Reliability-based Selection of Wind Turbines for Large-Scale Wind Farms

M. Fotuhi-Firuzabad, and A. Salehi Dobakhshari

***Abstract*—**This paper presents a reliability-based approach to select appropriate wind turbine types for a wind farm considering site-specific wind speed patterns. An actual wind farm in the northern region of Iran with the wind speed registration of one year is studied in this paper. An analytic approach based on total probability theorem is utilized in this paper to model the probabilistic behavior of both turbines' availability and wind speed. Well-known probabilistic reliability indices such as loss of load expectation (LOLE), expected energy not supplied (EENS) and incremental peak load carrying capability (IPLCC) for wind power integration in the Roy Billinton Test System (RBTS) are examined. The most appropriate turbine type achieving the highest reliability level is chosen for the studied wind farm.

***Keywords*—** Wind Turbine Generator, Wind Farm, Power System Reliability. Wind Turbine Type Selection.

I. Introduction

WIND farm (WF) projects have developed rapidly in the last decade. The unexpected increase in fossil-fuel prices and concerns about greenhouse effect have facilitated the use of renewable energy sources as an alternative for existing fossil-fueled power plants. Furthermore, none of renewable energy sources are able to compete with large power plants except wind energy [1]. Wind turbine generators (WTG) have reached a size of 4 MW and WFs are planned at a size of up to 300 MW [2]. However, many planning aspects have been ignored in the process of wind generation expansion because of law level of energy extracted from wind and other renewable energy sources.

Optimum selection of WTG type was first discussed in [3] which focused on maximizing capacity factor (defined as the ratio of average output power to the rated power) of WTGs due to a given wind speed probability density function in the WF. Capacity factors of several available WTGs were computed from the Weibull statistical model using cubic mean of wind speed data for eight different hours of four different months each of which represents a season.

Finally, the type of WTG resulting in the highest capacity factor was selected for the specified site. The drawback of the proposed method is the use of average output power as the desirable characteristics of a WTG type. The question is what can happen if most of the extracted power corresponds to the times when there is no need of this power (i.e., early hours of the day and late hours of the night). Therefore, capacity factor is not the right criterion for evaluating the efficiency of different WTG types in a WF.

Reliability indices have also been used in the assessment of different turbine types to be installed in a WF [4]. Since conventional indices such as LOLE, EENS and loss of load frequency (LOLF) resulted in conflicting indices for different WTG types (e.g., LOLE of one type was less than the other while its LOLF was more), two new reliability indices were introduced in [4] which showed a consistent behavior for WTG types.

Reliability-based selection of WTG type makes it possible to assess the actual benefit of wind power. Since system reliability is violated mostly in peak load hours, better reliability indices indicate more wind energy during peak hours. It should be noted that more wind power in the peak load hours brings more profit from the WF owner point of view. By injecting more wind energy during high-price hours (i.e., peak hours), not only is the profit of WF owner exploited, but also the security of system improves due to adding wind energy as a negative load to the system. On the other hand, at low-price hours (e. g., the early hours of morning), less energy is brought to the system resulting in preserving load patterns from the viewpoint of system operator. In this way, coincidence of load pattern and wind energy pattern can be assured at the most possible degree. Hence, in case of large WFs, capacity credit of wind power may be taken into account for reliability purposes due to the agreement of load pattern and wind power pattern [1].

In this paper, an analytic approach, based on total probability theorem, is utilized to analyze probabilistic model of a power system including a wind farm. The model, however, may be extended to account for several wind farms in the system. The proposed method in this paper forms the probability distribution of wind speed from raw data of wind speed. Then, the probability distribution of the output power of a single turbine may be obtained using WTG characteristics. Considering probabilistic failure events of WTGs, the probability distribution of the whole WF may be evaluated. Afterward, the probabilistic model of WF is convolved with the capacity outage probability table (COPT) of the original power system [5] to obtain the probabilistic model of total generation in the system.

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In this paper the historical data of wind speed at a WF in the north of Iran is studied to investigate the applicability of the proposed method and select appropriate turbine type for it. Different scenarios of adding wind power to the original RBTS with different turbine types are investigated and the related reliability indices for each scenario are determined to select the most appropriate turbine type.

The rest of this paper is structured as follows: in section II, probabilistic modeling of wind speed, output power of a single turbine and output power of a wind farm are performed, respectively. In section III, reliability evaluation of the composite generation system of conventional generating units and WTGs are discussed. Section IV introduces different alternatives for installing 60 MW wind power using different WTG types. The results of the case study are shown in Section V. Conclusions are given in Section VI.

II. Probabilistic Modeling of a Wind Farm

A. Probabilistic Model of Wind Speed

Wind speed as a time series can be modeled by a stochastic process. Markov chain may be utilized to model the variations of wind speed as transitions between Markov states, where each state represents a discrete wind speed. The number of states depends highly on the required accuracy of the model, but it has been shown that 1m/s steps are quite acceptable [6].

For a process to be represented by Markov process, it needs to be stationary. In other words, the transition rates between different states remain constant throughout the studied period. Since wind speed commonly has seasonal patterns, the mean and standard deviation of wind speed do not remain constant during the whole period. Therefore, wind speed is not actually a stationary process. This effect may be ignored if the time series do not tend to a definite behavior during any specific period or if the amount of data is large enough, which is valid in reliability studies [7].

Modeling wind speed by a stationary Markov process requires that the residence time of the states (here wind speed values) follows an exponential distribution [5]. However, the limiting state probabilities and frequencies of a process with non-exponential distribution are identical to those evaluated by exponential distribution assumption. Using actual distribution of transition rates is only important for studying time-dependent characteristics of a process and not the long-term expected values which are evaluated in reliability studies [7], [8].

The exponential distribution uses a constant transition rate between states i and j defined by

$$\lambda_{ij} = \frac{N_{ij}}{D_i} \tag{1}$$

where λ_{ij} is the transition rate, in occurrence per year, N_{ij} is the number of observed transitions between states i and j, and D_i is the duration of state i, in years, calculated during the whole period. Hence, the probability of occurrence of state i is given by

$$P_i = \frac{D_i}{\sum_{k=1}^{N_s} D_k} = \frac{D_i}{T} \tag{2}$$

where T is the entire period of observation, in year, and N_s is the total number of states. If the transition rate from state i, λ_i, is donated as the sum of transition rates from this state to other states then

$$\lambda_i = \sum_{j=1, j\neq i}^{N_s} \lambda_{ij} \tag{3}$$

The frequency of occurrence of state i, in occurrence per year, is then given by

$$F_i = \lambda_i P_i \tag{4}$$

B. Probabilistic Model of Wind Turbine Output Power

The output power of a wind turbine generator is nonlinearly related to the wind speed. This model has three parameters namely cut in speed (V_{ci}), rated speed (V_r) and cut out speed (V_{co}) [9]. Output power of a WTG unit may be approximated by the following expression:

$$P_w = \begin{cases} 0 & 0 \leq S_w < V_{ci} \\ [A + B\times S_w + C\times S_w^2]\times P_r & V_{ci} \leq S_w < V_r \\ P_r & V_r \leq S_w < V_{co} \\ 0 & V_{co} \leq S_w \end{cases} \tag{5}$$

where P_w and P_r are the hourly and rated output power of the WTG unit, respectively. A, B and C parameters are related to V_{ci}, V_r and V_{co} which in turn relate to the specified turbine type [9].

Total probability theorem may be employed to obtain the output power model of a wind turbine considering different values of wind speed. This theorem implies that if $\{B_1,\ldots,B_m\}$ is a partition of event space consisting of m mutually exclusive events, then the probability of any arbitrary event A of event space can be written as:

$$P(A) = \sum_{j=1}^{m} P(A \mid B_j) P(B_j) \tag{6}$$

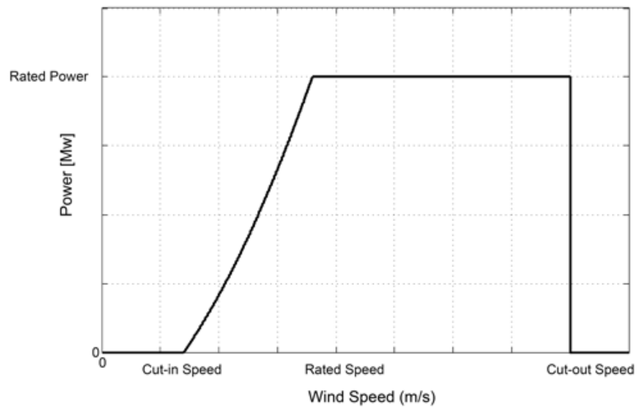

Fig. 1 Output power characteristics of a wind turbine generator

In order to model the output power of a wind turbine, event A represents the output power of P_w and B_j represent different values of wind speed resulting in the output power of P_w based on (5).

$$\text{Prob}^{P_t}(P_w) = \sum_{P_w(S_w^i)=P_w} \text{Prob}(S_w^i) \tag{7}$$

where $\text{Prob}^{P_t}(P_w)$ is the probability that the output power of a wind turbine becomes P_w; $\text{Prob}(S_w^i)$ is the probability that the wind speed becomes S_w^i ; and $P_w(S_w^i)$ is the output power of the turbine when wind speed is S_w^i which is given in (5). For example, when wind speed is between the rated speed and cut-out speed, the output power will be the rated power. In this case, $P_w = P_r$, $S_w^i = \{ S_w \mid V_r < S_w < V_{co} \}$ and $\text{Prob}(S_w^i)$ has already been calculated using (2).

C. Probabilistic Model of Wind Farm Output Power

A wind farm consists of several wind turbines and therefore the output power of a wind farm depends on the wind speed as well as the number of available wind turbines.

Wind turbine may be modeled by a two-state failure/repair model similar to conventional generating units. The failure rate of a turbine can be calculated using historical data of wind turbine functioning as:

$$\lambda_t = \frac{N_f}{D} \tag{8}$$

where λ_t is the failure rate of turbine, in occurrence per hour, D is the total number of hours of observation period, and N_f is the number of failure events observed.

The mean time to repair (r_t) of the turbine depends on many factors such as environment, maintenance schedule, and wind speed regime [7]. The repair rate (μ_t) is defined as the inverse of r_t. Fig. 2 shows the state-space diagram of one turbine.

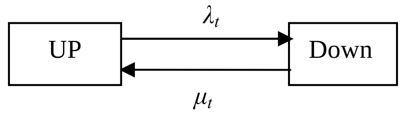

Fig. 2 State-space diagram of one wind turbine

In the case of N_t similar turbines, which is usually the case of a wind farm, the state-space of a single turbine in Fig. 2 may be extended as shown in Fig. 3. The availability of every wind turbine may be modeled by its forced outage rate (FOR_t) and availability (A_t) as

$$FOR_t = \frac{\lambda_t}{\lambda_t + r_t} \tag{9}$$

$$A_t = 1 - FOR_t = \frac{r_t}{\lambda_t + r_t} \tag{10}$$

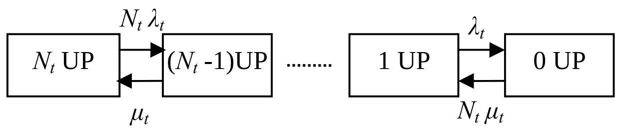

Fig. 3 State-space diagram of N_t wind turbines

Although it is not necessary to assume that all the turbines in a wind farm are alike, this assumption is valid in practice and significantly simplifies the calculations.

If total probability theorem is applied again, the probability distribution of the output power of a wind farm can be calculated using the probability distribution of the output power of a single turbine in (7).

$$\text{Prob}^{P_f}(P_{site}) = \sum_{N_a \times P_w = P_{site}} \sum_{N_a=0}^{N_t} \sum_{P_w=0}^{P_r} \binom{N_t}{N_a} FOR_t^{N_t - N_a} A_t^{N_a} \times \text{Prob}^{P_t}(P_w) \tag{11}$$

where $\text{Prob}^{P_f}(P_{site})$ is the probability that the output power of a wind farm becomes P_{site} and N_a is the number of available wind turbines in the farm.

D. Probabilistic Model of Power System Generation

Probabilistic model for the generation system was conventionally based on capacity outage probability table (COPT) utilizing forced outage rates of conventional generating units [5]. The difference between the power extracted from wind turbines and conventional generating units, from a reliability point of view, is that conventional units are assumed to be able to generate rated power unless they are out of action while the output power of wind turbine generators depends to the wind speed even if they are in operative state. By combining the developed model of a wind farm obtained in the previous part and the COPT, the probabilistic model of generation system can be obtained. Again, total probability theorem is used to develop the probability distribution of total generation of the power system.

$$\mathrm{Prob}^{P_{sys}}(P_{gen}) = \sum_{N_a \times P_w + P_{conv} = P_{gen}} \sum_{N_a=0}^{N_t} \sum_{P_w=0}^{P_r} \mathrm{Pr}(P_{conv}) \times \binom{N_t}{N_a} FOR_t^{N_t - N_a} A_t^{N_a} \times \mathrm{Prob}^{P_t}(P_w) \quad (12)$$

where $\mathrm{Prob}^{P_{sys}}(P_{gen})$ is the probability that the output power of the total power system (including both conventional units and wind farms) becomes P_{gen}. P_{conv} is the possible capacity of aggregated conventional capacity which can be obtained directly from COPT and Pr (P_{conv}) is the associated individual probability provided by the COPT.

Wind generation is incorporated in generation system as shown in Fig. 4.

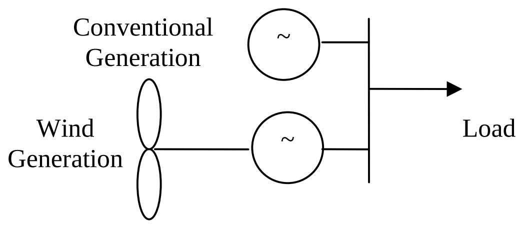

Fig. 4 Power system model with wind power

III. Reliability Evaluation

Reliability evaluation of any system may be performed by defining numerical indices known as reliability indices. Some of the well known reliability indices in the context of power systems are loss of load expectation (LOLE), expected energy not supplied (EENS) and incremental peak load carrying capability (IPLCC). LOLE and EENS for a power system consisting of both conventional units and wind farms may be calculated using conditional probability theorem in (6) as follows

$$LOLE = \sum_{P_{gen}} \mathrm{Prob}^{P_{sys}}(P_{gen}) \times LOLE(P_{gen}) \quad (13)$$

$$EENS = \sum_{P_{gen}} \mathrm{Prob}^{P_{sys}}(P_{gen}) \times EENS(P_{gen}) \quad (14)$$

where $LOLE$ (P_{gen}) and $EENS$ (P_{gen}) may be calculated by intersection of total capacity of P_{gen} with load duration curve (LDC) of the power system [5]. IPLCC, by definition, represents the increase in peak load which the additional capacity is capable to supply while maintaining the reliability level of the system. For calculation of IPLCC, LOLE is often used as the reliability level which should be maintained.

IV. Wind Turbine Alternatives

Two internationally recognized companies are chosen namely Vestas Wind Systems [10] and GE Energy [11] to investigate five turbine type options. A Forced Outage Rate (FOR) of 4% is assumed for each turbine. Technical specifications of studied wind turbines are listed in Table I.

TABLE I
TECHNICAL SPECIFICATIONS OF WIND TURBINE OPTIONS

Company	Turbine Model	Rated Power (MW)	Cut-in Speed (m/s)	Rated Speed (m/s)	Cut-out Speed (m/s)	# of Installed Turbines
Vestas	V80	2	4	15	25	30
	V90	3	4	15	25	20
GE Energy	1.5 sl	1.5	3.5	14	20	40
	1.5 se	1.5	4	13	25	40
	2.5 xl	2.5	3.5	12.5	25	24

V. Study Results

The flowchart of the proposed method for selection of appropriate wind turbine type for a wind farm is depicted in Fig. 5. The results of case study based on this flowchart are given in the following.

A. Wind Speed Data Used

The wind speed series of an actual Iranian wind site in the northern region, Aliabad, is utilized in this paper. The measurements interval is 10 min, with registration of one year (2003) as shown in Fig. 6 [12]. Since the time period is not long enough to use simulation-based methods such as ARMA time series [13], the proposed analytic method is applied to the turbine selection problem. The probability distribution of different wind speed values in 1m/s steps is plotted, as shown in Fig. 7. As it can be seen in Table II, which contains the statistical data of the wind speed time series, the mean speed is 9.84 m/s which is significantly high compared to typical wind sites. Based on the wind turbine characteristics demonstrated in Section II, the wind speed probability distribution in Fig. 7 results in an output power distribution from a single V80-2 MW wind turbine as shown in Fig. 8. The output power probability distribution of a wind turbine has two picks on zero output and rated output, respectively. The reason for this is the particular form of WTG output power characteristics as shown in Fig. 1 in which the speed values between rated and cut-out speed results in rated power and the speed either less than cut-in speed or more than cut-out speed results in zero output.

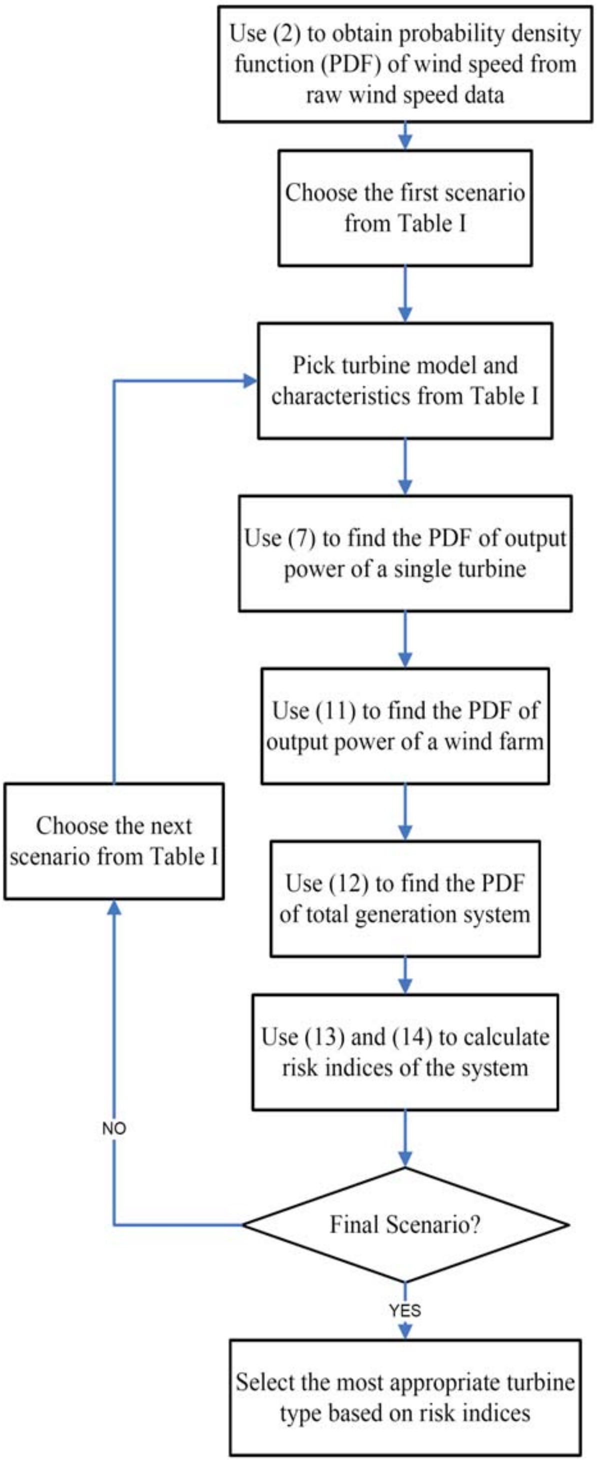

Fig. 5 Flowchart of the proposed method

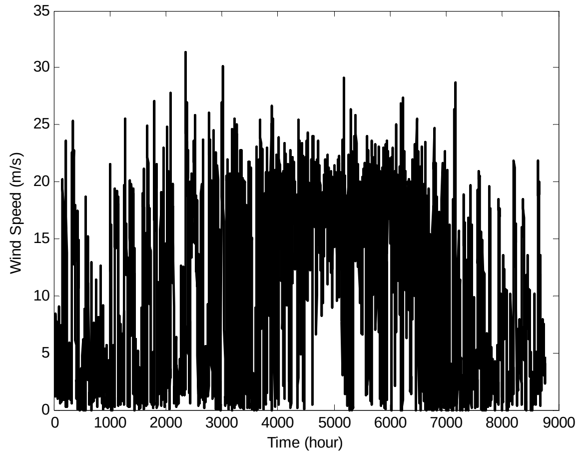

Fig. 6 Wind speed time series of Aliabad wind site in 2003

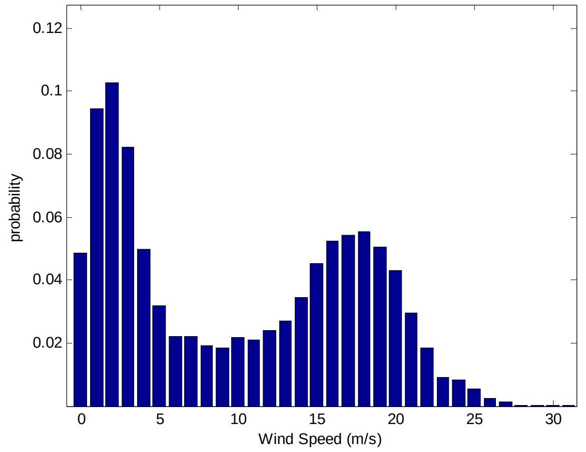

Fig. 7 Wind speed probability distribution of Aliabad wind site

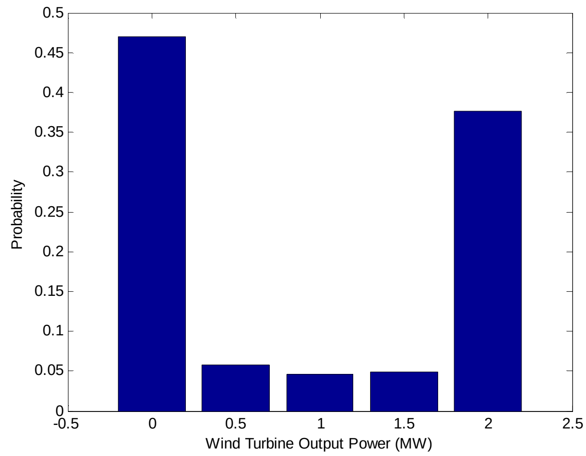

Fig. 8 Output power probability distribution of a V80 turbine

TABLE II
WIND SPEED STATISTICAL DATA OF ALIABAD WIND SITE

Wind speed average (m/s)	9.84
Wind speed standard deviation (m/s)	7.86

B. *Reliability*

The purpose of generation planning is to find adequate generating resources to supply forecasted load demand at an acceptable reliability level. The power system model for reliability evaluation in presence of wind power is shown in Fig. 4. The entire generation system includes WFs and conventional generating units. The output power of WFs is combined with the conventional generation to form the capacity model for the total generation system.

A reliability test system (RBTS) is used to examine the effects of different types of wind turbines on reliability indices. Original RBTS consists of three 40 MW, five 20 MW, one 10 MW and two 5 MW units, equivalent to 240 MW installed capacity. The annual peak load of this system is 185 MW [14]. The annual load growth in the RBTS is assumed to be 10% and the objective is to expand wind power so that the system reliability lies within an acceptable level.

An important aspect of wind power expansion is the optimal selection of wind turbine type. Based on the developed wind power model in Sections II and V, it is possible to calculate reliability indices for the composite system of conventional generating units and a wind farm consisting of several turbines.

Three reliability indices namely LOLE, EENS and IPLCC are calculated for different scenarios of Table I. The original RBTS (with no wind power), is considered as the base case.

The LOLE and EENS for the base case are 0.97 hours/year and 8.82 MWh/year, respectively. The LOLE obtained for the base case is used as the reliability level which should be maintained in calculation of IPLCC. To calculate LOLE and EENS, it is assumed that the annual peak load of the RBTS is increased by 10%. LOLE and EENS for a 10% increase in peak load without wind power are 4.3 hours/year and 45.5 MWh/year, respectively. It is intended to decrease these indices by installing 60 MW wind capacity in the original system. The most appropriate wind turbine type resulting in highest reliability level will be selected. The best turbine alternative will be the one with the least loss of load (LOLE and EENS) indices and the most peak load carrying capability (IPLCC) index. The results of reliability indices for different turbine alternatives are shown in Table III.

The first two rows of Table III contain the same elements; this is because of the similar characteristics of V80 and V90 models (see Table I). It can be deduced that the number of turbines and turbine rated power has no effect on reliability indices.

As shown in Table III, turbine types 1.5 sl and 2.5 xl result in the least and most reliability improvement, respectively.

TABLE III
RELIABILITY INDICES FOR DIFFERENT WIND TURBINE ALTERNATIVES

Turbine Model	Rated Power (MW)	# of Installed Turbines	LOLE (hr/yr)	EENS (MWh/yr)	IPLCC (MW)
V80	2	30	2.17	22.76	8.0
V90	3	20	2.17	22.76	8.0
1.5 sl	1.5	40	2.50	26.19	6.2
1.5 se	1.5	40	2.08	21.79	8.3
2.5 xl	2.5	24	2.04	21.41	8.5

C. *Sensitivity Analysis on Turbine Parameters*

The impacts of wind turbine parameters on system reliability are investigated in this section. Fig. 9 shows the impact of wind turbine cut-in speed on EENS index. It can be seen from Fig. 9 that cut-in speed has a slight effect on system reliability. The reason for this is the form of power curve where the cut-in peed has an insignificant effect on wind turbine output power.

Fig. 10 shows the impact of wind turbine rated speed on EENS index. In comparison with Fig. 9, system reliability is directly affected by wind turbine rated speed. It can be seen from Fig. 1 that lowering rated speed results in a wider range for rated power of wind turbine generator.

Fig. 11 shows the effect of cut-out speed on system reliability. It can be seen from Fig. 11 that at low values of cut-out speed, system reliability is highly sensitive to cut-out speed. However, at higher values of cut-out speed, the effect of cut-out speed on EENS index is insignificant. The reason for this is wind speed characteristics. Wind speed in the studied WF hardly reaches values as high as 25 m/s. Therefore, increasing cut-out speed has a slight effect on wind turbine output power at higher values of cut-out speed.

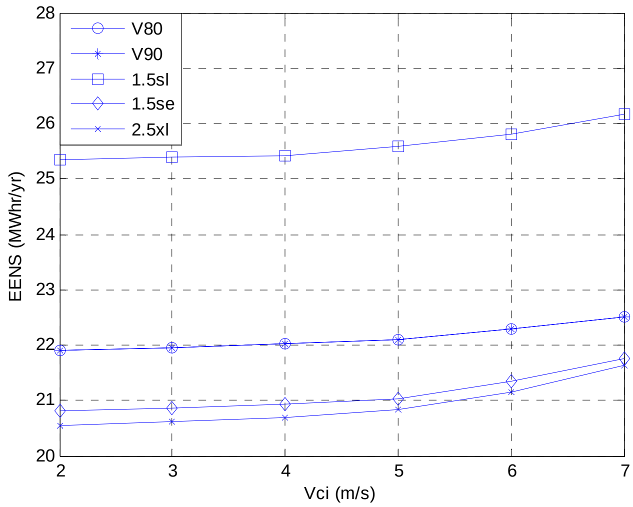

Fig. 9 EENS versus wind turbine cut-in speed

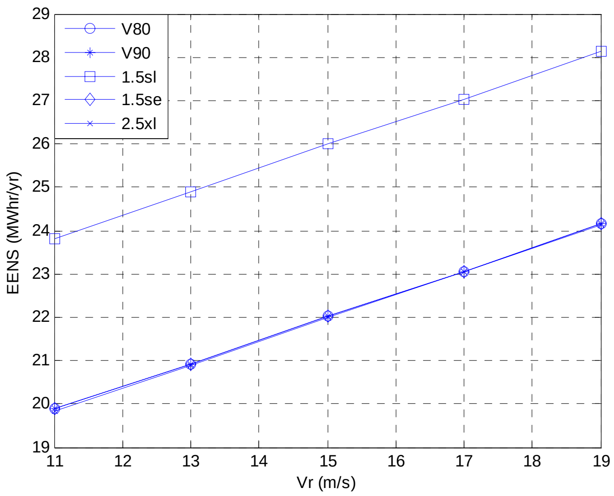

Fig. 10 EENS versus wind turbine rated speed

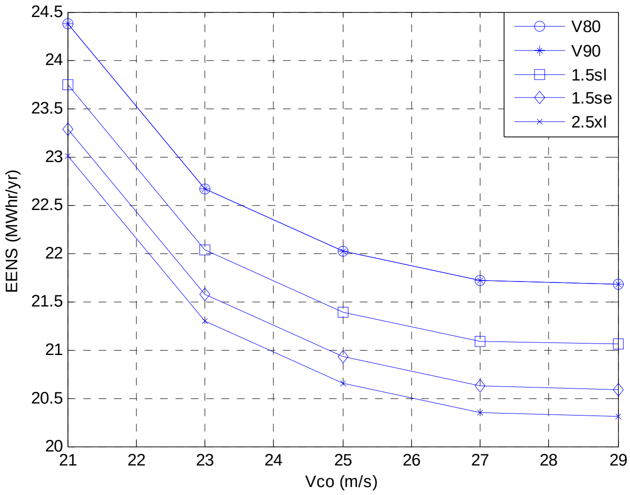

Fig. 11 EENS versus wind turbine cut-out speed

D. Turbine Type Selection

As it can be seen from Table III, turbine type 2.5 xl has the lowest LOLE and EENS and the most IPLCC. Hence, installing 24 turbines of type 2.5 xl results in maximum reliability. In addition, Figs. 9 to 11 show that this turbine type results in the best reliability statistics under different analyses on wind turbine parameters. The physical limitations for the installation of turbines however should be considered in case there is not enough space for installing large number of turbines or there is practical limitation in transporting huge wind turbines.

VI. Conclusion

A reliability-based approach to the selection of an appropriate wind turbine type for a large-scale wind farm is introduced in this paper. An actual wind site in the northern region of Iran is utilized to analyze different alternatives in the turbine type selection problem. Better reliability indices indicate more wind energy during peak hours. Wind energy in the peak load hours brings more profit from the WF owner point of view and therefore by injecting more wind energy during high-price hours (i.e., peak hours), not only is the profit of WF owner exploited, but also the security of system improves due to adding wind energy as a negative load to the system. The proposed methodology can be employed in turbine type selection of any wind farm given the long term wind speed data of the farm as well as power system characteristics.

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