An Optimization of Power Distribution Network Configuration with Distributed Generator Integration Using Genetic Algorithm

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***Abstract*— The limitations of fossil fuels make renewable energy system increasingly popular. The power plant is usually integrated into an electric power distribution network called a distributed generator (DG). The integration of DG in the distribution network makes the network scheme change. We need to do some re-planning with the presence of DG to improve distribution network performance. This paper discusses applying the genetic algorithm (GA) method for optimization to improve the network performance. The presence of DG makes the distribution network more dynamic. The GA method with the ability to avoid local minima is the answer to the existing problems. The system test was carried out on an IEEE 69-bus network model. The results showed that the GA method was able to produce distribution network optimization with a significant reduction in power losses while at the same time increasing the quality of the bus voltage.**

Keywords—Distribution network, distributed generation, optimization, genetic algorithm, power loss

I. INTRODUCTION

The distribution of electricity is a critical component of the electric power system. Typically, distribution networks are built radially to facilitate the coordination of its protective equipment. The penetration of generators across the distribution system is referred to as a distributed generation. The technique is based on hosting capacity. Host capacity is used to improve the voltage profile [1]. Distributed generation is a term that refers to a distributed energy supply derived from photovoltaics or sunshine. This study analyzes optimization strategies using the genetic algorithm (GA) method [2]. Hosting and distribution generation capacity addition, or capacity addition in distributed generation, is a power distribution system optimization strategy for increasing the capacity of remote generators to connect to current distribution networks. Radial distribution systems have various issues, including voltage drops, power losses, and high prices. This serves as the foundation for achieving these primary objectives. Voltage and hosting capacity are used to regulate voltage in the event of an overvoltage or overvoltage and an Undervoltage or voltage drop. This is a frequent occurrence in distribution systems. Typically, a lot happens during a voltage drop produced by electricity consumption at peak times [3].

Finally, the most recent effective computational method for evaluating capacity increase addresses grid parameter uncertainty and connected multi generators [4]-[5]. Several studies on the integration of DG on the grid of the electric power distribution network have been carried out, including the use of particle swarm optimization (PSO) to detect imbalances between phases in a feeder. Furthermore, in reference [6], the distribution system optimization test was carried out by selecting the conductor used. The selection of conductors, including the type of material, size, and resistance, greatly determines the performance of a distribution network. The performance of this network is an indicator of low power losses and a suitable voltage profile. In reference [7], research has been carried out on the effect of renewable energy power plants originating from wind and solar power on the characteristics of the distribution network. As it is known that wind power plants are very dynamic in their operations because they are highly dependent on the ever-changing wind speed. This dynamic can affect the magnitude of the bus voltage and network losses. Dynamics can also come from the load side, for example, the growth of electrical loads and major changes that occur at certain times.

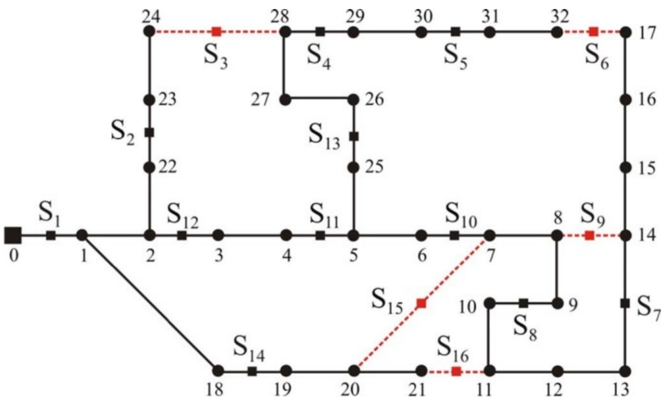
Several studies have carried out control solutions for integrated micro-grid systems, including solar PV, battery systems, and diesel power plants. In reference [8], applying the fuzzy multi-objective method for optimization of the radial distribution network has been carried out. The objective function used is to minimize power losses and maximize voltage magnitude while maintaining load balance. An essential issue in the research is the presence of DG in the distribution network. The fuzzy-based method models each objective function, namely each bus's power and voltage losses, into a trapezoidal fuzzy membership function. The optimal search for each cost function gives quite impressive results. Bridging the gap between European and Asian research on hosting capacity, particularly photovoltaic (PV) and other renewable energy sources [9]-[11]. In this research, we propose to use the genetic algorithm (GA) method to analyze a multi-objective situation involving the hosting capacity of a distribution system.

In this study, a genetic algorithm (GA) approach is proposed for the multi-objective optimization of a radial distribution network. The objective function is to minimize power losses and maximize distribution network bus voltages. The selection of GA is its reliable ability to produce a global optimum in the optimization process. Additionally, the following section will describe research methodologies in detail, including investigating the load flow, goal functions using GA, constraints, and objective functions.

II. DISTRIBUTION NETWORKS AS GRAPHS

From a topological standpoint, distribution networks can be seen as graphs. The main benefit of this modeling approach is that, because graph theory is a mathematical and computer science issue, it allows the reconfiguration problem to be solved using concepts, techniques, and theorems that are widely accepted in other academic fields [12]. A graph G is comprised of a set of nodes X and a set of edges A — G. (X, A). Each edge a(i,j) denotes an unoriented relationship between two items of X denoted by neighboring n(X) and n(A), where n(X) and n(A) denote the size of X and A, respectively.

Figure 1 shows In the cases, a fictitious distribution network was employed. In this case the electric power distribution network will be modeled in a graph. The graph in question is shown in Figure 2.



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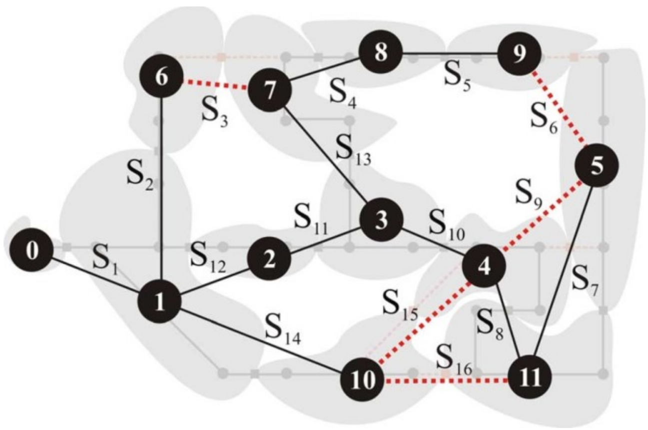

Fig. 2. Distribution network graph from Figure 1

Figure 1 shows a representation of a typical distribution network: a larger square represents a single substation, while circles represent the multiple load buses. Smaller squares indicate the switch's edges. Figure 2 depicts the generation from Figure 1. It's worth noting that the number of nodes drops from 33 to 12.

It is necessary to explain how the following electrical limitations are included in the graph model of the sectors to complete the abstraction: The following are the thermal limitations for branches: The branch current thermal limit, the minimal node voltage, and the substation power source limit are all factors to consider. The purpose is to show that a sector does not meet a constraint unless at least one of its components does. As a result, a) and b) apply to every node, while c) only applies to source nodes. The only limitation for the edges is a).

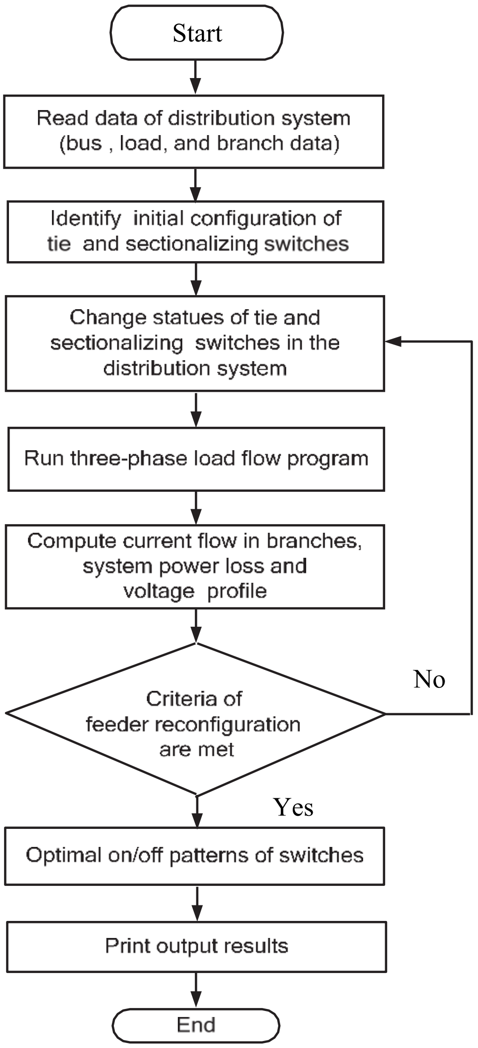

Fig. 3. Flowchart of distribution network reconfiguration

Figure 3 shows flow-chart of distribution network reconfiguration. Equivalent circuits can also be defined in nominal terms in a distribution network. This structure is comparable to that of a medium-distance transmission network. The nominal pi network model is highly realistic and enables network analysis, particularly for reconfiguration purposes.

The line capacitance is distributed uniformly down the line in this pi equivalent model. The circuit's series component is an array of resistance and inductance connected in series in the network. Additionally, the series impedance and shunt capacitance for the three-phase line are 3 3 complex matrices, with this component accounting for the phase-to-phase inductive coupling.

III. Genetic Algorithm

Chromosomes (input variables) generate a set of output function variable costs in genetic algorithms. This cost function may take the form of a mathematical expression. The objective is to adjust the output in a variety of desirable modes by determining the suitable value for the input variable [13]. As an illustration, consider the process of filling the bathtub with water. Thus, in this manner that the cost is the difference between the desired and actual water temperatures in this example. The input variable specifies the number of hot and cold spigots that change.

The cost function in this case is the experimental consequence of grasping your hand in water. As we can see, selecting an acceptable cost function and identifying which variables to employ are inextricably linked. The term fitness is frequently used in the GA literature to refer to the output of objective functions. Fitness entails a maximizing problem. Although fitness is more closely related to biology than term costs, we chose term costs because the majority of the optimization literature discusses minimization first, followed by costs. They are comparable.

GA begins by defining the optimization variables' chromosomal or array values. If the chromosome contains the Nvar variable, then the chromosome is expressed as the row vector of the Nvar element in the Nvar-dimensional optimization problem denoted by p1, p2,..., pNvar.

$$chrom = [p1, p2, p3, \ldots, pNvar] \tag{1}$$

For instance, calculating the greatest elevation on a topographic map involves a cost function with the input variables longitude (x) and latitude (y).

$$chrom = [x, y] \tag{2}$$

where Nvar = 2. Each chromosome has a cost that may be determined by evaluating the cost function, f, at the positions p1, p2,..., pNvar:

$$cost = f(chrom) = f(p1, p2, \ldots, pNvar) \tag{3}$$

Because we were attempting to locate a summit within a park, the cost function was expressed as negative from a height in order to represent it as a minimization algorithm:

$$f(x, y) = -elevation\ at\ (x, y) \tag{4}$$

In many circumstances, such as when optimizing a car's gas mileage, the cost function is extremely complex to solve. The user must determine which variable poses the most significant issue. The variables in this scenario are numerous. As a result, the GA procedure may result in traffic congestion. Among the elements considered while optimizing gas mileage are the vehicle's size, the engine's size, and the material's weight.

Other variables such as paint color and headlamp type have a negligible effect on the distance traveled by the car, and hence do not need to be included in the algorithm. Oftentimes, the optimal number and selection of variables are determined by experience or through optimization studies. Occasionally, an analytical cost function is used, which is determined by

$$f(w, x, y, z) = 2x + 3y + z/100000 + \sqrt{9876} \tag{5}$$

In this scenario, all variables are inside the range of 1 to 10, which simplifies the optimization procedure. Because the terms w and z are so minor in their respective areas of interest, they can be omitted for the majority of reasons. Thus, two variables in the area of interest are adequate to simulate the four-dimensional cost function.

In the majority of optimization problems, variable limitations or restrictions are required. Allowing the car's weight to be zero or its breadth to be ten meters is an unworkable variable value. Restricted variables are available in three flavors, but unrestricted variables accept any value. On variables, hard restrictions of the type>,,, and £ can be applied. If the variable has surpassed the limit, it is set to the value specified by the bound. If x has a value limit of 0 £ x £ 10 and the algorithm sets x = 11, x will be reset to 10. The variable can then be turned to a new variable that is intrinsically an impediment. If x has a limit of 0 £ x £ 10, then x = 5 sin y + 5 represents a transformation between a restricted variable x and an infinite variable y.

Changing y for any value is equivalent to changing x within its bounds. This type of transformation smoothly converts a constrained optimization problem to an unconstrained optimization problem. Finally, there may be a limited number of available value variables, and all values are inside the acceptable range. Such difficulties manifest themselves in the form of selecting a portion of a limited inventory.

Because modifying one variable affects the value of the other, the dependent variable will provide a unique difficulty for the optimization approach. For instance, the size and weight of the automobile are dependent. Except for a few other criteria, such as the type of material used, increasing the size of the car is likely to increase its weight as well. Independent variables, such as the coefficients of the Fourier series, do not interact with one another. If five coefficients are insufficient to express the function, additional coefficients can be added without recalculating the original five.

IV. Results and Discussion

The distribution network was reconfigured in this research using a test system for case studies, namely an IEEE 69-bus radial distribution system with seven laterals and five tie-lines, as illustrated in Figure 4. The No. 1-9 branch currently has a carrying capacity of 400 amps, the No. 46-49 and No. 52-64 branches have a carrying capacity of 300 amps, and the remaining branches, including the tie line, have a carrying capacity of 200 amps.

Additionally, the distribution network included four DG units with capacities of 300, 200, 100, and 400 kW installed on buses 14, 35, 46, and 53. 12.66 kV and 100 MVA are the fundamental voltage and power numbers. Each branch in the system is equipped with a division switch for reconfiguration. All sectionalize switches (switches 1-68) are initially closed, whereas all tie-switches (switches 69-73) are initially open.

This test system's total load is 3,801.89 kW and 2,694.10 kVAr. Minimum and maximum voltages are adjusted to 0.95 p.u. and 1.05 p.u., respectively. The reconfiguration of the network in this study was accomplished through the use of genetic algorithm-based optimization methods. This is a well-known algorithm in optimization techniques.

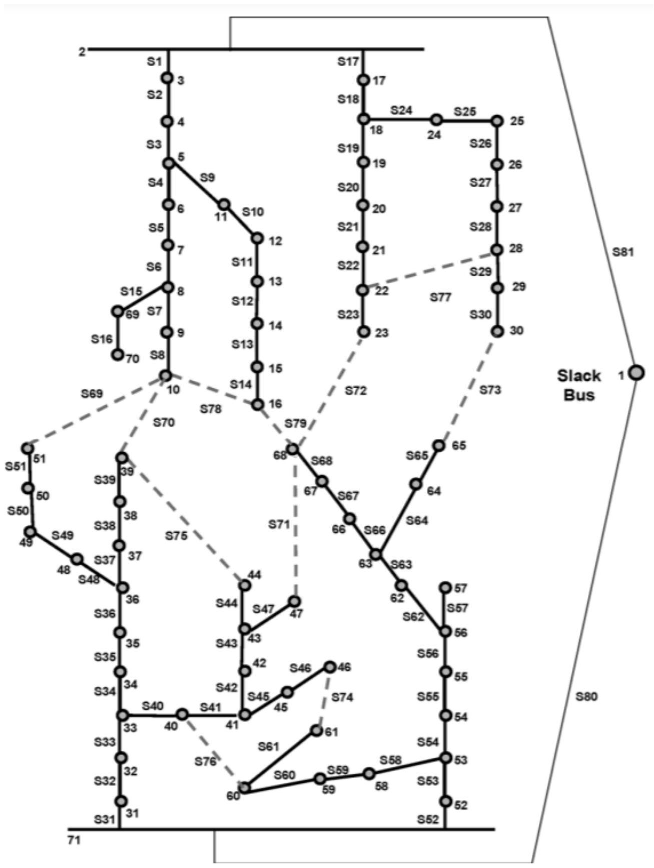

Fig. 4. IEEE 69-bus distribution network

The results of the optimization of the IEEE 69-bus distribution network are shown in Table 1. There were 6 test cases carried out in this work. In test case 1 is the original condition of the distribution network. In this original configuration, the power loss is 587 kW. The minimum voltage across the bus is 0.915 p.u. with a load balance index (LBI) of 2,366. The smaller the LBI, the better the load balance on each feeder. This finding demonstrates that DG units can typically, but not always, assist in reducing current flow in the feeder and hence contribute to a reduction in power losses, particularly because they are typically located close to the load supplied. No bus voltage is broken in situations 2 to 5, when the feeder is redesigned, and voltage limitations are placed throughout the optimization process.

As expected, the results indicate that case 2 has the lowest system power loss, case 3 has the lowest LBI index, and case 4 has the fewest switch switching operations. As seen in Case 5, genetic algorithms provide some degree of flexibility that can be used to make additional trade-offs between improving one cost function and worsening others. This flexibility is still within acceptable limits and has no adverse effect on system performance. While the power loss in instance 5 is slightly larger than in case 2, it is offset by the fact that case 5 requires only six, rather than eight, switching operations. Although LBI case 3 is superior to case 5, it consumes more power and requires more switching operations. When comparing instance 4 to case 5, an additional 18 kW of power loss from two switching processes can be avoided. The distribution network model with genetic algorithm-based optimization can tackle decision-making challenges associated with feeder reconfiguration by allowing decision makers to include their own assessments and priorities into the optimization model.

TABLE 1. RESULTS OF IEEE 69-BUS DISTRIBUTION NETWORK CASE STUDY HARDWARE SPECIFICATIONS

Test Case	SS to be NO	TS to be NC	Losses (kW)	Minimum Voltage (p.u.)	LBI	Operating Switch
Case 1	-	-	587	0.915	2.366	-
Case 2	12, 20, 52, 61	70, 71, 72, 73	247	0.955	1.812	8
Case 3	14, 20, 42, 52, 61	69, 70, 71, 72, 73	271	0.955	1.751	10
Case 4	52, 62	72, 73	304	0.954	1.923	4
Case 5	13, 52, 63	71, 72, 73	269	0.954	1.870	6
Case 6	12, 52, 61	71, 72, 73	252	0.967	1.795	6

The best optimization results were obtained during test case 6. In this test case, the power loss of the reconfigured IEEE 69-bus distribution network was 252 kW. It should be noted that the distribution network in case 6 has been integrated with DG so that, in general, the characteristics have improved. Optimization in case 6 recommends sectional switches (SS) numbers 12, 52, and 61 to be opened or made ordinarily open (NO). Tie-switches (TS), which are normally open, namely switches numbered 71, 72, and 73, are recommended to be closed or normally closed (NC). Case 6 produces a minimum bus voltage of 0.967 p.u. with LBI is 1,795, and the number of switches operating is six switches. When compared to case 3, the LBI value of case 6 is slightly higher. However, compared with the optimization results and voltage losses, case 6 provides the best results among all test cases in this research.

Figure 5 shows the voltage level on each bus of the IEEE 69 bus distribution network test system. The installation of DG on the distribution network plays an essential role in increasing the voltage level on the distribution network buses, especially those close to the DG location. DG placement also needs to be optimized, but this study did not optimize the location and size of DG. The location and size of DG were determined based on the results of previous research. With the increase in the bus voltage level due to DG installation, the reconfiguration of the distribution network will further increase the overall bus voltage level.

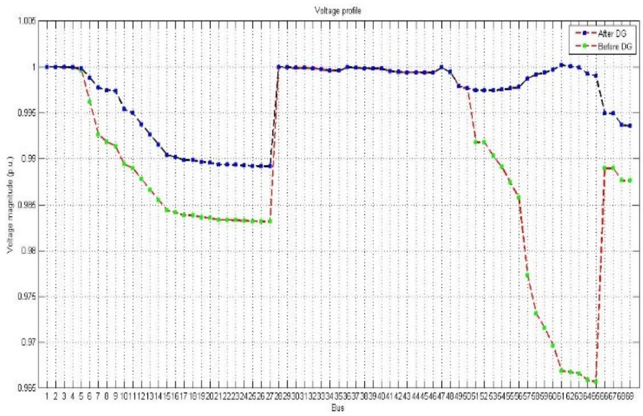

Fig. 5. Bus voltage of IEEE 69-bus distribution network

V. CONCLUSION

This work proposes a way for improving performance the simultaneous installation of DG units in a distribution system. The suggested technique of reducing distribution network power loss is also simulated to determine the proposed method's advantages. Genetic algorithm-based solutions are successful in optimizing configuration of network in the installation of DGs. The installation of DG in the distribution network makes the network more dynamic. The network dynamics are mainly due to the presence of power plants that experience significant parameter changes, such as wind power plants. In this study, the GA method has played a good role in optimizing the network configuration. Configuration by changing the switch status to normally open (NO) or normally closed (NC) position has been carried out on the IEEE 69-bus distribution network test system. The optimization results have shown that the GA method can provide lower power losses, and the overall voltage magnitude is better than before reconfiguration. The integration of DG on the network has reduced power losses and increased the voltage on buses close to the DG location. However, the network reconfiguration makes the network characteristics even better because the power losses are getting smaller, and the voltages on all buses are getting better. The results of this multi-objective optimization play a significant role in increasing the efficiency of the distribution network. In the electric power system, the distribution network is the component that experiences tremendous power losses. Thus, reducing losses plays an essential role in increasing the overall efficiency of the electric power system.

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