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Scenario-Set-Based Economic Dispatch of Power System With Wind Power and Energy Storage System

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ABSTRACT In view of uncertainties caused by large-scale wind power integration, energy storage system (ESS) is being considered to stabilize the fluctuation of wind power. In this paper, the influence of ESS on power system operation with wind power is analyzed in detail, and an economic dispatch (ED) model with wind power and ESS is proposed based on scenario set. First, the initial scenario set of wind power output is generated by the Monte Carlo sampling. To overcome the shortcoming of heavy dependence on the initial clustering centers, which usually leads to unstable clustering results, the k-means clustering is improved by combining self-organizing feature map neural network and particle swarm optimization (PSO). Then, the initial scenario set is reduced based on this improved k-means clustering method. Finally, an ED model solved by PSO is used to minimize the comprehensive power generation cost based on the reduced scenario set. Taking IEEE-39 bus system as an example, the scenario-set-based ED model is implemented in this paper. The simulation results show that, when solving the ED problem with wind power and ESS, the proposed method considering scenario reduction makes not only the clustering index better, but also the results of ED more reasonable.

INDEX TERMS Economic dispatch, energy storage system, wind power, clustering, scenario set, self-organizing feature map neural network, particle swarm optimization.

NOMENCLATURE

The main symbols used are defined below. Others are defined as required in the text.

A. INDICES

- j Index of thermal power units from 1 to n
- t Index of time periods from 1 to T
- s Index of scenarios from 1 to S
- i Index of batteries from 1 to n_{b}
- l Index of transmission lines from 1 to L

B. PARAMETERS

- Δt Time interval
- T_{60} One hour
- $a_j/b_j/c_j$ Coal consumption coefficient
- $T_j^{\mathrm{on}}/T_j^{\mathrm{off}}$ Minimum operating time/downtime of generator j
- T_j^{cold} Cold-start time of generator j
- $K_{\mathrm{up}}/K_{\mathrm{dn}}$ Cost coefficient of starting upward/downward spinning reserve
- $K_{\mathrm{m}i}$ Cost coefficient of operation and maintenance of battery i
- $C_{\mathrm{f}i}$ Investment cost of the complete life cycle of battery i
- K_{ls} Cost coefficient of load shedding
- K_{wc} Cost coefficient of wind power curtailment
- P_{wr} Installed capacity of the wind farm
- $P_l^{\mathrm{m}}/P_l^{\mathrm{M}}$ Minimum/maximum power flow of line l
- $\eta_{\mathrm{c}i}/\eta_{\mathrm{d}i}$ Charging/discharging efficiency of battery i
- R_i Total number of cycles of battery i
- $S_{\mathrm{oc}i}^{\mathrm{m}}/S_{\mathrm{oc}i}^{\mathrm{M}}$ Minimum/maximum SOC of battery i

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σ_i Self-discharge rate of battery i during a single period
$E_{\mathrm{N}i}$ Rated capacity of battery i
η_s Probability of scenario s

C. VARIABLES

$u_{j,t}$ State of generator j at period t
$\mu_{i,t,s}$ State of battery i at period t in scenario s, 1 represents the state of charge, -1 represents the state of discharge
$\rho_{i,t,s}$ Flag of whether the battery i completes a single charge/discharge at period t in scenario s
$P_{j,t,s}$ Active power output of generator j at period t in scenario s
$X_{j,t}^{\mathrm{on}}/X_{j,t}^{\mathrm{off}}$ Continuous operating time/downtime of generator j at period t
$\varepsilon_{\mathrm{w},t,s}$ Wind power forecast error at period t in scenario s
$P_{\mathrm{w},t,s}^{\mathrm{ac}}$ Actual output of wind power at period t in scenario s
$P_{\mathrm{w},t,s}^{\mathrm{p}}$ Planned output of wind power at period t in scenario s
$P_{\mathrm{w},t}^{\mathrm{f}}$ Wind power forecasting value at period t
$P_{\mathrm{b}i,t,s}$ Charging/discharging power of battery i at period t in scenario s, it is positive when charging, negative when discharging
$P_{\mathrm{ls},t,s}$ Expected power of load shedding at period t in scenario s
$P_{\mathrm{wc},t,s}$ Expected power of wind power curtailment at period t in scenario s
$P_{\mathrm{up},t,s}/P_{\mathrm{dn},t,s}$ Wind power output that the system can absorb when the thermal power units provide all upward/downward spinning reserve at period t in scenario s
$P_{\mathrm{sc},t,s}/P_{\mathrm{sd},t,s}$ Wind power output that the system can absorb when the energy storage reaches the charging/discharging power limit at period t in scenario s
$P_{\mathrm{load},t}$ Active load of system at period t
$P_{j,t}^{\mathrm{m}}/P_{j,t}^{\mathrm{M}}$ Minimum/maximum active power output of generator j at period t
$r_{l,t}$ Spinning reserve for load fluctuation at period t
$r_{\mathrm{w},t}$ Spinning reserve for wind power fluctuation at period t
$\Delta P_{j,t}^{\mathrm{dn}}/\Delta P_{j,t}^{\mathrm{up}}$ Maximum downward/upward ramp rate of generator j at period t
$P_{l,t,s}$ Power flow of line l at period t in scenario s
$P_{\mathrm{c}i,t}^{\mathrm{m}}/P_{\mathrm{c}i,t}^{\mathrm{M}}$ Minimum/maximum charging power of battery i at period t
$P_{\mathrm{d}i,t}^{\mathrm{m}}/P_{\mathrm{d}i,t}^{\mathrm{M}}$ Minimum/maximum discharging power of battery i at period t

I. INTRODUCTION

In recent years, with the depletion of traditional fossil energy resources and the aggravation of environmental pollution, renewable energy has developed rapidly with its advantages of cleanness and freedom from pollution. Among them, wind power has the largest development scale and the most mature technology. In China, the wind power industry has developed rapidly, the installed capacity of wind turbines continues to increase, and the development costs are gradually decreasing. However, with more and more wind power connected to the power grid, the secure and stable operation of the power grid has also been greatly impacted, and many wind farms are experiencing power curtailment.

With more and more wind power connected to the power grid, its impact on the secure and stable operation of the system cannot be ignored. In areas with abundant wind resources or areas with large-scale wind power integration, a certain scale of energy storage system (ESS) can be allocated to participate in economic dispatch (ED), which can stabilize the fluctuation of wind power output and reduce the wind power curtailment. In recent years, the development of energy storage technology has matured, and the costs of energy storage devices are gradually decreasing. Thus, the application of ESS to improve the optimal operation of power system with wind power will be a hot spot in the future. In [1], a stochastic unit commitment (SUC) model with ESS was presented to evaluate the short-term profitability of conventional generators and ESS under different levels of renewable penetrations. In [2], a thermal-storage joint dispatch model was built to optimize the operation of thermal power units after large-scale wind power integration, but the participation of wind power in the dispatch was ignored. Reference [3] presented cost-based formulation to determine the optimal size of the battery energy storage in the operation management of a microgrid. The role of energy storage in reducing operating costs and enhancing system flexibility was explored in [4]. Reference [5] presented a bulk energy storage dispatch model. This paper pointed out that higher wind penetration profits bulk storage ventures, especially for larger capacities. Reference [6] developed a chance-constrained ED model for a wind-thermal-ESS system. In [7], a battery energy storage system (BESS) was used to solve the problem of wind power curtailment caused by large-scale wind power integration. However, [6] and [7] did not conduct a detailed analysis of the influence of the capacity and location of the ESS on the results of ED. Reference [8] presented a two-step framework to evaluate the potential benefits of battery storage in power systems with renewable generation. The proposed flexible operating range method was able to take advantage of the flexibility of energy storage to provide higher cost savings.

ED with wind power mainly depends on the accuracy of wind power forecasting, whereas the accuracy of wind power forecasting is far lower than that of load forecasting. Therefore, describing the wind power output and the forecast error of wind power forecasting is the focus of the ED with

wind power. Considering the stochasticity and fluctuation of wind power, it is of great significance to explore an effective ED model with wind power. At present, there are many methods to solve this problem. The main methods are as follows:

A. INCREASE SPINNING RESERVE

References [9] and [10] dealt with the uncertainty of wind power forecasting by reserving a certain capacity of spinning reserve for wind power. This method is simple and reliable, but the forecast error of wind power is large, so it is difficult to determine the capacity of spinning reserve. The absolute security of the system can be guaranteed only by reserving the spinning reserve of the capacity of wind power. However, the results are too conservative, and the economy of ED becomes worse.

B. ROBUST OPTIMIZATION METHOD

In [11], two new robust unit commitment models were proposed: expanded robust unit commitment and risk-constrained robust unit commitment. According to the uncertainty of wind power and price-based demand response, a robust dispatch method was proposed in [12]. In [13], a double-level robust interval unit commitment model was established for joint operation of a wind-storage system. In the ED with wind power, robust optimization considers the extreme scenarios of wind power output. Although this method can ensure the security of the system, it makes the results of ED more conservative.

C. STOCHASTIC OPTIMIZATION METHOD BASED ON CHANCE CONSTRAINED PROGRAMMING

Reference [14] developed an adjustable chance-constrained approach to optimally allocate flexible ramping capacity reserves. In [15], a model based on chance-constrained-goal programming was proposed to optimize the risk-adjustable unit commitment problem. Reference [16] proposed a day-ahead scheduling model with wind power and energy storage based on chance-constrained programming. Based on the theory of chance-constrained programming, a determination method of optimal zonal reserve demand using the minimum confidence interval was proposed in [17]. For chance-constrained programming, some constraints are allowed with random variables that are not tenable during optimization, but the probability of the constraints to be tenable should meet a certain confidence level. Although this method can deal with the uncertainty of wind power, for a large-scale power system, it is difficult to derive an analytical chance-constrained model, and it is difficult to determine the confidence level objectively.

D. STOCHASTIC OPTIMIZATION METHOD BASED ON SCENARIO SET

The stochastic optimization method based on a scenario set consists of two stages: scenario generation and scenario reduction. The scenario generation of wind power is a process of dividing the probability distribution model of wind power into a large number of time series. In the ED model with wind power, a large number of scenarios will increase the computational complexity and reduce the calculation efficiency. Moreover, the initial scenario set usually contains some extreme scenarios with low probability. Considering these extreme scenarios during optimization will lead to conservative results. Therefore, it is necessary to merge and reduce the initial scenario set according to certain criteria on the premise of ensuring the accuracy of the results. This process is called scenario reduction.

Each scenario in the scenario set represents a set of possible wind power output time series. Therefore, the scenario set of wind power is essentially composed of a large number of time series that can cover all possible wind power output. These time series can be obtained according to the probability distribution of wind power or the point forecast value of wind power and the probability distribution of the forecast error. The ED problem with wind power based on a scenario set is usually modeled as a two-stage stochastic programming problem. In the first stage, the state of the thermal power units should be determined according to the point forecast value of wind power and the related constraints of the model. The second stage is to readjust the output of thermal power units according to the possible wind power output in each scenario. At the second stage, load shedding and wind power curtailment may occur. The ultimate goal is to minimize the weighted average value of the power generation cost in each scenario [18].

Compared with the former methods, the method based on scenario set has obvious advantages:

1) This method can consider the probability of various scenarios of wind power output and their impact on ED. From the statistical point of view, this method can also deal more objectively with the economic and security problems caused by the uncertainty of wind power forecasting [19].
2) Compared with the robust optimization method, this method generally consists of two stages: scenario generation and scenario reduction. To avoid the results of ED being too conservative, some extreme scenarios with low probability are merged and reduced by scenario reduction technology, so the power generation cost is reduced.
3) The probability distribution model of wind speed or wind power output is usually expressed in the form of calculus. In most cases, the operation planning of power grid cannot directly use it, such as in a SUC problem. Therefore, it is necessary to discretize the probability distribution model of wind power, and this method is an effective way to do so.

At present, there are many research results for the stochastic optimization method based on a scenario set. Reference [18] proposed a scenario representation method referred to as scenario mapping technology, which can compact a large number of scenarios while preserving the uncertainty and variability features of wind power as much

as possible. Compared with traditional scenario reduction methods (such as k-means clustering), the proposed method makes a significant improvement in cost efficiency and calculation efficiency when solving the SUC problem. However, this method needs to determine two parameters at the same time when solving. To obtain the most reasonable and optimal results, this method will be more difficult and complex when solving the model. In [20], Latin hypercube sampling (LHS) and Cholesky decomposition was used to generate the scenario set, and a new clustering method was proposed to reduce the number of scenarios. However, the representative scenarios are selected according to the system security and operation cost of the system and lack the relationship between the final selected scenarios and the initial scenario set.

Backward reduction (BR) and fast forward selection algorithm (FFSA) are common scenario reduction methods. Both of them continuously merge and reduce the initial scenario set by calculating the distance between scenarios. In [1], the scenario set was generated by Monte Carlo sampling (MCS), and the BR method was used to solve the SUC problem. In [21], an ED model considering the uncertainty of the load and wind power was proposed. MCS and roulette wheel mechanism were used to generate the scenario set, and the BR method was used to reduce the scenario set. In [22], a two-stage optimization model was proposed, in which the reduced scenario set by BR method and the extreme output scenarios are taken as the input, the extreme output scenarios were identified according to the results of the first stage, but this method was time-consuming. In [23] and [24], FFSA was preferred to reduce the initial scenario set. In [25], the scenarios are generated using MCS and constructed Rayleigh probability distribution function. Afterward, the desired number of scenarios were obtained by FFSA. In [26], wind and photovoltaic generation uncertainties were modeled using MCS, and FFSA was applied to reduce the initial scenario set. Reference [27] used MCS to generate a photovoltaic power generation scenario set and used the BR method to reduce the initial scenario set.

Scenario tree reduction method is to reduce the scenarios on the basis of the BR method. In [28], the temporal characteristic of the day-ahead wind power forecast error was modeled as scenario tree, but the method based on scenario tree had high computational complexity and was prone to ''dimension disaster'' as the number of scenarios increased.

K-means clustering and k-medoids clustering are both common scenario clustering methods. k-means clustering takes the mean value of the samples in each cluster as the clustering center, k-medoids clustering takes a real sample in each cluster as the clustering center. In [19], LHS was used to generate the initial scenario set of the wind power output, and an improved k-medoids clustering based on particle swarm optimization (PSO) was used to reduce the scenario set, which effectively improved the k-medoids clustering, which had the shortcoming of unstable clustering results. In [29], an improved bird swarm algorithm was used to optimize the clustering centers of k-means clustering. Then, the optimized clustering centers were used in k-means clustering. In [30], the clustering method k-means clustering based on numerical weather prediction (K-means-NWP) was adopted to describe the uncertainty of wind power output. Reference [31] proposed an improved k-means clustering method to reduce the annual scenario set in the planning of distributed generation. In [32], fuzzy c-mean-clustering comprehensive quality (FCM-CCQ) clustering method was used to describe typical output scenarios of wind and solar power. In [33], LHS was used to generate a scenario set for photovoltaic power generation. The improved k-means clustering based on Huffman tree was used to cluster the scenario set of photovoltaic power generation, so as to avoid the influence of the improper initial clustering centers that lead to the clustering was unable to effectively converge.

According to the above analysis, classical scenario reduction methods have some significant shortcomings. The BR method and FFSA are simple to calculate, but their computational complexity is relatively high, and the effect of merging extreme scenarios with low probability are not ideal. Based on the scenario tree method, when the number of scenarios increases, the method is prone to ''dimension disaster''. K-means clustering and k-medoids clustering are common scenario clustering methods, which are simple, fast, and widely used in the field of scenario reduction, but its clustering effect depends on the initial clustering centers. If the initial clustering centers are not determined properly, then the clustering effect will be poor [19]. The ED problem is solved based on the reduced scenario set. The effectiveness of the scenario reduction method determines the rationality of the results of ED. Therefore, it is very important to choose an appropriate and effective scenario reduction method.

In view of the uncertainty risk of wind power, this paper applies the ESS to stabilize the fluctuation of wind power output and weaken the wind power curtailment and load shedding in ED. In order to explore the influence of ESS on the optimal operation of power system with wind power, this paper establishes a wind-thermal-ESS joint dispatch model based on a scenario set. An improved k-means clustering method based on self-organizing feature map (SOM) neural network and PSO is proposed for scenario reduction. SOM neural network can adaptively change the network parameters and structure to realize unsupervised learning, which has a wide range of applications in pattern recognition, clustering, and other fields [34]. The SOM neural network is used to cluster the initial scenario set, which improves the dependence of k-means clustering on the initial clustering centers. After obtaining the clustering centers, PSO is used in the further optimization to improve the unstable clustering effect by k-means clustering. The scenario set of wind power output obtained by the proposed method is not only representative, but also able to maintain the characteristics of the initial scenario set as well as the appropriate scale. Therefore, the results of ED of the wind-thermal-ESS system are more reasonable.

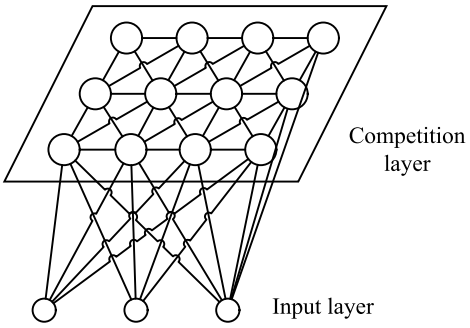

FIGURE 1. Structural diagram of SOM neural network.

II. ECONOMIC DISPATCH MODEL

A. PARTICLE SWARM OPTIMIZATION

The PSO algorithm was originally developed by studying the foraging behavior of birds. PSO is one of the swarm intelligence optimization algorithms. When the PSO algorithm is used to solve the optimization problem, each feasible solution is regarded as a ''particle'' in the search space, and all particles constitute the particle swarm. Each particle has a position, velocity, fitness function value, and other attributes. In the iterative process, particles update their position and velocity through two extreme values: the individual extreme value of the particles and the global extreme value of the population [35].

The individual extreme value of a particle is the best position that particle i experiences when it iterates from the initial state to the k-th generation, that is, $pbest_i^k$. At this time, this particle is called the individual optimal particle. The global extreme value of the population is the best position that the entire population experiences when it iterates to the k-th generation, that is, $gbest^k$. At this time, this particle is called the global optimal particle.

The iteration formulas of the PSO algorithm are as follows:

$$v_i^{k+1} = \omega v_i^k + c_1 r_1 \left(pbest_i^k - x_i^k\right) + c_2 r_2 \left(gbest^k - x_i^k\right) \quad (1)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (2)$$

where v_i^k is the velocity vector of particle i at the k-th iteration, ω is the inertia coefficient, c_1 and c_2 are acceleration coefficients, r_1 and r_2 are random numbers with uniform distribution in [0,1], and x_i^k is the position vector of particle i at the k-th iteration.

B. SOM NEURAL NETWORK

The SOM neural network can change the parameters and structure of the network adaptively. Its self-organizing ability is realized by a special network structure. As shown in Fig. 1, the network is divided into an input layer and competition layer. In the competition layer, each neuron has a horizontal connection, and each connection is given a weight. According to the Kohonen learning rules, only one neuron is activated in each competition. The activated neuron is called the winning neuron. The weights of the neurons in the neighborhood of the winning neuron will be adjusted to reflect the competition results, and the states of other neurons will be inhibited [34]. Applying the SOM neural network for clustering, when a sample is input, the neurons representing the cluster in the competition layer will produce the most intense response so that the input will be automatically clustered.

C. GENERATION OF SCENARIO SET

The actual output of wind power can be regarded as the sum of the forecast value and the forecast error of the wind power. It is assumed that the forecast error of the wind power follows the normal distribution with the mean value of zero and the standard deviation of ζ_w [36], as follows:

$$P_{w,t,s}^{ac} = P_{w,t}^{f} + \varepsilon_{w,t,s} \quad (3)$$

$$\zeta_{w,t} = P_{w,t}^{f}/5 + P_{wr}/50 \quad (4)$$

In this paper, first, the scenario set of the wind power forecast error is generated by MCS. Each scenario is added to the point forecast value of the wind power, and then the initial scenario set of the wind power is obtained. There are a large number of scenarios in the initial scenario set, so it will undoubtedly take a significant amount of time to perform a detailed analysis and calculation of each scenario. Moreover, the initial scenario set usually contains a certain number of extreme scenarios with very low probability. If these extreme scenarios are considered in the ED problem, the final results will be conservative. Therefore, it is very important to obtain a representative, preserving the features of the initial scenario set, and a small-scale scenario set through an appropriate scenario reduction method. In this paper, an improved k-means clustering based on SOM neural network and PSO is used to merge and reduce the initial scenario set of wind power. The specific steps are as follows, and the flow chart is shown in Fig. 2.

Step1: Generate the initial scenario set by MCS.

Step2: Cluster the scenario set with SOM neural network.

Step3: Take the reduced scenario set as the initial particle of PSO.

Step4: Judgment: whether the times of clustering have reached the population size of PSO?

Step5: If the times of clustering have reached the population size of PSO, each initial particle is used as the *pbest*, one of initial particles is selected randomly as the *gbest*. Otherwise, return to Step 2.

Step6: Calculate the Dunn index of each particle as the fitness function value in optimization.

Step7: Update the position vector and the velocity vector of each particle.

Step8: Use the updated position vector as the initial clustering centers, recluster the initial scenario set with k-means clustering, and the new clustering centers are obtained.

Step9: Update the fitness function value of new particle.

Step10: Update the *pbest* of each particle and the *gbest* of the population.

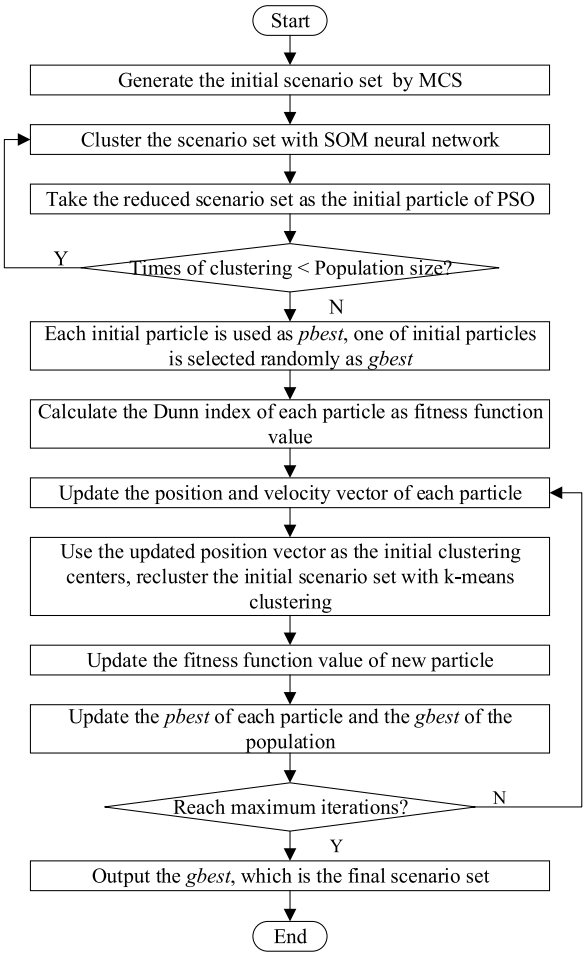

FIGURE 2. Flowchart of the proposed scenario reduction method.

Step11: Judgment: whether the maximum number of iterations has been reached?

Step12: If the maximum number of iterations has been reached, output the *gbest*, which is the final scenario set. Otherwise, return to Step 7.

Note: After updating the position vector and velocity vector of particles, new particles are not obtained directly. Instead, the updated position vector is used as the initial clustering center, and k-means clustering is used to recluster the scenarios in the initial scenario set to obtain new clustering centers. At this time, new particles are obtained. In the process of PSO, the position vector of the particle is composed of the clustering centers of k-means clustering. The velocity vector has the same dimension as the position vector, which is an adjustment of the cluster centers. The fitness function is the Dunn index calculated by the current clustering centers.

In this paper, the Dunn index is selected as the clustering evaluation index. The Dunn index is defined as the ratio of the minimum distance between the scenarios of any two clusters to the maximum distance between the scenarios in any cluster. The larger the ratio, the greater the distance between the clusters and the smaller the distance within a cluster, the better the clustering effect [37]. The calculation formula is as follows:

$$DI = \frac{\min\limits_{0<m\neq n<S}\left\{\min\limits_{\substack{\forall x_i\in\Omega_m\\ \forall x_j\in\Omega_n}}\left\{\left\|x_i-x_j\right\|\right\}\right\}}{\max\limits_{0<m\leq S}\max\limits_{\forall x_i,x_j\in\Omega_m}\left\{\left\|x_i-x_j\right\|\right\}} \tag{5}$$

where in this paper, the number of scenarios in the final wind power scenario set is S, that is, the number of clusters is S. Ω_m is the m-th cluster, and x_i is the scenario in Ω_m.

D. OBJECTIVE FUNCTION OF MODEL

Based on the reduced scenario set, an ED model with the objective of minimizing the comprehensive power generation cost is established. The comprehensive power generation cost consists of the operating cost of thermal power and the uncertainty risk cost of wind power. The objective function of the model is

$$f_{\text{sum}} = \min\sum_{t=1}^{T}\left[\left(\sum_{j=1}^{n} f_{\text{fire}}\left(j,t\right)\right)+f_{\text{wind}}\left(t\right)\right] \tag{6}$$

where f_{sum} is the comprehensive power generation cost for 24 hours a day, $f_{\text{fire}}\left(j,t\right)$ is the operating cost of generator j at period t, and $f_{\text{wind}}\left(t\right)$ is the uncertainty risk cost of wind power at period t.

1) OPERATING COST OF THERMAL POWER

The operating cost of thermal power mainly includes the fuel cost, startup cost, and shutdown cost. The fuel cost is usually expressed as a second-order polynomial of the active output of thermal power units. The startup cost can be approximately divided into cold start and hot start according to the downtime [38]. The shutdown cost is generally a fixed value that is very small compared with the startup cost and is usually ignored [35]. Therefore, the formulas are as follows:

$$f_{\text{fire}}\left(j,t\right) = u_{j,t}f_{\text{fuel}}\left(j,t\right)+u_{j,t}\left(1-u_{j,t-1}\right)S_{j,t} \tag{7}$$

$$f_{\text{fuel}}\left(j,t\right) = \sum_{s=1}^{S}\left(a_jP_{j,t,s}^2+b_jP_{j,t,s}+c_j\right)\cdot\eta_s \tag{8}$$

$$S_{j,t} = \begin{cases} X_j^{\text{off}} \leq T_j^{\text{cold}}+T_j^{\text{off}}, Sh_{j,t} \\ X_j^{\text{off}} > T_j^{\text{cold}}+T_j^{\text{off}}, Sc_{j,t} \end{cases} \tag{9}$$

where $f_{\text{fuel}}\left(j,t\right)$ is the fuel cost of generator j at period t, $S_{j,t}$ is the startup cost of generator j at period t, $Sh_{j,t}$ and $Sc_{j,t}$ are the hot start and cold start cost of generator j at period t, respectively.

2) UNCERTAINTY RISK COST OF WIND POWER

In this paper, reasonable wind power curtailment and load shedding are allowed to reduce the conservativeness of the results of ED. The uncertainty risk cost of wind power is essentially caused by the inconsistency between the actual output and the planned output of wind power. The planned

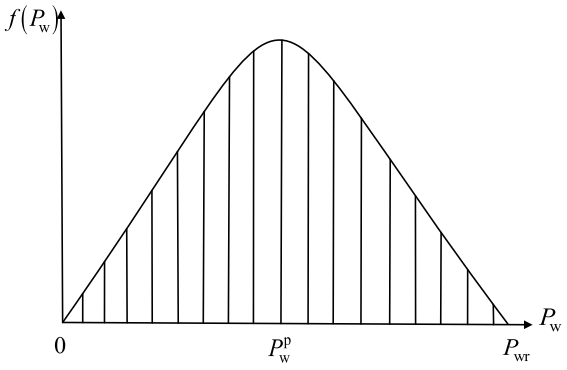

FIGURE 3. The PDF of wind power output after discretization.

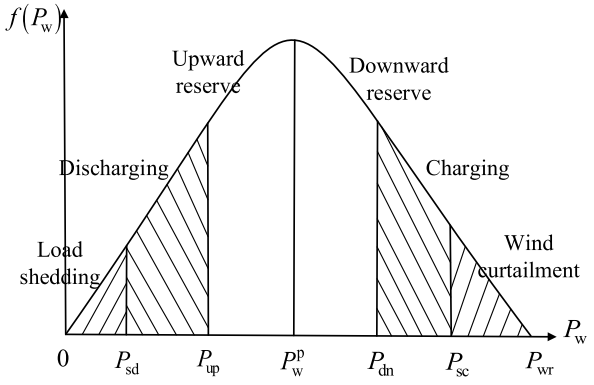

FIGURE 4. The PDF of wind power output when calculating.

output of wind power is a decision variable. Because this paper studies the day-ahead economic dispatch, the actual output of wind power is replaced by the sum of the forecast value and the forecast error of the wind power. Note that each scenario generated by MCS is a set of 24-dimensional time series, so the probability of wind power output at each time period is the same in a scenario. Before scenario reduction, to describe the fluctuation of wind power output, at a certain time period, the probability density function (PDF) of the wind power output is divided into numerous intervals, as shown in Fig. 3. After scenario reduction, the possible output scenarios of wind power at this time period are finally reduced to S. According to the actual situation, when calculating the uncertainty risk cost of wind power considering ESS, the scenarios of wind power output at a certain time period are divided into six situations, as shown in Fig. 4.

When the actual output of the wind power is less than the planned output, if the deviation (difference between the planned output and actual output of wind power) is less than the upward spinning reserve capacity of the system, it is necessary to start the upward spinning reserve. Otherwise, if there is an ESS, the ESS shall be discharging within the allowable discharging range. If the deviation still exceeds the upward spinning reserve capacity of the system and the discharging power of the ESS, it is necessary to cut off part of the load to maintain the active power balance. Similarly, when the actual output of the wind power is greater than the planned output, if the deviation (difference between the actual output and planned output of wind power) is less than the downward spinning reserve capacity of the system, it is necessary to start the downward spinning reserve. Otherwise, if there is an ESS, the ESS shall be charging within the allowable charging range. If the deviation still exceeds the downward spinning reserve capacity of the system and the charging power of the ESS, then it needs to abandon part of the wind power to maintain the active power balance.

The uncertainty risk cost of wind power includes the cost of starting spinning reserve $f_{\text{reserve}}(t)$, the cost of ESS $f_{\text{storage}}(t)$, and the penalty cost $f_{\text{penalty}}(t)$. The ESS configured in this paper is a BESS. Compared with thermal power, wind power, and other energy sources, currently, the investment cost of energy storage devices is still relatively high, and their operation life is relatively short compared with the above energy sources. In a long-term wind-thermal system, the introduction of a BESS may require multiple replacements of the BESS. Therefore, when studying the ED with wind power and BESS, in addition to the operation and maintenance cost of the BESS, the investment cost of BESS in each scheduling cycle must also be considered. The calculation of the investment cost of BESS is referred to [39]. Since the wind power output has been discretized before, it is unnecessary to carry out a complex integral operation. The calculation formulas for uncertainty risk cost are as follows:

$$f_{\text{wind}}(t) = f_{\text{reserve}}(t) + f_{\text{storage}}(t) + f_{\text{penalty}}(t) \tag{10}$$

$$f_{\text{reserve}}(t) = f_{\text{up}}(t) + f_{\text{dn}}(t) \tag{11}$$

$$f_{\text{up}}(t) = \begin{cases} \sum_{s=1}^{S} K_{\text{up}} \left(P_{\text{w},t,s}^{\text{p}} - P_{\text{up},t,s}\right) \cdot \eta_s, \\ \qquad P_{\text{w},t,s}^{\text{ac}} < P_{\text{up},t,s} \\ \sum_{s=1}^{S} K_{\text{up}} \left(P_{\text{w},t,s}^{\text{p}} - P_{\text{w},t,s}^{\text{ac}}\right) \cdot \eta_s, \\ \qquad P_{\text{up},t,s} \le P_{\text{w},t,s}^{\text{ac}} < P_{\text{w},t,s}^{\text{p}} \end{cases} \tag{12}$$

$$f_{\text{dn}}(t) = \begin{cases} \sum_{s=1}^{S} K_{\text{dn}} \left(P_{\text{dn},t,s} - P_{\text{w},t,s}^{\text{p}}\right) \cdot \eta_s, \\ \qquad P_{\text{w},t,s}^{\text{ac}} > P_{\text{dn},t,s} \\ \sum_{s=1}^{S} K_{\text{dn}} \left(P_{\text{w},t,s}^{\text{ac}} - P_{\text{w},t,s}^{\text{p}}\right) \cdot \eta_s, \\ \qquad P_{\text{w},t,s}^{\text{p}} \le P_{\text{w},t,s}^{\text{ac}} \le P_{\text{dn},t,s} \end{cases} \tag{13}$$

$$f_{\text{storage}}(t) = f_{\text{main}}(t) + f_{\text{fix}}(t) \tag{14}$$

$$\begin{cases} \mu_{i,t,s} = 1, & P_{\text{dn},t,s} < P_{\text{w},t,s}^{\text{ac}} \le P_{\text{sc},t,s} \\ \mu_{i,t,s} = -1, & P_{\text{sd},t,s} \le P_{\text{w},t,s}^{\text{ac}} < P_{\text{up},t,s} \end{cases} \tag{15}$$

$$f_{\text{main}}(t) = \sum_{s=1}^{S} \left(\sum_{i=1}^{n_{\text{b}}} K_{\text{m}i} \cdot \mu_{i,t,s} P_{\text{b}i,t,s} \cdot \Delta t \right) \cdot \eta_s \tag{16}$$

$$f_{\text{fix}}(t) = \sum_{s=1}^{S} \left(\sum_{i=1}^{n_{\text{b}}} \frac{\rho_{i,t,s} \cdot C_{\text{f}i}}{R_i} \right) \cdot \eta_s \tag{17}$$

$$f_{\text{penalty}}(t) = f_{\text{ls}}(t) + f_{\text{wc}}(t) \tag{18}$$

$$f_{\text{ls}}(t) = \sum_{s=1}^{S} K_{\text{ls}} \left(P_{\text{sd},t,s} - P_{\text{w},t,s}^{\text{ac}}\right) \cdot \eta_s, \quad 0 < P_{\text{w},t,s}^{\text{ac}} < P_{\text{sd},t,s} \tag{19}$$

$$f_{\text{wc}}(t) = \sum_{s=1}^{S} K_{\text{wc}} \left(P_{\text{w},t,s}^{\text{ac}} - P_{\text{sc},t,s}\right) \cdot \eta_s, \quad P_{\text{sc},t,s} < P_{\text{w},t,s}^{\text{ac}} < P_{\text{wr}} \tag{20}$$

where $f_{\text{up}}(t)$ and $f_{\text{dn}}(t)$ are the cost of the starting upward and downward spinning reserve, respectively; $f_{\text{main}}(t)$ is the operation and maintenance cost of the BESS at period t; $f_{\text{fix}}(t)$ is the investment cost at period t; $f_{\text{ls}}(t)$ and $f_{\text{wc}}(t)$ are the expected cost of load shedding and wind power curtailment, respectively.

E. CONSTRAINTS OF MODEL

1) Active power balance

$$\sum_{j=1}^{n} u_{j,t} P_{j,t,s} + \left(P_{\text{w},t,s}^{\text{p}} - P_{\text{wc},t,s}\right) - \sum_{i=1}^{n_{\text{b}}} P_{\text{b}i,t,s} = P_{\text{load},t} - P_{\text{ls},t,s} \tag{21}$$

2) Power limitation

$$\begin{cases} P_{j,t}^{m} \le P_{j,t,s} \le P_{j,t}^{M} \\ 0 \le P_{w,t,s}^{p} \le P_{\text{wr}} \end{cases} \tag{22}$$

3) Reserve

$$\sum_{j=1}^{n} u_{j,t} P_{j,t}^{\text{M}} + P_{\text{w},t}^{\text{f}} \ge P_{\text{load},t} + r_{l,t} + r_{\text{w},t} \tag{23}$$

where $r_{\text{w},t}$ is the spinning reserve added owing to the wind power forecast error at period t, which is related to the maximum wind power forecast error in each time period.

4) Ramp rate

$$\Delta P_{j,t}^{\text{dn}} \cdot T_{60} \le P_{j,t,s} - P_{j,t-1,s} \le \Delta P_{j,t}^{\text{up}} \cdot T_{60} \tag{24}$$

5) Minimum up/down time

$$\begin{cases} X_{j,t}^{\text{on}} \ge T_j^{\text{on}} \\ X_{j,t}^{\text{off}} \ge T_j^{\text{off}} \end{cases} \tag{25}$$

6) Branch power flow

$$P_l^{\text{m}} \le P_{l,t,s} \le P_l^{\text{M}} \tag{26}$$

The power flow model used in this paper is a DC power flow model, and the treatment of the branch power flow constraint is referred to [40].

7) State of charge (SOC)

$$S_{\text{oc}i}^{\text{m}} \le S_{\text{oc}i}(t,s) \le S_{\text{oc}i}^{\text{M}} \tag{27}$$

$$S_{\text{oc}i}(t,s) = (1-\sigma_i) S_{\text{oc}i}(t-1,s) + \Delta E_i(t,s)/E_{\text{N}i} \tag{28}$$

$$\Delta E_i(t,s) = \begin{cases} \eta_{\text{c}i} \cdot \mu_{i,t,s} P_{\text{b}i,t,s} \cdot \Delta t, & \mu_{i,t,s} = 1 \\ \mu_{i,t,s} P_{\text{b}i,t,s} \cdot \Delta t / \eta_{\text{d}i}, & \mu_{i,t,s} = -1 \end{cases} \tag{29}$$

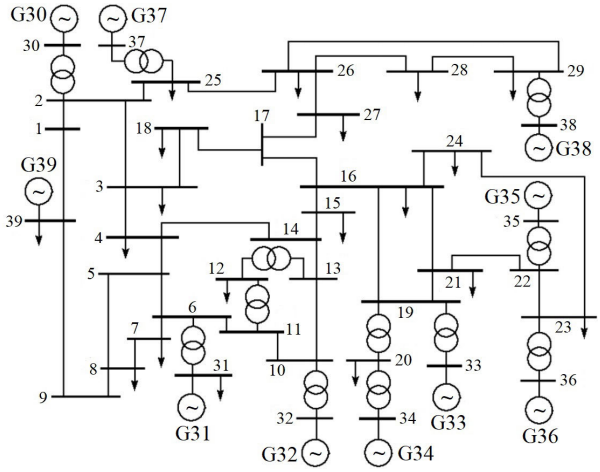

FIGURE 5. Topology chart of IEEE-39 bus system.

where $S_{\text{oc}i}(t,s)$ is the state of charge (SOC) of battery i at period t in scenario s, and $\Delta E_i(t,s)$ is the increment of the SOC of battery i at period t in scenario s.

8) Power limitation of battery

$$\begin{cases} P_{\text{c}i,t}^{\text{m}} \le \mu_{i,t,s} \cdot P_{\text{b}i,t,s} \le P_{\text{c}i,t}^{\text{M}}, & \mu_{i,t,s} = 1 \\ P_{\text{d}i,t}^{\text{m}} \le \mu_{i,t,s} \cdot P_{\text{b}i,t,s} \le P_{\text{d}i,t}^{\text{M}}, & \mu_{i,t,s} = -1 \end{cases} \tag{30}$$

F. SOLUTION OF MODEL

In this paper, the PSO algorithm is used to solve the ED problem. The variables to be optimized are the active output of thermal power units and the planned output of wind farms. The optimization process is divided into two stages. First, it is necessary to determine the state of thermal power units. This scheme is determined according to the forecast value of the wind power, and meanwhile it also needs to meet the reserve constraint, ramp constraint, minimum up/down time constraint, etc. Then, according to the wind power output in each scenario, the active output of thermal power units needs to be readjusted. At the same time, the constraints of the model still need to be satisfied. In general, load shedding and wind power curtailment will occur during this stage. The fitness function of PSO is that the weighted average value of the comprehensive power generation cost in each scenario. The position vector of each particle is composed of the active output of the thermal power units and the planned output of wind farms, and the velocity vector is the adjustment of the output.

III. CASE STUDY

Taking IEEE-39 bus system as an example to test the proposed model. A topology chart is shown in Fig. 5. Bus 31 is the balance node, the wind farm is connected to bus 21, and the BESS is connected to bus 13. The parameters of the thermal power units are listed in Table 1, the parameters of the wind farm are listed in Table 2, and the parameters of the BESS are listed in Table 3. The load parameters are from [41], and the branch parameters of the IEEE-39 bus

TABLE 1. Parameters of thermal power units.

Parameter	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10
a ($/MW^{2}h)	0.00048	0.00031	0.00211	0.002	0.00398	0.00712	0.00079	0.00413	0.00222	0.00173
b ($/MWh)	16.19	17.26	16.5	16.6	19.7	22.26	27.74	25.92	27.27	27.79
c ($/h)	1000	970	680	700	450	370	480	660	665	670
P_{max} (MW)	455	455	130	130	162	80	85	55	55	55
P_{min} (MW)	150	150	20	20	25	20	25	10	10	10
T_{on} (h)	5	5	2	2	2	2	1	0	0	0
T_{off} (h)	5	5	2	2	2	2	1	0	0	0
T_{cold} (h)	4	4	2	2	2	2	2	0	0	0
State (h)	8	8	-5	-5	-6	-3	-3	-1	-1	-1
Sh ($)	4500	5000	560	550	900	170	260	30	30	30
Sc ($)	9000	10000	1120	1100	1800	340	520	60	60	60
Ramp (MW)	80	80	30	30	40	25	25	20	20	20

TABLE 2. Wind power output of 24 hours a day (p.u.).

Hour	P_w	Hour	P_w	Hour	P_w	Hour	P_w
1	0.54	7	0.84	13	0.38	19	0.79
2	0.51	8	0.74	14	0.90	20	0.80
3	0.63	9	0.64	15	0.90	21	0.99
4	0.57	10	0.56	16	0.99	22	0.69
5	0.60	11	0.43	17	0.90	23	0.77
6	0.69	12	0.42	18	0.76	24	0.99

TABLE 3. Parameters of ESS.

Parameter	Value	Parameter	Value
Rated power/kW	300	C_f /($/kWh)	50
Rated capacity/kWh	1200	K_m/(¥/kWh)	0.05
Charging efficiency/%	80	Initial SOC	0.5
Discharge efficiency/%	80	State of battery	-1
Cycling life/times	1800	SOC upper limit	0.1
Self-discharge rate/(%/day)	0.1	SOC lower limit	0.9

system are from [42]. The value of $r_{l,t}$ is 5% of the load power at period t. $K_{\mathrm{up}} = 80, K_{\mathrm{dn}} = 40, K_{\mathrm{ls}} = 1000, K_{\mathrm{wc}} = 100$, unit: \$ /MW · h. Using the MATLAB neural network toolbox, the maximum number of training times is 50. The PSO parameters for clustering are as follows: population size 10, maximum number of iterations 50, and velocity interval [−2,2]. The PSO parameters for ED problem are as follows: population size 30, maximum number of iterations 500, and velocity interval $[-ur, ur]$, $ur = \min\left(\mathrm{Ramp}, P_{j,t}^{\mathrm{M}} - P_{j,t}^{\mathrm{m}}\right)$. The inertia coefficient decreases linearly from 0.9 to 0.4, and the acceleration constants are $c_1 = 2$ and $c_2 = 1$.

A. CASE A

First, 1000 time series are generated by MCS to form the initial scenario set of wind power output. According to the k-means (traditional k-means clustering), Huffman-k (improved k-means clustering based on a Huffman tree), k-PSO (improved k-means clustering based on PSO), and the SOM-PSO method proposed in this paper (improved k-means clustering based on SOM neural network and PSO), the initial scenario set is reduced. Each method is simulated 100 times, and the simulation results are listed in Table 4.

TABLE 4. Dunn index comparison of several methods.

Penetration (%)	Value (%)	k-means	Huffman-k	k-PSO	SOM-PSO
25%	max	0.285	0.267	0.289	0.295
	min	0.233	0.267	0.278	0.283
	average	0.264	0.267	0.284	0.287
35%	max	0.285	0.267	0.290	0.293
	min	0.233	0.267	0.278	0.283
	average	0.264	0.267	0.285	0.287
45%	max	0.282	0.267	0.288	0.293
	min	0.232	0.267	0.277	0.281
	average	0.263	0.267	0.282	0.285

The clustering effect of the k-means method depends heavily on the selection of the initial clustering centers, which are randomly generated, so the clustering results are not stable. It can be seen from the data in Table 4 that the clustering effects are very different. The Huffman-k method determines the initial clustering centers of k-means clustering by the idea of Huffman tree [33], and the clustering results are unique. This can effectively improve the shortcoming of the k-means clustering that the clustering results are not stable. However, it can be seen from the comparison of Dunn index, the improvement of this method on the clustering index is small.

The k-PSO method uses PSO to optimize the clustering centers after k-means clustering is completed [19]. It can be seen from the data in Table 4 that this method can improve upon the shortcoming of the k-means method that the clustering results are not stable. This can also significantly improve the clustering effect. The proposed method is similar to k-PSO method. The difference is that the initial clustering centers are not generated randomly but by the SOM neural network. It can be seen from the data in Table 4 that the proposed SOM-PSO method can also improve upon the

TABLE 5. Cost and simulation time comparison of several methods.

Penetration (%)	Cost (10^4$)	Initial scenario set	k-means	Huffman-k	k-PSO	SOM-PSO	backward
25%	f_{fire}	53.3777	50.4497	51.2743	50.7966	51.0170	51.4887
	f_{wind}	8.3714	2.9773	2.4462	3.0309	3.8484	6.3019
	f_{sum}	61.7491	53.4270	53.7205	53.8275	54.8654	57.7906
35%	f_{fire}	51.3414	47.2172	48.1143	46.9502	47.9972	48.9125
	f_{wind}	14.3512	5.0700	4.5109	4.9553	7.6485	10.7856
	f_{sum}	65.6926	52.2872	52.6252	51.9055	55.6456	59.6981
45%	f_{fire}	49.5450	43.7735	45.2042	43.9140	45.3403	46.7193
	f_{wind}	21.0854	7.1884	7.1668	7.4746	11.7812	16.4819
	f_{sum}	70.6304	50.9618	52.3710	51.3886	57.1214	63.2012
Simulation time(s)		263			36		

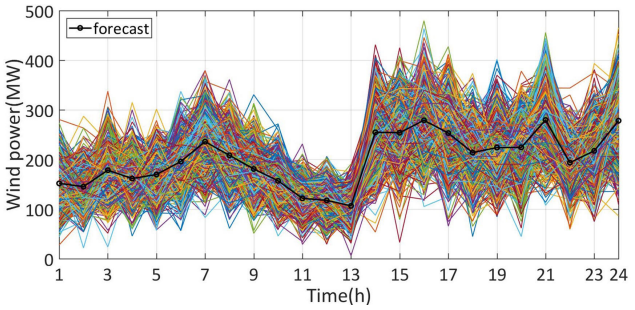

FIGURE 6. Initial scenario set of wind power.

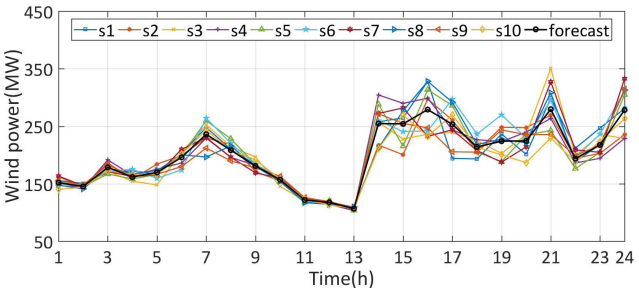

FIGURE 7. Scenario set of wind power by the k-means method.

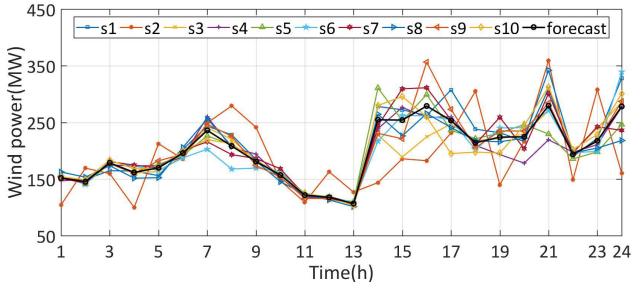

FIGURE 8. Scenario set of wind power by the Huffman-k method.

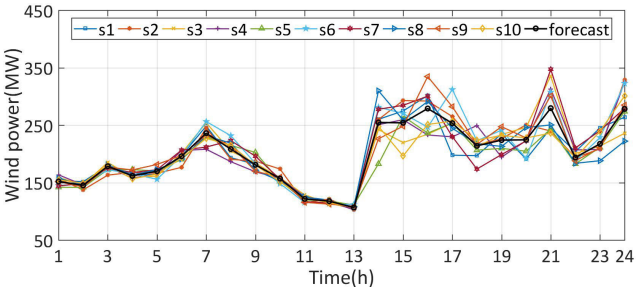

FIGURE 9. Scenario set of wind power by the k-PSO method.

shortcoming of the k-means method that the clustering results are not stable, and that the clustering index is slightly better than that of k-PSO method.

For the ED problem, it is not comprehensive to evaluate the effect of scenario reduction only by the clustering index. Table 5 lists the results of ED. The scenario sets are based on the initial scenario set, k-means, Huffman-k, k-PSO, SOM-PSO, and BR methods. Fig. 6 - Fig. 11 show the scenario sets corresponding to the above six methods (owing to limited space, only the scenario sets of 25% wind power penetration are shown). Fig. 12 shows the probability distribution corresponding to these methods. Note that for the k-means, k-PSO, and SOM-PSO methods, the final scenario set used for the simulation is the average value of the above simulation.

Table 5 also shows that the calculation time (the latter is the average value of the calculation time of ED based on five scenario reduction methods) of ED is greatly reduced after scenario reduction. No matter which scenario reduction method is used, the results of ED are lower than that without scenario reduction, but the corresponding reductions of different methods are different.

The case of 25% wind power penetration is analyzed in detail. From the data in Table 5, it can be seen that the ED with a scenario set obtained by the k-means method is relatively optimistic. From the observation in Fig. 7, it is mainly owing to the poor description effect of the scenario set on the wind power fluctuation from 1-13 h, resulting in the lower uncertainty risk cost of wind power. Thus, the final comprehensive power generation cost is relatively optimistic. Although the k-PSO method can effectively improve the clustering index compared with the k-means method, it can be seen from Fig. 9 that the description effect of the scenario set on the wind power fluctuation for 1-13 h is not significantly improved, the results of ED are still optimistic. It can be seen

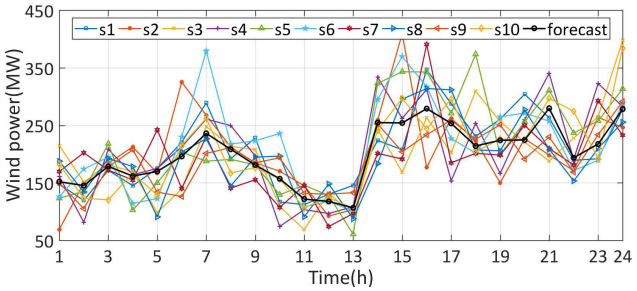

FIGURE 10. Scenario set of wind power by the BR method.

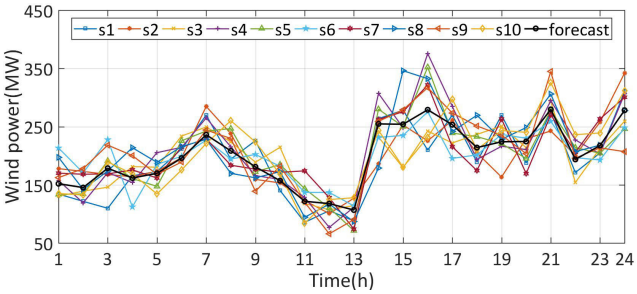

FIGURE 11. Scenario set of wind power by the proposed SOM-PSO method.

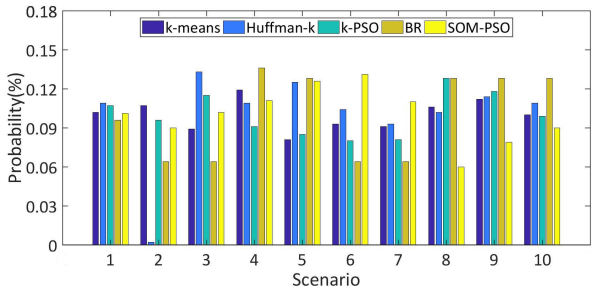

FIGURE 12. Comparison of probabilities of different methods.

from Fig. 8 and Fig. 12 that the probability of s_2 obtained by the Huffman-k method is too low. Except for s_2, the description effect of the scenario set on the wind power fluctuation for 1-13 h has not improved significantly, resulting in the optimistic results of ED.

The BR method is not a clustering method, so it is only evaluated from the perspective of the results of ED. It can be seen from Fig. 10 that the description of wind power output in some scenarios (such as 7 h in s_6, 15 h in s_2, and 18 h in s_5) is relatively extreme, which leads to the higher uncertainty risk cost of wind power and conservative results of ED. Compared with the results of ED without scenario reduction, the reduction is small. It can be seen from Table 5 that the smaller the wind power penetration, the smaller the reduction.

It can be seen from Fig. 11 that compared with the k-means method, K-PSO method, and Huffman-k method, the proposed SOM-PSO method improves the description effect of wind power fluctuation for 1-13 h. Compared with the BR method in that the description of wind power output in some scenarios is relatively extreme for some periods, the proposed SOM-PSO method also shows an obvious improvement, so the results of ED are avoided as relatively optimistic or relatively conservative.

If the results of ED are relatively optimistic or relatively conservative, this will lead to some problems. The above analysis showed that the results of ED based on the scenario sets obtained by the k-means method, k-PSO method, and Huffman-k method are relatively optimistic. From the data in Table 5, it can be seen that if scenario reduction is not carried out, then ED is carried out according to the initial scenario set. With the increase of the wind power penetration, the comprehensive power generation cost shows an increasing trend. However, owing to the poor description of wind power fluctuation for some time periods, the above three methods lead to the optimistic results for ED, and the trend of the comprehensive power generation cost is decreasing.

Although the comprehensive power generation cost corresponding to the BR method is increasing, it was analyzed previously, the scenario set obtained by this method describes the wind power output a little extremely for some time periods, which easily leads to the conservative results. Compared with the results without scenario reduction, the reduction in the comprehensive power generation cost is small, and the smaller the wind power penetration, the smaller the reduction. By comparison, the proposed SOM-PSO method is not only better in the clustering index but also more reasonable in the results of ED. It can not only maintain the trend of the ED based on the initial scenario set, but also the results of ED are neither relatively optimistic nor relatively conservative.

B. CASE B

In this paper, the influence of the ESS on the ED with wind power is studied. It was analyzed in Case A that when the scenario set obtained by the k-means, k-PSO, and Huffman-k method is used for ED, the description effect of the wind power fluctuation is not ideal for some time periods. This leads to the relatively optimistic results. Table 6 shows the comparison of comprehensive power generation cost after the ESS is introduced. It can be seen from the data in Table 6 that the comprehensive power generation cost corresponding to the three methods are still relatively lower, the results of ED are still relatively optimistic. The BR method is relatively extreme in describing the wind power fluctuation for some time periods, which results in the results of ED are relatively conservative. It can be seen from the data in Table 6 that the comprehensive power generation cost of this method is relatively higher. Therefore, after the ESS is introduced into the power system with wind power, the ED based on the proposed SOM-PSO method can still avoid the disadvantage of other methods whose results of ED are relatively optimistic or relatively conservative. The larger the wind power penetration, the more obvious the advantage.

Table 7 lists the results of ED after the ESS is introduced, including the expected penalty cost (the cost of load

TABLE 6. Comparison of comprehensive power generation cost of several methods after introducing the ESS.

Penetration (%)	Capacity of ESS(MW)	Initial scenario set	k-means	Huffman-k	k-PSO	SOM-PSO	BR
25%	0	61.7491	53.4270	53.7205	53.8275	54.8654	57.7906
	30	59.4154	52.2762	53.1870	52.1983	53.5464	56.1497
	60	58.6789	52.7648	53.4354	52.4028	53.9586	55.1195
	90	58.2596	53.1938	53.5381	53.5238	54.4410	55.6889
	120	58.5100	53.7330	53.8431	53.6191	54.6095	55.9235
35%	0	65.6926	52.2872	52.6252	51.9055	55.6456	59.6981
	30	62.4353	51.8592	51.8297	50.4060	52.9580	58.4772
	60	60.8589	51.9856	51.9663	51.3590	52.5757	56.7674
	90	59.7246	52.0694	52.1133	51.4787	52.8662	55.2909
	120	59.8712	52.1506	52.2452	51.9763	53.9116	55.8972
45%	0	70.6304	50.9618	52.3710	51.3886	57.1214	63.2012
	30	67.3310	48.3030	51.4583	50.4029	54.5964	60.1518
	60	63.8674	47.9857	50.3172	48.1554	53.3034	57.2819
	90	62.1586	49.5770	51.4929	49.1531	53.2817	56.2847
	120	61.6756	49.8120	51.7585	49.8743	53.8215	55.9405

TABLE 7. Cost comparison under different capacities of the ESS.

Capacity of ESS(MW)	Cost (10^4$)	25%	35%	45%
0	$f_{penalty}$	1.2234	4.3236	8.3914
	$f_{storage}$	0	0	0
	f_{sum}	54.8654	55.6456	57.1214
30	$f_{penalty}$	0.2303	1.3269	4.7260
	$f_{storage}$	0.3622	0.9905	1.7110
	f_{sum}	**53.5464**	52.9580	54.5964
60	$f_{penalty}$	0.1918	0.7820	2.0951
	$f_{storage}$	0.9230	1.1694	3.3681
	f_{sum}	53.9586	**52.5757**	53.3034
90	$f_{penalty}$	0.1242	0.6752	1.1152
	$f_{storage}$	1.4166	1.8883	4.5682
	f_{sum}	54.4410	52.8662	**53.2817**
120	$f_{penalty}$	0.0008	0.5019	0.9076
	$f_{storage}$	1.4706	2.5921	4.7986
	f_{sum}	54.6095	53.9116	53.8215

shedding and wind power curtailment), the cost of ESS, and the comprehensive power generation cost. Observe the data in Table 7 vertically, under a certain wind power penetration, the introduction of ESS can effectively reduce the expected penalty cost of the system. Moreover, the larger the capacity of ESS, the lower the expected penalty cost, the higher the cost of ESS at the same time. With the increase of the capacity of ESS, the comprehensive power generation cost first decreases and then increases, there is an ''inflection point'' (marked in Table 7) in the comprehensive power generation cost. At this time, the ESS can minimize the comprehensive power generation cost of the system under the corresponding capacity. The larger the wind power penetration, the later the inflection point appears, and the larger the reduction of the comprehensive power generation cost compared with that without ESS. Note that when the comprehensive power generation cost of the system reaches the inflection point, the expected penalty cost is not at a minimum. However, the later the inflection point occurs, the lower the expected penalty cost. Observe the data in Table 7 horizontally, under different capacities of the ESS, with the increase of wind power penetration, the comprehensive power generation cost presents different trends. When there is no ESS, with the increase of wind power penetration, the comprehensive power generation cost shows an increasing trend; when the capacity of ESS increases to a certain extent, the comprehensive power generation cost shows a trend of first decreasing and then increasing; the capacity of ESS continues to increase, the comprehensive power generation cost shows a decreasing trend.

As analyzed in Section 2, because the energy storage devices are currently expensive and have a shorter life than wind power, thermal power, and other energy sources, the investment cost of the ESS allocated to each scheduling cycle is considered in the ED model. Table 8 lists the impact of different capacities of ESS on the optimal operation of the system under different investment costs. It can be seen from Table 8 that under the fixed wind power penetration and investment cost, with the increase of the capacity of ESS, the expected penalty cost gradually decreases, the cost of ESS gradually increases, and the comprehensive power generation cost first decreases and then increases, there is an inflection point (marked in Table 8) in the comprehensive power generation cost. It can be seen from Table 8 that the lower the investment cost, the later the inflection point appears. Observe the data in Table 8 horizontally, under the fixed wind power penetration and the capacity of ESS, with the increase of the investment cost of ESS, the comprehensive power generation cost also increases. Therefore, the lower the investment cost of the ESS, the more beneficial to the results

TABLE 8. Cost comparison under different investment costs of the ESS.

		C_f =25($/kWh)			C_f =50($/kWh)			C_f =75($/kWh)		
Penetration (%)	Capacity of ESS(MW)	$f_{penalty}$	$f_{storage}$	f_{sum}	$f_{penalty}$	$f_{storage}$	f_{sum}	$f_{penalty}$	$f_{storage}$	f_{sum}
25%	0	1.2234	0	54.8654	1.2234	0	54.8654	1.2234	0	54.8654
	30	0.2560	0.1687	53.4411	0.2303	0.3622	**53.5464**	0.2513	0.4629	**53.8218**
	60	0.0669	0.3797	**53.3113**	0.1918	0.9230	53.9586	0.1286	0.9977	54.3222
	90	0.0199	0.5314	53.8031	0.1242	1.4166	54.4410	0.0865	1.5145	54.6133
	120	0	1.1105	54.1854	0.0008	1.4706	54.6095	0	1.7465	54.8718
35%	0	4.3236	0	55.6456	4.3236	0	55.6456	4.3236	0	55.6456
	30	1.3296	0.6341	52.5119	1.3269	0.9905	52.9580	1.3150	1.2049	53.3456
	60	0.2934	0.9907	52.0854	0.7820	1.1694	**52.5757**	0.6696	1.4899	**52.8262**
	90	0.0966	1.2608	**51.7441**	0.6752	1.8883	52.8662	0.4625	2.6591	53.6779
	120	0.0742	1.4172	52.0031	0.5019	2.5921	53.9116	0.2509	3.3694	54.3127
45%	0	8.3914	0	57.1214	8.3914	0	57.1214	8.3914	0	57.1214
	30	4.5379	1.2157	53.9513	4.7260	1.7110	54.5964	4.6797	2.2941	54.9084
	60	2.0940	2.0634	51.3679	2.0951	3.3681	53.3034	2.3512	3.4830	**53.5934**
	90	0.7899	2.3343	50.7174	1.1152	4.5682	**53.2817**	1.2196	4.6221	53.8807
	120	0.5725	2.4685	**50.6526**	0.9076	4.7986	53.8215	1.0890	5.0656	54.1837

of ED. Currently, it is still the trend to continue to research and develop the energy storage technology and reduce the investment cost of the ESS.

IV. CONCLUSION

In this paper, an ED model with wind power and ESS based on a scenario set is established, and the influence of ESS on the optimal operation of power system with wind power is analyzed in detail. The conclusion is as follows:

1) K-means clustering is a classical and effective scenario clustering method. In view of the shortcomings, such as the clustering effect depends heavily on the initial clustering centers and that the clustering results are not stable, this paper proposed an improved k-means clustering method based on SOM neural network and PSO algorithm. Then, this method was applied to the scenario reduction process to generate the final scenario set for ED. Simulation results show that the optimization of SOM neural network on the initial clustering centers can improve the dependence of k-means clustering on the initial clustering centers. The PSO algorithm can further optimize the clustering centers which can improve the unstable clustering effect by k-means clustering. Compared with other scenario reduction methods, the scenario set obtained by the proposed method is not only better in clustering index, but also the results of ED are more reasonable. The results of ED can not only retain the characteristics of the ED based on the initial scenario set, but also avoid that the results of ED are relatively optimistic or relatively conservative by using the scenario set obtained by other scenario reduction methods.
2) The introduction of ESS will affect the optimal operation of power system with wind power. In this paper, an ED problem with wind power and ESS was analyzed in detail. The simulation results show that after the ESS is introduced, the ED based on the scenario set obtained by the proposed method can still avoid the disadvantage of other methods that the results of ED are relatively optimistic or relatively conservative. In this paper, the investment cost of ESS is considered in the ED model. Under the fixed wind power penetration and investment cost, with the increase of the capacity of ESS, the comprehensive power generation cost first decreases and then increases, there is an inflection point. The larger the wind power penetration, or the lower the investment cost of ESS, the later the inflection point appears, the better the effect of ESS on stabilizing the wind power fluctuation.

The research in this paper can be improved in the following aspects:

1) In the future, more attention will be paid to the optimization of the ED model, and more factors and situations will be considered to make the model more complete. In this paper, the environmental benefits of renewable energy were not considered. A multi-objective optimization problem that seeks the lowest power generation cost and best environmental benefits of renewable energy will be studied.
2) The model did not consider the impact of ESS on the frequency, and did not distinguish between the automatic generation control (AGC) units and non-AGC units. This will be further improved in the future.
3) With the development of energy storage technology, the hybrid energy storage system (HESS) composed of various types of energy storage devices has become very popular. In the future, the ED and the capacity allocation of the HESS will continue to be studied.

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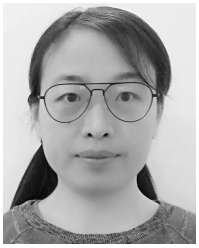

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