Security Constrained Unit Commitment with Extreme Wind Scenarios
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Abstract—The rapid development of economy and society stimulates the increase of power demand. Wind power has received great attention as a typical renewable energy, and the share of wind power is continually increasing in recent years. However, the high integration of wind power brings challenges to the secure and reliable operation of power grid due to the intermittent characteristic of wind power. In order to solve the operation risk caused by wind power uncertainty, this paper proposes to solve the problem of stochastic security-constrained unit commitment (SCUC) by considering the extreme scenarios of wind power output. Firstly, assuming that the probability density distribution of wind power approximately follows a normal distribution, a great number of scenarios are generated by Monte Carlo (MC) simulation method to capture the stochastic nature of wind power output. Then, the clustering by fast search and find of density peaks (CSFDP) is utilized to separate the generated scenarios into three types: extreme, normal and typical scenarios. The extreme scenarios are identified to determine the on/off statuses of generators, while the typical scenarios are used to solve the day-ahead security-constrained economic dispatch (SCED) problem. The advantage of the proposed method is to ensure the robustness of SCUC solution while reducing the conservativeness of the solution as much as possible. The effectiveness of the proposed method is verified by IEEE test systems.

Index Terms—Monte Carlo (MC) simulation, security-constrained unit commitment (SCUC), security-constrained economic dispatch (SCED), wind power.

I. INTRODUCTION

THE security-constrained unit commitment (SCUC) is an important tool in energy management system to guarantee the operation economy and safety of power system. However, the traditional SCUC is being challenged because of the high integration of wind power in recent years. It is reported by Electric Reliability Council of Texas (ERCOT) that the penetration of wind power reached 50% on the morning of March 23, 2017 [1]. However, the uncertainty of wind power poses a risk to the operation of power system [2]-[4] such as frequency drop, transmission overloads, and even cascading failures. To tackle this issue, several methods have been developed to take into account the wind power uncertainty in SCUC. The most popular ones are stochastic scenario-based approaches [5]-[10] and robust optimization methods [11]-[15].

Monte Carlo (MC) simulation method is a typical one of stochastic scenario-based approaches, in which a great number of scenarios are generated to simulate the output of wind power. In [6], MC simulation is used to deal with the uncertainty of SCUC caused by wind power forecasting errors, generator failures and outages of transmission lines. In [7], MC scenario simulation is utilized to deal with the volatility of wind power in the two-stage stochastic SCUC model. Reference [8] presents a risk-averse model to assess the solution of the two-stage stochastic SCUC under conditional value at risk (CVaR). Reference [9] considers the uncertainties of load and wind power scenarios at multiple operation time scales. Another stochastic scenario-based approach is the chance-constrained optimization method which deals with the wind power uncertainty by inserting probability constraints on possible wind power scenarios. For instance, [10] proposes the chance-constrained model to solve the day-ahead SCUC. In the model, the wind power uncertainty is represented by the expected value and variance information. The disadvantage of the stochastic scenario-based method is the poor robustness of the unit commitment (UC) solution. This is because there lacks a method to identify the set of the scenarios that contribute a UC solution with high robustness. Additionally, a large number of scenarios need to be generated in order to maintain the accuracy of the solution, which will put a huge burden on the computation efficiency in stochastic SCUC programs. Although some techniques can be used to reduce the number of scenarios such as k-means and fuzzy c-means, some important information might be lost due to these scenario reduction methods. As a result, the robustness of the stochastic method will be significantly impacted.

The general principle of the robust optimization is to find a UC solution that is still feasible in the worst wind power scenario. The advantage of the robust optimization is that it does not need to generate a large number of possible wind power scenarios. Reference [11] proposes an adaptive robust UC model for a UC problem with a deterministic uncertainty set of wind power. The Benders decomposition is used to
solve the min-max-min optimization problem. Reference [12] further introduces a robust risk-constrained UC (RRUC) model to deal with volatile and uncertain wind generations by an adjustable uncertainty set. In [13], a multi-stage adaptive robust optimization model is proposed which uses a dynamic uncertainty set to handle the correlation of renewable resources. In [14], a reduced SCUC formulation is developed by considering multiple stochastic wind power scenarios based on loadability sets. Reference [15] presents an adaptive robust AC UC model to capture the stochastic nature of wind power in terms of bounded intervals.

In robust optimization, the scenarios with very low probability of occurrence are considered, so the corresponding UC solution will be very conservative. However, one challenging problem is how to find a UC solution with high robustness while reducing the conservativeness as much as possible.

In recent years, some new methods have been proposed to deal with the uncertainty of wind power. In [16] and [17], a distributionally robust optimization model is presented to address the volatility of wind power. In particular, Kullback-Leibler (KL) divergence [18] is employed to solve a new distance-based distributionally robust UC, in which the expected cost in the worst case is restricted in an ambiguity set. In [19] and [20], an interval optimization is proposed to improve the security and economy of SCUC solution. Reference [21] proposes a hybrid stochastic and interval optimization technique to manage the uncertainty in a transmission-constrained UC. Reference [22] proposes a unified stochastic and robust UC, in which a weighting factor is introduced for the stochastic and robust parts in the objective function. In [23], a data-driven distributionally robust chance-constrained optimal power flow model is introduced to ensure that the probability of line overloads in the worst case is small. The whole optimization problem is formulated as a convex problem by a second-order cone programming.

As mentioned above, the critical issue for addressing the uncertainty of an SCUC problem is how to take a good balance between conservativeness and robustness. Although there are several methods proposed to address the uncertainty of wind power, the conservativeness and robustness of the solution still cannot be balanced in a satisfactory manner. In particular, there lacks a method to determine a UC solution that satisfies the following requirements: (1) its economy is close to that of the stochastic scenario-based method; (2) its robustness is high. The common drawback of the existing methods [6]-[23] is that either economy or robustness will be significantly sacrificed. For example, in robust optimization, the operation cost is still much higher than that of the stochastic scenario-based methods although some methods have been proposed to reduce the conservativeness. Additionally, for the stochastic scenario-based methods, the high robustness of the UC solution cannot be ensured since no efficient approaches have been proposed to identify and screen out extreme scenarios. Regarding the drawbacks of the existing methods, we propose a new scenario-based approach to find an economic UC solution with high robustness. Different from the existing methods, the economy of the dispatch schedule solved by our approach is close to that of the stochastic method, and the robustness is close to that of the robust optimization method.

The main contributions of this paper are as follow:

1) We propose a new scenario-based approach to deal with the uncertainty of wind power, in which the original scenarios can be automatically separated into typical, extreme and normal scenarios.

2) We propose a framework to deal with the scenarios of wind power. Extreme scenarios will be scored by counting the feasible cases of security-constrained economic dispatch (SCED) in all normal scenarios. The extreme scenario with the maximum score is selected to solve the UC solution for ensuring its high robustness. Typical scenarios are used to calculate SCED for improving the economy of the schedule.

3) We demonstrate the simulation results that the proposed method can generate an economic UC solution while ensuring its high robustness, and that the robustness of the UC solution can be guaranteed by a small number of extreme scenarios.

II. SCENARIO GENERATION AND CLUSTERING

In this section, we first generate a large quantity of wind power scenarios based on MC simulation method. Then, the clustering by fast search and find of density peaks (CSFDP) is used to classify these scenarios into extreme, normal and typical scenarios for solving SCUC model.

The method of the scenario simulation [24] has been widely used to address the uncertainty of wind power, in which a large number of scenarios are generated to simulate the possible scenarios that would occur in future. But the majority of scenarios are unnecessary for solving SCUC, which will also increase the computation burden. Thus, some representative scenarios need to be selected to calculate SCUC, which is significant for decreasing the computation burden and improving the accuracy of the model.

One of the most popular scenario simulation approaches is MC simulation, which can simulate a large number of scenarios following a given probability distribution function. The advantages of MC simulation method are explained in [6]. In this paper, MC is used to generate the random scenarios of wind power. Similar to [7], it is assumed that wind power scenarios are consistent with the normal distribution. According to the principle of MC, each scenario is independent with each other. If $M$ scenarios are simulated, the probability of occurrence for each scenario is $1/M$.

MC simulation method provides a tool to deal with the uncertainty of wind power, but a large number of scenarios must be simulated to capture the random nature of wind power scenarios. In reality, it is impossible to include all the generated wind scenarios for solving SCUC problem with wind power penetration. In other words, we need to screen out parts of or a small number of representative scenarios to guarantee both the robustness and economy of UC solution. Unfortunately, there lacks a method to separate these representative scenarios. Each scenario is assumed to have the same probability of occurrence.

Obviously, this is not consistent with the real situation. In practice, some scenarios are more likely to occur, which
should be satisfied when determining UC solution. On the contrary, the probabilities of the occurrence in some scenarios are relatively low. These scenarios are defined as extreme scenarios, which should also be considered in SCUC to ensure its robustness. The scenarios with very low probabilities of occurrence should be removed to reduce the conservativeness of the solution. Thus, it is necessary to utilize a method to screen out typical, normal and extreme scenarios. Consequently, the robustness and economy can be better balanced.

CSFDP is an effective clustering method to divide these scenarios. It was first presented in 2014 [25]. The scenario with the highest local density indicates the high probability of local occurrence. By setting a local density threshold, those scenarios in each cluster can be divided into three types according to the probability of occurrence. Typical scenarios and normal scenarios represent the scenarios with the relative high probabilities of occurrence, while extreme scenarios represent the scenarios with the low probabilities of occurrence.

CSFDP is a method to cluster some data which have similar information by local densities and distances. The local density \( \rho_j \) of scenario \( j \) is calculated by Gaussian kernel:

\[
\rho_j = \sum_{i=1}^{N_j} e^{-\left(\frac{d_{ij}}{d_i}\right)^2}, \quad j = 1, 2, \ldots, N, j \neq k
\]  

where \( d_{ij} \) is the cutoff distance that should be carefully selected; \( d_i \) is the distance between the \( j^{th} \) point and the \( k^{th} \) point; and \( N \) is the number of points.

\( \rho_j \) reflects its probability of occurrence. The scenarios in each cluster with low probabilities of occurrence are defined as extreme scenarios. In general, when a schedule can meet these extreme scenarios, it is very likely that other scenarios can also be met by the schedule. Thus, in order to improve the robustness of the schedule, these extreme scenarios of each cluster should be used to solve UC solution.

Then, the smallest distance \( \delta_{ij} \) between \( j^{th} \) point and other point with higher local density than \( j^{th} \) point is calculated.

\[
\gamma_j = \rho_j \delta_{ij}, \quad j = 1, 2, \ldots, N
\]

where \( \gamma_j \) is an important parameter to generate a decision graph for determining cluster centers. By arranging \( \gamma_j \) in descending order, the clustering decision graph in the new coordinate system is shown in Fig. 1.

It can be seen from Fig. 1 that the transition from these points below the dotted line to those points above the dotted line obviously jumps. These points above the dotted line are the center points of each cluster, and those points below the dotted line are divided into some clusters. The center point of each cluster has the highest local density, which is very likely to happen. These center points represent typical scenarios that will be selected to solve SCED solution for reducing the conservativeness of the solution. Consequently, the economy and robustness of the model can be better balanced.

III. PROBLEM FORMULATION

In this section, we will introduce the formulation of SCUC and then apply MC and CSFDP-based method to solve this model.

A. Mathematical Formulation of SCUC Problem

After the wind power scenarios are determined, the mathematical formulation of the day-ahead SCUC can be written as (3)-(8). Formula (3) is the objective function. Formula (4) is the power balance constraint. Formula (5) is the ramping up and down constraints of generators and the output power of a generator is bounded by (6). The unit minimum on/off time is modeled by (7) and (8) is the transmission network constraint [26].

\[
\min \left( \sum_{i=1}^{K} \sum_{j=1}^{N} \sum_{t=1}^{T} f_i(p_i(w)) + \sum_{i=1}^{N} \sum_{t=1}^{T} c_{ai} \right)
\]

\[
\text{s.t.} \quad \sum_{i=1}^{N} p_{in} + \sum_{i=1}^{N} p_{in} = D_{in}, \quad \forall i, \forall s
\]

\[
|p_{in} - p_{in-1}| \leq R^i_{in} \quad \forall i, \forall t, \forall s
\]

\[
|p_{in} - p_{in+1}| \leq R^i_{in} \quad \forall i, \forall t, \forall s
\]

\[
|p_{in,1} - p_{in,1}| \leq P_{min} I_{in} \quad \forall i, \forall t, \forall s
\]

\[
|X_{in,1} - T_{on}(1 - T_{off}) - I_{in} - I_{t}| \geq 0 \quad \forall i, \forall t, \forall s
\]

\[
|X_{in,1} - T_{off}(1 - T_{on}) - I_{in} - I_{t}| \geq 0 \quad \forall i, \forall t, \forall s
\]

\[
|S_(K, p + K, p_a - K, D)| \leq F_{max} \quad \forall i, \forall s
\]

where \( f_i(\cdot) \) is the generation cost function of unit \( i; C_{in}^{SU} \) is the startup cost of unit \( i \) at time \( t; p_{in} \) is the power output of unit \( i \) at time \( t \) for scenario \( s; \pi_{in} \) is the probability of occurrence of scenario \( s; K \) is the number of clusters; \( NG \) is the number of thermal generations; \( NT \) is the number of time; \( p_{in}^{w} \) is the power output of wind unit \( i \) at time \( t \) for scenario \( s; D_{in} \) is the load at time \( t \) for scenario \( s; NW \) is the number of wind generations; \( R^i_{in} \) and \( R^i_{in} \) are the ramping up and down rate limits of unit \( i \), respectively; \( p_{min} \) and \( p_{max} \) are the minimum and maximum output power of unit \( i \), respectively; \( I_{as} \) is the status of unit \( i \) at time \( t \) for scenario \( s; X_{in,1} \) and \( X_{in,1} \) are the on time and off time of unit \( i \) at time \( t \) for scenario \( s; T_{on} \) and \( T_{off} \) are the minimum on time and minimum off time of unit \( i \), respectively; \( S_F \) is the shift factor matrix; \( K_p \) is the bus-unit incidence matrix; \( K_e \) is the bus-wind unit incidence matrix; \( K_p \) is the bus-load incidence matrix; \( F_{max} \) is the line flow limit; \( p \) is the power output vector.
of thermal units; \( p_w \) is the power output vector of wind units; and \( D \) is the bus load vector.

The traditional SCUC does not consider the uncertainty of wind power. A good UC solution should satisfy the requirements of both economy and robustness. To ensure the robustness, some extreme scenarios need to be considered. At the same time, the operation cost should be controlled if the extreme scenarios are included in SCUC problem.

UC solution \( I_o \) is independent from each extreme scenario. When the UC solutions of all clusters are merged by the probability of each cluster \( \pi \), the weighted UC solution \( I'_o \) might be infeasible where \( I'_o \) is the weighted status of unit \( i \) at time \( t \). For example, the minimum on/off time constraints will be violated. To address this issue, we propose a supplementary model to revise the weighted UC solution, which will be discussed in the next section. Besides, we use the typical scenarios (center point of each cluster) to solve the stochastic SCED after the UC solution is determined for improving the economy of the schedule.

B. Supplementary UC Model and SCED Model

In scenario simulation methods, each scenario is treated independently, and the solutions obtained from each scenario will be weighted according to the probability of the occurrence in each scenario. However, as pointed in [6], this solution might be infeasible. To address this issue, we introduce a simple model to revise the weighted UC solution \( I'_o \).

The objective of the supplementary model is to revise the statuses of some units which do not meet the minimum on/off time limits by extending necessary turn-on times. Mathematically, the complementary model can be described by:

\[
\min \sum_{i=1}^{N} \sum_{t=1}^{T} \Delta I'_{i,t} \tag{9}
\]

s.t.

\[
I'_o + \Delta I_i = I''_o \quad \forall i, \forall t
\]

\[
(X_{on,i,t-1} - T_{on,i}) (I''_o - I'_o) \geq 0 \quad \forall i, \forall t
\]

\[
(X_{off,i,t-1} - T_{off,i}) (I''_o - I'_o) \geq 0 \quad \forall i, \forall t
\]

where \( \Delta I_i \) is the additional turn-on time of unit \( i \) at time \( t \); and \( I''_o \) is the revised status of unit \( i \) at time \( t \). Equation (10) is the supplementary turn-on time constraint while (11) is the set of unit minimum on/off time constraints. This model can enforce the minimum on/off constraints to be satisfied by revising the on/off statuses of some generators.

When UC solution is modified, we use typical scenarios to solve the stochastic SCED whose objection function is:

\[
\min \sum_{i=1}^{N} \sum_{t=1}^{T} \sum_{m=1}^{K} f_i(p_{m,i}) \tag{12}
\]

s.t. \((4)-(6),(8)\)

The stochastic SCUC model is built to get the power generation of each unit. Then, the stochastic SCUC is transformed into a deterministic optimization problem.

C. Solution Methodology

The day-ahead SCUC is solved by a two-stage optimization problem. In the first stage, the on/off statuses of generators are determined based on the selected extreme scenarios of wind power in each cluster. In the second stage, the typical scenarios of wind power are used to solve the dispatch problem for improving the economy of the solution.

In stochastic scenario methods, a large number of scenarios need to be generated for guaranteeing the accuracy of calculation, but many scenarios are in fact unnecessary for solving SCUC model. This paper uses MC simulation to generate scenarios and then cluster these scenarios. Figure 2 depicts the general scheme of the proposed SCUC framework. The first step is to generate a large number of wind power scenarios by MC simulation method. Then, these scenarios are divided into several clusters and the scenarios in each cluster are divided into typical, normal and extreme scenarios. In general, if a UC solution can satisfy extreme scenarios, it can also satisfy most of other scenarios. Thus, extreme scenarios will be used to solve UC problem for ensuring its high robustness, although these scenarios would happen with relative low probabilities. Each extreme scenario corresponds to a UC solution.

![Scheme of proposed SCUC.](image)

After that, the normal scenarios in each cluster will be used to score these UC solutions generated by extreme scenarios. This is achieved by solving the corresponding SCED problem for all normal scenarios and counting the number of feasible solutions. UC solution with the maximum number of feasible SCED solutions will be selected as the target UC solution for this cluster. All calculated UC solutions are merged to obtain the weighted UC solution \( I'_o \) by the probabilities of occurrence with the selected extreme scenarios.

Then, the resulting UC solution \( I'_o \) will be revised by the supplementary model discussed in Section III-B. The revised UC solution \( I''_o \) will meet all constraints. After the on/off statuses of generators are determined, we use typical scenarios of wind power (cluster centers) to obtain the dispatch schedule. This is because typical scenarios have the largest probabilities of occurrence in each cluster. The scenarios with low probabilities of occurrence in each cluster (extreme and normal scenarios) will not be considered when solving SCED. So the conservativeness of the UC solution can be reduced, while the economy of the schedule can also be improved. The detailed steps of the whole algorithm are shown in Fig. 3.

The whole algorithm of this paper can be summarized by the following steps.

1. **Step 1**: MC simulation is used to generate a large number of scenarios by the probability density function.
Step 2: the scenarios generated by MC simulation method are divided into some clusters by CSFDP. After that, these scenarios in each cluster are further divided into extreme, normal and typical scenarios.

Step 3: extreme scenario of each cluster is used to solve UC problem (3). If a solution exists for the extreme scenario of this cluster, this solution will be reserved. Otherwise, it will be discarded.

Step 4: the score of each UC solution in each cluster is recorded by determining whether an SCED solution with UC solution for normal scenarios in this cluster exists or not. If the SCED solution exists, the score of UC solution increases by 1 ($S^I = S^I + 1$).

Step 5: UC solution with the maximal $S^I$ in each cluster is selected. Then, these UC solutions are merged by the probability of each cluster.

Step 6: UC solution obtained in Step 5 will be revised by the supplementary model (9).

Step 7: the typical scenarios are selected to calculate the dispatch schedule with the determined UC solution using SCED model (12).

Step 8: these SCED solutions calculated in Step 7 will be merged by the probability of each cluster. Then, the dispatch schedule is obtained.

In this way, the probability information can be used effectively, the number of scenarios can be greatly decreased, and the accuracy of calculation results can be improved. Besides, the robustness and economy of this model can be better balanced. As each scenario is independent, the algorithm can be performed in a distributed manner. That is, for each scenario, the corresponding UC and SCED problems can be solved independently.

IV. CASE STUDY

In this section, we test the effectiveness of the proposed method by IEEE 118-bus system. Simulations are carried out on a 3.9 GHz personal computer with 8 GB of RAM. The model and algorithm are implemented in MATLAB.

A. Scenario Selection

IEEE 118-bus system consists of 54 units, 186 transmission lines and 91 load buses. The parameters of units, transmission lines and load profile can be found in [27]. The 118-bus system can be seen in Fig. 4. There are 5 wind generators located at buses 11, 37, 70, 101 and 103, respectively (the red circles). The probability density function of wind units is assumed to follow Gauss density function and the deviation of the normal distribution is set to be 20% of the predicted value. These data of wind units are from [28].

![Fig. 4. IEEE 118-bus system.](image-url)
os, 66 normal scenarios and 1 typical scenario. And the third cluster includes 36 extreme scenarios, 147 normal scenarios and 1 typical scenario. Each cluster has only one central point which is the point with the highest local density in each cluster, so each cluster has only one typical scenario. Figure 5 shows the distributions of the scenarios in clusters 1-3.

Each scenario contains the output power of five wind units, so five black solid lines are the output of five wind units in one scenario, respectively. It can be seen from Fig. 5(a), (c), (e) that typical scenarios are always surrounded by extreme and normal scenarios, and that they have the highest local densities in each cluster. This means that typical scenarios are most likely to happen. Normal scenarios are surrounded by extreme scenarios, which indicate that if the extreme scenarios can be met by a schedule, normal scenarios can be very likely met by this schedule. Thus, these extreme scenarios should be selected to solve UC problem.

Figure 5(a), (c), (e) shows the scenario distributions of clusters 1-3. And Fig. 5(b), (d), (f) presents the extreme scenarios and typical scenarios of those clusters selected by our proposed method. We use cluster 1 as an example. In Fig. 5(a), if all scenarios are used to calculate SCUC, the computation burden will be very heavy. But if these scenarios are divided by our method, the features of these scenarios are easy to find. The curves in Fig. 5(b) present the extreme and typical scenarios selected by our method. In Fig. 5(c)-(f), the same trend holds for clusters 2 and 3. The extreme scenarios in each cluster will be used to solve UC problem, and the typical scenarios are used to determine the dispatch schedule.

### TABLE I
**Penetration Level of Wind Power at Each Time**

| Time (hour) | Penetration level (%) |
|------------|-----------------------|
| 1          | 10.4                  |
| 2          | 11.1                  |
| 3          | 12.8                  |
| 4          | 18.0                  |
| 5          | 14.1                  |
| 6          | 11.5                  |
| 7          | 9.4                   |
| 8          | 8.5                   |
| 9          | 7.9                   |
| 10         | 7.0                   |
| 11         | 6.5                   |
| 12         | 6.7                   |

| Time (hour) | Penetration level (%) |
|------------|-----------------------|
| 13         | 7.0                   |
| 14         | 7.5                   |
| 15         | 6.6                   |
| 16         | 6.5                   |
| 17         | 7.1                   |
| 18         | 7.0                   |
| 19         | 6.9                   |
| 20         | 6.8                   |
| 21         | 6.9                   |
| 22         | 8.0                   |
| 23         | 8.4                   |
| 24         | 9.2                   |

#### B. Revised UC Solution

The weighted UC solution might be infeasible since we deal with each scenario independently. The minimum on/off coupling constraints might be violated. Each unit has its own minimum on/off time constraints. Since the scenarios are independent for each other and each UC solution is determined by an independent scenario, it might cause the infeasibility of the weighted UC solution. As discussed in Section III-B, we propose a supplementary model to adjust the generating UC solutions.

The UC solution without the adjustment and the adjusted solution are shown in Table III. It can be observed that units 37 and 48 will be turned on from hour 19 to hour 22, but the minimum turn-on time for these two units is 5 hours. So this UC solution is infeasible and needs an adjustment. Using the supplementary model in Section III-B, we obtain the revised UC solution where the turn-on time of units 37 and 48 is extended to hour 23. Then, all constraints in SCUC are met, and the solution is feasible. After the UC solution is determined, the typical scenarios with high probabilities of occurrence will be used to calculate the dispatch schedule.
### Revised Unit Statuses

| Time (hour) | Unrevised UC solution | Revised UC solution |
|------------|-----------------------|---------------------|
|            | Unit 37 | Unit 48 | Unit 37 | Unit 48 |
| 1          | 0      | 0       | 0      | 0       |
| 2          | 0      | 0       | 0      | 0       |
| 3          | 0      | 0       | 0      | 0       |
| 4          | 0      | 0       | 0      | 0       |
| 5          | 0      | 0       | 0      | 0       |
| 6          | 0      | 0       | 0      | 0       |
| 7          | 0      | 0       | 0      | 0       |
| 8          | 0      | 0       | 0      | 0       |
| 9          | 0      | 0       | 0      | 0       |
| 10         | 0      | 0       | 0      | 0       |
| 11         | 0      | 0       | 0      | 0       |
| 12         | 0      | 0       | 0      | 0       |
| 13         | 0      | 0       | 0      | 0       |
| 14         | 0      | 0       | 0      | 0       |
| 15         | 0      | 0       | 0      | 0       |
| 16         | 0      | 0       | 0      | 0       |
| 17         | 0      | 0       | 0      | 0       |
| 18         | 0      | 0       | 0      | 0       |
| 19         | 1      | 1       | 1      | 1       |
| 20         | 1      | 1       | 1      | 1       |
| 21         | 1      | 1       | 1      | 1       |
| 22         | 1      | 1       | 1      | 1       |
| 23         | 0      | 0       | 1      | 1       |
| 24         | 0      | 0       | 0      | 0       |

### Comparisons with Existing Methods

To prove the effectiveness of the proposed method, the performance of this method will be compared with MC simulation method, chance-constrained optimization method and robust optimization method. One thousand scenarios are generated by MC simulation. The scenarios selected by the proposed method are shown in Fig. 6(a). MC simulation method reduces 1000 scenarios to 80 scenarios by the scenario reduction techniques, which is shown in Fig. 6(b). The chance-constrained optimization method is solved by the predicted wind power with the deviation $\sigma$ in Fig. 6(c). It only considers the fluctuation of wind power that causes line overloaded with a probability. The robust optimization method is to find out the worst-case scenario from these scenarios in Fig. 6(d).

In Fig. 6(a), the solid lines are typical scenarios and the dotted lines are extreme scenarios selected by our method. In Fig. 6(b), the solid line is the predicted wind power and the reduced scenarios are represented by dotted lines. In Fig. 6(c), it can be seen that these solid lines representing predicted wind power are much the same as those of MC simulation method. And the dotted lines are the boundaries of the deviation $\sigma$. In SCUC, the chance-constrained optimization is to deal with the fluctuation of wind power by setting the probability of the constraint violation. In this paper, the deviation is set to be 20% of the predicted wind power, and the probability of the line flow violation is set to be 10%. The worst-case method is to find a solution that can satisfy the worst-case wind power scenario. It can be seen that if the schedule fits the worst scenario, it can also fit all the scenarios. The objective of this method is to generate a high robust schedule by sacrificing the economy. In Fig. 6(d), the worst scenario selected from those scenarios is shown by a dotted line.

In order to test the robustness of four methods, 1000 scenarios are generated by MC method. These scenarios will be used to solve SCED for evaluating the goodness of each UC solution. If one UC solution can satisfy most of scenarios, it means that the robustness of this UC solution is good. So the number of infeasible solutions can also be used to reflect the robustness of a UC solution. If the UC will lead to more infeasible solutions, it has a lower robustness. The proposed method has a dominant advantage over the other methods in terms of solution robustness. It can be seen from Fig. 7 that the number of infeasible SCED solutions of the proposed method is much less than those of MC and chance-constrained optimization methods. And the robustness of UC solution generated by the proposed method is close to the worst-case method. For instance, the numbers of infeasible SCED solutions of the proposed method and the worst-case method are 24 and 15, respectively. The numbers of infeasible SCED solutions of MC simulation and chance-constrained optimization methods are 277 and 714, respectively. This means that the schedules generated by MC simulation method and chance-constrained optimization method do not meet 27.7% and 71.4% wind power scenarios, respectively. In other words, the generating UC solution has a high risk with the disruption of wind power uncertainty.

Table IV gives the operation cost of the four methods. The cost of the chance-constrained optimization method is the lowest and the cost of the worst-case method is the high-
The cost of the proposed method is close to that of the MC simulation method, but much less than that of the worst-case method. These results verify that the robust optimization method has the highest robustness among these four methods, but the economy of the solution is the worst. The robustness of the proposed method is close to that of the worst-case method, and the operation cost is just a little higher than that of the MC simulation method. Thus, the proposed method is able to generate an economic UC solution with high robustness.

V. CONCLUSION AND FUTURE WORK

In this paper, a security-constrained UC with extreme wind power scenarios is proposed. MC simulation method is used to simulate possible scenarios of wind power. CSFDP is used to separate those scenarios into several clusters. The scenarios in each cluster are further divided into extreme, normal, and typical scenarios. The extreme and typical scenarios are selected to solve the SCUC problem for balancing the economy and robustness of UC solution.

In the future, it is expected to reduce the amount of extreme and typical scenarios that will be used in an SCUC problem. Besides, how to screen out extreme scenarios quickly is another future work.

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