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RESEARCH ARTICLE

Reliability Analysis and Economic Prospect of Wind Energy Sources Incorporated Microgrid System for Smart Buildings Environment

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ABSTRACT This work deals with assessing the reliability of wind energy sources incorporated into a microgrid system to increase grid stability. As the share of power generated from wind energy continues to increase due to environmental concerns and to reduce carbon footprints, the case study proposed is designing an effective wind energy system for a smart building environment to reduce the burden on the grid. Incorporating wind energy systems into grid-connected buildings increases the reliability of the microgrid system for smart building environments. Applying smart techniques with integrated automation in the built environment can play a key role in decreasing peak demand for load development in smart cities. This can also enhance the overall efficiency of power grids, reduce waste, and enable the effective use of energy resources. Furthermore, researchers are finding new ways to collect energy from renewable sources and power-built environments due to dwindling fossil fuel resources and increased environmental awareness. The analysis of wind-connected power systems has been initiated to satisfy the increasing demand for reliable supply systems by consumers. This has prompted the use of wind energy systems with controlled techniques to enhance the reliability of power systems and reduce carbon footprints generated by fossil fuel-based power systems. Therefore, the main purpose of this work is to understand the economic prospects of wind energy sources for smart building environments, reliability analysis of wind energy sources-based power systems, reduce carbon footprints, and balance power demand through wind energy systems. The Progressive Wind Model Taylor-Sequence Proliferation (PWMTSP) and Innovative Six Parameters Based Progressive Beta Creative Model (ISPBPBCM) approaches are proposed to understand the reliability of wind energy-based power systems in smart building environments. The work also provides an economic analysis of the proposed low-cost wind power system with different capacities for residential consumers in selected geographic location. Eight cases are considered for the proposed effective wind energy system for smart building environments ranging from 2 MW to 32 MW. Hence, the economic analysis of the proposed systems is discussed for residential users. All eight cases are eco-friendly and reduce carbon emissions as these generated units from wind energy sources need not be purchased from fossil fuel-based plants, which increases the reliability of the proposed system. The expected energy not supplied (EENS) in the planned work increases as wind power capacity increases. Loss of load expectation (LOLE), loss of load probability

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(LOLP), and failure rate all decrease with the installation of more wind power systems. Moreover, it can be seen that mean time to repair (MTTR) improves when wind energy capacity rises incrementally from 2 MW to 32 MW. The proposed progressive wind model Taylor-sequence proliferation (PWMTSP) improves MTTR while increasing the wind power capacity from 4.8 to 13.8. The value of MTTR rises from 5.2 to 14.7 with the novel six parameter progressive beta creative model (ISPBPBCM). The proposed method is anticipated to be adaptable to various types of wind energy systems where dependability is a crucial component of system design and scalable to large wind integrated power systems.

INDEX TERMS Carbon footprints, converters, economic analysis, failure rate, inverters, ISPBPBCM, microgrid, PWMTSP, renewable energy, residential users, reliability, smart buildings, wind energy system.

NOMENCLATURE

PWMTSP	Progressive wind model taylor-sequence proliferation.
ISPBPBCM	Innovative six parameters based progressive beta creative model.
WPFEs	Wind power forecast errors.
DG	Distributed Generation.
H	Random variable.
FL	Failure event.
h	Predetermined bound.
n	Wind energy system units.
a	Rate of forced outage predicted value.
$M(x)$	Capacity outage probability of x.
$M(y)$	Capacity outage probability of y.
b	Capacity of the wind units at their original value.
cp	Capacity of the wind units that are being added.
Jw, *Kw*, *Lw*	Failure rates.
MTTF	Mean time to failure.
LOLE	Loss of load expectation.
LOLP	Loss of load probability.
LOLF	Loss of load frequency.
LOEE	Loss of energy expectation.
EENS	Expected energy not served.
$\delta, \theta, \omega, \varkappa$, Ѫ, ꟿ	Positive integers.
g	Constant.

I. INTRODUCTION

The modernization of electrical power systems is important for ensuring secure and reliable power delivery, as well as for minimizing carbon footprints. This involves deregulating the electricity market and deploying recent technologies and infrastructure. Renewable energy sources, storage, electronic transmission, and distribution all play a significant role in upgrading power systems. The wind energy system market has been growing rapidly in recent years due to its environmental friendly nature and low operating costs, making it one of the latest and most promising sources of energy with a significant market share [1]. Although wind energy conversion systems offer many environmental benefits, large additions of wind energy conversion can pose a threat to system reliability. Therefore, a thorough and precise examination of the effects of adding wind energy conversion is necessary to provide a credible reference for the operation of power systems. Due to the urgent global energy demand, additional energy sources are required beyond coal-based power generation, which leads to environmental pollution and carbon footprints. Microgrid systems based on different energy generation sources, rather than coal-based plants, have become more popular in recent times, as they are less reliant on fossil fuels for power production. Therefore, wind energy-based power generation systems can help address environmental problems while fulfilling the load demand in different areas [2]. Rushing towards the implementation of wind and solar energy and decreasing the carbon footprints have become a common consent and determined act of different countries. The main source of the carbon emission is thermal power generation, therefore, switching from the thermal power plant to renewable energy based plant can decrease the global warming [3]. A microgrid can work in island mode or grid connected mode by this bidirectional power can flow between the main grid and the renewable energy resources [4], [5]. The small power wind energy system allows the increased power generation and improve the system reliability also for residential purpose [6]. The rapid nature of the wind energy system is one of the challenge for economical operation of the system, therefore many approaches are used, some need forecast model, but precisely determination of wind power is still a task, therefore reinforcement learning techniques is used to overcome this challenge [7]. A robust dynamic method has been proposed for energy management in the microgrid system, the energy flow can be controlled by the approach [8]. Furthermore, a new distributed algorithm has been proposed to solve the economic dispatch issue which comes from communiqué uncertainties [9]. The random nature of wind speed is main reason of uncertainties of the wind power system outputs, it can affect the residential demand…)) [10]. Therefore, proper location should be chosen to install the wind power plant. Whereas, the uncertainty of wind power generation can be modelled through a private of vague probability supplies. The load shedding problem can be settled out [11]. Further, to decrease the extra spending on wind energy system, the wind sector sees to advances in the intelligent approach, so it become economical [12]. As the increase in the share of wind power generation in grid continues to increase, it will affect the system reliability. Therefore, multi-source in- formation fusion technique has been developed to enumerate system with considering the uncertainties. Previous studies have typically used normal distribution or other standard distribution models to describe the uncertainty of wind power forecast errors (WPFEs), which only capture aleatory uncertainty. In reality, it's important to take into account the epistemic uncertainty in WPFE modelling brought on by the knowledge and data gaps [13]. Different schemes have been proposed to reduce the converter cost and improve the reliability of the system and improve the wind turbine output. The method improves the voltage of capacitor to store the energy, therefore, the problem of cost and reliability have been resolved by voltage-utilization boosting method [14].

While a novel approach based on a fuzzy fault tree has been put up for the power system, taking into account the impact of merging electric vehicles and renewable energy sources. For grid-integrated energy systems, our technique incorporates the effects of component failure rates and inducement Gaussian distribution effects under the motivating framework of fuzzy fault trees [15]. The use of analytical dependability methodologies becomes computationally rigid as wind turbine size increases. Therefore, a comprehensive approach that uses multi-state Markov processes and a general generating function has been suggested for the obtainability value of the offshore wind energy system [16].

Whereas the reliability calculation focuses on the number of components level, converters, and machine side components. Yearly damages and energy cycle for the converters are evaluated separately under the long time cycle and short time cycle [17].

Because of globally use of renewable based system are fronting stability problems as the converter which are used with renewable energy resources have lower inertia as well as the issue of reliability [18].The grid incorporated wind-hydrogen system is very delicate to the fault in grid and variation in the wind speed which can cause the wind turbine disconnection thus failing the safe operation of the system. Therefore, superconducting magnet energy storage system has been proposed to protect the system operation and to improve the system reliability [19].Furthermore, the Weibull probability density function has been introduced to know the detailed reliability, maintainability and availability of various subsystems of the wind energy system [20]. Besides, it is important to include the reliability model of the converter into the complete power system reliability determination [21]. The reliable controllers design for wind incorporated systems needs a good model and acute parameters for the wind generator. A dynamic model and the measurement of parameter and control of variable speed wind system has been proposed [22]. Due to the variability of wind energy production, it is necessary to set up a flexible energy reserve that can make up for any potential imbalances between the load and generation. In order to reduce the variability of wind power supply and loss of load during a generation shortage, operation strategies that combine battery energy storage with wind power output have been developed. The established computation model, which describes the key features and operational constraints of the batteries, is used to assess the effects of operation strategies on system reliability [23]. When determining the right size and position for a wind energy system in a radial distribution network, several factors relating to the dependability, operation, economics, and environmental impact of the wind energy system are taken into consideration [24]. Whereas adaptive model predictive control technique has been used to solve issues of system operation including the reliability issue [25].

The wind-turbine configuration that maximizes the wind farm's power output takes into account the wind decay brought on by the wake effect and is determined using the CSS algorithm. The layout's efficacy is checked using WAsP simulation software [26]. The ideal restoration procedures and system uncertainties have been highlighted in the reliability evaluation for distribution systems integrated with renewable distribution generation sources. The restoration optimization framework for reliability assessment takes into consideration the uncertainties related to the power generation from renewable resources, time-dependent load demand, random prediction errors, and random fault events [27]. Whereas, the main simulator modules are covered, and many simulation-based analyses of renewable energy sources are illustrated. These instances highlight the value of investigating grid-connected, independent and self-driving machines via simulation. The RPM-SIM is flexible and simple to use [28]. A suggested multi-scenario risk-oriented clustering technique takes into account renewable energy. The risk for various scenarios is calculated using the enumeration approach. The Fuzzy C-means clustering method, that optimizes the similarity of scenarios in a single cluster, is used to cluster the possibilities according to the possible hazards of each scenario [29]. In order to satisfy renewable objective under high security standards and renewable uncertainty, this study provides a two-stage min-max-min model for co-optimizing the growth of the transmission system and renewable generation capacity [30].

In this work, the reliability assessment of wind energy-incorporated systems in smart building environments has been proposed. Two approaches - Progressive Wind Model Taylor-Sequence Proliferation (PWMTSP) and Innovative Six Parameters based Progressive Beta Creative Model (ISPBPBCM) are proposed for the reliability analysis. The proposed models represent various scenarios of a wind-incorporated power system and load, and various reliability indices are generated to evaluate the system's reliability. The economic aspect of the proposed system with various plans for residential users in Madurai, Tamilnadu, is also taken into consideration. An economic analysis of the suggested low-cost wind power system with various capacities for residential consumers in a chosen geographic area is also provided in the study. The suggested efficient wind energy system is examined in eight instances, with capacities ranging from 2 MW to 32 MW for smart building environments. As a result, the economic analysis of the suggested systems for residential customers is covered. As these generated units from wind energy sources do not need to be purchased from fossil fuel-based plants, increasing the reliability of the suggested system, all eight cases are environmentally friendly and reduce carbon emissions.

Section II discusses the wind energy sources incorporated microgrid system for smart buildings environment, while Section III presents the wind-incorporated power system reliability analysis using the PWMTSP and ISPBPBCM techniques. Case studies and discussions are provided in Section IV, and finally, concluding statements are given in Section V.

II. WIND ENERGY SOURCES INCORPORATED MICROGRID SYSTEM FOR SMART BUILDINGS ENVIRONMENT

Intelligent and energy efficient buildings have become so popular for smart buildings, helpful for developing smart grids and smart cities. These days, the usage of a variety of smart appliances, the incorporation of different intelligent techniques, and on-site power generation from wind energy sources have all contributed to the residential buildings becoming smarter. The main issue in developing the control system for this kind of building is to cut back on energy use without compromising customer comfort. Due to increasing the large number of smart appliances day by day, hence reliability issues are also arising. A smart wind based system is becoming imperative given the concerns with energy scarcity and global warming since it helps to lower demand for electricity, especially during periods of peak load. With the increase in the cost of fossil fuels, grid incorporated coal-based systems bring the difficulties of the system in reliability degradation and carbon footprint emissions, these can be solved by using wind energy systems. The wind energy-based system is well-matched for overcoming this difficulty in the Madurai, Tamil Nadu, India as it reduces the use of fossil fuels and saves greenhouse gas emission costs. Fossil fuel based power plant creates the huge carbon emissions, it can be decreased with the used of wind power plants for residential users. Wind energy systems are eco-friendly and reliable also and so they are becoming popular these days around the world specially in developing countries like India which has huge potential of installing wind power plants, but evaluation of power system reliability is very important with increase in penetration of wind power generation into the grid because, the intermittent nature and volatility of the wind energy conversion system has restricted large penetration of wind power into power system network as it poses new uncertainties and challenges to power system reliability, therefore, it is thus important to assess the impact of wind power integration into the power system reliability. Also, site for installing the wind power system is also very important and is the main concern of power system planner, therefore in this work Madurai, Tamil Nadu, India area is chosen, it is best for extraction of the wind power based on the availability of wind and survey. Different parameters and specification of case study is mentioned in Table 1. A complete configuration of wind energy based power system consists of wind generator, gearbox, mechanical brake, hub, pitch system, blades, sensors, converters, inverters etc.

TABLE 1. Different parameters and specification of case study.

Set-up	Specifications
Set-up 1	2 MW wind energy plan, is connected to bus route 61.
Set-up 2	Extra 4 MW wind energy project is taken, and connected to bus 61.
Set-up 3	Extra 8 MW wind energy project is taken, and connected to bus 61.
Set-up 4	Extra 12 MW wind energy project is taken, and connected to bus 61.
Set-up 5	Extra 16 MW wind energy project is taken, and connected to bus 61.
Set-up 6	Extra 20 MW wind energy project is taken, and connected to bus 61.
Set-up 7	Extra 24 MW wind energy project is taken, and connected to bus 61.
Set-up 8	Extra 28 MW wind energy project is taken, and connected to bus 61.
Set-up 9	Extra 28 MW wind energy project is taken, and connected to bus 61.

When adding additional wind energy system units, various datasets are taken into account, and various actions are taken to determine the system's dependability.

In this work, case study for financial aspects and reliability issues of wind based power system at Madurai, Tamil Nadu is done. In the Indian state of Tamil Nadu, the capital city is Madurai. It serves as the cultural hub of Tamil Nadu as well as the administrative hub for the Madurai District. The average wind speed in Madurai is 5.2 m/s, and the maximum wind speed is roughly 12 m/s. The ambient temperature, which ranges from 19.2°C to 39.6°C, the relative humidity stays around 68,2 % on average. The wind speed range is suitable for installing the wind energy system for smart building environment.

The grid's incorporation of renewable energy sources gives the distributor a variety of options for how to operate and deliver the load. When operating in grid-connected mode, the distributor can leverage the adaptable qualities of the available renewable energy resources to modify the two-way power flow in the hybrid renewable energy system and modify the variable renewable power generation to satisfy the load demand at any given moment. Utility grids that operate in a bidirectional power mode are able to give and absorb energy from renewable energy sources. Bidirectional power, i.e., electricity from the external grid and power from renewable energy resources can be used to support a variety of loads in such an operation mode. Modern technologies are integrated into the grid system for precise grid power control in smart grid systems. Distributed Generation systems have become a good alternative to meet the rising demand for

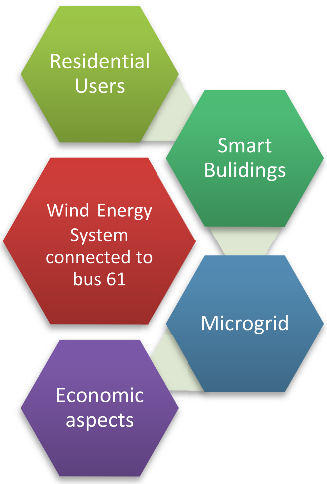

FIGURE 1. Proposed wind energy system for electrifying the residential users.

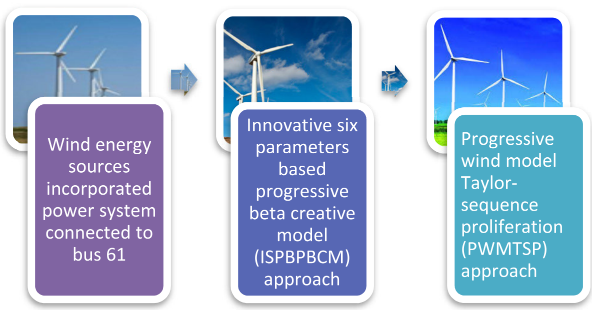

FIGURE 2. Proposed reliability analysis techniques of wind energy sources incorporated power system.

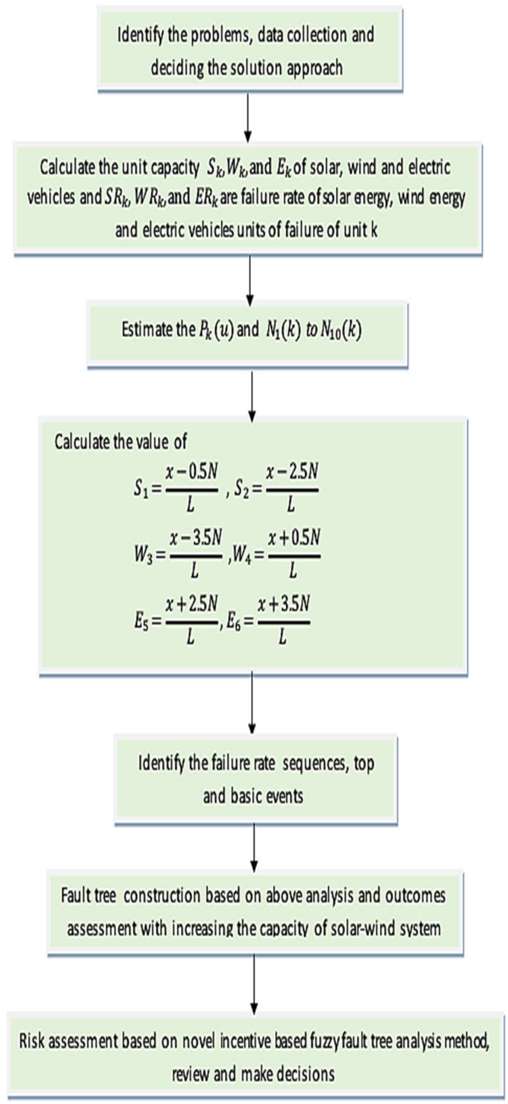

FIGURE 3. Flowchart for the progressive wind model Taylor-sequence proliferation (PWMTSP) for the advanced wind model.

consumer goods, reduce the consequences of climate change, and ultimately support the creation of a sustainable society. The use of DG systems, particularly those based on wind energy sources, has considerably expanded, mostly as a result of environmental legislation, the shortage of fossil fuels, and the decline in greenhouse gas emissions. If the amount of electricity produced by the wind power system is greater than the amount of power required, the excess power can be sold, which lowers carbon emissions since it eliminates the need to purchase the excess power from the coal-based power plant. Fig 1 shows the proposed wind energy system for electrifying the residential users and Fig 2 shows the proposed reliability analysis techniques of wind energy sources incorporated power system

III. WIND INCORPORATED POWER SYSTEM RELIABILITY ANALYSIS USING PROGRESSIVE WIND MODEL TAYLOR-SEQUENCE PROLIFERATION (PWMTSP)

In engineering applications, the performance of a structure can be specified by a random variable, H, and the failure event is described as FL = H > h, where h is a predetermined bound. As an illustration, consider an n-story skyscraper with random excitation. The failure event is defined as the exceeding of a threshold h in any of the inter-story drifts during the time period of interest n, which is discretized into different time instants. With the enhancement of wind energy systems in the power system, the power system reliability increases as overseen by this technique. This method, which is based on the Taylor-series increment of a novel function of various units, can be used to calculate the mean time to failure linked to the capacity outage prospect data. Fig. 3 depicts the proposed method's flowchart. The following steps should be taken to determine whether a wind energy-based power system is reliable:

Step 1 Covariance calculation of M(x) and M(y) after the increment of wind energy system

$$C[M(x), M(y)] = \sum_{e=1}^{n} \left(\frac{\partial M(x)}{\partial a_e}\right)\left(\frac{\partial M(y)}{\partial a_e}\right) V_a\left[a_e c p_e b_e\right]$$

$$+\sum_{f=e+2}^{n}\sum_{e=1}^{n}\left(\frac{\partial^2 M\left(x\right)}{\partial a_e \partial a_f}\right)\left(\frac{\partial^2 M(x)}{\partial s_a \partial s_b}\right)$$
$$\times\ V_a\left[a_e cp_e b_e\right] V_a\left[a_f cp_f b_f\right]$$
$$+\sum_{g=f+2}^{n}\sum_{f=e+2}^{n}\sum_{e=1}^{n}\left(\frac{\partial^3 M\left(x\right)}{\partial a_e \partial a_f \partial a_g}\right)\left(\frac{\partial^3 M\left(y\right)}{\partial a_e \partial a_f \partial a_g}\right)$$
$$\times\ V_a\left[a_e cp_e b_e\right] V_a\left[a_f cp_f b_f\right]$$
$$V_a\left[a_g cp_g b_g\right] \tag{1}$$

where, n stands for the wind energy system units, rate of forced outage predicted value is a, whenever extra number of units are added. M(x) represents the capacity outage probability of x or addition of extra units with x capacity outage level, M(y) represents the capacity outage probability of y or addition of extra units with x capacity outage level y, b is the capacity of the wind units at their original value, and cp is the capacity of the wind units that are being added.

Stage 2 the likelihood of the various capacity outage units is used to calculate the partial derivatives and the forced outage rate is subtracted from the original data set. With the aid of the aforementioned analysis, the failure rate Jw, Kw, and Lw are computed.

Step 3 Consider the step 2 results and list the contributing elements.

$$L_e\left(e\right)=\sum_{e=1}^{d} L\left(e\right) L_2\left(e\right)-a_e cp_e \tag{2}$$

$$L_f\left(f\right)=\sum_{e=1}^{d}\sum_{f=1}^{d} L\left(f\right) L_2\left(f\right) L\left(e\right) L_2\left(e\right)$$
$$-\ a_e a_f cp_e cp_f \tag{3}$$

$$L_g\left(g\right)=\sum_{e=1}^{g}\sum_{f=1}^{g}\sum_{g=1}^{g} L\left(g\right) L_2\left(g\right) L\left(f\right) L_2\left(f\right) L\left(e\right) L_2\left(e\right)$$
$$-\ a_e a_f a_g cp_e cp_f cp_g \tag{4}$$

Step 4 Consider the consequences of step 1, step 2, and step 3 to determine the rate of component failure.

With the aid of step, a component failure rate is computed using various capacity outage units and the forced outage rate from the initial data set.

Additionally, for the proposed study, mean time to failure (MTTF), rate of failures, loss of load expectation (LOLE), loss of load probability (LOLP), loss of load frequency (LOLF), loss of energy expectation (LOEE), and expected energy not served (EENS) are evaluated to recognize system dependability since these indices aid in power system analysis. Fig 3. Shows the flowchart for the progressive wind model Taylor-sequence proliferation (PWMTSP) for the advanced wind model

Reliability may be assessed in this way since each extra wind energy unit generates a new table. This method was designed with the wind-based power model in mind, and after calculating various reliability characteristics, its efficacy could be demonstrated by the outcomes.

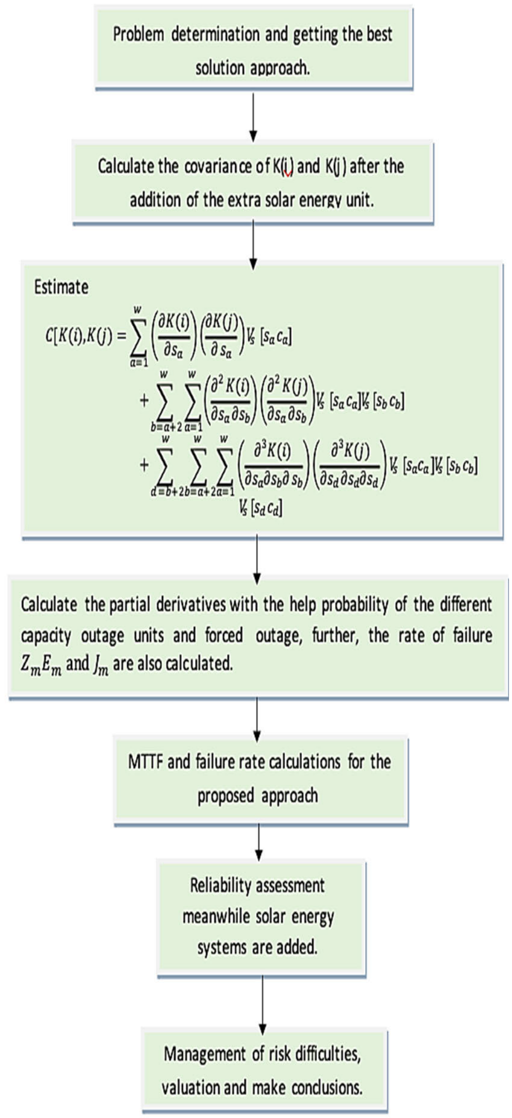

FIGURE 4. Flowchart of the innovative six parameters based progressive beta creative model (ISPBPBCM) approach for wind energy system.

IV. WIND INCORPORATED POWER SYSTEM RELIABILITY ANALYSIS USING INNOVATIVE SIX PARAMETERS BASED PROGRESSIVE BETA CREATIVE MODEL (ISPBPBCM)

Precise reliability assessment of wind energy incorporated microgrid system for smart building environment requires the determination of different collector system reliability, precise output, converters and inverter's reliability, wind turbine reliability including the gearbox. Though, only few cases have been deeply investigated in the literature. Therefore, there is a need of proper reliability analysis of wind energy incorporated microgrid system. Innovative six parameters based progressive beta creative model is proposed to determine the power system reliability with the precise penetration of power of wind incorporated power system. Fig 4 reveals the proposed model's flow diagram.

The following are a list of the suggested model's features:

$$P_1(t) = \frac{\delta}{(l-0.15)!}(\delta_t)^{\beta-0.15\frac{\eta e^{-\delta t}}{P_1(t)}} \tag{5}$$

$$P_1(t) = \sum_{h=0}^{\delta-0.15} \frac{(\delta_t)^h}{h!}\eta e^{-\delta t} \tag{6}$$

$$Q_2(t) = \frac{\theta}{(\beta-0.30)!}(\theta_t)^{\beta-0.15\frac{\eta e^{-\delta t}}{\mathrm{Q2}(t)}} \tag{7}$$

$$Q_2(t) = \sum_{h=0}^{\theta-0.30} \frac{(\theta_t)^h}{h!}\eta e^{-\theta t} \tag{8}$$

$$R_3(t) = \frac{\omega}{(\beta-0.45)!}(\omega_t)^{\beta-0.75\frac{\eta e^{-\omega t}}{R_3(t)}} \tag{9}$$

$$R_3(t) = \sum_{h=0}^{\omega-0.45} \frac{(\omega_t)^h}{h!}\eta e^{-\omega t} \tag{10}$$

$$S_4(t) = \frac{}{(\beta-0.60)!}({}_t)^{\beta-0.60\frac{\eta e^{-t}}{\mathrm{S4}(t)}} \tag{11}$$

$$S_4(t) = \sum_{h=0}^{\delta-0.60} \frac{({}_t)^h}{h!}\eta e^{-\delta t} \tag{12}$$

$$T_5(t) = \frac{\text{Ꭓ}}{(\beta-0.75)!}(\text{Ꭓ}_t)^{\beta-0.75\frac{\eta e^{-\text{Ꭓ}t}}{\mathrm{T5}(t)}} \tag{13}$$

$$T_5(t) = \sum_{h=0}^{\text{Ꭓ}-0.75} \frac{(\text{Ꭓ}_t)^h}{h!}\eta e^{-\text{Ꭓ}t} \tag{14}$$

$$U_6(t) = \frac{\text{Ⲙ}}{(\beta-0.45)!}(\text{Ⲙ}_t)^{\beta-0.90\frac{\eta e^{-\text{Ⲙ}_t}}{\mathrm{Q6}(t)}} \tag{15}$$

$$U_6(t) = \sum_{h=0}^{\text{Ⲙ}-0.90} \frac{(\text{Ⲙ}_t)^h}{h!}\eta e^{-\text{Ⲙ}_t} \tag{16}$$

(17), as shown at the bottom of the next page, where $\delta, \theta, \omega, \varkappa\text{ᏜⲘ}$ are positive integers and g is the constant.

$$MTT = \frac{g}{\delta\theta\omega\varkappa\text{ᏜⲘ}} \tag{18}$$

Twelve instances are selected based on the values of $\delta, \theta, \omega, \varkappa, \text{Ꭓ}, \text{Ⲙ}$:

Circumstance 1: If $\delta > 0.15$,

Determine the values of $P_1(t)$ and $F_h(t)$, by considering the value of the different integers, in this situation, $P_1(t)$ is slowly improved.

Circumstance 2: If $\delta = 0.15$,

Calculate the values of $P_1(t)$ and $F_h(t)$, by using the value of the different integers, in this case, $P_1(t)$ has a slow flat rate value.

Circumstance 3: If $\theta > 0.30$,

Determine the values of $Q_2(t)$ and $F_h(t)$, by considering the value of the different integers, in this situation, $Q_2(t)$ is more improved.

Circumstance 4: If $\theta = 0.30$,

Calculate the values of $Q_2(t)$ and $F_h(t)$, by using the value of the different integers, in this case, $Q_2(t)$ has a decent flat rate value.

Circumstance 5: If $\omega > 0.45$,

Determine the values of $R_3(t)$ and $F_h(t)$, by considering the value of the different integers, in this situation, $R_3(t)$ is slightly increased.

Circumstance 6: If $\omega = 0.45$,

Calculate the values of $R_3(t)$ and $F_h(t)$, by using the value of the different integers, in this case, $R_3(t)$ has a smooth rate value.

Circumstance 7: If $\delta > 0.60$,

Determine the values of $S_4(t)$ and $F_h(t)$, by considering the value of the different integers, in this situation, $S_4(t)$ is slowly improved.

Circumstance 8: If $\delta = 0.60$,

Calculate the values of $S_4(t)$ and $F_h(t)$, by using the value of the different integers, in this case, $S_4(t)$ has even rate value.

Circumstance 9: If $\theta > 0.75$,

Determine the values of $T_5(t)$ and $F_h(t)$, by considering the value of the different integers, in this situation, $T_5(t)$ is further improved.

Circumstance 10: If $\theta = 0.75$,

Calculate the values of $T_5(t)$ and $F_h(t)$, by using the value of the different integers, in this case, $T_5(t)$ has a more flat rate value.

Circumstance 11: If $\omega > 0.90$,

Determine the values of $U_6(t)$ and $F_h(t)$, by considering the value of the different integers, in this situation, $U_6(t)$ is somewhat more increased.

Circumstance 12: If $\omega = 0.90$,

Calculate the values of $U_6(t)$ and $F_h(t)$, by using the value of the different integers, in this case, $Q_6(t)$ has a unfluctuating rate value.

The influence of wind turbine output, reliability of the complete system including the converter fault consideration, on the wind power availability is taken. The innovative six parameters based progressive beta creative model (ISPBPBCM) approach is used to compline all faults and to determine the system reliability. Different integers and functions are considered to combine the function model of different components, overcoming the bad curve. This approach allows separating the complete network into segments while accounting for the output of wind power, and decreasing the computational burden. As a result, the reliability of the power system with the addition of a wind power system can be evaluated accurately using the proposed technique.

V. CASE STUDY

The wind energy based microgrid system is first modelled with the previous historical data based on the proposed two approaches namely progressive wind model Taylor-sequence proliferation (PWMTSP) and innovative six parameters based progressive beta creative model (ISPBPBCM).

The reliability assessment outcomes based on the progressive wind model Taylor-sequence proliferation (PWMTSP) tend to be positive because the PWMTSP model enhances the event probability with residential purpose wind energy system. Thus for better outcomes, an innovative six parameters based progressive beta creative model (ISPBPBCM) is also proposed, it gives the distribution curve and increase the reliability of the wind incorporated power system. The components of wind energy systems are comprised of many subsystems, which have some tendency of failure and consis-

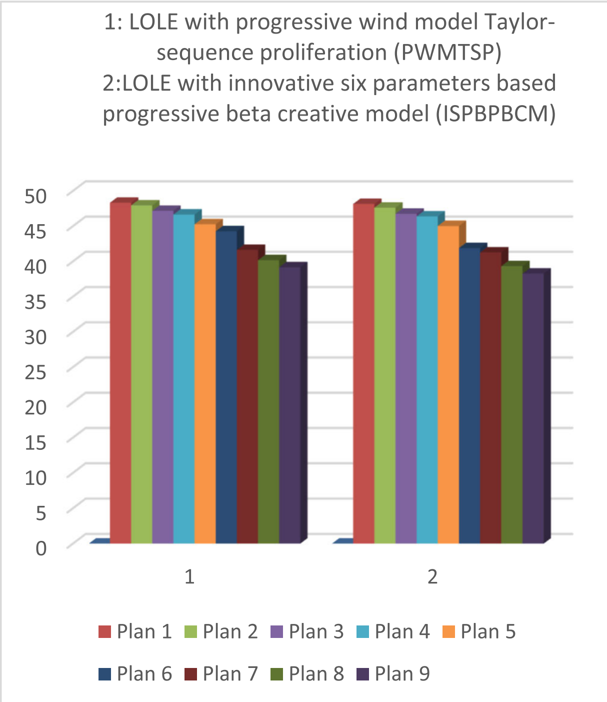

FIGURE 5. **LOLE with the recommended approaches by enhancing the capacity of wind energy systems.**

tent repair rates. Hence, this could be overcome by knowing the exact reliability indices, the impact of both approaches is demonstrated on a case study in Madurai, Tamil Nadu, India. Different dataset is considered and different steps are taken to know the reliability of the system while adding the extra wind energy system units.

Scenario 1: The original plan, a 2 MW wind energy plan, is connected to bus route 61.

Scenario 2- Additional 4 MW wind energy project is taken, and connected to bus 61.

Scenario 3- Additional 8 MW wind energy project is taken, and connected to bus 61.

Scenario 4- Additional 12 MW wind energy project is taken, and connected to bus 61.

Scenario 5- Additional 16 MW wind energy project is taken, and connected to bus 61.

Scenario 6- Additional 20 MW wind energy project is taken, and connected to bus 61.

Scenario 7- Additional 24 MW wind energy project is taken, and connected to bus 61.

Scenario 8- Additional 28 MW wind energy project is taken, and connected to bus 61.

Scenario 9- Additional 32 MW wind energy project is taken, and connected to bus 61.

The technique based only on previous historical data does not give accurate results, therefore the proposed techniques are used to sample the wind energy system models and compare with the traditional results. The proposed investigation uses wind energy connected power system rating from 2 MW to 32 MW and scenario 1 is the original case when no other wind energy systems are connected. It is used to give supply to residential areas, that's why Tamil Nadu state is selected where the wind speed is sufficient to install the wind turbine easily and supply to different users as well as the main grid.

By considering the proposed PWMTSP and ISPBPBCM methods, MTTF and rate of failure of different components of wind energy based power system are computed, since some components MTTF and rate of failure is too low and other components rate of failure and MTTF is too high so this would affect the system reliability. Table 2 shows Calculating MTTF and the failure rate for grid-connected wind energy system using suggested methodologies and Table 2 shows LOLE and LOLP calculation while expanding the wind energy system's capacity using the suggested ways. It could be observed from Table 2 that LOLE value is decreasing while adding the extra wind power systems. Fig 5 and fig. 6 shows the LOLE and LOLP with the recommended approaches by enhancing the capacity of wind energy systems respectively.

It is clear that the value of LOLE with the proposed advanced solar model Taylor-sequence increment continues to decline steadily from 48.32 to 39.16, as well as from 48.16 to 38.27 for LOLE with the suggested advanced solar model Taylor-sequence increment. Therefore, it can be observed from the Table 3, 1SPBPBCM provides better results in comparison with PWMTSP. Similarity, it can be seen that the value of LOLP with the suggested PWMTSP approach decreases as the wind energy capacity increases from 0.1598% to 0.1092%, likewise, the LOLP value with ISPBPBCM approach decreases from 0.1587% to 0.1068% as the wind energy capacity increases stepwise from 2 MW to 32 MW. Hence, In comparison to PWMTSP, ISPBPBCM gives better outcomes.

The EENS index determines the anticipated annual energy that, in respect to the maximum annual energy of the wind energy system, cannot be supplied to the point of common coupling. The EENS reliability indices using the suggested methods without changing the load profile are shown in Table 4. Figure 7 illustrates the EENS dependability parameter while increasing the capacity of the wind energy systems using the suggested methods.

It can be observed that the value of EENS starts decreasing when wind energy system capacity increase, it varies from 0.562 to 0.398 with progressive wind model Taylor-sequence

$$F_h(t) = \frac{\delta\theta\omega\varkappa\text{Ꭓ}\text{Ɱ}}{(g-0.15)!\,(g-0.30)!\,(g-0.45)!\,(g-0.60)!\,(g-0.75)!\,(g-0.90)!\,(g-1)!} \\ (\delta_t)^{g-1}\,e^{-\delta t}\,(\theta_t)^{g-1}\,e^{-\theta t}\,(\omega_t)^{g-1}\,e^{-\omega t}\,(\varkappa_t)^{g-1}\,e^{\varkappa-t}\,(\text{Ꭓ}_t)^{g-1}\,e^{-\text{Ꭓ}t}\,(\text{Ɱ}_t)^{g-1}\,e^{-\text{Ɱ}t} \quad (17)$$

TABLE 2. Calculating MTTF and failure rate for grid-connected wind energy system using suggested methodologies.

Components of wind energy system	MTTF with Progressive wind model Taylor-sequence proliferati-on (year)	Rate of failure with progressive wind model Taylor-sequence proliferation (failures/ Year 10^{-6})	MTTF with innovative six parameters based progressive beta creative model (Year)	Rate of failure with innovative six parameters based progressive beta creative model (failures/ Year 10^{-6})
Rotor Blade	4.3	26	4.8	24
Generator	5.6	8.2	5.9	7.9
Main shaft	7.2	12	8.3	11.6
Hub	8.1	6.7	9.2	4.6
Yaw system	3.7	12.6	4.1	11.7
Mechanical Brake	8.1	24.3	8.5	21.6
Pitch system	4.7	2.7	5.1	2.2
Converter	8.4	16.8	8.8	15.2
Inverter	8.6	18.8	9.3	16.2
Fuse	5.1	0.56	5.8	0.32
Switch, DC	6.8	0.67	7.2	0.35
Switch, AC	7.3	0.92	8.4	0.67
Connector	8.1	0.72	9.4	0.15
Grid protection	4.2	9.2	5.3	7.6

proliferation (PWMTSP). Similarly, it changes from 0.532 to 0.376 with innovative six parameters based progressive beta creative model (ISPBPBCM) while increasing wind power system capacity. EENS is also changing with changing the load from 100 % to 120% or 125%, therefore, EENS is affected in load changing cases.

Nine cases for the proposed work are implemented. In the earlier mentioned cases load is not more than 100%, but now load is increased from 100% to 120% and 125% that provides the better reliability analysis of the proposed system with adding the extra wind energy systems for comparison. The reliability indexes of the original system with no extra wind energy system and with adding the wind energy system capacity consideration of the different failure rates are calculated. The additional wind energy system capacity eventually increases the system reliability as now the power is sufficient to fulfil the load requirement. The reliability indexes of the system with considering all the cases are improved.

Table 5 displays the LOLE and LOLP calculations when increasing the load and capacity of the solar energy system in accordance with the advised methods. The LOLE parameter is shown in Fig. 8 together with expanding the wind energy system's capacity and the load using the suggested methods,

TABLE 3. LOLE and LOLP calculation while expanding the wind energy system's capacity using the suggested ways.

Wind energy system incorporated power system	**LOLE** with progressive wind model Taylor-sequence proliferation (PWMTSP)	**LOLP** with progressive wind model Taylor-sequence proliferation (PWMTSP)	**LOLE** with innovative six parameters based progressive beta creative model (ISPBPBCM)	**LOLP** with innovative six parameters based progressive beta creative model (ISPBPBCM)
Plan 1: Wind energy based power system 2 MW	48.32	0.1598%	48.15	0.1587%
Plan 2: Wind energy based power system 4 MW	47.94	0.1572%	47.61	0.1535%
Plan 3: Wind energy based power system 8 MW	47.17	0.1478%	46.75	0.1462%
Plan 4: Wind energy based power system 12 MW	46.64	0.1442%	46.38	0.1417%
Plan 5: Wind energy based power system 16 MW	45.26	0.1375%	45.02	0.1356%
Plan 6: Wind energy based power system 20 MW	44.27	0.1279%	41.88	0.1254%
Plan 7: Wind energy based power system 24 MW	41.63	0.1214%	41.26	0.1167%
Plan 8: Wind energy based power system 28 MW	40.16	0.1125%	39.32	0.1098%
Plan 9: Wind energy based power system 32 MW	39.16	0.1092%	38.27	0.1068%

and the LOLP parameter is shown in Fig. 9 along with doing the same. Because wind power systems help a system meet

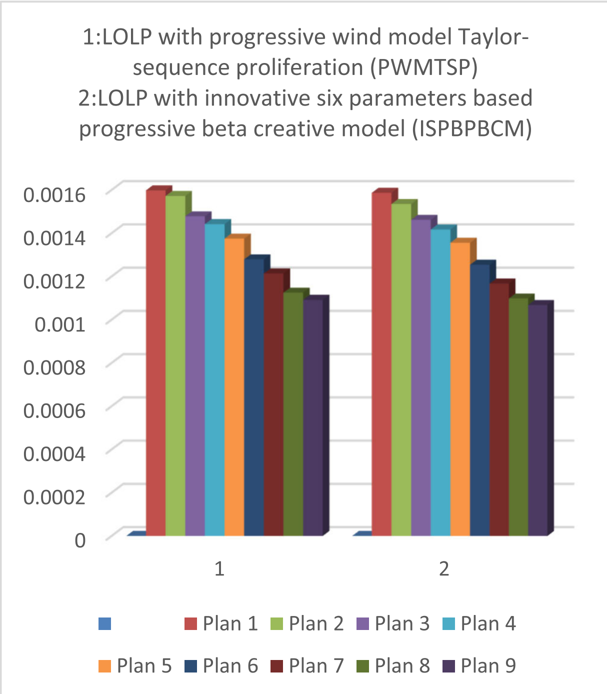

FIGURE 6. LOLP with the proposed approaches by enhancing the capacity of wind energy systems.

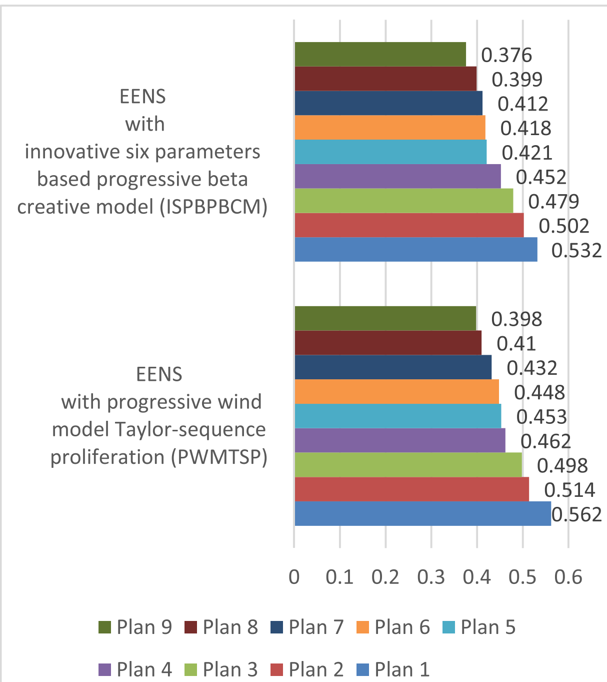

FIGURE 7. EENS reliability parameter with increasing the capacity of wind energy systems with the proposed approaches.

load demand, their integration with the grid increases the system's dependability. In various circumstances relative to the first scenario, the dependability metrics of the overall system are enhanced. LOLP gets improve while increasing the wind power capacity and load changes from 100 % to 120 %. (decreases from 0.1592% to 0.1010%) and from 100 % to

TABLE 4. EENS reliability indices with the proposed approaches.

Wind energy system incorporated power system	EENS 10^3MW with progressive wind model Taylor-sequence proliferation (PWMTSP)	EENS 10^3 MW with innovative six parameters based progressive beta creative model (ISPBPBCM)
Plan 1: Wind energy based power system 2 MW	0.562	0.532
Plan 2: Wind energy based power system 4 MW	0.514	0.502
Plan 3: Wind energy based power system 8 MW	0.498	0.479
Plan 4: Wind energy based power system 12 MW	0.462	0.452
Plan 5: Wind energy based power system 16 MW	0.453	0.421
Plan 6: Wind energy based power system 20 MW	0.448	0.418
Plan 7: Wind energy based power system 24 MW	0.432	0.412
Plan 8: Wind energy based power system 28 MW	0.410	0.399
Plan 9: Wind energy based power system 32 MW	0.398	0.376

TABLE 5. LOLE and LOLP calculation while increasing the wind energy system's capacity and the load using the suggested ways.

S.N.	Proposed Methods	LOLE at 120% load	LOLE at 125% load	LOLP at 120% load	LOLP at 125% load
Plan-1	PWMTSP	48.23	48.18	0.1592%	0.1586%
	ISPBPBCM	47.34	47.18	0.1573%	0.1538%
Plan -2	PWMTSP	47.03	46.98	0.1527%	0.1521%
	ISPBPBCM	46.36	46.12	0.1495%	0.1476%
Plan -3	PWMTSP	45.92	45.54	0.1464%	0.1458%
	ISPBPBCM	45.42	45.26	0.1427%	0.1398%
Plan -4	PWMTSP	45.12	44.94	0.1375%	0.1362%
	ISPBPBCM	44.64	44.26	0.1354%	0.1326%
Plan -5	PWMTSP	43.12	43.02	0.1296%	0.1278%
	ISPBPBCM	42.15	42.06	0.1165%	0.1145%
Plan -6	PWMTSP	41.26	41.10	0.1127%	0.1121%
	ISPBPBCM	40.78	40.62	0.1098%	0.1096%
Plan -7	PWMTSP	40.27	39.95	0.1085%	0.1082%
	ISPBPBCM	39.25	38.93	0.1075%	0.1071%
Plan -8	PWMTSP	38.64	37.92	0.1065%	0.1057%
	ISPBPBCM	36.17	35.67	0.1045%	0.1037%
Plan -9	PWMTSP	34.85	34.17	0.1025%	0.1012%
	ISPBPBCM	33.75	33.28	0.1010%	0.1002%

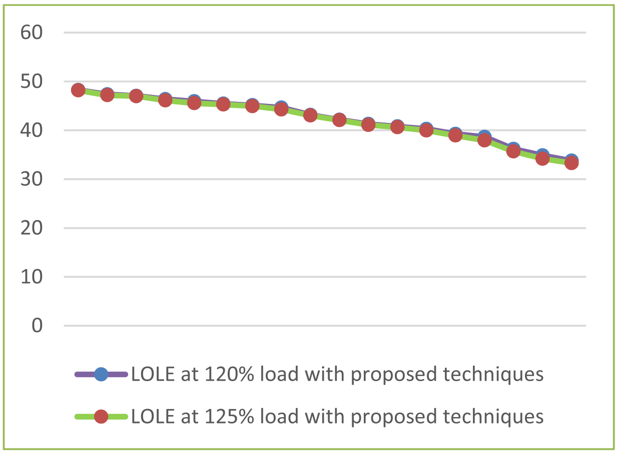

FIGURE 8. LOLE parameter with increasing the wind energy system's capacity and the load using the proposed ways.

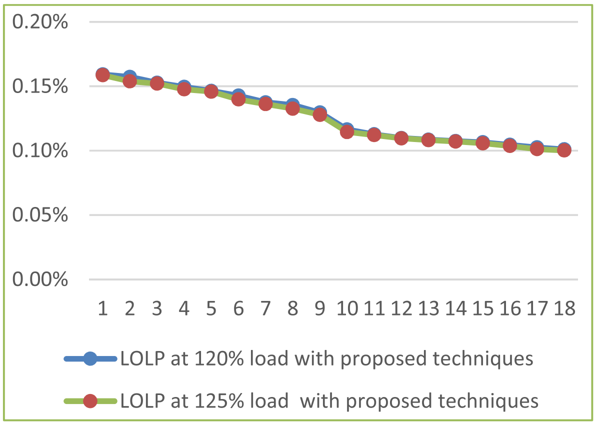

FIGURE 9. LOLP parameter with increasing the wind energy system's capacity and the load using the proposed techniques.

125 % (decreases from 0.1586% to 0.1002%). As a outcome, LOLP also reduces while growing the wind power capacity and load changes from 100 % to 120 %.(decreases from 48.23 to 33.75) and from 100 % to 125 % (decreases from 48.18 to 33.28). Hence, it can be seen that with increasing the load and wind power system capacity, LOLE and LOLP values start decreasing and the ISPBPBCM provides better results in comparison with PWMTSP approach.

When the capacity of a wind power system is increased, the reliability of the system may be seen to grow, and the influence of the relationship between wind energy capacity and load profile can be shown to have a more significant impact. So, higher reliability is achieved in plan 2 compared to plan1, similarly plan 9 gives better reliability compared with plan 8. If the correlation is not considered into account, wind connected system reliability may be wrongly estimated. The system's planning and operation with the integration of wind energy may be significantly impacted by this.

A proposed system consisting of 2 MW wind energy system with a addition of different wind power capacity

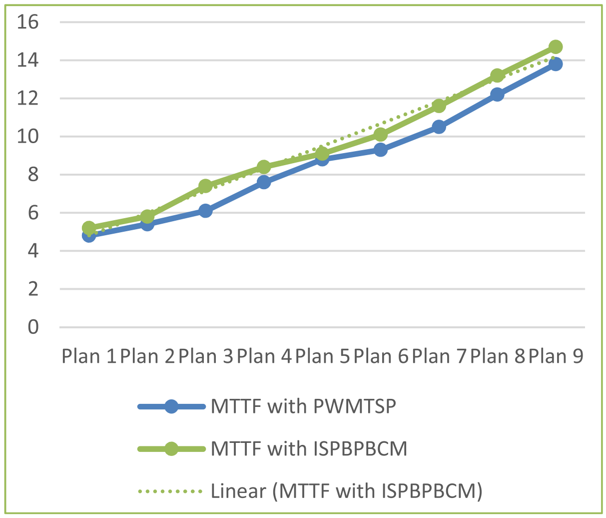

FIGURE 10. MTTF with increasing the capacity of the wind energy system using the provided methodologies.

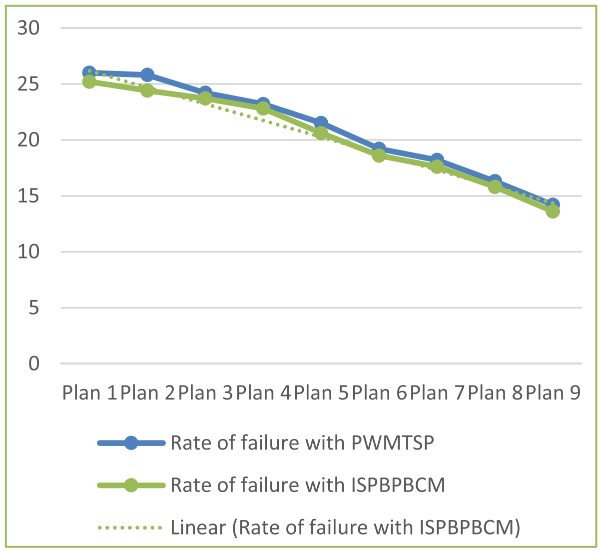

FIGURE 11. Rate of failure with enhancing the wind capacity with the proposed approaches.

till 32 MW at bus 61. MTTR and rate of failure are calculated for different cases as shown in Table 6 with increasing the wind power capacity gradually. Fig. 10 illustrates the MTTF when the capacity of the wind power system is increased utilizing the suggested techniques. Fig. 11 illustrates the rate of failure with suggested methods by expanding the system's capacity for wind generation.

The reliability parameters MTTR and rate of failure for system are calculated in different cases. MTTR gets improved while increasing the wind power capacity from 4.8 to 13.8 with the proposed progressive wind model Taylor-sequence proliferation (PWMTSP). The value of MTTR with innovative six parameters based progressive beta creative model (ISPBPBCM) gets improved from 5.2 to 14.7. As a consequence, rate of failure also

TABLE 6. MTTF and failure rate calculation with increasing the capacity of solar energy system with the proposed techniques.

Wind energy system incorporated power system	Plan 1	Plan 2	Plan 3	Plan 4	Plan 5	Plan 6	Plan 7	Plan 8	Plan 9
MTTF with PWMTSP	4.8	5.4	6.1	7.6	9.3	10.5	12.2	13.8	9.3
MTTF with ISPBPBCM	5.2	5.8	7.4	8.4	10.1	11.6	13.2	14.7	10.1
Rate of failure with PWMTSP	26	25.8	24.2	23.2	19.2	18.2	16.3	14.2	19.2
Rate of failure with PWMTSP	25.2	24.4	23.7	22.8	18.6	17.6	15.8	13.6	18.6

improves while increasing wind power capacity, such as 26 to14.2 with progressive wind model Taylor-sequence proliferation (PWMTSP) approach and 25.3 to 13.6 with innovative six parameters based progressive beta creative model (ISPBPBCM) approach.

Therefore, from the aforementioned statement, it can be seen that the proposed progressive wind model Taylor-sequence proliferation (PWMTSP) and innovative six parameters based progressive beta creative model (ISPBPBCM) approaches show that MTTR improves with increasing the wind energy capacity from 2 MW to 32 MW in steps and rate of failure decreases with increasing the capacity of wind energy system. It can also be observed that ISPBPBCM approach gives better consequences in comparison with PWMTSP.

In this paper the main target is to analyze the reliability analysis of wind energy sources-based power systems, the Progressive Wind Model Taylor-Sequence Proliferation (PWMTSP) and Innovative Six Parameters Based Progressive Beta Creative Model (ISPBPBCM) approaches are proposed to understand the reliability of wind energy-based power systems in smart building environments. Besides, the economic aspect of the proposed system with different plans for residential users is considered. It is clear that purchasing a unit from a coal-based power plant is more expensive than purchasing one from a wind energy system. If, the wind energy system is connected directly to the residential users without interfacing the net metering scheme, it gives less savings in compassion with net metering scheme. Because, when wind energy system generates extra units than the demand by the residential users, it can be sold out. Hence, it gives more savings. Although the cost of wind energy system is high initially, but with the time spam, it gives savings. So, if the economic aspect is considered, it is best supply system in coastal areas where wind speed is sufficient to generate the electricity. If, solar system is used in place of wind system, then it needs the storage devices and controlling system for storage devices, therefore cost of the entire system increases, it works less in coastal areas, and hence wind energy system is best choice for the selected area.

However, due to rising fuel prices, it is predicted that in the near future, the cost of power produced by wind energy-based systems would decrease even more while the cost of electricity generated from traditional energy sources will rise in India and other developing nations. Furthermore, all 9 cases are eco-friendly and they would lower the carbon footprints and

TABLE 7. Results comparison with existing models.

Method	ENNS
Frequency and duration method [31]	5643.81
Novel operating reliability evaluation framework [32]	5749.8
Holistic approach combining multi-state Markov processes [16]	3890
Proposed PWMTSP approach	398
Proposed ISPBPBCM approach	376

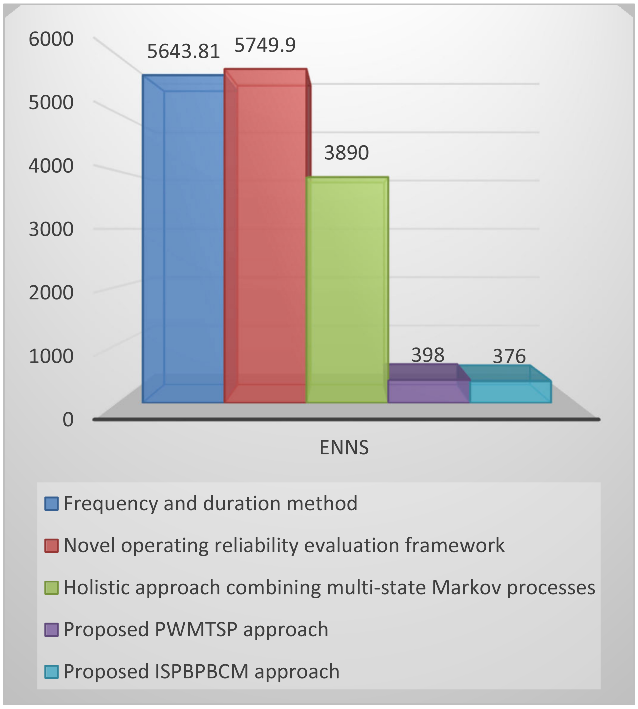

FIGURE 12. Results comparison with previous methods.

the contribution of wind energy system increases the power system reliability.

In the proposed work, two approaches are proposed for the reliability assessment of the wind incorporated power system. The reliability models with both approaches are developed and represented with increasing the wind power capacity. As compare with the previous methods, the proposed approaches provide better outcomes. Table 7 shows the different values of EENS with different methods, such as frequency and duration method [31], Novel operating reliability evaluation framework [32] and Holistic approach combining multi-state Markov processes [16] with corresponding value of EENS are 5643.81, 5749.8, 3890 respectively. Fig 12. Represents the results comparison with previous methods

The proposed progressive wind model Taylor-sequence proliferation (PWMTSP) and innovative six parameters based progressive beta creative model (ISPBPBCM) approaches provide the value of EENS as 398 and 376 respectively. It can be seen that proposed approach provides better results as compared to earlier techniques.

VI. CONCLUSION

In this study, two approaches, progressive wind model Taylor-series proliferation (PWMTSP) and innovative six-parameter based progressive beta creative model (ISPBPBCM) approaches, for the reliability assessment of wind energy incorporated systems in a smart building environment are proposed. Reliability models for different cases of wind incorporated power systems and loads are presented, and various reliability indices are computed. The proposed approaches make it simple to implement reliability models for wind energy systems with and without increasing the load above the prescribed load.

The results indicate that the ISPBPBCM approach provides a better response compared to the PWMTSP approach. By comparing the outcomes of the proposed approaches with previously developed methods, the effectiveness of the proposed work is noticeably validated

Increasing the wind energy capacity in the microgrid can enhance the operating system's reliability, which is affected by different factors such as the actual permissible time for wind power, previous system conditions, etc. In the suggested work, the expected energy not supplied (EENS) improves when the wind power capacity value rises. When an additional wind power system is introduced, loss of load expectation (LOLE), loss of load probability (LOLP), and the rate of failure drop. Additionally, it can be observed that mean time to repair (MTTR) improves when wind energy capacity rises incrementally from 2 MW to 32 MW. The suggested technique is expected to be scalable to vast wind incorporated power systems, adaptable to diverse types of wind energy systems where dependability is an important aspect in system design. In various scenarios, the system's rate of failure and MTTR reliability parameters are calculated. The suggested progressive wind model Taylor-sequence proliferation (PWMTSP) increases wind power capacity from 4.8 to 13.8 while improving MTTR. With the innovative six parameter progressive beta creative model (ISPBPBCM), the value of MTTR increases from 5.2 to 14.7. Consequently, as wind power capacity grows, the rate of failure also decreases, from 26 to 14.2 in the case of the progressive wind model Taylor-sequence proliferation (PWMTSP) approach to 25.3 to 13.6 in the case of the innovative six parameter based progressive beta creative model (ISPBPBCM) approach.

Furthermore, when the economic aspect of the proposed system with different plans for residential users in Madurai, Tamil Nadu is taken into account, it is clear that the cost of units produced by wind energy systems is less expensive than the cost of units bought from coal-based power plants. As a result, in terms of dependability and cost, a wind power incorporated system is most suited for the selected area. In future, these two approaches, progressive wind model Taylor-series proliferation (PWMTSP) and innovative six-parameter based progressive beta creative model (ISPBPBCM) approaches, for the reliability assessment of wind energy incorporated systems can be used for smart commercial and industrial sectors.

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