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A New Approach for Modeling Wind Power in Reliability Studies

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Abstract- *Tremendous growth of wind power worldwide in the past decade requires serious research in various fields. Because wind power is weather dependent, it is stochastic and varies over various time-scales. Therefore, accuracy in wind power modeling is recognized as a major contribution for reliable large-scale wind power integration. In this paper, a method for generating synthetic wind power is proposed. The proposed method combines the random nature of wind with the operational information of the wind turbines (i.e., failure and repair rates). It uses chronological or sequential Monte Carlo Simulation (MCS) instead of non-sequential one owing to its usefulness and flexibility in preserving statistical characteristics of the chronological processes. The validity of the synthetic values generated by the proposed method and the Auto Regressive Moving Average (ARMA) time series is compared with the measured data in terms of reliability indices. Finally, the effect of some network parameters, such as network dimensions, the average coefficient of wind speed on the reliability of the power system has been evaluated. In this regard, historical wind speed data of Manjil area located in the north of Iran is used*.

Keyword: Modeling wind power, Reliability, Markov Chain, Monte Carlo Simulation.

1. INTRODUCTION

Considering the environmental characteristics of wind energy as well as the reduction of fossil fuel resources, the use of renewable energy, especially wind energy, has become more common in the past few decades as a suitable option for generating electrical energy. However, the variable and randomness of wind speed, as the input energy of wind power plants, can affect the power systems from adequacy and security perspectives [1].

Reliability assessment of power system that is integrated with wind power is a complicated process. Wind speed/power modeling is an important step in reliability evaluation of power systems. Generally, there are different approaches for modeling the wind speed. However, these methods require historical wind speed data collected over a number years related to a specific site in order to determine the necessary parameters of the wind speed model. The wind speed time series can usually be represented by many distributions, including Weibull distribution [2] and normal distribution [3]. However, these models cannot consider the chronological order of wind speed. There are several publications that proposed an Auto Regressive Moving Average (ARMA) time series to simulate the hourly wind speed to create a wind speed model [4, 5]. These models were combined with the WTG power curve to create wind power time series [4]. In Ref. [5] the optimal placements of capacitors in a distorted distribution network have been determined while wind speed is simulated by an ARMA model. These models, however, can simulate the chronological persistence of original wind speed data, but they do not necessarily hold the probability distribution of the original wind speed data [6].

Another approach that received remarkable attention in synthetic generation of wind speed time series, is known as Markov Chain Monte Carlo (MCMC) [7]. In [8], a discrete Markov chain for the modeling of a wind power time series was proposed considering the uncertainty of the transition matrix by using Bayesian inference. Semi-Markov models used in wind energy generation were also recently examined in Ref. [9]. The authors consider the mean time to failure, which plays a significant role in the reliability studies. Some general applications of the semi-Markov processes have been considered in detail in Ref. [10] and [11]. In these studies, it is possible to find a very large amount of semi-Markov references; therefore, a comprehensive view of the SMC literature can be obtained. In Ref. [12] the modelling of energy generated by a WTG was examined using an indexed semi-Markov model to

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reproduce the statistical behavior of wind speed. Ref. [13] also proposed an indexed semi-Markov chain (ISMC) for wind speed modelling. The results showed that this model can generate the statistical characteristic of observed wind speed. The proposed model was applied to a 10 kW wind turbine generator and the forecasting results are also compared with the autoregressive models. Ref. [14] proposed second and higher order semi-Markov model for using in wind power generation. The authors tried to show different methods for calculating the moments of semi-Markov model in state and sojourn times. Ref. [15] proposed a modified Metropolis–coupled Markov chain Monte Carlo simulation to estimate the stochastic behaviour of different uncertainty sources in the planning of a stand-alone renewable energy-based micro grid. In this study, unlike mentioned approaches which use non-sequential Monte Carlo simulation, we proposed utilizing the sequential Monte Carlo simulation approach in Markov model of a wind farm in order to generate time series of wind power. The sequential Monte Carlo simulation approach according to its characteristics can provide frequency and duration of each state of the Markov model. Therefore, the sequential simulation can incorporate the chronological characteristics of wind speed and mechanical behaviour of the system components simultaneously, while the non-sequential method involves non-chronological system state considerations when utilizing the non-sequential simulation approach. In order to illustrate and compare the results of the proposed and ARMA time series methods with actual data, the IEEE-RTS system is used [16]. In this study, it is shown that, using the proposed method the total number of output power states of the wind farm reduces. Also, the appropriate number of states in multistate WTG model is determined when mechanical behaviour of WTG changes.

The remainder of the paper is organized as follows: Section 2 provides a general description of the WTG model, wind farm modelling and some performance reliability indices which are used in reliability evaluation. Section 3 presents the numerical results obtained by the proposed method and compares them with ARMA method. Section 4 evaluates the impact of some important parameters on power system reliability, and finally, some concluding remarks are made in Section 5.

2. WIND FARM MODELIN

2.1. WTG power curve

As mentioned earlier, the wind turbine output power is a function of its wind speed. Figure (1) shows the power output of a WTG at different wind speeds. Where, Vci, Vr, Vco, and Pr are cut-in, rated, cut-out speed, and the rated wind power generation respectively. To calculate the output power, we can use (1) [18]:

$$P_{WTG}=\begin{cases}0 & SW_t<V_{\mathrm{ci}}\\ (\mathrm{A}+\mathrm{B}\times SW_t+\mathrm{C}\times SW_t^{\,2}).\mathrm{P}_r & V_{\mathrm{ci}}\le SW_t<V\\ P_r & V_{\mathrm{r}}\le SW_t<V_{co}\\ 0 & V_{co}\le SW_t\end{cases}\tag{1}$$

Where, SW_t is the wind speed and the fixed values A, B and C are obtained by the following equations [12].

$$\begin{aligned}A&=\frac{1}{(v_{ci}-v_r)^2}\left\{v_{ci}(v_{ci}+v_r)-4v_{ci}v_r\left[\frac{(v_{ci}+v_r)}{2v_r}\right]^3\right\}\\ B&=\frac{1}{(v_{ci}-v_r)^2}\left\{4(v_{ci}+v_r)\left[\frac{(v_{ci}+v_r)}{2v_r}\right]^3-(3v_{ci}+v_r)\right\}\\ C&=\frac{1}{(v_{ci}-v_r)^2}\left\{2-4\left[\frac{(v_{ci}+v_r)}{2v_r}\right]^3\right\}\end{aligned}\tag{2}$$

2.2. Wind speed modelling with ARMA time series

As mentioned earlier, the ARMA time series approach can be used to predict hourly wind speed. In general, the wind speed at a specific hour is related to the wind speeds of previous hours. The ARMA model can be expressed as follows [19]:

$$\begin{aligned}y_t&=\varphi_1 y_{t-1}+\varphi_2 y_{t-2}+\ldots+\varphi_n y_{t-n}+\alpha_t\\ &\quad-\theta_1\alpha_{t-1}-\theta_2\alpha_{t-2}-\ldots-\theta_n\alpha_{t-m}\end{aligned}\tag{3}$$

where φ_i (i=1, 2, 3, …,n) and θ_j (j=1, 2, 3, …, m) are the Auto-Regressive and Moving Average parameters of the model respectively, and $\{\alpha_t\}$ is a normal white noise process with zero mean and variance $\sigma_a^{\,2}$. The linear least-squares method is used to estimate the parameters φ_i and σ_t when m is zero. However, when m is opposite to zero, the nonlinear least-squares method is used to estimate the φ_i, σ_t, and θ_j. After calculating the time series y_t at each hour t, the wind speed in each hour can be calculated using equation (4):

$$SW_t=\mu_t+\sigma_t y_t\tag{4}$$

Where μ_t and σ_t are the mean and standard deviation of wind speed at hour t. The ARMA model for Manjil is given in Eq. (5).

$$\begin{aligned}&y_t=1.1772y_{t-1}+0.1001y_{t-2}-0.3572y_{t-3}+0.0379y_{t-4}\\ &+\alpha_t-0.5030\alpha_{t-1}-0.2924\alpha_{t-2}+0.1317\alpha_{t-3}\\ &\alpha_t\in NID(0,0.409423^2)\end{aligned}\tag{5}$$

2.3. The proposed method for wind power modeling

2.3.1. Markov chain of the wind speed/power

A Markov process is statistically stationary if the probability of moving from each state to another state during one period does not change over time [20]. As mentioned before, wind speed is a continuous physical phenomenon that varies with time and location. Therefore, the wind speed model can be approximately considered as a stationary Markov process which implies that the distribution of the sojourn time in a given state is exponential. Historical data on hourly wind speed can be used to determine Markov chain with a finite number of states. The transition rates between any two states in a Markov chain with exponentially distributed sojourn time are defined by:

$$\lambda_{ij} = \frac{N_{ij}}{p_i} \qquad (6)$$

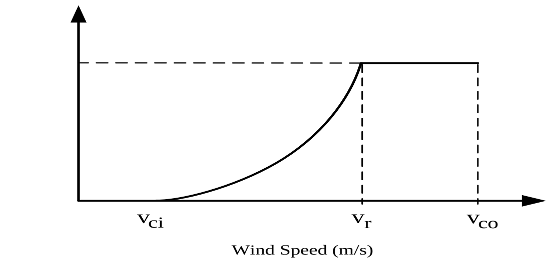

Fig. 1. Power curve of a WTG [17]

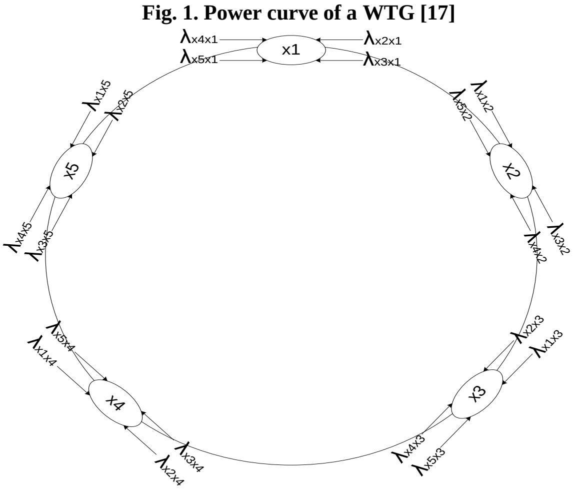

Fig. 2. Markov chain for 5-state wind speed

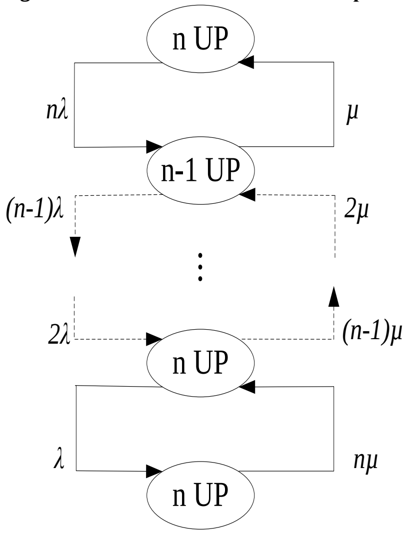

Fig. 3. The Markov Chain for *n* WTG units

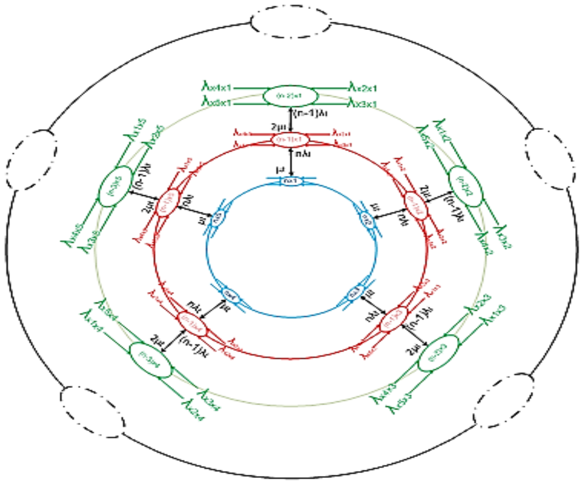

Fig. 4. Markov model of a wind farm with *n* turbines and five states

Where, N_{ij} and P_i are the number of transitions from state *i* to state *j* and the probability of state *i*, respectively. The Markov model for wind speed (m-state) is shown in figure (2).

2.3.2. Markov chain of WTGs

In general, each WTG in a wind farm has two possible states: the state of operation and the state of fail. Indeed, the power generated by a wind farm is not only dependent on wind regime, but also the changes of machine state that resulted from failure and repair rate of WTG's. Figure (3) shows the state diagram for n WTG units. It is assumed that all of the units are similar, where λ and μ are the failure and repair rates of the WTG units. The failure and repair rates of the WTG are the frequency with which it fails and is repaired, respectively.

2.3.3. Markov chain of a wind farm

For a wind farm with *n* similar turbines, the state space should consider both the wind speed/power states and the on/off state of each wind turbine. It should be noted that, at any point in time, the transition rates (i.e., failure and repair rates) between the WTG states are independent of the transition rates between the power states. In general, if we assume that the number of wind speed/power states of the geographical region is equal to *m*, the total number of states that can be considered as the output of the wind farm is given by Eq. (7).

$$k = m(n+1) \qquad (7)$$

Figure (4) shows the Markov model of a wind farm consisting of *n* turbine. It is assumed that m=5 as shown as x_1, x_2, x_3, x_4, and x_5.

2.3.4. Wind power time series generation

One of the advantages of this method is to consider the repair and failure rates of each wind turbine at the same time and during the modelling process. In general, the proposed method which benefits from simulation and analytical approaches consists of the following steps:

1) With regard to the wind speed in each hour and the status of each WTG, wind power time series for one year (8760 hours) is generated.

2) Base on the wind power time series generated in the previous step, the stochastic transitional probability matrix (*STM*) can be calculated as follows:

$$STM=\begin{bmatrix}1-SUM_1 & \lambda_{12} & \lambda_{13} & \cdots & \lambda_{1k}\\ \lambda_{21} & 1-SUM_2 & \lambda_{23} & \cdots & \lambda_{2k}\\ \vdots & \vdots & & \ddots & \vdots\\ \lambda_{k1} & \lambda_{k2} & \lambda_{k3} & \cdots & 1-SUM_k\end{bmatrix} \quad (8)$$

Where, λ_{xy} is the transition rate from state x to y and $SUM_i=\sum_{j=1}^{k}\lambda_{ij}$. It is assumed that the system is in the $X(N)=S_i$.

3) This state includes the following parts:

a. k uniformly distributed numbers (r_1, r_2, ...,r_k) between 0 and 1 are generated to sample the Time To Exit (*TTE*) in each state before moving to other states. By using the inverse transform method for the *n*-order Markov chain the *DTS* is calculated as:

$$TTE_{ci}=-\frac{1}{\lambda_{ci}}\ln(r_i) \quad \text{(i=1, 2, ..., k)} \quad (9)$$

b. The smallest TTE is selected as the next state of the system and the counter is updated as Equation (12). For example, if TTE_{cj} is smaller than any other, S_j is known as the next state of the system.

$$t=t+min(TTE) \quad (10)$$

c. Previous steps are repeated for one year (*t=8760*).

4) The power output of the wind farm is added to those of other conventional power plants and finally, reliability indices are calculated based on the given hourly load demand.

5) Steps 1 to 4 are repeated until convergence criteria (ϵ) are met.

2.4. Power system reliability indices

Loss of Load Expectation (*LOLE*), Expected Energy not supplied (*EENS*), loss of load frequency (*LOLF*), and loss of load duration (*LOLD*) are among the most important indices in power system reliability [21 and 22]. The index of *LOLE* represents the average number of hours the power system cannot supply its load while the index of *EENS* represents the average amount of energy that is not supplied.

$$LOLE=\frac{1}{N}\sum_{y=1}^{N}\sum_{h=1}^{8760}t_h \quad \text{(hours/year)}$$
$$t_h=\begin{cases}1 & \text{if Load > Generation in hour h}\\ 0 & \text{Otherwise}\end{cases} \quad (11)$$

$$EENS=\frac{1}{N}\sum_{y=1}^{N}\sum_{h=1}^{8760}e_h \quad \text{(MWH/year)}$$
$$e_h=\begin{cases}\text{Load-Generation} & \text{if Load > Generation in hour h}\\ 0 & \text{Otherwise}\end{cases} \quad (12)$$

LOLF and LOLD also can be calculated as follows:

$$LOLF=\frac{1}{N}\sum_{y=1}^{N}\sum_{h=1}^{8760}f_h \quad \text{(occurrence/year)}$$
$$f_h=\begin{cases}1 & \text{if Load > Generation in hour h}\\ & \text{and Load < Generation in hour h-1}\\ 0 & \text{Otherwise}\end{cases} \quad (13)$$

$$LOLD=\frac{\sum_{y=1}^{N}\sum_{h=1}^{8760}t_h}{\sum_{y=1}^{N}\sum_{h=1}^{8760}f_h} \quad \text{(hours/occurrence)} \quad (14)$$

3. TEST SYSTEM AND SIMULATION RESULTS

The IEEE Reliability Test System (RTS) was used to compare the previous method discussed in wind power modelling and reliability studies [14]. The IEEE-RTS consists of 24 buses with an installed capacity of 3,405 MW and a peak load of 2850 MW. Also, in this paper, it is assumed that wind turbines manufactured by Gamesa Company are used to inject electric power from wind power. The WTGs used in this study have a rated power of 2 MW, and the cut-in, rated, and cut-off speeds are 4, 16, and 25 m/s, respectively. In order to model wind power, hourly wind speed data in Manjil region has been used.

To compare the results of the proposed method and the ARMA time series one with actual results, 170 MW of wind power (85×2MW) is connected to the RTS. Figures (5-8) show the results of using different methods in calculating risk and frequency indices. It can be visually understand that proposed method is more reliable than ARMA model. It is owing to the fact that the sequential MCS provides more accurate frequency and duration assessments than the non-sequential MCS. In other words, the inherent benefit of the chronological representation used in the sequential MCS is the opportunity to model more accurately the power output of intermittent energy resources such as wind power. The proposed method is able to approximately reproduce the statistical properties of wind data which imposes statistical errors.

Table (1) shows the results obtained using mentioned methods in calculating reliability indices. As shown in this table, the proposed method has a better performance in comparison to the ARMA time series one especially in calculating LOLE and EENS. The percentage of error varies between 0.4% and 3.4% while it increases to 9.7% when ARMA approach is applied. Indeed, the simulation results validate the effectiveness of the proposed method in reproducing the statistical characteristics of wind power. Differences in the obtained results can have a significant effect on the power system designer's decision-making. Therefore, the correct way of evaluation can play an important role.

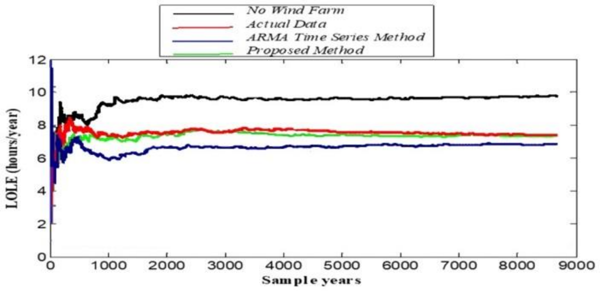

Fig. 5. Convergence trend of LOLE using different wind power modelling methods

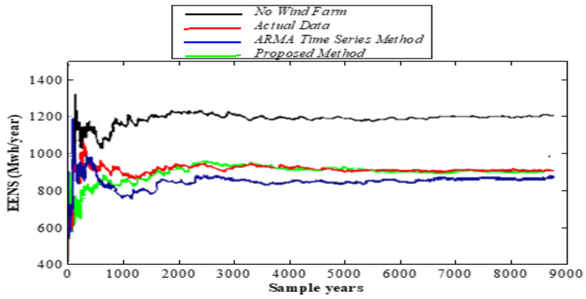

Fig. 6. Convergence trend of EENS using different wind power modelling methods

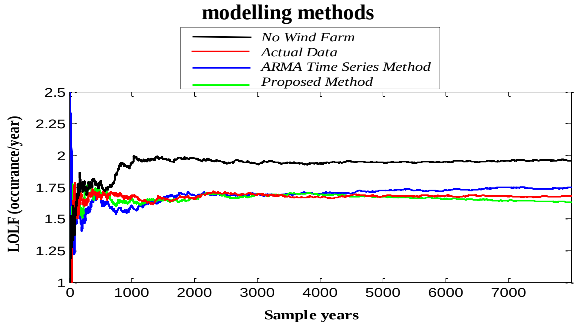

Fig. 7. Convergence trend of LOLF index using different wind power modelling methods

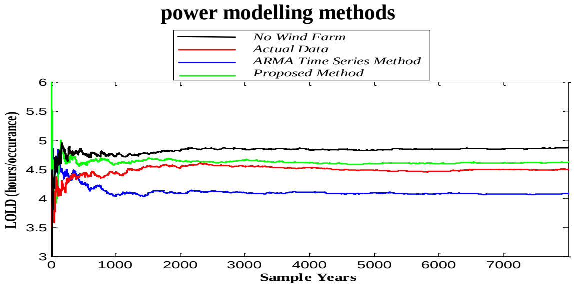

Fig. 8. Convergence trend of LOLD index using different wind power modelling methods

Table 1. Comparison of the proposed method and ARMA time series one

Reliability Indices	ARMA time series method	Error (%)	Proposed method	Error (%)	Actual wind data
LOLE (hr/year)	7.12	5.8	7.47	1.2	7.56
EENS (MWh/yr)	884	4.1	918	0.4	922
LOLF (occ./yr)	1.747	4.3	1.617	3.4	1.675
LOLD (hr/occ.)	4.078	9.7	4.619	2.3	4.515

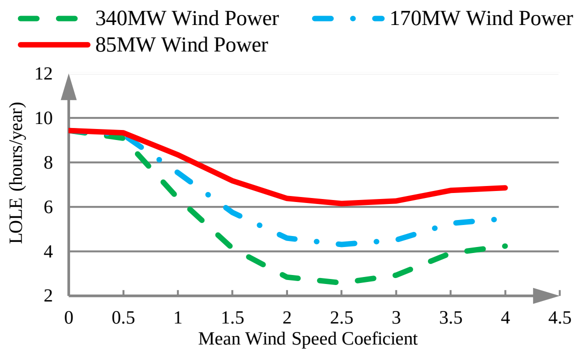

Figure 9: The effect of the mean wind speed on the LOLE index

4. SIMULATION CASE STUDIES

Having shown the superiority of the proposed method over the other conventional methods, it is necessary to evaluate the proposed method in practical applications. The synthetic wind power time series generated by the proposed method is used as input data in order to evaluate some important factors. For this purpose, some of these parameters will be evaluated in this study.

4.1. Average wind speed

Wind speed can have a significant effect on the output power of wind power plants. The average wind speed can be considered as a suitable parameter for assessing the impact of wind speed on the power system reliability indices. Figure (9) shows the effect of increasing the mean wind speed of the studied location on the LOLE index when 85, 170, and 340 Mw WTG are added to the RTS. As it can be seen, with increasing this coefficient, the LOLE decreases. Subsequently, it enters the saturated area, and eventually, the figure increases again. In fact, by increasing the average wind speed, the electrical power generated by WTGs will increase, and therefore, reliability improvement can be seen. However, when the average wind speed reaches 25 m/s, wind turbines cannot produce electrical energy due to mechanical restriction (as shown in figure (1)), and the reliability of the power system will be in danger again.

4.2. Mechanical restrictions of WTGs

The forced outage rate (FOR) of wind turbines is another parameter that can be considered for the reliability analysis of the power system. For this purpose, 85 MW wind power is assumed to be added to the RTS. Figure (10) shows the effect of increasing the FOR of wind turbines on the LOLE index. This analysis is conducted for various values of the mean wind speed.

As it can be seen, by the FOR of wind turbines increasing, the risk of the system grows. However, the effect of changes in the FOR is negligible when the wind regime changes. In other words, the region's wind regime is more important than the mechanical behaviour of WTGs in assessing the reliability of the studied power system.

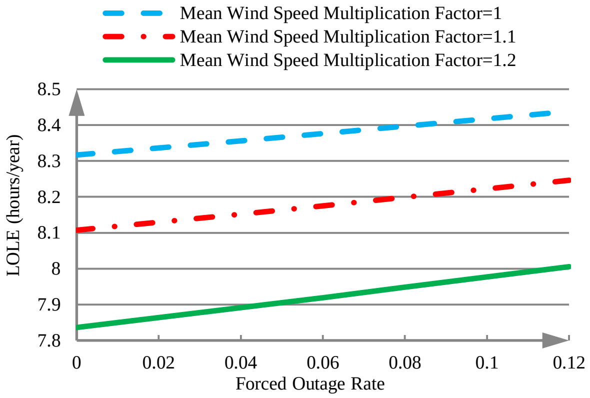

Fig.10. Effect of the FOR on the LOLE index for different values of the mean wind speed

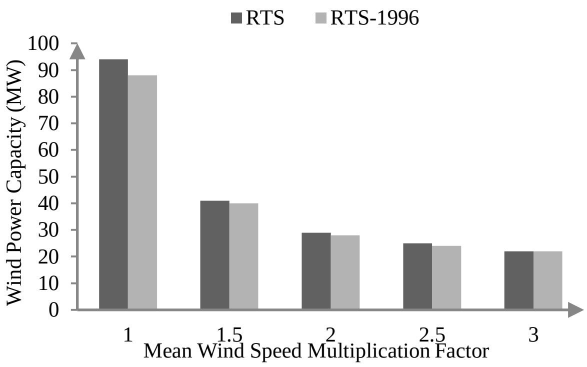

Fig. 11. Effect of system dimensions on the wind power capacity credit

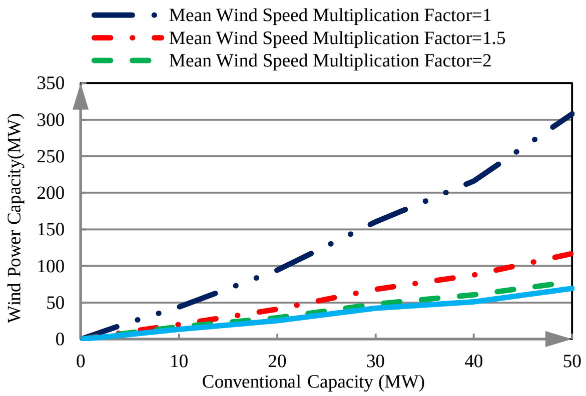

Fig. 12. The relationship between wind power plants and conventional ones in different wind regimes

4.3. Capacity credit of wind farms

Generally, to calculate the capacity credit of wind power plants, at first, one of the conventional units of the production system is eliminated, then the wind units are added to the system gradually. In each step of the reliability indices of the new production system are calculated. This trend continues until the index value reaches its initial value.

4.3.1. Effect of system dimensions on the reliability of wind power plants

To evaluate the effect of system dimensions on the capacity credit of wind power plants, RTS and RTS-1996 have been used [23]. In both systems, a unit of 20 Mw will be eliminated. As a result, the risk of the system is affected and increased. In the next step, it is necessary to inject the wind power plant gradually into the systems to achieve the desired reliability index to its initial value. It should be noted that in this study, wind speed data in the region of Manjil has been used. The LOLE index is also used as a criterion in both systems. Figure (11) shows the effect of system dimensions on the capacity credit of the wind farm in various amounts of the mean wind speed multiplication factor.

As can be seen, the dimensions of the system do not affect the capacity credit of the wind power plant, and with increasing average wind speed, this effect decreases further. Figure (11) also shows that with increasing average wind speed, the wind power reliability increases. In fact, by increasing the average wind speed, the capacity of the required power plant will be equivalent to the capacity of conventional power plants. Figure (12) shows the relationship between wind power plants and conventional power plants more tangibly.

5. CONCLUSION

In this study, a new method was proposed to generate synthetic wind power time series for a wind farm. The proposed methodology takes advantage of sequential Monte Carlo which can consider all of the transition rates of each state to other states in the simulation process. Hence, Not only it models the chronological order of wind speed but also it can consider accurately the probability distribution of original wind speed data. In this regard, the synthetic wind power time series generated by the proposed method and ARMA time series method were analysed in terms of reliability indices. The comparison between the measured wind power and the synthetic ones proved that the proposed method is able to reflect more comprehensive wind power characteristics. In this study, the effects of other important parameters in power system such as wind regime, mechanical behaviour of WTGs on reliability indices were also investigated. However, the proposed method and discussions, however, can provide useful information for power system planners.

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