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Integrated database approach in multi-objective network reconfiguration for distribution system using discrete optimisation techniques

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Abstract: Reconfiguring the link between buses is a crucial task to enhance the distribution system performance. Reconfiguration is a complex combinatorial process due to numerous feasible solutions. Therefore, to consistently find global optimum solutions within a short span of time is a challenging task. One of the factors that cause time consumption in finding optimal network configurations is the elimination of non-radiality network solutions during the optimisation process. To address this issue, this work proposes to store pre-determined network radiality solutions in a database. These sets of solutions are used in the network reconfiguration optimisation by a discrete evolutionary programming and a discrete evolutionary particle swarm optimisation techniques. These optimisation methods are based on a multi-objective problem which minimises power loss, voltage deviation, and a number of switching actions. Moreover, the quality of the solutions is measured in terms of computational time and consistency. To demonstrate the efficiency of the proposed technique, a comparative assessment is carried out on 33-bus and 118-bus distribution systems. It is found that the proposed technique outperforms other existing methods in terms of quality of the solutions.

1 Introduction

Existing power distribution systems are in the process of transforming from passive to an active network. This opens up new challenges and approaches, especially for power system operation. ‘Reconfiguration’ of electrical distribution system has been the primary solution to improve the operational performance of distribution networks. Finding an optimal reconfiguration solution is a complex optimisation task, which is required in a smart grid distribution system for specific strategies [1]. In a smart grid environment, optimal reconfiguration is vital for self-healing. After fault detection and isolation, it is imperative to restore the maximum number of customers with the minimum number of switching actions. Optimal switch configuration for the network reconfiguration has to be obtained from a large number of combinatorial search spaces. Network reconfiguration involves the process of opening normally closed sectionalising switches or closing normally open tie switches. During the reconfiguration process, distribution network has to maintain radiality with the maximum number of loads to be energised [2]. Furthermore, switching sequence in the reconfiguration operation has key importance as it leads to an optimal configuration. It also directly affects reliability indices including the restoration time, energy not supplied and power loss. Therefore, switching sequence consideration is equally important for optimal configuration and reliability improvement [3].

In a literature, reconfiguration has been proposed with mainly three categories of optimisation techniques, which are mathematical optimisation, heuristics, and meta-heuristics. Mathematical optimisation commonly uses the linear model with the combination of branch and bound algorithm to obtain the mixed-integer linear programming problem for distribution network reconfiguration. Heuristics and meta-heuristics optimisation techniques, on the other hand, consider the non-linear model of distribution network reconfiguration, thus making them a popular choice of optimisation technique in the last decade [4].

Merlin and Back [5] were among the first few researchers to implement the network reconfiguration in a distribution network for the minimisation of power loss using mixed-integer non-linear optimisation with branch and bound method. In [4], the network reconfiguration problem was solved using non-linear programming (NLP) due to non-convexity of NLP, which will not ensure the global optimum solution. In [6], mixed-integer quadratic programming is used to solve the network reconfiguration, which avoids the use of a binary variable for the linearisation process. In [7], a heuristic approach based on circular-updating-mechanism was used to obtain the optimal network configuration for minimum power loss and proposed two different methods for it. In the first method, the radial configuration was used for initialisation and subsequently on the basis of heuristic rule, the status of the switches was updated whereas, in the second method, switches were opened one by one until the radial solution was obtained.

Fireworks algorithm was used in [8], the optimal ordering of node during the power flow was required to solve the network reconfiguration under normal and abnormal conditions. In [9], bacterial foraging optimisation algorithm was used to solve network reconfiguration under abnormal state. However, the optimal configuration found with this proposed technique is non-radial in nature and this configuration is not valid for the distribution system. As in distribution network, the radial configuration is vital due to the protective reasons [4]. Numerous other optimisation algorithms such as fuzzy adaption evolutionary programming (EP) [10], binary particle swarm optimisation (PSO) [11], tabu search [12], plant growth simulation algorithm [13], harmonic search [14, 15], discrete artificial bee colony [16] and PSO with graph theory [17] have been proposed for network reconfiguration of a distribution network. In [18], the optimisation problem was studied as a multi-objective function and aggregation function was used to convert into the single objective function. The incompatibility of different criteria makes it difficult to find the global optima.

Most of the existing methods discussed in the literature have two major shortcomings, which are large computation time and inconsistency in providing an optimal solution [1]. Moreover, most of these methods only considered healthy conditions for reconfiguration of the distribution system in which all branches can be considered. In addition, unlike the mathematical optimisation, meta-heuristic optimisation uses an implicit radiality constraint. During this verification process, it allows the optimisation technique to generate many non-feasible solutions from 2*n* combinatorial search space ('*n*' number of switches for reconfiguration). These non-feasible solutions are required to be re-adjusted on a randomised basis [4, 19]. The re-adjustment during the searching process is a computational burden and it requires a new particle value to be generated until it obtains a feasible solution.

In this work, to reduce the computational burden of these non-feasible solutions, only the explicit radiality constraint, which obtains the feasible solution, is considered. This was carried out using 'All possible spanning tree (APSPT).' APSPT finds the radial solution and avoids all combinations which are disconnected sub-graphs. Thus, this algorithm generates a limited dataset with only feasible solutions. These solutions are stored in a database. By this approach, the computational burden can be reduced. Besides, two different algorithms have been proposed to find the optimal reconfiguration of the distribution network; they are discrete evolutional programming (DEP) and discrete evolutionary PSO (DEPSO) algorithms. In these optimisation techniques, the multi-objective function has been considered. The aims are to minimise the total power loss, voltage deviation and a number of switching actions for the distribution network. The proposed algorithm provides an optimal solution consistently in a short span of time. In order to consider a real-world scenario, the proposed methodology considers uniform and stochastic load patterns which are solved for each load level. Moreover, the investigation also considers the healthy and faulted condition of the distribution network. In case of healthy condition, optimal configuration is required to improve the system performance. In the event of the faulted condition, network configuration is used to provide power to the non-faulted area. In addition to that, this paper also provides the switching sequence for healthy and faulted distribution system. The switching sequence can be found after the optimal configuration has been identified. The proposed method is tested on the 33-bus and the 118-bus distribution systems. The performance of the proposed method is compared with recent methods available in the literature.

2 Problem formulation

Network reconfiguration changes the direction of power flow in a distribution system. The reconfiguration should significantly decrease the power loss and improve the voltage profile by minimising the voltage deviation at all buses. In this work, the main goal is to achieve the optimal configuration by minimising power loss, voltage deviation and a number of switching actions. Therefore, the objective function of this investigation is

$$\text{Obj} = \text{Min}\{w_1 * P_{\text{loss}} + w_2 * \Delta V_t + w_3 * N_{\text{sw}}\} \tag{1}$$

where P_{loss} is the total active power loss, ΔV_t is the voltage deviation index, N_{sw} is the total number of switching actions performed to reach the optimal solution, w_1, w_2, and w_3 are weighted sum coefficients and their values lies between zero and one,$w_1, w_2, w_3 \geq 0$. The parameters are also normalised in the range of zero to one [0, 1].

2.1 Total active power loss

The total active power loss is calculated using as

$$P_{\text{loss}} = \sum_{ij=1}^{Nb} \left(\frac{P_{ij}^2 + Q_{ij}^2}{V_j^2}\right) * R_{ij} * \gamma_{ij} \tag{2}$$

where P_{ij} and Q_{ij} are the active and reactive power flows in the branches *i*–*j*, R_{ij} is the resistance of branch, V_j^2 is the voltage of receiving bus, γ_{ij} is a binary variable, which defines the state of the branch and N_b is the total number of branches in a distribution system.

2.2 Voltage deviation index

Voltage deviation index is the difference between the nominal voltage and actual voltage at bus, where $i = 1, 2, 3, \ldots$, total number of buses

$$\max\{\Delta V_t\}_{i<j} = \gamma_{ij} V_n - \sqrt{V_i^2 - 2 * (R_{ij} * P_{ij} + X_{ij} * Q_{ij}) - I_{ij}^2 Z_{ij}^2 - \beta_{ij}} \tag{3}$$

$$\beta_{ij} = \begin{cases} 0 & \text{if} \quad \gamma_{ij} = 1 \\ V_i^2 - V_j^2 & \text{if} \quad \gamma_{ij} = 0 \end{cases} \tag{4}$$

where V_n is the nominal voltage; V_i is the sending bus voltage; V_j is the receiving bus voltage; R_{ij}, $X_{ij}$and Z_{ij} are the resistance, reactance and the impedance of the branches i, j, respectively, and I_{ij} is the current flowing in branches i, j.

2.3 Number of switching actions

The quality of a solution can be assessed in terms of the required number of switching actions (N_{sw}), which is calculated on the account of initial and final states of the branches. N_{sw} is calculated using as

$$N_{\text{sw}} = \sum_{ij=1}^{Nb} \left| x_{ij}^{\text{ini}} - x_{ij}^{\text{rec}} \right| \tag{5}$$

where x_{ij}^{ini} is the initial switching state of the branches i, j; and x_{ij}^{rec} is the switching state after reconfiguration.

2.4 Electrical constraints

During the network reconfiguration, electrical and thermal constraints have to be fulfilled according to

$$P_{g_i} - P_{d_i} - \sum_{ij} P_{\text{loss}_{ij}} = \sum_{ki} P_{ki} - \sum_{ij} P_{ij} \quad i \in \Omega_b,\ ij \in \Omega_l \tag{6}$$

$$Q_{g_i} - Q_{d_i} - \sum_{ij} Q_{\text{loss}} = \sum_{ki} Q_{ki} - \sum_{ij} Q_{ij} \quad i \in \Omega_b,\ ij \in \Omega_l \tag{7}$$

$$V_{\min} \leq V_i \leq V_{\max} \quad i \in \Omega_b \tag{8}$$

$$I_{ij} \leq I_{\max} \quad ij \in \Omega_l \tag{9}$$

where Ω_b is the set of buses and Ω_l is the set of branches.

3 Dataset development

In a distribution network, radiality of the network is considered as an important constraint. Hence during the reconfiguration of the distribution network, this constraint has to be adhered to. It also prevents it from generating unconnected or mesh graphs (in which either all nodes are not connected to a sub-graph or the nodes are connected in a mesh structure). Due to this, the meta-heuristic technique uses implicit radiality constraint, which adjusts the non-feasible solution generated during the initialisation or updating process to feasible ones (i.e. connected network). To avoid these non-feasible solutions generated by the particle during the optimisation process, dataset approach based on APSPT has been

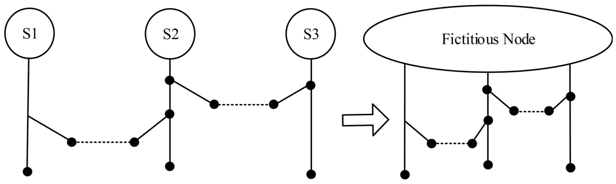

Fig. 1 *Conversion of multiple substations into single fictitious substation*

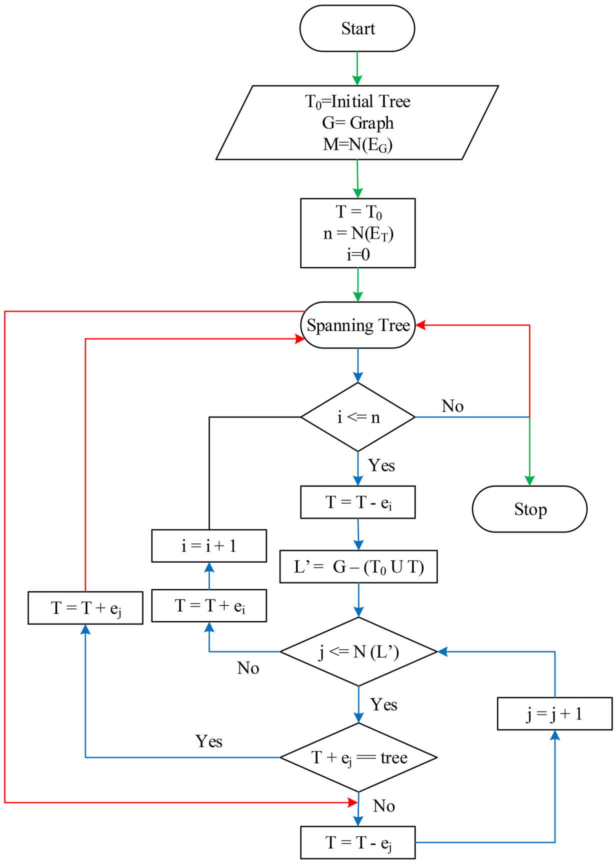

Fig. 2 *Flowchart of APSPT algorithm*

adopted. This will only generate all the possible radial combinations and subsequently, the optimisation technique will find the best combination amongst them.

3.1 Distribution network graph structure

Radial structure in a power distribution network originates from the source node. In terms of graph theory, nodes in an acyclic graph (spanning tree) will have only one path between two vertices and all nodes in a graph (G) will be connected to a single root node. A forest contains multiple disjoint trees. Tree in a forest have a disjoint set of vertices and no edge exists between the vertices of a tree.

In case of a single substation in a distribution network, APSPT algorithm can be used directly to generate all the possible trees in G. Each tree in G satisfies two conditions: (i) contains $N-1$ edges (N is the total number of nodes in a graph) and (ii) all nodes are connected. In the case in the event of multiple substations (S is the number of substations) in the distribution graph, the forest will have an S number of trees in G. To apply APSPT algorithm, G has to be modified as shown in Fig. 1. The multiple stations refer to the multiple root nodes of a tree in the forest. These root nodes are combined and replaced it with a single fictitious node [20]. This transformation of forest allows the APSPT algorithm to determine all the possible tree of transformed graph G'. Once the spanning tree determines all the feasible solutions, then these solutions are retransformed into the primary configuration by replacing the fictitious node G' with a node in G. This transformation generates all the possible forest which contains S disjoint trees. All these possible solutions are termed as 'Dataset.'

3.2 All possible spanning tree

G is a distribution network graph, which contains an N number of vertices (bus) and M number of edges (branches). Each subgraph G' contains $N-1$ edge and graph G contains $M-(N-1)$ number of independent loops 'c'. If $c = 0$ for graph G than graph has only one spanning tree.

Let $T_0 \subset G$ is initial tree, and using elementary transformation new T' has been formed $T' \subset G$, it can be achieved by removing the edge e_i from T_0 and adding in e_j, as shown in

$$T' = T_0 - e_i - e_j \tag{10}$$

The number of transformations required to transform from any tree $T \subset G$ to T' is at most 'c'. In this way, all trees can be generated from T_0 [21].

As shown in Fig. 2, initial tree and set of unconnected edges L of $G(L = G - T_0)$ is required to generate APSPT. Each edge $e_i \in T_0$ will be replaced with $e_j \in \mathrm{L}$ if it creates a new tree. Here, when e_i has been subtracted from the T, this will produce two sub-independent trees, which no vertices of sub-tree T_1 and T_2 have any common edges. Vertices of T_1 and T_2 may have a common edge from set L (e_j) which reconvened both independent tree and create new T. This process will replace with all the element of set L and this process will repeat for all e_i in T_0. The amortise time constant of this algorithm is $O(mn)$ [21].

3.3 Dataset grouping approach

The database contains the feasible solution with respect to radiality constraints. In earlier research, radiality constraints are implicitly verified. However, in this investigation, an explicit approach is utilised which allows the optimisation technique to search for the optimum solution.

During the minimisation process, the particles are frequently trapped in their local minima. In order to avoid this problem and increase the probability to achieve the global minima, the dataset is divided into overlapping sub-dataset as shown in Fig. 3. Each element in a dataset is represented twice in different groups of sub-datasets. This is done to ensure that the global optima are not missed during the search process. Another important characteristic of the dataset approach is that it is flexible towards integration of parallel processing. Since the dataset is divided into four sub-sets, the parallel search can be implemented in order to obtain an optimum solution in short span of time.

4 Optimisation technique

In this investigation, two different optimisation techniques are presented based on the discrete nature of the network reconfiguration process. They are the DEP optimisation technique and the DEPSO techniques. Both these optimisation techniques are used to solve the network reconfiguration problem in this investigation.

4.1 DEP optimisation technique

EP is a stochastic optimisation technique which belongs to the class of evolutionary algorithm. These algorithms inherit the characteristics of the biological process. In this process, population characteristic will change after each successive generation. For successive generation in EP, the Gaussian mutation has been used as

$$x_i^{\text{new}} = x_i^{\text{old}} + N(\mu, \gamma^2) \tag{11}$$

$$\gamma^2 = \beta(x_{\max} - x_{\min})\left(\frac{y_i}{y_{\max}}\right) \tag{12}$$

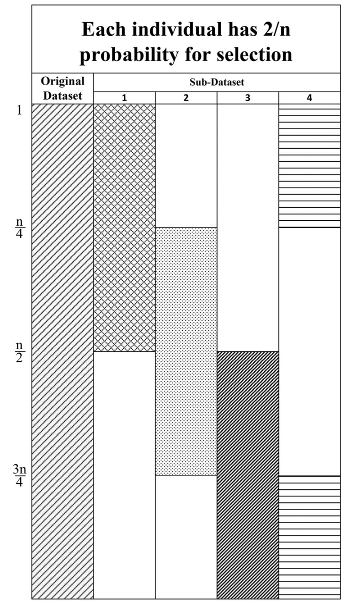

Fig. 3 *Distribution of dataset for the parallel optimisation algorithm*

where x_i^{old} is the parent, x_i^{new} is the off spring, i denotes the ith particle of the population, N is the Gaussian random variable, which is a function of mean μ and variance γ^2, β is the search step, $x_{\max}$ is the maximum value and $x_{\min}$ is the minimum value of the population, y_i is the fitness of ith particle and $y_{\max}$ is the maximum fitness of the population.

In the proposed DEP algorithm, 'L' number of dataset groups from all feasible solutions will be generated and these feasible solutions have been filtered on the basis of line conditions as discussed in Section 3.3. Equal number of parallel instances (PIs) will be generated. Each of the PI will have a unique dataset containing 'p' number of particles. All particles randomly select their value from PI dataset. Thereafter, their fitness will be calculated and the offspring will be generated using Gaussian formulation. These offspring can only attain a discrete value. Fitness of these offspring has been evaluated and they are combined with the initial population. Subsequently, this new combined population has been ranked on the basis of their fitness value. Only 'p' number of particles will survive and rest of the particles will be discarded from the PI dataset. This will ensure the rejected particle will not be selected again. In each of the iteration, there will be a higher probability to achieve better off spring values. In this way, it allows the DEP to acquire the local optimal solution of that PI in short span of time. Once all PIs have converged or reached to the maximum iteration, then the best value among all the PI's will be considered as a global optimal solution.

4.2 DEPSO optimisation technique

In this investigation, a group-based DEPSO optimises the network reconfiguration for the distribution system. The DEPSO is a hybrid optimisation technique obtained from EP and PSO. In this algorithm, combination, ranking and selection process of EP has been used with this PSO as shown in Fig. 4. Initial and updated particles are combined during the combination process and they are ranked on the basis of their objective value. During the selection process, only 'p' (number of particles) best solution will remain for the next iteration. This allows the algorithm to attain an optimal solution faster compared with conventional PSO.

The conventional PSO consists of two acceleration constants, cognitive parameter (c_1) and social parameter (c_2) which are calculated by

$$c_1 = (c_{\max} - c_{\min}) * \left(\frac{\text{iter}}{\text{iter}_{\max}}\right) + c_{\min} \tag{13}$$

$$c_2 = 2 - c_1 \tag{14}$$

In DEPSO, 'void spaces' in front of the particle are filled with other particles. The filling of void spaces is due to the EP's combination, rank and selection process. During this process, only high potential candidates have survived and these candidates remain in the new population, which move towards the optimal solution.

The new velocity and position of each particle are calculated using

$$\nu_i^{\text{new}} = \omega\nu_i^{\text{old}} + c_1 r_1\left(P_i^{\text{best}} - x_i^{\text{old}}\right) + c_2 r_2\left(G^{\text{best}} - x_i^{\text{old}}\right) \tag{15}$$

$$x_i^{\text{new}} = x_i^{\text{old}} + \nu_i^{\text{new}} \tag{16}$$

where x_i^{old} is a previous particle value, x_i^{new} is the updated particle value, i denotes the ith particle of the population, $r1$ and $r2$ are the random values of normal distribution function, P_i^{best} is the particle local best value and G^{best} is the population global best value.

5 Application of the DEPSO methodology to the reconfiguration of distribution systems

Step 1: In the proposed DEPSO algorithm, initially 'L' number of sub-dataset groups is generated and feasible solution is filtered on the basis of line conditions, as discussed in Section 3.3.

Step 2: PI of the DEPSO is created for each sub-dataset L_i. i denotes the PI number.

Step 3: Every instance PI_i contains 'p' number of particles, as shown in Fig. 4. Each $x_{l,m}^{\text{old}}$ is initialised with the random combination of switches selected from the dataset L_i of instance PI_i

$$\begin{bmatrix} X_{11}^{\text{old}} & X_{21}^{\text{old}} & \cdots & X_{m1}^{\text{old}} \\ X_{12}^{\text{old}} & X_{22}^{\text{old}} & \cdots & X_{m2}^{\text{old}} \\ X_{13}^{\text{old}} & X_{23}^{\text{old}} & \cdots & X_{m3}^{\text{old}} \\ \vdots & \vdots & \cdots & \vdots \\ X_{1l}^{\text{old}} & X_{2l}^{\text{old}} & \cdots & X_{ml}^{\text{old}} \end{bmatrix}$$

Step 4: Fitness of $x_{l,*}^{\text{old}}$ is calculated using (1). On the basis of these fitness values, global (Gbest) is selected.

$$\begin{bmatrix} F\left(X_{11}^{\text{old}}\right) & F\left(X_{21}^{\text{old}}\right) & \cdots & F\left(X_{m1}^{\text{old}}\right) \\ F\left(X_{12}^{\text{old}}\right) & F\left(X_{22}^{\text{old}}\right) & \cdots & F\left(X_{m2}^{\text{old}}\right) \\ F\left(X_{13}^{\text{old}}\right) & F\left(X_{23}^{\text{old}}\right) & \cdots & F\left(X_{m3}^{\text{old}}\right) \\ \vdots & \vdots & \cdots & \vdots \\ F\left(X_{1l}^{\text{old}}\right) & F\left(X_{2l}^{\text{old}}\right) & \cdots & F\left(X_{ml}^{\text{old}}\right) \end{bmatrix}$$

Step 5: By using (15) and (16), new combination of switches is selected from dataset L_i

$$\begin{bmatrix} X_{11}^{\text{new}} & X_{21}^{\text{new}} & \cdots & X_{m1}^{\text{new}} \\ X_{12}^{\text{new}} & X_{22}^{\text{new}} & \cdots & X_{m2}^{\text{new}} \\ X_{13}^{\text{new}} & X_{23}^{\text{new}} & \cdots & X_{m3}^{\text{new}} \\ \vdots & \vdots & \cdots & \vdots \\ X_{1l}^{\text{new}} & X_{2l}^{\text{new}} & \cdots & X_{ml}^{\text{new}} \end{bmatrix}$$

Step 6: Fitness of $x_{l,*}^{\text{new}}$ is calculated using (1)

$$\begin{bmatrix} F(X_{11}^{\text{new}}) & F(X_{21}^{\text{new}}) & \cdots & F(X_{m1}^{\text{new}}) \\ F(X_{12}^{\text{new}}) & F(X_{22}^{\text{new}}) & \cdots & F(X_{m2}^{\text{new}}) \\ F(X_{13}^{\text{new}}) & F(X_{23}^{\text{new}}) & \cdots & F(X_{m3}^{\text{new}}) \\ \vdots & \vdots & \cdots & \vdots \\ F(X_{1l}^{\text{new}}) & F(X_{2l}^{\text{new}}) & \cdots & F(X_{ml}^{\text{new}}) \end{bmatrix}$$

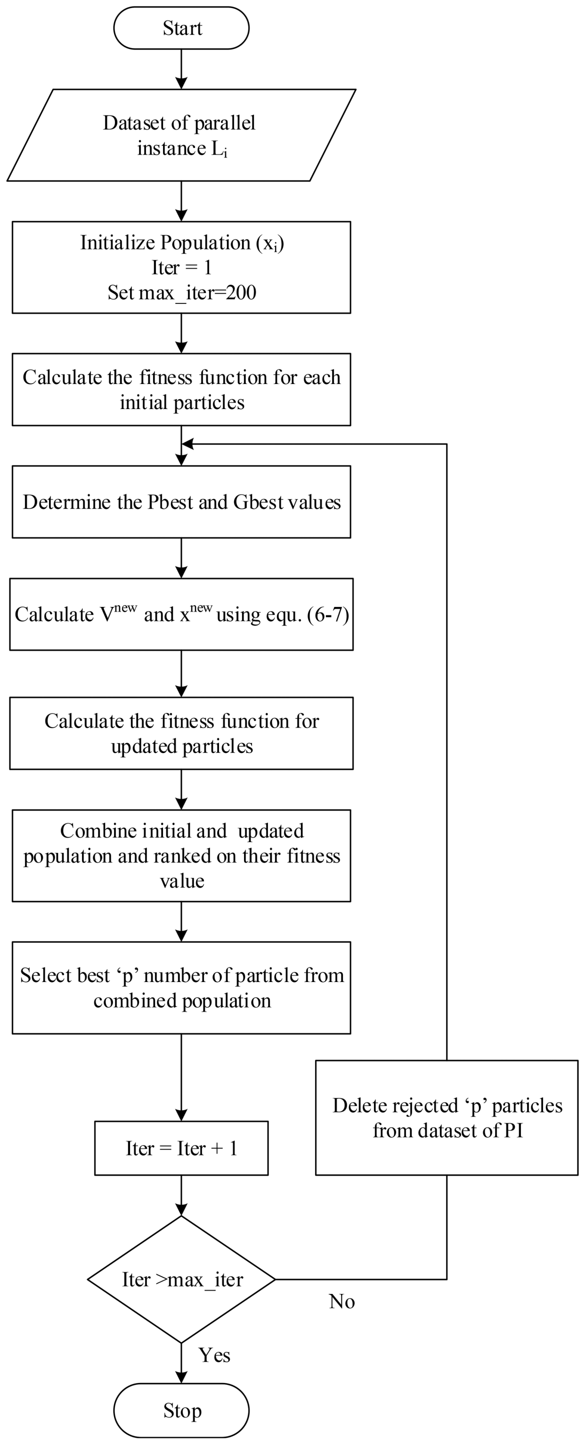

Fig. 4 *Flowchart for single parallel instance of DEPSO*

Step 7: By using evolutionary process, it will select the best particle from the previous and updated population. Both of these population are combined to generate a new population, Q of length.
Step 8: Ranking of the particle is performed for elements in Q based on their fitness value.
Step 9: From the ranked population, 'p' number of particles is selected for the next iteration.
Step 10: All the particles which are rejected during the selection process are removed from the dataset L_i. This will ensure that these particles will not be selected for a future iteration.
Step 11: If all the particles of the instance PI_i have converged or reached the max iteration limit, PI_i will return the *G*best. If in case both of the conditions have not been satisfied, the algorithm will go to step 6 for further searching.
Step 12: All the instances of which return their local best and the minimum fitness value found by them is considered as an optimum solution (global best) for the network reconfiguration.

In the DEPSO technique, by using evolutionary process (combination, ranking, and selection) along with variable acceleration, it will boost the search process and obtain the optimal solution in short span of time.

6 Results and discussion

In this investigation, medium and large-scale distribution systems have been used to evaluate the performance of the proposed approach. These distribution systems consist of sectionalising and tie switches, which are the candidates for network reconfiguration. Furthermore, network reconfiguration is evaluated on healthy and faulted conditions over these distribution systems. In the proposed technique, DEP search step has been initialised with a constant value of 0.85 and in the DEPSO the cognitive and social parameter values have been initialised with 0.1 and 1.9, respectively. These parameter values are selected on a trial basis. Moreover, a computer with an Intel core i7 4th Gen processor and 8 GB RAM has been used for this investigation.

6.1 Medium-scale distribution system

The 33-bus distribution system shown in Fig. 5 is a medium-scale distribution system which is connected to a 12.66 kV substation with active and reactive load demands of 3750 kW and 2300 kVAr, respectively [24]. It consists of 32 normally closed sectionalising switches and 5 normally open tie switches. The power loss in the system is 208.459 kW based on the initial tie switches (33–37). The minimum voltage magnitude and maximum voltage deviation occur at bus 18 which are 0.9108 and 0.0892 p.u., respectively.

The optimal configuration obtained from the proposed technique is 7, 9, 14, 32, 37, which has an active power loss of 138.928 kW. This reduces the total power loss by 33.35%. After the reconfiguration, the minimum voltage magnitude and maximum voltage deviation have been improved to 0.9423 and 0.0577 p.u., respectively.

Fig. 6*a* shows the voltage profile of the distribution system before and after the reconfigurations. The minimum voltage of the system has been improved by 3.46%. It can be observed that the voltage of buses 19–22 decreases after the reconfiguration. This is due to the load is transferred from the middle of the main feeder to the sub-branches.

Active power flows before and after the reconfiguration of the system is shown in Fig. 6. It can be observed that the active power flow in most of the lines of the network has been reduced after the reconfiguration.

This happens since power has been redistributed to all lines in the network. With this reduction, system loadability has been also improved. The active power flows in the lines 18, 19, 20, 21, 33, 34, and 35 increase because the network reconfiguration raises the load in the sub-lateral, which proportionally increases the power flow in the lines.

In order to evaluate the performance of the proposed technique, the power loss value is compared with other techniques from the literature, as shown in Tables 1 and 2. The optimal combination found by other approaches has been re-evaluated with the power flow used in this investigation to make the results comparable. Statistical analysis is performed on the power loss to obtain the best, worst, average and standard deviation values after 200 iterations. The effectiveness of the proposed algorithm can be seen based on the optimal configuration, computational time and consistency of the results.

Table 1 shows the global optimal configuration is obtained by GA, DEP, and DEPSO while HSA (harmony search algorithm), ITS (improved tabu search), FWA (fireworks algorithm) are only able to find near optimal configuration. The worst power loss is found by GA, which is 208.456 kW. This shows that the solution using GA is trapped inside the local optima. Furthermore, compared to other methods, FWA is more consistent in obtaining the configuration over 200 trials within a short span time. The

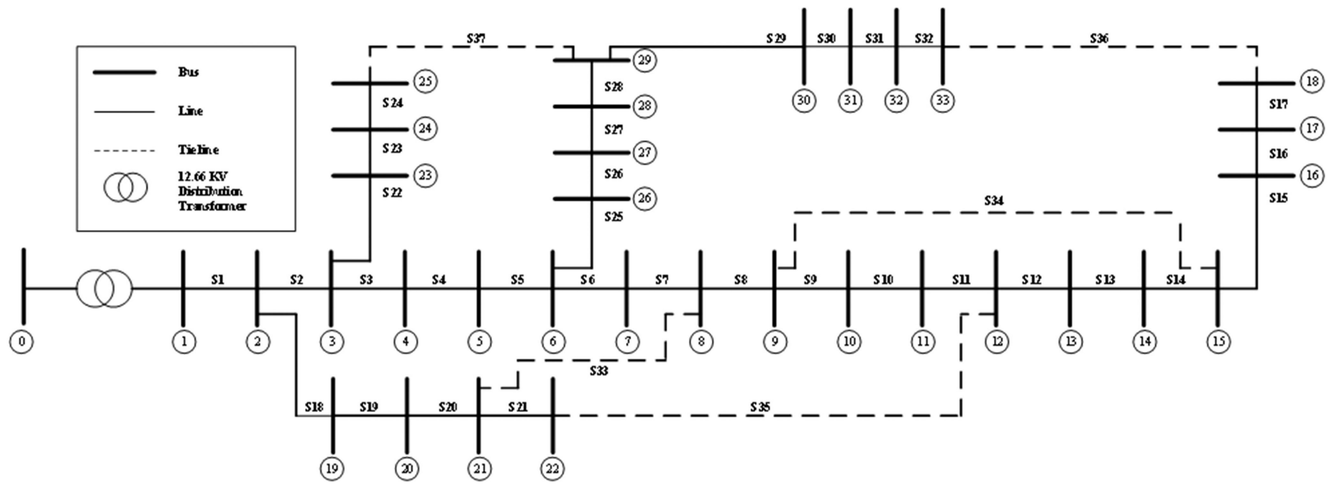

Fig. 5 *Topology of the 33-bus distribution system*

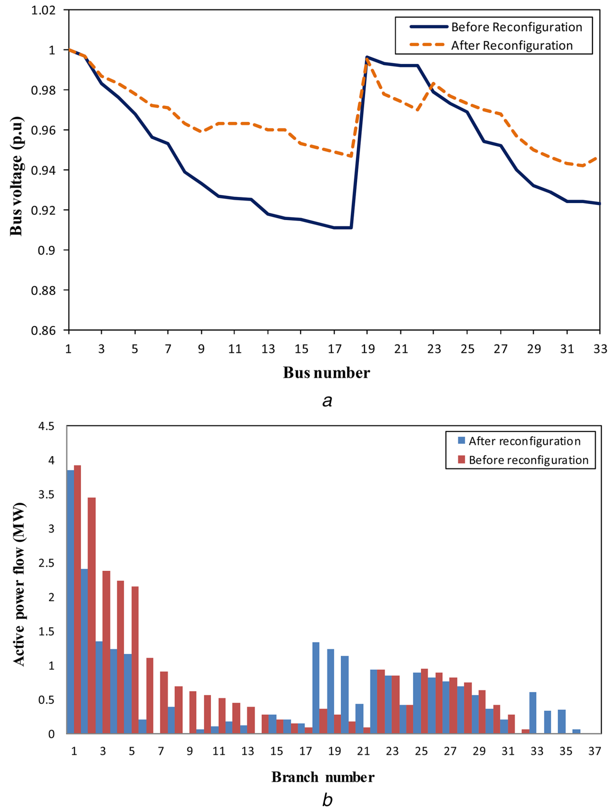

Fig. 6 *Profile of 33-bus distribution system*
(a) Voltage profile of 33-bus distribution system, *(b)* Active power profile of 33-bus distribution system

average power loss, standard deviation and average time of FWA are 145.63 kW, 5.49 kW, and 6.4 s, respectively. In comparison with FWA, the proposed DEP and DEPSO methods are more consistent in finding the global optimal in a short span of time.

Results for the reconfiguration problem solved with the EP and PSO methods are shown in Table 2. Both algorithms obtain optimum solutions, although not in a consistent way. The average power losses obtained by the EP and the PSO are 150.36 and 146.46 kW, respectively. The average times of the EP and the PSO in obtaining optimum solution are 16.19 and 8.36 s. On the other hand, the average times of the DEP and the DEPSO are 4.7 and 6.07 s, which are better than the one required by the classical methodology. Furthermore, standard deviations of the proposed algorithm are 0.136 and 0.051, which are comparatively smaller than the values of the EP and the PSO methods (5.68 and 5.78). Therefore, the DEP and the DEPSO have obtained the optimum solution consistently within a short span of time as compared to previously proposed methodologies.

However, the average time of the DEP to obtain an optimal solution is 4.7 s, which is better than the DEPSO. The DEPSO obtains the optimal solution in 6.07 s. In spite of that, the DEPSO outperforms the DEP and other methodologies in terms of consistency.

To evaluate the performance of the proposed model under the load variation, it was assumed that the load varies uniformly or stochastically. As shown in Fig. 7, all the loads in the distribution system have uniform variation. In this scenario, the optimum solution obtained by the proposed model is that the branches 7, 9, 14, 32, and 37 should be opened. This solution is similar to the optimum solution in normal scenario. On the other hand, when loads are varying stochastically, as shown in Fig. 8, the configuration of the tie switches also varies. It can be observed from Table 3 that the configurations 7, 9, 14, 28, and 32 have a high frequency of occurrence in obtaining optimal solution, which means that this is a dominant configuration with respect to other configurations in a dataset.

Table 1 Comparative analysis of reconfiguration methods for the 33-bus distribution system

	Tie line configuration	Power loss, kW				Average loss reduction, %	Maximum loss reduction, %	V_{min}, p.u.	ΔV, p.u.
		Best	Worst	Average	Standard deviation				
Initial configuration	33, 34, 35, 36, 37	208.459				—	—	0.9108	0.0892
Final configuration									
GA [22]	7, 9, 14, 32, 37	138.928	208.459	166.2	14.53	20.27	33.35	0.9423	0.0577
ITS [23]	7, 9, 14, 36, 37	141.431	198.4	164.9	13.34	20.9	32.15	0.9383	0.0617
HSA [14]	7, 10, 14, 36, 37	141.944	195.1	152.33	11.28	26.93	31.91	0.9383	0.0617
FWA [8]	7, 9, 14, 28, 32	139.98	155.75	145.63	5.49	30.14	32.85	0.9413	0.0587
Proposed method									
DEP	7, 9, 14, 32, 37	138.928	139.981	139.15	0.136	33.24	33.35	0.9423	0.0577
DEPSO	7, 9, 14, 32, 37	138.928	139.655	138.931	0.051	33.35	33.35	0.9423	0.0577

Table 2 Comparative analysis of the classical and the proposed reconfiguration methods for the 33 bus distribution system

	Tie line configuration	Power loss, kW				Average loss reduction, %	Average time, s
		Best	Worst	Average	Standard deviation		
Classical method							
EP	7, 9, 14, 32, 37	138.928	174.31	150.36	5.68	27.87	16.19
PSO	7, 9, 14, 32, 37	138.928	150.81	146.64	5.78	29.65	8.36
Proposed method							
DEP	7, 9, 14, 32, 37	138.928	139.981	139.15	0.136	33.24	4.7
DEPSO	7, 9, 14, 32, 37	138.928	139.655	138.931	0.051	33.35	6.07

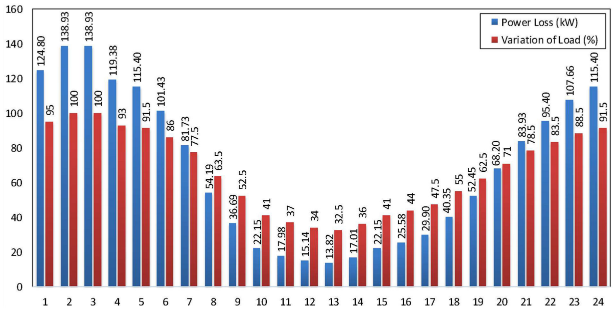

Fig. 7 *Uniform load variation and power loss for the 33-bus distribution system*

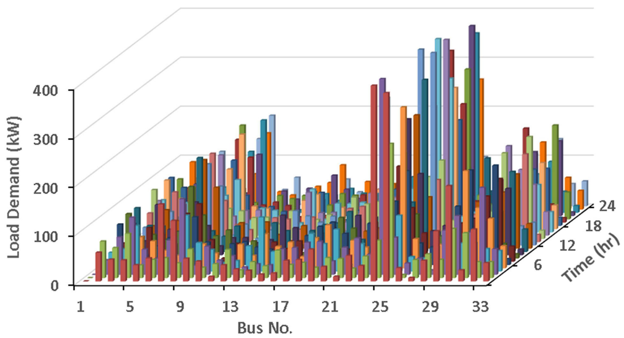

Fig. 8 *Stochastic load variation of 33-bus distribution system*

To evaluate the proposed methodology in faulted condition, different cases are considered. In this investigation, the fault cases which the downstream node cannot be restored are not considered during this evaluation

i. *Case I:* Fault in line 17 where this fault is randomly selected in a distribution system.
ii. *Case II:* Fault in lines 7 and 34 where these lines have the longest line length in this distribution system.
iii. *Case III:* Fault in lines 3, 14 and 33 is selected on the basis that they have the combination of smallest, medium and longest line lengths for this distribution system.

As shown in Table 4, voltage deviation in each of the faulted cases is within an acceptable range. In [8], a fault at branch 17 has been analysed and tie switches 7, 9, 14, 17, 28 are found as the optimal configuration for the restoration. From Table 5, it can be observed that weightage in the objective function has prioritised individual parameters. When $w_1 = 1$, the optimal configuration is found only on the basis of power loss. While considering this objective function, the power loss, voltage deviation, and a number of switching actions attained by the proposed technique are 146.293 kW, 0.0673 p.u., and four switching actions, respectively.

Fig. 9 shows the interpolated weighted sum graph for case II when the fault occurs at bus 17. From this figure, it can be observed that the objective function has different values when different weighting coefficients are considered. Minimum objective value of 0.140 is obtained when $w_1 = 0.05$, $w_2 = 0.931$, and $w_3 = 0.019$. The optimal configuration for the minimum objective function of 0.140 is 7, 9, 14, 17, and 28. The power loss, voltage deviation, and a number of switching actions are 146.293 kW, 0.0673, and 4, respectively.

Table 6 shows the optimal switching sequence for the 33-bus distribution system. Eight switching actions are required when branches 3, 14, and 33 are unavailable due to a fault and the total power loss is 672.64 kW. The sequence of the switching operation should maintain the radiality of the network, e.g. switch 9 has to be opened before the closing switch 35. Furthermore, in case of the fault at branch 17 or 7 and 34, it requires four switching operations. The total power loss during their switching process is 286.27 and 282.71 kW, respectively.

6.2 Large-scale distribution system

The proposed technique is further tested on the 118-bus test system to investigate its efficiency (see Fig. 10). The 118-bus distribution system is a large-scale distribution system, which is connected to an 11 kV substation with active and reactive load demands of 22.709 MW and 17.041 MVAr, respectively [23]. It consists of 117 normally closed sectionalising switches and 15 normally open tie switches. The power loss in the system is 1.298 MW for the initial tie switches (118–132). The minimum voltage magnitude and the maximum voltage deviation occur at bus 77, which are 0.869 and 0.131 p.u., respectively.

The optimal configurations obtained by the proposed technique are 23, 25, 34, 39, 42, 50, 58, 71, 74, 95, 97, 109, 121, 129, 130, which have an active power loss of 854.031 kW. This reduces the total power loss by 34.21%. After the reconfiguration, the minimum voltage magnitude and the maximum deviation are improved to 0.9323 and 0.0677 p.u., respectively.

Similar to the comparative investigation carried out for the medium scale distribution system, the performance of the proposed technique for this large-scale distribution system is evaluated by comparing the power loss values with other techniques from the literature, as shown in Table 7. It can be observed that the global optimal configuration for this test system is obtained from the FWA, the DEP, and the DEPSO methods, while the HSA, the ITS, the RGA approaches are only able to find near optimal configuration. The FWA method is more consistent in obtaining the configuration over 200 trials with a low computational burden. The average power loss, standard deviation, and average time attained by the FWA are 887.54, 29.58 kW and 8.61 s, respectively. In compared with the FWA, the standard deviations of the proposed DEP and DEPSO methods are 14.97 and 11.20, respectively. These algorithms attain 49.39 and 65.17% better consistency as compared to the FWA approach.

From Table 8, it can be observed that the proposed methodology not only obtained the optimum solution consistently but the DEP and the DEPSO attain the optimum solution in a short span of time. The classical PSO manages to obtain a near optimal solution which is 854.21 kW and its standard deviation is 44.46. Moreover, the average time of PSO to reach its optimum solution is 22.65 s. On the other hand, the DEP and DEPSO obtain the optimum solution in 6.02 and 7.09 s. Similar to the medium-scale distribution, the DEP and the DEPSO methods outperform previous methodologies in large-scale distribution system when it comes to the consistency to obtain an optimum solution. Furthermore, these algorithms attain the optimum solution in a short span of time.

Nevertheless, the average time of DEP to obtain an optimal solution is 6.02 s, which is better than DEPSO. DEPSO obtains the optimal solution in 7.09 s. On the contrary, the average power loss and standard deviation of DEPSO is 11.20 kW and 855.996, respectively, which outperforms DEP and other methodologies in terms of consistency.

Similar to the 33-bus distribution system, the 118-bus distribution system has been also evaluated with uniform and stochastic load variation. Fig. 11 shows the power loss of 118-bus test under uniform load variation. The optimum solutions obtained by the proposed methodology are 42, 25, 23,121, 50, 58, 39, 95, 71, 74, 97, 129, 130, 109, and 34, which are similar to the normal case. Likewise in Table 9, reconfiguration also varies with the stochastic variation of load. Therefore, it can be concluded that if the load is varying uniformly, then the optimal configuration will have no effect on it; but if the load varies stochastically, then no single combination will provide an optimum solution for all scenarios.

To evaluate the proposed methodology in the faulted distribution system, different cases have been considered. In this investigation, the fault cases, which the downstream node cannot be restored, were not considered during this evaluation:

i. *Case I:* Fault in line 30 has been considered. This fault is randomly selected in the distribution system.

Table 3 Reconfiguration of the 33-bus distribution system for stochastic load variation

Time, h	Power loss, kW	Tie branches
1	59.80	7, 9, 14, 37, 31
2	25.20	7, 9, 14, 37, 32
3	51.09	7, 9, 14, 28, 32
4	31.91	7, 9, 14, 36, 37
5	53.46	7, 9, 14, 37, 31
6	59.15	7, 9, 14, 28, 32
7	35.54	7, 9, 14, 28, 32
8	22.67	7, 9, 14, 28, 31
9	30.44	7, 9, 14, 28, 32
10	57.29	7, 9, 14, 28, 32
11	35.59	7, 9, 14, 28, 32
12	41.51	7, 9, 14, 36, 37
13	33.90	7, 9, 14, 28, 32
14	49.31	7, 9, 14, 28, 32
15	62.14	7, 9, 14, 37, 31
16	51.10	7, 9, 14, 37, 32
17	42.88	7, 9, 14, 37, 32
18	26.04	7, 9, 14, 28, 32
19	51.96	7, 9, 14, 37, 30
20	43.24	7, 9, 14, 28, 32
21	47.20	7, 9, 14, 37, 32
22	30.23	7, 9, 14, 37, 31
23	46.48	7, 9, 14, 28, 32
24	24.96	7, 9, 14, 36, 28

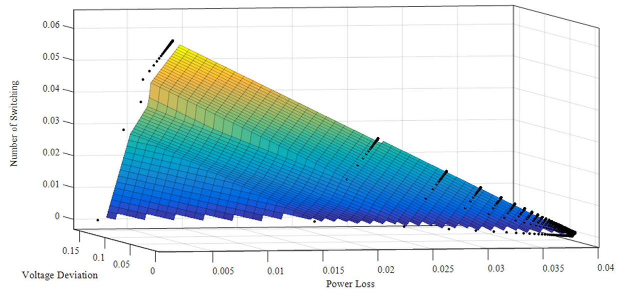

Fig. 9 *Interpolated weight sum chart for 33 bus distribution system, when fault occurs at branch 17*

ii. *Case II:* Fault in lines 22 and 41 has been considered. These lines have longest line length in this distribution system.

iii. *Case III:* Fault in lines 3, 14 and 33 is selected on the basis that they have the combination of smallest, medium and longest line lengths for this distribution system.

As shown in Table 10, after a fault occurs in line 30, in order to restore the healthy zones, the system configuration is changed to 22, 39, 42,5 3, 70, 73, 75, 95, 109, 129, 130, 122, 132, 119. This configuration increases the voltage deviation by 13.73% from the optimal configuration and requires two switching operations to restore the zones. In case of faults occurring in lines 22, 41, the voltage deviation increases by 6.35% but in case of faults occurring on lines 8, 53, 117, the voltage deviation increases by 41.80%. Moreover, for case III, six operations are required, whereas, for case II, eight switching operations are required to restore all buses.

7 Conclusion

In this work, database approach and DEP and DEPSO techniques have been successfully proposed to optimise the network reconfiguration of a distribution system. Optimisation of network reconfiguration is based on the minimisation of power loss, voltage deviation and number of switchings. Medium- and large-scale distribution networks were investigated to evaluate the quality of solution obtained through the proposed technique and further compared with results published in the recent literature. Multiple scenarios of network reconfiguration have been considered to verify the efficiency of the proposed technique in healthy and faulted distribution system. In case of medium-scale distribution, the proposed technique obtains the optimal switch configuration of 7, 9, 14, 32, 37 and the power loss is improved by 33.35%. Furthermore, the proposed the DEP and the DEPSO methods have the lowest power loss standard deviation of 0.136 and 0.051, respectively, compared to the GA, ITA, HSA, PSO, and FWA, which have a higher standard deviation of 5.49. The average time taken by the DEP to acquire the optimal configuration is 4.7 s, which is faster than other methodologies as shown in Table 2. In case of a large-distribution system, the maximum power loss has been improved by 34.21%. Similar to the medium-scale distribution system, the DEP manages to acquire the optimal solution faster than other methodologies. Hence, from this work, it

Table 4 Fault analysis at different branches of 33-bus distribution system

Case	Faulted branch	Final configuration	Power loss, kW	ΔV, p.u.	No. of switching actions
I	17	7, 9, 14, 17, 28	146.293	0.0673	4
II	7, 34	7, 11, 32, 34, 37	142.135	0.0602	4
III	3, 14, 33	3, 6, 14, 33, 36	216.533	0.0797	8

Table 5 Fault analysis at bus 17 with different weighting values

W_1	W_2	W_3	Power loss, kW	ΔV, p.u.	No. of switching actions	Configuration
1	0	0	146.293	0.0673	4	7, 9, 14, 17, 28
0	1	0	146.603	0.0643	4	6, 9, 14, 17, 37
0	0	1	146.650	0.0676	2	7, 9, 14, 17, 37
0.05	0.931	0.019	146.293	0.0673	4	7, 9, 14, 17, 28

Table 6 Switching sequence of 33-bus distribution system

Initial configuration	Final configuration	Faulted branch	Switching sequence	Power loss, kW	Total power loss, kW
33, 34, 35, 36, 37	7, 9, 14, 32, 37		9 – open	153.58	579.35
			35 – close		
			7 – open	145.42	
			33 – close		
			14 – open	141.43	
			34 – close		
			32 – open	138.92	
			36 – close		
7, 9, 14, 32, 37	7, 9, 14, 17, 28	17	17 – open	139.98	286.27
			32 – close		
			28 – open	146.29	
			37 – close		
7, 9, 14, 32, 37	7, 11, 32, 34, 37	7, 34	11 – open	140.58	282.71
			9 – close		
			34 – open	142.13	
			14 – close		
7, 9, 14, 32, 37	3, 6, 14, 33, 36	3, 14, 33	36 – open	141.43	672.64
			30 – close		
			6 – open	143.59	
			7 – close		
			33 – open	171.09	
			9 –close		
			3 – open	216.53	
			14 – close		

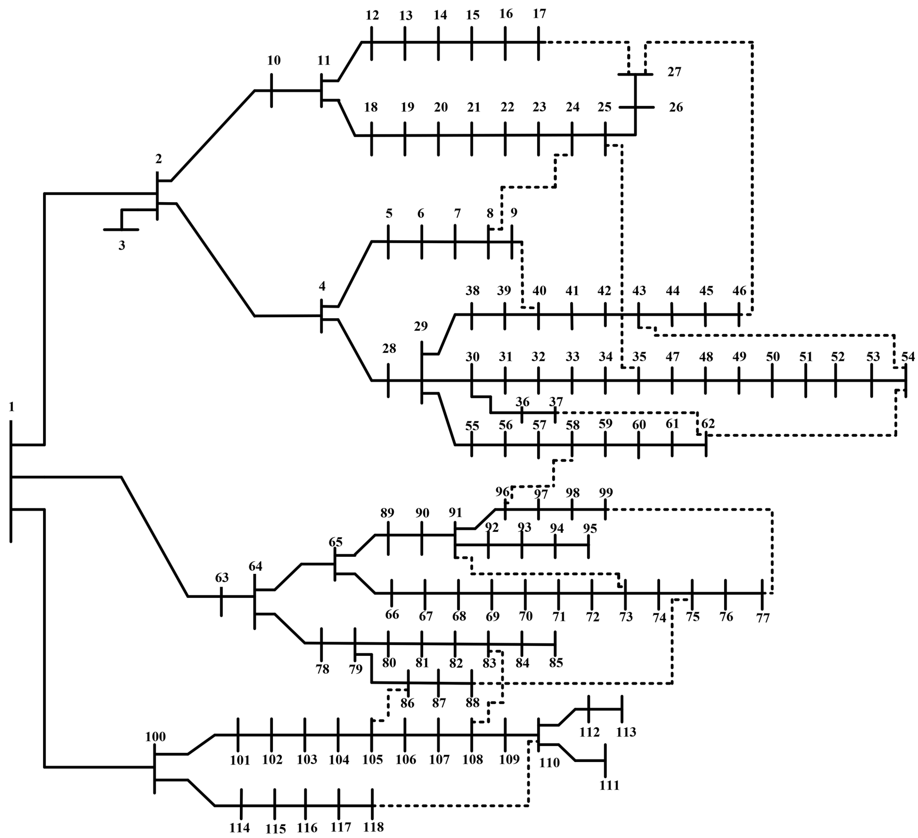

Fig. 10 *118-Bus distribution system*

can be concluded that the DEP obtained the optimal configuration faster but it is not as consistent as the DEPSO. On the contrary, the results obtained by the proposed the DEP and the DEPSO methods outperform the GA, RGA, ITS, HSA, PSO, and FWA in terms of obtaining the optimal solution consistently in a short span of time. In addition to that, this paper also presents the switching sequence for healthy and faulted distribution system. Moreover, the proposed network reconfiguration model has been evaluated with uniform and stochastic load pattern to show its applicability in practical scenarios.

8 Acknowledgments

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Table 7 Comparative analysis of 118-bus distribution system

	Tie line configuration	Power loss, kW				Average loss reduction, %	Maximum loss reduction, %	V_{min}, p.u.	ΔV, p.u.
		Best	Worst	Average	Standard deviation				
Initial configuration	118, 119, 120, 121, 122, 123, 124, 125, 126, 127, 128, 129, 130, 131, 132	1298.092						0.869	0.131
Final configuration									
RGA [25]	42, 26, 22, 51, 48, 61, 39, 127, 73, 72, 76, 82, 130, 109, 32	891.741	1297.34	963.1	77.4	25.6	31.78	0.9321	0.0679
ITS [23]	42, 26, 23, 51, 119, 58, 39, 95, 74, 71, 97, 129, 130, 109, 34	871.639	1288.17	952.6	73.2	25.81	31.97	0.9321	0.0679
HSA [14]	42, 26, 22, 52, 122, 61, 124, 125, 74, 71, 128, 129, 130, 131, 32	854.21	1282.73	935.01	69.3	27.97	34.19	0.9323	0.0677
FWA [8]	42, 25, 23, 121, 50, 58, 39, 95, 71, 74, 97, 129, 130, 109, 34	854.031	942.34	887.54	29.58	31.63	34.21	0.9323	0.0677
Proposed method									
DEP	42, 25, 23, 121, 50, 58, 39, 95, 71, 74, 97, 129, 130, 109, 34	854.031	919.53	857.63	14.97	33.93	34.21	0.9323	0.0677
DEPSO	42, 25, 23, 121, 50, 58, 39, 95, 71, 74, 97, 129, 130, 109, 34	854.031	919.53	855.996	11.20	34.05	34.21	0.9323	0.0677

Table 8 Comparative analysis of the classical and proposed reconfiguration algorithms for the 118-bus distribution system

	Tie line configuration	Power loss, kW				Average loss reduction, %	Average time, s
		Best	Worst	Average	Standard deviation		
Classical method							
PSO	42, 26, 22, 52, 122, 61, 124, 125, 74, 71, 128, 129, 130, 131, 32	854.21	1290.51	928.93	44.66	28.43	22.65
Proposed method							
DEP	42, 25, 23, 121, 50, 58, 39, 95, 71, 74, 97, 129, 130, 109, 34	854.031	919.53	857.63	14.97	33.93	6.02
DEPSO	42, 25, 23, 121, 50, 58, 39, 95, 71, 74, 97, 129, 130, 109, 34	854.031	919.53	855.996	11.20	34.05	7.09

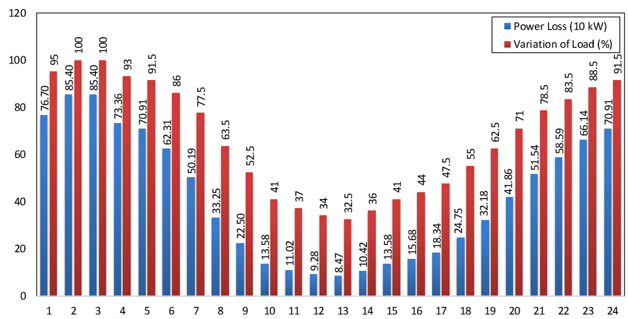

Fig. 11 *Uniform load variation and power loss of the 118-bus distribution system*

Table 9 118-Bus distribution system reconfiguration for stochastic load variation

Time, h	Power loss, kW	Tie branches
1	285.0233	23, 25, 34, 39, 42, 50, 60, 71, 73, 82, 109, 121, 125, 128, 130
2	269.2651	23, 25, 34, 39, 42, 50, 58, 70, 73, 75, 95, 109, 121, 129, 130
3	332.3365	23, 25, 34, 39, 42, 50, 58, 71, 74, 95, 97, 109, 121, 129, 130
4	232.4125	22, 25, 34, 39, 42, 51, 58, 71, 74, 82, 95, 96, 109, 121, 130
5	331.2463	23, 25, 34, 39, 41, 50, 58, 72, 74, 95, 97, 109, 121, 129, 130
6	270.1212	23, 25, 34, 39, 42, 50, 58, 71, 74, 95, 97, 109, 121, 129, 130
7	203.8194	22, 26, 34, 39, 42, 51, 58, 70, 73, 75, 95, 109, 121, 129, 130
8	306.5999	23, 25, 34, 39, 42, 50, 58, 72, 74, 95, 97, 109, 121, 129, 130
9	317.9757	23, 25, 34, 39, 42, 50, 58, 72, 74, 95, 97, 109, 121, 129, 130
10	245.3246	23, 25, 34, 39, 42, 50, 58, 70, 73, 76, 95, 109, 121, 129, 130
11	273.5239	23, 25, 34, 39, 42, 50, 58, 71, 74, 82, 95, 97, 109, 121, 130
12	300.5832	23, 25, 34, 39, 41, 50, 58, 70, 73, 75, 95, 109, 121, 129, 130
13	264.7238	23, 25, 34, 39, 42, 50, 58, 71, 74, 95, 97, 109, 121, 129, 130
14	231.9794	23, 25, 34, 39, 42, 51, 61, 71, 73, 75, 82, 109, 121, 125, 130
15	278.2621	23, 25, 34, 39, 42, 50, 58, 72, 74, 82, 95, 96, 109, 121, 130
16	197.7657	23, 25, 34, 39, 42, 52, 58, 70, 73, 95, 108, 121, 128, 129, 130
17	284.0128	22, 25, 34, 39, 41, 50, 58, 70, 73, 75, 95, 109, 121, 129, 130
18	241.6694	23, 25, 34, 39, 42, 50, 58, 70, 73, 75, 82, 95, 109, 121, 130
19	193.9488	23, 25, 34, 39, 42, 50, 58, 72, 74, 95, 109, 121, 128, 129, 130
20	246.4726	23, 25, 34, 39, 42, 50, 58, 70, 73, 75, 95, 109, 121, 129, 130
21	219.8553	22, 25, 34, 39, 42, 51, 58, 72, 74, 95, 96, 109, 121, 129, 130
22	175.7494	23, 25, 34, 39, 42, 50, 61, 71, 73, 97, 109, 121, 125, 129, 130
23	299.2915	23, 25, 34, 39, 42, 50, 58, 72, 74, 95, 97, 109, 121, 129, 130
24	337.5438	23, 25, 34, 39, 42, 50, 60, 73, 75, 109, 121, 125, 126, 129, 130

Table 10 Fault analysis at different branches of 118-bus distribution system

Case	Faulted branch	Final configuration	Power loss, kW	ΔV, p.u.	No. of switching actions
I	30	23, 25, 30, 39, 42, 50, 58, 71, 74, 95, 97, 109, 121, 129, 130	954.66	0.077	2
II	22, 41	22, 26, 39, 34, 41, 50, 58, 71, 74, 95, 96, 109, 121, 129, 130	874.33	0.072	8
III	8, 53, 117	8, 23, 25, 34, 42, 53, 58, 71, 74, 95, 97, 117, 121, 129, 130	1016.84	0.096	6

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