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Location and Capacity Determination of Energy Storage System Based on Improved Whale Optimization Algorithm

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Abstract. *Considering the randomness and fluctuation of power generation by new energy, and the influence of its access on the stability of power system, an optimization model of location and capacity selection of energy storage power systems is established with the voltage deviation of system nodes, network loss and the scale of energy storage as the objective functions. A weight coefficient is introduced to improve whale optimization algorithm, which can avert the algorithm entering local optimum and increase the computation rate. The good performance of the improved whale optimization algorithm is verified by MATLAB simulation. Taking IEEE-33 bus system with new energy generation to carry out the simulation analysis of the example and the improved whale optimization algorithm is used for verification. The results show that the energy storage systems location and capacity determination results solved by this algorithm can be connected to the energy storage, which can better reduce the voltage fluctuation and active power network losses of the system, improve the working effect of new energy power generation, and reduce the impact of power fluctuations on the system.*
Keywords: improved whale optimization algorithm, new energy generation power, power system stability, energy storage systems, MATLAB

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1. **Introduction.** In order to protect the environment, clean energy power generation is vigorously promoted all over the world, and the proportion of new energy power generation is increasing year by year. The volatility of new energy generation will also have a serious impact on the transient stability of power grid [1,2]. Energy storage technology is one of the regulation methods of modern power system. Because of its sensitive response and easy control. It has obvious advantages in ensuring the stability of power supply. Therefore, it can improve the quality of electric energy, enhance the safety level of power supply operation, smooth the output of new energy generation, and improve the capacity of new energy consumption [3,4]. Reasonable configuration of the capacity and installation location of the energy storage system (BEE) can not only play a better role in regulating energy storage, but also save costs.

In the problem of BEE location and capacity of new energy combined power generation system. Scholars at home and abroad have introduced the optimization algorithm to conduct in-depth research on it, and achieved certain research results. Optimization is an important problem in many fields of science and engineering. In the practical engineering field, there are many problems that need to be optimized, and the most appropriate results should be calculated in the jumbled and huge search space [5,6]. Inspired by the evolution of many animals in the biological world, people have designed many algorithms, such as genetic algorithm [7], ant colony optimization algorithm [8], particle swarm optimization algorithm [9] and so on, and calculated many complicated optimization problems. In [10], an improved artificial bee colony algorithm is proposed to solve the hybrid energy storage model, and the entropy weight method is used to find the best BEE capacity scheme suitable for microgrid. In [11] Liu et al established an optimization model of wind power cluster combined BEE , and uses ant-lion algorithm to solve it, so as to obtain the optimal allocation scheme of power reserve, energy storage power and capacity of wind power cluster. In [12], the inertia weight improved multi-objective particle swarm optimization algorithm is used to guide the selection of the global optimal solution of the population. In [13], Xu et al. improved genetic algorithm based on random weight strategy, combined with PV curve to establish energy storage model to solve the location scheme of BEE. In [14], Deng et al. proposed a hybrid intelligent optimization algorithm, which greatly improved the optimization performance of the algorithm. In [15], Li et al. by establishing a two-layer partition model of bidirectional dynamic reconfiguration and cluster partition, the location and capacity of BEE are determined. In [16], Ding et al. considering the power fluctuation of new energy sources, an energy storage model is constructed for BEE location and capacity determination. At present, most researches focus on the capacity allocation of BEE, but less on the location and capacity of BEE.

Whale Optimization Algorithm, (WOA) is an excellent algorithm , which is modeled by simulating the behavior of whale hunting [17]. An example shows that WOA has more advantages than other algorithms in principle. It is easy to implement in computer, and it hardly needs to change parameters. Moreover, WOA has a faster convergence speed and higher calculation accuracy. Since it was put forward, it has been favored by researchers in the field of optimization computing, and it is one of the excellent optimization algorithms [18-20]. But the parameter adjustment strategy can't fully reflect the actual optimization search process. This makes it difficult to coordinate the global exploration and local development capabilities of the algorithm. In the late iteration, all individuals gather to the optimal individual, which makes the algorithm easy to fall into local optimum. This paper is based on the WOA algorithm to solve the optimization model. In order to better solve the problem of finding the optimal solution, improve the global optimization performance and application ability of the algorithm, and increase the calculation speed of the algorithm. In this paper, nonlinear weight coefficient is introduced to improve

WOA [21, 22]. Taking the system voltage deviation and the minimum network loss as the objective function, the problem of location and capacity determination of BEE in new energy system is solved.

2. **Optimal model of location and capacity selection of ESS.**

2.1. **The objective function.** The location and capacity determination of ESS are affected by many factors, which is a multi-objective optimization problem. After a large number of new energy sources are connected to the power system, the instability of new energy sources will seriously affect the power quality of the power grid. Therefore, it is necessary to configure the ESS to solve these adverse consequences to some extent [23]. And because the cost of energy storage system is relatively high, the capacity of energy storage system has to be considered when it is configured. Therefore, comprehensively considers the influence and the cost of the ESS, and selects the following three indicators as the objective function.

(1) Node voltage deviates

Node voltage stability is one of the important indexes of system stability. The voltage of each node in the system should be kept at a certain level, and its fluctuation should also be kept at a small level. After the access of new energy, the power supply level of nodes has been improved to a certain extent, but its fluctuation has intensified. Therefore, the sum of node voltage deviates is selected as the target function of the location and capacity determination of the ESS, and its arithmetical formula is:

$$f_1 = \Delta U = \sum_{i=1}^{N} \left| \frac{V_i - V_{ref}}{V_{ref}} \right| \tag{1}$$

In the formula: ΔU indicates deviation of node voltage, and N represents the amount of network nodes; V_i represents the voltage amplitude of i node; V_{ref} is the voltage reference amplitude of i node.

(2) Active power network loss

After the new energy place in the network, the fluctuation of its power will raise the network power fluctuation, which will adversely affect the load. The ESS is sensitive and can respond quickly to changes in the power system in time, smoothing the power fluctuations of the system and reducing active power network losses. The calculation formula is shown in (2):

$$f_2 = \Delta P = \sum_{l=1}^{B} \frac{V_i^2 + V_j^2 - 2V_iV_j \cos\theta_{ij}}{R_l} \tag{2}$$

In the formula: ΔP is the active network loss, B indicates the number of branches of the system, V_i and V_j are the node voltages at both ends of branch l, R_l is the resistance of branch L , and θ_{ij} represents the voltage phase angle difference about nodes i and j.

(3) Capacity of ESS

Due to the high construction cost of the ESS, the scale of the established energy storage power station is as small as possible, so the total ESS capacity is chosen as the optimization target. The rated capacity S is defined as the maximum charge/discharge amount of stored energy in time T.

$$f_3 = S = \sum_{j=1}^{N_{\mathrm{ESS}}} \sum_{i=t_0}^{t_0+n\Delta t} P_{ESS,j}(i)\Delta t \tag{3}$$

In the formula: t_0 is the starting time of maximum charge/discharge; $t_0+n\Delta t$ is the maximum charge/discharge termination time; $P_{ESS},_j(i)$ is the working power of the ESS j at time i; Δt represents the time interval; N_{ESS} represents the number of energy storage battery.

Therefore, the nodal point voltage deviates from normal value., active power network losses and energy storage scale are taken as evaluation indexes, and the minimum sum of node voltage deviates and active power losses under the minimum energy storage scale is taken as the objective function:

$$f = \min\left[f_1, f_2, f_3\right] \tag{4}$$

2.2. **constraints.** (1) Power balance constraints

In order to maintain stability, system power balance is needed:

$$P_{load}(t) = P_{pv}(t) + P_{wt}(t) + P_{ESS}(t) \tag{5}$$

$$Q_{load}(t) = Q_{pv}(t) + Q_{wt}(t) + Q_{ESS}(t) \tag{6}$$

In the formula, $P_{load}(t)$, $Q_{load}(t)$, $P_{wt}(t)$, $Q_{wt}(t)$, $P_{PV}(t)$, $Q_{PV}(t)$, $P_{ESS}(t)$ and $Q_{ESS}(t)$ are the active and reactive outputs of user load, wind turbine, photovoltaic cell and energy storage equipment in the t period respectively.

(2) Node voltage constraint

When the new energy station and energy storage system affect the power grid operation, the voltage of every node ought to within the safe range.

$$U_{i,min} \le U_i(t) \le U_{i,max} \tag{7}$$

In the formula: $U_{i,min}$ and $U_{i,max}$ are the highest and lowest values of voltage amplitude of network node i; U_i represents the voltage amplitude of the system at i node in t period.

(3) Energy storage characteristic constraint

When selecting the location and the capacity of the ESS, not only the operation constraints of the system, but also the working energy balance of the ESS should be considered.

Power constraints during energy storage are expressed as:

$$-P_{bess,max} \le P_{bess,i}(t) \le P_{bess,max} \tag{8}$$

In the formula: $P_{bess,max}$ represents the maximum power when the ESS works.; $P_{bess,i}$ represents the discharging/charging power of the ESS at node i in t period.

During the working of the ESS, it is also essential to monitor the state of charge (SOC) of the battery of ESS, which is numerically the ratio of the remaining capacity of battery E_{stack} to the rated capacity E_C:

$$\mathrm{SOC} = \frac{E_{stach}}{E_C} \tag{9}$$

$$\mathrm{SOC}_{min} \le \mathrm{SOC} \le \mathrm{SOC}_{max} \tag{10}$$

In the formula: SOC_{max} and SOC_{min} are the maximum and minimum values of SOC.

3. **Model based on improved WOA.**

3.1. **Original WOA.** The WOA is a new and excellent type of intelligent algorithm proposed, to imitate the hunt for food pattern of whale populations. Compared with other population optimization algorithms, the main difference of current research lies in using random or optimal search agent to simulate hunting behavior, and using spiral to imitate the foam network attack behavior of whales. The algorithm includes three search methods: encirclement predation, bubble net hunting and random mutation.

(1) encirclement and predation

The foraging behavior of whale population surrounded by predation was simulated. When the leader of the whale finds the position of the hunting target, the rest of the whales use the current position of the leader as a reference, update their positions by certain methods, and gradually surround the target. The individual position update formula is:

$$\begin{cases} \vec{D} = \left|\vec{C} \cdot \vec{X}^*(t) - \vec{X}(t)\right| \\ \vec{X}(t+1) = \vec{X}^*(t) - \vec{A} \cdot \vec{D} \end{cases} \tag{11}$$

In the formula: vector D represents the distance vector between the currently found optimal solution and the search volume; t represents the current iteration number; X^* represents the location vector of the optimal solution at this moment; X represents the location vector of the search volume.

Where vectors A and vectors C are coefficient vectors

$$\begin{cases} \vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a} \\ \vec{C} = 2\vec{r}_2 \\ \vec{a} = 2 - 2\frac{t}{T_{\max}} \end{cases} \tag{12}$$

The vectors r_1 and r_2 are random vectors between [0,1]. Vector a is the convergence factor that linearly diminish from 2 to 0 with the increase of iteration times.

(2) Bubble net hunting

It is a unique hunting strategy for whales to swim in a spiral while spitting bubbles. In this way, the prey is surrounded and approached to the surface of the ocean to capture the prey in the best way. The following mathematical model can be used to describe this rare hunting behavior:

$$\begin{cases} \vec{D}' = \left|\vec{X}^*(t) - \vec{X}(t)\right| \\ \vec{X}(t+1) = \vec{D}' e^{bl} \cos(2\pi l) + \vec{X}^*(t) \end{cases} \tag{13}$$

In the formula, l is a number randomly selected from [0,1]; the vector $\vec{D}'$ represents the distance from the whale individual to the present best solution; b is 1 for the constant defining the spiral shape.

In particular, that the humpback whales move around their target in a reducing circle while swimming along a spiral way. In order to simulate this concurrent action, it is suppose that there is one half chance of random selection between contraction enclosing mechanism and spiral model, so as to update the position of the whale in the whole calculation process. Let the probability p be a random number between [0,1]. The mathematical model is as follows:

$$\vec{X}(t+1) = \begin{cases} \vec{X}^*(t) - \vec{A} \cdot \vec{D} & P < 0.5 \\ \vec{D}' e^{bl} \cos(2\pi l) + \vec{X}^*(t) & P \geq 0.5 \end{cases} \tag{14}$$

(3) random mutation

Besides the above methods, the algorithm can also randomly determine the target. Introducing this update mechanism can expand the search scope and in order to avoid getting stuck in a local optimal solution. The vector X_{rand} is defined as a stochastic location vector (representing a stochastic whale) chosen from the present populations. The individual position update formula is:

$$\begin{cases} \vec{D} = \left|\vec{C} \cdot \vec{X}\text{rand}(t) - \vec{X}(t)\right| \\ \vec{X}(t+1) = \vec{X}\text{rand}(t) - \vec{A} \cdot \vec{D} \end{cases} \tag{15}$$

WOA algorithm firstly randomize a group of solution for initialization, and in every iteration, the search agents update their locations based on the stochastic chosen agents or the latest optimal solution obtained. The parameter a will gradually decrease from 2 to 0 with the iterative process, from random search to use. Stochastic chosen agent when |OA| <1, and select the best solution to update the search target agent position when |OA| <1. According to the value of p, WOA can convert between the two algorithms until the conditions are met and the results are output. The pseudo code of WOA algorithm is shown Table 1.

Table 1. Pseudo code

Pseudo code of WOA
1. initialize the whales population $Xi(i = 1, 2, 3....n)$
2. compute the adaptedness of every search agent
3. X^*=the best search agent
4. while(t <max iteration times)
5. for every search agent
6. Update vector a,A,C,L,and probability p
7. if1(p <0.5)
8. if2(|A|<1)
9. Update the position of search agent use formula (3-1)
10. else if2(|A|>1)
11. Select a random search agent (Xrand)
12. Update position of search agent use formula (3-5)
13. end if2
14. else if1(p>0.5)
15. update the position with spiral formula (3-3)
16. end if1
17. end for
18. Check whether any search agent goes beyond the search scope and modify it
19. compute the adaptedness of each search agent
20. Update X*if there is a better solution
21. $t = t + 1$
22. end while
23. return x*

3.2. **Improved the WOA.** The WOA, like other swarm intelligence algorithms, how to allocate the global search and local development capabilities is the main idea to improve the algorithm [24, 25]. Weight plays a significant role in whale optimization algorithm. When the weight is bigger, the convergence pace is more quickly and the search range of the algorithm is larger. When the weight is small, the search is more detailed and it is not easy to miss the optimal solution [26, 27].

Nonlinear weights W_1 and W_2 are added to the WOA to adjust the current optimal position and the surrounding step size respectively.

$$\begin{cases} W_1 = -\gamma \left[\cos\left(\frac{\pi t}{T_{\max}}\right) - \lambda\right] \\ W_2 = \gamma \left[\cos\left(\frac{\pi t}{T_{\max}}\right) + \lambda\right] \end{cases} \tag{16}$$

In the formula: γ is the value range of W_1 and W_2, taking 0.5; λ is the step size of W_1 and W_2, and takes 1. T_{max} is the maximum number of iterations.

The nonlinear weights $W1$ and $W2$ are introduced into formulas (11), (13) and (15), and the processes of surrounding prey, bubble attack and searching for prey are carried out:

$$\vec{X}(t+1) = \vec{X}^*(t) - W_2\vec{A} \cdot \vec{D} \tag{17}$$

$$\vec{X}(t+1) = W_1 \left[\vec{D}\prime e^{bl} \cos(2\pi l) + \vec{X}^*(t)\right] \tag{18}$$

$$\vec{X}(t{+}1) = \vec{X}\mathrm{rand}(t) - W_2\vec{A} \cdot \vec{D} \tag{19}$$

3.3. **Solution steps.** Step 1: Setting the whale number N and the maximum iteration number T_{max} of the algorithm, and initializing the position information;

Step 2: Solve the adaptedness of each whale, find the current optimal whale position and keep it;

Step 3: Calculate parameters A and P and coefficient vectors A and C. Judge whether the probability p is less than 50%, if so, go directly to step 4, otherwise, adopt the bubble net predation mechanism: use formula (18) to update the position;

Step 4: Judge whether the absolute value of coefficient vector A is less than 1, if so, surround the prey: update the position according to formula (17); Otherwise, globally randomly search for prey: update the position according to formula (19);

Step 5: After the position update, calculate the fitness of each whale, and compare it with the previously reserved optimal whale position. If it is better, replace it with a new optimal solution;

Step 6: Determine whether the current calculation has reached the set number of iterations, if so, get the optimal solution and finish the calculation, otherwise, enter the next iteration and return to Step 3.

The standard WOA mainly depends on the coefficient vector A to select the path to search for target, and the probability P is used to determine the final predation mechanism. The calculation process of standard WOA is shown in the figure, as shown in Figure 1 below:

3.4. **Performance analysis of improved WOA.** For verifying the optimization ability of the algorithm is put forward in the previous chapter, the performance of PSO algorithm, WOA algorithm and NWOA algorithm are compared under CEC2013 test suite, and numerical experiments are carried out on the proposed algorithm and other algorithms. See Table 2 for the function expression and related information of benchmark.

All the experiments were carried out in the computing environment of MATLAB R2018a. The computing environment was Intel coret Mi5(3.40 GHz)CPU, RAM was 8 GB, and Microsoft Windows 10. The related parameter settings of various algorithm are shown in Table 3.

To ensure the fairness of the comparative experiment, the above six algorithms were run separately on the benchmark function for 30 times, and the optimization results of various algorithms were recorded as shown in Table 4. The lowest accuracy of the data obtained in this paper was 10^{-300}, and when the accuracy of the data obtained was lower than the accuracy, it was shown as 0.

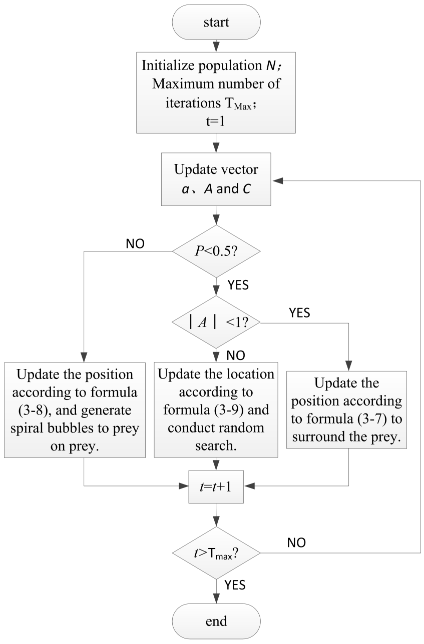

FIGURE 1. algorithm flow chart

TABLE 2. Benchmark function

Expressions	Dimensions	Ranges	Rational Expressions
$F_1 = \sum_{i=1}^{n} x_i^2$	30	$[-100, 100]$	0
$F_2 = \sum_{i=1}^{n} \|x_i\| + \prod_{i=1}^{n} \|x_i\|$	30	$[-10, 10]$	0
$F_3 = \sum_{i=1}^{n} \left(\sum_{j=1}^{i} x_i^2 \right)^2$	30	$[-100, 100]$	0
$F_4 = \max \{ \|x_i\|, 1 \leq i \leq D \}$	30	$[-100, 100]$	0
$F_5 = \sum_{i=1}^{n} i_i^4 + \text{random}(0, 1)$	30	$[-1.28, 1.28]$	0
$F_6 = -20 \exp(-0.2\sqrt{\frac{1}{n} \sum_{i=1}^{n} x_i^2}) - \exp(\frac{1}{n} \sum_{i=1}^{n} \cos(2\pi x_i)) + 20 + e$	30	$[-32, 32]$	0

TABLE 3. Algorithm parameters

algorithm	Parameter setting
WOA	N=30, T_{max}=500, Dim=30
PSO	N=30, T_{max}=500, c1=c2=2, V_{MAX}=1, V_{MIN}=-1
NWOA	N=30, T_{max}=500, Dim=30, γ=0.5, λ=1, F=0.5

According to Table 4 that NWOA algorithm outperforms the other two algorithms. This shows that the improvement of this algorithm is effective. This is because W_1 increases nonlinearly with the number of iterations, which makes the population move to the optimal position. W_2 decreases nonlinearly with the increase of iteration times, and there is a smaller step in the later iteration period to accelerate the convergence rate.The convergence curves of WOA and NWOA are compared as shown in Figure 2 below. Combined with Figure 2, it can be seen that the optimization power of the algorithm is enhanced, the local optimum is prevented.

4. **Example simulation analysis.**

TABLE 4. Performance test results

Function	PSO		WOA		NWOA	
	Mean	Std	Mean	Std	Mean	Std
F_1	6.421	2.287	8.777E-79	2.334E-78	0	0
F_2	12.41	1.263	7.596E-58	6.730E-56	0	0
F_3	11.62	3.478	3169	954	0	0
F_4	0.6420	0.0885	80.93	63.21	0	0
F_5	5.957	2.521	7.776E-02	4.813E-02	9.402E-05	7.150E-05
F_6	4.120	1.857	4.481E-14	1.720E-14	8.881E-16	0

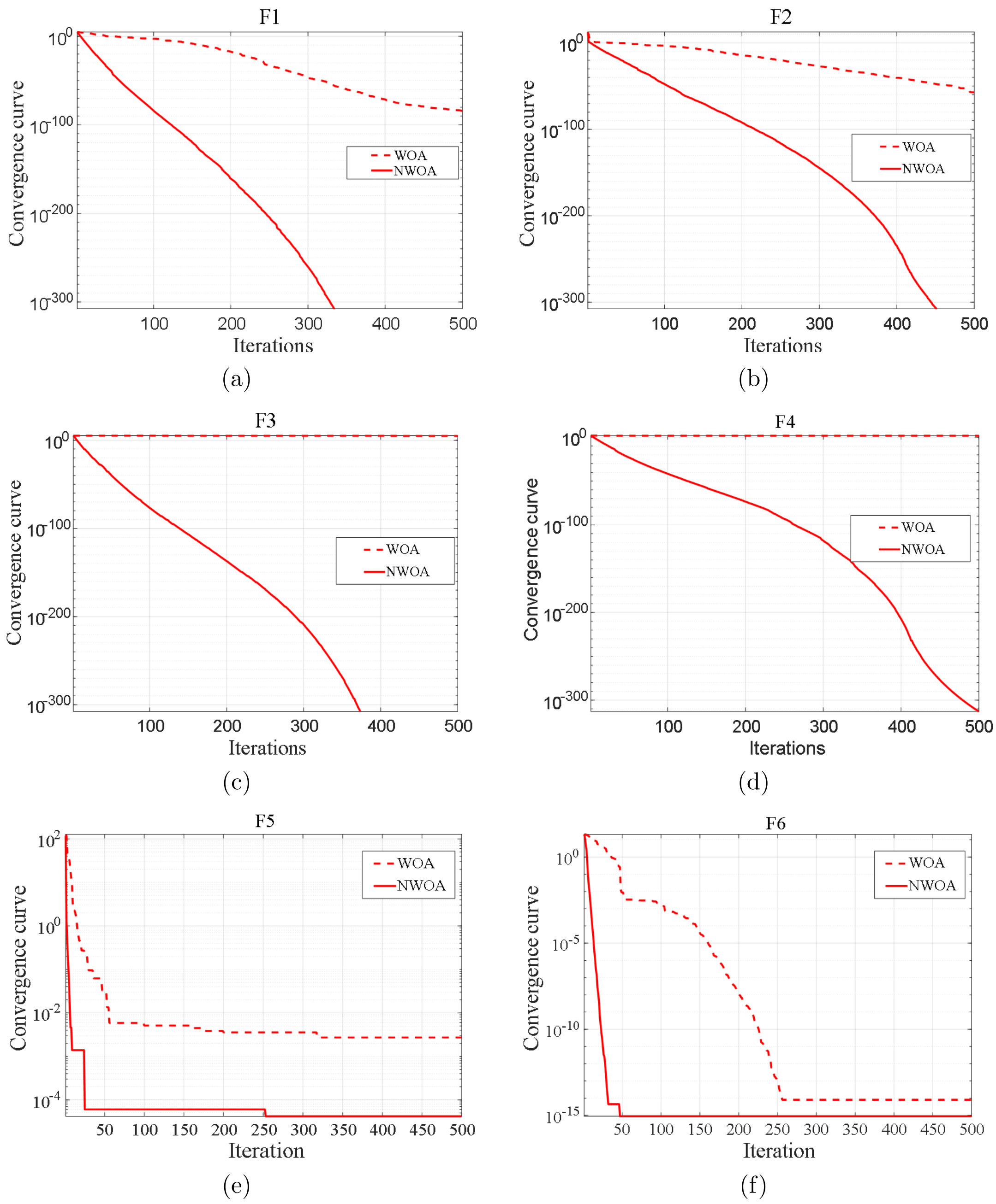

FIGURE 2. Optimal convergence curve of function

4.1. **simulation settings.** Taking a wind and solar storage system as a design case, the IEEE-33-node network standard example is adopted for example analysis [28], See figure 3. Among them, nodes 8 and 28 are connected to photovoltaics, and nodes 14 and 27 are connected to wind power. The voltage level is 12.66 kV, the reference power is 100 MVA, the total active load and reactive load are 3715 kW and 2300 kvar respectively, and the allowable range of node voltage is 0.9 ˜ 1.10 pu(pu is the nominal value, which is 90% to 110% of the rated power). NWOA is used to solve the optimization the location and capacity selection of ESS. Taking the wind and light resources and load power in this area as an example. The forecast power of wind power, photovoltaic and load on a typical day is shown in Figure 4.

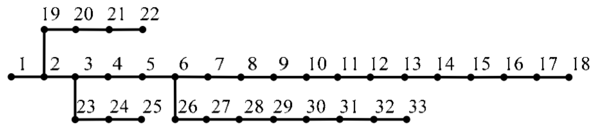

FIGURE 3. IEEE-33 Section System

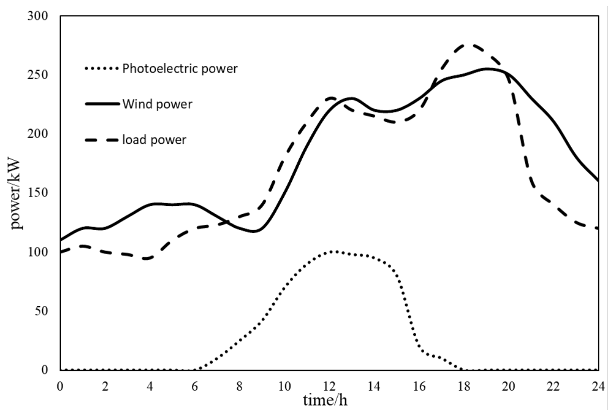

FIGURE 4. Wind-light-load daily characteristic curve

4.2. **Analysis of optimization results.** For the sake of geting the best access position and capacity of ESS in the power grids, the following scenarios are selected for comparison:

Scenario 1: The network is not connected to energy storage;

Scenario 2: The network is connected to ESS, and WOA is used to calculate and solve it;

Scenario 3: The network is connected to ESS, and NWOA is used to calculate and solve it.

The optimization results in different scenarios are shown in Table 5.

TABLE 5. Performance test results

Scenario	Energy storage number	Energy storage position	Energy storage capacity/MWh	f1/pu	f2/pu	f3/MWh
1	0	—	—	0.125	0.0894	—
3	2	8 14	0.552 0.576	0.0702	0.0315	1.128
4	3	10 14	0.541 0.592	0.0617	0.0220	1.133

As can be seen from the above table 5. By comparing the scenario 1 with scenarios 2 and 3. Because of the uncertainty and volatility of new energy, the original system has large voltage deviation and network loss. When the ESS is connected to the system, the voltage deviation of the system decreased from the original 0.125pu(pu is the standard value) to 0.0702pu and 0.0617pu respectively, and the network loss decreased from 0.0894pu to 0.0315pu and 0.0220pu respectively.

By comparing scenario 2 with scenario 3. The result can be obtained that the NWOA algorithm made in this paper installed ESS at nodes 10 and 14, compared with the conventional WOA algorithm installed ESS at nodes 8 and 14. Although the total capacity of energy storage has increased from 1.128MWh to 1.133MWh, the voltage deviation and network loss have further decreased. The overall solution of NWOA is better than that of conventional WOA. It shows that NWOA can find the optimal solution better than the original WOA algorithm in practical application.

5. **Conclusions.** In this paper, the whale optimization algorithm is improved by introducing nonlinear weight coefficient, and it is verified by standard test function. The comparison data make clear that NWOA has preferable global search capability than conventional WOA , and it is superior with respect to convergence speed and accuracy.

Next, the simulation modeling of energy storage related issues is studied and builds a power system model with energy storage. Taking the IEEE33 node system as an example, New energy sources such as wind power and photovoltaic are configured in the IEEE33 node system. To stabilize the power fluctuation of new energy power generation, the optimal solution of the multi-objective objectives optimization problem of ESS location and capacity determination is carried out. The solution flow of energy storage model is designed by NWOA, and compared with the conventional WOA. The experimental results show that the energy storage site selection and capacity determination results solved by the NWOA can better reduce the voltage functions and network losses of the system, improve the working effect of new energy power generation, and reduce the impact of power fluctuations on the system.

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