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Hybrid PIPSO-SQP Algorithm for Real Power Loss Minimization in Radial Distribution Systems with Optimal Placement of Distributed Generation

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Abstract: This paper proposes the hybrid sequential quadratic programming (SQP) technique based on active set method for identifying the optimal placement and rating of distribution generation (DG) incorporated in radial distribution systems (RDS) for minimizing the real power loss satisfying power balance equations and voltage limits. SQP runs quadratic programming sequentially as a sub-program to obtain the best solution by using an active set method. In this paper, the best optimal solution is selected with less computation time by combining the benefits of both classical and meta-heuristic methods. SQP is a classical method that is more sensitive to initial value selection and the evolutionary methods give approximate solution. Hence, the initial values for the SQP technique were obtained from the meta-heuristic method of Parameter Improved Particle Swarm Optimization (PIPSO) algorithm. The proposed hybrid PIPSO–SQP method was implemented in IEEE 33-bus RDS, IEEE 69-bus RDS, and IEEE 118-bus RDS under different loading conditions. The results show that the proposed method has efficient reduction in real power loss minimization through the enhancement of the bus voltage profile.

Keywords: radial distribution systems; sequential quadratic programming; Distributed Generation; power loss minimization; Parameter Improved Particle Swarm Optimization

1. Introduction

Distributed Generation (DG) has become more popular presently owing to its advantages, such as reduced transmission and distribution losses, connection near the customers, improved reliability [1], enhanced voltage stability [2], and increased efficiency. DGs are referred to as the heart of the micro grid, which is defined as the low voltage network comprising of various micro sources and renewable sources, storage elements, and the loads [3]. In radial distribution systems (RDS), it is stated that the real power loss contributes more to the total loss occurred in the distribution line conductors due to the high value of resistance/reactance ratio [4]. Hence, real power loss minimization in a distribution system plays a vital part from commercial operations and planning conditions.

The primary motivation behind this work is to reduce the real power loss in RDS, satisfying the power balance equation, and maintain power and voltage limits. The loss minimization can be achieved through various methods, such as (i) Placement of DGs, (ii) Placement of capacitors, (iii) Feeder reconfiguration [5]. In the above methods of loss minimization, DG allocation and feeder reconfiguration could be used in low voltage networks, whereas capacitor placement could be done in high voltage distribution network [5]. Incorporation of a DGs into the existing distribution network

has several advantages such as loss reduction, improvement of voltage profile, increase in generation efficiency, and reduction pollution in nature. The DGs could be placed in distribution networks at an optimal location and with an optimum size for minimizing the loss significantly.

The excellent rating and placing of DGs are determined by many optimization algorithms that can be categorized [6] as (i) analytical techniques (ii) conventional techniques (iii) evolutionary methods and (iv) different techniques. Most of the techniques are implemented in the standard test systems of IEEE 33-bus system and IEEE 69-bus system for the validation of the proposed algorithm by considering the optimal DG placement and sizing as the primary objective function.

Eigen value-based analysis for stability analysis uses three methods, namely index method [7] that calculates the deviation of any parameter, (mostly voltage), the sensitivity-based method that finds the change in a variable due to the change in another variable, and point estimation method that is based on uncertainty calculation [6] in analytical techniques. A novel analytical approach was proposed for a balanced RDS in [3,7]. In addition to the placement and sizing, power factor and the number of DGs are also included in the power loss determination with a simplified analytical approach [8]. Efficient analytical (EA) method integrated with an optimal power flow was proposed in [9] for the optimal installment of multiple DGs for reducing the power loss in distribution systems. Sensitivity-based analysis was proposed in [10] for the connection of DG with genetic algorithm and optimal power flow.

The following are the classical or conventional approaches used for identifying the optimal DG rating/or placing in RDS: linear programming [6], mixed non-linear programming (MNL) [11] (consisting of two phases namely siting planning model for finding the candidate buses and capacity planning model for optimal location and sizing), sequential quadratic programming with trust region [12] method (which approximates the constraints as linear ones for reducing the optimization scale), dynamic programming (DP) [13] for loss reduction, and reliability improvement methods. The global criterion of multi-objective method was proposed in [14] for power loss minimization and DG investment cost reduction with optimal sizing and sitting of DG.

Recent evolutionary methods in the literature for power loss minimization in RDS include various naturally available bio-inspired algorithms. Intelligent water drop algorithm was used in [15] for DG sizing with loss sensitivity factor. Ant lion optimization [16] method, which emulates the hunting mechanism was proposed for power loss minimization in RDS by using loss sensitivity method for optimal location and sizing of DGs. A distributed optimization technique of bacterial foraging combined with loss sensitivity factor is implemented in [17]. Multi-objective function of power loss reduction and improvement in voltage stability index is attained by using adaptive shuffled frog-leaping algorithm in [18]; and the results were compared with adaptive cuckoo search and shuffled frog-leaping methods. The combining of shuffled frog leap, best features of bat algorithm, and shuffled bat algorithm [19] was proposed for the same objective function.

Salp-swarm optimization [20] for real power loss reduction and muted salp swarm optimization [21] for compensation of reactive power were proposed in distribution systems. Meta-heuristic optimization techniques called salp swarm algorithm (SSA) and whale optimization algorithm (WOA), and a new hybrid method of WOA-SSA were explored in [22] for reducing the voltage deviation in IEEE 13 and 123 node RDS. Multi-objective optimization was attained with whale optimization algorithm by placing real and reactive power injecting DGs in RDS [23]. Population-based algorithm, namely invasive weed optimization algorithm is employed for cost reduction and voltage enhancement by decreasing the losses [24]. Stud selection and cross-over is deployed in stud krill herd algorithm for IEEE 33, 69 and 94 Portuguese RDS based on the minimum distance of the Krill individual from food and the highest density of the herd [25].

Improved raven roosting optimization algorithm, which uses Pareto optimality and game theory for the selection of the best solution is discussed in RDS for the same objective [26]. The symbiotic relationship among different biological species was implemented in RDS for DG location by using symbiotic organism search (SOS) technique [27]. The review of real power loss minimization in RDS

with different algorithms is discussed in [28] through network reconfiguration, capacitor allocation, DG placement and DSTATCOM allocation by keeping optimal operation and planning as key considerations. A comprehensive study was obtained in [29] for the minimization of power loss and the improvement of voltage stability in distribution systems through optimum DG placement.

The real power loss in RDS is in a quadratic form and it can be solved by Quadratic Programming (QP), which is a unique variant of non-linear programming problem with an objective in quadratic form and subjected to linear constraints. Many QP techniques were analyzed to determine the solution for the optimal power flow problem with various objective functions, such as reduction of transmission line real and reactive power losses, and reduction of fuel cost. QP is a significant optimization technique for the engineering problems with quadratic objective function, and it forms as a sub-problem in the case of SQP technique to solve the non-linearly constrained problems. Since the SQP technique iteratively works out successive of quadratic sub-problems, it is known as recursive QP or iterative QP. A SQP technique based on interior point (IP) method is employed for OPF problem, and thus SQP is the most efficient method to find solutions for the power system related problems in a faster and effective manner, when compared to other optimization techniques. Although many classical and evolutionary methods are available in the literature to find the real power loss in radial distribution systems, each one has its own merits and drawbacks. The real power loss equation is in a quadratic form and the reduction of real power loss could be done iteratively by using SQP.

SQP method developed by Wilson, Han and Powell is more popular since the 1970s due to its ability of solving non-linearly constrained optimization problems. It has been considered to be the conceptual method rather than a single algorithm [30]. This method finds the approximate solution for the minimization of the objective function using a sequence of quadratic programming sub-problems [31]. The added advantage of this method is the regularization of the QP sub-problem which has a known feasible point and usage of gradient method for the identification of QP active set [32]. The algorithm combining active set and filter method was proposed in [33] to solve the non-linear model assuming a few standards. An improved SQP was proposed in [34] by obtaining the search direction combining the QP sub-problem and the system of linear equations to obtain global and super linear convergence. A hybrid algorithm of SQP and differential evolution (DE) algorithm was proposed in [35] by solving the optimal flow problem. Since SQP is a local optimization method and it gives local optimum solution, it performs initially and then initial individual value from SQP is given to the DE algorithm. Hybrid PSO and SQP algorithm was investigated in [36] for the optimization of cluster flying orbit in spacecraft. PSO was used for finding the initial values for the SQP and SQP was used to reduce the time with improved convergence.

In this paper, reducing the real power loss in the RDS is perceived as the main objective function, subject to constraints, such as net power flow equations, DG power generation limits, and node voltage limits. Conventional methods like SQP are sensitive to the selection of initial value and might sometimes settle at the local optima value and evolutionary methods reach the approximate solution. Hence, in this paper, PIPSO [37] is first implemented for initial point selection and for narrowing down the selection, and SQP is then performed to get better results. This algorithm was developed by adding DGs one by one and by finding out the maximum number of DGs to be added in RDS. In addition, it was tested with different loadings such as light load, nominal load, and peak load conditions and the results are compared to the basic load flow methods. An active set method of SQP algorithm was implemented for optimum location and rating of DGs in IEEE 33-bus, IEEE 69-bus, and IEEE 118-bus distribution networks and the outcomes were compared with other methods to emphasize the superiority of the proposed approach. The implementation of the hybrid PIPSO–SQP algorithm for the real power loss reduction in radial distribution systems is a novel concept and has been validated by comparing the results with other classical and evolutionary methods.

2. Problem Formulation

Loss (P_L) minimization for 'N' bus RDS through the integration of DGs at appropriate locations with the optimum size is considered to be the main objective function. The power flow between the buses 'i' and 'j' is shown in Figure 1. The loss formula can be expressed as in Equation (1) [37]:

$$\text{Minimize } P_L = \sum_{i=1}^N \sum_{j=1}^N [\alpha_{ij}(P_i P_j + Q_i Q_j) + \beta_{ij}(Q_i P_j - P_i Q_j)] \quad (1)$$

where

$$\alpha_{ij} = \frac{r_{ij}}{V_i V_j} \cos(\delta_i - \delta_j); \quad (2)$$

$$\beta_{ij} = \frac{r_{ij}}{V_i V_j} \sin(\delta_i - \delta_j); \quad (3)$$

$$Z_{ij} = r_{ij} + x_{ij}; \quad (4)$$

where P_L -Power loss in kW; N -number of buses; r_{ij} , x_{ij} , Z_{ij} -resistance, reactance and impedance respectively for the nodes i and j ; V_i , V_j and δ_i , δ_j -voltage magnitudes and angles at nodes i, j correspondingly; P_i , P_j and Q_i , Q_j -real and reactive power injections at nodes i and j respectively.

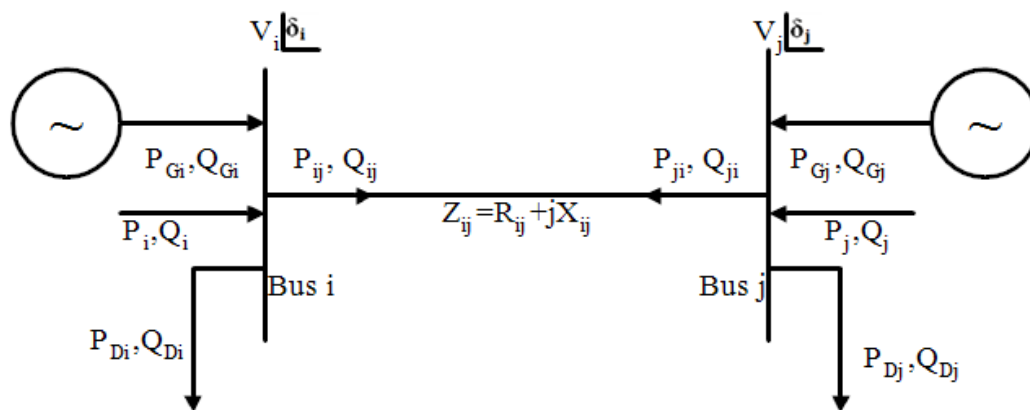


Figure 1. Two bus system with real and reactive power injections from DG.

Subject to the constraints:

(a) Net power flow constraints

$$P_{Gi} - P_{Di} = \sum_{i=1}^N V_i V_j [G_{ij} \cos(\delta_i - \delta_j) + B_{ij} \sin(\delta_i - \delta_j)] \quad (5)$$

$$Q_{Gi} - Q_{Di} = \sum_{i=1}^N V_i V_j [G_{ij} \sin(\delta_i - \delta_j) - B_{ij} \cos(\delta_i - \delta_j)] \quad (6)$$

where P_{Gi} , P_{Gj} and Q_{Gi} , Q_{Gj} -real and reactive power added by optimally placed DG at node i and j respectively; The total installed capacity of the DGs are limited to the total demand of the network. P_{Di} , P_{Dj} and Q_{Di} , Q_{Dj} -real and reactive demand at node i, j respectively; P_{ij} , P_{ji} and Q_{ij} , Q_{ji} are the real and reactive power flows in the line $i-j$ and $j-i$ respectively; G_{ij} and B_{ij} -conductance and susceptance of the distribution line between node i and j respectively.

(b) Generation constraints of DG

$$P_{Gmin} \leq P_{Gi} \leq P_{Gmax} \quad (7)$$

where P_{Gmin} and P_{Gmax} -minimum and maximum limits of DG generation. The maximum power generation from DG is the total load of the system and the minimum power generation is considered to be zero.

(c) Node voltage constraints

$$V_{min} \leq V_i \leq V_{max} \quad (8)$$

where V_{min} and V_{max} -minimum and maximum node voltage limits. In this work, the voltage limits were considered to be 1.05 per unit (p.u) maximum and 0.9 p.u minimum.

3. Sequential Quadratic Programming

Since power loss is the quadratic function of current, the SQP method was chosen for solving the objective function by running QP as the sub-problem. The objective function in Equation (1) and the constraints (5) to (8) are cumulatively formulated as a non-linearly constrained optimization problem and are solved by using the SQP technique, which shows its effectiveness while solving a problem with large nonlinearities in the constraints [38].

3.1. Quadratic Programming

QP pertaining to the optimization of linearly constrained problems with quadratic objective function. In addition, it provides solution for sub-problems in non-linearly constrained techniques, like SQP, augmented Lagrangian methods, and IP methods [39].

The general objective of the QP problem is represented as follows,

$$\text{Minimize } f(x) = \frac{1}{2}x^T Hx + x^T c \quad (9)$$

subjected to

$$a_i^T .x - b_i = 0; i \in E, \text{ where } i = 1, 2, \dots, m_e \quad (10)$$

$$a_i^T .x - b_i \leq 0; i \in I, \text{ where } i = m_e + 1, 2, \dots, m \quad (11)$$

where x -design vector with n parameters; $f(x)$ -objective function, which is quadratic in nature; m -total constraints; m_e , $m-m_e$ are equality and inequality constraints, H -symmetric matrix of $n \times n$ Hessian; a_i , b_i , c -vectors in constraints. The optimization problem stated in Equations (9)–(11) is a convex quadratic program, if H is positive and semi definite. When H is indefinite, then the problem will be non-convex, and it is tough to find the optimum global solution since the problem may have several locally optimal solutions.

Sequential Quadratic Programming depends on a fundamental theoretical basis and renders potential algorithmic rules to prevail optimum solutions in large-scale engineering problems. Typically, the non-linearly constrained problem could be expressed as in Equation (12):

$$\text{Minimize } f(x) \quad (12)$$

Subjected to

$$h_i(x) = 0; \text{ for } i = 1, 2, \dots, m_e \quad (13)$$

$$h_i(x) \leq 0; \text{ for } i = m_e + 1, \dots, m \quad (14)$$

The Lagrangian equation for the non-linearly constrained problem mentioned from (12) to (14) can be written as:

$$\Gamma(x, \lambda) = f(x) + \sum_{i=1}^m \lambda_i h_i(x) \quad (15)$$

where ‘ Γ ’ is the Lagrangian function & ‘ λ ’ is the Lagrangian multiplier; The great advantage of SQP is its ability to elucidate problems with non-linear limitations $h(x)$. The assumption is that the non-linear programming problem should contain a minimum of one non-linear constraint. SQP is modeled as a non-linear programming through an iterative technique as mentioned in Equations (12)–(14). This procedure is repeated for creating a sequence of solutions, which lead to a convergence with the optimum solution x^* .

3.2. Implementation of SQP Technique

In this proposed approach, the term $f(x)$ in the Lagrangian equation of non-linearly constrained problem (15) represents the active power loss P_L (1) and the term $h(x)$ in Equation (15) symbolizes the non-linear constraints as in Equations (5) and (6). Therefore, the function $f(x)$ and the constraints $h(x)$ in Equation (15) can be expressed as,

$$\text{Minimize } f(x) \quad P_L = \sum_{i=1}^N \sum_{j=1}^N [\alpha_{ij}(P_i P_j + Q_i Q_j) + \beta_{ij}(Q_i P_j - P_i Q_j)] \quad (16)$$

The design vector x for the problem described in Equations (16) and (17) comprises of the magnitude of bus voltage V , angle δ , injected DG real power P_G and injected DG reactive power Q_G . Let ‘ n_{bus} ’ be the number of buses in RDS and the design vector x is expressed as shown in Equation (18). subject to: Equality constraints:

$$h_i(x) = P_{Gi} - P_{Di} = \sum_{j=1}^N V_i V_j [G_{ij} \cos(\delta_i - \delta_j) + B_{ij} \sin(\delta_i - \delta_j)]; \text{ for } i = 1 \text{ to } n_{bus} \quad (17)$$

$$Q_{Gi} - Q_{Di} = \sum_{j=1}^N V_i V_j [G_{ij} \sin(\delta_i - \delta_j) - B_{ij} \cos(\delta_i - \delta_j)]; \text{ for } i = n_{bus} + 1 \text{ to } 2 * n_{bus} \quad (18)$$

Inequality constraints:

$$P_{Gmin} \leq P_{Gi} \leq P_{Gmax} \quad (19)$$

$$V_{min} \leq V_i \leq V_{max} \quad (20)$$

The maximum number of DGs to be incorporated in the RDN has been determined using the flowchart as shown in Figure 2, in which ‘ α' ’ is the step length parameter which can be determined by line search method and ‘ s' ’ is the search direction obtained from Quadratic Programming sub problem.

The design vector ‘ x' ’ for the problem described comprises of bus voltage magnitude ‘ V' ’, bus voltage angle ‘ δ' ’, injected DG real power ‘ P_G' ’ and injected DG reactive power ‘ Q_G' ’. Let ‘ n_{bus} ’ be the no of buses in RDN.

The design vector ‘ x' ’ is expressed as shown in Equation (21):

$$x = [V_2, \dots, V_{n_{bus}}, \delta_2, \dots, \delta_{n_{bus}}, P_{G1}, P_{G2}, \dots, P_{Gn_{bus}}, Q_{G1}, Q_{G2}, \dots, Q_{Gn_{bus}}] \quad (21)$$

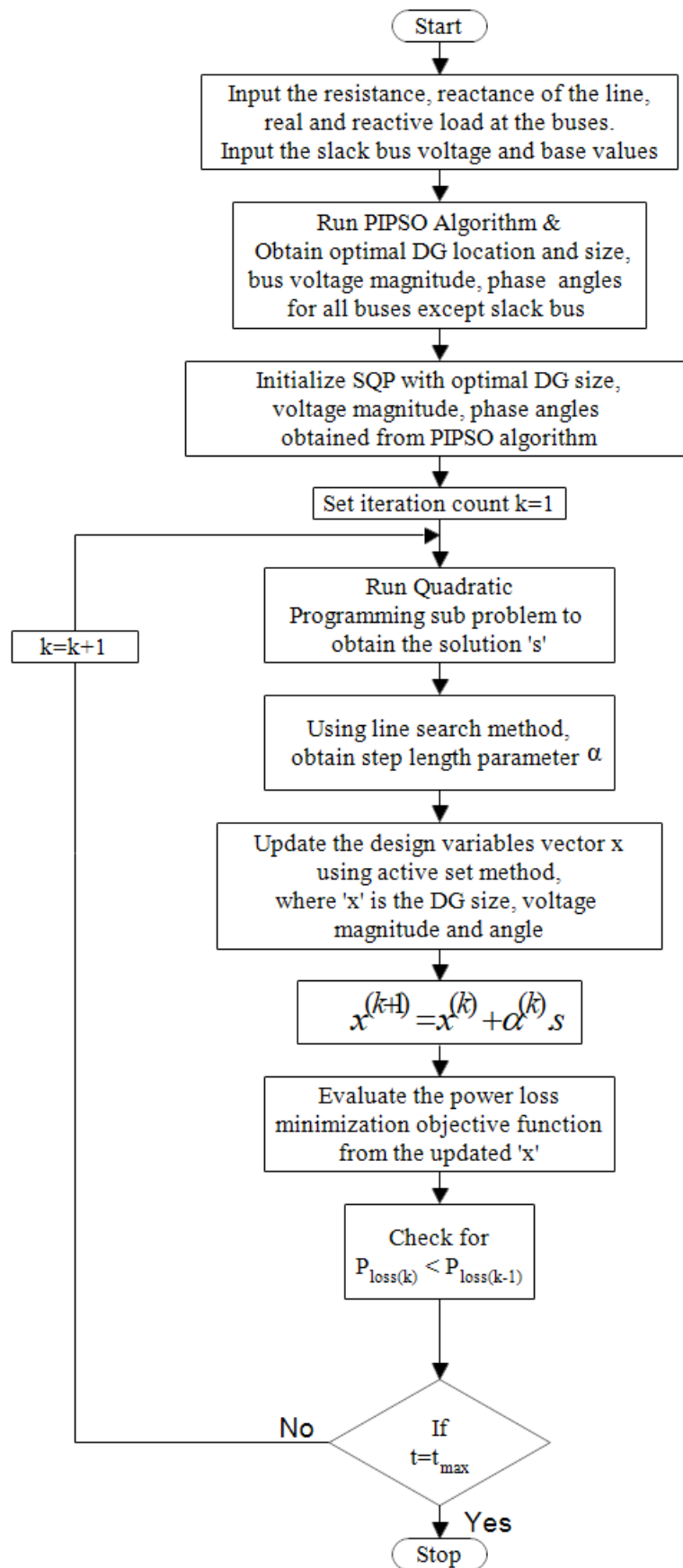


Figure 2. Flowchart of PIPSO–SQP optimization algorithm for power loss minimization of RDN.

As from Equation (21), the design vector x has a size of $2*(nbus - 1) + 2*nbus$. In this study, it is considered that the radial distribution network is exclusively equipped with the real power supporting DGs such as PV source or fuel cell. Therefore, the reactive power supported by these sources becomes zero. Consequently, the reactive power term in Equation (21) can be eliminated, the design vector x is written in Equation (22), and its size is reduced to $2*(nbus - 1) + nbus$:

$$x = [V_2, \dots, V_{nbus}, \delta_2, \dots, \delta_{nbus}, P_{G1}, P_{G2}, \dots, P_{Gnbus}] \quad (22)$$

Suppose the number of DG incorporated in a radial distribution network is limited to ' n ' and Bus_{DG} be the DG location vector with size n . Then P_G becomes zero for all buses except the DG located buses.

$$P_{Gi} = 0, i = 1, 2, \dots, nbus, i \notin Bus_{DG} \quad (23)$$

$$P_{Gi} = P_{DGj}, i = 1, 2, \dots, nbus, j = 1, 2, \dots, n, i \in Bus_{DG} \quad (24)$$

From Equation (23), the consideration of all ' P_G ' terms in design vector is not meaningful. Hence, the final design vector ' x ' used for active power loss minimization problem is rearranged as in Equation (24):

$$x = [V_2, \dots, V_{nbus}, \delta_2, \dots, \delta_{nbus}, P_{DG1}, P_{DG2}, \dots, P_{DGn}] \quad (25)$$

From equations, it is clear that the dimension of the proposed real power loss minimization problem is $2*(nbus - 1) + n$. The gradient vector for the objective function $f(x)$ is with vector length of $[nbus]*[2*(nbus - 1) + n]$. Similarly, there are $2*nbus$ non-linear equality constraints $h(x)$, each with gradient vector with vector length of $2*(nbus - 1) + n$. The minimum power generation from DG is considered to be zero and the maximum is the total load in the system.

The steps involved in solving the quadratic sub-problem by using the active set method are discussed as follows:

Step 1: Read distribution network bus data and line data. Run PIPSO to compute optimal DG location, bus voltage magnitude V and bus voltage angle δ . Initialize P_{DGi} randomly between P_{Gmin} and P_{Gmax} for all DG candidate buses ($i = 1$ to n). Create initial feasible design vector x_0 using V , δ and P_{DGi} such that $x_0 = [V_2, \dots, V_{nbus}, \delta_2, \dots, \delta_{nbus}, P_{DG1}, \dots, P_{DGn}]$.

Step 2: Set the iteration counter k to be zero, i.e., $k = 0$.

Step 3: Form the initial active set as a subset with the constraints at the initial vector which is active.

Step 4: Articulate the QP sub-problem with the constraints.

Step 5: Find the solution for QP sub-problem by solving Karush–Kuhn–Tucker system of linear equations.

Step 6: Repeat the above steps until the convergence criteria are satisfied by increasing the iteration count.

Step 7: The solution of the QP is used to update the vector of voltages, phase angles and the power using the following equation:

$$x^{k+1} = x^k + \alpha^k \cdot s \quad (26)$$

where $\alpha(k)$ is the step length parameter that can be determined by using the line search technique. The line search assumes an initial value for α as 1 and calculates the ' x ' vector. The power loss determined from the ' x ' vector was checked with the previous value. If it is less than the previous one, then the corresponding alpha is considered. Otherwise, the value of α is reduced to its half and it then proceeds with the calculation of ' x '.

The maximum generation limit of DG in RDS comes from the idea of power balance constraint in lossless economic dispatch problem, i.e.,

$$\sum_{i=1}^{ng} P_{Gi} = P_D \quad (27)$$

where P_{Gi} -output power of generator i , P_D -total power demand and ng -number of generators in power balance problem. Therefore, the maximum generation limit for DG in RDS is defined as:

$$P_{Gmax} = \sum_{i=1}^N P_{Di} \quad (28)$$

The minimum generation limit for DG is taken as zero.

$$P_{Gmin} = 0 \quad (29)$$

QP is the sub-problem of SQP and is obtained by the quadratic approximation of the Lagrangian Equation (15), and the non-linear constraints (5) to (8) are linearized. The QP sub-problem was referred from [39] and implemented for power loss minimization, as mentioned in the flow chart. Generally, the classical methods tend to converge at local optima due to the improper selection of initial value selection; hence, the parameter improved particle swarm optimization (PIPSO) method was chosen for the initial value selection in this paper. Figure 2 illustrates the flow chart of PIPSO–SQP real power loss minimization objective function by using QP as the sub-problem.

4. Test Case and Results Comparison

The optimal location/rating of DGs was implemented in MATLAB environment and the optimal real power losses were performed in IEEE 33-bus, IEEE 69-bus and IEEE 118-bus RDS. The structure of the test systems are presented in Annexure I. In this simulation study, the number of DGs to be installed increased one by one and the maximum number was attained. Since the load demand in a RDS is stochastic in nature, the various test cases were considered for different loading conditions, such as lightly loaded (50% of the base load), base load and heavily loaded (160% of the base load). The simulations were carried out for various loading conditions and the positioning of DG and its rating varied when it was installed with one or more DGs. Thus, the different locations of DG obtained for the same system under different loading environment were not suitable for real-time implementation. Practically, it is necessary to attain a unique DG location in a network, and that should suit for all loading conditions. The proposed method has been tested with various loading conditions with inclusion of three DGs and the results are compared with the conventional load flow methods. Both real and reactive power losses are reduced, and the minimum and maximum voltage profile are enhanced under all loading conditions.

In this proposed work, a novel PIPSO–SQP strategy was accomplished for each distribution test system to determine the maximum number of allowable DGs to be incorporated. This strategy was implemented in the radial system simulation analysis with single DG and then one DG was added in each step and iteration. The network objective function was evaluated for the addition of single DG and the maximum numbers of DGs was then identified for each distribution system. Once the optimal quantity of DGs was found, the optimal number of DG was fixed, and its location/rating was found by the proposed PIPSO–SQP algorithm.

4.1. Case 1: IEEE 33-bus RDS

The total demand in IEEE 33–bus RDS is (3715 + j 2300) kVA and the base voltage is 12.66 kV. The real and the reactive power loss of the base system are calculated as 210.84 kW and 143.12 kVAR, respectively. The maximum number of required DGs was identified for this system by applying the strategy mentioned in the previous section and the outcome are given in Table 1. It shows that power losses decreased when the number of DG sources increased. The real and the reactive power losses increased when the number of DGs was four; however, both losses were less with three DGs.

Since the maximum power from DG was considered to be the total load, the power from each DG varied according to the increase in the number of DGs. The power loss started to reduce after the inclusion of three DGs. When the fourth DG was added, the power generation was shared among four DGs and its location changed due to the lateral structure of the network. However, the loss increased due to the difference in the power generation of the four DGs. Hence, it was inferred that the maximum number of allowable DGs to be installed for IEEE 33-bus RDS was three.

Table 1. Results after placing multiple DGs in IEEE 33 bus system using PIPSO–SQP.

Number of DGs	DG Location	DG Power Rating in MW	Real Power Loss in kW	Reactive Power Loss in kVAR	Voltage Deviation Index p.u	Simulation Time in s
1	6	2.59	111.01	81.71	0.9237	10.22
2	13	0.84	87.17	59.77	0.6876	13.85
	30	1.14				
3	13	0.73	72.78	50.66	0.6302	15.91
	30	1.09				
	24	1.07				
4	24	1.25	76.50	52.89	0.6903	17.05
	19	0.19				
	9	1.01				
	31	0.8				

It is understood from Table 1 that the system loss reduced to 72.7853 kW when the system was integrated with three DGs from the base loss of 210.84 kW. Figure 3 demonstrates the comparison of voltage summary with respect to DG units.

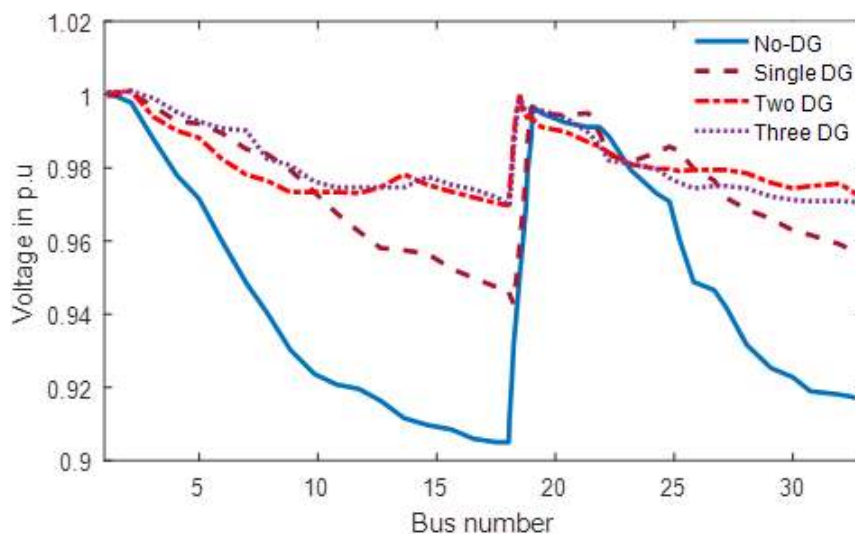


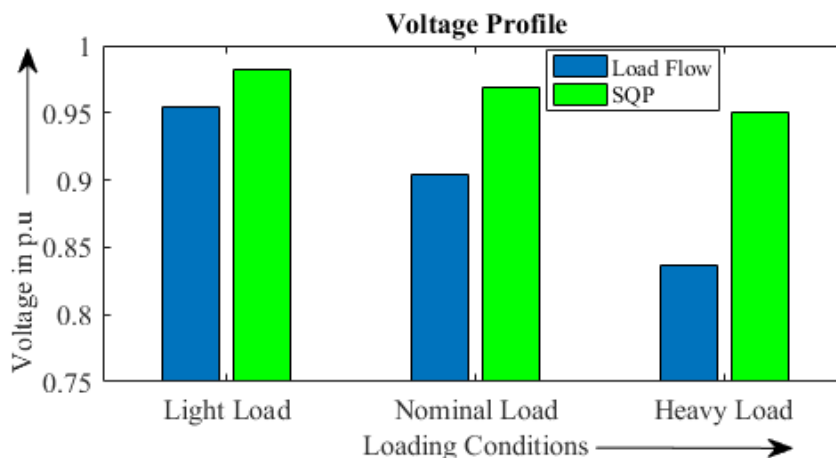
Figure 3. Bus voltage profile comparison with the inclusion of DGs in IEEE 33-bus system.

Table 1 displays the identification of optimal location in the DG placement problem as bus number 6 in single DG placement, buses 13 and 30 for double DG placement, and buses 13, 24, and 30 for three DG placement, along with the identification of its optimal DG rating. The voltage profile was maintained within the allowable limits and a remarkable reduction was observed in the losses for all test cases. A maximum loss reduction of 65.5% was achieved. Table 2 indicates the effects of power loss in the IEEE 33-bus system under different loading conditions. It was perceived that the lowest voltage magnitude was enhanced at all load levels by including DGs.

Table 2. Summary of results with different load conditions – IEEE 33 bus system –with 3 DGs–PIPSO–SQP.

Parameters	Load Flow Results		
	Light Load (0.5)	Nominal Load (1.0)	Peak Load (1.6)
Ploss in kW	48.787	210.9876	603.4308
Qloss in kVAR	33.0486	143.1284	410.2075
Vmin in pu/bus no	0.954/18	0.9038/18	0.836/18
Vmax in pu/bus no	0.9986/2	0.997/2	0.995/2
Sequential Quadratic Programming			
Optimal DG location (size in kW)	12/445.9889	30/1053.6346	14/1062.5833
	30/504.5479	24/1091.385	31/1233.5485
	24/486.0889	13/801.8118	6/1645.5499
Ploss in kW	17.7977	72.7853	208.9403
Qloss in kVAR	12.3427	50.6601	145.2327
Vmin in pu/bus no	0.9824/18	0.9687/33	0.9505/18
Vmax in pu/bus no	0.9994/2	0.9988/2	0.9976/2

The smallest voltage profile at bus 18 improved from 0.836 to 0.9505 during heavy load (160%) and the voltage improved for other loading conditions. The voltage value improved at bus 18, as shown in Figure 4.

**Figure 4.** Comparison of voltage profile with the load flow and the proposed SQP at bus 18 for different loading conditions.

The attained results were compared with other conventional and meta-heuristic methods found in the literature as shown in Table 3. It was inferred that the PIPSO–SQP had better results in all the cases. The minimum voltage at bus 18 was improved at light load, nominal load, and substantial load conditions.

Table 3. Comparison of hybrid PIPSO–SQP results with other methods for IEEE 33 bus system.

Method	Single DG		Two DGs		Three DGs	
	Bus Number/Size of DG, MW	Power Loss, kW	Bus No./Size of DG, MW	Power Loss, kW	Bus Number/Size of DG, MW	Power Loss, kW
Backtracking search [40]	8/1.8575	118.12	13/0.880, 31/ 0.924	89.34	13/0.632, 28/0.487, 31/0.550	89.05
Intelligent Water drop [15]	6/2.49	111.01	–	–	9/0.6003, 16/0.300, 30/1.0112	85.78
Bacterial Forging [17]	–	–	–	–	14/0.6521, 18/0.1984, 32/1.0672	89.90
GA+PSO [41]	–	–	–	–	32/1.200, 16/0.8630, 11/0.9250	103.40
Loss Sensitivity [42]	10/1.4	123.82	–	–	–	–
Repeated load flow [42]	6/2.6	111.10	–	–	–	–
Analytical [42]	6/2.49	111.24	–	–	–	–
Loss Sensitivity factor [43]	18/0.743	146.82	18/0.72 33/0.9	100.69	18/0.72 33/0.81 25/0.9	85.07
Improved Analytical [43]	6/2.601	111.10	6/0.18 14/0.72	91.63	6/0.9 12/0.9 31/0.72	81.05
Exhaustive Load flow [43]	6/2.601	111.10	12/1.02 30/1.02	87.63	13/0.9 30/0.9 24/0.9	74.27
PSO [44]	6/3.151	115.29	–	–	–	–
PIPSO [37]	6/2.59	111.02	–	–	–	–
SQP [45]	–	–	–	–	13/0.8018 24/1.0913 30/1.0536	72.951
Proposed PIPSO-SQP	6/2.590	111.0188	13/0.8516 30/1.1576	87.1656	30/1.0507, 24/1.0697, 13/0.8055	72.79

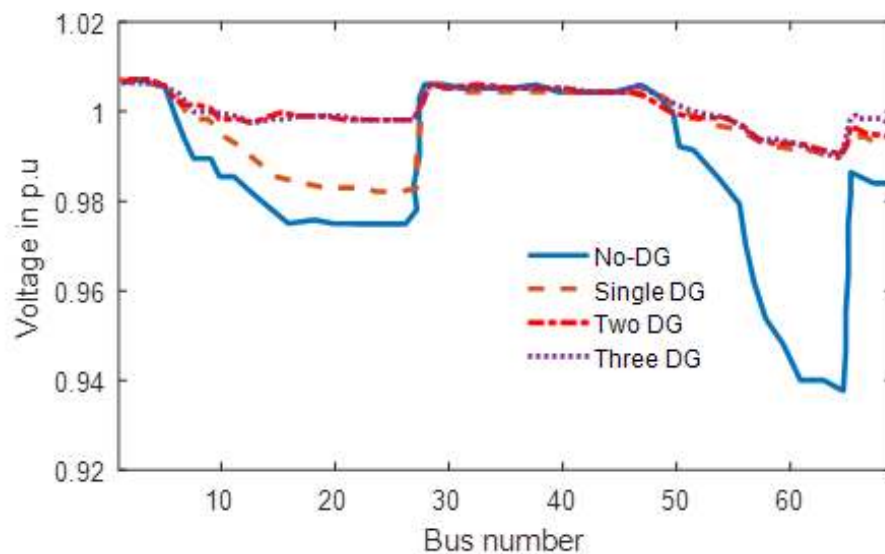
4.2. Case 2: IEEE 69-bus RDS

In the RDS of IEEE 69-bus, the base value of the voltage is 12.66 kV and the total load is considered to be $(3.80 + j2.69)$ MVA [37]. The proposed PIPSO–SQP method was employed on IEEE 69 bus system and the power loss without DG was calculated as 224.8949 kW and 102.1155 kVAR. The optimal DG locations and sizes are presented in Table 4. In order to find the maximum allowable DG to be located in IEEE 69-bus system, the strategy explained in the previous section was implemented and the results are presented in Table 4. It is perceived that both losses decreased with the increase of DGs, because the losses were reduced when there were four DGs. Hence, the maximum number of DGs to be installed in IEEE 69-bus RDS was three.

Table 4. Results after placing multiple DGs in IEEE 69-bus system using PIPSO-SQP.

Number of DGs	DG Location	DG Power Rating in MW	Real Power Loss in kW	Reactive Power Loss in kVAR	Simulation Time in s
1	61	1.86	81.60	40.49	25.70
2	17	0.52	70.40	35.96	34.06
	61	1.77			
3	61	1.77	69.16	33.04	37.13
	16	0.53			
	49	1.07			
4	28	1.14	70.61	32.53	41.33
	50	0.75			
	15	0.50			
	61	1.7			

The bus voltage profile of test system IEEE 69-bus is presented in Figure 5. The P_L was reduced to 70.8681 kW after the employment of DG and the minimum voltage was 0.9799 at bus 65. It can be observed in Figure 5 that power loss considerably decreased with the inclusion of DGs, when compared to the base case.

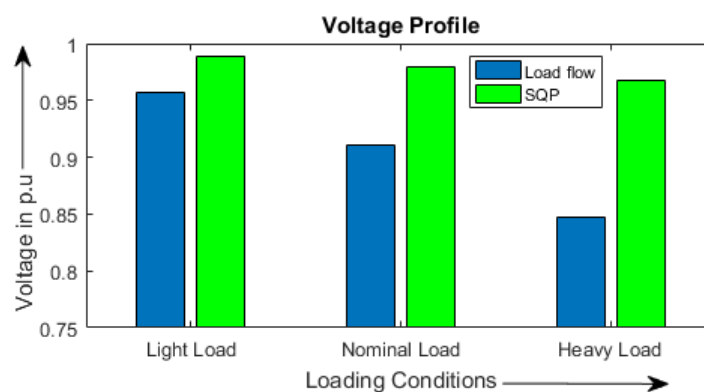
**Figure 5.** Bus voltage profile comparison with the inclusion of DGs in IEEE 69-bus system.

In Table 5, the various parameters are presented for different loading conditions. It is proved that the voltage profile at bus 65 for the SQP improved even for different loading conditions.

Table 5. Summary of results with different load conditions – IEEE 69 bus system –Inclusion of 3 DGs–PIPSO–SQP.

Parameters	Load Flow Results		
	Light Load (0.5)	Nominal Load (1.0)	Peak Load (1.6)
Ploss in kW	50.64	224.89	638.08
Qloss in kVAR	23.09	102.11	287.42
Vmin in pu/bus no	0.957/65	0.9105/65	0.8469/65
Vmax in pu/bus no	1.0/2, 3, 28, 36	1.0/2, 28	0.999/2, 3, 28, 36
Sequential Quadratic Programming			
Optimal DG location/size in kW	24/52.6136	49/1067.92	20/553.175
	1/873.58	61/1777.24	61/2814.58
	16/218.796	16/533.24	11/914.49
Ploss in kW	17.2131	69.16	178.4262
Qloss in kVAR	8.6632	33.0426	89.7021
Vmin in pu/bus number	0.9894/65	0.9799/65	0.9679/65
Vmax in pu/bus number	1.0/2,3,28,29,36	1.0/2,3,28	1.0/2,28

In this bus system, the minimum voltage at bus 65 improved from 0.8469 to 0.9679 and the bus voltage improved even for other loading conditions. In order to confirm the effectiveness of the proposed PIPSO–SQP algorithm, the analysis was done with light load, nominal load and heavy load, and the results were analyzed with the load flow method. The voltage profile improvement at bus 65 is shown in Figure 6.

**Figure 6.** Comparison of voltage profile with load flow and the proposed PIPSO–SQP at bus 65 for different loading conditions in IEEE 69 bus system.

The SQP results were compared with other classical and meta-heuristic methods in the literature. It is evident from the comparison in Table 6 that the PIPSO–SQP is effective to solve the problems of the power system.

Table 6. Comparison of PIPSO–SQP results with other methods for IEEE–69 bus RDS.

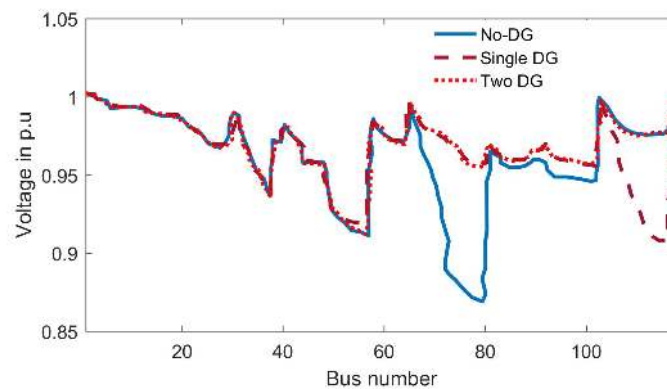
Method	Single DG		Two DGs		Three DGs	
	Bus Number /Size of DG, MW	Power Loss, kW	Bus Number. /Size of DG, MW	Power Loss, kW	Bus Number /Size of DG, MW	Power Loss, kW
Intelligent Water drop [15]	60/1.82	80.12	–	–	17/0.2999 60/1.320 63/0.4388	73.55
Bacterial Forging [17]	–	–	–	–	27/0.2954, 65/ 0.4476, 61/1.3451	75.238
GA with PSO [41]	–	–	–	–	63/0.8849 61/1.1926 21/0.9105	81.1
Loss Sensitivity [42]	61/1.9	81.33	–	–	–	–
Repeated load flow [42]	61/1.9	81.330	–	–	–	–
Analytical [42]	61/1.81	81.44	–	–	–	–
Loss Sensitivity factor [43]	65/1.52	109.77	65/1.44 27/0.54	98.74	65/1.36 27/0.51 61/0.51	90.84
Improved Analytical [43]	61/1.9	81.33	61/1.7 17/0.51	70.3	61/1.7 17/0.51 11/0.34	68.38
Exhaustive Load flow [43]	61/1.9	81.33	61/1.7 17/0.51	70.3	61/1.7 17/0.51 11/0.34	68.38
PSO [44]	61/1.80	83.37	–	–	–	–
PIPSO [37]	61/1.87	83.147	–	–	–	–
Proposed PIPSO–SQP	61/1.86	81.60	61/1.77 17/0.52	70.4	61/1.7 16/0.53 49/1.07	69.16

4.3. Case 3: IEEE 118-bus RDS

In the 118-bus RDS, 11kV is the base voltage and the total load is (22.7097 + j 17.0411) MVA. The PIPSO–SQP method was applied in 118-bus system to identify the optimum DG locations/sizes and the attained results are arranged in Table 7. The losses decreased as the number of DGs increased, as observed in Table 7. In comparison to the system with two DGs, the losses increased when three DGs were added. Therefore, it is evident that the number of allowable DGs to be connected in IEEE 118–bus is two. The graphical representations of voltage profiles with various DGs are given in Figure 7.

Table 7. Results after placing multiple DGs in IEEE 118 bus system using PIPSO–SQP.

Number of DGs	DG Location	DG Power Rating in MW	Real Power Loss in kW	Reactive Power Loss in kVAR	Simulation Time, s
1	72	2.9785	1016.8	776.152	42.0828
2	71 111	3.0768 2.8902	809.778	660.218	51.7138
3	72 112 48	1.3904 4.2562 2.5894	820.703	601.146	51.1177

**Figure 7.** Voltage profile comparison with the inclusion of DGs in the IEEE 118-bus RDS.

From Figure 7, it is perceived that the voltage value improves due to the inclusion of DGs. Table 8 presents the assessment of the results implemented by the proposed PIPSO–SQP method with other methods in the literature. It was observed that the inclusion of one DG and two DGs had a reduced power loss than the other methods. However, the power loss started increasing when three DGs were added, which indicated that the maximum number of allowable DGs was two in this case.

Table 8. Comparison of PIPSO–SQP results with other methods for IEEE 118–bus RDS.

Method	Single DG		Two DGs		Three DGs	
	Bus Number /Size of DG, MW	Power Loss, kW	Bus Number /Size of DG, MW	Power Loss, kW	Bus Number /Size of DG, MW	Power Loss, kW
HSA-PABC (Harmonic search algorithm -Particle artificial bee colony) [46]	70/3.05	1021.09	–	–	80/2.6 30/6.8 47/6.4	904.38
SOS (Symbiotic Organism Search) [47]	70/3.0482	1021.089	–	–	70/2.3788 104/4.7958 68/1.2591	875.2687
Whale optimization algorithm [48]	113/2.704	1092.46	–	–	–	–
Proposed PIPSO-SQP	72/2.9785	1016.8	71/3.0768 111/2.8902	809.778	72/1.3094 112/4.256 48/2.5894	820.703

5. Conclusions

A hybrid PIPSO–SQP-based active power loss minimization problem is presented to identify the optimum DG rating/location in a radial distribution power network. The presented novel active set method provides the optimal value for real and reactive power loss minimization problems. The analysis is highly stabilized, and it converges rapidly in the working set region through the active set method. To reduce the local optimum settling, the initial values of voltage and angles are determined from the evolutionary method, followed by the implementation of the classical method. The results obtained from the PIPSO–SQP method show improved real power loss reduction, and enhanced voltage profile with less computational time. The SQP based on the active set method can satisfy the objective function along with the constraints from an economic and technical point of view. Thus, the proposed hybrid algorithm can be applied similarly for large power distribution systems and for identifying the optimum location/size of DGs.

6. Annexure

The Radial distribution network of IEEE 33 bus structure, IEEE 69 bus structure and IEEE 118 bus structure are shown in Figures 8–10 respectively.

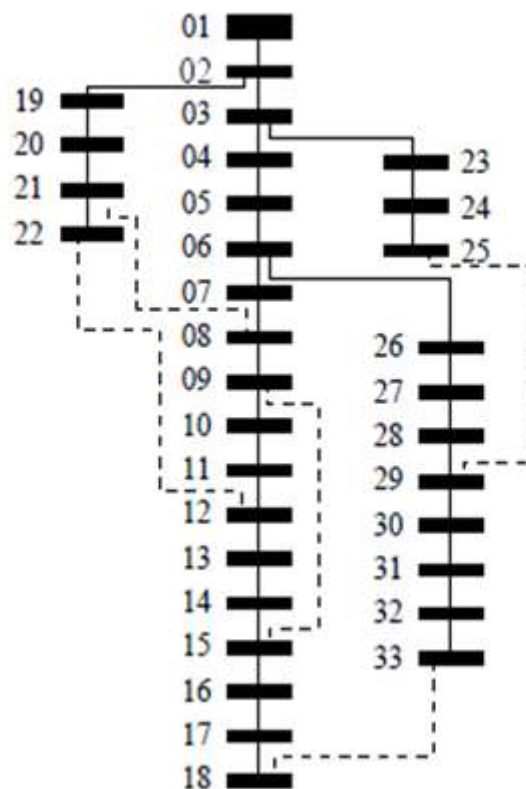


Figure 8. Single line diagram structure of IEEE 33 bus system.

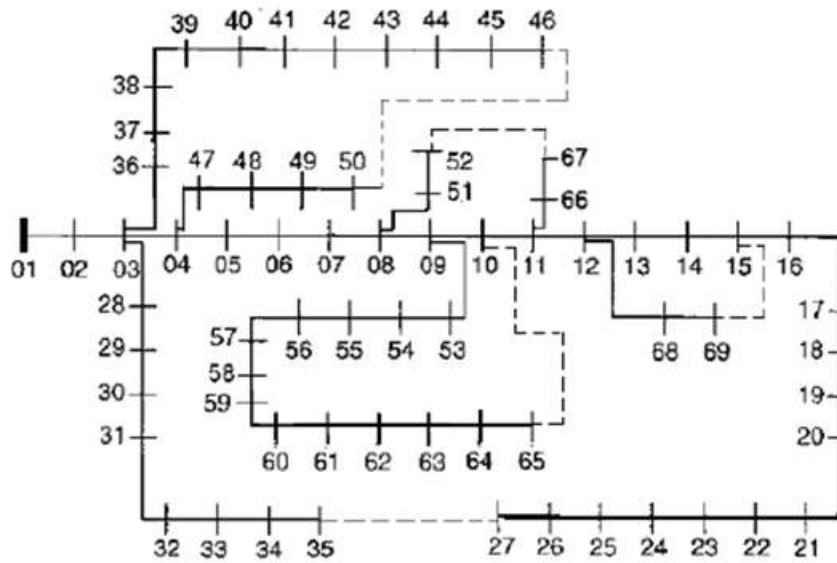


Figure 9. Single line diagram structure of IEEE 69 bus system.

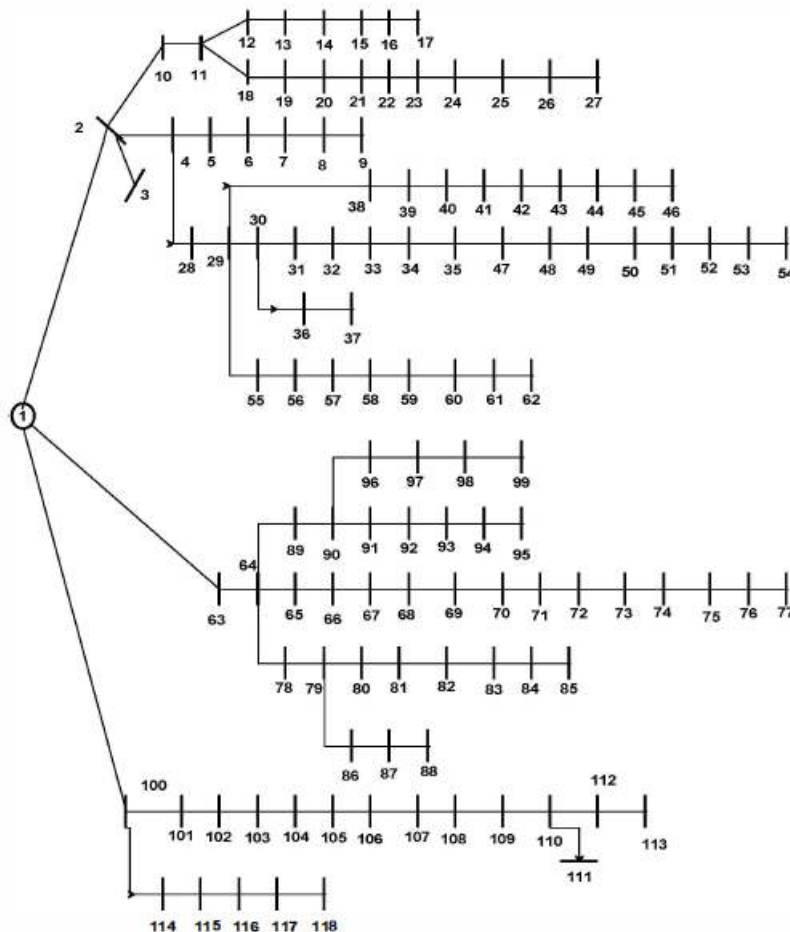


Figure 10. Single line diagram structure of IEEE 118 bus system.

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