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Quantitative risk associated with intermittent wind generation

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Abstract: Wind energy is a propitious alternative to fossil-fuel generation due to its benign environmental footprint and sustainability. However, the intermittent nature of wind turbine output may scale up the risk of not meeting current or future load demand. A quantitative risk measure associated with introducing wind turbines into the generation fleet is investigated in this paper. Due to the randomness of the wind speed profile, a common wind speed model employing a multistate wind generation pattern, representing various production levels, was adopted, as opposed to conventional generator models, which are suitably represented with a two-state model. Using a hybrid method that combines the analytical technique with Monte Carlo simulation, risk measures such as loss of load probability were evaluated and applied to the RBTS and IEEE-RTS test systems. The expected demand not supplied, due to contemplated uncertainties, was further quantified. Test results show that the capacity credit of wind turbine generators could vary widely depending on system size and configuration. Furthermore, the use of an 11-state wind representation model along with the normal distribution of wind speed produces very close results compared with the Weibull distribution of wind speed.

Key words: Risk assessment, Monte Carlo simulation, wind turbine generation, capacity credit

1. Introduction

Electricity generation is a major contributing factor to air pollution as it releases a massive amount of carbon dioxide (CO_2) into the atmosphere. This has subsequently increased the risk of global warming, which may lead ultimately to a dangerous anthropogenic climate change. To prevent such disastrous consequences, wind energy is being adopted in many countries worldwide, as a part of renewable energy resources, to reduce reliance on fossil fuels as well as to maintain sustainable growth and a cleaner environment [1]. Despite possessing a great potential for future energy generation, wind generation is not fully dispatchable. The generated output power from a wind turbine generator (WTG) is fluctuating, since it is dependent on wind speed characteristics. These created fluctuations could seriously challenge the system's capability to serve the committed load demand to the full extent.

Generation system adequacy is related to the ability of the installed generation resources to meet aggregate consumer power demand at all times [2]. A combination of generation resources that differ in their inherent characteristics, such as wind power and thermal generation, for instance, should satisfy the adequacy criterion. Capacity credit of wind generation measures the amount of installed conventional power generation that can be reduced without altering the system reliability level, quantified by an index such as loss of load probability (LOLP). The capacity credit can be used by system operators to evaluate the risk of a generation capacity deficit [3].

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Whereas there are different approaches to assess the capacity credit of wind generation [4–6], the analytical method using the capacity outage probability table (COPT) along with forced outage rates (FORs) of respective generators is the preferred one [7]. Nonetheless, the model of a wind system is a crucial issue.

Appropriate modeling of wind speed requires an elaborate prospecting process, since historical wind speed data from a wind site need to be compiled over a long period of time. On the other hand, lack of reliable and adequate data could make the analysis spurious. There are several ways to characterize the variability of wind plant output, such as the autoregressive and moving average (ARMA) models [8]. However, the complexity of these models precludes their application in practice [9]. Aggregate modeling of a wind farm was applied to the stability investigation of a power system containing numerous WTGs to minimize the simulation time [10]. Nevertheless, aggregate models could provide inaccurate results since they amalgamate WTGs' power fluctuation effects. Generation system adequacy is typically investigated using unit-based enumeration approaches to determine the system capability to satisfy the load demand under different capacity levels from available generation units.

To get around these difficulties, a common wind speed model is considered in this paper. The model can generate wind speed probability distributions for any geographic location and for multiple wind farm sites if the annual mean wind speed and standard deviation of a particular site are identified [9].

The risk associated with uncertainties arising in generation system adequacy, due to wind energy contribution, can be approached either through deterministic or probabilistic techniques [11]. The deterministic assessment is carried out via reserve margin calculation or the largest unit reserve [2]. However, deterministic analysis could lead to very different risk levels using the two methods, which widens even more with growing wind penetration[12]. Therefore, probabilistic assessment is preferable for risk analysis in the presence of wind power.

In this paper, probabilistic assessment is utilized to evaluate the risk related to attaching WTGs to the grid system. The effect of various penetration levels of WTGs in the system is studied. A hybrid method, in which the analytical technique using the COPT is combined with the Monte Carlo simulation (MCS), is developed to assess risk metrics such as LOLP and expected demand not supplied (EDNS). The effect of load increment on the capacity credit of WTGs is also considered. Further aspects related to different wind speed probability distributions and increased stages of partial WTG outputs are discussed as well.

The paper is organized as follows: a detailed description of the WTG model is given in Section 2. The proposed risk assessment method is presented in Section 3. Case studies along with the results are reported in Section 4. Section 5 concludes the paper.

2. WTG modeling

2.1. Wind speed model

Wind speed is the most critical piece of data needed to appraise the energy-capture potential of a candidate site for installing WTGs. Wind speed varies continually by the year, season, day, and even hour. The variation of wind speed is intrinsically random. However, it is likely to follow a statistical distribution. Wind speed data can be produced directly by numerical weather prediction models. In this vein, hourly wind speeds are first forecasted for a sampling year, and the annual mean speed needs to be averaged over 10 or more years [9]. Notwithstanding, compiling wind speed data over an extended period of time is an intricate process that requires considerable computing power and special expertise. Alternatively, chronological wind speed can be modeled by time series models from the actual data.

An ARMA time series model was employed to generate the portfolio of hourly mean wind speeds [8]. ARMA models reflect the probabilistic characteristics of wind speed and provide a reasonable representation of the actual wind regime. Nonetheless, it requires complex techniques to estimate its kernel parameters, in addition to historical wind data collection over a significant period of time, which may hinder its application from a practical point of view. On the other hand, using a Markov chain approach to model the wind speed [6] could produce significant discrepancy in comparison with observed data since it assumes exponentially distributed residence times of wind speeds.

In this paper, a common wind speed model is used [9]. The model is based on time series ARMA mode. It combines different wind farm locations to generate wind speed probability distributions for any geographic location, with similar wind conditions, provided that the annual mean wind speed (μ) and standard deviation (σ) of the specific site are known. The validity of the model was established for reliability evaluation of power systems containing wind farms [9].

As wind probability distribution over protracted time periods is known to be well represented by the Weibull probability density function, it has been reported that the probability distribution of long-term actual wind speed is near to a normal distribution [9, 13, 14]. This assumption is discussed and tested in this paper, which uses the normal probability distribution to model the wind speed for a particular geographical site in terms of annual mean wind speed (μ) and standard deviation (σ), through the common wind speed model. The randomness associated with wind speed can be captured through these two parameters. The site-specific wind speed model is then integrated with the WTG power curve to obtain the wind generation model.

2.2. Development of wind generation output

Power generated from a wind farm is usually fluctuating due to the stochastic attributes of wind. Therefore, wind power curves are used to characterize the nonlinear speed-power relationship of a WTG. The amount of wind power generated (P) corresponding to a given simulated wind speed (V) can be obtained as [9, 14]:

$$
\begin{aligned}
P &= 0, 0 \leq V < V_{ci} \\
&= P_r(A + B \times V + C \times V^2), V_{ci} \leq V < V_r \\
&= P_r, V_r \leq V \leq V_{co} \\
&= 0, V > V_{co}
\end{aligned}
\tag{1}
$$

where

$$A = \frac{1}{(V_{ci} - V_r)^2}\left[V_{ci}(V_{ci} + V_r) - 4(V_{ci}V_r)\left(\frac{V_{ci} + V_r}{2V_r}\right)^3\right]$$

$$B = \frac{1}{(V_{ci} - V_r)^2}\left[4(V_{ci} + V_r)\left(\frac{V_{ci} + V_r}{2V_r}\right)^3 - (3V_{ci} + V_r)\right]$$

$$C = \frac{1}{(V_{ci} - V_r)^2}\left[2 - 4\left(\frac{V_{ci} + V_r}{2V_r}\right)^3\right]$$

V_{ci}, V_r, V_{co}, and P_r are the cut-in speed, rated speed, cut-out speed, and rated power of a WTG unit, respectively.

Eq. (1) is a function of the wind speed (V) and the constants A, B, and C that depend entirely on specific WTG unit characteristics. A set of wind power outputs can thus be obtained from Eq. (1), and the wind power distribution can then be created from the data. Subsequently, COPTs are constructed, including those of the WTGs.

2.3. Multistate WTG model

Uncertainties in the availabilities of generating units, due to variable generation, can be quantified through analytical and simulation techniques. MCS belongs to the class of probabilistic simulation techniques, which simulates the actual process through randomization [2]. Generating random numbers from probability distributions describing variables of interest is the main element of the MCS. A sufficiently large number of samples is required to perform MCS.

The characteristics of wind output power are somewhat different compared to conventional generation as far as availability is concerned. While a simple two-state model, representing availability or unavailability, suffices to characterize a conventional generator, a multistate model is required to model partial capacity states corresponding to various levels of energy output from the WTG. In this case, the WTG is considered as a generating unit with many derated states. Neglecting the FORs of WTGs does not affect the calculated risk indices [15].

The common wind speed model, based on the normal probability distribution, is combined with the WTG output power curve of Eq. (1) to create the multistate WTG model using MCS as follows:

i. Generate a random number for wind speed between $\mu \pm 5\sigma$, or an 11-interval representation of normal distribution. The distribution ensures including extreme wind values despite their low probability of occurrence.

ii. Step 1 is repeated until the wind speed profile is generated depending on the number of simulations. Figure 1 shows the generated wind profile.

iii. The resulting wind speed profile is substituted in the nonlinear wind output relation of Eq. (1), where negative wind speed values have no physical significance and are converted to zero.

iv. The WTG outputs are categorized into five states: 0%, 25%, 50%, 75%, and 100%. These represent fractions of rated power of the WTG unit(s). A five-state model can reasonably represent the intermittent characteristics of WTGs [15]. An 11-state model is further pursued in this paper with different wind probability distributions.

v. The number of times where a power output corresponding to the wind speed profile falls within one of the output states is determined.

vi. The total number of occurrences for each state is divided by the total number of simulations to estimate the cumulative probability of each state. Ultimately, each state would have two parameters: the power output P and its corresponding probability.

Wind farms usually contain many identical WTG units that share the same geographic location and meteorological conditions in order to maximize the energy yield. Therefore, the multistate wind generation model will be similar to the single WTG unit, albeit with different output power (multiples of a single unit's output).

The cumulative wind probability distribution is employed in conjunction with existing conventional generating units to construct the COPT. The COPT is then used to quantify the risk indices.

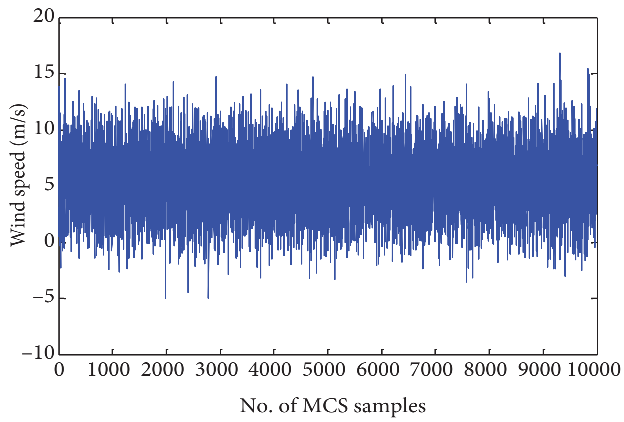

Figure 1. Simulated wind speed model using normal random density function.

3. Quantification of risk indices

Generating capacity models, including WTGs, can be combined with the chronological load to obtain system risk indices. The probability of system risk is obtained using the COPT, whereas MCS is used to estimate the indices by simulating the actual process and the random behavior of the system. The COPT gives the probability of occurrence of each possible capacity outage (or capacity levels) of all generators in the system.

The risk level in the grid system is analyzed in this paper as the difference between total generating capacity available and the system load. When the total generating capacity falls short of supplying the load, the system is at risk. The LOLP is computed to correlate the effect of generation uncertainties due to the intermittency of wind energy, in part, with available load. The EDNS is adopted as a load-interruption risk index as well [8].

3.1. Capacity outage probability table

The COPT is an array of capacity levels and associated probabilities of occurrence. Since a wind farm consists of identical WTG units, wind generation can be convolved with conventional generation, using the COPT, together with an appropriate load representation to obtain a quantitative measure for generation shortfall. The COPT contains three parameters, namely available capacity, the outage magnitude (complement of the available capacity), and the associated cumulative probabilities indicating each capacity level. The COPT is a useful method in power systems to identify the probability of specified outages [2]. In this paper, two types of COPT are presented, one for the WTGs using MCS and one for conventional generation units using an analytical technique involving generator outage rates.

FORs are used to capture conventional generation uncertainties represented by a two-state model. Nonetheless, the FORs of the WTGs can be neglected without having a significant impact on the calculated system reliability indices [15]. Therefore, FORs were not considered in constructing the analytical COPT for WTGs, which were developed using MCS along with the multistate model.

3.2. Loss of load probability

In steady-state operation of the system, there should be a supply-demand balance between total operating generation capacity with the load and losses, which can be expressed as ($Gen = Load + Losses$). In the case of generation unavailability or failure and peak demand increase in extreme weather, the load may exceed the generation capacity (i.e. G <L). In other words, loss of load is defined as the system's failure to match the demand with the available generation capacity [2, 11].

The objective of the simulation is to estimate the risk level in the grid system by using probabilistic assessment. The LOLP is defined as the overall probability that load demand will not be met because of the load exceeding the available generating capacity, under the assumption that peak load of each day lasts all day [2]. It is given as:

$$LOLP = \sum_{i=1}^{n} P_i \left[(C_i - L_i) < 0 \right] \tag{2}$$

where C_i is the available capacity at day i, L_i is the peak load at day i, and $P_i\left[(C_i - L_i) < 0\right]$ is the probability of loss of load on day i. The latter is obtained directly from the COPT. Sample pairs are generated randomly from the combination of the two variables, generation (G) and load (L), to estimate the LOLP. The load variable L is to be selected from the probability distribution of the daily peak load. A random number between 1 and 364 days is selected, representing a random day. Then the load value, in MW, that corresponds to the selected day is determined from the daily peak load variation curve. The quantity of the available generation variable G is subsequently selected through the COPT. The LOLP can then be computed based on the occurrence of pairs that render the demand greater than the generation over the total number of simulations, using the MCS.

3.3. Expected demand not supplied

While the LOLP represents the likelihood that load is not supplied, a quantification of that amount of unsupplied load corresponding to the LOLP is necessary. It captures the likelihood and severity of the risk associated with load interruption. Following the computation of the LOLP, the EDNS can be calculated as the product of the state probability and the amount of load shortage in the system. An expression of the statistical EDNS is given as [16]:

$$EDNS = \sum_{B} P_r \left\{ X = x \right\} . \left(MW_d - MW_s \right) \tag{3}$$

where:

B set of all unacceptable states: states where demands are not fully satisfied (e.g., exceeding the generation)

MW amount in MW

d, s [demand, supply]

The LOLP and the statistical EDNS are to be calculated as measures of system risk incurred due to the incorporation of WTGs into existing conventional generating units.

4. Case studies

4.1. Test systems

Two reliability test systems are used to validate the proposed hybrid analytical MCS risk-based method. These are the Roy Billinton Test System (RBTS) and the IEEE Reliability Test System (IEEE-RTS). The RBTS, displayed in Figure 2, consists of 11 conventional generating units with 240 MW total capacities [11, 17]. The IEEE-RTS, shown in Figure 3, is a much larger system and is composed of 32 conventional generating units, with a total generating capacity of 3405 MW. Detailed parameters of the IEEE-RTS are presented in [11].

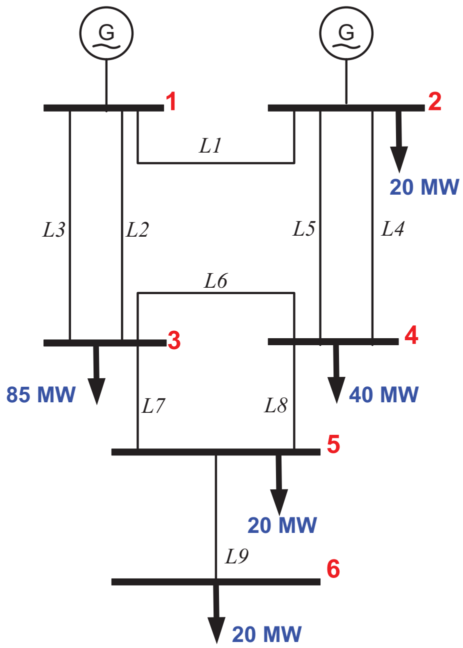

Figure 2. RBTS test system.

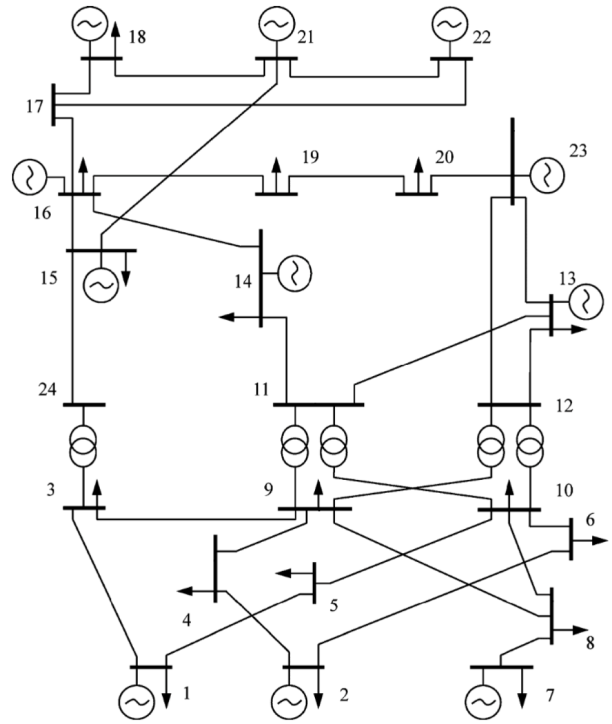

Figure 3. IEEE RTS test system.

4.2. Load model

The load model for both test systems has utilized the IEEE-RTS chronological load profile in per unit basis, which consists of 364 load points for a year (52 weeks *times* 7 days/week). Annual peak load for the RBTS and IEEE-RTS is 185 MW and 2850 MW, respectively. The annual daily peak load, assumed to occur over the entire duration of the day, is developed by multiplying the load model, in per unit values, by the annual peak load [11].

4.3. Integration of the WTG model into the generation system

The impacts of incorporating the WTGs into the generation fleet on system risk are to be determined. Using the common wind speed model, three different site wind regimes in Canada are combined, where the annual mean wind speed mu and standard deviation σ are 5.425 m/s and 2.794 m/s, respectively [9]. WTG parameters V_{ci}, V_r, and V_{co} of 4, 12, and 25 m/s, respectively, were used in this study. When wind speed lies between the rated speed V_r and the cut-out speed V_{co}, the generated P will be equivalent to rated power, P_r (2 MW). It is assumed that wind farms have identical WTGs, where each individual WTG unit has a rated capacity (P_r) of 2 MW. The WTG type used is Vestas V90-2.0 MW, with a doubly fed induction generator. In order to combine WTG units and conventional generating units, the COPT is constructed. Several cases are studied using the proposed method, and the risk indices are determined by the MCS. The number of MCSs is bounded to 10,000.

4.3.1. Capacity credit of a WTG for the RBTS

An important characteristic of a generation resource is its capacity credit. Capacity credit for WTGs can be defined as the amount of WTG output, in MW, required to replace a given amount of conventional generation output in MW while maintaining existing levels of reliability [3]. The final megawatt value of the added wind energy capacity neutralizes the influence of the WTG on system risk, bringing it back as the base system (not including the WTG), denoting the capacity value or capacity credit.

In this test case, a 10 MW conventional generation unit was removed and is replaced with the same capacity of WTGs (five WTG units). The COPT is constructed, combining the WTG units of 10 MW with the 230 MW remaining capacity of the conventional generation units.

The combined COPT for the RBTS is depicted in Table 1. Studies are done by evaluating the system LOLP and EDNS with sufficient identical 2 MW WTG units. In this study, the original LOLP and EDNS for the RBTS are calculated as 0.00247 [9] and 0.0207492 MW respectively. The base system without renewable resources is benchmarked for its contemporary reliability level.

Table 1. Capacity outage probability table (COPT) for a 10 MW conventional generation unit in the RBTS.

Capacity outage	Available capacity	Individual probability	Cumulative probability
0	240	0.442853	1
2.5	237.5	0.031702	0.557147
5	235	0.040839	0.525446
7.5	232.5	0.048873	0.484607
10	230	0.275462	0.435734
.	.	.	.
.	.	.	.
.	.	.	.
240	0	7.55E-19	1.84E-09

The annual system LOLP and statistical EDNS for the 10 MW WTG replacement are presented in Figure 4. Seemingly, the LOLP is decreasing as the number of identical WTG units increases. Moreover, the graph indicates that the reliability level of the 10 MW wind generation is not comparable to its counterpart from the conventional generation until 24.76 MW (or almost 25 MW) is approached. In other words, 1 MW of conventional generation is equivalent to almost 2.5 MW of WTGs or, more specifically, the capacity credit for the WTGs in this case mounts to around 40%. The statistical EDNS comes with a similar pattern to the LOLP graph. The result is, nonetheless, dependent on the accepted level of the LOLP and EDNS. Lower levels of LOLP could, intuitively, require higher wind contribution.

Apparently, the nameplate capacity of WTGs is not indicative of the extent to which wind generation contributes to meeting load demand. The capacity credit of a WTG is directly related to the wind speed model adopted, which in turn depends on the site's wind regime. Higher wind speed and less intermittency could make the capacity credit estimates higher, albeit having no effect on economic aspects. Furthermore, higher capacity credits of WTGs as compared with conventional generation are in line with the need to purchase additional transmission access rights (over nominal MW values) to facilitate integrating wind energy into existing power systems [18]. Whereas conventional generation is notoriously more reliable as compared with wind generation, the latter comes with energy sustainability and environmental friendliness.

4.3.2. Increased WTG penetration level

When wind represents a small percentage of power system generation, its impact on the system may not generally be significant. However, as the wind penetration level is increased, comprehensive analysis is required to appraise its impact on many system operational aspects. The impacts of various WTG penetration levels in the RBTS system on system risk are examined in this case as shown in Figure 5. Clearly the LOLP index increases exponentially with a higher wind penetration level, underscoring the higher risk associated with deeper wind penetration into the power system.

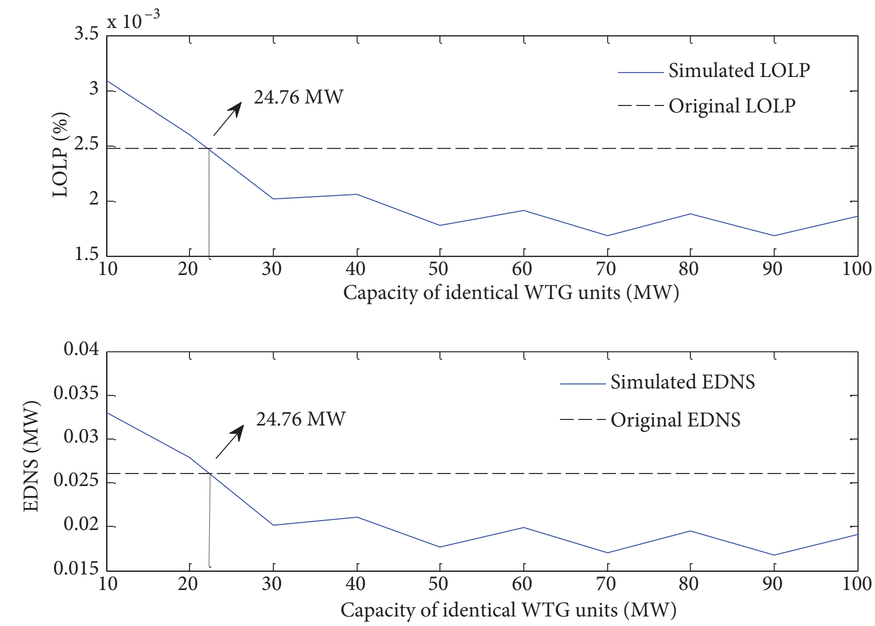

Figure 4. Risk indices against various capacity levels of identical WTG units for the RBTS.

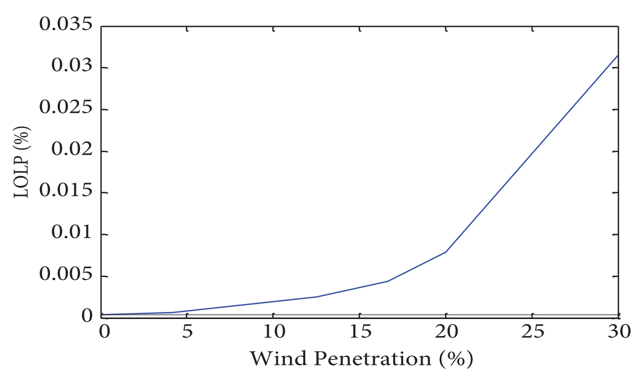

Figure 5. Different wind penetration levels against the LOLP index for the RBTS.

4.3.3. Normal wind distribution versus Weibull distribution

It is widely known that wind speed distribution matches the statistical Weibull distribution [13]. However, in this paper, it is conjectured that the probability distribution of long-term actual wind speed is close to the normal distribution. In this test case, this notion is to be examined. Table 2 shows the Weibull wind distribution with its probability for each state.

The value representing the failure to meet the load is shown in Figure 6 via Weibull wind speed distribution. From the figure, it can be identified that a 16.52 MW WTG is needed to replace the 10 MW conventional generator employing Weibull distribution, as compared with 24.76 MW using normal distribution. The discrepancy in the results indicates that the normal distribution gives a conservative estimation of the wind capacity credit, allowing more megawatts of wind energy to be integrated into the grid system.

Table 2. WTG percentage output power using Weibull distribution.

Percentage (%)	Individual probability
0	0.20236
25	0.10326
50	0.06988
75	0.06076
100	0.56374

4.3.4. Eleven-state WTG output level versus 5-state

In this case, an 11-state output level of a WTG is considered to investigate its effect on risk reliability assessment. The normal wind speed distribution is assumed and the MCS is used to generate the 11-state wind output levels. Table 3 shows the WTG's 11 states with the probability corresponding to each state, whereas the results using the 11 states as compared with 5 states are illustrated in Figure 7.

Table 3. WTG with 11-states output power.

Percentage (%)	Individual probability
0	0.33136
10	0.029733
20	0.019933
30	0.017553
40	0.0161
50	0.015697
60	0.015183
70	0.015163
80	0.01429
90	0.013953
100	0.511033

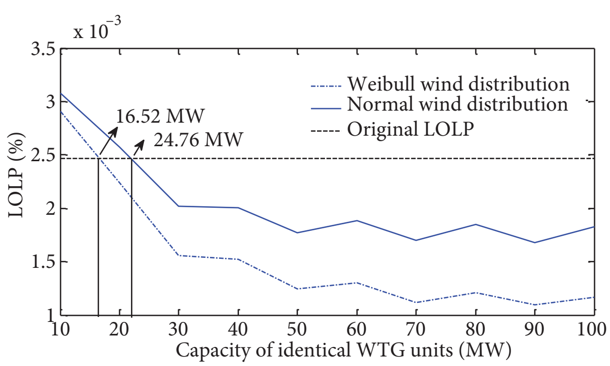

Figure 6. Weibull vs. normal wind speed distributions for the RBTS.

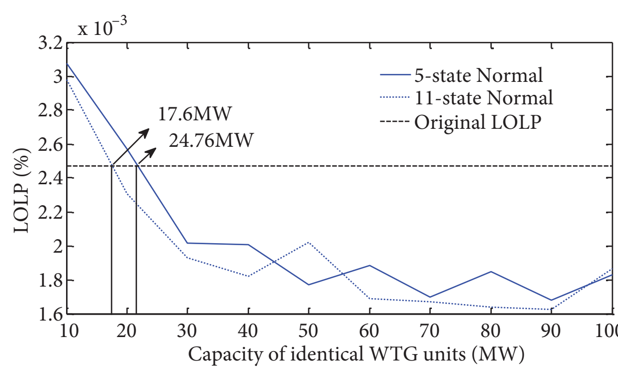

Figure 7. Different WTG states against the LOLP index for the RBTS.

It is apparent that, using 11 state output levels, a 17.6 MW WTG is needed to maintain the original RBTS risk level. Although 11 states of WTG partial output representation are more accurate, it comes with a heftier computational burden. It was reported that 5-state WTG output levels should be enough for reliability risk assessment [15]. On the other hand, comparing Figure 6 and Figure 7, it appears that using the 11-state

WTG output level compensates the effect of using normal distribution as opposed to Weibull distribution, which is widely used in wind resource assessment studies. In other words, using the 11-state WTG output level with normal distribution of wind speed is equivalent to using 5 states with the Weibull distribution.

4.4. IEEE-RTS

The proposed study was also applied to the IEEE-RTS [11]. The system has 24 buses, 32 generating units, and 17 load buses, as shown in Figure 3. This particular test system has larger generation capacities with higher reserve margins and more load points, typical for a real-world practical system. Several case studies are undertaken to illustrate the effect of introducing WTGs on the overall system risk. In these cases, the 11-state model of wind levels using normal distribution is adopted. Using the proposed hybrid method, the LOLP for the IEEE-RTS, without including WTGs, is calculated as 0.087437 [11, 19], whereas the EDNS is 17.75 MW.

4.4.1. Capacity credit of WTGs

In this case, the effect of displacing conventional generating units in the IEEE-RTS with sufficient identical 2 MW WTG units is investigated. A 12 MW conventional unit was removed and replaced with six WTG units.

As demonstrated in Figure 8, the intersection between the simulated LOLP and base-case LOLP (the dotted line) shows that the corresponding WTG capacity needed to replace the 12 MW of conventional generation is 20.003 MW in this case. For various compositions of reference capacities of conventional generation from coal or other fuel, 100 MW, 200 MW, and 350 MW units were selected to simulate different levels of wind penetration and identify the corresponding capacity credit, respectively. The result presented in Figure 9 shows an exponential increase in the equivalent incremental wind capacity procured to counteract the effect of conventional generation.

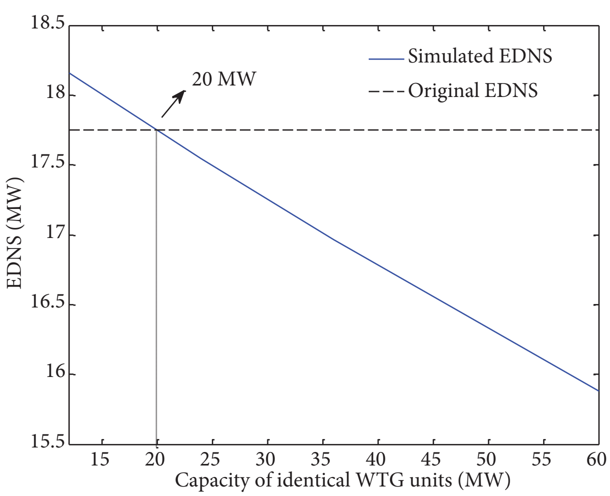

Figure 8. Capacity credit for displacing a 12 MW conventional generation with WTGs in the IEEE-RTS.

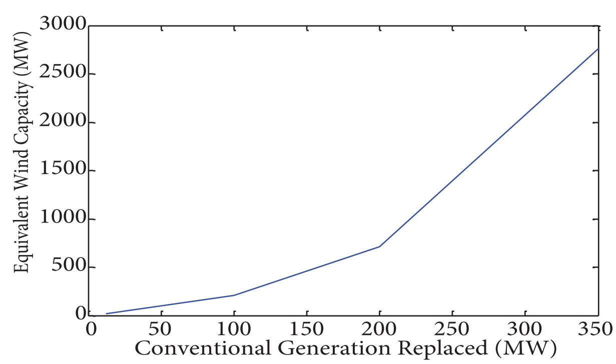

Figure 9. Conventional generation capacity replacement with WTGs in the IEEE-RTS.

Figure 10 illustrates that the capacity credit declines rapidly for larger wind power penetration levels, construed through the increased magnitude of conventional generation of reference capacity. Table 4 further demonstrates the capacity credit relevant to different wind penetration levels.

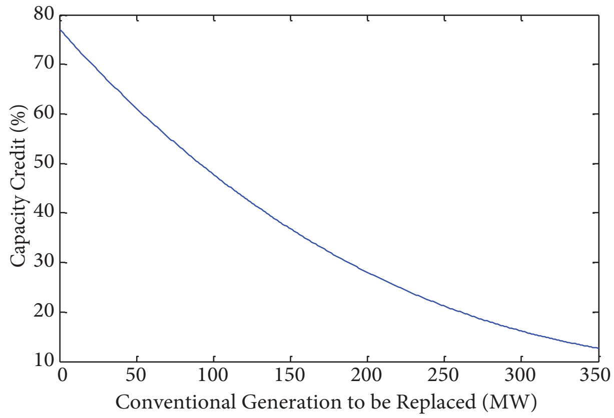

Figure 10. Capacity credit as a function wind penetration level for the IEEE-RTS.

Table 4. Capacity credit corresponding to various wind penetration levels.

Capacity replaced (MW)	Capacity credit (%)	Equivalent capacity (MW)	Penetration level (%)
12	60	20.00	0.35
100	47.77	209.33	2.94
200	28	714.286	5.87
350	12.68	2760	10.3

The results further imply that there is a correlation between the capacity credit and the LOLP. The capacity credit tends to become higher for larger values of LOLP, i.e. the capacity credit is dependent on the accepted level of LOLP and system risk. A more stringent risk criterion results in lower capacity credit of wind resources. In fact, there may be numerous factors that can possibly influence the capacity credit of WTGs. These include wind speed model and the spatial spread of WTGs, composition of reference conventional capacities, penetration level, chronological properties of load models, risk levels, capacity factors, and the calculation method. Such factors need to be adequately addressed in the development of the grid system with larger contribution of renewable resources.

4.4.2. Incremental peak load analysis

When wind power resources are added to the power system, the system's ability to satisfy a higher peak demand is enhanced at a certain measure of risk. Pursuant with the bona fide transition to a greener economy and decarbonization, electrification of the transport system, for instance, would potentially lead to a higher electricity demand above current levels. It is therefore inevitable to assess the consequence of the peak load increase on system risk.

The LOLP associated with meeting various peak load levels is displayed in Figure 11. It is clear that the LOLP soars with peak demand increase. While the current load level has an LOLP of 0.087437, at a 30% peak load increase, the LOLP ramps up to 0.164884 annually.

The relation between the WTG capacity needed to fulfil the incremental peak load increase is plotted in Figure 12. With the original peak load level of the IEEE-RTS at 2850 MW, higher peak demand entails relatively larger proportions of WTG capacity. It is also conceivable that increased peak demand would have a diminishing capacity credit value. The above results are limited by the way WTGs are substituted in the COPT, reflecting additional generation. Different staging of the added WTG units necessitates major changes and increases in the size of the COPT table. Nevertheless, the graph provides a very useful estimation of wind generation capacities needed for future load scenarios.

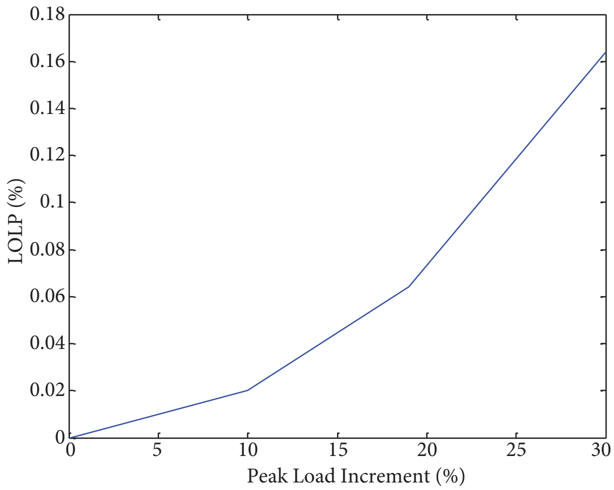

Figure 11. LOLP as a function of the incremental peak load for the IEEE-RTS.

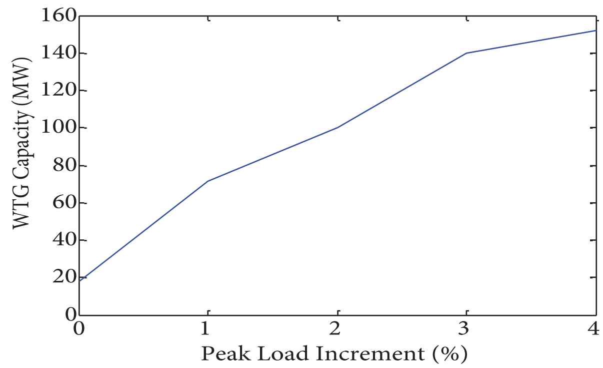

Figure 12. WTG capacity required for different peak load levels for the IEEE-RTS.

5. Conclusions

A hybrid method combining the analytical COPT with the MCS generation has been added to the existing portfolio of generation resources. The risk is quantified in two main metrics: the LOLP and the statistical EDNS. A common wind speed model is adopted to expedite the construction of a multistate WTG model. The latter has an emphatic role to better exemplify the partial production levels of the WTGs due to its fickle characteristics. Application of the proposed method to the RBTS and IEEE-RTS test systems showed that larger wind penetration levels come typically with a deteriorating capacity credit for WTGs. Similarly, embracing a stringent risk criterion for the system or growth of peak demand would erode the capacity credits as well. Results indicate that the use of normal probability to represent the wind speed distribution gives a conservative estimation of WTGs' capacity credit in the system as compared with Weibull distribution. Nonetheless, increasing the number of partial output levels representing wind turbine output uncertainty using normal distribution can indeed offset the conservativeness exhibited by using a lower number of output states, as well as producing more or less capacity credit and EDNS as with the Weibull distribution.

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