

A Wind Farm Reliability Model Considering Both Wind Variability and Turbine Forced Outages

Samer Sulaeman, *Student Member, IEEE*, Mohammed Benidris, *Member, IEEE*,
Joydeep Mitra, *Senior Member, IEEE*, and Chanan Singh, *Fellow, IEEE*

Abstract—This paper presents an analytical method to model the output of large wind farms for power system reliability assessment. The model considers the variability of wind, random failures (forced outages) of turbines, as well as the correlation between turbine outputs that results from the turbines on a farm being subjected to similar incident wind speeds. Due to this correlation, the outputs of individual turbines cannot be modeled as independent random variables. The problem is addressed here by separately modeling the independent outages of wind turbines and the dependency on wind speed, and then convolving the two distributions. The resulting model includes both probability and frequency distributions of the power output of the wind farm. The proposed method is demonstrated on the IEEE Reliability Test System (IEEE RTS). Monte Carlo simulation is used to validate the results.

Index Terms—Discrete convolution, generation adequacy, reliability model, turbine failure, wind energy, wind correlation.

I. INTRODUCTION

IN view of the increasing role of wind power generation, there is an evolving body of reliability methods that are concerned with improved modeling of wind generation and related phenomena. Planning studies should take into account not only the stochastic nature of wind speed but also the forced outages (a forced outage is an unanticipated failure) of turbines and the correlation between the outputs of wind turbines.

A wind farm comprises a multitude of wind turbine generators (WTGs) spread out over a geographic area. The operating characteristics of wind turbines differ from those of traditional power plants in terms of their capability and dispatchability. Wind turbines on the same farm produce output power that are related to the incident wind speed and are correlated between turbines. Therefore, the outputs of individual wind turbines cannot be modeled as independent random variables. This motivates the development of a method that combines a cluster of turbines into a single equivalent multi-state unit that captures their correlation, output variability, and forced outages.

The reliability assessment of systems that integrate wind power and the associated planning metrics such as adequacy and capacity values have been amply addressed in the literature

[1]–[6]. In [7] a discrete state algorithm is utilized to model the reliability of unconventional energy resources. The hourly modified generation model of unconventional generators based on their generation capacity is combined with conventional generators to determine the hourly loss of load expectation and the frequency of capacity deficiency. In [8], load and wind are treated as correlated random variables. Monte Carlo simulation was used to evaluate system reliability. The time correlation between load and wind power is considered in the clustering process by assigning for each value of load a specific value of wind power that occurs in the same time-frame.

A method to determine an equivalent capacity of wind farms based on Monte Carlo simulation is presented in [9]. Monte Carlo simulation has also been used to evaluate the reliability indices of wind power in [10], [11]. Although Monte Carlo simulation can be used for evaluation of complex systems, analytical methods using system data and characteristics are considered more suited for construction of reliability models. Therefore, the purpose of this research is to build a model for a cluster of wind turbines using a direct analytical method. In this work, Monte Carlo simulation is used only for model validation.

Several methods have been proposed for analytical reliability modeling of wind farms to include the effect of forced outages of WTGs. For instance, a multi-state capacity outage probability model has been proposed in [12]. However, frequency and duration indices cannot be calculated using such a model. A more comprehensive model that takes into account frequency and duration indices has been proposed in [13]. This model combines the wind speed model and the turbine reliability model using a multi-layer concept. In [13], the wind speed is classified into a finite number of states, and a birth-death Markov process is used to model wind speed transitions. However, in reality, wind speeds cannot be assumed to transit smoothly to immediate neighboring states through a birth-death process unless the sampling time is close to zero. Therefore, in such a model, there is a possibility of losing some transitions, thereby compromising the calculated probabilities and transition rates. Another challenge in considering turbine failures is that if one considers the product space of possible wind speed states and turbine outage states, the number of states becomes unmanageably large. Several techniques [6], [14]–[16] have been developed to counter this problem, such as combining or clustering the states.

In this paper an analytical method is described for constructing a reliability model of a wind farm, considering turbine correlation, output variability, and forced outages. The resulting model resembles a multi-state generating unit

S. Sulaeman and J. Mitra are with the Department of Electrical and Computer Engineering, Michigan State University, East Lansing, MI 48824, USA; e-mail: samersul@msu.edu and mitraj@msu.edu.

M. Benidris is with the Department of Electrical and Biomedical Engineering, University of Nevada, Reno, NV 89557 USA, e-mail: mbenidris@unr.edu

C. Singh is with the Department of Electrical and Computer Engineering, Texas A&M University, College Station, TX 77843, USA; e-mail: singh@ece.tamu.edu.

with probability and frequency distributions of the discrete capacity states, expressed in the form of a capacity outage probability and frequency table (COPAFT) [17]. This affords the advantage that now the entire wind farm can be treated as a single, equivalent generating unit that can be incorporated in traditional probabilistic planning methods, without further regard to the correlation between turbines within the farm.

In constructing the proposed wind farm model, several distinctive and innovative approaches are utilized. These contributions are summarized below and described further in section III.

- 1) The number of states is reduced without compromising the model accuracy. This is achieved by first converting the time series wind speed data into turbine output power and then clustering the output power data, which is less dispersed and easier to cluster. The method considers transition of output power between all clusters, not just adjacent clusters (unlike a birth-death process).
- 2) The model is comprehensive in that it captures (a) wind variability, (b) turbine outages, and (c) WTG output correlations. This is achieved by separately modeling the independent outages of wind turbines and the dependency on wind speed, and then convolving the two distributions. The overall approach is depicted in Fig. 1.
- 3) A generalized approach is developed for calculating not only the probabilities but also the frequencies within the multi-state convolution process described above, where the tracking of transitions between so many states is fairly complex.

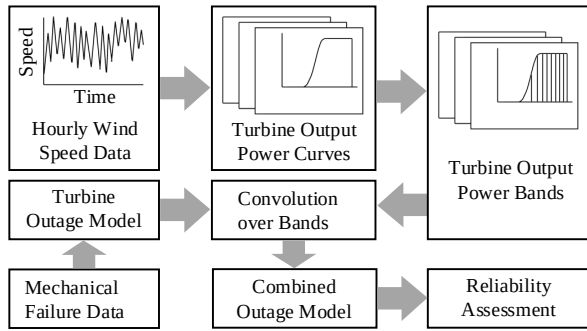


Fig. 1. Model combining wind variability and turbine failures.

The remainder of this paper is organized as follows: section II discusses the characteristics of wind power in terms of wind variability and failures of wind turbines, section III presents modeling of wind farms in power system reliability assessment, section IV defines the reliability indices, section V shows the application of the proposed method and section VI provides some discussion and concluding remarks.

II. ATTRIBUTES OF WIND POWER OUTPUT

In power system reliability assessment, several wind power models have been utilized to calculate the output power of wind farms. For instance, the actual value and the mean value of the recorded wind speed data at certain wind farm locations have been utilized to estimate the outputs of WTGs [18], [19]. The output of wind turbines are known to vary with wind speed

and the design characteristics of wind generators. This section describes the characteristics of wind power in terms of WTG output power and the correlation between the output of WTGs and changes in the wind speed across the farm.

A. Wind Turbine Output Power Curve

Wind turbine power curve provides a quantitative relationship between wind speed and the output power. It describes the operational characteristics of a WTG. The output power that can be extracted from a wind turbine can be calculated as follows [20],

$$P = \frac{1}{2} C_p \rho A v^3, \quad (1)$$

where P is the output power (watts), ρ is the air density (kg/m^3), v is the wind speed (m/sec), A is the swept area of the turbine (m^2), and C_p is the power coefficient.

The output power curve combines (1) with the physical constraints in the system, and can be expressed as follows.

$$P = \begin{cases} 0, & \text{if } v < v_{\text{cut-in}} \\ \frac{1}{2} \rho A C_p v^3, & \text{if } v_{\text{cut-in}} \leq v < v_r \\ P_r, & \text{if } v_r \leq v < v_{\text{cut-out}} \\ 0, & \text{if } v_{\text{cut-out}} \leq v \end{cases}, \quad (2)$$

where $v_{\text{cut-in}}$ is the designed cut-in speed, $v_{\text{cut-out}}$ is the designed cut-out speed, v_r is the rated speed and P_r is the rated power of the wind turbine.

B. Correlation Between Turbine Outputs

Several studies have investigated the effect of the correlation between the output power of WTGs and the change in the wind speed within the same farm [21]–[25]. The degree of the correlation depends on several factors such as geographic location, separation distances between WTGs, terrain and number of WTGs on the wind farm and their influence on wake effects and turbulence [26]–[28]. These correlations also vary with time scales (the frequency of wind speed observations can be intervals of 5 minutes, 10 minutes, hourly, etc.). Thus, determining the exact degree of correlation between individual WTGs and the change in the wind speed within the same farm is a challenging and complex task particularly for large wind farms [29]. However, it has been reported that WTGs within a wind farm are approximately driven by same values of wind speed and the power outputs of WTGs show consistent behavior among individual WTGs with the change in the wind speed on the entire farm [22]–[25], [30]. Hence, similar WTGs will produce similar outputs with some dispersion; these outputs can be represented by a cluster, with the cluster mean representing their average output. This notion is used here, and the approach is described in section III-B.

C. Correlation with Other Stochastic Elements

Correlations have also been observed between wind production and other stochastic elements that are considered in power system analyses. For instance, [31] reports negative correlations between wind and solar production, and [32] reports positive, negative, and negligible correlations between

wind production and system loads depending on time scales, time of day, and seasons. While some researchers [6], [33] have modeled the correlation with load, others [34] have postulated that the correlation is negligible. Moreover, the impact of correlation is also affected by such factors as differences in scale (sizes of wind or solar installations and load), geographic location, and electrical distances between points of insertion.

Another challenge in modeling correlation between wind production and system load is that most of these models treat wind injections as negative loads, inherently assuming that all energy that can be produced by a wind farm is completely accepted by the system. Despite wind production being designated as “must take” in many regulatory regimes, it is well known that prevailing system conditions such as low loads or network congestion often necessitates spillage of wind generation.

In view of the above reasons, as well as the fact that the stated intent of the work reported here focuses on the construction of a reliability model of the production of a wind farm, this work does not attempt to model correlations between wind production and other stochastic elements. It does, however, evaluate some of the impacts in the case studies in section V-C.

III. RELIABILITY MODELING OF WIND FARMS

Generation adequacy assessment is used to evaluate short-term and long-term risks in generation capacity planning. In this context, when variable energy resources such as wind generation are integrated into power grids, it is important to investigate their effect on the system reliability. This section presents a reliability model for the output power of a wind farm in the form of discrete probability and frequency distribution, i.e., a COPAFT. The overall approach used in this work is depicted in Fig. 1.

In this paper, the variation in WTG output due to input variability and the outages of WTGs due to failures are treated as independent processes. Further, failure of a wind turbine is treated as independent of the state of the other WTGs. The reliability models consist of probability and frequency distributions of the discrete capacity states of the total output of the farm, resulting from a combination of the two processes, i.e., wind variability and forced outages of turbines; these distributions are expressed in the form of a COPAFT [7], [35].

Unlike variable resources, the COPAFT of conventional generators can be easily built using the well-known unit addition algorithm due to the fact that the inputs of conventional generators are totally independent. In other words, conventional generators are driven by independent inputs; therefore, the output power of each unit is *independent* of the outputs the other units. However, WTGs are driven by wind, which can be considered similar, with some dispersion, for all WTGs that are located at the same wind farm; therefore, a *correlation* exists between the outputs of WTGs.

In this work, the problem is addressed by separately modeling failures of WTGs and the output variability of WTGs due the wind in two stages. In the first stage, only forced outages

are considered, and WTGs outputs are held at rated capacity, to build the COPAFT_f, which comprises the failure model. The variability model, i.e., the distribution over power bands, is then convolved with COPAFT_f to produce the COPAFT of the entire farm (COPAFT_C), as explained in section III-C.

A. Modeling of Forced Outages of WTGs

In the assessment of the effect of wind power on power system reliability, failures of WTGs have a significant impact on the available power [36]–[40]. Several studies show that the size of turbines, operation and environmental factors could lead to different failure modes of wind turbines. Failures of WTGs usually occur due to ageing, worn out parts or manufacturing defects [36]–[39]. Considering failures of WTGs as *independent* events, the probability of failure of WTG can be modeled as Markovian components with two states, *up* and *down* states with known failure and repair rates, λ and μ respectively (λ is the failure transition rate from an *up* state to a *down* state, and μ is the repair transition rate from a *down* state to an *up* state).

Based on the FOR (forced outage rate is the failure probability) of turbines, the COPAFT_f of wind turbines can be built using the *unit addition algorithm*. This is a recursive algorithm that starts with the distribution of one unit (a WTG in this case) and successively convolves with it the distributions of the remaining units, one unit at a time. In general, when adding a new unit of capacity C , forced outage rate q and repair rate μ , the cumulative probability and frequency of an outage state X can be determined by the following expressions [35].

$$P(X) = \bar{P}(X)(1 - q) + \bar{P}(X - C)q, \quad (3)$$

where $P(X)$ and $\bar{P}(X)$ denote the cumulative probabilities of the capacity outage state before and after the units are added. Equation (3) is initialized as follows.

$$P(X) = \begin{cases} 1, & \text{if } X \leq 0 \\ 0, & \text{otherwise,} \end{cases}$$

The cumulative probability $P(X)$ for a forced outage of X MW or greater can be in general represented by (4).

$$P(X) = \sum_i P(X_i), \quad \forall X_i \leq X, \quad (4)$$

where

$$\bar{P}(X) = 1, \quad \forall X \leq C$$

In the case of multi-state generating units, (3) can be modified as follows.

$$P(X) = \sum_{i=1}^n P_i \times \bar{P}(X - C_i). \quad (5)$$

The cumulative frequency $F(X)$ of capacity outage X can also be calculated using the same approach, as shown in (6).

$$F(X) = F_i(1 - q) + F_jq + (P_j - P_i)q\mu, \quad (6)$$

where P_i , P_j , F_i , and F_j are determined from the old COPAFT; i is the index of the existing capacity outage state $C_i = X$, and j is the index of existing capacity outage state C_j such that $C_j = X - C$; F_i and F_j are cumulative frequencies of states i and j respectively.

B. Clustering of WTG Outputs

The first step in the proposed method consists of converting the wind speed time-series data into output power data using (2). The values of wind power that correspond to the observed wind data are clustered into several bands (states) based on their similarities. In the clustered wind power, every observation belongs to one and only one band based on minimum Euclidean distances between the observed data points. By converting the observed wind speed into power using power curve characteristics of WTGs, several dissimilar and often different observed wind speed points (that result in similar output powers) will be grouped in the same bands. For example, wind speeds that range from 0 (m/sec) to the cut-in speed of the WTG and the wind speeds range from the cut-out speed of WTG to the maximum observed value are grouped in one band, i.e., the band that have zero output power which is denoted band 1 in Fig. 2. Also, wind speeds that range from the rated speed of WTG to the cut-out speed of WTG are grouped in one band (band n in Fig. 2).

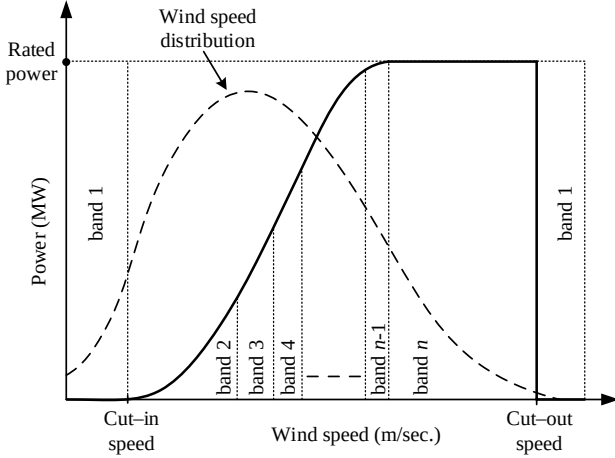


Fig. 2. Bands of the output power and wind speed distribution.

C. Combining Variability and Failure Models

A capacity outage probability and frequency table for a wind farm can be constructed by combining the COPAFT_f that represents the rated capacities and failures of WTGs (section III-A) and the clustered wind power table (section III-B). The COPAFT_f is convolved over each wind power band to construct a COPAFT for the entire wind farm (COPAFT_c). This section explains the combination procedure of these two tables. Fig. 3 shows the process of combining the outages of wind power due to (1) wind power transitions between bands and (2) failures of WTGs. Horizontal transitions represent the transitions due to the change in the wind power between bands and vertical transitions represent transitions due to failures of WTGs. The new outage states due to wind power band transitions and failures can be obtained by scanning through all bands in both vertical and horizontal directions. In convolving the states of the COPAFT_f of wind turbines over each band, the capacity outage state i in the COPAFT_c with $C_o \geq X$ occurs in both vertical and horizontal directions.

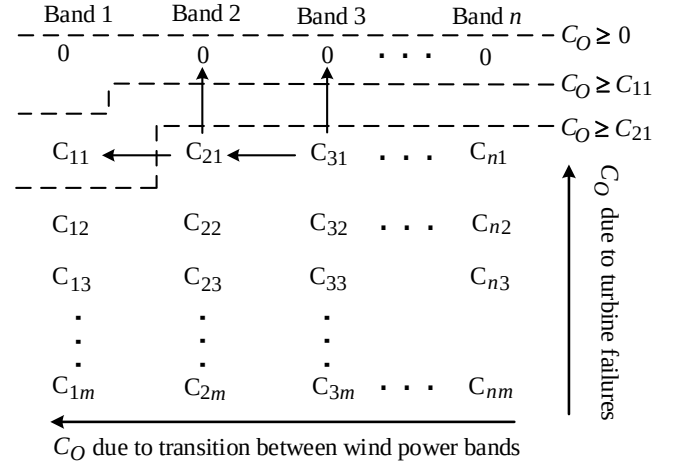


Fig. 3. The combined outage due to transition of wind power (horizontal transitions) and failures of wind turbines (vertical transitions).

The procedure of the proposed method of clustering wind power into bands, modeling failures of WTGs and building the generation model COPAFT_c for a wind farm is summarized in the following steps:

- 1) From the observed wind speed data and the output power curve of WTGs, determine the output power time series of the wind farm.
- 2) Use nearest centroid sorting to cluster the output power into bands; then calculate the cluster (band) means, cluster probabilities, and inter-cluster transition rates.
- 3) Build COPAFT_f using the method described in section III-A.
- 4) Convolve COPAFT_f with the probability and frequency of each wind power band. The failure and repair rates of the WTGs remain the same in each band. Only the output power changes from band to band due to the effect of wind power transition from state k to state $k + 1$.
- 5) The available capacity and capacity outage for state i in COPAFT_f that exists in band k can be calculated using (7) and (8) respectively.

$$M_{i,k} = \frac{A_i}{C_R} \times W_k, \quad (7)$$

$$O_{i,k} = C_R - M_{i,k}, \quad (8)$$

where $M_{i,k}$ is the new available capacity in state i of the COPAFT_f being in band k , A_i is the available capacity in state i of the COPAFT, C_R is the total installed capacity of the wind farm, W_k is the available wind power in band k and $O_{i,k}$ is the new outage capacity of state i of the COPAFT_f being in band k .

- 6) The probability of the new outage state is given by

$$P_{i,k} = \sum P_{W(k)} \times P_{M(i)}, \quad (9)$$

where $P_{i,k}$ is the probability of capacity outage for state i being in band k , $P_{W(k)}$ is the band probability, and $P_{M(i)}$ is the COPAFT_f state outage probability.

- 7) The cumulative outage probability of an outage state with $C_o \geq X$ can be obtained by scanning through all bands.

Whenever an outage state with outage capacity of $C_o \geq X$ is encountered, its probability is accumulated as follows,

$$P(C_o \geq X) = \sum_{i=1}^n \sum_{k=1}^m P_{i,k}, \quad (10)$$

where n is the number of COPAFT_f states and m is the number of bands.

- 8) Scan through all states in the COPAFT_c and combine the duplicated states.
- 9) The transition rates of wind power between bands from state i in band (k) to state $(i+1)$ in band $(k+1)$ is given by (11). The exact transition rates between bands are considered [6].

$$\lambda = \frac{n_{(i \rightarrow i+1)}}{D}, \quad (11)$$

where $n_{(i \rightarrow i+1)}$ counts the number of wind power transitions between bands from state $(wp_i < wp)$ to $(wp \geq wp_i)$ and D is the time period of study.

- 10) The frequency of wind power of band (k) can be calculated by

$$f_{W(k)} = P_{W(k)} \times \lambda, \quad (12)$$

- 11) The cumulative outage frequency of encountering an outage state with an outage capacity of $(C_o \geq X)$ due to the transition of COPAFT_f states between wind power bands can be calculated by (14).

$$F(C_o \geq X) = F_k + F_{WTG}, \quad (13)$$

where

$$F_{WTG} = \sum P_{W(k)} \times F_{M(i)} \quad (14)$$

where $F_{M(i)}$ is the cumulative outage frequency of i^{th} outage state and,

$$F_k = \sum P_{M(i)} \times f_{W(k)}. \quad (15)$$

As a result, the reliability model of wind farms can be represented by a single generation unit with multiple states.

IV. RELIABILITY ASSESSMENT

The resulting COPAFT_c of a wind farm can now be treated as the reliability model of a single equivalent unit with multiple states [35], for purposes of generation adequacy analysis or composite reliability analysis. In this work, we have evaluated the most common indices that have been used in power system reliability analysis to test the proposed method and determine the capacity value of a wind farm. These indices can be defined as follows:

- A *Loss of Load* (LOL) event is one in which a system is unable to meet its total demand.
- *Loss of Load Probability* (LOLP) is the probability of encountering one or more LOL events during a given time period.
- *Expected Demand Not Served* (EDNS) is the expected (average) demand that the system is unable to serve as a result of LOL events during a given period. It is calculated as the weighted sum of the demands curtailed during the LOL events, the weights being the probabilities of the

corresponding LOL events. It is expressed in MW/year or GWh/year.

- *Loss of Energy Expectation* (LOEE) is the expected energy that the system is unable to serve as a result of LOL events during a given period. It is calculated as the weighted sum of the energies curtailed during the LOL events, the weights being the probabilities of the corresponding LOL events. It is expressed in MWh/year or GWh/year.
- *Loss of Load Expectation* (LOLE) is the expected number of LOL hours during a given time period. It is expressed in hr/year.
- *Loss of Load Frequency* (LOLF) is the expected frequency of encountering one or more LOL events during a given time period.
- *Loss of Load Duration* (LOLD) is the expected duration of LOL events occurring during a given time period.

V. CASE STUDIES

The proposed method is applied on the IEEE RTS [41]. This system has been extensively used in the literature for purposes of benchmarking. The IEEE RTS consists of 32 generating units with total generation capacity of 3405 MW and total peak load of 2850 MW.

In this case study, a typical wind turbine characteristic is assumed (type Vesta V90-3.0 MW [42]; rated power: 3 MW; rated, cut-in and cut-out speeds: 15 m/s, 3.5 m/s, 25 m/s). In the cases reported here, the effect of different values of WTG failure probabilities were studied, and the reliability data used are shown in Table I. The failure rates and mean time to failure (MTTF) shown here lie in the ranges for actual WTGs, as reported in [43]. Repair times are calculated from the FORs and failure rates of WTGs and are expressed as mean time to repair (MTTR).

TABLE I
WIND TURBINE RELIABILITY DATA USED IN TEST CASES

FOR	λ (failure/yr)	MTTF (hour)	MTTR (hour)
0.04	2.43333	3600	150
0.08	2.72050	3220	280
0.12	3.61983	2420	330

Three wind data sets are used: data set A [44], data set B [45], and data set C [46]. The correlation coefficients between these data sets and the load of the IEEE RTS are as follows: (1) -0.002 for data set A, (2) 0.0686 for data set B, and (3) -0.1059 for data set C. Whereas data set A and the load are almost uncorrelated, data set B has positive correlation and data set C has negative correlation with the load.

A wind farm consisting of 50 WTGs (150 MW total capacity) is added to the IEEE RTS. In the studies reported below, this farm is assumed to be subjected to each of the three wind speed data sets. For convenience, these are referred to as *Farm A*, *Farm B*, and *Farm C*. In each case, the outputs of the corresponding wind farm are grouped into ten clusters.

As an illustration, Table II shows the mean output of each band, individual and cumulative probabilities, and the cumulative frequencies of transition across bands of wind output for the Farm A. The COPAFT_f of WTGs is built using the reliability data corresponding to FOR of 0.04 shown in

Table I, and then convolved with the distributions of the farm output power bands (variability model) using the procedure described in section III-C to produce the combined COPAFT, i.e., COPAFT_C. Table III is the COPAFT_C of Farm A. The COPAFT_C shows the available capacity C_i , individual and cumulative probabilities, and the cumulative frequency of each wind output state i .

TABLE II

VARIABILITY MODEL: FARM A OUTPUT STATES AND PROBABILITIES

No.	Output Power (MW)	Exact State Probability	Cumulative Probability	Cumulative Frequency
1	0	0.13653	1	0
2	8.59	0.17648	0.86347	0.1862
3	20.55	0.13025	0.68698	0.3892
4	40.58	0.14486	0.55673	0.4226
5	58.04	0.08482	0.41187	0.2978
6	74.64	0.03721	0.32705	0.3158
7	94.37	0.05993	0.28984	0.2836
8	117.15	0.02819	0.22991	0.2396
9	125.55	0.03025	0.20171	0.1860
10	149.23	0.17146	0.17146	0.1301

TABLE III

RELIABILITY MODEL: FARM A OUTPUT STATES AND PROBABILITIES

No.	Output Power (MW)	Exact State Probability	Cumulative Probability	Cumulative Frequency
i	C_i	$P\{C = C_i\}$	$P\{C \geq C_i\}$	$F\{C \geq C_i\}$
1	0	0.003133	1	0
2	2.984	0.013057	0.9968662	0.0037882
3	5.968	0.026658	0.9838091	0.0080676
4	8.953	0.035544	0.9571506	0.0112011
5	11.937	0.034804	0.9216061	0.0114028
6	14.922	0.026683	0.8868021	0.0090757
7	17.906	0.016676	0.8601190	0.0058807
8	20.891	0.008735	0.8434421	0.0031896
9	23.875	0.014417	0.8347065	0.0035518
10	29.844	0.013514	0.8202890	0.0085116
11	34.415	0.013085	0.8067750	0.0207453
12	39.101	0.033351	0.7936900	0.0349233
13	43.787	0.017900	0.7603390	0.0286773
14	47.751	0.008530	0.7424390	0.0074431
15	71.903	0.023100	0.7339090	0.1055822
16	90.714	0.037809	0.7108090	0.0648995
17	99.316	0.081800	0.6730000	0.1159003
18	129.085	0.160200	0.5912000	0.2455493
19	140.974	0.162100	0.4310000	0.1444312
20	149.223	0.268900	0.2689000	0.1188310

Generation adequacy or composite system reliability assessment can be performed by using a multi-state model such as that shown in Table III to represent the output of the wind farm. In the next section, the following case studies are presented: (1) reliability analysis including forced outages of WTGs, (2) the effect of correlation between wind power and system load on reliability indices, and (3) determination of capacity values of wind farms.

A. Reliability Analysis—Base Case

In this section, the reliability indices of the IEEE RTS are calculated prior to adding the wind farm. These indices are calculated using discrete convolution and Monte Carlo simulation. The results are shown in Table IV where the second row shows the reliability indices of the IEEE RTS as calculated using Monte Carlo simulation.

TABLE IV
RELIABILITY INDICES OF THE IEEE RTS—BASE CASE

Method	LOLP	LOLE hr/yr	LOLF occ./yr	LOLD hr	EDNS MW/yr	LOEE MWh/yr
DC	0.001069	9.36881	2.01600	4.64723	0.1348396	1181.195
MCS	0.001070	9.37407	2.01800	4.64522	0.1349867	1182.483

DC: Discrete convolution; MCS: Monte Carlo simulation

B. Reliability Analysis—After Adding Wind Farm A

In this case study, the IEEE RTS with Farm A added is used to test the proposed method and to investigate the effect of forced outages of WTGs on the reliability indices. The rated capacity of the wind farm is 150 MW. The reliability indices are evaluated for different values of FOR as shown in Table V. As expected, ignoring the WTG failures in adequacy studies produces optimistic results.

TABLE V

ANNUAL RELIABILITY INDICES OF IEEE RTS AFTER ADDING FARM A
CONSIDERING DIFFERENT VALUES OF TURBINE FOR

FOR	LOLP	LOLE hr/yr	LOLF occ./yr	LOLD hr	EDNS MW/yr	LOEE MWh/yr
0.04	0.0007664	6.713700	1.603389	4.187400	0.093696	820.778
0.08	0.0007756	6.794491	1.626876	4.176403	0.094894	831.270
0.12	0.0007852	6.878366	1.645477	4.180165	0.096148	842.254

In this case study, Monte Carlo simulation is also performed on the same system (with Farm A), and the results are very close to those calculated using the proposed method as shown in Table VI. This observation is not surprising since the wind speeds for Farm A are almost uncorrelated with the load.

TABLE VI

ANNUAL RELIABILITY INDICES OF IEEE RTS AFTER ADDING FARM A
CONSIDERING DIFFERENT VALUES OF TURBINE FOR, USING MONTE
CARLO SIMULATION

FOR	LOLP	LOLE hr/yr	LOLF occ./yr	LOLD hr	EDNS MW/yr	LOEE MWh/yr
0.04	0.0007642	6.694428	1.603279	4.175438	0.093653	820.401
0.08	0.0007748	6.786822	1.619107	4.173034	0.094841	830.808
0.12	0.0007876	6.899390	1.647222	4.188492	0.096248	843.130

C. Effect of Correlation with Load

To investigate the effect of correlation between wind speed and load, the results of adding Farms B and C to the IEEE RTS are studied. The reliability indices, as calculated analytically by convolving the multi-state farm model with the generation model of the IEEE RTS are compared with those obtained from Monte Carlo simulation. (For simplicity, turbine failures are neglected, as they have no effect on correlation with load.) Since the Monte Carlo method uses a sequential simulation that tracks hourly load and wind production, thereby intrinsically capturing their correlation, it enables us to assess the error introduced by ignoring the correlation in the proposed analytical method.

Table VII shows the reliability indices after adding Farm B to the IEEE RTS. The results in Table VII show that for Farm B, where there is a positive correlation between wind speed and load, the proposed method produces *pessimistic* results with an average error of -2.17% .

TABLE VII
RELIABILITY INDICES OF THE IEEE RTS AFTER ADDING FARM B

Method	LOLP	LOLE hr/yr	LOLF occ./yr	EDNS MW/yr	LOEE MWh/yr
Proposed	0.00067	5.90528	1.41762	0.080620	706.248
MCS	0.00065	5.69402	1.33438	0.080138	702.011

Table VIII shows the reliability indices after adding Farm C to the IEEE RTS. These results show that for Farm C, where there is a negative correlation between wind speed and load, the proposed method produces *optimistic* results with an average error of 2.07%.

TABLE VIII
RELIABILITY INDICES OF THE IEEE RTS AFTER ADDING FARM C

Method	LOLP	LOLE hr/yr	LOLF occ./yr	EDNS MW/yr	LOEE MWh/yr
Proposed	0.0007998	7.005971	1.558705	0.0974247	853.4403
MCS	0.0008132	7.124022	1.598659	0.0994838	871.4785

The above results show that the proposed method is effective in building an accurate reliability model of a wind farm, but small errors are introduced in adequacy analyses due to external correlations. However, where the benefits of being able to use an equivalent model in analytical studies outweigh those of detailed Monte Carlo simulation, as well as for the reasons discussed in section II-C, the proposed method offers the advantage of producing an accurate and reusable model.

D. Capacity Value of Wind Power

The capacity value of wind power is used to measure the contribution of wind power to the adequacy of the generation to meet the demand. The most commonly used approaches to estimate the capacity value of wind power are discussed in [47]. The effective load carrying capability (ELCC) approach is generally considered more applicable for determining the capacity value of wind power [47]. The ELCC method is based on calculating the amount of load increase that would result in reliability indices equal to those obtained before adding the wind farm. In this work, we have used the ELCC approach [48] to estimate the capacity value of wind power. Two reliability indices are considered to calculate the capacity value, LOLE and LOLF. For both test systems an iterative process is used, where the peak load is increased by a specified increment ΔL , and the LOLE or LOLF is recalculated at each step until the target value of the LOLE or LOLF indices are reached. The target values of the LOLE and LOLF indices are the values prior to adding wind power. The increase in peak load that achieves the reliability target is considered the capacity value of the wind farm. In this section, wherever WTG failures are considered, reliability corresponding to FOR of 0.04 is used.

The changes in the LOLE and LOLF reliability indices for increases in system loading after adding Farm A are shown in Fig. 4 and Fig. 5. These figures also show the effect of ignoring and considering failures of WTGs on capacity values of wind farms. The capacity values are calculated by determining the point at which the curve of the reliability index, after adding the wind and incrementally increasing the load, intersects the base case curve for the same index.

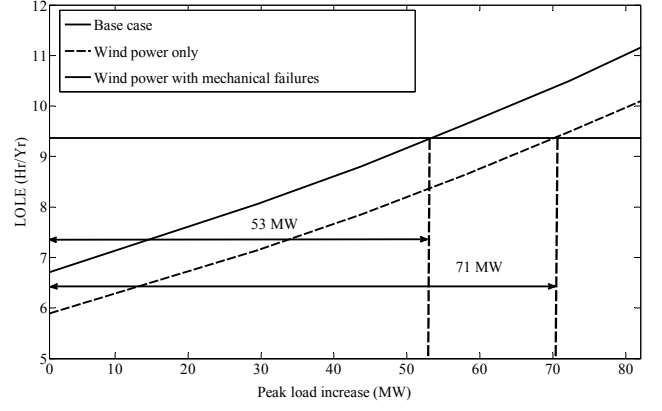


Fig. 4. LOLE as a function of load increase for the IEEE RTS.

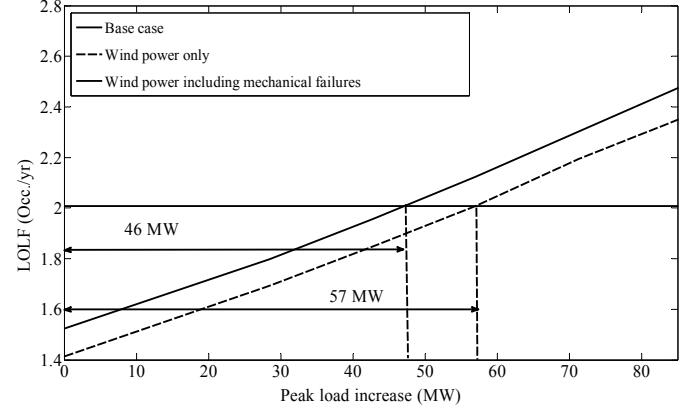


Fig. 5. LOLF as a function of load increase for the IEEE RTS.

It can be seen from these figures that ignoring failures of WTGs produces optimistic capacity values compared to the cases where failures of WTGs are considered. In the case of assuming perfectly reliable WTG, if the LOLE index is used, about 71 MW of load increase can be compensated by 150 MW of wind farm nameplate capacity. On the other hand, when failures of WTGs are considered, only about 53 MW of load increase can be compensated by 150 MW of rated wind power.

In the case of assuming perfectly reliable WTG, if the LOLF index is used as an index to determine the capacity value, about 57 MW of load increase can be compensated by 150 MW of rated wind power. On the other hand, when failures of WTGs are considered, about 46 MW of load increase can be compensated by 150 MW of rated wind power.

In evaluating the capacity value of wind farms, it can be seen that ignoring failures of WTGs produces optimistic results (higher capacity values). Also, the LOLE and LOLF indices produce different values for the capacity values of wind farms and the planner or operator has the option to consider either index. For instance, if the concern is the expected load curtailment, the LOLE index can be used to determine the capacity value. On the other hand, if the concern is how often service to customers is interrupted, the LOLF index can be used.

VI. DISCUSSION AND CONCLUSION

This paper presented an analytical method of constructing reliability models of wind farms for planning studies involving wind integration. The proposed method uses a recursive technique to build a generation model that considers wind variability, correlation between turbine outputs, and forced outages of turbines.

An illustrative reliability model was constructed using real wind speed data and real turbine characteristics, as described in section V. The effectiveness of the proposed method was demonstrated on a well-known test system. A comparison of several reliability indices (LOLP, LOLF, EDNS, LOLE and LOEE), as well as wind farm capacity value, with and without consideration of turbine forced outages was provided in each case. The results obtained by the proposed method were validated using Monte Carlo simulation.

The work presented here focused on the development of the reliability model of the farm; it did not attempt to capture correlations with other stochastic elements such as system load, for reasons described in section II-C. The results of the case studies indicate that neglecting this correlation introduces small errors in some cases, but the advantages of an accurate and reusable model that can be used in analytical methods of adequacy assessment or capacity valuation may overshadow these errors. In applications where it is deemed necessary to consider such correlation, the approach described in [8] may be used. However, for the purpose of constructing an accurate reliability model of a wind farm, the proposed method was shown to be effective.

REFERENCES

- [1] S. Persaud, B. Fox, and D. Flynn, "Modelling the Impact of Wind Power Fluctuations on the Load Following Capability of an Isolated Thermal Power System," *Wind Engineering*, vol. 24, no. 6, pp. 399–415, July 2009.
- [2] Y. V. Makarov, C. Loutan, A. M., and P. de Mello, "Operational Impacts of Wind Generation on California Power Systems," *IEEE Trans. Power Syst.*, vol. 24, no. 2, pp. 1039–1050, May 2009.
- [3] J. C. Smith, M. R. Milligan, E. A. DeMeo, and B. Parsons, "Utility Wind Integration and Operating Impact State of the Art," *IEEE Trans. Power App. Syst.*, vol. 22, no. 3, pp. 900–908, Aug. 2007.
- [4] D. Brooks, E. Lo, R. Zavadil, S. Santos, and J. Smith, "Characterizing the Impacts of Significant Wind Generation Facilities on Bulk Power System Operation Planning," prepared for Utility Wind Integration Group, Arlington, VA, Tech. Rep., 2003. [Online]. Available: <http://www.uwig.org/UWIGOpImpactsFinal7-15-03.pdf>
- [5] L. Soder, L. Hofmann, A. Orths, H. Holttinen, Y. Wan, and A. Tuohy, "Experience From Wind Integration in Some High Penetration Areas," *IEEE Trans. Energy Convers.*, vol. 22, no. 1, pp. 4–12, Mar. 2007.
- [6] H. Kim, C. Singh, and A. Sprintson, "Simulation and Estimation of Reliability in a Wind Farm Considering the Wake Effect," *IEEE Trans. Sustainable Energy*, vol. 3, no. 2, pp. 274–282, Apr. 2012.
- [7] C. Singh and A. Lago-Gonzalez, "Reliability Modeling of Generation Systems Including Unconventional Energy Sources," *IEEE Trans. Power App. Syst.*, vol. PAS-104, no. 5, pp. 1049–1056, May 1985.
- [8] C. Singh and Y. Kim, "An Efficient Technique for Reliability Analysis of Power Systems Including Time Dependent Sources," *IEEE Trans. Power Syst.*, vol. 3, no. 3, pp. 1090–1096, Aug. 1988.
- [9] F. Vallee, J. Lobry, and O. Deblecker, "System Reliability Assessment Method for Wind Power Integration," *IEEE Trans. Power Syst.*, vol. 23, no. 3, pp. 1288–1297, Aug. 2008.
- [10] G. Papaefthymiou and B. Klockl, "MCMC for Wind Power Simulation," *IEEE Trans. Energy Convers.*, vol. 23, no. 1, pp. 234–240, Mar. 2008.
- [11] Y. G. Hegazy, M. M. A. Salama, and A. Y. Chikhani, "Adequacy Assessment of Distributed Generation Systems Using Monte Carlo Simulation," *IEEE Trans. Power Syst.*, vol. 18, no. 1, pp. 48–52, Feb. 2003.
- [12] P. Giorsetto and K. F. Utsurogi, "Development of a New Procedure for Reliability Modeling of Wind Turbine Generators," *IEEE Trans. Power App. Syst.*, vol. PAS-102, no. 1, pp. 134–143, Jan. 1983.
- [13] F. C. Sayas and R. Allan, "Generation Availability Assessment of Wind Farms," in *IEE Proceedings—Generation, Transmission and Distribution*, vol. 143, no. 5. IET, 1996, pp. 507–518.
- [14] A. P. Leite, C. L. Borges, and D. M. Falcao, "Probabilistic Wind Farms Generation Model for Reliability Studies Applied to Brazilian Sites," *IEEE Trans. on Power Syst.*, vol. 21, no. 4, pp. 1493–1501, 2006.
- [15] A. R. Di Fazio and M. Russo, "Wind Farm Modelling for Reliability Assessment," *IET Renewable Power Generation*, vol. 2, no. 4, pp. 239–248, 2008.
- [16] J. Lin, L. Cheng, Y. Chang, K. Zhang, B. Shu, and G. Liu, "Reliability Based Power Systems Planning and Operation with Wind Power Integration: A Review to Models, Algorithms and Applications," *Renewable and Sustainable Energy Reviews*, vol. 31, pp. 921–934, 2014.
- [17] C. Singh and Q. Chen, "Generation System Reliability Evaluation Using a Cluster Based Load Model," *IEEE Trans. Power Syst.*, vol. 4, no. 1, pp. 102–107, 1989.
- [18] R. Billinton and D. Huang, "Incorporating Wind power in Generating Capacity Reliability Evaluation Using Different Models," *IEEE Trans. Power Syst.*, vol. 26, no. 4, pp. 2509–2517, Nov. 2011.
- [19] R. Billinton, H. Chen, and R. Ghajar, "Time-Series Models for Reliability Evaluation of Power Systems Including Wind Energy," *Microelectronics Reliability*, vol. 36, no. 9, pp. 1253–1261, Sep. 1996.
- [20] J. F. Manwell, J. G. McGowan, and A. L. Rogers, *Wind Energy Explained: Theory, Design and Application*. John Wiley & Sons, 2010.
- [21] J. Ge, M. Du, and C. Zhang, "A Study on Correlation of Wind Farms Output in the Large-Scale Wind Power Base," in *Proc. of the 4th International Conference on Electric Utility Deregulation and Restructuring and Power Technologies*, Weihai, Shandong, July, 2011, pp. 1316–1319.
- [22] B. Hasche, "General Statistics of Geographically Dispersed Wind Power," *Wind Energy*, vol. 13, no. 8, pp. 773–784, Nov. 2010.
- [23] B. Ernst, Y.-H. Wan, and B. Kirby, "Short-Term Power Fluctuation of Wind Turbines: Analyzing Data from the German 250-MW Measurement Program from the Ancillary Services Viewpoint," in *Proc. of the Wind Power '99 Conference*, Burlington, Vermont, June 20–23, 1999, pp. 1–10.
- [24] Y. Wan, M. Milligan, and B. Parsons, "Output Power Correlation Between Adjacent Wind Power Plants," *Journal of Solar Energy Engineering*, vol. 125, no. 4, pp. 551–555, Nov. 2003.
- [25] H. Louie, "Correlation and Statistical Characteristics of Aggregate Wind Power in Large Transcontinental Systems," *Wind Energy*, vol. 17, no. 6, pp. 793–810, June 2014.
- [26] P. Kádár, "Evaluation of Correlation the Wind Speed Measurements and Wind Turbine Characteristics," in *Proc. of the 8th International Symposium of Hungarian Researchers on Computational Intelligence and Informatics*, Budapest, Hungary, Nov. 15–17, 2007, pp. 15–17.
- [27] J. R. Ubeda and M. A. R. Rodriguez Garcia, "Reliability and Production Assessment of Wind Energy Production Connected to the Electric Network Supply," vol. 146, no. 2, pp. 169–175, Mar. 1999.
- [28] H. Sipeng, Z. Yangfei, L. Xianyun, and Y. Yue, "Equivalent Wind Speed Model in Wind Farm Dynamic Analysis," in *4th International Conference on Electric Utility Deregulation and Restructuring and Power Technologies*, Weihai, Shandong, July 6–9, 2011, pp. 1751–1755.
- [29] S. Tanneeru, "Reliability Modeling of DG Clusters," Master Thesis, New Mexico State University, 2008.
- [30] T. Nanahara, M. Asari, T. Maejima, T. Sato, K. Yamaguchi, and M. Shibata, "Smoothing Effects of Distributed Wind Turbines. Part 2. Coherence Among Power Output of Distant Wind Turbines," *Wind Energy*, vol. 7, no. 2, pp. 75–85, Apr./June 2004.
- [31] C. Loutan and D. Hawkins, "Integration of Renewable Resources: Transmission and Operating Issues and Recommendations for Integrating Renewable Resources on the California ISO-Controlled Grid," California ISO, Folsom, CA, Tech. Rep., August 2010.
- [32] K. Coughlin and J. H. Eto, "Analysis of Wind Power and Load Data at Multiple Time Scales," Technical Report LBNL-4147E, U.S. Department of Energy, Washington, DC, USA, Tech. Rep., 2010.
- [33] W. Wangdee and R. Billinton, "Considering Load-Carrying Capability and Wind Speed Correlation of WECS in Generation Adequacy Assessment," *IEEE Trans. Energy Convers.*, vol. 21, no. 3, pp. 734–741, 2006.

- [34] B. Martin and J. Carlin, "Wind-Load Correlation and Estimates of the Capacity Credit of Wind Power: An empirical Investigation," *Wind Engineering*, vol. 7, no. 2, p. 79, 1983.
- [35] R. Billinton, C. L. Wee, and G. Hamoud, "Digital Computer Algorithms for the Calculation of Generating Capacity Reliability Indices," *IEEE Power Eng. Rev.*, vol. PAS-101, no. 1, pp. 34–35, Jan. 1982.
- [36] K. Fischer, F. Besnard, and L. Bertling, "Reliability-Centered Maintenance for Wind Turbines Based on Statistical Analysis and Practical Experience," *IEEE Trans. Energy Convers.*, vol. 27, no. 1, pp. 184–195, Mar. 2012.
- [37] J. Ribrant and L. M. Bertling, "Survey of Failures in Wind Power Systems With Focus on Swedish Wind Power Plants During 1997 ndash;2005," *IEEE Trans. Energy Convers.*, vol. 22, no. 1, pp. 167–173, Mar. 2007.
- [38] F. Spinato, P. J. Tavner, G. J. W. Van Bussel, and E. Koutoulakos, "Reliability of Wind Turbine Subassemblies," *IET Renewable Power Generation*, vol. 3, no. 4, pp. 387–401, Dec. 2009.
- [39] H. Guo, S. Watson, P. Tavner, and J. Xiang, "Reliability Analysis for Wind Turbines With Incomplete Failure Data Collected From After the Date of Initial Installation," *Reliability Engineering & System Safety*, vol. 94, no. 6, pp. 1057–1063, June 2009.
- [40] Y. Feng, P. J. Tavner, and H. Long, "Early Experiences With UK Round 1 Offshore Wind Farms," *Proceedings of the ICE-Energy*, vol. 163, no. 4, pp. 167–181, Nov. 2010.
- [41] Reliability Test System Task Force, "The IEEE Reliability Test System-1996," *IEEE Trans. Power Syst.*, vol. 14, no. 3, pp. 1010–1020, Aug. 1999.
- [42] Vesta Products and Services. (2015). [Online]. Available: http://www.vestas.com/en/products_and_services_turbines/v90_3_mw_technical-specifications.
- [43] F. Spinato, P. J. Tavner, G. J. W. V. Bussel, and E. Koutoulakos, "Reliability of Wind Turbine Subassemblies," *IET Renewable Power Generation*, vol. 3, no. 4, pp. 387–401, December 2009.
- [44] National Climate Data and Information Archive. (2007) Bonavista Newfoundland, Canada. [Online]. Available: http://www.climate.weatherofce.gc.ca/climateData/canada_e.html.
- [45] National Renewable Energy Laboratory. NREL Wind Prospector. [Online]. Available: <https://maps.nrel.gov/wind-prospector/>
- [46] Great Lakes Environmental Research Laboratory. (2005). [Online]. Available: <http://www.glerl.noaa.gov/metdata/mil/archive/mil2005.01t.txt>
- [47] R. M. G. Castro and L. A. F. M. Ferreira, "A Comparison Between Chronological and Probabilistic Methods to Estimate Wind Power Capacity Credit," *IEEE Trans. on Power Syst.*, vol. 16, no. 4, pp. 904–909, Nov. 2001.
- [48] L. L. Garver, "Effective Load Carrying Capability of Generating Units," *IEEE Trans. Power App. Syst.*, vol. PAS-85, no. 8, pp. 910–919, Aug. 1966.

Samer Sulaeman (S'11) received his B.Sc. degree in Electrical and Electronic Engineering from the University of Al Zawiya University, Libya. Thereafter he joined the Department of Electrical and Electronic Engineering of the same university as an Assistant Lecturer. He subsequently earned his M.Sc. degree in Electrical Engineering with specialization in Power Systems in 2005.

Currently, he is pursuing a Ph.D. degree at Michigan State University. His areas of interest include power system reliability, stability and power system planning in the presence of renewable resources.

Mohammed Benidris (S'10–M'14) received a Ph.D. degree in Electrical Engineering from Michigan State University, East Lansing in 2014, and MSc. and BSc. degrees in Electrical Engineering from University of Benghazi, Benghazi, Libya in 2005 and 1998 respectively.

He is an Assistant Professor of Electrical Engineering with the University of Nevada, Reno (UNR), Reno, NV, USA. Prior to joining the UNR, he was Research Associate and Visiting Lecturer at Michigan State University. Prior to this, he was an Assistant Lecturer at the department of Electrical and Electronics Engineering, University of Benghazi, Benghazi, Libya, where he served as the Chair of the Engineering Departments branch of Almaraj. His main research interests include power system reliability, stability and resilience and Cyber-physical systems.

Joydeep Mitra (S'94–M'97–SM'02) received the B. Tech. (Hons.) degrees in electrical engineering from Indian Institute of Technology, Kharagpur, India, and the Ph.D. degree in electrical engineering from Texas A&M University, College Station, TX, USA.

He is an Associate Professor of Electrical Engineering at Michigan State University, East Lansing, Director of the Energy Reliability & Security (ERiSe) Laboratory, and Senior Faculty Associate at the Institute of Public Utilities. His research interests include reliability, planning, stability and control of power systems.

Chanan Singh (S'71–M'72–F'91) received the Ph.D. degree in electrical engineering from the University of Saskatchewan, Saskatoon, SK, Canada, in 1972. In 1997, he was awarded an honorary D.Sc. by the University of Saskatchewan for his research and educational contributions.

He is a Regents Professor and Irma Runyon Chair Professor with the Department of Electrical and Computer Engineering, Texas A&M University, College Station, TX, USA. He has also served as a Guest Professor with Tsinghua University, Beijing, China. He has authored or coauthored over 300 technical papers and three books and has contributed to several books. He has consulted with many major corporations and given short courses nationally and internationally. His research interests include the application of probabilistic methods to power systems.

Dr. Singh was the recipient of the 1998 Outstanding Power Engineering Educator Award from the IEEE Power Engineering Society (IEEE PES). In 2008, he was recognized with the Merit Award by the PMAPS International Society. In 2010, he was the inaugural recipient of the IEEE PES Roy Billinton Power System Reliability Award.