^{\text{Actual}}_{i,t} < Q^{S}_{i,t} \\ Q^{\text{Actual}}_{i,t} - Q^{b}_{i,t}, & \text{when } Q^{\text{Actual}}_{i,t} > Q^{b}_{i,t} \end{cases} \tag{7}$$

where $\Delta Q_{i,t}$ is the energy deviation for participant i at time t. $Q^{Order}_{i,t}$ is the energy in pre-matched order. $Q^{Actual}_{i,t}$ is the measured actual energy. $\Delta Q^{+}_{i,t}$ represents the ESD and $\Delta Q^{-}_{i,t}$ represents the EDD.

When penalty measures are used in the energy market, energy deviations are treated as defaults and fined accordingly. Studies on the pricing of the penalty have been conducted extensively, and some have recommended setting different penalty prices for ESDs and EDDs [26, 29, 30, 45], whereas others have suggested setting the same penalty price for both [18, 24, 25, 31, 46]. For example, the penalty price for EDD/ESD is higher/lower than the day-ahead market price [45]. The penalty price is set same for EDD and ESD with 0.0685\$/kWh [46], 0.01\$/kWh [24] and 0.13\$/kWh [31], respectively. For a generator i with energy deviation, the default clearing process can be expressed as:

$$\text{if } \Delta Q > 0, \varphi_{i,t} = C_t \cdot \left(Q^{\text{Order}}_{i,t} + \Delta Q^{+}_{i,t} \right) - p^{\text{penal}}_{i,t} \cdot \Delta Q^{+}_{i,t} \tag{8}$$

$$\text{if } \Delta Q < 0, \varphi_{i,t} = C_t \cdot \left(Q^{\text{order}}_{i,t} - \Delta Q^{-}_{i,t} \right) - p^{\text{penal}}_{i,t} \cdot \Delta Q^{-}_{i,t} \tag{9}$$

where $\varphi_{i,t}$ is the energy bill at t. $p^{\text{penal}}_{i,t}$ is the penalty price at t. C_t it the clearing price.

Notably, there has been little discussion regarding punitive measures against P2P energy trading. According to the research on P2P energy trading, Refs [12, 15, 47, 48] point out that the net power flow between the community grid and utility grid could be compensated according to the Feed-in Tariff scheme. The Feed-in Tariff scheme allows prosumers to purchase energy deficits at a retail price and sell energy surplus at an export price. Many countries set export prices below retail prices to encourage local energy consumption. The clearing price in the P2P market is typically between the retail price and the export price. Accordingly, the defaulting participants can purchase EDD at a higher retail price and sell ESD at a lower export price than the clearing price. Additionally, Refs [19, 49] stated that the real-time energy deviation could be purchased on the balancing market at a specific price. For a prosumer i with energy deviation, the default clearing process can be expressed as:

$$\text{If } \Delta Q_{i,t} > 0, \varphi_{i,t} = Q^{\text{Order}}_{i,t} \cdot C_t + \Delta Q^{+}_{i,t} \cdot p^{\text{Sell}}_{i,t} \tag{10}$$

$$\text{If } \Delta Q_t < 0, \varphi_{i,t} = Q^{\text{Order}}_{i,t} \cdot C_t - \Delta Q^{-}_{i,t} \cdot p^{Buy}_{t} \tag{11}$$

where $p^{\text{Sell}}_{i,t}$ is the price of purchasing energy from the utility grid. p^{Buy}_{t} is price of selling energy from the utility grid.

3. Default and Penalty in the P2P Energy Trading

3.1. The impact of energy deviations on trading outcomes

Fig. 2 illustrates two examples of ESD and EDD's impact on a DA process. A single clearing price is determined by the intersection of the aggregate demand and supply curves, and all participants trade at this price, C . Each order is shown as a horizontal line, on which the y-axis represents the price, and the length of the horizontal lines represents the energy quantity. Suppose a certain amount of ESD exists and other parameters remain unchanged, the sorting curve of asks (the green solid line) generated according to actual measured quantities is different from that (the red dotted line) generated according to ordered quantities, as Fig. 2(a) shows. As a result, the new clearing price C' generated by using the actual sorting curve is higher than the pre-determined clearing price C . In practice, the market will not regenerate C' based upon the actual measured quantities, which means the clearing price used in the settlement process will be C

rather than C'. Profit space refers to the difference between the clearing price and the cost. If the cost is fixed, the profit space depends on the change in the clearing price. Therefore, the clearing price deviation will affect non-defaulting participants. When using C for settlement, the non-defaulting seller's/buyer's profit space will be lower/higher than that of using C', respectively. Similarly, Fig. 2(b) shows that the actual bid curve containing EDD leads to a lower clearing price C' than C , resulting in opposite changes in profit space in contrast with Fig. 2(a).

Participants' income and expenditure are expressed as the product of price and quantity. Eq. (12) shows that when using C' for settlement, the seller will earn more income while the buyer will spend more than using C for settlement. Likewise, when C' is less than C, the settlement amount will be the opposite, as shown in (13). Therefore, regardless of whether the clearing price deviation is upward or downward, a party who complies with the agreement will suffer from the loss of economic interest (the buyer will spend more, and the seller will earn less).

$$\text{If } C'_t > C_t, \begin{cases} \sum_{i}^{NS} Q_i^s \cdot C'_t > \sum_{i}^{NS} Q_i^s \cdot C_t \\ \sum_{i}^{NB} -Q_i^b \cdot C'_t < \sum_{i}^{NB} -Q_i^b \cdot C_t \end{cases} \tag{12}$$

$$\text{If } C'_t < C_t, \begin{cases} \sum_{i}^{NS} Q_i^s \cdot C'_t < \sum_{i}^{NS} Q_i^s \cdot C_t \\ \sum_{i}^{NB} -Q_i^b \cdot C'_t > \sum_{i}^{NB} -Q_i^b \cdot C_t \end{cases} \tag{13}$$

Given the examples, it can be inferred that when ESD and EDD co-occur, the resulting clearing price deviations resulting from them can be partially offset. Additionally, there can be correlations between uncertainties, i.e., energy deficits and surplus can be compensated for by each other. Thus, an acceptable deviation range can be specified, within which the ESD and EDD will not cause the clearing price to deviate. It can be determined based on the effect of energy deviation on the clearing price, as Eqs. (14)-(16) describes.

$$\Delta Q^H = q_c - q_1 \tag{14}$$

$$\Delta Q^L = q_2 - q_c \tag{15}$$

$$(C'_t, C_t) \begin{cases} \text{If } \sum_{i=1}^{N} \Delta Q_i^+ - \sum_{i=1}^{N} \Delta Q_j^- > \Delta Q_t^H, C'_t > C_t \\ \text{If } \sum_{i=1}^{N} \Delta Q_i^+ - \sum_{i=1}^{N} \Delta Q_j^- < -\Delta Q_t^L, C'_t < C_t \\ \text{If } -\Delta Q_t^L \le \sum_{i=1}^{N} \Delta Q_i^+ - \sum_{i=1}^{N} \Delta Q_j^- \le \Delta Q_t^H, \\ C'_t = C_t \end{cases} \tag{16}$$

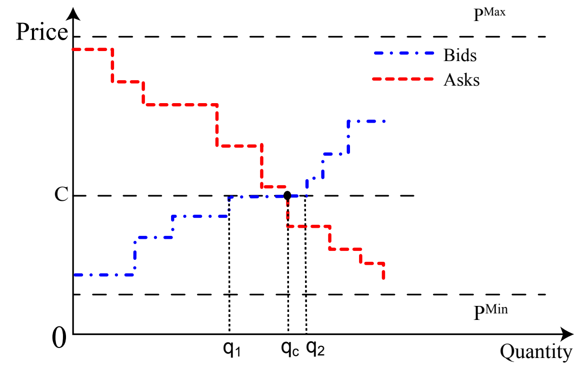


Fig. 3: Double auction trading process

Where qc is the quantity corresponding to the clearing price C. $q1$ and $q2$ represent the sorting position and quantity of the order at the clearing point, as Fig. 3 shows; ΔQ^H is the limitation for extra ESD; ΔQ^L is the limitation for extra EDD.

For comparison purposes, the C generated during the trading period is referred to as the Pre-determined Clearing Price (PCP), and the C' generated by using the actual measurements is referred to as the Actual Clearing Price (ACP). The part of energy deviation that the community ultimately needs to be exchanged with the utility grid, which is referred to as Overall Energy Deviation (OED), can be defined as:

$$\text{OED} = \sum_{i=1}^{N} \left(\Delta Q_{i,t}^+ - \Delta Q_{i,t}^- \right) \tag{17}$$

As mentioned above, ESD and EDD change the sorting curves in the DA trading process. It is worth noting that the OED is the ultimate factor determining the clearing price deviation degree. Clearing price deviations will impact the profit space of participants and further alter their income and expenditures. As a result of ensuring market fairness, the operator should ensure that the ACP and PCP are consistent, thereby attempting to minimize the impact of clearing price deviations on participants.

3.2. Undesired consequences of the penalty

As mentioned in Section 2.3, energy deviations can be settled at the Feed-in Tariff scheme and ancillary prices in the P2P market. Although these settlement processes are not explicitly defined as the penalty mechanism, they have a similarly punitive effect. As shown in Eq. (10), ESD is settled according to a selling price, such as the export price set by the Feed-in Tariff scheme or ancillary service prices. EDD is settled at the buying price, such as retail and ancillary service prices, as determined by Eq. (11). These processes can be equivalent to a default clearing process with different penalty prices for ESD and EDD:

$$\Delta p_t^{\text{Sell}} = C_t - p_t^{\text{Sell}} \tag{18}$$

$$\varphi_{i,t} = \left(Q_{i,t}^{\text{Order}} + \Delta Q_{i,t}^+ \right) \cdot C_t - \Delta p_t^{\text{Sell}} \cdot \Delta Q_{i,t}^+ \tag{19}$$

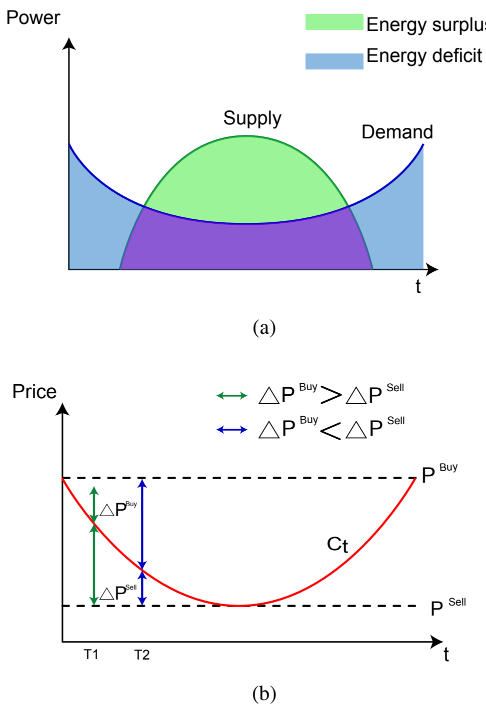


Fig. 4: Schematic of the power curve and corresponding clearing price in a P2P market. (a) Power curve of a clear sky day; (b) Corresponding clearing price

$$\Delta p_t^{Buy} = p_t^{Buy} - C_t \tag{20}$$

$$\varphi_{i,t} = \left(Q_{i,t}^{\text{Order}} - \Delta Q_{i,t}^{-}\right) \cdot C_t - \Delta p_t^{Buy} \cdot \Delta Q_{i,t}^{-} \tag{21}$$

where Δp_t^{Sell} is the price difference between PCP and selling price, which can be equivalent as a penalty price for ESD; Δp_t^{Buy} is the price difference between PCP and buying price, it can be regarded as a penalty price for EDD.

Fig. 4 shows a schematic of the supply-demand curve and the corresponding price curve in the P2P market. When penalizing participants based on different prices for ESD and EDD, they can reduce the expenditure on energy deviations through strategic approaches. For example, when the supply is less than the demand as $T1$ shows, the penalty price Δp_t^{Sell} for ESD is higher than the penalty price Δp_t^{Buy} for EDD. To avoid a higher penalty, participants can reduce the ask's energy quantity and increase the bid's energy quantity during the trading period. Alternatively, participants may ignore the EDD correction when the compensation cost for self-regulation is higher than the penalty price. These factors will eventually lead to the EDD being larger than ESD on the market and may cause the ACP lower than PCP. Similarly, the penalty price Δp_t^{Buy} is higher than Δp_t^{Sell} when the demand exceeds the supply at $T2$, which results in ESD exceeding EDD. Therefore, imposing differentiated penalty prices will result in biased energy deviations, as illustrated in Eq.(22). It is critical to note that only by setting penalty

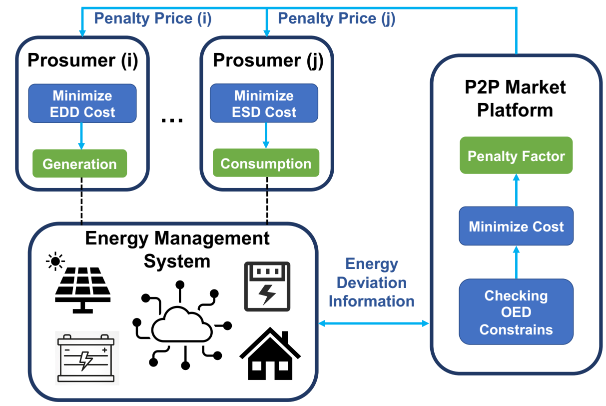


Fig. 5: The work-flow of the proposed APM

prices uniformly will the participants not take strategic measures that would result in excessive EDD or ESD.

$$\text{when} \begin{cases} \Delta p_t^{\text{Sell}} > \Delta p_t^{Buy}, \left|\Delta Q_t^{+}\right| < \left|\Delta Q_t^{-}\right| \\ \Delta p_t^{\text{Sell}} < \Delta p_t^{\text{Buy}}, \left|\Delta Q_t^{+}\right| > \left|\Delta Q_t^{-}\right| \\ \Delta p_t^{\text{Sell}} = \Delta p_t^{\text{Buy}}, \left|\Delta Q_t^{+}\right| = \left|\Delta Q_t^{-}\right| \end{cases} \tag{22}$$

The above examples show that penalty measures may prevent participants from offering all their capacity to the market and result in unjustifiable fines for rational parties. Furthermore, enforcing strict penalties to decrease the probability of default may not be feasible since it reduces the expected revenues of the participants and discourages them from participating in the market. In this regard, the penalty mechanism used in the P2P market should accommodate the participants' limited self-regulation capability and the market conditions.

4. Proposed adaptive penalty mechanism

Fig. 5 shows the work-flow of the proposed APM. The market operator collects penalties from defaulting participants according to market conditions. Participants willing to change their energy scheduling will adjust their controllable devices and ESS accordingly. The extensive installation of advanced metering infrastructure has made it possible to enable active interaction among grid components to achieve effective communication and response between market operators and participants at a higher frequency [50], such as at a second interval. Intelligent automatic systems carry out decision-making and information exchange functions for them. In the workflow, the functions of the participants are: (1) optimizing the individual objective function when receiving penalty information and (2) utilizing EMS to compensate for energy deviations automatically. The functions of the market platform are: (1) monitoring whether participants compensate for energy deviations; (2) initializing and updating penalty factors determined by the market condition; (3) determining the amount of final energy deviation and obtaining compensation from the utility grid.

4.1. Penalty Price Formulation

Due to the difficulty of ensuring that no energy deviation occurs during the trading process, an excessive penalty may reduce prosumers' willingness to participate in the P2P market. In view of this, the parameter Deviation Percentage (DP) is introduced to measure the magnitude of a participant's defaults, as Eq. (14) shows. The three-dimensional penalty is formulated as Eq. (15) shows. Participants with lower deviation percentages are subject to lighter penalties. On the contrary, participants who fail to meet market obligations will suffer from more severe consequences.

$$dp_{t,i} = \left| \frac{\Delta Q_{i,t}}{Q_{i,t}} \right| \cdot 100\% \tag{23}$$

$$p_{i,t}^{\text{penal}} = dp_{i,t} \cdot kp_t \cdot \left| \Delta Q_{i,t} \right| \tag{24}$$

where $dp_{i,t}$ is the deviation percentage. kp_t represents the penalty factor.

The difference between two-dimensional and three-dimensional penalties is illustrated in Fig. 6. The lines of different colors correspond to different penalty prices. Under the three-dimensional penalty, a relatively small degree of DP (e.g., within 20%) will not result in high fines with the increase of the penalty factor. Thus, an essential way for participants is to reduce their DP to avoid high fines. In contrast, the two-dimensional penalty imposes more significant fines on participants with a greater energy deviation, regardless of their default degree. Participants with large energy quantity orders may be more at risk than those with significant prediction errors. Consequently, the two-dimensional penalty could potentially result in losing key prosumers with high transaction volumes and frequency. In this regard, introducing the DP parameter can effectively reduce the risks associated with their participation in the market.

4.2. Energy Deviation Management Model for Participants

EMS can assist prosumers in managing DERs and using bidding strategies to participate in energy transactions. In terms of self-regulation, Ref.[17] describes a method for controlling electrical appliances to reduce energy deviations. Energy storage equipment can also be used as a backup system to correct the energy deviation in [45]. This paper assumes that market participants can simultaneously control electrical appliances and energy storage equipment for self-regulation.

According to [17], modifying the energy plan will negatively affect the welfare of the corresponding customers, and a quadratic function can be used to express the cost of discomfort introduced:

$$c_{i,t}^{com} = \left(Q_{i,t}^{\text{com}} \right)^2 \cdot \lambda_{i,t}^{\text{com}} \tag{25}$$

where $c_{i,t}^{com}$ denotes the participant's discomfort cost, $Q_{i,t}^{\text{com}}$ is the energy from controllable devices, $\lambda_{i,t}^{\text{com}}$ is the cost coefficients for the controllable devices.

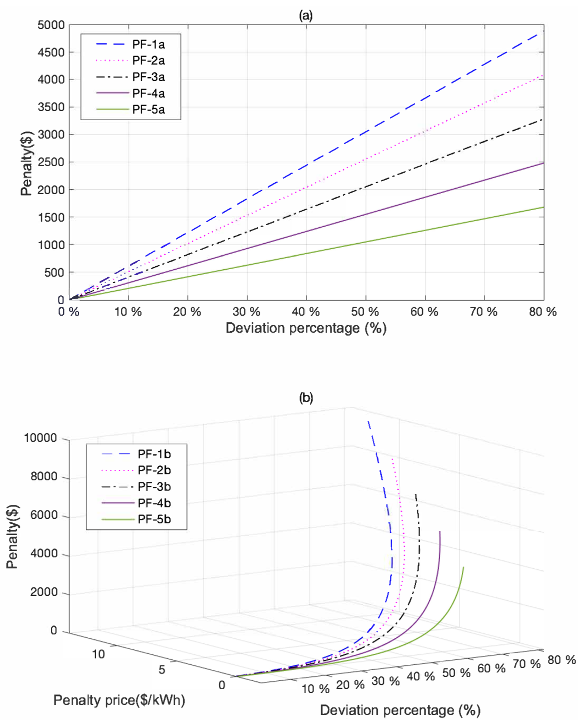


Fig. 6: Comparison of two-dimensional and three-dimensional penalty. (a) Two-dimensional penalty; (b) Three-dimensional penalty

According to [45], the operational cost of ESS is supposed to be a linear function of the absolute value of charged/discharged capacity. It is typically measured using its power storage capacity in kWh or MWh when the ESS is used for peak shaving or load leveling. This paper assumes that the EMS will use available ESS capacity to adjust the relevant energy deviation. Therefore, the state-of-charge constraint of ESS is not considered. The ESS operating costs incurred to compensate for energy deviations are as follows:

$$c_{i,t}^{ESS} = \left| Q_{i,t}^{ESS} \right| \cdot \lambda_{i,t}^{ESS} \tag{26}$$

where $c_{i,t}^{ESS}$ denotes the ESS operation cost, $Q_{i,t}^{ESS}$ is the energy form ESS, $\lambda_{i,t}^{ESS}$ is the cost coefficients for the ESS.

The participation of prosumers in the DA-based P2P market has been extensively discussed, and many strategies have been proposed and analyzed, such as zero intelligence (ZI) [51], best-offer, and market power approach [36]. One way to reduce the default risk associated with energy trading is to improve the accuracy of predictions. Another effective method is to enhance prosumers' energy self-regulation ability during the order execution period to reduce energy deviations. As this paper focuses primarily on the influence of the penalty mechanism on participants' self-regulation, the strategies of bidding and prediction are not discussed.

To maximize the welfare of participants, EMS may need to modify the energy plan in real-time to solve the arbitrary behavior of users and the uncertainty of renewable energy generation forecasts. It is necessary to consider the balance between compensation costs and penalties. The objective function for the optimization is presented by:

$$\min \sum_{t\in T} c_{i,t}^{com} + c_{i,t}^{ESS} + p_{i,t}^{\text{penal}} \cdot \Delta Q_{i,t} \tag{27}$$

With the penalty price and cost Eqs. (23)-(26) substituted into the objective equation, the objective function can be derived as following:

$$\begin{aligned} \min \sum_{t\in T} \left(Q_{i,t}^{\text{com}}\right)^2 \cdot \lambda_{i,t}^{\text{com}} + \left|Q_{i,t}^{ESS}\right| \cdot \lambda_{i,t}^{ESS} \\ + kp_t \cdot \left| \frac{\left(Q_{i,t}^{\text{order}} - Q_{i,t}^{\text{Actual}} + Q_{i,t}^{ESS} + Q_{i,t}^{\text{com}}\right)^2}{Q_{i,t}^{\text{order}}} \right| \end{aligned} \tag{28}$$

$$\text{s.t. } Q_{i,t}^{cl\_com} \le Q_{i,t}^{com} \le Q_{i,t}^{ch\_com} \tag{29}$$

$$Q_{i,t^c}^{cl\_ESS} \le Q_{i,t}^{ESS} \le Q_{i,t}^{ch\_ESS} \tag{30}$$

where $Q_{i,t}^{cl\_com}$ and $Q_{i,t}^{ch\_com}$ is the available capacity limitation of controllable devices for EDD and ESD, respectively. $Q_{i,t}^{cl\_ESS}$ and $Q_{i,t}^{ch\_ESS}$ is the available charging and discharging capacity of self-equipped ESS, respectively. Eqs. (29) and (30) denote the constraints that the energy scheduling needs to be within the available scheduling range.

4.3. Decision-Making model for the P2P Market Operator

The ideal situation for the P2P market would be when the total selling energy quantity equals the total buying energy quantity. The utility grid will provide a paid balancing service if unexpected energy deviations are observed. The penalty imposed on energy deviations can be collected by the P2P market to compensate for the net costs caused by maintaining the power grid balance. The retail/export prices and the ancillary services prices are determined by the whole market and the balancing market operator. The system operator is responsible for managing the system constraints and balancing the power; these roles are beyond the scope of this paper.

The goal of the P2P market operator is to reduce the economic risks related to transactions by determining the overall energy deviation target in the market, adjusting the penalty factors, and transparently deciding the penalty price to promote the fairness of the market transactions. The objective function of the optimization is to minimize the sum of the penalty and net costs of the community:

$$\min \left\{ \sum_i^{\text{N}} dp_{i,t} \cdot kp_t \cdot \left(\Delta Q_{i,t}^{+} + \Delta Q_{i,t}^{-}\right) + p_t^{Grid} \cdot Q_t^{Grid} \right\} \tag{31}$$

$$\text{s.t.} \quad \sum_i^{N} \left(\Delta Q_{i,t}^{+} - \Delta Q_{i,t}^{-}\right) + Q_t^{\text{Grid}} = 0 \tag{32}$$

$$Q_t^{\min} \le \sum_i^{N} \left(\Delta Q_{i,t}^{+} + \Delta Q_{i,t}^{-}\right) \le Q_t^{\max} \tag{33}$$

$$\Delta Q_t^{L} \le \sum_i^{N} \left(\Delta Q_{i,t}^{+} - \Delta Q_{i,t}^{-}\right) \le \Delta Q_t^{H} \tag{34}$$

$$\sum_i^{\text{N}} dp_{t,i} \cdot kp_t \cdot \left(\Delta Q_{i,t}^{+} + \Delta Q_{i,t}^{-}\right) \ge p_t^{\text{Grid}} \cdot Q_t^{\text{Grid}} \tag{35}$$

$$kp_t^{\min} \le kp_t \le kp_t^{\max} \tag{36}$$

where $p_t^{\text{Grid}} \cdot Q_t^{\text{Grid}}$ is the net costs for compensating energy deviation from utility grid, $kp_t^{\max}$ is the maximum penalty factor and $kp_t^{\max}$ is the minimum penalty factor. Eq. (32) describes the constraint of energy balance in the community. Eq. (33) describes the market's constraint of maximum energy deviation. Eq. (34) describes the constraint of the acceptable range of energy deviation to ensure that the PCP and ACP are consistent, as described in Section 3.1. Eq. (35) describes the fines collected should be sufficient to pay the additional net cost to the utility grid. Eq. (36) describes the constraint of the penalty factor.

4.4. Distributed Default Clearing Algorithm

Implementing optimization in a centralized manner requires full access of the market operator to participants' facilities, including getting information data and controlling adjustable devices directly, which could compromise the participants' privacy and control. In contrast, decomposing the optimization problem can reduce the information required to ensure default clearing efficiency, thereby improving the privacy level of participants' utility and cost. Each participant collects data and computation separately in the distributed optimization approach. As such, this paper developed a default clearing algorithm in a distributed manner without requiring individual device information from participants.

Under the presented APM, each participant is considered a rational agent who makes the best decisions and attempts to maximize welfare. Consequently, all involved participants focus only on solving their individual cost minimization problems, thus contributing to the goal of overall cost minimization through a distributed solution. The market regulators solve Eq. (34) by adjusting the level of the penalty factor. Upon receiving the operator's penalty factor signal, the participators will correct the energy deviation in line with their objective function. This algorithm is illustrated in the Fig. 7, and the process is explained as follows:

Step 1: The P2P marker platform assigns an initial value kp_t^0 to the penalty factor and sets the OED constraints.

Step 2:Once receiving the penalty factor from the P2P market operator, the prosumers run their EMS by solving optimization problems. The optimal decision is the energy scheduling for controllable devices and ESS.

Step 3: Once the corresponding results from prosumers are observed, the P2P market operator determines whether the OED exceeds the established limit. Meanwhile, the operator updates its penalty factor, subject to the elasticities in the generation and consumption sides. The elasticity of the penalty factor indicates that the change of penalty price

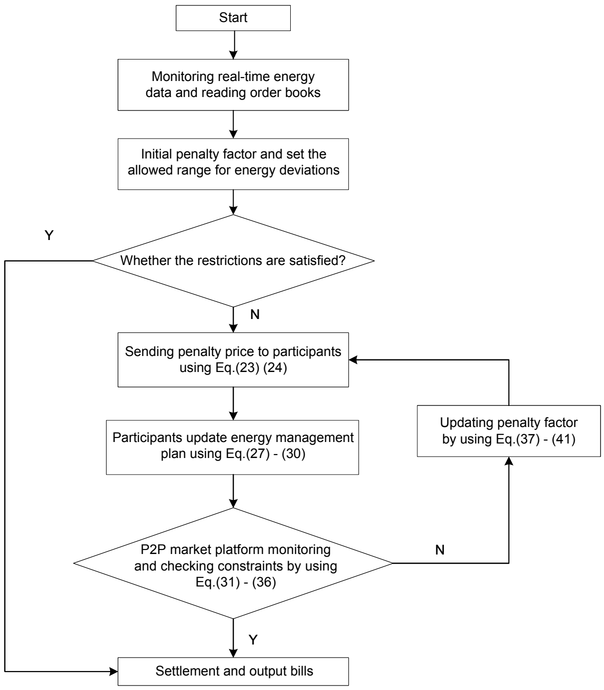


Fig. 7: Distributed default clearing algorithm

will lead to the change of OED by prosumers. Prosumers can be prompted to correct their energy deviation by increasing the penalty factor. Let k denote the iteration number of the interaction. The ESD, EDD, OED, and penalty factor values are normalized to the value at the initial iteration, i.e., $k = 1$. Following the collection of energy deviation information, the market operator will modify and disclose the penalty factors following actual information as:

$$kp_t^{(k+1)} = kp_t^k + \zeta_t^k \tag{37}$$

where ζ_t^k is the elasticity of the penalty factor, which is determined according to the monitoring data.

The elasticity will be updated if the OED does not meet the market restrictions at this time, as demonstrated in Eq. (38). As shown in (39), the elasticity will not be updated when OED meets the market restrictions. In addition, the participants make decisions based on the available capacity limit for the active intervention, which means that even if the penalty is increased, the participant may run out of capacity and can not to reduce the energy deviation further. Therefore, the elastic update formula appears in Eq. (40).

$$Q_t^{\max} \le \sum_i^N \Delta Q_{i,t}^k \le Q_t^{\min}, \varsigma_t^k = \sigma_t^k \tag{38}$$

$$Q_t^{\min} \le \sum_i^N \Delta Q_{i,t}^k \le Q_t^{\max}, \zeta_t^k = 0 \tag{39}$$

$$\sum_i^N \Delta Q_{i,t}^k - \sum_i^N \Delta Q_{i,t}^{(k-1)} \le \varpi_t, \varsigma_t^k = 0 \tag{40}$$

where ϖ_t is the capacity limitation parameter; σ_t^k is the elasticity parameter of the penalty factor. As studied in [52], the elasticity factor that is affected by monetary variables and can be expressed as follows:

$$\sigma_t^k = \frac{\left(\sum_i^N \Delta Q_{i,t}^k - \sum_i^N \Delta Q_{i,t}^{(k-1)}\right) / \sum_i^N \Delta Q_{i,t}^{k=1}}{\Delta kp_t^k / kp_t^{k=1}} \tag{41}$$

Step 4: Participants change their responding strategies by solving their optimization problems and receiving the updated penalty factor from the market operator. The iterative interaction continues until reaching convergence. The criteria of the convergence are the required OED to meet the constraints, or the variation is narrowed down to the allowable range, and the penalty factor remains unchanged as

$$kp_t^{(k+1)} = kp_t^k \tag{42}$$

Proof: The iterative process between the market operator and participants to the convergence if Eq.(42) holds. The penalty will continue to rise when OED fails to meet market expectations, as represented in Eq.(38), i.e., $kp_t^{(k+1)} > kp_t^k$. The iterative process will continue. When OED meets the market restrictions as (39) and (40), the penalty factor remains unchanged. This is the point at which the iterative process converges.

This paper aims to demonstrate the penalty concept by analyzing interactions between the market and participants on a distributed level. The proposed APM is intended to ensure accurate implementation of market-clearing results but not to ensure the safe operation of distribution systems. Therefore, this paper does not take account of physical constraints, such as three-phase power flow, operations reserve, node voltage, and network losses.

5. Simulation and Results

Evaluations on the proposed model are conducted in the context of a P2P market with commercial participants. The simulations are conducted on a computer with the Intel(R) Xeon(R) processor L5630*2. All the cases were simulated using MATLAB, among which the proposed model calls the CPLEX optimization toolbox and Yalmip toolbox.

Three sets of case studies were designed and simulated based on the local P2P energy trading, in which 25 commercial participants with aggregated demand response-based smart buildings. Load data is derived from measurements in electricity energy usage data in Council buildings in 2020 [53]. Generation data from real-world measurements is taken from Pecan Street in June 2021 [54]. Assuming that the price of energy exchange between the P2P operator and the utility grid is 0.6$/kWh for the energy deficit compensation and 0.2$/kWh for export energy surplus. The bidding range of participants is also between this price range, and that ZI strategy is adopted to participate in the DA-based P2P market. There is a set range for penalty factors of 0 to 1 and applied to all cases. Fig. 8 shows the penalty price for the corresponding value. The initial value of the penalty factor is regarded as the minimum penalty factor.

In the first case study, the goal is to test and verify the effectiveness of the proposed APM by adjusting the

Table 1
Results of the no-penalty.

	MDP	0%	10%	20%	30%	40%	50%	60%	70%	80%
No-penalty	ESD (kWh)	0	17.9333	40.0139	47.0869	67.3036	98.5535	111.285	71.0556	138.9136
	EDD (kWh)	0	-17.1552	-27.7086	-68.768	-82.9118	-59.1742	-111.6057	-60.907	-101.7419
	OED (kWh)	0	0.7781	12.3053	-21.6811	-15.6082	39.3793	-0.3207	10.1486	37.1717
	ACP ($/kWh)	0.4963	0.4963	0.4992	0.4852	0.4963	0.5334	0.4963	0.4992	0.5334

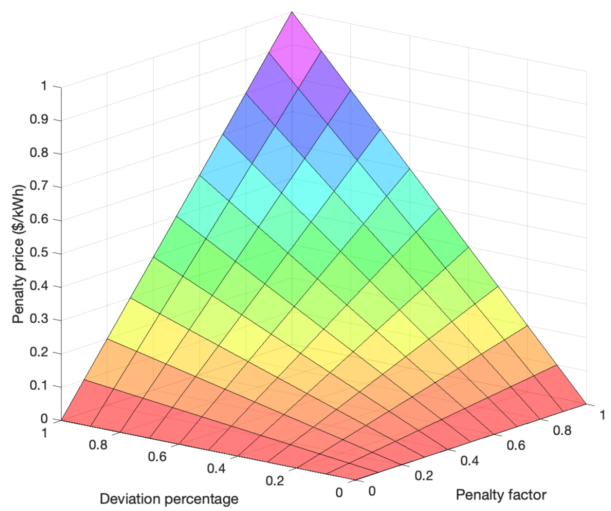


Fig. 8: The relationship between penalty price, deviation percentage and penalty factor

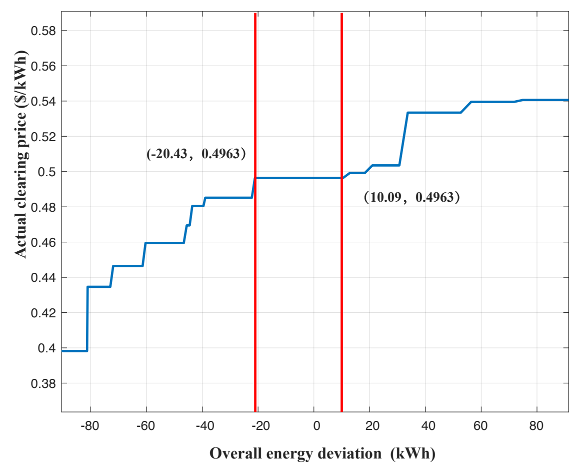


Fig. 9: The relationship between overall energy deviation and actual clearing price

Maximum Deviation Percentage (MDP). The second case study is intended to explore the limitations of the penalty mechanism by varying the participants' reserve capacity for energy deviation. The third case study investigates the correlation between the self-regulation cost and the APM by altering participants' discomfort and ESS operational cost.

Fig. 9 illustrates the impact of energy deviation on the clearing price when different energy deviations are set randomly for different participants. In line with the conclusion of Section 3.1, there is a high possibility of significant clearing price deviations when substantial OED appears. If OED is controlled within the specific range (-20.43 to 10.09 kWh), price deviation will not occur, as PRC and ARC are consistent (0.4963$/kWh). The maximum deviation range allowed by the market is set to be between - 10 kWh and 10 kWh, reducing the amount of energy exchanged with the utility grid and maintaining the clearing price.

5.1. Case study 1: Base case assessing the performance of the APM

This case study acts as the base case and consists of 4 scenarios for validating and assessing the P2P energy trading performance with different penalty mechanisms. The energy exchange price between P2P operators and the utility grid is ignored in this case to assess the penalty mechanism efficiency better. The ESS cost coefficient is 0.4, and the discomfort cost coefficient is 0.04. The energy deviation values are randomly generated for each participant within the MDP range to simulate the uncertainty, as Eq. (43) shows. An MDP of 0% indicates that the participant has fully fulfilled the order.

$$\Delta Q_{i,t} = MDP \cdot Q_{i,t}^{\text{order}} \cdot \alpha_{i,t} \tag{43}$$

where α is the is a defaulting coefficient.

Table 1 shows the results of the no-penalty scenario. The prosumer would not compensate for energy deviations in this scenario. It is observed that the OED shows significant randomness since a high MDP does not necessarily correspond to a large amount of OED. For example, when the MDP is 60%, the OED is even less than 1. The ESD and EDD are approximately equal in value at this point, so they can be offset against each other. When OED exceeds the specific range shown in Fig.9, it will lead to inconsistency with the PCP and ACP. The clearing price deviation generates misleading price signal and destroys the fairness of the market.

Table 2 shows the energy deviation and ACP results under the three penalty mechanisms. Two two-dimensional penalties are analyzed (one is higher than the ESS cost and the second is lower) to better compare with the APM, representing excessive and insufficient penalty, respectively. Results show that the APM and severe penalty (0.6$/kWh) mechanisms can ensure the consistency of the ACP and PCP within any of the MDP. The severe penalty forces the participants to compensate for all energy deviation, thus fulfilling the order ultimately. By comparison, the APM regulates the OED within the allowed range (-10 kWh to

Table 2
Results under different penalty mechanisms.

Penalty mechanism	MDP	0%	10%	20%	30%	40%	50%	60%	70%	80%
Adaptive penalty	ESD (kWh)	0	17.9333	30.1215	19.3324	25.2976	38.7335	111.285	63.016	94.0356
	EDD (kWh)	0	-17.1552	-20.4661	-29.1593	-34.929	-29.1489	-111.6057	-55.7733	-87.0888
	OED (kWh)	0	0.7781	9.6554	-9.827	-9.6314	9.5846	-0.3207	7.2427	6.9468
	ACP ($/kWh)	0.4963	0.4963	0.4963	0.4963	0.4963	0.4963	0.4963	0.4963	0.4963
Mild penalty (0.2$/kWh)	ESD (kWh)	0	2.4467	19.0634	23.7674	40.9896	71.0529	91.7012	58.5553	121.4131
	EDD (kWh)	0	-4.539	-11.997	-48.4855	-63.7247	-45.8609	-87.5317	-43.8644	-86.7418
	OED (kWh)	0	-2.0923	7.0664	-24.7181	-22.7351	25.192	4.1695	14.6909	34.6713
	ACP ($/kWh)	0.4963	0.4963	0.4963	0.4852	0.4852	0.5035	0.4963	0.4992	0.5334
Severe penalty (0.6$/kWh)	ESD (kWh)	0	0	0	0	0	0	0	0	0
	EDD (kWh)	0	0	0	0	0	0	0	0	0
	OED (kWh)	0	0	0	0	0	0	0	0	0
	ACP ($/kWh)	0.4963	0.4963	0.4963	0.4963	0.4963	0.4963	0.4963	0.4963	0.4963

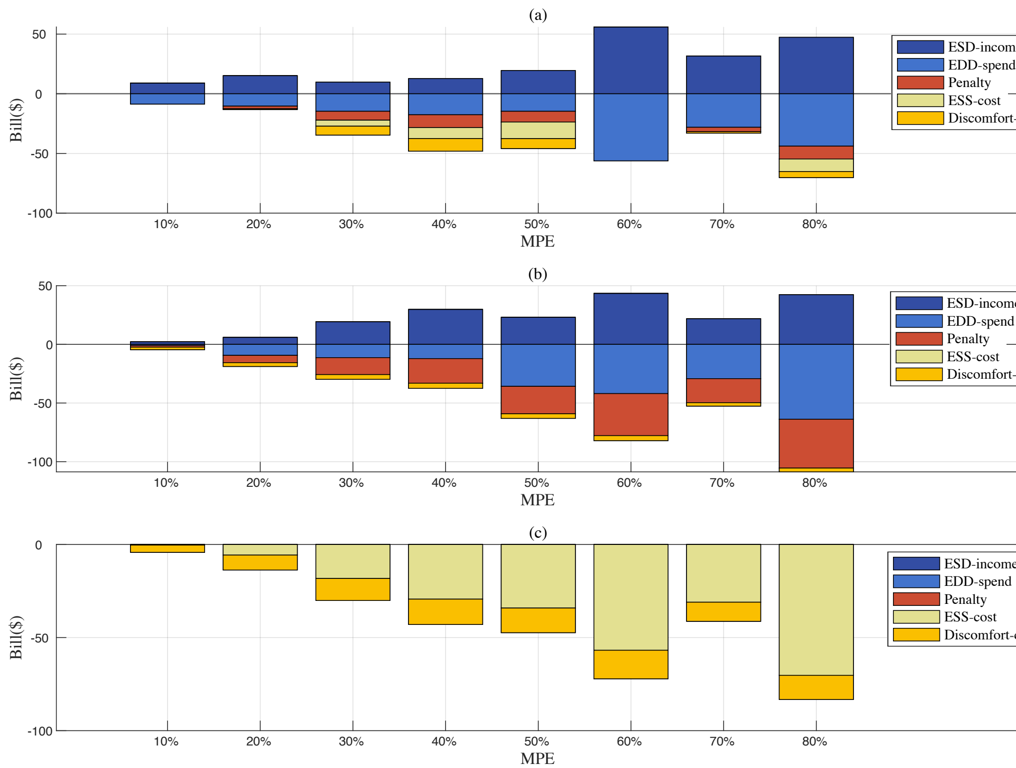


Fig. 10: Comparison of bills under different Maximum Deviation Percentage (MDP). (a) Proposed adaptive penalty mechanism; (b) Mild penalty mechanism; (c) Severe penalty mechanism

10 kWh), and participants do not correct the ESD and EDD entirely. Although the mild penalty (0.2 $/kWh) can encourage participants to correct a portion of the energy deviation, it is ineffective in preventing price deviations. Furthermore, although the values of ESD and EDD decreased to a certain degree under this penalty, the value of OED is even more significant than the no-penalty scenario in some circumstances (10%, 30%, 40%, 60%, 70% MDP).

Fig. 10 illustrates a comparison of the bills under three penalty mechanisms. The bill includes the income from selling ESD, the spend for purchasing DED, penalties, the cost of operating the ESS, and the cost of discomfort. Fig. 10(a) illustrates the bill related to the APM, which sets different levels of penalties according to the variation of OED. The penalties are not imposed when the MDP is 10% or 60%, as the OED is in the allowable range. A lesser penalty is applied when the MDP is 20% or 70% as the OED is close to 10kWh. In other instances, there is necessary to compensate for the energy deviation by utilizing both ESS and controllable devices, so the penalties tend to be more significant. As Fig. 10(b) shows, participants always use controllable devices when a mild penalty is applied to compensate for the energy deviation. They prefer accepting the penalty since it is not economical to use ESS simultaneously. The expenses are more significant when the severe penalty mechanism is imposed, as shown in Fig. 10(c). To avoid the penalty, participants must use both ESS and controllable devices to correct all energy deviation. It can be concluded that the traditional two-dimensional penalty mechanism follows

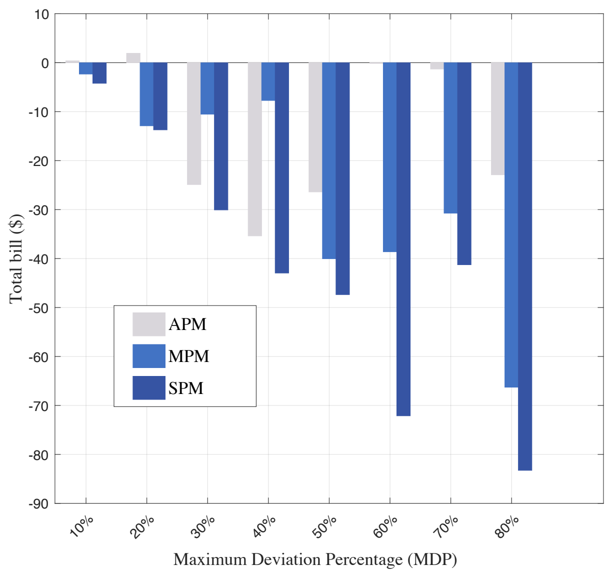


Fig. 11: Comparison of total bills under different MDP. (Where APM represents the adaptive penalty mechanism, MPM is the mild penalty mechanism and SPM represents the severe penalty mechanism.)

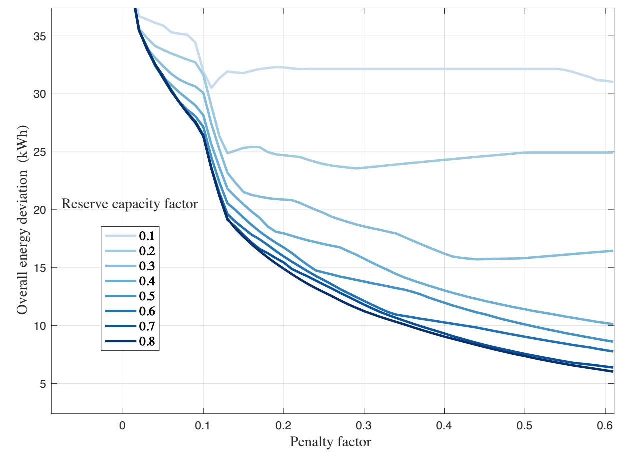


Fig. 12: Relationship of penalty factor and overall energy deviation under different reserve capacity factor

similar patterns under any MDP, which makes it inflexible to changes in market conditions.

Fig. 11 shows the total bill for the three penalty scenarios. The severe penalty provides the most effective way of ensuring full compliance with all orders. Nevertheless, it typically requires participants to suffer the highest cost. According to the results, the proposed APM has a less total bill than the mild penalty mechanism in most instances (except for those with MDP of 20% and 30%). In contrast, the APM can strike a balance between economy and effectiveness.

5.2. Case study 2: Performance with different reserve capacity

This case study focuses on assessing the performance of the penalty mechanisms in situations where participants have varying reserve capacities. For this case, the energy deviation scenario is selected from case 1, MDP=50% (the OED value reaches the maximum). The cost coefficients are the same as in case 1. The capacity limitation parameter ϖ_t is set to 0.05 in this case. It should be noted that the smaller the value, the lower the participantsâĂŹ available capacity to compensate for energy deviation. Given that the prosumer cannot predict the $\alpha_{i,t}$ exactly, then the reserve capacity can be planned by using the MPD as follows:

$$Q_{i,t}^{cl} = MPD \cdot \left| Q_{i,t}^{\text{order}} \right| \cdot \beta_{i,t}^{cl} \tag{44}$$

$$Q_{i,t}^{ch} = -MPD \cdot \left| Q_{i,t}^{\text{order}} \right| \cdot \beta_{i,t}^{ch} \tag{45}$$

where $\beta_{i,t}^{ch}$ is the reserved capacity factor for ESD; $\beta_{i,t}^{cl}$ is the reserved capacity factor for DED.

The reserved capacity factor is a fixed number ranging from 0 to 1, which represents the amount of capacity the prosumer is willing to reserve for self-regulation in advance, e.g. $\beta_{i,t} = 1$ represents the reserved capacity setting is sufficient to ensure that any energy deviation generated by chance can be corrected. In this case, it is assumed that the capacity of the ESS and the controllable devices share the reserved capacity equally.

Fig. 12 illustrates the variation in OED due to an increase in penalty and reserve capacity factors under the APM. With the increase in penalty factor, the OED consistently exceeds 30kWh when the reserve capacity factor β is 0.10. As the reserve capacity increases, the OED decreases more rapidly, implying that the penalty's effectiveness becomes increasingly apparent. For example, at a penalty factor of 0.4, the OED is within the acceptable range when the reserve capacity factor is 0.7 and 0.8. Following Eq. (40) in section 4.4, the penalty factor will not continuously increase across the limited reserve capacity. Similarly, the three curves ($\beta = 0.1, 0.2, 0.3$) confirm that continuously increasing the penalty factor does not promote the prosumer's self-regulation when the reserve capacity is insufficient.

Fig. 13 shows the energy deviation under different reserve capacity factors. The energy deviation under the severe penalty decreases significantly as the reserve capacity factor increases. A reserve capacity factor greater than 0.5 is required to achieve control of OED within the allowable range. Under the mild penalty, there is no noticeable difference in energy deviation with an increase in reserve capacity factor, which means that the reserve capacity is not fully utilized. The APM's reduced energy deviation rate is between severe and mild penalties, suggesting a reserve capacity factor greater than 0.4 is necessary to limit OED. Although participants' compensation for energy deviation under the APM is lower than that under severe penalty, less reserve capacity is required. It is essential to note that the choice of reserve capacity by the prosumer will also be based on economic considerations.

Fig. 14 illustrates the bills under different reserve capacity factors. The OED results show that the market requirements cannot be met when β is smaller than 0.4, whichever

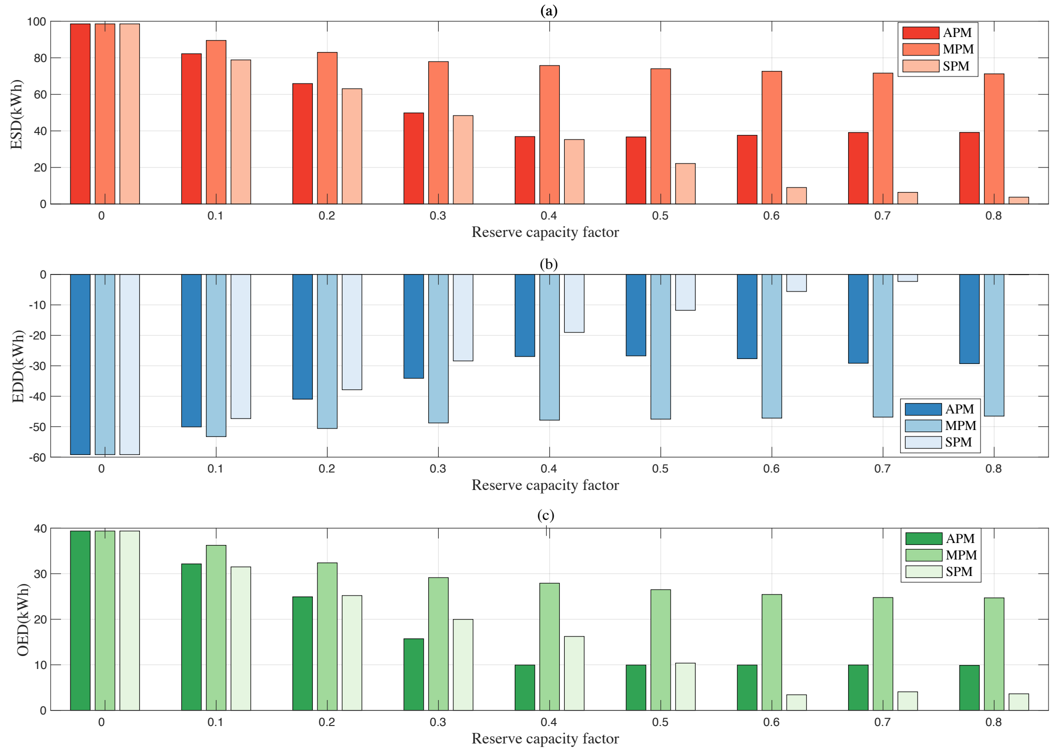


Fig. 13: Comparison of energy deviation with different reserve capacity factor. (a) Energy surplus deviation; (b) Energy deficit deviation; (c) Overall energy deviation. (Where APM represents the adaptive penalty mechanism, MPM is the mild penalty mechanism and SPM is the severe penalty mechanism.)

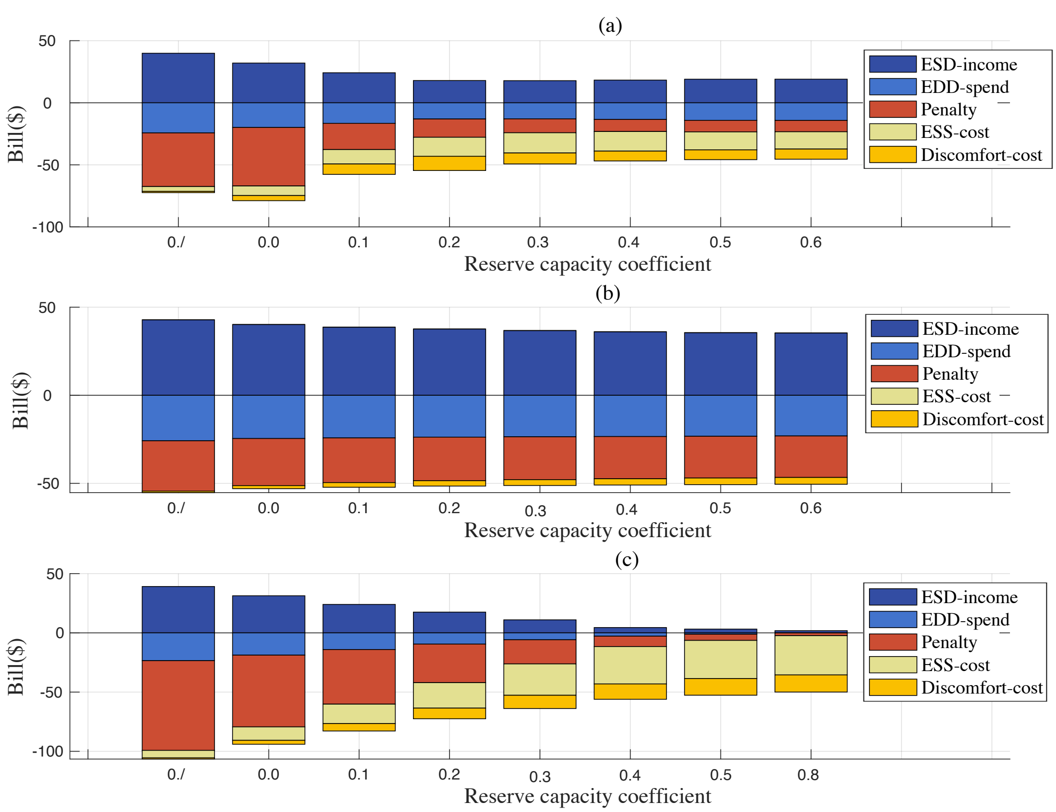


Fig. 14: Comparison of bills under different reserve capacity factor. (a) Adaptive penalty mechanism; (b) Mild penalty mechanism; (c) Severe penalty mechanism

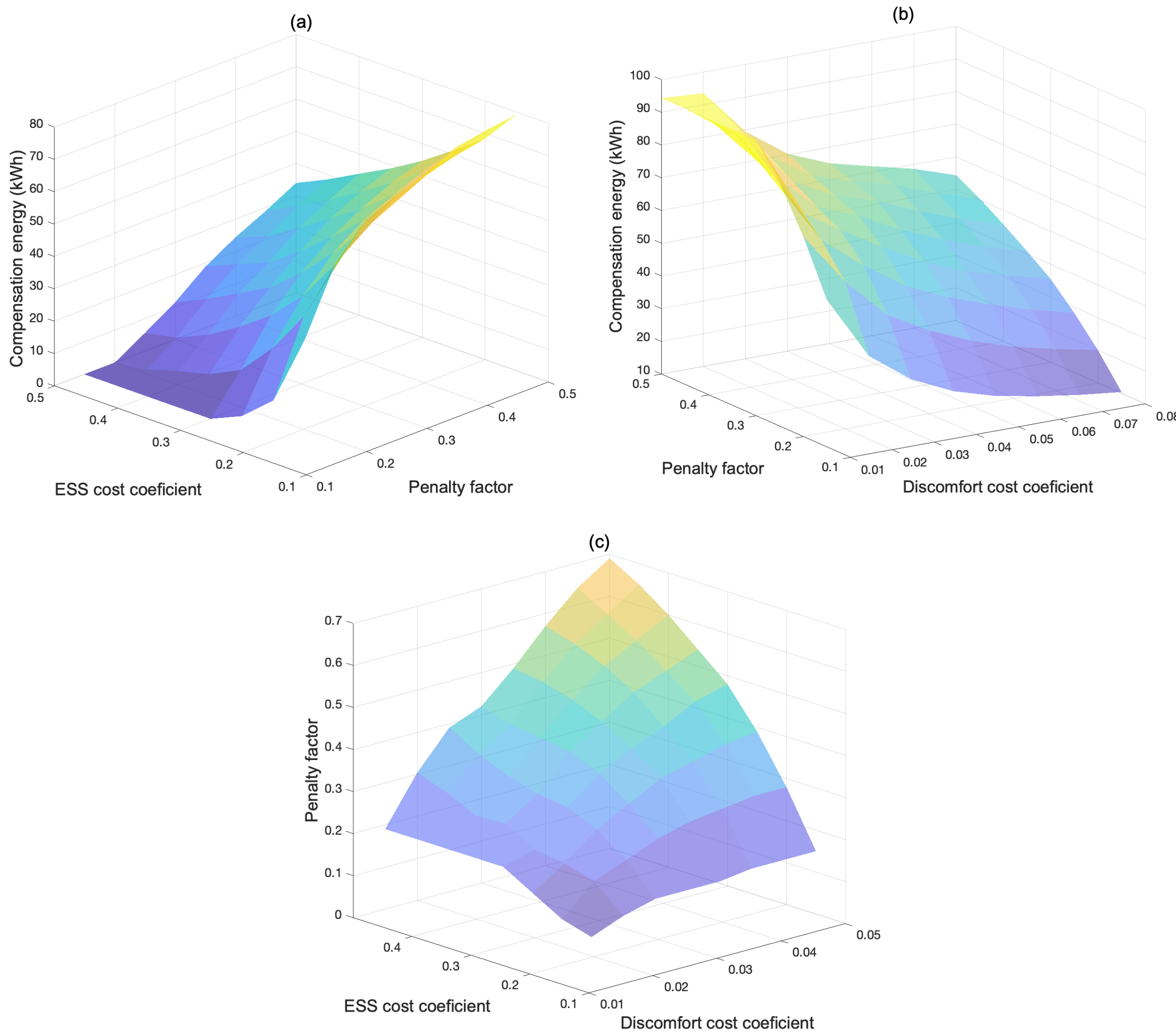


Fig. 15: Comparison of results under different cost (a) Relationship of ESS cost, compensation energy and penalty factor; (b) Relationship of discomfort cost, compensation energy and penalty factor; (c) Relationship of ESS cost, discomfort cost and penalty factor

penalty mechanism is employed. Under these circumstances, the severe penalty will result in high expenditures, e.g., the total expense exceeds 100$ for a β at 0.1. Increasing the reserve capacity can reduce expenses. Thus, prosumers may prefer to select a higher reserve capacity ($\beta > 0.8$) to minimize cost. With the increase in reserve capacity factor, the total cost remains essentially unchanged under the mild penalty mechanism. It indicates that prosumers always accept the penalty, so they will not prepare enough reserve capacity for self-regulation. Fig. 14(a) illustrates that when the prosumers' reserve capacity factor reaches an appropriate value ($\beta > 0.5$), the bill does not change significantly as β increases. As a result, participants do not need to blindly choose a sufficient reserve capacity but typically select a suitable one. The participants would determine reserve capacity based on different penalty mechanisms to maximize economic benefits. The APM and severe penalty mechanism can encourage participants to improve their self-regulation abilities. The APM requires fewer reserve capacities than the severe penalty when similar OED results are obtained, so it with a lower risk of wasted opportunity costs.

5.3. Case study 3: Performance with different self-regulation cost

This case study examines the performance of the proposed APM when the prosumers' compensation cost for self-regulation varies. Assuming prosumers have sufficient reserve capacity, the energy deviation scenario is the same as in case study 2. Two-dimensional penalty mechanisms will no longer be tested. As discussed in case study 1, a penalty price above the cost coefficient can be considered a severe penalty mechanism. In contrast, the penalty price below the cost coefficient can be regarded as a mild penalty mechanism. The performance can be referred to as the results of case study 1.

Testing the APM has been conducted by modifying the discomfort and ESS cost coefficient, and all results meet the market requirements (-10kWh< OED<10kwh). Figs. 15(a) and 15(b) indicate that when the ESS or discomfort cost is low, a relatively small penalty factor can promote the devices to provide compensation energy for self-regulation. When ESS and discomfort costs increase, only an increased penalty factor would effectively promote participants to use energy-correcting devices. According to Fig. 15(c), the penalty factor rises proportionally to the increase of ESS and discomfort cost. In other words, the penalty factor is aligned with the compensation cost those prosumers are willing to bear to achieve the desired outcome. If one of the devices is low-cost and has sufficient capacity, the cost of the other will not significantly affect the penalty factor. That is, it is necessary for participants to have at least a low-cost piece of equipment for compensating energy deviations.

On the other hand, market operators should investigate participants' equipment conditions and related risks. When participants possess the necessary equipment for self-regulation that is both cost-effective and capacity adequacy, the penalty mechanism can provide effective market regulation. However, when participants' self-regulation is costly, only the simultaneous imposition of high penalty factors can achieve the desired effect. In this situation, participants would face the risk of significant fines and self-regulation costs, thus reducing enthusiasm for participating in the market.

6. Conclusion

This paper proposes a novel APM for the P2P market regulation. In addition to monitoring the P2P energy trading within a distribution network, this method can encourage participants to compensate for energy deviations between their actual generation/consumption and the quantity specified in orders. The energy deviations will lead to the inconsistency between the pre-determined clearing price and the actual clearing price, which can be controlled into acceptable ranges by implementing the APM. As a result, it is possible to avoid deviations in the clearing prices to ensure the fairness of the market. In comparison to the traditional two-dimensional penalty mechanism described in the literature, the APM in this paper offers the following advantages:

- Considering there are many uncertainties in the P2P market due to the high penetration of renewable energy sources and the arbitrary behavior of participants. The proposed APM embraces the uncertain nature of the participants by using a three-dimensional penalty to reduce excessive penalty risks, benefiting the participants with a low deviation percentage.

- The APM helps limit the accumulation of unnecessary penalties by adjusting the penalty factor to adapt to the market conditions. It permits partial energy deviation to achieve low-risk dispatch by purchasing/selling energy from/to participants with complementary generation/consumption energy deviations.

- The case studies demonstrate the feasibility of utilizing the APM in the P2P market. When similar energy deviation results are obtained, the reserve capacity and compensation costs required by the APM are less than the severe penalty. As a result, the APM can mitigate the risks associated with the heavy fines resulting from energy deviation and the potential opportunity costs wastage caused by the reserve capacity.

This paper explores the prerequisites for adopting the APM in the market. The results suggest that market operators should analyze participants' reserve capacity and compensation costs before implementing a penalty mechanism. Insufficient reserve capacity may result in penalty mechanisms not being effective and resulting in additional expenses. Additionally, when compensation costs are high, it has been found that only imposing higher fines can encourage participants to engage in active participation. Therefore, applying a penalty mechanism without considering the limitations of the participants may compromise their willingness to participate. Furthermore, the setting of penalty mechanisms should also consider the limitations of existing forecasting technologies as well as the reaction ability of participants, which will be investigated in the future.

CRediT authorship contribution statement

Bidan Zhang: Conceptualisation, Methodology, Software, Investigation, Visualisation, Writing - original draft. **Yang Du:** Conceptualisation, Methodology, Writing - review & editing, Supervision. **Xiaoyang Chen:** Writing - review & editing, Validation. **Eng Gee Lim:** Project administration, Resources. **Lin Jiang:** Supervision. **Ke Yan:** Validation.

Declaration of Competing Interest

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

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