

Optimal Feeder Reconfiguration and Distributed Generation Placement for Reliability Improvement

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Abstract—This paper presents a methodology to determine the optimal distribution system feeder reconfiguration and distributed generation placement simultaneously, and is optimal in that the system reliability is maximized. An important consideration in optimal distribution system feeder reconfiguration is the effect of the variable output of intermittent resources. The work presented in this paper considers the stochastic behavior of variable resources, and open/close status of the sectionalizing and tie-switches as variables in determining the optimal DG locations and optimal configuration that enhance system reliability. Genetic algorithm is applied to search for the optimal or near-optimal solution. The proposed method is demonstrated on a 33-bus radial distribution system, which is extensively used as an example in solving the distribution system reconfiguration problem.

Index Terms—Distribution system reconfiguration, distributed generation, genetic algorithm, reliability

I. INTRODUCTION

One of the fundamental goals of an electric utility is to provide its customers with a reliable power supply. With the increasing complexity of industry operation and rising load demand, the power system is operating under a significant stress. Unlike transmission and sub-transmission systems, distribution systems have characteristics such as higher voltage drop, radial structure and load tapped all along the line. The radial topology facilitate the control and coordination of the protective devices used at the distribution system level. However, the loads far from the source node may suffer relatively less reliable power supply, since a single fault occurs in the upstream would cause service interruptions to all the downstream loads. In order to improve the reliability and to reduce the impact of abnormal operations, distribution system reconfiguration can be applied by altering the open/close status of switches. Besides, installing distributed generation (DG) units could also provide benefit in enhancing system reliability.

Reliability indices, such as the system average interruption frequency index (SAIFI), system average interruption duration index (SAIDI) and customer average interruption duration index (CAIDI) are commonly evaluated when quantifying reliability for distribution systems. Energy index of reliability (EIR) and expected energy not supplied (EDNS) are applied in this paper to reflect the reliability [1]. We consider these reliability indices are more appropriate for reconfiguring and planning purposes, since they are able to capture the expected severity of outages.

Due to the increasing role of environmental considerations in power generation, distributed renewable energy resources are expanding rapidly. Increased generation from renewable resources reduces emissions, consumption of fossil fuels and load curtailment. Various types of DG units are available, such as microturbines, photovoltaic (PV), wind, batteries [2]. This paper focuses on two types of DG units: wind and PV. An important consideration of optimal distribution system feeder reconfiguration is the effect of output variability of intermittent resources. The stochastic nature of these renewable resources is considered using a probabilistic multi-state model [3], [4] instead of modeling the output of the DG units as a constant value.

Previously, several researchers realized the importance of finding the optimal feeder reconfiguration or optimal locations to install appropriate size of distributed generators so that the benefit can be maximized. One simple approach to find the optimal feeder reconfiguration and DG placement is to perform the permutation and combination and then evaluate the reliability for all the feasible solutions. This is simple and straightforward, but is also computationally demanding even for off-line planning problems. In order to decrease the computational burden, some nontraditional optimization techniques are applied in solving combinatorial problems. For example, reference [5] presents a reliability driven distribution feeder reconfiguration model and solved by particle swarm optimization (PSO). Reference [6] proposes a new DG interconnection planning study framework that includes a coordinated feeder reconfiguration and voltage control solved by PSO. In [7], the authors use a refined genetic algorithm (GA) for distribution feeder reconfiguration to reduce losses. In [8], a fuzzy mutated genetic algorithm for optimal reconfiguration aiming at minimizing real power loss and improving power quality is presented. Moreover, several researches have been conducted in finding the optimal allocation of DG units. For instance, reference [2] uses dynamic programming, while others use intelligent methods such as simulated annealing [9], [10], PSO [11], and GA [12]–[14]. All the mentioned evolutionary optimization techniques merit in easy implementation with simple formulas and global search capability. In this work we utilize GA as the optimization algorithm, since it is naturally suitable for maximization problems [15]. In previous studies, little attention has been paid to the consideration of DGs

influence on feeder reconfiguration problem with respect to reliability improvement. This work here is able to obtain the optimal or near-optimal feeder configuration and DG locations at the same time solved by GA.

This paper presents a reliability based optimization problem to optimally reconfigure the distribution system feeders as well as determine the optimal locations of DG units. The objective is maximizing the reliability of the distribution system and the solution is obtained by genetic algorithm. Each configuration has its own fitness value which is determined by the system reliability. After several operations, such as reproduction, crossover and mutation, the solution has maximum system reliability will survive. Then the optimal feeder configuration and best location for distributed resources can be obtained simultaneously. The fitness value used in this study is EIR and it is obtained by calculating the power flow in the system.

II. PROBLEM FORMULATION

This study aims to find the optimal feeder reconfiguration and DG locations which maximize the reliability of the distribution system and subject to equality and inequality constraints of the system operation limits and also the distribution system topological constraint. Due to its capability of capturing the expected severity of outages, the EIR is utilized in this paper as the reliability index which is an appropriate index for this planning problem. The EIR of the system is given by:

$$EIR = 1 - \frac{EDNS}{E_{Total}} \quad (1)$$

where $EDNS$ is the expected demand not supplied and E_{Total} is the total energy demand. If all the load demands are sufficiently supplied, then EIR is one, since $EDNS$ is zero. If the system fails to serve the load and all the load need to be curtailed, then EIR would be zero, since $EDNS$ equals E_{Total} . Therefore, we want to maximize EIR in this planning study to ensure a more reliable system.

The variables are status of the sectionalizing and tie-switches and also the locations for DG units which can be represented by binary numbers. A binary string can be applied to represent the variables. Assume a distribution system has m normally closed switches, n normally open switches and M possible locations for N DG units. Then $(m + n)$ binary bits can be used to represent the open/close status of all the switches by 0/1 and similarly an M -bit binary string can be utilized to represent the decision: install/not install a DG unit on the positions by 1/0. Thus, the variables is encoded by a $(m + n + M)$ bits binary string X . Mathematically, the optimization model can be expressed as below,

$$\text{Maximize } f = \text{EIR}(X) \quad (2)$$

Subject to

$$\sum_{i=1}^{m+n} X_i = m \quad (3)$$

$$\sum_{i=m+n+1}^{m+n+M} X_i \leq N \quad (4)$$

$$\det(\hat{A}) = \pm 1 \quad (5)$$

The total number of normally open switches should be a constant value for all the configurations. If the string satisfies (3), then it is a feasible configuration; otherwise it is considered as infeasible. Similarly, the string should meet the requirement of (4), which ensures the total number of locations where have DGs should be less or equal to N .

Besides, distribution systems are configured radially to facilitate the control and coordination of their protective devices. The radial topological structure of the distribution system is taken as a necessary condition during the realization of the presented work [5]. It should thus be maintained at all times and for all possible configurations. For this purpose, one constraint based on graph theory [16], [17] is introduced to the distribution system reconfiguration problem. If $\det(\hat{A}) = \pm 1$ then the system topology is radial; otherwise if $\det(\hat{A}) = 0$ it is weakly-meshed and considered infeasible.

III. MODELING AND RELIABILITY EVALUATION

The modeling of component and system and the reliability evaluation method is briefly described in this section.

A. Modeling of System Components

System components, including distribution lines, circuit breakers, sectionalizing switches and so on are modeled by two states: up (available) and down (unavailable), and are characterized by their failure rates (λ) and repair rates (μ). The probability P that a component is in up state can be represented as [18],

$$P = \frac{1/\lambda}{1/\lambda + 1/\mu} = \frac{\mu}{\mu + \lambda} \quad (6)$$

The output of renewable DG units varies based on solar insolation or wind, which is modeled by a multi-state model as described in [3] and [4].

B. Attributes of Variable Resources

For proper evaluation and modeling of the effect of system input variability on the output power of a PV system and wind farm, the method presented in [3], [4] is adopted to model the output of DGs (wind and PV). Since this work focuses on optimal feeder reconfiguration and distributed generation placement, modeling detail of the output of DGs (wind and PV) and formulation are not reproduced in this paper; rather, readers are encouraged to consult the above mentioned references.

1) *Wind Power*: Wind turbine power curve provides a quantitative relationship between wind speed and the output power. It describes the operational characteristics of a wind turbine generator. The output power that can be extracted from wind turbines can be calculated as follows [19].

$$P = \frac{1}{2} C_p \rho A v^3, \quad (7)$$

where P is the output power (W), ρ is the air density (Kg/m³), v is the wind speed (m/s), A is the swept area of the turbine (m²), and C_p is the power coefficient.

The output power curve which combines (7) with the physical constrains in the system can be expressed as follows.

$$P = \begin{cases} 0, & \text{if } v < v_{cut-in} \\ \frac{1}{2} \rho A C_p v^3, & \text{if } v_{cut-in} \leq v < v_r \\ P_r, & \text{if } v_r \leq v < v_{cut-out} \\ 0, & \text{if } v_{cut-out} \leq v \end{cases}, \quad (8)$$

where v_{cut-in} is the designed cut-in speed, $v_{cut-out}$ is the designed cut-out speed, v_r is the rated speed and P_r is the rated power of the wind turbine.

2) *PV power*: The maximum output power ratings of PV systems are provided by manufacturers on the specification sheets. The current-voltage characteristics (I-V characteristics) under the standard test conditions (the radiation level of 1 kW/m² is given for temperature of 25°C) can be calculated using the following relationships [20].

$$I = s [I_{sc} + K_I (T_c - 25)] \quad (9)$$

$$V = V_{oc} - K_V T_c \quad (10)$$

where s is the normalized radiation level, I_{sc} is the short circuit current, K_I is the short circuit current temperature coefficient in A/°C, V_{oc} is the open circuit voltage, K_V is the open circuit voltage temperature coefficient in V/°C and T_c is the cell temperature in °C which can be expressed as follows [20].

$$T_c = T_a + s \left(\frac{T_{no} - 20}{0.8} \right) \quad (11)$$

where T_a is the ambient temperature and T_{no} is the nominal operating temperature of the cell (°C).

The output power, P_{pv} , assuming 100% efficient maximum power point tracking (MPPT), for a given radiation level, ambient temperature and the current-voltage characteristics can be calculated using the following relationships [20].

$$P_{pv} = N \times FF \times I \times V \quad (12)$$

where N is the number of panels and FF is the fill factor, which depends on the module characteristics, and can be expressed as follows [20].

$$FF = \frac{V_{mpp} I_{mpp}}{V_{oc} I_{sc}} \quad (13)$$

where V_{mpp} and I_{mpp} are the current and voltage at the maximum power point.

C. Power Flow Model

Power flow studies are usually carried out when conducting system reliability evaluation. The sufficiency of power supply to each load is a combined effect of operation, generation and distribution constraints. The objective function is to minimize the load curtailment which is subjected to the equality and inequality constraints of the power system operation limits. For each configuration, the minimum load curtailment would be calculated by the power flow model. In general, the power flow model used here can be stated as follows.

$$\text{Loss of Load} = \min \left(\sum_{i=1}^{N_b} C_i \right) \quad (14)$$

Subject to

Power balance conditions

Equipment availability and capacity constraints

where C_i is the curtailed power at the i th bus and N_b is the number of buses. The formulation and incorporation of the objective function of minimum load curtailment is described as above. For any encountered scenario (component availability, feeder configuration and DG location), the minimum system curtailment (load shed or demand not met) can be obtained by this model [21].

In this work, the reliability indices are obtained by applying a linearized distribution power flow method using only real power flows, as described in [22]. Since this planning study includes DG, which typically has inadequate reactive power capacity, it is reasonable to plan for real power generation first and then for reactive power support. Besides, a large number of power flow calculations are needed within the genetic algorithm or any other evolutionary optimization approach [21]. The linearized power flow model is fast and robust, which is able to reduce the computation time; the method used here [22] fits the need. Therefore, we consider this linearized model an appropriate approach in this work.

D. Reliability Measure and Evaluation

The expected index of reliability (EIR) is as expressed in (1) and ENDS can be calculated as the weighted sum of the curtailed demands, the weights are the probabilities of the corresponding outage events which can be calculated by the higher probability order approximation method. The detail of this method is described in [5]. If the contribution of a DG is assumed as a constant value, the expected demand not supplied is calculated as below [5].

$$EDNS = \sum_{i=1}^{N_C} C(i) \times P_C(i) \quad (15)$$

where $C(i)$ is the loss of load of contingency i , which is equivalent to load curtailment of contingency i , $P_C(i)$ is the probability of contingency i , and N_C is the number of contingencies.

The output power of DG may not be a constant; some maybe variable resources. When dealing with time varying resources

such as wind and PV, the injection of DGs can be modeled by multiple states to capture their stochastic nature. For each state, if the output and its corresponding probability is provided, then the EDNS can be expressed as (16).

$$EDNS = \sum_{i=1}^{N_{DG}} \left[\sum_{j=1}^{N_C} C(i, j) P_C(j) \right] P_{DG}(i) \quad (16)$$

where $P_{DG}(i)$ is the probability at state i , N_{DG} is the total number of DG output states. $C(i, j)$ is the loss of load of contingency j when the DG output is at state i , $P_C(j)$ is the probability of contingency j , and N_C is the total number of contingencies.

IV. OPTIMIZATION ALGORITHM

This section briefly describes the principal and operators in genetic algorithm. It also presents the algorithm for searching the optimal feeder configuration and meanwhile seeking for the optimal DG locations with regarding to a more reliable distribution network.

A. Genetic Algorithm

Genetic algorithm is an effective and widely used population based method for solving optimization problems, which mimics the process of natural selection and reproduction [23]. In GA, the variables are presented as chromosomes which are composed of genes. In a maximization problem, genes with larger fitness function values are considered as better genes. The evolution of the chromosomes leads to the survival of genes with higher fitness value and elimination of genes with lower fitness value. After several iterations and operations, all the chromosomes should evolve to the chromosome with highest fitness value so far and this is the optimal or near-optimal solution of the problem.

Operators such as reproduction, crossover and mutation are included in the genetic algorithm. The essential idea of reproduction is to select above-average strings in a population to form a mating pool [15]. After forming the mating pool, crossover operation is applied. This step is mainly responsible for searching new strings. First, two strings are picked at random and a random number is generated and compared with the crossover probability p_c to check whether a crossover is desired or not. If the random number is smaller than p_c , a crossing point is randomly chosen and then exchange all the bits on one side of the crossing point to generate new strings. The step after the crossover operation is to perform mutation on each string. For each bit of all the strings, a random number is compared with the probability of mutation p_m . If the random number is smaller than p_m , then the value changes from 1 to 0 or from 0 to 1. Once the iteration time is equal to the maximum allowable generation number t_{max} or other termination criteria is satisfied, the process is terminated.

B. Solution Algorithm

In this optimization problem, variables are coded by binary numbers. The binary strings can be divided into two categories,

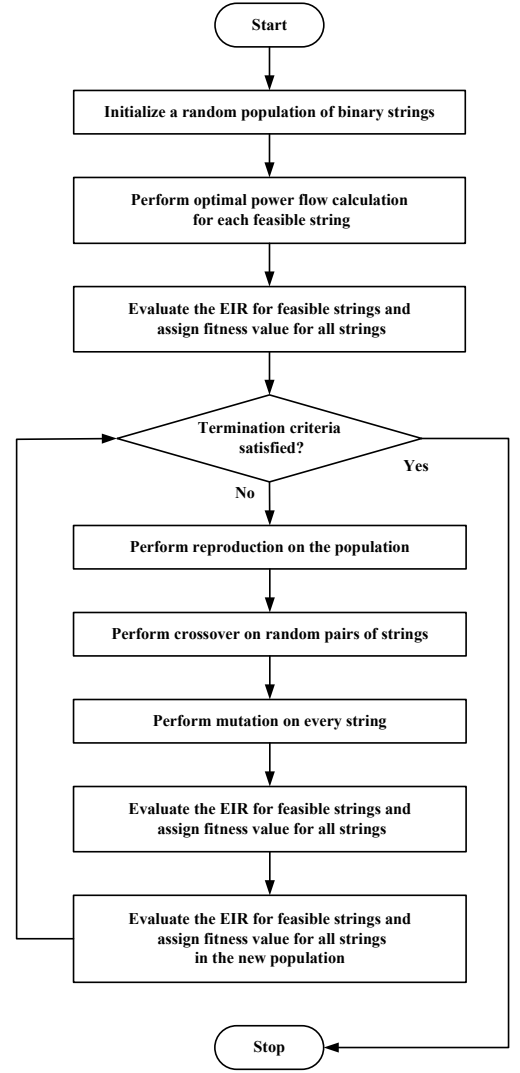


Fig. 1. Computation procedure of the solution algorithm.

feasible and infeasible. Evaluating the fitness value of each string is crucial in GA. If the string satisfies the requirement of (3)– (5), then it is a feasible string and its fitness value is the EIR of the representing configuration; EIR is obtained by solving the linearized power flow problem. If the string is infeasible, the fitness value should be set as zero. After several iterations, the infeasible solutions will be eliminated during the evolving process. Fig.1 displays the flowchart of the whole process.

V. CASE STUDIES AND RESULTS

In this section, a modified 33-bus radial distribution system [5] is used to validate the proposed method. This system is extensively used as an example in solving the distribution system reconfiguration problem [24].

TABLE I
SUMMARY OF THE 33-BUS TEST SYSTEM RELIABILITY DATA

Component	Failure rate (failure/year)	Repair rate (hr)
Transformer	0.05882	144
Bus	0.0045	24
Circuit Breaker	0.1	20
Distribution Line	0.13	5
Sectionalizing Switch	0.2	5

A. Test System Description and Data

This test system contains of 33 buses, 32 branches, 3 laterals, and 5 tie lines. The total real and reactive power loads of the system are 3715 kW and 2300 kVar. The single line diagram of this distribution system is displayed in Fig. 2. For the initial configuration as shown in the figure, S_{33} to S_{37} are the normally open switches (tie-lines) as indicated by dotted lines. Switches S_1 to S_{32} are normally closed and are represented by solid lines. The data related to reliability calculation is given in Table I [25].

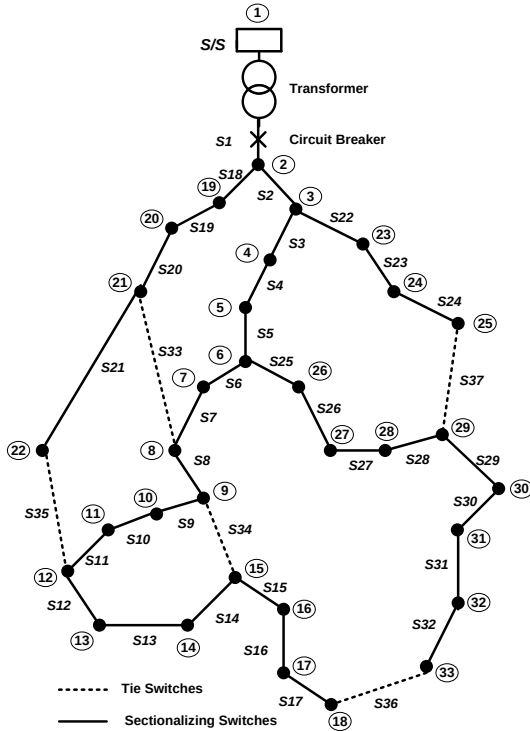


Fig. 2. Single-line diagram of the 33-bus distribution system.

To indicate the status of switches S_1 to S_{37} , a 37-bit binary string are applied. If one switch is tagged as 1 then it is a normally closed switch, otherwise it is a normally open switch. For example, the initial status can be expressed as 32 1s following by five 0s. We assume there are six possible locations to install the distributed generation in this distribution system, which are with bus number 7, 8, 24, 25, 30 and 32. Then six more binary bits are used to represent the decisions

TABLE II
WIND POWER OUTPUT AND STATE PROBABILITY

No.	Wind Type DG		PV Type DG	
	Output (kW)	Probability	Output (kW)	Probability
1	0	0.1149	0	0.4803
2	5.9395	0.0873	4.0980	0.0421
3	8.1664	0.0933	18.2943	0.0607
4	12.2725	0.1008	34.0897	0.0574
5	22.2408	0.1099	51.6267	0.0489
6	34.4837	0.1140	68.3920	0.0618
7	56.8708	0.1135	81.4940	0.0747
8	98.1802	0.2663	90.1757	0.1741

for the candidate locations. Thus, a 43-bit chromosome can be applied to represent the two status of switches and the locations of DGs.

B. Case Studies

In all case studies, the failure rates of all components are considered, including transformers, buses, the main circuit breaker, distribution lines, and sectionalizing switches. Furthermore, an assumption that a sectionalizing switch is placed on every distribution line is made. Besides, two DGs with 100 kW capacity each need to be placed in the distribution system. The multi-state output model presented in [3] and [4] is applied to express the time varying DG output. Table II lists the injection of DGs with the corresponding state probability for the wind and PV type DGs with 100 kW capacity.

Case 1: It is the base case, in which the initial configuration is applied. In this case, switches S_{33} to S_{37} are normally open switches and two DG units are assumed to be installed at bus 8 and bus 24.

Case 2: Optimal distribution feeder reconfiguration is conducted in this case. However optimal DG placement is not considered, as two DGs are assumed to inject to bus 8 and bus 24 as in the base case.

Case 3: In this case study, the optimal DG placement is performed without considering distribution feeder reconfiguration.

Case 4: This case study aims at optimizing both distribution feeder reconfiguration and DG placement so that the reliability of the system can be maximized.

From case 1 to case 4, the distributed generation output is assumed as a constant value 100 kW, equation (15) is applied to calculate EDNS for feasible strings. From case 5 to case 12 (as described below), the stochastic nature of wind or PV is considered. Equation (16) and Table II are utilized for reliability evaluation.

Case 5: In this case, the configuration and DG locations are the same as in case 1, however, the time varying wind power output is captured by the multi-state output as given in Table II.

Case 6: This case study is similar to case 2 which only focuses on the optimal distribution feeder configuration, but

TABLE III
COMPARISON AMONG ALL CASE STUDIES

Case No.	Optimal feeder reconfiguration	Optimal DG locations	Constant DG output
1	No	No	Yes
2	Yes	No	Yes
3	No	Yes	Yes
4	Yes	Yes	Yes
5	No	No	No
6	Yes	No	No
7	No	Yes	No
8	Yes	Yes	No
9	No	No	No
10	Yes	No	No
11	No	Yes	No
12	Yes	Yes	No

TABLE IV
RESULTS OF ALL CASE STUDIES

Case No.	open switches	DG locations	EDNS (kW/year)	EDNS Reduction (%)
1	S33 S34 S35 S36 S37	8 24	9.3259	—
2	S7 S10 S13 S17 S26	8 24	8.0707	13.46
3	S33 S34 S35 S36 S37	32 32	9.0699	2.75
4	S6 S10 S14 S25 S36	32 32	7.9355	14.91
5	S33 S34 S35 S36 S37	8 24	9.5929	—
6	S6 S10 S14 S25 S36	8 24	8.3016	13.46
7	S33 S34 S35 S36 S37	32 32	9.4854	1.12
8	S7 S10 S14 S26 S36	30 32	8.2583	13.91
9	S33 S34 S35 S36 S37	8 24	9.6372	—
10	S6 S10 S13 S27 S36	8 24	8.3420	13.44
11	S33 S34 S35 S36 S37	32 32	9.5550	0.85
12	S6 S10 S13 S26 S36	30 32	8.3101	13.77

differs in that the multi-state power output model for DG is applied.

Case 7: Like case 3, the initial feeder configuration is used and only conducts research on optimal DG placement. But unlike case 3, the output power of DG units is not assumed as a constant number.

Case 8: This case study takes all the aspects of the above cases into account. The optimal feeder reconfiguration and optimal DG placement with the stochastic nature considered is obtained.

Cases 9 to 12 are similar to cases 5 to 8, except that case 9 to case 12 consider PV type DGs instead of wind type DGs. The comparison and results of all the 12 cases are displayed in Table III and Table IV.

As seen from table III and IV, by comparing the results of either case 1 and 2, case 5 and 6, or case 9 and 10, it is evident to state that by reconfiguring the system topology, the reliability of the distribution system can be greatly improved. The differences in EDNS between case 1 and 3, case 5 and

7, and case 9 and 11 prove that by placing DG units at appropriate locations, the reliability of the system can be enhanced and the benefit of DG can be maximized. Moreover, the EDNS is reduced by 14.85%, 13.91% and 13.77% from case 1 to case 4, from case 5 to case 8 and from case 9 to case 12, respectively.

VI. DISCUSSION AND CONCLUSION

In this paper, an optimization model to improve the distribution system reliability via optimal feeder reconfiguration and optimal DG placement is presented. This planning problem is computationally intensive and reliability evaluation for each possible solution contributes to the majority of the simulation time. Applying GA enables it to solve the problem in a reasonable time. In the model, current carrying capacities of distribution feeders, real power limits, topology constraints and stochastic nature of renewable resources are all under consideration. The proposed approach is tested on a 33-bus radial distribution system and the optimal feeder reconfiguration and DG locations with regarding to reliability enhancement are simultaneously obtained.

The solution algorithm presented here is generalized and flexible; it permits optimization of both feeder reconfiguration and location of DG units. The framework mainly focuses on PV and wind types of distributed generators; however it is amenable to other DG categories. Moreover, the solution strategy can be extended to consider reactive power constraints.

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