Network Reconfiguration of Distribution System with Distributed Generation, Shunt Capacitors and Electric Vehicle Charging Stations

Surender Reddy Salkuti

Abstract This chapter presents a heuristic-based technique for solving the optimal network reconfiguration (ONR) in a radial distribution system (RDS) using the fuzzy-based multi-objective methodology. Minimization of real power losses and deviation of nodes voltage is considered as the multiple objectives in this work and they are modeled with fuzzy sets. The developed algorithm determines the optimal reconfiguration of feeders with the minimum number of tie-line switch operations. This work focuses on different combinations of ONR along with renewable-based distributed generation (DG) units, shunt capacitors, and electric vehicle charging stations (EVCSs). The load flow analysis implemented in this chapter is based on an iterative approach of the receiving end voltage of RDS. The effectiveness of the proposed heuristic-based methodology has been implemented on the IEEE 69 bus RDS.

Keywords Network reconfiguration · Distributed generation · Power loss · Voltage stability · Distribution system load flow · Radial distribution system · Shunt capacitors · Electric vehicles

Nomenclature

NR	Network reconfiguration
DG	Distributed generation
DSLF	Distribution system load flow
RDS	Radial distribution system
EVs	Electric vehicles
DERs	Distributed energy resources
PEVs	Plugin electric vehicles

S. R. Salkuti (✉)
Department of Railroad and Electrical Engineering, Woosong University, 171 Dongdaejeon-ro (155-3 Jayang-dong), Dong-gu, Daejeon 34606, Republic of Korea
e-mail: surender@wsu.ac.kr

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BFS	Backward forward sweep
LIM	Load impedance matrix
OFR	Optimal feeder reconfiguration
ONR	Optimal network reconfiguration
N_{EV}^{c}, N_{EV}^{d}	Number of EVs charging and discharging
P_{G2V}, P_{V2G}	Active powers from vehicle-to-grid and grid-to-vehicle
η_c, η_d	Charging and discharging efficiencies
R_c, R_d	Charging and discharging rates
N_{tie}	Number of tie-line switches

1 Introduction

The distribution system plays a crucial role among the other components of the electrical power system that is generation and transmission. The power system is becoming more and more complex with the increasing demand. In developing countries, power generation is usually insufficient to meet the increasing load demand. Therefore, it is necessary to reduce the total losses in the network of which the major part is contributed by the distribution system. The power industry is adopting deregulation to obtain the economic efficiency of power system operation. In the deregulated scenario, both generation and distribution companies are dedicated to their function [1], which avoids the monopoly and creates a competitive market environment between them. This forces the power utilities to fulfill the energy demand of the consumers at a reasonable cost.

Recently the electric vehicles (EVs) have gained importance due to the increasing air pollution, climate change, and increased oil prices. Distributed energy resources (DERs) such as EVs and distributed generation (DG) are growing as an opportunity to decarbonize the energy system. The necessity of EVs is very clear with their great potential to electrify the transportation sector [2]. The renewable-based DG sources create uncertainty in the power distribution system. At the same time, they also pose new technical challenges to the power system, which can be addressed with increased flexibility. For better utilization of electrical energy, the optimization of both distribution system operation and control becomes necessary. This can be achieved through the automation of the distribution system. One of the methods adopted is the remote control of the configuration by which losses in the branches of the entire system can be minimized. The distribution system reconfiguration is carried out by modifying the topological structure of the network by changing the status of the sectionalizing and tie-line switches [3, 4]. And also, the optimal switch operations may reduce losses in the system. Both of these are met by reconfiguration. Hence, both the ONR and less number of switching operations will reduce the power losses and they are met by the proposed ONR approach.

Most of the distribution systems generally operated in radial topology which enables suitable voltage and power flow control, reduced fault current, and easier protection coordination schemes over the meshed system. Typically, the radial distribution systems (RDSs) have two types of switches, namely, sectionalizing switches which are usually open, and tie-line switches which are usually closed [5]. When the fault occurs either on distributors or feeders, the tie-line switch allows some portion of the faulted part to be restored promptly, thereby enhancing the reliability of the system. According to Ref. [2], the power loss in the distribution network constitutes 70% of the total power loss. Therefore, the major cause of power interruption is due to problems in the distribution system.

1.1 Related Work

There has been considerable interest in the recent past to develop algorithms for feeder reconfiguration (FR) of the distribution system under various operating contingencies. Usually, distribution companies try to keep active power losses below the standard ones to gain profit rather than paying penalties. Thus the active power loss minimization is a major concern of the distribution system researchers, which has a significant impact on the maximum loadability of the network and hence, on the power system stability particularly in overburdened networks. Some of the established techniques to handle distribution systems under such a competitive scenario include network reconfiguration (NR), DG allocation, shunt capacitor placement, and simultaneous NR and DG allocation [6]. Hence, the existing distribution system requires to be optimized to satisfy the demand in the most reliable, economical, and environmentally friendlier way, while meeting the associated geographical or operational constraints.

A high-performance nonlinear sliding mode controller has been proposed in Ref. [7] for an EV charging system to improve the power factor (pf) to handle the unbalanced EV chargers and to compensate for voltage distortions. The super sense genetic algorithm (SSGA) is applied in Ref. [8] to solve the problem of complex combinatorial NR problem of RDSs. An approach for the optimal network rearrangement by incorporating the plugin electric vehicles (PEVs) proposed in Ref. [9] is based on the random programming model of the Monte Carlo simulation method. An approach for optimal placement and sizing of electric vehicle charging stations (EVCSs) on a distribution network is proposed in [10]. A fuzzy approach-based multi-objective heuristic technique for ONR in distribution systems considering the DGs is proposed in [11]. A single-phase (1-φ) EV charging coordination approach with the three-phase (3-φ) supply and chargers connected to the EVs with the less loaded phase of the feeder at the starting of charging has been proposed in [12]. The optimal planning approach of EVCSs and shunt capacitors is proposed in [13] and it is solved by using the dragonfly algorithm (DA).

An equilibrium optimizer algorithm has been applied to the ONR problem in Ref. [14] with loss reduction, voltage magnitude enhancement, and reliability indices improvement objectives. An efficient technique for balanced and unbalanced RDSs optimization by ONR and optimal capacitor placement has been proposed in [15].

The ONR allows better penetration of renewable energy sources (RESs) in the RDS and it is solved in Ref. [16] using the mixed particle swarm optimization (PSO) for loss minimization and voltage profile enhancement improvement. Reference [17] proposes optimal battery energy storage systems and allocation of PV-based DG have been solved by the PSO algorithm.

1.2 Scope and Contributions

From the literature on ONR with loss minimization objective in the distribution system, the research gap has been identified and explored the work area with current research performance and its limitations. From the literature, it has been identified that there is a requirement for solving the ONR problem by simultaneously installing the renewable-based DG units, shunt capacitors, and EVCSs. Renewable-based DG units, i.e., wind plants and solar PV farms have wind speed and solar insolation as input parameters and they are highly intermittent. The distribution load flow (DLF) used in this chapter is based on the iterative approach. The potential of this approach has made the ONR approach is very powerful and can be applied to any size of the distribution network. The ONR and DG allocation to strengthen the efficiency of distribution systems based on power loss minimization and voltage deviation minimization, as these are two major issues in the recent competitive power scenario, and they are considered as the objective functions with the presence of shunt capacitors and EVCSs. The simulation has occurred to both balanced as well as unbalanced radial distribution systems (RDSs).

This chapter is organized as follows: The description of RDS, ONR, and the summary of the literature work has been presented in Sect. 1. A brief description of distribution load flow (DLF) analysis has been presented in Sect. 2. Section 3 describes the modeling of shunt capacitors and EVCSs in the distribution system. Problem formulation is presented in Sect. 4. Section 5 describes the solution methodology. Section 6 describes the results and discussion on the 69 bus test system. The conclusions of this chapter have been summarized in Sect. 7.

2 Distribution Load Flow (DLF) Analysis

The analysis of DLF is basic but it is an essential mathematical tool for the analysis of distribution systems in both the planning and operational stages. The primary aim of the power flow analysis is to determine the magnitude and phase of steady-state voltage at all buses, active and reactive power flows in each line, for a specified loading. There are numerous power flow methods like Newton Raphson, Gauss-Seidel, fast decoupled methods, and many more methods with a modification in conventional ones. Due to the different properties of the distribution systems, these methods are not suitable for load flow analysis [18]. Certain applications including distribution automation and power system optimization require efficient and robust load flow solutions. Over the last few decades, these load flow methods have been evolved in several different dimensions to handle both static and dynamic power distribution system problems. Traditionally, the Backward Forward Sweep (BFS) load flow techniques are applied to distribution systems and it has two-step analyses. Other load flow methods include little modification into existing techniques for their advantage over the older ones. In literature, several conventional methods have been utilized to solve distribution system problems [19]. The open branches are electrically represented with very high impedance. Whenever a branch is connected, then its parameters are replaced with actual values (i.e., resistance and reactance values) and vice versa when a branch is removed or disconnected. In other words, when a branch exchange takes place, only those parameters will be modified accordingly for further processing. This saves a lot of computation burden.

The proposed load flow solution presented in this chapter depends on an iterative approach of the receiving end voltage of the RDS. It is successfully applied on ill-conditioned RDS with consideration of realistic load [20]. In the first step, the effective power at each bus is determined after forming adjacent branches and adjacent node matrices. A sparse technique is used to determine the branches and nodes beyond a particular node. The detailed mathematical formulation is given below considering the electrical equivalent of a branch connected between the nodes a and b of RDS, and it is shown in Fig. 1.

The amount of current flowing from node a to node b can be expressed as [20],

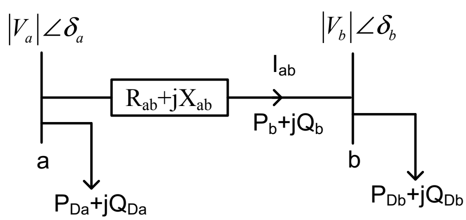
$$I_{ab} = \frac{|V_a|\angle\delta_a - |V_b|\angle\delta_b}{R_{ab} + jX_{ab}} = \frac{P_b - jQ_b}{(|V_b|\angle\delta_b)^*} \tag{1}$$

where active power (P_b) can be expressed in terms of active power load at a bus/node i (P_{Di}) and active power loss of line k ($P_{loss,k}$). Mathematically, it can be expressed as,

$$P_b = \sum_{i=1}^{N_b} P_{Di} + \sum_{k=1}^{N_{br}} P_{loss,k} \tag{2}$$

where N_b shows all the buses beyond the bus b. N_{br} shows all the branches beyond the bus b. From Eq. (1), P_b can be expressed as [21],

Fig. 1 Electrical equivalent of a typical distribution system branch



$$P_b = \frac{|V_a||V_b|\sin(\delta_a - \delta_b) + R_{ab}Q_b}{X_{ab}} \tag{3}$$

From the above equation, the voltage magnitude ($|V_b|$) and angle (δ_b) at the end of receiving node can be calculated by using,

$$|V_b| = -\left[|V_a|\left(\frac{R_{ab}}{X_{ab}}\sin\delta - \cos\delta\right)\right] + \left[\left(|V_a|\frac{R_{ab}}{X_{ab}}\sin\delta - \cos\delta\right)^2 - 4Q_b\left(\frac{R_{ab}^2}{X_{ab}} + X_{ab}\right)\right]^{1/2} \tag{4}$$

where $\delta = \delta_a - \delta_b$.

$$\delta_b = \delta_a - \tan^{-1}\left[\frac{P_b X_{ab} - Q_b R_{ab}}{|V_b|^2 + P_b R_{ab} + Q_b X_{ab}}\right] \tag{5}$$

The active and reactive power losses are calculated by using Eq. (3), and they are expressed as,

$$P_{loss,ab} = \frac{\left(P_b^2 + Q_b^2\right)R_{ab}}{|V_b|^2} \tag{6}$$

$$Q_{loss,ab} = \frac{\left(P_b^2 + Q_b^2\right)X_{ab}}{|V_b|^2} \tag{7}$$

All such techniques work well with static systems where there is no change in the topology of the network [22]. Again under critical loading conditions, there is no guarantee of their convergence. Even in converged cases, these methods are very inefficient in respect of storage requirements and solution speed. Moreover, for dynamic systems, it is a challenge to arrange the line data as per the load flow requirement and to maintain the radiality, and ensure connectivity. This necessitates the utilization of improved data structure-based techniques.

3 Modeling of Shunt Capacitor and EVCS in the Distribution System

The ever-growing population leads to a significant increment in customer load demand. It leads to the placement of DGs in RDS being nearer to the load demand. Among the various renewable-based DGs, solar PV and wind energy are widely used as they are abundantly available. As there is a rapid growth in load demand, the line losses in the distribution network are quite high and need to be taken care of [23].

Various techniques have been implemented to RDSs apart from the DG penetration to optimize the power losses in the RDS. This section presents the modeling of shunt capacitors and EVCSs in the RDS.

3.1 Modeling of Shunt Capacitor

Shunt capacitors supply the amount of reactive power to the RDS at the bus where they are connected. This in turn causes a reduction in reactive power flowing in the line. If the reactive power and the system voltage are assumed to be constant, then the losses are inversely proportional to the power factor, and hence improvement in the power factor causes a reduction in system losses. The other benefits of installing the shunt capacitors are voltage profile improvement, decrease in kVA loading, and reduces system improvement cost/kVA of load supplied [24]. And also, to overcome the compensation during the light load conditions, the automatic switching units can be provided but this switching equipment is costly and this, in turn, will limit the number of capacitors and thus the minimum capacity of the capacitor bank that has to be provided on the feeder.

The placement of shunt capacitors in the DS reduces the system losses, enhances the voltage profile, and also corrects the power factor. Figure 2 depicts the representation of the shunt capacitor in the DS. This capacitor injects reactive power (Q_c) into the system.

Amount of reactive power injected at bus b ($Q_{inj,b}$) can be expressed by [25],

$$Q_{inj,b} = Q_{Db} - Q_c \tag{8}$$

Now the active power loss with shunt capacitor ($P^c_{loss,ab}$) can be expressed as [25],

$$P^c_{loss,ab} = \frac{\left(P_b^2 + Q_{inj,b}^2\right)R_{ab}}{|V_b|^2} = \frac{\left[P_b^2 + (Q_{Db} - Q_c)^2\right]R_{ab}}{|V_b|^2} \tag{9}$$

$$P^c_{loss,ab} = \frac{\left(P_b^2 + Q_b^2\right)R_{ab}}{|V_b|^2} + \frac{\left(Q_c^2 - 2Q_{Db}Q_c\right)R_{ab}}{|V_b|^2} = P_{loss,ab} + \Delta P^c_{loss,ab} \tag{10}$$

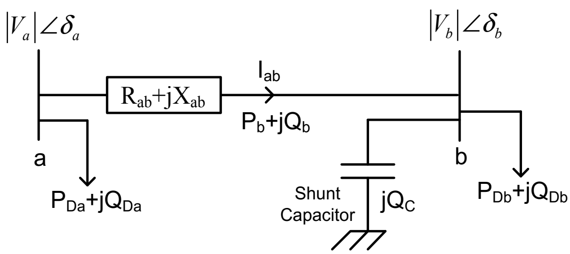


Fig. 2 Representation of shunt capacitor in the distribution system

where $\Delta P_{loss,ab}^{c}$ is the reduction in power loss, i.e., active power loss before and after placing the shunt capacitor [26], and it can be expressed from Eq. (10) as,

$$\Delta P_{loss,ab}^{c} = \frac{\left(Q_c^2 - 2Q_{Db}Q_c\right)R_{ab}}{|V_b|^2} \tag{11}$$

3.2 Modeling of EVCS in the Distribution System

Figure 3 depicts the representation of EVCS in the distribution system.

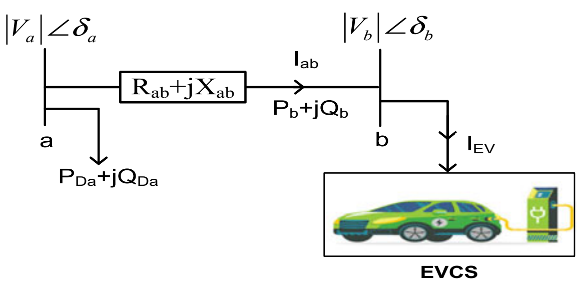
The power demand of EVCS at bus b (P_{Db}^{EVCS}) can be calculated by using [27, 28],

$$P_{Db}^{EVCS} = N_{EV}^{c} P_{G2V} \eta_c R_c - N_{EV}^{d} P_{V2G} \eta_d R_d \tag{12}$$

4 Problem Formulation

This section presents the general description of distribution systems and the mathematical modeling of optimal feeder reconfiguration (OFR) or optimal network reconfiguration (ONR). Factors that are affecting the increase in the power losses in the distribution network are feeder length, low voltage, low power factor, poor workmanship in fittings, and reduction of line losses. Various methods used for the reduction of distribution system losses are the construction of a new substation, reinforcement of feeder, reactive power compensation, HV distribution system, grading of conductors, and feeder reconfiguration [29]. In this work, two objectives, i.e., real power loss and voltage deviations are modeled with fuzzy sets [29, 30]. Some heuristics are developed to reduce the number of tie-line switching operations.

Fig. 3 Representation of EVCS in the RDS



4.1 Fuzzy Membership Function for Active Power Loss Reduction (μL_i)

The basic purpose for membership function, i.e., objective in the fuzzy domain is to minimize the active power loss of the system. The variable α_i can be defined as

$$\alpha_i = \frac{P_{loss}(i)}{P_{loss}^0} \quad for\ i = 1, 2, \ldots, N_k \tag{13}$$

where N_k is total number of lines in loop including the tie-line, when the kth tie-switch is closed, $P_{loss}(i)$ is total active power loss when ith line in the loop is opened, and P_{loss}^0 is total real power loss before the NR. Membership/objective function for active power loss reduction (μL_i) can be written as [30],

$$\mu L_i = \begin{cases} \frac{\alpha_{\max} - \alpha_i}{\alpha_{\max} - \alpha_{\min}} & for\ \alpha_{\min} < \alpha_i < \alpha_{\max} \\ 1 & for\ \alpha_i \le \alpha_{\min} \\ 0 & for\ \alpha_i \ge \alpha_{\max} \end{cases} \tag{14}$$

4.2 Fuzzy Membership Function for Maximum Node Voltage Deviation (μV_i)

The main aim of this function is to minimize the deviation of nodes' voltage. The variable β_i can be expressed as

$$\beta_i = \max\left(\left|V_{i,j} - V_s\right|\right) \quad for\ i = 1, 2, \ldots, N_k; \quad j = 1, 2, \ldots, N_B \tag{15}$$

where N_B is total number of buses in RDS, V_s is substation voltage, and $V_{i,j}$ is jth bus voltage corresponding to the opening of the ith line [29, 30]. The fuzzy membership function for maximum bus voltage deviation (μV_i) can be expressed as,

$$\mu V_i = \begin{cases} \frac{\beta_{\max} - \beta_i}{\beta_{\max} - \beta_{\min}} & for\ \beta_{\min} < \beta_i < \beta_{\max} \\ 1 & for\ \beta_i \le \beta_{\min} \\ 0 & for\ \beta_i \ge \beta_{\max} \end{cases} \tag{16}$$

4.3 Constraints

The active and reactive power balances of the RDS system including the DG units, shunt capacitors, and EVCSs are expressed as [31, 32],

$$P_D = P_G^{Grid} + P_{Db}^{EVCS} + \sum_{i=1}^{N_{DG}} P_{DG,i} \tag{17}$$

$$Q_D = Q_G^{Grid} + \sum_{i=1}^{N_{DG}} Q_{DG,i} + \sum_{j=1}^{N_c} Q_{c,j} \tag{18}$$

Voltages at each bus can be expressed as,

$$0.95 \le V_i \le 1.05 \tag{19}$$

Active and reactive powers of DG units can be expressed as [33, 34],

$$P_{DG,i}^{\min} \le P_{DG,i} \le P_{DG,i}^{\max} \tag{20}$$

$$Q_{DG,i}^{\min} \le Q_{DG,i} \le Q_{DG,i}^{\max} \tag{21}$$

4.4 Selection of Best-Compromised Solution

When optimizing two or more objectives simultaneously, a best-compromised solution needs to be determined [35]. The procedure for determining the best-compromised solution using the min-max principle is determined next:

The membership function values of the two objectives are determined. When the kth tie-line switch of RDS is closed, a loop is formed with number of lines in the loop N_k. After opening the ith line in the loop, run the DLF to determine μL_i and μV_i for $i = 1, 2, \ldots, N_k$. Determine the fuzzy decision for overall satisfaction [36, 37] by using,

$$D_{k,i} = \min(\mu L_i, \mu V_i) \quad for\ 1, 2, \ldots, N_k \tag{22}$$

The optimal solution is the maximum of overall degrees of satisfaction, and it is expressed as [38],

$$OS_k = \max\left(D_{k,i}\right) \quad for\ 1, 2, \ldots, N_k \tag{23}$$

5 Solution Methodology

This section presents heuristics for minimizing the number of operations of tie-line switches. Here, heuristic rules are developed to minimize the number of tie-line switch operations [39, 40]. The flow chart of the proposed solution methodology has been depicted in Fig. 4, and the step-by-step approach is presented next:

- **Step 1**: Read the RDS test system data.

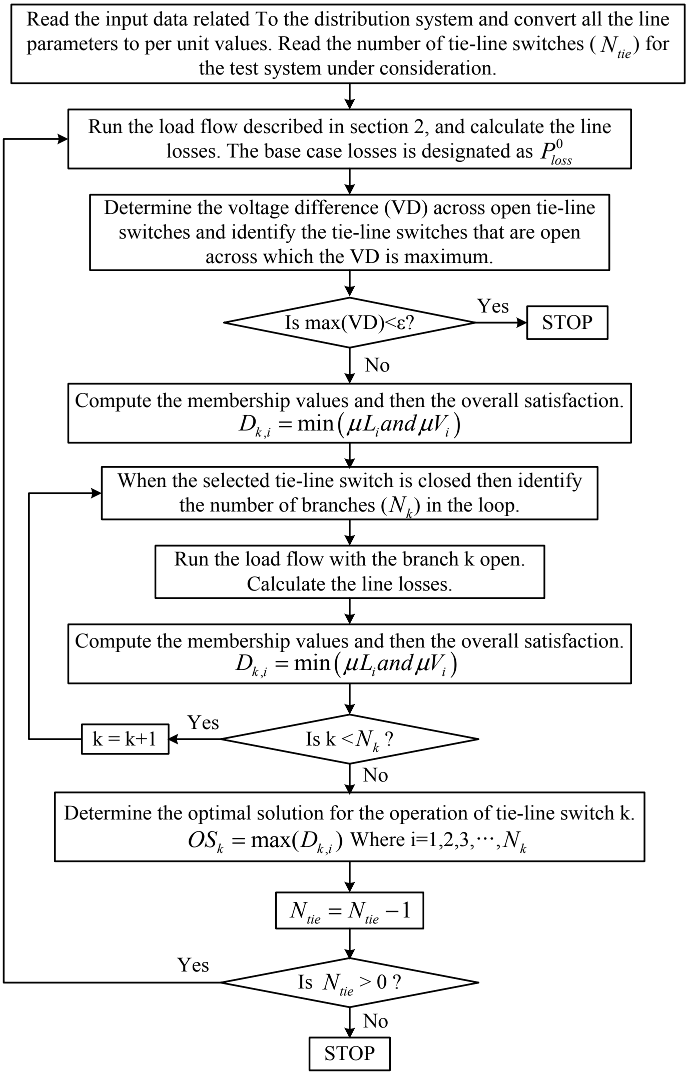


Fig. 4 Flow chart of the proposed ONR/OFR algorithm

- **Step 2**: Execute the load flow solution as described in Sect. 2.
- **Step 3**: Determine voltage difference (ΔV_{tie}) across the open tie-line switches.
- **Step 4**: Identify the open tie-line switch across which ΔV_{tie} is maximum, and it can be represented as ($\Delta \mathrm{V}_{tie}^{\max}$).
- **Step 5**: If $\Delta \mathrm{V}_{tie}^{\max}$ > specified value (ε), then go to Step 6 else go to Step 11.
- **Step 6**: When the selected tie-line switch is closed then identify the number of branches (N_k) in the loop.
- **Step 7**: Open one line at a time in the loop, and determine the membership value for each objective function. Compute μL_i and μV_i using the Eqs. (14) and (16), respectively.
- **Step 8**: Compute the overall degree of satisfaction using Eq. (22).
- **Step 9**: Determine the optimal solution for the operation of the kth tie-line switch using Eq. (23).
- **Step 10**: Make the number of tie-line switches (N_{tie}) equal to $N_{tie} - 1$, and rearrange the coding of the rest of the tie-line switches, and go to Step 2.
- **Step 11**: Display the output results.

6 Results and Discussion

The proposed ONR methodology has been implemented on IEEE 69 bus test system which has a single feeder with a single substation [41]. Figure 5 depicts the single-line diagram of 69 bus RDS. System load demand, line, and tie-line data have been taken from Ref. [42]. This system has 68 lines, i.e., sectionalizing switches, they are 1–68 and they are normally closed. Five tie-line switches (which form 5 loops) considered in this work are 69, 70, 71, 72, and 73, they open tie switches. The base voltage and kVA are 12.66 kV and 1000 kVA, respectively. The real and reactive power load of 3,802 kW and 2,694 kVAr, respectively. In this test system, the DG units are placed at buses 5, 28, 45, and 60; shunt capacitors are placed at buses 22, 36, and 64; EVCSs are placed at buses 18 and 59.

In the present work, the convergence criterion (ε) is considered as 0.01, and it has been assumed that $\alpha_{\min}$ is 0.5, $\alpha_{\max}$ is 1, $\beta_{\min}$ is 0.05 and $\beta_{\max}$ is 0.10. The active power loss obtained in the base case condition is 224.96 kW, and all the tie-line switches, i.e., 69, 70, 71, 72, and 73. The minimum voltage obtained in this base case is 0.9066 p.u. at bus 54.

6.1 Case 1: Tie-Line Switch Operation 1

In this case, the voltage difference across each tie-line switch is determined. The voltage differences across tie-line switches 69, 70, 71, 72 and 73 are 0.0031 p.u., 0.0008 p.u., 0.0416 p.u., 0.0742 p.u. and 0.0471 p.u., respectively. From these voltages, it can be observed that voltage difference across line number 72 is maximum,

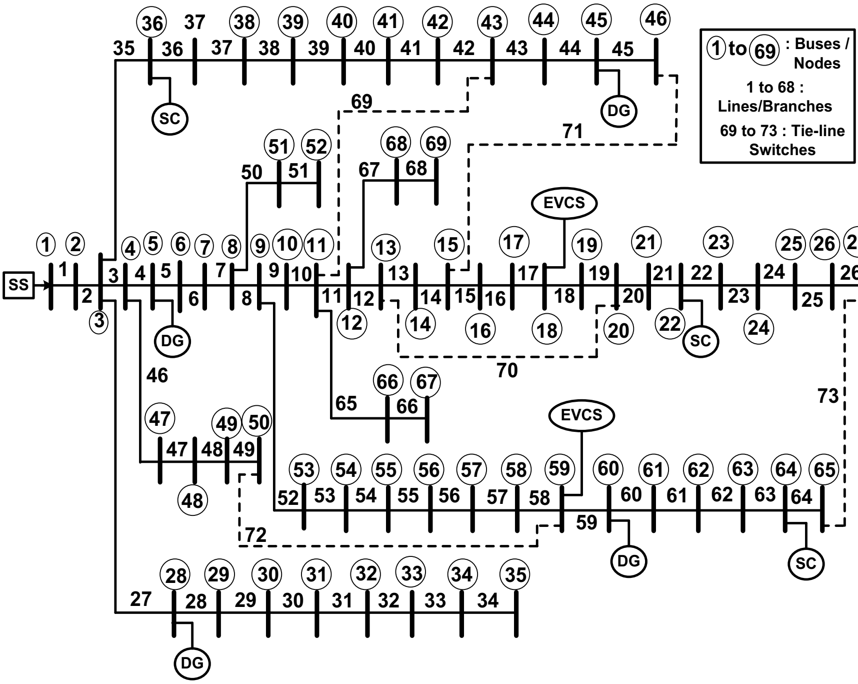


Fig. 5 SLD of IEEE 69 bus RDS before ONR

i.e., 0.0742 p.u. Table 1 presents the membership values of power loss and voltage deviation, and the overall satisfaction for tie-line switch operation 1. In this case, line number 72 is closed and the membership values for opened lines are presented in Table 1. The overall satisfaction has been determined by using Eq. (23), and they are presented in the table. From the results obtained, it is observed that by using the fuzzy set intersection, the fuzzy decision for overall satisfaction is obtained when line 46 is open and line 72 is closed. The obtained value of overall satisfaction is 0.7362, which is the maximum of $D_{k,i}$.

6.2 Case 2: Tie-Line Switch Operation 2

The voltage differences across tie-line switches 69, 70, 71, 72 and 73 are 0.00312 p.u., 0.0008 p.u., 0.0416 p.u., 0.0742 p.u. and 0.0471 p.u., respectively. From these voltages, after the tie-line switch operation 1, it can be observed that voltage difference across line number 73 is maximum, i.e., 0.0471 p.u. Table 2 presents the membership values of power loss and voltage deviation, and the overall satisfaction for tie-line switch operation 2. In this case, line number 73 is closed and the membership values for opened lines are presented in Table 2. The overall satisfaction has been determined

Table 1 Membership values for tie-line switch operation 1

Closed line	Opened line	Membership values of power loss and voltage deviation		$D_{k,i} = \min(\mu L_i, \mu V_i)$
		μL_i	μV_i	
Base case		1	0.5654	0.5654
72	38	0	0.4378	0
72	37	0	0.3937	0
72	36	0	0.3515	0
72	35	0	0.3518	0
72	47	0.7353	0.8742	0.7353
72	**46**	**0.7362**	**0.8745**	**0.7362**
72	45	0.7352	0.8734	0.7352
72	44	0.7350	0.8734	0.7350
72	43	0.7224	0.8642	0.7224
72	42	0.7082	0.8540	0.7082
72	41	0.7052	0.8540	0.7052
72	8	0	0.1457	0
72	7	0	0	0
72	6	0	0	0
72	5	0	0	0
72	4	0	0	0

by using Eq. (23), and they are presented in the table. From the results obtained, it is observed that by using the fuzzy set intersection, the fuzzy decision for overall satisfaction is obtained when line 53 is open and line 73 is closed. The obtained value of overall satisfaction is 0.7575 which is the maximum of $D_{k,i}$.

6.3 *Case 3: Tie-Line Switch Operation 3*

The voltage differences across tie-line switches 69, 70, 71, 72 and 73 are 0.00312 p.u., 0.0008 p.u., 0.0416 p.u., 0.0742 p.u. and 0.0471 p.u., respectively. From these voltages, after the tie-line switch operations 1 and 2, it can be observed that voltage difference across line number 71 is maximum, i.e., 0.0416 p.u. Table 3 presents the membership values of power loss and voltage deviation, and the overall satisfaction for tie-line switch operation 3. In this case, line number 71 is closed and the membership values for opened lines are presented in Table 3. The overall satisfaction has been determined by using Eq. (23), and they are presented in the table. From the results obtained, it is observed that by using the fuzzy set intersection, the fuzzy decision

Table 2 Membership values for tie-line switch operation 2

Closed line	Opened line	Membership values of power loss and voltage deviation		$D_{k,i} = \min(\mu L_i, \mu V_i)$
		μL_i	μV_i	
After tie-line switch operation 1		0.7386	0.8632	0.7386
73	26	0.7203	0.8621	0.7203
73	25	0.7225	0.8520	0.7225
73	24	0.7265	0.8505	0.7265
73	23	0.7071	0.8248	0.7071
73	22	0.7078	0.8246	0.7078
73	21	0.7046	0.7051	0.7046
73	20	0.6199	0.7056	0.6199
73	19	0.6175	0.7062	0.6175
73	18	0.6163	0.7120	0.6163
73	17	0.5656	0.6485	0.5656
73	16	0.5152	0.5836	0.5152
73	15	0.4420	0.5352	0.4420
73	14	0.4447	0.5360	0.4447
73	13	0.4338	0.5225	0.4338
73	12	0.4232	0.5122	0.4232
73	11	0.0774	0.1995	0.0774
73	10	0	0	0
73	9	0	0	0
73	8	0	0	0
73	7	0	0	0
73	6	0	0	0
73	5	0	0	0
73	4	0	0	0
73	**53**	**0.7575**	**0.9129**	**0.7575**
73	52	0.7548	1	0.7548
73	51	0.7542	1	0.7542
73	50	0.7435	0.9792	0.7435
73	49	0	0	0
73	48	0	0	0
73	72	0	0	0
73	38	0	0	0
73	37	0	0	0
73	36	0	0	0

(continued)

Table 2 (continued)

Closed line	Opened line	Membership values of power loss and voltage deviation		$D_{k,i} = \min(\mu L_i, \mu V_i)$
		μL_i	μV_i	
73	35	0	0	0

The bold values in the table represent the fuzzy decision for overall satisfaction by using the fuzzy set intersection

Table 3 Membership values for tie-line switch operation 3

Closed line	Opened line	Membership values of power loss and voltage deviation		$D_{k,i} = \min(\mu L_i, \mu V_i)$
		μL_i	μV_i	
After tie-line switch operation 2		0.7252	0.8625	0.7252
71	14	0.8618	0.9321	0.8618
71	**13**	**0.8712**	**0.9652**	**0.8712**
71	12	0.8706	0.9025	0.8706
71	11	0.8568	0.9158	0.8568
71	10	0.7990	0.9198	0.7990
71	9	0.7887	0.9138	0.7887
71	8	0.7458	0.9166	0.7458
71	7	0.3452	0.8252	0.3452
71	6	0.2898	0.7879	0.2898
71	5	0.2898	0.7842	0.2898
71	4	0.2858	0.7840	0.2858
71	68	0.7365	0.9198	0.7365
71	67	0.7165	0.9174	0.7165
71	66	0.7138	0.9133	0.7138
71	65	0.7086	0.9165	0.7086
71	64	0.7152	0.9114	0.7152
71	63	0.7098	0.9144	0.7098
71	62	0.6954	0.9100	0.6954
71	61	0.6788	0.9152	0.6788
71	60	0.6763	0.9126	0.6763
71	59	0.6552	0.9126	0.6552
71	58	0.6466	0.9126	0.6466

The bold values in the table represent the fuzzy decision for overall satisfaction by using the fuzzy set intersection

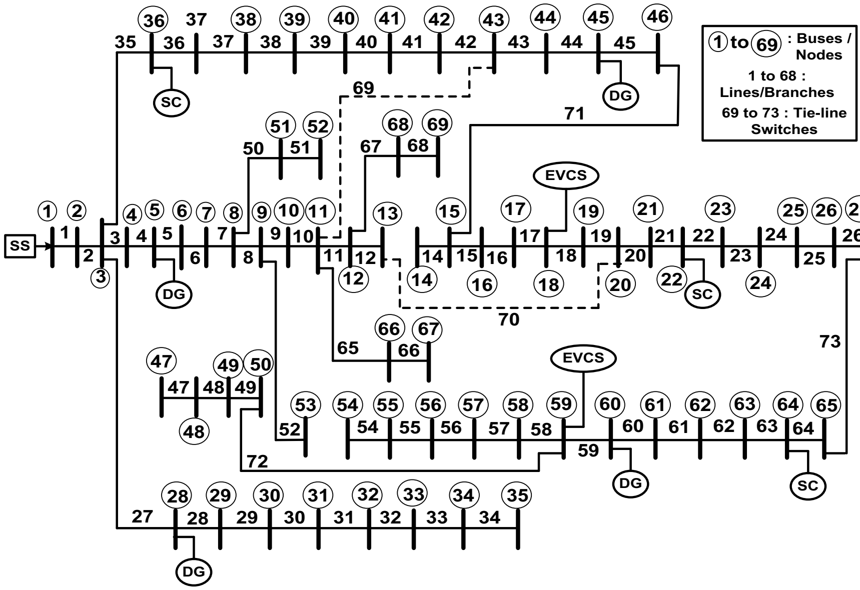


Fig. 6 SLD of IEEE 69 bus RDS after ONR

for overall satisfaction is obtained when line 13 is open and line 71 is closed. The obtained value of overall satisfaction is 0.8712 which is the maximum of $D_{k,i}$.

6.4 Case 4: Tie-Line Switch Operation 4

The voltage differences across tie-line switches 69, 70, 71, 72 and 73 are 0.0031 p.u., 0.0008 p.u., 0.0416 p.u., 0.0742 p.u. and 0.0471 p.u., respectively. From these voltages, after the tie-line switch operations 1, 2, and 3, it can be observed that voltage difference across line number 69 is maximum, i.e., 0.0031 p.u. However, this voltage difference is less than ε (0.01). Therefore, there is no further network reconfiguration is required. Figure 6 depicts the final topology of IEEE 69 bus RDS after ONR. Bus voltages before and after the ONR are presented in Table 4. From this table, it can be observed the voltage profile has been improved after the proposed ONR approach.

7 Conclusions

This paper proposes an optimal network/feeder reconfiguration (ONR/OFR) problem of the radial distribution system (RDS), and it is solved by simultaneously allocating the distributed generation (DG), shunt capacitors, and electric vehicle charging

Table 4 Bus voltages before and after the ONR

Bus number	Before ONR	After ONR	Bus Number	Before ONR	After ONR
1	1.0000	1.0000	36	0.9998	0.9997
2	1.0000	1.0000	37	0.9990	0.9965
3	0.9999	0.9999	38	0.9967	0.9855
4	0.9998	0.9998	39	0.9962	0.9828
5	0.9989	0.9996	40	0.9756	0.9921
6	0.9889	0.9968	41	0.9756	0.9932
7	0.9784	0.9941	42	0.9720	0.9921
8	0.9759	0.9934	43	0.9687	0.9920
9	0.9748	0.9932	44	0.9643	0.9919
10	0.9698	0.9896	45	0.9599	0.9920
11	0.9687	0.9890	46	0.9374	0.9922
12	0.9655	0.9879	47	0.9264	0.9919
13	0.9626	0.9874	48	0.9221	0.9458
14	0.9597	0.9875	49	0.9171	0.9411
15	0.9568	0.9872	50	0.9097	0.9342
16	0.9563	0.9871	51	0.9094	0.9339
17	0.9554	0.9856	52	0.9090	0.9336
18	0.9554	0.9856	53	0.9071	0.9327
19	0.9549	0.9850	54	0.9066	0.9820
20	0.9546	0.9846	55	0.9686	0.9889
21	0.9542	0.9840	56	0.9686	0.9889
22	0.9541	0.9844	57	0.9652	0.9876
23	0.9541	0.9838	58	0.9652	0.9876
24	0.9539	0.9835	59	0.9999	0.9999
25	0.9538	0.9837	60	0.9997	0.9993
26	0.9537	0.9828	61	0.9996	0.9986
27	0.9537	0.9827	62	0.9995	0.9984
28	0.9999	0.9999	63	0.9995	0.9984
29	0.9999	0.9999	64	0.9988	0.9947
30	0.9997	0.9997	65	0.9986	0.9925
31	0.9997	0.9997	66	0.9985	0.9924
32	0.9996	0.9996	67	0.9985	0.9923
33	0.9993	0.9993	68	0.9984	0.9916
34	0.9990	0.9990	69	0.9984	0.9919
35	0.9989	0.9989			

stations (EVCSs). In the proposed ONR problem, the objectives, i.e., active power loss and voltage deviation minimizations are solved by using the fuzzy-based multi-objective methodology. An iterative approach-based distribution load flow (DLF) has been used in this work. The proposed algorithm identifies the ONR of feeders with the minimum number of tie-line switch operations. Simulation studies have been performed on 69 bus RDS.

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