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RESEARCH ARTICLE

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Annual energy loss reduction of distribution network through reconfiguration and renewable energy sources

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Summary

Renewable energy sources are becoming popular day by day for distributed generation as technology is becoming cheaper and modular. Power loss reduction is a powerful incentive for a distribution system operator to promote distributed generation. This paper presents a method to minimize annual energy losses through the integration of nondispatchable renewable distributed generation (DG) units and network reconfiguration under varying load demand condition. The optimal location and DG power level are calculated, and then these data are used to determine DG plant size taking into account the nonavailability of renewable energy at certain times. A network reconfiguration strategy is proposed, which takes into account both the time-varying load and the renewable energy source such that annual energy loss is minimum. The proposed methodology is applied to 33-node and 118-node test distribution system with different scenarios. Results show a substantial reduction in energy loss. A cost-benefit analysis is also carried out.

KEYWORDS

energy loss minimization, location and sizing, network reconfiguration, renewable energy sources

1 | INTRODUCTION

Renewable energy sources are attracting increasing interest because of their inexhaustible and nonpolluting nature. Wind and photovoltaic technologies are relatively matured and are competing against conventional sources. PV plants are easy to install because of their modular nature, require little maintenance, and have a long life whereas wind power plants tend to have a higher capacity factor and can generate power during night time also. India has committed that by 2030, at least 40% of its electricity demand will be met by nonfossil fuel-based sources by signing the Paris climate change agreement.[1] It will help to reduce emissions to limit global temperature rise to below 2° C. Currently, the bulk of electricity generated in India is coal-based, and 23% of generated power in India is lost in transmission and distribution, a majority of which is lost at the distribution level.[2] As a result of this, even a small reduction in energy loss or demand at the distribution level leads to a significant decrease in carbon emissions at the generation level. Network reconfiguration and renewable energy-based distributed generation (DG) are helpful in this regard.

Reconfiguration and proper placement of DG will reduce active and reactive power losses, improve voltage profile, relieve heavily loaded lines, and enhance reliability.[3] Distribution network reconfiguration can also help in higher penetration of DG.[4-6] Hourly and seasonal variation in load demand, as well as renewable power generation, complicate the design process. Researchers have suggested many techniques for DG sizing and placement. These methods can be classified into analytic methods, heuristic methods, and metaheuristic methods. Some authors have proposed hybrid methods.

The most common objective of their research work is to minimize real power loss. Many authors use multiobjective functions including minimizing active and reactive power losses, voltage deviation, and generation cost.

An analytic approach for DG sizing is proposed in Acharya et al.[7] The sensitivity factor of real power loss with respect to real power injection from the DG unit is derived from the exact loss formula, and a priority list including 30% of the total number of buses is formed. Optimal DG at each priority bus is found using analytic expressions and least loss causing DG unit is recommended. In Mahmoud et al,[8] an efficient analytical (EA) method is proposed, which considers the power factor as a state variable. The power flow is viewed as a combination of the base case from the grid to load, and a counter DG power flow to the grid and a new loss formula is proposed based on this. A new optimal power flow method is also proposed in which DG unit location is found using the EA method, and sizing is done by the OPF method, which takes into account the constraints. In Quoc and Nadarajah,[9] an improved analytical (IA) method is proposed and the parameters of which could be calculated using load flow results. This method is compared with the loss sensitivity factor (LSF) method and exhaustive load flow (ELF) method. Hung et al[10] proposed analytical expressions for optimal sizing of DG units. Optimal DG was found for each location, and the location with the least power loss was chosen. The study considered nondispatchable DG also. In Rajkumar and Khatod,[11] loads and DG units are converted into a current source using base case load flow data, and this linearized system is used to find optimal DG power injection. In Ochoa and Harrison,[12] renewable source generation and load demand are discretized, and instances that have the same generation and load levels are clubbed together. The total loss is minimized using ac OPF. In Masteri and Venkatesh,[13] network reconfiguration is formulated as a nonlinear optimization problem using complementarity technique.

A heuristic technique for loss minimization was proposed in El-Hawary and Abu-Mouti.[14] Total system real power loss as a function of DG unit size was approximated to a parabola. The parabola was plotted by finding power loss at 10%, 20%, 70%, and 80% of total system load demand. The quadratic equation representing parabola was differentiated to find the optimal size of DG.

Mohamed et al[15] proposed a fireworks algorithm-based technique for the problem of power loss minimization and voltage stability enhancement by reconfiguration and DG. The nodes with the least voltage stability index were chosen for DG placement. The study did not consider nondispatchable DG units. In Wu et al,[16] ant colony algorithm is used to minimize power loss through reconfiguration, but the load is assumed constant, and only dispatchable DG units are considered. In Srinivasa Rao et al,[17] LSF is calculated to find the location for dispatchable DG units, and harmony search algorithm was used to compute the size of the DG units and for reconfiguration. A bacterial foraging optimization algorithm-based method is proposed in Kumar and Jayabarathi[18] to minimize power loss. The minimization of the total annual energy losses is formulated as a nonlinear programming problem in Sfikas et al.[19] The study considers nondispatchable DG units and batteries. The solution method is applied at each candidate node to find optimal DG size. In El-Fergany,[20] high potential buses are identified by fuzzy expert rules using LSF for the optimum DG placement. After reducing the search space, backtracking search optimization algorithm-based method is applied to optimally place DG units such that active power loss and cumulative voltage deviation is minimized. The study did not consider nondispatchable DG units and load variation. Effect of DG on voltage stability margin is studied in Al Abri et al,[21] and a method is proposed to place DG units optimally to improve voltage stability margin. Candidate buses for the DG installation are selected by analyzing the Jacobian matrix. DG sizing problem is formulated as a mixed-integer nonlinear programming (MINLP) problem considering the intermittent nature of renewable DG units.

An artificial bee colony algorithm-based approach to minimize power loss is proposed in Abu-Mouti and El-Hawary.[22] The method was applied to the standard, and overloaded condition and significant loss reduction were recorded. The technique did not consider nondispatchable DG units. In García and Mena,[23] a modified teaching learning-based optimization (MTLBO) algorithm is proposed to determine the optimal placement and size of DG units. The optimal size of DG at a location is found using a simplified version of exact loss formula, and the place was found using MTLBO algorithm. In Kaur et al,[24] DG optimization problem was solved in two stages. In siting planning model, search space is reduced to 30% of buses by ranking them according to combined loss sensitivity. In capacity planning model, DG sizing problem is modeled as an MINLP problem and solved. Load level variation is neglected. In Majid and Sharique,[25] a repeated load flow method is used for optimal sizing of a single DG, and it is reported that instead of placing the DG unit at a single location if the capacity is split and placed at many locations reduces the power losses and improves the average voltage. In Sultana et al,[26] an approach based on the grey wolf optimizer (GWO) for multiple DG units allocation is proposed. The multiobjective function included reactive power loss reduction index and voltage profile deviation index. The results are compared with the gravitational search algorithm and the bat algorithm-based metaheuristic methods. In Sanjay et al,[27] optimal DG allocation problem is solved using a hybrid GWO technique. The power factor of the DG units is varied between 0.7 to unity, and the optimal power factor is calculated. The results are compared with various other methods.

A hybrid method combining analytical and genetic algorithm (GA) methods is proposed in Vatani et al[28] to minimize the losses. The optimum size of DG units was found using analytic expressions for assumed locations and power factors. GA was used to find the site and power factor of DG units to minimize loss. Load level variation is not considered. In Kansal et al,[29] a hybrid method is proposed combining the IA method and particle swarm optimization (PSO) technique. IA method is proposed to find the sizes of DG units, but optimal locations are found using PSO-based technique.

The distribution network reconfiguration problem has been the interest of many researchers. One of the approaches to network reconfiguration is to close all tie switches to form a meshed network and selectively open switches until the radial nature of the distribution system (DS) is restored. In Gupta et al,[30] an adaptive particle swarm optimization is proposed to open the meshed network. Random unfeasible solutions generated by the PSO algorithm are converted into feasible ones by applying heuristic rules based on graph theory. In Romero-Ramos et al,[31] network reconfiguration problem is formulated as a mixed integer programming problem with quadratic constraint. In Niknam,[32] multiobjective network reconfiguration problem is solved using a combination of discrete particle swarm optimization and honey bee mating optimization (HBMO) algorithm. The objective is to minimize real power loss, voltage deviation, the number of switching operations, and to balance the loads on the feeders. The problem is formulated to maximize the norm2 distance of objective functions from their worst case. In Niknam et al,[33] modified HBMO algorithm is used to solve the multiobjective network reconfiguration problem, and a fuzzy-based decision maker is used to select the best nondominated solution. In Shariatkhah and Haghifam, [34] network reconfiguration problem was formulated as to avoid congestion because of DG and solved using GA. In Tomoiaga et al,[35] a method based on GA and connected graphs is proposed.

Another popular approach is to close one tie line at a time and selectively open a sectionalizing switch to maintain radial nature.[36,37] In Fan et al,[37] network reconfiguration is studied as an integer linear programming problem, and a switching algorithm is developed assuming load to be current sources. In Das,[38] fuzzy membership functions are defined for multiple objectives such as minimizing power loss, voltage deviation, etc. Tie switches are rated according to the voltage difference across them, and tie switch with the highest voltage difference was closed for reconfiguration. Fuzzy multiobjective functions are also used in Syahputra et al[39] to reconfigure distribution networks with DGs. Dorostkar-Ghamsari et al[40] analyzed the worthiness of the hourly network reconfiguration and found it economically attractive. In Bayat,[41] a constructive method is proposed based on the assumption that when the voltage in the network is uniform, the configuration is globally optimal.

In Kirthiga et al,[42] a multiobjective PSO-based method was proposed to find the optimal number, size, and location of DG units. A method to reconfigure was also proposed by introducing tie switches between nodes, but the method did not maintain radial nature. A distribution feeder reconfiguration method is proposed in Olamaei et al[43] to reduce total cost. The size and location of DG units are assumed in the data. The optimization problem is solved using PSO, GA, tabu search, and differential evolution methods, and PSO is recommended. In Franco et al,[44] a linearized model is developed to solve the reconfiguration problem as a mixed-integer linear programming (MILP) problem. The effect of DG is also considered, but the location is fixed initially. In Aboelsood and El-Saadany,[45] a probabilistic model is proposed considering uncertainties in renewable energy generation and load demand. The loss and switching cost was minimized using GA. In Nasiraghdam and Jadid,[46] multiobjective artificial bee colony algorithm (MOABC) was used for DG sizing and reconfiguration, but the DG location was predefined. Decimal coded quantum particle swarm optimization is applied to solve the reconfiguration problem in Guan et al[47] using various models for DG units. A new methodology to perform the automatic reconfiguration of distribution networks incorporating DG units is proposed in the previous studies.[48,49] Analytic hierarchy process is used to determine the best sequence of switching. A discrete teaching learning-based optimization algorithm is used in Pfitscher et al.[50] In Arash and Hossein,[51] a market-based method is proposed taking into account locational marginal prices at different connection points between distribution and transmission systems. In Sattarpour et al,[52] optimal sizing and siting of DG units and smart meters problem is solved using GA. The analysis is performed considering demand response programs, and the power loss reduction is selected as the objective. In Sattarpour et al,[53] hybrid GA and is employed for optimal sizing and siting of DG units and remote terminal units (RTUs) in smart distribution grids. The results of hybrid GA is used for assigning importance degrees to the two objectives considered using the technique for order preference by similarity to ideal solution (TOPSIS) approach. However, both the studies[52,53] did not consider renewable DG and reconfiguration. Researchers have also used other optimization techniques such as simulated annealing,[54] artificial immune algorithm,[55,56] vaccine-enhanced artificial immune system,[57] modified plant growth simulation algorithm,[58] PSO,[59,60] GA[61-63], runner root algorithm,[64] harmony search algorithm,[65] artificial bee colony algorithm,[66,67] hybrid Harmony search and particle artificial bee colony algorithm,[68] interval analysis,[69] stochastic MILP,[70] Ant Colony Optimization,[71] hybrid receding horizon control and scenario analysis,[72] nondominated sorting GA,[73] fuzzy mutated GA,[74] tabu search,[75] Benders decomposition approach,[76] and evolutionary programming.[77] Summary of the reviewed literature is presented in Tables 1 and 2.

From the above literature survey, it is seen that most of the researchers have studied either DG installation or network reconfiguration for power loss minimization. The issue of network reconfiguration in the presence of renewable DG units has not received much attention. Moreover, it can be seen from Tables 1 and 2 that most of the research works have neglected the seasonal variation in load demand and renewable resources availability. These gaps in the literature, the annual energy loss reduction is selected as the objective to account for the seasonal variation in load demand and renewable resources availability. A methodology is suggested for finding out the optimal power injection by nondispatchable DG units (solar and wind) and then their size is determined by a simple methodology to account for the unavailability of the renewable resources. Reconfiguration of the distribution network is carried out to minimize power loss considering the seasonal variation of load and generation of nondispatchable DG units. The proposed method is applied to two test systems including a large scale DS for five different scenarios, and cost-benefit analysis is carried out to test the effectiveness of the proposed method.

Rest of the paper is organized as follows. In Section 2, the modeling of load and renewable DG is explained. The proposed method is described in detail in Section 3. The proposed method is validated by applying to two different test systems

TABLE 1 Summary of literature

Ref #	Reconfiguration	DG Presence	Load Variation	Renew. Source Variation	Optimization Technique
[4]	Y	Y	Y	Y	binary PSO
[6]	Y	Y	Y	Y	multi-objective MINLP
[7]	-	Y	-	-	analytical method
[8]	-	Y	-	-	efficient analytical method
[9]	-	Y	-	-	improved analytical method
[10]	-	Y	Y	Y	analytical method
[11]	-	Y	-	-	analytical method
[12]	-	Y	Y	Y	multiperiod AC OPF
[13]	Y	-	-	-	complementarity technique
[14]	-	Y	-	-	heuristic method
15, [15]	Y	Y	-	-	fireworks algorithm
[16]	Y	Y	-	-	ant colony algorithm
[17]	Y	Y	Y	-	harmony search algorithm
[18]	Y	-	-	-	bacterial foraging algorithm
[19]	-	Y	Y	Y	sequential quadratic programming
[20]	-	Y	-	-	backtracking search algorithm
[21]	-	Y	Y	Y	MINLP
[22]	-	Y	-	-	artificial bee colony algorithm
[23]	-	Y	-	-	modified TLBO
[24]	-	Y	-	-	MINLP
[25]	-	Y	-	-	analytical method
[26]	-	Y	-	-	grey wolf optimizer
[27]	-	Y	-	-	hybrid GWO
[28]	-	Y	-	-	hybrid analytical and GA method
[29]	-	Y	-	-	hybrid analytical and PSO method
[30]	Y	-	-	-	adaptive PSO method
[31]	Y	Y	Y	-	mixed-integer quadratic method
[32]	Y	-	-	-	hybrid evolutionary algorithm
[33]	Y	Y	-	Y	modified HBMO
[34]	Y	Y	-	-	GA
[38]	Y	-	-	-	fuzzy multiobjective approach
[39]	Y	Y	-	-	fuzzy multiobjective approach
[40]	Y	Y	Y	Y	mixed integer cone programming
[42]	Y	Y	Y	Y	PSO and GA
[43]	Y	Y	-	-	PSO
[44]	Y	Y	-	-	mixed integer LP

TABLE 2 Summary of literature Contd

Ref #	Reconfiguration	DG presence	Load Variation	Renew. Source Variation	Optimization Technique
[45]	Y	Y	Y	Y	GA
46, [46]	Y	Y	-	-	MOABC
47, [47]	Y	Y	-	-	quantum PSO
[48]	Y	Y	Y	Y	analytic hierarchy process
[50]	Y	Y	-	-	discrete TLBO
[51]	Y	Y	Y	-	GA
[52]	-	Y	-	-	GA
[53]	-	Y	-	-	hybrid GA and TOPSIS
[55]	Y	-	Y	-	artificial immune algorithm
[57]	Y	Y	Y	Y	many evolutionary methods
[58]	Y	Y	-	-	modified plant growth simulation
[59]	Y	Y	Y	Y	real time OPF
[61]	Y	-	-	-	GA
[62]	Y	Y	Y	-	GA
[63]	Y	-	-	-	enhanced GA
[64]	Y	-	-	-	runner-root algorithm
[66]	Y	-	-	-	artificial bee colony algorithm
[68]	Y	Y	Y	-	hybrid heuristic search method
[69]	Y	Y	Y	Y	artificial immune systems
[70]	Y	Y	Y	Y	stochastic MILP
[71]	Y	Y	Y	Y	ant colony optimization
[73]	Y	Y	Y	-	non-dominated Sorting GA
[74]	Y	-	-	-	fuzzy mutated GA

in Section 4. The results of the techno-economic analysis are presented and discussed in Section 5, and conclusions are drawn in Section 6.

2 | LOAD AND RENEWABLE RESOURCES MODELING

2.1 | Load modeling

The load pattern is assumed to vary as mentioned in The IEEE RTS.[78] Each year is divided into four seasons: winter, summer, spring, and fall. Spring and fall seasons follow the same pattern. The demand varies differently on weekdays and weekends in a season. The load variation for a year is represented by two hourly load curves of four days (one day representing each season), one representing weekday and the other weekend as shown in Figure 1 and Figure 2.

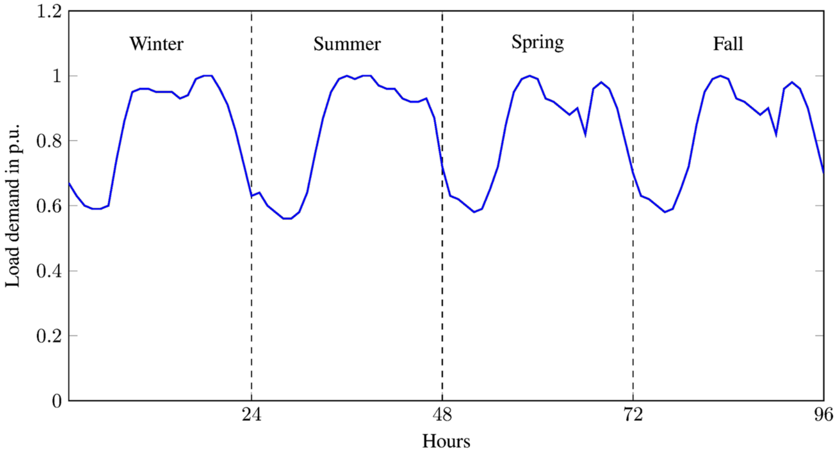

FIGURE 1 Hourly load demand curve on weekdays

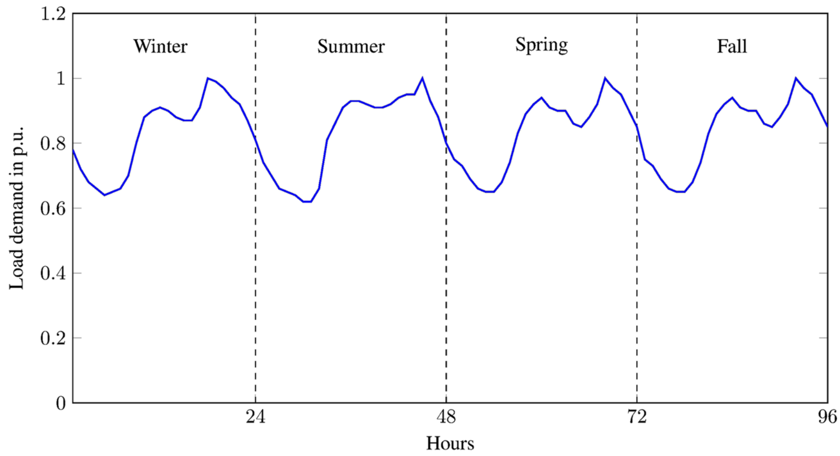

FIGURE 2 Hourly load demand curve on weekends

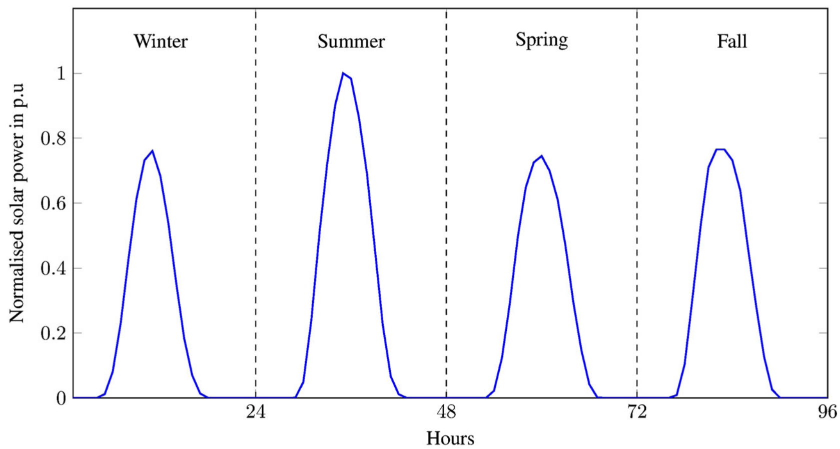

FIGURE 3 Hourly solar output

2.2 | Renewable resources modeling

2.2.1 | Solar DG

The DG units are assumed to operate at constant power factor mode. The DS is assumed to be spread across a small geographical area such that the availability of the wind and solar energy does not vary. Variation in solar power is captured by the test systems placed at a location within the DS. The test system provides data of hourly power generated by it, and these data are used to calculate the hourly power variation in each season similar to load variation as shown in Figure 3.[79] For example, solar power generated during the interval 09:00 AM to 10:00 AM in winter weekday is found by taking the average of power generated on all weekdays in winter season during the same interval. If the hourly power generated data are not available, then it can be estimated using solar insolation data of the area. The solar data used in this paper was obtained from a 100 kW peak solar PV plant installed at the rooftop of IIT Kharagpur[79] (see Appendix Table A1). In the absence of such data, the power generated by the test system can be estimated from the solar insolation data using the following equation[80]:

$$P_{PV}^{test}(h) = S \times \eta_{inv} \times \eta_{PV} \times f_{PV} \times \left(\frac{I(h)}{I^{st}} \right) \times (1 + \alpha_{PV}[T_C(h) - T_C^{st}]). \tag{1}$$

2.2.2 | Wind DG

Wind energy variation is taken into account using the hourly wind velocity data. The hourly per unit power generated by a wind turbine in a year is estimated using the following equation:

$$P_{wind}^{test,pu}(h) = \begin{cases} 0 & V_w < V_{c-in} \\ (237.1 - 176.8V_w + 37.8V_w^2 - 1.752V_w^3)/500 & V_{c-in} \le V_w \le V_{w,rated} \\ 1.0 & V_{w,rated} \le V_w \le V_{c-out} \\ 0 & V_w \ge V_{c-out} \end{cases} \tag{2}$$

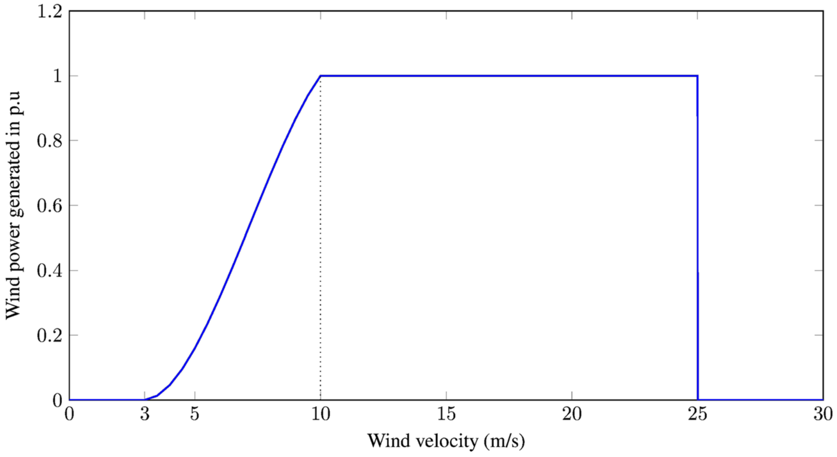

FIGURE 4 Wind turbine characteristics

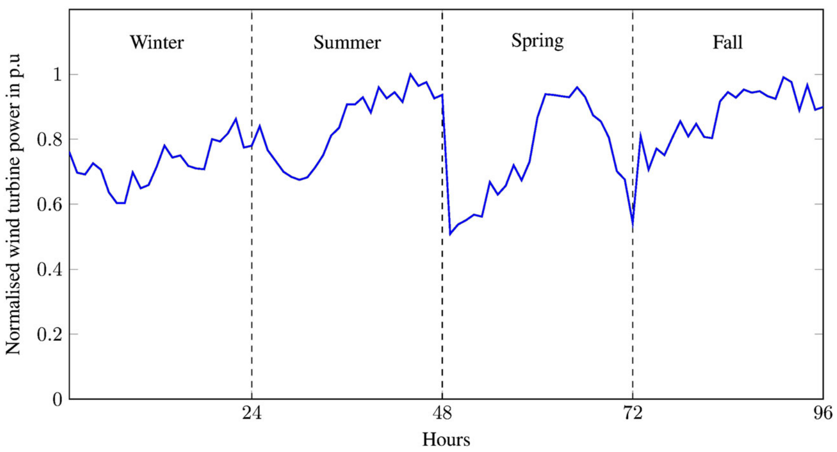

FIGURE 5 Hourly wind turbine power

The Equation 2 is obtained by fitting a cubic equation to an actual 500 kW wind turbine characteristics[81] with V_{c-in}=3 m/s, $V_{w,rated}$=10 m/s, and V_{c-out}=25 m/s as shown in Figure 4. These data are used to calculate the average hourly power generated in each season as explained in Section 2.2.1 (Figure 5 and Table A1).

2.3 | Scenarios

In this work, we have considered PQ$^+$ type of DG units, which can supply both real and reactive power.[27] Moreover, the renewable DG units are assumed to operate at constant power factor. The following scenarios are considered to study the effect of the proposed approach. In each scenario, the analysis is done twice for the cases with and without reconfiguration.

Scenario 1 Base case (no DG)
Scenario 2 Single solar DG unit
Scenario 3 Single wind DG unit
Scenario 4 Wind DG_1 at first location and solar DG_2 at the second location
Scenario 5 Solar DG_1 at first location and wind DG_2 at the second location

Scenario 1 pertains to the base case with no DG connected to the system. In scenarios 2 and 3, the effect of a single nondispatchable DG at an optimal location is studied. In scenarios 4 and 5, the impact of multiple nondispatchable DG units is studied.

3 | PROPOSED METHODOLOGY

3.1 | Energy loss

Each year is represented by four seasons, and each season is represented by a weekday and weekend. The total annual energy loss would be

$$E_{loss} = \sum_{season=1}^{4} N_{weak}(5\sum_{h=1}^{24} P_{loss}^{wd}(h, season) + 2\sum_{h=1}^{24} P_{loss}^{we}(h, season)), \tag{3}$$

Where P_{loss}^{wd} is power loss on a weekday; P_{loss}^{we} is power loss on a weekend; N_{weak} is the number of weeks in a season and $P_{loss} = \sum_{k}^{N_{br}} |I_k|^2 R_k$. The weighting factors are due to the fact that a week consists of five weekdays and two weekends. The objective is to minimize the energy loss, ie,

$$Min. \quad E_{loss} \tag{4}$$

subject to,

1. Maintain radial nature of DS.
2. Voltage constraints,

$$V_{min} \leq V_i \leq V_{max} \tag{5}$$

3. Branch current constraints,

$$|I_k| \leq I_k^{max} \qquad \forall \quad k \leq N_{br} \tag{6}$$

4. Distributed generator constraint

$$\sum_{i}^{N_{DG}} P_{DGi}(h) \leq P_{load}(h) \qquad \forall h \tag{7}$$

5. Load flow constraints

$$P_{DGi} - P_{Li} = \sum_{n=1}^{N_{node}} |V_i V_n Y_{in}| cos(\theta_{in} + \delta_n - \delta_i) \tag{8}$$

$$Q_{DGi} - Q_{Li} = -\sum_{n=1}^{N_{node}} |V_i V_n Y_{in}| sin(\theta_{in} + \delta_n - \delta_i). \tag{9}$$

In a radial DS, only one end of the feeders is connected to the substation. The power in the feeders flows only in one direction, and hence, generally nondirectional over current relays are used for protection as opposed to the directional relays used in the meshed transmission networks. During the reconfiguration process, special care must be taken such that the final network solution does not contain any loops, which may jeopardize the protection of the DS. The first constraint is included to force the solution to not have any meshes in the solution. The consumers at the far end of feeders often experience large voltage fluctuations. The second constraint is included to ensure good quality power to the consumers as per the standards. The third constraint is included to ensure that the current flowing in each segment of the feeders is within limits. The fourth constraint is added to make sure that there is no reverse power flow to the grid. The loads are assumed to be of constant power type with constant power factor. The Newton-Raphson's method is used for load flow analysis.

3.2 | DG sizing and location

The optimal DG power was found using ELF method proposed in Quoc and Nadarajah.[9] Optimal DG power at each node, which minimizes the power loss, is calculated at peak load. A DG unit is placed at a node. The power injected by the DG unit is increased in steps, and load flow is run to find out the total power loss. The active power loss decreases as injected power increases. The power factor is maintained constant. The DG unit power is optimal just before the power loss starts to increases. The location, which gives minimum loss, is selected. The second location is found using the same procedure but changing the load data at the first location by converting the optimal DG power into a negative load. This process is repeated for different power factors of 0.7, 0.8, 0.9 lag, and UPF to optimize the power factor.[20,27] This procedure can be generalized for multiple DG units.

Dispatchable DG capacities can be designed to be equal to the optimal power injection found out. Whereas the optimal size of nondispatchable DG is determined by taking into account the uncertainties. Solar PV plants rarely receive rated solar radiation and have a very low capacity factor. Hence, they should have a larger size than a dispatchable DG at the same place such that it produces the same power most of the times. Solar PV size is calculated taking Panel Generation Factor (PGF) of that particular area into account,[82] ie,

$$P_{PV}^{max} = \frac{P_{optimal} \times max(E_{day})}{P_{test}^{max} \times PGF}, \tag{10}$$

where

$$PGF = \frac{\text{total energy generated}}{\text{no of days} \times P_{rated}}. \tag{11}$$

$P_{optimal}$ is the optimal solar DG power injection, which minimizes power loss, E_{day} is the solar energy produced in a representative day of a season (Figure 3), and P_{test}^{max} is the actual average peak power generated by the test PV system (maximum power generated in Figure 3), and P_{rated} is the power rating of the test system (100 kW for the rooftop PV example considered). The PGF for a particular location is calculated over a long period; hence, the denominator in Equation 10 denotes average energy generated in a day. Accordingly, PV DG size is chosen as $P_{optimal}$ boosted by a factor, which is the ratio of average daily energy produced in the summer season to overall average energy generated in a day.

Wind power plants have a higher capacity factor as they are operating during the night also. Because of the flat power characteristics till cut out velocity wind power plants provide the same optimal rated power even when the wind speed is higher than the rated speed. The size of the wind power plant is determined in such a way that it injects the optimal power at peak. Therefore, the size of wind DG is found using the following expression.

$$P_{wind}^{max} = \frac{P_{optimal}}{P_w}, \tag{12}$$

where P_w is the peak power generated by the wind turbine (Figure 5) in per unit.

3.3 | Reconfiguration

DS consists of sectionalizing switches (normally closed) and tie switches (normally open). Reconfiguration is achieved by altering these switches. Often the number of possible switching combination is so large that evaluating each combination becomes prohibitive. Hence, heuristic methods are most commonly used.

This paper uses an iterative method to reconfigure DS while maintaining the radial structure. This method is similar to the one proposed in Baran Mesut and Wu.[36] When a tie switch is closed in a radial DS, it forms a loop. A sectionalizing switch in the loop must be opened to maintain the radial structure. If more than one switch is opened, then some nodes will get de-energized. Hence, to maintain the radial nature of the DS and serve all the loads, the number of open switches must remain constant. For example, consider a system as shown in Figure 6. When tie switch T1 is closed, a loop is formed, and to maintain radial structure, one of the sectionalizing switches S3, S4, S5, S6, S7, S10, S11, S12, S13, and S14 must be opened, and that switch takes the position of T1. The proposed algorithm maintains a list of open switches,which is continuously updated. The algorithm continuously tests whether an open switch (instead of examining all open switches as in Baran Mesut and Wu[36]) can be closed and replaced by any other closed switch resulting in a better objective. It terminates when no improvement is achieved by altering any open switch. This method ensures at the least a local minimum. The detailed procedure for a system with a N_{tie} number of tie switches is described as follows.

Step 1 Read system load, generation, line, tie switches, and sectionalizing switches data. Prepare a list of open switches with all tie switches as elements. Run load flow to get P_{global} = total power loss.
Step 2 Close the open switch OS_k. Identify the closed switches that form a loop. Open one such closed switch at a time and run load flow to get the power loss. Discard the solution if any constraints are violated.
Step 3 Select the closed switch CS_j, which when opened gives minimum loss P_{local} without violating constraints.
Step 4 If $P_{global} > P_{local}$, update the actual system and the list of open switches by replacing $OS_k \leftrightarrow CS_j$, $P_{global} = P_{local}$ and $exit = 0$. Else $exit = exit + 1$
Step 5 If $exit < N_{tie}$ go to step 2 with next open switch. Else display the results and stop.

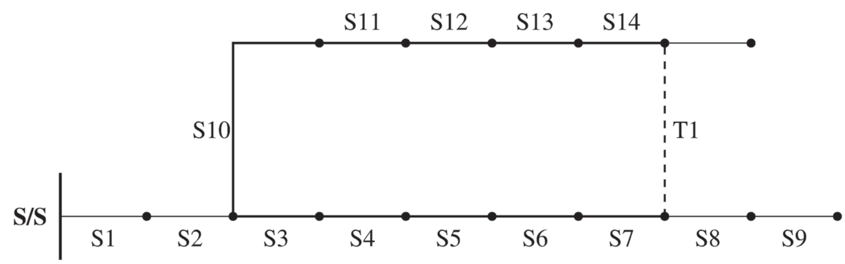

FIGURE 6 Example system

3.4 | Computational procedure

The procedure to calculate total energy loss is explained below. After each reconfiguration operation, a list of open switches is entered into a look-up table, which will be used in the actual operation of DS.

Scenario 1: Run load flow for each hour of the load curve and find the total energy loss in a year using Equation 3. Now, perform reconfiguration at each hour and again find annual energy loss.

Scenario 2: Find out the optimal size and location for solar DG as explained in Section 3.2. The solar power generated in each hour follows the pattern given in Figure 3. Find annual energy loss for both cases, with and without performing reconfiguration.

Scenario 3: Find out the optimal size for wind DG as explained in Section 3.2. The wind power generated in each hour follows the pattern given in Figure 5. Find annual energy loss for both cases, with and without performing reconfiguration.

Scenario 4 and 5: Find out the optimal size and location for DG_1 as explained in Section 3.2. Now, to find the location and size for DG_2 convert the optimal DG obtained previously (DG_1) into a negative load and repeat the process as explained in Section 3.2. Consider DG_1 to be solar based and DG_2 to be wind-based. Find annual energy loss for both cases, ie, with and without performing reconfiguration. Repeat the process considering DG_2 to be solar based and DG_1 to be wind based.

4 | VALIDATION

4.1 | Test system

4.1.1 | 33-Node

The proposed method is examined on a medium scale 12.66 kV, 33-node radial DS.[36] The system has 32 branches and five tie switches as shown in Figure 7. Branch 33 to 37 represent tie branches. The total real and reactive power demand of this system at the peak is 3.715 MW and 2.3 MVAr, respectively. At peak load level, this system has a total real power loss of 202.68 kW without any DG unit. A minimum real power loss of 139.55 kW was obtained at peak load condition through reconfiguration and without any DG unit such that branches 7, 14, 9, 32, and 37 are open. This is in agreement with the results obtained in the previous studies. [30-32]

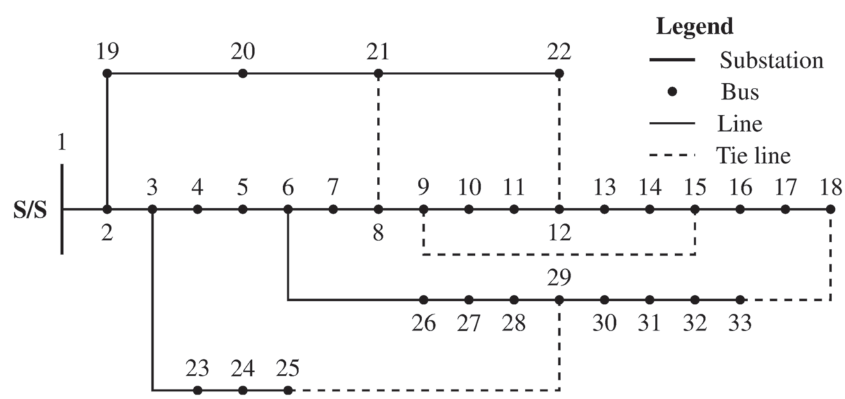

FIGURE 7 33-bus test system line diagram

4.1.2 | 118-Node

The proposed method is also applied on a large scale 11 kV, 118-node radial DS.[83] The system has 117 branches and 15 tie switches. Branch 118 to 132 represent the tie branches. The total real and reactive power demand of this system at the peak is 22.71 MW and 17.04 MVAr, respectively. The results of reconfiguration at peak load condition is given in Table 3

4.2 | DG size

Table 4 shows the optimal location and power injection by the DG unit for the considered systems. The analysis is done assuming a constant power factor for the DG unit. Optimal DG power injection at each node is calculated as shown in Figure 8. For 33-node system, the power loss is minimum (61.58 kW) when a DG power of 2469 kW at 0.8-pf lag is injected at node 6. The panel generation factor of the area as computed using Equation 11 was 3.52, and size of the PV plant is computed using Equation 10. The average energy produced in the summer is highest, ie, $max(E_{day})$=445.52 kWh, and the peak power average power produced by the test system is during summer at 12:00 noon as shown in Figure 3, ie, P^{max}_{test}=65.4 kW; hence, the size of the PV DG unit is $\frac{2469\times 445.52}{3.52\times 65.4}$=4778 kW. Similarly, the size of the wind power plant is computed using Equation 12 at the same location is 4078 kW.

TABLE 3 Reconfigured system at peak load

	Before Reconfiguration		After Reconfiguration		
System	**P_{loss} (kW)**	**V_{min} (pu)**	**P_{loss} (kW)**	**V_{min} (pu)**	**Open Lines**
33-Node	202.68	V_{18}=0.9131	139.55	V_{32}=0.9378	7, 9, 14, 32, 37
118-Node	1296.57	V_{77}=0.8688	853.58	V_{111}=0.9323	23,25,34,39,42, 50,58,71,74,95,97, 109,121,129,130

TABLE 4 Optimal $P_{optimal}$ at peak load

Sys	# of DGs	pf	P_{DG}(node)	Power Loss(kW)
33-node	Single DG	0.7 lag	2124 kW(6)	66.12
		0.8 lag	2469 kW(6)	61.58
		0.9 lag	2751 kW(6)	64.31
		1.0	2575 kW(6)	103.97
	Two DGs	0.7 lag	2124 kW(6), 433 kW(31)	50.64
		0.8 lag	2469 kW(6), 488 kW(31)	46.62
		0.9 lag	2751 kW(6), 512 kW(32)	50.61
		1.0	2575 kW(6), 405 kW(16)	93.44
118-node	Single DG	0.7 lag	2387 kW(71)	933.99
		0.8 lag	2785 kW(71)	919.95
		0.9 lag	3120 kW(71)	922.94
		1.0	2979 kW(71)	1015.24
	Two DGs	0.7 lag	2387 kW(71), 2529 kW(110)	602.20
		0.8 lag	2785 kW(71), 2906 kW(110)	585.67
		0.9 lag	3120 kW(71), 3192 kW(110)	604.60
		1.0	2979 kW(71), 3120 kW(109)	803.73

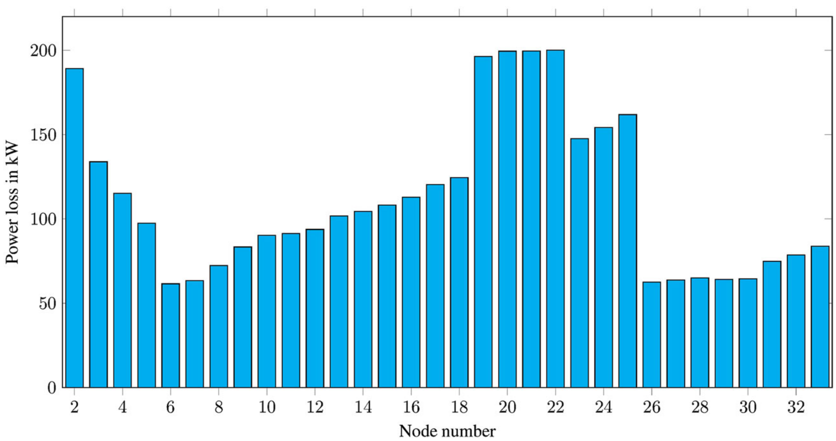

FIGURE 8 Optimal power loss with DG at various nodes (33-node system, 0.8-lag p.f)

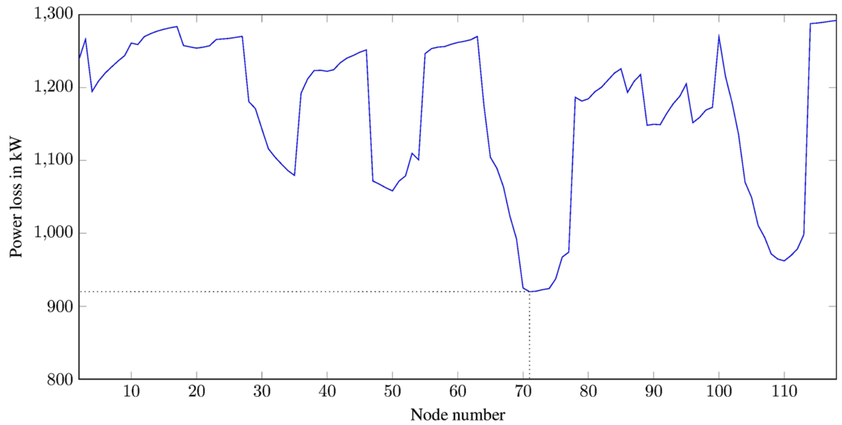

FIGURE 9 Optimal power loss with DG at various nodes (118-node system, 0.8-lag p.f)

For two DG units, the DG power of 2469 kW at node 6 is converted into a negative load. Optimal DG power injection at each node (except node 6) is calculated again. The power loss is minimum when a DG power of 488 kW is injected at node 31. This leads to the size of the solar and wind DG unit at node 31 to be 944 kW and 806 kW, respectively. Similar analysis is carried out for the 118-node system (Figure 9), and the results of DG allocation for different power factors for both the systems are given in Table 4. The optimal power factor for minimum power loss is found to be 0.8 pf lag for all the cases of both the test systems (see Table 4)

4.3 | Cost-benefit analysis

The annual savings (AS) achieved by the proposed method is found by cost-benefit analysis. The earnings are due to the power generated by DG units and energy saved by the reduction of power loss. The expenditures are annual installment to repay capital cost (CC) and operation and maintenance cost. Therefore,

$$AS = aE_{DG} + a(E'_{loss} - E_{loss}) - AI - bE_{DG}, \tag{13}$$

where

$$AI = CRF \times CC, \tag{14}$$

$$CRF = \frac{i(i+1)^N}{(i+1)^N - 1}. \tag{15}$$

E_{DG} is the total annual energy generated by DG in MWh, E'_{loss} is the total annual energy loss without DG and reconfiguration in MWh, E_{loss} is the total annual energy loss with DG and reconfiguration in MWh, a is the cost of energy in \$/MWh, b is the operation and maintenance cost in \$/MWh, AI is annual installment in \$/year, CRF is capital recovery factor, which determines the annual installment for the capital borrowed for N years at the interest rate of i. The life cycle was assumed to be of 20 years and the interest rate to be 10%. The cost of DG units is given in Appendix.[84]

5 | ENERGY LOSS AND SAVINGS

The detailed simulations are carried out for both 33-node and 118-node systems with different power factor DG units for each scenario. However, only the simulation results of the optimal power factor (0.8-pf lag) case are provided for brevity.

5.1 | Scenario 1: Base case (without any DG)

In this case, load flow is carried out at each hour according to seasonal variations of load on weekdays and weekends as shown in Figure 1 and Figure 2, respectively. Annual energy imported from the grid, energy loss, and savings before and after reconfiguration is given in Table 6. From Table 6, it is seen that without DG and without reconfiguration energy imported from the grid is E_{grid}=28 127.83 MWh, and energy loss is E_{loss} = 1229.15 MWh. But without DG and with reconfiguration, E_{grid}=27750.78 MWh and E_{loss}= 852.10 MWh. Hence, annual energy imported from the grid decreases after reconfiguration and percentage of reduction is 1.34%. Similarly, reduction of energy loss after network reconfiguration is (1229.15-852.1)/1229.15 = 30.67%. From Table 6, it is also seen that the net annual saving is \$64 098. This saving is due to network reconfiguration without any DG. However, for the 118-node system, the reduction of energy loss after network reconfiguration is 33.26%.

5.2 | Scenario 2: Single solar DG unit (0.8-pf lag)

For this case, results are presented in Table -7. If the solar PV DG unit is connected at node 6, energy (E_{DG}) supplied by the PV DG unit is 4797.66 MWh, annual energy loss is 896.58 MWh, and annual savings are $392 007 without reconfiguration. When network reconfiguration is carried out with the PV DG unit placed at node 6, annual energy loss is 645.32 MWh, and annual savings is $434 721. Therefore, the reduction of annual energy loss is (896.58-645.32)/896.58 = 28.02%. The annual increase in savings is (434 721-392 007)/392 007 = 10.9%. The reduction in annual energy loss due to reconfiguration for the 118-node system is 30.76%, and the increase in savings is 67.32%.

5.3 | Scenario 3: Single wind DG unit (0.8 pf lag)

For this case, results are presented in Table 8. If a wind DG unit is placed at node 6, annual energy supplied by the wind DG unit is 16948.209 MWh, annual energy loss is 403.08 MWh, and annual savings are $902274 without reconfiguration. If reconfiguration is carried out with a 0.8 pf lag power factor DG unit placed at node 6, annual energy loss is 347.65 MWh. Hence, annual energy loss reduction is equal to (403.08 - 347.65) = 55.43 MWh (ie, 13.75%). For 118-node system, it is 1625.80 MWh (28.74%). The annual savings for the 33-node system is $911696. Therefore, the increase in savings due to network reconfiguration is equal to (911 696-902 274) = $9422 (ie, 1.04%).

5.4 | Scenario 4: Wind DG_1 at first location and solar DG_2 at second location

For this case, results are presented in Table 9. In this scenario, annual energy supplied by PV, and wind DG units is 948.26 MWh and 16 948.21 MWh, respectively. Before reconfiguration, annual energy loss is 353.67 MWh, and yearly savings is $976 978. After reconfiguration, annual energy loss is 307.92 MWh, and annual savings is $984 757. Therefore, reduction of annual energy loss is (353.67-307.92) = 45.75 MWh (ie, 12.94%), and increase in annual savings is (984757 - 976978) = $7779 (ie, 0.8%). The results for 118-node system is given Table 10. The increase in savings due to reconfiguration is $222695 (12.57%).

5.5 | Scenario 5: Solar DG_1 at first location and wind DG_2 at second location

For this case also, results are presented in Table 9. From Table 9, it is seen that annual energy supplied by solar and wind DG units are 4797.66 MWh and 3349.83 MWh, respectively. Before network reconfiguration, annual energy loss is 560.12 MWh, and annual savings is $599 785. After network reconfiguration, annual energy loss is 402.44 MWh, and annual savings is $626 590. Hence, reduction in annual energy loss is (560.12-402.44) = 157.68 MWh (ie, 28.15%), and the increase in annual savings is (626 590-599 785)=$26 805 (ie, 4.47%). As shown in Table 10, the reconfiguration process brought the energy loss from 4983.74 MWh to 3481.90 MWh (30.13% reduction) for the 118-node system.

5.6 | Power loss and peak voltage

Figures 10 and 11 show the effect of reconfiguration on power loss for 33-node system with DG units operating at 0.8 pf lag. Reconfiguring the network leads to a significant reduction in power loss. The curves for scenarios 1 and 2 coincide with each other during night time as solar DG unit cannot provide power at night. Table 5 shows the maximum and minimum voltages before and after reconfiguration. In every scenario, there is an improvement in minimum voltage after reconfiguration. Moreover, the improvement is more significant for the cases with DG units when compared with the base case with no DG units.

5.7 | Discussion

Tables 6 to 10 show the annual savings and annual energy loss achieved by the proposed method. In the case of single DG unit operation, the savings were maximum for the wind power plant at node 6 (scenario 3, Table 8). For two DG cases, scenario 4 resulted in a maximum savings of $984 757 and a minimum energy loss of 307.92 MWh per year. Figure 12 shows the optimal generation curve on weekdays with DG units operating at 0.8 pf for scenario 4. Similarly for 118-node system, scenario 5 was found to be the most economical with a maximum savings of $2 026 186 and a minimum energy loss of 3481.90 MWh per year. Figure 13 shows the optimal generation curve on weekdays with DG units operating at

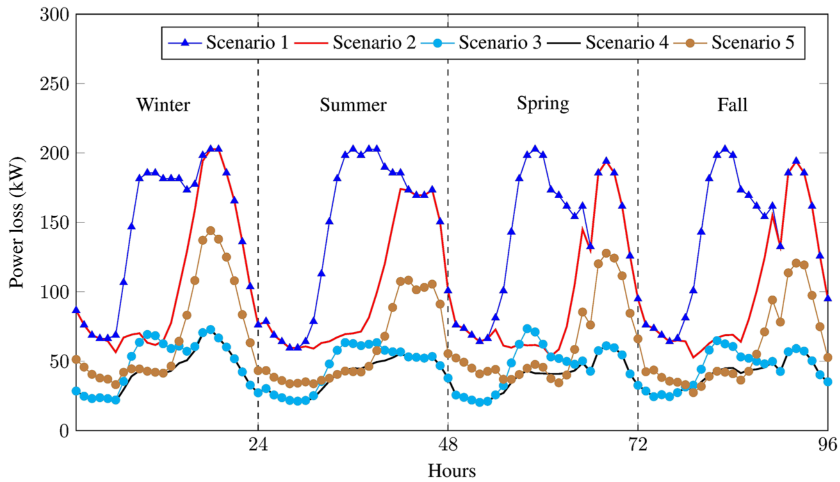

FIGURE 10 Hourly power loss curve on weekdays, without reconfiguration

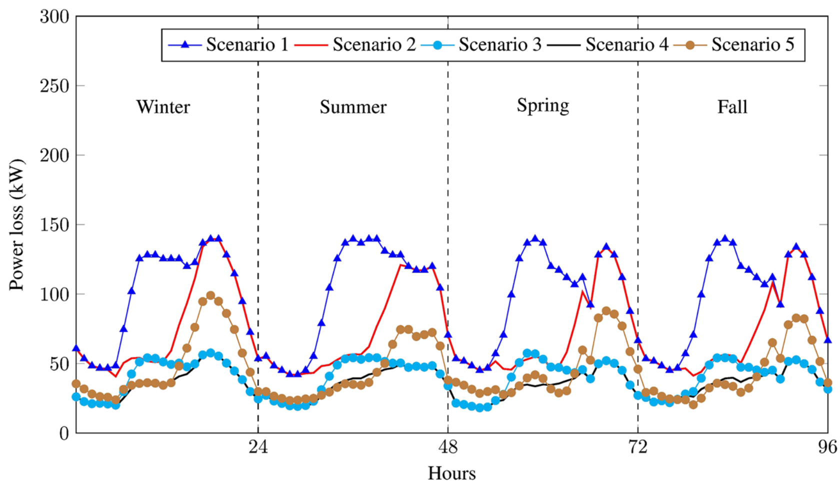

FIGURE 11 Hourly power loss curve on weekdays, after reconfiguration

TABLE 5 Peak voltages (pu) before and after reconfiguration

		Before Reconfiguration		After Reconfiguration	
System	**scenario**	V_{min}	V_{max}	V_{min}	V_{max}
33-Node	1	$V_{18} = 0.9131$	$V_1 = 1.0000$	$V_{32} = 0.9378$	$V_1 = 1.0000$
	2	$V_{18} = 0.9204$	$V_6 = 1.0075$	$V_{32} = 0.9432$	$V_6 = 1.0076$
	3	$V_{18} = 0.9531$	$V_6 = 1.0166$	$V_{32} = 0.9696$	$V_6 = 1.0104$
	4	$V_{18} = 0.9531$	$V_6 = 1.0166$	$V_{32} = 0.9696$	$V_6 = 1.0104$
	5	$V_{18} = 0.9286$	$V_6 = 1.0147$	$V_{18} = 0.9574$	$V_6 = 1.0092$
118-Node	1	$V_{77} = 0.8688$	$V_1 = 1.0000$	$V_{111} = 0.9323$	$V_1 = 1.0000$
	2	$V_{77} = 0.8810$	$V_{71} = 1.0105$	$V_{111} = 0.9323$	$V_1 = 1.0000$
	3	$V_{111} = 0.9053$	$V_{71} = 1.0292$	$V_{111} = 0.9323$	$V_{71} = 1.0054$
	4	$V_{54} = 0.9117$	$V_{71} = 1.0292$	$V_{111} = 0.9389$	$V_{71} = 1.0054$
	5	$V_{77} = 0.8810$	$V_{110} = 1.0250$	$V_{74} = 0.9416$	$V_{110} = 1.0025$

TABLE 6 Annual savings for base case (scenario 1, no DG)

	Without Reconfiguration			Reconfiguration		
System	E_{grid}**(MWh)**	E_{loss}**(MWh)**	**Savings ($)**	E_{grid}**(MWh)**	E_{loss}**(MWh)**	**Savings ($)**
33-Node	28127.83	1229.15	0	27750.78	852.10	64098
118-Node	173627.47	7900.12	0	171000.08	5272.72	446658

0.8 pf for scenario 5. Hourly generation curves of DG units and grid plotted in Figure 12 and Figure 13 follow the hourly load demand curve in Figure 1 as total power generated should balance the total load and losses. Annual saving due to wind DG unit is more because it operates all the time, but solar DG unit only works in the daytime.

As reconfiguration is carried out in every hour, therefore it is not possible to present reconfiguration networks at every hour. Opening branches and closing branches are the same for the 33-node system at all hours without any DG unit.

TABLE 7 Annual savings for a single PV DG (scenario 2)

System	DG Size	E_{DG}(MWh)	Without Reconfiguration			Reconfiguration		
			E_{grid}(MWh)	E_{loss}(MWh)	Savings ($)	E_{grid}(MWh)	E_{loss}(MWh)	Savings ($)
33-Node	4778 kW (6)	4797.66	23005.33	896.58	392007	22754.07	645.32	434721
118-Node	5390 kW(71)	5411.70	166016.34	6949.71	539948	163878.23	4811.60	903427

TABLE 8 Annual savings for a single wind DG (scenario 3)

System	DG size	E_{DG}(MWh)	Without Reconfiguration			Reconfiguration		
			E_{grid}(MWh)	E_{loss}(MWh)	Savings ($)	E_{grid}(MWh)	E_{loss}(MWh)	Savings ($)
33-Node	4078 kW(6)	16948.21	10361.27	403.08	902274	10305.85	347.65	911696
118-Node	4600 kW(71)	19117.36	151017.08	5656.12	1240827	149391.29	4030.32	1517213

TABLE 9 Annual savings for two DGs (33-node system)

Scenario	DG size		E_{PV} (MWh)	E_{Wind} (MWh)	No Reconfiguration			Reconfiguration		
	Wind	PV			E_{grid} (MWh)	E_{loss} (MWh)	Savings ($)	E_{grid} (MWh)	E_{loss} (MWh)	Savings ($)
4	4078 kW(6)	944 kW(31)	948.26	16 948.21	9363.61	353.67	976 978	9317.85	307.92	984 757
5	806 kW(31)	4778 kW (6)	4797.66	3349.83	19 319.03	560.12	599785	19 161.36	402.44	626 590

TABLE 10 Annual savings for two DGs (118-node system)

Scenario	DG Size		E_{PV} (MWh)	E_{Wind} (MWh)	No Reconfiguration			Reconfiguration		
	Wind	PV			E_{grid} (MWh)	E_{loss} (MWh)	Savings ($)	E_{grid} (MWh)	E_{loss} (MWh)	Savings ($)
4	4600 kW (71)	5624 kW (110)	5646.82	19 117.36	144 571.52	4857.38	1 771 460	143 261.50	3547.41	1 994 155
5	4800 kW(110)	5390 kW (71)	5411.70	19 947.95	144 102.41	4983.74	1 770 874	142 600.54	3481.90	2 026 186

Figure 14 shows the reconfigured network without any DG; it is identical at every hour. But with DG units, opening and closing branches are not the same. However, for the 118-node system, the reconfigured network is not the same for every hour even for scenario 1. The list of open switches after reconfiguration for scenario 1 is 23, 25, 34, 39, 42, 50, (61 or 58), 71, (73 or 74), (76 or 95), (82 or 97), 109, 121, (125 or 129), and 130. The proposed method was able to reduce the annual energy loss by 74.95% for the 33-node system (scenario 4) and 55.93% for the 118-node system (scenario 5), thus achieving its objective.

5.8 | Practical aspects

This work proposes to minimize energy loss through renewable DG and reconfiguration. The line losses at the distribution level are usually borne by the distribution company (DISCOM). Hence, the DISCOM has a strong incentive to minimize the losses. However, the government-owned, cash-starved, loss-making distribution company (which is the case for most of the developing world) may not show interest in the installation of DG units because of the costs associated with it whereas a private for-profit company may show interest. Even then the DISCOM is bound to provide quality power to the customers with voltage limits as per the regulations. The DISCOM may show interest in implementing network reconfiguration, which does not cost as much as DG unit installation but provides good voltage profile improvements as shown in Table 5.

Many simplifying assumptions are made during the analysis, which may not hold while implementing for a practical system. Each branch section is assumed to have a sectionalizing switch with remote or manual control. The cost of switching is neglected in this study. Whereas in a practical system, there may be a few remotely controlled switches (RCS) as they incur a significant cost for installation. However, there is a natural tendency to incorporate RCSs and smart meters to encourage demand response and local DG. Special incentive mechanisms and government policies triggered by fear of climate change are expected to accelerate the modernization of the distribution network into a smart grid with communication infrastructure. Hence, switching cost is likely to reduce in the future as other factors are also driving the installation of RCS. Moreover, in developing countries, manual switching may be more economical compared with RCS owing to the cheap labor cost. The optimal allocation of RCS for maximum economic benefits is discussed in the previous studies.[85,86]

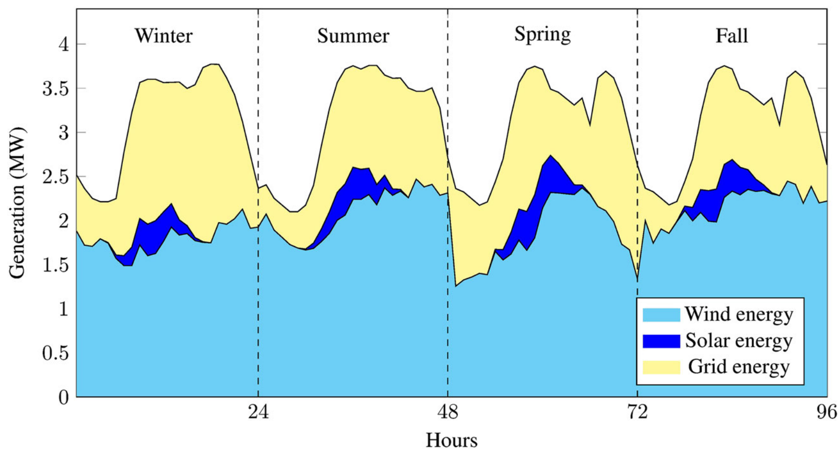

FIGURE 12 Optimal generation curve on weekdays with 2 DGs (33-node system, 0.8 lag)

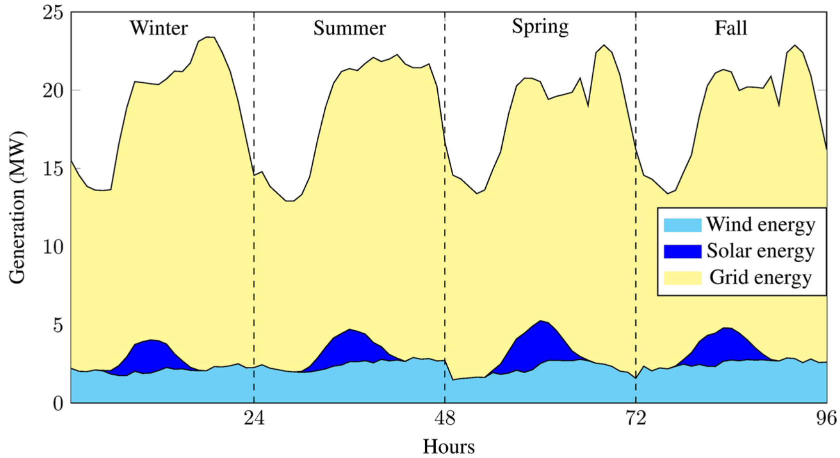

FIGURE 13 Optimal generation curve on weekdays with 2 DGs (33-node system, 0.8 lag)

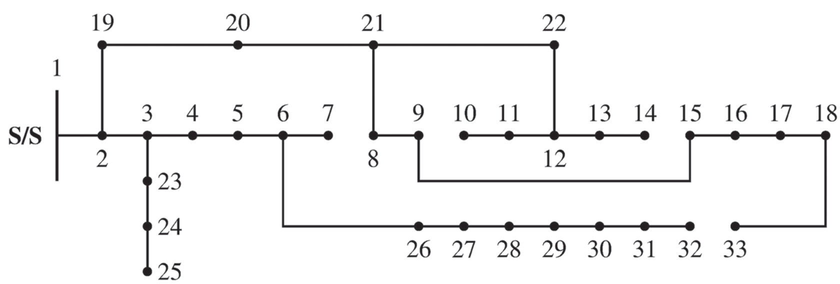

FIGURE 14 Reconfigured network for scenario 1 (peak load)

The implementation of the proposed method should be preceded by a detailed protection analysis as the introduction of DG alters the short circuit level around the point of coupling. The protective relay parameters must be redesigned to account for the effect of DG and reconfiguration. A suitable mechanism must be there to isolate the DG unit from the network in the event of any fault. The systems considered cannot operate independently of the grid as there is no dispatchable DG unit to control the frequency. However, the energy storage system can be introduced to control the frequency when the grid is unavailable.

We had assumed a simplified per kW cost for installation of DG units as shown in Table 11. However, while implementing one has to consider all the costs including planning cost, cost of land, equipment (PV modules or wind turbine) cost, power converter cost, transportation cost, wiring cost, SCADA system and communication infrastructure cost, labor cost for installation, government or license fees (if any), etc. Moreover, the DG unit installation at the optimal location may be infeasible because of unavailability of land, government regulation, noise, aesthetics, etc. Proper risk analysis should be performed to safeguard the investors, for example, a consequent fall in the grid electricity price would adversely affect the earnings in the future. Such risk factors should be identified and hedged.

TABLE 11 Cost of DG units

Type of DG	Capital Cost ($/kW)	Operation and Maintenance Costs ($/MWh)
Solar photovoltaic	770	10
Wind	4000	12

6 | CONCLUSIONS

In this paper, a method has been proposed to minimize annual energy loss by incorporating renewable DG units and reconfiguration. The DG plant size and location have been determined using the optimal power injection, which minimizes the power loss at peak load. The DS is reconfigured at every hour considering varying demand and renewable DG units. The proposed method has been examined on a medium size 33-node network and a large scale 118-node network for various scenarios with multiple DG units and power factors. Cost-benefit analysis has been compared for different scenarios. The study reveals that for single DG unit operation, savings is maximum for a wind DG power plant at node 6 (node 71 for the 118-node system) (scenario 3). For two DG case, the wind power plant at node 6 and PV power plant at node 16 (scenario 4) give maximum savings (scenario 5 for the 118-node system). The analysis also reveals that the hourly switching pattern for network reconfiguration is the same without any DG for the 33-node system only. However, these hourly switching pattern is not the same after network reconfiguration with DG units. It was also found that there is a significant improvement of the voltage profile for all the scenarios with DG after reconfiguration.

LIST OF SYMBOLS AND ABBREVIATIONS

α_{PV} temperature coefficient of PV panels
η_{inv} efficiency of the power converter of the solar DG unit
η_{PV} efficiency of the PV panels
a cost of energy in $/MWh
AI annual installment in $/year
AS annual savings in $
b operation and maintenance cost in $/MWh
CC capital cost in $
CRF capital recovery factor
$CS_j j^{th}$ closed switch
E_{day} solar energy produced in a representative day of a season in kWh
E_{DG} energy supplied by DG unit in a year in MWh
E_{loss} total annual energy loss with DG and reconfiguration in MWh
E'_{loss} total annual energy loss without DG and reconfiguration in MWh
f_{PV} derating factor for PV panels
i interest rate at which capital cost is borrowed
I^{st} rated solar insolation of PV panels
I_k^{max} maximum current limit of k^{th} branch
I_k magnitude of current in k^{th} branch
N life cycle of DG units in years
N_{br} number of branches in the DS
N_{node} number of nodes in the DS
N_{tie} number of tie switches in the DS
N_{weak} number of weeks in a season
$OS_k k^{th}$ open switch
P_w peak power generated by the wind turbine
P_{global} global minimum power loss in kW
P_{local} local minimum power loss when when a particular tie switch is opened
P_{loss}^{wd} power loss on weekdays
P_{loss}^{we} power loss on weekends

$P_{optimal}$ optimal DG power injection which minimizes power loss in kW
P_{PV}^{max} size of PV DG unit in kW
P_{wind}^{max} size of wind DG unit in kW
PGF panel generation factor
R_k resistance of the k^{th} branch
S Total area of PV panels
T_C^{st} rated cell temperature of PV panels
V_{c-in} cut-in wind speed
V_{c-out} cut-out wind speed
V_{min}, V_{max} minimum and maximum voltage limits in p.u.
$V_{w,rated}$ rated wind speed

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REFERENCES

1. The Guardian. India to ratify Paris climate change agreement at UN. https://www.theguardian.com/environment/2016/oct/02/india-paris-climate-change-agreement-un-narendra-modi; 2016.
2. Central Electricity Authority. Executive Summary: Power Sector. http://cea.nic.in/reports/monthly/executivesummary/2015/exe_summary-08.pdf; 2015.
3. Kavousi-Fard A, Akbari-Zadeh M-R. Reliability enhancement using optimal distribution feeder reconfiguration. *Neurocomputing*. 2013;106:1-11.
4. Su S-Y, Lu C-N, Chang R-F, Gutierrez-Alcaraz G. Distributed generation interconnection planning: a wind power case study. *IEEE Trans Smart Grid*. 2011;2:181-189.
5. Lueken C, Carvalho PMS, Apt J. Distribution grid reconfiguration reduces power losses and helps integrate renewables. *Energy Policy*. 2012;48:260-273.
6. Zidan A, Shaaban MF, El-Saadany EF. Long-term multi-objective distribution network planning by DG allocation and feeders' reconfiguration. *Electr Pow Syst Res*. 2013;105:95-104.
7. Acharya N, Mahat P, Mithulananthan N. An analytical approach for DG allocation in primary distribution network. *Int J Electr Power Energy Syst*. 2006;28:669-678.
8. Mahmoud K, Yorino N, Ahmed A. Optimal distributed generation allocation in distribution systems for loss minimization. *IEEE Trans Power Syst*. 2016;31:960-969.
9. Quoc HD, Nadarajah M. Multiple distributed generator placement in primary distribution networks for loss reduction. *IEEE Trans Ind Electron*. 2013;60:1700-1708.
10. Hung DQ, Mithulananthan N, Lee KY. Optimal placement of dispatchable and nondispatchable renewable DG units in distribution networks for minimizing energy loss. *Int J Electr Power Energy Syst*. 2014;55:179-186.
11. Rajkumar V, Khatod DK. An analytical approach for sizing and siting of DGs in balanced radial distribution networks for loss minimization. *Int J Electr Power Energy Syst*. 2015;67:191-201.
12. Ochoa LF, Harrison GP. Minimizing energy losses: optimal accommodation and smart operation of renewable distributed generation. *IEEE Trans Power Syst*. 2011;26:198-205.
13. Masteri K, Venkatesh B. Real-time smart distribution system reconfiguration using complementarity. *Electr Power Syst Res*. 2016;134:97-104.
14. El-Hawary FS, Abu-Mouti ME. Heuristic curve-fitted technique for distributed generation optimisation in radial distribution feeder systems. *IET Gener Transm Distrib*. 2011;5:172-180.
15. Mohamed IA, Kowsalya M, Kothari DP. A novel integration technique for optimal network reconfiguration and distributed generation placement in power distribution networks. *Int J Electr Power Energy Syst*. 2014;63:461-472.
16. Wu Y-K, Lee C-Y, Liu L-C, Tsai S-H. Study of reconfiguration for the distribution system with distributed generators. *IEEE Trans Power Delivery*. 2010;25:1678-1685.
17. Srinivasa Rao R, Ravindra K, Satish K, Narasimham SVL. Power loss minimization in distribution system using network reconfiguration in the presence of distributed generation. *IEEE Trans Power Syst*. 2013;28:317-325.
18. Kumar SK, Jayabarathi T. Power system reconfiguration and loss minimization for an distribution systems using bacterial foraging optimization algorithm. *Int J Electr Power Energy Syst*. 2012;36:13-17.
19. Sfikas EE, Katsigiannis YA, Georgilakis PS. Simultaneous capacity optimization of distributed generation and storage in medium voltage microgrids. *Int J Electr Power Energy Syst*. 2015;67:101-113.
20. El-Fergany A. Optimal allocation of multi-type distributed generators using backtracking search optimization algorithm. *Int J Electr Power Energy Syst*. 2015;64:1197-1205.

21. Al Abri RS, El-Saadany EF, Atwa YM. Optimal placement and sizing method to improve the voltage stability margin in a distribution system using distributed generation. *IEEE Trans Power Syst*. 2013;28:326-334.
22. Abu-Mouti FS, El-Hawary ME. Optimal distributed generation allocation and sizing in distribution systems via artificial bee colony algorithm. *IEEE Trans Power Delivery*. 2011;26:2090-2101.
23. García JAM, Mena AJG. Optimal distributed generation location and size using a modified teaching-learning based optimization algorithm. *Int J Electr Power Energy Syst*. 2013;50:65-75.
24. Kaur S, Kumbhar G, Sharma J. A MINLP technique for optimal placement of multiple DG units in distribution systems. *Int J Electr Power Energy Syst*. 2014;63:609-617.
25. Majid J, Sharique AA. Optimal sizing and location of SPV (solar photovoltaic) based MLDG (multiple location distributed generator) in distribution system for loss reduction, voltage profile improvement with economical benefits. *Energy*. 2016;103:231-239.
26. Sultana U, Khairuddin AB, Mokhtar AS, Zareen N, Sultana B. Grey wolf optimizer based placement and sizing of multiple distributed generation in the distribution system. *Energy*. 2016;111:525-536.
27. Sanjay R, Jayabarathi T, Raghunathan T, Ramesh V, Mithulananthan N. Optimal Allocation of Distributed Generation Using Hybrid Grey Wolf Optimizer. *IEEE Access*. 2017;5:14807-14818.
28. Vatani M, Alkaran DS, Sanjari MJ, Gharehpetian GB. Multiple distributed generation units allocation in distribution network for loss reduction based on a combination of analytical and genetic algorithm methods. *IET Gener Transm Distrib*. 2016;10:66-72.
29. Kansal S, Kumar V, Tyagi B. Hybrid approach for optimal placement of multiple DGs of multiple types in distribution networks. *Int J Electr Power Energy Syst*. 2016;75:226-235.
30. Gupta N, Swarnkar A, Niazi KR. Reconfiguration of distribution systems for real power loss minimization using adaptive particle swarm optimization. *Electr Power Compon Syst*. 2011;39:317-330.
31. Romero-Ramos E, Riquelme-Santos J, Reyes J. A simpler and exact mathematical model for the computation of the minimal power losses tree. *Electr Power Syst Res*. 2010;80:562-571.
32. Niknam T. An efficient hybrid evolutionary algorithm based on PSO and HBMO algorithms for multi-objective Distribution Feeder Reconfiguration. *Energy Conversion and Management*. 2009;50:2074-2082.
33. Niknam T, Fard AK, Seifi A. Distribution feeder reconfiguration considering fuel cell/wind/photovoltaic power plants. *Renew Energy*. 2012;37:213-225.
34. Shariatkhah MH, Haghifam MR. Using feeder reconfiguration for congestion management of smart distribution network with high DG penetration. In: CIRED 2012 Workshop: Integration of Renewables into the Distribution Grid. Lisbon, Portugal; 2012:1-4.
35. Tomoiagă B, Chindriş M, Sumper A, Villafafila-Robles R, Sudria-Andreu A. Distribution system reconfiguration using genetic algorithm based on connected graphs. *Electr Power Syst Res*. 2013;104:216-225.
36. Baran Mesut E, Wu Felix F. Network reconfiguration in distribution systems for loss reduction and load balancing. *IEEE Trans Power Delivery*. 1989;4:1401-1407.
37. Fan J-Y, Zhang L, McDonald JD. Distribution network reconfiguration: single loop optimization. *IEEE Trans Power Syst*. 1996;11:1643-1647.
38. Das D. A fuzzy multiobjective approach for network reconfiguration of distribution systems. *IEEE Trans Power Delivery*. 2006;21:202-209.
39. Syahputra R, Robandi I, Ashari M. Reconfiguration of distribution network with DG using fuzzy multi-objective method. In: 2012 International Conference on Innovation Management and Technology Research. Malacca, Malaysia; 2012:316-321.
40. Dorostkar-Ghamsari MR, Fotuhi-Firuzabad M, Lehtonen M, Safdarian A. Value of distribution network reconfiguration in presence of renewable energy resources. *IEEE Trans Power Syst*. 2016;31:1879-1888.
41. Bayat A. Uniform voltage distribution based constructive algorithm for optimal reconfiguration of electric distribution networks. *Electr Pow Syst Res*. 2013;104:146-155.
42. Kirthiga MV, Daniel SA, Gurunathan S. A methodology for transforming an existing distribution network into a sustainable autonomous micro-grid. *IEEE Trans Sustainable Energy*. 2013;4:31-41.
43. Olamaei J, Niknam T, Gharehpetian G. Application of particle swarm optimization for distribution feeder reconfiguration considering distributed generators. *Appl Math Comput*. 2008;201:575-586.
44. Franco JF, Rider MJ, Lavorato M, Romero R. A mixed-integer LP model for the reconfiguration of radial electric distribution systems considering distributed generation. *Electr Pow Syst Res*. 2013;97:51-60.
45. Aboelsood Z, El-Saadany EF. Distribution system reconfiguration for energy loss reduction considering the variability of load and local renewable generation. *Energy*. 2013;59:698-707.
46. Nasiraghdam H, Jadid S. Optimal hybrid PV/WT/FC sizing and distribution system reconfiguration using multi-objective artificial bee colony (MOABC) algorithm. *Solar Energy*. 2012;86:3057-3071.
47. Guan W, Tan Y, Zhang H, Song J. Distribution system feeder reconfiguration considering different model of DG sources. *Int J Electr Power Energy Syst*. 2015;68:210-221.
48. Bernardon DP, Mello APC, Pfitscher LL, Canha LN, Abaide AR, Ferreira AAB. Real-time reconfiguration of distribution network with distributed generation. *Electr Pow Syst Res*. 2014;107:59-67.
49. Pfitscher LL, Bernardon DP, Canha LN, Montagner VF, Garcia VJ, Abaide AR. Intelligent system for automatic reconfiguration of distribution network in real time. *Electr Pow Syst Res*. 2013;97:84-92.
50. Arash L, Hossein A. A discrete Teaching–Learning-Based Optimization algorithm to solve distribution system reconfiguration in presence of distributed generation. *Int J Electr Power Energy Syst*. 2016;82:264-273.

51. Alemohammad SH, Mashhour E, Saniei M. A market-based method for reconfiguration of distribution network. *Electr Pow Syst Res*. 2015;125:15-22.
52. Sattarpour T, Nazarpour D, Golshannavaz S, Siano P. An optimal procedure for sizing and siting of DGs and smart meters in active distribution networks considering loss reduction. *J Electr Eng Technol*. 2015;10:804-811.
53. Sattarpour T, Nazarpour D, Golshannavaz S, Siano P. A multi-objective hybrid GA and TOPSIS approach for sizing and siting of DG and RTU in smart distribution grids. *J Ambient Intell Humaniz Comput*. 2018;9:105-122.
54. Nie S, Fu X, Li P, et al. Analysis of the impact of DG on distribution network reconfiguration using OpenDSS. In: IEEE PES Innovative Smart Grid Technologies; 2012; Tianjin, China:1-5.
55. Souza SS, Romero R, Pereira J, Saraiva JT. Artificial immune algorithm applied to distribution system reconfiguration with variable demand. *Int J Electr Power Energy Syst*. 2016;82:561-568.
56. Souza SS, Romero R, Franco JF. Artificial immune networks Copt-aiNet and Opt-aiNet applied to the reconfiguration problem of radial electrical distribution systems. *Electr Pow Syst Res*. 2015;119:304-312.
57. Tan S, Xu JX, Panda SK. Optimization of distribution network incorporating distributed generators: an integrated approach. *IEEE Trans Power Syst*. 2013;28:2421-2432.
58. Rajaram R, Kumar KS, Rajasekar N. Power system reconfiguration in a radial distribution network for reducing losses and to improve voltage profile using modified plant growth simulation algorithm with Distributed Generation (DG). *Energy Reports*. 2015;1:116-122.
59. Gutiérrez-Alcaraz G, Galván E, González-Cabrera N, Javadi MS. Renewable energy resources short-term scheduling and dynamic network reconfiguration for sustainable energy consumption. *Renew Sustain Energy Rev*. 2015;52:256-264.
60. Zarei M, Zangeneh A. Multi-objective optimization model for distribution network reconfiguration in the presence of distributed generations. *Int Trans Electr Energy Systems*. 2017;27:e2425.
61. Abdelaziz M. Distribution network reconfiguration using a genetic algorithm with varying population size. *Electr Pow Syst Res*. 2017;142:9-11.
62. Chidanandappa R, Ananthapadmanabha T, Ranjith HC. Genetic algorithm based network reconfiguration in distribution systems with multiple dgs for time varying loads. *Procedia Technol*. 2015;21:460-467.
63. Duan D-L, Ling X-D, Wu X-Y, Zhong B. Reconfiguration of distribution network for loss reduction and reliability improvement based on an enhanced genetic algorithm. *Int J Electr Power Energy Syst*. 2015;64:88-95.
64. Nguyen TT, Nguyen TT, Truong AV, Nguyen QT, Phung TA. Multi-objective electric distribution network reconfiguration solution using runner-root algorithm. *Appl Soft Comput*. 2017;52:93-108.
65. Safavi V, Vahidi B, Abedi M. Optimal DG placement and sizing in distribution network with reconfiguration. *Sci Int*. 2014;26:1071-1077.
66. Rao RS, Narasimham SVL, Ramalingaraju M. Optimization of distribution network configuration for loss reduction using artificial bee colony algorithm. *Int J Elect Pow Energy Syst Eng*. 2008;1:116-122.
67. Jamian JJ, Dahalan WM, Mokhlis H, Mustafa MW, Lim ZJ, Abdullah MN. Power losses reduction via simultaneous optimal distributed generation output and reconfiguration using ABC optimization. *J Electr Eng Technol*. 2014;9:1229-1239.
68. Muthukumar K, Jayalalitha S. Integrated approach of network reconfiguration with distributed generation and shunt capacitors placement for power loss minimization in radial distribution networks. *Appl Soft Comput*. 2017;52:1262-1284.
69. de Oliveira LW, Seta FDS, de Oliveira EJ. Optimal reconfiguration of distribution systems with representation of uncertainties through interval analysis. *Int J Electr Power Energy Syst*. 2016;83:382-391.
70. Santos Sérgio F, Fitiwi DZ, Cruz MR, Cabrita CM, Catalão JP. Impacts of optimal energy storage deployment and network reconfiguration on renewable integration level in distribution systems. *Appl Energy*. 2017;185:44-55.
71. Ameli A, Ahmadifar A, Shariatkhah MH, Vakilian M, Haghifam MR. A dynamic method for feeder reconfiguration and capacitor switching in smart distribution systems. *Int J Electr Power Energy Syst*. 2017;85:200-211.
72. Ramaswamy PC, Tant J, Pillai JR, Deconinck G. Novel methodology for optimal reconfiguration of distribution networks with distributed energy resources. *Electr Pow Syst Res*. 2015;127:165-176.
73. Abbasi F, Hosseini SM. Optimal DG allocation and sizing in presence of storage systems considering network configuration effects in distribution systems. *IET Gener Transm Distrib*. 2016;10:617-624.
74. Prasad K, Ranjan R, Sahoo NC, Chaturvedi A. Optimal reconfiguration of radial distribution systems using a fuzzy mutated genetic algorithm. *IEEE Trans Power Delivery*. 2005;20:1211-1213.
75. Hemdan NG, Deppe B, Pielke M, Kurrat M, Schmedes T, Wieben E. Optimal reconfiguration of radial MV networks with load profiles in the presence of renewable energy based decentralized generation. *Electr Pow Syst Res*. 2014;116:355-366.
76. Khodr HM, Martínez-Crespo J, Vale ZA, Ramos C. Optimal methodology for distribution systems reconfiguration based on OPF and solved by decomposition technique. *Eur Trans Electr Power*. 2010;20:730-746.
77. Mohd Dahalan W, Mokhlis H, Ahmad R, Abu Bakar AH, Musirin I. Simultaneous network reconfiguration and DG using EP method. *Int Trans Elect Energy Syst*. 2015;25:2577-2594.
78. Grigg C, Wong P, Albrecht P, et al. The IEEE reliability test system-1996. A report prepared by the reliability test system task force of the application of probability methods subcommittee. *IEEE Trans Power Syst*. 1999;14:1010-1020.
79. IIT Kharagpur. Energy System Lab Manual. http://ee.iitkgp.ac.in/TeachingLabs/EnergySys/solar_pv_plant.pdf; 2016.
80. Abedini M, Moradi MH, Hosseinian SM. Optimal management of microgrids including renewable energy scources using GPSO-GM algorithm. *Renew Energy*. 2016;90:430-439.
81. Emergya Wind Technologies. High Yield 500 kW Direct Drive Wind Turbine. https://ewtdirectwind.com/products/dw54/; 2018.

82. Barik S, Das D. Determining the sizes of renewable DGs considering seasonal variation of generation and load and their impact on system load growth. *IET Renew Power Gener*. 2018;12:1101-1110.
83. Zhang D, Fu Z, Zhang L. An improved TS algorithm for loss-minimum reconfiguration in large-scale distribution systems. *Electr Pow Syst Res*. 2007;77:685-694.
84. Gampa SR, Das D. Optimum placement and sizing of DGs considering average hourly variations of load. *Int J Electr Power Energy Syst*. 2015;66:25-40.
85. Ghofrani-Jahromi Z, Kazemi M, Ehsan M. Distribution switches upgrade for loss reduction and reliability improvement. *IEEE Trans Power Delivery*. 2015;30:684-692.
86. Li Z, Jazebi S, de León F. Determination of the optimal switching frequency for distribution system reconfiguration. *IEEE Trans Power Delivery*. 2017;32:2060-2069.

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APPENDIX A

TABLE A1 Seasonal solar and wind generation data in per unit[79]

Hour	Winter		Summer		Spring		Fall	
	Solar	Wind	Solar	Wind	Solar	Wind	Solar	Wind
1	0.0000	0.7611	0.0000	0.8399	0.0000	0.5086	0.0000	0.8091
2	0.0000	0.6968	0.0000	0.7663	0.0000	0.5372	0.0000	0.7063
3	0.0000	0.6915	0.0000	0.7332	0.0000	0.5503	0.0000	0.7710
4	0.0000	0.7258	0.0000	0.6996	0.0000	0.5673	0.0000	0.7510
5	0.0118	0.7061	0.0000	0.6838	0.0009	0.5614	0.0087	0.8049
6	0.0804	0.6359	0.0222	0.6748	0.0493	0.6679	0.1036	0.8554
7	0.2294	0.6031	0.1239	0.6822	0.2390	0.6294	0.3111	0.8086
8	0.4304	0.6032	0.2939	0.7134	0.5005	0.6564	0.5277	0.8473
9	0.6137	0.6977	0.4966	0.7509	0.7206	0.7198	0.7101	0.8069
10	0.7317	0.6487	0.6480	0.8113	0.9012	0.6734	0.7653	0.8034
11	0.7606	0.6588	0.7250	0.8350	1.0000	0.7304	0.7651	0.9166
12	0.6834	0.7142	0.7449	0.9074	0.9837	0.8675	0.7318	0.9451
13	0.5390	0.7803	0.6990	0.9070	0.8628	0.9387	0.6383	0.9283
14	0.3536	0.7434	0.6120	0.9291	0.6921	0.9364	0.4575	0.9530
15	0.1833	0.7501	0.4687	0.8821	0.4601	0.9326	0.2836	0.9435
16	0.0702	0.7177	0.2929	0.9598	0.2242	0.9294	0.1270	0.9480
17	0.0138	0.7099	0.1472	0.9259	0.0665	0.9600	0.0257	0.9326
18	0.0002	0.7075	0.0416	0.9447	0.0114	0.9303	0.0004	0.9245
19	0.0000	0.8002	0.0017	0.9147	0.0000	0.8739	0.0000	0.9908
20	0.0000	0.7931	0.0000	1.0000	0.0000	0.8546	0.0000	0.9762
21	0.0000	0.8182	0.0000	0.9645	0.0000	0.8048	0.0000	0.8890
22	0.0000	0.8621	0.0000	0.9758	0.0000	0.7013	0.0000	0.9665
23	0.0000	0.7744	0.0000	0.9259	0.0000	0.6757	0.0000	0.8908
24	0.0000	0.7799	0.0000	0.9367	0.0000	0.5423	0.0000	0.8991