Unit Commitment Risk Evaluation Considering Load Uncertainty and Wind Power

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Manuscript received 24 October, 2021; revised 29 July, 2022; accepted 10 March, 2023. Paper no. JEMT-2110-1342.

Given the importance of unit commitment risk (UCR) assessment in determining the probability of meeting load demand in the ahead short-term operation period, in this paper, a new analytical model for UCR assessment is presented. In the proposed model to consider the impact of wind power participation in the entire short-term period of operation of the system, using the developed risk area concept, a new model for UCR assessment is presented. Furthermore, uncertainties of wind power and load demand are considered simultaneously. Unlike the models presented in previous research for UCR assessment, which consider the share of wind power in the last period of operation, the proposed model for UCR assessment considers the share of wind power in all periods of operation. The proposed model was tested and evaluated on the RBTS system with a wind farm. Moreover, the results obtained from the simulation were reported. According to the results, in all cases, the value of UCR in the proposed model is lower than the modified PJM (M-PJM) method. The effectiveness of this innovative approach in evaluating the UCR of the power system despite wind power and load uncertainties was confirmed based on the results.

keywords: *Unit commitment risk; wind power; risk area; uncertainty; modified PJM method.*

http://dx.doi.org/10.22109/JEMT.2023.311870.1342

1. INTRODUCTION

Nowadays, due to the widespread use of fossil fuels and the emission of greenhouse gases, the use of renewable resources, especially wind power, has increased significantly. Despite the many advantages of wind resources, the output power of these sources is variable and cannot be accurately predicted [1]. This issue has significant effects on assessing the short-term reliability of power systems. Based on the explanations provided, more detailed studies should be conducted on the impact of the presence of wind farms on the short-term reliability of power systems [1].

In the power systems, the value of spinning reserve, which is determined in the unit commitment (UC) step, is responsible for responding to load changes or changes in output power of generating units. The generation capacity of a power system with high wind power penetration will change significantly due to variations in the wind farms' output power. Therefore, the power system operator must consider the participation of wind power in determining the value of the spinning reserve to ensure system short-term reliability [2, 3]. In most of the presented methods for evaluating the short-term reliability of power systems with wind farms to take into account wind and load power uncertainties, the units are scheduled periodically [2]. At the end of each period, the power system situation is updated based on the information obtained from the values of load demand and the output power of wind farms [3].

In general, short-term reliability studies of power systems are divided into two different categories in terms of system operation conditions: system adequacy and system security [4, 5]. System adequacy is an index of the existence of sufficient facilities in the system to provide the required load and meet the operational limitations of the system. System security is a measure of a system's ability to respond to dynamic and transient disturbances [6]. The short-term reliability of the power systems can be calculated using deterministic and probabilistic methods [5]. In deterministic methods, the situation of the power system is limited to a set of constant values, and uncertainty is not considered. The main weakness of these methods is the inability to evaluate random system behaviors such as a forced outage of system elements and uncertainty in consumers' demand. In probabilistic methods, possible aspects of the system are also considered. For this reason, these methods can provide more in-depth information for the design, scheduling, and allocation of generating units [6].

In another category, short-term reliability evaluation of power systems using probable techniques is divided into two categories of analytical and non-analytical methods [6]. Analytical methods are based on mathematical equations, and mathematical modeling is system behavior, while non-analytical methods are based on simulation. In analytical models, the capacity model, known as the capacity outage probability table (COPT), determines the probability of occurrence of any level of generation capacity outage. The Monte Carlo simulation method is the most well-known non-analytical method. This method is based on simulation of all system elements to evaluate system performance [7–9].

UCR evaluation is a probabilistic method to specify an acceptable value for the required spinning reserve [10]. This method was first introduced by the Pennsylvania-New Jersey-Maryland (PJM) system to determine the value of the required spinning reserve of the system to achieve a certain amount of UCR criteria [11]. Studies in the field of UCR show that wind power and load uncertainties have a significant effect on the UCR value [12, 13]. In [12], the effect of different uncertainties on UC studies in power systems is investigated. In [10], using the concept of risk area, an approach to calculate the UCR value in a power system is presented. One of the advantages of this approach is considering wind power in UCR calculation. One of the disadvantages of the approach presented in [10] is not considering the effect of load uncertainty in UCR calculation.

In [14], to minimize the total operation cost including generation and maintenance costs and risk costs, a risk-based coordination model of maintenance planning and UC is presented. According to the results presented in [14] by controlling the operational risk of the system, it is observed that the total operation cost is reduced by coordination, which indicates the effectiveness of the proposed model. In [15], to reduce the price spikes in the short-term operational planning process, a new indicator for energy tariff risk is presented. According to the results obtained from the enactment of the proposed method in a power system with the wind farm, price fluctuations in the short-term operational planning process have been effectively reduced. One of the disadvantages of the approach presented in [15] is not considering the effect of load uncertainty in price spike calculation.

In [16], by combining the chance-constrained programming method with the purposeful programming method, a new model for solving the risk-constrained UC problem is proposed. Considering the impact of transmission lines in solving the risk-constrained UC problem is one of the strengths of the approach presented in [16]. In [17], the UC is investigated by considering the high level of wind penetration. This paper states that stochastic programming is not sufficient to model all aspects of the decision-making process. In [18], the performance of stochastic programming and robust optimization methods in UC solving has been evaluated, considering the risk. In this work, CVaR (Conditional Value at Risk) is used to risk evaluation. One of the disadvantages of the approach presented in [18] is not considering the effect of load uncertainty in UC evaluation. In [19], the UC has been formulated and solved by considering the wind power uncertainty and the probability of congestion of lines. One of the strengths of the study presented in [19] is considering the wind power uncertainty in the power system and considering the transmission capacity of the lines to evaluate the UC more efficiently during the operation period.

Based on the explanations provided, UCR evaluation has not been studied in previous works by simultaneously considering the wind power and load uncertainties. Concerning this issue, this paper focused on evaluating UCR in power systems by considering wind power and load uncertainties. To this work, the conditional probability method and the developed type of risk area are used to analyze the impact of uncertainties of wind power and load demand in the UCR. Finally, to demonstrate the effectiveness of the proposed UCR model, the proposed UCR model is compared with the modified PJM (M-PJM) method. Given the above, the innovations of this study are summarized as follows:

- Introduce a new UCR model using the concept of extended risk area (RA-UCR).
- Consider the effect of wind power in all divided intervals of the operation period to calculate the UCR value of the short-term operation period.
- Simultaneous consideration of wind power and load demand uncertainties in UCR assessment to make system operator decisions more realistic.

The organization of this paper is as follows. In Section 2, modeling wind power and load uncertainties are expressed. Section 3 describes the RA-UCR method. Section 4 describes the result of numerical studies. Section 5 concludes the paper.

2. MODELING WIND POWER AND LOAD UNCERTAINTIES

The wind speed in a specific area in a short period of several hours depends on the initial wind speed and the features of the time series of wind variations in a given area. Therefore, the initial wind speed conditions are used to calculate variations in wind speed and wind power over a short period [10, 13]. In many of the proposed methods for risk assessment, hourly wind data based on long-term measurements for a specific area are not sufficient to generate the probability distribution function used in the short-term reliability studies. To solve this problem, time series are used to generate the required wind data [20]. In this work, the ARMA (Auto-Regressive Moving-Average) time-series presented in [21] have been used to generate data to modeling wind speed. In Eq. (1), using the ARMA time series, wind speed at time t is calculated based on historical data [21]:

$$SW_t = \mu_t + \delta_t \cdot Q_t \tag{1}$$

Where, SW_t is the modeled wind speed at time t, also μ_t and δ_t are the mean and standard deviation of wind data in a specific area, respectively [21]. According to Eq. (1), in addition to μ_t and δ_t, the Q_t parameter is required to calculate wind speed. The Q_t parameter, which is a time series, is calculated using Eq. (2) [21]:

$$\begin{aligned} Q_t = \phi_1 Q_{t-1} + \phi_2 Q_{t-2} + \ldots + \phi_n Q_{t-n} + \\ \beta_t - \beta_{t-1}\lambda_1 - \beta_{t-2}\lambda_2 - \ldots - \beta_{t-m}\lambda_m \end{aligned} \tag{2}$$

Where, ϕ_i $(i = 1, 2, \ldots, n)$ is the regression of the model, λ_j $(j = 1, 2, \ldots, m)$ is the moving average of the model and $\beta_t \in NID(0, \delta_a^2)$ is normal white noise with zero mean and variance δ_a^2 [21].

The wind speed distribution obtained using the time series model indicates the hourly variations in wind speed over a short period ahead for a specific initial condition in the study area

[10]. Finally, according to the studies performed in [1, 10, 22], the wind speed distribution function obtained in the previous step is converted into a wind power distribution function using the wind turbine speed–power relationship. The amount of load variation is less than the wind speed variation because the load changes slowly and is largely predictable. However, load demand prediction error for large power systems is in the range of megawatt and significant. A well-known method for modeling load uncertainty is the use of normal probability distribution functions [23]. In this research, by considering the different forecasts for the load demand and using the prediction error probability distribution function with zero mean and different standard deviations, the value of load demand uncertainty is obtained. According to the above, for the load demand, probable distributions with different standard deviations are considered. Each probable distribution is then divided into thirteen equal parts. In the following, thirteen error values are calculated relative to the mean value, with a specific probability for each error and standard deviation [24]. Therefore, for each standard deviation, thirteen scenarios are achieved with a specified probability for the load demand.

3. DESCRIPTION OF THE PROPOSED RA-UCR METHOD

In the proposed RA-UCR method, a new approach to calculate the UCR value is presented, taking into account wind and load uncertainties and considering the wind power contribution in all intervals of the short-term operating period.

A. The modified PJM method

In the PJM method presented in [11], UCR is defined as the probability that the predicted load demand for the ahead period will not be met. In the PJM method, with the initial conditions of the units being clear, uncertainties increase when the system operator wants to evaluate the system state for the ahead period. Uncertainties in the system state in the ahead period are since the allocated units may be failed in the ahead period when support is not possible [5]. The primary PJM method for the participation of rapid start and hot reserve units, where the decision to use them was made in initial time and will be online in the ahead period, has been modified in [25]. Fig. 1 shows the risk curve of a power system, including rapid start and hot reserve units. In the M-PJM method, the total risk of participation of units that come online during the initial period or later is equal to the sum of partial risks in each part or area under the risk curve. The value of total risk for the system shown in Fig. 1 is calculated using Eq. (3) [10].

$$P(failure) = \int_0^{T1} F(R1)dt + \int_{T1}^{T2} F(R2)dt + \int_{T2}^{T} F(R3)dt \quad \textbf{(3)}$$

According to Fig. 1, three different periodic risks have been created so that the rapid start and hot reserve units come online at times H1 and H2, respectively, and both units are expected to be online until the end of the H time [10]. Hence, the total system risk will be equal to the sum of the partial risks in the three periods. In the M-PJM method, the risk of periods is obtained using the partial risk assessment method presented in [5]. For example, the partial risk in the H2-H period is achieved using the COPT by considering the forced outage rate values calculated at time H for the committed units [5, 10]. This method can be developed to consider wind power participation, whose power and probability are known in each scenario.

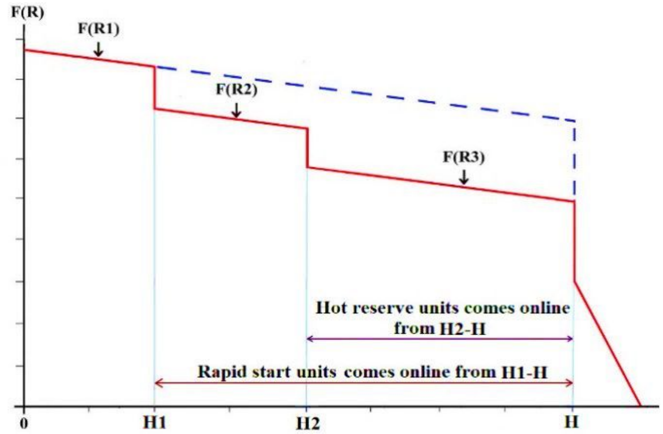

Fig. 1. Concept of risk area in short-term reliability evaluation [10].

Short-term variations in wind farm output power are quantified as discrete-state capacities, and the probability of each state occurring is calculated using the conditional probability distribution function. In the M-PJM method, to consider the impact of wind power participation, the COPT of units are combined with the wind probability distribution function generated in the last interval of the short-term operation period [13]. This process is shown in Fig. 2. According to Figure 2, it can be seen that the distribution function of demand over 4 hours and wind probability distribution function generated in the last interval of the short-term operation period, is combined with the risk function of allocated units over 4 hours.

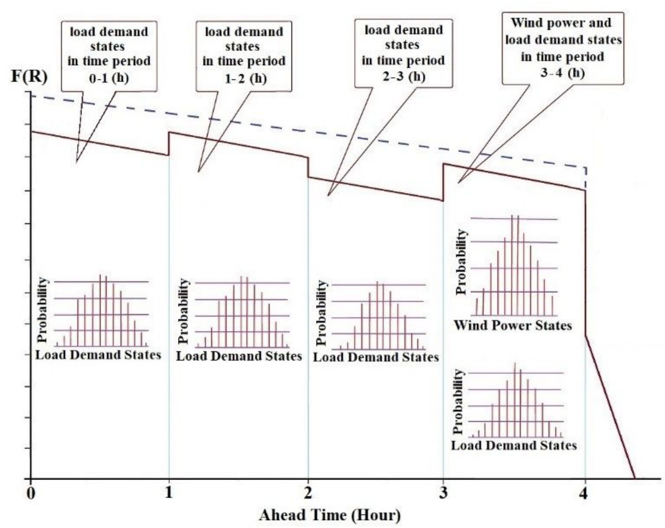

Fig. 2. The use of the concept of risk area in the M-PJM method to calculate UCR with wind power participation.

B. The RA-UCR method

Because the wind speed increases or decreases sharply over the entire ahead period, the wind probability distribution function obtained in the latest interval may not correctly show the share of wind power across the overall ahead period. In the proposed

RA-UCR method for risk assessment, the variations obtained for wind power and load in each interval belonging to the ahead period are combined with the capacity model of allocated units at a suitable time. This process is shown in Fig. 3. In this figure, the distribution function of wind and demand over 4 hours, achieved for a specific initial condition, is combined with the risk function of allocated units over 4 hours.

The generating capacity of the wind farm in a short period in the future depends on the initial conditions of wind. In this study, the initial conditions of the wind power and load will remain unchanged in the first half-hour of the first period. Wind power and demand modeling based on historical data is stored uniformly. Therefore, in the proposed model, the obtained values of load demand and wind farm output power for H hour are used for 30 minutes before and 30 minutes after H hour, which is clearly shown in Fig. 3.

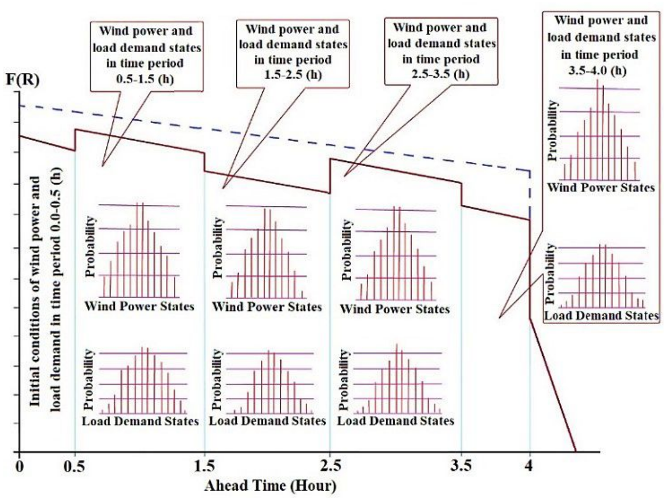

Fig. 3. The use of the concept of risk area in the proposed RA-UCR method to calculate UCR with wind power participation.

According to the explanations provided, the risk amount of the allocated units for the first half-hour is determined using the initial values of wind power and load. For the hourly periods after the first period, the risk amount of the allocated units is determined using the conditional distribution of wind power and load demand in each of the ahead periods. Finally, based on equations (4) - (9), a UCR evaluation is performed for each period.

$$Ar_{(0.0-0.5)} = R_{0.5+W0+L0} \tag{4}$$

$$Ar_{(0.5-1.5)} = R_{1.5+W1+L1} - R_{0.5+W1+L1} \tag{5}$$

$$Ar_{(1.5-2.5)} = R_{2.5+W2+L2} - R_{1.5+W2+L2} \tag{6}$$

$$Ar_{(2.5-3.5)} = R_{3.5+W3+L3} - R_{2.5+W3+L3} \tag{7}$$

$$Ar_{(3.5-4.0)} = R_{4.0+W4+L4} - R_{3.5+W4+L4} \tag{8}$$

$$UCR_{(0-4)} = Ar_{(0.0-0.5)} + Ar_{(0.5-1.5)} + Ar_{(1.5-2.5)} + Ar_{(2.5-3.5)} + Ar_{(3.5-4.0)} \tag{9}$$

Where, R_t is the partial risk achieved of the COPT of allocated units during the operating period t, $R_t + W_x + L_x$ is the partial risk derived from the modified COPT with the conditional distribution of wind power and demand at x hours after the initial conditions and At is the risk value for period t.

4. NUMERICAL STUDIES

In this section, to evaluate the effectiveness of the proposed method, the RA-UCR method is applied to the RBTS test system with a wind farm. Table 1 presents the information on the generation units of the RBTS system [26]. The priority of allocation of generation units is based on the priority list arranged in Table 1. For UCR evaluation in the RBTS test system, the proposed RA-UCR method is compared with the M-PJM method presented in [13]. In this study, wind data in Toronto, Canada, has been used to analyze the effect of wind power on the UCR value [20]. The wind farm connected to the system includes 26 wind turbines with a nominal power of 1.8 MW [10, 22]. Also, the failure rate of wind turbines is ignored and assumed that in the ahead period (4 hours), the wind generators will operate without failure. The probability of each prediction error of load demand for different standard deviations is shown in Table 2. All calculations are performed in a MATLAB environment with a machine running at Intel(R) Core (TM) i5-8250u 1.6 GHz CPU and 8GB RAM.

Table 1. Information on RBTS system units [26].

priority of coming online	Nominal capacity (MW)	Unit type	Failure rate (failure/year)
1	40	Hydraulic	3
2	20	Hydraulic	2.4
3, 4	40	Thermal	6
5	20	Thermal	5
6	10	Thermal	4
7, 8	20	Hydraulic	2.4
9, 10	5	Hydraulic	2

A. Generation of the probability distribution function for wind power

Based on the results presented in [20], the ARMA model has good accuracy. At most wind speeds modeled by the ARMA model, the simulated and actual values are almost the same. This study uses historical wind speed data from Toronto, Canada over a year to simulate wind speed. The ARMA model obtained for these historical wind data is in the form of Eq. (10). [10, 22]:

$$Q_t = 0.4709Q_{t-1} + 0.5017Q_{t-2} - 0.0822Q_{t-3} + \beta_t + 0.1876\beta_{t-1} - 0.2274\beta_{t-2} \qquad \beta_t \in NID\left(0, 0.5508^2\right) \tag{10}$$

The value of wind speed in the coming hours after obtaining Q_t values is determined. Fig. 4 shows the wind speed probability distribution considering different values of the initial speed. Based on Eq. (10), the wind speed distribution curve depends on the mean and standard deviation of the wind data.

Table 2. The probability of each prediction error of load demand for different standard deviations.

Percentage prediction error	Probability of prediction error for standard deviation= 0.025	Probability of prediction error for standard deviation= 0.050	Probability of prediction error for standard deviation= 0.075	Probability of prediction error for standard deviation= 0.100
30 %	0	0	0.0001	0.003
25 %	0	0	0.0012	0.0092
20 %	0	0.0002	0.0085	0.0278
15 %	0	0.006	0.038	0.0656
10 %	0.0013	0.0606	0.1109	0.1210
5 %	0.1573	0.2417	0.2108	0.1747
0 %	0.6828	0.383	0.261	0.1974
-5 %	0.1573	0.2417	0.2108	0.1747
-10 %	0.0013	0.0606	0.1109	0.1210
-15 %	0	0.006	0.038	0.0656
-20 %	0	0.0002	0.0085	0.0278
-25 %	0	0	0.0012	0.0092
-30 %	0	0	0.0001	0.003

According to Fig. 4, with the initial wind speed increasing, the wind distribution curve shifts to the right, indicating an increase in the probability of occurrence of larger wind speeds. In addition, an increase in initial speed increases the bandwidth of the probability distribution curve. An increase in bandwidth indicates an increase in the standard deviation of wind speeds with the initial speed increases.

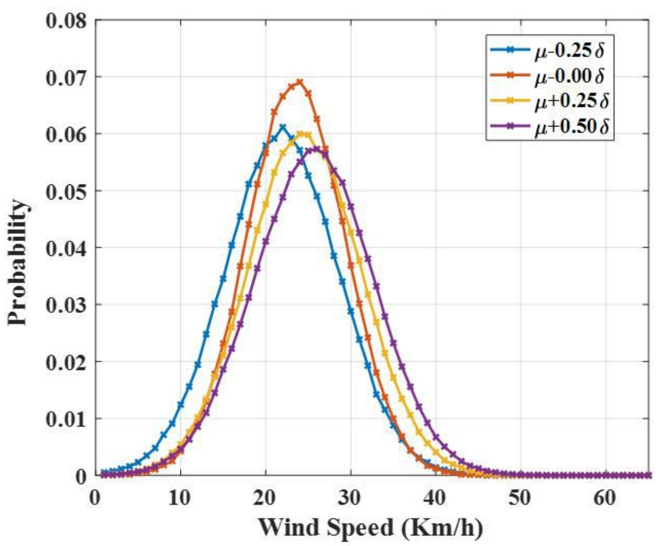

Fig. 4. Wind speed probability distribution for different initial speed values.

Considering the wind speed curve at different hours, using the speed-power relationship, the probabilistic distribution set of wind speed is transformed into the probabilistic distribution set of the wind farm output power. Fig. 5 shows the probable distribution of wind turbine output power in each hour for four consecutive hours (8 to 11 o'clock). Fig. 5 shows that at 8 o'clock, given that the initial wind speed is low, the wind turbine output power is low. Also, in the following hours, with the increase of the initial wind speed, wind turbine output power will increase.

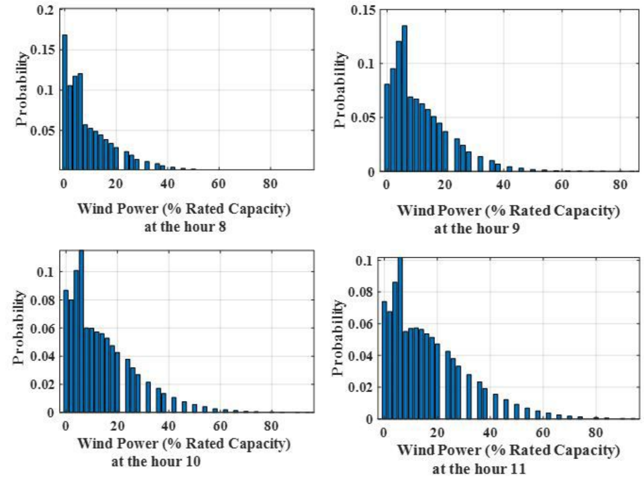

Fig. 5. Probability distribution of wind farm output power for different hours.

B. Impact of wind power on UCR value

Fig. 6 shows the UCR value for four different modes without considering wind power for the next 4 hours. Four different modes include the allocation of 5, 6, 7, and 8 units of RBTS system units based on the priority of Table 1. It can be seen from Fig. 6 that with increasing the load of the RBTS system, the value of UCR in each mode increases. Because with increasing system load, the number of generation units that must be coming online increases. With increasing the number of online generation units, the probability of failure of one of the online units increases. On the other hand, as shown in Fig. 6, due to the discrete capacity of the generation units, the amount of UCR increases step by step with increasing load. In other words, by increasing the load from a specific value, a new unit must be turned on and committed. This leads to a step-by-step increase in the available capacity and consequently increases step by step in UCR. In addition, it is clear that for a specific value of the load, increasing the number of committed units decreases the UCR value. The value of UCR remains constant as the load increases until there is no need to add a new unit.

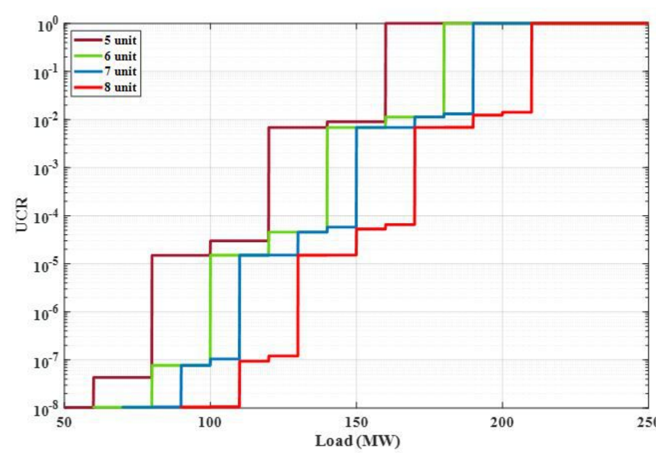

Fig. 6. UCR value without considering wind power.

This analysis is repeated by considering the wind power in the UCR evaluation. Fig. 7 shows the UCR values by considering the wind farm with a nominal capacity of 46.8 MW for the next 4 hours. According to Fig. 7, it is clear that, as in the previous case, increasing the load has increased the UCR value, but in this case, the increase in UCR value is gradual. This is due to the presence of wind power which can supply part of the load increase. This shows that despite the uncertainty in the output power of the wind farm, the use of wind farms reduces the UCR value compared to the case without considering the wind power.

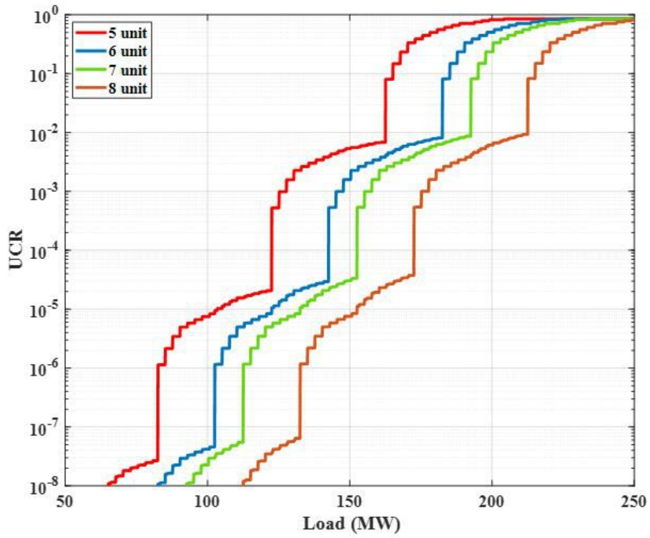

Fig. 7. The UCR value considering wind power.

C. Assessing the UCR value taking into account wind power and load demand uncertainties

In this section, the performance of the proposed RA-UCR method is evaluated by comparing the results of the proposed RA-UCR method and the M-PJM method. Initially, in both methods, COPT is used to evaluate the probability of outage of generation units and the results are combined with the probability distribution of wind power. The UCR value is then is obtained by calculating the cumulative probability distribution of the available capacity states of generation units, which is equal to or less than the expected load. Tables 3 and 4 show the values obtained for UCR in the short-term operation period (8 to 11 o'clock) using the M-PJM method and the RA-UCR method with considering wind power, for cases with load uncertainty and without load uncertainty. In both methods for UCR evaluation, all system conditions in the study period are completely the same. In the M-PJM method, to calculate the UCR value, the wind power distribution obtained in the last interval is used. In the proposed RA-UCR method, to calculate the UCR value, the wind power distribution obtained in the entire short-term operation period is used. In Tables 3 and 4, the UCR values for the load in the range of 140 to 200 MW and considering the allocation of 8 generation units with a wind farm connected to the system are presented for the two mentioned methods.

According to Tables 3 and 4, it can be seen that the value of UCR obtained in RA-UCR method for all load levels in two cases with load uncertainty and without load uncertainty is less than the values obtained in M-PJM method. As we know, with increasing ahead period, the scatter of wind power distri-

Table 3. UCR values for both M-PJM and proposed RA-UCR methods in the ahead short-term period for mode without load uncertainty.

Load (MW)	M-PJM method	RA-UCR method
140	0.0000143	0.0000111
145	0.0000144	0.0000130
150	0.0000144	0.0000137
155	0.0000503	0.0000311
160	0.0000503	0.0000419
165	0.0000621	0.0000523
170	0.0000621	0.0000576
175	0.0065113	0.0029405
180	0.0065113	0.0053471
185	0.0065209	0.0060543
190	0.0065209	0.0062988
195	0.0117530	0.0087401
200	0.0117530	0.0107290

Table 4. UCR values for both M-PJM and proposed RA-UCR methods in the ahead short-term period for mode with load uncertainty for different standard deviations.

Load (MW)	M-PJM method	RA-UCR method
140	0.0000403	0.0000227
145	0.0001097	0.0000563
150	0.0002983	0.0001203
155	0.0007974	0.0002380
160	0.0008763	0.0005828
165	0.0029319	0.0010777
170	0.0056377	0.0025555
175	0.0085719	0.0064336
180	0.0187611	0.0164690
185	0.0466070	0.0178310
190	0.0470980	0.0449110
195	0.1205100	0.0459380
200	0.1205100	0.1177800

bution also increases, which indicates an increase in variations. Therefore, increasing the scatter of wind power distribution will increase the UCR value. As explained, in the M-PJM method, only the wind power distribution in the latest interval (latest hour) is used to calculate the UCR value in the entire 4-hour period, while in the proposed RA-UCR method, wind power distribution in all leading intervals is used to calculate the UCR value in the entire 4-hour period. Therefore, this is why the UCR values in the proposed RA-UCR method are smaller than the M-PJM method.

Fig. 8 shows the values obtained for UCR in the short-term operation period using the M-PJM method and the RA-UCR method with considering wind power, for cases with load uncertainty and without load uncertainty. According to the UCR values in Fig. 8, it is clear that the simultaneous consideration of wind power and load demand uncertainties has a significant effect on UCR values. For all load levels, the value of UCR in the mode with load uncertainty is much increased compared to the mode without load uncertainty. The reason for the intense increase in the UCR value for load levels more than 175 MW in mode with load uncertainty compared to the mode without load uncertainty is that in some scenarios, the load demand is more than the sum of the nominal power of the generation units and the wind farm. In these scenarios, because the load demand is more than the sum of the nominal power of the generation units and the wind farm, the UCR value is equal to one, which in turn increases the UCR value for that load level. For example, in both methods for a load of 200 MW, the UCR value is more than ten times higher in the mode with load uncertainty than in the mode without load uncertainty. Therefore, in the UCR evaluation, it is necessary to model the uncertainty of wind farms and especially the load demand uncertainty with high accuracy.

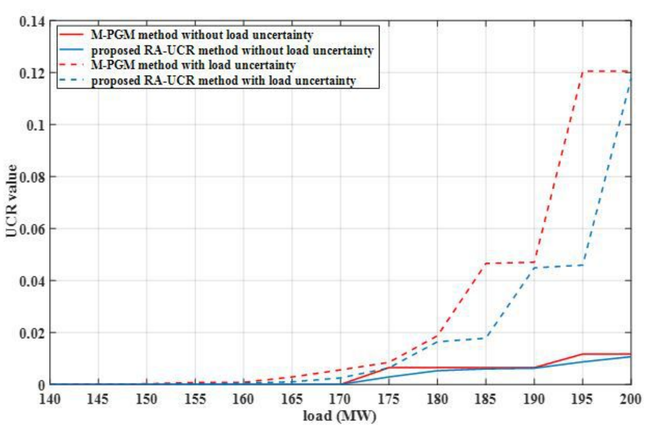

Fig. 8. The UCR values in the short-term operation period using the M-PJM method and the RA-UCR method with considering wind power, for cases with load uncertainty and without load uncertainty

5. CONCLUSION

In this study, an analytical model for evaluating UCR in the power system by considering wind power and load demand uncertainties in the short-term operation period is presented. The main feature of the proposed RA-UCR method is the calculation of UCR taking into account uncertainties related to wind farm output power and load demand. In the proposed RA-UCR method for evaluating UCR in a power system with the wind farm, the conditional probability, and developed type of risk area are used to consider the effect of wind power and load demand uncertainties on the UCR value. To evaluate the effectiveness of the proposed RA-UCR method, the proposed method and M-PJM method were applied to the RBTS system. According to the numerical results for the cases with load uncertainty and without load uncertainty, in the proposed RA-UCR method, the UCR value in the short-term operation period in all load levels is less than the M-PJM method. Therefore, the proposed RA-UCR method for calculating the UCR value in the short-term operation period is much more powerful than the M-PJM method.

Also, considering the UCR values calculated in the numerical results, it is clear that the simultaneous consideration of wind power and load demand uncertainties has a significant effect on UCR values. In both methods at all load levels, the value of UCR in the mode with load uncertainty is much increased compared to the mode without load uncertainty. According to Fig. 8 and Tables 3 and 4, the reason for the increase in UCR value for load levels more than 175 MW in mode with load uncertainty compared to the mode without load uncertainty is that in some scenarios, the load demand is more than the sum of the nominal power of the generation units and the wind farm. As a result, in these scenarios, the UCR value is equal to one, which in turn increases the UCR value for that load level. For example, in the RA-UCR method for a load of 200 MW, the UCR value in the mode without load uncertainty has increased from 0.0107290 to 0.1177800 in the mode with load uncertainty. Similarly, in the M-PJM method for a load of 200 MW, the UCR value in the mode without load uncertainty has increased from 0.0117530 to 0.1205100 in the mode with load uncertainty. As a result, in both methods for a load of 200 MW, the UCR value is more than ten times higher in the mode with load uncertainty than in the mode without load uncertainty. Therefore, in the UCR evaluation, it is necessary to model the uncertainty of wind farms and especially the load demand uncertainty with high accuracy.

In general, it can be said that the proposed RA-UCR method provides high accuracy and capability in evaluating the UCR value of power systems with wind farms and is a suitable criterion for evaluating the short-term reliability of the power system with wind power penetration despite load uncertainty.

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