Applied Energy 328 (2022) 120167

Contents lists available at ScienceDirect

Applied Energy

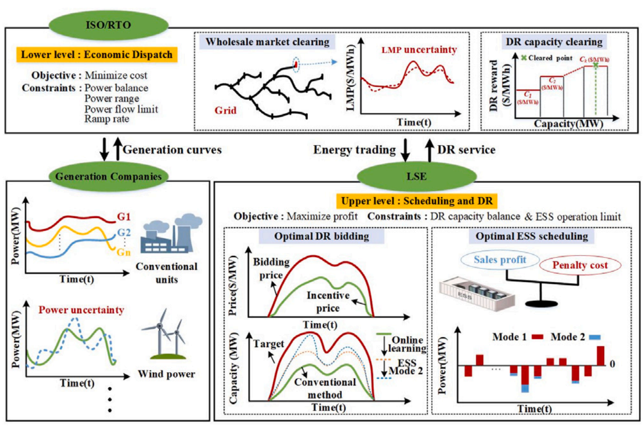
journal homepage: www.elsevier.com/locate/apenergy

An optimal bidding and scheduling method for load service entities considering demand response uncertainty

Rushuai Han [a], Qinran Hu [a,*], Hantao Cui [b], Tao Chen [a,c], Xiangjun Quan [a], Zaijun Wu [a]

[a] School of Electrical Engineering, Southeast University, Nanjing, China
[b] Electrical & Computer Engineering, Oklahoma State University, OK, United States
[c] Department of Electrical Engineering, Tampere University, Tampere, Finland

GRAPHICAL ABSTRACT



ARTICLE INFO

Keywords:
Load serving entity
Aggregation deviation
Bi-level scheduling model
Online learning
Energy storage system

ABSTRACT

With the rapid development of demand-side management technologies, load serving entities (LSEs) may offer demand response (DR) programs to improve the flexibility of power system operation. Reliable load aggregation is critical for LSEs to improve profits in electricity markets. Due to the uncertainty, the actual aggregated response of loads obtained by conventional aggregation methods can experience significant deviations from the bidding value, making it difficult for LSEs to develop an optimal bidding and scheduling strategy. In this paper, a bi-level scheduling model is proposed to maximize the net revenue of the LSE from optimal DR bidding and energy storage systems ESS scheduling by considering the impacts of the uncertainty of demand response. An online learning method is adopted to improve aggregation reliability. Additionally, the net profit for LSEs can be raised by strategically switching ESS between two modes, namely, energy arbitrage and deviation mitigation. With Karush–Kuhn–Tucker (KKT) optimality condition-based decoupling and piecewise linearization applied, this bi-level optimization model can be reformulated and converted into a mixed-integer linear programming (MILP) problem. The effectiveness and advantages of the proposed method are verified in a modified IEEE RTS-24 bus system.

* Corresponding author.
E-mail address: qhu@seu.edu.cn (Q. Hu).

https://doi.org/10.1016/j.apenergy.2022.120167
Received 10 August 2022; Received in revised form 10 October 2022; Accepted 15 October 2022
Available online 31 October 2022

Nomenclature

Abbreviations

AC	Air conditioner
CMAB	Combined multi-armed bandits
DCOPF	DC optimal power flow
DR	Demand response
ESS	Energy storage system
ISO/RTO	Independent System Operator/Regional Transmission Organization
KKT	Karush–Kuhn–Tucker
LMP	Locational marginal electricity price
LSE	Load serving entity
MILP	Mixed integer linear programming
MPEC	Mathematical program with equilibrium constraints
SOC	State of charge

Variables

λ_t^s	Dual variables related to power balance limit
$\mu_{l,t}^{s,\min}/\mu_{l,t}^{s,\max}$	Dual variables related to power flow limit
$\pi_{i,t}$	LMP at bus i and time slot t, \$/MWh
$\sigma_{i,t}^c$	Charge status indicator variable for ESS
$\sigma_{i,t}^d$	Discharge status indicator variable for ESS
$D_{i,t}$	Load at bus i and time slot t, MW
$P_{i,t}^c$	Charging power of ESS, MW
$P_{i,t}^D$	Load aggregation deviation, MW
$P_{i,t}^d$	Discharge power of ESS for energy sales, MW
$P_{i,t}^E$	Power of ESS, MW
$P_{i,t}^R$	Final DR deviation, MW
$P_{i,t}^{s,m}$	Discharge power of ESS for DR deviation compensation, MW
$P_{i,t}^{tar}$	Bidding capacity at bus i and time slot t, MW
$R_{i,t}$	Bidding price at bus i and time slot t, \$/MWh
$r_{i,t}$	Incentive price at bus i and time slot t, \$/MWh
$\omega_{g_i,t}^{s,\min}/\omega_{g_i,t}^{s,\max}$	Dual variables related to output power limit of conventional unit g_i
$\varphi_{w_i,t}^{s,\min}/\varphi_{w_i,t}^{s,\max}$	Dual variables related to output power limit of wind generator w_i
$P_{g_i,t}^s$	Power of conventional unit g_i at time slot t under scenarios s, MW
$P_{w_i,t}^s$	Power of wind generator w_i at time slot t under scenarios s, MW
$SOC_{i,t}$	State of charge of ESS
$\upsilon_{g_i,t}^{s,d}/\upsilon_{g_i,t}^{s,u}$	Dual variables related to ramping limit of conventional unit g_i

Parameters

$\eta_{i,c}$	Charging efficiency coefficient of ESS
$\eta_{i,d}$	Discharging efficiency coefficient of ESS
η_i	Electricity retail price, \$/MWh
τ	Penalty cost coefficient for DR deviation
ξ	Maximum load reduction coefficient
ζ	Cost of curtailing per unit capacity for wind generator, \$/MWh
$D_{i,t}^0$	Primary baseline load at bus i and time slot t, MW
GSF_{l-i}	Generation shift factor to line l from bus i
P_l	Limit power of transmission line l, MW
p_s	Occurrence probability of the scenario s
C_{g_i}	Power generation cost of per unit capacity for conventional unit g_i, \$/MWh
$E_{i,c}$	Maximum capacity of ESS
$P_{g_i}^{\max}$	Maximum Power of conventional unit g_i, MW
$P_{g_i}^{\min}$	Minimum Power of conventional unit g_i, MW
$P_i^{c,\max}$	Maximum charging power of ESS, MW
$P_i^{d,\max}$	Maximum discharge power of ESS, MW
$P_{w_i,t}^{s,0}$	Forecast power of wind generator w_i at time slot t under scenarios s, MW
$R_{g_i}^{\text{down}}/R_{g_i}^{\text{up}}$	Ramping limit of conventional unit g_i, MW/h
$SOC_i^{\max}$	Maximum state of charge of ESS
$SOC_i^{\min}$	Minimum state of charge of ESS

Sets

B	Bus set managed by the LSE
S_t	Set of residents selected to receive DR signals
T_{DR}	Time set of DR execution
U	Set of wind power output scenarios
V	Set of residents who have signed DR contracts

1. Introduction

Load Serving Entities (LSE) are profit-seeking electricity retailers that purchase energy from electricity markets and sell the energy to consumers [1]. Meanwhile, LSEs usually aggregate various loads for participating in electricity market bidding. Demand response (DR) bidding means that LSEs submit their tradable capacities and prices in the day-ahead electricity market, and the market operator clears capacities according to the system's adjustment requirements. As demand-side participation increases, new opportunities and challenges offered by this competitive market coexist. For example, the unexpected increase in peak demand or decrease in generation tends to produce extreme locational marginal prices (LMPs). The purchase price of electricity (i.e., LMPs) may be higher than the retail price which can lead to tremendous financial losses for LSEs. DR can alleviate the shortage of power supply by curtailing the load on the demand side. It enables LMPs to be decreased. Therefore, LSEs are motivated to implement optimal DR bidding strategies to averse trading risks.

Previous studies have partially investigated the topic of designing appropriate DR bidding strategies for LSEs. In [2], DR capacity considering retail prices' elasticity and contract incentives are evaluated, and an approach with system-level constraints is proposed for LSEs to achieve economic bids. Ref. [3] proposed a novel bidding optimization model combined with price-based and incentive-based DR, and it benefits multiple agents, including LSEs and residents. In [4], a market-based operation mechanism for DR resources is proposed, enabling the aggregator to bid strategically for profit improvement. In [5], a time-coupled multistage stochastic optimization model is formulated to achieve the optimal demand bidding for shiftable loads

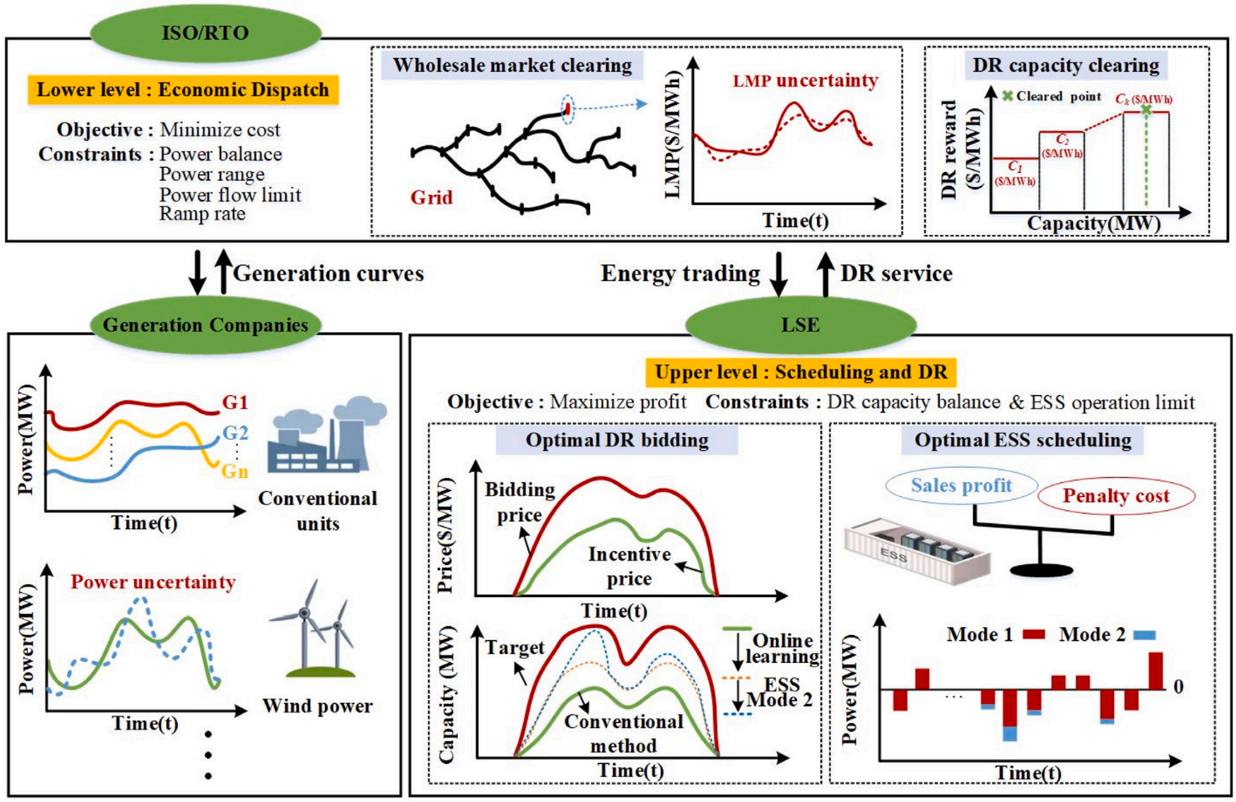


Fig. 1. Overall schematic diagram of the proposed scheduling method.

in both deregulated day-ahead and real-time markets. Ref. [6] proposes a coupon settlement method for flexible loads to minimize the energy procurement cost. Utility functions are assumed in these works to formulate the relationship between energy consumption and coupon rewards, which can be unrealistic due to unpredictable random factors, and thus can result in a significant increase in cost [7]. In [8], a probabilistic residential demand reduction model is established based on energy consumption and survey datasets. Nonetheless, establishing such probabilistic models for residents on long-time scales can be tedious and time-consuming due to the time-varying response characteristics of users. An inevitable but challenging task for LSEs is to ensure that these selected offer bids can be delivered to the market operator as promised.

Among different types of loads, residential loads account for approximately 38% of electricity consumption [9]. Nonetheless, due to their considerable amount and the uncertain aggregated behavior of residents, it becomes challenging for LSEs to reliably aggregate their loads. It means there can be a deviation between the actual response capacity and the LSE's cleared bid value. On the one hand, LSEs could confront severe financial penalties or even be barred from bidding if the deviation exceeds a tolerance band [10,11]. On the other hand, potential operation risks of limit violation might be imposed on power systems for the sake of satisfying LSE service. For example, due to the failure to meet the expected load aggregation capacity, transmission lines remain congested during peak load periods.

Efforts are made to reduce DR uncertainty through comfort constraints [12] and reward and punishment mechanism design [13,14]. In [12], a DR control strategy for large-scale residential air conditioner loads by adjusting the indoor temperature set-point is established considering users' comfort. In [13,14], additional rewards are given to those who respond positively, and unexpected finical punishments are imposed on those non-participants. With the proliferation of intelligent Internet-of-Things (IoT) devices, there are also works to assist LSEs in handling the uncertainty with data-driven approaches [15–18]. For example, in [18], an optimization strategy model combining heuristic algorithm and neural network modeling is proposed to enable LSEs to determine differentiated incentive prices by predicting the corresponding behavior of residents. Unfortunately, the impact of DR uncertainty on LSEs' profits tends to be ignored due to the unqualified aggregation deviations. Although authors in Ref. [19] propose to impose a penalty for resulting aggregation deviations, there is little discussion on DR uncertainty. It becomes unprecedentedly difficult for LSEs to develop an optimal bidding and scheduling strategy considering DR uncertainty.

For LSEs, the critical problem is to improve load aggregation reliability. Various load aggregation methods are proposed in the literature, including stochastic optimization [20,21], interval methods [22], and fuzzy methods [23]. The stochastic optimization and interval methods require the actual probability distribution of residential customers' responses, which is hard to obtain in reality. The fuzzy methods cannot guarantee optimal solutions. There are also some improvements in those three methods, but most of them hold ideal hypotheses or constraints while ignoring the real features of residential customers. With these extensive conventional aggregation methods, LSEs cannot adjust the subsequent bidding strategy timely according to residents' feedback after the DR event, and the load aggregation reliability is difficult to be guaranteed. Due to the limited bidding rewards, it is uneconomical to provide residents with extremely high monetary incentives for adequate response capacity. In recent years, online learning becomes an efficient method for solving dynamic decision-making problems under complex uncertainty [24,25]. Closed-loop systems created by the online learning method can be quickly built by quickly adopting online feedback data. It is capable of managing residents' highly ambiguous aggregated behavior. For example, Ref. [26] proposes an online aggregation method based on Thompson sampling considering the influence of time-varying environmental factors on DR uncertainty.

In addition to DR resources, energy storage systems (ESS) participating in the electricity market have gradually become another research hotspot to alleviate the shortage of power supply. In [27–29], a bilevel profit maximization model is proposed to maximize ESS arbitrage. The results demonstrate that the strategic behavior of ESS can improve its profitability. The main technique is that the upper-level problem is modeled as profit maximization for ESS operators, and the lower-level problem simulates market clearing. Although the impact of ESS on the LMPs is modeled in these works, there are two concerns for LSEs. One concern is that limited by capacities and installed locations, ESS may have less impact on LMPs [30]. The coordination between ESS and DR resources to reduce the energy purchase costs for LSEs becomes an unconsidered but promising avenue. Another concern is that agents in the above previous works are only responsible for ESS bids. Methods proposed by these works cannot apply to LSEs that are also electricity retailers. Therefore, this paper assumes the LSE is equipped with ESS and studies the profit maximization problem.

As shown in Fig. 1, this paper focuses on a bi-level optimization problem with the LSE's net revenue maximization as the upper-level problem and the ISO's economic dispatch (ED) for generation cost minimization as the lower-level problem, while considering the impacts of DR uncertainty. Note that the LSE makes DR bidding in the day-ahead wholesale market to mitigate the cost and the volatility of LMPs. To improve the load aggregation reliability, we introduce an online learning method particularly to capture the stochastic features of DR in this paper. We also conducted an ad hoc survey with 1996 samples in Jiangsu Province, China, and qualified the relationship between aggregation deviations and incentives. At the upper level, the coordination between the load aggregation and energy storage systems (ESS) dispatch is considered due to its demonstrated performance on profit improvement [11]. In particular, ESS is enabled to mitigate the DR's deviation. The main contributions of this paper are summarized as follows:

(1) Considering the impact of DR uncertainty on the LMP and demand response bidding, a new optimization model is formulated for LSEs to develop optimal DR bidding and scheduling strategies. This model enables LSEs to alleviate the risk of retail profit decrease caused by extreme energy purchase prices. Making use of the survey dataset, this model also overcomes the problem of optimal incentives design under different system requirements.

(2) Two modes, including energy arbitrage and DR's deviation mitigation, are designed for energy storage systems (ESS). The switching strategy for these two modes is also developed by trading off the profits of energy arbitrage against the finical penalties of DR deviation. It is found that the strategic switching behavior of ESS between the two modes can further improve LSEs' profits than traditionally undertaking energy arbitrage.

(3) The quantitative relationship between aggregation targets and DR deviations under different incentives is established by combining survey datasets and the online-learning-based load aggregation method. Also, by incorporating this method with the proposed model, more reliable and economical load aggregation is achieved compared with adopting conventional aggregation methods.

The remainder of this paper is organized as follows: Section 2 presents the load aggregation with the online learning method and the ESS with two modes. Section 3 proposes the bi-level scheduling model. Section 4 discusses the mathematical solution of the model. Section 5 demonstrates the effectiveness of this work in a modified IEEE RTS-24 bus system. Section 6 draws conclusions.

2. Load aggregation

2.1. Impact of DR uncertainty on LSEs' profits

In electricity markets, the typical demand response (DR) bid mainly consists of location information, time and duration of DR, the offer quantity blocks, and corresponding bid prices [31]. To better explain the impact of DR uncertainty on LSEs' profits, two illustrative examples are provided.

(1) Impact on DR bidding. As shown in Fig. 2(a), two clearing points, i.e, (B_1, C_k) and (B_2, C_{k+1}) are assumed. Interactions (B_i, R_i) and (B_i, P_i) denote the corresponding aggregation deviation R_i and DR profit P_i under the cleared capacity B_i, respectively. The penalty price for unit capacity deviation is generally the clearing price C_k multiplied by a coefficient τ [19]. Under capacity B_1, the net profit difference $B_1(i1 - i2) + \tau C_k(R_1 - R_2)$ given by the incentive $i2$ and $i1$ $(i2 > i1)$ is positive, indicating an increased profit from P_1 to P_2. When a higher capacity B_2 is cleared, a negative value $B_2(i1 - i2) + \tau C_k(R_3 - R_4)$ can result in the lower profit, i.e., $P_4 < P_3$. The root of this problem is the profit loss caused by the inevitable aggregation deviation. Meanwhile, the deviation varies with various elements of DR bidding in Fig. 2(a), such as the capacity and the incentive. Therefore, it is critical for LSEs to consider aggregation deviations in developing bidding strategies.

(2) Impact on LMP. The uncertainty of bidding-type DR programs, which is different from coupon-based ones in [8], can also affect the LMP, as shown in Fig. 2(b). Here, the impact of renewables uncertainty on the energy supply curve is ignored. The LSE is bidding in the market for a DR program with the capacity $D_1 - D_3$. If the aggregation deviation is omitted, due to the net load change at a specific bus, the LMP will drop from π_1 to π_3, making the LSE's retail profit $\eta - \pi_3$ positive. Likewise, the DR uncertainty may result in a reduction in load shedding by $D_2 - D_3$ so that the profit $\eta - \pi_2$ becomes negative.

Consequently, it is necessary to take into account how DR uncertainty will affect the bidding and LMP, and for LSEs to devise practical bid strategies to lessen its impact.

2.2. Load aggregation with online learning method

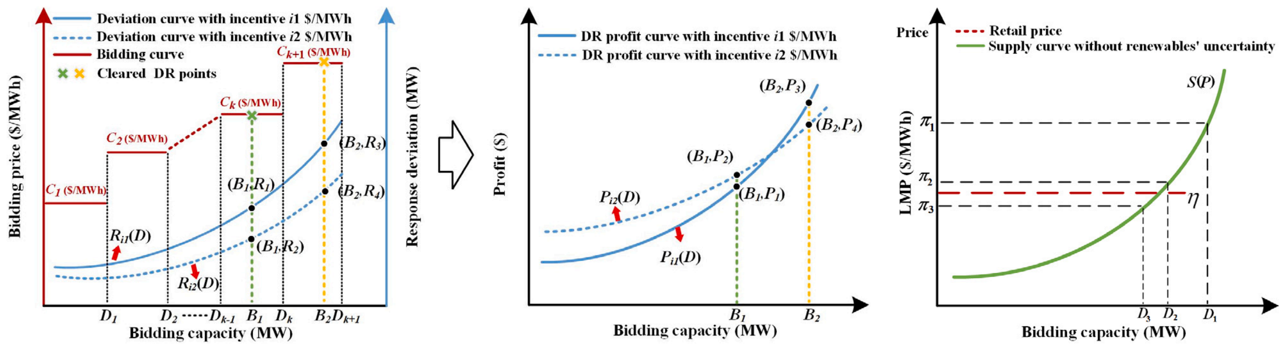
As discussed, it is more difficult for LSEs to aggregate residential loads due to the strong randomness of residents' behavior. A recent report shows that the electricity consumption of residential air conditioners (AC) has accounted for more than 40% of total urban electricity consumption in summer around the world [1]. It is thus a challenging yet demanding task to develop efficient aggregation methods for residential loads, especially for residential air conditioner loads.

Typically, a load aggregation problem can be formulated in the following way [32]. We assume an LSE has a number of residents V. At time slot t, the LSE sends a load reduction request to a set of residents S_t $(S_t \in V)$ to meet the bidding capacity D_t. In response to the request, the actual load reduction of resident i is represented by a random variable $X_{i,t}$. The load aggregation problem can be formulated as

$$\min_{S_t} \mathbb{E}\left(\sum_{i\in S_t} X_{i,t} - D_t\right)^2 \tag{1}$$

The uncertain response of resident i can be featured by the response probability $p_{i,t}$. As aforementioned, $p_{i,t}$ can be affected by many factors, such as incentive price. To identify the response level of air conditioner users (ACs) under different incentive prices, a survey with 1996 samples is conducted in Jiangsu Province, China. The users' participation rates under five incentives between 3 \$/MWh and 15 \$/MWh are displayed in Fig. 3. The survey results suggest that in terms of ACs, the actual response probability approximately follows a skewness distribution. The survey results also show that the response probability of some users is always high, implying the different features of users.

However, the actual response probability $p_{i,t}$ has not been well integrated into conventional aggregation methods, such as the random selection method. This method skips the different $p_{i,t}$ of each resident and selects residents in a random way. As a result, the value of actual DR capacity will be low when the majority of residents are with low $p_{i,t}$. In contrast, the offline method assumes the actual $p_{i,t}$ of each resident is pre-known and selects residents according to their $p_{i,t}$, such that achieving optimal load aggregation [32]. In practice, it is very hard to pre-know the actual $p_{i,t}$ of residents because LSEs cannot quickly interview residents and accurately evaluate their response to different



(a) Impact of various factors on the DR profit (b) Impact of deviation on the LMP

Fig. 2. Problem analysis of the LSE's net revenue.

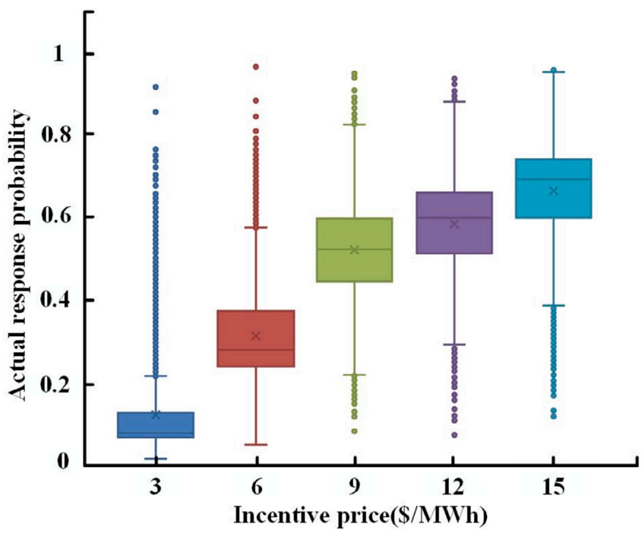


Fig. 3. Actual user response probabilities under different incentives.

incentives [33]. To address those issues, we develop an online learning method to estimate the response probability $p_{i,t}$ from the residents' historical response events and select the residents with high $p_{i,t}$.

During the online learning process, LSEs need to make a decision of whether control signals should be sent to residents currently with high returns (conservation) or to those selected fewer times before but may have higher potential returns (exploration). This decision-making problem is similar to the basic setting of the combined multi-armed bandits (CMAB) problem, in which the decision-maker needs to choose some arms from the entire set with the unknown distribution of rewards. Thus, we make use of the CMAB framework in the online learning process.

To better explain the proposed online learning method with CMAB, an example is provided here. Assuming that at time slot t, an LSE has 14,250 residents where each resident has a running AC (the power of each AC is randomly distributed between 2 kW and 3 kW). The CMAB framework can be referred to in our previous work [34]. We take the random selection and offline methods as reference benchmarks, which generate lower and upper bounds of load aggregation, respectively. We also take the ratio of the aggregation deviation and the target as a metric. As a result, the load aggregation performances under the three methods are compared in Fig. 4. It is found that the online learning method outperforms the random selection method and obtains comparable results with the offline method. Note that there is no difference in the aggregation deviation using three different methods when the aggregation target is large due to all residents being selected.

To further study the features of the optimal bidding strategy, we assume that all aggregation targets can be cleared, and the LSE's bidding price is fixed at 25 \$/MWh. Also, the deviation penalty coefficient τ is 1.2 [19]. Applying the three methods, the optimal incentive price and the maximum net profit under different aggregation targets are shown in Fig. 5. In terms of the online learning method, when the bidding capacity is 17.8 MW, the net profit is the highest, but the corresponding incentive price is only 9 \$/MWh. It would be unwise to blindly increase this price to the maximum value 15 \$/MWh, as the corresponding return is negative. Although the penalty cost is slightly lower, the incentive cost increases by about 33%. Similar observations can be found in the remaining two methods. It suggests that the key to obtaining higher profit for LSEs is to trade off the DR service costs and returns. There is optimal bidding capacity and incentive price for owned DR resources, and the net profit is not always positively correlated with the increasing incentive price and bidding capacity. Note that the bidding price is assumed to be fixed here. The formulation of the optimal DR bidding strategy varying with the bidding price would be more complicated. The established relationship between aggregation deviations and targets under different incentive prices based on the online learning method can provide a decision basis for the optimization model, which will be discussed in Section 3.

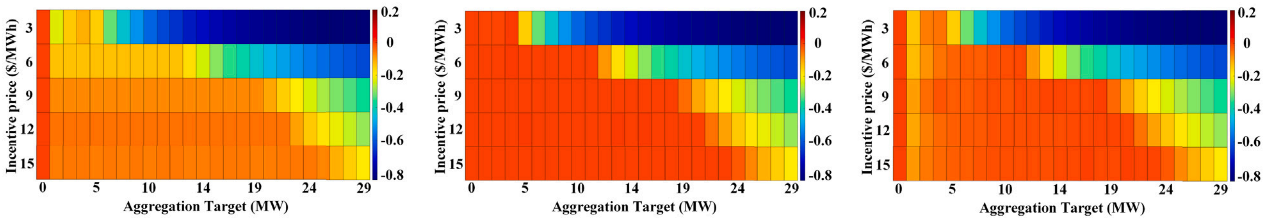
2.3. Load aggregation coordinating with ESS

As aforementioned in Section 1, the demand response uncertainty may exert multiple effects on LSEs' net revenues. Unfortunately, the absolute aggregation deviation tends to be inevitable [35]. In recent years, the coordination between ESS and DR has had significant value in improving the system's economics and flexibility [11], in which the ESS is assumed to participate in electricity markets [36]. Therefore, we propose enabling ESS with two modes, including energy arbitrage and DR's deviation mitigation, denoted as Mode 1 and Mode 2, respectively.

For the capacity of the excess response, the LSE should be paid the corresponding reward [37]. Thus, the ESS undertaking Mode 2 only compensates for negative aggregation deviations. The energy of the ESS discharging is directly supplied to those residents causing the deviation. The net load demand at the bus is reduced, equivalent to implementing DR with the same capacity.

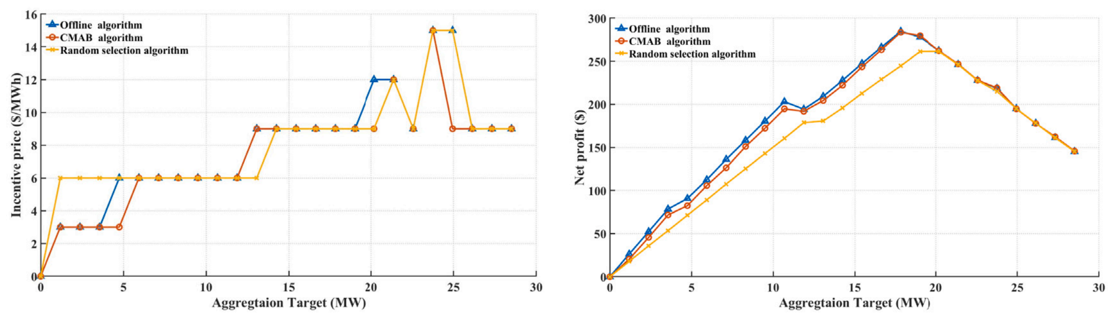
$$P_{i,t}^{sm} = \begin{cases} P_{i,t}^{D} & , -P_i^{d,\max} \le P_{i,t}^{D} < 0 \& \pi_{i,t} < \tau R_{i,t} \\ -P_i^{d,\max} & , -P_i^{d,\max} \ge P_{i,t}^{D} \& \pi_{i,t} < \tau R_{i,t} \\ 0 & , P_{i,t}^{D} < 0 \& \pi_{i,t} \ge \tau R_{i,t} \\ 0 & , P_{i,t}^{D} \ge 0 \end{cases},$$
$$\forall t \in T_{DR}, \forall i \in B, \sigma_{i,t}^{d} = 1 \tag{2}$$

Eq. (2) stipulates how to switch between these two modes of the ESS, i.e., when $P_{i,t}^{sm}$ is zero, only Mode 1 is undertaken. As shown in



(a) Random selection method (b) Offline method (c) CMAB method

Fig. 4. Comparison of aggregation deviation ratios under different aggregation methods.



(a) Optimal incentive price (b) Maximum net profit

Fig. 5. Optimal incentive price and maximum net profit under different aggregation targets.

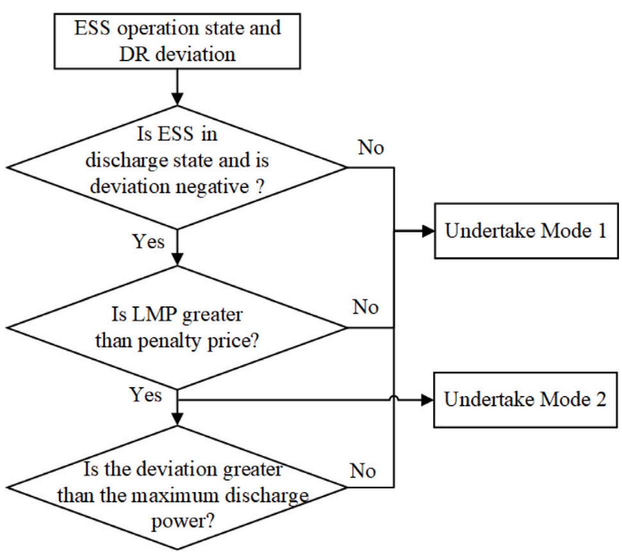


Fig. 6. Switching ESS between Mode 1 and Mode 2.

Fig. 6, multiple factors are considered comprehensively, including LMP, penalty price, and the current status of ESS. In addition to must being in the discharge state, the comparison between the penalty cost and the electricity sales profit for unit capacity is crucial for decision-making on whether the ESS undertakes Mode 2. Note that when the absolute aggregation deviation is lower than the maximum discharge power, ESS can undertake both Mode 1 and 2.

3. Problem formulation

This work studies a bi-level optimization problem in electricity marketing. On the energy consumption side, the LSE needs optimal strategies for electricity retail, DR bidding, and ESS economic dispatch to maximize its net revenue. On the energy generation side, the ISO/RTO needs optimal strategies of LMP and energy management to minimize the energy supply cost. Considering the impact of DR uncertainty on LMP and DR bidding, this work formulates the bi-level optimization between the LSE and the ISO/RTO, where the LSE is modeled as the upper level (i.e., leader) and the ISO/RTO is modeled as the lower level (i.e., the follower), respectively.

3.1. Upper-level model

At the upper level, the primary goal is to maximize the net revenue for LSEs. Decision variables contain (1) bidding price $R_{i,t}$, (2) incentive price $r_{i,t}$, (3) bidding capacity $P^{tar}_{i,t}$, (3) discharge power $P^{s,m}_{i,t}$ of ESS for DR deviation compensation, (4) discharge power $P^{d}_{i,t}$ of ESS for energy sale, (5) charging power $P^{c}_{i,t}$ of ESS, and (6) power $P^{E}_{i,t}$ of ESS.

At each time slot t and each managed bus i, the LSE's net revenue is represented by the difference between the incomes from electricity retail, DR rewards, and ESS's energy sales and the payment on energy purchases, incentive costs, and response deviation penalties. The LSE's net revenue in one day is formulated as

$$R_n = \sum_{t=1}^{24}\sum_{i\in B}\Big(\eta_i D_{i,t} + R_{i,t}(D^0_{i,t} - D_{i,t} - P^{sm}_{i,t}) - \pi_{i,t}P^d_{i,t} - \pi_{i,t}(D_{i,t} - P^c_{i,t} - P^{sm}_{i,t}) - r_{i,t}(D^0_{i,t} - D_{i,t}) - \tau R_{i,t}P^R_{i,t}\Big) \tag{3}$$

where the load buses set managed by the LSE is referred to as B, and the profit loss for mitigating DR's deviation by ESS is referred to as the product of the nodal LMP $\pi_{i,t}$ and the supplemental power $P^{sm}_{i,t}$.

Adopting $P^{E}_{i,t}$ to represent both the charging power and the discharge power of the ESS, where the charging power is positive, and the discharge power is negative. The upper-level problem can be formulated as

$$\max \sum_{t=1}^{24}\sum_{i\in B}\Big(\eta_i D_{i,t} + (R_{i,t} - r_{i,t})(D^0_{i,t} - D_{i,t}) - R_{i,t}P^{sm}_{i,t} - \pi_{i,t}(D_{i,t} + P^E_{i,t} - P^{sm}_{i,t}) - \tau R_{i,t}P^R_{i,t}\Big) \tag{4}$$

$$s.t. \quad \text{Constraint in (2)} \tag{5}$$

$$D^0_{i,t} - D_{i,t} = P^{tar}_{i,t} + P^D_{i,t} \tag{6}$$

$$P^D_{i,t} = f\left(P^{tar}_{i,t}, r_{i,t}\right) \tag{7}$$

$$0 \le P_{i,t}^{tar} \le \min\{P_{i,t}^{\max}, \xi D_{i,t}^{0}\} \tag{8}$$

$$\begin{cases} SOC_{i,t+1} = SOC_{i,t} + \frac{\eta_{i,c} P_{i,t+1}^{E}}{E_{i,c}} \ , & \sigma_{t+1}^{c} = 1 \\ SOC_{i,t+1} = SOC_{i,t} + \frac{P_{i,t+1}^{E}}{\eta_{i,d} E_{i,c}} \ , & \sigma_{t+1}^{d} = 1 \end{cases} \tag{9}$$

$$SOC_i^{\min} \le SOC_{i,t} \le SOC_i^{\max} \tag{10}$$

$$SOC_{i,24} = SOC_{i,0} \tag{11}$$

$$\sigma_{i,t+1}^{d} + \sigma_{i,t+1}^{c} = 1 \tag{12}$$

$$\begin{cases} P_{i,t}^{E} = P_{i,t}^{d} + P_{i,t}^{sm} \\ -P_i^{d,\max} \le P_{i,t}^{E} \le 0 \ , \quad \sigma_{i,t}^{d} = 1 \\ -P_i^{d,\max} \le P_{i,t}^{d} \le 0 \end{cases} \tag{13}$$

$$\begin{cases} P_{i,t}^{E} = P_{i,t}^{c} \\ 0 \le P_{i,t}^{E} \le P_i^{c,\max} \ , \quad \sigma_{i,t}^{c} = 1 \\ 0 \le P_{i,t}^{c} \le P_i^{c,\max} \end{cases} \tag{14}$$

where (5)–(14) are constraints of the upper problem. Constrain (6) refers to the actual response value of the residential air conditioner loads. Constraint (7) refers to the DR deviation varying with different aggregation methods in Section 2. Constraint (8) means that the capacity bid by the LSE should be less than the minimum value between the maximum power of the DR resource and the maximum load that can be curtailed [31]. Constraints related to ESS can be found in (5) and (9)–(14). Constraints (9)–(11) calculate and enforce the dynamic SOC limit. Constraint (12) ensures that the ESS cannot charge and discharge simultaneously. $\sigma_{i,t}^{c}$ and $\sigma_{i,t}^{d}$ are binary variables identifying the charging/ discharging status of ESS on bus i at time t ($\sigma_{i,t}^{c} = 1$, the ESS is charging and $\sigma_{i,t}^{d} = 1$, the ESS is discharging). Constraints (13) and (14) enable that the ESS's power under different states should be within limits.

Note that those constraints are against load buses managed by the LSE. Also, in light of residents' routines, the DR is not carried out for a whole day. Instead, it is only executed between 9 A.M. and 9 P.M., denoted as set T_{DR}.

3.2. Lower-level model

At the lower level, the optimization problem can be modeled as a dc optimal power flow (DCOPF) problem for economic dispatch [38]. Decision variables contain (1) power $P_{g_i,t}^{s}$ of conventional units, and (2) power $P_{w_i,t}^{s}$ of wind generators.

Here, we introduce the penalty cost of wind power curtailment to the objective function to meet renewable energy consumption procedures. Considering wind energy's uncertainty, we also induce multiple wind power output scenarios, denoted as set U. As a result, the problem can be formulated as follows

$$\min \sum_{t=1}^{24} \left(\sum_{i=1}^{N} C_{g_i} P_{g_i,t}^{s} + \sum_{i=1}^{N} \zeta \left(P_{w_i,t}^{s,0} - P_{w_i,t}^{s} \right) \right) \tag{15}$$

$$s.t. \quad \sum_{i=1}^{N} P_{g_i,t}^{s} + \sum_{i=1}^{N} P_{w_i,t}^{s} = \sum_{i=1}^{N} (D_{i,t} + P_{i,t}^{E}) : \lambda_t^{s}, \quad \forall s = 1,2,\dots,U, \forall t = 1,2,\dots,24 \tag{16}$$

$$-P_l \le \sum_{i=1}^{N} GSF_{l-i} \left(P_{g_i,t}^{s} + P_{w_i,t}^{s} - D_{i,t} - P_{i,t}^{E} \right) \le P_l : \mu_{l,t}^{s,\min}, \mu_{l,t}^{s,\max}, \forall l = 1,2,\dots,M, \forall s = 1,2,\dots,U, \forall t = 1,2,\dots,24 \tag{17}$$

$$P_{g_i}^{\min} \le P_{g_i,t}^{s} \le P_{g_i}^{\max} : \omega_{g_i,t}^{s,\min}, \omega_{g_i,t}^{s,\max}, \forall s = 1,2,\dots,U, \forall t = 1,2,\dots,24 \tag{18}$$

$$0 \le P_{w_i,t}^{s} \le P_{w_i,t}^{s,0} : \varphi_{w_i,t}^{s,\min}, \varphi_{w_i,t}^{s,\max}, \forall s = 1,2,\dots,U, \forall t = 1,2,\dots,24 \tag{19}$$

$$-R_{g_i}^{\text{down}} \le P_{g_i,t}^{s} - P_{g_i,t-1}^{s} \le R_{g_i}^{\text{up}} : \upsilon_{g_i,t}^{s,d}, \upsilon_{g_i,t}^{s,u}, \quad \forall s = 1,2,\dots,U, \forall t = 2,3,\dots,24 \tag{20}$$

where (16)–(20) represent the system operation constraints in different scenarios, including active power balance, line power flow limits, unit output limits, and ramping limits.

After formulating the Lagrangian function of the lower-level model as (21), the LMP $\pi_{i,t}^{s}$ for the load bus i under scenario s can be calculated in the following way.

$$\begin{aligned} L^{s} = & \sum_{t=1}^{24} \left(\sum_{i=1}^{N} C_{g_i} P_{g_i,t}^{s} + \sum_{i=1}^{N} \zeta \left(P_{w_i,t}^{s,0} - P_{w_i,t}^{s} \right) \right) \\ & - \sum_{t=1}^{24} \left(\begin{aligned} & \lambda_t^{s} \left(\sum_{i=1}^{N} P_{g_i,t}^{s} + \sum_{i=1}^{N} P_{w_i,t}^{s} - \sum_{i=1}^{N} \left(D_{i,t} + P_{i,t}^{E} \right) \right) \\ & + \sum_{l=1}^{M} \mu_{l,t}^{s,\min} \left(\sum_{i=1}^{N} GSF_{l-i} \left(P_{g_i,t}^{s} + P_{w_i,t}^{s} - D_{i,t} - P_{i,t}^{E} \right) + P_l \right) + \sum_{l=1}^{M} \mu_{l,t}^{s,\max} \left(P_l - \sum_{i=1}^{N} GSF_{l-i} \left(P_{g_i,t}^{s} + P_{w_i,t}^{s} - D_{i,t} - P_{i,t}^{E} \right) \right) \\ & + \sum_{i=1}^{N} \omega_{g_i,t}^{s,\min} \left(P_{g_i,t}^{s} - P_{g_i}^{\min} \right) - \sum_{i=1}^{N} \omega_{g_i,t}^{s,\max} \left(P_{g_i}^{\max} - P_{g_i,t}^{s} \right) \\ & + \sum_{i=1}^{N} \varphi_{w_i,t}^{s,\min} P_{w_i,t}^{s} - \sum_{i=1}^{N} \varphi_{w_i,t}^{s,\max} \left(P_{w_i,t}^{s,0} - P_{w_i,t}^{s} \right) \end{aligned} \right) \\ & - \sum_{t=2}^{24} \left(\sum_{i=1}^{N} \upsilon_{g_i,t}^{s,d} \left(P_{g_i,t}^{s} - P_{g_i,t-1}^{s} + R_{g_i}^{\text{down}} \right) + \upsilon_{g_i,t}^{s,u} \left(-P_{g_i,t}^{s} + P_{g_i,t-1}^{s} + R_{g_i}^{\text{up}} \right) \right) \end{aligned} \tag{21}$$

$$\pi_{i,t}^{s} = \frac{\partial L^{s}}{\partial \left(D_{i,t} + P_{i,t}^{E} \right)} = \lambda_t^{s} + \sum_{l=1}^{M} GSF_{l-i} \left(\mu_{l,t}^{s,\min} - \mu_{l,t}^{s,\max} \right) \tag{22}$$

The LSE needs to make robust decisions to deal with the uncertainty of scenarios. The excepted LMP is calculated as (23), and the objective function in the upper model should be reformulated as (24) combined with the lower model.

$$\pi_{i,t} = \mathbb{E}(\pi_{i,t}^{s}) = \sum_{s=1}^{U} p_s \pi_{i,t}^{s} \tag{23}$$

$$\begin{aligned} & \max \sum_{s=1}^{U} p_s \left(\sum_{t=1}^{24} \sum_{i \in B} \left(\eta_i D_{i,t} + \left(R_{i,t} - r_{i,t} \right) \left(D_{i,t}^{0} - D_{i,t} \right) - R_{i,t} P_{i,t}^{sm} - \pi_{i,t}^{s} \left(D_{i,t} + P_{i,t}^{E} - P_{i,t}^{sm} \right) - \tau R_{i,t} P_{i,t}^{R} \right) \right) \\ \Rightarrow & \max \sum_{t=1}^{24} \sum_{i \in B} \left(\eta_i D_{i,t} + \left(R_{i,t} - r_{i,t} \right) \left(D_{i,t}^{0} - D_{i,t} \right) - R_{i,t} P_{i,t}^{sm} + \pi_{i,t} P_{i,t}^{sm} - \tau R_{i,t} P_{i,t}^{R} \right) - \sum_{s=1}^{U} p_s \left(\sum_{t=1}^{24} \sum_{i \in B} \pi_{i,t}^{s} \left(D_{i,t} + P_{i,t}^{E} \right) \right) \end{aligned} \tag{24}$$

where the sum of p_s is 1.

4. Mathematical solution

Mathematically, the formulated problem involves bi-level models, nonlinear objectives, and nonlinear constraints, yielding very high computational costs. The mathematical solution to address this issue is presented in this section.

4.1. Two-layer model decoupling

In the proposed problem formulation, the solution of the upper-level model depends on the LMP provided by the lower-level model, and the economic dispatch in the lower level would be affected by the DR capacity and the ESS output in the upper level. Thanks to the lower-level model as a linear programming problem, the KKT conditions can be complementary constraints inserted into the upper-level model. Ultimately, the bi-level optimization model can be reformulated as a mathematical program with equilibrium constraints (MPEC) with the objective function (24). The KKT constraints can be represented as (25)–(37).

Constraint in (16) (25)

$$C_{g_i} - \lambda_t^s - \sum_{l=1}^{M} GSF_{l-i}\left(\mu_{l,t}^{s,\min} - \mu_{l,t}^{s,\max}\right) - \omega_{g_i,t}^{s,\min} + \omega_{g_i,t}^{s,\max} + \upsilon_{g_i,t}^{s,d} - \upsilon_{g_i,t}^{s,u} = 0, \forall s = 1,2,\dots,U, t = 1 \tag{26}$$

$$C_{g_i} - \lambda_t^s - \sum_{l=1}^{M} GSF_{l-i}\left(\mu_{l,t}^{s,\min} - \mu_{l,t}^{s,\max}\right) - \omega_{g_i,t}^{s,\min} + \omega_{g_i,t}^{s,\max} - \upsilon_{g_i,t}^{s,d} + \upsilon_{g_i,t+1}^{s,d} + \upsilon_{g_i,t}^{s,u} - \upsilon_{g_i,t+1}^{s,u} = 0, \forall s = 1,2,\dots,U, \forall t = 2,3,\dots,23 \tag{27}$$

$$C_{g_i} - \lambda_t^s - \sum_{l=1}^{M} GSF_{l-i}\left(\mu_{l,t}^{s,\min} - \mu_{l,t}^{s,\max}\right) - \omega_{g_i,t}^{s,\min} + \omega_{g_i,t}^{s,\max} - \upsilon_{g_i,t}^{s,d} + \upsilon_{g_i,t}^{s,u} = 0, \forall s = 1,2,\dots,U, t = 24 \tag{28}$$

$$\zeta + \lambda_t^s + \sum_{l=1}^{M} GSF_{l-i}\left(\mu_{l,t}^{s,\min} - \mu_{l,t}^{s,\max}\right) + \varphi_{w_i,t}^{s,\min} - \varphi_{w_i,t}^{s,\max} = 0, \forall s = 1,2,\dots,U, \forall t = 1,2,\dots,24 \tag{29}$$

$$0 \le \mu_{l,t}^{s,\min} \perp \sum_{i=1}^{N} GSF_{l-i}\left(P_{g_i,t}^{s} + P_{w_i,t}^{s} - D_{i,t} - P_{i,t}^{E}\right) + P_l \ge 0, \forall s = 1,2,\dots,U, \forall t = 1,2,\dots,24 \tag{30}$$

$$0 \le \mu_{l,t}^{s,\max} \perp P_l - \sum_{i=1}^{N} GSF_{l-i}\left(P_{g_i,t}^{s} + P_{w_i,t}^{s} - D_{i,t} - P_{i,t}^{E}\right) \ge 0, \forall s = 1,2,\dots,U, \forall t = 1,2,\dots,24 \tag{31}$$

$$0 \le \omega_{g_i,t}^{s,\min} \perp P_{g_i,t}^{s} - P_{g_i}^{\min} \ge 0, \forall s = 1,2,\dots,U, \forall t = 1,2,\dots,24 \tag{32}$$

$$0 \le \omega_{g_i,t}^{s,\max} \perp P_{g_i}^{\max} - P_{g_i,t}^{s} \ge 0, \forall s = 1,2,\dots,U, \forall t = 1,2,\dots,24 \tag{33}$$

$$0 \le \varphi_{w_i,t}^{s,\min} \perp P_{w_i,t}^{s} \ge 0, \forall s = 1,2,\dots,U, \forall t = 1,2,\dots,24 \tag{34}$$

$$0 \le \varphi_{w_i,t}^{s,\max} \perp P_{w_i,t}^{s,0} - P_{w_i,t}^{s} \ge 0, \forall s = 1,2,\dots,U, \forall t = 1,2,\dots,24 \tag{35}$$

$$0 \le \upsilon_{g_i,t}^{s,\mathrm{down}} \perp P_{g_i,t}^{s} - P_{g_i,t-1}^{s} + R_{g_i}^{\mathrm{down}} \ge 0, \forall s = 1,2,\dots,U, \forall t = 2,3,\dots,24 \tag{36}$$

$$0 \le \upsilon_{g_i,t}^{s,\mathrm{up}} \perp -P_{g_i,t}^{s} + P_{g_i,t-1}^{s} + R_{g_i}^{\mathrm{up}} \ge 0, \forall s = 1,2,\dots,U, \forall t = 2,3,\dots,24 \tag{37}$$

where the perpendicular sign $\perp$ denotes a zero cross-product of the corresponding variables in vector form [39].

4.2. Linearization of objective function

In the MPEC problem, the objective function (24) contains the following nonlinear terms: (1) DR reward $R_{i,t}(D_{i,t}^0 - D_{i,t})$, (2) DR cost $r_{i,t}(D_{i,t}^0 - D_{i,t})$, (3) ESS's lost profit $\pi_{i,t}P_{i,t}^{sm}$, (4) DR deviation penalty $\tau R_{i,t}P_{i,t}^{R}$, and (5) energy purchase cost (profits from the ESS's electricity sales are considered negative expenses) $\pi_{i,t}^{s}(D_{i,t} + P_{i,t}^{E})$.

The linearization processes for terms (1)–(4) are similar. Taking linearizing $R_{i,t}(D_{i,t}^0 - D_{i,t} - P_{i,t}^{sm})$ as an example. As aforementioned in Section 1, the LSE divides the maximum available DR capacity into blocks and makes incremental bidding [31]. Thus, the piecewise linearization method is adopted, and $R_{i,t}(D_{i,t}^0 - D_{i,t})$ is denoted as $\Psi_{i,t}^{R}$.

$$\Psi_{i,t}^{R} = p\left(P_{i,t}^{tar} + \sum_{j=1}^{N} \kappa_{i,t,j}^{k} d_{i,t,j}^{k} - P_{i,t}^{sm}\right), \forall t \in T_{DR}, \forall i \in B, \gamma_{i,t,l} = 1 \tag{38}$$

$$\gamma_{i,t,l} = \begin{cases} 1, P_{i,t}^{tar} \in \left[B_{i,t,l}, B_{i,t,l+1}\right) \\ 0, \text{ otherelse} \end{cases}, \forall t \in T_{DR}, \forall i \in B \tag{39}$$

$$\sum_{p=1}^{N} \gamma_{i,t,l} = 1, \forall t \in T_{DR}, \forall i \in B \tag{40}$$

where $\gamma_{i,t,l}$ is the auxiliary binary variable, and p is the bidding price corresponding to the bidding capacity interval $[B_{i,t,l}, B_{i,t,l+1})$.

Similarly, nonlinear terms (2)–(4) are reformulated as follows

$$\Psi_{i,t}^{r} = k\left(P_{i,t}^{tar} + \sum_{j=1}^{N} \kappa_{i,t,j}^{k} d_{i,t,j}^{k}\right), \forall t \in T_{DR}, \forall i \in B, \sigma_{i,t,l}^{k} = 1 \tag{41}$$

$$\Psi_{i,t}^{d} = \begin{cases} \pi_{i,t} \sum_{j=1}^{N} \kappa_{i,t,j}^{k} d_{i,t,j}^{k}, & -P_i^{d,\max} \le P_{i,t}^{D} < 0, \pi_{i,t} < \tau R_{i,t} \\ -\pi_{i,t} P_i^{d,\max} & , -P_i^{d,\max} \ge P_{i,t}^{D} \& \pi_{i,t} < \tau R_{i,t} \\ 0 & , P_{i,t}^{D} < 0 \& \pi_{i,t} \ge \tau R_{i,t} \\ 0 & , P_{i,t}^{D} \ge 0 \end{cases}, \forall t \in T_{DR}, \forall i \in B, \sigma_{i,t}^{d} = 1 \tag{42}$$

$$\Psi_{i,t}^{p} = \tau p\left|\sum_{j=1}^{N} \kappa_{i,t,j}^{k} d_{i,t,j}^{k} - P_{i,t}^{sm}\right|, \forall t \in T_{DR}, \forall i \in B, \gamma_{i,t,l} = 1 \tag{43}$$

Next, the nonlinear term (5) is linearized as (44) based on the strong duality theory. The linearization process is presented in A.1.

$$\sum_{t=1}^{24} \sum_{i \in B} \pi_{i,t}^{s}\left(D_{i,t} + P_{i,t}^{E}\right) = \Psi_{s,t}^{o} + \Psi_{s,t}^{l} + \Psi_{s,t}^{c} \tag{44}$$

where

$$\Psi_{s,t}^{o} = \sum_{t=1}^{24} \left(\begin{aligned} &\lambda_t^s \left(\sum_{i=1}^{N} P_{w_i,t}^{s,0} + \sum_{i=1, i \notin B}^{N} \left(D_{i,t} + P_{i,t}^{E}\right) \right) \\ &+ \sum_{l=1}^{M} \mu_{l,t}^{s,\min} \left(\sum_{i=1}^{N} GSF_{l-i} P_{w_i,t}^{s,0} - \sum_{i=1, i \notin B}^{N} GSF_{l-i}\left(D_{i,t} + P_{i,t}^{E}\right) + P_l \right) \\ &+ \sum_{l=1}^{M} \mu_{l,t}^{s,\max} \left(P_l - \sum_{i=1}^{N} GSF_{l-i} P_{w_i,t}^{s,0} + \sum_{i=1, i \notin B}^{N} GSF_{l-i}\left(D_{i,t} + P_{i,t}^{E}\right) \right) - \sum_{i=1}^{N} \omega_{g_i,t}^{s,\min} P_{g_i}^{\min} \\ &+ \sum_{i=1}^{N} \omega_{g_i,t}^{s,\max} P_{g_i}^{\max} + \sum_{i=1}^{N} \varphi_{w_i,t}^{s,\min} P_{w_i,t}^{s,0} \end{aligned} \right)$$

$$\Psi^{l}_{s,t} = \sum_{t=1}^{24}\left(\sum_{i=1}^{N} C_{g_i} P^{s}_{g_i,t} + \sum_{i=1}^{N} \zeta\left(P^{s,0}_{w_i,t} - P^{s}_{w_i,t}\right)\right)$$

$$\Psi^{c}_{s,t} = \sum_{t=2}^{24}\left(\sum_{i=1}^{N} v^{s,d}_{g_i,t} R^{\text{down}}_{g_i} + v^{s,u}_{g_i,t} R^{\text{up}}_{g_i}\right)$$

4.3. Linearization of constraints

As constraint (7) is difficult to be characterized with an exact mathematical formula, the piecewise linearization method is adopted to describe that relationship as (45)–(47).

$$P^{D}_{i,t} = \sum_{j=1}^{N} \kappa^{k}_{i,t,j} d^{k}_{i,t,j}, \forall t \in T_{DR}, \forall i \in B, r_{i,t} = k \tag{45}$$

$$\kappa^{k}_{i,t,j} = \begin{cases} 1, P^{tar}_{i,t} \in [A_{j,t}, A_{j+1,t}) \\ 0, \quad \text{otherelse} \end{cases},$$

$$\forall t \in T_{DR}, \forall i \in B, r_{i,t} = k \tag{46}$$

$$\sum_{j=1}^{N} \kappa^{k}_{i,t,j} = 1, \forall t \in T_{DR}, \forall i \in B, r_{i,t} = k$$

$$\begin{cases} r_{i,t} = \sum_{l=1}^{N} \sigma^{k}_{i,t,l} k \\ \sum_{l=1}^{N} \sigma^{k}_{i,t,l} = 1 \end{cases}, \forall t \in T_{DR}, \forall i \in B \tag{47}$$

where $[A_{j,t}, A_{j+1,t})$ denotes the aggregation capacity segment interval j, different from the interval in Section 4.2. $d^{k}_{j,t}$ is the aggregation deviation constant value corresponding to the interval, and $\kappa^{k}_{i,t,j}$ and $\sigma^{k}_{i,t,l}$ are auxiliary binary variables.

Additionally, complementary slackness constraints (30)–(37) are nonlinear. They can be converted to linear constraints by the Big-M approach [40,41], presented as (51)–(66) in Appendix A.2.

Consequently, the bi-level optimization problem can be reformulated as a mixed integer linear programming (MILP) problem as

$$\max \sum_{t=1}^{24} \sum_{i \in B} \left(\eta_i D_{i,t} + \Psi^{R}_{i,t} - \Psi^{r}_{i,t} + \Psi^{d}_{i,t} - \Psi^{p}_{i,t}\right) - \sum_{s=1}^{U} p_s \left(\Psi^{l}_{s,t} + \Psi^{o}_{s,t} + \Psi^{c}_{s,t}\right) \tag{48}$$

s.t. (5), (6), (8)–(14), (25)–(29), (38)–(43),(45)–(66)

5. Case studies

In this section, the proposed bi-level scheduling model for the LSE is tested on a modified IEEE RTS-24 bus system, as shown in Fig. 7. The MILP problem is solved by the GUROBI solver on MATLAB 2021a.

In the test system, some conventional generators are replaced by wind turbine generators with the same capacities. Applying the Monte Carlo method, 5000 wind speed scenarios are generated. Adopting the previous method in [42], the number is reduced to 10 to reduce the computation burden. The penalty cost ζ of wind power curtailment for unit capacity is 35 $/MWh, and the unit power generation costs of generators at different buses are noted in Fig. 7.

Loads at bus 6, bus 7, and bus 8 are assumed to be managed by the LSE. The flat retail rate η_i is 35 $/MWh. The DR resources at each bus consist of 25,000 residents. The power of their air conditioners is randomly distributed between 2 kW and 3 kW, and the utilization rates at different time slots are derived from [43]. During the periods of DR execution, the LSE divides the maximum available aggregation power into 5 intervals evenly with incremental bidding price (i.e., 20 $/MWh, 25 $/MWh, 30 $/MWh, 50 $/MWh and 60 $/MWh). The maximum load reduction coefficient ξ is 7% [31]. In addition, these buses are equipped with an ESS with identical parameters, as shown in Table 1.

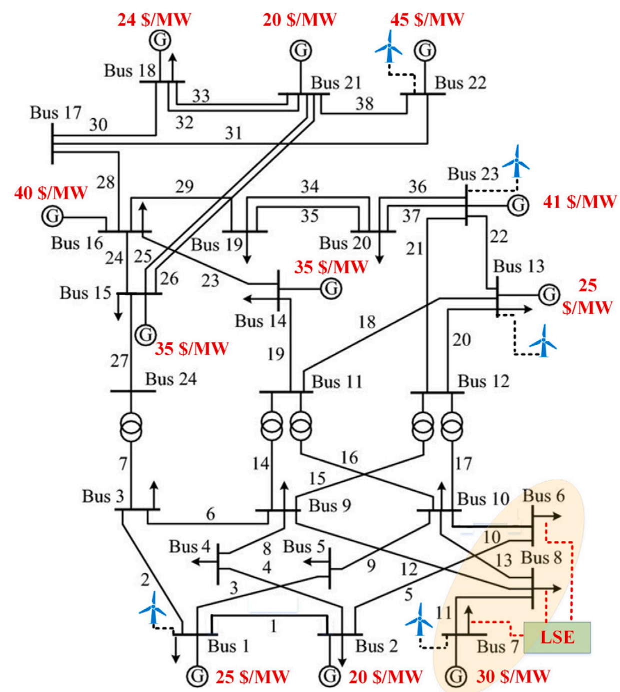


Fig. 7. Modified IEEE RTS-24 bus system.

Table 1
Parameters of ESS.

Parameters	Value
Maximum capacity $E_{i,c}$	30 MWh
Maximum discharge power $P_i^{d,max}$	9 MW
Maximum charging power $P_i^{c,max}$	8 MW
Discharging efficiency $\eta_{i,d}$	0.9
Charging efficiency $\eta_{i,c}$	0.9
Initial state of charge $SOC_{i,0}$	0.5
Maximum state of charge $SOC_i^{\max}$	0.9
Minimum state of charge $SOC_i^{\min}$	0.1

5.1. Performance of CMAB-based online learning method

To further investigate the performance of the CMAB-based online learning method in improving the LSE's profitability and DR's reliability, we study the following cases with different load aggregation methods (over 24 hours). Here, all ESSs can be dispatched in two modes.

Case 1: The load aggregation method adopts the random selection method.

Case 2: The load aggregation method adopts the offline method.

Case 3: The load aggregation method adopts the online learning CMAB method.

Note that the offline method and the random selection method can be assumed to obtain the upper and lower bounds of the load aggregation, respectively [32]. The corresponding profits are shown in Table 2.

The profit in case 2 is the highest due to the ideal load aggregation, where the actual response probabilities of residents are assumed pre-known for the LSE. However, this is unrealistic as the inducers of DR uncertainty are very complex. In case 1, the random selection method causes a significant deviation such that more capacities of ESS are used

Table 2
Profits in five cases (Unit: $).

Case	Total profit	Load management		ESS management		DR service		
		Purchase[a]	Energy retail[b]	Purchase[a]	Energy sales[b]	Incentive[a]	Reward[b]	Deviation penalty[a]
1	51993	539939	567575	4069	3752	6985	31716	58
2	53128	538090	565664	4298	4841	7802	32816	2
3	52617	538902	566484	4061	4315	7436	32251	68
4	46477	544404	566158	/	/	8266	34261	1272
5	52326	538561	566131	4267	5280	7832	32858	1293

[a]Payment costs for LSE.
[b]Income for LSE.

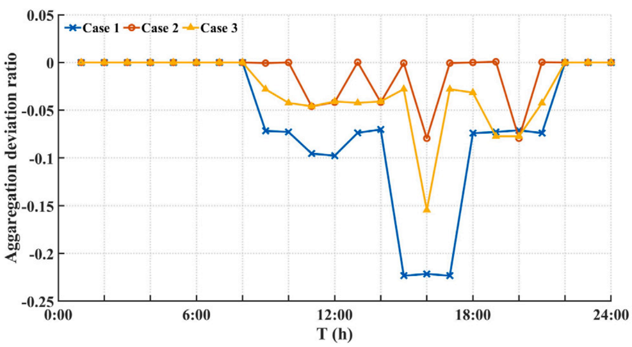


Fig. 8. Bidding capacities at bus 7 under different cases.

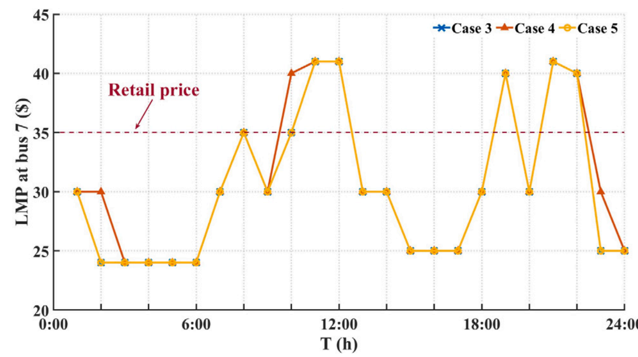


Fig. 11. Effect of ESS on LMP.

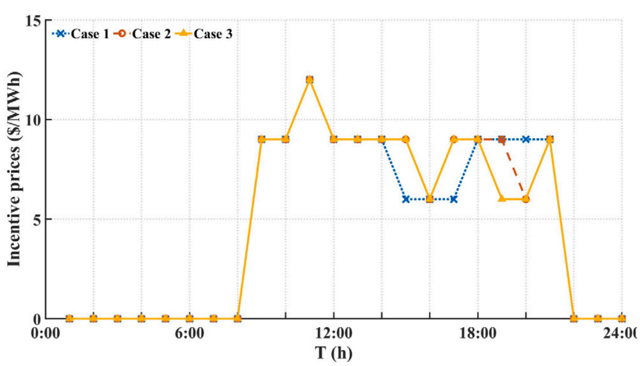


Fig. 9. Aggregation deviation ratios at bus 7 under different cases.

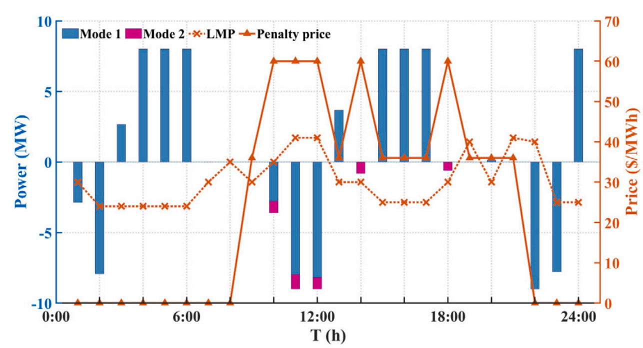


Fig. 12. Dispatch of the ESS with two modes at bus 7.

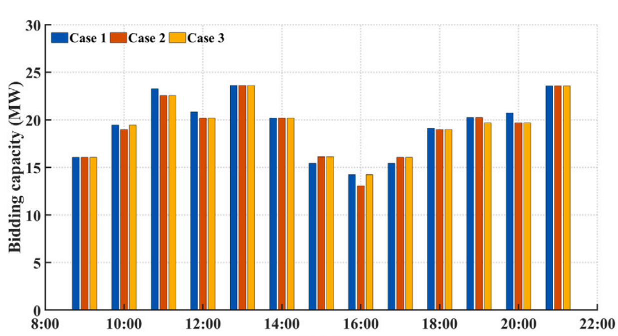


Fig. 10. Various incentive prices at bus 7 under different cases.

to undertake Mode 2 and cannot be sold for profit. The net revenue of ESS management is even negative. The CMAB method in case 3 enables the LSE to reduce the profit difference between case 1 and case 2 by around 55%.

Fig. 8 shows the bidding capacities at bus 7 under different cases. The aggregation deviation ratios and incentive prices are shown in Figs. 9 and 10, respectively. In terms of the overall performance of aggregation reliability, the offline method performs the best, followed by the CMAB method, and the random selection method is the worst. At 4 P.M., the AC utilization rate is only 57%, and the incentive price is 6 $/MWh. The low level of overall residents' response results in a significant deviation for all cases. However, as the AC utilization rate increases to 74% at 7 P.M., we have more residents with relatively high response probabilities. The CMAB method achieves nearly the same aggregation deviation ratio and bidding capacity at a lower incentive price compared with the random selection method.

5.2. Impact of ESS

We design the following two cases to demonstrate the effectiveness of the ESS with two modes in case 3. Note that the load aggregation in these cases adopts the CMAB-based online learning method due to its outstanding performance in Section 5.1.

Case 4: All ESS do not participate in the dispatch. The LSE only implements DR programs.

Case 5: ESS scheduling and DR are executed independently at the same time. The former only undertakes Mode 1.

The income and expenses for the LSE under the above cases are shown in Table 2. First, compared with case 4, flexible dispatch of

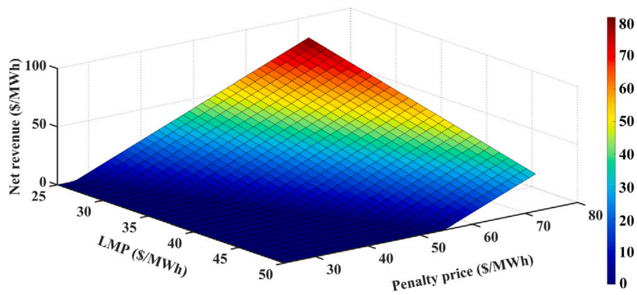


Fig. 13. Increased net profit for per unit deviation capacity.

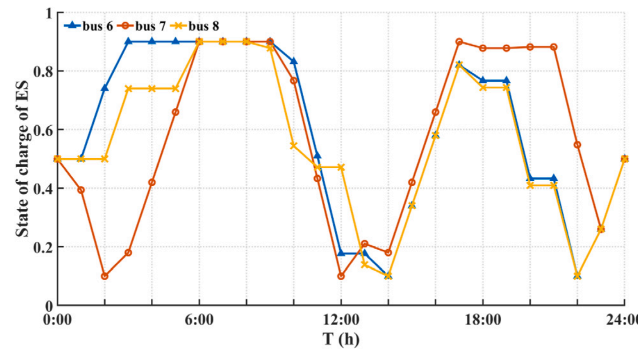


Fig. 14. SOC of ESS at different buses.

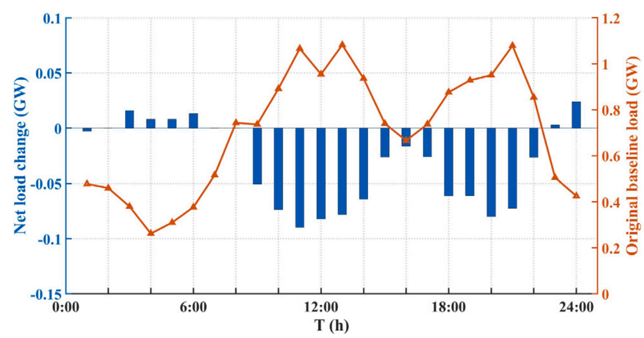


Fig. 15. Total net load change for buses managed by the LSE.

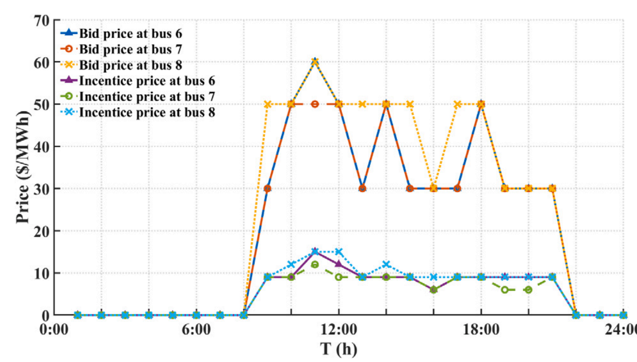


Fig. 16. DR bidding and incentive price strategy for different buses.

ESS in case 5 significantly helps LSE improve margins by around 12%. As shown in Fig. 11, during specific time slots, the LMP at bus 7 is significantly reduced. Especially at 10 A.M., the original LMP is higher than the retail price due to the proximity of the load peak, but benefiting from the ESS's discharging, the LSE effectively avoids the risk of negative revenues at this time slot. This suggests that the main reason for increasing profits is that the cost of energy purchasement is significantly reduced, except for the small additional profit that the ESS makes by the LMP difference. Second, the ESS with two modes creates higher net profits for the LSE than those undertaking single Mode 1 in case 5. The dispatch of ESS under different modes in case 3 is shown in Fig. 12. The ESS with Mode 1 can flexibly adjust the operation state and power according to the LMP. During the execution of the DR plan, the LSE trades off the energy sale revenue and penalty cost under the unit capacity and makes the dispatch strategy for the ESS with Mode 2. For example, between 10 A.M. and noon, the aggregation deviations are fully compensated because of the high penalty cost. Therefore, the ESS can be flexibly switched between two modes to maximize the total Profit through the proposed model.

For the LSE, the profit difference of the ESS to compensate for the aggregation deviation instead of selling equal capacity electricity at time slot t can be expressed as $P^{D}_{i,t}[(1+\tau)R_{i,t} - 2\pi_{i,t}]$. For per unit deviation capacity, it is shown in Fig. 13. Note that negative revenues are replaced by zero. Compared with undertaking single Mode 1, the increased profit of ESS with two modes is proportional to the deviation and the penalty price. In other words, its economic value would be more prominent. For example, when the load aggregation method in case 4 and case 5 adopts the random selection method, the total load deviation is higher, and the net profit increases by nearly $700.

5.3. Optimal scheduling and DR bidding strategies

The proposed bi-level scheduling model with the CMAB method enables the LSE to flexibly dispatch ESS at different time slots and design the optimal DR bidding strategy to maximize profit.

In case 3, the SOC of ESS at different buses and total net load change are shown in Figs. 14 and 15. The remarkable feature is that the ESS follows the principle of charging during low load periods and discharging during peak periods. Through the coordination between ESS and DR, the load peak–valley difference in the area managed by the LSE has been reduced by about 84 MW.

Figs. 16 and 17 show the optimal DR bidding prices, incentive prices, and bidding capacities at different buses. It can be found that the proposed model formulates differentiated strategies for DR resources at various time slots. There are mainly the following aspects that may affect the optimal strategy:

(1) The DR bidding capacity is positively related to system demand. Especially during the peak load periods, to reduce the operation risk of the system and the LMP at different buses, the LSE must provide DR resources with a larger capacity to meet the demand. For example, compared with 4 P.M., the DR bidding capacity at bus 6 increased by about 74.6% at 11 A.M.

(2) The incentive and bidding price levels depend on the system demand and the scarcity of available DR resources. When the DR resources are few, and the demand is enormous, since many users with high response probability are needed to ensure aggregation reliability, the LSE must increase the incentive price to improve the overall response level of the users. Meanwhile, unequal demand and supply further highlight the value of DR resources, and the bidding prices for the LSE are higher. For example, at 11 A.M. and 9 P.M., the AC utilization rates are 57% and 94.5%, respectively. Despite the close DR bidding capacity at bus 6, the incentive and bidding prices at 11 A.M. are significantly higher than the latter.

6. Conclusion

This paper proposes a bi-level scheduling model for the LSE considering the impact of demand response uncertainty on LMP and DR bidding. The quantitative relationship between aggregation deviations based on the survey dataset is established, and the coordination between ESS and DR resources to avoid extreme energy purchase prices

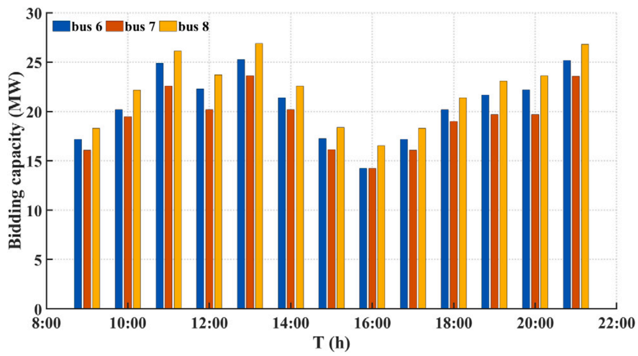


Fig. 17. DR bidding capacities for different buses.

is investigated. The simulation results showcase the advantages of the proposed method and demonstrate that:

(1) Reliable load aggregation helps reduce the incentive cost under the same bidding capacity, further increasing the LSE's profit. Compared with the extensive conventional aggregation method, the LSE can achieve more economical and reliable load aggregation through the CMAB method, especially when DR resources are not abundant.

(2) The ESS with two modes could help reduce energy purchasing costs and create greater profits than those with a single mode, especially when the aggregation deviation and the penalty costs are high.

(3) With the proposed model, the LSE can effectively assist the system operation by strategically dispatching ESS and DR resources, such as reducing the peak-to-valley difference. Also, the optimal DR bidding strategies at different buses and time intervals could be flexibly formulated considering the overall system demand and the scarcity of DR resources.

In future work, the optimal bidding model for coordinating multiple LSEs in the electricity market will be studied with consideration of the ancillary service requirements of the system. Moreover, the category of DR flexible resources will be expanded, such as electric vehicles, electric water heaters, etc.

CRediT authorship contribution statement

Rushuai Han: Conceptualization, Methodology, Software, Formal analysis, Writing – original draft. **Qinran Hu:** Conceptualization, Investigation, Supervision, Writing – review & editing. **Hantao Cui:** Writing – review & editing. **Tao Chen:** Writing – review & editing. **Xiangjun Quan:** Review & editing. **Zaijun Wu:** Review & editing.

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.

Data availability

No data was used for the research described in the article.

Acknowledgments

This research is supported by the National Natural Science Foundation of China (51907026), Natural Science Foundation of Jiangsu Province, China (BK20190361), Key Research and Development Program of Jiangsu Province, China (BE2020081-2), and Chinese Society of Electrical Engineering (JLB-2020-186).

Appendix

A.1. Linearization of nonlinear term based on the strong duality theory

In order to linearize term $\pi_{i,t}^{s}(D_{i,t}+P_{i,t}^{E})$, formula (22) is substituted into this term, and (49) is calculated.

$$\sum_{t=1}^{24}\sum_{i\in B}\pi_{i,t}^{s}\left(D_{i,t}+P_{i,t}^{E}\right)=\sum_{t=1}^{24}\sum_{i\in B}\left(\lambda_{t}^{s}\left(D_{i,t}+P_{i,t}^{E}\right)+\sum_{l=1}^{M}GSF_{l-i}\left(\mu_{l,t}^{s,\min}-\mu_{l,t}^{s,\max}\right)\left(D_{i,t}+P_{i,t}^{E}\right)\right) \tag{49}$$

For the lower-level model, the objectives of the primal problem and the corresponding dual problem at the optimal solution are equal based on the strong duality theory, and thus it can be described as (50).

$$\begin{aligned}&\sum_{t=1}^{24}\left(\begin{array}{l}-\lambda_{t}^{s}\left(\sum_{i=1}^{N}P_{w_i,t}^{s,0}-\sum_{i=1}^{N}\left(D_{i,t}+P_{i,t}^{E}\right)\right)\\-\sum_{l=1}^{M}\mu_{l,t}^{s,\min}\left(\sum_{i=1}^{N}GSF_{l-i}\left(P_{w_i,t}^{s,0}-D_{i,t}-P_{i,t}^{E}\right)\right.\\\left.+P_{l}\right)-\sum_{l=1}^{M}\mu_{l,t}^{s,\max}\left(P_{l}-\sum_{i=1}^{N}GSF_{l-i}\left(P_{w_i,t}^{s,0}\right.\right.\\\left.\left.-D_{i,t}-P_{i,t}^{E}\right)\right)+\sum_{i=1}^{N}\omega_{g_i,t}^{s,\min}P_{g_i}^{\min}\\-\sum_{i=1}^{N}\omega_{g_i,t}^{s,\max}P_{g_i}^{\max}-\sum_{i=1}^{N}\varphi_{w_i,t}^{s,\min}P_{w_i,t}^{s,0}\end{array}\right)\\&-\sum_{t=2}^{24}\left(\sum_{i=1}^{N}\upsilon_{g_i,t}^{s,d}R_{g_i}^{\mathrm{down}}+\upsilon_{g_i,t}^{s,u}R_{g_i}^{\mathrm{up}}\right)\\&=\sum_{t=1}^{24}\left(\sum_{i=1}^{N}C_{g_i}P_{g_i,t}^{s}+\sum_{i=1}^{N}\zeta\left(P_{w_i,t}^{s,0}-P_{w_i,t}^{s}\right)\right)\end{aligned} \tag{50}$$

Note that the net load at bus i not managed by the LSE is the baseline constant. Substituting (49) into (50), the latter can be replaced by (44), and the nonlinear term is linearized.

A.2. Linearization of KKT conditions

$$0\le\mu_{l,t}^{s,\min}\le M_{\mu}^{s,\min}\upsilon_{l,t}^{s,\min} \tag{51}$$

$$0\le\sum_{i=1}^{N}GSF_{l-i}\left(P_{g_i,t}^{s}+P_{w_i,t}^{s}-D_{i,t}-P_{i,t}^{E}\right)+P_{l}\le M_{\mu}^{s,\min}\left(1-\upsilon_{l,t}^{s,\min}\right) \tag{52}$$

$$0\le\mu_{l,t}^{s,\max}\le M_{\mu}^{s,\max}\upsilon_{l,t}^{s,\max} \tag{53}$$

$$0\le P_{l}-\sum_{i=1}^{N}GSF_{l-i}\left(P_{g_i,t}^{s}+P_{w_i,t}^{s}-D_{i,t}-P_{i,t}^{E}\right)\le M_{\mu}^{s,\max}\left(1-\upsilon_{l,t}^{s,\max}\right) \tag{54}$$

$$0\le\omega_{g_i,t}^{s,\min}\le M_{\omega}^{s,\min}\upsilon_{\omega,t}^{s,\min} \tag{55}$$

$$0\le P_{g_i,t}^{s}-P_{g_i}^{\min}\le M_{\omega}^{s,\min}\left(1-\upsilon_{\omega,t}^{s,\min}\right) \tag{56}$$

$$0\le\omega_{g_i,t}^{s,\max}\le M_{\omega}^{s,\max}\upsilon_{\omega,t}^{s,\max} \tag{57}$$

$$0\le P_{g_i}^{\max}-P_{g_i,t}^{s}\le M_{\omega}^{s,\max}\left(1-\upsilon_{\omega,t}^{s,\max}\right) \tag{58}$$

$$0\le\varphi_{w_i,t}^{s,\min}\le M_{\varphi}^{s,\min}\upsilon_{\varphi,t}^{s,\min} \tag{59}$$

$$0 \le P^{s}_{w_i,t} \le M^{s,\min}_{\varphi}\left(1 - \upsilon^{s,\min}_{\varphi,t}\right) \quad (60)$$

$$0 \le \varphi^{s,\max}_{w_i,t} \le M^{s,\max}_{\varphi} \upsilon^{s,\max}_{\varphi,t} \quad (61)$$

$$0 \le P^{s,0}_{w_i,t} - P^{s}_{w_i,t} \le M^{s,\max}_{\varphi}\left(1 - \upsilon^{s,\max}_{\varphi,t}\right) \quad (62)$$

$$0 \le \upsilon^{s,d}_{g_i,t} \le M^{s,d}_{\upsilon} \upsilon^{s,d}_{\upsilon,t} \quad (63)$$

$$0 \le P^{s}_{g_i,t} - P^{s}_{g_i,t-1} + R^{\mathrm{down}}_{g_i} \le M^{s,d}_{\upsilon}\left(1 - \upsilon^{s,d}_{\upsilon,t}\right) \quad (64)$$

$$0 \le \upsilon^{s,u}_{g_i,t} \le M^{s,u}_{\upsilon} \upsilon^{s,u}_{\upsilon,t} \quad (65)$$

$$0 \le -P^{s}_{g_i,t} + P^{s}_{g_{i,t},t-1} + R^{\mathrm{up}}_{g_i} \le M^{s,u}_{\upsilon}\left(1 - \upsilon^{s,u}_{\upsilon,t}\right) \quad (66)$$

where $\upsilon^{s,\min}_{l,t}$, $\upsilon^{s,\max}_{l,t}$, $\upsilon^{s,\min}_{\omega,t}$, $\upsilon^{s,\max}_{\omega,t}$, $\upsilon^{s,\min}_{\omega,t}$, $\upsilon^{s,\max}_{\omega,t}$, $\upsilon^{s,\min}_{\varphi,t}$, $\upsilon^{s,\max}_{\varphi,t}$, $\upsilon^{s,d}_{\upsilon,t}$, $\upsilon^{s,u}_{\upsilon,t}$ are auxiliary binary variables, and $M^{s,\min}_{\mu}$, $M^{s,\max}_{\mu}$, $M^{s,\min}_{\omega}$, $M^{s,\max}_{\omega}$, $M^{s,\min}_{\varphi}$, $M^{s,\max}_{\varphi}$, $M^{s,d}_{\upsilon}$, $M^{s,u}_{\upsilon}$ are large enough positive constants.

References

[1] Asadinejad A, Rahimpour A, Tomsovic K, Qi H, Chen C-f. Evaluation of residential customer elasticity for incentive based demand response programs. Electr Power Syst Res 2018;158:26–36.

[2] Ostadijafari M, Jha RR, Dubey A. Demand-side participation via economic bidding of responsive loads and local energy resources. IEEE Open Access J Power Energy 2020;8:11–22.

[3] Asadinejad A, Tomsovic K. Optimal use of incentive and price based demand response to reduce costs and price volatility. Electr Power Syst Res 2017;144:215–23.

[4] Wang X, Yang J, Zhang K, Zhang S, Wu L. Game-theoretic analysis of market-based operation mechanism for demand response resources. Int J Electr Power Energy Syst 2022;134:107456.

[5] Mohsenian-Rad H. Optimal demand bidding for time-shiftable loads. IEEE Trans Power Syst 2014;30(2):939–51.

[6] Hui H, Ding Y, Luan K, Chen T, Song Y, Rahman S. Coupon-based demand response for consumers facing flat-rate retail pricing. CSEE J Power Energy Syst 2022.

[7] Wang F, Ge X, Yang P, Li K, Mi Z, Siano P, et al. Day-ahead optimal bidding and scheduling strategies for DER aggregator considering responsive uncertainty under real-time pricing. Energy 2020;213:118765.

[8] Fang X, Hu Q, Li F, Wang B, Li Y. Coupon-based demand response considering wind power uncertainty: A strategic bidding model for load serving entities. IEEE Trans Power Syst 2015;31(2):1025–37.

[9] Heidari A, Mortazavi SS, Bansal RC. Stochastic effects of ice storage on improvement of an energy hub optimal operation including demand response and renewable energies. Appl Energy 2020;261:114393.

[10] Lu X, Li K, Xu H, Wang F, Zhou Z, Zhang Y. Fundamentals and business model for resource aggregator of demand response in electricity markets. Energy 2020;204:117885.

[11] Zhang X, Hug G, Kolter JZ, Harjunkoski I. Demand response of ancillary service from industrial loads coordinated with energy storage. IEEE Trans Power Syst 2017;33(1):951–61.

[12] Wang J, Chen X, Xie J, Xu S, Yu K, Gan L. Characteristics and control strategies of large-scale residential air conditionings for demand response programs. CSEE J Power Energy Syst 2020.

[13] Gamma K, Mai R, Cometta C, Loock M. Engaging customers in demand response programs: The role of reward and punishment in customer adoption in Switzerland. Energy Res Soc Sci 2021;74:101927.

[14] Kong X, Sun B, Zhang J, Li S, Yang Q. Power retailer air-conditioning load aggregation operation control method and demand response. IEEE Access 2020;8:112041–56.

[15] Xu H, Sun H, Nikovski D, Kitamura S, Mori K, Hashimoto H. Deep reinforcement learning for joint bidding and pricing of load serving entity. IEEE Trans Smart Grid 2019;10(6):6366–75.

[16] Schneider I, Roozbehani M, Dahleh M. An online learning framework for targeting demand response customers. IEEE Trans Smart Grid 2021;13(1):293–301.

[17] Zhang X, Pipattanasomporn M, Chen T, Rahman S. An IoT-based thermal model learning framework for smart buildings. IEEE Internet Things J 2019;7(1):518–27.

[18] Liu D, Sun Y, Li B, Xiangying X, Yudong L. Differentiated incentive strategy for demand response in electric market considering the difference in user response flexibility. IEEE Access 2020;8:17080–92.

[19] Pop C, Cioara T, Antal M, Anghel I, Salomie I, Bertoncini M. Blockchain based decentralized management of demand response programs in smart energy grids. Sensors 2018;18(1):162.

[20] Li P, Wang Z, Wang J, Yang W, Guo T, Yin Y. Two-stage optimal operation of integrated energy system considering multiple uncertainties and integrated demand response. Energy 2021;225:120256.

[21] Nojavan S, Nourollahi R, Pashaei-Didani H, Zare K. Uncertainty-based electricity procurement by retailer using robust optimization approach in the presence of demand response exchange. Int J Electr Power Energy Syst 2019;105:237–48.

[22] Liu W, Huang Y, Li Z, Yang Y, Yi F. Optimal allocation for coupling device in an integrated energy system considering complex uncertainties of demand response. Energy 2020;198:117279.

[23] Zeng B, Wei X, Zhao D, Singh C, Zhang J. Hybrid probabilistic-possibilistic approach for capacity credit evaluation of demand response considering both exogenous and endogenous uncertainties. Appl Energy 2018;229:186–200.

[24] Bahrami S, Wong VWS, Huang J. An online learning algorithm for demand response in smart grid. IEEE Trans Smart Grid 2017;9(5):4712–25.

[25] Yoon A-Y, Kim Y-J, Zakula T, Moon S-I. Retail electricity pricing via online-learning of data-driven demand response of HVAC systems. Appl Energy 2020;265:114771.

[26] Chen X, Nie Y, Li N. Online residential demand response via contextual multi-armed bandits. IEEE Control Syst Lett 2020;5(2):433–8.

[27] Dimitriadis CN, Tsimopoulos EG, Georgiadis MC. Strategic bidding of an energy storage agent in a joint energy and reserve market under stochastic generation. Energy 2022;242:123026.

[28] Schillemans A, Serrano GDV, Bruninx K. Strategic participation of merchant energy storage in joint energy-reserve and balancing markets. IET; 2018.

[29] Vespermann N, Delikaraoglou S, Pinson P. Offering strategy of a price-maker energy storage system in day-ahead and balancing markets. In: 2017 IEEE Manchester PowerTech. IEEE; 2017, p. 1–6.

[30] Pandžić H, Kuzle I. Energy storage operation in the day-ahead electricity market. In: 2015 12th International conference on the European energy market. IEEE; 2015, p. 1–6.

[31] Durvasulu V, Hansen TM. Benefits of a demand response exchange participating in existing bulk-power markets. Energies 2018;11(12):3361.

[32] Li Y, Hu Q, Li N. A reliability-aware multi-armed bandit approach to learn and select users in demand response. Automatica 2020;119:109015.

[33] Li P, Wang H, Zhang B. A distributed online pricing strategy for demand response programs. IEEE Trans Smart Grid 2017;10(1):350–60.

[34] Han R, Hu Q, Guo Z, Quan X, Wu Z, Hu R. Optimal allocation method of residential air-conditioners: Trade-off solutions between economic costs and aggregation reliability. IEEE Open Access J Power Energy 2022.

[35] Lakshmanan V, Marinelli M, Kosek AM, Nørgård PB, Bindner HW. Impact of thermostatically controlled loads' demand response activation on aggregated power: A field experiment. Energy 2016;94:705–14.

[36] Karimi H, Jadid S, Saboori H. Multi-objective bi-level optimisation to design real-time pricing for demand response programs in retail markets. IET Gener Transm Distrib 2019;13(8):1287–96.

[37] Demand response compensation in organized wholesale energy markets. Docket No. RM10-17-000; Order No. 745, Washington, DC, USA: Federal Energy Regulatory Commission; 2011, [Online]. Available: URL https://www.ferc.gov/sites/default/files/2020-06/Order-745.pdf%29.pdf.

[38] Fei W, Xg A, Peng YD, Kl A, Zmab C, Ps E, et al. Day-ahead optimal bidding and scheduling strategies for DER aggregator considering responsive uncertainty under real-time pricing. Energy 2020;213.

[39] Zhang R, Jiang T, Li G, Li X, Chen H. Stochastic optimal energy management and pricing for load serving entity with aggregated TCLs of smart buildings: A stackelberg game approach. IEEE Trans Ind Inf 2020;17(3):1821–30.

[40] Lee J, Leyffer S. Mixed integer nonlinear programming, vol. 154. Springer Science & Business Media; 2011.

[41] Nasrolahpour E, Kazempour J, Zareipour H, Rosehart WD. A bilevel model for participation of a storage system in energy and reserve markets. IEEE Trans Sustain Energy 2017;9(2):582–98.

[42] Razali NMM, Hashim AH. Backward reduction application for minimizing wind power scenarios in stochastic programming. In: 2010 4th International power engineering and optimization conference. IEEE; 2010, p. 430–4.

[43] Gong F, Han N, Zhang L, Ruan W. Analysis of electricity consumption behavior of air conditioning based on the perspective of power demand response. In: 2020 IEEE international conference on advances in electrical engineering and computer applications. IEEE; 2020, p. 412–6.