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Distribution System Restoration with Renewable Resources for Reliability Improvement under System Uncertainties

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***Abstract*—Integration of renewable distributed generation (DG) units into distribution networks is gaining widespread popularity. However, uncertainties in generation availability associated with renewable DG units pose a major challenge. These uncertainties should be properly addressed to ensure acceptable system performance and improve customer side reliability. In this paper, the reliability assessment of distribution systems embedded with renewable DG sources has been carried out giving emphasis to system uncertainties and optimal restoration strategies. The uncertainties associated with the power output from renewable resources, time varying load demand, stochastic prediction errors, and random fault events have been accounted in the restoration optimization formulation for reliability evaluation. A parameter free particle swarm optimization (PSO) technique is applied in the paper to address the complexity involved in the formulation. Moreover, a problem specific encoding scheme is also proposed in conjunction with PSO to ensure optimality.**

***Index Terms*—distribution system reliability, distributed generation, wind power generation, solar power generation, load restoration, and optimization.**

I. Introduction

Renewable distributed generation (DG) units, such as solar photovoltaic (PV) systems and wind turbine generators (WTG) are seen to be increasingly embedded into existing power systems. Such units not only provide support to power systems under normal operating conditions but also provide reliability benefits to both customers and utilities during contingencies. However, system operating constraints, uncertainties in generation availability for renewable DG systems, and time-varying load demand are major barriers in their effective integration.

Some of the pioneering research on reliability evaluation of power generation and transmission systems containing renewable generating systems have been reported in [1], [2]. The reliability impacts of major smart grid resources such as renewables, demand response and storage have been critically reviewed in [3]. Reliability issues of small isolated power systems containing PV, WTG and energy storage have been explored in [4]. The reliability assessment of distribution systems with optimal placement of conventional DG units (such as diesel generators and gas turbines) have been elaborated in [5] by considering the reliability worth. In [6], clustering algorithms are used to determine specific system states considering the correlation between hourly load demand and power generation. Although some of the probabilistic analytical methods based on clustering techniques for system reliability assessment are efficient, these methods may not be suitable for modeling the behavior of transitional nature of different system states in successive time intervals due to the loss of inherent features of the time correlated system variables.

In terms of restoration strategies, a decentralized multi-agent system based service restoration of radial distribution networks is presented in [7] but the renewable DG units and associated uncertainties are not considered. A mixed-integer second-order cone programming formulation is proposed in [8] for service restoration of a distribution network with DG units however, the uncertainties associated with the renewable resources are not considered. In [9], a mixed-integer non-linear programming model is presented for the optimal restoration/maintenance of the switching sequence of an unbalanced three-phase distribution system without the consideration of renewable energy resources. A new methodology to include cold load pickup events in the reliability assessment of power distribution systems is proposed in [10] that only considers the demand uncertainty. A methodology based on multi-objective evolutionary algorithms is presented in [11] for minimizing computational burden associated with system restoration problem with the conventional power sources.

In comparison to extensive reliability studies carried out for power generation and transmission systems, limited work exists in relation to distribution networks inclusive of renewable DG units in the literature. In [12], the reliability benefits associated with adding DG units to a distribution system are investigated by simulating restoration procedures following events associated with faults. In [13], the probability of successful islanding operation with renewable DG units has been assessed where the impact of the islanded system reliability has also been considered with regard to overall system reliability evaluation. The customer reliability for a microgrid with DG units has been assessed in [14]. In [15], the impacts of optimal DG placement on system reliability and efficiency are investigated using particle swarm optimization (PSO) by considering comprehensive factors such as customer types, daily and monthly load patterns, and weather conditions.

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Analytical expressions for finding optimal size and power factor of different types of DG units to minimize losses in primary distribution systems are proposed in [16]. In practice, conventional distribution systems are designed with sufficient margin between the supply capacity and maximum load demand to supply customers without considering any support from DG units. Generally, constant load demand and constant DG output are used for short term restoration. Such consideration may mask system uncertainties and impact on the switching actions, resulting in unrealistic solutions. As a result, fewer customers will be restored or the restored customers may experience additional interruptions due to the mismatch between actual generation and load demand. Furthermore, the impact of uncertainties in renewable power generation prediction on system reliability has not been recognized since prediction analysis has not been thoroughly carried out to deal with short term planning. It is of utmost interest to quantify the impact of prediction error in distribution system reliability evaluation associated with renewable DG units. The major contributions of the paper are as follows:

1) A novel restoration strategy is proposed using the Heuristic model, where the islanding features and network reconfiguration options are effectively combined to reduce the loss of load (load shedding) and achieve fast service restoration. Moreover, the presented restoration strategy is based on the uncertain circumstances that may arise in different practical situations. In order to generate real conditions for the validation of the proposed strategy, auto-regressive probabilistic models incorporating statistical characteristics of the uncertain parameters such as the load demands, the intermittent generation and the random fault events are embedded into the proposed restoration strategy. Furthermore, the stochastic prediction errors of these uncertain parameters are incorporated in the proposed strategy to adjust the global range of uncertainty.
2) The proposed strategy uses time sequential Monte Carlo simulations to effectively estimate system reliability under wider range of system conditions. Furthermore, a tuning parameter free TRIBE PSO algorithm is proposed to solve the presented combinatorial, nonlinear constrained optimization problem thereby ensuring convergence to either optimal or near optimal feasible solutions.
3) A novel encoding strategy with a dynamic selection scheme rather than the traditional binary encoding scheme is embedded into the proposed tuning parameter free TRIBE PSO algorithm to reduce the search space and hence, the computational burden to achieve fast and effective solution.

It is to be noted that an islanded operation of a practical distribution network in the presence of uncertain generation and loads of different steady state and dynamic properties is challenging and exhibits certain limitations as outlined in [17]. However, if the necessary conditions [18] related to the islanded operation of distribution nertwork, especially in accordance with the *IEEE Std. 1547, 2003-2013* are properly implemented then the islanding features can be utilized for improving the reliability of supply.

The paper is organized as follows: Section II presents an optimization formulation and a solution algorithm for supply restoration considering time-varying generation and load patterns. Probabilistic models for addressing system uncertainties are introduced in Section III. The time sequential Monte Carlo approach for reliability evaluation of DG systems is presented in Section IV. The simulation results are reported in Section V, and Section VI summarizes the broad outcomes of the work described in the paper.

II. Network Restoration Optimization

The network restoration encompassing DG units is a combinatorial, nonlinear constrained optimization problem. Due to the complexity of the formulated problem, a parameter free PSO based algorithm is employed to derive the optimal solution. In order to reduce the search space and to improve the quality of the solution, the restoration optimization problem is encoded in PSO incorporating a dynamic selection scheme.

A. Mathematical Formulation of Restoration Process

In this paper, the minimization of total customer interruption duration is considered as an objective in the optimization formulation of the restoration process involving nonlinearities associated with time varying load and generation. If the customer interruption duration of each fault event is minimized, then the customer side supply reliability in terms of system average interruption duration index (SAIDI) can be consequently minimized. The associated objective function f, which will result in optimal switch configuration, can be expressed as:

$$f = min \quad \sum_{t=1}^{T}\sum_{n=1}^{N}(1 - B_{t,n})L_n \tag{1}$$

where, T is the total interruption hours due to a system fault event, N is the total number of system nodes in the out-of-service areas, $B_{t,n}$ is the binary status of load point n at time t ($B_{t,n} = 1$ represents the restored load point), and L_n is the number of customers at load point n. The total number of switches in the out-of-service areas can be represented by M. Accordingly, SW is a $M \times T$ binary matrix representing the status of switches at each time step, which can be expressed as:

$$SW = \begin{bmatrix} SW_{1,1} & SW_{1,2} & \cdots & SW_{1,T} \\ SW_{2,1} & \ddots & \ddots & \vdots \\ \vdots & \cdots & SW_{m,t} & \vdots \\ SW_{M,1} & SW_{M,2} & \cdots & SW_{M,T} \end{bmatrix} \tag{2}$$

For system restoration encompassing DG units, the constraints involved in the optimization formulation are briefly discussed below.

1) System Topology Constraint: The relationship between the two nodes in a distribution system can be depicted as shown in Fig. 1. A load point (i.e. the child node) can possibly be restored only if the associated candidate node (i.e. the parent node) is restored and the switch between the load point

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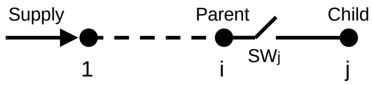

Fig. 1. Relationship of two nodes

and the candidate node is closed. The above constraint can be expressed as:

$$B_{j,t} \leq SW_{j,t} B_{i,t} \tag{3}$$

where, $SW_{j,t}$ is the binary status of the j^{th} switch at time step t.

2) DG Capacity Limit: The total loads restored by a DG unit should not exceed its available capacity in each time step t:

$$P_{DG_t} \geq \sum_{n \in \beta_t} B_{t,n} P_{t,n} \tag{4}$$

where, β_t is a set of load points restored by the DG unit at time step t, and $P_{t,n}(kW)$ is the required capacity at load point n including its associated loss component in time t. It is important to note that in case, the available DG power output is in excess with respect to the load, then restoration is performed by capping the DG output at a level of the restored load.

3) Capacity Limit of a Feeder Section: The capacity flow $S_{fd_t}(kVA)$ of a feeder section in each time step t, which is calculated using probabilistic power flow detailed in [19], should not exceed its rated capacity $S_{fdr}(kVA)$:

$$S_{fd_t} \leq S_{fdr} \tag{5}$$

4) Time Constraint for Manual Switching: The time difference between two sequential manual switching operations should not be less than the minimum time t_{min} that is needed to operate the corresponding manual switches:

$$SW_{m,t_1} = SW_{m,t_2} \qquad \forall \ \ |t_1 - t_2| < t_{min} \tag{6}$$

5) System Energization Constraint: It is expected that the re-energized load point at an earlier stage should not be de-energized again at a later stage. In this paper, the system energization constraint involving binary variables has been used for ensuring certainty of supply to support requisite load in the restoration period:

$$B_{t,n} \geq B_{t-1,n} \tag{7}$$

B. Encoding Process for Optimization Algorithm

As described in the last subsection, the variables for the restoration problem are the status of all switches in the out-of-service areas during the interruption period. A restoration area under investigation, including M switches with an interruption period of T hours, will have a solution space of 2^{MT} possible combinations if a binary encoding scheme is used. However, only a few combinations may result in feasible solutions due to the problem constraints.

Rather than using a traditional binary encoding scheme, a dynamic selection scheme is proposed in this paper. The problem variables in the matrix SW can be transferred into a vector that includes two sets of integer variables given as:

$$X = \left\{ \{\underbrace{x_1, \ldots, x_i, \ldots, x_T}_{X_1}\}, \{\underbrace{x_{T+1}, \ldots, x_{T+N}}_{X_2}\} \right\} \tag{8}$$

The first set has T integers representing the decision of either restoring or not restoring additional customers. The second set has N integers indicating the selection of the candidate restoration nodes. Since the original problem variables are converted to a vector with $T+N$ integers, the integers can be mapped into meaningful decisions by applying a proposed transformation function given as:

$$y_i = 1 + x_i - floor(\frac{x_i}{a_i}) \cdot a_i \tag{9}$$

where, x_i is the ith integer input, $floor$ is a function for deriving a nearest integer that is less than or equal to x_i/a_i, a_i is the number of alternative choices or number of candidate nodes, and y_i is the ith selection guide indicating the priority index of the nodes to be restored.

By applying (9) from two different sets of a vector, the selection guide y_i can be derived as follows:

1) Selection Guide with Integers from the First Set: From the first set of vectors X_1, it is known that there will be always two choices ($a_i = 2, \forall i = 1, \ldots, T$) associated with the issue of either restoring or not restoring additional customers. By applying (9) with $a_i = 2$, it can be calculated that y_i will always be either 1 or 2 associated with the value of x_i in the first set X_1. In such case, $y_i = 1$ denotes restoration of additional customers and $y_i = 2$ symbolizes maintaining current system status.

2) Selection Guide with Integers from the Second Set: An example feeder shown in Fig. 2 is used to illustrate the capability of the dynamic selection scheme for deciding the candidate restoration nodes and generation of a unique restoration sequence list based on the integers in the second set of the vector. It can be observed in Fig. 2 that the load points 1-8 are located at downstream of the fault and a DG unit can be used as a back-up supply to restore a limited number of interrupted load points. Eight integers are randomly selected by the solution algorithm to form the second set of the vector X_2 = [5 8 10 12 15 18 28 77]. These integers need to be dynamically mapped to a selection decision to restore the nodes sequentially.

In Fig. 2, it can be seen that node 1 will be the first candidate node if the DG starts restoring the interrupted area. By applying (9) with $x = 5$ (i.e. first element of the second set, X_2) and $a = 1$, the solution $y = 1$ can be established. This means that the first candidate node, which is the only candidate node is selected in the restoration sequence list.

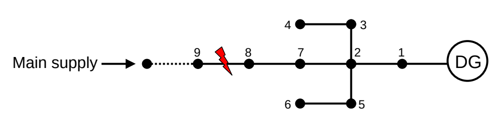

Fig. 2. An example feeder

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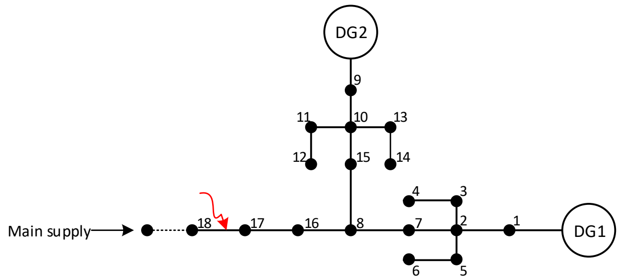

Fig. 3. An example feeder with two DGs

Similarly, node 2 can be added to the restoration sequence list. Subsequently, nodes 3, 7 and 5 are the potential candidate nodes that can be added to the restoration sequence list ranked based on the higher to lower load demand. By applying (9) with $a = 3$ and the 3^{rd} integer $x = 10$, the solution $y = 2$ can be established. This means that the second candidate node (node 7) is selected. Once a node gets added to the restoration sequence list, it will be removed from the candidate node list and the associated load points will be added to the candidate node list. In this case, after adding node 7 to the restoration sequence list, nodes 3, 8, and 5 will be in the candidate node list and the selection depends on the value of the 4^{th} integer. By applying an iterative process, all nodes will be added to the restoration sequence list. It should be noted that the number of choices will be dynamically changed. By using the proposed dynamic selection scheme, a meaningful selection can always be derived. Finally, a unique restoration sequence of [1 2 7 3 4 8 5 6] can be generated with the given integers and the corresponding selection guide will be [1 1 2 1 1 1 1 1].

3) Selection Guide for a Multi-generator System: In case of multiple DGs, the proposed dynamic selection scheme is applied to each DG and a unique restoration sequence is determined. If the multiple restoration sequences overlap, then the restoration sequence is determined by considering these DG units as a single unit and the biggest DG node as a candidate node. It is to be noted that the infeasible restoration sequences with higher fitness values are discarded by the TRIBE PSO algorithm. As an instance, for the system in Fig. 3, the restoration sequence of DG1 is [1 2 7 3 4 8 5 6 16] and DG2 is [9 10 13 14 11 12 15 8 7 2]. Since the restoration sequences are overlapping, the bigger DG node, i.e., DG1 at node 1, is considered as a candidate node and combined restoration sequence is determined that can be [1 2 7 3 4 8 5 6 15 10 13 14 11 12 9 16 17]. In case, the DG units have independent restoration sequences, then every DG will be restoring a unique island in the distribution network. By using the proposed dynamic selection scheme subject to the constraints related to optimization formulation, a feasible solution can be ensured.

C. Restoration Optimization using TRIBE PSO

The restoration problem in this paper is solved by using a PSO variant based on TRIBE concept [20] as illustrated in Fig. 4. The advantage of this algorithm over other intelligent-based algorithm is that it does not require any algorithmic parameters while a sufficiently good solution can still be reached [20]. The basic elements of TRIBE PSO include particles, informers, and tribes. The particle is comprised of problem variables X, representing a potential solution in a problem space. The informer is a particle, which can inform its best solution to another specified particle. The tribe is a group of particles, which shares the information inside the group. The TRIBE PSO exploration mechanism including swarm initialization, particle movement and swarm adaptation are described below:

1) Initialization of Swarm: The TRIBE PSO initially has only a single tribe with only one particle. It dynamically adds or deletes particles according to the self-adaptive rules and the performance of the swarm (as discussed in step 3). A random feasible solution X encoded in Section II.*B* can be used to initialize the optimization algorithm.

2) Particle Movement: The TRIBE PSO increases the particle memory to maintain the last two fitness values. Accordingly, based on the fitness improvement, the performance of each particle can be categorized into three classes: bad, neutral, and good. The particles labeled 'bad' will be updated using a strategy known as 'simple pivot strategy' whereas the particles in the other two classes will be updated using a 'noisy pivot strategy'.

In the simple pivot strategy as illustrated in Fig. 5(a), the best positions of a particle X^p and its informer X^q are used to guide the move of the particle p. Accordingly, the new value of the i^{th} problem variable $x_{p,i,k}$ in vector X^p at iteration k can be obtained using:

$$x_{p,i,k} = \frac{(r_1 R_{pq} + x_{p,i,k-1})F(X^p)}{F(X^p) + F(X^q)} + \frac{(r_2 R_{pq} + x_{q,i,k-1})F(X^q)}{F(X^p) + F(X^q)} \tag{10}$$

where $R_{pq} = |x_{p,i,k-1} - x_{q,i,k-1}|$, r_1 and r_2 ($r_1, r_2 \in [-1, 1]$) are two random numbers, and $F(\cdot)$ is the objective function

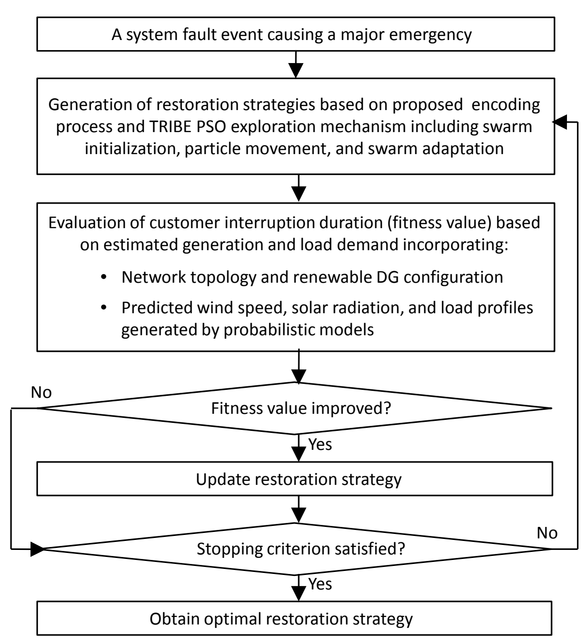

Fig. 4. Restoration optimization using TRIBE PSO

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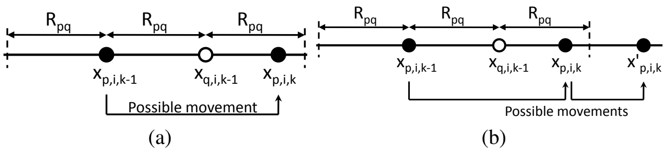

Fig. 5. Movement of a particle by using (a) simple pivot strategy, (b) noisy pivot strategy

for evaluation of the fitness value with respect to a candidate solution.

The noisy pivot strategy as shown in Fig. 5(b) begins in a manner similar to the simple pivot strategy. If noisy pivot strategy is applied, additional Gaussian noises $G(0, \sigma_{par})$ with zero mean and standard deviation of σ_{par} are added to the problem variables as given in (11). In this case, the particles may jump out of the surrounding areas and explore a different problem space.

$$x'_{p,i,k} = x_{p,i,k}(1 + G(0, \sigma_{par})) \tag{11}$$

3) Swarm Adaptation: A swarm adaptation strategy is used to add or remove particles or tribes based on the performance of the tribes and particles. The adaptation will be carried out when a finite number of iterations have been carried out using TRIBE PSO. The number of iterations N_{iter} can be derived as:

$$N_{iter} = \frac{1}{2} N_{par}(N_{par} - 1) \tag{12}$$

where N_{par} is the total number of particles in the whole swarm.

III. Modeling of System Uncertainties

In order to conduct realistic assessment of distribution system reliability associated with the integration of renewable DG units, the uncertainties in terms of time-varying load demands, intermittent generation, stochastic prediction errors, and random fault events need to be modeled accurately. This section introduces probabilistic models that address the above mentioned uncertainties.

A. Autoregressive (AR) Model

The variation of load demand, wind speed and solar radiation presents certain levels of correlation with respect to time. The time series forecast errors for these variables also exhibit autocorrelation features. The modeling of time correlated variables can be achieved by adopting an AR model [21] given as:

$$E_t = c_r E_{t-1} + r_g \sqrt{1 - c_r^2} \tag{13}$$

As indicated in (13), the value of E_t for time step t is related to its previous value E_{t-1} for time step $t-1$ with a correlation factor c_r and an additional standard Gaussian noise r_g. The correlation factor used in (13) can be obtained using the historical measured data.

B. Probability Transformation

Although modeling of the time correlated variables can be achieved using the AR model, the statistical characteristics of these variables may not be correctly represented if only an AR model is used. It is noticed that the time series variables generated by (13) follows the standard Gaussian distribution (zero mean and standard deviation of unity) due to the standard Gaussian noises. However, the variables such as wind speed and solar radiation typically follow the Weibull distribution and Beta distribution respectively with different means and deviations in different seasons, even over days and hours [21], [22]. Therefore, it is necessary to transfer the series of values which are generated by (13) to a new series of values that follow the respective probability distribution functions (PDFs). The transformation can be done by using the cumulative distribution functions (CDF) expressed as:

$$u = CDF_{old}(E_t|\mu, \sigma) \tag{14}$$

$$E'_t = CDF^{-1}_{new}(u|\mu', \sigma') \tag{15}$$

In (14), the cumulative probability u of a value E_t is calculated with a given mean μ and a standard deviation σ. Function CDF_{old} describes the statistical characteristics of the values generated by the AR model. In (15), the calculated cumulative probability u is substituted into a new cumulative distribution function CDF_{new} with new references of mean μ' and standard deviation σ'. The CDF_{new} describes the statistical features of the transferred values. The transferred values can be derived using the inverse of CDF_{new}. The transferred value E'_t will follow new specified probability distribution functions derived based on the historical measured data.

C. Modeling of Time Series Variables

By using the AR model as a basic model for generation of time dependent values and applying the probability transformation method for derivation of the statistical characteristics, the time series variables with uncertainties can be simulated. In this subsection, the statistical characteristics of these variables are introduced and the corresponding cumulative distribution functions are also discussed.

1) Load Demand: The probability distribution of load demand follows the Gaussian distribution function [23]. With a mean μ_l and a standard deviation of σ_l derived based on the historical data, the hourly load demand $P_{t,n}(kW)$ of a load point n at time t can be obtained as:

$$P_{t,n} = \left\{ P_{t,n} : \frac{1}{\sigma_l \sqrt{2\pi}} \int_{-\infty}^{P_{t,n}} e^{\frac{-(z-\mu_l)^2}{2\sigma_l^2}} dz = u_{t,n} \right\} \tag{16}$$

where, $u_{t,n}$ is the cumulative probability of the values generated by the AR model.

2) Wind Power Generation: In this paper, it is assumed that the wind speed follows the Weibull distribution function [22]. Hence, wind speed $v_t(ms^{-1})$ at time t can be derived as:

$$v_t = \left\{ v_t : \int_0^{v_t} c b^{-c} z^{c-l} e^{-(\frac{z}{b})^c} dz = u_t \right\} \tag{17}$$

where the Weibull parameters $b = \mu_w/\Gamma(1+c)$ and $c = (\sigma_w/\mu_w)^{-1.086}$ can be estimated using the Gamma function

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$\Gamma(\cdot)$, the mean μ_w, and standard deviation σ_w related to wind speeds in the observation period.

Associated with the simulated wind speed, the power generated by individual WTG units can be estimated using the WTG power curve.

3) Solar Power Generation: In [21], it has been indicated that the major cause of uncertainty in solar radiation over a PV array is the stochastic cloudy weather conditions. The cloudy weather condition can be simulated using a Beta distributed clearness index. The solar radiation absorbed by a PV array $H_{pv(t)}(kWm^{-2})$ can be estimated based on the accurately calculated extra-terrestrial solar radiation $H_{ex(t)}(kWm^{-2})$ and the clearness index k_t:

$$H_{pv(t)} = k_t H_{ex(t)} \tag{18}$$

In (18), the $H_{ex(t)}$ can be derived based on the geographical information of the site and the orbit of the earth. The clearness index k_t can be generated using Graham's algorithm [21]. Once the solar radiation is simulated, the power generated by a PV array having a rated capacity of $P_{rs}(kW)$ and rated solar radiation of $H_r(kWm^{-2})$ can be calculated [24] using:

$$P_{pv(t)} = \frac{H_{pv(t)}}{H_r} P_{rs} \tag{19}$$

4) Load Demand Prediction: The prediction error in load demand can be simulated using a Gaussian distribution function while considering the time correlation feature [23]. The load demand prediction $P'_{t,n}(kW)$ can be simulated using the actual load demand $P_{t,n}(kW)$ and the Gaussian distributed prediction errors $\varepsilon_{l(t,n)}$ as:

$$P'_{t,n} = P_{t,n}(1 + \varepsilon_{l(t,n)}) \tag{20}$$

5) Wind Power Generation Prediction: In this paper, the probabilistic wind power generation prediction is modeled using a Beta distribution function [25]. Similar to other time series variables, the characteristics of the prediction is carried out using the AR model and the probability transformation approach. Therefore, the wind power generation prediction can be given as:

$$P'_{wd(t)} = \left\{ P'_{wd(t)} : B \int_0^{P'_{wd(t)}} z^{g-1}(z')^{f-1} dz = u_t \right\} \tag{21}$$

where, $P'_{wd(t)}(kW)$ is the predicted wind speed, the physical parameters $B(g,f) = \Gamma(g+f)/\Gamma(g)\Gamma(f)$, $z' = 1-z$, $g = \mu_a(1-\mu_a-\sigma_a^2)/\sigma_a^2$ and $f = g(1-\mu_a)/\mu_a$ can be calculated using the statistical mean μ_a and standard variance σ_a of a given data set [21].

For wind power generation prediction, the hourly actual wind power generation can be used as the mean value for deriving the Beta parameters. The standard deviation σ_a between the actual wind generation and the prediction can be derived using a polynomial function [25]:

$$\sigma_a = \sqrt{\mu_a(1-\mu_a)(k_1\mu_a - k_2\mu_a^2)} \tag{22}$$

where k_1 and k_2 are the approximation parameters.

6) Solar Power Generation Prediction: Similar to the wind power generation prediction, the solar power generation prediction could also be simulated using a Beta distribution function as given in (21) and (22). The only difference is that the accuracy of the solar power generation prediction is affected by weather conditions [26]. Since the weather conditions can be simulated using the clearness index, the standard deviation of the solar power prediction error can be also formulated using (22) incorporating clearness index as an input. With this formulation, it is anticipated that prediction quality will be relatively high for a very cloudy day ($k_t = 0$) or a very sunny day ($k_t = 1$). The forecast error will be large on a partly cloudy day [26].

7) Modeling of System Fault Events: In this paper, the failures of system components such as feeder line sections, transformers, switches, fuses, and DG units are considered and used for simulating the fault events. The component reliability parameters including mean time to failure (MTTF) (h) and mean time to repair (MTTR) (h) are used as inputs for the logarithm distribution function [27] given as:

$$UP = -MTTF \times \ln(r_1) \tag{23}$$

$$DOWN = -MTTR \times \ln(r_2) \tag{24}$$

where r_1 and r_2 are two random numbers with standard uniform distribution, UP is the number of hours that a system component is in healthy state, and $DOWN$ is the number of hours that a system component is in failure state.

IV. Reliability Assessment Procedure

The reliability assessment of a distribution system containing renewable DG units is carried out by addressing the system uncertainties. The time sequential Monte Carlo simulation technique is used in this paper to evaluate system reliability indices. One of the major advantages of Monte Carlo simulation over analytical evaluation methods is that the former technique can efficiently estimate system reliability under wide range of conditions by assessing only limited number of sampled system states. This feature makes Monte Carlo simulation suitable for reliability estimation of large-scale distribution systems with the consideration of various system uncertainties. In this paper, the time sequential Monte Carlo simulation procedure includes the following steps:

Step-1: Generate time-varying load demand, wind and solar power generation, and the corresponding prediction values for a specified period based on the historical measured data and the related DG configuration using (13)-(22).

Step-2: Generate fault events on various system components of the feeder using (23) and (24).

Step-3: If a failure on a system component is detected, the system interruption duration caused by this failure will be evaluated considering the specified time to identify, isolate and repair the faulty component.

Step-4: The restoration procedure will be executed within the simulated time. It is assumed that the forecasts for load demand, wind power generation, solar generation are available for the interruption hours. The predicted values are used as inputs to determine the restoration strategy.

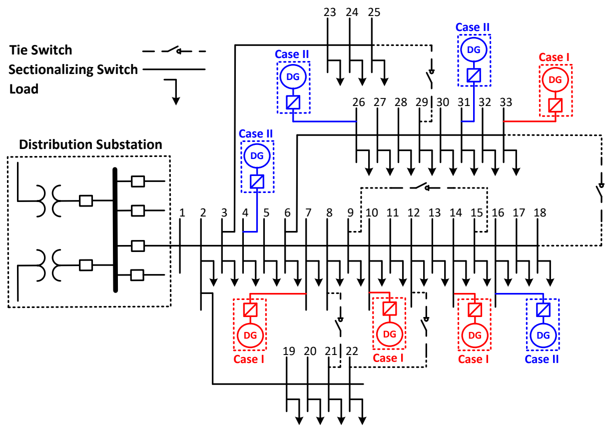

Fig. 6. 33 bus distribution system

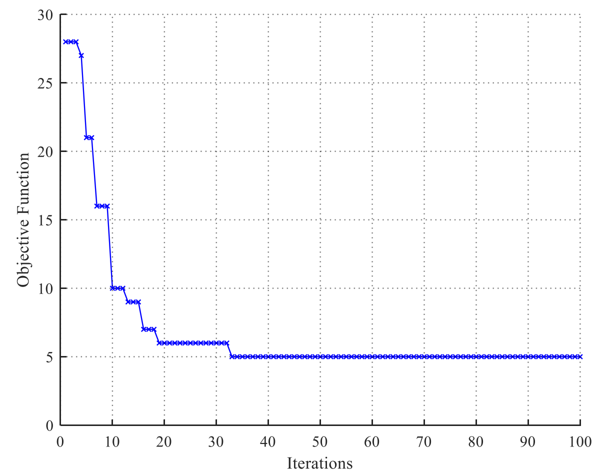

Fig. 7. Convergence curve for a fault in the branch 2-3

Step-5: It is assumed that the available DG units can be reconnected to the network without any delay after the isolation of a fault. If all the system loads can be fully restored through the substation and DG units immediately after the fault isolation, then the restoration optimization will not be performed. In case of insufficient DG capacity to restore all load points within the islands, the proposed restoration optimization will be conducted to minimize the customer interruption duration by selecting optimal restoration sequence and coordinating the switching operations.

Step-6: Simulate the restoration process using the derived restoration strategy with the actual load demand, and available DG power to calculate the actual customer interruption duration due to the system failure.

Step-7: Determine the system reliability in terms of SAIDI and SAIFI after the completion of requisite simulation time period.

Step-8: The yearly average values of SAIDI and SAIFI and associated probability distributions are obtained after completing the simulation studies for a stipulated number of years.

V. Case Studies

The MATLAB based simulation studies are conducted for a 33-bus system [28] shown in Fig. 6 and an 11 kV distribution feeder, derived from the realistic network of New South Wales (NSW) electricity distribution system in Australia [29], shown in Fig. 8.

A. Implementation of the proposed Restoration Strategy

1) The 33-bus distribution system: In this section, the effectiveess of the proposed restoration strategy is demonstrated on the 33-bus system with DGs as shown in Fig. 6. The system data is taken from [28]. Each branch is equipped with a remotely controllable switch that can be operated automatically in the service restoration process. The control switches are depicted as a number in Fig. 6. The voltage at the substation bus is set to 1.0 p.u. The lower and upper voltage values of all the load buses are set to 0.9 p.u. and 1.05 p.u., respectively. Please note all the loads are modelled as constant power loads. The elapsed time of the out-of-service restoration

TABLE I
Output Information of DGs

Case	DG bus	$\mathbf{P_{DG}(kW)}$	$\mathbf{Q_{DG}(kVar)}$
I	7	350	169.5
	10	400	193.7
	14	450	217.9
	33	500	242.2
II	4	600	261.5
	16	800	388.7
	26	600	0
	31	1000	0

time in the practical implementation contains three parts: calculation time, switching actions time and communication time. The communication time should be less than 10 s from control system to terminal, and the switching action time should be less than 0.04 s.

The locations and capacities of DGs operating in the PQ mode (negative load) are given in Table I, while the restoration results are given in Table II. Considering the fault branch 2-3 in Case I for example, the optimum restoration sequence calculated by the proposed restoration strategy taking bus 33 as a candidate node is [33 32 36 31 18 17 16 15 14 13 12 11 10 9 8 7 6 21 5 4 3 23 24 25 22 20 19 2]. As a result of the restoration sequence, the corresponding switches to be turned on are 33 and 36, while the switches to be turned off are 25 and 30. The switching times, lost loads and the computation times are given in the Table II. The convergence curve of the proposed restoration strategy for the fault in branch 2-3 in Case-I is shown in Fig. 7.

The proposed restoration strategy is compared with the mixed-integer second order cone programming (MISOCP) [8], harmony search algorithm (HAS) [30], interval algorithm (IA) [31], point estimation method (PEM) [32], IA plus proposed restoration strategy (IA+PRS) [33], PEM+PRS [33], stochastic response surface method plus PRS (SRSM+PRS) [33] and SRSM plus restoration strategy (SRSM+RS) [34]. The results show that the proposed strategy is efficient in comparison with the other restoration strategies.

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TABLE II
RESTORATION RESULTS FOR 33-BUS SYSTEM

Case	Fault Branch	Method	Switches On	Switches Off	Load Shedding Nodes	Switching Times	Lost Loads (%)	Computational Time (Seconds)
I	2-3	MISOCP [8]	33, 36	26, 31	27, 28, 29, 30, 31	4	15.88	–
		Proposed	33, 36	25, 30	26, 27, 28, 29, 30	4	12.67	9.06
	4-5	MISOCP [8]	36, 37	-	-	2	0	-
		Proposed	33, 37	-	-	2	0	9.54
	13-14	MISOCP [8]	36, 37	-	-	2	0	-
		Proposed	33, 34, 35	-	-	3	0	9.56
	2-19	MISOCP [8]	35	-	-	2	0	-
		Proposed	33,35,36	-	-	3	0	9.25
	9-10	MISOCP [8]	35, 37	-	-	2	0	1.14
		HSA [30]	34, 35, 37	12	-	4	0	2.93
		Proposed	33, 35, 37	-	-	3	0	10.67
	26-27	MISOCP [8]	35, 37	-	-	2	0	1.14
		HSA [30]	34, 35, 37	12	-	4	0	2.93
		Proposed	35, 37	-	-	2	0	7.13
II	4-5	IA [31]	33, 34, 35, 37	9, 14, 28, 31	32, 33	8	9.69	15.3
		PEM [32]	33, 34, 35, 36, 37	9, 14, 28, 31	-	9	0	8.5
		IA+PRS [33]	33, 34, 35, 37	9, 14, 28, 31	32, 33	8	9.69	15.3
		PEM+PRS [33]	33, 34, 35, 36, 37	9, 14, 28, 31	-	9	0	8.5
		SRSM+PRS [33]	33, 34, 35, 36, 37	9, 14, 28, 31	-	9	0	18.2
		SRSM+RS [34]	33, 34, 35, 36, 37	9, 14, 28, 31	-	9	0	18.7
		Proposed	33, 35, 36, 37	8, 25, 32	-	7	0	8.53
	8-9, 19-20	IA [31]	33, 35, 37	14, 27	15-18, 32, 33	5	17.78	14
		PEM [32]	33, 35, 37	14, 27	15-18, 32, 33	5	17.78	9.6
		IA+PRS [33]	33, 35, 37	14, 27	15-18, 32, 33	5	17.78	15.4
		PEM+PRS [33]	33, 35, 36, 37	27, 31, 16, 14	15, 16	8	4.85	11.4
		SRSM+PRS [33]	33, 35, 36, 37	27, 31, 15, 14	16	8	1.62	22.7
		SRSM+RS [34]	33, 35, 37	27, 14	16, 17, 18, 32, 33	5	14.54	19.5
		Proposed	33, 35, 36, 37	20, 24, 32	-	7	0	9.01

2) The 86-bus distribution system: The simulation studies were conducted for an 11 kV distribution feeder based on a realistic network from NSW, Australia as shown in Fig. 8 [29]. It is assumed that the entire distribution feeder of the test system is 35 km long with 42 manual switches, 3 reclosers, and 60 load points and hence 60 distribution transformers, which are individually protected by fuses. It is assumed that the failed component can be identified within an hour and each manual switching can be performed within an hour provided sequential switching is conducted within the minimum time specified by the distribution network service provider. The sustainable failure rates of 0.065, 0.006, 0.006 and 0.015 failure/year and repair time of 6, 4, 4, and 10 hours are used for feeder section, switches, fuses, and transformers respectively [35] in the simulation. The historical data including hourly average total load demand, wind speed, and solar radiation of each month of specified observation period is obtained from [36].

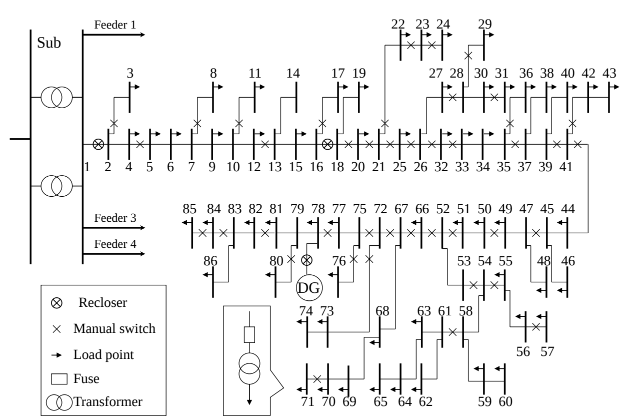

Fig. 8. Distribution system under study

Reliability assessment has been carried out for the base system with and without DG inclusion. It is found that SAIDI and SAIFI values for the base system without DG are 7.39 hours/year and 2.44 interruptions/year respectively. These values can be used as a benchmark for assessing reliability improvement of the system with DG. In this paper, a hybrid

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DG system inclusive of biofuel generator, WTG unit, and solar PV unit rated at 300 KVA, 100 kVA, and 100 kVA respectively and operating at unity power factor has been considered for evaluating the distribution system reliability. It is assumed that the DG system is located at node no. 78, which is an optimal location from economic considerations as reported in [37], as shown in Fig. 8. This is one of the possible alternatives for network planners' perspective, which can be used for assessing network reliability. Also, it is assumed that the DG system is capable of an islanded operation. The approximated load demand and DG generation can be estimated based on the historical measurement data and the system conditions recorded before the occurrence of the fault event. The forecasting methodologies for short-term time-varying load demand and renewable power generation [25], [26], [38] can also be used along with a standby power supply in terms of energy storage to assist practical implementation of system restoration.

It is assumed that the biofuel, PV, and WTG based DG units have MTTF of 950, 4380, and 1920 hours respectively and MTTR of 50, 90, 80 hours respectively [27]. It is also assumed that the WTG unit operates with a cut-in wind speed of 3.5 m/s, rated wind speed of 12.5 m/s, and cut-out wind speed of 25 m/s. The stochastic nature of renewable energy resources is considered in the restoration process. Based on the historical data, capacity factor can be estimated for each renewable resource. In this study, DG capacity factor is considered to be a ratio of the average power output relative to the rated power output.

In order to examine the effects of varying capacity factors of renewable DG units on system reliability, the wind speed and solar radiation data are accordingly manipulated. In this paper, mean absolute percentage error (MAPE) for load demand prediction was assumed to be 5% and normalized mean absolute error (NMAE) for wind power prediction, and relative root mean square error (rRMSE) for solar power generation were assumed to be 10% and 15% respectively.

The restoration results for the faults in the branches 1-2 and 32-33 for the 86-bus system for a particular hour are presented in Table III. The biofuel generator is operating at the peak load of 275 kW, while the output of the Wind and Solar PV units are predicted to be 64.5 kW and 55 kW respectively. For the fault in the branch 1-2, the switches to be turned off are 46, 70 and 79 and no switch is to be turned on. Please note that the switches which are by default in on or off state are not enlisted here. The island 1 formed as a result of restoration process for fault branch 1-2 is shown in Fig. 9. The load restored by the optimal sequence is 387.32 kW. Similarly, for the fault in the branch 32-33, the switches to be turned off are: 31, 46, 70 and 79. The two islands 1 and 2 formed as a result of fault in branch 32-33 are shown in Fig. 9. The system is restored from both mains supply and hybrid DG system and thus, the restored load is 576.32 kW. The computation times and the lost loads for the above-mentioned faults are given in Table III.

As seen, the proposed Tribe PSO algorithm with encoding process effectively calculates the optimal restoration sequence. Since the main focus of the paper is on the reliability assessment of a distribution network embedded with distributed generation by adopting an optimal restoration strategy with a novel encoding scheme and addressing the uncertainties associated with the renewable DG system and load demand, the impact of restoration strategy and prediction errors on SAIDI and SAIFI is discussed in the following section.

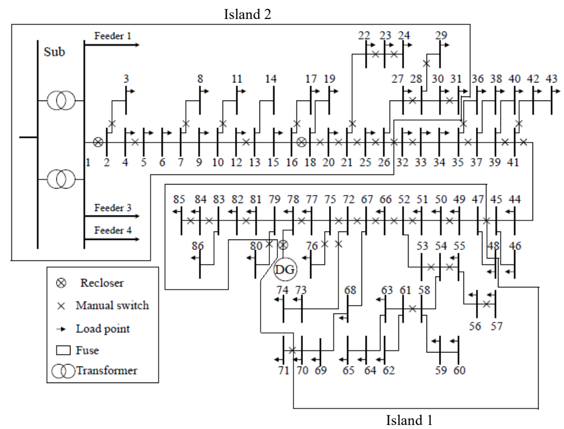

Fig. 9. Island formations due to the faults at branch 1-2 and branch 32-33

B. Impact of Restoration Strategies and Prediction Errors on SAIDI and SAIFI in 86-bus NSW System

This section proposes a service restoration strategy considering time-varying load demand and intermittent power generation. In this subsection, the hybrid DG test system with 300 kW from biofuel generator, 100 kW from WTG unit, and 100 kW from solar PV unit is considered for evaluating the distribution system reliability. Five scenarios were studied to compare the impacts of restoration strategies and prediction errors on system reliability in terms of yearly average SAIDI and SAIFI by considering different capacity factors of wind and solar PV units.

1) Neglecting the Prediction Errors (Scenario 1-3): Three scenarios were considered to highlight the reliability benefits of using restoration optimization with time-varying load and generation. In scenario-1, the hourly time-varying load demands and renewable power generation over the interruption period are used as inputs for every possible restoration strategy in the Monte Carlo simulation. In scenario-2, the constant load demand and generation calculated based on the time-varying variables by using the method described in [39] are used as inputs for solving the same restoration optimization problem. In scenario-3, a deterministic breadth-first search method [40] considering maximum load demand and average power generation is used to implement the restoration strategy. It does not account for the restoration optimization and uncertainties in load and generation. Moreover, it is assumed that the prediction errors are neglected for scenario-1 and scenario-2. With different considerations in three scenarios, different restoration strategies will be generated. Consequently, the system reliability can be affected when different restoration strategies are applied. The impact of different DG capacity factors are also considered for the above three scenarios.

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TABLE III
RESTORATION RESULTS FOR 86-BUS NSW SYSTEM

Faulty Branch	Switches On	Switches Off	Load Shedding Nodes	Load Restored (kW)	Lost Load (%)	Computational Time (Seconds)
1-2	-	46, 70, 79	2-46, 71, 80	387.32	37.87	2.24
32-33	-	31, 46, 70, 79	32-46	576.32	13.48	2.28

It can be observed from Fig. 10 that the yearly average SAIDI improvement for scenario-1 is of the order of 17.8%, 16.8%, and 15.8% for DG capacity factors of 20%, 25%, and 30% respectively as compared to scenario-2. Similarly, the yearly average SAIFI improvement of 9.3%, 8.7%, and 8.2% can be seen in case of scenario-1 as shown in Fig. 10. In scenario-3, the exclusion of restoration optimization and uncertainties results in the highest yearly average SAIDI and SAIFI for all considered DG capacity factors as compared to scenarios 1 and 2. As compared to scenario-2, the yearly average SAIDI in scenario-3 increases by 10.2% 12%, and 10.1% for DG capacity factors of 20%, 25%, and 30% respectively. The yearly average SAIFI in scenario-3 also increases by 0.8%, 1.7%, and 1.7% as compared to scenario-2. It can be seen that both SAIDI and SAIFI show significant reductions if optimal restoration and uncertainty in terms of time-varying load demand and power generation are considered for deriving the optimal restoration strategy.

Monte Carlo simulation can also be used to establish probability distributions of reliability indices, which could provide valuable information for system operators. Fig. 11(a) and Fig. 11(b) show the cumulative probability distributions of SAIDI and SAIFI respectively with a capacity factor of 20% for wind and solar PV based DG units while Fig. 12(a) and Fig. 12(b) show cumulative probability distribution with a capacity factor of 30%.

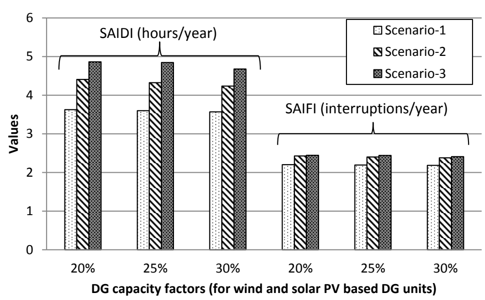

Fig. 10. Comparison of yearly average SAIDI and SAIFI (Neglecting prediction errors)

2) Considering the Prediction Errors (Scenario 4 and 5): The predicted values of time-varying load demand and renewable power generation are used as inputs in scenario-4 for every possible restoration scheme in the Monte Carlo simulations, whereas scenario-5 emphasizes on the constant load demand and generation, calculated based on the predicted values, as inputs.

In Fig. 13, the yearly average SAIDI in scenario-4 show improvement of 7.9%, 7.3%, and 6.6% in comparison with scenario-5 for the DG capacity factors of 20%, 25%, and 30% respectively. Similarly, the yearly average SAIFI improvement of 3.2%, 2.9%, and 2.7% can be observed in case of scenario-4 as shown in Fig. 13.

It can be seen that there is a small change in SAIDI and SAIFI values for scenarios 2 and 5, which indicates that the use of constant inputs can significantly reduce the impact of prediction error. The use of constant input in restoration may overestimate the uncertainties posed by the renewable generation, thus resulting into declination of SAIDI and SAIFI.

VI. CONCLUSION AND FUTURE WORK

In this paper, the reliability assessment of a distribution system with hybrid DG systems was undertaken considering optimal restoration strategies and system uncertainties.

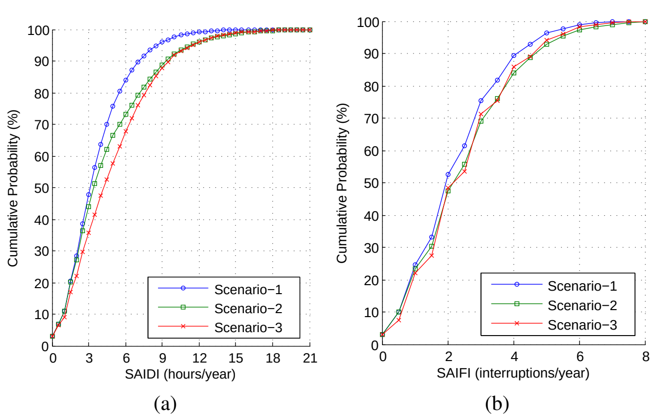

Fig. 11. Cumulative probability distributions of (a) SAIDI and (b) SAIFI with a capacity factor of 20% for wind and solar PV based DG units

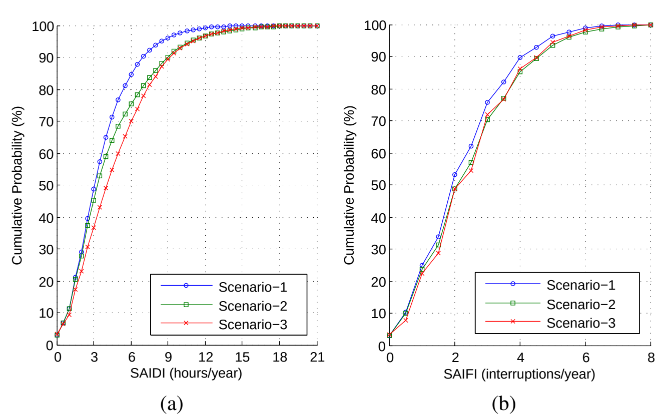

Fig. 12. Cumulative probability distributions of (a) SAIDI and (b) SAIFI with a capacity factor of 30% for wind and solar PV based DG units

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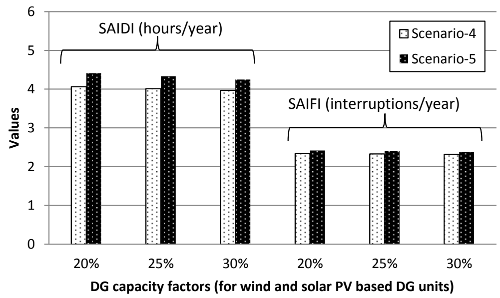

Fig. 13. Comparison of yearly average SAIDI and SAIFI (Considering prediction errors)

A restoration optimization algorithm including time-varying load demand and stochastic generations was formulated. The restoration problem was solved using the parameter free intelligent-based TRIBE PSO incorporating a novel encoding scheme. The uncertainties in terms of renewable power availability, time-varying load demand, stochastic prediction error, and random faults have been simulated using probabilistic models. The time correlation and statistical characteristics of time series variables were also simulated using probabilistic models. These models were developed based on an AR model and the utilization of probability transformation technique. The distribution system reliability was evaluated for different scenarios using a time sequential Monte Carlo simulation approach. It was found that the system is seen to be more reliable (in terms of yearly average SAIDI and SAIFI) when time-varying load demand and generation are taken into consideration in the restoration process. As a future work, the proposed strategy can be extended to the meshed networks. Also, the islanded operation of radial and meshed distribution networks can be undertaken in accordance with the technical standards. Moreover, the proposed research can be realized practically by incorporating necessary amendments in the fault management and system restoration module of distribution management systems.

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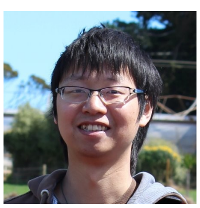

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