Pertanika J. Sci. & Technol. 32 (4): 1687 - 1706 (2024)

SCIENCE & TECHNOLOGY

Journal homepage: http://www.pertanika.upm.edu.my/

Effects of Unavailability of Conventional Energy Units on Power Generation System Adequacy

Athraa Ali Kadhem[1,2]* and Noor Izzri Abdul Wahab[1]

[1]*Faculty of Engineering, University Putra Malaysia, 43400 UPM, Serdang, Selangor, Malaysia*
[2]*General Directorate of Educational Planning, Ministry of Education, Baghdad, Iraq*

ABSTRACT

Presently, aside from conventional power, wind energy is considered an important power source in electrical power supply systems. The prime factor affecting electrical power supply systems is the blackout of electrical power for load demand-supply. Therefore, the safe operation of interconnected large power systems integrated with wind energy cannot be carried out without understanding the system's behavior during abnormal and emergencies. In power generation systems, failure of the conventional generating units (CGUs) and wind turbine generating units (WTGUs) will lead to service interruption and subsequent disconnection of load points. This paper analyzes the impact of frequent failures of the CGUs and WTGUs on the output power systems. A Sequential Monte Carlo Simulation (SMCS) method and the Frequency and Duration (F&D) method are extremely effective for estimating the variation of risk indices when additional wind turbine generators are incorporated into the generation system. The results demonstrate the variation of reliability indices in the adequacy systems when additional WTGUs are incorporated into the generation system.

Keywords: Conventional generating unit, component failure, power system adequacy, sequential Monte Carlo simulation, wind turbine unit

ARTICLE INFO

Article history:
Received: 21 August 2023
Accepted: 02 January 2024
Published: 25 July 2024

DOI: https://doi.org/10.47836/pjst.32.4.13

E-mail addresses:
athraaonoz2007@yahoo.com (Athraa Ali Kadhem)
izzri@upm.edu.my (Izzri Abdul Wahab)
* Corresponding author

INTRODUCTION

The numerous adequacy problems in future power systems have been addressed (Alham et al., 2023). Generation system reliability is an important aspect and a big challenge in the planning for future system capacity expansion to ensure that the total installed capacity is sufficient to provide adequate

ISSN: 0128-7680
e-ISSN: 2231-8526

electricity when needed (Khoo et al., 2020a; Khoo et al., 2020b; Almutairi et al., 2015). Wind power is clean, renewable, and sustainable (Kadhem et al., 2017a). The growth rate and global installed wind power capacity (WPC) worldwide from 2015 to 2021 are shown in Table 1 and Figure 1, respectively. Where a growth rate is about (43%), and 705 MW of capacity had been installed worldwide by the end of 2022. Accordingly, when the percentage of wind penetration arrives at (>30%), the maximum penetration level for wind power in the system grid is indicated (Baloch et al., 2017). Therefore, the consumption of wind power farms is between 17 and 39 times as much as the consumption of conventional power.

Table 1
Growth rate (%) of wind power installation from 2015–2021

Countries	China	US	Germany	India	Spain	United Kingdom	Brazil	France	Canada	Italy
Growth Rate (%)	43	53	69	62	79	54	37	56	79	50
Total Growth Rate		43 %		Total Installed Wind Capacity					705 MW	

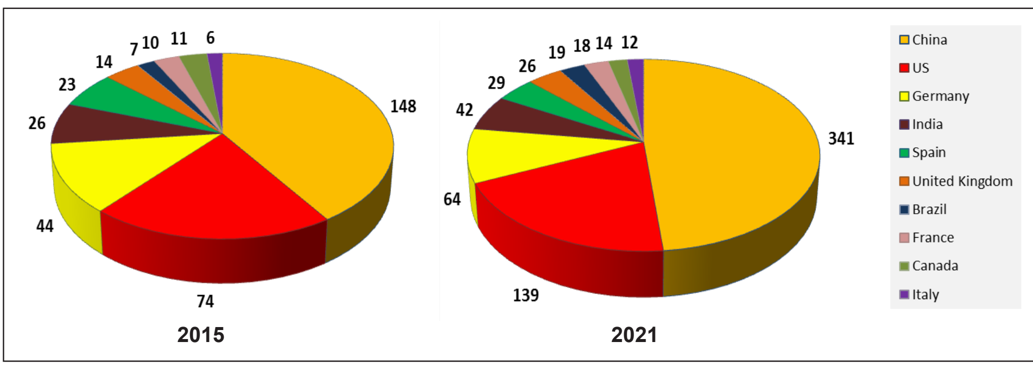

Figure 1. Total wind power cumulative installed capacity by country (website "Top 10 countries with largest wind energy capacity") in 2015 and 2021

The electrical grid is a vital component of modern society that requires significant and cost-effective investments to ensure its reliability (Lai et al., 2023). Various methods can be used to evaluate the reliability of power systems. One approach involves using energy consumption as a "benchmark," while others focus on determining the performance of individual system components and identifying instances of success or failure (Ibrahim, 2017). The effectiveness of these methods on various systems depends on the system's intricacy and the desired precision level. Consequently, the failure of any component in a power system will cause the entire system to fail (Kadhem et al., 2017b; Abdalla et al., 2020). The reliability assessment approaches for adequacy systems are generally divided into the analytical technique, the Monte Carlo simulation technique, and the intelligent search technique (Kadhem et al., 2017d). Reliability indices are considered for system adequacy assessment (Roy et al., 2017; Arabali et al., 2014). This study employs the simulation method, whereby the state of all the CGUs is considered.

The increasing flexibility of active distribution systems coupled with the high penetration of renewable distributed generators leads to an increase in the complexity of power systems (Su & Teh, 2023). Many works of literature have focused on studying the availability of renewable generation units in electric power systems integrated with wind energy (Ma et al., 2023; Ziegler et al., 2023). Meanwhile, the problem of measuring the unavailability of CGU in electric power systems integrated with wind energy has not been sufficiently addressed in the literature by using the SMCS method. Accordingly, this paper aims to find out the weaknesses of the CGU of the power supply system integrated with wind energy and also to figure out the amount of loss of capacity caused by the failure of CGU. Therefore, measuring system unit availability is vital and is considered the basic aspect of most reliability-related studies (Li et al., 2019; Peeters et al., 2018). This paper evaluates the efficiency of generating systems that use wind energy. Two models are used: one for the CGUs and one for the WTGUs. Additionally, a load model is used to serve as a reliability indicator. This paper examines the reliability of these systems when undesirable failures occur during their lifespan. To conduct this study, the researchers adopted the SMCS technique, a powerful tool for assessing the safety and reliability of power systems. The findings of this study can help to identify areas for improvement.

When integrating WTGUs with conventional generating plants, certain considerations need to be considered for adequacy assessment (Kadhem et al., 2016). In this report, we utilize the Weibull Distribution Probability (WDP) model to generate and duplicate wind speed data for each hour of the year in the SMCS simulation process. The attainable power generated from the CGUs and WTGUs during power systems operation is computed, and the reliability index of the suggested technique indicates the efficiency of estimating the power output. The SMCS method is extremely effective for estimating the variation of risk indices when additional wind turbine generators are incorporated into the generation system. The proposed algorithm has been tested on Standard MRTS, IEEE-79, and IEEE-96 test systems.

RELIABILITY ASSESSMENT OF ADEQUACY SYSTEM WITH WTGUS

It is crucial to consider certain important factors to ensure the successful integration of wind energy systems into the adequacy assessment of conventional generating plants. Figure 2 presents a concise overview of these factors, which primarily includes the development of a model for conventional generation and creating an appropriate wind velocity model. Both steps are essential for achieving optimal results. The output energy from WTGUs and conventional generators differ significantly in their characteristics. Conventional generators supply power at their rated values unless they experience partial or complete failure. However, WTGUs generate power output that varies due to the wind speed fluctuation and the power curve's design characteristics.

Reliability indices are utilized as design constraints for generating system adequacy assessment to ensure reliable system operation. These concepts are discussed in Wang and Singh (2007) and Wang et al. (2007). Two important indices are employed to compute the reliability of the power system adequacy, represented by Equations 1 and 2. The functions of these indices can be summarized as follows:

LOLE (hr/yr or days/yr): To determine the required time to be considered when the system's power capacity does not satisfy the load demand.

LOEE (MWh/year): To determine the required power capacity to be considered when the system's power capacity is less and does not satisfy the load demand.

$$LOLE = \frac{i}{n} \sum_{i=1}^{8736 \times n} LOLE_I \qquad [1]$$

$$LOEE = \frac{i}{n} \sum_{i=1}^{8736 \times n} LOEE_I \qquad [2]$$

A level of LOLE is usually used as the reliability criteria of the generation systems. The standard level of LOLE is one-day-in ten years or less (Phoon, 2006). It does not mean a full day of shortages once every ten years; rather, it refers to the total accumulated time of shortages that should not exceed one day in ten years. Now, LOLE represents the reliability standard utilized in various countries. The reliability standard adopted in various countries is presented in Table 2 (Shi, 2014). The LOLE is also smaller than the popularly used criterion (LOLE ≤ 2.4 hours/year) (Gao, 2013).

Table 2
Reliability standard LOLE in 10 countries

Countries	LOLE value (days/year)	LOLE value (hours/year)
Australia		(5 ≈ 7)
Belgium		(16)
Brazil	(2.5)	
Canada	(0.1)	
France		(3)
Japan	(0.3)	
Republic of Ireland		(8)
Spain	(0.1)	
China	(1 ≈ 2)	
UK		(3)

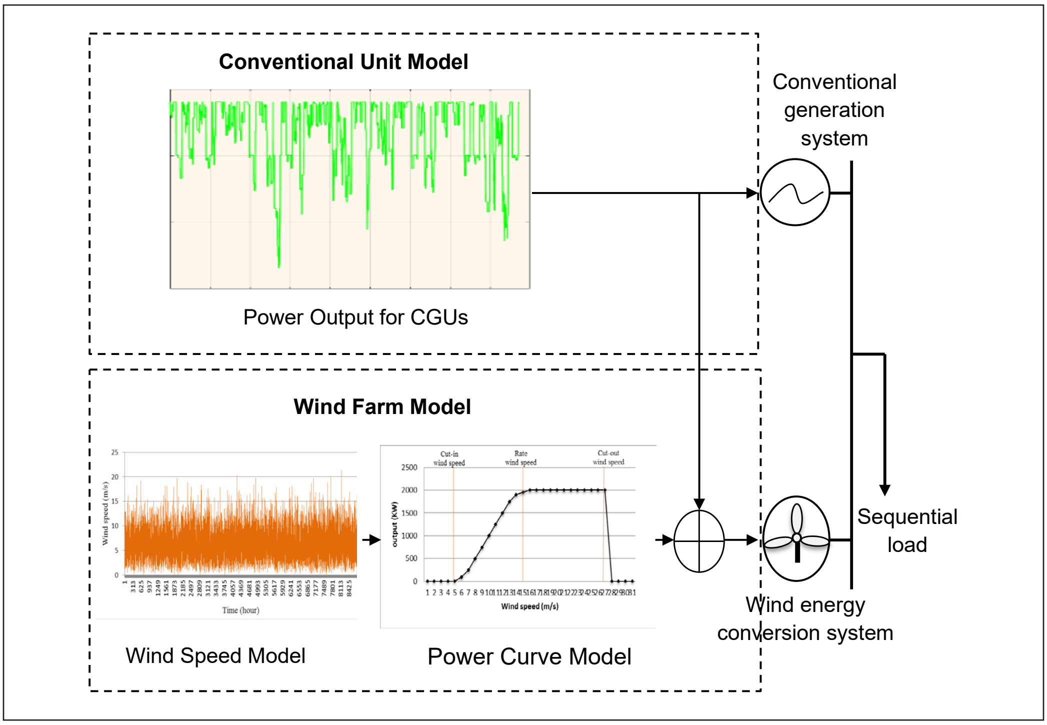

Figure 2. Adequacy systems modeling

METHODOLOGY

Conventional Unit Model

The available capacity of all system-generating units is added together to determine the adequacy of the system's power capacity. Each generating unit in power systems has two states (2-states), "where the generating units are regarded as either being entirely out of service (down, or MW =0) or totally in service (up, or MW = total power output of unit)" (Billinton & Li, 1994). Figure 3 shows the operation cycle for each generating unit in the MRTS test system and the relationship between the reliability parameters. In this study, the Capacity Outage Probability Table (COPT) has been adopted as the methodology of system adequacy assessment, in addition to knowing the relationships between the FOR value of CGUs and the reliability parameters of units, which are λ, μ, MTTF, MTTR, and MTBF.

In this manner, the status of all system components is sampled between 0 and 1 in each simulation interval (Wang et al., 2007). Each simulation interval of sampled system states is randomly selected and independent from the preceding and succeeding samples (Hou et al., 2016). The operation cycle per hour per year of the CGUs for the MRTS system is demonstrated in Figure 3. In the case of a two-state model, the value of a random number is compared with the FOR of the system units, where the generation unit is presented as either a fully rated state (Up= 1) or a failed state (Down= 0).

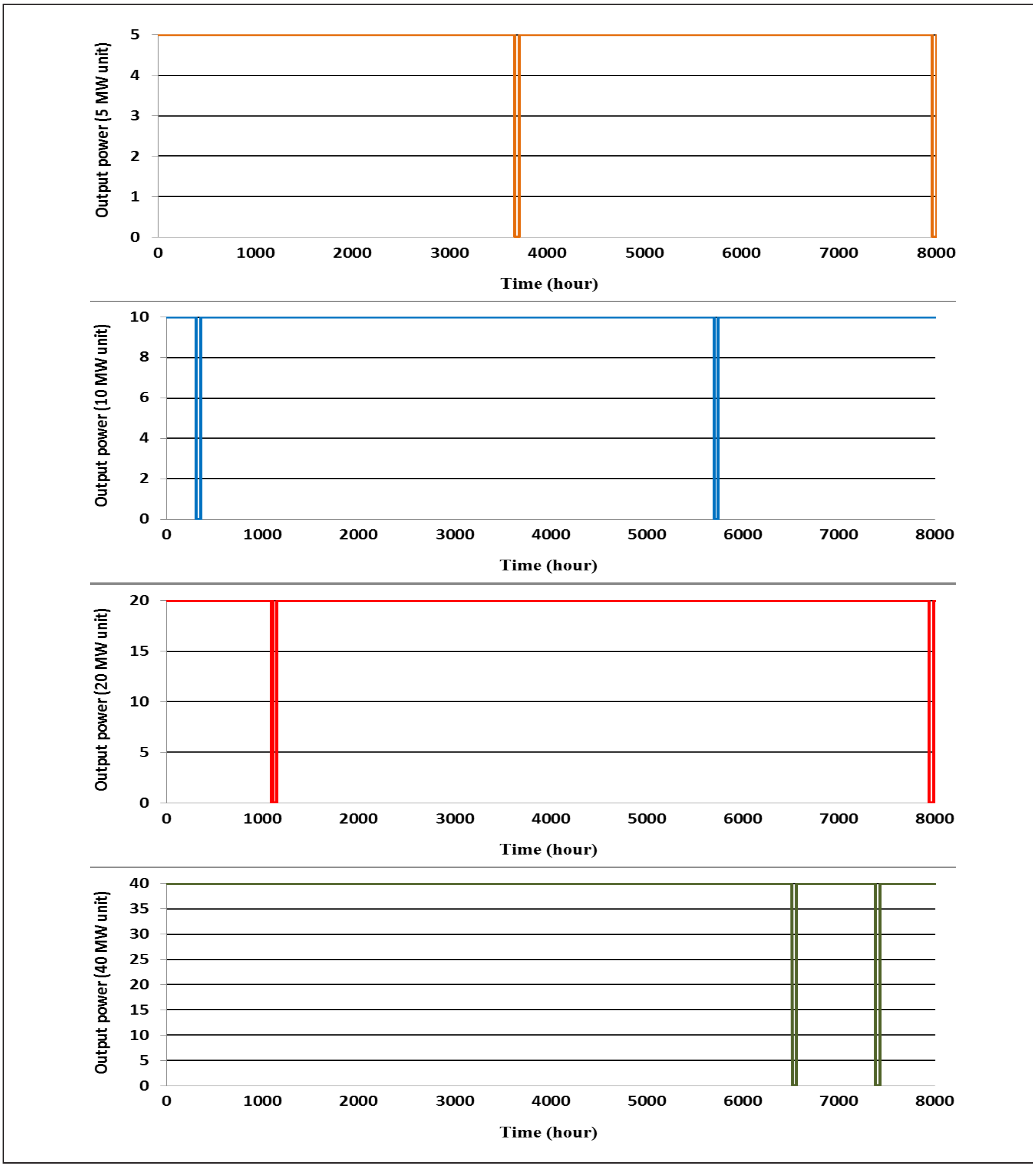

Figure 3. The operation cycle per hour year of some generating units for the MRTS test system

Wind Farm Model

Wind Speed Model

Obtaining accurate wind speed data for wind resource estimation can be difficult (Chauhan & Saini, 2015). Therefore, an effective model for estimating wind power is necessary for power system reliability evaluation (Saltani et al., 2014; Soleymani et al., 2015). However, wind speed data forecasting is still a problem that requires a distribution math model. This paper utilizes the Weibull Distribution model (WDM), which consists of two parameters: scale parameter c and shape parameter k. These parameters effectively depict wind speed data and frequency distribution and predict wind energy output from a wind turbine (Kadhem et al., 2017c). Figure 4 displays the representation of the two Weibull distribution parameters with different values.

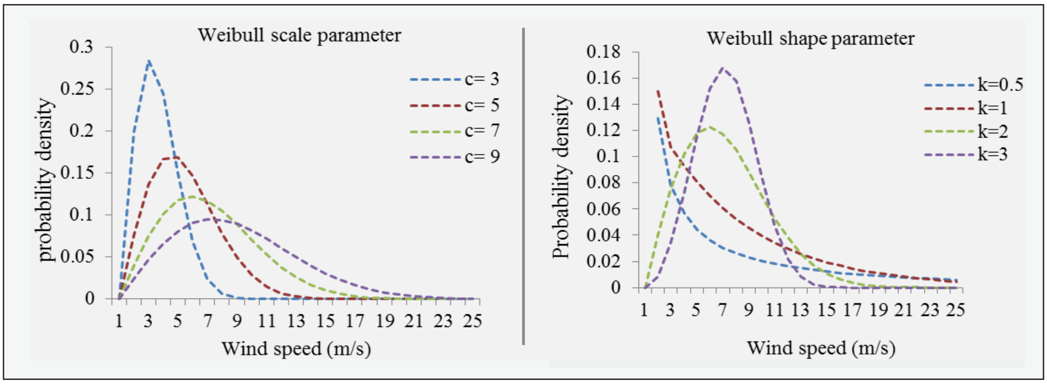

Figure 4. Different values of the k and c of the Weibull Distribution density

The shape parameter k controls the shape of the WDM. Therefore, the parameter k shows the width of the wind speed distribution (*V*). Meanwhile, in the wind simulation, c is the "mean value" of the speed. By applying Equation 3, wind can be reproduced "artificially," which can be used to generate a power output of the WTGUs by setting the value *k*=2 and *c* =7.

$$V = C\left[-Ln\,(U)^{1/k}\right] \qquad [3]$$

In Equation 3, the WD parameters are set to c = 7 and k = 2 (Azad et al., 2014). The wind speed profile in Figure 5 shows hourly variations over ten years. Moderate winds are common, with rare occurrences of strong or weak winds. The available wind data measurements for one year and ten years show convergence. Wind speed data in the time series are commonly arranged in a frequency distribution format due to easier interpretation using statistical analysis. Table 3 reanalyzes the simulation for all-time series average wind speed using Weibull cumulative distribution functions, demonstrating that the average wind speed measurements are reliable. Based on the data presented in Figure 5, it is evident that wind speeds are predominantly distributed within the range of 6 to 15 m/s. As a result, the Weibull Model can effectively simulate the wind speed profile by appropriately adjusting its scale and shape parameters.

Table 3
Shows a reanalysis of the simulation for average wind speed

Years	1	2	3	4	5	6	7	8	9	10
Wind (m/s)	7.21	7.22	7.22	7.17	7.22	7.25	7.22	7.23	7.15	7.21

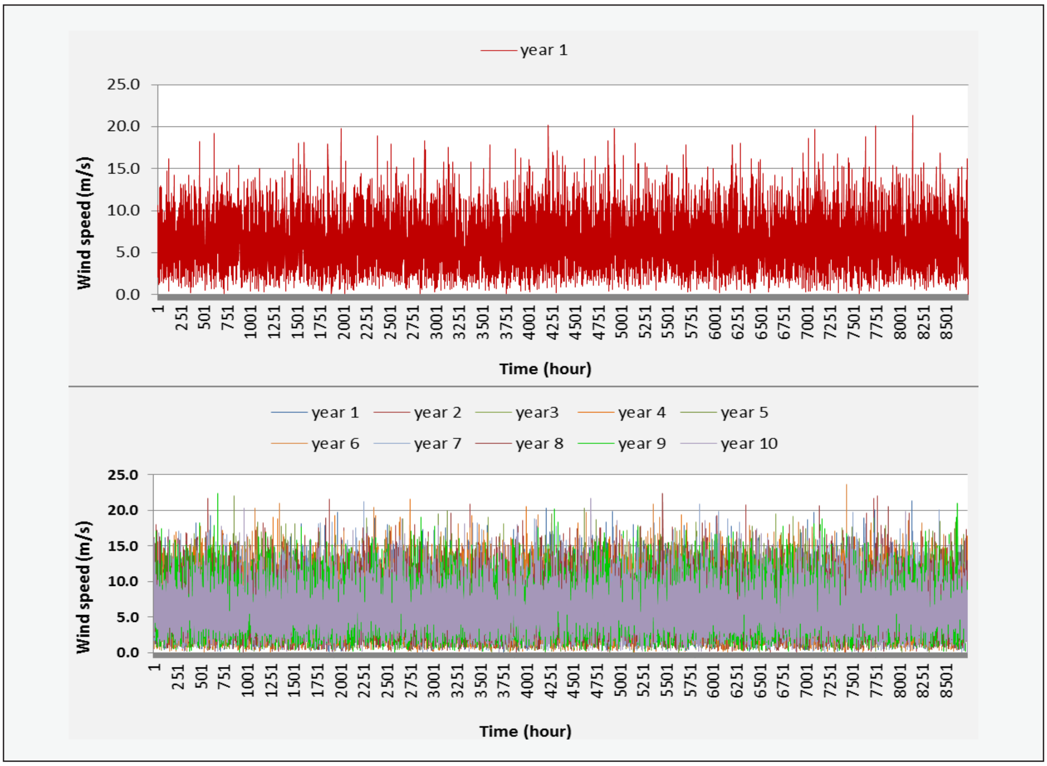

Figure 5. Picture of simulated wind speed an hour per year and an hour per for ten years

Power Curve Model (Wind Turbine Model)

Because the WTGUs can supply power with no fuel cost, wind energy is considered economically effective. In this study, the WDM represents the wind speed model expressing the WTGU realized output power based on wind speed variations for a specific site. Estimating wind energy can be challenging due to the random nature of wind velocity and variation in wind turbine power curves, which lead to uncertainties. During simulation, the power output from WTGUs can be determined based on the wind speed input using Equation 4.

$$P_{WTGUs} = \begin{cases} 0 & w < V_{ci} \\ (a + b + w + c * w) \times P_r & V_{ci} \leq w < V_r \\ P_r & V_r \leq w < V_{co} \\ 0 & w > V_{co} \end{cases} \qquad [4]$$

This study explores the potential for generating wind energy at varying levels that correspond to fluctuations in wind speed. As a result, the wind power model can produce energy with different levels of capacity, ranging from instantaneous to hourly. Simulation of the profiles of the wind speed was employed to simulate the ability of WTGUs to generate wind output power. From Equation 4, the values *a, b*, and *c* are constants presented in Khare et al. (2016) and Chauhan and Saini (2015). Based on this equation, the WTGU does not produce any value energy "when the wind speed *w* (m/s) is less than the cut-in rate *Vci* (m/s) of the turbine speed and shuts down power production from WTGU when the wind speed exceeds the cut-out speed *Vco* (m/s) from the turbine speed ."The output power *(Pr)* increases as the wind speed increases within the range where the rated speed of the wind *Vr* (m/s) remains fixed, and WTGU generates a rate of output power.

This study focuses on the characteristics of WTGU, specifically the "cut-in-speed, cut-out-speed, and rate speed of 4, 25, and 19 m/s, respectively, with a rated power of 2 MW" (Kadhem et al., 2019b). Figures 6 and 7 show the hourly wind speed forecast and simulated wind power output of a WTGU with a 2 MW power rate for a year.

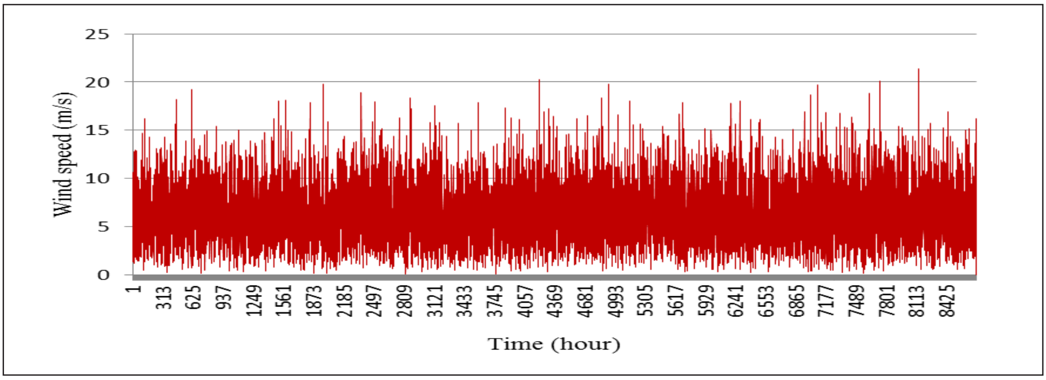

Figure 6. Shows the forecast for hourly wind speed over a year

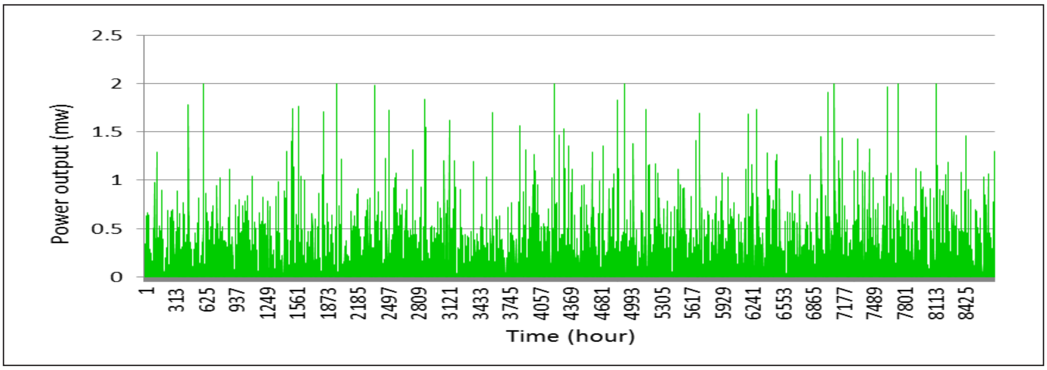

Figure 7. Indicates for the simulation wind power output for WTGU with a power rate of 2 MW for a similar period

Steps of Evaluation Procedure

When assessing the adequacy of power generation involving wind energy, the first step is to create a capacity model based on the operational characteristics of the CGUs and WTGs. This process is illustrated in Figure 8. The capacity and load models are used to develop a risk model. This paper presents a power systems reliability assessment that combines the SMCS method with the F&D method (Shi & Lo, 2012). The F&D technique offers insights into the frequency and length of the insufficient capacity situation. Here are the primary steps involved in carrying out the procedures for assessing the adequacy of generation systems:

Step 1: Input the reliability data for the CGUs (λ, μ, MTTF, MTTR) to create a system components capacity and total system capacity model.

Step 2: Input the sequential load duration curve level to create values of load demand hourly states—the annual SLDC models for MRTS and IEEE-RTS-79.

Step 3: Run the system to calculate probability values of the COPT of the system units, select failed states for the CGUs, and additionally know the system contingency state and determine the priority order of the unit's more failed states.

Step 4: Calculate the reliability indices using Equations 1 and 2 for a number of sample years.

Step 5: Adjust the power system parameters again, the parameters of WTGUs and wind farm conditions.

Step 6: Obtain the power output for WTUGs using Equations 3 and 4. Repeat steps 1–5.

Step 7: Generate a capacity outage probability table for both conventional generating units and wind farm units using the SMCS and F&D methods.

Step 8: Calculate the results of the reliability indices.

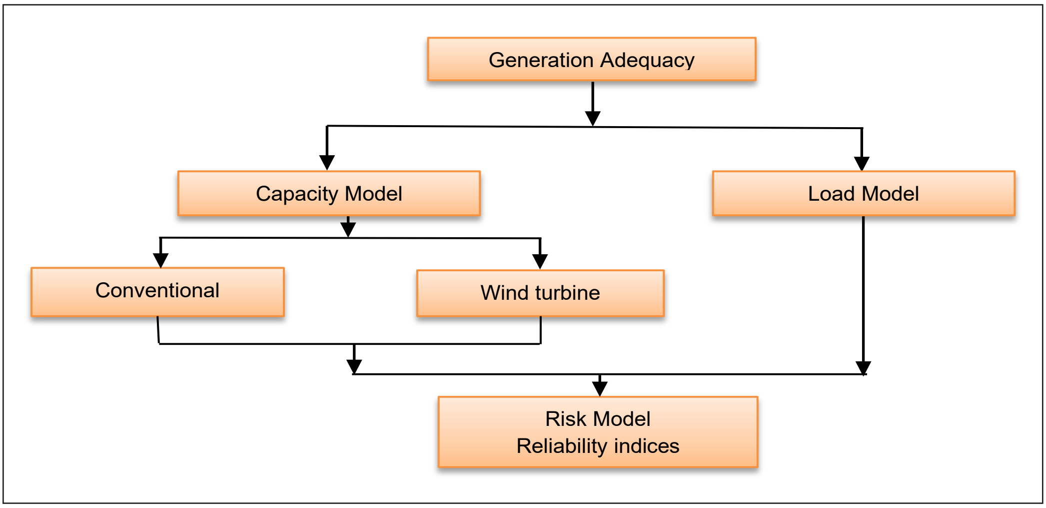

Figure 8. The risk model for assessing the adequacy of a generating system

SEQUENTIAL LOAD MODEL

The system's reliability is analyzed using the Time Series Load forecasting technique. Load designs can be either non-sequential or sequential paradigms with various algorithmic approaches. The Sequential Load Duration Curve (SLDC) method can produce hourly load demand state values. Around “8736 hours” of separate states can be recorded yearly (Kadhem et al., 2019b). The annual SLDC models for MRTS & IEEE-RTS-79-96 are shown in Figure 9.

As shown in Table 4, the test systems of the reliability indexes consist of total power output, peak load, and generation units (Grigg & Wong, 1999).

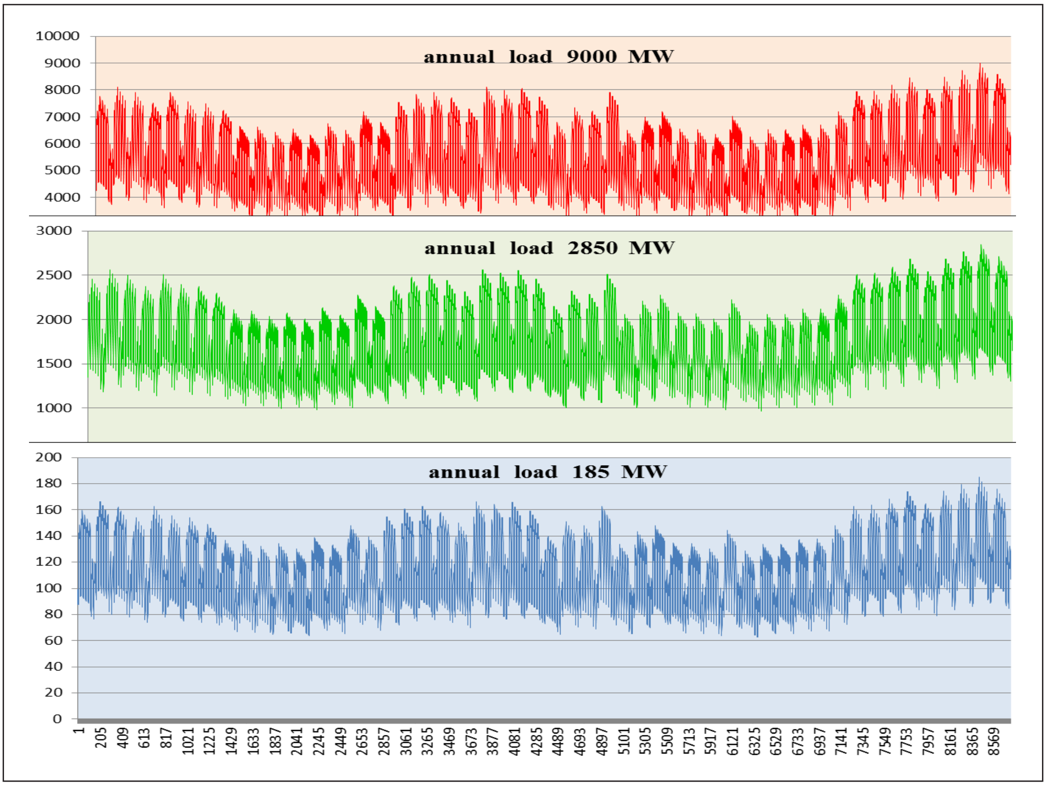

Figure 9. Annual SLDC model for MRTS and IEEE-79-96

Table 4
Total power output, peak load, and generation units for reliability test systems

Test System	Load (MW)	Capacity (MW)	No. units	MIM Cap. unit	MAX Cap. unit
MRTS	185	240	11	5	40
IEEE-79	2850	3405	32	12	400
IEEE-96	9000	10215	96	12	400

RESULTS AND DISCUSSION

This paper presents a method developed and tested using two different test systems: MRTS and IEEE-RTS-79-96. These systems are used to validate the performance of the SMCS method in assessing the reliability of generating systems’ adequacy.

Case (1): System with only CGUs

As shown in Table 4, the test systems of the reliability indexes applied in this paper consist of total power output, peak load, and generation units. The SMCS and F & D methods calculate generation systems' adequacy by iterative selection and measurement of system failure states. Because it relies on proportionate sampling, it is very efficient in locating failure states.

In this search, the threshold probability (t_p) equals t_p = 1e-6, t_p = 1e-15 and t_p = 1e-20 for MRTS and IEEE-79-96 test systems, respectively. As the system size increases, the threshold probability is predicted to decrease.

The system's capacity adequacy is determined by adding up the available capacities of all the units that generate power. Each generating unit in power systems is in one of two states, either out of service (MW =0) or totally in service (MW = total power output of unit). Figures 10 and 11 explain the operation cycle for each CGU in the test systems and the relationship between the reliability parameters. By combining reliability parameters (λ, MTTR) for a certain duration (usually one year), the operation cycle of every system unit can be estimated. Consequently, Figures 10 and 11 show a simulated scenario for the most frequent test system failure run for several years (800 years). In addition, these figures show the results recorded in Tables 6 and 7.

When simulating the system, running over a large number of years is more useful to identify additional cases of failure that happen or are repeated. Figures 10 and 11 depict the operation cycle per hour per year of the generating units for the MRTS and IEEE-79 test systems running with a number of samples between 100–800. From these figures, we can conclude that the units with a capacity of 40 MW and 400 MW for MRTS and IEEE-79-96 test systems, respectively, have more repeated failed states.

As seen in Table 5, in the case where the sample number is 800, we can see that available units in the system operation cycle are 2×5, 1×10, 4×20, and 1×40 MW, with a total capacity of 140 MW and failure probabilities value of 0.0013. Meanwhile, the unavailable units in the system operation cycle are 1×20 and 2×40 MW. In Table 6, for the IEEE-79 test system in the case where the sample number is 800, we can see that available units in the system operation cycle are 5×12, 2×20, 6×50, 4×76, 3×100, 4×155, 3×197, 0×350, and 0×400 MW, with a total capacity of 2215 MW and failure probabilities value of 0.0017. Meanwhile, the unavailable units in the system operation cycle are 2×20, 1×350, and 2×400 MW. In Table 7, for the IEEE-96 test system, where the sample number is 800, we can see that available units in the system operation cycle are 15×12, 11×20, 17×50, 10×76, 9×100, 9×155, 9×197, 3×350, and 2×400 MW, with a total capacity of 7928 MW and failure probabilities value of 0.00608. Meanwhile, the unavailable units in the system operation cycle are 1×20, 1×50, 2×76, 3×155, and 4×400 MW.

Calculations of the COPT for the system units are set out in Tables 5, 6 and 7. The results show the contingency state and priority order of the units' more failed states. The reliability assessment indices generated by the system are compared with other methods reported in the literature to validate the effectiveness of the proposed method. This comparison is shown in Table 8 (Kadhem et al., 2019a).

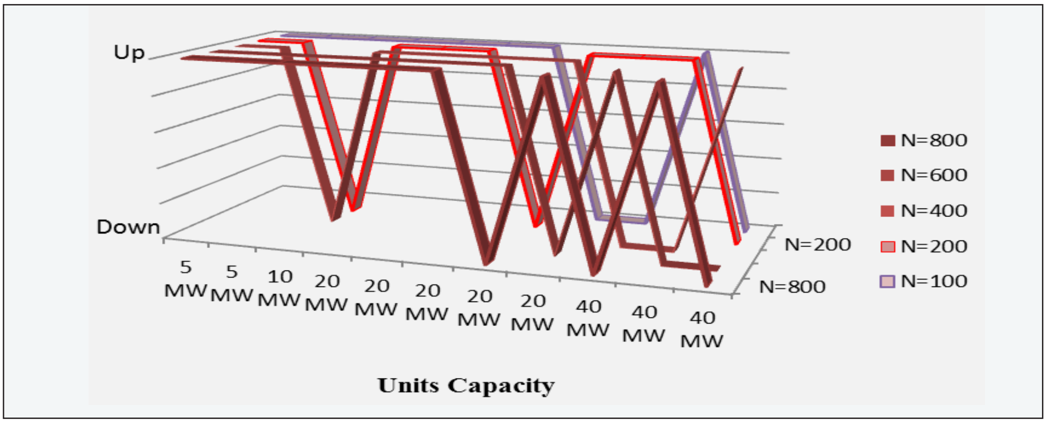

Figure 10. The operation cycle per hour per year of the generating units for the MRTS test system with a number of samples between (100–800) without wind power

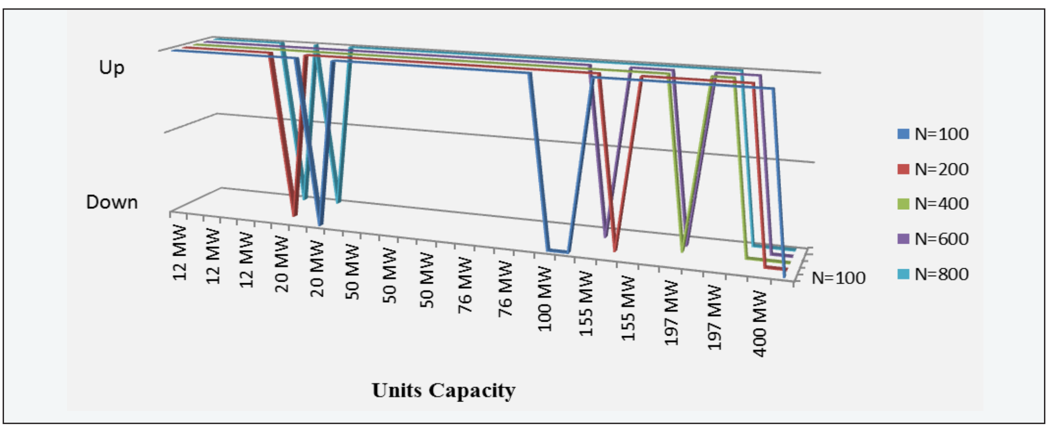

Figure 11. The operation cycle per hour per year of the generating units for the IEEE 79 test system with a number of samples between 100–800) without wind power

Table 5
The COPT from the SMCS for MRTS-System

No. of samples	Unit number and capacity				Failure Prob.	Total (MW)
	2 ×5 MW	1×10 MW	5×20 MW	3×40 MW		
N=100	2	1	4	1	0.0013	140
N=200	2	0	4	2	0.0012	170
N=400	2	0	5	1	0.0017	150
N=600	2	1	4	1	0.041	160
N=800	2	1	4	1	0.0013	140

Table 6
The COPT from the SMCS for IEEE-RTS-79-System

No of samples	Unit number and capacity									Failure Prob.	Total (MW)
	5×12 MW	4×20 MW	6×50 MW	4×76 MW	3×100 MW	4×155 MW	3×197 MW	1×350 MW	2×400 MW		
N=100	5	3	6	4	1	4	3	1	1	0.0024	2785
N=200	5	3	6	4	2	4	3	0	1	0.0038	2535
N=400	5	4	6	4	3	4	2	0	0	0.0033	2058
N=600	5	4	6	4	3	3	2	1	0	0.0029	2253
N=800	5	2	6	4	3	4	3	0	0	0.0017	2215

Table 7
The COPT from the SMCS for IEEE-RTS-96-System

No of samples	Unit number and capacity									Failure Prob.	Total (MW)
	15×12 MW	12×20 MW	18×50 MW	12×76 MW	9×100 MW	12×155 MW	9×197 MW	3×350 MW	6×400 MW		
N=100	15	7	18	12	7	9	7	3	2	0.00471	7456
N=200	15	8	17	11	7	9	7	3	3	0.00154	7750
N=400	15	7	18	10	7	9	9	3	2	0.00081	7698
N=600	15	8	17	10	8	10	7	3	2	0.00035	7529
N=800	15	11	17	10	9	9	9	3	2	0.00608	7928

Table 8
Reliability indices of the MRTS and IEEE-RTS-79-96 system

Test System		Reliability Indices			
		LOLE	LOEE	LOFE	LOLD
MRTS-System	Ref. (Kadhem et al., 2017d)	1.161	10.32	0.239	4.856
	Compute	1.232	11.61	0.333	3.698
IEEE-79-System	Ref. (Soleymani et al., 2015)	9.385	1120.3	2.72	3.45
	Compute	9.355	2311.5	2.019	4.633
IEEE-96-System	Ref. (Kadhem et al., 2019a)	0.140	23.97	-	-
	Compute	0.160	17.11	-	-

Case (2): System with CGUs and WTGUs

The WTGUs installed in wind farms have the following specifications: $V_{ci} = 5.3$, $V_{co} = 21$, and $V_r = 12$ m/s. The rated output power of every WTGU is given as $P_r = 2.5$ MW (Almutairi et al., 2015; Billinton & Gan, 1993). A wind farm with 16 identical 2.5 MW and a total wind power capacity of 40 MW is added into the MRTS, whereby the wind power penetration level is about 16.6 %. For IEEE-79, wind farms include 160 identical 2.5 MW and a total capacity of 400 MW is added with a wind power penetration level of about 11.6%. With the installation of 16 and 160 WTGUs of 2.5 MW, the total installed capacity is 40 and 400

MW, respectively. Figures 12 and 13 show the simulated output power with the associated failure of individual units for the MRTS and IEEE-79 test system running with a number of samples between 100–800. From these figures, we can conclude that the units with a capacity of 40 MW and 350 MW for MRTS and IEEE-79 test systems, respectively, have more repeated failed states even with wind power penetration.

It is well known that a 40-MW and 400-MW wind farm cannot replace the same size CGU with a capacity of 40 MW and 400 MW, respectively, due to the intermittent wind speed characteristics. Therefore, the capacity credit of a wind farm is required to replace a given number of CGUs for the same system reliability (Billinton & Chen, 1998; Castro & Ferreira, 2001).

From Table 9, in the case where the sample number is 800, we can see that available units in the MRTS system operation cycle are 2×5, 1×10, 4×20, and 2×40 MW, with a total capacity of 180 MW and failure probabilities value of 0.0334. Meanwhile, the unavailable

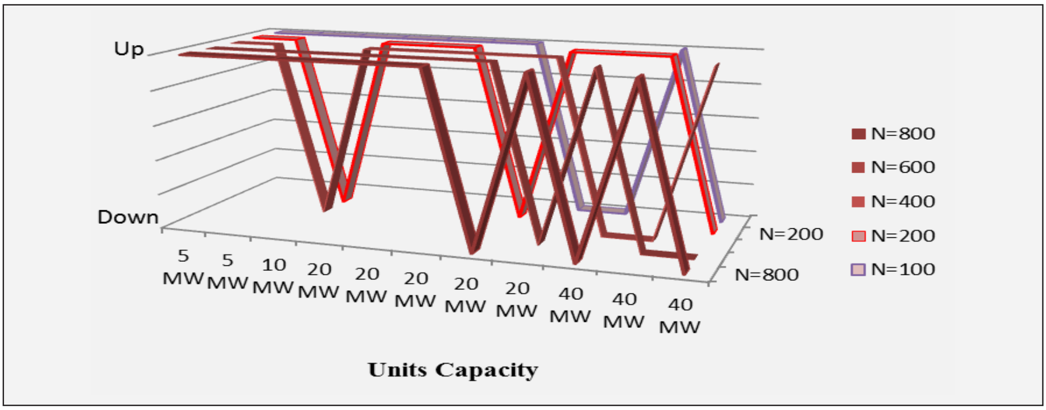

Figure 12. The operation cycle per hour per year of the generating units for the MRTS test system with number samples between 100–800 with added wind power (40 MW)

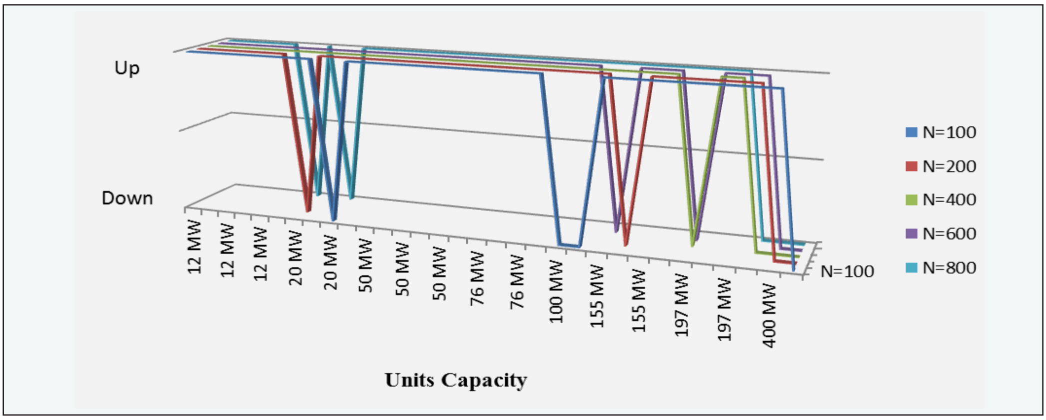

Figure 13. The operation cycle per hour per year of the generating units for the IEEE 79 test system with number samples between 100–800 with added wind power (400 MW)

units in the system operation cycle are 1×20 and 1×40 MW. In Table 10, for the IEEE-79 test system in the case where the sample number is 800, we can see that available units in the system operation cycle are 5×12, 3×20, 6×50, 4×76, 3×100, 4×155, 2×197, 0×350, and 2×400 MW, with a total capacity of 2838 MW and failure probabilities value of 0.0273. Meanwhile, the unavailable units in the system operation cycle are 1×20, 1×197, and 1×350 MW.

Table 9
The COPT from the SMCS for MRTS-System with wind power

No. of samples	Unit number and capacity with wind power (40 MW)				Failure Prob.	Total (MW)
	2 ×5 MW	1×10 MW	5×20 MW	3×40 MW		
N=100	2	1	4	2	0.0452	180
N=200	2	1	5	1	0.0461	160
N=400	2	1	5	1	0.0362	160
N=600	2	1	4	2	0.0258	180
N=800	2	1	4	2	0.0334	180

The Capacity Outage Probability Table (COPT) calculations for the system units are shown in Tables 9 and 10. The results show the contingency state and priority order of the more failed states of the unit. Additionally, to confirm the effectiveness of our proposed method, we compared the results of our system's reliability assessment indices with those of other methods presented in the literature (Table 11).

Table 10
The COPT from the SMCS for IEEE-RTS-79-System with wind power

No. of samples	Unit number and capacity with wind power (400 MW)									Failure Prob.	Total (MW)
	5×12 MW	4×20 MW	6×50 MW	4×76 MW	3×100 MW	4×155 MW	3×197 MW	1×350 MW	2×400 MW		
N=100	5	4	6	4	2	4	3	0	1	0.0113	2555
N=200	5	3	6	4	3	4	3	0	1	0.0338	2635
N=400	5	4	6	4	3	3	3	1	0	0.0206	2450
N=600	5	4	6	4	3	2	3	1	1	0.0153	2695
N=800	5	3	6	4	3	4	2	0	2	0.0273	2838

Table 11
Reliability indices of the MRTS and IEEE-RTS-79 system

Test System		Reliability Indices			
		LOLE	LOEE	LOFE	LOLD
MRTS-System	Ref. (Almutairi et al., 2015)	0.98	7.36	0.22	4.48
	Compute	0.85	12.66	0.17	4.99
IEEE-79-System	Ref. (Kadhem et al., 2017c)	7.43	823.78	0.29	25.6
	Compute	7.18	989.94	0.31	23.3

CONCLUSION

One of the most common problems in calculating the adequacy of generation systems is stochastic conventional units' failure, which could expose an electrical network to unexpected power outages. This paper presents the impact of the conventional generation units' failure frequency on the output power systems. The sequential Monte Carlo simulation method (SMCSM) is utilized to assess the reliability of power systems. When the simulation of generation systems runs over many years, it is more useful to identify additional failure cases that happen or are repeated. In this paper, the assessment of reliability indices in the adequacy systems is carried out in two scenarios, where the test system without wind turbine units is treated as the base case, and the test system with wind turbine units is the subsequent case. In the first scenario (System With Only CGUS), Figures 10 and 11 depict the operation cycle per hour per year of the generating units for the MRTS and IEEE-79 test system running with a number of samples between 100–800.

From these figures, we can conclude that the units with 40 MW and 400 MW capacity for MRTS and IEEE-79 test systems have more repeated failed states. In the second scenario (System With CGUs & WTGUs), Figures 12 and 13 show the simulated output power with the associated failure of individual units for the MRTS and IEEE-79 test system running with a number of samples between 100–800. From these Figures, we can conclude that the units with a capacity of 40 MW and 350 MW for MRTS and IEEE-79 test systems have more repeated failed states even with wind power penetration. The attainable power generated from the CGUs and WTGUs during power systems operation was computed, and the reliability index of the suggested technique indicates the efficiency of estimating the power output. This paper's proposed reliability model and SMCS method can generate comprehensive reliability indexes based on the findings. The proposed method has been tested on Standard MRTS, IEEE-79, and IEEE-96 test systems.

ACKNOWLEDGMENTS

The authors would like to thank University Putra Malaysia (UPM) for supporting this study.

REFERENCES

Abdalla, A. N., Nazir, M. S., Jiang, M., Kadhem, A. A., Izzri, N., Wahab, A., & Cao, S. (2020). Metaheuristic searching genetic algorithm based reliability assessment of hybrid power generation system. *Energy Exploration & Exploitation, 39*(1), 488-501. https://doi.org/10.1177/0144598720959749

Alham, M. H., Gad, M. F., & Ibrahim, D. K. (2023). Potential of wind energy and economic assessment in Egypt considering optimal hub height by equilibrium optimizer. *Ain Shams Engineering Journal*, *14*(1), Article 101816. https://doi.org/10.1016/j.asej.2022.101816

Almutairi, A., Ahmed, M. H., & Salama, M. M. A. (2015). Probabilistic generating capacity adequacy evaluation: Research roadmap. *Electric Power Systems Research*, *129*, 83-93. https://doi.org/10.1016/j.epsr.2015.07.013

Arabali, A., Ghofrani, M., Etezadi-Amoli, M., & Fadali, M. S. (2014). Stochastic performance assessment and sizing for a hybrid power system of Solar/Wind/Energy Storage. *IEEE Transactions on Sustainable Energy*, *5*(2), 363-371. https://doi.org/10.1109/TSTE.2013.2288083

Azad, A. K., Rasul, M. G., & Yusaf, T. (2014). Statistical diagnosis of the best Weibull methods for wind power assessment for agricultural applications. *Energies*, *7*(5), 3056-3085. https://doi.org/10.3390/en7053056

Baloch, M. H., Abro, S. A., Kaloi, G. S., & Mirjat, N. H., Tahir, S., Nadeem, M. H., Gul, M., Memon, Z. A., & Kumar, M. (2017). A research on electricity generation from wind corridors of Pakistan (two provinces): A technical proposal for remote zones. *Sustainability, 9*(9), Article 1611. https://doi.org/10.3390/su9091611

Billinton, R., & Chen, H. (1998). Assessment of risk-based capacity benefit factors associated with wind energy conversion Systems. *IEEE Transactions on Power Systems*, *13*(3), 1191-1196. https://doi.org/10.1109/59.709119

Billinton, R., & Gan, L. (1993). Wind power modeling and application in generating adequacy assessment. In *IEEE WESCANEX 93 Communications, Computers and Power in the Modern Environment Conference Proceedings* (pp. 100-106). IEEE Publishing. https://doi.org/10.1109/wescan.1993.270560

Billinton, Roy, & Li, W. (1994). *Reliability Assessment of Electric Power Systems Using Monte Carlo Methods*. Springer. https://doi.org/10.1007/978-1-4899-1346-3

Castro, R. M. G., & Ferreira, L. A. F. M. (2001). A comparison between chronological and probabilistic methods to estimate wind power capacity credit. *IEEE Transactions on Power Systems*, *16*(4), 904-909. https://doi.org/10.1109/59.962444

Chauhan, A., & Saini, R. P. (2015). Statistical analysis of wind speed data using Weibull Distribution Parameters. In *2014 1st International Conference on Non-Conventional Energy (ICONCE 2014)* (pp. 160-163). IEEE Publishing. https://doi.org/ 10.1109/ICONCE.2014.6808712

Gao, Z. (2013). *Reliability Management of Power Systems with Wind Power Generation and Energy Storage* [Doctoral dissertation, Nanyang Technological University]. NTU Library.

Grigg, C., & Wong, P. (1999). The IEEE reliability test system-1996 a report prepared by the reliability test system task force of the application of probability methods subcommittee. *IEEE Transactions on Power Systems*, *14*(3), 1010-1020. https://doi.org/10.1109/59.780914

Hou, K., Jia, H., Yu, X., Li, Y., Xie, C., & Yan, J. (2016). Composite generation and transmission system reliability assessment using impact increment based state enumeration method. In *2016 International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)* (pp. 1-6). IEEE Publishing. https://doi.org/10.1109/PMAPS.2016.7764119

Ibrahim, H. (2017). Electrical engineering 398. In H. Ibrahim, S. Iqbal, S. S. Teoh, & M. T. Mustaffa (Eds.), *9th International Conference on Robotic, Vision, Signal Processing and Power Applications* (pp. 37-45). Springer.

Kadhem, A., Wahab, N. I. A., Bin Aris, I., Bt Jasni, J., & Abdalla, A. N. (2016). Effect of wind energy unit availability on power system adequacy. *Indian Journal of Science and Technology*, *9*(28). 1-7. https://doi.org/10.17485/ijst/2016/v9i28/97962

Kadhem, A. A., Izzri, N., Wahab, A., Aris, I., Jasni, J., & Abdalla, A. N. (2017a). Advanced wind speed prediction model based on a combination of Weibull Distribution and an artificial neural network. *Energies, 10*(11), Article 1744. https://doi.org/10.3390/en10111744

Kadhem, A. A., Wahab, N. I. A., Aris, I., Jasni, J., & Abdalla, A. N. (2017b). Reliability assessment of power generation systems using intelligent search based on disparity theory. *Energies*, *10*(3), Article 343. https://doi.org/10.3390/en10030343

Kadhem, A. A., Wahab, N. I. A., Aris, I., Jasni, J., Abdalla, A. N., & Matsukawa, Y. (2017c). Reliability assessment of generating systems with wind power penetration via BPSO. *International Journal on Advanced Science, Engineering and Information Technology*, *7*(4), 1248-1254.

Kadhem, A., Wahab, N. I. A., Aris, I., Jasni, J., & Abdalla, A. N. (2017d). Computational techniques for assessing the reliability and sustainability of electrical power systems: A review. *Renewable and Sustainable Energy Reviews*, *80*, 1175-1186. https://doi.org/10.1016/j.rser.2017.05.276

Kadhem, A. A., Wahab, N. I. A., & AbdAlla, A. N. (2019a). Differential evolution optimization algorithm based on generation systems reliability assessment integrated with wind energy. In *5th International Conference on Power Generation Systems and Renewable Energy Technologies, PGSRET 2019* (pp. 1-6). IEEE Publishing. https://doi.org/10.1109/PGSRET.2019.8882705

Kadhem, A. A., Wahab, N. I. A., & Abdalla, A. N. (2019b). Wind energy generation assessment at specific sites in a Peninsula in Malaysia based on reliability indices. *Processes*, *7*(7), Article 399. https://doi.org/10.3390/pr7070399

Khare, V., Nema, S., & Baredar, P. (2016). Solar-wind hybrid renewable energy system: A review. *Renewable and Sustainable Energy Reviews*, *58*, 23-33. https://doi.org/10.1016/j.rser.2015.12.223

Khoo, W. C., Teh, J., & Lai, C. M. (2020a). Demand response and dynamic line ratings for optimum power network reliability and ageing. *IEEE Access*, *8*, 175319-175328. https://doi.org/10.1109/ACCESS.2020.3026049

Khoo, W. C., Teh, J., & Lai, C. M. (2020b). Integration of wind and demand response for optimum generation reliability, cost and carbon emission. *IEEE Access*, *8*, 183606-183618. https://doi.org/10.1109/ACCESS.2020.3029273

Lai, C. M., Teh, J., Alharbi, B., AlKassem, A., Aljabr, A., Alshammari, N. (2023). Optimisation of generation unit commitment and network topology with the dynamic thermal rating system considering N-1 reliability. *Journal of Electric Power Systems Research, (221)*, Article 109444. https://doi.org/10.1016/j.epsr.2023.109444

Li, K., Yang, Q., Cui, Z., Zhao, Y., & Lin, S. (2019). Reliability evaluation of a metro traction substation based on the Monte Carlo method. *IEEE Access*, *7*, 172974-172980. https://doi.org/10.1109/ACCESS.2019.2957151

Ma, J., Liu, Y., Zhang, S., Wu, L., & Yang, Z. (2023). Comprehensive probabilistic assessment on capacity adequacy and flexibility of generation resources. *International Journal of Electrical Power and Energy Systems*, *145*, Article 108677. https://doi.org/10.1016/j.ijepes.2022.108677

Peeters, J. F. W., Basten, R. J. I., & Tinga, T. (2018). Improving failure analysis efficiency by combining FTA and FMEA in a recursive manner. *Reliability Engineering and System Safety*, *172*, 36-44. https://doi.org/10.1016/j.ress.2017.11.024

Phoon, H. Y. (2006). Generation System Reliability Evaluations with Intermittent Renewables [Master dissertation, University of Strathclyde]. University of Strathclyde.

Roy, A., Sahoo, S. S., & Chatterjee, K. (2017). A reliability assessment model of a wind farm for generation adequacy studies of wind integrated power system. In *3rd IEEE International Conference on Science Technology, Engineering and Management* (*ICONSTEM 2017)* (pp. 566-570). IEEE Publishing. https://doi.org/10.1109/ICONSTEM.2017.8261386

Saltani, S., Mahmood-Reza Haghifam, N. S., & Jahromi, and M. Z. (2014). Novel method for feasibility study of wind farm installation based on reliability indices. In *2014 International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)* (pp. 1-6). IEEE Publishing. https://doi.org/10.1109/PMAPS.2014.6960654.

Shi, S. (2014). *Operation and Assessment of Wind Energy on Power System Reliability Evaluation Declaration of Author's Right* [Master dissertation, University of Strathclyde]. University of Strathclyde.

Shi, S., & Lo, K. L. (2012). Reliability assessment of power system considering the impact of wind energy. In *2012 47th International Proceedings of the Universities Power Engineering Conference* (pp. 1-6). IEEE Publishing. https://doi.org/10.1109/UPEC.2012.6398666

Soleymani, S., Mosayebian, M. E., & Mohammadi, S., (2015). A combination method for modeling wind power plants in power systems reliability evaluation. *Computers and Electrical Engineering*, *41*, 28-39. https://doi.org/10.1016/j.compeleceng.2014.12.005

Su, Y., & Teh, J. (2023). Two-stage optimal dispatching of AC/DC hybrid active distribution systems considering network flexibility. *Journal of Modern Power Systems and Clean Energy*, *11*(1), 52-65. https://doi.org/10.35833/MPCE.2022.000424

Wang, L., & Singh, C. (2007). Adequacy assessment of power-generating systems including wind power integration based on ant colony system algorithm. In *2007 IEEE Lausanne Power Tech* (pp. 1629-1634). IEEE Publishing. https://doi.org/10.1109/PCT.2007.4538559

Wang, L., Singh, C., & Tan, K. C. (2007). Reliability evaluation of power-generating systems including time-dependent sources based on binary particle swarm optimization. In *2007 IEEE Congress on Evolutionary Computation* (pp. 3346-3352). IEEE Publishing. https://doi.org/10.1109/CEC.2007.4424904

Ziegler, D. U., Prettico, G., Mateo, C., & Gómez San Román, T. (2023). Methodology for integrating flexibility into realistic large-scale distribution network planning using Tabu search. *International Journal of Electrical Power and Energy Systems*, *152*, Article 109201. https://doi.org/10.1016/j.ijepes.2023.109201