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Research Article

The Cost Efficiency of the Electricity Retailers with the Integration of the Cloud Energy Storage

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As a result of market liberalisation, a large number of electricity retailers have emerged in the electricity market. Acting as the intermediaries between the electricity producers and the customers, the electricity retailers aim to balance the supply and demand and shoulder substantial risks generated from both sides. Due to the randomness of the electricity load, it is difficult for electricity retailers to make an accurate electricity purchasing plan in advance to meet customer demand. This deviation leads to a proportion of spot electricity purchases that require a higher purchase cost. As a result, one of the most serious concerns facing electricity retailers is how to improve their balancing abilities and reduce power purchase deviation. In contrast to previous research, which has generally recommended that electricity retailers invest in energy storage systems or develop optimised purchasing strategies, this paper proposes a new strategy for the electricity retailers, which is renting external flexible resources to solve the market uncertainty of the electricity retailers, thereby lowering purchase costs and increasing profits. The proposed business model makes use of the cloud energy storage to solve the supply-demand imbalance issue of electricity retailers. The cost calculation model and decision optimisation model have been established in the process of renting cloud energy storage. Charging and discharging cloud energy storage have been separately rented to deal with different positive and negative load deviations, which can simplify the optimisation model. As an experimental paper, the proposed model has been tested in the PJM power market in the United States and the New South Wales power market in Australia. The findings confirm that renting the cloud energy storage capacities can significantly reduce costs and maximise profits for the electricity retailers when compared to the situation without the cloud energy storage. The biggest saving can reach 24.5% in the PJM market. With the rapid fall of battery prices, the advantage of the proposed strategy will be more obvious.

1. Introduction

Along with the adjustment of energy supply structure and higher requirement for energy efficiency, many countries, including the UK, Australia, European countries, and the US, started to reform the electricity market since the 1990s. The key purpose of the reform is to unbundle the traditional vertically integrated electricity market into four sectors including electricity generation, transmission, distribution, and supply, so as to introduce the competition mechanism through privatisation, restructuring, and deregulation [1]. Taking the US as an example, except for the transmission grids which are still operated by the nonprofit organisations, about 80% of the national electricity generation, about 75% of the electricity distribution, and about 72% of the customer service are now shouldered by private utility firms [2, 3]. Along with this market liberalisation process, a large number of electricity retailers have emerged. Acting as the intermediary between the electricity producers and the customers, the retailers purchase electricity from the generators and resale it to the end users. The prosperity of such newly emerged electricity retail sector has offered the customers with more choices and assisted the whole power industry to improve its efficiency further.

In contrast to the normal commodities, electricity cannot be stored in large-scale nor can the supply-demand relation be simply adjusted via inventory management. The production and consumption of electricity must be kept at equilibrium at all times to avoid power wastage and extremely high electricity price [4, 5]. When the electricity supply and demand is unbalanced in a large amount or for a long time, it may lead to additional maintenance expenses, lower energy efficiency, and even market failure, such as the California crisis [6]. To balance the electricity supply and demand and to survive under tough competition, retailers need to work carefully with both of the consumer and the wholesale market sides. This has therefore triggered extensive studies on consumer load forecasting, energy procurement strategies, and related risk management [7–18].

As for load forecasting, various techniques, such as the artificial neural networks [16, 19–23], the linear regression model [14], the semiparametric additive model [24], statistical method [15], and fuzzy regression [14, 25], are proposed to forecast the short-term load (up to several weeks). And the long-term load forecasting models (up to a few years) are often developed based on the short-term models [10, 15, 18, 26–28]. Regarding the energy procurement strategies, various internal and external factors including the electricity price volatility and price elasticity of demand as well as market competition are all considered when making the optimal purchasing decision from different sources such as the spot market, forward contracts, call options, and self-production facilities [18]. To capture the volatilities of the electricity price, a series of models have been proposed such as the GARCH model and the GARCH-jump model [9, 29, 30], the mean-reverting Ornstein-Uhlenbeck stochastic process [31], and the envelope bound model [13]. As for the energy procurement optimisation, two main types, the stochastic optimisation models [17] and the bilevel optimisation models [32], are widely adopted. The demand-side responses are often considered into the purchasing models [28, 33–35]. Finally, for the risk management of electricity retailers, some studies have focused on the trade-off between the expected profit and risk [11, 12, 36–38], while some others have analysed the hedging strategies that can be adopted by the electricity generators and retailers [7, 8, 39]. However, some hedging choice could be inefficient, and the seasonal variation of the electricity consumption may cause the systematic mismatch of hedging demand [40].

Among all the measures and efforts that the electricity retailers have made to balance the supply and demand, the development of energy storage brings new possibilities to them. Energy storage is a set of technologies that transform one kind of energy that is hard to store to other kinds of energy that can be easily stored and used at a later time [41]. Such time difference in electricity production and consumption can significantly reduce the imbalance between energy supply and demand [42]. The rapid development of the energy storage is along with the increasing penetration of renewable energies. As a sustainable and environmentally friendly energy source, renewable energy capacity started to grow globally at rates of 10–60% annually from the end of 2004 [43] and will continually grow to become the dominant energy source in the fight against climate change. However, the nature of renewable energies makes them unstable and intermittent. Based on such intermittent nature, the technologies for storing renewable energies and taking full advantage of them have achieved huge development in recent years. The energy storage facilities can be installed flexibly in any place on the power system, from the generation supplier, through the transmission network, and to the final consumer, to integrate with the comprehensive operation of the power system [44, 45]. At present, electricity production and consumption must be completed at the same time. After using the effective business model to consume more energy storage, the order of energy consumption can be changed, implying that the degree of coupling between production and consumption can be greatly reduced.

Actually, the use of energy storage techniques to maintain the grid balance is not a new research topic for the power system. However, majority of the previous studies tend to focus on the integration of stored energy into the grid from the aspects of electricity generation, transmission, and distribution sectors [46–49]. Little attention has been paid on the role played by electricity retailers, as the energy storage technologies were not that well developed at the time. Along with the advancement in energy storage technologies, the lower cost and faster response speed made it possible for the retailers to make use of the energy storage devices to balance the load deviation and optimise the procurement strategies. Since then, an increasing number of models have been proposed to simulate this optimisation process.

Hu et al. [50] built a purchase model of energy storage system and distributed the renewable energy to control the load forecast deviation risk and increase the total profit of the power-selling company. Wei et al. [51] proposed a two-stage two-level optimisation model for the retailers to cope with the procurement problems incorporating the storage units. In the first stage, the consumer's attitude to the retail price is reflected by the demand response, and this phenomenon is characterised by a Stackelberg game in which the leader of the market moves first, and then, the followers move afterward. In the second stage, dispatching of energy storage and energy contracts is operated by the retailers, and it is verified by the case studies that building larger storage units may help the retailers maximise their profits. Ju et al. [52] put forward a new two-stage demand response for electricity retailers with energy storage system and a corresponding two-layer coordinated optimal model for purchase and retail transactions, respectively. The results show that higher energy storage capacity with proper dimension can enhance the demand response efficiency. Yang et al. [53] constructed a multiobjective stochastic optimisation model of the electricity retailers with energy storage system to minimise the cost of electricity retailers and maximise the consumption of clean energy power generation considering the uncertainties of clean energy power generation and demand response in four different scenarios. Liu et al. [54] established an optimal planning model for multiple electricity retailers who shared the energy storage and analysed the cost benefit of them. The electricity retailers are screened and classified into groups with high- or low-matching degree based on the correlation degree of load curve. The results demonstrate that energy storage can effectively reduce the cost for all groups, while the groups with higher-matching degree tend to benefit more. Sun et al. [55] built a data-model hybrid-driven bilevel optimisation model to maximise profit of the electricity retailer by combining real-time price and energy storage system as demand response strategy simultaneously. The result shows that the retailer's extra profit increases by 7.19% after configurating energy storage system.

All the above studies have approved the feasibility of using energy storage for cost cutting and profit maximisation by the electricity retailers from different angles. It has also been confirmed that a higher level of energy storage capacity and more flexible consumption patterns are more likely to lead to higher profit and efficiency gains. Nevertheless, Liu et al. [56] pointed out that despite of all these potential benefits, in practice, the high maintenance cost, policy restriction, and low control efficiency have made many domestic users and small commercial users reluctant to invest into the energy storage devices. To overcome this issue, a new business concept, cloud energy storage (CES), was developed [56]. In this virtual energy storage service system, the CES operator would invest and operate centralised energy storage facilities. Different kinds of energy storage devices can be deployed according to different situations to optimise the operations. CES users can make a virtual request of their load demand to the central operator and store or withdraw the real electrical energy to and from central energy storage facilities based on the support of the power grid. Due to the sharing of storage resources and the function of scale economy, the CES has made it possible for the achievement of a higher level of social benefits at a lower level of social costs.

Considering that the amount of energy that needs to be charged or discharged by energy retailers to deal with supply and demand fluctuations is volatile, renting the CES capacities seems a better choice, as it is more flexible and cheaper in a short period. Due to tough competition, it is important for the electricity retailers to keep the cost down, and therefore, we believe that the adoption of CES may offer new business opportunities to the retailers. However, how can we fully utilise the CES system to achieve an equilibrised electricity supply and demand while ensuring that the profits of the retailers are maximised? We construct a new business model to estimate the optimal CES rental amount required to achieve a balanced supply and demand on a daily basis. Based on this, we further calculate the minimal costs incurred. Data from the advanced PJM (PJM, the Pennsylvania-New Jersey-Maryland Interconnection, a regional transmission organisation (RTO) that coordinates the movement of wholesale electricity in all or parts of 13 states and the District of Columbia in the United States) market are used to test the feasibility of the model. The contribution of this paper lies in the following aspects:

(1) To the best of our knowledge, this is the first paper which tries to link the two agents, the electricity retailers and the CES suppliers, together for potential collaborations. As agents, they have more resources to gather comprehensive market information compared with individuals, while compared with the power system, they tend to be more flexible. As a result, if the two agents can collaborate with each other, a win-win situation can be created for more efficient allocation of resources and more stable supply of power

(2) This paper proposes a new energy storage model for electricity retailers. Unlike the previous studies that require electricity retailers to purchase the energy storage devices, this model proposes a dynamic renting mode, allowing the electricity retailers to rent the energy storage capacities from the CES suppliers according to their daily needs. In this way, the idle energy storage devices can be fully utilised, and the financial burden of the electricity retailers can be significantly reduced. With a much higher capital utilisation rate, returns generated from investments in energy storage can be greatly improved

(3) The CES-based business model requires the estimation of a set of energy storage devices' whole cost [56]. This paper advances the former model further by providing a more accurate estimation of the single rental price of the CES. It takes account of all key factors including the time value of the capital, battery life, and charge-discharge cycle times. In practice, to maximise profit, electricity retailers can use this estimated single rental price as a key reference when it searches for electricity supplies from different sources

(4) The newly proposed business model in this paper is very practical, and it can be easily adapted in different electricity markets with minor adjustments. The case study uses data from the PJM electricity market and proves that the proposed method can significantly reduce the total cost of the electricity retailers and improve their operational efficiency. As the electricity consumption behaviours, the electricity price trend, and battery price share many common characters in different countries and regions, our newly proposed business model can also be applied in different markets with a sound level of confidence. In addition, over the longer term, when costs of the electricity retailers are reduced, the electricity price would be lower. This may save energy and reduce the carbon emissions

The rest of the paper is organised as follows. Section 2 describes the cooperation between the electricity retailers and the CES suppliers and establishes the business model for the electricity retailers to incorporate the CES. Section 3 builds the model to calculate the single rental cost of the CES and confirm the optimal rented amount of the CES. Section 4 explains the data selection and analysis approaches. Section 5 conducts the case study to

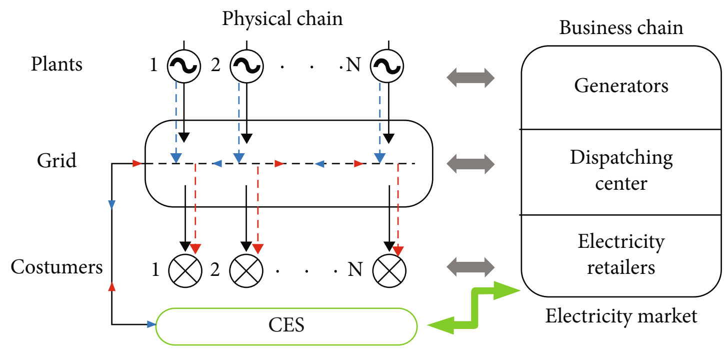

Figure 1: ER-CES model.

Table 1: Load data of the PJM on December 11, 2020.

Time	Predicted load/MW	Real load/MW	Load deviation ratio
12 am	1290	1352.5	4.62%
1 am	1258	1292.9	2.70%
2 am	1244	1277.6	2.63%
3 am	1243	1249.8	0.54%
4 am	1266	1262.1	-0.31%
5 am	1326	1284	-3.27%
6 am	1418	1355.7	-4.60%
7 am	1494	1446.8	-3.26%
8 am	1522	1509.5	-0.83%
9 am	1537	1539.2	0.14%
10 am	1538	1525.2	-0.84%
11 am	1527	1496.1	-2.07%
12 pm	1514	1493.7	-1.36%
1 pm	1499	1478	-1.42%
2 pm	1481	1452.1	-1.99%
3 pm	1470	1423.1	-3.30%
4 pm	1487	1408	-5.61%
5 pm	1548	1414.6	-9.43%
6 pm	1532	1509	-1.52%
7 pm	1499	1501.6	0.17%
8 pm	1458	1486.7	1.93%
9 pm	1408	1465.5	3.92%
10 pm	1345	1417.5	5.11%
11 pm	1276	1361.9	6.31%

demonstrate the effectiveness of the proposed model in different scenarios. Section 6 highlights the contributions and draws conclusions of this paper.

2. The Cooperation between the Electricity Retailers and the CES Suppliers

2.1. Operation Mechanism of the Electricity Retailers. To understand the relationship between the electricity retailers and CES suppliers, we first discuss the purchasing process of the electricity retailers. In general, the purchasing decision of the electricity retailers is determined by the load of consumers which can be highly volatile sometimes. To reduce the uncertainties, the electricity retailers often divide the purchasing amount into the fixed and the fluctuated parts and engage into transactions on both medium-to-long term financial market and the short-term spot market [32]. For the fixed part, electricity retailers can sign the procurement contracts with the generators directly at a relatively low price. They can also use futures and other financial derivatives to hedge against the potential risk exposure. In practice, this fixed amount is often estimated conservatively, as any deviation from this figure may lead to penalties or high balance fee cost [50]. Meanwhile, generators and electricity retailers also bid and offer in the short-term spot market where the price is constantly fluctuating. As a result, under the widely adopted time-of-use (TOU) pricing scheme, the electricity retailers would bear the price risks from the spot market. In particular, if it is very close to the electricity consumption time, a very high cost could incur to balance the supply and demand [57]. Consequently, this leads to the development of energy storage which can be used as an effective way to balance the supply and demand on both of the medium-long term markets and the short-term spot market [50, 58, 59]. For the electricity retailers, they could purchase a certain amount of electricity when the price is low and then discharge it when needed. This would reduce the demand for high-cost electricity on the spot market while allowing the additional electricity generated from the medium-long-term market to get absorbed. In the meantime, due to the increased demand in the medium-long-term market, large scale energy generated from renewable sources could be encouraged, and this would further lower the overall electricity generation costs.

2.2. Business Model. As shown in Figure 1, the flow of the electricity can be explained from both of the physical and economic aspects. From the perspective of the natural science, the whole process of electricity production, transmission, and consumption is completed almost at the same time by continuously flowing. The generators produce the electricity, and the power gird companies transmit the electricity to the consumers through high voltage transmission grid and low voltage distribution grid, and then, the electricity will be consumed by users immediately. This process can be regarded as a physical chain of electricity flow, while on the other hand, from the perspective of the economics, a business chain should be established for electricity

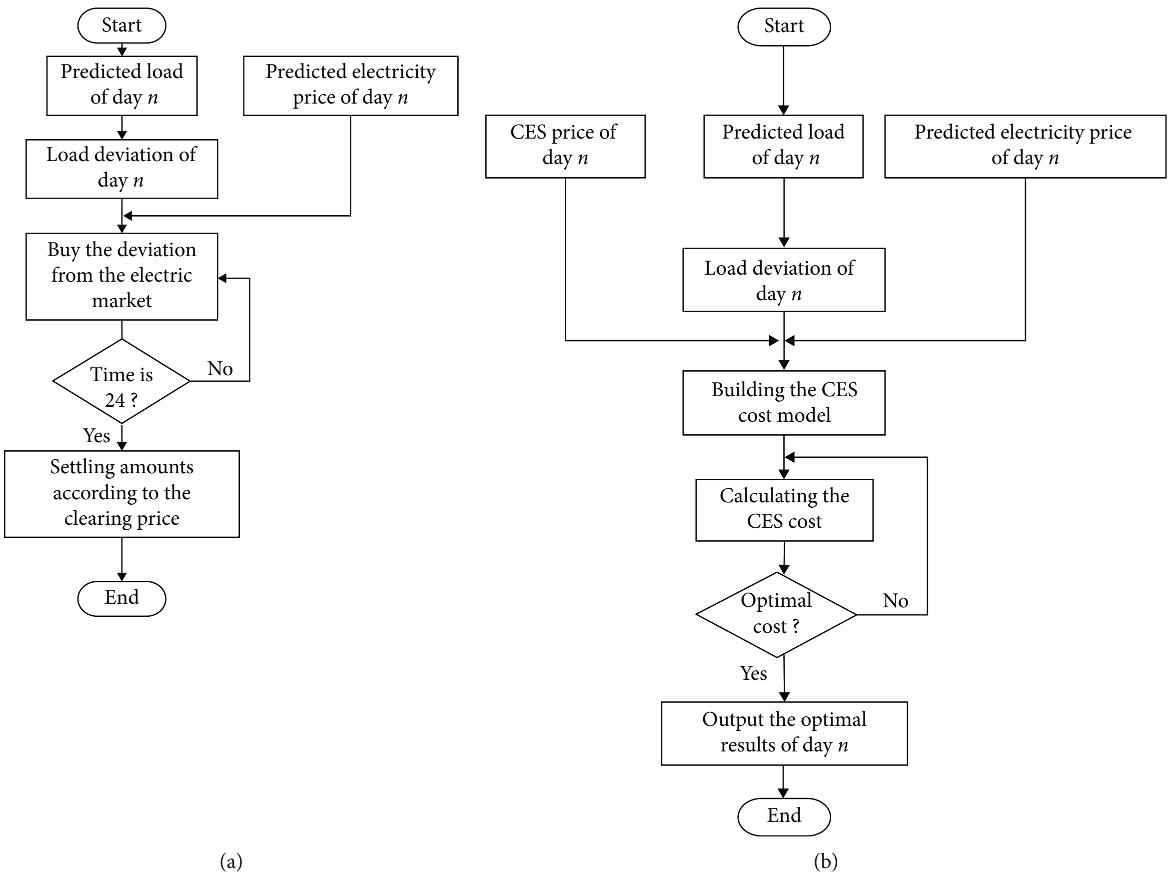

Figure 2: (a) Flow chart of the No-CES model. (b) Flow chart of the ER-CES model.

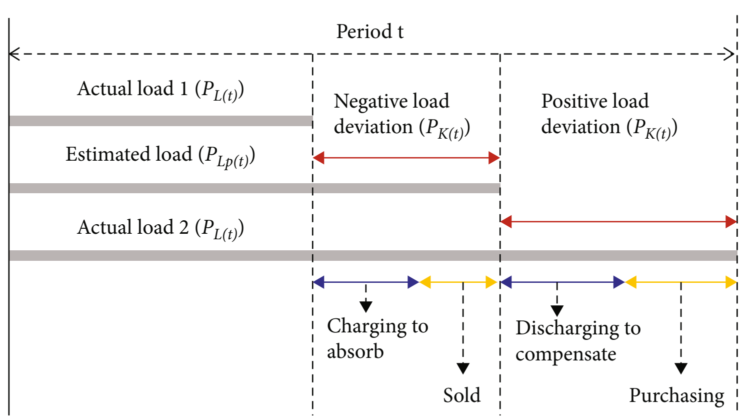

Figure 3: Load deviation.

consumption. The central platform of the business chain is the electricity market which incorporates all parts of the physical chain. As a professional agency, the retailers do not exist in this physical chain but are inevitable in the business chain. Through renting from the CES suppliers, the adjustment ability of the electricity retailers can be significantly improved. As a result, in the next part, an optimisation model for the electricity retailers with the CES (ER-CES) would be proposed. In order to keep the balance of electricity supply and demand, ER-CES will rent certain amount of energy storage capacities from the CES for charging or discharging. However, considering that the real-time electricity price would be cheaper than the cost of the CES in some periods, it is not advisable to balance all the deviation through renting the CES. So the optimal rental amount of CES will be calculated by this model at first, and accordingly, the total minimal cost can be generated.

3. Research Methods

3.1. Flow of the ER-CES Model. The basic business mode of electricity retailers is to purchase electricity from the

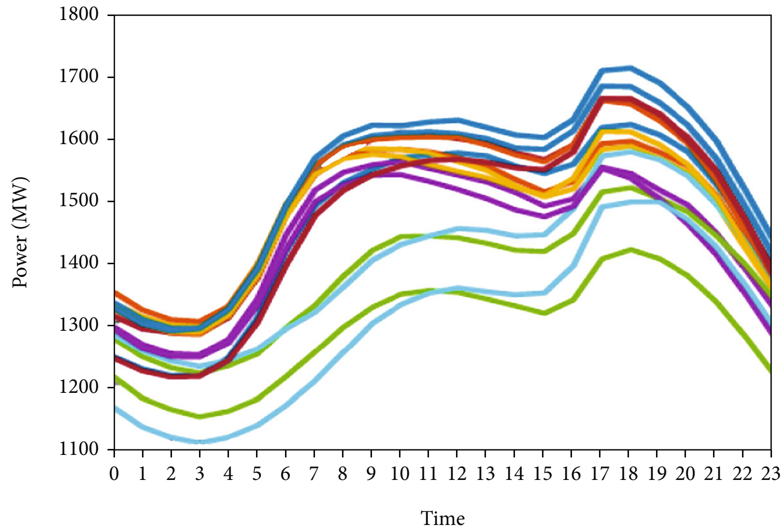

Figure 4: The predicted load curve (Dec).

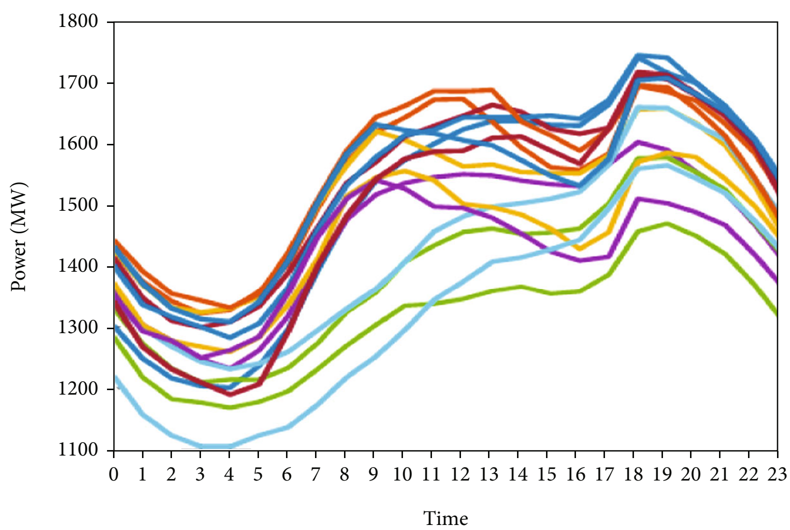

Figure 5: The actual load curve (Dec).

electricity market based on customer demand and then sell it to customers, taking advantage of the wholesale-retail arbitrage. Customer demand is dynamic, however, leading to a difference between the amount of electricity purchased in advance and the actual demand of customers, which means that there is always a load deviation between the predicted load and the real load. Taking one day's load data of the PJM power market in the United States as an example, Table 1 shows the predicted load, real load, and load deviation ratio of one load area on December 11, 2020. After calculation, the load deviation ratios vary from -9.43% to 6.31%. The parts of positive deviation should be purchased from the spot power market to compensate the shortage, while the negative deviation should still be paid according to the contract.

Figure 2(a) shows electricity retailers' actual processing procedure for the load deviation at present, which is to solve the problem by purchasing electricity in the spot power market. The purchase price is the spot price for that day, and it would be cleared by the end of the day. In general, the spot price is much higher than the contract price, and if the load deviation is too large, it may further pay a penalty.

Figure 2(b) illustrates how an electricity retailer can minimise its costs after incorporating the CES. The predicted load, the predicted electricity price, and the single CES price of day n would be obtained first. Then, they will be used for the calculation of the total cost of ER-CES and the optimal CES rental amount. When a positive deviation occurs on day n, the CES will discharge for compensation, while in the case of a negative deviation, the CES is charged to absorb the extra power.

3.2. Definition of Load Deviation. The price of energy storage devices is determined by two factors, the power (P) and the

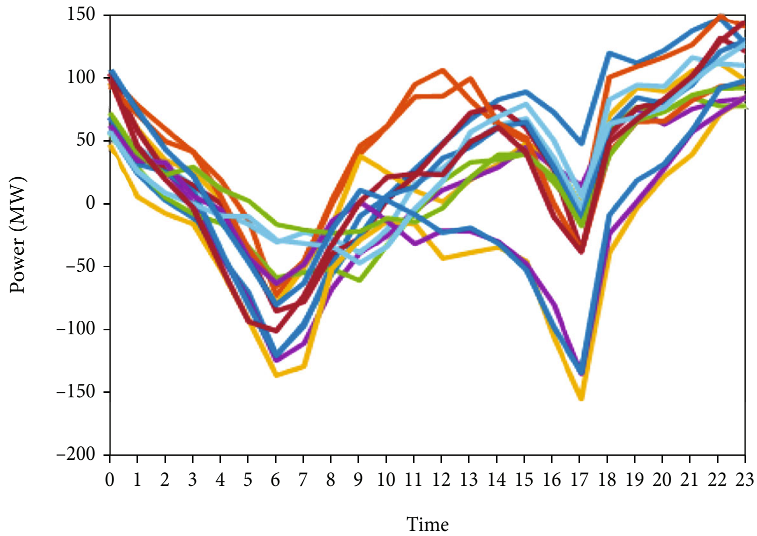

FIGURE 6: Load deviation curves of 15 days (Dec).

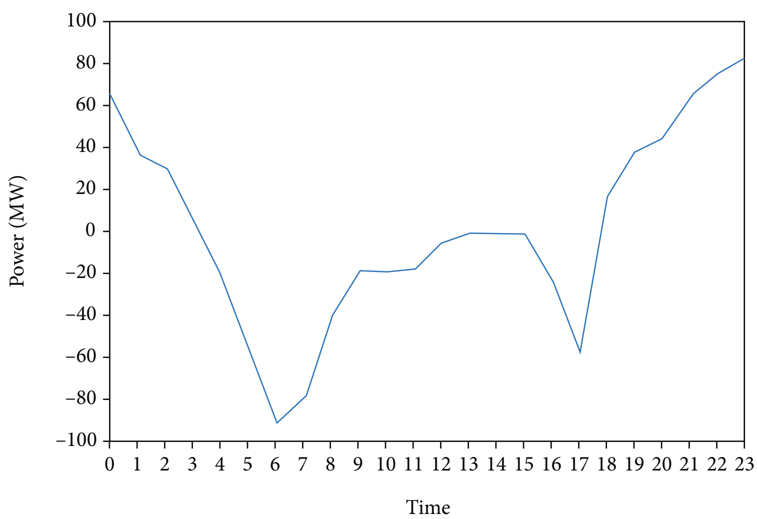

FIGURE 7: Predicted load deviation curve of day n (Dec).

capacity (Q) ($Q = P\Delta t$). To respond rapidly to charging and discharging needs and to avoid the repeated charging and discharging of the same equipment, two sets of energy storage devices are normally required to compensate and absorb the deviated load, respectively. If an hour is set as one trading period, there will be 24 trading periods in a day. The estimated load for period t of day n can then be represented by $P_{\mathrm{Lp}(t)}$. Assuming the actual load is $P_{L(t)}$, so the deviation $P_{K(t)}$ is

$$P_{K(t)} = P_{L(t)} - P_{\mathrm{Lp}(t)}. \quad (1)$$

The size of $P_{K(t)}$depends on the accuracy of load forecasting, and the prediction error is inevitable due to the randomness of electricity consumption. As the load forecasting is not the research object of this paper, the load deviation curve of day n will be estimated in a simple way. From Figure 3, when $P_{K(t)} > 0$ in period t, it is called the positive load deviation, and it means that the actual load is greater than the estimated load [50]. The optimal discharging CES capacities should then be calculated to compensate. Assume that the power discharged is $P_{\mathrm{ESD}(t)}$, so for all the period t with a positive $P_{K(t)}$, the total capacity is Q_{ESD}. When $P_{K(t)} < 0$, it is called a negative load deviation, and it means that the actual load is less than the estimated load [50]. The optimal charging CES capacities should then be calculated to absorb. Set the power of absorption as $P_{\mathrm{ESC}(t)}$; so for all the period t with a negative $P_{K(t)}$, the total capacity is Q_{ESC}. Consequently, the left amount of positive and negative deviations, represented by the yellow parts in Figure 3, would be traded directly in the real-time electricity market.

3.3. The Electricity Cost of ER-CES. In order to balance the daily load deviation though CES, it is necessary to calculate the cost of electricity charging and discharging separately. The charging electricity needs to be purchased, while the

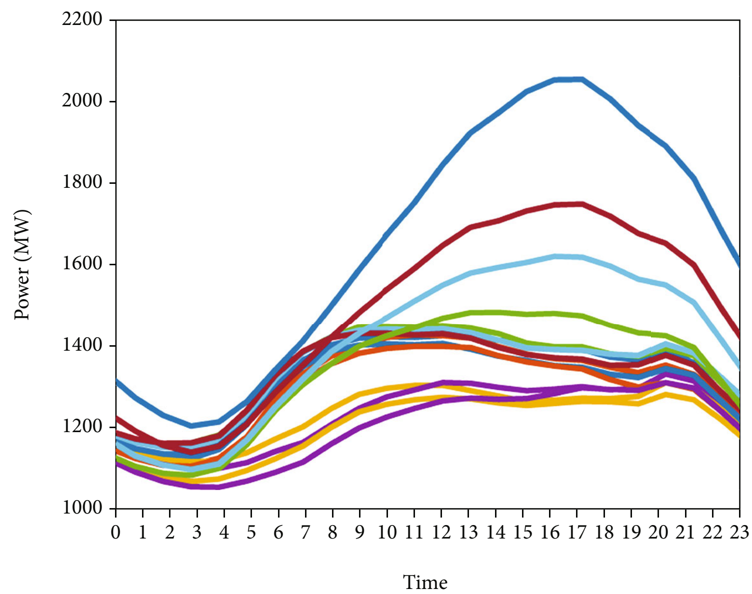

FIGURE 8: The predicted load curve (May).

discharging electricity can be sold. Assuming there are N periods for charging and M periods for discharging, so the difference between the two parts could be positive or negative. Refer to the electricity price curve of day n and set $\gamma_{(t)}$ as the estimated real-time electricity price for day n, so the cost is

$$C_{\mathrm{ES}} = \sum_{t=1}^{N}\left(P_{\mathrm{ESC}(t)} \times \Delta t \times \gamma_{(t)}\right) - \sum_{t=1}^{M}\left(P_{\mathrm{ESD}(t)} \times \Delta t \times \gamma_{(t)}\right). \tag{2}$$

According to the model, the optimal charging and discharging amount may not fully match the deviation; so for the part that cannot be perfectly matched by the energy storage capacity, it is still needed to trade in the spot market. Using $\gamma_{(t)}$ as the trading price, the difference cost for charging and discharging is

$$\begin{aligned} C_{\mathrm{ES}}^{+} &= \sum_{t=1}^{M}\left[\left(P_{K(t)} - P_{\mathrm{ESD}(t)}\right) \times \Delta t \times \gamma_{(t)}\right], P_{K(t)} > 0, \\ C_{\mathrm{ES}}^{-} &= \sum_{t=1}^{N}\left[\left(-P_{K(t)} - P_{\mathrm{ESC}(t)}\right) \times \Delta t \times \gamma_{(t)}\right], P_{K(t)} < 0. \end{aligned} \tag{3}$$

So the total electricity costs after using the CES would be

$$C_{\mathrm{ES}}^{E} = C_{\mathrm{ES}} + C_{\mathrm{ES}}^{+} + C_{\mathrm{ES}}^{-}. \tag{4}$$

3.4. The Equipment Cost of ER-CES. The total equipment cost includes two parts, namely, the energy capacity ($/kWh) and power capacity ($/kW):

$$C_{\mathrm{ESP}} = \left(\alpha_{\mathrm{ES}} Q_{\mathrm{ESM}} + \beta_{\mathrm{ES}} P_{\mathrm{ESM}}\right). \tag{5}$$

$\alpha_{\mathrm{ES}}$and β_{ES} are the unit investment cost of the energy capacity ($/kWh) and power capacity ($/kW), respectively. Q_{ESM} and P_{ESM} are the purchasing energy capacity and power capacity of energy storage.

After considering the time value of the capital, the annualised equipment cost (C_Y) over Y years can be estimated as the following, assuming r is the discount rate [56]:

$$C_Y = \frac{r}{1-(1+r)^{-Y}} \times C_{\mathrm{ESP}} = \frac{r}{1-(1+r)^{-Y}} \times \left(\alpha_{\mathrm{ES}} Q_{\mathrm{ESM}} + \beta_{\mathrm{ES}} P_{\mathrm{ESM}}\right). \tag{6}$$

The single rental price is related to the service times of the equipment that has limited number of use. Set the circle times for charging and discharging as K, one year's using days as ρ, and one circle for one day, so the service life of the energy storage equipment is

$$Y = \frac{K}{\rho}. \tag{7}$$

Set the single rental price of energy capacity and power capacity as α and β, so

$$\begin{aligned} \alpha &= \frac{\left(r/(1-(1+r))^{(-K/\rho)}\right) \times \alpha_{\mathrm{ES}}}{\rho}, \\ \beta &= \frac{\left(r/(1-(1+r))^{(-K/\rho)}\right) \times \beta_{\mathrm{ES}}}{\rho}. \end{aligned} \tag{8}$$

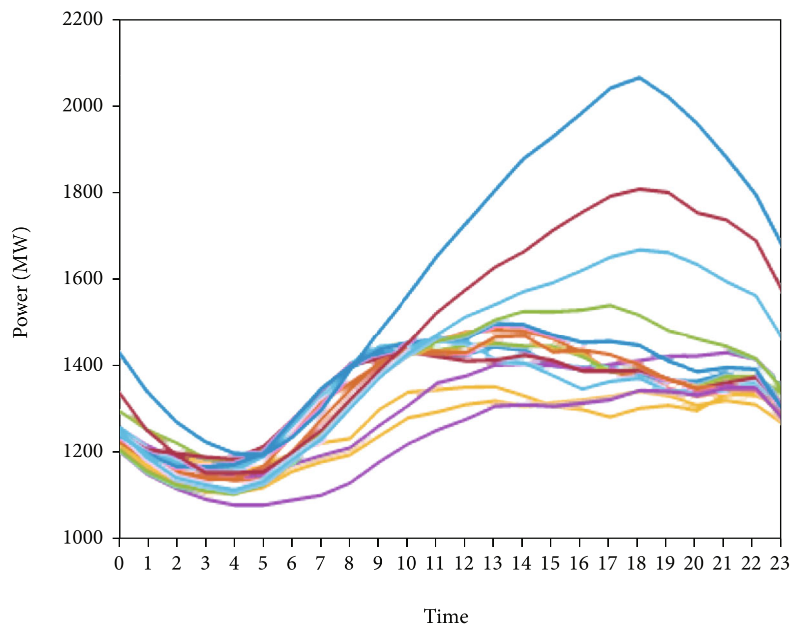

FIGURE 9: The actual load curve (May).

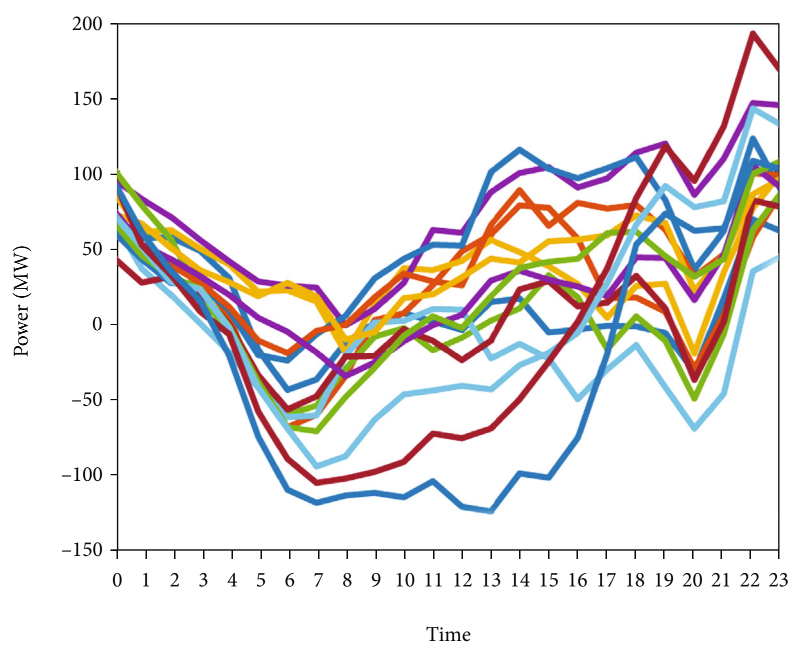

FIGURE 10: Load deviation curves of 15 days (May).

Set P_{ESCM} as the rental power capacity for charging, and it should meet the largest one:

$$P_{\mathrm{ESPCM}} = \max \left\{ P_{\mathrm{ESC}(t)} \right\}, \mathrm{t} = 0, 1, 2 \cdots 23. \tag{9}$$

Set P_{ESDM} as the rental power capacity for discharging, and it also should meet the largest one:

$$P_{\mathrm{ESPDM}} = \max \left\{ \mathrm{P}_{\mathrm{ESD(t)}} \right\}, \mathrm{t} = 0, 1, 2 \cdots 23. \tag{10}$$

So the rental energy capacity for charging is

$$Q_{\mathrm{ESC}} = \sum_{t-1}^{N} \left(P_{\mathrm{ESC}(t)} \times \Delta t \right). \tag{11}$$

The rental energy capacity for discharging is

$$Q_{\mathrm{ESD}} = \sum_{t-1}^{N} \left(P_{\mathrm{ESD}(t)} \times \Delta t \right). \tag{12}$$

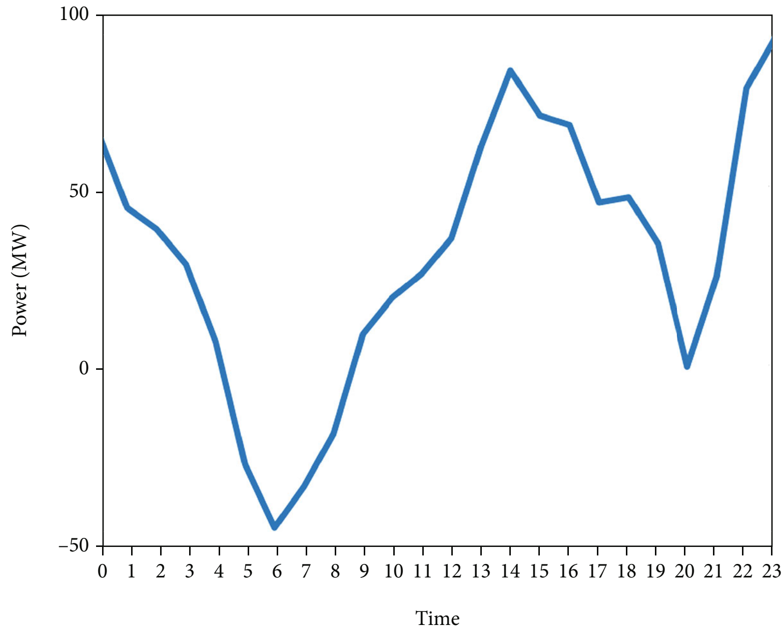

Figure 11: Predicted load deviation curve of day n (May).

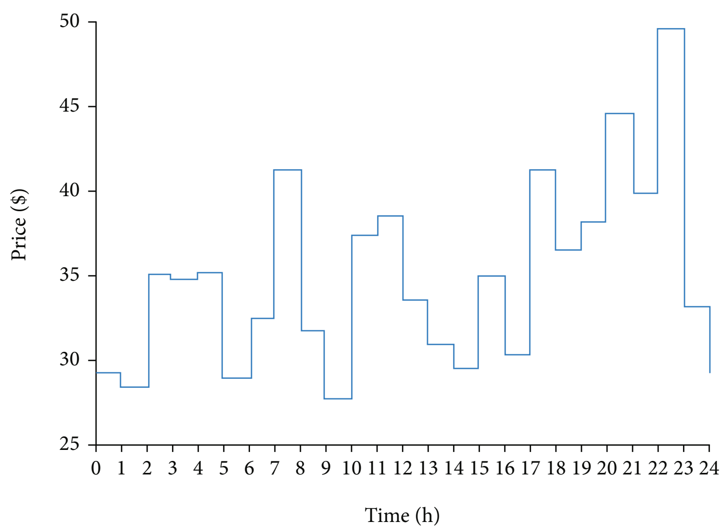

Figure 12: Real-time electricity prices of day $n-1$ (Dec).

Because the charging and discharging capacities are rented separately, charging and discharging only complete half of one charge-discharge cycle, which means that only half of the full cost should be calculated for charging (C_{ESC}) and discharging (C_{ESD}) separately:

$$\begin{aligned} C_{\mathrm{ESC}} &= \frac{1}{2} \times (\alpha Q_{\mathrm{ESC}} + \beta P_{\mathrm{ESCM}}), \\ C_{\mathrm{ESD}} &= \frac{1}{2} \times (\alpha Q_{\mathrm{ESD}} + \beta P_{\mathrm{ESDM}}). \end{aligned} \tag{13}$$

The total equipment cost for using the CES is

$$C_{\mathrm{ESP}} = C_{\mathrm{ESC}} + C_{\mathrm{ESD}}. \tag{14}$$

3.5. Upfront Cost of ER-CES. For the charging equipment prepared to absorb the electricity, it needs to be kept empty. On the other hand, the discharging equipment should be charged in advance to guarantee the supply. The amount will be confirmed based on the optimised energy capacity and power capacity, so the cost for day n is

$$C_{\mathrm{ESD}'} = \gamma_{(p)} \times Q_{\mathrm{ESD}} = \gamma_{p1} \times \sum_{t=1}^{M} \left(P_{\mathrm{ESD}(t)} \times \Delta t \right). \tag{15}$$

γ_{p1} is the clearing price of day $n-1$. Furthermore, the electricity that is absorbed in day $n-1$ can be traded at the clearing price of day $n\,(\gamma_{p2})$, generating an income of

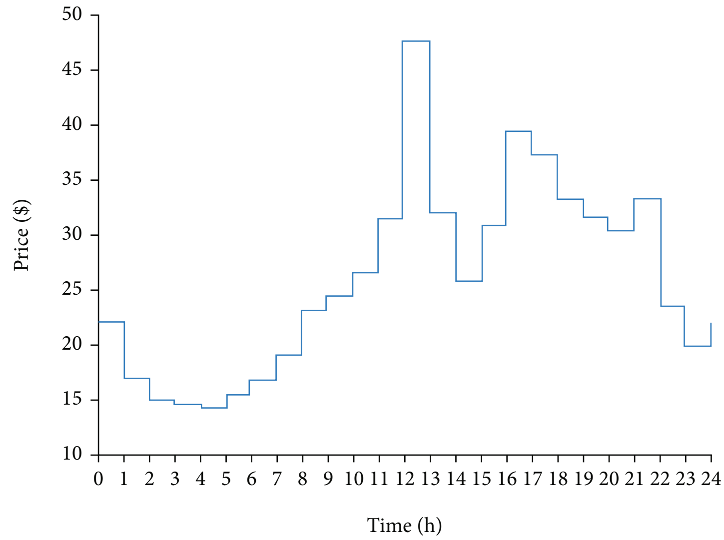

Figure 13: Real-time electricity prices of day $n-1$ (May).

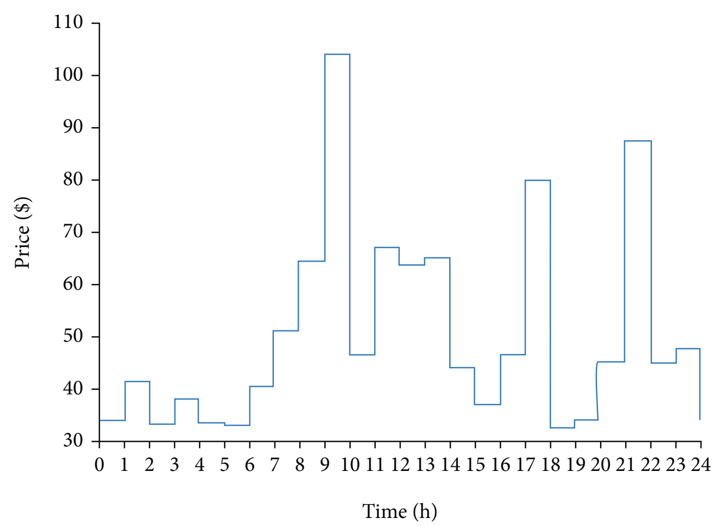

Figure 14: Predicted real-time prices of day n (Dec).

absorbed electricity; so the actual cost incurred would be

$$C_{\mathrm{ESD}'(n-1)} = \gamma_p \times Q_{\mathrm{ESC}(n-1)} = \gamma_{p2} \times \sum_{t=1}^{N} \left(P_{\mathrm{ESC}(n-1)} \times \Delta t \right). \tag{16}$$

The upfront cost of CES is

$$C_{\mathrm{ESQ}} = C_{\mathrm{ESD}} - C_{\mathrm{ESC}(n-1).} \tag{17}$$

3.6. Total Cost of ER-CES. The total cost of the ER-CES is the sum of all three parts, which are the real-time electricity cost, equipment cost, and upfront electricity cost:

$$C_{\mathrm{total}} = C_{\mathrm{ES}}^{E} + C_{\mathrm{ESP}} + C_{\mathrm{ESQ}}. \tag{18}$$

4. Data Collection and Analysis Approaches

To test the feasibility of our model, data from the PJM electricity market of the US would be used. Two sets of 15 days of data are chosen in December 2020 and May 2021, respectively. As this paper intends to balance the load deviation on a daily basis, we use data of winter purposely, as the season tends to have a higher demand for electricity due to increased heating needs. This may also result in a larger fluctuation in the load and price curves, making it ideal to verify the feasibility of the model proposed. For the rest of the year, the load curve tends be relatively smooth (the summer is not

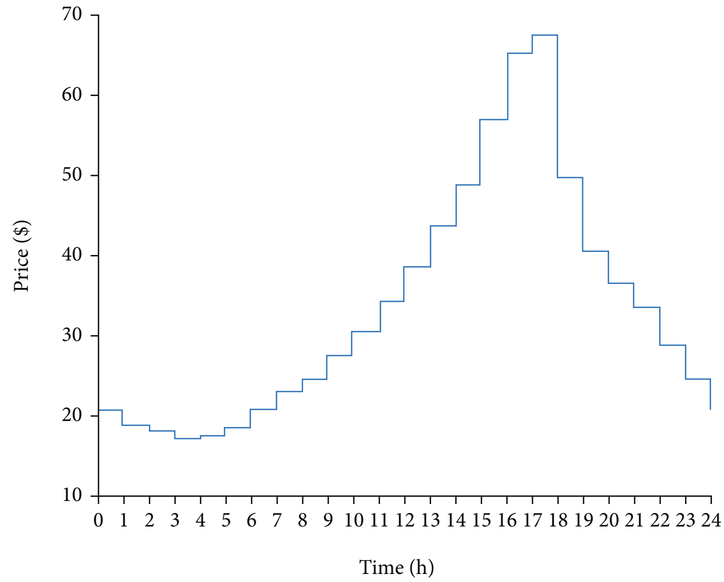

Figure 15: Predicted real-time prices of day n (May).

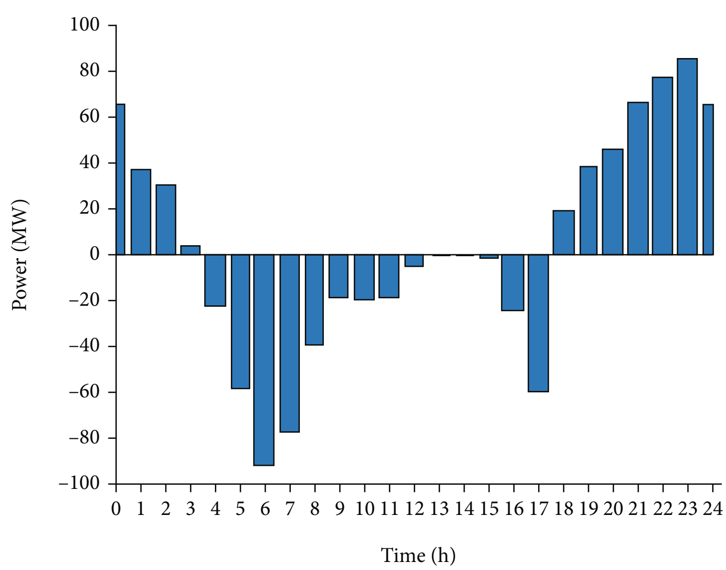

Figure 16: Load deviation of day n in bar chart.

hot in the north part of the US, which means that the demand for electricity tends to remain stable). As a result, data of May 2021 is used for comparative analysis, as it further testifies the validity of our model when it is applied in a period with lower load fluctuations.

In total, three types of data are collected for the case study. They are the users' load data, electricity price in the spot market, and parameters of energy storage devices. The former two kinds of data were collected from PJM electricity market (http://dataminer2.pjm.com/feed/da_hrl_lmps/definition), and the third one came from the literature [56, 60]. The reasons for choosing data from PJM are stated as follows. Firstly, PJM is a regional transmission organisation (RTO) in the US serving several states, including Pennsylvania, New Jersey, and Maryland, in the Eastern area. It was the world's largest competitive electricity market until the development of the European integrated energy market in the 2000s [61]. The successful operation of PJM made it the research case for many studies [62–65]. Secondly, PJM provides high-quality data for this research. As it is impossible for one electricity retailer to serve the whole country, the load data at the city level or even a smaller scale would be suitable. The load data of PJM are released by load areas which can be a very small town or area. It provides us with a relatively precise estimation of the service coverage of an electricity retailer. Meanwhile, except for the actual load

Table 2: Charging and discharging capacities of the three scenarios.

Time	Charging capacity/MW (scenario 1)	Discharging capacity/MW (scenario 1)	Charging capacity/MW (scenario 2)	Discharging capacity/MW (scenario 2)	Charging capacity/MW (scenario 3)	Discharging capacity/MW (scenario 3)
0	0	0	0	0	0	65.70
1	0	0	0	37.10	0	37.10
2	0	0	0	0	0	30.75
3	0	0	0	3.70	0	3.70
4	0	0	18.65	0	21.80	0
5	0	0	18.65	0	58.60	0
6	0	0	18.65	0	58.60	0
7	0	0	18.65	0	58.60	0
8	0	0	18.65	0	39.55	0
9	0	0	18.10	0	18.10	0
10	0	0	18.65	0	18.65	0
11	0	0	17.50	0	17.50	0
12	0	0	4.30	0	4.30	0
13	0	0	0.15	0	0.15	0
14	0	0	0	0.35	0	0.35
15	0	0	0.65	0	0.65	0
16	0	0	18.65	0	24.30	0
17	0	0	18.65	0	58.60	0
18	0	0	0	0	0	0
19	0	0	0	0	0	11.10
20	0	0	0	46.00	0	46.00
21	0	66.50	0	66.50	0	66.50
22	0	0	0	66.50	0	77.15
23	0	0	0	66.50	0	77.15
Sum	0	66.50	189.90	286.65	379.40	415.50

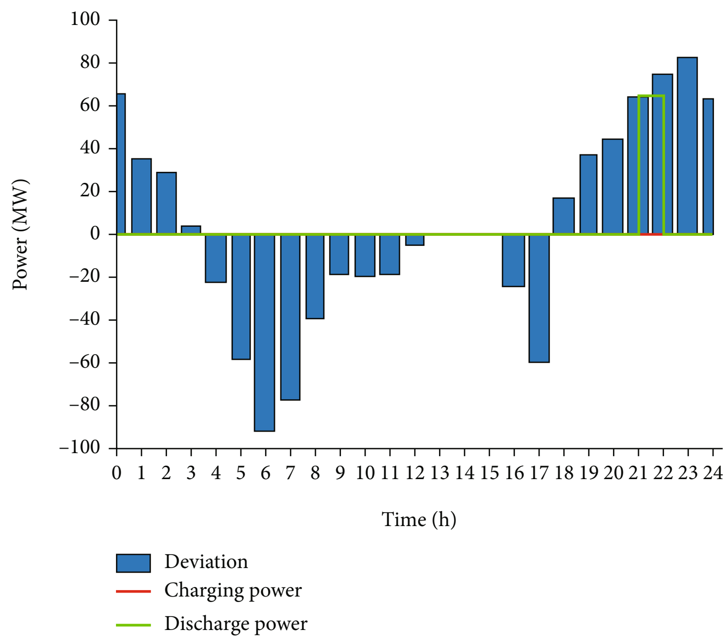

Figure 17: Application of energy storage in scenario 1.

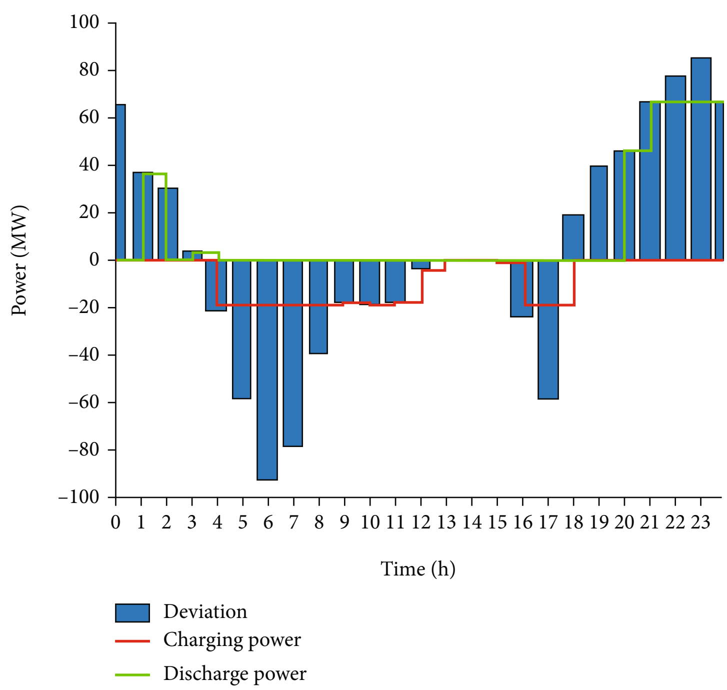

Figure 18: Application of energy storage in scenario 2.

and price data, the predicted load and price data are also readily accessible in the PJM market. Therefore, the quality of data ensures that the results generated by the newly proposed model are reliable and hence can be generalised with a high level of confidence. Valuable lessons can also be provided to countries like China that is trying hard to build up its own electricity market. Last but not the least, as big and well-developed cities are also believed to have sound infrastructure and well-educated labour force, they are also more likely to invest into new technologies and adopt new business models. Duquesne, the metropolitan area of Pittsburgh (the second largest and the second-most populous city in Pennsylvania known as "the Steel City," leader in manufacturing, computing, electronics, and the automotive industry), has therefore made it a suitable choice to prove the validity of our business model.

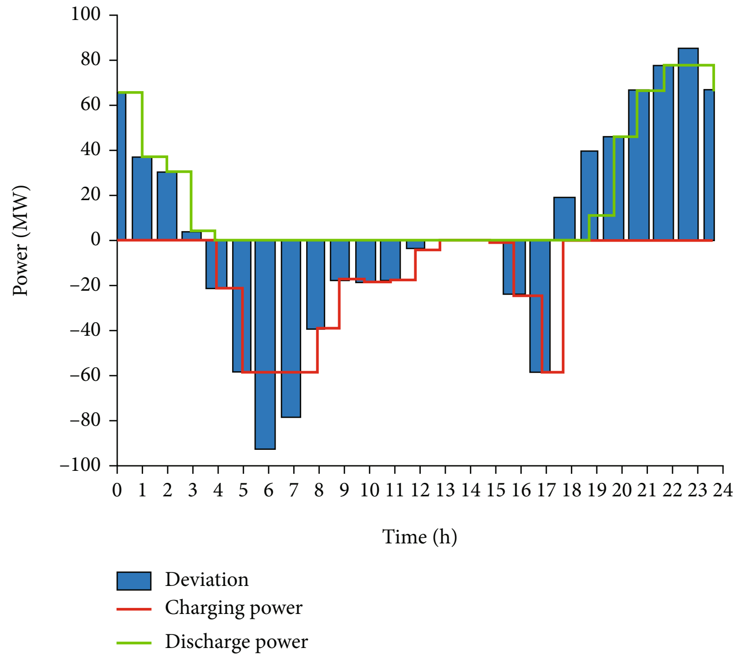

Figure 19: Application of energy storage in scenario 3.

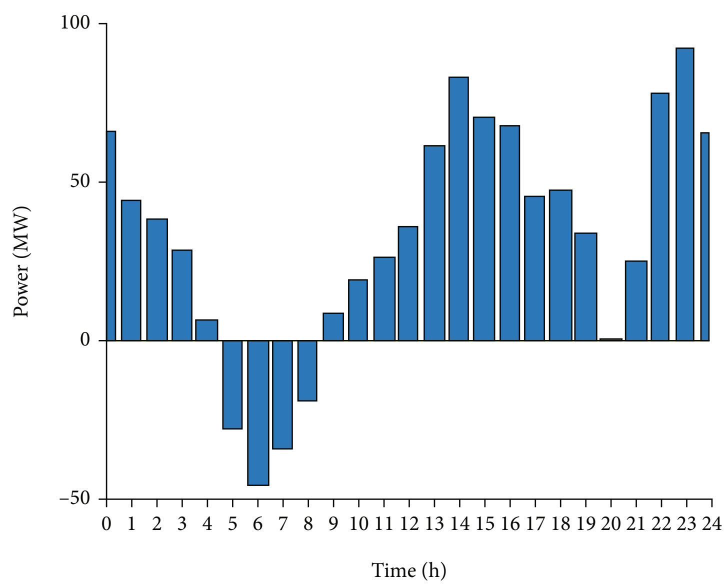

Figure 20: Load deviation of day n in bar chart (May).

We also employ the power market of New South Wales (NSW), Australia, as a robustness test for the adaptability of the proposed model in different regions. The load data for November 1, 2022, is randomly selected and scaled down to simulate the scale of an electricity retailer. For simplification, we directly present the results of the NSW power market in Finding and Discussion rather than showing the detail of their various types of data in the following parts as we did for the PJM market.

4.1. Load Data. The daily predicted load curve (Figure 4) and the actual load curve (Figure 5) of 15 days in December 2020 in Duquesne, Pittsburgh, with a time interval of one hour, were collected from the website of PJM. The data covered a period from December 4 to 18. Christmas was not included in the data, because the commercial and industrial load demand was very low during the holiday period.

The load deviation curve for each day can be calculated based on two sets of loads (Figure 6). Considering the different load characteristics of weekday and weekend, the load curves of the weekday are more representative, as there is less commercial and industrial demand during the weekend. Moreover, Monday is not suitable to be chosen as day n, as the electricity data of day $n-1$, which is Sunday, will be used

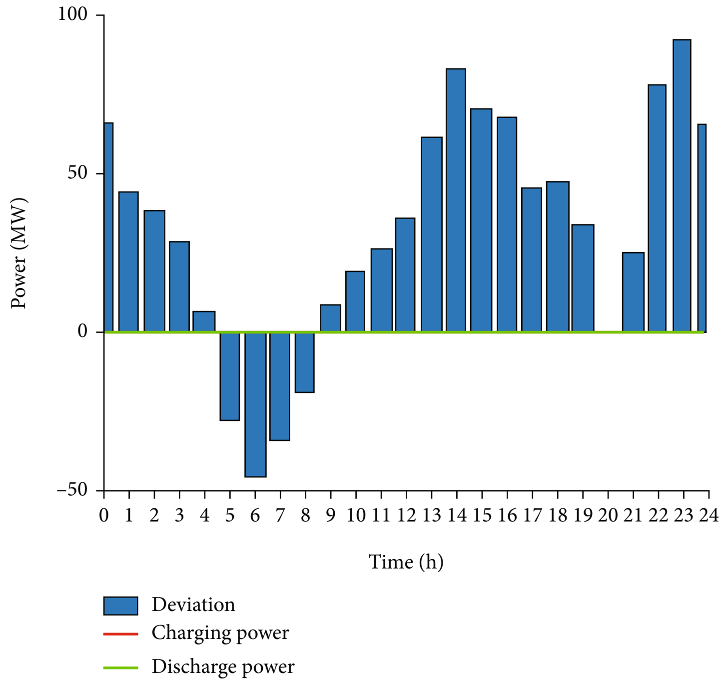

Figure 21: Application of energy storage in scenario 1 (May).

for calculation of upfront cost. As a result, one day from Tuesday to Friday can be randomly chosen as day n. At last, 18 December 2020 (Friday) was chosen as day n, because it is the last day of our data period. For simplicity, the mean value of the former two Friday's load deviations (4 December and 11 December) is used as the predicted load deviation for day n (Figure 7).

As for the comparative sample, data over the period of 7 to 21 May 2021 was chosen randomly, and May 21 (Friday) was chosen as day n. Figures 8 and 9 are the predicted and actual load curves of May, respectively. Figure 10 is the load deviation curves, and Figure 11 is the predicted load deviation of day n (mean value of May 7and 14). Apparently, the majority of load curves of May are more stable than that of December.

4.2. Electricity Price. The real-time electricity prices of day $n-1$ were collected, and the price of the last time period was chosen as the clearing price. Figures 12 and 13 are the data of December 2020 and May 2021, respectively. It is apparent that the price curve of May 2021 is less volatile than that of December 2020. Figures 14 and 15 are the predicted real-time electricity prices curve of day n in December and May, respectively.

4.3. Energy Storage Parameters. The lithium-ion battery is widely used for energy storage because of its high energy density, small size, fast response speed, and flexible regulation, which make it convenient to deploy on the user side. According to the literature and the price trend of the lithium-ion battery [56, 60], two sets of costs are assumed for comparison, \$293.7/kWh for energy capacity (kWh) and \$154.8/kW for power capacity (kW) and \$180/kWh for energy capacity (kWh) and \$100/kW for power capacity (kW). In practice, the latter is more closely related to the actual average price of the battery. The discount rate, using days of a year, and the cycle index are assumed to be 6%, 300, and 3000, respectively [56]. Moreover, lithium-ion batteries are selected as an example in this paper to validate the proposed business model. Electricity retailers can choose any other more suitable energy storage devices in the real market just by changing the relevant parameters in the model.

5. Finding and Discussion

5.1. Results of the PJM Power Market in December 2020. This section tests the effectiveness of the ER-CES model in the PJM market in December 2020. The situation without the CES is set as the baseline model, which will be compared with the model with CES. To evaluate the models with varied CES costs and electricity prices, three scenarios are examined. The first scenario has a higher CES cost and a lower electricity price, while the second scenario has a lower CES cost and a lower electricity price. At last, the third scenario has a lower CES cost and a higher electricity price.

5.1.1. No-CES Baseline Model. When electricity retailers do not have energy storage configurations, all load deviations should be traded in the real-time electricity market to achieve supply and demand balance. This situation without the CES is set as the baseline model. Figure 16 shows a bar chart of the load deviation on day n. After calculation, it would cost \$45,231 for the electricity retailers to balance supply and demand.

5.1.2. ER-CES Model: Scenario 1. In scenario 1, the investments of energy capacity and power capacity were set as \$293.7/kWh and \$154.8/kW, respectively; r, ρ, and K were

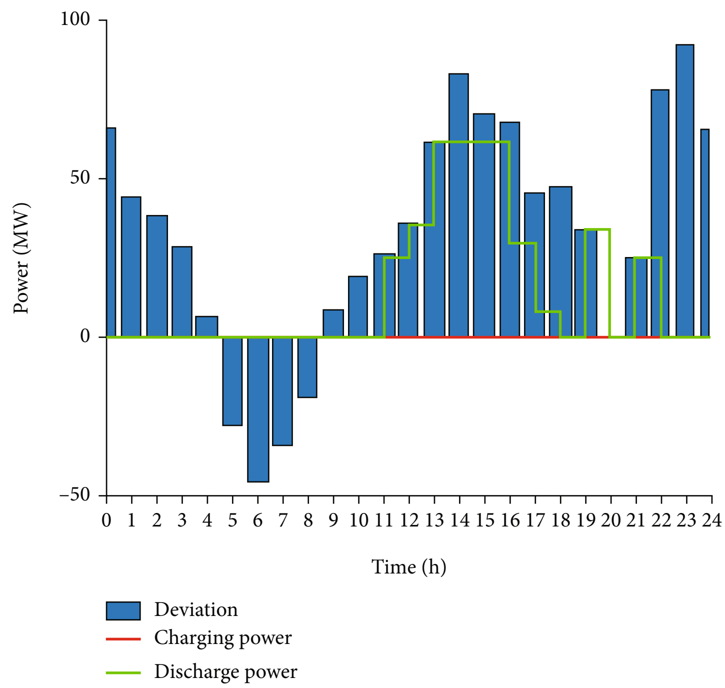

Figure 22: Application of energy storage in scenario 2 (May).

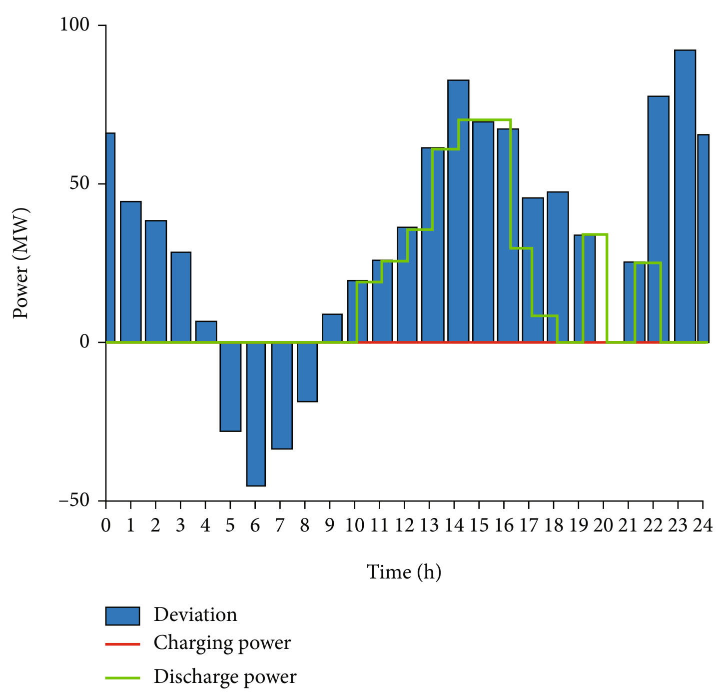

Figure 23: Application of energy storage in scenario 3 (May).

assumed to be 6%, 300, and 3000, respectively. Then, α and β are calculated as \$133/MWh and \$70/MW. The clearing price is \$33.16/MWh of day $n-1$ and \$47.13/MWh of day n. Based on our calculation, the optimised charging capacity is 0 and discharging capacity is 66.5 MWh (Table 2). The total cost is \$44,864 which saves \$367 than the situation without energy storage devices. From Figure 17, it can be seen that the positive deviation is not completely compensated by the energy storage capacity for most time periods, and all the negative deviation is sold in the real-time market. The results suggest that the investment of energy storage is less cost effective in most time periods when the cost of energy storage is relatively higher than the real-time electricity prices.

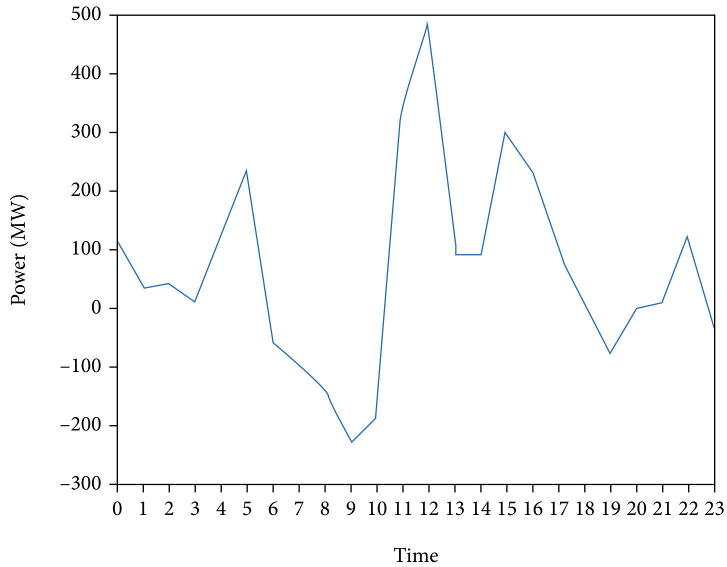

FIGURE 24: Predicted load deviation curve of day n (Nov).

5.1.3. ER-CES Model: Scenario 2. In scenario 2, the cost of the energy storage devices is assumed to be \$180/kWh and \$100/kWh, while other parameters remain the same. α and β would become \$81.5/MWh and \$45.3/MW. With the decrease of the battery price, the optimised charging and discharging capacities would increase to 189.9 MWh and 286.65 MWh, respectively (Table 2). The total cost decreases to \$37,651, representing a saving of \$7,580 (or C_{saving} = 16.8%). It is clear that a lower cost of battery can significantly enhance the amount of the energy storage capacities in the purchase strategy, lowering the total costs further. It should be pointed out that while the discharging capacity increases with the amount of load deviation, the charging capacity remains roughly the same across all time periods (Figure 18).

5.1.4. Cost with the CES: Scenario 3. In scenario 3, to simulate the power shortage that might be caused by some natural disasters, such as snowstorm and hailstone, a higher predicted real-time electricity price, \$5 increase per hour on day n, is assumed. Setting all other parameters the same as scenario 2, the cost without the CES would increase to \$49,751. The results show that the optimised charging and discharging capacities would increase further to 379.4 MWh and 415.5 MWh, respectively (Table 2). The total cost would decrease to \$37,549, representing a saving of \$12,202 (or C_{saving} = 24.5%). According to Figure 19, when the real-time electricity price is higher, majority of the positive and negative load deviations are traded with the CES.

5.2. Comparative Test: May 2021 of the PJM Power Market. For comparison purpose, all parameters and scenarios are set the same as the December figures apart from the data of load and electricity price. The clearing electricity prices of day $n-1$ and day n are \$19.82/MWh and \$24.51/MWh, respectively. The results are presented by Figures 20–23 below. Without the use of CES, the balancing cost of the load deviation is \$36,292 (Figure 20).

Figure 21 (scenario 1) shows that both the optimised charging and discharging capacities are 0, which means that it is not suitable to adopt the energy storage system under this situation. This is due to the low clearing price and relatively high CES cost, resulting in no CES configuration as the optimisation result.

In scenario 2 (Figure 22), when the CES cost falls, the optimised charging capacity is 0 and the discharging capacity is 345 MWh. This would result in a decreased total cost to \$32,218 or a saving of \$4,074 (or C_{saving} = 11.2%). Because of the lower CES cost, the model chooses to discharge when the electricity price is relatively high on day n and trade in the real-time market for the rest of the periods when the electricity price is relatively low.

Finally, as for scenario 3 (Figure 23), when predicted real-time electricity price increases by \$5 per hour, the cost without the CES would increase to \$41,284, and the optimised charging is still 0 and the discharging capacities has increased to 381 MWh. Consequently, the total cost would decrease by \$5,877 (or C_{saving} =14.2%), reaching \$35,407.

Through comparison, it can be concluded that even when the load and price fluctuations are relatively stable, our newly proposed model remains effective in cost saving. However, when the cost of energy storage devices is higher, such positive effect tends to be less significant.

5.3. Comparative Test: Results of the NSW Power Market in November 2022. In order to verify the adaptability of the proposed model in different regions, the data of New South Wales (NSW), Australia, are selected for testing. Data are obtained from the Australian power market operator AEMO's website.

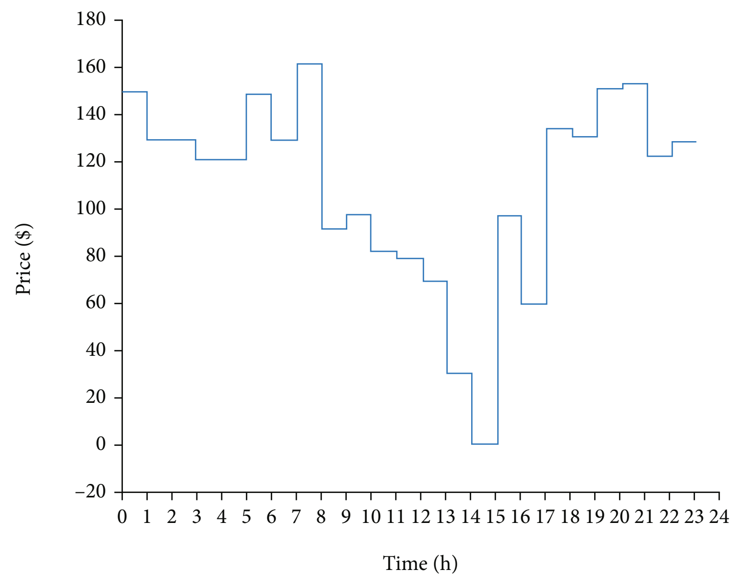

FIGURE 25: Predicted real-time prices of day n (Nov).

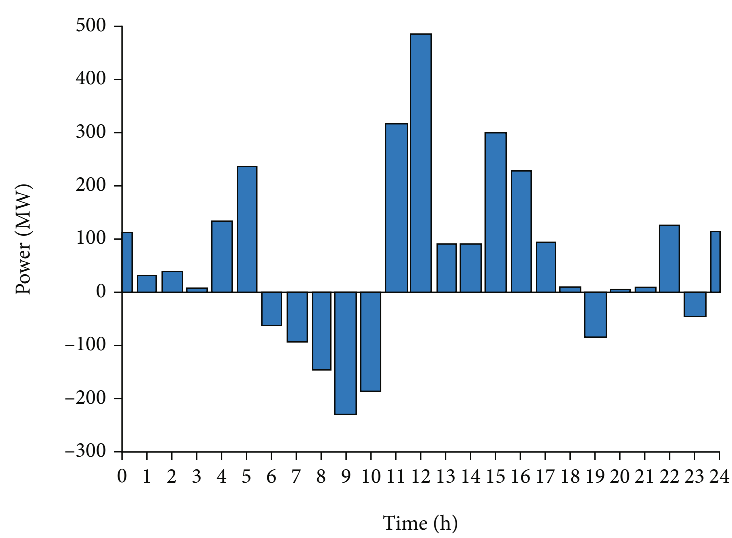

FIGURE 26: Load deviation of day n in bar chart (Nov).

The load data of November 1, 2022, is randomly selected and scaled down to simulate the scale of an electricity retailer. The load deviation curve (Figure 24) and electricity price curve (Figure 25) of this day are obtained by the same method described above. For simplification, only scenario 1 with the higher CES cost is tested to compare with the scenario without CES. The clearing electricity prices of day $n-1$ and day n are \$128.25/MWh and \$149/MWh, respectively. All the other parameters remain the same as in the PJM market.

As shown in Figure 26, the cost of balancing without the use of CES is \$30,948 after calculation. After incorporating the CES, Figure 27 shows that the optimised charging capacity is 1204.8 MWh and the discharging capacity is 625.5 MWh. In general, the CES discharges when the load deviation is positive while charges with negative load deviation. During the period of 11-12, the electricity price is relatively high, so no compensation was made. While for the period 13-14, the discharge should be made, but the electricity price fell to the lowest point at this time, so the optimisation decision was made to charge during this period to obtain greater benefits. The total cost decreased to \$20,378 or a saving of \$10,569 ($C_{\text{saving}} = 34.2\%$). It can be seen that although the electricity price in the Australian power market is much higher than that in the PJM power market, a satisfactory profit can still be obtained by renting the CES.

The above experiments verify that the decision variables of the proposed model are only related to factors like user demand, electricity price, battery price, and battery parameters. The model can be employed in different seasons and

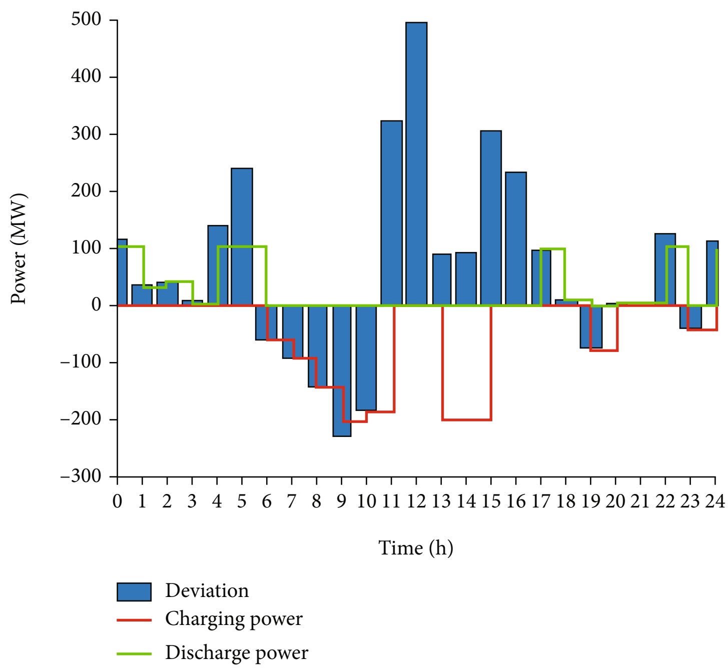

FIGURE 27: Application of energy storage in scenario 1 (Nov).

TABLE 3: Comparison between the No-CES baseline model and the ER-CES model (PJM market).

Scenario	Cost		
	No-CES baseline model	ER-CES model	C_{saving}
1	\$45,231	\$44,864	0.8%
2 (CES cost decrease)	\$45,231	\$37,651	16.8%
3 (electricity price increase)	\$49,751	\$37,549	24.5%

regions with good results, which can significantly reduce the cost of electricity retailers and improve their response ability to different customers.

5.4. Comparison Analysis

5.4.1. No-CES Baseline Model and ER-CES Model (PJM Market). Table 3 compares the No-CES baseline model and the ER-CES model in the three scenarios. It can be seen that the savings continuously increase along with the decrease in CES costs and the increase in electricity prices. It can be concluded that the ER-CES model can effectively smoothen the fluctuation and lower the risk of some extreme situations, such as the power shortage caused by some natural disasters, with a robust cost saving for the electricity retailers.

5.4.2. Coinvestment Energy Storage Model and ER-CES Model. Liu et al. [54] propose an approach to optimally plan the energy storage shared by multiple electricity retailers to minimise their electricity procurement cost, which can be reduced through arbitraging the shared energy storage in the day-ahead market and real-time market. Different from the proposed strategy in this paper, this scheme of coinvestment and couse of energy storage pursues overall optimisation, and it may not be an optimal choice to compensate the load deviation of individual electricity retailer. Furthermore, as the load pattern of the electricity retailers changes over time, so will the investment optimisation circumstance. As a result, the flexibility of such fixed investments may deteriorate, and the investment income may become uncertain. In this paper, the independent electricity retailer adopts the method of renting CES, which relieves it of the burden of fixed asset amortisation and generates stable cost savings.

5.4.3. Renewable Energy-Energy Storage Mix Model and ER-CES Model. Ju et al. [52] put forward a two-stage demand response optimisation approach for electricity retailers with energy storage, which takes into account the uncertainties of renewable energy on the supply side. Through adjusting the charging and discharging strategy, the power purchase cost and transaction risk can be reduced. It also proves that the demand response is best when the capacity ratio between solar energy and storage is 4 : 1. Unlike making optimal power purchase scheme based on energy storage and renewable energy, our research focuses on a common situation that a large number of electricity retailers have neither energy storage nor renewable energy supply. The proposed solution aims at lowering the cost of electricity retailers by renting energy storage, which can meet the needs of the majority of electricity retailers.

6. Conclusions

The energy supply-demand imbalance has always been a critical issue that triggers profound discussion and debate.

Acting as intermediaries, the electricity retailers have tried hard to achieve equilibrium in supply and demand. Among all the proposed methods, energy storage is an effective solution. However, the majority of electricity retailers have not developed a practical business model to take advantage of energy storage on a large scale. Based on the development of a new business concept, cloud energy storage (CES), a virtual energy storage service system, this paper discusses the cooperation between the electricity retailers and CES suppliers and puts forward a novel ER-CES model that can effectively take advantage of the CES to reduce the load deviation and realise the cost efficiency of the electricity retailers. The main research results are summarised as follows: (1) through renting the CES, the electricity retailers can flexibly use the energy storage resources and real-time electricity price mechanism to achieve the dynamic balance between power purchase and sale and maximise profits. This option eliminates the need for electricity retailers to make upfront investments in fixed assets (energy storage devices) or endure the amortisation pressure of fixed assets. They can flexibly adjust the amount and duration of renting energy storage in response to changes in customer demand for electricity. At present, a large number of electricity retailers have neither energy storage devices nor distributed power supply, so they can choose this mode to achieve the optimal cost efficiency. (2) The method considers the cost of renting CES, the time value of investment, the price of power on the market, and other factors before establishing an optimisation model using the CES rental amount as the decision variable. This model can not only give the total amount of the next day's rented CES, total cost, and total profits but also give the charge and discharge plan of CES for each period of the next day, which is convenient for the electricity retailers to carry out as planned. (3) A decision method of separately renting charge energy storage and discharge energy storage is adopted to simplify the optimisation model and solve the optimisation decision problem when there are both positive and negative load deviations. (4) After testing in both the PJM market in the United States and the NSW market in Australia, the effectiveness of the model has been verified, demonstrating that renting CES can significantly reduce the cost of electricity retailers in different seasons and regions.

Based on our research findings, it can be suggested that for the policy makers, they should further encourage the development of the energy storage industry. This may speed up the technological progression process, lowering the battery price and the application costs further. Consequently, an increasing amount of the energy storage capacities could be purchased by the electricity retailers, and the cost efficiency which can be brought about by the CES would be much stronger. In turn, this could allow the retailers to gain better control over the load deviation and adjusting the balance of supply and demand more flexibly. The successful cooperation between the two agents will not only bring win-win situation to themselves but also decrease the electricity cost of the consumers, strengthen the stability of the power system, and more importantly improve the energy efficiency, which is critical for the progress of energy transformation and the fight against climate change. In addition, the successful application of the newly proposed business model could expand the business scope of the CES suppliers, assisting them to achieve a much higher investment return. As a result, more investors can be attracted into the market, leading to more competition, and hence more rapid technological progression, in the energy sector. Nevertheless, it should also be aware that although the feasibility of the proposed model has been proved in our study, it should be tested in more electricity markets to identify the boundary of application and other potential limitations. In addition, over the longer term, the studies could further compare the cost efficiency of the electricity retailers between the renting of CES capacities and the purchasing of the energy storage equipment by themselves. The results may provide more guidance to the electricity retailers in the future.

Data Availability

The data sources used to support the findings of this study are included within the article.

Conflicts of 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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