

Impact of Correlation Between Wind Speed and Turbine Availability on Wind Farm Reliability

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Abstract—This paper proposes a new method to evaluate the reliability of a wind farm considering the correlation between wind turbine reliability and wind speed. With increasing integration of wind generation into the grid, the reliability and stability of the grid are increasingly impacted. Although there are obvious benefits from wind generation, the stochastic nature of wind speed causes several operational challenges. Recent research has shown that wind speeds also impact the failure rates of the turbines, thereby compounding the effect of wind speed variation. The objective of the work reported here is to evaluate the impact of wind speed on the reliability of a wind farm considering the correlation between wind speed and wind turbine failure rate. The method proposed in this paper is implemented using discrete convolution. The effectiveness of the proposed method is proved by comparing reliability indexes of the modified IEEE RTS-79 system with and without considering the impacts of the negative correlation between wind turbine reliability and wind speed.

Index Terms—Correlation, failure rate, reliability, repair rate, wind speed, wind turbine.

I. INTRODUCTION

RELIABILITY models of wind farms have been amply developed and presented in literature, using both analytical and probabilistic methods [1]–[4]. In these works, the models of wind farms take into account many different aspects that impact the reliability. In [5]–[7], probabilistic models of wind farms or wind turbines considering the effects of stochastic nature of wind, different wind regimes on wind turbine reliability, wake effects, and spatial wind speed correlation were investigated. Effect of different wind turbine technologies on reliability model was presented in [8]. Impact of locations, the difference between off-shore and onshore environment of wind farm while developing reliability model was included in [9], [10]. The combination of the effects of wind turbine forced outage rates and varying power output due to wind speed variations was studied in [11], [12]. In [13], load-carrying capability and wind speed correlation in adequacy assessment was considered. Correlations between wind power outputs and load with the optimal distribution of wind turbines to improve wind farm reliability were shown in [14]. In [15], the effect of grid connection configuration on reliability indices was considered. Impact of the wind geographical correlation level for reliability studies was also investigated [16]. In [17], impact of frequency security constraint, low inertia, and effect of wind penetration on wind farm reliability was analyzed. The inclusion of protection system failures [18], and the correlation between wind power generation and hydro generation and load [19] in the reliability model was evaluated. Impact of a large number of wind turbines [20] on wind farm reliability was also presented. The reliability of a system with large-scale

wind power integration considering transmission constraints [21] was also considered.

In the aforementioned research, only the correlation between wind power output and wind speed, load-carrying capability and wind speeds, wind power outputs and load, wind geographical correlation level were considered. The effect of correlation between wind speed and failure rate of wind turbine on a wind farm reliability has never been analyzed. Most studies in literature assumed that the failure rates of all components of a wind turbine are independent of the transitions between wind speed states. These works neglected the correlation between different wind speeds and the reliability of each component of a wind turbine.

It was shown in [22], from the data collected [23], that there is a significant negative correlation between wind speeds and the failure rates of the components of a wind turbine. This motivates the development of a reliability model for wind farms that captures this correlation.

The work presented in this paper extends the prior art by adding the following contributions:

- (i) It develops an improved reliability model of a wind farm considering the negative impacts of wind speed on wind turbine failures rates;
- (ii) It develops the turbine reliability model as a combination of many components;
- (iii) It develops a direct, analytical method, based on discrete convolution, to evaluate the wind farm reliability with a diversity of failure rates of wind turbines.

The paper is organized as follows. Section II presents the model of correlation between wind turbine reliability and wind speeds. Section III develops the reliability model of a wind farm using discrete convolution with the inclusion of the negative correlation between wind speeds and wind turbine failure rates. The effectiveness of the proposed method is proved by simulation results that compare system reliability indexes with and without considering the proposed impact in section IV. Finally, section V provides concluding remarks on the work presented.

II. CORRELATION BETWEEN WIND SPEEDS AND WIND TURBINE RELIABILITY

Besides the relationship between the power output of wind turbines and wind speeds, the correlation between wind speeds and components of a wind turbine was investigated in [22]. Using the real data collected from Windstats for historic, maintained, Danish wind turbines and on-line data collected for the Danish weather, the reliability of all components of a wind turbine in response to different weather condition was

analyzed. The method utilized to determine the correlation is summarized here for convenience. The analysis includes three techniques [22]:

1) Auto-Correlation Function

The analysis used the auto-correlation function as follows [22].

$$R_f(\tau) = \frac{\int_{-\infty}^{\infty} f(t)f(t+\tau)dt}{\int_{-\infty}^{\infty} (f(t))^2 dt} \quad (1)$$

This function is utilized to examine the correlation between values of function $f(t)$ differing by a lag τ . The function is time-dependent and has the following properties:

$$-1 \leq R(t) \leq 1 \quad (2)$$

$$R(t) = R(-t) \quad (3)$$

If $R = 1$, $f(t)$ and $f(t_\tau)$ are positively correlated. If $R = -1$, $f(t)$ and $f(t_\tau)$ are negatively correlated. If $R = 0$, two functions do not have any correlation.

The auto-correlation coefficients are determined by evaluating numbers of auto-covariance values:

$$c_\tau = \frac{1}{N_I} \sum_{i=1}^{N_I-\tau} (f_{t+\tau} - \bar{f})(f_t - \bar{f}) \quad (4)$$

The auto-correlation coefficient then can be found by:

$$r_\tau = \frac{c_\tau}{c_0} \quad (5)$$

where c_0 is c_τ at $\tau = 0$.

2) Spectral Analysis

The spectral function $I(w_p)$ is shown as follows:

$$I(w_p) = \frac{2}{\pi} (c_0 + 2 \sum_{i=1}^{N_I-1} c_\tau \cos w_p \tau) \quad (6)$$

where w_p is the angular frequency.

3) Cross-Correlation Function

The function has the same properties as the auto-correlation function except that $r_{fg}(\tau) \neq r_{fg}(-\tau)$ and takes the form:

$$R_{fg}(\tau) = \frac{\int_{-\infty}^{\infty} f^*(t+\tau)g(t)dt}{\int_{-\infty}^{\infty} f(t)g(t)dt} \quad (7)$$

where $f(t)$ and $g(t)$ are two separate series, time dependent functions. The cross-covariance function is evaluated as follows:

$$c_{f,g}(\tau) = \begin{cases} \frac{1}{N_I} \sum_{i=1}^{N_I-\tau} (f_t - \bar{f})(g_{t+\tau} - \bar{g}) & \tau = 0, N-1 \\ \frac{1}{N_I} \sum_{i=1}^{N_I} (f_t - \bar{f})(g_{t+\tau} - \bar{g}) & \tau = -1, -(N-1) \end{cases} \quad (8)$$

The cross-correlation coefficient then can be found by:

$$r_{f,g}(\tau) = \frac{c_{f,g}(\tau)}{\sqrt{c_{f,f}(\tau=0)c_{g,g}(\tau=0)}} \quad (9)$$

Periodicity of wind data and failure data rate are evaluated using the three discussed techniques. Then, the cross-correlation of wind and failure rate data is generated. Cross-correlation with all associated components of the turbine is

produced. More details about this procedure can be found in [22]. By considering all the main components of a wind turbine, the relationship between reliability of each component of the wind turbine and the change of wind speed are examined. Using the above method, the correlation between the components of a wind turbine and wind speeds was determined to be negative [22]. Although the higher speed of wind within cut-in and cut-off speed produces higher power output, it also deteriorates the reliability of wind turbines. As a result, the failure rates of wind turbines at different wind speeds are not identical. This is against the assumption used by most current research in wind turbine reliability. Therefore, the model of wind farm reliability must be re-evaluated considering the impact of wind speeds on wind turbine reliability.

III. RELIABILITY MODEL OF A WIND FARM USING DISCRETE CONVOLUTION WITH THE CORRELATION BETWEEN WIND SPEEDS AND WIND TURBINE RELIABILITY

As a wind turbine is a combination of different components, the reliability model of a wind turbine must consider the combination of these components. Being different from two-state unit model of conventional generators, a multi-state model is utilized for wind turbine reliability. Due to the dependence of wind turbine power output on wind speed variation, the transition rates between the wind speeds are considered besides the transition rates of the components of the wind turbine. The model of a wind farm reliability is developed based on wind speed, wind turbine output, and wind turbine outage. The reliability model is developed with four steps as follows:

- Developing reliability model of a wind turbine with multiple components.
- Modeling wind speed by the discrete Markov process.
- Determining the output power of a wind turbine based on wind speed and components availability.
- Developing wind farm capacity outage model for discrete convolution considering the correlation between wind speed and wind turbine's components reliability.

In this paper, the influence of wind speed variation on the failure rates of all components of a wind turbine, which was often neglected in the literature, will be considered and analyzed. The details of each step are presented as follows.

A. Reliability model of a wind turbine with multi-components

In the reliability model of a wind turbine, twelve types of components will be considered and shown in Table I [24].

Each component of a turbine is modeled as a two-state unit (up or down). All components are assumed to be stochastically independent. The state of a wind turbine T is the combination of states of all components as follows:

$$T = \prod_{s=1}^k Co_s \quad (10)$$

where k is the number of components and Co_s is the state of s^{th} component. This means that a wind turbine is available only when all its components are in up state. If one component

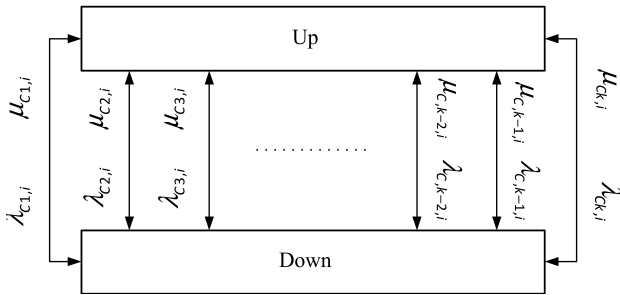
TABLE I
WIND TURBINE COMPONENTS

Component number	Component name
C1	Electrical system
C2	Electronic control
C3	Sensors
C4	Hydraulic system
C5	Yaw system
C6	Rotor Blades
C7	Mechanical Brake
C8	Rotor hub
C9	Gear box
C10	Generator
C11	Supporting structure
C12	Drive train

fails, the turbine is down. The availability P_u of a wind turbine is determined as follows:

$$P_u = \prod_{s=1}^k P_{C_{O,s}} \quad (11)$$

where $P_{C_{O,s}}$ is the availability of s^{th} component. It should be emphasized that the failure/repair rates of different turbines in a wind farm are considered independent. Because the failure rates and repair rates of each component are different, the failure/repair rates of a wind turbine are two sets of failure rates and repair rates of each component of a wind turbine. The reliability model of a wind turbine with multiple components are shown in Fig. 1.


 Fig. 1. Reliability model of a wind turbine with k components.

In Fig. 1, $\mu_{Ck,i}$ and $\lambda_{Ck,i}$ are the repair and failure rates of component k^{th} at wind class i .

B. Wind speed model by the discrete Markov process

A discrete Markov chain is utilized to model wind speed time-series data [5], [7]. A Markov chain has the ability to capture both probability and frequency of each wind speed state. It also gives information about duration attribute of wind speed. A model of wind speed using Markov chain with a finite number of states is shown in Fig. 2. This model implies the preservation of statistical parameters. Wind speed follows a random probability distribution at any considered moment.

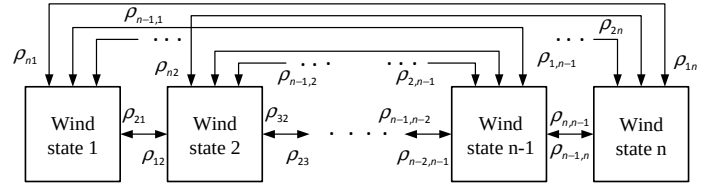
As the transition of wind speed from one state to another state is random, transition among all wind speed states are possible and will be considered. The distribution of residence times in a given state of the Markov process is exponential [5]. The transition rate (the number of transitions from one state to another state over a specific residence time) between any states are evaluated using the frequency balance between them when considering a very large number of samples. If N_{ij} is the number of transitions from state i to state j and D_i is the duration of state i , the transition rate from state i to state j is determined as follows [5]:

$$\rho_{i,j} = \frac{N_{ij}}{D_i} \quad (12)$$

With a large number of samples, the probability $p_{c,i}$ of wind being in state i can be estimated as follows [5]:

$$p_{c,i} = \frac{\sum_{j=1}^N n_{ij}}{\sum_{k=1}^N \sum_{j=1}^N n_{kj}} \quad (13)$$

where n_{ij} is the number of transitions from state i to state j , and N is the number of states.


 Fig. 2. Wind speed model with n states.

C. Modeling the output power of wind turbine

The output of a wind turbine depends on the size of the turbine, the availability of turbine's components, and the wind speed through the rotor. The kinetic energy from wind speed is converted to electrical energy by wind turbine. Presenting by a mathematical equation, the output power of a wind turbine is a non-linear function of wind speed and wind turbine availability. The relationship of wind power output and wind speed is illustrated in Fig. 3.

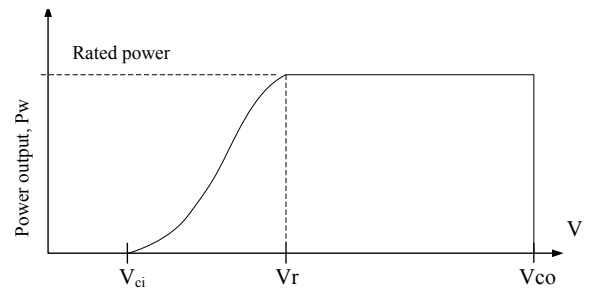


Fig. 3. Typical wind speed and wind power output relationship.

If V_{ci} is cut-in speed, V_{co} is cut-out speed, V_r is rated speed, and P_r are rated power of the wind turbine, all the turbine's

components are available, the output of a wind turbine is represented by the below function [25]:

$$P_w = \begin{cases} 0 & 0 \leq V \leq V_{ci} \\ (A + B \times V + C \times V^2)P_r & V_{ci} < V \leq V_r \\ P_r & V_r < V \leq V_{co} \\ 0 & V_{co} < V \end{cases} \quad (14)$$

where A , B , and C are three constants and are defined as follows [11]:

$$\begin{aligned} A &= \frac{1}{(V_{ci} - V_r)^2} [V_{ci}(V_{ci} + V_r) - 4(V_{ci}V_r) \frac{(V_{ci} + V_r)^3}{2V_r}] \\ B &= \frac{1}{(V_{ci} - V_r)^2} [4(V_{ci} + V_r) \frac{(V_{ci} + V_r)^3}{2V_r} - (3V_{ci} + V_r)] \\ C &= \frac{1}{(V_{ci} - V_r)^2} [2 - 4 \frac{(V_{ci} + V_r)^3}{2V_r}] \end{aligned}$$

This relationship between wind speed and output power is deterministic. It is possible to additionally capture non-deterministic effects as has been done in [26] for solar output using a regression-based model. However, in our work the intent is to capture the impact of wind speed on turbine reliability, on which non-deterministic components of power output have negligible impact.

D. Modeling of wind farm capacity outage considering the correlation between wind speed and wind turbine components reliability

As discrete convolution will be used to evaluate the system reliability, a wind farm capacity outage model is constructed. This model includes both wind speed model and wind turbine model. In this model, it is approximated that all the turbines in a wind farm are subjected to the same wind speed at one considered moment. Hence, all wind turbines have the same power output. It is also assumed that all turbines have the same failure rates λ_t and repair rates μ_t when being subjected to the same wind speed.

Besides the relationship between wind speed and wind turbine output, the model of a wind farm capacity outage will address the correlation between the variation of wind speed and wind turbine failure rate, which was neglected by most of the previous works available in the literature. This consideration will lead to the denial of a popular assumption in literature that the failure rates of wind turbines at all wind speeds are identical.

By using discrete convolution to evaluate the wind farm reliability, only the individual probability for each outage power state of the wind farm and its frequency to the lower outage capacity states are considered. This is the advantage of this method when avoiding the calculation of the transition frequencies to higher outage capacity states. Fig. 4 shows the matrix form of wind farm outage. It should be noted that due to the correlation of wind speed and wind turbine reliability, different failure rates of wind turbines due to the change of wind speed are included. In Fig. 4, the capacity outage corresponding to each state is given. It should be noted that

transitions between non-adjacent states are not shown in order to reduce clutter.

In Fig. 4, the notations used are as follows:

- m = number of wind turbines.
- μ_{ti} = a set of repair rates of a turbine at wind speed i .
- G_j = the output power of a turbine at wind class j .
- N = number of wind class.

It should be mentioned that μ_{ti} is a set of k repair rates of k components of a turbine.

$$\mu_{ti} = (\mu_{C1,i}, \mu_{C2,i}, \dots, \mu_{C,k-1,i}, \mu_{Ck,i})$$

Each state in Fig. 4 has a capacity outage which is the result of the subtraction the available capacity from the total capacity:

$$C_{i,j} = mG_N - (m - i + 1)G_j \quad (15)$$

If p_u and p_d are the probabilities of a wind turbine being up and down, the probability of all wind turbines at state (i, j) is evaluated as:

$$p_{tb,i} = C_m^{m-i+1} p_u^{m-i+1} p_d^{i-1} \quad (16)$$

where C_m^{m-i+1} is the combination of m turbines taken $m - i + 1$ at a time. The probability of a turbine in up state p_u is calculated by equation (11). The probability of each state then can be represented by the following equation:

$$p_{i,j} = p_{tb,i} p_{c,j} \quad (17)$$

Due to the consideration of the correlation of wind speeds and reliability of all wind turbine components, the frequency of moving to the lower capacity outage states of one state in Fig. 4 is shown as:

$$f_{i,j} = p_{i,j} \sum \rho_{i,j}^+ \quad (18)$$

where $\rho_{i,j}^+$ is the transition rate of state (i, j) to other states with lower capacity outages and this value includes not only the transition rates of wind speed but also transition rate of each component of wind turbine at wind speed i .

All states with the same capacity outages will be combined into one state, the probability of a capacity outage X and its frequency to the lower outage capacity is shown as follows:

$$P_r(X) = \sum_{i,j} p_{i,j}(X) \quad (19)$$

$$\beta^+(X) = \frac{\sum_{i,j} f_{i,j}(X)}{P_r(X)} \quad (20)$$

This is the advantage of discrete convolution when considering a turbine with multiple components. The frequency to the lower outage capacity can be used due to the frequency balance rule to reduce the complication of the model.

With the combination of the negative correlation between wind speed and turbine reliability, the reliability model of a wind farm is re-evaluated. The failure rates of wind turbines are directly proportional to wind speed, which means that the system reliability is negatively impacted. Considering this negative correlation is the main contribution of this paper.

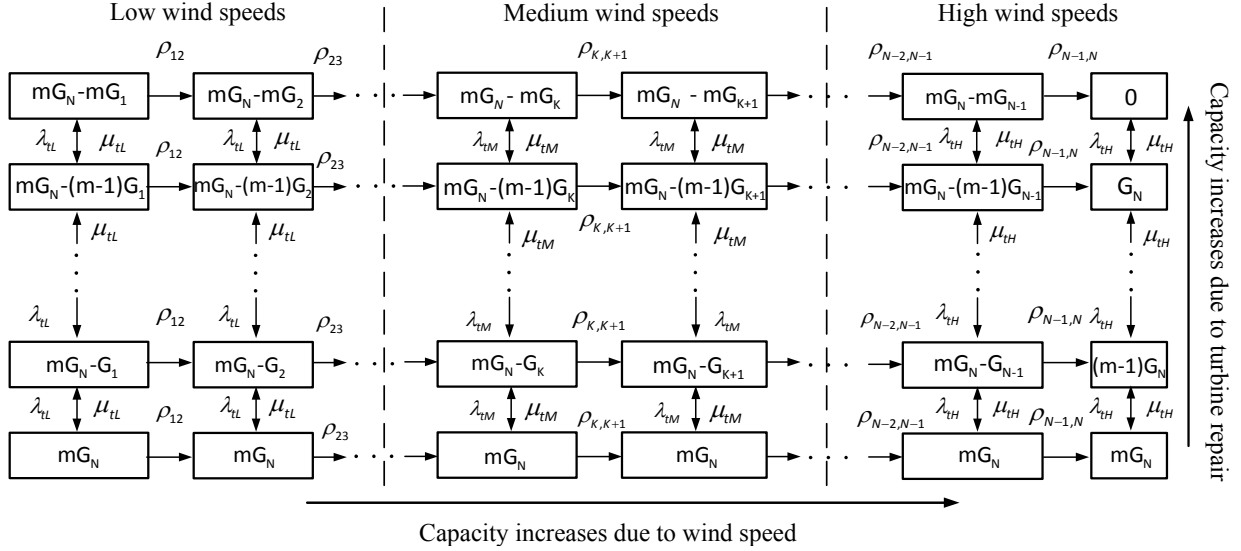


Fig. 4. State transition diagram for wind farm (transitions between non-adjacent states and transitions from higher to lower wind speed states are not shown in order to reduce clutter).

E. Capacity Outage Probability and Frequency Table

Due to the dependence of power output on wind speed, a wind farm is considered a multi-state generator. Each capacity outage level has its probability and frequency of transition to lower outage level due to the frequency balance feature of the system. The Unit Addition Algorithm with discrete convolution is used to develop a Capacity Outage Probability and Frequency Table (COPAF) [27] as follows. The cumulative probability and frequency of the capacity outage state X MW is calculated as follows:

$$P(X) = \sum_{i=1}^N P'(X - C_{w,i}) P_{r,i} \quad (21)$$

$$\begin{aligned} F(X) = & \sum_{i=1}^N F'(X - C_{w,i}) P_{r,i} \\ & + \sum_{i=1}^{N-1} (P'(X - C_{w,i+1}) - P'(X - C_{w,i})) P_{r,i+1} \beta_{i+1}^+ \\ & + (P'(X - C_{w,N}) - P'(X - C_{w,1})) P_{r,N} \beta_N^+ \end{aligned} \quad (22)$$

The equation for probability is straightforward. The frequency calculations may be analyzed as shown in Fig. 5. In Fig. 5, the first column shows the outage states due to the addition of the unit in state 1. The next column shows the new outage states created by adding the unit in state 2 and so on. Inside the polygon are the group of states that have outage capacity greater than $(x_i + C_1)$. Due to frequency balance [27], the frequency of transitions entering the polygon, which gives the cumulative frequency of encountering outage capacities greater than $(x_i + C_1)$, can be more easily calculated from the frequency of transitions exiting the polygon. The latter transitions are represented by the arrows in Fig. 5. Therefore, in equation (22), the first summation results from the changes in states of unit other than the unit being added, the second

summation and the last term results from the changes in the states of the unit being added. This analysis is applied to all other outage levels. Since the resulting model of the wind farm has multiple states, the state frequency diagram has the form shown in Fig. 5.

Based on above analysis, the COPAF of a wind farm is developed to evaluate its reliability. As can be seen on the COPAF for a wind farm, the conventional generator with two states (up and down) can be considered as a multi-state generator with $N = 2$.

IV. SIMULATION AND RESULTS

The proposed method is implemented on IEEE RTS-79 system. The system is modified with three wind farms having ten wind turbines each. Each wind turbine has a rated power capacity of 8 MW. The original IEEE RTS-79 system includes 32 conventional generators with a total capacity of 3405 MW. The data for IEEE-RTS system can be found in [28]. The maximum load of the system is 2850 MW. The reliability of the modified system is examined in two cases: i) considering and ii) neglecting the negative correlation between wind speed and wind turbine reliability. Wind data is provided by National Renewable Energy Laboratory (NREL) from [29] and clustered into one-hour interval (the original wind data are collected over the intervals of ten minutes). The cut-in, cut-out and rated speeds of a wind turbine are 5, 25, and 12 m/s, respectively.

Based on cut-in, cut-out, rated speeds, wind speed is divided into eight states with a step size of 1 m/s. Although the wind speeds are from 1 to 30 m/s, some of the states were combined together since their output are identical and their speeds are in the same levels (states 1–5 have 0 MW output, states 12 – 30 have 8 MW output). The transition rates among eight wind speed states are evaluated using equation (12) and given in Table II. The failure frequency and the repair time for wind

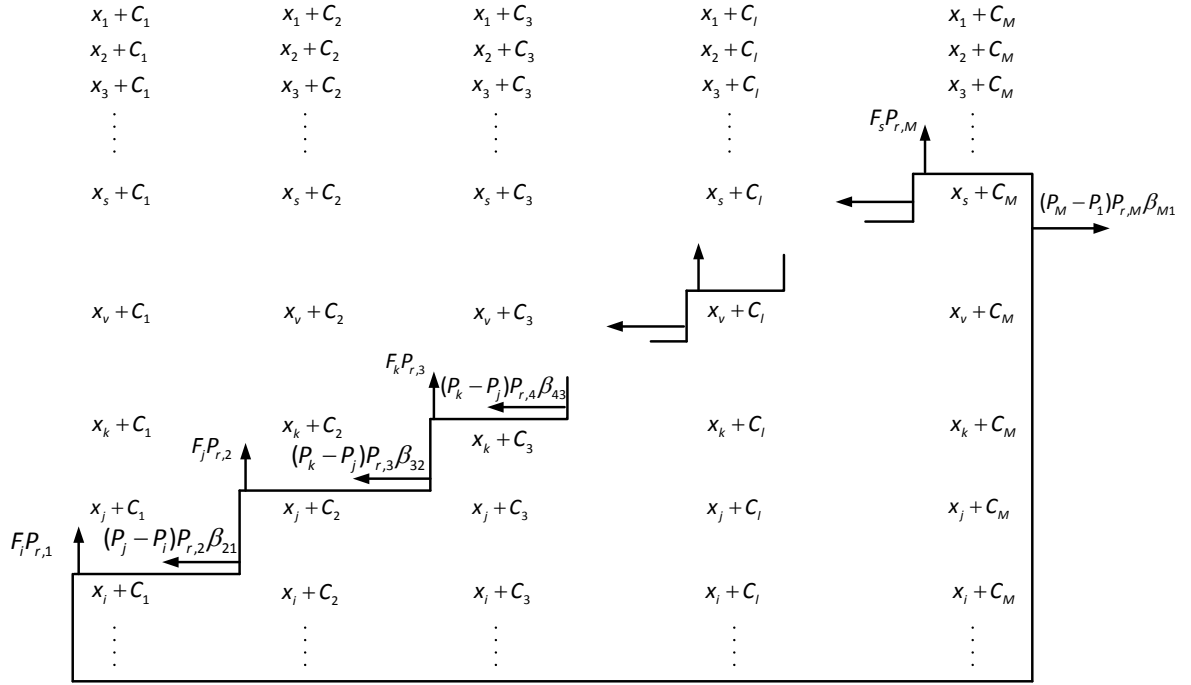


Fig. 5. State frequency diagram for a multi-state unit [27].

TABLE II
TRANSITION RATES BETWEEN WIND SPEED STATES

State	8	7	6	5	4	3	2	1
8	0.846	0.289	0.099	0.018	0.008	0.000	0.000	0.000
7	0.106	0.354	0.202	0.066	0.027	0.006	0.004	0.001
6	0.031	0.251	0.335	0.212	0.077	0.026	0.006	0.001
5	0.01	0.076	0.257	0.351	0.202	0.061	0.022	0.004
4	0.004	0.02	0.074	0.246	0.374	0.221	0.08	0.015
3	0.003	0.009	0.024	0.085	0.237	0.377	0.215	0.032
2	0.000	0.000	0.007	0.016	0.058	0.204	0.388	0.126
1	0.000	0.002	0.003	0.006	0.02	0.106	0.285	0.822

turbines at different wind speed levels are extracted from [24] and shown in Table III for convenience. The failure frequency of each component (over a year) at low, medium, and high wind speed, and repair time of each component (days) in Table III show a significant sensitivity to wind speed, with failure frequency increasing by more than a factor of three.

To show the effect of the negative correlation between wind speeds and wind turbine reliability, the following four cases will be investigated:

Case 1: In this case, the reliability of the wind farms are evaluated in a traditional way: the negative correlation is neglected in the model of wind farm reliability. This makes the transitions in the vertical direction (shown in Fig. 4) of all turbines identical. All the repair rates and failure rates associated with each turbine are considered constant regardless of the wind speeds. This means that $\mu_{tL} = \mu_{tM} = \mu_{tH}$ and $\lambda_{tL} = \lambda_{tM} = \lambda_{tH}$. From this assumption, the probability of each capacity outage and its frequency of transition to the lower outage capacity are calculated from equations (17, 18,

19, 20). Then the Capacity Outage Probability and Frequency Table is set up using equation (21) and equation (22). Using data for failure frequency and repair time and wind speed in Table III, the reliability results of the IEEE RTS-79 system adding wind farms are evaluated by the discrete convolution process using the COPAFT and shown in Table IV for comparison with case 2.

Case 2: In this case, the negative correlation is included in the reliability model. The vertical transition (shown in Fig. 4) of each turbine is a set of transitions of each component. These transitions are dependent variables of wind speeds and inversely proportional to wind speed. The higher wind speed, the higher failure rates of wind turbines. In this case, $\lambda_{tL} \neq \lambda_{tM} \neq \lambda_{tH}$. The considered correlation causes the change in the probability of each capacity outage and its frequency to the lower outage capacity, which in turn change the cumulative probability and frequency of the capacity outage state X MW in the COPAFT. As a consequence, the wind farm reliability is negatively impacted compared to case 1 when wind speed increases. Using the data for different wind speeds in Table III, wind turbine data, and applying the proposed approach, the reliability indexes of IEEE RTS-79 system adding wind farms using the discrete convolution process are calculated for comparison with case 1 and shown in Table IV.

Case 3 and Case 4: These cases are similar to case 1 and case 2 except that the number of wind farms decreases to one to see how the impact of the correlation between wind speeds and wind failure rates changes when the total contribution of wind power generation changes. In case 3, the correlation between wind speeds and wind turbine failures is neglected. In case 4, this correlation is included to compare to case 3. Then, these two cases are compared to case 1 and case 2.

TABLE III
FAILURE FREQUENCY AND REPAIR TIME OF WIND TURBINES

Component	1	2	3	4	5	6	7	8	9	10	11	12
Failure frequency (low wind)	0.83	0.62	0.37	0.35	0.27	0.26	0.2	0.16	0.15	0.14	0.13	0.08
Failure frequency (medium wind)	2.0	1.49	0.89	0.85	0.66	0.63	0.48	0.4	0.36	0.33	0.32	0.19
Failure frequency (high wind)	3.0	2.23	1.34	1.28	1.0	0.94	0.72	0.6	0.54	0.5	0.49	0.28
Repair time	1.8	2.3	1.8	1.4	3.3	5.1	3.3	4.4	7.9	9.3	4.1	7.1

A. Simulation Results

Five cases for simulation are implemented: four cases mentioned in the previous subsection and one case that shows the reliability of the original IEEE-RTS 79 system without adding wind farms for comparison. The reliability indexes of the original IEEE-RTS 79 system and the modified IEEE-RTS 79 system with and without consideration of the negative correlation between wind speeds and wind turbine failure rates are calculated using discrete convolution and shown in Table IV. The indexes for the system reliability include: LOLE (Loss of Load Expectation), LOLF (Loss of Load Frequency), LOLP (Loss of Load Probability), EDNS (Energy Demand Not Supplied), LOEE (Loss of Energy Expectation).

TABLE IV
THE RELIABILITY INDEXES OF THE AUGMENTED IEEE-RTS SYSTEM FOR THREE CASES

Index	LOLE h/y	LOLF f/y	LOLP	EDNS MW/y	LOEE MWh/y
Base case	9.369	2.016	0.0012	0.1641	1433.75
Case 1	4.1267	0.9766	0.000471	0.0554	485.6219
Case 2	4.3869	1.0420	0.000501	0.0591	518.0950
Case 3	8.2628	1.7209	0.000943	0.1117	978.5276
Case 4	8.3735	1.7306	0.000956	0.1137	996.0952

B. Discussion

The simulation results in Table IV show that:

- The presence of wind power integration improves the system reliability due to the contribution of wind generation to satisfy the demand. The reliability indexes of the system are improved in both case 1 and case 2 compared to the base case. The LOLP gets better when wind generation is installed in the system (decreases from 0.0012 to 0.000471 and 0.000501). As a result, the LOLE also decreases from 9.369 to 4.1267 and 4.3869 hours/year (h/y). A similar situation happens with LOEE and EDNS. LOEE reduces from 1433.75 to 485.6219 and 518.0950 (MWh/year). EDNS improves from 0.1641 to 0.0554 and 0.0591 (MW/year). When EDNS decreases, LOEE reduces accordingly. LOLF is also improved from 2.016 to 0.9766 and 1.0420 failures/year (f/y).
- The simulation results also show that the correlation between wind speed and wind turbine reliability has a negative impact on system reliability. Due to this correlation, system reliability indexes get worse. The reduction in system indexes can be seen clearly when

comparing case 1 and case 2 in Table IV. LOLP gets worse from 0.000471 to 0.000501. LOLE is degraded from 0.9766 to 1.0420 f/y. LOLE also increases from 4.1267 to 4.3869 hours/year. EDNS changes from 0.0554 to 0.0591 (MW/year). As a result, LOEE increases from 485.6219 to 518.0950 (MWh/year).

- From the difference in reliability indexes of case 1 compared to case 2 and the difference in reliability indexes of case 3 and case 4, it can be seen that when the wind power contribution to grid increases, the impact of the correlation between wind speeds and wind turbine reliability can be seen more clearly. The result table shows that the increase in the reliability indexes of case 2 compared to case 1 is higher than the increase in the reliability indexes of case 4 compared to case 3.

The simulation results and analysis indicate that considering the negative relationship between wind speed and wind turbine reliability is important in estimating system reliability. If this correlation is not taken into account, the reliability of wind integrated system might be over estimated. This can cause a serious effect on planning and operation of the system with renewable energy integration.

V. CONCLUSION

The negative correlation between wind speeds and wind turbine reliability has been shown to have an impact on the reliability of a wind farm. Higher wind speeds improve power output yet worsen the turbine reliability. The mathematical model of the wind farm reliability with the correlation has been developed and implemented by simulation. The results indicate that if the correlation between wind speed and wind turbine is not considered, the evaluation of a wind farm reliability and even the reliability of wind integrated system can be too optimistic. The proposed approach is helpful for system operator in operating and planning power system with increasing integration of renewable sources. The paper has added to the literature three main contributions: (i) it improved the reliability model of a wind farm by taking into account the correlation between wind speed and wind turbine failures rates; (ii) it developed the turbine reliability model as a combination of many components; and (iii) it presented a direct, analytical method, based on discrete convolution, to evaluate the wind farm reliability with a diversity of failure rates of wind turbines.

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