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ENERGY STORAGE CAPACITY ALLOCATION OF MICROGRIDS WITH WIND AND SOLAR ENERGY BASED ON SOURCE-LOAD MATCHING

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Abstract: Aiming at the problem of source-load imbalance in the microgrid connected to wind and solar energy, this paper proposes an energy storage capacity allocation method based on dynamic correction of source-load matching. Firstly, the source-load matching index of the fusion time series trend similarity and power deviation is constructed to evaluate the correction direction and amplitude of the energy storage capacity of the system. Secondly, a basic model of energy storage configuration with the goal of minimizing the average daily planning cost is established, and the energy storage configuration results are corrected by using the source-load matching degree: the energy storage capacity is increased for the system with poor matching degree to improve stability, and the capacity of the system with good matching degree is reduced to reduce the cost. The example shows that the proposed method can significantly improve the problem of reverse peak shaving and effectively optimize the investment cost.
Keywords: Microgrid; Source-load matching; Wind and solar energy; Capacity allocation

1 INTRODUCTION

The large-scale connection of a high proportion of wind and solar energy has exacerbated the power volatility of the power system, and the rationality of energy storage technology, as a key support means to stabilize fluctuations and improve the consumption capacity of renewable energy, is directly related to the economy and stability of system operation[1]. Specifically, energy storage technology can effectively stabilize the random fluctuations of wind and solar output by storing surplus electricity during peak wind and solar power generation periods and releasing power generation during peak or load peak periods, which can not only effectively stabilize the random fluctuations of wind and solar output, but also alleviate the peak shaving pressure of the power grid, providing a technical guarantee for the stable consumption of renewable energy. Therefore, it is of great significance to scientifically configure energy storage devices in power systems containing new energy: it can not only ensure the safe and efficient grid connection of wind and solar energy, but also fully tap the potential value of wind and solar power generation and promote the transformation of the system to a high proportion of clean energy.

Some studies focus on the analysis of the complementary characteristics of wind and photovoltaics.Ref. [2] establishes a microgrid reliability evaluation model considering wind and solar complementarity, and uses the penetration rate and consumption rate of new energy with optimal capacity as indicators to evaluate complementarity. Quantitatively analyze the effect of complementary wind and solar resources on system reliability. Ref. [3] studied the spatiotemporal and local complementarity of wind and solar power generation on annual, seasonal, and weekly time scales in a given region, and used the bias correction method to identify the impact of deviation on power estimation and the reliability of long-term capacity factor analysis. Ref. [4] analyzes the output of wind power and photovoltaic power from the perspective of seasonal characteristics, and confirms that there is natural complementarity between wind energy and solar energy in time and space, such as strong wind at night and light foot during the day.

Other scholars are concerned about the cost economy of microgrid energy storage. Ref. [5] constructed a microgrid energy storage model with the goal of minimizing the whole life cycle cost, designed a variety of resource combination allocation schemes, and found that grid-connected microgrids including wind, solar, diesel, and storage are the most reliable and cost-effective systems. After analyzing the current situation of wind and solar operation, Ref. [6] takes wind and solar resources, energy storage cost, operating power, etc. as constraints, and solves the energy storage capacity allocation with the maximum net present value and the energy storage power configuration with the minimum difference payback period. Ref. [7] proposed a two-tier low-carbon economic scheduling model that takes into account carbon trading and source-load interaction. The upper level aims to minimize the total cost and carbon emissions of the system to achieve low-carbon and economical operation of the system. The lower layer aims to minimize the fluctuation of the net load of the system, and "peak shaving and valley filling" of the net load curve through source-load interaction to further explore the potential of low-carbon economy and peak shaving and valley filling of the system.

Ref. [8] explores the idea of source-load matching to a certain extent, and proposes a preliminary idea of constructing a source-load matching index based on the Spearman correlation coefficient and Euclidean distance, but does not further deepen the application of this index in energy storage capacity correction, making it difficult to accurately adapt to the dynamic change of source load in energy storage configuration. In summary, the existing research does not pay enough attention to the accurate measurement and application of source-load matching degree in the allocation of energy storage capacity in microgrids. Therefore, this paper proposes an energy storage capacity allocation method that takes into account the matching degree of source and load. Firstly, the K-means algorithm is used to generate typical scenarios that characterize the operating characteristics of the system, and the source-load matching index is constructed based on the change trend of load and wind and solar output to evaluate the adaptability of the initial capacity configuration in each scenario. Secondly, a capacity allocation optimization model with the goal of minimizing daily operating costs is constructed, and the energy storage configuration results are corrected by using the source-load matching degree, aiming to provide theoretical basis and practical guidance for the energy storage capacity planning of microgrid systems

2 MICROGRID OPERATION MODE

A microgrid is a small local power system that can operate independently or in connection with the main power grid, and its core components include distributed power generation, energy storage system, distribution network, power load, and control system [9]. Figure 1 is a typical schematic diagram of the structure of a microgrid, in which the power generation modules are mainly wind and solar power generation systems and a small number of traditional energy units, which provide electrical energy to the system through energy conversion. When the power supply is in a state of surplus, the energy storage system can store the surplus energy, and then release the stored power when the electricity demand reaches the peak and the power supply is tight, so as to effectively achieve system load balance and stability

As the core resource of the distribution network to achieve stable power balance, microgrids need to rely on precise energy regulation to maintain dynamic balance in different operating modes: when the microgrid operates independently and does not exchange power with the main network, the power generation capacity of internal wind power, photovoltaic and other power generation equipment needs to be matched with the load demand in real time, and this balance relationship is mainly maintained by the dynamic charging and discharging of the energy storage system - energy storage absorbs electricity when power generation is excessive, and energy storage releases power when power generation is insufficient to stabilize the volatility of wind and solar output; When the microgrid and the main network are connected and need to supply power to the main network or absorb the main grid power, the system needs to ensure the balance of internal power generation and load base, and flexibly adjust the power exchange according to the needs of the main network such as peak shaving and frequency regulation.

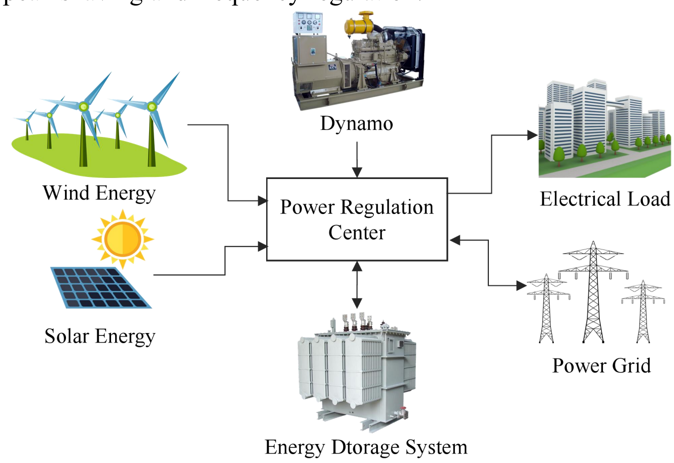

Figure 1 Schematic Diagram of a Typical Microgrid

3 SOURCE-LOAD MATCHING ANALYSIS

3.1 Source-Load Scenario Generation

In order to solve the problem of accuracy degradation caused by the large amount of data in the full-time simulation, the k-means clustering method is selected to extract the typical operating data of wind, light and load in the regional power grid. The k-means clustering algorithm not only has the advantages of simple calculation, rapid convergence, and local optimization, but also has good scalability and efficiency, and the analysis results obtained based on this method can be repeatedly applied after data update [10].

The input of the algorithm is the number of clusters k and the wind and solar load operation dataset containing n objects, the core of which is to determine k clustering centers through iterative calculation, and finally output k clusters when the clustering centers no longer change, each cluster represents a class of typical operation modes of wind and solar charges with similar characteristics. The specific process is as follows: firstly, K initial clustering centers are selected from the historical operation data of wind and solar loads. Then, the distance between all wind and solar load data objects and each initial clustering center is calculated, and each object is assigned to the cluster corresponding to the nearest clustering center. Then, the clustering center is recalculated according to the wind and solar load data in each cluster. The above allocation and update steps are repeated until the clustering center is stable, and the k clusters obtained are the typical running data clusters of wind and solar charges. The specific flow of the k-means clustering algorithm is shown in the figure 2 below

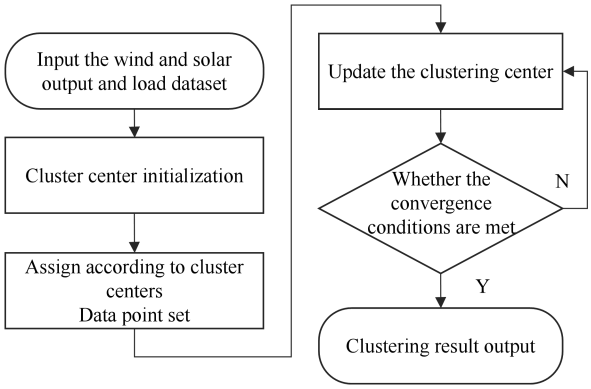

Figure 2 The Process of Clustering by the K-Means Method

3.2 Source-Load Matching Degree Index

In the microgrid with high penetration rate of wind power and photovoltaic, the output of wind power and photovoltaic reflects a certain volatility with the change of time, and the output of wind power and photovoltaic has a certain complementarity, which can suppress the volatility of the sum of wind and solar output to a certain extent. In addition, the load in the system also has a certain fluctuation, and the consistency of wind and solar output and load fluctuation trend can reduce the pressure of system regulation and promote consumption. This source-load matching idea can be applied to the energy storage configuration of microgrids. In order to measure the source-load matching degree in the system, considering the trends of wind power, photovoltaic output curves and daily load curves in the system, the source-load matching index of wind and solar microgrids with wind and solar power grids based on Spearman correlation coefficient and Euclidean distance is established.

（1）Calculate the Spearman correlation coefficient. Spearman correlation coefficient is an index in statistics that uses monotonic equations to evaluate the correlation between two statistical variables, representing the correlation direction of two independent variables, and calculating the rank of each period according to the arbitrary sorting rule according to the data of the endogenous load curve of the day, and substituting the vector dimension to obtain the Spearman correlation coefficient, as shown in the following formula.

$$\rho = 1 - \frac{6\sum_{j=1}^{N} d_j^2}{N(N^2-1)} \tag{1}$$

In the formula, ρ is the correlation coefficient between any two vectors, 6 is the coefficient of the Spearman correlation coefficient standard formula, J is the vector dimension, N is the number of observed samples, and d_j is the difference in rank of the elements in the ascending sequence in the two vectors.

（2）Calculate the Euclidean distance. Input the data of the power grid source-load curve within one day, and the Euclidean distance of the specified location is calculated by the following mathematical formula, and the corresponding set is formed.

$$d_t = \sqrt{\left(x_t - y_t\right)^2} \tag{2}$$

In the formula, x_t and y_t is the position of the two variables in space, d_t is the Euclidean distance between x_t and y_t.

（3）Calculate the source-load matching degree. Since the Spearman rank correlation coefficient only reflects the rank size, when the rank of the variable remains unchanged and the value changes, it will still be judged as the original degree of correlation. The Euclidean distance only considers the distance and ignores the similarity of the figures. Therefore, according to the complementary characteristics of Spearman coefficient and Euclidean distance in measuring similarity, a comprehensive index to determine the degree of matching between communities is proposed according to the weight distribution, and the normalization method is used to eliminate the dimensional difference, and finally the following formula for calculating the degree of source-load matching is obtained

$$\rho_{\text{new}} = \lambda\rho + (\frac{1-\lambda}{24})\sum_{t=1}^{24} \frac{d_t - d_{\min}}{(d_{\max} - d_{\min})} \tag{3}$$

In the formula, ρ_{new} is the new source-load matching degree measurement index, λ is the weight coefficient, $d_{\max}, d_{\min}$ is the maximum and minimum values of the Euclidean distance.

4 OPTIMIZATION MODEL OF ENERGY STORAGE CAPACITY

4.1 Model construction

（1）The objective function is the minimum daily average planning cost, including investment cost, operation and maintenance cost, and source-load matching deviation penalty cost, which can be expressed as the following formula.

$$\min f = f_1 + f_2 + f_3 \tag{4}$$

$$f_1 = \frac{(V_s \times C_1 + P_s \times C_2)}{365} \times \frac{r \times (1+r)^T}{(1+r)^T - 1} \tag{5}$$

$$f_2 = f_1 \times C_3 \tag{6}$$

$$f_3 = \sum_{t=1}^{N} \left| L_t - K_t - S_t \right| \times C_4 \tag{7}$$

In the formula, V_s is the energy storage configuration capacity, P_s is the energy storage configuration power, C_1 is the cost coefficient per unit capacity of the energy storage system, C_2 is the unit power cost coefficient of the energy storage system, C_3 is the maintenance cost coefficient of the day, C_4 is the penalty coefficient for deviation, r is the discount rate, T is the life of the energy storage system, L_t is the load power at the moment of t, K_t is the total output power of wind power and photovoltaic at t moment, S_t is the charging and discharging power of the energy storage system at the moment of t.

（2）The constraints are as follows.

1）The state of charge is limited to the specified range.

$$V_{\min} \le V_t \le V_{\max} \tag{8}$$

$$V_{t+1} = V_t + \delta Q_i^c - \frac{Q_i^d}{\delta} \tag{9}$$

In the formula, $V_{\min}$ and $V_{\max}$ are the upper and lower limits of the energy storage state of charge, respectively.

2) The charging and discharging of the energy storage system cannot be carried out at the same time.

$$Q_t^c \times Q_t^c = 0 \tag{10}$$

3) The state of charge at the beginning and end of a scheduling cycle is equal.

$$\sum_{t=1}^{N} \delta Q_t^c = \sum_{t=1}^{N} \frac{Q_t^d}{\delta} \tag{11}$$

In the formula, δ is the charging and discharging conversion efficiency, Q_t^c and Q_t^d are the charging and discharging amounts in the i period, respectively.

4) The continuous discharge time is within the specified range.

$$H_{\min} \le H = \frac{V_s}{P_s} \le H_{\max} \tag{12}$$

In the formula, H is the continuous discharge time of the energy storage system. $H_{\min}$ and $H_{\max}$ are the minimum and maximum continuous discharge times, respectively.

4.2 Capacity Correction

In the process of solving the above nonlinear programming problem to obtain the initial energy storage capacity, in order to ensure the stable operation of the energy storage system, the energy storage power parameters determined by the existing model are not directly adjusted, but the optimal operating power is readjusted in the system optimization model by modifying the energy storage configuration capacity.

The capacity correction function designed in this paper [11] introduces the linear interpolation method to adjust the correction formula between the two basic segmentation functions to avoid the problem of excessive stepped jump amplitude. Specifically, the matching degree is divided into stable guarantee section, smooth transition section, and economic optimization section (as shown in Table 1), which retains a clear scenario classification logic while alleviating the threshold jump problem and adapts to the scenario requirements of microgrid energy storage capacity correction.

$$V_{new} = V \cdot \begin{cases} (2-\rho_{new}), \rho_{new} \le \varphi - \Delta \\ (2-\rho_{new}) + \dfrac{(\rho_{new}-1)(\rho_{new}-\varphi+\Delta)}{\Delta}, \varphi - \Delta \le \rho_{new} < \varphi + \Delta \\ \rho_{new}, \rho_{new} \ge \varphi + \Delta \end{cases} \tag{13}$$

In the formula, V_{new} is the corrected energy storage capacity, V is the initial energy storage capacity, φ is the discriminant threshold for correction，Δ is a smooth width.

Table 1 Classification of Energy Storage Capacity Correction Stages

stage	range	logic

Stability guarantee stage	$\rho_{new} \ll \varphi$	When the matching degree is low, the capacity is enlarged by a high correction coefficient to ensure the stable operation of the microgrid first.
Smooth transition phase	$\rho_{new} \approx \varphi$	When the matching degree is close to the threshold, the correction coefficient is linearly connected to eliminate the threshold jump.
Economic optimization section	$\rho_{new} \gg \varphi$	When the matching degree is high, the correlation coefficient is used to directly correlate the capacity to control the cost of energy storage construction.

5 EXAMPLE ANALYSIS

5.1 Source-Load Scenario Generation

The object of the case is a microgrid containing a 1000kW wind turbine, a 1000kW photovoltaic unit and a load in a certain place. The K-means clustering algorithm is used to mine the historical operation data of the microgrid, and two representative typical operation scenarios are extracted, and the fluctuations of wind power output and load are shown in the figure 3 below

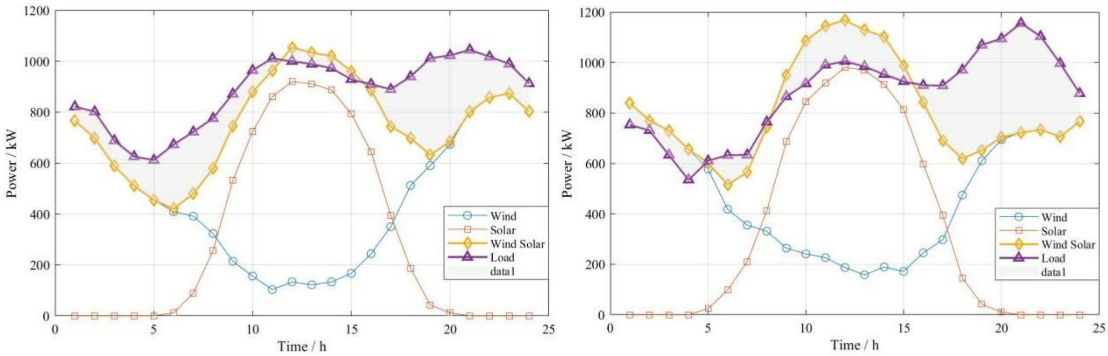

Figure 3 Electrical Load and Wind and Solar Output

For different systems, the Spearman discriminant coefficient ranges are different, and the discriminant coefficient in Comprehensive Reference [11] is 0.45 as the critical threshold for judging the degree of source-load trend matching. According to the calculation of equations (1)-(3), the source-load matching degrees of the two typical scenarios are 0.536 and 0.329, respectively. Among them, the value of scenario 2 is low, indicating that the temporal change trend of total wind and solar output and load in this scenario is poor, and the power deviation in each period is large, and the anti-peak shaving characteristics are prominent. In this case, the system needs to increase the energy storage capacity to enhance the regulation capacity, so as to alleviate the mismatch between wind and solar output fluctuations and load demand, and improve the new energy consumption rate. The matching degree of source and load in scenario 1 meets the basic requirements of stable operation of the system, indicating that the change trend of wind and solar output and load curve in this scenario is consistent in most periods, and the phenomenon of reverse peak shaving basically does not exist. Therefore, the allocation of energy storage capacity can be appropriately reduced, and the investment cost of energy storage can be optimized without affecting the effective consumption of wind and solar resources.

5.2 Simulation Result Analysis

Other relevant information in the example includes cost information, energy storage parameter information and operation parameter information. First of all, in terms of cost, the upper and lower limits of the battery state of charge are 90% and 10% respectively. Regarding the cost parameters, the cost coefficient per unit capacity of lithium batteries in the energy storage system is 1500 Yuan/kWh, the cost coefficient per unit power is 900 Yuan/kWh, the operation and maintenance cost coefficient is 2%, and the penalty coefficient is 0.5 Yuan/kWh. The energy storage system has a design life of 10 years and a discount rate of 5%. Secondly, regarding the technical parameters of energy storage, the charging and discharging efficiency is 90%, the maximum battery state of charge is 90%, the minimum battery state of charge is 10%, and the initial state of charge is 30%~50%. The energy storage discharge price is 0.8 Yuan/kWh, and the charging price is 0.4 Yuan/kWh. Thirdly, regarding the operating parameters, the minimum continuous discharge time is 1h, the maximum continuous discharge time is 4h.

Using MATLAB to solve the nonlinear programming problem in Section 4.1, the initial capacity of Scenario 1 is 243.06kWh and the initial power is 156.00kW. The initial capacity of scenario 2 is 319.50kWh, the initial power is 284.00kW. The setting φ =0.5, Δ =0.05, the corrected capacity configuration of scenario 1 calculated by Equation (13) is 160.26kWh, and the capacity configuration of scenario 2 is 533.88kWh. On the basis of determining the capacity configuration, it is brought back to the model to solve the energy storage operation plan, as shown in the figure 4 below.

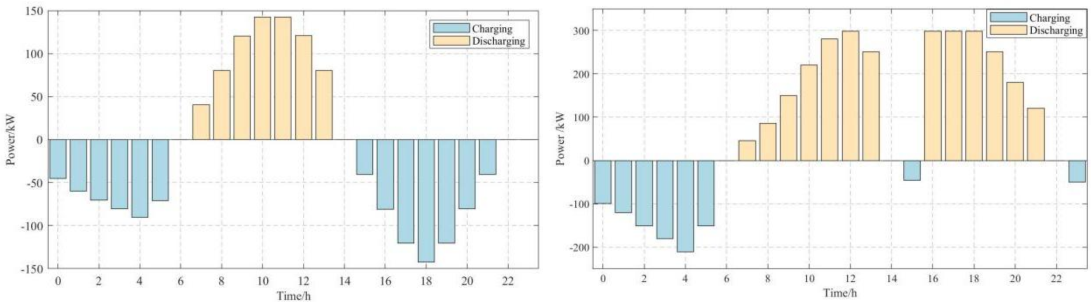

Figure 4 Energy Storage Operation Plan

From the perspective of source-load matching, the significant difference between the energy storage operation mode in scenario 1 and scenario 2 is mainly due to the spatio-temporal mismatch characteristics of wind and solar output curve and load demand curve. In scenario 1, the wind and solar output and load demand show a high synchronization, and energy storage only needs to be regulated by shallow charge and discharge, which reflects a relatively good source-load matching state. In scenario 2, the peak of wind and solar power generation is concentrated at noon, while the peak of load demand lags in the evening, which leads to a significant reduction in the matching degree of source and load of up to 4 hours, forcing the energy storage system to carry out deep charging and discharging to bridge the gap between supply and demand. This phenomenon essentially reveals the contradiction between the volatility of renewable energy and the rigid demand for loads. Therefore, identifying the characteristics of source-load mismatch can optimize the energy storage scheduling strategy, and can also provide a key decision-making basis for energy storage capacity planning, market mechanism design, and collaborative optimization of source-grid-load-storage of high-proportion renewable energy systems.

6 CONCLUSION

This paper proposes a correction optimization method for energy storage configuration based on the source-load matching degree. The core of this method is to deeply integrate the idea of source-load matching into the energy storage configuration of microgrids. By constructing the source-load matching index that fuses the similarity of time series trend and power deviation, and using the K-means algorithm to generate typical scenarios, this method can scientifically evaluate the adaptability of the initial energy storage configuration of the system. On this basis, a basic model of energy storage configuration with the goal of minimizing the average daily planning cost is established, and a capacity correction function is innovatively introduced to dynamically adjust the configuration results according to the source-load matching degree of each scenario. In summary, the method realizes the efficient balance between stability and economy of microgrid energy storage configuration through the accurate evaluation and dynamic correction of the source-load matching degree, and provides a scientific and practical new idea for the optimization of microgrid energy storage configuration.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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