J. COMBIN. MATH. COMBIN. COMPUT. 127a (2025) 4041--4057

Journal of Combinatorial Mathematics and Combinatorial Computing
www.combinatorialpress.com/jcmcc

Research on the application of BP algorithm incorporating GWO in distributed energy storage scheduling optimization

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ABSTRACT

Distributed energy storage technology can effectively solve the load peak-to-valley difference and voltage quality problems faced by distribution networks. Reasonable and efficient scheduling of distributed energy storage in distribution networks is an important means to play its role. The study proposes a power prediction-based optimized scheduling strategy for distributed energy storage in distribution grids with hierarchical zoning. Firstly, power prediction is carried out using GWO-EEMD-BP neural network. Then partition optimization is carried out according to distributed power and load distribution, and the energy storage scheduling strategy is formulated based on the energy storage power prediction interval. Finally, experiments and arithmetic examples are analyzed based on the data related to the distribution system of the IEEE-33 distribution node. The predicted SOC values based on GWO-EEMD-BP neural network are basically consistent with the real SOC values. After applying the energy storage scheduling strategy designed in this paper, the system power loss decreased by 260.86 kW·h and the load volatility decreased by 67.5%. In addition, this strategy has significant advantages in terms of system operation economic efficiency and voltage quality improvement, and it is capable of scheduling distributed energy storage in the distribution network in a reasonable manner.

Keywords: distributed energy storage, GWO algorithm, BP algorithm, dispatch optimization

1. Introduction

Since entering the 21st century, new energy sources have always been developing at an extremely fast rate and high efficiency. China's distributed power (DG) represented by photovoltaic (PV), wind power and hydropower has made a significant breakthrough in the distribution network. However, when distributed power sources are connected to the distribution network, the distribution network often suffers from frequency fluctuations, power back-feeding, degradation of reliability and stability, as well as waste of resources due to the abandonment of new energy sources [1-3]. The fluctuations caused

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Received 05 March 2024; Revised 20 April 2024; Accepted 05 December 2024; Published Online 15 April 2025.
DOI: 10.61091/jcmcc127a-228

by distributed power grid integration cannot be solved under the existing conditions, so it has been necessary to take certain abandonment of new energy output, resulting in resource waste [4-6]. The energy storage system can carry out charging and discharging actions according to the real-time demand of the power grid, reduce the voltage fluctuation of the system, narrow the peak-to-valley difference of the load, and improve the stability of the system operation [7-8].

For the optimal configuration of the energy storage system, it refers to the problem of optimizing the station site, station capacity and distribution line path of the future energy storage power station at the level of distribution network planning, and the requirements to be met include economic factors, capacity constraints, voltage constraints, and other grid operation requirements [9-11]. At the generation side of the grid, the ultimate goal of accessing distributed power sources containing energy storage is to maintain the real-time operational requirements of the grid at a lower cost [12-13]. The analysis of distributed power scheduling and allocation with energy storage is to optimize the scheduling of grid resources by simultaneously changing the distribution network structure in order to limit the power fluctuation of the grid [14-15]. The energy complementary scheduling problem generally does not have an optimal solution, but only a feasible solution set within the range, and the corresponding multi-objective solution is obtained after information screening at a later stage [16-17]. With the development of computer technology and modern information technology, deep learning algorithms are widely used in solving the optimal allocation of energy storage systems.

Literature [18] proposes a real-time optimal scheduling strategy for regenerative power generation based on multi-intelligence deep reinforcement learning (MADRL), which takes into full consideration the uncertain attributes of distributed power sources, such as generation, load, and tariff, and combines with the regional ownership of distributed resources, to achieve the zonal optimization of the active distribution system in an uncertain environment. Literature [19] investigates the detailed linear model of large-scale distribution systems, and proposes a mixed integer linear programming model by linearly modeling the reactive and apparent power flow limits on the basis of a battery system, and the results of the example tests show that the proposed model has high accuracy and efficiency. Literature [20] develops a two-tier optimization model for active distribution systems using robust and dictionary-ordered optimization methods, where the first tier optimizes distributed power scheduling and electrical switching based on the designed optimal offer strategy, while the second tier performs real-time optimal scheduling of the optimized system resources. Literature [21] proposes a load forecasting model for the energy imbalance problem in the distribution network caused by large-scale distributed power supply access, establishes a system model consisting of the distribution network layer and the source-load-storage aggregation groups (SAGs) layer and performs load forecasting optimization, and constructs a two-layer optimization framework for solving the objective model at the same time. Literature [22] shows that a distributed energy storage power (ESS) distribution system can be understood as a multi-period optimal tidal problem, and proposes a methodology and modeling framework applicable to it that is able to account for the uncertainty caused by distributed wind and solar PV generation that is beyond the planning horizon in order to achieve the optimal scheduling task. Literature [23] develops a mathematical model for maintaining the stability of peaking power with distributed battery storage systems and proposes a real-time dispatch peak load shedding algorithm that can be applied to peaking tasks under different conditions and demands. Literature [24] examined the intermittency problem arising in renewable energy distributed distribution networks, connected the battery energy storage system to the distribution network, proposed to establish a global centralized dispatch model with the objective of cost minimization, and solved the problem by using the second-order cone planning method and the large M-method pair.

The study first constructs a power prediction model for distribution networks based on GWO-EEMD-BP neural network. The model is applied to the distribution network distributed energy storage hierarchical zoning optimization scheduling strategy. With the objective of minimizing the transmission power of the contact line, combined with the distributed power output power, the distribution network is operated in zoning. Then, based on the partitioning results, the distributed energy storage layered zoning optimization scheduling strategy is formulated. Finally, the model prediction effect is judged based on the predicted SOC value and relative error value. And the simulation analysis of the implementation effect of the distributed energy storage dispatch optimization strategy incorporating the GWO-EEMD-BP power prediction model is carried out.

2. Distributed energy storage scheduling optimization strategy

In this paper, distributed energy storage system in distribution network is taken as the research object to explore the scheduling optimization method. Optimal scheduling of active power is one of the key technologies of distribution network, using the actual measurement data and power prediction data of each part in the distribution network to find the optimal power allocation scheme of the distribution system under certain optimization objectives and constraints, which helps to realize the safe and stable operation of the distribution network.

2.1. Power prediction model based on GWO-EEMD-BP

This chapter builds a power prediction model based on the GWO algorithm coupled with the EEMD technique and BP neural network algorithm to optimize distributed energy storage scheduling in distribution networks.

2.1.1. EEMD algorithm. EEMD algorithm is proposed on the basis of EMD algorithm, which can effectively solve the EMD algorithm in the signal polar value distribution is not uniform, easy to appear modal chaos.The core of the EEMD is to add the Gaussian white noise in the existing signal and then carry out the EMD decomposition, the introduction of the Gaussian white noise maximally avoids the scale mixing problem.The computational flow of the EEMD is as follows:

1) A Gaussian white noise $e_i(t)$ sequence is added to the original sequence $x(t)$. The new sequence after adding Gaussian white noise is:

$$x_i(t)=x(t)+e_i(t) \tag{1}$$

2) Decompose the new sequence $x_i(t)$ using EMD to obtain k endowment modal components (IMF) $c_j(t)$ and 1 residual component $r_0(t)$.

3) Re-add Gaussian white noise to the original sequence and perform step (2):

$$x_i(t)=\sum_{j=1}^{k} c_j(t)+r_0(t) \tag{2}$$

4) By averaging the calculated IMF components, the IMF components of the original sequence can be expressed by the following equation:

$$c_i(t)=\frac{1}{N}\sum_{i=1}^{N} c_{ij}(t) \tag{3}$$

5) Eventually the original sequence $x(t)$ is decomposed into:

$$x(t)=\sum_{j=1}^{k} c_j(t)+r(t) \tag{4}$$

Where: N is the number of times white noise is added.

2.1.2. BP Neural Network Algorithm. BP neural network technology is a multilayer forward transfer algorithm, based on a large amount of sample information, through iterative training to continuously optimize the computational model in order to achieve the purpose of obtaining the optimal solution [25]. The BP neural network algorithm mainly consists of an input layer, an intermediate layer, and an implicit layer. The input of the neural network mainly consists of the historical daily power generation intermediate frequency component, daily maximum temperature, daily minimum temperature, daily average temperature and relative humidity, and the output mainly represents the predicted daily power generation, and the range of neurons in the hidden layer is mostly calculated in the following three ways:

$$l < n - 1 \tag{5}$$

$$l = \sqrt{m+n} + C \tag{6}$$

$$l = \sqrt{mn} \tag{7}$$

Where: l is the number of nodes in the hidden layer, n is the number of nodes in the input layer, m is the number of nodes in the output layer. C is the adjustment constant, whose value range is $[1,10]$. If the number of hidden layer nodes is too small, the BP neural network algorithm cannot be effectively trained or has poor performance. If the number of hidden layer nodes is too large, the BP neural network algorithm can reduce the systematic error, but the training time is longer and it is easy to fall into the local optimum without getting the global optimal solution. The network learning rate and the number of iterations are the key parameters of the BP neural network, if the learning rate is smaller, the convergence time is longer and easy to fall into the local optimum. If the learning rate is larger, it is easier to obtain the optimal solution in the early stage, but the fluctuation is drastic in the later stage. If the number of iterations is larger, the longer the running time, and a small number of iterations will speed up the computation rate, but will lead to insufficient iterations.

2.1.3. GWO algorithm. In the GWO algorithm, the population is divided into four categories, namely $\alpha, \beta, \delta, \omega$. α denotes the head wolf, which is responsible for decision making within the pack, β assists in decision making, δ is responsible for scouting, sentry, hunting and guarding affairs, and ω is responsible for balancing the relationships within the pack [26]. During the optimization process, the wolves update the population position according to Eq. (8) and Eq. (9):

$$\vec{D} = |\vec{C} \cdot \vec{X}_p(t) - \vec{X}(t)| \tag{8}$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \tag{9}$$

where $\vec{A} = 2a \times \vec{r}_1 - a, \vec{C} = 2 \cdot \vec{r}_2$, t denote the current number of selections, $\hat{X}_p$ denotes the position vector of the prey, $\hat{X}$ denotes the position vector of the gray wolf, α is descending linearly from 2 to 0 during the iteration process, and r_1, r_2 is a random vector in the position $[0,1]$.

In the GWO algorithm, it is always assumed that α, β, δ is the most probable position of the prey (optimal position). In the optimization process, the optimal solution for each of the first three variables so far is set to α, β, δ. After that, the other gray wolves are seen as ω and are able to reposition themselves according to α, β, δ. The mathematical model for repositioning wolf pack ω is as follows:

$$\vec{D}_\alpha = |\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}| \tag{10}$$

$$\vec{D}_\beta = |\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}| \tag{11}$$

$$\vec{D}_\delta = |\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}| \tag{12}$$

where $\vec{X}_\alpha, \vec{X}_\beta, \vec{X}_\delta$ denotes the position of α, β, δ, $\vec{C}_1, \vec{C}_2, \vec{C}_3$ denotes the random vector, and $\vec{X}$ denotes the position of the current solution, respectively. The approximate distance between the current solution and α, β, δ is calculated according to Eq. (10), Eq. (11) and Eq. (12), respectively. After defining the distance, the final position of the current solution is calculated as follows:

$$\hat{X}_1 = \hat{X}_\alpha - \overline{A}_1 \cdot (\vec{D}_\alpha) \tag{13}$$

$$\hat{X}_2 = \hat{X}_\beta - \vec{A}_2 \cdot (\vec{D}_\beta) \tag{14}$$

$$\vec{X}_3 = \vec{X}_s - \vec{A}_3 \cdot (\vec{D}_s) \tag{15}$$

$$\hat{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{16}$$

where $\vec{X}_\alpha, \vec{X}_\beta, \vec{X}_\delta$ denotes the position of α, β, δ, respectively, $\vec{A}_1, \vec{A}_2, \vec{A}_3$ denotes the random vector, and t denotes the number of iterations.

2.1.4. Power prediction model construction. In this paper, the GWO-EEMD-BP algorithm is used to effectively predict the power in the distribution network under different meteorological conditions, which not only reduces the volatility of the historical generation power in the distribution network under extreme weather conditions using the EEMD algorithm, but also optimizes the weights and thresholds of the stochastic distribution of the BP neural network through the GWO algorithm, which improves the computational accuracy of the BP neural network prediction model.

The calculation steps of the GWO-EEMD-BP neural network prediction model are as follows:

1) Classify the historical power generation into three categories: sunny, cloudy and rainy days, and normalize the power generation and meteorological parameters under different weather.

2) Decompose the PV power generation under different weather using the EEMD algorithm, and decompose to obtain the mid-frequency component for the short-term power generation prediction of PV power plants.

3) The number of neurons in the neural network model is given based on the input and output information, and the parameters such as transfer, training and learning functions required in the neural network computation process are determined at the same time.

4) Assign the initial values of the relevant parameters to the GWO optimization algorithm to optimize the weights and thresholds of the random distribution in the BP neural network.

5) Based on the valid meteorological information and the mid-frequency components calculated in step (2) and the optimized neural network algorithm in step (4), the model is trained, and when the error is less than the set error ε or reaches the maximum training step k_{max}, the relevant information of the forecast day is input to forecast the short-term power generation of the photovoltaic power plant.

In this paper, the root mean square error ε_r, the average relative error ε_m and the absolute error ε_a are used to quantitatively analyze the prediction results to evaluate the accuracy and validity of the prediction results.

The root mean square error ε_r is:

$$\varepsilon_r = \sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(Y_i - y_i\right)^2} \tag{17}$$

Mean relative error ε_m is:

$$\varepsilon_m = \frac{1}{m}\sum_{i=1}^{m}\left|\frac{Y_i - y_i}{y_i}\right| \times 100\% \tag{18}$$

Absolute error ε_a is:

$$\varepsilon_a = \left|Y_i - y_i\right| \tag{19}$$

Where: m is the number of prediction points. Y_i is the exact value of power at moment i. y_i is the predicted value of power at moment i.

2.2. Distributed energy storage hierarchical zoning optimization scheduling strategy for distribution network

In distributed energy storage hierarchical zonal optimal scheduling, the difference of system frequency fluctuation can be calculated by global tidal current calculation, thus reflecting the impact of power unrest on system stability. When the frequency is detected to be larger than the specified interval, the power fluctuation is eliminated step by step by inter-area power coordination and intra-area reduction. Among them, the inter-area power coordination layer is based on the results of the zonal dimensionality reduction clustering, which combines the extra-area characteristic power and the intra-area energy storage resources for power allocation.

2.2.1. Distribution network partitioning and dimensionality reduction clustering models:

1) Distribution network partitioning method. In this paper, following the principle of new energy power generation "close to the consumption", with the goal of minimizing the exchange power of the contact line, searching for the optimal partitioning scheme, and its adaptability function is:

$$\min\left(FF\right)=\frac{\sum_{1}^{r}\sum_{1}^{N}\left(P_i^B(t)^2\right)+\sum_{1}^{r}\sum_{1}^{N}\left(Q_i^B(t)^2\right)}{N*T} \tag{20}$$

$$P_i^B(t)=P_i^L(t)-P_i^G(t) \tag{21}$$

$$Q_i^B(t)=Q_i^L(t)-Q_i^G(t) \tag{22}$$

Where $P_i^B(t)$ is the difference in active power of the i rd partition at the moment t. $Q_i^B(t)$ is the reactive power difference of the i th partition at the moment of t. T is the partition period. N is the number of zones. $P_i^L(t)$ and $Q_i^L(t)$ are the active power and reactive power of loads in the i th partition, respectively. $P_t^G(t)$ and $Q_t^G(t)$ are the active power and reactive power of the power supply in the i th partition, respectively.

2) Dimensionality reduction clustering model of distribution network. After the dimensionality reduction clustering of the distribution network area, based on the power prediction method designed above, the external characteristics presented by the area can be obtained by calculating the power generated by the distributed power sources in the area, the load power, and setting the adjustable power in the area, which can be expressed as:

$$P_1^k=\sum_{i=1}^{M}\left(P_{Gi,t}^k+\Delta P_{Gi,t}^k\right)-\sum_{j=1}^{N}\left(P_{I,j,t}^k+\Delta P_{I,j,t}^k\right) \tag{23}$$

$$Q_i^k=\sum_{i=1}^{M}\left(Q_{Gi,t}^k+\Delta Q_{Gi,t}^k\right)-\sum_{j=1}^{N}\left(Q_{I,j,t}^k+\Delta Q_{I,j,t}^k\right) \tag{24}$$

Where P_t^k is the equivalent active power of the krd partition at the t moment. $P_{Gi,t}^k$ and $\Delta P_{Gi,t}^k$ are the active power and adjustable power from the i th distributed power source in the kth partition at the t th moment, respectively. $P_{I,j,t}^k$ and $\Delta P_{I,j,t}^k$ are the active power and adjustable power required by the jth load in the kth partition at the tth moment, respectively. M and N are the number of distributed power sources and the number of loads, respectively. Q_t^k are the equivalent reactive power of the kth partition at the tth moment. $Q_{Gi,t}^{k}$ and $\Delta Q_{Gi,t}^{k}$ are the reactive power and adjustable power from the ird distributed power source in the knd partition at the tst moment, respectively. $Q_{I,j,t}^{k}$ and $\Delta Q_{I,j,t}^{k}$ are the reactive power required by the jth load in the kth partition at the tth moment, respectively. M and N are the number of distributed power sources and the number of loads, respectively.

The distributed energy storage resources in each zone after partitioning need to be summarized and counted, which can be obtained by calculating the capacity and SOC status of distributed energy storage resources in the zone [27]. Since the energy storage performance is more stable when the SOC of energy storage is within the [0.2-0.8] interval, when calculating the energy storage resources within the region, for the energy storage with SOC lower than 0.2, it is not involved in the discharge scheduling. For energy storage devices with SOC higher than 0.8, they do not participate in charging scheduling. Considering that the energy storage in each sub-area needs to prioritize to meet the power balance demand in the sub-area, combined with the sub-area equivalent power to leave a certain amount of energy storage resources, this paper only considers the active power balance in the sub-area, so for the energy storage devices in the area to meet the requirements, the regional energy storage residual storage power and residual storage space can be expressed as follows:

$$\begin{cases} C_{dts,t}^{k} = \sum_{i=1}^{X}\left[C_{i}^{k}\times\left(SOC_{i,t}^{k}-0.2\right)\right]+\int P_{i}^{k}dt \\ C_{ch,t}^{k} = \sum_{i=1}^{\gamma}\left[\times\left(0.8-SOC_{h,t}^{k}\right)\right]-\int P_{l}^{k}dt \end{cases} \tag{25}$$

$$SOC_{t}^{k} = \frac{\sum_{i=1}^{z} SOC_{i,t}^{k}\times C_{i}^{k}}{\sum_{i=1}^{z} C_{i}^{k}} \tag{26}$$

Where C_{ds}^{k} and C_{ch}^{k} denote the remaining storage power and the remaining storage space of the energy storage in the region of t moments k, respectively: X is the number of energy storage in the region of k satisfying the SOC constraints of discharging. Y is the number of energy storage in the k region that satisfies the charging SOC constraint. C_{i}^{k} for t moment the capacity of the ith energy storage device in the k region. $SOC_{i,t}^{k}$ is the SOC state of the ith energy storage device in the k region at the t moment of time: SOC_{t}^{k} is the SOC state of the k region at the t moment of time. Z for the number of all energy storage in the k region.

2.2.2. Optimized Scheduling Strategy for Distributed Energy Storage in Layers and Zones. When relying only on the distribution system itself for power regulation, the power inequality measure ΔP can be decomposed into two parts: one part is the power reduced by the regulation effect of the customer loads ΔP_{L}. The other part is the power supplied by the power supply from the regulation effect of the distributed power supply ΔP_{P}, at which time the resulting frequency deviation $\Delta f'$ is:

$$\Delta f' = -\frac{\Delta P-\Delta P_{L}-\Delta P_{P}}{K_{L}+K_{P}} \tag{27}$$

$$\Delta P_{P} = \sum_{i=1}^{M}\Delta P_{P_i} \tag{28}$$

$$K_{P} = \sum_{i=1}^{M} K_{Pi} \tag{29}$$

Where, ΔP_L is the load power variable. ΔP_P is the distributed power power variable. K_L is the load unit regulation power. K_P is the distributed power unit regulation power. M is the total number of distributed power sources. ΔP_{P_i} is the i th distributed power variable. K_{Pi} is the i th distributed power unit regulation power.

The system frequency f' can be calculated as:

$$f' = f_0 + \Delta f' \tag{30}$$

where f_0 is the rated frequency.

If the system frequency f' after the regulation of distributed power sources and loads still does not satisfy the system frequency constraints, power regulation can be carried out by energy storage.

When energy storage is involved in power regulation, the power inequality measure ΔP can be decomposed into three parts: one part is the power reduced by the regulation effect of the user load ΔP_L. The other part is the power provided by the power supply from the adjustment effect of the distributed power supply ΔP_P. The third part is the power reduced by the regulation effect from the energy storage ΔP_{ES}, and the resulting frequency deviation Δf^* is:

$$\Delta f^* = -\frac{\Delta P - \Delta P_L - \Delta P_P - \Delta P_{ES}}{K_L + K_P + K_{ES}} \tag{31}$$

Where ΔP_{ES} is the power provided by the energy storage. K_{ES} is the energy storage unit regulation power.

From Eq. (31), if the frequency is to be realized without differential regulation, the power required to be invested by the energy storage for power regulation is:

$$\Delta P_{ES} = \Delta P - \Delta P_L - \Delta P_P \tag{32}$$

In the inter-division power allocation, in order to ensure that the distribution network can operate quickly and normally under the power fluctuation state, it is not enough to rely only on the energy storage capacity of a certain region, and it is also necessary to make the power reasonably distributed among the various inter-division areas, i.e., to realize the uniform distribution of power regulation in each sub-division. This paper combines the power fluctuation value and the remaining storage capacity or remaining storage space of the corresponding regional energy storage in each partition, and carries out the scheduling power allocation according to the proportion of capacity. The corresponding power allocated to each partition is:

$$P_{dis,t}^k = \frac{C_{dis,t}^k}{\sum_{k=1}^{K} C_{dis,t}^k} \tag{33}$$

Or:

$$P_{ch,t}^k = \frac{C_{ch,t}^k}{\sum_{k=1}^{K} C_{ch,t}^k} \tag{34}$$

where $P_{dis,t}^k$ and $P_{ch,t}^k$ are the discharge power or charge power of region k at moment t, respectively.

The equation constraints to be satisfied during the scheduling process are:

$$P_{Gi}^0 - P_{Li}^0 - V_i^0 Y_{ij} \sum_{j=1}^{N} V_j^0 \cos\left(\delta_i^0 - \delta_j^0 - \alpha_{ij}\right) = 0 \tag{35}$$

$$Q_{Gi}^0 - Q_{Li}^0 - V_i^0 Y_{ij} \sum_{j=1}^{N} V_j^0 \sin\left(\delta_i^0 - \delta_j^0 - \alpha_{ij}\right) = 0 \quad i, j \in S_a \tag{36}$$

Where, P_G and Q_{Gi} are the zonal active and reactive power outputs of the i rd equivalent power supply, respectively. P_{Li} and Q_{Li} are the active and reactive power outputs of the i th partition which is equal to the load, respectively. Y_{ij} and α_{ij} are the conductance amplitude and phase angle from partition i to partition j, respectively. V_i and δ_i are the partition i voltage magnitude and phase angle, respectively.

In addition, the inequality constraints to be satisfied are:

$$P_{Gi,\min} \le P_{Gi} \le P_{Gi,\max} \tag{37}$$

$$Q_{Gi,\min} \le Q_{Gi} \le Q_{Gi,\max} \tag{38}$$

$$P_{ij,\min} \le P_{ij} \le P_{i,\max} \tag{39}$$

where P_{ij} is the transmission power of the contact line between Subarea i and Subarea j. Subscripts $\min$ and $\max$ indicate minimum and maximum values.

3. Experimental results and arithmetic analysis

In order to verify the reasonableness and effectiveness of the distributed energy storage scheduling optimization strategy of the distribution network, this section adopts the IEEE-33 node distribution system for the arithmetic case analysis.The structure of the IEEE-33 node distribution network test system is shown in Fig. 1. The network reference rated voltage U_N is 12.66kV, the total load is 3715.0+j2300.0kvar, and the upper and lower limits of the node voltage are taken as 1.05U_N and 0.95U_N respectively.

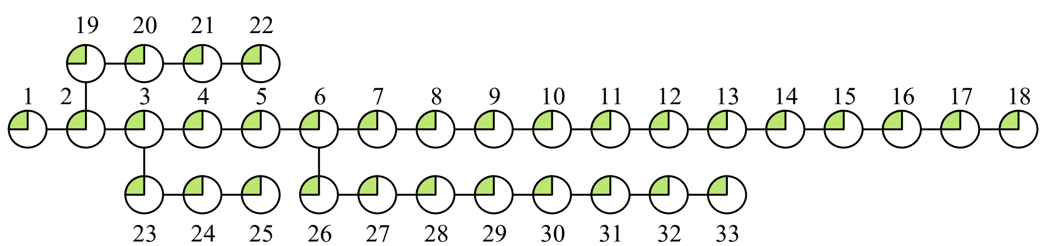


Fig. 1. IEEE-33 node distribution network test system

The parameters of the energy storage devices are shown in Table 1 for a total of six energy storage types.

Table 1. Parameters of energy storage

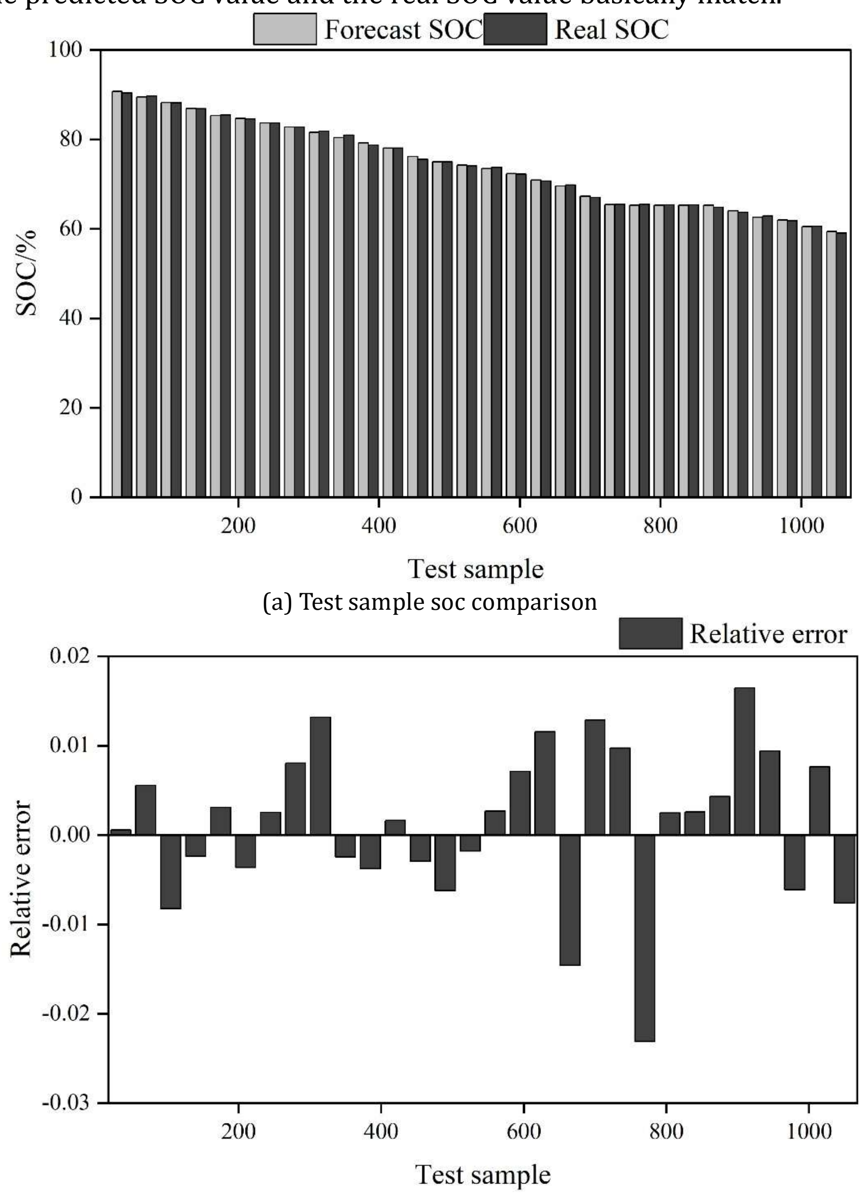
Energy storage name	Battery type	Energy storage capacity/(kW·h)	Power/kW	Charging power	Discharge power
Energy storage 1	Nimh	60	30	0.88	0.96
Energy storage 2	Lithium electricity	2300	1650	0.88	0.91
Energy storage 3	Zinc bromide flow	60	20	0.89	0.92

Energy storage 4	Zinc bromide flow	120	60	0.87	0.96
Energy storage5	Lithium electricity	200	100	0.88	0.93
Energy storage 6	Lead acid	130	130	0.98	0.94

3.1. Analysis of power prediction model results

Two hundred and fifty-nine sets of cloud platform data are selected as test samples, including 1,069 sets for the discharge process and 1,440 sets for the charging process, to test the accuracy of the GWO-EEMD-BP neural network for charging and discharging power prediction of the energy storage in the distribution network at IEEE-33 nodes.

The SOC prediction effect and error statistics of the discharging process are shown in Fig. 2. (a) and (b) represent the comparison of SOC values of test samples, and the relative error of test samples, respectively. The average relative error of the discharge process is 1.29% and the maximum relative error is 2.31%. The predicted SOC value and the real SOC value basically match.

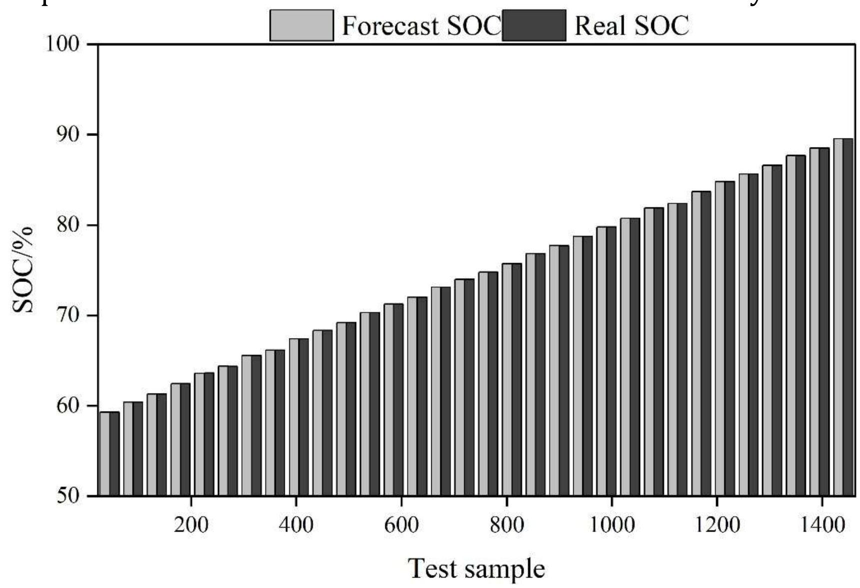


(a) Test sample soc comparison

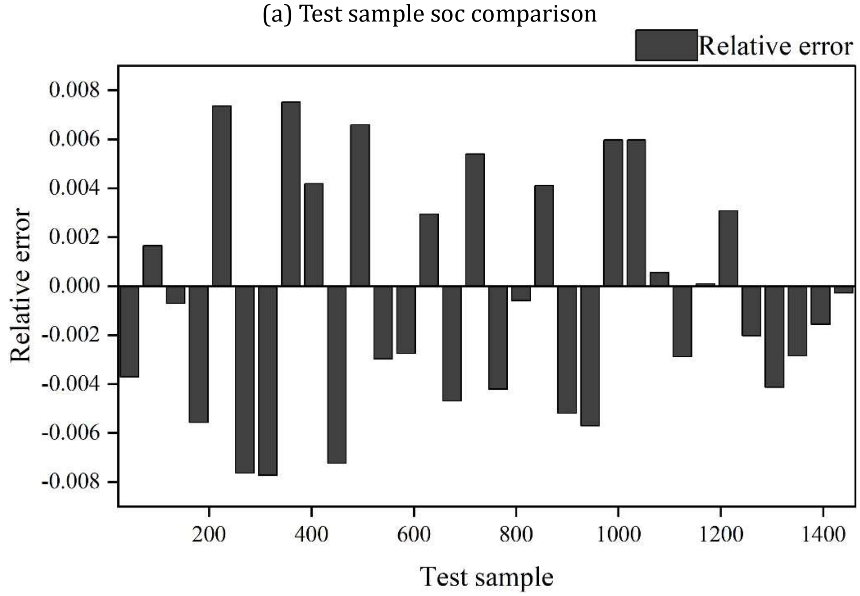
(b) Test sample relative error

Fig. 2. SOC prediction effect and error statistics of discharge process

The SOC prediction effect and error statistics of the charging process are shown in Fig. 3. (a) and (b) represent the comparison of SOC values of test samples and the relative error of test samples, respectively. The average relative error of the charging process is 0.53% and the maximum relative error is 0.773%. The predicted SOC value and the real SOC value also basically match.



(a) Test sample soc comparison



(b) Test sample relative error

Fig. 3. SOC prediction effect and error statistics of charging process

3.2. Comparison of scheduling optimization results

The choice of charging and discharging time of the energy storage equipment will directly affect the operating efficiency of the distribution network and the economic returns of the investors of the energy storage equipment, and the life of the energy storage equipment is directly related to the number of times of charging and discharging, so the number of times of charging and discharging should be limited. At present, there are the following 2 types of energy storage charging and discharging time period selection.

1) Mode 1: Determine the charging and discharging hours according to the time-sharing tariff. In the peak tariff time (8:00am-21:00pm) discharge, valley tariff time (21:00pm-8:00am) charging, this

charging mode can ensure that investors in energy storage equipment to earn tariff difference profit maximization.

2) Mode 2: Determine the charging and discharging periods according to the load. According to the load forecast to get the average load of the time period to be optimized, when the forecast load is higher than the average load energy storage discharge, when the forecast load is lower than the average load energy storage charging. The second choice of charging and discharging time period has the risk of too many times of storage charging and discharging, so it is also necessary to analyze the predicted load curve beforehand to avoid the occurrence of the above situation. At present, the more typical load curve for the whole day type, single-peak type, double-peak type and night type, these four types of load curve will not occur storage charging and discharging too many times, so the second charging and discharging time selection is feasible in the vast majority of cases.

Taking a typical daily load of the distribution network as an example, the energy storage charging and discharging mode is selected as mode 2 for the optimization of energy storage charging and discharging strategy. According to the load prediction, the average load of the time period to be optimized is obtained, and when the predicted load is higher than the average load, the energy storage is discharged, and when the predicted load is lower than the average load, the energy storage is charged. The system power loss and load fluctuation before and after optimization are shown in Table 2. The following conclusions can be drawn:

(1) When optimizing the distributed energy storage scheduling with the minimum power loss as the objective function, the system power loss decreases by 95.05kW·h, and the fluctuation rate also decreases by 44.9%.

(2) When the distributed energy storage scheduling optimization is performed with the minimum load fluctuation as the objective function, the system fluctuation rate decreases by 80.6%, but the power loss increases by 18.24kW·h.

(3) With the distributed energy storage scheduling optimization strategy designed in this paper, the system power loss decreased by 260.86kW·h and the load fluctuation rate decreased by 67.5%. The optimization effect is more ideal compared to the first two strategies.

Table 2. Load curve with or without energy storage

Parameter	No energy storage	Minimum loss	Minimum fluctuation	Ours
Power loss/(kW·h)	6693.22	6598.17	6711.46	6432.36
Load fluctuation/kW2	9.57×106	5.27×106	1.86×106	3.11×106

3.3. Configuration analysis considering real-time operational scheduling of energy storage

To verify the superiority of the distributed energy storage scheduling optimization strategy designed in this paper, the following 2 scenarios are used in this section for comparison, respectively:

1) Scenario 1: without considering real-time power scheduling, constant power charging and discharging of energy storage is only performed at a set fixed time period according to the typical load profile.

2) Scenario 2: The distributed energy storage scheduling optimization strategy designed in this paper is used to consider real-time charging and discharging power scheduling of energy storage devices.

The results of the configuration of energy storage devices in the two scenarios are shown in Table 3, and the comparison of the annual costs of the system is shown in Table 4. Comparison of the cost indicators in Table 4 reveals that: scenario 2 considers the real-time operation power scheduling of the energy storage device, and the system network loss cost and the main grid power purchase cost are both reduced compared with scenario 1, and the network loss cost and the user's annual power purchase cost from the higher-level main grid are reduced by 19.06% and 19.46%, respectively. This is due to the fact that, relative to the former, the real-time power dispatch considering the energy storage device further smoothes the load fluctuation of the system at each moment, and the corresponding network loss cost and user power purchase cost from the main grid are also reduced, and the total operation cost of the system is reduced. Therefore, the superiority of the distributed energy storage scheduling optimization strategy designed in this paper in terms of system operation economics is verified.

Table 3. Results of two ESS scenario configuraton

Scene	Node	Power capacity/MW	Energy capacity/(MW·h)
Scene 1	2,9,16	(2)0.170	(2)0.832
		(9)0.170	(9)0.832
		(16)0.170	(16)0.832
Scene 2	6,23,31	(6)0.266	(6)1.056
		(23)0.217	(23)0.822
		(31)0.217	(31)0.822

Table 4. Comparison of system cost of two scenario

Cost and cost name	Cost and cost results/ ten thousand yuan	
	Scene 1	Scene 2
Energy storage cost	146.39	141.36
Line loss cost	26.39	21.36
The cost of purchasing the net	316.98	255.31
Total cost	511.96	427.33

A comparison of the daily characteristics of the load after configuring energy storage in the two scenarios is shown in Fig. 4. Scenario 2 considers that the energy storage device under real-time power optimization scheduling absorbs more power than Scenario 1 in the load trough 00:00-5:00 time period, and the peak load period starts at 8:00, and Scenario 2 produces more power than the energy storage device in Scenario 1 in the time periods from 8:00-12:00, respectively 181.54kW, 132.66kW 182.76kW and 69.97kW respectively, and the energy storage device of Scenario 2 releases more power than that of Scenario 1 during the whole peak load period before 17:00. In summary, in terms of suppressing load fluctuation and shaving peaks and filling valleys, the effect of Scenario 2's energy storage configuration scenario is more significant than that of Scenario 1, and therefore, compared with the constant-power charging and discharging of the energy storage device, the optimal scheduling that considers the real-time power is more conducive to energy saving and further achieve the purpose of reducing network losses.

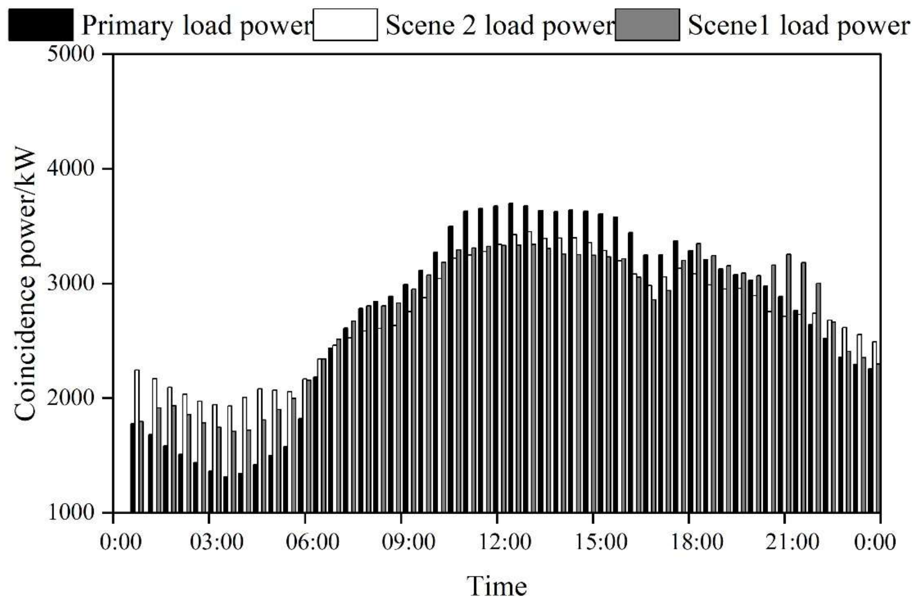


Fig. 4. Daily load curve under different scenes

3.4. *Analysis of energy storage configurations to improve voltage quality*

The system voltage conditions when energy storage is configured and when energy storage is not connected are analyzed and compared.The changes in the node voltage deviation indexes in the two cases are shown in Table 5. During the peak load period, the line power supply capacity is insufficient, the system node voltage deviation becomes larger, and the voltage quality is reduced. The node voltage deviation of the system before accessing the energy storage device is larger, the maximum is as high as 8.104%, and the node voltage deviation of the system after accessing the energy storage device is obviously improved compared with that before accessing the energy storage device, and the voltage deviation is reduced to less than 5%, which meets the system requirement level, and the quality of the system voltage is improved. It shows that the method of this paper can improve the phenomenon of system voltage fluctuation and low voltage after optimizing the energy storage configuration.

Table 5. The variation of the node voltage deviation in two cases

Node	Access-Node voltage deviation/%	Unconnected-Node voltage deviation/%
1	0.187	0.059
2	0.436	0.523
3	1.712	1.570
4	2.343	2.123
5	3.041	2.746
6	4.937	4.608
7	5.249	4.756
8	5.739	4.880
9	6.076	4.943
10	5.499	4.583
11	5.702	4.596
12	5.899	4.712
13	5.954	4.823
14	6.015	4.816
15	6.019	4.794
16	6.019	4.788

17	6.019	4.629
18	5.789	4.199
19	1.944	0.967
20	0.752	0.793
21	0.848	0.783
22	0.843	0.897
23	1.947	1.968
24	2.726	2.544
25	3.068	2.868
26	4.440	4.183
27	5.361	4.812
28	6.490	4.895
29	7.195	4.750
30	7.684	4.776
31	8.104	4.247
32	8.236	4.180
33	8.223	4.386

4. Conclusion

The study predicts the charging and discharging power of IEEE-33 node distribution network energy storage based on GWO-EEMD-BP neural network. The predicted SOC values and the real SOC values basically match.

The optimization strategy of distributed energy storage scheduling is analyzed by considering the charging and discharging periods of energy storage devices and the configuration of real-time operation and scheduling of energy storage. In this paper, the system power loss is reduced by 260.86kW·h, and the load fluctuation rate is reduced by 67.5%. The method in this paper obtains a good effect of peak shaving and valley filling at the expense of a very small amount of power loss. The cost of network losses and the annual cost of power purchased by users from the upper main grid are reduced by 19.06% and 19.46%, respectively. The distributed energy storage scheduling optimization strategy designed in this paper can reduce the cost and improve the economic benefits.

In addition, the design of this paper can significantly improve the system voltage quality and can reduce the voltage deviation of the distribution network system to less than 5%.

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