A novel Monte Carlo based modeling strategy for wind based renewable energy sources

A.Y. Abdelaziz
Electrical Power & Machines, Faculty of Engineering
Ain Shams University
Cairo, Egypt
almoatazabdelaziz@hotmail.com

M.Ezzat
Electrical Power & Machines, Faculty of Engineering
Ain Shams University
Cairo, Egypt
moh_ezzat@yahoo.com

Mahmoud M.Othman
Electrical Power & Machines, Faculty of Engineering
Ain Shams University
Cairo, Egypt
eng_mmo@yahoo.com

A.M. Mahmoud
Electrical Power & Machines, Faculty of Engineering
Ain Shams University
11517 Cairo
Cairo, Egypt
amahmoud_89@yahoo.com

Abstract— **This paper introduces a new algorithm strategy in order to model wind based renewable energy sources which are used for planning purposes in distribution systems. Initially, the available data of the wind speeds are divided into seasonal data (i.e. the available data of each season is separated) then the available separated data is divided into hourly data (i.e. 24-hours for each season). This algorithm is based on Monte Carlo Simulation Method which considers the stochastic nature of the wind power through the correct determination of the appropriate cumulative distribution function. Monte Carlo Simulation technique is utilized for obtaining the most likelihood wind turbine output power at each hour at each season. The results of the proposed strategy is compared with another probabilistic model to show the effectiveness of the proposed algorithm. The proposed algorithm is tested using MATLAB environment and the results and comparisons show that the proposed modeling algorithm gives accurate results.**

Keywords—Modeling, Monte Carlo, Renewable Energy, Wind

I. INTRODUCTION

The traditional sources of energy which are based on fossil fuels, are unsustainable and harmful for the environment so a shift is needed in the direction of using renewable energy sources (RES) which are unpredictable and uncontrollable as they strongly depend on climate, ambient temperature, season and time [1]. Wind energy is considered the lowest risk technology which is used for energy production due to the recent developments in both technical and commercial options. However, the wind power follows a stochastic nature dependent on the wind speed ,Thus, a precise strategy is required for modeling the wind power including their uncertainties [2]. Moreover, the uncertainty of the wind power should be integrated in the modeling strategy because the existence of only one single-point forecast value makes it less sensitive in power system operation ,Thus, wind power follows a stochastic distribution dependent on the uncontrollable wind speed, Thus, the output wind power distribution for certain forecasted values can be described by a theoretical distribution (Weibull distribution in case of modeling wind power) [3].

The electric power system is most commonly analyzed by using deterministic power flows analysis; however, the recent change in load magnitudes and uncertainty of output power of renewable generators cannot be dealed with in this type of power flows because it uses a certain values of power and these values may not be accurate values. Probabilistic power flow is used to overcome these problems because they consider the uncertainty of the input quantities so it leads to more accurate values. Monte Carlo simulation (MCS) methodology is commonly used in probabilistic power flows because it develops non-linear power flow equations. MCS provides results with accurate values when it is compared with analytical methods in spite of taking a huge computational time and their complexity Results of analytical methods give only an indication as they perform a simplified assumptions which consider only one snapshot for the loading of the power system so they don't require a huge time for implementation and they are easy to be implemented [4] so numerical methods which based on MCS is preferred rather than analytical methods.

The probabilistic power flow (PPF) based on MCS can be defined as a numerical method which is used to estimate the output power of the renewable energy sources based on probabilistic approach, sequential monte carlo simulation (SMCS) was used in order to evaluate power system parameters including wind energy, simulating the hourly wind speed values and for evaluating the contribution of wind energy sources to the reliability of the generating systems as presented in [5]. In [6] the author proposes a new technique for studying the effect of uncertainties of wind power generation on short-term power system operation by using MCS in order to obtain a set of wind generation scenarios which are then used into the problem formulation of the unit commitment problem in order to show the effects of the generation of the wind energy on the electricity market prices, load shedding, social welfare and power system capacity.

Authors in [7] presented a new formulation of probabilistic load flow for distribution systems considering high penetration of renewable energy sources considering the dependency between

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load magnitude and different generation resources using cumulants method which is considered one of the analytical methods that have been provided in assessments of generation systems contains wind and photovoltaic power. Ref [8] proposed a novel for probabilistic power flow to improve transmission system inadequacy based on the combination of the concept of cumulants and Gram-Charlier expansion theory in order to have the probability distribution functions of transmission line flows.

In [9] the authors presents a novel in order to obtain probabilistic load flow analysis when dependence between input powers is considered by using MCS which is the only choice that can be used in this case because analytical methods cannot be applied in this case, Moreover the author indicated the role of stochastic dependence which indicates the relation between random variables, not taking this correlation into account can lead to a great underestimation of the power system results which leads to wrong design decisions. Authors in [10] provided a new method in correlated probabilistic load flow (PLF) which is called the method of Zhao's point estimate method (PEM) combined with Nataf transformation, this method can deal with input random variables which are correlated with normal or non-normal probability distribution also this method requires both the data of the marginal distribution function for all input random variables (RVs) and their correlation coefficients instead of joint probability density function (PDF).

In [11] a method based on two point estimate method (2PEM) is used for taking uncertainties into account in the optimal power flow for the competitive electricity markets , one of the advantages of this method that the derivatives of the nonlinear functions are not required which are used in the computation of the probability distributions. In ref. [12] An efficient approach for probabilistic transmission expansion planning considering the uncertainties of wind power generation by using both Benders decomposition algorithm in conjunction with MCS for studying the effect of increasing wind power generation in transmission systems and to study reliability requirements.

Authors in [13] presented an empirical strategy that uses the incomplete wind data to get a wind farm wind speed model by employing Monte Carlo to evaluate system parameters. In [14] both MCS and market based optimal power flow make into consideration the different combinations for wind generation which are introduced to have the integration of wind turbines in the distribution systems, the proposed algorithm allows to evaluate power that may be injected into the grid in addition to the impact of high penetration of wind power on the social welfare and on marginal prices of distributed generators.

This paper proposes a probabilistic new modeling strategy for wind power generation. The proposed probabilistic strategy is dependent on MCS and considers the stochastic nature of wind power through the determination of the appropriate cumulative distribution function (CDF). The seasonally/hourly variations of the wind power is considered in the modeling strategy. The results of the presented strategy is compared with a probabilistic model presented in [15] and [16] which is based on calculating the appropriate probability density function (PDF). The rest of the paper is organized in 4 sections. Section II describes the methodology strategy. Section III describes the modeling strategy in [15] and [16]. Results and conclusions are finally presented in sections IV and V, respectively. The discussed algorithms are tested in MATLAB environment. The comparison shows that the results of the two methods are in close which validates the proposed modeling strategy.

II. Modeling Strategy

This section explains the introduced model algorithm of wind power, the introduced probabilistic model is based on Monte Carlo simulation according to of historical data among the years 1983-2013 (i.e. 31 years) with one reading of the wind speed available at each hour. The available data is divided into seasonal data (i.e. the available data of each season is separated). Moreover, the divided seasonal data is further subdivided into 24- hours time segments, each segment refers to a specific hourly interval for each season. Thus, for each year there are 96 time segments (i.e. 24 time segments for each season). The behavior of wind speeds is modeled by using the Weibull CDF. Finally, the following strategy is used for determining the output wind power from the wind turbine.

(1) Start with h=1 (i.e. the first hour) of the 96 hours (24 hours*4seasons).

(2) Calculate the Weibull CDF of the wind speed data for each hour.

(3) Generate a vector which consists of 10,000 uniformly distributed random numbers and their values are between [0, 1].

(4) Calculate from inverse CDF function (CDF^{-1}) the corresponding simulated wind speeds according to the value of the random number.

(5) The output wind power depends on two parameters the wind speed of the site in addition to the characteristics of the wind turbine. For each hour of the 96 hours and at each value of the simulated wind speed. The corresponding wind power can be calculated using (1).

$$P(W) = \begin{cases} 0 & W \leq Wci \\ Prated\left(\frac{W-Wci}{Wr-Wci}\right) & Wci \leq W \leq Wr \\ Prated & Wr \leq W \leq Wco \\ 0 & W \geq Wco \end{cases} \quad (1)$$

where W is the simulated wind speed (m/s), W_{ci} is the cut in speed, W_r is the rated speed, W_{co} is the cut out speed and P_{rated} is the rated turbine power (MW).

(6) Determine the most likelihood value of the obtained 10000 random wind powers at each hour at each season by using MCS method. The average wind power is determined by using Monte Carlo convergence. For 10000 simulation which is considered a very large number, the Monte Carlo convergence is

considered to be accurate. The most likelihood wind power value is calculated by using (2).

$$P_{ave}=\frac{1}{NS}\sum_{J=1}^{NS} P(J) \qquad (2)$$

Where P_{ave} is the most likelihood wind power value which is calculated at each time segment, P (j) is the power random variable at each time segment and NS is the total number of simulations (i.e.10,000). The MCS method is done to all time segments in order to obtain the most likelihood values of wind powers at each time segment at each season so that a typical day model is formed for each season in order to represent the behavior of output wind powers during the different periods in that season. The above steps are shown in Fig.1.

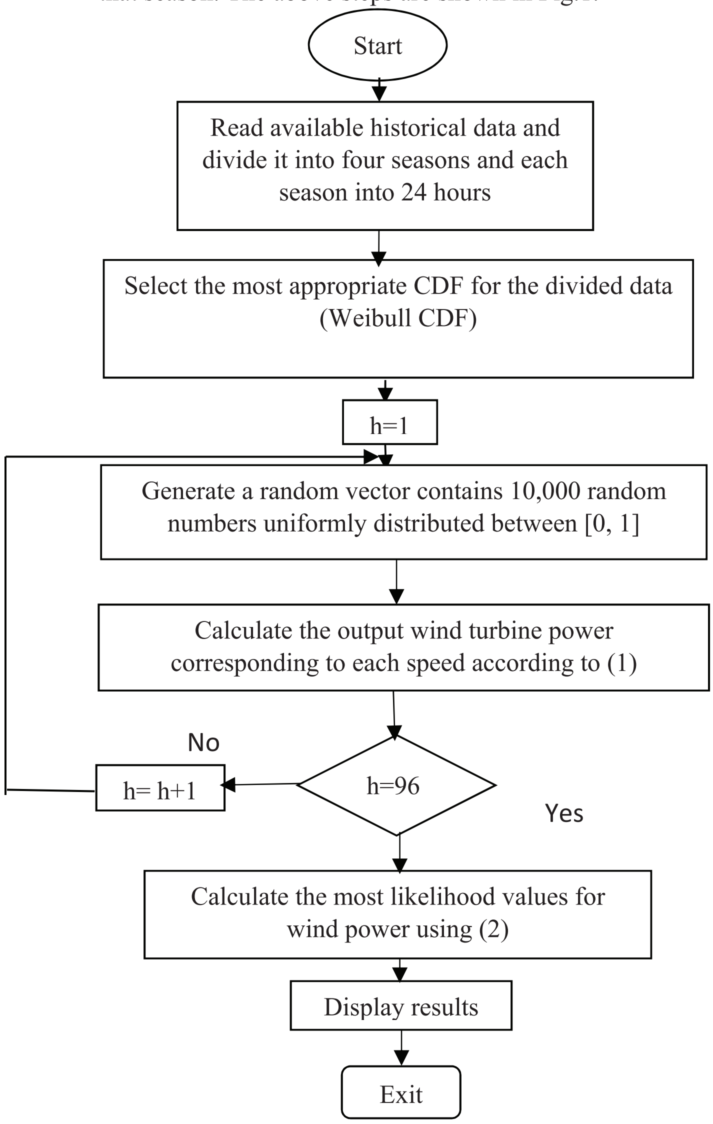

Fig.1. Modeling strategy flow chart.

III. Model described in [15] and [16]

This section highlights the modeling strategy described in [15] and [16] for the purpose of comparison with the proposed method. The model can be explained in the following procedure.

(1) Start with h=1 (i.e. the first hour) of the 96 hours (24 hours*4seasons).

(2) Calculate the PDF for each hour by dividing the wind speeds at each hour into several states, each state has a specific limit of wind speed is presented as in Table 1. The number of multi-states is carefully selected because having a small number of states can have an effect on the accuracy while having a larger number of states increases the complexity of the problem.

Table 1

Appropriate states of wind speed

Wind speed state	Wind speed limits m/s
1	0-1
2	1-2
.	.
.	.
Last state	Wmax-1 to Wmax

(3) Calculate the power at each state using (1). For simplicity the output power of each state is calculated for the midpoint speed of each state (i.e. if the limits of the first state is 0 and 1 m/s so the value of wind speed at this state is chosen to be 0.5 m/s).

(4) Calculate the most probable power for each hour using (3).

$$P_{ave}=\sum\big(P\ state * (probabillity\ of\ each\ state)\big) \qquad (3)$$

Where the probability of each state is the number of wind speeds in each state divided by the total number of available data.

IV. Results

The algorithm which is used in modeling of wind-based power presented in section II is applied to historical data for a certain Netherlands windfarm containing the wind speed at each hour at each day for 31 years. The results are organized as follow.

(i) CDF and PDF for the available data

The hourly Weibull CDF's are obtained for each hour in each season. Fig.2. shows the obtained CDF at h=3 (i.e. 03:00 a.m. of the typical day of winter season).

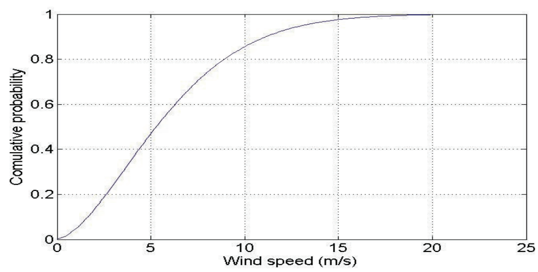

Fig.2. Cumulative distribution function at (03:00 a.m.) of winter season.

From the above CDF it can be deduced that at h=3 (i.e. 03:00 a.m. at the winter typical season) there are 64.58% of wind speeds in this hour is between W_{ci} and W_{co} so it results in a certain value for the output power (i.e. not equal to zero), 34.34% of wind speeds are below W_{ci} (i.e. the output power=0) and 1.08% of the wind speeds are above W_{co} (the output power=0). The hourly PDFs are obtained for each hour in each season. Fig.3 shows the obtained PDF at h=3 (i.e. 03:00 a.m. of the typical day of the winter season).

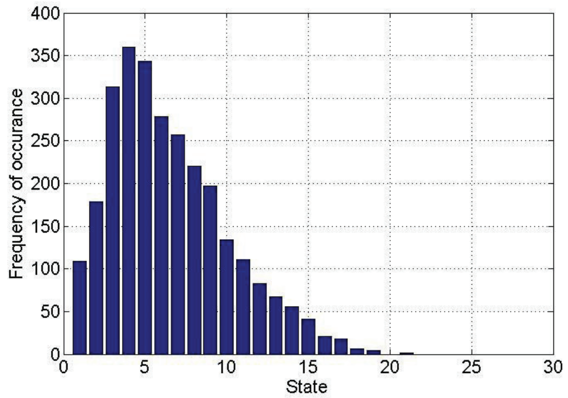

Fig.3. Probability Density function at (03:00 a.m.) of winter season.

Fig.4. shows another obtained CDF at h=51 (i.e. 03:00 a.m. of the typical day of summer season).

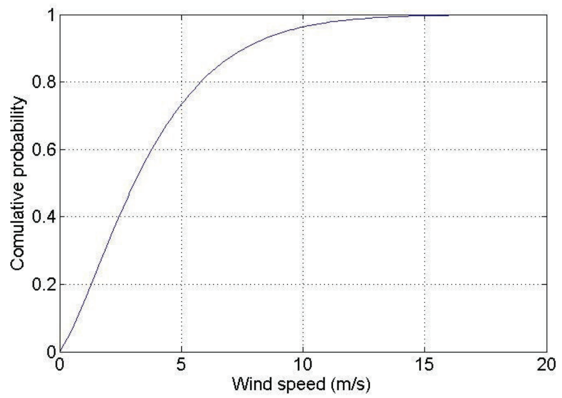

Fig.4. Cumulative distribution function at (03:00 a.m.) of summer season.

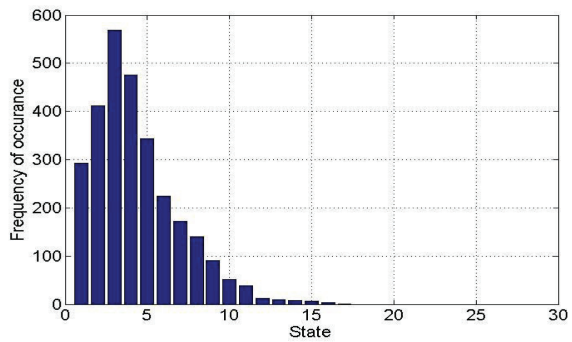

Fig.5. Probability Density function at (03:00 a.m.) of summer season.

Fig.5 shows another obtained PDF at h=51 (i.e. 03:00 a.m. of the typical day of summer season.

(ii) Results of the proposed method

The converged MCS results of the 96h (i.e. all time segments) of the four seasons are obtained for a wind turbine of the characteristics which is presented in table 2.

Table 2

Characteristics of the available wind turbine

Features	Turbine
Rated power	1 MW
Cut in speed (W_{ci})(m/s)	4
Rated speed (W_r) (m/s)	8
Cut out speed (W_{co})(m/s)	16

The converged MC results of the average power of the wind turbine (output power from the wind turbine at each hour of the 96 hours for the 4 seasons) are presented in Fig.6.

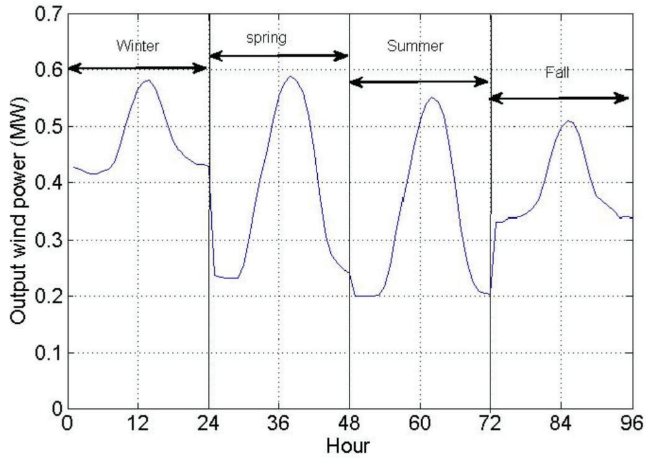

Fig.6. Output wind power over all the hours (i.e. 96 hours).

(iii) Validation of MCS results

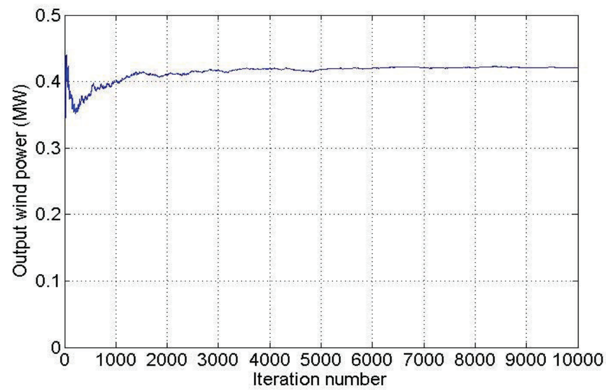

Fig.7. MC Simulation for h=3 of the winter season.

Fig.7. shows the relation between the output wind power and number of iterations (i.e. 10000 iteration) at h=3.

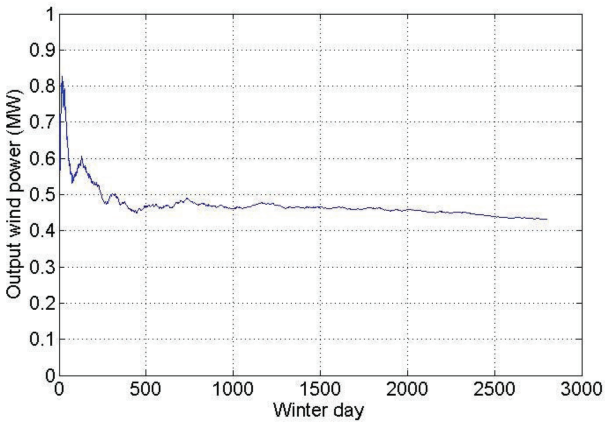

Fig.8. Output power for the original data at h=3 of the winter season.

Fig.8. shows the relation between the output wind power and winter days (i.e. 2798 days) at h=3.

It can be shown that from the above two figures (i.e. Fig.7., Fig.8.) the results obtained from Monte Carlo Simulation is very near to the results obtained from the actual data which proves the effectiveness of the proposed algorithm.

(iv) Comparison with [15] and [16]

Fig.9. shows the relation between the average wind power and hours (i.e.96 hours) of the second algorithm which is so near to the results obtained from the proposed algorithm. Fig.6. and Fig.9. show the fact that the peak output power from the wind turbine is obtained at mid-day of the typical day of each season as this hour is corresponding to the system peak at this typical day at each season.

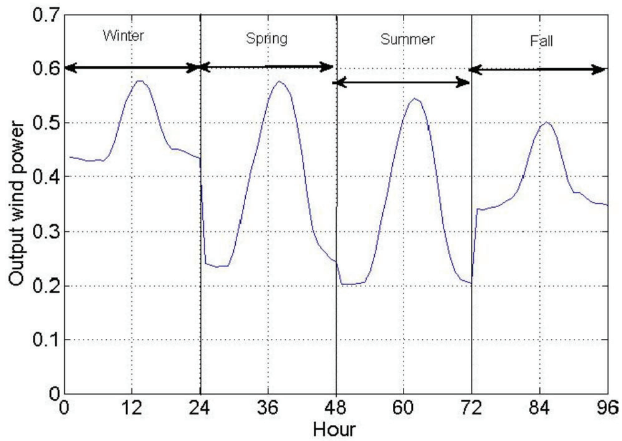

Fig.9. Output wind power over all the hours (i.e. 96 hours).

The following tables shows a comparison between the proposed method and the method in [15] and [16]. Table 3 shows the hourly typical winter season output power from the wind turbine. Table 4 shows the hourly typical spring season output power from the wind turbine.

Table 5 shows the hourly typical summer season output power from the wind turbine.

Table 6 shows the hourly typical fall season output power from the wind turbine.

Table 3
Hourly typical winter season output power

Hour	Method 1	Method 2
1	0.42787	0.43670
2	0.42582	0.43410
3	0.42040	0.43254
4	0.41559	0.42968
5	0.41628	0.42924
6	0.42239	0.43053
7	0.42509	0.42959
8	0.43628	0.44036
9	0.46696	0.46560
10	0.50553	0.50232
11	0.53809	0.53762
12	0.56991	0.56348
13	0.58040	0.57814
14	0.58406	0.57943
15	0.57117	0.56478
16	0.54342	0.53440
17	0.50591	0.49227
18	0.47562	0.46591
19	0.45928	0.45202
20	0.44619	0.45113
21	0.43985	0.44800
22	0.43356	0.44322
23	0.43331	0.43786
24	0.43001	0.43442

Table 4
Hourly typical spring season output power

Hour	Method 1	Method 2
1	0.23316	0.23966
2	0.23034	0.23637
3	0.22889	0.23304
4	0.22897	0.23523
5	0.22863	0.23527
6	0.25201	0.26223
7	0.30310	0.30943
8	0.35940	0.36347
9	0.41197	0.41168
10	0.45931	0.45345
11	0.50937	0.50118
12	0.55309	0.54089
13	0.57616	0.56715
14	0.58800	0.57885
15	0.58049	0.57192
16	0.56022	0.55321
17	0.51656	0.50675
18	0.45189	0.44592
19	0.37011	0.36904
20	0.30211	0.30501
21	0.26948	0.27595
22	0.25358	0.26175
23	0.24305	0.25000
24	0.23617	0.24115

Table 5
Hourly typical summer season output power

Hour	Method 1	Method 2
1	0.19620	0.20249
2	0.19672	0.20293
3	0.19667	0.20297
4	0.19673	0.20367
5	0.19890	0.20643
6	0.21272	0.22261
7	0.25039	0.26056
8	0.31074	0.31623
9	0.36782	0.36921
10	0.41886	0.42273
11	0.47006	0.47107
12	0.51159	0.50903
13	0.53981	0.53682
14	0.55182	0.54663
15	0.54364	0.53914
16	0.51804	0.51166
17	0.46170	0.45306
18	0.39253	0.38372
19	0.31540	0.30834
20	0.25327	0.25276
21	0.22036	0.22344
22	0.20536	0.21130
23	0.20134	0.20735
24	0.19981	0.20499

Table 6
Hourly typical fall season output power

Hour	Method 1	Method 2
1	0.33077	0.34159
2	0.33055	0.34039
3	0.33623	0.34358
4	0.33644	0.34558
5	0.33907	0.34753
6	0.34435	0.35453
7	0.35206	0.36051
8	0.36647	0.37429
9	0.39990	0.40052
10	0.44026	0.43770
11	0.47449	0.47226
12	0.49802	0.49211
13	0.51014	0.50261
14	0.50687	0.49544
15	0.48562	0.47155
16	0.44742	0.43123
17	0.40576	0.39396
18	0.37592	0.37221
19	0.36657	0.37154
20	0.35647	0.36375
21	0.34746	0.35524
22	0.33603	0.35231
23	0.33764	0.35134
24	0.33726	0.34793

V. Conclusions

The proposed novel algorithm for modeling wind power based on their stochastic nature of the wind speed is presented in the paper and it is compared with a different way for modeling which is presented in previous literature. The proposed algorithm is based on MCS method and used to determine the hourly/seasonal output wind power from the wind turbine. There are two ways for modeling the wind power one based on cumulative distribution function (CDF) and the other based on probability density function (PDF) , the two ways gives results near to each other as presented in the paper (i.e. the proposed method depends on CDF and the other method depends on PDF).

The results might be more promising if it used in applications in the distribution system such as load management using energy storage systems (ESS) in order to maximize the arbitrage benefit (i.e. it is the difference in price of the electricity while selling it with high price in on-peak periods and buying it with a small price in off-peak periods).

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