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Reliability enhancement of electrical power system including impacts of renewable energy sources: a comprehensive review

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Abstract: This study presents a comprehensive survey on the reliability evaluation of the electrical network system. The impacts of integration of new and renewable energy sources (electric vehicle, energy storage system, solar, and wind) on the reliability of electrical power system (EPS) are discussed. The impacts of these renewable sources have merits/demerits when these sources are integrated with the conventional electric power system. However, the merits are predominant as it includes unlimited, free, and cost-effective resources. The recent researches depict that the uncertainties of renewable energy resources leads to the probabilistic and reliability analyses of EPS. EPS includes offshore and onshore wind farms, micro-grid, energy storage system, and other high voltage grids. It also contains the failure-prone components related to the power systems. For the accomplishment of these aspects, the handling methods of uncertainty parameters in generation, transmission, and distribution systems are discussed. The incorporation of electric vehicles, wind energy system, and energy storage system for reliability assessment is also discussed briefly. This study also presents the scope of a new research area for the researchers on the reliability assessment of renewable energy integrated power system.

1 Introduction

Reliability evaluation (RE) is an integral part of the power systems when generation transmission distribution (GTD) networks are studied either individually or compositely. This paper is mainly associated with the RE and improvement of the renewable energy integrated power systems. The reliability improvements are seen for electrical network planning and operation when the integration of renewable sources including electric vehicle (EV), wind turbine generator, energy storage system (ESS), and photovoltaic (PV) are incorporated into the main electrical power system (EPS) [1–4]. However, due to the proliferation of renewable sources, an increase in the uncertain parameters as well as the severity of uncertainty (also referred to as unreliability) in renewable energy integrated power system is also observed. Wind power, solar power, EV's charging and discharging behaviour and their allocation, and battery energy storage system (BESS) are the uncertainty parameters [5–9]. These parameters affect the restructuring of the power system. Thus, a thought process is developed among the researchers regarding the uncertainty analysis with RE. The analysis is done to establish a reliable operation. It is observed from [10] that the research trend on reliability assessments is increasing tremendously since last decade. The optimal and reliable working conditions during the three operational stages including GTD are necessary. Thus, the study on the handling of uncertainty parameters for the reliability analysis is required. In this context, Goswami *et al.* [11] have given a Monte-Carlo Simulation (MCS) method for evaluating the reliability indicators. These indicators include average service availability index (ASAI), average service unavailability index (ASUI), customer average interruption duration index (CAIDI), system average interruption frequency index (SAIFI), system average interruption duration index (SAIDI), expected energy not supplied (EENS), and so on at load points. The calculation of these indices are accomplished by simulating the random behaviours. The random behaviours are classified as failures of control systems, communication systems, and protection systems, and disturbances like human errors and lightning of the EPSs. The significance of reliability is thus described in [12]. A load-based reliability index is introduced to implement reward and penalty scheme for utility companies to improve the reliability of the system. The paper also gives a proper understanding to the readers about the unreliability and its handling approaches. The reliability improvement and assessment methods and models are also described for the readers. In this regard, Table 1 is given to analyse the work of previous researches on RE and enhancement methods of the renewable energy integrated power systems.

The important contributions of this paper are that the discussion on uncertainty handling processes in EPSs is done so far in the literature. After getting exposure to uncertainties handling analysis, the RE in distribution systems is properly described by including EV and BESS. Then reliability improvement methods are discussed for electrical power distribution systems (EPDSs) and wind integrated power systems (WIPSs).

The reliability analysis and improvement techniques for EPDS and WIPS are discussed cumulatively in this paper. Therefore, authors have discussed the basics of reliability analysis in Section 2, the reliability improvement techniques of EPDSs using EV and ESS are discussed in Sections 3. Reliability improvement methods in WIPS are presented in Section 4. In Section 5, reliability impacts on reactive power, unit commitment and protection system are described. Conclusions and scope of future work are presented in Section 6.

2 Unreliability in EPSs

In EPSs, it is essential to consider the uncertain parameters of renewable energy sources. It is also mentioned that why uncertainty parameters are needed to be analysed? 'Uncertainty' which leads to the unreliability of the system, requires possibilistic and probabilistic handling approaches. In possibilistic approach, fuzzy membership functions are used to represent the uncertain parameters and it is solved with fuzzy arithmetic. In probabilistic approach, the modelling of uncertain parameters is done by probability density functions (PDFs) and then analysed with MCS and point estimate method (PEM). Figs. 1 and 2 show the classification of uncertainties and their dealing approaches, respectively [6].

Table 1 Important attributes of research work on RE in an EPS

S. No.	Work consideration(s)	Method(s)	Remarks	Ref.
1	To regulate the annual reliability performance of utilities	Advanced metering infrastructure architecture	The feeder reliability performance is evaluated by a proposed utility reward/penalty scheme	[12]
2	Distribution system reliability by OMS study, expansion planning, CLPU events	MCS, SMCM, Novel 2-step algorithm, LSA, GA	SAIFI, SAIDI, CAIDI, AENS, ASAI are calculated, load curtailments and cost in power system is minimised to improve the reliability of the distribution system	[13, 14], [15, 16], [17, 18]
3	Reliability improvement using PL, EV's PL allocation, stochastic traffic flow and charging load of EVs	V-G programs, non-MCS, car following models, MCM, Markov Chain theory, FLS, Dynamic traffic flow model	The PLs are utilised in reliability improvement, effect on reliability improvement by integrating PL, suppression of stochastic disturbances, EV charging load benefits, reliability cost and SAIDI are minimised	[19, 20], [21, 22], [23]
4	Reliability during grid outages	SMCM, optimisation function to minimise the ENS	Reliability of EPDS is improved with V-G and V-H centralised and dispersed EV charging, respectively	[14]
5	Reliability assessment with MBESS integration	Markov models verified by MCM, an AMCM, CCP	Modeling of MBESS and EPDS, EENS and CAIDI are applied to RE, BESS is integrated to get the efficient reliability	[24, 25], [26]
6	Improving reliability by reducing peak demand and electricity charges for consumers	PMS algorithm	A PMS for an integrated residential PV and ESU is proposed to improve the reliability	[27]
7	WECS uncertainty and reliability improvement	MCS, Power law process, RE approach, condition monitoring system (CMS), demand side management (DSM), MCS, Column and Constraint Generation (CCG) algorithm	Reliability analysis of WT components is done, PSR with or without intermittency consideration, cost of CMS	[28, 29], [30, 31], [18, 32]
8	Reliability analysis of the hybrid system	Analytical process	Reliability indices LOLE and LOEE are calculated for a hybrid system	[33]
9	To schedule the conventional generator outputs in response to increase in renewable energy penetration	GRA	Transmission system reliability with renewable energy penetration is given	[34]
10	EPS incorporates DTR and WF to enhance reliability	SMCM, ARMA model	The higher penetration of wind energy may be allowed on DTR consideration	[35]
11	To avoid the volatility of wind power integration	TBDRP, CBDRP	The proposed approach examines the effect of DRPs on LOLP, LOEE, ECOST, OPCOST, and TCOST	[36]
12	Reactive power optimisation problem in active distribution networks formulated	CCG algorithm	To address the uncertainties in WP output, a two-stage robust reactive power optimisation model is proposed	[37]
13	An increased probability of undesirable interactions between multiple SIPS	Markov modelling, SMCM	Procedure to assess the risk of SIPS maloperations and undesirable interactions between different SIPSs is implemented	[38]
14	Computation time in evaluating PSR	MCM with MLKNN	The reliability indices are evaluated for accuracy and analysis time is obtained for reducing computational burden	[39]

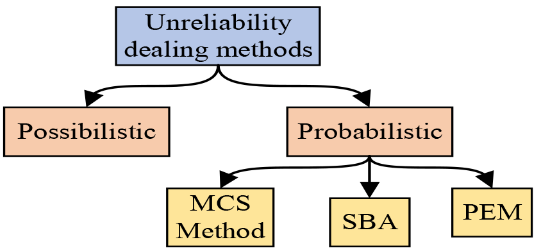

Fig. 1 *Flow chart of unreliability dealing methods*

2.1 Possibilistic handling approach

In [40], Zadeh has mentioned the concept of possibilistic modelling of uncertain parameters. The concept is mainly aimed at the input uncertain parameters for their fuzzy membership function representation. The membership function of the input variables is applied to get the output membership function variables by using the α-cut method. After getting the membership function, a centroid method for defuzzification is applied to defuzzify the variable outputs and produce the crisp output values. In [41–43], it is seen that the possibilistic methods are applied to handle the uncertainty parameters of the EPS.

2.2 Probabilistic handling approach

It is a general method to address the uncertainties including wind power generation, EV dynamics, load, PV generation, and electric rate in RE of the EPS. Equations (1)–(5) are the PDFs of uncertain parameters including load, wind power, PV, and electricity price, respectively. The uncertain parameters are first modelled into PDF and then solved by probabilistic methods including MCS, PEM, and scenario-based approach (SBA). According to applications, the MCS method is further studied as accelerated, sequential, non-sequential, bayes, and quasi Monte-Carlo methods (MCM) as discussed in [13, 19, 20]

$$\mathrm{PDF}(L) = \frac{1}{\sqrt{2\pi\alpha}}\left[\exp\left(-\frac{(L-\beta)^2}{2\alpha^2}\right)\right] \tag{1}$$

where L denotes the apparent power of the load, α is the forecasted load mean value, β is the apparent power's standard deviation

$$\mathrm{PDF}(V)=\left(\frac{S_{\mathrm{h}}}{S_{\mathrm{c}}}\right)\left(\frac{V}{S_{\mathrm{c}}}\right)^{S_{\mathrm{h}}-1}\exp\left(-\frac{V}{S_{\mathrm{c}}}\right)^{S_{\mathrm{h}}} \tag{2}$$

where S_{h} and S_{c} are termed as shape and scale parameters, respectively, and wind speed is denoted by V, and $P(V)$ is the wind power generated

$$P(V)=\begin{cases}0, & V\le V_{\mathrm{in}}^{\mathrm{c}}\ge V_{\mathrm{out}}^{\mathrm{c}}\\ \dfrac{V-V_{\mathrm{in}}^{\mathrm{c}}}{V_{\mathrm{rated}}^{\mathrm{c}}-V_{\mathrm{in}}^{\mathrm{c}}}, & V_{\mathrm{in}}^{\mathrm{c}}\le V\le V_{\mathrm{rated}}^{\mathrm{c}}\\ P_{\mathrm{r}}, & \text{otherwise}\end{cases} \tag{3}$$

where $V_{\mathrm{in}}^{\mathrm{c}}$ and $V_{\mathrm{out}}^{\mathrm{c}}$ are referred as to cut-in and cut-out speeds, respectively, $V_{\mathrm{rated}}^{\mathrm{c}}$ is referred as rated speed of wind turbine (WT), P_{r} is power rated for WT

$$\mathrm{PDF}(S)=\begin{cases}\dfrac{\Gamma(k'+c')}{\Gamma(k')(c')}S^{k-1}(1-S)^{c}-1, & \text{if } 0\le S\le 1\\ 0, & \text{otherwise}\end{cases} \tag{4}$$

where k' and c' are the parameters of beta distribution and 'S' is the solar irradiation power

$$\mathrm{PDF}(P_E)=\frac{1}{\sqrt{2\pi\alpha_{\mathrm{p}}}}\left[\exp\left(-\frac{(p_E-\beta_{\mathrm{p}})^2}{2\alpha_{\mathrm{p}}^2}\right)\right] \tag{5}$$

where P_E denotes electricity price, α_{p} and β_{p} are referred to standard deviation and the expected value of the electricity price.

The Gaussian PDF representation of uncertain loads which is modelled as an expected value equals the forecasted value as seen in (1). It is known that the wind power generated is completely dependent on the wind speed [44–52]. The modelling of wind speed data is done as a Weibull function (2) [53, 54]. The PV power is mainly dependent on the solar irradiation [55–58]. The solar irradiation is generally modelled as the beta distribution function as represented in (4). The last-mentioned uncertain parameter is electricity price [59]. It is also modelled as Gaussian distribution function whose mean value equals to the forecasted price [60]. The uncertain parameter modelling is done by common PDF. Then, probabilistic methods are applied and analysed for handling the uncertainty as described in [61–71].

In the next section of the paper, the latest researches are assessed for RE in power system distribution network.

3 Reliability assessment in EPS

PDFs are utilised in handling the uncertainty parameters as described in Section 2. Reliability function of any system is defined by using PDF as given in (6) [72]. The EPDSs are the significant individual contributors to the unreliability of customer power supply [59]. The EPDSs are mainly recognised as the part of highest occurring failure events. The reliability with economical cost must be included in optimal dynamic expansion planning of EPDS with the proliferation of renewable energy resources [15]. The failures in an EPDSs are having limited effects. Therefore, the quantitative analyses on the adequacy of other EPDS's designs are of less concern. Hence, the efforts devoted are still less till date. On the other side of analysis, it is observed that the statistics of customer related failures shows the maximum contribution to the unavailability of supply as set by the electrical utilities. Table 2 shows the mean unavailability of customers index per year. This table is also referred to as the customer unavailability statistics [73]

$$R(t)=\int_t^{\infty} f(t)\cdot \mathrm{d}t \tag{6}$$

where $R(t)$ and $f(t)$ are the reliability function and PDF, respectively, at a time 't'.

The important aspects in RE of EPDS are balanced GTD operation, outage management system (OMS), expansion planning,

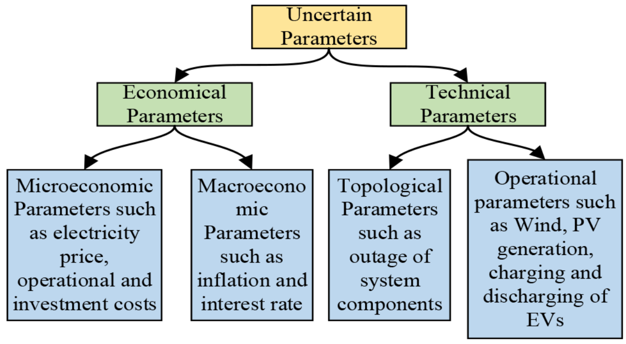

Fig. 2 *Sources of unreliability parameters*

Table 2 Usual unavailability index of customers

Contributor	Mean unavailability per customer per year	
	Time, min	Percent, %
transmission and generation	0.5	0.5
LV	10.9	12
11 and 6.6 kV	59.5	61
66 and 33 kV	7	8
132 kV	2.1	2
planned shutdowns	16.9	16.5
total	96.90	100

allocation of backups, and improvement in maintenance policy. But due to outage events like cold load pick-up (CLPU) during OMS study, time-based reliability indices including SAIFI, CAIDI, energy not supplied (ENS) are evaluated. These events are improved by using lightning surge algorithm optimisation method [16]. CLPU events signify that the reliability of the system decreases. Thus, optimal restoration using the LSA method is applied to bring reliability indices SAIDI, CAIDI, ENS as close as a normal system.

The indexes for RE including mean failure rate, mean annual outage time (or unavailability) and mean outage time are defined. But these indexes are unable to show the significance or severity of an EPS outage. Therefore, extra customer-related reliability indices including ASAI, ASUI, CAIDI, CAIFI, SAIDI, and SAIFI, are frequently defined for further study. While ENS, average energy not supplied (AENS), and average customer curtailment index are the load and energy-related indices. All indices are helpful and Table 3 shows that the previous researches have used different reliability indices in the evaluation of power system reliability (PSR).

The CRIs are evaluated because the transmission lines, busbars, isolators, cables, and so on are the series of components in the radial EPDS. Hence, all series components are required in between any points of operation in load and supply. Also, the generating capacity indices, for example loss of load probability (LOLP) and capacity outage probability indicate the electrical generation is sufficient or deficient. So, considering all the above facts, this paper focuses mainly on the RE and improvement methods in renewable energy integrated EPS. In this context, this section demonstrates the various reliability improvement methods in the distribution network of power systems.

3.1 Power system reliability using MCS and multi-label K-nearest neighbour (MLKNN)

The power system network is well known for its complexity. This complexity of a power system increases with the integration of renewable sources into it. The reliability assessment becomes more important for the renewable integrated power system. The reliability is analysed by the adequacy and security of the power system. Security is defined with the dynamic state of the system. Hence, in most of the cases, adequacy is considered for the PSR

Table 3 Insight on reliability indices and energy resources utilised in previous literature for reliability improvement in EPS

Paper	Reliability indicator	Economic analysis	Energy resource used
	Reliability improvement in electrical distribution system		
[1]	EENS	yes	wind, PV, battery
[2]	SAIDI, SAIFI, CAIDI, ENS, EENS, AENS, IEAR	yes	wind, PV, battery
[3]	LOLP, LOEE	yes	wind
[14]	SAIDI, SAIFI, EENS, ASAI	no	conventional
[15]	SAIDI, EENS	yes	conventional
[16]	SAIDI, SAIFI, CAIDI, ENS	no	conventional
[17]	AENS	no	EV
[18]	SAIDI, SAIFI, ENS	no	wind, PV
[22]	Information reliability	no	EV
[23]	LOLE, LOEE, EWEB	no	wind, PV
[24]	EENS, CAIDI, ASAI, ASUI	no	MBESS
[25]	FMEA	no	BESS
[26]	Optimal scheduling	yes	MBESS
[30]	LOLE, LOLF, LOLP, LOEE, EDNS	no	conventional
[33]	LOLE, LOEE	no	wind, PV, battery
[74]	EENS	yes	MBESS
[75]	ENS	no	wind, PV
[76]	LOLP	yes	PEV

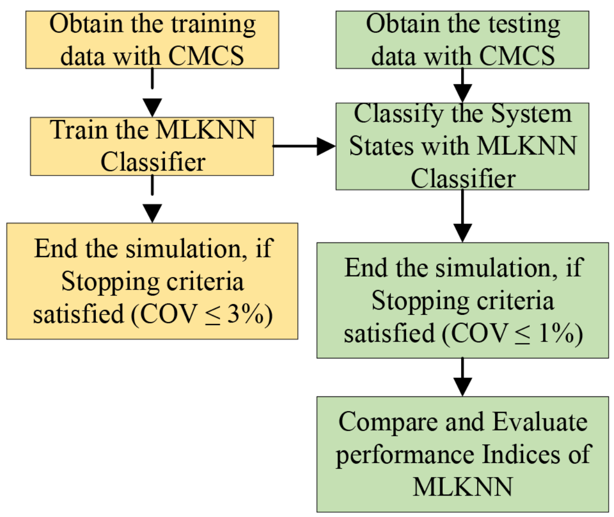

Fig. 3 *Combined process of MCS method and MLKNN method for composite PSR*

Table 4 Approximate value of reliability indices with and without EVs [14]

Indices	V-G	V-H	V-H with V-G	Centralised	Dispersed
EENS	53.40	17.30	14.60	14.30	14.20
SAIFI	1.20	1.19	0.70	0.65	0.65
SAIDI	1.70	1.68	1.10	1.00	1.00
ASAI	0.999798	0.999800	0.999870	0.999880	0.999880

assessment [77]. The adequacy is described as the supply fulfilment for the load connected. So, the adequacy of the system is analysed by using LOLP index for RE. Transmission line flow constraints and generator outage are accounted for in the LOLP calculation. Thus, to assess the reliability of the composite power system, MCS with MLKNN algorithm is used as a state classifier [39].

MCS with MLKNN algorithm classify the states including failure and success level at the bus of a composite power system without performing the optimal power flow (OPF) analysis because it decreases the computational burden. Some of the researchers have suggested fuzzy OPF [78], state-space pruning [79], variance reduction techniques [80] to classify the failure and success states of the system. Some population-based intelligent search algorithms including genetic algorithm (GA) [81, 82], particle swarm optimisation [83], ant colony algorithm [84] are used for state classification. The pattern classification is also one of the techniques used for state classification. These techniques are artificial immune recognition system [85], artificial neural network [86], least-square support vector machine [87]. The above-mentioned techniques are used to determine the system states (success and failure) by incorporating proper classification technique. Thus, it enhances the computational competency of RE by decreasing the computational efforts of OPF analysis.

IEEE-30 bus system and IEEE-RTS are compared to calculate the accuracy in classification and time of computation to evaluate the composite PSR indices. The indices including success states, failure states, loss of load, sensitivity, specificity, G-mean, and analysis time are analysed. The procedures to evaluate these aspects are mentioned in Fig. 3. The origination of multi-label intelligence is from text classification problem [88]. Firstly, a training database is generated by MLKNN with an MCS technique. Success and failure states are defined by MCS and a dataset is created. Then the datasets are to be trained by the MLKNN classifier. The dataset size is obtained by the specific number of samples (SNS) or the coefficient of variation (COV). SNS or COV is proportional to the LOLP of the system and it is a sufficient number to determine the attributes in the input training patterns. After creating a balanced training pattern, the MLKNN gets training for the selected group of input and output patterns. After training the MLKNN classifier, the MCS follows the same previous steps except for DC-OPF implementation. By following these steps, the reliability indices are calculated without OPF calculations which reduces the computational burden and enhance the system's reliability.

3.2 EPDS reliability assessment using EV

EV has two modes of operations including centralised and dispersed EV charging. These modes are suggested by Xu and Chung [14]. In these two modes, residential demands are fulfilled by vehicle to home (V-H) or/and vehicle to grid (V-G) during the islanding condition. Further, as a part of planning, the reconfiguration of electrical network for the PSR improvement is presented in [89]. The implementation of EVs' V-G programs is effectively considered in [17] for reliability and adequacy analysis of EPDSs. A comparative analysis is done and mentioned in Table 4, where it is observed that the reliability improves with EVs proper mode of scheduled operations. The reliability assessment techniques and models are discussed in this subsection as follows.

3.2.1 Traffic flow model: It is elaborated under two scenarios. First scenario is the impact of time interval of reliability statistics on traffic flow system. Second scenario is the impact on the stability of traffic system. These scenarios provide the significance of information reliability on the stability of traffic stream. It is analysed by using analytic methods [21]. Therefore, the two car-following models are developed to solve the above-mentioned problems on optimal velocity [90] and the dynamics of information reliability. The equations based on car following models are explained as follows:

$$\frac{\mathrm{d}v_k(t)}{\mathrm{d}t} = \gamma(V(\Delta S(t)) - v_k(t)) \tag{7}$$

$$V(\Delta s_k) = \frac{v_{\max}}{2}(\tanh(\Delta s_k - s_c) + \tanh(s_c)) \tag{8}$$

$$\frac{dv_k(t)}{dt} = \gamma\left(V\left(\sum_{L=1}^{P}\alpha_L\eta_L\Delta s_{k+L-1}(t)\right)\right) \tag{9}$$

γ is constant which is termed as driver's sensitivity
s_k is the distance of kth vehicle
v_k is the kth vehicle velocity
Δs_k is the head to head distance between k vehicles and its immediate next vehicle ahead
$V(*)$ is the expected velocity which is dependent on Δs_k
s_c is the distance of safety
α_L is a variable which shows the information which is shared by Lth vehicle, if available
η_L is the coefficient of influence of the Pth preceding vehicle on other vehicles
P is the Pth vehicle which is coming before of present vehicle k;
where, $L < P$; $L \in 1, 2, 3, \ldots, P$

Also, EV charging load modelling methods with EV charging controlling to avoid the power system unreliability are reported in Table 5 [22].

In [21], the information reliability effect is analysed in two situations. Situation '1' is a stochastic method of traffic flow model. It has suppressed the disturbances to obtain the stable vehicular system. Situation '2' is the communication data availability due to time gap effect on traffic-flow dynamics. It is seen that a free flow model is achieved if time gap of 5 s is set. The extension of the vehicular stream into a crimp-anti crimp wave is achieved when the stochastic period is greater than 25 s.

3.2.2 Monte-Carlo method (MCM) for EV charging: The charging load of EVs has problems in EPS operation, electricity market, and planning. It is due to the imbalanced spatial distribution of EVs. The MCM is suitable in determining the charging time span and charging power of EV. MCM is completely dependent on the probabilistic distribution of conventional vehicle. Thus, improves the reliability of an EPDS. Equations (10) and (11) describe the charging start time and PDF of daily mileage

$$f_x(y) = \begin{cases} \dfrac{1}{\sigma_x\sqrt{2\pi}}\left[\exp\left(-\dfrac{(y-\mu_x)^2}{2\sigma_x^2}\right)\right], & \mu_x - 12 < y \le 24 \\ \dfrac{1}{\sigma_x\sqrt{2\pi}}\left[\exp\left(-\dfrac{(y+24-\mu_x)^2}{2\sigma_x^2}\right)\right], & 0 < y \le \mu_x - 12 \end{cases} \tag{10}$$

$$f_z(y) = \frac{1}{y\sigma_z\sqrt{2\pi}}\left[\exp\left(-\frac{(\ln y - \mu_z)^2}{2\sigma_z^2}\right)\right] \tag{11}$$

where P_E denotes electricity price, α_p and β_p are referred to standard deviation and the expected value of the electricity price; σ_x, σ_Z, and μ_Z are the respective shape parameters.

3.2.3 Markov and fuzzy theory: The Markov chain theory consists of three parameters including the starting point of time, residence time, and destination time. These parameters are described by Markov chain process for each EV as shown in Fig. 4 [91]. It describes the states of the EVs with state transition probabilities.

On the other hand, fuzzy logic system (FLS) is applied where the difficulty in assessment of the battery charging state is observed. Also, FLS is implemented where the parameters like residence time are to issue a charging decision. Hence, the states of charging like 'high', 'low', and 'medium' and residence time 'long', 'short', 'middle', are narrated as fuzzy criteria as shown in Fig. 5.

3.2.4 MCM for EV dynamics: The EVs are extensively integrated into the systems including conventional power system, charging service network, and transportation network. The dynamic models of EVs are applied in predicting the charging load of a transportation network station. Also, the MCM is used for driving,

Table 5 Usual unavailability index of customers

Temporal dimension	Spatial dimension
MCM (i) PDF (ii) differentiating scenario sampling	the dynamic traffic flow model (i) traffic network (ii) the Floyd algorithm
Markov chain theory (i) state transition theory (ii) state duration and transition probability	demographic model (i) regional population distribution
FLS (i) fuzzy criteria (ii) charging behaviour decision	parking generation rate model (i) regional parking demand
	traffic simulation software (i) vehicle individual behaviour

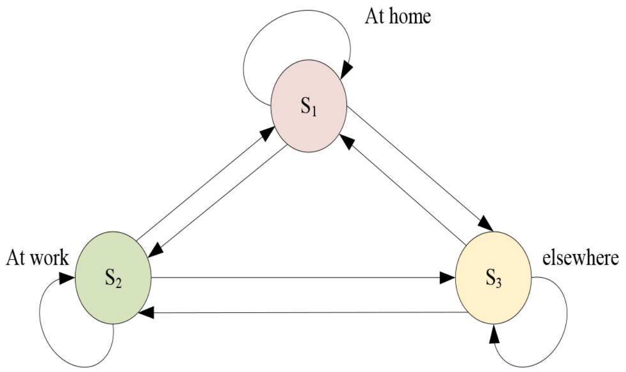

Fig. 4 *Markov process for EV travelling*

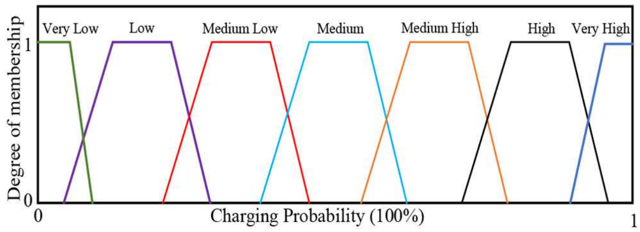

Fig. 5 *Fuzzy logic criteria for EV charging*

parking, and EV charging load forecasting. The MCS method uses the queuing theory and the Floyd algorithm for reliability assessment of the system. The queuing theory algorithm and Floyd algorithm are applied to find the minimum path from all the initial point to the endpoint of traffic network [92]. Parking generation rate and demographic models; and the software on traffic simulation are also crucial in power system planning and electricity market development. Also, the operation with EV charging load modelling leads to resolve the problems like power supply unreliability, voltage drops, equipment overload, and power loss. In [22], a proposed model explores and rectifies the EV charging load modelling limitations. In this reliability handling technique, the limitations are observed by adopting the methods based on spatial, temporal, and hybrid uncertainties.

3.2.5 Vehicle-to-home and vehicle-to-grid: The V-H and V-G are incorporated into the EPDS for reliability assessment. V-G is to assist the grid during outages by providing the regulation in frequency and spinning reserve [93–95]. The energy available from EVs is dependent on the duration of outages, charging requirement time, and spatial patterns. Electric V-H acts as an energy source which supplies household demands. EVs are useful when the power loss along the lines are involved. Then an optimisation problem is established. The purpose of this optimisation problem is to get a minimal residual amount of ENS at all nodes. So to achieve a minimum loss and improved reliability, a non-linear optimisation method is implemented.

It is also observed that the V-G capability of plug-in EVs (PEVs) enhances MG reliability. Shams *et al.* [76] has proposed mixed-integer non-linear programming (MINLP) to obtain the optimal planning of MG when PEVs are present. Reliability is improved at a reduced cost by implementing a suitable charge and discharge strategy of PEVs. The LOLP and total operational cost for three cases are mentioned in Fig. 6. Case 1 is considered when the charging station is not taken. A high power rate charging station is considered in case 2. Finally, case 3 is taken when an optimised power rate is considered for a charging station.

3.2.6 Optimisation of EV charging: The aim of non-linear optimisation [96] is to minimise the losses over the power network throughout EV charging. The power flow calculation uses the quadratic programming technique. This technique serves as a most effective tool. An iterative backward–forward sweep method may be applied in power flow calculation for better results. On the other study of optimisation, the interior point method is described to obtain the optimum values. While in each trial the optimum flow algorithm is run to get the maximum power imported at each node of the system [97]. In the EV charging, the reliability of EPDS is improved together with the basic participation of EVs. There is the involvement of local V-G for centralised charging and local V-H for dispersed charging. This involvement leads to the reliability improvement of EPDS. The EPDS has gained interests as EV industries with large power capacities and energy are growing frequently. The sequential Monte-Carlo method (SMCM) method for this assessment provides reliable results and enhanced reliability.

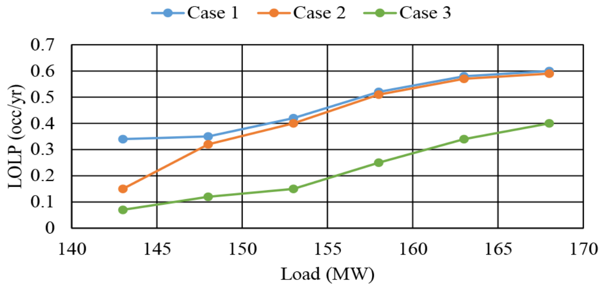

Fig. 6 *Reliability index LOLP with load variation using MINLP [76]*

3.2.7 General discussion on EV and reliability: An integration of different DG technologies is considered in the adequacy study of EPDSs. This can be achieved when the EV's V-G programs with their associated charging load are successfully implemented. The probabilistic model of the uncertainties associated with wind power generation offers available energy from V-G programs. The historical association of different energy demands is developed in RE. The general analytic approach to reliability studies is shown in Fig. 7.

The interfacing between energy consumers, and transportation infrastructure, and generating units are the different forms of energy in an energy hub [98]. To model the interactions between various DG technologies, a renewable-based energy hub is considered. The related reliability indices SAIDI and EENS during grid-connected and islanded conditions are obtained [27]. Also, the implementation of the proposed framework is done on the calculation of reliability indices. The test system is calculated by taking various working energy hub strategies. Thus, the reliability improvement of energy demands is achieved by using bi- or tri-generation converters in an energy hub. At last, the reliability is also improved by energy hubs which are dependent on the component's reliability, energy networks' level, and operation planning [17].

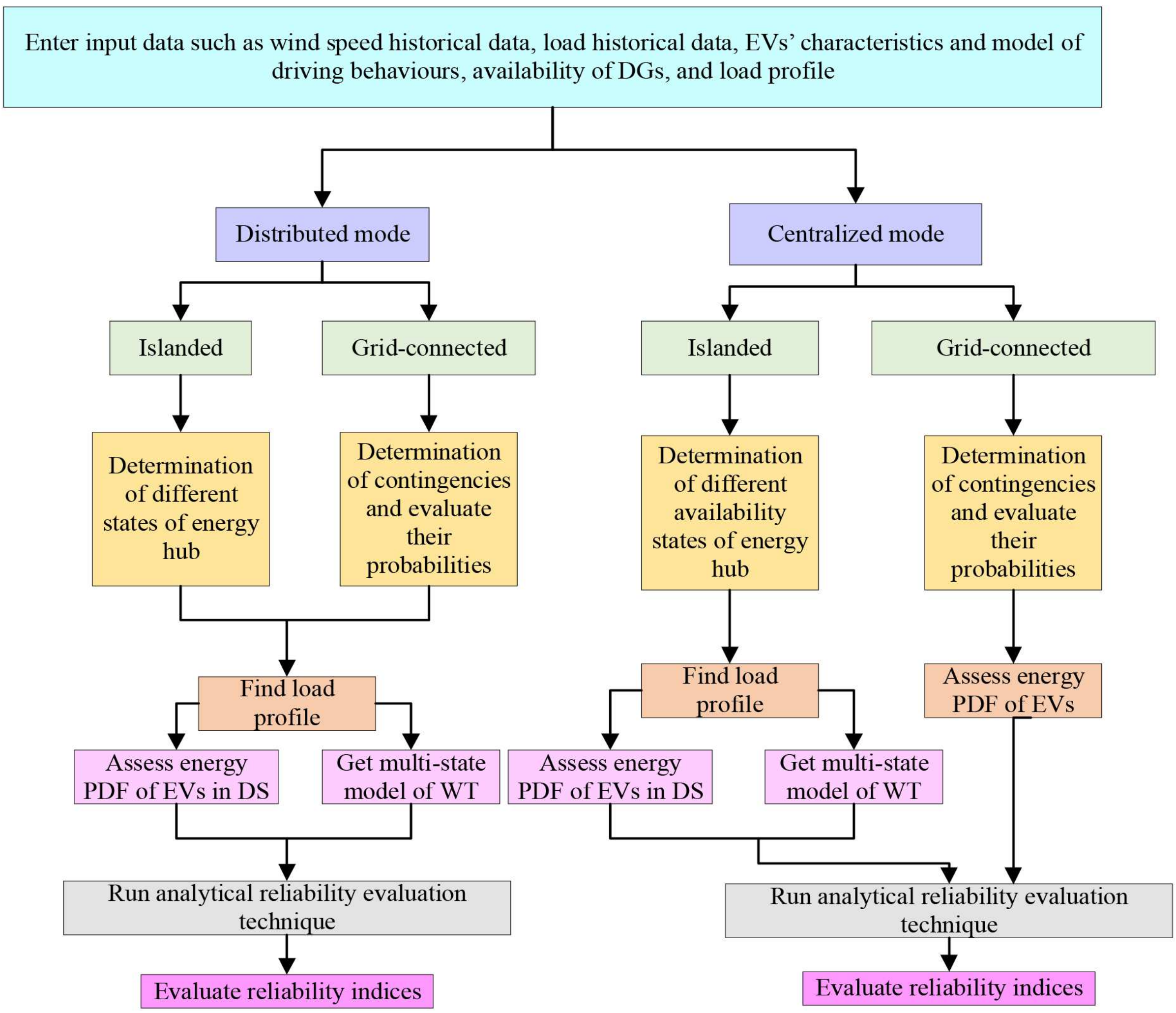

Fig. 7 *Reliability studies with a systematic approach*

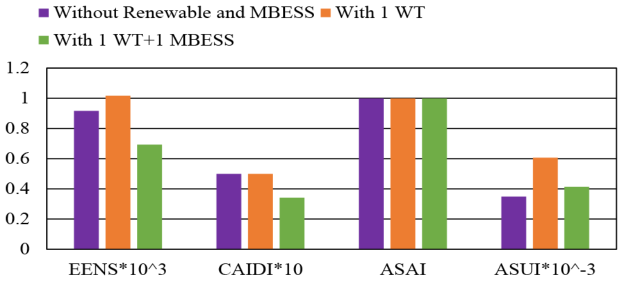

Fig. 8 *Approximate values of reliability indices with and without MBESS [24]*

3.3 EPDS reliability improvement by the ESS

The integration of mobile battery energy storage system (MBESS) and BESS is described in [24, 25], respectively, and a stochastic model is proposed by Mohammadi-Hosseininejad *et al.* [20] which are developed for reliability improvement and support the microgrids (MGs) in OMS during contingency events. The effect of MBESS is observed on reliability indices as shown in Fig. 8. EENS and CAIDI are measured in kWh and hour, respectively. The reliability enhancement techniques and models are discussed in this subsection as follows.

3.3.1 ESS as spinning reserve: The uncertainty in renewable energy resources confirms the supply security and operational reliability studies. ESS is also used as a spinning reserve for a segregated MG. The uncertainty modelling of MGs is probabilistic WT, PV, load injection, and load models. A chance constrained programming (CCP) is used to study the uncertainty in optimisation [26]. This programming is utilised to provide the services for segregated MGs as a spinning reserve. The reliability is thus improved. The probability optimisation function is described using

(see (12))

$$H_j(k) \leq 0;\ j = 1, 2, 3, \ldots, ND; \tag{13}$$

where Prob(.) is an event occurrence probability, $H_j(k)$ is termed as deterministic constraint, η, γ are confidence levels, δ is a random variable.

3.3.2 Chance constrained programming method: It is required to minimise the problem of uncertainties in renewable generation and load during main grid support. A CCP-based scheduling model is used. An ESS is used as a reserve for an isolated MG. A discretised step transformation method is evolved to transform the model into a MILP difficulty. It is because of the readily solvable capability of the MILP. This approach ensures the MG operation to get a trade-off between economy and reliability by fixing a suitable level of confidence.

3.3.3 Integrated residential ESS unit and PV (IREPV) system: The system's reliability is improved by using an IREPV system. It reduces the electricity charges for residential customers and the peak demand of the EPDSs. To achieve this, an algorithm on power management strategy (PMS) is given in [27]. The PMS algorithm is an integrated residential ESS unit. PV arrangement is suggested for islanded and grid-connected conditions to get the benefits of time-of-use pricing. The PMS algorithm is shown in Fig. 9.

At the start, if the grid is 'ON' the GIC mode for DC link voltage control is opted. If the grid is 'OFF' then GIC mode for sliding mode control (SMC) is selected. In SMC, either ESU or PV with ESU operate according to the status of PV power and state of charge (SOC). In Fig. 9, seven modes are explained and the DC-link voltage is regulated by the following five operational modes.

- Mode 1: The islanding scenario of an IREPV is observed in this mode. PV energy is not available but DC link voltage is controlled by the energy storage unit (ESU).
- Mode 2: Still an islanded scenario is observed. But the PV power is accessible now.
- Mode 3: This mode comes at peak time. IREPV works in the grid interaction control (GIC) mode. It implies that the ESU and PV are all set to supply local load.
- Mode 4: This mode comes at an off-peak time. ESU is charged on constant current and constant voltage technique.
- Mode 5: This mode is operated at shoulder time which is between peak and off-peak times. IREPV works in GIC mode. It checks the availability of PV power and saves the ESU energy for peak time use.
- Mode 6: This mode comes when ESU is not fully charged. Thus, the DC link voltage is controlled by the ESU controller with MPP.
- Mode 7: It is also in the islanded case. When ESU is fully charged and MPPT controller provides a constant boost DC voltage.

3.3.4 Effect analysis and accelerated MCM (AMCM): The MCM is implemented and the reliability indices are estimated which takes considerable computational time in the context of adopting multi-state model (MSM) of distributed energy resources (DERs). In MSM, BESS is especially integrated to obtain efficient reliability. Yan *et al.* [25] have also suggested planning oriented RE improvement techniques, which include a two-dimensional MSM for BESS and an effective procedure for a sampled isolated MG state analysis. AMCM method is described for the effect analysis process where the required simulation time is fixed to one year, hence, realises the reliability improvement. The flow charts of the effective analysis and behaviour AMCM method are described in Figs. 10 and 11, respectively. The terms used in flow chart are referred as: $E(R_{IT})$ is expectation of interruption time of each load point, $E(R_{ID})$ is expectation of interruption duration of each load point, M_{PS} and M_{SS} are the power shortage and SOC state matrices, respectively, P_{PS} is the power difference of total demand and supply resources, NL is the subsequent SOC states, i, j, k_1, k_{TTR} are count numbers and set at 1, (i, j) is the state, $n \times N$ is the number of states in BESS state space, $n \times N \times m^{TTR}$ is the total number of all possible scenarios.

In Fig. 10, the effect analysis is suggested to measure the value of reliability indices for customers fed by an isolated MG. Consider the main grid fault at tth time interval. Then isolated microgrid (IMG) starts operating with various DGs and BESS. But due to the uncertainty in DGs and BESS operation, it is very typical to obtain load point reliability assessment by determining the indices. Hence, a method is given which is based on a two-dimensional MSM of the BESS. The probabilities of all BESS states during the TTRth interval is given by

$$p_{\text{BESS},i,j}(TTR) = \sum_{sce=1}^{n \times N \times m^{TTR}} p_{sce}(sce) \times \alpha_{\text{BESS},i,j}(sce) \tag{14}$$

where IMG may also expose to a power interruption while the extinction of a fault. The reliability assessment at faulty load points is important in this interruption. So, the RE technique is given in Fig. 11. This technique is based on a SMCM which nesting the failure mode and effect analysis (FMEA) method. MCM will sample a sequence of BESS states which cannot be known prior to the simulation process. In AMCM, it does not need to do as MCM. Since all the possible states of a BESS are given in advance, the

$$\begin{cases} \min \overline{\text{Fun}} \\ s.t.\ \ \text{Prob}[\text{Fun}(k,\ \delta) \leq \overline{\text{Fun}}] \geq \gamma,\ \text{objectivefunction} \\ \text{Prob}[G_h(k,\ \delta) \leq 0] \leq \eta;\ \ \$\ h = 1, 2, 3, \ldots, NP\ \$\ ,\ \text{uncertaintyconstraints} \end{cases} \tag{12}$$

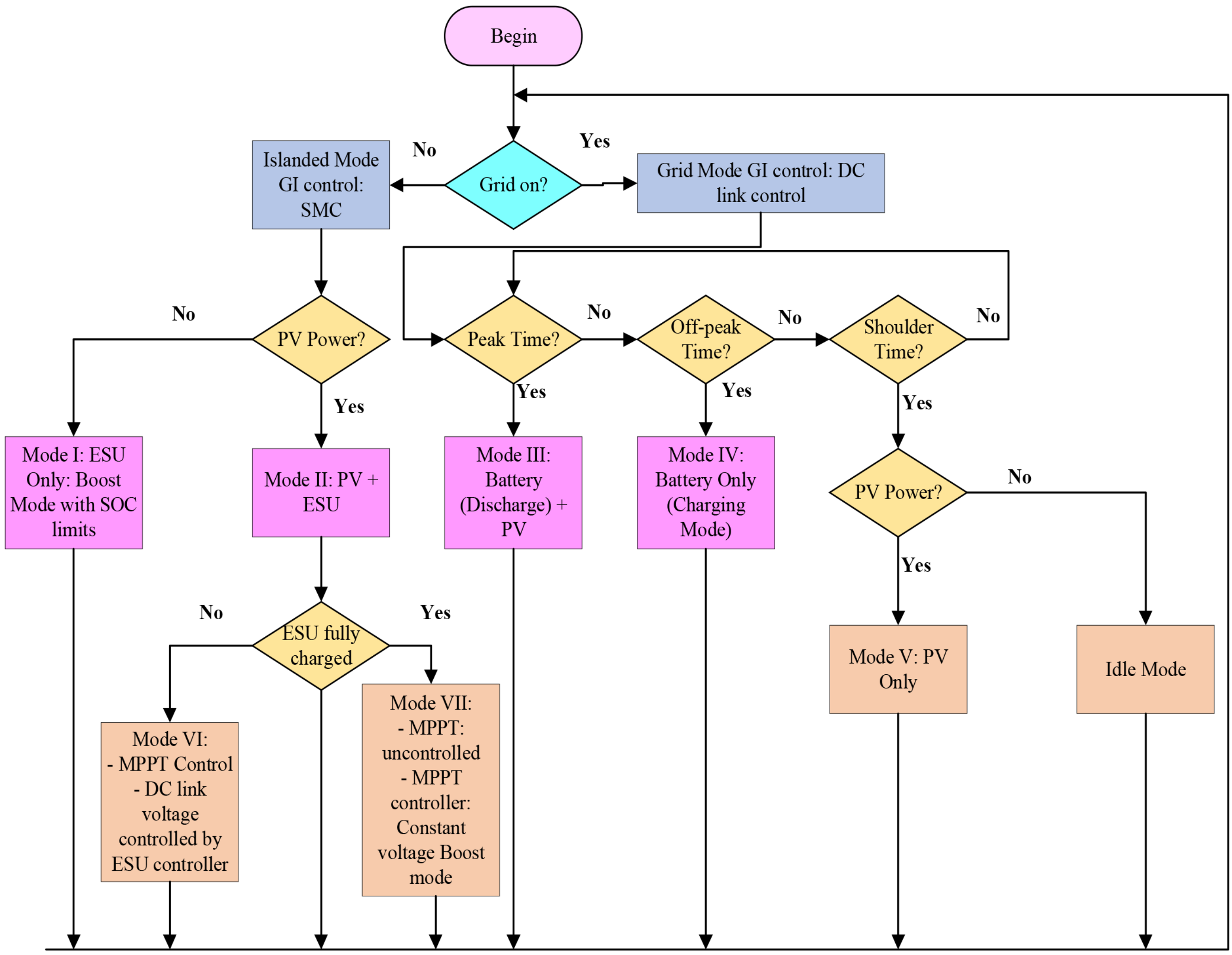

Fig. 9 *Algorithm for power management strategy*

only matter to concern is to determine the state probabilities varying with the preceding simulation process.

3.3.5 Modelling and Markov process of BESS: The reliability models for EPDSs with MGs are the MSMs of net load and BESS. In this model, the available capacity rate SOC is modelled to get the improved PSR. Then the model is implemented on the modified IEEE-RBTS Bus 6 F4 test system [99]. DERs like MBESS enhance the reliability of the EPDSs. MBESS facilitates the grid in the islanded situation. MBESS with uncertain DERs is modelled for reliability analysis (DER generation and demand) by using Markov models. These models are then verified using the MCS method. To determine the island operation time and restore time of the concerned zone, a MBESS model is used. The models for RE include MBESS modelling in time-varying demand and DG output, and EPDS modelling is shown in Fig. 12. The block diagram for reliability assessment with MBESS integration is shown in Fig. 13 [74]. Where λ_1 is Unit 1 failure rate, μ_1 is Unit 1 rate of repair subsequent to battery installation, λ_2 is Unit 2 failure rate, μ_2 is Unit 2 repair rate, I_{ns} is the rate of battery installation. IEEE 15 bus system and modified RBTS system are compared for RE by calculating EENS and CAIDI. It concludes that the reliability is improved for the latter case. The investigation about the robustness and stability of the overall power system is done under different modes of operation of the ESS unit. It enhances the EPS reliability as mentioned in [27].

Fig. 12 shows the time table of a power system. T_{fault}, T_{start}, and T_{restore} are the fault occurrence time, MBESS start time, and power system restoration time, respectively. The integration of MBESS depicts that the radial distribution system facilitates the isolated (downstream) section during post-fault. Therefore, this arrangement enhances the reliability of the system. The reliability index EENS is improved with MBESS integration, therefore the reliability as given in (15). A two-section distribution system is used to describe the Markov process in Fig. 13

$$\begin{aligned} EENS = \{ & p_2 \times \overline{L(2)} + p_3[\overline{L(1)} + \overline{L(2)}]\}8760 \\ & + p_4[\overline{L(1)} + \overline{L(2)}(1 - p_{\text{island}})]8760 \end{aligned} \tag{15}$$

where p_2, p_3, p_4 are the average ratio of success probability of island operation mode during fault, p_{island} is the success probability of island mode, 'i' is referred as number of section; here it is 2, $L(i) \le P_i^{\text{Dis}}(t) + P_i^{\text{DG}}(t)$ viz discharging for MBESS plus distribution generation output.

4 Reliability improvement methods for WIPS

The authors of this paper present their views on RE and improvement by focusing only on WIPS. The main cause to focus on WIPS is the volatility including (i) penetration, (ii) wake effect, (iii) output power correlation for WTs, (iv) the effect of parameters, and (v) environment. The above-mentioned causes are incorporated in reliability assessment [28] because these are the major contributors for reduction in PSR. Some researches [29, 30, 33, 34] are done on reliability analysis of WIPS.

It is suggested to integrate wind/PV/battery in the EPDS to enhance the electrical system's reliability. Also, the effect of BESS is explained in the wind farm (WF) integrated electrical system under four scenarios as given in Fig. 14. Scenario no. 1 is taken when intermittency and inertia of WT are not considered. The spinning reserve requirement is considered in Scenario 2. Scenario 3 includes Scenario 2 with the inclusion of the wind penetration

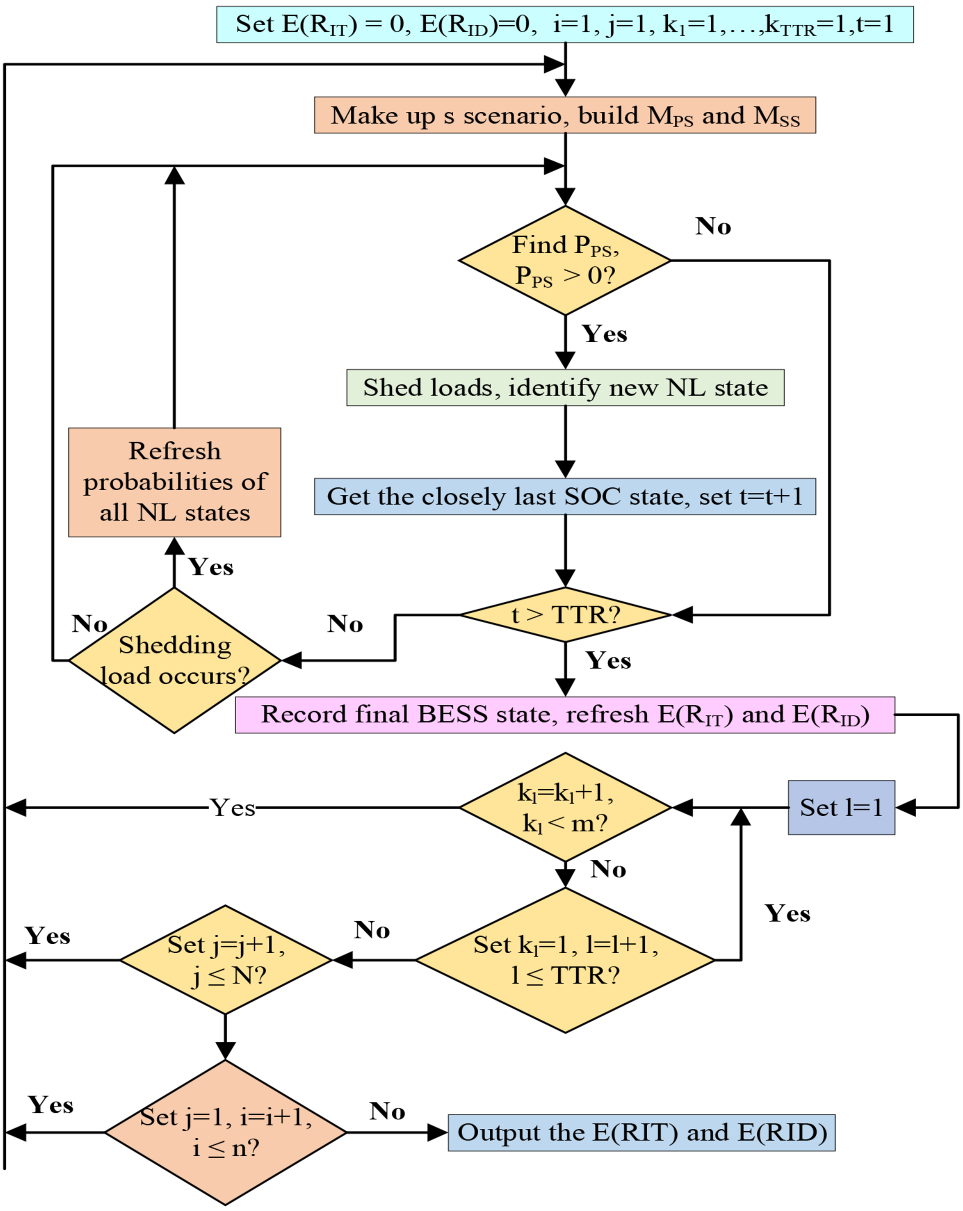

Fig. 10 *Flow chart of effect analysis*

limit in watts. Lastly, large-scale ESS is considered in Scenario 4. In Fig. 14, loss of load expectation (LOLE) is measured in hour/year, LOLF is in failure/year, EDNS is in MW/year, and loss of energy expectation (LOEE) is in MWh/year. Further discussion on WIPS reliability improvement methods is described in the later part of this section. The pros and cons of WIPS reliability improvement methods are explained in Table 6.

4.1 Generation rescheduling algorithm (GRA)

GRA is implemented in [34], which provides adjustable output generation. The output generation removes the fluctuations of power flows in the transmission branch and also the probability of overloading is relieved. This algorithm is used to schedule the conventional generation in order to increase the transmission system reliability with wind energy penetration. It is done in response to wind penetration and power uncertainty impacts. Although, GRA is mainly useful in preventing the congestion in power and the balance in DERs and power system loads. The previous methods like participation factor control are unable to consider the locations of the generators. Hence, the GRA is developed to increase the reliability with load and wind power uncertainty. Overall, the GRA is applicable in determining the optimal generator rescheduling solution. This solution is useful for mitigating the overloading scenarios and minimising the weighted sum of variances of electrical line power flow. The method is explained briefly in flow chart of Fig. 15.

To evaluate the uncertainty effects of renewable energy on the power system, the GRA method is implemented. It is a probabilistic method and applied to evaluate the reliability indices considering branch power flows. These indices signify as power variances which are needed to be minimised. The variances are mainly because of uncertainty in renewable resources and loads. In the previous analysis, only thermal limits are considered but weighting factors are introduced to take care of uncertainties as well.

4.2 Condition monitoring (CM) of semiconductor

Moeini *et al.* [31] have described a CM system method to improve WIPS reliability. The WTs are dependent on the reliability of power electronics converters as the occurrence of failure is maximum (32%) in power module of WT [100]. The IGBTs used in grid side converter are affected by the abnormal variations in temperature. CM reduces the costs related to maintenance and limit the unexpected interruptions of the power generation. The usual cost of a CM system is about € 10,000 per year per WT [101]. This cost is comparably very low to the maintenance cost of remotely located WTs, e.g. € 100,000 to € 300,000 (for 2–3 MW) offshore WTs and € 200,000 to € 720,000 for offshore WTs larger than 3 MW [102]. Thus, the CM of semiconductor devices is required to

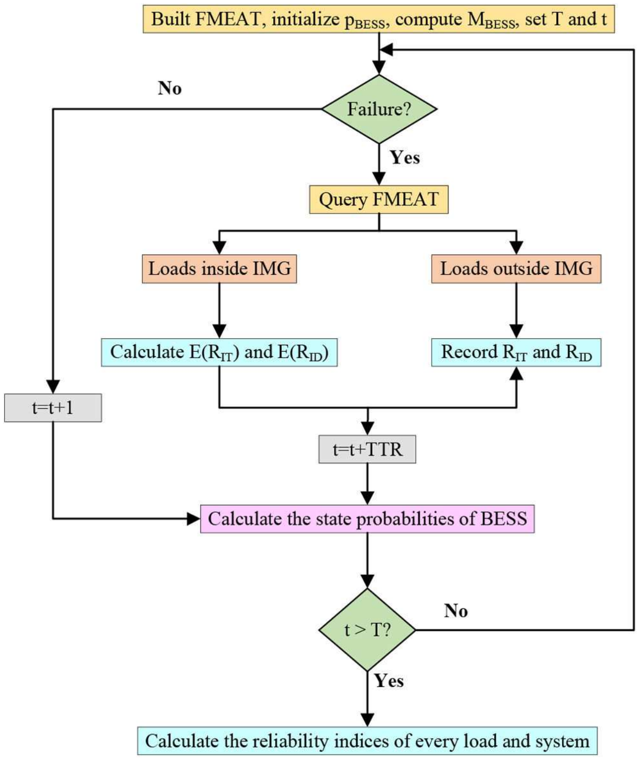

Fig. 11 *Flow chart of AMCM algorithm*

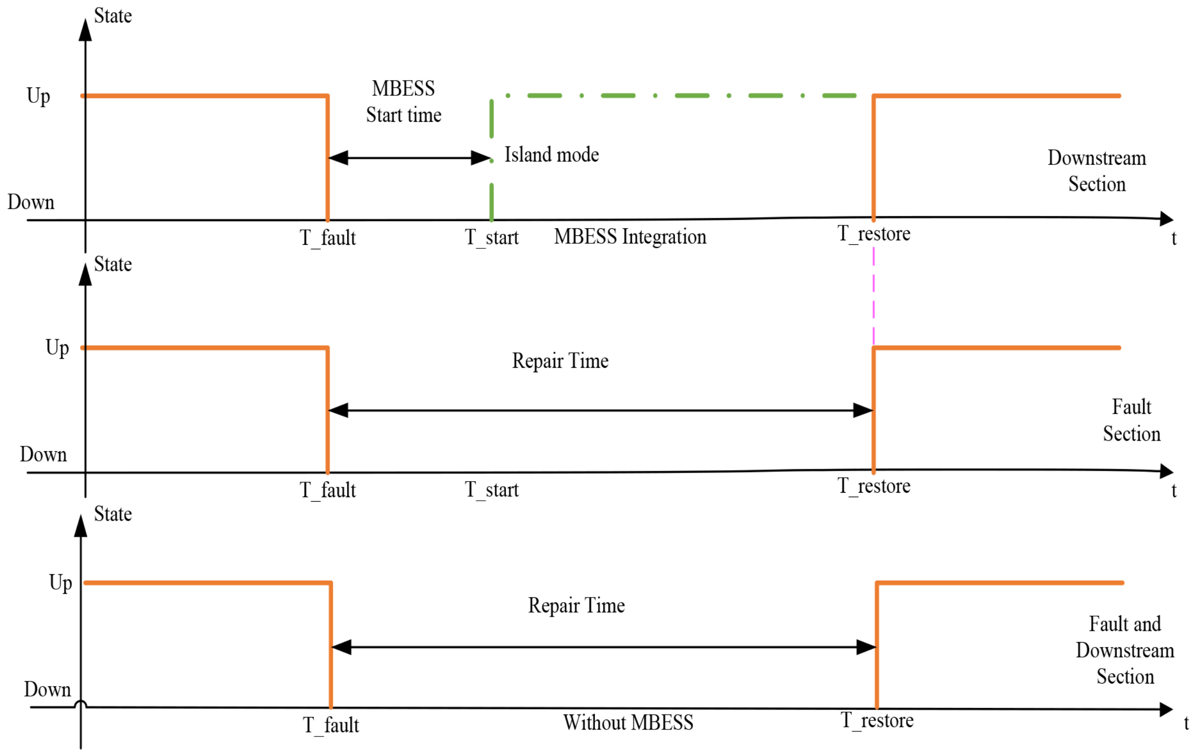

Fig. 12 *EPDS modelling include MBESS modelling time-varying demand and DG output*

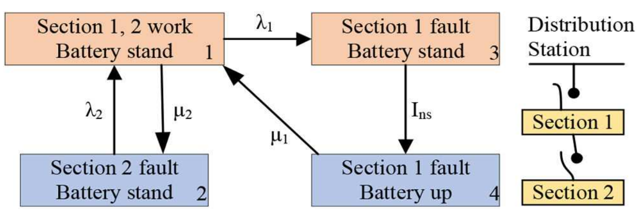

Fig. 13 *Markov process for reliability assessment with MBESS integration*

increase the reliability of WTs because CM also limits the uncertain disturbance in power generation.

4.3 Auto-regressive moving average model (ARMA)

ARMA model is described to improve the WIPS reliability. An ARMA model is a series of models. These models assess statistical data to produce higher-order autocorrelation. The daytime and seasonal data are thus useful in WIPS's reliability studies. The ARMA model and simulated wind speed model are given in (16)–(19) [103–105]. The main advantage of using the ARMA model is that an enormous number of years of data is not required so the

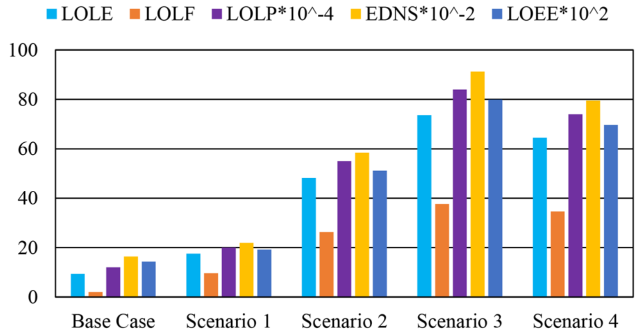

Fig. 14 *Reliability indices with 26 conventional generators and 43 WFs on IEEE-RTS 69 Bus system [30]*

Table 6 Reliability improvement methods with their pros and cons

S. No.	Method	Pros	Cons
1	GRA	(i) Power flow variations are taken out from the transmission line (ii) It minimises the probability of overburdening (iii) Increases the transmission system reliability	Gives a flexible output power generation by ignoring the congestion in power, and stabilises the wind energy resources with power system loads
2	CM	(i) Identifies the faults and degradation in semiconductor devices (ii) It is cheap and limits the uncertain interruptions of power generation (iii) Enhances generation reliability	The assumptions such as upper-lower limits of voltage and current are taken on the characteristics of power electronics devices
3	ARMA	(i) Years of big data are not needed (ii) WECS is explained in the ARMA model	(i) The noise changes in various ways even yet the equations of the system remain deterministic (ii) Single reliable statistical test for chaoticity is not possible, incorporating multiple tests is a crucial aspect, especially when one is handling with limited and noisy datasets like wind speed and impedance loading
4	DTLR	(i) More penetration of wind energy is supported due to current carrying capability of aerial lines (ii) Raises the PSR	(i) The DLR saturates after a particular stage of installed wind power (ii) The maximum utilisation of power transmission capability is discontinued for long transmission lines
5	DRP	(i) Eliminates the opposite impacts of wind energy volatility on PSR (ii) Evaluates short term reliability of WIPS.	Real-world uncertainties influence the reliability enhancement feature of DRP
6	ESS	(i) It includes reliability enhancement with analysing the power system service recovery (ii) It utilises PL as a substitute for a disturbed zone	(i) Energy loss in charging–discharging makes it inefficient (ii) It is complex and not cheap and requires infrastructure and space
7	DSM	(i) It evaluates the load side reliability (ii) Reliability increases for the combined stage of hybrid energy and DSM	(i) Users have a restricted resource to use the DSM (ii) DSM is a better fit for greater energy consumers or those with complex energy demands

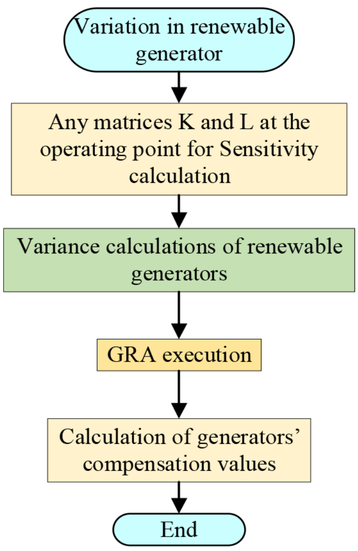

Fig. 15 *Steps of GRA execution*

incorporation of wind energy conversion system (WECS) is justified in the ARMA model

$$y_T = f(x_1, x_2, x_3, x_4, x_5, \ldots) \tag{16}$$

$$y_T = \phi_1' y_{T-1} + \phi_2' y_{T-2} + \cdots \phi_n' y_{T-n} + \beta_T - \theta_1' \beta_{T-1} - \theta_2' \beta_{T-2} \cdots - \theta_m' \beta_{T-m} \tag{17}$$

$$SWS_T = \mu_T + \sigma_T\, y_T \tag{18}$$

where SWS_T is the simulated wind speed, μ_T is wind speed hourly mean value for T hour, σ_T= wind speed standard deviation for T hour. The swift current site ARMA model in Canada is [106]

$$\begin{aligned} y_T = {} & 1.17y_{T-1} + 0.10y_{T-2} + 0.35y_{T-3} + 0.037y_{T-4} \\ & + \beta_T - 0.50\beta_{T-1} - 0.29\beta_{T-2} \\ & - 0.13\beta_{T-m} \end{aligned} \tag{19}$$

where Φ_k and β_l are the two ARMA parameters. $k = 1, 2, \ldots, n$; $l = 1, 2, \ldots, m$ β_T is a typical white noise with mean value 0 and variance σ_a^2 that is $\beta_T \in N\ (0,\ \sigma_a^2)$, N denotes NID (normally independently distributed). To determine the order (n, m), F-criterion test is used to find n which provides the best fit solution.

4.4 Dynamic thermal line rating (DTLR)

The consideration of DTLR reliability becomes crucial when renewable energy sources are integrated with power system [107]. The operation of the transmission line under a considerable impact of wind online ratings (current carrying capacity of overhead lines) is termed as DTLR. Thus, the electrical network incorporating DTLR and WF needs to evaluate reliability. It shows that DTLR system has increased the PSR with more wind energy penetration is allowed. SMCM method is used due to the dependencies of wind power and line ratings on time. Hence, the time-series data modelling is done by the ARMA model as discussed in Section 4.3 of this paper. The steady-state ratings of transmission line are described in (20). The wind-powered IEEE-24 bus reliability network for testing is elaborated in [35]. The procedure to calculate the reliability improvement of dynamic thermal rating (DTR) method is implemented

$$H_C(Q_C, Q_A, V_W, \phi) + H_R(Q_C, Q_A) = Q_s(\theta) + i^2 r(Q_C), \quad (20)$$

where H_C is the convection heat loss, Q_C is the operating temperature, Q_A is the air temperature, V_W is the speed of the wind, ϕ is the wind angle, H_R is the heat loss due to radiation, Q_S is the solar heat gain, θ is the angle of solar radiation, i is the current in the conductor, r is the conductor resistance.

4.5 Demand response program (DRP)

A DRP is implemented to meet the reliability requirements in WIPS. The implementation of DRPs is a beneficial solution for avoiding uncertainties. Hence, reliability improvement is achieved in the EPS. The RE study of composite power systems with the influence of the lead time and unlike initial states of system components of demand response (DR) is explained in [36]. DR is divided into direct and indirect impacts including the contingency-based demand response program (CBDRP) and time-based demand response program (TBDRP), respectively. A deterministic model of DRPs is developed, in which curtailed load programs (CLP) are executed by system operators directly. Hence, the programs are not needed to be modelled on the basis of market signals. The modelling of the DRPs is based on the price flexibility of demand [108–112]. DRPs are also based on the penalty and incentive of programs [113–115]. The RBTS [116] is used to apply the proposed approach over the daily horizon time with a maximum demand of 185 MW. The cross elasticity equations are described between price and demand in (21)–(28) [117]

The TBDRP model is

$$\widetilde{\mathrm{dem}}^{i}_{\mathrm{TBDRP}} = \mathrm{Dem}_{\mathrm{TBDRP}}(1 + \delta\widetilde{\mathrm{dem}}^{i}_{\mathrm{TBDRP}}) \quad (21)$$

$$\delta\widetilde{\mathrm{dem}}^{i}_{\mathrm{TBDRP}} = \sum_{N=1}^{24} \tilde{\varphi}^{i,j}_{N} \,.\, \delta P^{j}_{a} \quad (22)$$

$$\tilde{\varphi}^{i,j}_{N} = \varphi^{i,j}_{N} + N^{i,j}_{\epsilon} \quad (23)$$

where $\widetilde{\mathrm{dem}}^{i}_{\mathrm{TBDRP}}$ is the final demand in time 'i', $\delta\widetilde{\mathrm{dem}}^{i}_{\mathrm{TBDRP}}$ is the final change in demand in time 'i', $\varphi^{i,j}_{N}$ is the cross elasticity in normal condition (between demand and price in periods i and j, respectively), δP^{j}_{a} is the change in actual price in period 'i', $N^{i,j}_{\epsilon}$ is the random variable which is characterised with mean=0 and variance for normally distributed data, Dem_{TBDRP} is the total demand which responds to variations in price.

The CBDRP model is

$$\widetilde{\mathrm{dem}}^{i}_{\mathrm{CBDRP}} = \widetilde{\mathrm{Dem}}^{i}_{\mathrm{CBDRP}}(1 + \delta\widetilde{\mathrm{dem}}^{i}_{\mathrm{TBDRP}}) \quad (24)$$

$$\widetilde{\mathrm{Dem}_{\mathrm{CBDRP}}}^{i} = \mathrm{Dem}_{\mathrm{CBDRP}}{}^{i}(Z^{CS})\left(1 - \exp\left(-\frac{(\eta_{\alpha}{}^{i} \,.\, \alpha^{i} + \eta_{\beta}{}^{i} \,.\, \beta^{i})}{\eta_{P_e}{}^{i} \,.\, P_e{}^{i}}\right)\right) \quad (25)$$

$$\delta\widetilde{\mathrm{dem}}^{i}_{\mathrm{TBDRP}} = \begin{cases} \tilde{\varphi}^{i,i}_{E}\left(\delta P^{i}_{a} + \dfrac{\alpha^{i} + \beta^{i}}{P^{i}_{e}}\right), & -\dfrac{\gamma^{i}}{\mathrm{Dem}^{i}} < \delta\mathrm{dem}^{i} \le 0 \\ \tilde{\varphi}^{i,i}_{E} \,.\, \delta P^{i}_{a}, \ \delta\mathrm{dem}^{i} \le -\dfrac{\gamma^{i}}{\mathrm{Dem}^{i}} & \text{or } \delta\mathrm{dem}^{i} > 0 \end{cases} \quad (26)$$

where $\alpha^i, \beta^i, and\, \gamma^i$ are the level of load reductions as an incentive, penalty, and contractual, respectively, in a DRP for the period of 'i', P^{j}_{e} is the expected price in period 'i'. The CLP model is

$$\widetilde{\mathrm{dem}}^{i}_{\mathrm{CLP}} = \widetilde{\mathrm{Dem}}^{i}_{\mathrm{CLP}}(1 - \delta\mathrm{dem}^{i}_{\mathrm{CLP}}) \quad (27)$$

$$\widetilde{\mathrm{Dem}}^{i}_{\mathrm{CLP}} = \mathrm{Dem}^{i}_{\mathrm{CLP}}(Z^{C}S) \quad (28)$$

where Z^{CS} represents a random variable and $\mathrm{Dem}^{i}_{\mathrm{CBDRP}}(Z^{\mathrm{CS}})$ and $\mathrm{Dem}^{i}_{\mathrm{CLP}}(Z^{C}S)$ are the demand values, $\eta_{\alpha}{}^{i}$, $\eta_{\beta}{}^{i}$ and $\eta_{P_e}{}^{i}$ are the participation coefficients, $\tilde{\varphi}^{i,i}_{E}$ refers cross elasticity in emergency condition (between price and demand in periods i).

The DRP effect is seen on LOLP, LOLE, expected interruption cost (ECOST), operational cost (OPCOST), expected total cost (TCOST), and interrupted energy assessment rate (IEAR) which are referred to the EPS reliability indices.

4.6 Energy storage system

A MCS technique is implemented to inspect the PSR benefits from ESS. The SAIDI and total reliability cost are minimised. The cost is dependent on the aggregate interruption cost of the consumer. The aggregate installation cost of a parking lot (PL), and incorporation cost are considered. The PL acts as a unit which provides the back-up for the interrupted zone (reduces the interruption time). It also acts as a unit which provides the storage in the back-up feeder (reduced the congestion frequency) as battery ESS unit. The voltage deviation and energy costs are also taken into consideration during reliability cost determination. The overall objective function is the combination of operative and reliability objectives. The stochastic model and MCS technique are proposed in [23]. This technique is useful in determining the PL effects to nearby services. It also contributes to reliability enhancement with the consideration of service restoration. The reliability-based objective functions of EV parking lot allocation problem is described in (29) and (30). The minimisation of two reliability indices E_{SAIDI} and E_{T_C} is accomplished for reliability improvement

$$O.F.^{\mathrm{rel}} : \left\{\alpha_1\left(\frac{E_{T_C} - T_{C_{\mathrm{OPT}}}}{T_{C_{\mathrm{OPT}}}}\right) + \alpha_2\left(\frac{E_{\mathrm{SAIDI}} - \mathrm{SAIDI}_{\mathrm{OPT}}}{\mathrm{SAIDI}_{\mathrm{OPT}}}\right)\right. \quad (29)$$

where $O.F.^{\mathrm{rel}}$ is the optimisation function, $T_{c_{\mathrm{OPT}}}$ and $\mathrm{SAIDI}_{\mathrm{OPT}}$ are determined optimally by putting any of the weighting factors 'zero' [75]

$$E_{T_C} = E_{T_{IC}} + E_{T_{PIC}} + T_{IMC} \quad (30)$$

where E_{T_C}, $E_{T_{IC}}$, $E_{T_{PIC}}$, and T_{IMC} are the expected overall reliability cost, interruption cost, PLs incorporation cost in service restoration, and overall investment and maintenance costs of PL.

4.7 Demand side management (DSM)

To assess the load side reliability, DSM method is proposed [18]. The method is implemented in EPDS to achieve efficient PSR. Hence, MCS and a local load system method are developed for RE and assessment, respectively. The developed method incorporates DSM and wind as described in Fig. 16.

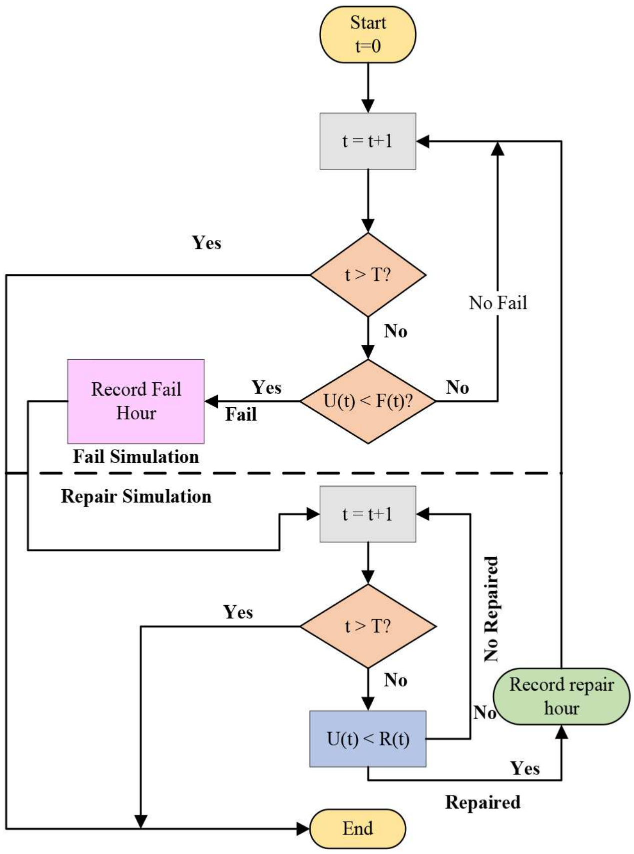

Fig. 16 *Monte-Carlo simulation implementation in DSM*

The DSM method modelling [118] is applied to get the improved load reliability; ENS.

In Fig. 16, $F(t)$ is the cumulative distribution function at hour 't', $U(t)$ is the unavailability of system or device, $R(t)$ is the curtailment level in % that specifies when to consider the generation unavailable. There are four operational stages namely the base stage, the hybrid renewable system stage, the DSM stage, and the hybrid plus DSM stage. The reliability increases for the combined hybrid and DSM stage. This algorithm is implemented to simulate and extract failure and repair times. Thus, reliability assessment is accomplished.

5 Reliability impacts on reactive power, unit commitment, and protection system

5.1 Reactive power optimisation

The reliability impacts on reactive power optimisation [37] are caused by the stochastic nature and integration of renewable energy creates the biggest challenge to traditional operation and planning. The optimisation problem of reactive power in EPDS is solved by a mixed-integer convex programming model. It is applied where the WFs are integrated centrally. Hence, a bi-level robust reactive power optimisation model is used to synchronise the continuous and discrete reactive power compensators. The robust optimal solution is also obtained when wind power uncertainty is to be addressed. The 'wait-and-see' decisions are implemented for continuous reactive power compensators. These compensators may adjust the actual WT output while the 'here-and-now' decisions for discrete reactive power compensators are performed. In the 'here-and-now' decision, compensators are not adjustable after the revelation of uncertainty. The 33, 69, and 123 bus systems mentioned in [119] are used to compare the results analytically. The robust reactive power optimisation model is given as

$$P_m = \sum_{n \in \pi(m)} (H_{nm} - r_{nm} I_{nm}) - \sum_{k \in \delta(m)} H_{mk}, \forall m \in B \tag{31}$$

$$Q_m = \sum_{n \in \pi(m)} (G_{nm} - x_{nm} I_{nm}) - \sum_{k \in \delta(m)} G_{mk} + b_{s,m} u_m, \quad \forall m \notin \Omega \tag{32}$$

$$u_m = u_n - 2(r_{nm} H_{nm} + x_{nm} G_{nm}) + (r_{nm}^2 + x_{nm}^2) I_{nm}, \quad \forall (n,m) \in ET \tag{33}$$

where P_m, Q_m are referred to real and reactive powers of bus m; r_{nm}, x_{nm} are the resistance and reactance of the branch (n, m); H_{nm}, G_{nm} are the real and reactive power flows from the bus n to bus m, $b_{s,m}$ is the shunt susceptance from m to ground, u_m is the voltage magnitude of bus m.

5.2 Unit commitment (UC) in wind generation

The reliability impact is observed on wind generation unit commitment. The absorption of wind power by the bulk power system during the UC scheme is one of the biggest problems in the power system. Hence, a risk-based assessment approach is proposed. A risk-minimisation model is developed and solved by using a CCG algorithm. The mathematical formulation for admissibility of wind generation is described in (34) and (35). The risk-based admissibility measure is described in recent researches [32, 120]. Admissible wind generation (AWG) is referred to as a subset of the wind generation. For AWG, no load shedding or wind generation curtailment is needed for reliability reasons. So, the wind generation admissibility is explained and examined by solving the bi-level programs

$$F = \sum_{t=1}^{T} \left(\sum_{m=1}^{M} e_m t \Delta\omega_{mt} + \sum_{j=1}^{J} f_{jt} \Delta D_{jt} \right) \tag{34}$$

$$s.t.\ U_{gt} P_{\min}^{g} \le p_{gt} \le U_{gt} P_{\max}^{g}, \forall g, \forall t \tag{35}$$

where F defines the economical loss during operation, T is the number of time periods, M is the number of WFs, e_{mt} is the price curtailment of generation WF m in time period t, $\Delta\Omega_{mt}$ is the WF m generation curtailment in time period t, J is the total number of load buses, f_{jt} is load shedding price of bus j in time period t, ΔD_{jt} is load bus j load shedding in time span t, U_{gt} is taken as binary variable which refers that on and off of generator g in time span of t, $P_{\max}^{g}$ and $P_{\min}^{g}$ are maximum and minimum outputs of generator g at running condition, p_{gt} output generation of generator g in time period t, g is the generators' index.

The above equations are used for the maximum admissibility of wind generation. Then, it is required a UC strategy and used for the economic dispatch (ED) strategy. These strategies impact admissible wind generation. Therefore, the admissible assessment problem is converted into an optimisation problem as described in (34) and (35).

5.3 Protection schemes

The reliability impacts on protection schemes are discussed in this subsection. The system integrated protection schemes (SIPS) is applied to adjust the new interconnections especially WFs. This depicts that the uncertainty in interactions between SIPS raises the interest in SIPS reliability. Hence, the Pennsylvania-New Jersey-Maryland (PJM) 5-bus system is presented in [38] to describe the SIPSs performances. It involves advanced Information and Communications Technology (ICT) and Wide Area Management (WAM), protection, and control. The risk assessment procedure methodologies are demonstrated to evaluate the system's reliability as shown in Figs. 17 and 18. The methodologies including reliability assessment at the component level, Markov model at the system level, integration of wind power, assessment of SIPS impact, and assessment method of risk are incorporated.

The suggested assessment procedures on risk facilitate the electric power utilities in managing the effect of ICT on the reliability of the SIPS. To measure the probabilities of unplanned

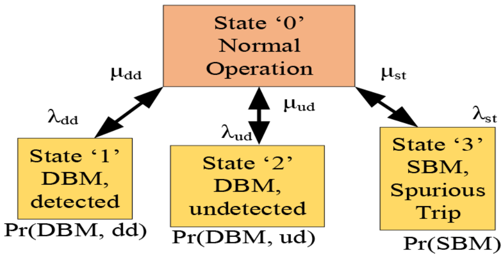

Fig. 17 *Markov model applied for reliability assessment*

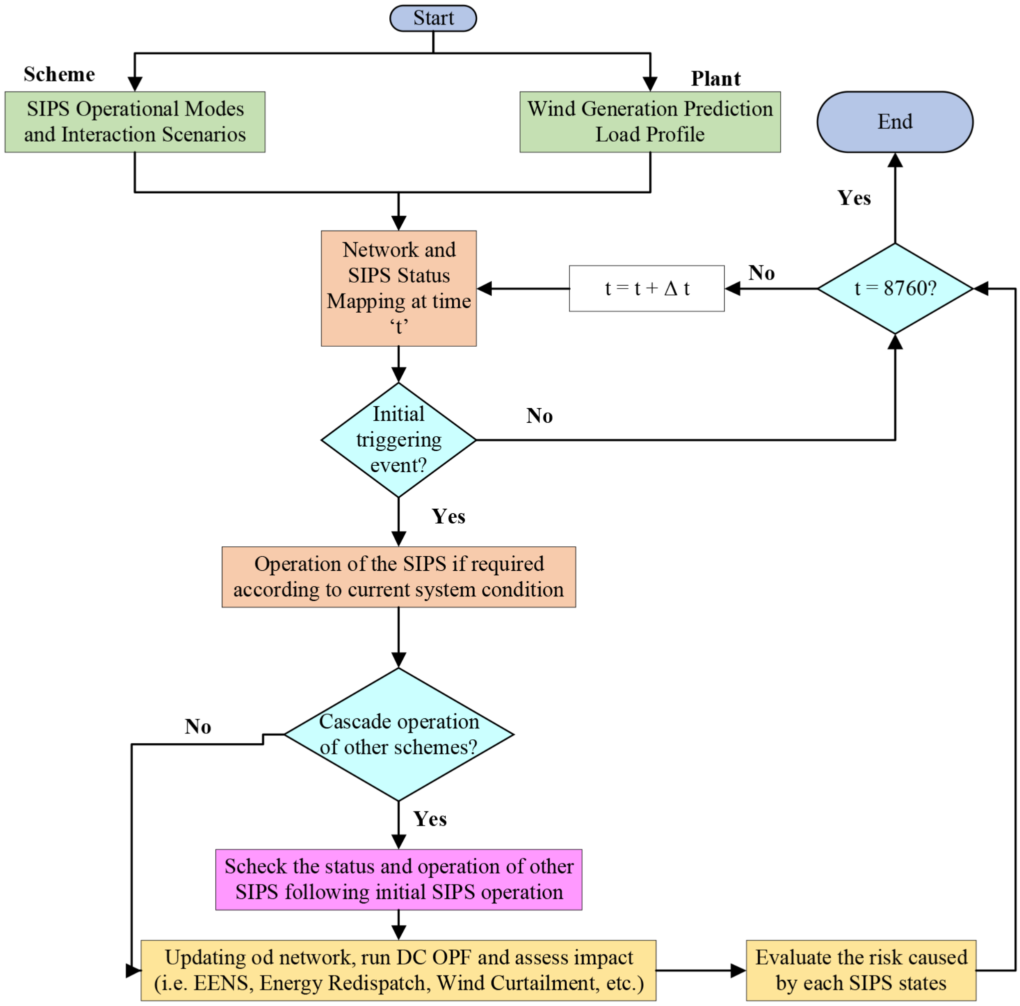

Fig. 18 *Reliability assessment using SMCM method in SIPS*

contacts of SIPS, assessment procedures are utilised. The method is also useful in maintaining the balance between the operational and planning costs. It also balances the system reliability in transmission and generation expansion and operation planning. Hence, the reliability analysis in composite power system is necessary as already described in Section 3.1

SIPS fails to operate in two ways: (i) dependability-based mal-operation (DBM) and (ii) security-based mal-operation (SBM). DBM is a mal-operation to operate when SIPS is needed and SBM is an unwanted SIPS operation when there is no disruption present in the system. FMEA method is used to obtain all the modes of failure. Then the reliability assessment is done using the Markov model as shown in Fig. 17. The four operational states '0', '1', '2', and '3' are determined. In-state '0', component works to accomplish the operations of SIPS. The mal-functioned components are repaired and replaced before leading to a SIPS DBM in state '1'. But when state '1' is not detected the SIPS fails to operate. At state '3' a component operates even though not needed. It may be due to the spurious function of the protection system.

Another method known as SMCM is implemented as a risk assessment procedure. It is also implemented to analyse the impact of SIPS operation as shown in Fig. 18. It is well suited for time-based events. ARMA models in Section 4.3 for load and WF output profiles are incorporated into the SMCM model. Then each stage of Markov models is mapped into the SMCM model to simulate the behaviour of the system.

6 Conclusions

The uncertainty parameters lead to the unreliable operation of EPSs; thus, it is needed to do a lucrative study on reliability assessment of such a system. The paper is concentrated on the crucial methods which are useful in the handling of uncertainty parameters; and also, in RE with improvement in EPDSs. The probabilistic and possibilistic approaches are discussed for dealing with the uncertainty parameters when there is an integration of renewables into EPSs. The probabilistic approach leads to the study of MCS, PEM and SBA methods in dealing with modelled uncertain parameters.

The MCS method is being used in SIPS, composite power system, and so on, and reliability enhancement of the system is observed. The aspects including OMS, expansion planning, allocation of backups, and improvement in maintenance policy, outage events are focused by the authors. It is found that the time-based reliability indices including SAIFI, CAIDI, ENS are evaluated during reliability assessment and improvement. Further, it is mentioned in this paper that how the reliability of EPDSs is improved with the integration of EV, BESS, and so on, and some studies on CM of semiconductor, DTR, DRP, DSM, and so on are useful in WIPS in RE. At last, the paper has given an overview of reliability impacts on reactive power compensation, UC, and protection schemes in the renewable integrated EPSs. Present studies explore the following future research scopes:

(i) The uncertainties may be dealt rigorously by using a combination of probabilistic and possibilistic approaches in RE.

(ii) The power system becomes a complex network because of the incorporation of new energy sources; hence, needed to be analysed for the trade-off between reliability and economic, reliability and planning, and so on.

(iii) Due to the availability of very few researches on EV and ESS unit as a reliability improvement means; thus, the work on operation and planning can be done on these renewables.

(iv) The paper introduces the reliability impacts on UC, reactive power optimisation and power system protection schemes in WIPS, which may be further explored and analysed in detail to find out the methods to mitigate the negative impacts on PSR.

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