A Spanning Tree-based Genetic Algorithm for Distribution Network Reconfiguration

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Abstract—This paper presents a spanning tree-based genetic algorithm (GA) for the reconfiguration of electrical distribution systems with the objective of minimizing active power losses. Due to low voltage levels at distribution systems, power losses are high and sensitive to system configuration. Therefore, optimal reconfiguration is an important factor in the operation of distribution systems to minimize active power losses. Smart and automated electric distribution systems are able to reconfigure as a response to changes in load levels to minimize active power losses. The proposed method searches spanning trees of potential configurations and finds the optimal spanning tree using genetic algorithm in two steps. In the first step, all invalid combinations of branches and tie-lines (i.e., switching combinations that do not provide power to some of loads or violate the radiality and connectivity conditions) generated by initial population of GA are filtered out with the help of spanning tree search algorithm. In the second step, power flow analyses are performed only for combinations that form spanning trees. The optimal configuration is then determined based on the amount of active power losses (optimal configuration is the one that results in minimum power losses). The proposed method is implemented on several systems including the well-known 33-node and 69-node systems. The results show that the proposed method is accurate and efficient in comparison with existing methods.

Index Terms—Distribution system, genetic algorithm, network reconfiguration, power loss, spanning tree.

I. INTRODUCTION

Power losses minimization is an important factor in the operation of electrical distribution systems. Electrical distribution systems are characterized by having high resistance-to-reactance ratio, low voltage levels, and radial or weakly-meshed structures. Active power losses ($I^2R$ loss) is high due to high branch resistances and low voltage level (i.e., requires high current flows). Therefore, it is critical to develop methods for optimal reconfiguration to minimize power losses. Although this is a well-known and amply studied problem, many technical and mathematical problems still exist. Spanning tree based genetic algorithm methods have the potential to find optimal or near-optimal solutions for this type of problems.

Distribution network reconfiguration (DNR) is an important real-time operation task which is performed to achieve various objectives (e.g., power loss minimization, reliability improvement, maximum load restoration, voltage deviation minimization, load balancing, peak shaving, and operational cost minimization). Distribution systems are generally equipped with two types of switches: sectionalizing switches (normally closed) and tie-switches (normally open) to serve the maximum loads during the normal and the contingency conditions. The DNR is the process of modifying the configuration of distribution networks through changing statuses of sectionalizing and tie switches to achieve targeted objective(s) while satisfying system constraints (operational and technical). Therefore, DNR can be viewed as an optimization problem. The simplest method of solving the DNR problem is to exhaustively search for all possible combinations. However, exhaustive search techniques are not computationally attractive in the case of electrical distribution systems because of the large search space and the dynamic nature of electrical loads. Numerous analytical and population-based intelligent search techniques (e.g., branch and bound methods, expert systems, and evolutionary algorithms) have been developed and used in literature to solve DNR problems.

The early work on DNR dates back to 1975 when Merlin and Back [1] first proposed branch and bound method for reducing active power losses in distribution networks. An algorithm to determine switching decisions for DNR has been proposed in [2]. A reconfiguration algorithm based on the interaction between service restoration and load balance has been proposed in [3]. A heuristic algorithm based on branch-and-bound strategy has been employed in [4] to solve the network reconfiguration problem for minimum power loss and maximum network current. In [5], the authors have proposed a network reconfiguration algorithm based on a fuzzy multi-objective approach. A two-stage sequential Monte Carlo simulation (MCS)-based stochastic strategy has been proposed in [6] to determine the minimum size of movable energy resources (MERs) for service restoration and reliability enhancement. In the approach proposed in [6], the authors have incorporated a spanning tree search algorithm for optimal network configuration, Dijkstra’s shortest path algorithm for optimal routes to deploy MERs, and the traveling time of MERs for distribution systems optimal operation. A meta-heuristic Harmony Search Algorithm (HSA) has been used
in [7] for optimal reconfiguration and Distributed Generation (DG) placement in distribution systems. A new rule-based codification for various meta-heuristic techniques has been proposed in [8] to solve the reconfiguration problems of distribution network. A modified form of particle swarm optimization (PSO) has been proposed in [2] for effective identification of the optimal configuration of distribution network. The online reconfiguration of active distribution networks for maximum integration of DG has been proposed in [10]. Although numerous analytical and population-based methods have been proposed in literature for solving the DNR problem, spanning tree based methods have been given little attention. The authors in [11] have proposed minimum spanning tree using Kruskal’s algorithm for distribution network reconfiguration. In our paper, both spanning tree search algorithm and genetic algorithm are combined for solving DNR problem.

In this paper, a spanning tree based genetic algorithm (GA) is proposed for the reconfiguration of electrical distribution systems for minimum active power losses. The proposed method starts by initializing a population of randomly generated configurations. After performing crossover and mutation operations, the population is passed through selection process where each of the individuals is evaluated in two steps. In first step, all invalid combinations of branches and tie-lines in each chromosome of GA are filtered out with the help of spanning tree search algorithm. In the second step, power flow analyses are performed for only those combinations that form spanning trees and the optimal configuration is determined based on the amount of active power losses (optimal configuration is one with minimum power losses). The proposed method is implemented on several test systems including the 33-node and 69-node distribution systems.

The remainder of the paper is organized as follows. Section II describes the problem of distribution network reconfiguration. Section III presents the proposed methodology for the implementation of spanning tree based genetic algorithm. Section IV validates the proposed approach with case studies and discussions. Section V provides concluding remarks.

II. PROBLEM FORMULATION

Power loss is an important operational measure which has significant impact on both technical and economic aspects of distribution system operation. Therefore, proper consideration should be given for minimizing power losses in distribution systems. The total active power loss can be calculated as follows.

\[ P_{loss} = \sum_{k=1}^{E_s} I_k^2 R_k \]  \hspace{50pt} (1)

In (1), \( I_k \) and \( R_k \) are, respectively, current and resistance of branch \( k \) and \( E_s \) is the total number of branches (edges in spanning tree). The power loss minimization function, \( P_{loss} \), of (1) can be converted into maximization fitness function, \( F \), as follows.

\[ F = \frac{1}{1 + P_{loss}} \]  \hspace{50pt} (2)

Subject to:

\[ \sum_{S_G,i} S_{G,i} - \sum_{S_L,i} S_{L,i} - P_{loss} = 0, \]  \hspace{50pt} (3)

\[ G_{min} \leq S_G \leq G_{max}, \]  \hspace{50pt} (4)

\[ V_{kmin} \leq V_k \leq V_{kmax}, \]  \hspace{50pt} (5)

Radial topology constraints, \hspace{50pt} (6)

Node traversing, \hspace{50pt} (7)

where (3) denotes the power balance equation (\( S_{G,i}, S_{L,i}, \) and \( P_{loss} \) represents the generation, load, and line loss, respectively); equation (4) refers to the generation limits constraint; equation (5) represents voltage limits constraint; equation (4) represents topology constraints to maintain the radial topology of the distribution system; and equation (7) denotes node traversing constraints to supply all loads.

As several combinations of reconfigurations are possible for large networks, it is very challenging to solve this problem. The complexity of the reconfiguration can be presented as follows.

\[ C(E, E_s) = \frac{E!}{(E - E_s)! \times E_s!} \]  \hspace{50pt} (8)

where \( E \) is the total number of edges and \( E_s \) is the number of edges in a spanning tree.

If this problem is solved by exhaustively searching all combinations of candidate solutions, the search space will be very large. From (8), it is obvious that the search space increases as the size of network increases. For example, the search space would be 435,897 and 15,020,334 respectively for 33-node and 69-node distribution test systems.

As DNR is a large-scale, non-convex, complex, and non-linear problem with a large number of local optima [12], this problem has been solved using various heuristic, meta-heuristic, and artificial intelligence techniques to determine the global optima. These methods not only simplify the problem but also reduce the computation time. Therefore, GA is adopted with spanning tree search algorithm in this paper to solve the DNR problem to minimize active power losses.

III. METHODOLOGY

This paper proposes a spanning tree based genetic algorithm for solving the DNR problem. The proposed method starts by searching all possible configurations using the spanning tree search algorithm and the optimal reconfiguration that minimizes the power losses which is determined using genetic algorithm. This section describes the spanning tree search algorithm, genetic algorithm, and the proposed solution approach for optimal feeder reconfiguration to reduce active power losses.

A. Spanning Tree Search Algorithm

For a graph \( G \) with \( V \) vertices and \( E \) edges, a spanning tree can be defined as a subset of the graph, which has a minimum number of edges (say, \( E_s \)) connecting all vertices (or nodes). The number of edges of a spanning tree (\( E_s \)) is less than the number of vertices by 1. A spanning tree does not have loops and it is not disconnected. A connected graph can have several
spanning trees and all possible spanning trees will have the same number of edges and nodes. Each of the edges in the graph \( G \) has certain values (or weights). The edge weights are problem specific. While determining the minimum spanning tree, the total sum of all edge weights of a spanning tree is minimized.

Electrical distribution networks are composed of nodes and lines similar to vertices and edges of a graph in graph theory. Therefore, an electric distribution network can be viewed as a graph \( G \) with \( V \) vertices (or nodes) and \( E \) edges (or lines). If all nodes are radially connected, they will obviously represent a spanning tree. In case of electric distribution network, edge weights can represent the active power loss of the line. Since the active power loss is proportional to the square of line current, the edge weight in this case changes with the change in network configuration. This is different from the standard graph in which edge weight is assumed to remain constant while determining the minimum spanning tree.

B. Genetic Algorithm

Genetic algorithm is one of the evolutionary techniques that attempts to mimic some of the processes taking place in natural evolutions. The GA, which is based on Darwin’s theory of natural evolution, was first proposed by Holland in 1975 [13]. A GA allows a population composed of many individuals to evolve in such a way that the fitness function is maximized (i.e., the loss is minimized). The fittest individuals are selected for reproduction in GA. The advantages of GA are as follows.

- Can optimize both continuous and discrete variables;
- Does not require derivative information;
- Searches for global optima rather than local optima of even non-convex and non-linear problems; and
- Can deal with large number of variables.

C. Solution Representation

Several methods have been used to represent or encode possible combinations of lines and switches in a particular distribution network. Most of previous work in the literature have used binary numbers to represent the status (open/close) of lines and switches. However, in this work, all edges (lines and switches) are numbered from 1 to total number of edges. Edge numbers are used to generate population of chromosomes because integer number representation reduces the dimensionality of GA search space. For example, in case of the 33-node system, all 37 edges are numbered from 1 to 37 where these numbers are used to generate a string of numbers having string length of 32.

D. GA Operations

The GA operations such as cross-over, mutation, and selection used in this work are explained as follows.

1) Cross-over: The partially matched crossover (PMX) is used as a crossover operator in this work. Under PMX, two chromosome strings are aligned, and two cross-over sites are picked randomly along each chromosome string. These two points define a matching section that is used for performing crossover through position-by-position exchange operations [14].

2) Mutation: In this work, each individual chromosome is composed of \( E_s \) number of edges out of total \( E \) number of edges. For performing the mutation operation, a random edge from \( E_s \) edges is replaced by another random edge from the remaining \((E - E_s)\) edges.

3) Elitist Selection: Elites are the individuals with best fitness in current generation. In the selection methods other than elitist selection, there is a chance of elites being eliminated through cross-over and mutation operations. Therefore, in this work, elitist selection is applied for preserving the

![Fig. 1. The flowchart of the proposed methodology.](image-url)
best fit individuals, which are automatically passed to the next generation.

The flowchart of the proposed methodology is shown in Fig. 1.

IV. Case Studies and Discussion

The proposed methodology is implemented on the 33-node and 69-node distribution systems. The 33-node distribution test system is 100 kVA, 12.66 kV radial distribution system with 33 nodes, 32 branches and 5 tie-lines \(^{(15)}\). Therefore, the total number of branches in this system is 37. The 33-node system is shown in Fig. 2 where all the branches (including tie-lines) are numbered from 1 to 37.

For the determination of base case power loss, all the tie-lines are opened. This results in total active power loss of 202.3 kW. The results obtained using the proposed method are compared with Harmony Search Algorithm (HSA) used by authors in \(^{(7)}\) and a heuristic method used by authors in \(^{(16)}\). The comparison of results for 33-node distribution test system is presented in Table I. The voltage profile of 33-node system before and after reconfiguration is shown in Fig. 3.

The 69-node distribution test system is 12.66 kV radial distribution system with 69 nodes, 68 branches and 5 tie-lines (detail data is given in \(^{(5)}\)). Therefore, the total number of branches in this system is 73. The 69-node system is
Fig. 4. Voltage profile all nodes of 33-node system

Fig. 5. Voltage profile of all nodes of 69-node system
shown in Fig.\ref{fig:comparison} where all the branches (including tie-lines) are numbered from 1 to 73.

For the determination of base case power loss, all the tie-lines are opened. This results in total active power loss of 224.2 kW. The results obtained using the proposed method are compared with a Harmony Search Algorithm (HSA) that has been used in \cite{16}, a heuristic method that has been used in \cite{8}, and a meta-heuristic method that has been used in \cite{7}. The comparison of results for the 69-node distribution test system presented in Table \ref{tab:comparison}. The voltage profile of the 69-node system before and after the reconfiguration is shown in Fig.\ref{fig:voltage_profile}.

The comparison of results for different methods after the implementation of the proposed method on the 33-node and 69-node distribution test systems shows that the proposed method can determine the configuration that has lower active power loss compared to the other methods, which demonstrates its accuracy and efficiency.

V. Conclusion

This paper has proposed a spanning tree based genetic algorithm for optimal electric distribution system reconfiguration to minimize total active power losses. Spanning tree search algorithm was used to filter all invalid combinations of configurations that are generated during selection operation of genetic algorithm. The genetic algorithm was used to determine the optimal reconfiguration that reduces the total active power losses of distribution systems. Real (integer) numbers, instead of binary numbers, were used for the representation of individual chromosomes in the population as it reduces the dimensionality of GA search space. The proposed method was implemented on the 33-node and 69-node distribution test systems. The results obtained for both the test systems show that the method is accurate and efficient compared to existing methods.

\begin{table}[h]
\centering
\caption{Comparison of different methods for 69-node system}
\begin{tabular}{|l|c|c|}
\hline
Methods & Total active power loss (kW) & Opened branches after reconfiguration \\
\hline
Proposed & 96.20 & 14, 57, 61, 69, 70 \\
HSA \cite{7} & 99.35 & 13, 18, 56, 61, 69 \\
Heuristic Method \cite{16} & 99.59 & 14, 56, 61, 69, 70 \\
Meta-heuristic \cite{8} & 99.59 & 14, 56, 61, 69, 70 \\
\hline
\end{tabular}
\end{table}

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