Research on Optimization Methods for User-Side Energy Storage Configuration in New Power Systems

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Abstract. The global economy is steadily rising, and the power industry is rapidly developing, leading to a significant increase in global electricity consumption. However, the difference between peak and off-peak electricity demand is becoming more pronounced, causing an imbalance in the supply-demand relationship. Therefore, new solutions are urgently needed. This paper proposes an optimization model for user-side energy storage allocation that considers multiple revenue streams. The model takes into account the full life cycle cost income of user-side energy storage, along with different auxiliary revenue streams. Using an optimization algorithm, we calculate the net lifetime income of a major industrial user and optimize the capacity allocation for user-side energy storage in the Nanjing energy storage service market. Finally, we compare various service types and provide optimal investment recommendations.

Keywords: User-side energy storage; requirements management; demand response; energy storage optimization; Energy storage configuration

1 Introduction

Energy is an important support for social development, how to improve energy utilization efficiency, reduce energy consumption costs and optimize energy structure has become a common challenge for the world. Energy storage technology, as a technology that can store energy and release it when needed, can improve energy utilization and solve the problem of grid instability, so it has attracted much attention. In recent years, with the continuous development and application of energy storage technology, the scope of its application in power systems has been gradually expanding, mainly in frequency regulation, voltage regulation and peak and valley reduction. At the same time, the policy support and the introduction of peak-to-valley tariff provide a larger optimization space for the evaluation of energy storage economics.

The economic evaluation of energy storage technology is an important prerequisite for its application and promotion. At present, the economic evaluation of energy storage technology is mainly considered in terms of grid participation in auxiliary services, peak-valley arbitrage and energy storage incentive policies to ensure the operational benefits of energy storage[1]. However, the existing research on peak and valley reduction with energy storage technology is mostly conducted on the generation side,

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while there is little research on the installation of energy storage components on the user side. The research on the application of user-side energy storage technology is mainly focused on the application of peak-to-valley tariff peak shaving and valley filling, which effectively alleviates the tension of grid peaking and frequency regulation and enhances the stability of the grid. In addition, the application of energy storage technology in power systems also includes improving power supply reliability, emergency power supply, demand response and improving power quality[2].

This paper reviews the current status of the economic evaluation of energy storage technology, discusses the application of energy storage technology in power systems and its economic benefits, and conducts an in-depth study on the optimal configuration, dispatching and investment economic evaluation of customer-side energy storage, and proposes an efficient energy storage configuration and operation scheme. In addition, this paper also proposes future research directions and priorities for the economic evaluation of energy storage technology, combining relevant research results at home and abroad[3], in order to provide theoretical support and practical guidance for the application and promotion of energy storage technology.

2 User load curve selection

User load curve analysis is an important foundation for providing personalized services in the power system. It can be used to extract typical load curves, perform user clustering analysis, and provide a basis for short-term load forecasting and time-of-use pricing. By processing and analyzing grid load data, typical load curves for each user can be obtained, and similar users can be grouped together to uncover different electricity usage characteristics[4]. Choosing appropriate user load data is key to optimizing models, with commonly used methods including monthly peak-day method, weighted average method, mean method, and clustering algorithm. These methods provide different choices and can be selected based on actual situations. In this study, data obtained from four different user load extraction methods were compared with actual user load data from August 2020 in Nanjing (maximum load: 2425 kW) to select the typical curve with the lowest deviation. The monthly peak-day method had significant numerical fluctuations and differed greatly from the curves obtained by the other three methods. The monthly peak-day method selects the typical day with the highest load in the month as the analysis object and uses its load curve as the curve for the entire month, making it easier to calculate and obtain results. The curves obtained by the other three methods are more stable as they use mathematical analysis to merge data. By comparing the three curves, it was found that the fuzzy C-means clustering algorithm can better reflect load fluctuations. In addition, strategies for reducing electricity costs in cost-cutting analysis include time-of-use pricing reductions, two-part pricing reductions, demand response profits, and emergency power supply profits. The data obtained by the monthly peak-day method was closest to the original data and is more suitable for actual use of user load.

3 Energy Storage Configuration and Operation Optimization

This paper adopts an optimal configuration model to achieve the optimal configuration of energy storage systems, with the objective of maximizing the net profit over the system's lifetime and taking into account the constraints imposed by various policies.

Objective Function: The user-side energy storage optimization configuration model is constructed and validated, with the target function established as the net profit over the energy storage system's lifetime, including peak shaving profit, demand management profit, demand response profit, emergency power supply profit, as well as the initial investment and operating and maintenance costs. The objective function can be expressed as $\boldsymbol{max\,F_1 = f_1 + f_2 + f_3 + f_4 - C_{inv} - C_{ope}}$, where $\boldsymbol{F_1}$represents the net profit over the lifetime of the energy storage system, $\boldsymbol{f_1}$ to $\boldsymbol{f_4}$represent the various components of the revenue, and $\boldsymbol{C_{inv}}$ and $\boldsymbol{C_{ope}}$ represent the initial investment and operating and maintenance costs, respectively.

Constraints: The user's energy storage revenue is subject to different constraints under different circumstances, mainly including three types of constraints. The first type is the energy storage constraints, including the state of charge, power, continuity of charge state, maximum demand, charge/discharge status, and charge/discharge constraints. Translation: The second type of constraint is related to demand response. When users participate in demand response, they need to meet the maximum load during the response period, and the average load is used as a constraint. Specifically, the maximum load of the baseline cannot be less than the load during the response period, and the difference between the average load during the response period and the average baseline load must be greater than or equal to 0.8 times the agreed response power reported by the user. This is expressed as $\boldsymbol{max(P_{load,j+t_0} + P_{ch,j+t_0} - P_{dis,j+t_0}) \leq maxmax\,P^{d_0}_{load,j+t_0}}$; $\boldsymbol{mean(P_{load,j+t_0} + P_{ch,j+t_0} - P_{dis,j+t_0}) - meanmean\left(P^{d_0}_{load,j+t_0}\right) \geq 0.8P_{DSM,P}}$ .In the above equations, $\boldsymbol{t_0}$=0,1,2,3,4,5,6,7 represents the time period involved in the user's demand response process, and$\boldsymbol{d_0}$ is the response baseline calculated within 5 days prior to the demand response day. Specifically, $\boldsymbol{d_0 = d_{DSM} - 5}$, $\boldsymbol{d_{DSM} - 4}$, $\boldsymbol{d_{DSM} - 3}$, $\boldsymbol{d_{DSM} - 2}$, $\boldsymbol{d_{DSM} - 1}$, where $\boldsymbol{d_{DSM}}$ represents the typical day for demand response. Therefore, during the demand response period, if the difference between the average load and the average response day load exceeds 0.8 times the declared demand response capability, and the maximum response day load is lower than the maximum baseline, the effective demand response multiple can be considered. The third type of constraint is related to power supply, which ensures that the reported power by the user does not exceed the working power of the energy storage system. This is expressed as $\boldsymbol{-P \leq P_{EMS,q} \leq P}$.

4 User-Side Energy Storage Configuration and Operation Optimization

For large power consumers, electricity costs account for a significant portion of their operating costs. Therefore, energy storage can adopt a "low storage, high discharge" strategy to reduce the maximum monthly electricity load and further reduce electricity costs without changing user behavior[5]. The objective of user-side energy storage is simple and its influencing factors are fewer, which is beneficial for energy storage operations. Hence, we aim to establish an optimization configuration model to achieve the optimal load. First, we set clear constraints on the battery's state, and then based on the load data selected in Chapter 2, we establish a pre-optimization model and an intra-day rolling optimization model. The intra-day rolling optimization model is a real-time process that continuously updates data, enabling user-side energy storage to obtain more economic benefits.

4.1 User-Side Energy Storage Optimization Configuration Model

Based on the most suitable user load curve and energy storage optimization configuration mentioned in the previous section, we have established a monthly optimization model. Due to the uncertainty of load forecasting and electricity prices in demand response, we have also established a real-time rolling optimization model.

In the process of computing optimization configuration, we have adopted a basic electricity cost of 40 yuan per kW and a time-of-use electricity price policy. The energy storage system we used is a lithium iron phosphate battery with a charge/discharge efficiency of 0.9, a maximum charge ratio of 0.9, and a minimum charge ratio of 0.1. The parameters used in this paper are from the power consumption of an industrial user in Nanjing in August. The electricity cost includes the basic electricity cost and various preferential electricity price policies. The industrial user also enjoys preferential electricity price policies, including a basic electricity cost of 34 yuan per kW and a time-of-use electricity price policy with a price of 0.6261 yuan per kWh during 07:00-23:00 and 0.3131 yuan per kWh during 23:00-07:00. Our optimization goal is to determine the appropriate configuration selection and the monthly demand defense value of demand protection. We have chosen a time interval of 15 minutes for data selection, which provides 96 data points per day.

Monthly Pre-Optimization Model: Based on the energy storage configuration data on the user side mentioned in the previous section, we calculate the monthly demand defense value and optimize the value of $max\, F_{mon}$. The purpose is to reduce the total revenue of demand management and peak-valley arbitrage. During the entire process, reducing the user-side load does not have any usable impact on the optimization maximum value, so we do not consider the revenue generated by demand response. The optimization model can be expressed as follows: $max\, F_{mon} = D_{mon}f_1 + f_2$, where f_1 is the energy storage revenue generated by peak-valley arbitrage in one day, and f_2 is the income from the reduction of basic electricity fees by installing energy storage equipment in a month. Before the month, the constraints of the optimization model are consistent with the constraints of demand management.

Intra-day Rolling Optimization Model: The objective function of the energy storage pre-operation optimization model is generally to minimize the daily electricity bills of users with demand management as a constraint. The specific steps are as follows: $min\,F_{day} = \sum_{i=0}^{95}\left[P_{load,i} + P_{ch,i} - P_{dis,i}\right] P_i \Delta t$, where $P_i$is the time-of-use electricity price, $P_{dis,i}$ is the original load power of the user at time i, and $P_{ch,i}$ is the charge power of the energy storage system at time i. However, due to potential errors in pre-optimization, there may be risks and inaccuracies between the energy storage optimization model and the actual operation results[6]. Therefore, we need to construct an Intra-day Rolling Optimization Model to address these issues. The model is divided into two response models: one when grid invitations are accepted and one when grid invitations are not accepted. The model aims to minimize the loss of energy storage operation and maximize the economic benefits for users. The specific formulas are as follows:

$$min\,F_D = \begin{cases} \sum_{i=0}^{95}\left[P_{load,i} + P_{dis,i} - P_{ch,i}\right] p_i \Delta t, K_{re} = 0 \\ \sum_{i=j}^{j+3} P_{load,i} p_i \Delta t - 30 P_{DSM}, K_{re} = 1 \end{cases}$$

K_{re} represents the status of grid invitations.

4.2 Energy Storage Operation Optimization Algorithm

The energy storage operation optimization algorithm is based on the model built using the YALMIP toolbox in MATLAB software, and solved using the CPLEX solver. The algorithm flowchart is shown in the figure, and the specific steps are as follows:1) Based on the monthly load forecast data, optimize and solve for the daily demand defense value.2) For the response day and time, the daily load data used for optimization is treated as the known actual load data before that hour, and the load forecast data for the next day is used for that hour and subsequent time points. Based on the created Intra-day Optimization Model and the solution to the first-hour constraints, the operating capacity of the energy storage system is obtained, and the order of implementing the energy storage system is given.3) Determine if the user-side energy storage has received an invitation. If the selected invitation is received, the demand response coefficient is set to 1; if no invitation is received, the demand response coefficient is set to 0.4) Determine if the time is over 24. If it exceeds 24, it means that the rolling optimization is completed within one day; if it is less than 24, continue with the rolling optimization model.

4.3 Case Study Analysis

We utilized a deep long short-term memory network for ultra-short-term load forecasting to predict the pre-operational load curve. Based on a year of instantaneous data from a large industrial user in Nanjing, the user data was optimized and analyzed, and the predicted results were discussed. After determining the optimal energy storage configuration, load data from August 2020 in Nanjing was selected with a time interval of 15 minutes, and the user's voltage level was 10kV with a basic electricity fee of 34 yuan per kW.

The energy storage configuration optimization model determined that the energy storage system was limited to a maximum of two cycles per day. For demand response, a subsidy price of 12 yuan per kW was provided for every 1 kW response with a speed coefficient of 1, while the subsidy price for emergency power supply was 22 yuan per kW. Both demand response and emergency power supply response were limited to within 9 times. The optimal energy storage capacity was 550 kW, the optimal charge/discharge power was 255 kW, and the reported response amount for demand response was 210.4 kW.

The rolling optimization curve for a typical day of demand response is shown in Figure 1, and the SOC curve of the energy storage system is shown in Figure 2. It can be clearly seen from the graphs that the peak of the original curve of the energy storage system during the 09:00-12:00 period has been reduced, and the energy storage system is appropriately charged during the 4:00-6:00 and 12:00-16:00 periods. During the pre-set demand response time (13:00-15:00), the energy storage system is discharged to reduce the energy absorbed by the user side and reduce energy loss. According to the load curve shown in Figure1, it can be determined that the maximum load of the user has decreased by 124.1 kW, which satisfies the parameter settings for demand response, further demonstrating the effectiveness of the optimization model. From the typical day load curve of demand response, it can be clearly seen that the optimized load values during the 04:00-07:00 and 12:00-13:00 periods are significantly higher than the optimized load values, while during the 09:00-11:00 and 19:00-20:00 periods, the optimized load values are much lower than the optimized load values. As shown in Figure 1 and Figure 2, 11:00 is the peak electricity consumption time, and the nighttime load is significantly lower than the daytime load. Taking 0:00-24:00 as an example, during the period of 0:00-4:00, corresponding to the low-priced electricity generated during off-peak hours, the energy storage system is charged; during the 9:00-12:00 period, the energy storage system is discharged during the high-priced electricity peak to arbitrage between the peak and off-peak periods; during the 12:00-15:00 period, the energy storage system is charged to participate in the release of stored energy during the subsequent emergency power protection period; during the 19:00-20:00 period, the energy storage system interferes with the emergency power supply and is in a discharge state.

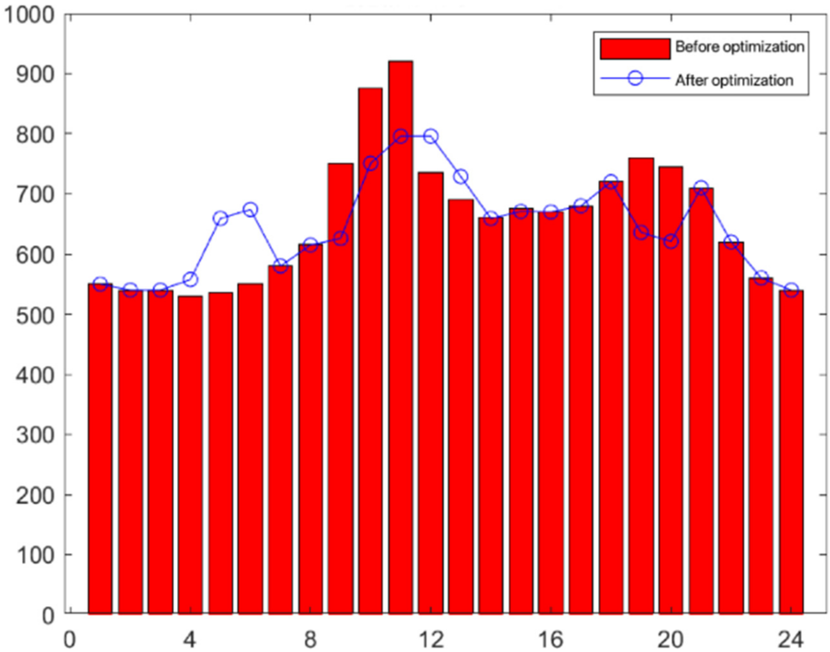

Fig. 1. Typical day load curve for demand response

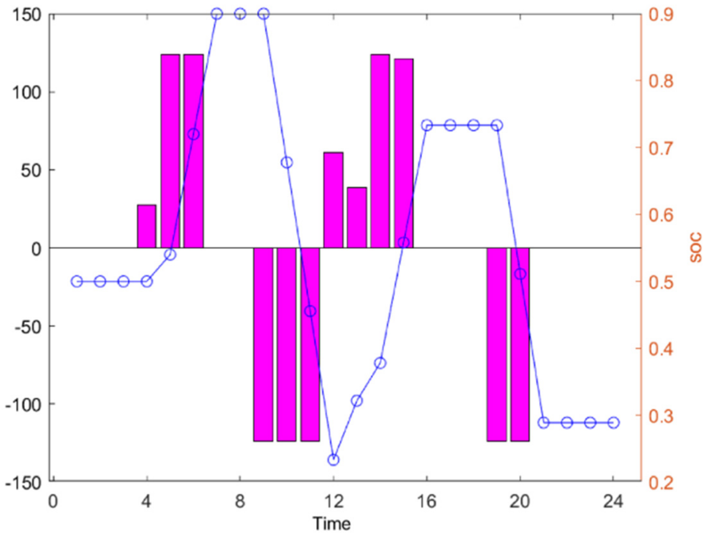

Fig. 2. Energy storage charge and discharge power. SOC curve

As shown in Figure 3, we can see that the peak electricity price occurs during the 08:00-12:00 period, while the off-peak electricity prices occur during the 0:00-06:00 and 23:00-24:00 periods. At the same time, the optimization model for demand response is conducted in real-time on a daily basis, and a comparison with the demand response from the previous month shows significant improvement in economic benefits. Comparing the two optimization models, it can be seen that the total benefits obtained from the demand response optimization for a typical day have increased by 372.53 yuan. Compared with the rolling optimization benefits from the previous day, the monthly benefits of the daily rolling optimization algorithm are 12,302.4 yuan and 9,421.23 yuan, respectively, which is 2,881.17 yuan higher than the previous rolling optimization algorithm. Therefore, we can conclude that the suitable optimization model has been identified.

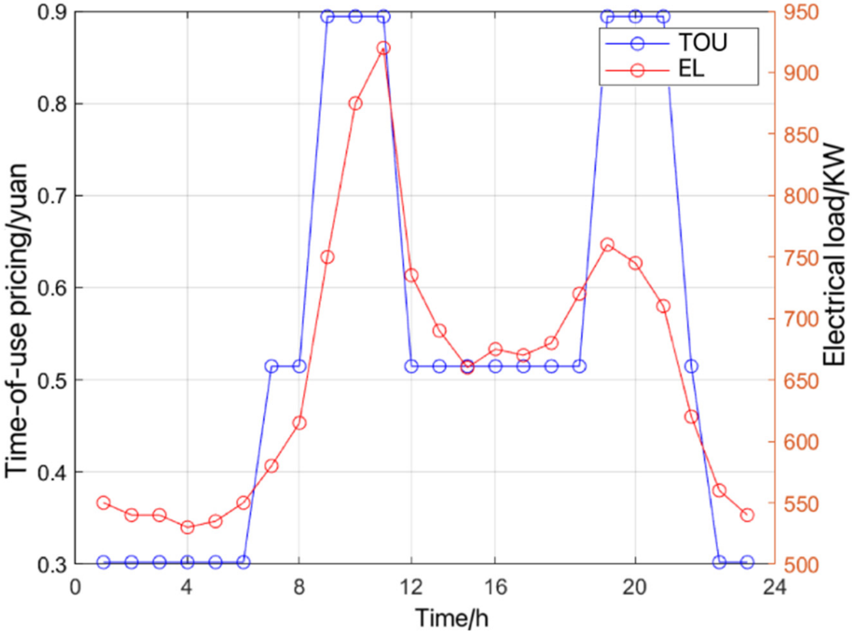

Fig. 3. Time-of-use pricing

5 Conclusion

As the gap between peak and off-peak electricity consumption widens, demand response and energy storage technologies are playing an increasingly important role in the power industry. This study proposes an optimized configuration model for energy storage on the user side, which is based on the extraction method of the user load curve and the revenue model under different service categories. The results show that the proposed method effectively processes data and achieves excellent results in optimizing revenue models and user-side energy storage configurations on typical demand response days. The study also proposes the optimal energy storage strategy of discharging during peak periods and charging during off-peak periods, providing valuable experience and guidance for the sustainable development of the power industry.

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