Reliability Evaluation for Distribution System With Renewable Distributed Generation During Islanded Mode of Operation

Yasser M. Atwa, *Student Member, IEEE*, and Ehab F. El-Saadany, *Senior Member, IEEE*

***Abstract*—Keen interest in the development and utilization of wind-based distributed generations (DGs) has been currently observed worldwide for several reasons. Among those is controlling the emission of environmentally harmful substances, limiting the growth in energy costs associated with the use of conventional energy sources and encouraging the independent power producers for participation in the electricity market system. One of the most important issues is to quantitatively assess the impact of such type of DGs on the distribution system reliability. This paper presents a probabilistic technique to evaluate the distribution system reliability utilizing segmentation concept and a novel constrained Grey predictor technique for wind speed profile estimation.**

***Index Terms*—Distributed power generation, distribution system reliability, uncertainty, wind power.**

I. Introduction

WIND power is an environmentally attractive form of renewable energy from an overall fuel consumption perspective. Currently wind power is accounted for 1.2% of the electricity generation in Canada [1], with an annual growth rate of 35% from (2000–2005). This growth rate has increased in 2006 reaching 54% with total installed capacity of 1218 MW, and it is expected to reach 5000 MW by 2012 as shown in Fig. 1. If wind power can be supplied to consumers at reasonable prices without degrading the distribution system security and reliability, it will be a technology with a vast potential. In achieving this goal, the intermittent nature of wind power generation represents the most technical and economical challenges that we must overcome before wind power can effectively proliferate into the electricity supply.

The power generated by wind-based distributed generation (DG) is well recognized as being unpredictable, and subjected to the most variability among all other DG technologies. Distribution system reliability is one of the most important challenges that the system planers encounter, especially when wind-based DGs are deployed in the system. The reliability aspects of utilizing wind energy have largely been ignored in the past due the relatively insignificant contribution of these sources in major power systems, and also due to the lack of appropriate techniques.

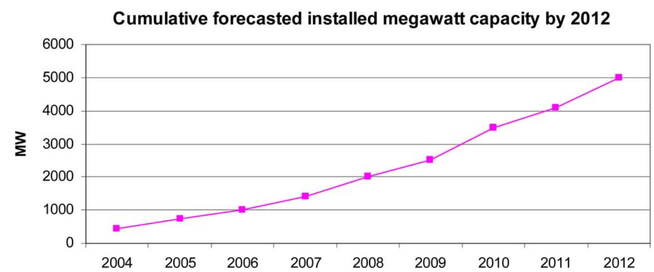

Fig. 1. Wind power growth in Canada.

However, the global trends toward increasing the sustainable power penetration in existing power system dictate a very serious need to consider their effect on the system reliability.

Research interest in the reliability assessment of power systems with renewable energy sources dates back to the early 1970s. The work in [2] proposed two probabilistic techniques to model the wind generation system. The first one was in the form of capacity outage probability table based on the Weibull distribution of the wind speed, while the second was a Markov model based on the detailed hourly mean speed data. In [3], a probabilistic approach to capture the uncertainty associated with the renewable sources was used. Analytical approaches were proposed in [4]–[8]. In [4] analytical approach to model wind turbine generators as multi-state unit was used, however, [5] and [6] proposed an analytical approach to model renewable energy sources considering the correlation between the load and the renewable sources. In [7] and [8] an approach to estimate the loss of power supply probability (LPSP) of stand-alone solar generation system was developed. Deterministic chronological simulation was proposed in [9] and [10] to estimate (LPSP). Monte Carlo simulation (MCS) was extensively used in [11]–[13] to evaluate the system reliability by modeling the random output of the renewable sources, load variation and the forced outage rate of the system component over a sufficiently long study period. During the beginning of the 21st century, [14]–[17] made pioneering efforts to apply system well-being criteria to the small autonomous power system (SAPS) including renewable energy sources. They used sequential (MCS) approach for adequacy assessment of the SAPSs with renewable energy sources. Later [18]–[20] applied sequential (MCS) approach to calculate the loss of load expectation (LOLE) and the loss of energy expectation (LOEE) of the renewable energy sources based SAPSs with battery storage.

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The authors are with the Department of Electrical and Computer Engineering, University of Waterloo, ON N2L 3G1, Canada (ymoustaf@uwaterloo.ca).

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From the above discussion, it is obvious that sufficient work has been done to assess the reliability of SAPS as well as grid-connected systems with renewable DGs. The system well-being approach is a relatively new concept which combines the deterministic and probabilistic methods to evaluate the system adequacy. Only MCS method has been used for the well-being assessment of a system with renewable DGs, and analytical methods have not yet been developed. The main drawback of MCS is the enormous number of time consuming iterations required for proper convergence and hence, becomes complex and unsuitable in some case studies. Moreover, to the authors' knowledge, most of the work presented in literature concentrated on grid-connected mode of DG operation and did not address the impacts of the renewable DGs on the reliability of the system under islanded-mode of operation. When an island is created, it can be treated as a SAPS for the islanding duration that is typically short. Within this period of time the DGs connected to the island are assumed to be characterized by zero failure rates. Due to the aforementioned assumption the well-being approach, which determines the system state (healthy, marginal or at risk) can not be applied when assessing the island reliability. Because the most important issue during the islanded-mode of operation is to determine the probability of the island to be a success (the DG power output within the island matches the load) or to fail (there is a deficit in power generation). In this paper an analytical technique is proposed to assess the reliability of an island containing renewable DGs. Further, the paper will investigate how the island reliability will impact the distribution system reliability at large. The proposed technique in this paper is based on a combination of a new methodology for wind speed profile estimation, and a probabilistic correlation between wind-based DGs and load profile during the islanded-mode of operation. The following control strategies are applied in the study.

- The wind-based DGs are controlled to operate at unity power factor.
- The wind speed data used are the average hourly values and the variations within the hour are not considered.
- Only dispatchable DGs are allowed to supply reactive power in the island.
- There is no storage option, so wind-based DG output power is regulated based on load requirement; no surplus is allowed.

Moreover, both the island load and the connected wind-based DGs are characterized by variable nature. However, the inclusion of dispatchable DGs in the island (Diesel) renders this fact to mimic a constant behavior for both of them during the islanding duration, always short period. This means that if the supply matches the load at the moment of island creation, the situation will be retained for the whole duration of islanding, and vise versa.

The paper is organized as follows: Section II presents the proposed technique of wind speed estimation, while in Section III the validation of this technique is being checked. Section IV introduces the proposed technique of reliability assessment. The details of the system under study, the simulation results, and the sensitivity analysis are revealed in Sections V and VI, respectively. Finally, the conclusion is presented in Section VII.

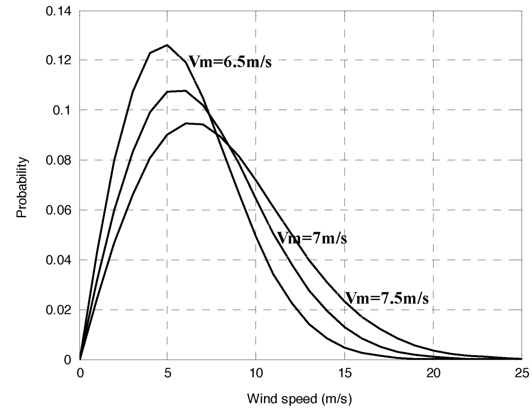

Fig. 2. Weibull probability density functions with different values of scale index c.

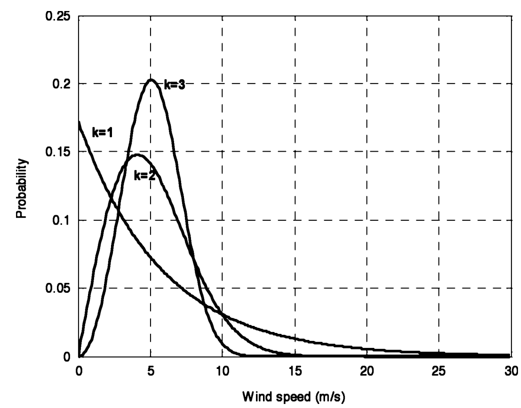

Fig. 3. Weibull probability density functions with different values of shape index k.

II. Wind Speed Estimation

A good expression that is often recommended to model the random behavior of the wind speed is Weibull probability density function (pdf) given as [21]

$$f(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} \exp\left[-\left(\frac{v}{c}\right)^{k}\right] \quad \text{Weibull pdf} \qquad (1)$$

where k is the shape index that is adjusted to match the wind speed profile in the site under study, while c is the scale index that is calculated based on the annual mean wind speed which is not constant from year to another. This means that these two factors are calculated based on data that exhibit great amount of uncertainty. This fact indicates a significant level of error associated with this method since the shape of the Weibull pdf is highly sensitive to the variation of these two indices as shown in Figs. 2 and 3.

Yet, the methodology proposed to estimate the annual wind speed profile, and hence, the output power of the wind turbine is based on two steps utilizing three years of historical data. The first step is to divide the data into clusters based on the seasonality nature of the wind speed. While in the second step, a Grey predictor will be utilized to estimate the wind speed profile.

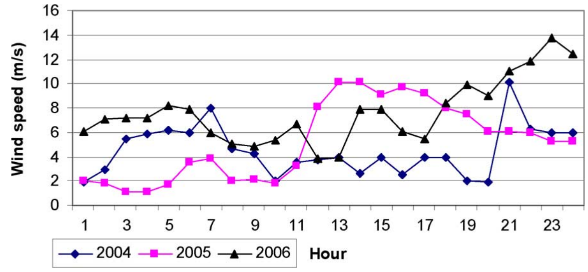

Fig. 4. Wind speed profile during the same day in different years.

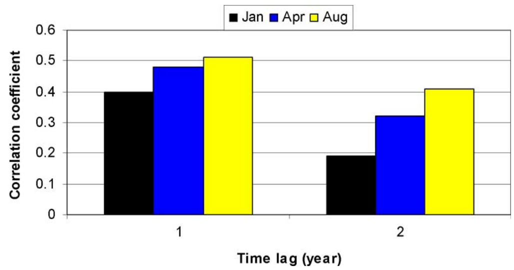

Fig. 5. Correlation coefficient of wind speed at different lag times.

a) Data Clustering: In this step the data will be divided into clusters based on the seasonality of the wind. This will provide a good correlation among the data in the same cluster which will positively be reflected upon the estimated wind profile. In order to reach a reasonable clustering outcome, three years of historical data for the site under study (2004–2006) are utilized (better clustering might be achieved if more data are available). The correlation coefficient between any two variables X and Y can be given by (2) as

$$\rho_{x,y} = \frac{\sum (x-\mu_x)(y-\mu_y)}{\sqrt{\sum (x-\mu_x)^2 \sum (y-\mu_y)^2}} \tag{2}$$

where $\rho_{x,y}$ is the correlation coefficient between X and Y, and μ_x, μ_y are the mean of X and Y.

By analyzing the available data, and calculating the correlation coefficient among the wind speeds of the same period of time for different years, the following features were observed:

- The wind speed profile varies randomly during the same period of time for different years with very weak correlation as shown in Figs. 4, and 5, respectively. This indicates that even artificial intelligence techniques, such as ANN, which has the ability to extract the correlation between data without the need of explicit relations, will not be able to effectively estimate the annual wind speed profile.
- The annual wind speed data are divided into clusters, where each cluster includes the hourly data of one month in the year. Further, each monthly cluster is divided into sub-clusters based on the wind speed. Each sub-cluster includes the number of hours in which the wind will be within certain limits as shown in Table I, where 4 m/s, 14 m/s, and 25 m/s are the common cut in speed, rated speed and cut off speed of most commercial wind turbines and j is the sub-cluster index. This means that at the end of the clustering process there will be, for each year, 12 monthly clusters each contains 12 elements (sub-clusters). This can be represented in vector form as $\mathrm{S_c}\ (\mathrm{j})$ where c is the month index $(\mathrm{c} = 1, 2 \ldots 12)$, (i.e., $\mathrm{S_3}$ (4) means the number of hours in which the wind speed is within 6–7 m/s in March). To evaluate the effect of clustering on the reduction of randomness, the clustering technique is applied to the wind speed data of Fig. 4 as shown in Fig. 6. By comparing Figs. 4–6, it can be found that the amount of randomness is decreased among the daily clustered data of different years. Moreover, a more reduction in the amount of randomness is achieved when the period is extended from one day to one month (the proposed clustering period) as in Fig. 7. In addition, the correlation coefficient among the annual historical data are improved as shown in Fig. 8.

TABLE I
WIND SPEED LIMITS

Sub-cluster (j)	Wind speed limits (m/s)
1	0 to 4
2	4 to 5
3	5 to 6
4	6 to 7
5	7 to 8
6	8 to 9
7	9 to 10
8	10 to 11
9	11 to 12
10	12 to13
11	13 to 14
12	14 to 25

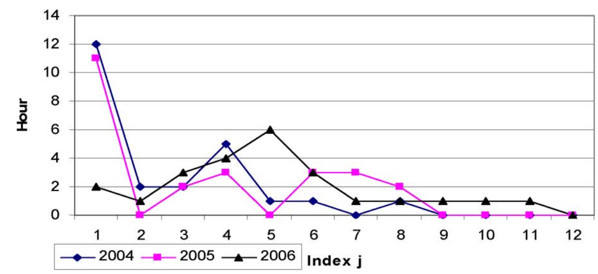

Fig. 6. Wind speed clusters of same day at different years.

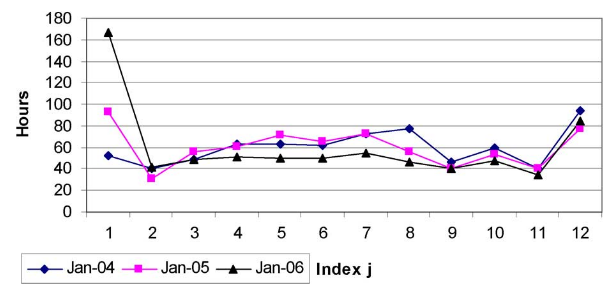

Fig. 7. Wind speed clusters of same month at different years.

b) Wind Speed Estimation: Based on the results in the previous step, it can be concluded that utilizing a clustering technique is better than using a time-based technique to estimate the wind speed profile because it reduces the randomness and improves the correlation coefficient among the historical data. However, in the clustering technique some randomness still exists, especially in the winter season due to the high probability of wind gust. In order to minimize this amount of randomness, a Grey predictor GM(1,1) will be utilized to estimate the annual

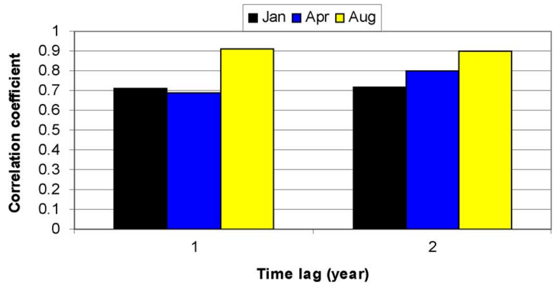

Fig. 8. Correlation coefficient of wind speed using the proposed technique.

wind speed profile of the site under study. Grey predictors have been widely applied in different fields [22]–[24] and applied for short-term forecasting of the wind speed [25]. The main advantages of the Grey predictor technique are:

- utilizing accumulated generating operation (AGO) technique to convert the original set of data into a new set of data (AGO) series. This new set of data is characterized by reduced noise and randomness and more smoothed pattern;
- small amount of data is required in the estimation process; just three points are utilized to estimate the forth one.

However, the main disadvantage of the traditional GM(1,1) model is the occurrence of overshoots in the predicted data that reduce the prediction accuracy [26]. These overshoots are mitigated in this work by the proposed constraints that controlling the prediction process.

The different steps required to estimate the wind speed profile using Grey predictor GM(1,1) are as follows.

1) *Accumulated Generating Operation* (AGO): The aim of this operation is to convert the original set of data $X^{(0)}$ into a new set $X^{(1)}$ using

$$X^{(1)}(K) = \sum_{i=1}^{k} X^{(0)}(i), \quad \forall K = 1, \ldots n. \tag{3}$$

2) *Grey differential equation*: The general differential equation of GM(1,1) model can be expressed as follows:

$$\frac{dX^{(1)}}{dt} + aX^{(1)} = b \tag{4}$$

where X represents the independent variable. The coefficients a and b are determined using the least-square method.

3) *Prediction equation for the GM(1,1)*: In this step, estimated values of the AGO series are calculated using the following equation:

$$X'^{(1)}(i+1) = \left(X^{(0)}(1) - \frac{b}{a}\right) e^{-ai} + \frac{b}{a}. \tag{5}$$

4) *Inverse Accumulated Generating Operation* (IAGO): In this step the original set of data is calculated based on the estimated AGO using the following equations:

$$X'^{(0)}(1) = X'^{(1)}(1) \tag{6}$$

$$X'^{(0)}(i+1) = X'^{(1)}(i+1) - X'^{(1)}(i). \tag{7}$$

The application of this technique required 12 Grey predictors for each month with 12 different a and b constants. To estimate certain element, in the year under study, the Grey predictor, assigned for this element, will utilize the same element of the last *three* years (i.e., $K = 1, 2, 3$). Since, the total number of estimated hours in any cluster S must equal to the number of hours in the month presented by this cluster, this condition might not be fulfilled because the 12 Grey predictors of each cluster estimate the elements independently. To overcome this problem a constrained Grey predictor was developed. The key idea of this predictor is to calculate the constants a and b of the Grey predictors for all elements of any cluster S by formulating a nonlinear optimization problem (NLP) with an objective to minimize the summation of square errors of all the Grey predictors of each cluster while one of the constrains is that the total number of estimated hours in each cluster S must equal to the number of hours of the month presented by this cluster. The formulation of the NLP, for each month, is as follows.

Objective: The objective is to minimize the total square errors

$$\text{Minimize} \quad C = \sum_{j=1}^{12} e_j. \tag{8}$$

Constraints:

1) AGO

$$X_j^{(1)}(K) = \sum_{i=1}^{k} X_j^{(0)}(i), \quad \forall K. \tag{9}$$

2) *Prediction equation for the GM(1,1)*

$$X_j'^{(1)}(i+1) = \left(X_j^{(0)}(1) - \frac{b_j}{a_j}\right) e^{-a_j i} + \frac{b_j}{a_j}, \quad \forall j. \tag{10}$$

3) *Summation of square errors for each predictor*

$$e_j = \sum_{i=1}^{3} \left(X_j'^{(1)}(i) - X_j^{(1)}(i)\right)^2, \quad \forall j. \tag{11}$$

4) *Inverse Accumulated Generating Operation* (IAGO)

$$X_j'^{(0)}(4) = X_j'^{(1)}(4) - X_j'^{(1)}(3), \quad \forall j. \tag{12}$$

5) *Monthly hours constrain*

$$\sum_{j=1}^{12} X_j'^{(0)}(4) = H \tag{13}$$

where H is the number of hours in the month under study. This NLP was developed in GAMS, while MINOS was the solver.

III. Technique Validation

In order to check the validation of the proposed technique, three years of hourly historical data (2004–2006) of the site under study was collected, while the proposed technique was used to estimate the wind speed profile in 2007. Figs. 9–11

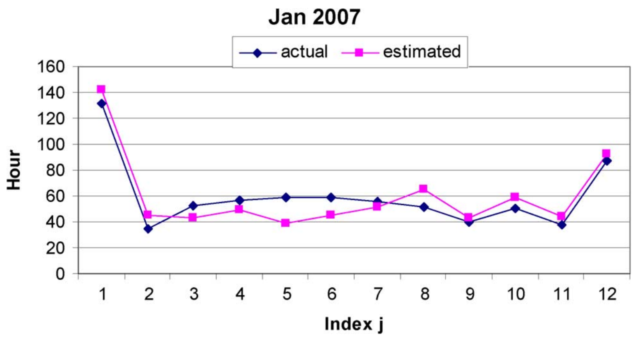

Fig. 9. Comparison between the actual data and the estimated data for January.

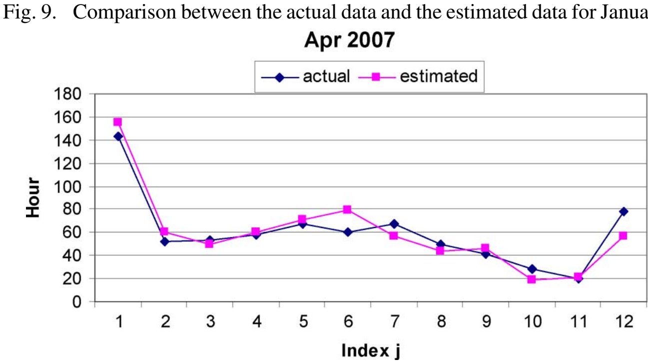

Fig. 10. Comparison between the actual data and the estimated data for April.

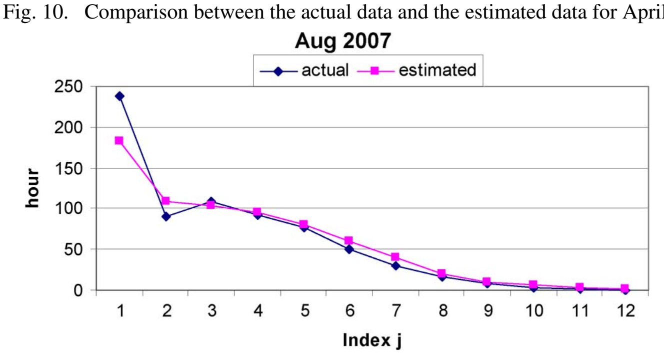

Fig. 11. Comparison between the actual data and the estimated data for August.

TABLE II
ANNUAL AVERAGE ABSOLUTE ERROR

Technique	Annual average absolute error
Proposed technique	13.4%
Common method	19.8%

present a comparison between the actual data and the estimated data using this technique for different months.

Moreover, a comparison was conducted between the proposed technique and the common method of estimating the wind speed profile using Weibull pdf. Table II shows that the proposed technique outperforms the Weibull pdf method as apparent from comparison of the annual average absolute error calculation with respect to the actual data.

IV. Proposed Technique of Reliability Analysis

As mentioned above, the well-being concept can not be applied with its straight meaning when assessing the island reliability. Yet, the measure that evaluates the island reliability is to

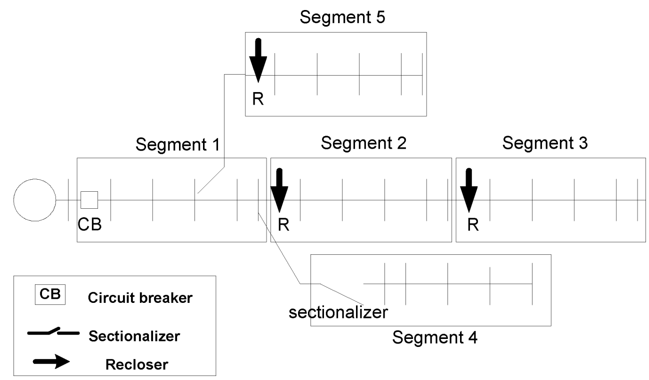

Fig. 12. Segment reliability.

check whether the island is to succeed or not. In order to achieve this task, two steps have to be accomplished. In the first step, the probability of creating an island will be determined which depends on the system configuration, the failure rate, and the repair time of the system components. While in the second step, the probability of the island to be a success will be measured depending on the stochastic behavior of the load and the DGs connected to the island. Detailed elaboration of the techniques utilized to carry out each step is hereunder.

a) ***Step 1: Segmentation concept for reliability assessment***
In order to measure the probability of island creation, a segmentation concept will be utilized [27], [28]. The segmentation concept means that the distribution system will be modeled in terms of segments not components. A segment is a group of components whose entry component is a switch or a protective device, and each segment will have only one switch or protective device. This means that any segment can operate in the islanded-mode if and only if there is a DG, connected to the segment, with an output power matching the segment's load during the island period. The concept of segmentation as shown in Fig. 12 is based on the fact that any fault in a component downstream of a protection device and within its zone of protection will cause an interruption of power to those customers in that zone. This means that all the customers in any zone have the same reliability level and can be treated as one customer. The advantages of using the proposed segmentation concept are:

- the great reduction in reliability calculations;
- it gives an estimation of the DG size that if installed within certain segment will improve its reliability, as will be explained thoroughly later.

The down time of any segment depends on the set (G) which contains all segments in the series path between the main substation and the segment under study including the segment itself. This means that a failure of any component in any of these segments requires waiting the repair time of this component in order to successfully restore power. As shown in Fig. 11, if we calculate the down time of seg #3, then set G : $\{\text{seg}\,\#1,\ \text{seg}\,\#2,\ \text{seg}\,\#3\ \text{and substation}\}$.

Based on this concept the down time of any segment can be calculated as follows:

$$\mathrm{DT}_g = \left(\sum_{j \in \mathrm{set}\, G} \sum_{i=1}^{m} \mathrm{sfr}_i \times \mathrm{rt}_i \right) \tag{14}$$

where

DT_g	down time of segment g;
sfr_i	sustained failure rate of component i.in segment j;
rt_i	repair time of component i. in segment j;
m	number of components in segment $j \in set\, G$.

Since all the customers in any given segment are treated as one customer, then the down time of any segment will be equal to the *System Average Interruption Duration Index* $(\mathrm{SAIDI_g})$ of this segment. To calculate SAIDI of the whole system $(\mathrm{SAIDI_s})$, $\mathrm{SAIDI}s_{\mathrm{g}}$ must be weighted based on the number of customers in each segment as follows:

$$\mathrm{SAIDI}_s = \sum_g \mathrm{SAIDI}_g \times W_g \tag{15}$$

$$W_g = \frac{C_g}{C_s} \tag{16}$$

where

C_g	number of customers in segment g;
C_s	total number of customers in the system.

However, the island will be created when the fault is occurred in any segment of set G except the segment under study. For example segment 3 will operate in the islanding mode if the fault occurred in the substation, segment 1, or segment 2. Hence, the probability of segment g to be working in the islanded mode $(P_g\,\{\text{island}\})$ in each instant of the year can be calculated as follows:

$$P_g\{\text{island}\} = \frac{\left(\sum_{\substack{j \in set\ G \\ j \neq g}} DT_j\right)}{8760}. \tag{17}$$

b) ***Step 2: Probabilistic based technique to calculate the probability of the island to be a success***

In the first step, the probability of creating an island is calculated, while in this step the probability of an island to be a success will be calculated. The necessary condition for an island to be a success is

$$S_G \geq S_L + S_{\text{loss}} \tag{18}$$

where

S_G	generated power of the DGs connected to the island;
S_L	load power of the same island;
$\mathrm{S_{loss}}$	power loss in the island (assumed to be 5% [29] of the current load).

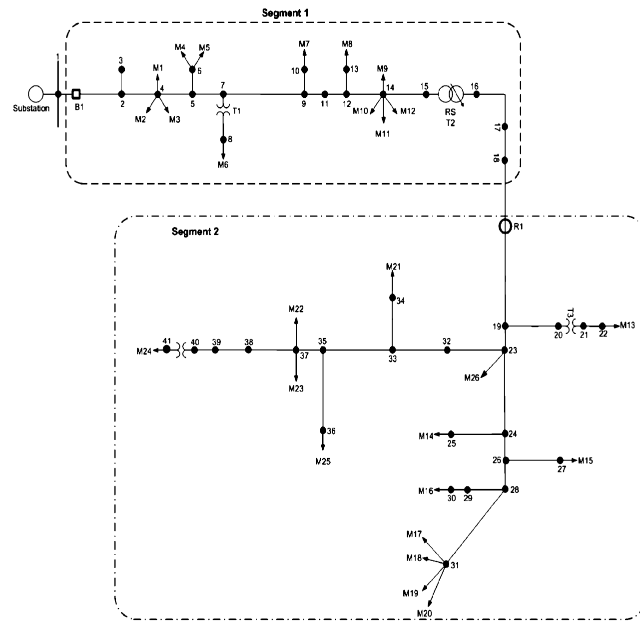

Fig. 13. System under study.

So the probability of an island to be a success $(P_g\{\text{success}\})$ depends on the probability of the DGs in the island to match the total island load and the island losses $(P_g\{\text{enoughDG}\})$ during the period of islanding. Given that the probability that the DGs match the load and the probability of creating an island are independent, therefore, the probability of the islanded mode happens and is success can be obtained by convolving the two probabilities as shown in the following equation:

$$P_g\{\text{success}\} = P_g\{\text{island}\} \times P_g\{\text{enoughDG}\}. \tag{19}$$

V. Case Study

The system under study, as shown in Fig. 13, is a practical rural distribution system. The main substation at bus 1 is used to feed a rural area. The regulating station between buses 15 and 16 is used to boost the voltage in order to maintain the voltage drop at the end users within accepted limits. The data of the system are given in Appendix A. Based on the segmentation concept this system is divided into two segments, where segment 1 has an aggregated peak load of 8.096 MW and is protected by the circuit breaker B1. Segment 2 has an aggregated peak load of 8.165 MW and is protected with the recloser R1. Based on the load points provided in Appendix A, the total number of customers in the system is 26: 12 of them lay in segment 1 and 14 are in segment 2.

If the distribution system is to rely only on the wind-based DGs to supply the load during the islanding operation, stability problems might arise. This is due to the fact that wind-based DGs are characterized by high level of random power fluctuations that is relatively higher than load fluctuations leading to power mismatch. Conventional DG units, such as diesel generators, respond to these stability problems by changing the supply power to match the demand through either excitation or governor controls, which consequently control the island frequency and voltage. This calls for sharing the load between wind-based

TABLE III
COMPONENTS RELIABILITY DATA

	Sustained failure rate (failures/year)	Repair time (hr)
CB and Reclosere	0.36/100	32
Cables	3.5/100	18
Sectionalizer	0.3/100	10
Substation	0.6/100	24
Busbar	0.001	15

TABLE IV
RELIABILITY SET

Segment no	Set G
1	{substation,segment1}
2	{substation, segment 1, segment 2}

TABLE V
SEGMENTS' $\mathrm{SAIDI}_{\mathrm{g}}$

Segment number	$\mathrm{SAIDI}_{\mathrm{g}}$ (hr/year)
1	7.3692
2	15.2394

$\mathrm{SAIDI}_{\mathrm{s}}$=11.607

and conventional DGs. In this way, the useful capacity of the wind-based DGs is calculated and added to the available capacity of the conventional DGs in order to create the generation model.

Therefore, two types of DGs will be connected to the distribution system; the first one is a diesel DG with a rating of 5 MW (60% of the peak load in segment 2) [30] connected to bus 28, and the second one is wind-based DG consist of five wind turbines each of 1 MW connected at bus 39. The five wind turbines have the same characteristics as follows:

— cut in speed $= 4$ m/s;
— nominal speed $= 14$ m/s;
— cut off speed $= 25$ m/s;
— a 4% Forced Outage Rate (FOR) ($\mathrm{MTTF} = 1920$ h, $\mathrm{MTTR} = 80$ h) [30] is assumed for all wind turbines.

From the location of the DGs it can be concluded that only segment 2 can work in the islanding mode if the generated power of the DGs matches the load during the islanding period. The following procedures are conducted to asses the system reliability during the islanding mode and its impacts on the whole system reliability.

A. SAIDI_g *Calculations*

Based on the segmentation concept, (14), the failure rate, and repair time of different components in the system [31] as shown in Table III, $\mathrm{SAIDI}_{\mathrm{g}}$ of each segment is calculated. Tables IV and V show the set (G) and $\mathrm{SAIDI}_{\mathrm{g}}$ for each segment, respectively.

The probability of segment 2 to work in the islanding mode is calculated to be $\boldsymbol{P_2\{\mathrm{island}\} = 0.00084}$ using (17).

TABLE VI
ESTIMATED WIND SPEED PROFILE

Wind speed limits (m/s)	Hours
0 to 4	1804
4 to 5	579
5 to 6	984
6 to 7	908
7 to 8	983
8 to 9	799
9 to 10	677
10 to 11	439
11 to 12	395
12 to13	286
13 to 14	219
14 to 25	687

TABLE VII
PROBABILITY OF WIND TURBINE OUTPUT POWER

Output Power level	$P_g\{DGwithoutfailure\}$	$P_g\{DGwithfailure\}$
5000	0.0761	0.073
4748.48	0.0252	0.024
4248.64	0.0331	0.032
3748.8	0.0457	0.044
3248.96	0.04837	0.046
2749.12	0.0783	0.075
2249.28	0.0923	0.089
1749.44	0.1136	0.109
999.68	0.1050	0.101
749.76	0.1137	0.109
249.92	0.0648	0.062
0	0.2039	0.236

B. *Calculation of the Wind Output Power Probabilistic Model*

In this step the probability of the wind turbine to generate certain amount of power was calculated. Two scenarios were proposed in this work:

1) Neglecting the Wind Turbines Failure: In this case the proposed constrained Grey predictor technique was utilized to estimate the wind speed profile in the site under study by estimating the elements of the 12 clusters and aggregating them together to estimate the annual wind speed profile. The results of this process are presented in Table VI. Hence, these data are applied to the five wind turbines to calculate the aggregated output power levels and their probabilities $(P_g\{\mathrm{DGwithoutfailure}\})$ as shown in Table VII.

2) Considering the Wind Turbine Failure: In this case the probability of the wind turbine to generate certain amount of power $(P_g\{\mathrm{DGwithfailure}\})$ is calculated for all output power levels as follows:

$$P_g\{\mathrm{DGwithfailure}\} = P_g\{\mathrm{DGwithoutfailure}\} \times (1 - \mathrm{FOR}). \quad (20)$$

The last output power level (i.e., wind output $\mathrm{power} = 0$) presents the unavailability of the wind turbine which can be either from a failure or a wind speed outside the operating range. Therefore, its probability is as the one calculated in scenario 1 in addition to the FOR. The results of this scenario are shown in Table VII.

TABLE VIII
CUMULATIVE PROBABILITY OF THE WIND TURBINE OUTPUT POWER

Power level KW	Cumulative probability	
	Without failure	With failure
Output power is 5000	0.0761	0.0728
Output power is 4748.48 or more	0.1013	0.0969
Output power is 4248.64 or more	0.1344	0.1285
Output power is 3748.8 or more	0.1800	0.1722
Output power is 3248.96 or more	0.2284	0.2184
Output power is 2749.12 or more	0.3067	0.2932
Output power is 2249.28 or more	0.3991	0.3815
Output power is 1749.44 or more	0.5126	0.4901
Output power is 999.68 or more	0.6176	0.5904
Output power is749.76 or more	0.7313	0.6991
Output power is 249.92 or more	0.7961	0.7611
Output power is 0 or more	0.9999	0.9999

TABLE IX
LOAD MODEL

% Peak load	Load level (KW)	Probability
100	8165	0.01
85.3	6964.745	0.056
77.4	6319.71	0.1057
71.3	5821.645	0.1654
65	5307.25	0.1654
58.5	4776.525	0.163
51	4164.15	0.163
45.1	3682.415	0.0912
40.6	3314.99	0.0473
35.1	2865.915	0.033

C. *Success Island Probability Calculation*

In order to calculate the probability of the island to be a success, the cumulative probability of the wind-based DG to generate power more than certain level, for the two scenarios, is calculated as shown in Table VIII.

In order to proceed with an accurate reliability assessment, the system peak load was assumed to follow the hourly load shape of the IEEE-RTS [32]. Based on this assumption the load is divided into ten levels using the clustering technique, based on the central centroid sorting process, developed in [33] and [34] which verifies that choosing ten equivalent load levels provide a reasonable trade-off between accuracy and fast numerical evaluation. Table IX shows the ten load levels accompanied by their probabilities.

The probability of the DG units in the island to match the load can then be calculated using the following equation:

$$P_g\{\mathrm{enoughDG}\} = \sum_T (P_g\{\mathrm{DGoutput}\} \times P_g\{\mathrm{load}\}) \tag{21}$$

where

$P_g\{\mathrm{DGoutput}\}$ cumulative probability of the DG units to generate power equals or more than certain level, for both scenarios;

$P_g\{\mathrm{load}\}$ probability of the load to have certain value;

T set includes all the combinations of the power generated and load in which the power generated is equal or greater than the load.

TABLE X
RESULTS

Variable name	Without failure	With failure
P_g*{islands}*	0.00084	0.00084
P_g*{enoughDG}*	0.80451	0.791221
P_g*{success}*	0.00067	0.00066
New SAIDI_g of segment 2	9.31078	9.4578
Improvement in SAIDI_g of segment 2	38.9033%	37.934%
New SAIDI_s	8.4147	8.4938
Improvement in SAIDI_s	27.5035%	26.821%

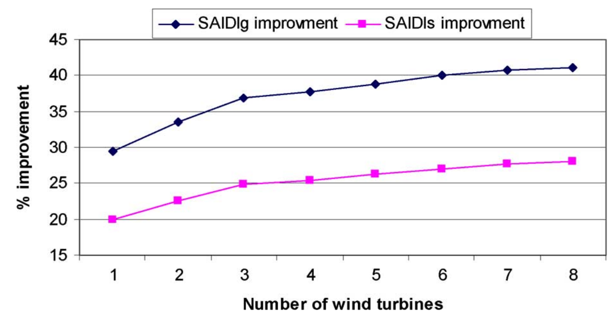

Fig. 14. Sensitivity of the system reliability to the changes in the wind penetration.

Based on (14)–(20) the probability of the island to be a success, the improvement in the overall system reliability (improvement in SAIDI_s) are calculated and summarized in Table X.

Moreover, the improvement in the sustained failure duration is positively affects the *system average interruption frequency index* (SAIFI); however, calculating the improvement in SAIFI is beyond the scope of this paper.

VI. SENSITIVITY ANALYSIS

In this section the impact of adding different amounts of wind capacity on both the island and system reliability is studied. This was done by starting with small amount of wind power penetration (1 MW) and then increases this amount with a step of 1 MW. In each case the improvement in the island and system reliability are calculated. It was found that the improvement in the reliability tend to saturate with the increase of the wind penetration as shown in Fig. 14. The reason for that is, after certain penetration level, even the minimum output of the wind-based DGs plus the output power of the dispatchable DG will cover most of the load, and the only improvement will be in the peak load case which has the lowest probability of occurrence (1%) among all load levels. This means that, from reliability perspective, it is not necessary to increase the wind penetration beyond certain level. This level of penetration depends on many factors, such as the system topology, the island load, load profile, and wind speed profile. However, the increase of wind penetration

TABLE XI
LOAD POINT DATA

Load Point	KVA	Load Point	KVA
M1	4381.01	M14	305
M2	160	M15	660
M3	10	M16	205
M4	216	M17	150
M5	822	M18	130
M6	1355	M19	610
M7	768	M20	655
M8	19	M21	215
M9	20	M22	50
M10	150	M23	60
M11	170	M24	2280
M12	25	M25	585
M13	1050	M26	1210

may have other advantages rather than improving the system reliability. Consequently, beside the benefit of reducing environmental harmful emissions, it may be economically beneficial to install wind power at a time when the system reliability may be well above the satisfactory level. This can be determined by comparing the savings resulting from fuel offset against the installation, maintenance and operating costs of wind-based DGs.

VII. CONCLUSION

In this paper, the reliability of the distribution system with wind-based DGs is assessed during the islanding mode of operation. A novel constrained Grey predictor technique was utilized to estimate the wind speed profile. The validity of the proposed technique was checked by comparing the estimated wind speed profile of this technique with estimated wind speed profile using the common Weibull pdf. After estimating the wind speed profile a probabilistic technique was utilized to correlate the stochastic behaviors of the load and DGs power output to calculate the probability of the generation in order to satisfy the load during the islanding period, hence, improving both island and system reliability. Moreover, a sensitivity analysis was carried out to study the impact of changing the wind penetration on the system reliability. It was found that as the penetration level increases, the reliability improvement starts to saturate. However, other advantages of the increasing the wind penetration can be gained such as the offset in the conventional fuel consumption.

APPENDIX

Table XI lists the load point data.

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Yasser M. Attwa (S'06) was born in Alexandria, Egypt, in 1975. He received the B.Sc. and M.Sc. degrees in electrical engineering from Alexandria University, Alexandria, Egypt, in 1998, and 2004, respectively. He is currently pursuing the Ph.D. degree in the Department of Electrical and Computer Engineering, University of Waterloo, Waterloo, ON, Canada.

His research interests are distribution system planning, power quality, reliability, and distributed generation.

Ehab F. El-Saadany (SM'05) was born in Cairo, Egypt, in 1964. He received the B.Sc. and M.Sc. degrees in electrical engineering from Ain Shams University, Cairo, Egypt, in 1986 and 1990, respectively, and the Ph.D. degree in electrical engineering from the University of Waterloo, Waterloo, ON, Canada, in 1998.

Currently, he is an Associate Professor in the Department of Electrical and Computer Engineering, University of Waterloo. His research interests are distribution system control and operation, power quality, distributed generation, power electronics, digital signal processing applications to power systems, and mechatronics.