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Research on Smart Power Sales Strategy Considering Load Forecasting and Optimal Allocation of Energy Storage System in China

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Abstract: With the deepening reform of the power system, power sales companies need to adopt new power sales strategies to provide customers with better economic marketing solutions. Customer-side configuration of an energy storage system (ESS) can participate in power-related policies to reduce the comprehensive cost of electricity for commercial and industrial customers and improve customer revenue. For power sales companies, this can also attract new customers, expand sales and quickly capture the market. However, most of the ESS evaluation models studied so far are based on historical data configuration of typical daily storage capacity and charging and discharging scheduling instructions. In addition, most models do not adequately consider the performance characteristics of the ESS and cannot accurately assess the economics of the energy storage model. This study proposes an intelligent power sales strategy based on load forecasting with the participation of optimal allocation of ESS. Based on long short-term memory (LSTM) artificial neural network for predictive analysis of customer load, we evaluate the economics of adding energy storage to customers. Based on the premise of the two-part tariff, the ESS evaluation model is constructed with the objective of minimizing the annual comprehensive cost to the user by considering the energy tariff and the savings benefits of the basic tariff, assessing the annualized cost of ESS over its entire life cycle, and the impact of battery capacity decay on economics. The particle swarm optimization (PSO) algorithm is introduced to solve the model. By simulating the arithmetic example for real customers, their integrated electricity costs are significantly reduced. Moreover, this smart power sales strategy can provide different sales strategies according to the expected payback period of customers. This smart sales strategy can output more accurate declared maximum demand values than other traditional sales strategies, providing a more economical solution for customers.

Keywords: energy storage systems (ESS); smart power sales; peak-valley electricity arbitrage; demand control; load forecast; particle swarm optimization (PSO); long short-term memory (LSTM)

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1. Introduction

In order to reduce peak carbon dioxide emissions and achieve the carbon neutrality target background of power security and supply, strengthen power operation regulation and deepen power load management, China's National Development and Reform Commission issued a series of policies: (1) "Notice on Improving the Implementation of Basic Electricity Tariff for Users of the Two-Part Tariff System", (2) "Implementation of the 'Guidance on Promoting Energy Storage Technology and Industry Development' 2019 to 2020 Action Plan", and (3) "Notice of the Comprehensive Department of the National Energy Administration on Promoting the Construction of a New Electricity Load Management System". The first policy calls for changing the energy tariff for commercial and industrial customers to a two-part tariff consisting of the energy tariff and the basic tariff. The second policy addresses energy storage technology, which is widely used in various areas of power systems due to its flexible throughput and increasing economics by using battery storage systems. The third policy comes into play after users configure the energy storage system (ESS). Users can reduce their own maximum energy demand and gain basic tariff savings [1–8] or they can choose low storage and high generation, i.e., peak-to-valley arbitrage, to gain revenue [9–15]. In addition, according to the user's load history data, the ESS can predict the user's future need for grid enterprises and report the maximum demand value period load data [16,17]. This allows for more accurate capacity allocation for energy storage systems and output of energy storage charging and discharging schedule commands to provide maximum benefits to the user.

Broadly speaking, load forecasting models can be divided into classical forecasting methods and modern forecasting methods. The classical forecasting methods are more mature, and the forecasting results have some reference value. However, to further improve forecasting accuracy, it is necessary to introduce modern methods, such as support vector machine (SVM) [18], K nearest neighbor (KNN) [19], LSTM [20], etc. For example, based on convolutional neural network and LSTM, Pramono et al. proposed a load forecasting method to support demand response planning in hybrid energy systems [17].

Zhang et al. considered the effect of charge/discharge multiplier on the life cycle of energy storage based on a genetic algorithm to achieve a balance between the life cycle and charge/discharge rate of ESS [21]. Hassan et al. proposed a time-of-use electricity price-based optimal dispatching method for ESS charging and discharging and evaluated the economic benefits of ESS in distribution networks [22]. Lo et al. investigated the charge/discharge state of ESS with daily and seasonal load variations [23].

Chen et al. studied in depth the theory and application of ESS in auxiliary services based on the premise of the characteristics of the Chinese electricity market environment [24]. Mu et al. proposed a tariff package for ESS configuration that takes into account the reliability of power supply and energy tariff saving requirements of customers, which reduces the cost of electricity for customers [25]. Yang et al. studied the analysis model for calculating the economic benefits of ESS under different business operation models and analyzed in detail the composition structure and calculation methods of various economic benefits under various business operation models [26]. Based on hierarchical analysis, Xiu et al. proposed a method to evaluate the configuration of energy storage systems considering demand response as well as peak-to-valley arbitrage from the perspective of techno-economic indicators [27]. Chen et al. proposed an optimal operation model for ESS considering physical, variable and lifetime constraints based on the maximum demand lower bound calculation and transformed it into a linear model for solution. Gao et al. proposed an optimal allocation model for customer-side ESS with the objective of full life-cycle net present value of ESS in order to solve the ESS planning problem affected by two-part tariff and full life-cycle [28]. Song et al. considered the investment cost and operation and maintenance cost of the energy storage system, set up an ESS evaluation model with the highest return as the goal, and proposed two energy storage revenue schemes based on the number of daily storage charges and discharges [29].

Most of the above-mentioned scholars in the literature have studied the customer electricity savings with the participation of ESS. However, most of the models do not perform predictive analysis of the customer load, and the result is a typical daily ESS capacity and charging and discharging scheduling instruction based on historical data configuration. It does not consider the difference in electricity consumption per day within a month or the change in maximum demand per month in different years. The capacity and charging/discharging state of the derived ESS cannot meet the actual changing demand. In addition, most models do not adequately consider the performance characteristics of the ESS, such as the effect of the number of ESS charges and discharges on the battery capacity. This results in the inability to accurately assess the economics of the ESS model and output the optimal configuration. The key contributions of this study, when compared to the current literature, can be summed up as follows:

1. Based on the premise of two-part tariff, this paper predicts the future electricity consumption load of customers by LSTM. It also analyzes the performance of LSTM models under different training times according to MAE, MAPE and RMSE evaluation metrics.
2. Economic analysis is conducted for the cost and benefit model of customer-side ESS, considering the savings benefits of energy tariffs and basic tariffs. It evaluates the full life-cycle annualized cost of ESS and the impact of ESS capacity degradation on economics. It also constructs an ESS evaluation model with the goal of minimizing the comprehensive annual cost to the user.
3. The particle swarm optimization (PSO) algorithm is introduced to solve the ESS evaluation model and its performance is analyzed by the number of iterations of PSO. Using the electricity load data of a commercial and industrial customer in Beijing as an arithmetic example, the economic evaluation analysis after the participation of the smart power sales strategy in this paper is verified.

Section 2 describes the LSTM-based load prediction method. Section 3 proposes an ESS evaluation model that integrates the energy tariff saving benefit, basic tariff saving benefit, ESS investment cost, ESS decay equivalence function, and ESS penalty function. Section 4 describes the smart power sales strategy based on load forecasting and optimal allocation of ESS participation. Section 5 uses an industrial and commercial customer in Beijing, China, as an arithmetic example to verify the economics of the smart power sales strategy proposed in this paper. It also proposes different smart power sales strategies according to different expected cost recovery cycles of customers and it also compares the superiority of this smart power sales strategy with the general strategy. The work is finally summarized in Section 6.

2. Customer Power Load Forecasting Model

Considering the problem of large initial investment and the need for a long business time to recover the cost of the user configuration ESS, in this paper, we analyze the historical load data of industrial and commercial customers to forecast their loads. It is possible to more accurately evaluate the economics of a smart power sales strategy for the full life cycle of ESS and to output more accurate declared maximum demand values and storage charge and discharge commands to assist users in making energy storage investment decisions in specific scenarios to create economic returns.

2.1. Principles of Artificial Neural Networks for LSTM

LSTM is a type of temporal recurrent neural network. It is widely used because it can solve the long-term dependence problem of general recurrent neural network (RNN) [30] and can compensate for the shortcomings of RNN gradient descent. Its memory unit structure is shown in Figure 1.

In the figure: f_t is the output of the forget gate; i_t is the output of the input gate; o_t is the output of the output gate; h_{t-1}, h_t are the previous output and the current output; c_{t-1}, c_t are the state before and after the update; $\widetilde{c_t}$ is the content after the update.

As shown in Figure 1, each neural network layer of the LSTM model uses forget gate, input gate and output gate to protect and control the information. The memory cell is used to store the status information at a certain moment. The forgetting gate consists of the current moment input and the previous moment output. The sigmoid function output and the state memory cell output at the previous moment together determine what needs to be forgotten in the current state memory cell. The input gate combines current input and previous output, uses sigmoid and tanh functions to generate new information and potentially needed information. The product of this, together with the forgotten content in the current state memory cell generated by the forget gate, generates the complete state memory cell at the current time. This means that the current state cell has forgotten the historical information that needs to be forgotten and retains the new information. The forget gate and input gate together form the current state memory cell, which compared with RNN, will not result in a decrease in the perception of past historical information. In the output gate, the input at the current time and the output from the previous time are used with a sigmoid function and the state memory cell that has already passed through the tanh function to determine the current output gate status. In this paper, the LSTM model for power load forecasting is based on univariate power load forecasting, where the input variable is a single column matrix.

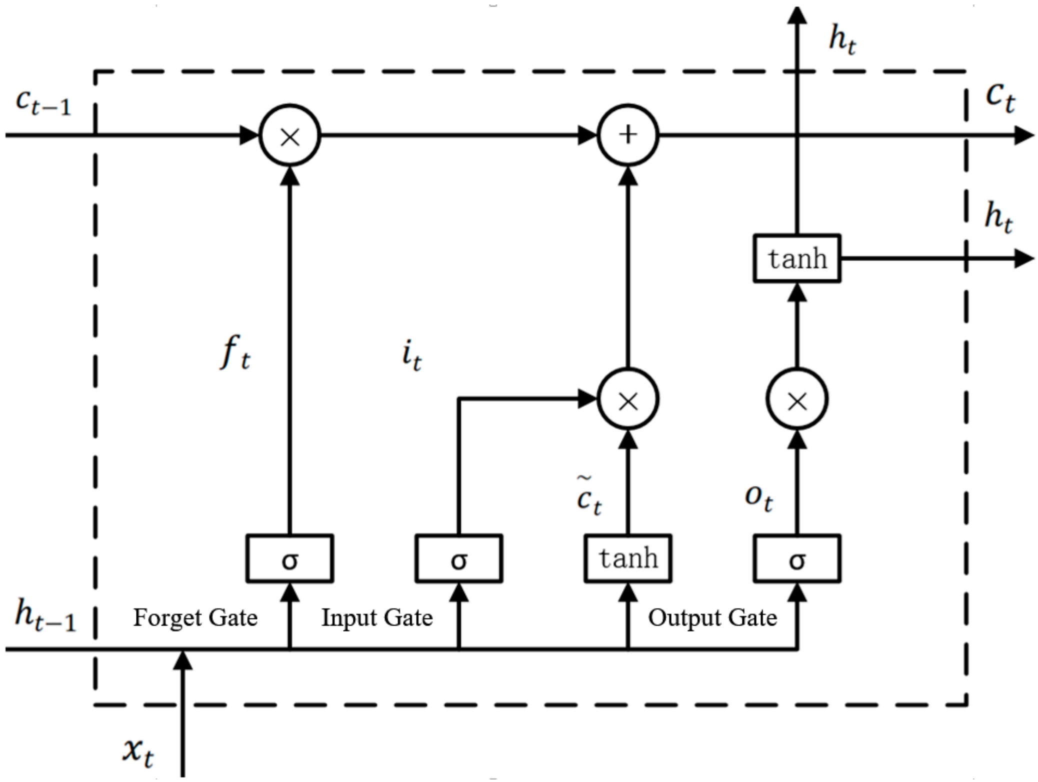

Figure 1. Memory unit structure of LSTM.

2.2. LSTM Model

The calculation of the forgetting gate layer is shown in Equation (1), the calculation of the input gate layer is shown in Equations (2)–(4), and the calculation of the output gate layer is shown in Equations (5) and (6).

$$f_t = \sigma(W_\mathrm{f}[h_{t-1}, x_t] + b_\mathrm{f}), \tag{1}$$

$$i_t = \sigma(W_\mathrm{i}[h_{t-1}, x_t] + b_\mathrm{i}), \tag{2}$$

$$\widetilde{c_t} = tanh(W_\mathrm{c}[h_{t-1}, x_t] + b_\mathrm{c}), \tag{3}$$

$$c_t = f_t c_{t-1} + i_t \widetilde{c}_t, \tag{4}$$

$$o_t = \sigma(W_\mathrm{o}[h_{t-1}, x_t] + b_\mathrm{o}), \tag{5}$$

$$h_t = \sigma_t tanhc_t, \tag{6}$$

where W_f, W_i, W_c, W_o are the weight matrices of the LSTM; b_f, b_i, b_c, b_o are the biases of the LSTM; σ is the sigmoid activation function.

3. Energy Storage Evaluation Model

3.1. Objective Function

The ESS evaluation model is established by considering the energy tariffs and basic tariffs saved by users after adding ESS, the annualized investment cost of ESS, and the ESS power penalty constraint. This can be expressed specifically as follows:

$$maxF_1 = C_{\mathrm{BE}} + C_{\mathrm{EC}}, \tag{7}$$

$$minF_2 = C_{\mathrm{sys\_y}} + B_{\mathrm{FD}} + B_{\mathrm{LSM}}, \tag{8}$$

$$minF = min(F_2 - F_1), \tag{9}$$

where F_1 is the comprehensive revenue of the ESS; C_{BE} is the basic tariffs savings benefit from configuring ESS; C_{EC} is the electricity saving benefit of the electricity bill; F_2 is the integrated cost of the ESS; C_{sys} is the annualized ESS investment cost; B_{FD} considers the discounted cost of the reduction in battery capacity over the remaining life of the battery by its characteristics; B_{LSM} is the ESS power penalty constraint.

3.1.1. Energy Tariffs Saving Benefit

The revenue from the user's electricity bill is mainly derived from the peak-to-valley arbitrage of the user's electricity after the participation of energy storage in the intelligent sale of electricity. The formula for calculating the customer's annual energy tariffs savings benefit is as follows:

$$C_{EC} = \sum_{j=1}^{T_{\mathrm{mon}}} \sum_{i=1}^{T_{\mathrm{day}}} \int_0^T \left[\left(\eta_{\mathrm{c}} \cdot p_{\mathrm{bc}}^{i,j}(t) - \frac{1}{\eta_{\mathrm{d}}} \cdot p_{\mathrm{bd}}^{i,j}(t) \right) \cdot e_p^{i,j}(t) \right] dt, \tag{10}$$

where T_{mon} is the number of months of energy storage operation; T_{day} is the number of days in the declared demand month; T is the number of daily sampling loads; $p_{\mathrm{bc}}^{i,j}(t)$, $p_{\mathrm{bd}}^{i,j}(t)$ are the values of the charging and discharging power of the ESS at moment t on day j of month i, kW; $e_{\mathrm{p}}^{i,j}(t)$ is the price of electricity at moment t on day j of month i, CNY/kWh; η_{c}, η_{d} are the ESS and discharging efficiency, %.

3.1.2. Basic Tariffs Saving Benefits

According to the current regulations in China, customers are required to report the maximum demand value to the grid enterprise. The basic tariffs amount is charged according to the declared value, and the basic tariffs for the part exceeding 105% of the declared value is doubled.

Therefore, the optimal configuration of the ESS can reasonably reduce the basic tariffs by reducing the maximum customer demand through the ESS storing energy during the low peak period of electricity consumption and generating during the peak period of electricity consumption. According to the demand billing rules, the annual savings in basic tariffs can be expressed as:

$$C_{\mathrm{BE}} = \sum_{i=1}^{T_{\mathrm{mon}}} \left[S_{\mathrm{BE}}(i) - S'_{\mathrm{BE}}(i) \right], \tag{11}$$

$$S = \begin{cases} c_{\mathrm{d}} P_{\mathrm{NM}} & P_{\mathrm{AC}} \leqslant P_{\mathrm{NM}} \\ c_{\mathrm{d}} P_{\mathrm{AC}} & P_{\mathrm{NM}} < P_{\mathrm{AC}} \leqslant 1.05 P_{\mathrm{NM}} \\ c_{\mathrm{d}}(2P_{\mathrm{AC}} - 1.05 P_{\mathrm{NM}}) & P_{\mathrm{AC}} > 1.05 \mathrm{P}_{\mathrm{NM}} \end{cases}, \tag{12}$$

where $S'_{\mathrm{BE}}(i)$, $S_{\mathrm{BE}}(i)$ are the base electricity charges for the i th month before and after the energy storage participation, respectively, CNY/kW·month; S is the customer's basic tariffs, CNY/kW·month; P_{NM} is the maximum demand value declared by the user, kW·month; P_{AC} is the actual maximum demand value, kW·month.

3.1.3. ESS Investment Cost

The investment cost of ESS can be generally divided into the equipment cost of battery body and power conversion system (PCS), the engineering cost of installing ESS and its supporting devices, and the subsequent operation and maintenance cost of ESS. The investment cost of the energy storage system can be expressed as:

$$C_{\mathrm{sys}} = C_{\mathrm{eq}} + C_{\mathrm{wb}} + C_{\mathrm{ope}}, \tag{13}$$

where C_{sys} is the comprehensive investment cost of the ESS; C_{eq} equipment cost of the battery body and PCS; C_{wb} is the engineering cost of installing ESS and its supporting devices; C_{ope} is the operation and maintenance cost of the ESS.

To simplify the calculation processing consideration, the cost of the battery body is proportional to the capacity of the ESS, the PCS cost is proportional to the rated power of ESS, and the operation and maintenance cost and engineering cost are proportional to the capacity of ESS.

Setting the ESS to operate with a full life cycle of N_{y} years and setting a discount rate of r%, the annualized battery energy storage investment cost can be expressed as:

$$C_{\mathrm{sys\_y}} = \left[\left(\frac{c_{\mathrm{E}}}{\eta} + c_{\mathrm{W}} + c_{\mathrm{O}}\right)E_{\mathrm{r}} + c_{\mathrm{P}}P_{\mathrm{r}}\right]\frac{r(1+r)^{N_{\mathrm{y}}}}{(1+r)^{N_{\mathrm{y}}} - 1}, \tag{14}$$

where c_{E} is the cost factor of battery body per unit capacity; η is the charge/discharge conversion efficiency of the ESS, %; c_{W} is the engineering cost factor for installing ESS and its supporting devices per unit capacity; c_{O} is the cost factor for the annual operation and maintenance of the ESS per unit capacity; E_{r} is the rated capacity of the ESS, kWh; c_{P} is the cost factor of PCS per unit of power; P_{r} is the rated power of the ESS, kW; N_{y} is the operating cycle of the ESS project, in years.

3.1.4. Battery Decay Equivalence Function

The charging and discharging working condition of ESS will increase its capacity decay, which in turn brings down the economic return of ESS. Equating the ESS capacity loss function to the annualized cost of the ESS, it can be expressed as:

$$B_{\mathrm{FD}} = \frac{1}{2}\left(N_{\mathrm{y}} - 1\right)\left[E_{\mathrm{pv}}^{i,j} + (N-1)\cdot E_{\mathrm{ps}}^{i,j}\right]C_{\mathrm{FD}}, \tag{15}$$

where $E_{\mathrm{pv}}^{i,j}$, $E_{\mathrm{ps}}^{i,j}$ is the peak-to-valley tariff difference and peak-to-shoulder tariff difference on the j th day of the i th month; N is the set number of daily cycles of the energy storage system; C_{FD} ESS capacity decay amount.

The depth of discharge (DOD) and the number of cycles are the main factors affecting the amount of ESS capacity decay. At a certain maximum DOD, the capacity decay of the ESS is approximately proportional to its set number of daily cycles. Therefore, considering the simplified computational treatment, it can be expressed as follows:

$$C_{\mathrm{FD}} = \frac{S_{\mathrm{s}} - S_{\mathrm{e}}}{2dod}\cdot\frac{D}{M_{\mathrm{c}}}\cdot\sum_{i=1}^{T_{\mathrm{mon}}}\sum_{j=1}^{T_{\mathrm{day}}}\int_0^T\left(\eta\cdot\left|p_{\mathrm{b}}^{i,j}(t)\right|dt\right), \tag{16}$$

where S_{s}, S_{e} are the capacity of ESS before and after decay, respectively, in kWh; dod is the depth of discharge of ESS, %; M_{c} is the number of cycles of the whole life cycle of ESS, times; D is the number of days of ESS operation in the year.

3.1.5. ESS Penalty Function

When ESS is connected to the distribution grid, its objectives are demand control and peak-to-valley arbitrage. Without additional constraints, the charging and discharging action of the ESS will be uncertain. Therefore, the randomness of the ESS power action should be limited here as a constraint to reduce the impact of power fluctuations on the grid system. Converting constraints into penalty terms for constrained optimization problems, converting from constrained optimization problems to solving unconstrained optimization problems, and constructing penalty functions. Constructing the function by least squares, it can be expressed as:

$$B_{\mathrm{LSM}} = \frac{1}{2} \cdot \beta \cdot \sum_{i=1}^{T_{\mathrm{mon}}} \sum_{j=1}^{T_{\mathrm{day}}} \int_0^T (p_{\mathrm{b}}^{i,j}(t) \cdot B \cdot p_{\mathrm{b}}^{i,j}\left(t\right)^T\Big)\mathrm{d}t, \tag{17}$$

where β is the constraint coefficient; $B \in R^{t \cdot t}$ is the symmetric matrix.

3.2. Binding Conditions

3.2.1. ESS State of Charge (SOC) Constraint

The power constraint of the ESS should be satisfied that its charging and discharging power does not exceed the power limit. In order to improve the normal service life years of ESS and keep it in a suitable operating environment, the SOC of ESS needs to be constrained. It can be expressed as:

$$S_{\min} \leqslant S^{i,j}(t) \leqslant S_{\max}, \tag{18}$$

where $S^{i,j}(t)$ is the SOC at moment t on day j of month i of ESS; $S_{\min}$ is the lower limit of SOC; $S_{\max}$ is the upper limit of the SOC.

3.2.2. ESS Charge/Discharge State Constraint

To ensure the service life of the ESS, the ESS is set to be charged and discharged for N cycles per day. In addition, to make the ESS cycle in the same SOC at 0:00 and 24:00 every day, the ESS charge and discharge state is constrained. It can be expressed as:

$$\sum_{\mathrm{t}=0}^{\mathrm{T}} \eta \cdot p_{\mathrm{b}}^{i,j}(t) = 0 \quad j \in T_{\mathrm{day}}, i \in T_{\mathrm{mon}}, \tag{19}$$

$$\sum_{\mathrm{t}=0}^{\mathrm{T}} \eta \cdot \left|p_{\mathrm{b}}^{i,j}(t)\right| \leqslant 2 \cdot N \cdot dod \cdot E_r \quad j \in T_{\mathrm{day}}, i \in T_{\mathrm{mon}}, \tag{20}$$

3.2.3. ESS Power Constraint

The ESS operating state charging and discharging power under the rated power constraint can be expressed as:

$$|P_{\mathrm{b}}(t)| \leqslant P_{\mathrm{r}} \quad \forall t \in T, \tag{21}$$

where $P_{\mathrm{b}}(t)$ is the ESS charging and discharging power for any time t.

3.2.4. Load Peak and Valley Constraints

In order to avoid the formation of new load spikes by ESS guided by peak and valley tariffs difference, the charging and discharging power of ESS leads to backward power delivery or exceeds the control demand. The power control constraint for the load power after the ESS participation with the grid can be expressed as:

$$p_{\mathrm{b}}^{ij}(t) + p_{\mathrm{l}}^{ij}(t) = p_{\mathrm{n}}^{i,j}(t) \quad t \in T, j \in T_{\mathrm{day}}, i \in T_{\mathrm{mon}}, \tag{22}$$

$$P_n^{i,j}(t) \geqslant P_{min} \quad t \in T, j \in T_{\mathrm{day}}, i \in T_{\mathrm{mon}}, \tag{23}$$

$$P_n^{i,j}(t) \leqslant P_{NM}(i) \quad t \in T, j \in T_{\text{day}}, i \in T_{\text{mon}}, \tag{24}$$

where $p_{\text{b}}^{i,j}(t)$ are the operating power values of the ESS at moment t on day j of month i, kW; $P_n^{i,j}(t)$, $p_1^{ij}(t)$ is the load power before and after the user adds ESS at moment t on day j of month i, kW; $P_{NM}(i)$ is the declared maximum demand value to be requested by the user in month i, kW·month.

4. Smart Power Sales Strategy

4.1. PSO Algorithm Solving Model

On the basis of completing the construction of the energy storage evaluation model, the model was solved using a PSO algorithm [31].

The initialized particle population moves within the region of the optimal solution and gradually approaches the limit by continuously adjusting its speed and position according to its distance from the extreme value of the individual and the extreme value of the population. On this basis, the extreme value of the individual is the best population fitness that can be obtained by searching within the range of a particular optimal solution. In addition, the extremum of the population means that almost all individual particles in a particular population or population system can be searched within its most efficient solution, thus obtaining a better population fitness.

Assume that a population is in some J-dimensional solution space and the population $x = (x_1, x_2, \ldots, x_n)$ consists of n particles. The spatial relative spatial position of each particle i in the D-dimensional solution space group can be represented by the vector $x_{IJ} = (x_{1J}, x_{2J}, \ldots, x_{3J})^{\text{T}}$, $I = 1, 2, \ldots, n$. By finding the objective function of each particle, the value of the adaptation degree of each particle x_{IJ} is found.

The velocity and position of the particle keep changing as the number of iterations increases, and the update formula can be expressed as:

$$v_{IJ}^{K+1} = \omega v_{IJ}^{K} + c_1 r_1 \left(p_{IJ}^{K} - x_{IJ}^{K}\right) + c_2 r_2 \left(g_{IJ}^{K} - x_{IJ}^{K}\right), \tag{25}$$

$$x_{IJ}^{K+1} = x_{IJ}^{K} + v_{IJ}^{K+1}, \tag{26}$$

where K is the number of iterative behaviors occurring; v_{IJ}^{K} is the training velocity of the Kth iteration particle swarm algorithm; ω is the inertia weight of velocity; $c_1$is the individual learning factor; c_2 is the social learning factor; r is the polar coordinate; p_{IJ}^{K} is the Kth iteration particle I individual polar in space coordinate; g_{IJ}^{K} is the population polar in space coordinate; x_{IJ}^{K} is the position where the K th iteration particle is located; J is the dimension of the particle in space.

The Equation (25) for the particle velocity contains three random components. The first component $\omega \cdot v_{IJ}^{K}$ denotes the initial velocity of the particle, and as the parameter ω increases, the particle the initial velocity also increases. The second component $c_1 r_1 \left(p_{IJ}^{K} - x_{IJ}^{K}\right)$ represents the current optimal fitness of each particle and is optimized for each particle. If the Ith particle finds a better solution than the others, extreme value of the individual p_{IJ}^{K} is updated. The third component $c_2 r_2 \left(g_{IJ}^{K} - x_{IJ}^{K}\right)$ represents the best fitness value among all particles, the extreme value of each particle is saved, and the superiority and inferiority of each particle g_{IJ}^{K} is compared.

The optimal value of the energy storage assessment model is iterated according to the above equation. A globally optimal particle solution is obtained after the iteration, and this solution is taken as the optimal solution of the energy storage assessment model.

4.2. Smart Power Sales Process

The smart power sales strategy designed in this paper is based on the pre-acquisition of electricity load data from commercial and industrial customers. This section analyzes their forecasts and evaluates the projected electricity savings for commercial and industrial customers after retrofitting ESS.

In the evaluation phase of the smart power sales strategy, the first step is to determine whether the customer's load characteristics have the potential to save money and whether it is suitable to add ESS. The optimal ESS capacity configuration is output for users suitable for retrofitting based on the optimal solution solved by the PSO algorithm in Section 4.1. At the stage of optimizing ESS charging and discharging, monthly ESS charging and discharging scheduling instructions are formulated for users based on the load forecast results of the month in which the user declares the maximum demand value and the optimal ESS capacity configuration. The maximum demand value is reported to the grid enterprise based on the load optimized by the smart power sales strategy. The specific optimization process is shown in Figure 2.

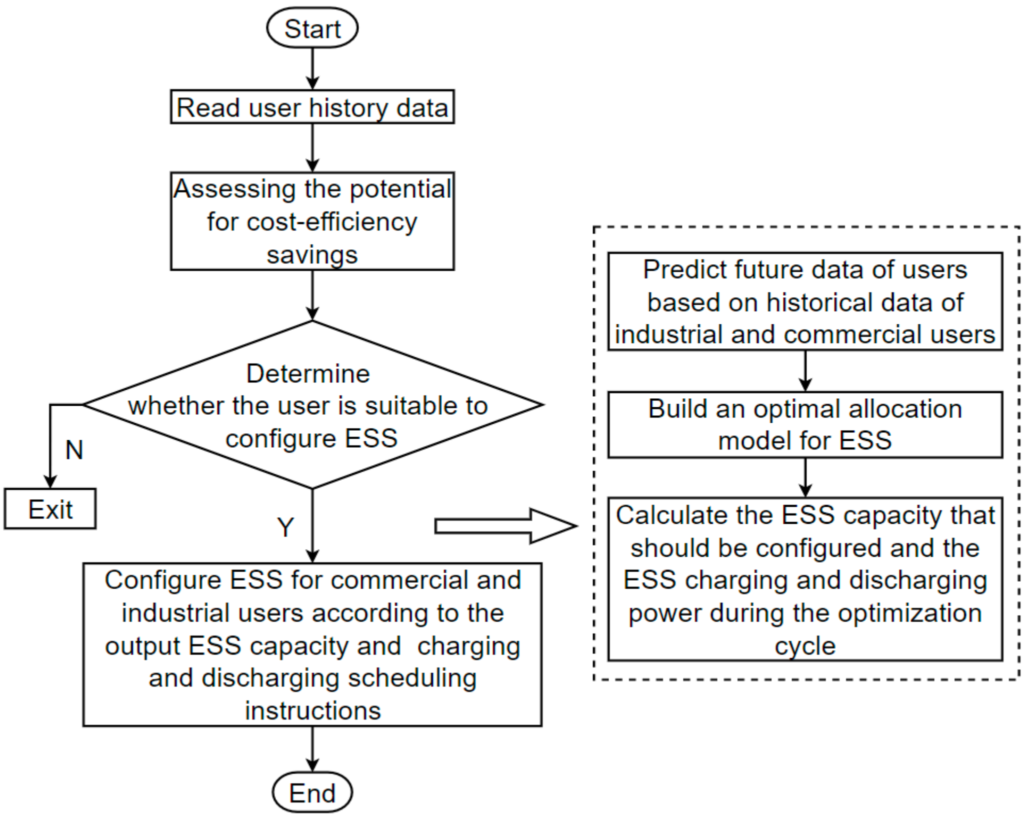

Figure 2. Smart power sales process.

4.3. The Benefit for the Energy Provider

For customers, this smart power sales strategy can effectively reduce their electricity costs and increase their revenue. For energy providers, the benefits of this smart sales strategy can be seen in the following areas [32]:

1. This smart power sales strategy can attract consumer attention and increase sales. Especially for customers with high electricity consumption, lower electricity costs are often one of the main deciding factors for consumers when shopping for an energy provider.
2. This smart power sales strategy can help brands to better promote their products and increase their market share. It also enables consumers to have more access to the products.

3. This smart power sales strategy can counteract the growth in sales of competing branded products and reduce customer interest in competitive products. In addition, by promoting consumers to buy in large quantities or in advance, to capture market share and combat competitors.
4. This smart power sales strategy can generate a certain advertising effect for energy provider, creating an image of quality products at low prices and attracting similar consumers to buy them.
5. Users have a certain payback period after adding ESS, which can be a long-term trading contract between users and energy provider to form a stable existing consumer base.

5. Case Study

In this paper, the electricity load of an industrial and commercial customer in Beijing, China, is selected as an example for calculation. We begin by applying the forecasting model in Section 2.2 for load forecasting based on the customer's historical electricity load data and apply the method in Section 2.1 to construct the objective function. The capacity of ESS is optimally configured to determine the charging and discharging power of the ESS and the maximum demand value reported by the user to the grid enterprise. The return on investment from the participation of ESS in the smart power sales strategy is predicted using the expected maximum fee saving benefit of the whole life cycle ESS as the main criterion.

Because lithium iron phosphate battery is widely used, the cost is low, so it is selected as the type of ESS battery. Lithium iron phosphate battery charge and discharge is not greater than 0.5 C. The upper and lower limits of the operating SOC of the ESS are set to 10% and 100%. The basic parameters of the energy storage system are shown in Table 1.

Table 1. Relevant parameters of energy storage system.

Lithium Iron Phosphate Battery Parameters	Value
Maximum DOD (%)	90
Maximum number of cycles (times)	3500
ESS unit capacity cost (CNY·kWh^{-1})	1600
PCS unit power cost (CNY·kW^{-1})	600
ESS charge/discharge conversion efficiency (%)	95
Discount rate (%)	0.08

The basic tariff of demand-based metering for this commercial and industrial customer tariff is CNY 48 /kWh, and the time-of-use electricity price is shown in Figure 3.

5.1. Load Forecasting

Based on the LSTM prediction method mentioned in Section 2.2, load prediction is performed by reading and analyzing this customer's historical load data, as shown in Figure 4.

The smart power sales strategy is able to solve the ESS configuration and the ESS charging and discharging power for different loads of different customers. In the paper, a representative power consumption curve of one day is selected in this prediction result for analyzing the ESS configuration, as shown in Figure 5.

According to the test results in Table 2, MAE, MAPE and RMSE gradually increase after 400 training steps, which means that overfitting starts to occur at 500 training steps. Therefore, the number of training steps in the LSTM model should be 400.

5.2. Optimal Allocation of ESS

As can be seen from Figures 4 and 5, the peak electricity consumption of this customer occurs during the daytime, and a lower electricity consumption load is used to maintain basic operation at night. Secondly, the load of this customer shows obvious cyclical characteristics. Combined with the load characteristics of such diurnal load with large peak-to-valley differences, it is concluded that the customer is suitable for retrofitting ESS with good economics and can apply smart power sales strategy.

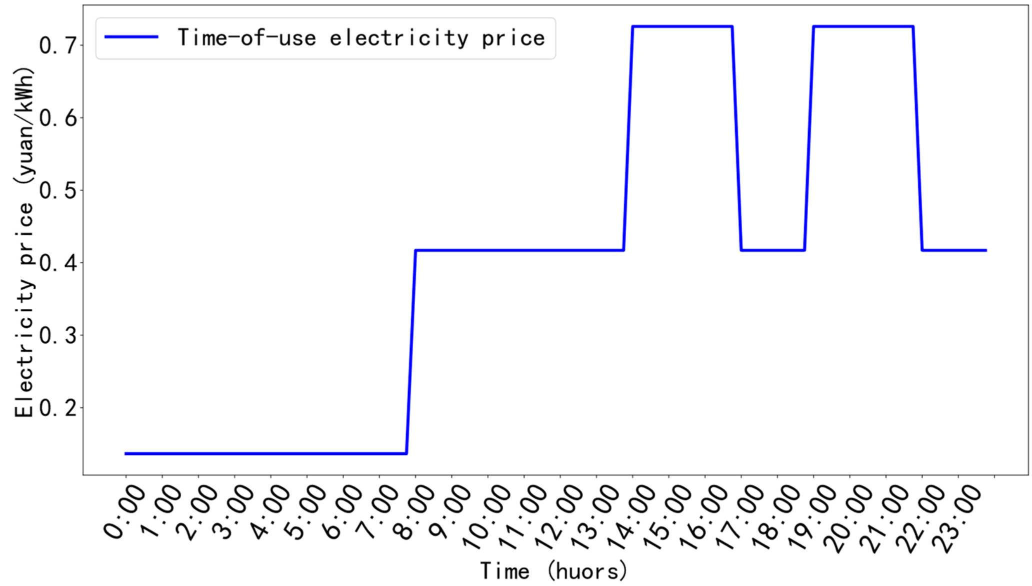

Figure 3. Time-of-use electricity price curve.

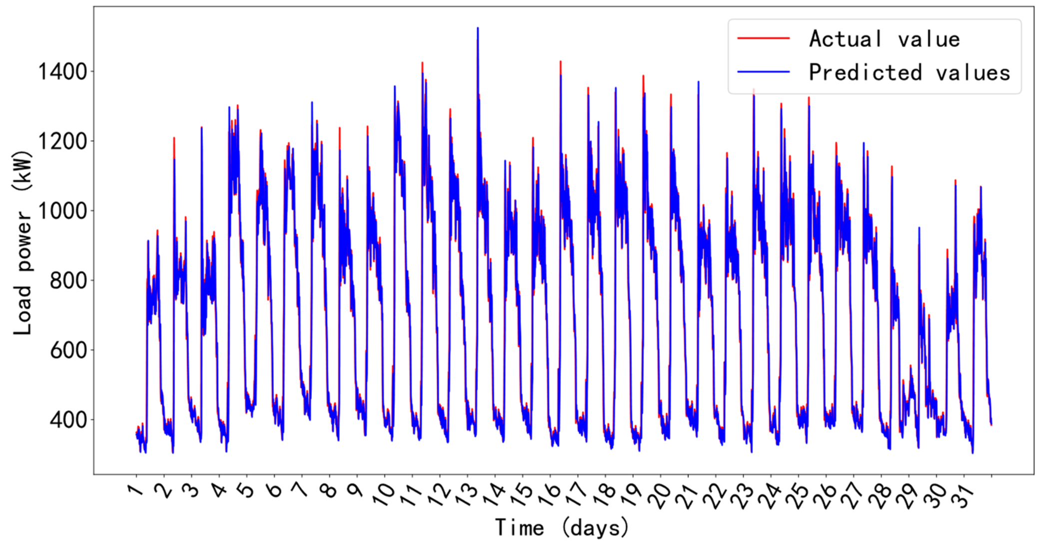

Figure 4. Monthly load forecasting results.

Table 2. Comparison of training times test results.

Training Times	MAE (KW)	RMSE (KW)	MAPE (%)
100	30.239	33.687	2.717
200	28.866	31.475	2.366
300	28.003	30.361	2.247
400	27.774	29.792	2.154
500	27.956	30.432	2.239
600	28.637	31.539	2.216
700	29.396	31.997	2.413

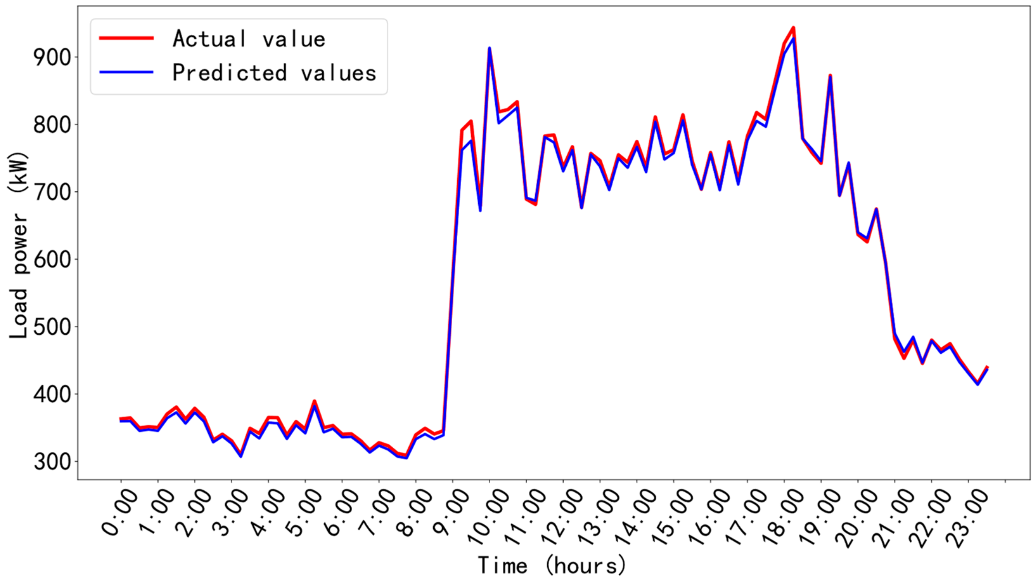

Figure 5. Typical daily load forecasting results.

In this paper, the capacity configuration of the ESS is solved using the PSO algorithm in Section 3.1 by combining the predicted load power of this customer with the objective function in Section 2.1 and setting different number of daily cycles. The results of the solution are shown in Table 3.

Table 3. Results of optimized configuration of ESS.

Daily Cycle Limit (Times)	1	1.5	2
Optimal rated capacity of ESS (kWh)	2400	1600	897
Optimal power rating of ESS (kW)	300	293	256
Initial investment cost of ESS (CNY million)	4.0721	31,905	18,437
ESS full life cycle annualized revenue (CNY million)	0.5546	0.4754	0.3565
Expected payback period (years)	7.34	6.71	5.17
ESS operating life (years)	20	14	10
Return on Investment (ROI) (%)	172.39	108.61	93.36

As shown in Table 3, this customer can recover the investment cost within the ESS life cycle after applying the smart power sales strategy. Over the full working life of the ESS, the user can realize more than 90% return on investment.

In addition, as the number of ESS charging and discharging cycles set for a single day changes, the configured value of ESS capacity and power decreases as the number of cycles decreases, and the total revenue and ROI of the project decreases. However, this can also reduce the ESS investment cost and shorten the expected payback time. Therefore, for customers who want a low investment and fast payback, the smart power sales strategy will recommend a single-day, multi-cycle configuration.

From Figure 6, it can be seen that the particle swarm algorithm converges to the global optimum after more than 200 iterations when calculating the annualized income over the full life of the ESS. The maximum annualized revenue of ESS over its full life cycle is calculated to be CNY 55,467.

In order to more visually illustrate the impact of ESS configuration capacity on the customer's revenue, the integrated cost of electricity consumption and the trend change of total expected revenue over the whole lifetime of this customer under different ESS configuration capacities were calculated separately, as shown in Figure 6.

As shown in Figure 7, the trend of the combined cost and total expected benefits over the whole life of this customer can be seen in the analysis of different ESS configuration capacities. The rated capacity of ESS and the combined cost to the user tend to decrease first and then increase, while the expected benefit to the user is the opposite. This is mainly because after the rated capacity of ESS increases to a certain value, the rate of growth of the monthly basic and electricity tariff savings benefits are limited by the customer load and cannot continue to grow. Meanwhile, the growth of ESS cost is not limited, so it results in the situation that the comprehensive cost to users first falls and then rises, and the expected revenue first rises and then falls. It can be seen that the best economy of adding energy storage for users is when the capacity of ESS configuration is 2400 kWh.

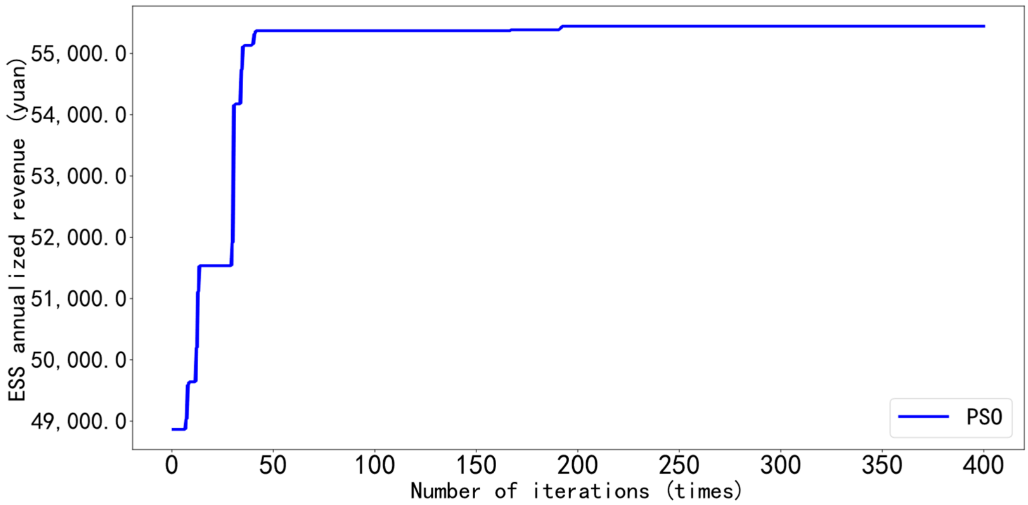

Figure 6. PSO to calculate the annualized return iteration results.

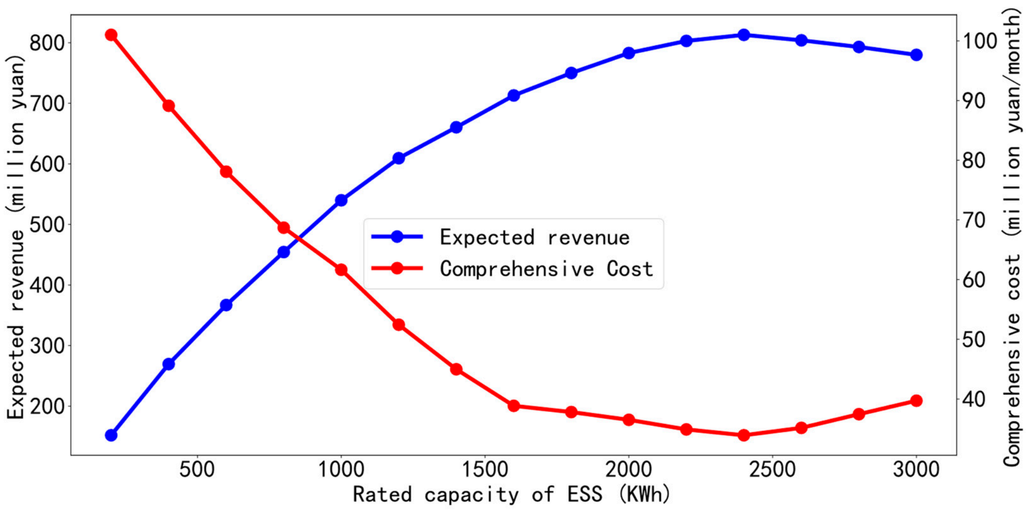

Figure 7. Impact of energy storage configuration on user income.

The load curves before and after the smart power sales for this customer are shown in Figure 8, which shows results under the guidance of ESS charging and discharging obtained from the smart power sales strategy, charging during low tariff periods and generating electricity during high tariff periods according to the time-of-use electricity price. At the same time, the maximum customer demand is reduced by reducing the customer demand and smoothing the load curve to maximize customer benefits. The ESS in a typical day's operation is shown in Figure 9.

5.3. Smart Power Sales Strategy

According to Figure 10, it can be seen that the declared maximum demand of this smart power sales strategy is not significantly different from the actual maximum demand based on the load forecast. Only one of these months had an actual maximum demand that exceeded the declared demand and did not exceed 105%, resulting in no additional base electricity costs. However, the declared demand without load forecasting is significantly different from the actual demand. In four months, the actual maximum demand exceeded 105% of the declared demand, and in five months the actual maximum demand was much less than the declared demand, causing customers to incur additional basic tariffs.

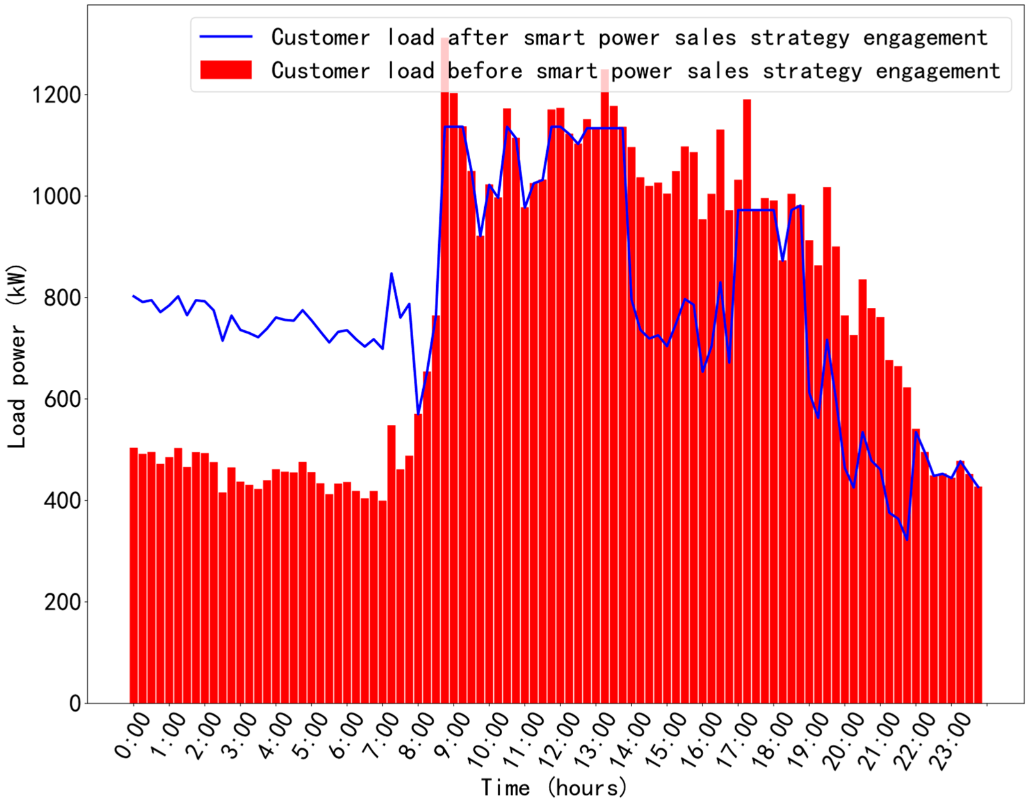

Figure 8. User load before and after a typical daily ESS configuration.

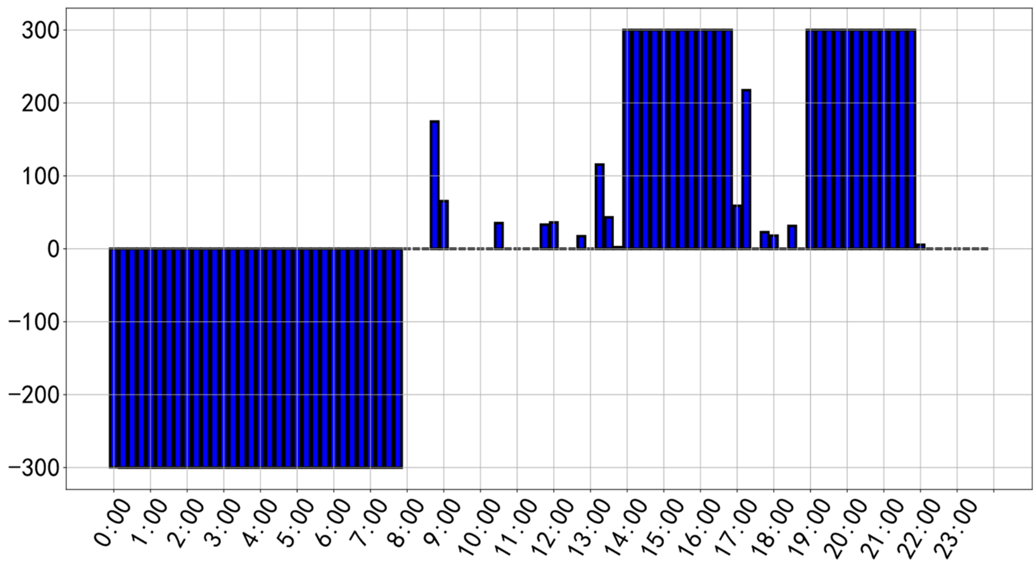

Figure 9. Typical daily energy storage charging and discharging power.

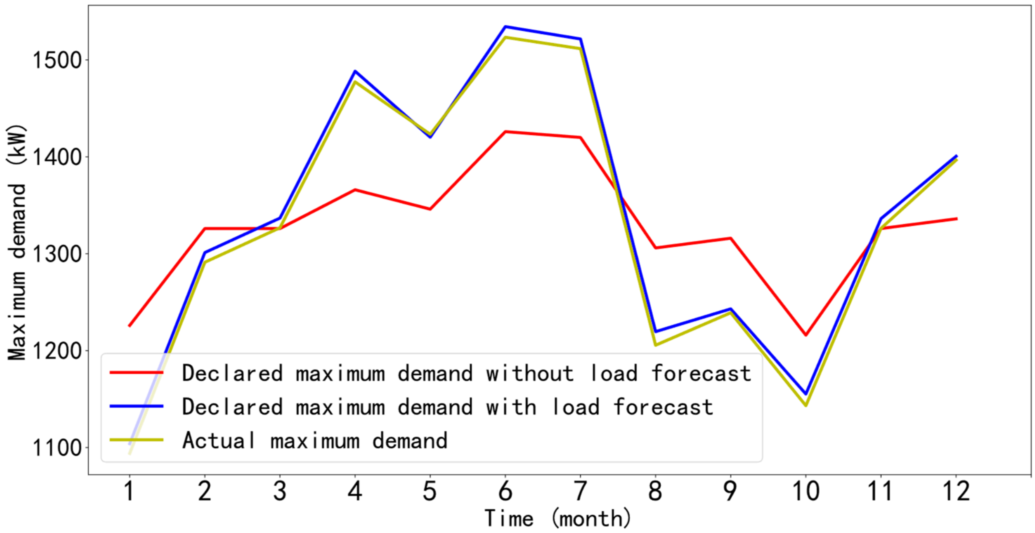

Figure 10. Change curve of declared demand with and without load forecast.

In summary, it can be seen that the annual base cost of electricity for customers under the no-load forecast would result in an additional cost of CNY 0.4176 million. Compared with this, the smart power sales strategy proposed in this paper does not generate additional basic tariffs, and the demand arbitrage of basic tariffs is 58.75% higher. Finally, with the objective of minimizing the combined annual cost to the customer, the typical monthly results of the smart power sales strategy optimization, based on the results in Section 4.3, are shown in Table 4.

Table 4. Optimization results of smart power selling strategy.

Smart Power Sales Strategy Output Results	Value
Optimal rated capacity of ESS (kWh)	2400
Optimal power rating of ESS (kW)	300
Annualized revenue over the whole life cycle of the ESS (CNY million)	0.5546
Expected payback period (years)	7.34
Declared maximum demand (kW)	1356.61
Demand arbitrage (CNY·month^{-1})	8437
Peak-valley arbitrage (CNY·month^{-1})	37,793
Total monthly revenue (CNY·month^{-1})	46,230
Return on Investment (ROI) (%)	172.39

According to the output result of the smart power sales strategy, the ESS scheduling instruction for the declared demand month is output for this industrial and commercial customer, and the ESS charging and discharging power is shown in Figure 11.

In summary, there is a significant reduction in the overall cost of electricity for customers under this smart electricity sales strategy compared to traditional electricity sales strategies. This makes it more likely that customers will choose to use the smart sales strategy to increase their revenue. For the electricity sales company, the smart sales strategy can attract consumers' attention and increase sales. It can also help brands to better promote their products, capture market share and combat competitors. Moreover, there is a certain payback period for customers to add energy storage systems, which can be a long-term contract between the customer and the power sales company, creating a stable existing consumer base.

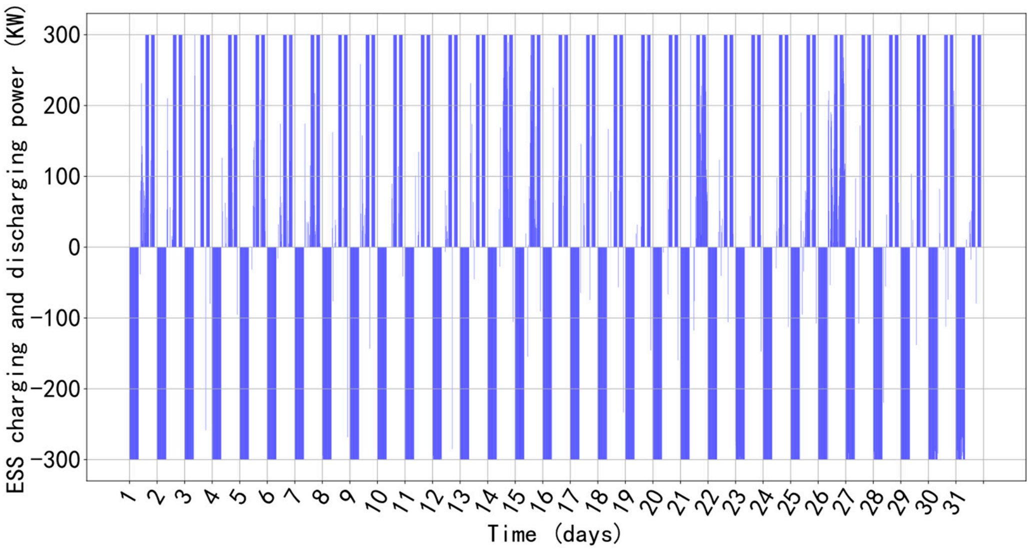

Figure 11. Monthly ESS charging and discharging power.

6. Conclusions

In this paper, we propose an intelligent power sales strategy for optimal allocation of energy storage based on load forecast data, which is mainly as follows.

Firstly, the historical load power data of industrial and commercial customers is used as the basis for load forecasting by LSTM for the future months when customers are about to declare their maximum demand. Secondly, an ESS evaluation model that integrates ESS equipment, installation and O&M costs, and ESS capacity decay costs to improve the combined benefits of peak-to-valley tariff arbitrage and lower base tariffs is established. The PSO algorithm is introduced for solving the model. The results of the algorithm show that with the use of load forecast-based energy storage participation in smart power sales strategy, the difference between the user′s declared maximum demand value and the actual maximum demand is not large, which improves the user′s benefit. Finally, the smart power sales strategy outputs a series of optimized configurations that deliver a high ROI for the customer throughout the life cycle of the energy storage system. This strategy provides the power sales company with the ability to attract consumer attention, increase sales, capture market share and stabilize existing consumer base.

However, the load forecasting approach adopted in this smart power sales strategy does not consider the impact of load characteristics on the forecasting results. In addition, reducing the cost of electricity to the customer will reduce the revenue that the power sales company receives from that customer. Therefore, the next research in this study focuses on the uncertainty of different characteristic loads in the forecasting process to further improve this smart power sales strategy as well as finding a balance between reducing the cost for customers and the revenue for the power sales company.

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Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to the user load data in this article is suspected to be commercially confidential.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Chakraborty, M.R.; Dawn, S.; Saha, P.K.; Basu, J.B.; Ustun, T.S. A Comparative Review on Energy Storage Systems and Their Application in Deregulated Systems. *Batteries* **2022**, *8*, 124. [CrossRef]
2. Han, K.B.; Jung, J.; Kang, B.O. Real-Time Load Variability Control Using Energy Storage System for Demand-Side Management in South Korea. *Energies* **2021**, *14*, 6292. [CrossRef]
3. Ullah, H.; Khan, M.; Hussain, I.; Ullah, I.; Uthansakul, P.; Khan, N. An Optimal Energy Management System for University Campus Using the Hybrid Firefly Lion Algorithm (FLA). *Energies* **2021**, *14*, 6028. [CrossRef]
4. Kim, S.S.; Lee, W.; Bhang, B.G.; Choi, J.H.; Lee, S.H.; Woo, S.C.; Nam, W.J.; Ahn, H.K. Return of Interest Planning for Photovoltaics Connected with Energy Storage System by Considering Maximum Power Demand. *Appl. Sci.* **2020**, *10*, 786. [CrossRef]
5. Han, H.; Luo, J.; Zhao, S. Research on the Optimal Scheduling Strategy of Energy Storage Plants for Peak-shaving and Valley-filling. *J. Phys. Conf. Ser.* **2022**, *2306*, 012013. [CrossRef]
6. Usman, R.; Mirzania, P.; Alnaser, S.W.; Hart, P.; Long, C. Systematic Review of Demand-Side Management Strategies in Power Systems of Developed and Developing Countries. *Energies* **2022**, *15*, 7858. [CrossRef]
7. Castellucci, V.; Wallberg, A.; Flygare, C. Potential of Load Shifting in a Parking Garage with Electric Vehicle Chargers, Local Energy Production and Storage. *World Electr. Veh. J.* **2022**, *13*, 166. [CrossRef]
8. Jeong, H.C.; Jung, J.; Kang, B.O. Development of Operational Strategies of Energy Storage System Using Classification of Customer Load Profiles under Time-of-Use Tariffs in South Korea. *Energies* **2020**, *13*, 1723. [CrossRef]
9. Ji, Y.; Hou, X.; Kou, L.; Wu, M.; Zhang, Y.; Xiong, X.; Ding, B.; Xue, P.; Li, J.; Xiang, Y. Cost–Benefit Analysis of Energy Storage in Distribution Networks. *Energies* **2019**, *12*, 3363. [CrossRef]
10. Tagayi, R.K.; Kim, J. Binary-phase service battery energy storage system strategy for peak demand shaving and enhanced power quality. *Sustain. Energy Technol. Assess.* **2022**, *52*, 102328. [CrossRef]
11. Ebrahimi, A.; Ziabasharhagh, M. Introducing a novel control algorithm and scheduling procedure for optimal operation of energy storage systems. *Energy* **2022**, *252*, 123991. [CrossRef]
12. Rana, M.M.; Atef, M.; Sarkar, M.R.; Uddin, M.; Shafiullah, G.M. A review on peak load shaving in microgrid—Potential benefits, challenges, and future trend. *Energies* **2022**, *15*, 2278. [CrossRef]
13. Rocha, A.V.; Maia, T.A.C. Improving the Battery Energy Storage System Performance in Peak Load Shaving Applications. *Energies* **2023**, *16*, 382. [CrossRef]
14. Kuźniak, R.; Pawelec, A.; Bartosik, A.; Pawełczyk, M. Determination of the Electricity Storage Power and Capacity for Cooperation with the Microgrid Implementing the Peak Shaving Strategy in Selected Industrial Enterprises. *Energies* **2022**, *15*, 4793. [CrossRef]
15. Feng, J.; Zhou, H. Bi-Level Optimal Capacity Planning of Load-Side Electric Energy Storage Using an Emission-Considered Carbon Incentive Mechanism. *Energies* **2022**, *15*, 4592. [CrossRef]
16. Moradzadeh, A.; Zakeri, S.; Shoaran, M.; Mohammadi-Ivatloo, B.; Mohammadi, F. Short-term load forecasting of microgrid via hybrid support vector regression and long short-term memory algorithms. *Sustainability* **2020**, *12*, 7076. [CrossRef]
17. Pramono, S.H.; Rohmatillah, M.; Maulana, E.; Hasanah, R.N.; Hario, F. Deep learning-based short-term load forecasting for supporting demand response program in hybrid energy system. *Energies* **2019**, *12*, 3359. [CrossRef]
18. Niu, D.; Wang, Y.; Wu, D.D. Power load forecasting using support vector machine and ant colony optimization. *Expert Syst. Appl.* **2010**, *37*, 2531–2539. [CrossRef]
19. Fan, G.F.; Guo, Y.H.; Zheng, J.M.; Hong, W.C. Application of the weighted k-nearest neighbor algorithm for short-term load forecasting. *Energies* **2019**, *12*, 916. [CrossRef]
20. Hochreiter, S.; Schmidhuber, J. Long short-term memory. *Neural Comput.* **1997**, *9*, 1735–1780. [CrossRef]
21. Zhang, C.; Jiang, J.; Gao, Y.; Zhang, W.; Liu, Q.; Hu, X. Charging optimization in lithium-ion batteries based on temperature rise and charge time. *Appl. Energy* **2017**, *194*, 569–577. [CrossRef]
22. Hassan, A.S.; Cipcigan, L.; Jenkins, N. Optimal battery storage operation for PV systems with tariff incentives. *Appl. Energy* **2017**, *203*, 422–441. [CrossRef]
23. Lo, C.H.; Anderson, M.D. Economic dispatch and optimal sizing of battery energy storage systems in utility load-leveling operations. *IEEE Trans. Energy Convers.* **1999**, *14*, 824–829. [CrossRef]
24. Dayu, C.; Lizi, Z.; Liguo, W. Control strategy of energy storage system for frequency regulation and evaluation of investment income. *Mod. Electr. Power* **2016**, *33*, 80–86.
25. Mu, Q.; Gao, Y.; Yang, Y.; Liang, H. Design of power supply package for electricity sales companies considering user side energy storage configuration. *Energies* **2019**, *12*, 3219. [CrossRef]
26. Yang, J.; Huang, Y.; Fei, F.; Guo, M.; Pang, A. Research of economic benefits of energy storage technique under different business operational modes. *Electr. Eng.* **2018**, *19*, 80–84.
27. Xiu, X.Q.; Tang, W.; Li, J.L. Comprehensive evaluation technology of energy storage configuration based on analytic hierarchy process. *Autom. Electr. Power Syst.* **2018**, *42*, 72–78.
28. Gao, F.; Song, X.; Zhang, Y.; Li, Y.; Li, J. Optimal configuration of industrial user-side energy storage considering power demand income in life cycle. In Proceedings of the 2021 China International Conference on Electricity Distribution (CICED), Shanghai, China, 7–9 April 2021; IEEE: Piscataway, NJ, USA, 2021; pp. 768–774.
29. Song, Y.; He, K.; Shi, J.; Ke, H. Study on economic evaluation model of user-side energy storage scheme based on cost analysis. *Electr. Appl. Energy Effic. Manag. Technol.* **2020**, *6*, 86–90.

30. Hossain, M.S.; Mahmood, H. Short-term load forecasting using an LSTM neural network. In Proceedings of the 2020 IEEE Power and Energy Conference at Illinois (PECI), Champaign, IL, USA, 27–28 February 2020; IEEE: Piscataway, NJ, USA, 2020; pp. 1–6.
31. Ren, X.; Li, T.G.; Ma, J.Y.; Huang, Y.H.; Zhang, D.L.; Wu, Y.J. Optimal allocation of hybrid energy storage capacity in PV micro-grid considering SOC. *Electr. Meas. Instrum.* **2021**, 1–8. Available online: https://kns.cnki.net/kcms/detail/23.1202.TH.20210419.1341.008.html (accessed on 4 April 2023). (In Chinese)
32. Da Costa VB, F.; de Doile GN, D.; Troiano, G.; Dias, B.H.; Bonatto, B.D.; Soares, T.; de Freitas Filho, W. Electricity Markets in the Context of Distributed Energy Resources and Demand Response Programs: Main Developments and Challenges Based on a Systematic Literature Review. *Energies* **2022**, *15*, 7784. [CrossRef]

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