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

YUAN ZENG¹, (Member, IEEE), CHEN LI¹, AND HONGMEI WANG²,³

¹School of Electrical and Information Engineering, Tianjin University, Tianjin 300072, China
²School of Electrical and Computer Engineering, Cornell University, Ithaca, NY 14850, USA
³School of Basic Medical Sciences, Tianjin Medical University, Tianjin 300070, China

Corresponding author: Yuan Zeng (zengyuan@tju.edu.cn)

This work was supported by the National Key Research and Development Project of China under Grant 2018YFB0904500.

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 \( L \)

\[ B. PARAMETERS \]
- \( \Delta t \) Time interval
- \( T_{60} \) One hour

\[ a_j/b_j/c_j \] Coal consumption coefficient

\[ T_j^{\text{on}}/T_j^{\text{off}} \] Minimum operating time/downtime of generator \( j \)

\[ T_j^{\text{cold}} \] Cold-start time of generator \( j \)

\[ K_{a\uparrow}/K_{d\downarrow} \] Cost coefficient of starting upward/downward spinning reserve

\[ K_{m} \] Cost coefficient of operation and maintenance of battery \( i \)

\[ C_{fi} \] 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

\[ P_{l}^{\text{min}}/P_{l}^{\text{max}} \] Minimum/maximum power flow of line \( l \)

\[ \eta_{ci}/\eta_{di} \] Charging/discharging efficiency of battery \( i \)

\[ R_{i} \] Total number of cycles of battery \( i \)

\[ S_{oc\text{i}}^{\text{min}}/S_{oc\text{i}}^{\text{max}} \] Minimum/maximum SOC of battery \( i \)
\[ \sigma_i \] Self-discharge rate of battery i during a single period

\[ E_{Ni} \] Rated capacity of battery i

\[ \eta_s \] Probability of scenario s

### C. VARIABLES

- \( h_{j,t} \): State of generator \( j \) at period \( t \)
- \( \mu_{i,j,t,s} \): 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 \( s \)
- \( \chi_{on,t}/\chi_{off,t} \): Continuous operating time/downtime of generator \( j \) at period \( t \)
- \( \varepsilon_{w,t,s} \): Wind power forecast error at period \( t \) in scenario \( s \)
- \( P_{ac,t,s} \): Actual output of wind power at period \( t \) in scenario \( s \)
- \( P_{p,t,s} \): Planned output of wind power at period \( t \) in scenario \( s \)
- \( P_{f,t,s} \): Wind power forecasting value at period \( t \) in scenario \( s \)
- \( P_{ch,t,s} \): Charging/discharging power of battery \( i \) at period \( t \) in scenario \( s \), it is positive when charging, negative when discharging
- \( P_{sh,t,s} \): Expected power of load shedding at period \( t \) in scenario \( s \)
- \( P_{wc,t,s} \): Expected power of wind power curtailment at period \( t \) in scenario \( s \)
- \( P_{up,t,s}/P_{dn,t,s} \): Wind power output that the system can absorb when the thermal power units provide all upward/downward spinning reserve at period \( t \) in scenario \( s \)
- \( P_{sc,t,s}/P_{sd,t,s} \): Wind power output that the system can absorb when the energy storage reaches the charging/discharging power limit at period \( t \) in scenario \( s \)
- \( P_{load,t} \): Active load of system at period \( t \)
- \( P_{min,t}/P_{max,t} \): Minimum/maximum active power output of generator \( j \) at period \( t \)
- \( r_{l,t} \): Spinning reserve for load fluctuation at period \( t \)
- \( r_{w,t} \): Spinning reserve for wind power fluctuation at period \( t \)
- \( \Delta P_{dn,t}/\Delta P_{up,t} \): Maximum downward/upward ramp rate of generator \( j \) at period \( t \)
- \( P_{1,t,s} \): Power flow of line \( l \) at period \( t \) in scenario \( s \)
- \( P_{min,ci,t}/P_{max,ci,t} \): Minimum/maximum charging power of battery \( i \) at period \( t \)
- \( P_{min,di,t}/P_{max,di,t} \): Minimum/maximum discharging power of battery \( i \) at period \( t \)
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.
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 were 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.
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:

$$v_{i}^{k+1} = \omega v_{i}^{k} + c_{1} r_{1} \left(pbest_{i}^{k} - x_{i}^{k}\right) + c_{2} r_{2} \left(gbest^{k} - x_{i}^{k}\right)$$  \hspace{1cm} (1)

$$x_{i}^{k+1} = x_{i}^{k} + v_{i}^{k+1}$$ \hspace{1cm} (2)

where $v_{i}^{k}$ is the velocity vector of particle $i$ at the $k$-th iteration, $\omega$ 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 $\xi_w$ [36], as follows:

$$P_{w,i,s}^{\text{true}} = P_{w,i,s}^f + \xi_{w,i,s}$$  \hspace{1cm} (3)

$$\xi_{w,i,s} = \frac{P_{w,i,s}^f}{5} + P_{w_s}/50$$ \hspace{1cm} (4)

In this paper, the first 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 flowchart 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.
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:

\[
DI = \frac{\min_{0<m\neq n<\text{m}} \min_{x_i \in \Omega_m, x_j \in \Omega_n} \| x_i - x_j \|}{\max_{0<m\leq S} \max_{x_i \in \Omega_m} \min_{x_j \in \Omega_m} \| x_i - x_j \|}
\]  

(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 \( S \). \( \Omega_m \) is the \( m \)-th cluster, and \( x_i \) is the scenario in \( \Omega_m \).

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

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

(6)

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

\[
f_{\text{fire}}(j, t) = u_{j,t} f_{\text{fuel}}(j, t) + u_{j,t} (1 - u_{j,t-1}) S_{j,t}
\]

(7)

\[
f_{\text{fuel}}(j, t) = \sum_{s=1}^{S} \left( a_{j,s} P_{j,t,s}^2 + b_{j,s} P_{j,t,s} + c_{j,s} \right) \cdot \eta_k
\]

(8)

\[
S_{j,t} = \begin{cases} 
            x_{j,t}^{\text{off}} \leq T_j^{\text{cold}} + T_j^{\text{off}}, & \text{Sh}_{j,t} \\
            x_{j,t}^{\text{off}} > T_j^{\text{cold}} + T_j^{\text{off}}, & S_{j,t}
\end{cases}
\]

(9)

where \( f_{\text{fuel}}(j, t) \) 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
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 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 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 discharging within the allowable discharging 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 load 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:

\[
f_{\text{wind}} (t) = f_{\text{reserve}} (t) + f_{\text{storage}} (t) + f_{\text{penalty}} (t)
\]

\[
f_{\text{reserve}} (t) = f_{\text{up}} (t) + f_{\text{dn}} (t)
\]

\[
f_{\text{up}} (t) = \begin{cases} 
\sum_{s=1}^{S} K_{\text{up}} (P_{w,t,s}^p - P_{up,t,s}) \cdot \eta_s, & P_{w,t,s}^p < P_{up,t,s} \\
\sum_{s=1}^{S} K_{\text{up}} (P_{w,t,s}^p - P_{w,t,s}^{ac}) \cdot \eta_s, & P_{up,t,s} \leq P_{w,t,s}^{ac} < P_{w,t,s}^p 
\end{cases}
\]

\[
f_{\text{dn}} (t) = \begin{cases} 
\sum_{s=1}^{S} K_{\text{dn}} (P_{dn,t,s} - P_{w,t,s}^{ac}) \cdot \eta_s, & P_{w,t,s}^{ac} > P_{dn,t,s} \\
\sum_{s=1}^{S} K_{\text{dn}} (P_{w,t,s}^{ac} - P_{w,t,s}^p) \cdot \eta_s, & P_{w,t,s}^p \leq P_{w,t,s}^{ac} \leq P_{dn,t,s} 
\end{cases}
\]

\[
f_{\text{storage}} (t) = f_{\text{main}} (t) + f_{\text{fix}} (t)
\]

\[
f_{\text{main}} (t) = \sum_{s=1}^{S} \left( \sum_{i=1}^{n_b} K_{\text{bli}} \cdot \mu_{i,t,s} \cdot P_{bli,t,s} \cdot \Delta t \right) \cdot \eta_s
\]

\[
f_{\text{fix}} (t) = \sum_{s=1}^{S} \left( \sum_{i=1}^{n_b} \frac{\rho_{i,t,s} \cdot C_{li}}{R_i} \right) \cdot \eta_s
\]
f_{\text{penalty}} (t) = f_{\text{ls}} (t) + f_{\text{wc}} (t) \tag{18}

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

f_{\text{wc}} (t) = \sum_{s=1}^{S} K_{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{wt}} \tag{20}

where \( f_{\text{up}} (t) \) and \( f_{\text{du}} (t) \) 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 \( t \); \( f_{\text{ls}} (t) \) is the investment cost at period \( t \); \( f_{\text{wc}} (t) \) 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

\[
\sum_{j=1}^{n} u_{j,t} P_{j,t,s} + \left( P_{\text{w},t,s}^{\text{up}} - P_{\text{w},t,s}^{\text{dn}} \right) - \sum_{i=1}^{n_b} P_{bi,t,s} = P_{\text{load},t} - P_{ls,t,s} \tag{21}
\]

2) Power limitation

\[
\begin{align*}
P_{j,t}^{\text{up}} & \leq P_{j,t,s} \leq P_{j,t}^{\text{M}} \\
0 & \leq P_{w,t,s}^{\text{p}} \leq P_{\text{wt}}
\end{align*}
\tag{22}
\]

3) Reserve

\[\sum_{j=1}^{n} u_{j,t} P_{j,t,s}^{\text{M}} + P_{w,t,s}^{\text{p}} \geq P_{\text{load},t} + r_{l,t} + r_{w,t} \tag{23}\]

where \( r_{w,t} \) 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

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

5) Minimum up/down time

\[
\begin{align*}
\chi_{j,t}^{\text{on}} & \geq T_{\text{on}} \\
\chi_{j,t}^{\text{off}} & \geq T_{\text{off}}
\end{align*}
\tag{25}\]

6) Branch power flow

\[P_{j,t}^{\text{M}} \leq P_{j,t,s} \leq P_{j,t}^{\text{M}} \tag{26}\]

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)

\[
\begin{align*}
S_{\text{soc}}^{\text{m}} & \leq S_{\text{soc}} (t, s) \leq S_{\text{soc}}^{\text{M}} \\
S_{\text{soc}} (t, s) & = (1 - \sigma_i) S_{\text{soc}} (t-1, s) + \Delta E_{i} (t, s) / E_{Ni}
\end{align*}
\tag{27, 28}\]

\[\Delta E_{i} (t, s) = \begin{cases} \eta_{i} \cdot \mu_{i,t,s} \cdot P_{bi,t,s} \cdot \Delta t, & \mu_{i,t,s} = 1 \\
\mu_{i,t,s} \cdot P_{bi,t,s} \cdot \Delta t / \eta_{di}, & \mu_{i,t,s} = -1 \end{cases} \tag{29}\]

where \( S_{\text{soc}} (t, s) \) 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

\[
\begin{align*}
\mu_{i,t,s} \cdot P_{bi,t,s} & \leq P_{M_{ci,t}} \quad \mu_{i,t,s} = 1 \\
\mu_{i,t,s} \cdot P_{bi,t,s} & \leq P_{M_{di,t}} \quad \mu_{i,t,s} = -1
\end{align*}
\tag{30}\]

### 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 system

![FIGURE 5. Topology chart of IEEE-39 bus system.](image-url)
system are from [42]. The value of $r_{ij}$ is 5% of the load power at period $t$. $K_{up} = 80$, $K_{dn} = 40$, $K_{ls} = 1000$, $K_{wc} = 100$, unit: $$/MW \cdot 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 $[-ur, ur]$, $ur = \min \left(Ramp, P^j_M - P^j_m\right)$. 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.

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 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 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 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 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 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 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 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 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 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.
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 |
|-----------------|--------------|----------------------|---------|-----------|-------|---------|----------|
|                 | $f_{tot}$    | $f_{wind}$           | $f_{em}$| $f_{tot}$ | $f_{wind}$ | $f_{em}$ | $f_{tot}$ | $f_{wind}$ | $f_{em}$ | $f_{tot}$ | $f_{wind}$ | $f_{em}$ |
| 25%             | 53.3777      | 50.4497              | 51.2743 | 50.7966   | 51.0170 | 51.4887 |
| 35%             | 51.3414      | 47.2172              | 48.1143 | 46.9502   | 47.9972 | 48.9125 |
| 45%             | 49.5450      | 43.7735              | 45.2042 | 43.9140   | 45.3403 | 46.7193 |

Simulation time(s) 263 36

**FIGURE 6.** Initial scenario set of wind power.

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
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 |
|----------------|---------------------|----------------------|---------|-----------|-------|---------|----|
| 0              | 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              | 53.4554 | 52.4028   | 53.9586 | 55.1195 |
| 90             | 58.2596             | 53.1938              | 53.5381 | 53.5238   | 54.4410 | 56.6889 |
| 120            | 58.5100             | 53.7330              | 53.8431 | 53.6191   | 54.6095 | 55.9235 |

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

| Capacity of ESS(MW) | Cost (10^4$) | 25%  | 35%  | 45%  |
|---------------------|--------------|------|------|------|
| 0                   | f_PEly       | 1.2234 | 4.326 | 8.3914 |
|                     | f Geile     | 4.326 | 8.3914 | 12.714 |
|                     | f Pre     | 54.8654 | 55.6456 | 57.1214 |
| 30                  | f PEly       | 0.2303 | 1.3269 | 4.7260 |
|                     | f Geile     | 0.9905 | 1.7110 | 3.681 |
|                     | f Pre     | 53.5464 | 52.9580 | 54.5964 |
| 60                  | f PEly       | 0.1918 | 0.7820 | 2.0951 |
|                     | f Geile     | 0.9905 | 1.7110 | 3.681 |
|                     | f Pre     | 53.9586 | 52.5787 | 53.3034 |
| 90                  | f PEly       | 0.1242 | 0.6752 | 1.1152 |
|                     | f Geile     | 1.4166 | 1.8883 | 4.5682 |
|                     | f Pre     | 54.4410 | 52.8662 | 53.2817 |
| 120                 | f PEly       | 0.0008 | 0.5019 | 0.9076 |
|                     | f Geile     | 1.4706 | 2.5921 | 4.7986 |
|                     | f Pre     | 54.6095 | 53.9116 | 53.8215 |

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, the comprehensive power generation cost increases, the investment cost of the ESS, the more beneficial to the results.
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. 

| Penetration (%) | Capacity of ESS(MW) | $C_r=25($/kWh) | $C_r=50($/kWh) | $C_r=75($/kWh) |
|-----------------|---------------------|----------------|----------------|----------------|
| 0               | 1.2234              | 0              | 54.8654        | 1.2234         | 0              | 54.8654        |
| 25%             | 0.2560 0.1687 53.4411 0.2303 0.3622 53.5464 0.2513 0.4629 53.8218 |
| 30              | 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 54.6905 0 1.7465 54.8718 |
| 0               | 4.3236              | 0              | 55.6456        | 4.3236         | 0              | 55.6456        |
| 35%             | 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 |
| 0               | 8.3914              | 0              | 57.1214        | 8.3914         | 0              | 57.1214        |
| 45%             | 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 |
REFERENCES

[1] N. Li and K. W. Hedman, “Economic assessment of energy storage in systems with high levels of renewable resources,” IEEE Trans. Sustain. Energy, vol. 6, no. 3, pp. 1103–1111, Jul. 2015.

[2] S. Q. Zhao, Y. Wang, and X. Xu, “Dependent chance programming dispatching of integrated thermal power generation and energy storage system based on wind power forecasting error,” Proc. CSEE, vol. 34, no. 81, pp. 9–16, Nov. 2014.

[3] B. Bahmani-Firouzi and R. Azizipanah-Abarghoee, “Optimal sizing of battery energy storage for micro-grid operation management using a new improved bat algorithm,” Int. J. Electr. Power Energy Syst., vol. 56, pp. 42–54, Mar. 2014.

[4] C. O’Dwyer and D. Flynn, “Using energy storage to manage high net load variability at sub-hourly time-scales,” IEEE Trans. Power Syst., vol. 30, no. 4, pp. 2139–2148, Jul. 2015.

[5] T. Das, V. Krishnan, and J. D. McCalley, “Assessing the benefits and economics of bulk energy storage technologies in the power grid,” Appl. Energy, vol. 139, pp. 104–118, Feb. 2015.

[6] Y. Hu, Y. Li, M. Xu, L. Zhou, and M. Cui, “A chance-constrained economical dispatch model in Wind-Thermal-Energy storage system,” Energies, vol. 10, no. 3, p. 326, Mar. 2017.

[7] X. S. Zhang, Y. Yuan, and Y. Cao, “Modeling and scheduling for battery energy storage station with consideration of wearing costs,” Power Syst. Technol., vol. 41, no. 5, pp. 1541–1548, May 2017.

[8] N. Li, C. Uckun, E. M. Constantinescu, J. R. Birge, K. W. Hedman, and A. Botterud, “Flexible operation of batteries in power system scheduling with renewable energy,” IEEE Trans. Sustain. Energy, vol. 7, no. 2, pp. 685–696, Apr. 2016.

[9] T.-Y. Lee, “Optimal scheduling of wind farm system using EIPS0,” IEEE Trans. Power Syst., vol. 22, no. 4, pp. 1612–1621, Nov. 2007.

[10] C.-L. Chen, “Optimal wind-thermal generating unit commitment,” IEEE Trans. Energy Convers., vol. 23, no. 1, pp. 273–280, Mar. 2008.

[11] Y. An and B. Zeng, “Exploring the modeling capability of two-stage robust optimization: Variants of robust unit commitment model,” IEEE Trans. Power Syst., vol. 30, no. 1, pp. 109–122, Jan. 2015.

[12] M. L. Zhang, Z. J. Hu, Y. Li, and S. W. Xie, “A robust optimization method for unit commitment considering wind power and demand response based on feasibility testing,” Proc. CSEE, vol. 38, no. 11, pp. 3184–3194, Jun. 2018.

[13] L. D. Zhang, Y. B. Yuan, D. Y. Sun, X. D. Yuan, Q. Li, and D. W. Su, “Joint operation model of wind-storage system based on two-stage robust interval optimization,” Electr. Power Autom. Equip., vol. 38, no. 12, pp. 59–66, Dec. 2018.

[14] Z. Wang, C. Shen, F. Liu, J. Wang, and X. Wu, “An adjustable chance-constrained approach for flexible ramping capacity allocation,” IEEE Trans. Sustain. Energy, vol. 9, no. 4, pp. 1798–1811, Oct. 2018.

[15] Y. Wang, S. Zhao, Z. Zhou, A. Botterud, Y. Xu, and R. Chen, “Risk adjustable day-ahead unit commitment with wind power based on chance constrained goal programming,” IEEE Trans. Sustain. Energy, vol. 8, no. 2, pp. 530–541, Apr. 2017.

[16] W.-S. Tan, M. Shaaban, and M. P. Abdullah, “Chance-constrained programming for day-ahead scheduling of variable wind power amongst conventional generation mix and energy storage,” IET Renew. Power Gener., vol. 11, no. 14, pp. 1785–1793, Dec. 2017.

[17] F. Liu, Z. Bie, S. Liu, and T. Ding, “Day-ahead optimal dispatch for wind integrated power system considering zonal reserve requirements,” Appl. Energy, vol. 188, pp. 399–408, Feb. 2017.

[18] E. Du, N. Zhang, C. Kang, and Q. Xia, “Scenario map based stochastic unit commitment,” IEEE Trans. Power Syst., vol. 33, no. 5, pp. 4694–4705, Sep. 2018.

[19] D. L. Ji, “Multi energy resource combined unit commitment under high wind power penetration level system,” M.S. thesis, Dept. Elect. Eng., Shandong Univ., Shandong, China, 2017.

[20] A. Shukla and S. N. Singh, “Clustering based unit commitment with wind power uncertainty,” Energy Convers. Manage., vol. 111, pp. 89–102, Mar. 2016.

[21] J. Aghaei, T. Niknam, R. Azizipanah-Abarghoee, and J. M. Arroyo, “Scenario-based dynamic economic emission dispatch considering load and wind power uncertainties,” Int. J. Electr. Power Energy Syst., vol. 47, pp. 351–367, May 2013.
YUAN ZENG (Member, IEEE) was born in Henan, China, in 1975. He received the B.S., M.S., and Ph.D. degrees in electric power system and automation from Tianjin University, Tianjin, China. Since 2006, he has been an Assistant Professor with the School of Electrical and Information Engineering, Tianjin University. His current research interests include electrical power system security and stability, electrical power system reliability and risk assessment, and electrical power system planning.

CHEN LI received the B.E. degree in electrical engineering and automation from Tianjin University, Tianjin, in 2018, where she is currently pursuing the M.S. degree in electric power system and automation. Her current research interests include optimal allocation of renewable energy power generation and research on the optimal scheduling of renewable energy.

HONGMEI WANG received the B.S. degree in machinery manufacturing and its automation from the Shandong University of Science and Technology, Zibo, Shandong, China, and the M.S. degree in electrical engineering and the Ph.D. degree in computer applied technology from Tianjin University, Tianjin, China. She is currently a Visiting Scholar with Cornell University, Ithaca, NY, USA. Her research interests include privacy preserving distributed data mining, deep learning, and computer applied technology.