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A multi-objective hybrid algorithm for feeder reconfiguration and planning of electrical distribution system

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Abstract

In this paper, a multi-objective Gravitational Search Algorithm (GSA) and Tabu search heuristic for feeder reconfiguration and planning of an electrical distribution system are proposed. In this strategy, the GSA has reduced the power losses and voltage deviations using relevant constraints. The optimal sizing of a distributed generator (DG) includes the best location with reduced electrical losses. The Gravitational Search Algorithm (GSA) hastens convergence with integration of a Tabu search heuristic. Then, the proposed multi-objective hybrid algorithm for planning an electrical distribution system is implemented on a MATLAB/Simulink platform. Its effectiveness is scrutinized by contrasting the results of the method under study with those of existing techniques such as ALO, LSA, CALMS and BBO-PSO. This comparison reveals the superiority of the proposed approach and affirms its potential to reduce power losses and voltage deviations.

Keywords: GSA, Tabu search, DG, Power loss, Voltage deviation, Feeder reconfiguration

1. Introduction

The high demand in the electricity market combined with high-tech growth and ecological damage has triggered interest in distributed generators (DG), [1]. Electric power distribution system design has arisen as a very momentous technology for power utilities [2-3]. The main focus of the current power system economics targets ensuring a distribution system with the less installations and process cost[4]. The concerns facing distribution system planning include various factors such as determining the optimum numbers and locations of the supply substations and the optimum technique of linking the load nodes to these substations by means of inter-linking of feeders [5]. This calls for proper planning which will, in the long term, substantially reduce costs without affecting customers. As a result, distribution system planning has become a multi-objective optimization problem [6-7]. Conversely, one of the vital issues faced by distribution system planning models is that an optimal plan with low expenditures is required [8].

The intent of distribution system planning (DSP) is providing a consistent and cost effective service to clients while guaranteeing that voltages and power quality are delivered at benchmark levels [9–11]. Cost reduction involves quite a few factors including capital and overhead of planned and existing facilities, purchases of power from other electric utilities, and the magnitude of electric system power losses [12-13]. The distribution power system planning technique involves two important phases. The first phase is preliminary system planning, which is followed by optimization of the resulting plan [14 The smart grid incorporation of dispatch able renewable DG units like biomass generators has become as one of the remarkable alternatives to satisfy the ever zooming load demands At the same time they enhance system reliability and reduce emissions [15].

Reactive power planning for a distribution network is carried out with the proper positioning of shunt capacitor banks [16]. Evolutionary calculation methods are employed as solution techniques to do most of the Pareto-based multi-objective planning [17-19]. Multi-objective algorithms' core objectives are based on slowly moving with the collection of optimal solutions that would lead to a set of varied solutions. Henceforth it can be confirmed that the multi-objective algorithm sets the goal with the high motivation for an instant perfect convergence achievement [20-21]. In the study, a multi-objective Gravitational Search Algorithm (GSA) and Tabu search for feeder reconfiguration and planning of an electrical distribution system is proposed. Use of the GSA yields solutions with lower power losses and voltage deviations of DGs with appropriate constraints. The best size of a DG is planned at an optimum location with reduced electrical losses. GSA speeds convergence when combined with a Tabu search strategy. Relevant literature is reviewed

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in Section 2. The proposed hybrid technique and the UPFC power flow model are discussed in Section 3. The results and discussion are presented in Section 4. Conclusions are drawn and presented in Section 5.

2. Recent research works: a brief review

The literature has innumerable investigations of distribution system planning. Several of these are discussed below.

Kumawat et al. [22] presented an approach for multiple distributed generator planning with the objectives of minimizing system energy losses and enhancing voltage profiles using a Particle Swarm Optimization PSO-based algorithm. That approach mimicked a real load scenario in a distribution system with time-varying electrical load demand. Sekhavatmanesh and Cherkaoui [23] made two original contributions. The first was clusters of nodes supplied each by a unique resource. . Furthermore, this unique clustering solution is valid at all fault locations. The second contribution was formulation of a solution approach that finds the optimal number, location and size of distributed energy resources (DERs). It also determines the optimal sizes of the clusters with an optimal set of controllable loads that need to be shed. Such highly combinatorial problems are normally formulated using non-convex optimization that a heuristic method is utilized to solve.

To develop a hardening strategy for a distribution system, Lin and Bie [24] constructed a tri-level defender-attacker-defender DAD model that considers the operational resilience of a reconfigurable distribution system with DG islanding capability. Case studies illustrate the topology reconfiguration, where a DG installation uses hardening strategies. In the rapid emergence of smart distribution systems, as well introduction of hardening strategies, operational resilience is playing a more critical role in enhancing system resilience. For the current smart distribution systems, they much more effective than the earlier DAD models. Jain et al. [25] have entitled a comprehensive review and critical discussion of state-of-the-art analytical techniques for optimal planning of renewable distributed generation. The analytical techniques were discussed in detail in six categories, i.e. exact loss formula, loss sensitivity factor, branch current loss formula, branch power flow loss formula, equivalent current injection and phasor feeder current injection. In addition, a comparative analysis of analytical techniques was presented to show their suitability for distributed generation planning in terms of various optimization criteria.

A new risk-based planning scheme was presented by Bai et al. [26]. It emphasizes low-probability but highly consequential events in energy supply systems. This approach was adopted for defining the optimal structure of a medium voltage network where risk-based determination of the radial network structures was accomplished using an uncertainty model of the system's variables based on discrete states, called scenarios. The monetary effects of technical risks were expressed using the convenient model of Rupolo et al. [27]. They suggested a distributed energy storage system planning model for active distribution networks that integrates emerging advanced power electronic devices called soft open points. The proposed planning model incorporates co-optimization of distributed energy storage system (DESSs) operation with other emerging active distribution network (ADN) technologies. These technologies include smart inverter based DGs given reactive power support where short-term network reconfiguration is done hourly. For efficient solutions, the model was mathematically formulated as a Mixed Integer Second-Order Cone Programming problem. Esmaeeli et al. [28] presented a new methodology that considers medium-voltage (MV) and low-voltage (LV) systems to carry out distribution network planning. The integrated planning of a MV/LV distribution system was posed as a mixed-integer non-linear program and aims at lessening investment (for substations, transformers, conductors, poles, and structures) as well as operating and reliability expenses. The power flow equations for the MV/LV modeling of transformers represent coupling constraints between MV/LV networks.

Typically, one objective function of the distribution system planning model is formulated. The objective function may require minimization of installation costs, energy losses or profit maximization. In a competitive power market, distribution system stability is important. The overall costs resulting from power outages, customer interruptions, and the contingency load loss index are the core of stability in a distribution system. Various approaches have been utilized for optimizing the objective functions of cost and stability in planning models. That approaches have used single-solution problems and multi-objective decision making. The primary challenge is to formulate a solution strategy as objective functions that are typically nonlinear, non-convex, and non-differentiable with many variables. Complexity increases greatly and depends on the number of buses in the system. Complexity is addressed using two strategies, deterministic algorithms and optimization algorithms. Deterministic algorithms involve mathematical optimization that can reliably generate outputs for certain inputs. Their solutions employ nonlinear, dynamic and mixed type programming methods. Optimization algorithms generate feasible solutions to many practical problems, but there are some random variations in the solutions. These optimization algorithms include genetic algorithms, Tabu search, artificial immune system, particle swarm optimization and honey bee mating optimization among others. However, these algorithms often have convergence problems that can be overcome with new search techniques.

3. Formulation of a multi-objective function

An objective function is used for minimization of power losses and voltage deviations. Various approaches have been utilized for optimizing power losses and voltage stability in planning models employing single-solution or multi-objective decision making problems. In this type of planning model, the key challenge is to formulate a solution strategy with objective functions that are typically nonlinear, non-convex, and non-differentiable with appropriate parameters. In the current study, a multi-objective model is developed for reducing power losses and voltage deviations. The multi-objective function is described in equation (1).

$$Fitness = \Psi = Min\{f_1, f_2\} \tag{1}$$

where, the total power loss is given as $f_1 = P_{LOSS}$ and the voltage deviation is $f_2 = \Delta V_{dev}$ .The proposed multi-objective function follows [11] in equations (2) and (3).

$$P_{Loss} = \sum_{i=1}^{N_b} P_L\{i, j\} \tag{2}$$

$$\Delta V_{dev} = \left(\frac{V_{ref} - V_i}{V_{ref}} \right) \quad (3)$$

where, $P_L\{i,j\}$are the power losses in a feeder connecting bus i to bus j, the total number of buses achievable to an associated a DG is given as N_b .The reference voltage magnitude is given as V_{ref} and the voltage magnitude at bus is V_i. The objective equations are utilized in planning the distribution system. During planning period, the network must adhere to safety and configuration constraints. These constraints deal with power balance, apparent power flow limit, bus voltage, distribution of substation capacity and costs.

(a) Power balance constraints

Power balance is most essential constraint in distribution system planning, since power production must meet the load demand and losses. The power balance constraint is utilized to achieve stability of the distribution system at the lowest cost. This constraint has two considerations, the active power and reactive power balance equations. The active power balance equation is characterized [1, 11] in equation (4).

$$(P_{DGi} + P_{Gi}) - P_i^d - \sum_{j=1} P_{ij} = 0 \quad (4)$$

where $P_{ij} = Y_{ij}\{V_i^2 \cos(\theta_{ij}) - V_i V_j \cos(\delta_j - \delta_i + \theta_{ij})\}$ is the power flow in a feeder connecting bus i to j (MW). P_{Gi} is the active power dispatched from transmission company i (MW). V_i is the voltage at bus i. V_j is the voltage at bus j, while δ and θ are the load and admittance angle, respectively. Y_{ij} is the admittance between bus I and j while P_i^d is the total active power demand at bus i (MW). Equation (5) describes the reactive power balance.

$$Q_{Gi} - Q_i^d - \sum_{j=1} Q_{ij} = 0 \quad (5)$$

where, Q_{Gi} is the reactive power dispatched from transmission company i $(MVar)$. Q_i^d is the total reactive power demand at bus$i$ $(MVar)$.Q_{ij} is the reactive power flow in the feeder connecting bus i to bus j $(MVar)$.

(b) Distribution substation capacity constraints

A substation in the distribution system must have the required capacity to satisfy the load demand and this is its allotted production limit. Depending upon the capacity of a particular distribution system substation, the load buses dispatching has been determined. Violation of the distribution substation capacity increases the cost and instability. The active and the reactive power capacity limited have been presented [29] and are given by equations (6) and (7).

$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max} \quad (6)$$

$$0 \le P_{DGi} \le P_{DGi}^{\max} \qquad \forall i = 1,2 \ldots N_b \quad (7)$$

where, Q_{Gi}^{min} is the minimum reactive power dispatched from transmission company i $(MVar)$.Q_{Gi}^{max} is the maximum reactive power dispatched from transmission company i $(MVar)$. and P_{DGi}^{max} is the maximum active power dispatched from the transmission company i (MW). These equations are the capacity limits of the DG resources, which should also consider the financial constraints of DG investment. This constraint imposes a limit on the DG capacity [11] as describe by equation (8).

$$\sum_{i=1}^{N_b} C_i^{inv} P_{DGi}^{\max} \le DBL \quad (8)$$

where, *DBL* is the distribution company budgetary limit.

(c) Apparent power flow limit of power transmission lines

The apparent power flow limit of a distribution system is described by equation (9).

$$\left| S_{ij} \right| \le S_{ij}^{\max} \quad (9)$$

where, S_{ij} is the apparent power flow through a transmission line connecting i and j. S_{ij}^{max} is the maximum transmission line power flow.

(d) Bus voltage limits

The distribution system planning must consider the bus voltage profile limits of the system. The bus voltage profile is kept with in specified limits for the stability of the system. The voltage profile of the bus is influenced by increases in the load demand, among other factors. The DG resources are allocated to minimize investment and enhance system stability. The required distribution system voltage limit [15] is expressed by equation (10).

$$V_i^{\min} \le V_i \le V_i^{\max} \quad (10)$$

where, V_i^{min} is the minimum permissible voltage at bus i $(V)$and while V_i^{max} is the maximum permissible voltage at bus i (V). Equation (1) is advanced as a multi-objective function. The multi-objective function reflects reduced distribution system losses while enhancing voltage stability. Then, the proposed technique to plan the distribution system is presented in Section 3.1.

3.1. Hybrid technique based Network Reconfiguration with a DG

A hybrid technique based system reconfiguration with a DG is presented here. It is noteworthy that meta-heuristic optimization algorithms are the best search solutions because they balance two related concepts, exploration and exploitation [30]. Exploration is defined as visiting entirely new regions of a search space. This is helpful to a global optimal solution. Exploration is the search for better optimal solutions in adjacent areas of the visited domain. This can aid in convergence of local search. So an algorithm should improve exploration in the first stage and enhance exploitation in the second stage with emphasis on expansion. The solutions in the GSA population are called agents; these agents interact with each other through the gravity force. In the standard GSA, the direction of movement of each agent is controlled by the total force of other agents acting upon it, with no communications between the agents. Thus, the GSA algorithm is hybridized with a Tabu search algorithm. A Tabu search algorithm places restrictions on the searches of neighboring solutions, aspiration allowing exception and accessible solutions. Here, GSA refreshes the agent positions could be beyond the boundary or not. If the boundary, a Tabu process is invoked or else the normal process is performed. Finally, the best solution is determined by the utilization of proposed technique. The DG factors and limits are involved in the hybrid technique as input requirements and the optimal reconfigured DG is the output. The hybrid technique input parameters are the IEEE distribution system bus voltages and the power losses, which are delineated in equation (11).

$$X_i = [(V_1, P_{L1})^1, (V_2, P_{L2})^2, (V_3, P_{L3})^3 \ldots (V_n, P_{Ln})^n] \quad (11)$$

where, $(V_i, P_{Li})^d = X_i^d$ defines the position of the i^{th} agent in the d^{th} dimension. According to Newton's gravitational theory, the total force acting on an agent is described by equation (12).

$$force_i^d(t) = \sum_{j \neq i} rand_j \left(force_{ij}^d(t) \right) \quad (12)$$

where, $force_{ij}^d(t) = G(t) \frac{M_{pi}(t) * M_{aj}(t)}{R_{ij} + \varepsilon} * (X_j^d(t) - X_i^d(t))$ with, $R_{ij} = \|X_i(t), X_j(t)\|_2$ is the Euclidian distance between two agents I and j, $rand_j$ is a random values, i.e., [0, 1], ε is a small constant, M_{aj} and M_{pi} are active and passive gravitational masses associated with agents i and j. The acceleration of the i^{th} agent can be expressed by equation (17).

$$a_i^d(t) = \frac{force_i^d(t)}{M_i(t)}$$

Here, acceleration of the i^{th} agent is specified as $a_i^d(t)$, inertial mass of the i^{th} agent is specified as $M_i(t)$. An agent's position is updated, utilizing the following velocity equation (13).

$$V_i^d(t+1) = rand_i . [V_i^d] + a_i^d(t) \quad (13)$$

To expand to new agents, a velocity function is used which can be expressed as equation (14).

$$X_i^d(t+1) = X_i^d(t) + V_i^d(t+1) \quad (14)$$

where, $V_i^d(t)$and $X_i^d(t)$ are the velocity and position of an agent at t time and d dimension, $rand_i$ is a random number in the interval [0, 1].

If $X_i^d(t+1) > U_b(d)$; $X_i^d(t+1) = U_b(d)$ or
If $X_i^d(t+1) < L_b(d)$; $X_i^d(t+1) = L_b(d)$

where, $U_b(d)$ and $L_b(d)$ are the upper and lower limits of agents in the d^{th} dimension. All off-boundary agents are gathered at the boundary after such processing, which will cause a huge force compelling other agents to shift towards the boundary in accordance with law of gravity and the uniform distribution of agents is disrupted. This hinders global exploration when there are local optima at the boundary. Therefore, a Tabu search strategy is utilized in the current work. This strategy helps to enhance the search capability of the agents. New agents created by a Tabu search are illustrated by equation (15).

$$X_{New}^d(t+1) = \begin{cases} X_{TS}^{11}(t+1) \\ X_{TS}^{21}(t+1) \\ \vdots \\ X_{TS}^{N1}(t+1) \end{cases} \quad (15)$$

Eqution (15) signifies the new updated position with the combination of N number of agents. The steps for planning a DG in a distribution system utilizing the proposed hybrid technique are briefly explained below.

(a) Steps for plan a DG in a distribution system

Step 1: Initialize the input parameters (agents) like DG variables and configuration limits, bus voltage and the line losses.

Step 2: In this step, randomly generate the initialized input variables.

Step 3: The high mass agents are chosen as the best solutions and the load flow is examined.

Step 4: The determined solutions are isolated into two groups. The first group has the minimum best solutions and the other has the best maximal solutions.

Step 5: For each solution group, the agent positions and velocities are refitted.

Step 6: Run load flow to evaluate the new agents. Select the best agent from each group.

Step 7: Check whether the new position of the agent is beyond the limit. If the new position of the agent is beyond the limit, a Tabu search is invoked or else the process goes directly to step 9.

Step 8: Evaluate the fitness of the new position of each agent. If it is accessible, then the current agent's position is restored. Otherwise, the second best agent position is used and its accessibility is checked. This is done until the optimal accessible agent's position is found.

Step 9: The better of the GSA and Tabu search processes is found.

Step 10: The optimal voltage, real and reactive power flow as well as the power loss are determined.

Step 11: Check the termination criterion. If it is fulfilled, print the result or else go to step 12.

Step 12: Generate the new agents for the next solution (i=i+1).

Once the process is finished, the system is ready to provide the optimal allocation and capacity of DG planning in a radial distribution system with the minimal power losses and voltage deviations according to the projected demand growth. Structure of the proposed hybrid technique has been clarified in the Figure 1. Additionally, the general structure of Tabu search process is schematically depicted in Figure 2. A system is proposed with an optimal arrangement of the distribution network with DGs. This system will have reduced power losses and voltage deviations. Then the best proposed hybrid technique is tested in an IEEE standard radial distribution system.

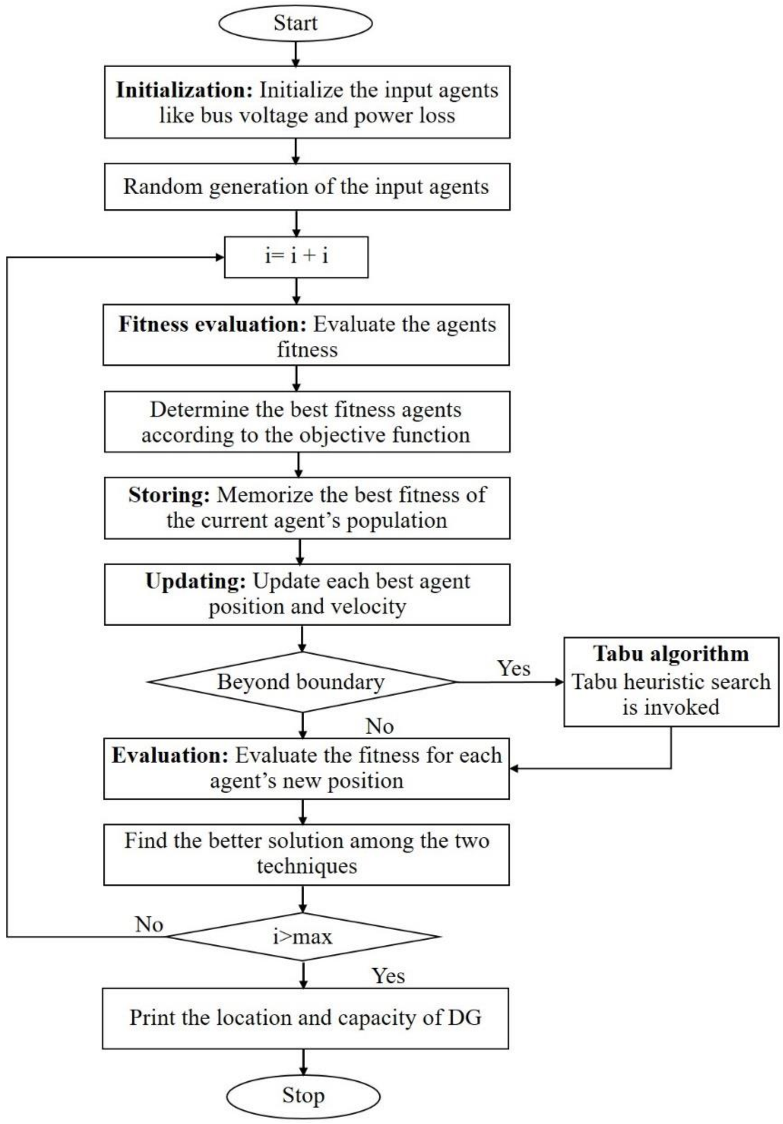

Figure 1 Structure of the proposed hybrid technique

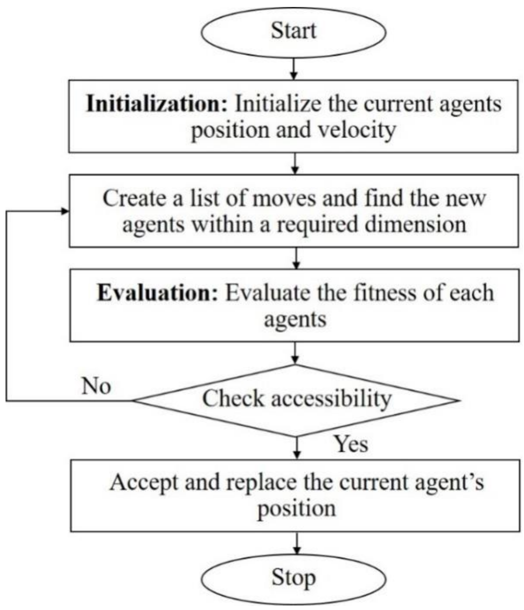

Figure 2 Structure of the Tabu search algorithm

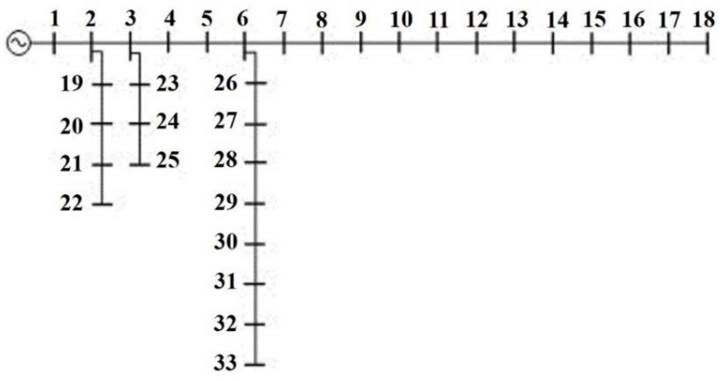

Figure 3 Structure of the IEEE 33 bus distribution system

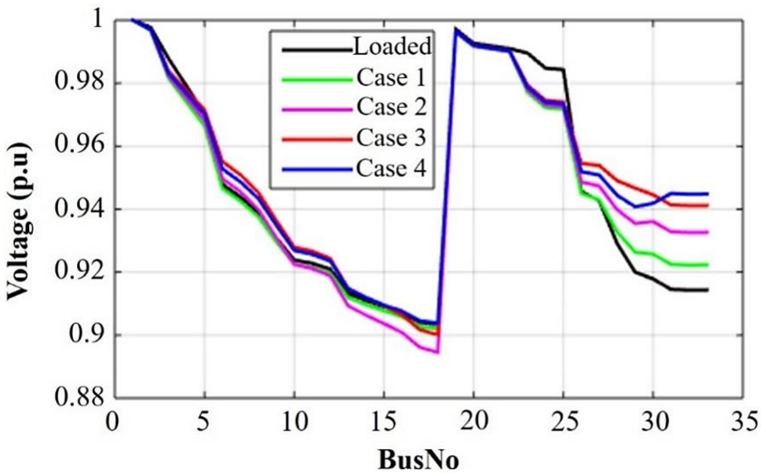

Figure 5 Estimated voltage at load 2 condition for the different cases

4. Results and discussion

The proposed method was implemented in MATLAB/Simulink 7.10.0 (R2012a) platform, with 4GB RAM and an Intel(R) core(TM) i5. Here, the objective functions of the DGs are considered as the minimization of power losses and voltage deviations. Depending on the objective function, the proposed technique finds the optimal feeder reconfiguration of the DG, which enhanced the planning for a DG in the distribution system. For planning of the DG in the distribution system, an IEEE standard bench mark system, such as anIEEE33 bus radial distribution, is utilized. The effectiveness of the proposed hybrid technique is recognized by using comparative analysis with the GSA technique. The IEEE 33 radial distribution system structure is described [1, 31] in Figure 3. This section specifies a correlated investigation that employs diverse cases.

- **Case 1:** Without reconfiguration of the bus system and DG units.
- **Case 2:** Optimal reconfiguration of the bus system using available sectionalizing and tie switches.
- **Case 3:** Optimal size of DG units installed at the candidate bus.
- **Case 4:** Optimal reconfiguration of the system in the presence of optimally sized DG units installed at the candidate bus.

The bus voltage profile of the IEEE 33 radial distribution system at load 1 for the four different cases is given in Figure 4. Similarly, for loads 2 and 3, the various cases of the distribution system are demonstrated in Figures 5 and 6, respectively. From these figures, it can be seen that the load changed from 5% to 25 % of the total system load demand. At the system limits, the normal conditions of the system bus voltages are retained, which is determined at the fault time (increasing load period).

In this critical circumstance, the bus voltage limits are changed by selection of a DG with optimal capacity. It is not certain that DG planning using existing techniques will reduce voltage profile deviations of an IEEE 33 bus distribution system. Improper voltage deviations of the distribution system are handled by the proposed method. The power losses of the IEEE 33 bus radial distribution system in all of the four cases for loads 1, 2 and 3 are given in Figures 7, 8 and 9 respectively. From these figures, the adequacy of the proposed method is tested by utilizing the IEEE 33 bus radial distribution power losses under these load conditions. It was seen that in under a normal condition the system power losses are maintained at the specified limit. The power losses grew due to the variation in the load in each of the cases. The power losses are minimized by the proposed hybrid technique as are the power losses and voltage deviations.

Figure 10 shows a comparison analysis of the voltage of the proposed model with existing techniques such as LSA, ALO, CALMS, and BBO-PSO. As seen in Figure 10, at the initial condition with a voltage of 1 p.u., LSA, ALO, CALMS, and BBO-PSO, showed voltage reductions to 0.908, 0.909, 0.91 and 0.946 p.u., respectively. In the proposed model, the initial condition of 1 p.u. decreased to 0.958 p.u.

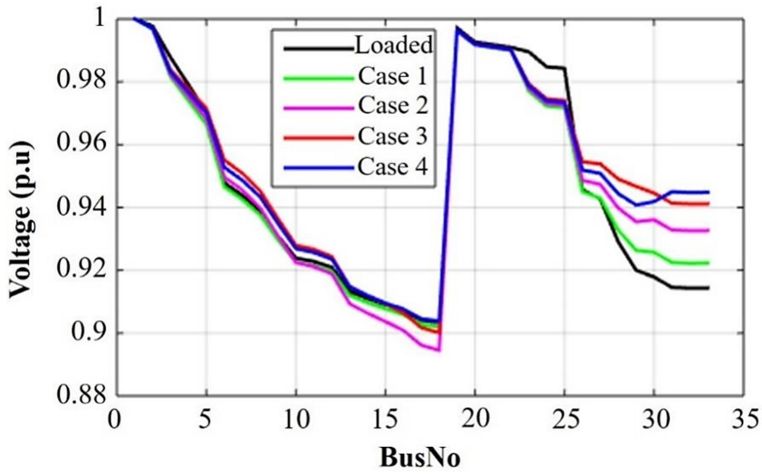

Figure 5 Estimated voltage at load 2 condition for the different cases

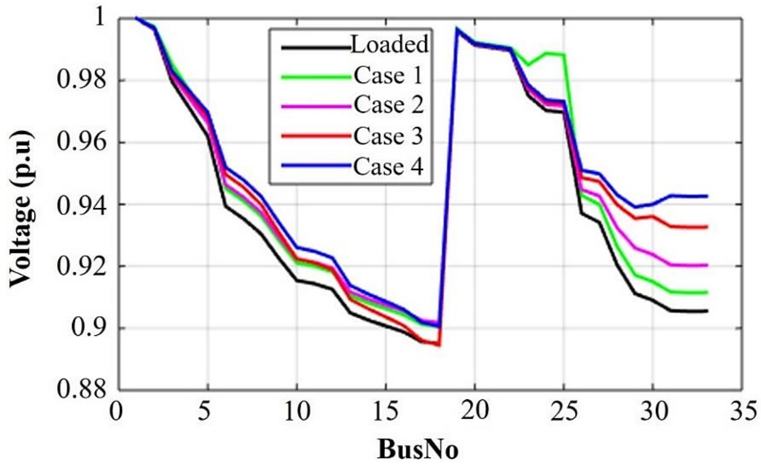

Figure 6 Estimated voltage at load 3 condition for the different cases

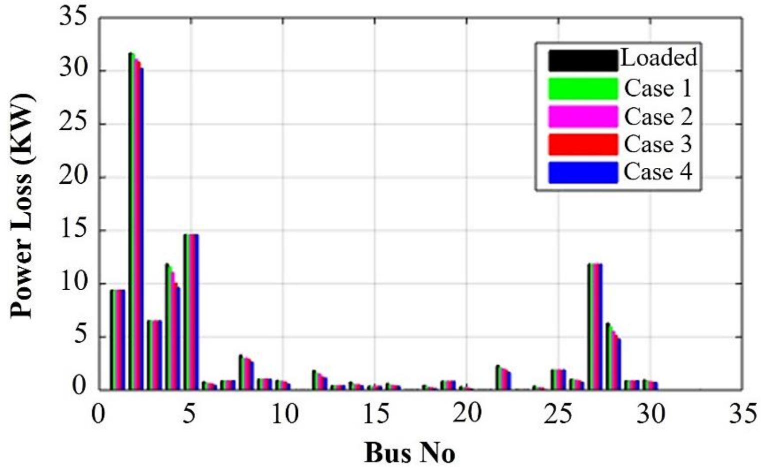

Figure 7 Estimated power losses at a load 1 condition for the different cases

Using LSA, ALO, CALMS, BBO-PSO the voltage profile of the IEEE 33 bus radial distribution system and proposed strategy are depicted in the Figures 11 and 12 under various load conditions. By comparing the existing techniques, the proposed technique has less voltage deviation. The CALMS contains 5% higher deviation with reference to the proposed strategy. Utilizing the IEEE 33 bus distribution system indicates that the proposed strategy clearly decreases the voltage deviation under all the three load conditions.

At this point, the results of using various procedures such as LSA, ALO, CALMS, BBO-PSO and the proposed technique to determine the power losses of the IEEE 33 bus radial distribution system are shown in Figures 13, 14 and 15 for each of the three load conditions.

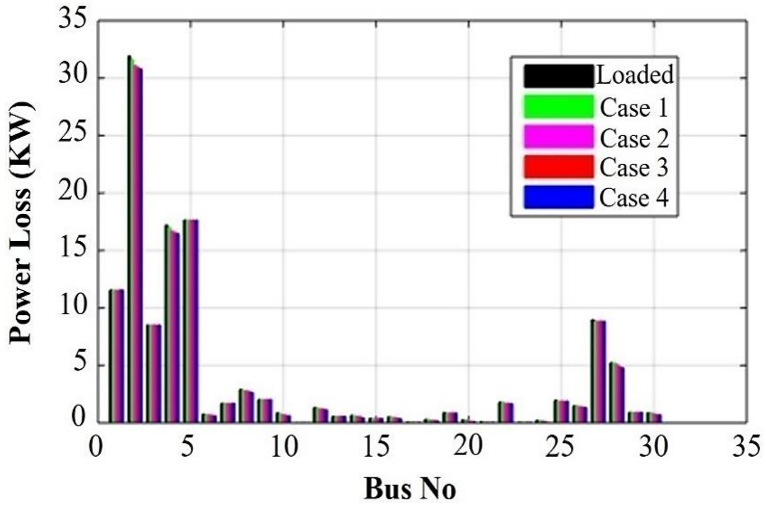

Figure 8 Estimated power losses at a load 2 condition for the different cases

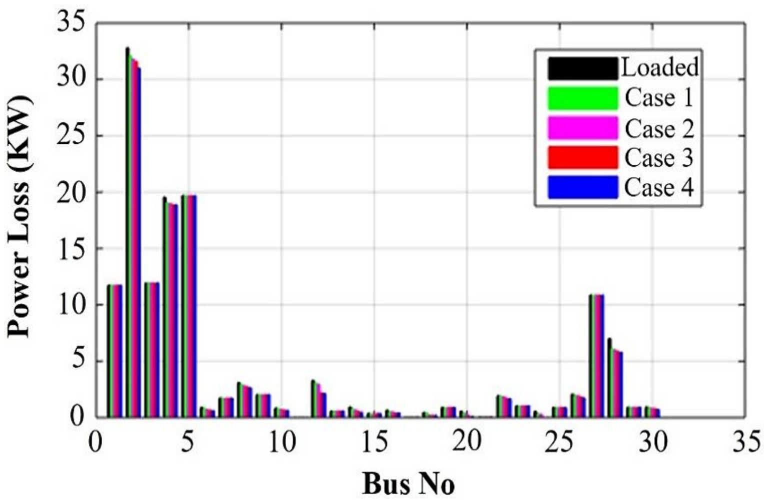

Figure 9 Estimated power losses at a load 3 condition for the different cases

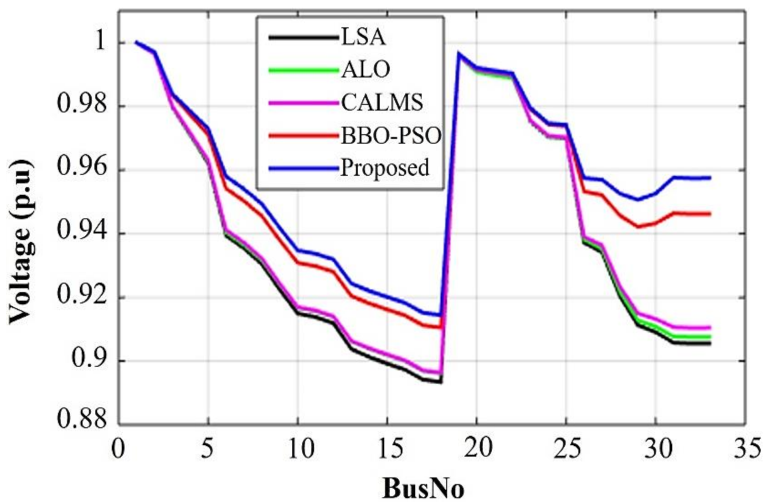

Figure 10 Voltage comparison with the existing techniques at a load 1 condition

The bus power losses are considered during the planning of a DG to understand the load demand in each case. The power losses of the existing techniques are high, 10% from the CALMS technique. The CALMS predicts5% higher losses than the proposed hybrid method. Comparison with the existing techniques at three loading condition for all the four cases and the effectiveness of the proposed method is also verified and the results shown in Table 1.

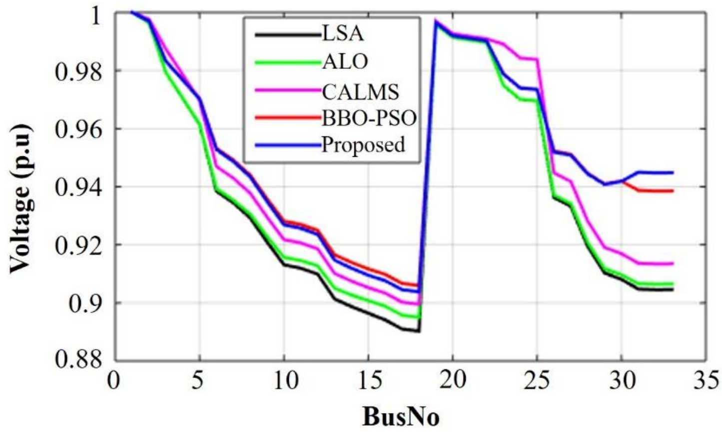

Figure 11 voltage comparison with the existing techniques at a load 2 condition

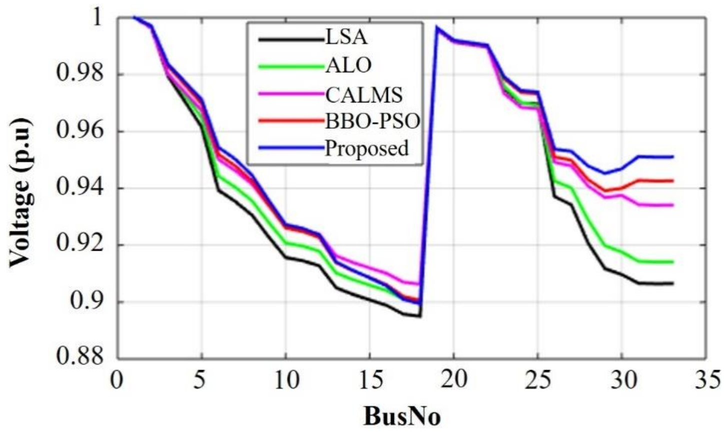

Figure 12 voltage comparison with the existing techniques at a load 3 condition

Table 1 Optimum solutions for the various methods

Cases	Load (%)	Objective	Solution techniques				
			LSA	ALO	CALMS [32]	BBO-PSO	Proposed
Case 1	Light	Power loss (w)	210.094	210.074	210.054	210.034	210.0257
		Δv_{dev} (v)	0.996477	0.996468	0.996536	0.996678	0.997013
	Nominal	Power loss (w)	210.394	210.374	210.354	210.294	210.2757
		Δv_{dev} (v)	0.995477	0.995468	0.995536	0.995678	0.996765
	Heavy	Power loss (w)	215.394	215.374	215.354	215.294	215.1578
		Δv_{dev} (v)	0.993477	0.995468	0.995536	0.996778	0.997340
Case 2	Light	Power loss (w)	135.394	135.374	135.354	135.294	135.2176
		Δv_{dev} (v)	0.996477	0.996468	0.996536	0.996678	0.997096
	Nominal	Power loss (w)	142.394	142.374	142.354	142.294	142.258
		Δv_{dev} (v)	0.995477	0.995468	0.995536	0.995678	0.996899
	Heavy	Power loss (w)	145.394	145.374	145.354	145.294	145.287
		Δv_{dev} (v)	0.995377	0.995368	0.995436	0.995578	0.996756
Case 3	Light	Power loss (w)	131.394	131.374	131.354	131.294	131.1633
		Δv_{dev} (v)	0.996477	0.996468	0.996536	0.996678	0.997212
	Nominal	Power loss (w)	135.394	135.374	135.354	135.294	135.2756
		Δv_{dev} (v)	0.994477	0.996468	0.996636	0.996878	0.997127
	Heavy	Power loss (w)	139.394	139.374	139.354	139.294	139.2461
		Δv_{dev} (v)	0.995477	0.995468	0.995536	0.995678	0.996899
Case 4	Light	Power loss (w)	129.394	129.374	129.354	129.294	129.1418
		Δv_{dev} (v)	0.994497	0.996488	0.996656	0.996898	0.997146
	Nominal	Power loss (w)	133.394	133.374	133.354	133.294	133.1782
		Δv_{dev} (v)	0.996377	0.996568	0.996536	0.996778	0.997029
	Heavy	Power loss (w)	134.394	134.374	134.354	134.294	134.1452
		Δv_{dev} (v)	0.996277	0.996468	0.996536	0.996678	0.996995

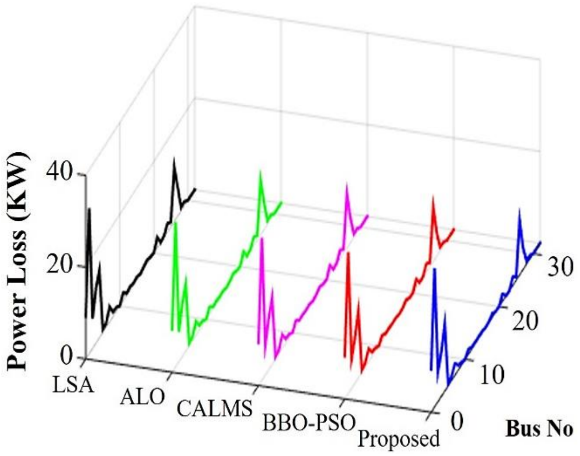

Figure 13 Power loss comparison with the existing techniques at a load 1 condition

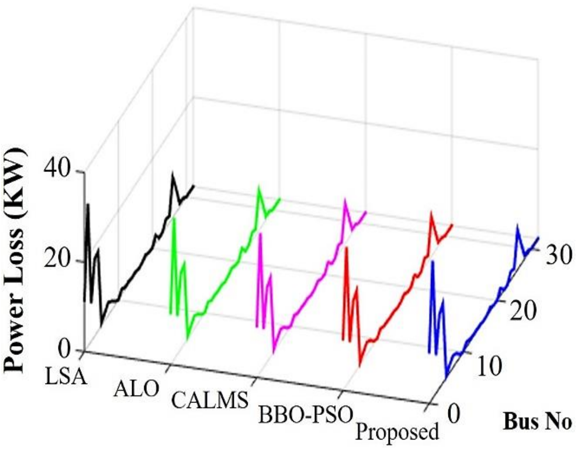

Figure 14 Power loss comparison with the existing techniques at a load 2 condition

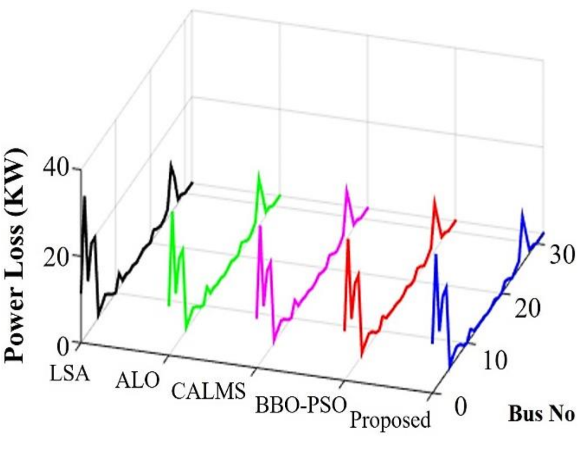

Figure 15 Power loss comparison with the existing techniques at a load 3 condition

The IEEE 33 bus distribution system planning utilizing existing techniques and proposed method are illustrated. Finally it is concluded that the proposed method minimizes the power losses and voltage deviations more optimally in all the loading conditions when compared to the existing techniques.

5. Conclusions

This paper proposes a multi-objective hybrid algorithm for reconfiguration of a feeder and for planning an electrical distribution system. The electrical distribution system planning is done by a combined GSA and a Tabu search method. The GSA actively reduces the power losses and voltage deviations, which is then utilized to optimally locate the DG with optimum capacity. GSA speeds convergence when it is combined a Tabu search method. The proposed method is verified using an IEEE 33 bus radial distribution system and the performance was examined with various techniques that examined distribution system without using DG and GSA. Comparison results was done for a radial distribution system power losses and voltages under various conditions. From the results, it can be seen that the proposed method is the most effect technique for planning an electrical distribution system.

6. References

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