Reliability Assessment of Generating Systems with Wind Power Penetration via BPSO

Athraa Ali Kadhem[#], Noor Izzri Abdul Wahab[#], Ishak Aris[#], Jasronita Jasni[#], Ahmed N. Abdalla[*], Yoshiaki Matsukawa[+]

[#]Faculty of Electrical & Electronic Engineering, University Putra Malaysia, Selangor, 43400, Malaysia
E-mail: athraaonoz2007@yahoo.com, izzri@upm.edu.my, ishak_ar@upm.edu.my, jas@upm.edu.my

[*]Faculty of Engineering Technology, University Malaysia Pahang, Kuantan 26300, Malaysia
E-mail: ahmed@ump.edu.my

[+]Faculty of Electrical & Electronic Engineering, Kyushu Institute of Technology,
1-1, Sensul-cho Tobataku Kitakyushu Fukuoka 8048550, Japan
E-mail: P349532y@mail.kyutech.jp

***Abstract*— The growing pervasiveness of the Wind Energy Conversion System (WECS) in power systems has a great influence on the electrical system reliability in relation to other conventional sources for power generation. This current study offers a binary particle swarm optimisation (BPSO) application with Weibull model to reliably evaluate the generation systems with a WECS. The proposed methodology is based on hourly time series wind speed and uses Weibull model and simulation of the operation of generation system, taking into consideration the random failures of conventional units of the system and the fluctuating wind energy of a WECS. The BPSO algorithm adopts intelligent research to explore the meaningful system states and accelerate their integrated convergence, so that makes it feasible to locate all possible failure states in the system states space in order to calculate the reliability indices with WECS. The numerical simulation of the suggested solution is compared with the established Monte Carlo simulation (MCS). The reliability test system (IEEE-RTS-79) is employed to show the effectiveness of the proposed algorithm.**

***Keywords*— reliability assessment; wind power; generating system; binary particle swarm optimisation; Weibull model**

I. INTRODUCTION

Currently, much attention is being paid to the advancement of renewable generation owing to the fear associated with declining fossil fuel reserves and the possible adverse effects of conventional energy units on the environment. Therefore, the use of renewable energy, particularly wind energy for the generation of electric power is being widely practiced in nations such Spain, Denmark, China, USA, and Germany, where WECS is extensively used [1]. The irregular and irregular characteristic of wind energy poses a great challenge to the planning and operation of power systems. Therefore, it turns out to be increasingly crucial to assess the impact of wind power on the reliability of the generating system adequacy.

Assessing the reliability of power system penetration with wind energy is a multifaceted procedure. A significant step in assessing the reliability of wind-powered system involves wind power, and the speed of the wind, which is a critical factor that must be considered at the design phase of a WECS. The WECS system consists of two major models, namely; the wind speed model and the wind turbine generator model (WTG) [2]. Numerous models have been designed and used to simulate the hourly wind speed to produce wind speed, models like the Markov model and autoregressive moving average (ARMA) [3], [4]. These models are required in combination with the power curve of a wind turbine generator to produce the power output of a wind turbine generator model. Thus, this model can be engaged in evaluating the reliability of a power system integrated with wind power. It is another significant model for creating artificial wind speed data, which is essential in the search to find the appropriate probability distribution of wind speed. In numerous studies, Weibull distribution has been used to represent the variation of mean wind speed for an hour, day, month, and year [5], [6]. The use of the Weibull model with a sequential Monte Carlo simulation (SMCS) technique along with the Frequency and Duration method as an appropriate representation of the WECS output power and the reliability assessment of power systems, has been discussed [1], [7].

The reliability assessment of the generating system adequacy normally requires an analysis or simulation. The Monte Carlo simulation (MCS) method enables accurate evaluation of reliability indices. Due to the involvement of several system states in system operations, required by penetration wind energy, Monte Carlo simulation can be beneficial for this purpose but requires large computational efforts, which would be time-consuming if efficient convergence is to be achieved [8], [9]. This study offers an alternative of the SMCS, population-based intelligent search method (PBI) and is employed for the purpose of identifying a set of probable failure states, which play a role in contributing to the calculation of the system adequacy indices with wind power penetration from the WECS. A proposed method is to assess the power systems reliability on the basis of the PBI namely, the binary particle swarm optimisation (BPSO). Previous studies have confirmed that algorithms particle swarm optimisation, evolutionary particle swarm optimisation, and directed particle swarm optimization are adapted to searching in the state space where contributions to the formation of a reliability index may exist, instead of carrying out a random sampling of the space, consequently, the convergence mechanisms improved [10]-[12]. This paper presents an application of BPSO with the Weibull model for reliability evaluation of generation systems containing a WECS. It is revealed that using the proposed method, the wind speed at any hour is generated artificially to assess the reliability of the power system. The main improvements achieved in this work compared to earlier studies [10], can be summarised as follows; 1) using the BPSO algorithm as an alternative to an MCS for guided intelligent search; 2) the creation of the capacity outage probability table (COPT) of the WTG unit by application of the time series hourly wind speed to the power curve of the WTG; 3) incorporating the WECS into the generating systems, thus revising the reliability assessment procedure to account for this change into the reliability of the system. Meanwhile, reliability indices for generating systems are calculated for period spans with load cycle for a year. To equate the outcomes of the suggested Weibull distribution model with actual data, and comparing the BPSO approach with the conventional MCS the RTS system is carried out, to show the effectiveness of the proposed algorithm.

II. Material and Method

A. Wind Speed Model

Various models have been utilised to simulate the WECS power system for forecasting wind speed and evaluating the reliability of the output power [13], [14]. Annually, the hourly wind speed is the first forecast to acquire the hourly available output of the WECS. Statistical methods can be employed for the modelling of wind speed changes and to forecast future wind speeds. Since the Weibull distribution has a property that can modify parameters, such as the shape k and the scale c, it is generally used in simulating the difference in the speed of the wind. Hence, the Weibull distribution model can be employed to simulate the speed of the wind at any point in time during the simulation period [15]. The wind speed, v can be reproduced artificially [16], by applying the inverse transform function in Equation (1). The first step utilises the actual hourly wind data obtained at a specific location, and this data is used to analyse and estimate the scale and shape parameters of the Weibull distribution, where, c is an average wind speed for Weibull distribution and k shows the characteristics of wind. The second step, applying the Weibull distribution function with equation (1), the wind speed at any given time for a specific geographic location can be simulated. Where the Weibull parameters set to c=19 is average actual wind speed data for Swift site in Ref. [17], and k=2, suggest that the characteristics of wind are regular [15]. The results illustrate that the simulation wind data offers an acceptable representation for adequacy assessment. The simulated wind speed for (300) hours is depicted in Fig. 1, Weibull distribution can have an excellent performance in simulating the wind profile by modifying its scale and shape parameters.

$$v = c\left[-Ln(U)^{\frac{1}{k}}\right] \tag{1}$$

where: c & k are Weibull parameters, U is a uniform distribution of random variable between [0, 1], and v is wind speed. By applying the wind speed into the output model of the wind turbine, the Equation of the power output of the wind turbine can be derived as shown in Equation (2).

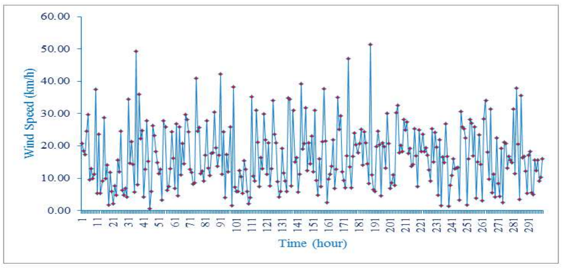

Fig. 1 Simulated wind speed sample for (300) hours

B. Model of a Wind Turbine

After obtaining the hourly wind speed, the power output of the WTG is established as a function of the wind speed. An available capacity of a WTG unit can be generated through the application and relationship between the power output and the hourly wind speed to the power curve. The relationship between the output power of the WTG at any hour of time and that of the wind speed is not constant. Equation (2), shows how the WTG output power and the wind speed are related. Fig. 2 shows a graphical representation of the WTG power curve, the cut-in, cut-out, and rate speed of the WTG used in this study, which are 4, 25, 19 m/s. as well as, the power rate from each WTG is 2 MW [4].

$$P_{WTG} = \begin{cases} 0 & ws < V_{ci} \\ (A + B_x + Cx^2)\times P_r & V_{ci} \le ws < V_r \\ P_r & V_r \le ws < V_{co} \\ 0 & ws > V_{co} \end{cases} \tag{2}$$

From Fig. 2, it can be seen that the WTG does not produce a reasonable level of power when the wind speed, ws (m/s) is less than the cut-in speed Vci (m/s) and invariably shuts down power production when the wind speed is greater than the cut-out speed Vco (m/s). When the output power (Pr) of the WTG increases as the speed of the wind increases within the range of Vci the rated speed of the wind Vr (m/s) remains fixed and WTG generates a capacity of power to which it is rated. A, B and Cx parameters are obtained from (3-5) [18].

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

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

$$C=\frac{1}{(V-V_r)^2}\left[2-4\left(\frac{V_{ci}+V_r}{2V_r}\right)^3\right] \quad (5)$$

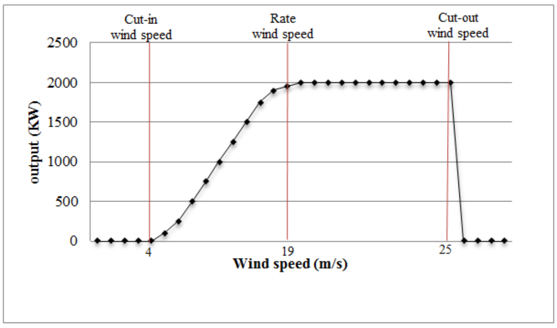

Fig. 2 WTG power curve

C. Generating System Reliability

The generating system reliability is determined based on the ability of the system to ensure an adequate supply of electricity to satisfy the load demand. In the quest to evaluate the adequacy of power generation with the WECS, an application of a suitable model consisting a conventional generating and unconventional generating unit models, along with the annual load curve model. These two models are incorporated to represents the risk system model. This study only considered any available generating capacity to represent the risk model in comparison with the expected load of the system. Consequently, the representation of the risk model through one or more quantitative risk reliability indices as part of the criterion to decide the system risk model is used. The fundamental reliability indices that are evaluated in this paper to estimate the reliability level of the power generating systems with the inclusion of the WECS are Loss of Load Expectation (LOLE) and Loss of Energy Expectation (LOEE). Hence, by employing the BPSO algorithm, each particles swarm represents available capacity in the system during the simulation process. Within the state space of the system, the individual with an available capacity that is below than the load represents a failure state of the system, whereas the individual with an available capacity that is greater than the load demand represents a success state of the system. In order to construct the system state array to estimate the generating system adequacy, this study considered individual in the failure state during a search in the state space pruning of the system.

D. Reliability Indices

The reliability indices for LOLE and LOEE were calculated on the basis of the achieved state array and the convolution of the hourly load values. State array individuals are responsible for the highest contribution to the loss states in a load. This study considered the Li, to represent the discrete values for the load levels at the hour (t). The loss of load probability (LOLP) at the different load values was evaluated as follows [19].

$$LOLP(LH_i)=\sum_{j=1}^{sa} S_j.P_j.copy_j \quad (6)$$

where: sa represents the total number of state arrays, while, the status of the system state is S_j. The status value will be equal to zero if it is a success state, i.e., $Cap_j \geq LHi$, while the status value is equal to one in the case of a failure state, i.e. $Cap_j < LHi$. After the LOLP was done for all load levels, the LOLE per year in an hour was measured using Equation (7):

$$LOLE=\sum_{j=1}^{8736} LOLP(HL_j) \quad (7)$$

The expected power not supplied (PNS) in each load level per hour (in megawatts) was calculated using the following equation.

$$LOEE=\sum_{j=1}^{8736} PNS\left(LH_j\right) \quad (8)$$

The next section explains the use of the BPSO algorithm to construct the state array by tracking a failure state in space states of the system.

E. BPSO Algorithm

The BPSO is one of the most powerful techniques [20], [21], based on metaheuristic searching for the truncated sampling of state-space of the system for reliability assessment of the power generation system adequacy. First proposed in [22], the adjusted trajectory positions are changed using a discrete operation instead of continuous operation so the coordinate will take a zero or one value. The proposed BPSO is used as an optimisation search tool based on population to reduce the probability state space and to select the most probable failure states of the system. To perform the search process, for each iteration, particle velocity v_i or the direction of movement of particle i from position x_i can be directed by the velocity update rule [11], which generates a new individual as a weighted combination of parents, which are; a given individual, it's best ancestor, and the best ancestor of present generation. This may be perceived as a form of intermediary recombination. In this operator, a new individual emerges from a weighted mix of ancestors, and this weighted mix may differ in each spatial dimension. The mutation operator is only applied to the weights particle x_i, a new particle x_i^{new} is derived from

$$X_i^{k+1}=X_i^{(k)}+V_i^{(k+1)} \quad (9)$$

$$V_i^{(k+1)}=WV_i^{(k)}+C_1q_1.(Pb-X_i^{(k)})+C_2q_2.(gb-X_i^{(k)}) \quad (10)$$

Where: W is the weighting factor, C_1 and C_2 represent the acceleration factors, q_1 and q_2 are a random variable between 0 and 1 which represents the weight for the mutation operators at each iteration, k, is the number of generations, $X_i^{(k)}$ is the location of an individual at generation k; $V_i^{(k)} = X_i^{(k)} - X_i^{(k-1)}$ is the velocity of X_i in generation k.
Meanwhile, *Pb* is the personal best particle in i^{th} and *gb* is the global best of the group.

III. Results and Discussion

A. Simulation Procedures

The implemented methodology is a combination of a generated artificial wind along with BPSO algorithm to calculate the reliability of the generation system incorporated with the WECS. The hourly mean wind speed and output for the WTG unit, without consideration for its forced outage rate, are generated on the basis of the Weibull time series model and the power curve, respectively. In this study, the WECS comprises several identical WTG units with zero forced outage rate [23]. The COPT of wind turbine unit can describe the output states for WTG unit as the rated power at each hour. Applying the Weibull distribution function with Equation (1), the wind speed at any given time for a specific geographic location can be simulated. Where the Weibull parameters set to c=19 & k=2, Fig. 3 shows the simulation of the wind speed profile for the Swift site for one year. Then, the power output of the wind turbine can be obtained by applying the wind speed into the wind turbine output model.

Fig. 4 shows the output power in relation to Swift site wind farm (with 85 WTG) simulation for (300) hours in line with wind speed at the same time and power curve of the wind turbine. The proposed methodology to calculate the reliability of the power system including WECS is summarized as follows.

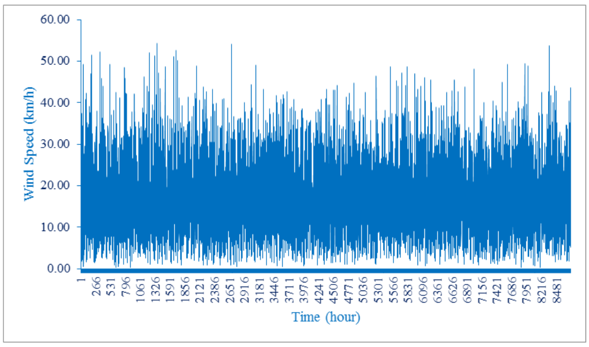

Fig. 3 Simulated wind speed sample for one year

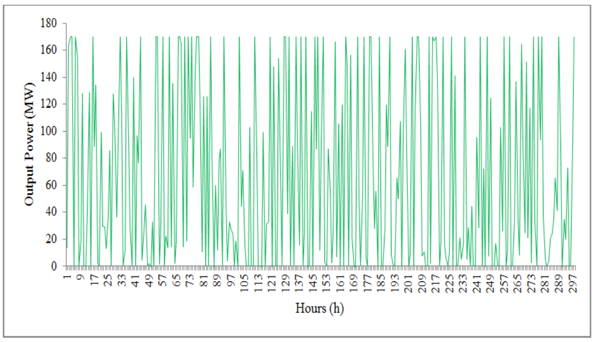

Fig. 4 Simulation depicted the wind turbine output power for (300) hour

1) Step-1: For the wind speed time series sampling according to the following procedure:

- Set the two Weibull parameters, scale c, and the shape k, normally the value of k is 2 [15].
- A uniformly distributed random number U between [0, 1] is generated. Calculate the artificial wind speed v with equation (1).
- The WTG has the following specifications: the cut-out, cut-in, rate speed and output power as 25,4,19 (m/s), and 2 MW [6].
- To estimate the output power from the WTG calculate the wind turbine power output with equation (2), meanwhile, calculate A, B, and C with equations (3-5).

2) Step-2: Read information regarding reliability parameters, hourly load levels, and wind time series, besides the following parameters as maximum-gen, the reliability parameters (FOR, λ, μ) for the conventional unit, and threshold probability (t_p).

3) Step-3: The initial population was randomly generated, by vectors of binary numbers with [0, 1]; this procedure was repeated for all initial populations of the individuals. Therefore, each individual represented the system state capacity. Each individual was arranged in "n" parts; each part included adjacent binary number representation for the conventional generating units, with the same reliability parameters and MW capacity.

4) Step-4: Evaluate the actual capacity of the generating units for the system state i; with equation (11):

$$cap_i = \sum_{j=1}^{mg} b_j . g_j \qquad (11)$$

Where: b_j represents the state of the generating unit j; m_g refers to the number of generating units; g_j refers to the MW capacity of each unit. If the capacity Capi > L_{mxa} it represents the individual state of success, therefore, the fitness of its corresponding individual is allocated a very small value in order to minimise its chance to influence the next generation population.

5) Step-5: The failure state of the system state i; was calculated, if Capi < Lmxa, then the state was in the failure state. Therefore, the individual failure probability was calculated as follows.

$$P_i = \prod_{j=1}^{mg} P_j \qquad (12)$$

Where: mg is the number of conventional unit j; whereas pj is the expected probability values, that can be presented by one of these two values of probabilities as following: if bj=1, than pj=1-FORj, and if bj=0, than pj=FORj. The number of all the possible permutations for the evaluated state i were distinguished as follows.

$$copy_i = \binom{L_1}{O_1} \cdots \binom{L_j}{O_j} \cdots \binom{L_n}{O_n} \qquad (13)$$

where: O_j refers to the number of "noes" in group j of length L_n.

6) Step-6: Equation (13) was used to calculate the fitness of the system state:

$$Fit_i = P_i \tag{14}$$

7) Step-7: The information on the eligible individual state was saved. The above process was repeated for all the individuals until all the remaining states were evaluated. All individuals were checked before being evaluated to ensure that they were not previously saved from another evaluation step. If the state had been saved previously, a very small number of the fitness was assigned so that the probability of this state could be multiplied to reduce the chance of it appearing in the next generation. This state was disregarded and was not added to the state array.

8) Step-8: The number of iterations was increased by one.

9) Step-9: Each stopping criterion was checked to determine whether it was met so that the algorithm could be paused, and the output of the state array could be derived. If the stopping criterion was not met, step 10 would be conducted.

10) Step-10: BPSO mutation operators with equation (9-10) were adopted to produce the next generation, and then steps repeated until all stopping criteria were met.

11) Step-11: The reliability indices were calculated based on the previously achieved state arrays. Due to inconsistent wind power, the calculation of the total actual generating capacity of state i at hour t should be done with equation (15)

$$cap_{i,t} = \sum_{j=1}^{mg} b_j g_j + \sum_{j=1}^{mg} w_j \tag{15}$$

where: w_j is the actual output of WTG_j at hour t, it can be computed by wind turbine power output with equation (2) from step 1, at hour t. It represents percentage from output power rate since the WTG is working according to the available wind speed. In this study, the derating factor is designed as a stochastic variable. Therefore, the derating factor is offered or derived employing the wind speed forecasting procedure. It is usually modelled as a random variable by time series techniques such as Weibull distribution with a random variable model. The derating changes over time, but for a given time interval, it considered as a constant value and this will be taken into consideration this study for reliability calculation. The reliability indices for LOLE, LOEE were calculated on the basis of achieved state array and the convolution of the hourly load values with equation (7-8).

B. *Case study*

The reliability simulation technique suggested in this paper is implemented for an IEEE-Reliability Test System and contains the WECS [24]. The IEEE-RTS-79 consisted of 32 generation units, with unit capacities ranging from 12 MW to 400 MW. Meanwhile, the system had a total power output of 3405 MW and a peak load of 2850 MW. The unconventional units comprising multiple identical WTGs with zero forced outage rate, each one had the rated power output 2MW, the total installed capacity from unconventional units 170 MW (85 WTGs) is added to RTS. The WTGs that are installed in the WECS has the following specifications: Vci=4 m/s, Vr=19 m/s and Vco=25 m/s [4].

The BPSO algorithm control parameters employ for the run in this study should be selected carefully for the efficient performance of the algorithm. The recorded value settings of the control parameters for the BPSO were taken as follows: pop_size = 60, the acceleration constants are chosen as C_1=1.3 and C_2=0.5 respectively, W=1.1, while the reliability parameters (FOR, μ, λ) for generation unit settings followed the data reported in [25], and t_p = 1e-15. The LDC model is used to generate annual load values, which produced 8736-hour values for the given year. Here, the BPSO the stopping criterion used is the number of maximum iterations, which is set to 100 generations. It turns out to be a reasonable number since comparable results are attained by this generation [26].

To verify the strength and confidence of the discrete BPSO, a series of 250 repeated runs of the algorithm have been made before adding wind power and in the same conditions as previously discussed. The results obtained are listed in Table 1 and are compared with results reported in [27]. From Fig. 5 and 6, it can be observed that after runs with 250 iterations, the reliability indices values were oscillating around the real value. The repeated runs of the experiment with the algorithm showed that this algorithm has high accuracy when estimating the reliability indices.

TABLE I
RESULTS OF 250 REPEATED RUNS OF BPSO

Reliability Indices	**Analysis Method**	**BPSO (Mean)**	**Error (%)**
LOLE (h/year)	9.394	9.361	0.35%
LOEE (MWh/year)	1176	1063	9.60%

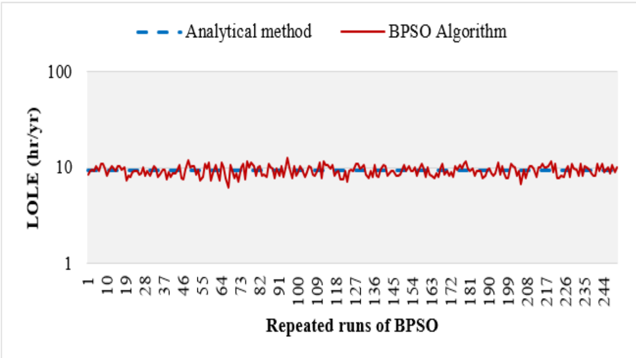

Fig. 5 RTS-79 Evolution of estimated LOLE with the number of 250 repeated runs

In this study, reliability indices are recalculated using SMCS along with frequency and duration to compare with the proposed BPSO algorithm. Fig. 7 represents the available capacity of the system obtained from conventional units and WECS.

In Fig. 8 the available capacity for the power system from the simulated process which is superimposed with the chronological load model is shown. It can be seen from this state of the system, that the available capacity of the power generating system is not sufficient to meet the load demands. So, there are some intersections which are seen in the diagram.

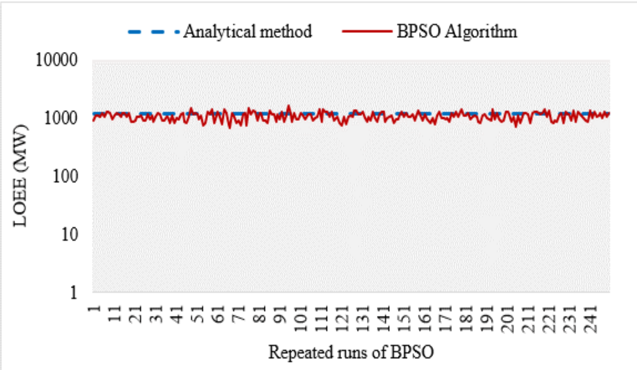

Fig. 6 RTS-79 Evolution of estimated LOEE with the number of 250 repeated runs

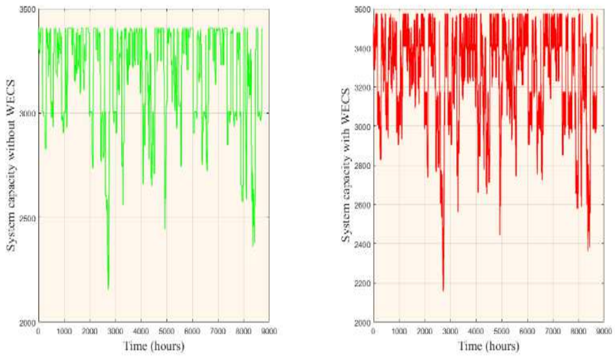

Fig. 7 The available capacity of the system obtained from generating unit and WECS

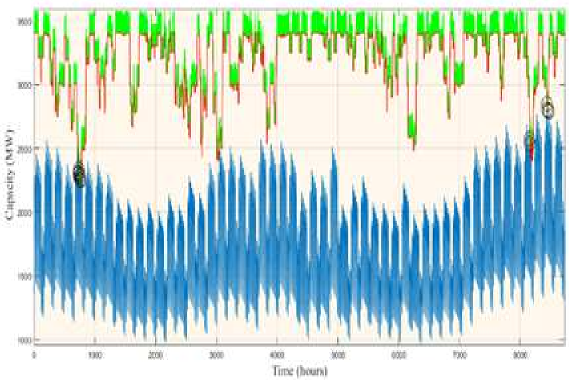

Fig. 8 The available capacity of the system which, superimposition with chronological available load model

Fig. 9 represents numbers of the frequency and duration for (200) selected sampling years of the SMCS. For a peak load of 2850 MW with wind power penetration 170 MW, the system adequacy indices were acquired with both the SMCS and proposed BPSO methods and listed in Table 2. The SMCS can be employed for this purpose by iterative selection and measurement of the system states. However, because of its reliance on proportionate sampling, it may not be very efficient in locating failure states. The SMCS may be at its worst in terms of the time taken to converge. In addition, the BPSO has shortest convergence time due to its operational simplicity. Furthermore, the results of the reliability assessment of the generating system were demonstrated by comparing them with other methods so that the efficiency of the algorithm proposed could be validated.

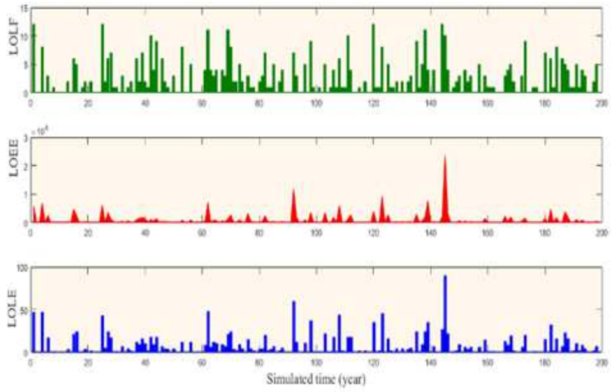

Fig. 9 Frequency and duration of capacity outages probability with associated failure

These BPSO and SMCS results obtained were compared with results obtained from methods reported in [4], as listed in Table 3. The results represent the comparison of reliability indices between five methods from the literature. The reliability indices were calculated using MCS with different wind speed modelling. The Markov method, Normal and Weibull distribution, ARMA time series model, and actual wind speed data were used for this procedure. It was clearly shown that the results from using BPSO were closer to the actual wind speed data results which were obtained using MCS.

TABLE II
COMPARISON BETWEEN SMCS AND BPSO METHODS

Methods	**LOLE (h/yr)**	**LOEE (MWh/yr)**	**Time (s)**
SMCS	7.55	941.07	64.641
BPSO	7.43	823.78	8.979

TABLE III
COMPARISON BETWEEN DIFFERENT METHODS

Methods	**LOLE (h/yr)**	**LOEE (MWh/yr)**
Proposed method (BPSO)	7.43	823.78
Weibull model SMCS	7.55	941.07
Actual data MCS	7.45	908.70
Markov model MCS	7.47	918.10
ARMA method MCS	7.12	884.90
Weibull model MCS	7.78	976.70
Normal model MCS	6.95	858.50

IV. CONCLUSION

In this paper, a new approach was suggested to demonstrate the contribution of the WECS in power system reliability using BPSO algorithm. The BPSO which utilized an optimisation search tool for the reliability indices of a power generating system with WECS is assumed to be a viable replacement for the SMCS in measuring non-chronological system reliability indices. The WECS has an important role in the reliability performance of a generating system adequacy. This study presented the SMCS technique and BPSO algorithm with wind power modelling for the reliability assessment of power generation systems. The Weibull distribution model was utilised to replicate the hourly wind speed. On the other hand, Weibull model was found to have been significantly affected by the selected parameters. This method proved highly accurate in estimating the reliability indices, and also could be applied to a different time series wind speed models, and this is evident in the way it speeds up the computation to achieve higher accuracy with less computation effort. This claim was established by comparing it to earlier reports and with a pure optimisation strategy. This paper will assist system designers to quantitatively evaluate the worth of the WECS so that it can be an essential input for the decision making process.

REFERENCES

[1] A. A. Kadhem, N. I. A. Wahab, I. Aris, J. Jasni, and A. N. Abdalla, “Effect of wind Energy Unit Availability on Power System Adequacy,” Indian Journal of Science and Technology, vol. 9(28), pp. 1-7, July 2016.

[2] P. Xu, Y. Li., Q. Chen, W. Liu, and Z. Liu, “ A new Approach for Fast Reliability Evaluation of Composite Power System Considering Wind Farm”, IEEE Conference, 2015 China, pp. 2736-2740, 2015

[3] R. Billinton, D. Huang, “Incorporating wind power in generating capacity reliability evaluation using different models,” IEEE Transactions on power systems, vol. 26, pp. 2509-2517, March. 2011

[4] S. Soleymani, M. E. Mosayebian, S. Mohammadi, “A combination method for modeling wind power plants in power systems reliability evaluation,” Computers and Electrical Engineering, vol. 41, pp. 28-39, January 2015.

[5] B. G. Kumaraswamy, B. K. Keshavan, and Y. T. Ravikiran, “Analysis of seasonal wind speed and wind power density distribution in Aimangala wind form at Chitradurga Karnataka using two parameter Weibull distribution function”, Power and Energy Society General Meeting, Proc. IEEE, 2011.

[6] S. Shuai, K. L. Lo., “Reliability assessment of power system considering the impact of wind energy”, Proc. Universities power Engineering Conference (UPEC), 2012.

[7] S. Shuai, K. L. Lo, “An overview of wind energy development and associated power system reliability evaluation methods", Proc. Universities power Engineering Conference (UPEC), 2013.

[8] H. J. Jayatheertha, “Evaluation of composite electric system performance indices using Sequential Monte Carlo simulation”, Internation Journal of Advanced Engineering Research and Studies, vol. I, pp. 4-7, September 2012.

[9] A. M. L. Silva, W. S. L. A. F. Manso, R. A. Gonzalez-Fernandez, “Reliability assessment of time-dependent systems via Quasi-Sequential Monte Carlo simulation”, Proc. IEEE (PMAPS), 2010.

[10] L. Wang, C. Singh, “Population-Based Intelligent Search in Reliability Evaluation of Generation Systems with Wind Power Penetration”, IEEE Transactions on Power Systems, vol. 23 (3), pp. 1336-1345, May 2008.

[11] V. M. Fellow, L. M. Carvalho, M. A. Rosa, A. M. L. Silva, “Improving power system reliability calculation efficiency with EPSO variants”, IEEE Transactions on Power Systems, vol. 24, pp. 1772-1776, November 2009.

[12] M. Benidris, S. Elsaiah, J. Mitra,“Power system reliability evaluation using a state space classification technique and particle swarm optimisation search method”, IET Generation Transmission & Distribution, pp. 1-11, July 2015.

[13] R. Billiinton, D. Huang, “Incorporating wind power in generating capacity reliability evaluation using different models”, IEEE Transactions on Power Systems, vol. 26(4), pp. 2509-2517, November 2011.

[14] R. Billiinton, R. Karki, Y. Gao, D. Huang, P. Hu, W. Wangdee, “ Adequacy Assessment Considerations in Wind Integrated Power Systems”, IEEE Transactions on Power Systems, vol.27, pp.2297-2305, July 2012.

[15] A. K. Azad, M. G. Rasul, M. M. Alam, S. M. Ameer Uddin, S. K. Mondal, “Analysis of wind conversion system using Weibull distribution”, Procedia Engineering, 10th International Conference on Mechanical Engineering (ICME), vol. 90, pp. 725-732, 2014.

[16] S. Shi, K. KL. Lo, “Reliability Assessment of Power System Considering the Impact of Wind Energy”, in Proc Universities Power Engineering Conference (UPEC), 47th International, 4-7 September 2012.

[17] R. Karki, P. Hu, R. Billinton, “A Simplified Wind Power Generation Model for Reliability Evaluation”, IEEE Transactions on Energy Conversion, vol.21(2), pp. 533-540, June 2006.

[18] R. Karki, S. Thapa, R. Billinton, “ A Simplified Risk-Based Method for Short-Term Wind Power Commitment”, IEEE Transactions on Sustainable Energy, vol. 3(3), pp. 498-505, July 2012.

[19] N. Samaan, C. Singh, “Adequacy Assessment of Power System Generation Using a Modified Simple Genetic Algorithm,” IEEE Transactions on Power Systems, vol. 17(4), pp. 974-980, November 2002.

[20] I. M. Yassin, A. Zabidi, M. S. A. M. Ali, N. M. Tahir, H. Z. Abidin, and Z. I. Rizman, “ Binary Particle Swarm Optimization Structure Selection of Nonlinear Autoregressive Moving Average with Exogenous Inputs (NARMAX) Model of a Flexible Robot Arm". International Journal on Advanced Science Engineering Information Technology, vol. 6, pp. 630-637, 2017.

[21] M. K. M. Zamani, I. Musirin, S. I. Suliman, M. M. Othman, M. F. M. Kamal, “Multi-Area Economic Dispatch Performance Using Swarm Intelligence Technique Considering Voltage Stability”. International Journal on Advanced Science Engineering Information Technology, vol. 7, pp. 1-7, 2017.

[22] J. Kennedy, R. C. Eberhart, “A Discrete Binary Version of the Particle Swarm Algorithm”, in Porc. IEEE International Conference 1997.

[23] R. Billinton, Y. Gao, “ Multistate Wind Energy Conversion System Models for Adequacy Assessment of Generating Systems Incorporating Wind Energy”, IEEE Transactions on Energy Conversion, 2008, vol. 23(1), pp. 163-170.

[24] IEEE Committee Report, 'IEEE Reliability Test System, IEEE Transactions on Power Apparatus and System, 1979, PAS-98 (6), PP. 2047-2054.

[25] R. Billinton, W. Li,”Reliability Assessment of Electric Power Systems Using Monte Carlo Methods”, Plenum Press:New York, NY, USA, 1994.

[26] R. C. Green II, L. Wange, and C. Singh, “State Space Pruning for Power System Reliability Evaluation using Genetic Algorithm”, IEEE Conference Power and Energy Society General Meeting, July 2010, pp.1-6.

[27] R. N. Allan. R. Billinton, and N. M. K. Abdel-Gawad, “The IEEE Reliability Test System-Extensions to and Evaluation of the Generating System”, IEEE Transactions on Power Systems, vol. PWRS-1, pp. 1-7, November 1986.