**Optimal Network Reconfiguration of the Distribution Network for Minimization of Power Loss and Voltage Deviation using NSGA-II Algorithm**

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*Abstract -* **For efficient power flow in the distribution system, one of the most important components is the accurate loss and voltage deviation minimization. This work gives an insight into the minimization process of the loss and voltage deviation in the power distribution system by using the network reconfiguration. Non-dominated sorting genetic algorithm – II (NSGA-II) has been used as the tool for solving the problem. The power flow is incorporated with the Genetic Algorithm until the best results are obtained. For power flow calculation, Power System Analysis Toolbox (PSAT) is used, while the whole algorithm was written in MATLAB. The proposed algorithm is tested on a real 10 kV distribution network, Gracanica. Results obtained show that the presented methodology can be efficiently applied to reconfigure distribution networks to select the optimal distribution network topology in order to achieve savings in power losses and improve voltage profile.**

*Keywords -* ***Non-dominated sorting genetic algorithm–II (NSGA-II), reconfiguration, power loss, voltage profile, PSAT*.**

1. **Introduction**

Between 30 and 40% of total investments in the power sector are going to distribution systems. Most of the distribution networks operate using only a minimal number of control systems and are not having proper computer support for the system operator. Therefore, to improve the reliability and efficiency of the system, in recent years, the increasing importance is given to the automation of distribution systems. Another essential segment that strongly influences the need for automation of the distribution system is the increasing complexity of the distribution systems. Consequently, it has become of great significance to automate certain management functions of the distribution system that have so far operated manually, with the aim of minimizing losses and at the same time give the quality power to consumers. It was found that using modern technology, distribution companies in this way can save more than 10% of their annual costs.

Many researchers have proposed different tools to reduce power losses and hence increase the system efficiency, without the need for major construction to the existing system. These approaches include reconfiguration, capacitor placement and installation of distributed generation [1- 4]. Network reconfiguration is the easiest and least expensive method used to reduce the losses. The reconfiguration of the network is essentially made up of changes in the network topology in a way that activation and deactivation of switch set in the distribution system are done. Thus, the topology of the network and the power flow from the substation to the consumer change. New topology is obtained in order to meet the objectives such as reducing power losses, load balancing, improving the voltage profile, improving the power quality, service to all consumers, minimizing areas without electricity and increasing the network reliability.

Reconfiguration of the network consists of changes in the network topology and is done in a way to include or exclude the sectional switches. After turning off the network shares, or equipment that is defective, the remaining nodes of the network, who remain without power, can be fed through interconnection with the correct lines or substations, or the nodes that belong to the same feeder, but their power is not interrupted. Since the distribution system usually works with radial topological structure, its properties determine the state of the switch. The whole problem consists of determining the state of the sectional switches in the network (on / off), with the aim to reduce power losses and improve voltage profile with respect to topological constraints [3].

The problem of the reconfiguration of the network can be classified as a combinational nonlinear optimization problem with multiple constraints. Some network configurations are not allowed to choose because of the violation of constraints such as radial network, the energizing at all nodes and the violation of operation constraints such as allowable limits for voltage and current. The optimization method that should solve the problem of reconfiguration must quickly find a network configuration that will meet desired objectives while satisfying system constraints. The literature related to this problem mainly refers to the application of heuristic algorithms and artificial intelligence-based algorithms, including the ant colony search algorithm [2], artificial bee colony [3], ant lion algorithm [6], particle swarm optimization [8] and genetic algorithms [4, 5]. Among these algorithms, heuristic algorithms are all greedy search algorithms. They are easy to be implemented and with high searching efficiency. A variety of studies addresses active power loss reduction, voltage profile improvement, load balancing improvement and improvement of reliability indexes. As the simultaneous optimization of two or more objectives could bring better results, the distribution network reconfiguration can be represented as a multi-objective problem.

This paper is focused on the application of a multi-objective genetic algorithm (non-dominated sorting genetic algorithm-II – NSGA-II) to the problem of reconfiguration of the distribution network. The effect of reconfiguration on voltage in the network, taking into account two objective functions: power loss and voltage deviation is presented. The effectiveness of the methodology is demonstrated on real 10 kV distribution network.

1. **Problem formulation**

The problem of reconfiguration may be represented by an objective function that minimizes the power losses in the network and voltage deviation. As the optimal results of the defined functions do not lead to the same optimal network topology, tradeoff between voltage deviation and power losses function is created. The efficient solution of the described problem requires the choice of the optimal topology of a radial network within the set of possible solutions.

Although the power losses in a distribution network can occur in a variety of devices that make up the system, the losses given in power line segments and transformers often take a major share on the overall losses. Mathematically, the total active power losses in the distribution network can be calculated by summing up the power loss of each line through the following equation:

 (1)

where: is the function of losses in MW, resistance of the ith branch, real power flowing through the ith branch, reactive power flowing through the ith branch, voltage at the receiving end of the branch, n is a total number of lines. The total power losses are calculated by summing the losses from all branches after reconfiguration and are compared with the total power losses from previous iteration.

As a result of topology changes, loading of the line segments may vary. Therefore, the voltage of load buses may be altered. The total voltage deviation in the distribution network can be calculated by summing up the voltage deviation of each bus through the following equation:

 (2)

where: is the function of voltage deviation in kV, voltage of the ith bus, nominal voltage of ith bus, n is a total number of buses. The reconfiguration process will try to minimize the fv closer to zero and thereby improve the voltage stability and network performance.

Electrical distribution systems are operated in radial configuration, and therefore the number of tie line must be opened. So, solution structure for distribution network reconfiguration problem includes network switches which must be opened. In order to solve distribution network reconfiguration problem properly, first governing constraints of the network must be satisfied and then the objective functions should be optimized.

With this aim, the power flow analysis will be derived during the reconfiguration process. For each new proposed network configuration, the power flow analysis will be carried out to compute the nodal voltage, power loss of system and current of each branch. Furthermore, it is necessary to consider an appropriate operation of the system regarding electrical variables such as currents and voltage levels. These values are considered through defined constraints:

 (3)

Current limits - Current in every element of the network must be within acceptable limits.

 (4)

Voltage limits - Voltage of each node must be within acceptable limits.

 (5)

Network radiality - Each node has to be supplied from a single feeder.

is the current of ith line in A; maximum accepted current of ith line in A; accepted limits of voltage in nodes in kV; and n number of nodes in the network.

Inspection of the defined constraints requires the knowledge about voltage magnitude and the angle at each bus in the system at any time. When the voltage magnitude at any bus in the system is not within the defined limits, the current network configuration cannot be considered as a possible solution. In order to inspect objective functions and system constraints power flow studies should be performed for each configuration.

1. **Optimization method**

Since the problem of reconfiguration of the distribution system includes two objectives, it is hard to find a globally optimal solution. Hence, there is a set of solutions from the Pareto front within the accepted search area. Multi-objective genetic algorithm, NSGA-II, gives wider Pareto front when compared to classic methods, and that is the reason it is used to address this optimization problem. This ensures that there will be a wider choice of quality solutions with a better overview of all possible solutions.

The basic concept hidden behind the genetic algorithm (GA) is optimization. This algorithm uses a population of candidates to go through the area of a solution space. It is done simultaneously and adaptively. The GA has been used at most for solving the combinatorial optimization problem. In addition, they have provided very good results in the reconfiguration of distribution systems. The Genetic algorithm works with a population of individuals where each of those individuals is a potential solution to the problem.

The solutions are most commonly showed as a fixed-length binary string that matches a real-world chromosome. The description of the genetic algorithms is provided in [7]. The main advantage of GA is that it can find global optimum regardless of the characteristics of an objective function. GA can solve complex problems and search the solution area in different directions, which reduces the possibility to end in a local optimum.

**3.1. Non-dominated sorting genetic algorithm – II**

Non-dominated sorting genetic algorithm – II (NSGA-II) is a multi-objective optimization method also known as Pareto optimization. Its main advantage over conventional GAs is that it can preserve population diversity. NSGA-II estimates the density of solutions surrounding a particular solution in the population by calculating the average distance of two points along each of the objectives of the problem. This value is called the crowding distance. Rank of possible solutions is done through a fast-non-dominant sort strategy, with the goal to define dominant solutions and classifications in Pareto front. Pareto front represents a set of solutions where a single solution cannot be improved for one objective without degrading another objective [11]. Furthermore, NSGA II uses an elite strategy that significantly helps in speeding up the performance of the genetic algorithm.

1. **Proposed algorithm**

The proposed algorithm starts with a randomly selected radial functional solution, as a basis for the first generation of trade-offs in the part of a genetic algorithm code. The binary alphabet has been used to implement the optimization model, in which every bit of chromosome represents the status of switches (open/closed). Since the switches can be either in on or off state, the type of population is represented by a binary string including ones or zeros. One represents that the switch is closed, while zero shows that the switch is opened. For example, chromosome [1 1 0 1 0 1 1 1 0 1] illustrates the status of 10 switches in the network, where switches 3, 5, and 9 are opened (their value equals zero) and others are closed (value equals one). Every individual, or his chromosome, represents a possible topological solution for the distribution networks. The power distribution systems encoding/decoding method not only should generate radial configuration but also needs to prevent “infeasible radial network” that refers to the generated topologies in which the buses with no switch in between are connected. In the problems of reconfiguration, only a certain number of switches can be changed, and therefore only those switches are subject to genetic operators, crossover and mutation, while others are always kept closed (having the value 1 in operation).

After the initial configuration is set, topological constraints (radial conditions) are inspected and evaluation of the objective functions is carried out, i.e. power flow and calculation of objective functions are performed. Power flow calculations are implemented using PSAT (Power System Analysis Toolbox), while the whole algorithm is written in MATLAB. PSAT toolbox is used for static and dynamic analysis and control of electric power systems (Milano, 2006). Power flow calculation in PSAT is based on the Newton-Raphson method and is included in the algorithm code for the need of objective functions evaluation, transfer of variables and storage of diverging solutions.

Based on the power flow results, a convergence of specific network configuration is verified, as well as other constraints that refer to the capacities of lines and network radiality. To maintain the radial topology, the voltage on any bus in the system should not be zero. Configurations that do not satisfy defined constraints are eliminated or penalized, depending on a convergence of power flow calculation. When configurations are penalized, they undertake the process of reproduction. New population is generated using the operators of genetic algorithm including selection, mutation and crossover, and again the power flow is computed, and process repeated. For configurations that meet defined limits, evaluation of the objective function is done.

The procedure is repeated until stopping criteria are met. The criteria for stopping calculation can be based on a maximum number of generations, average change in solution distribution, time limits to simulation, etc.

The suggested method uses the concept of Pareto domination in the evaluation of the objective functions. Input data to describe multi-objective optimization problems are system parameters and constraints, lines and reliability parameters. The result of the described algorithm is represented as Pareto front of possible optimal topological solutions for the electrical distribution network.

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**Figure 1**. Proposed algorithm

1. **Results**

The proposed method has been tested on the 10 kV radial distribution system. It includes 598 buses, 392 switches, 215 transformers, 2 generators and 211 loads. The base voltage and base power of the network are 10 kV and 10 MVA, respectively. As the network has 392 lines, that implies that it has 392 switches, that can be used for reconfiguration. For analysis 128 of them are used, while the rest of them are kept closed.

**Table 1**. Initial power ratings

|  |
| --- |
| **TOTAL GENERATION** |
| Real power [p.u.] | 0.43978 |
| Reactive power [p.u.] | 0.19121 |
| **TOTAL LOAD** |
| Real power [p.u.] | 0.43484 |
| Reactive power [p.u.] | 0.21557 |
| **TOTAL LOSSES** |
| Real power [p.u.] | 0.00493 |
| Reactive power [p.u.] | - 0.02436 |

The testing of proposed algorithms was performed by launching a large number of simulations for different parameters. During the simulation for NSGA-II, two crossover fractions were used, namely 0.7 and 0.8. Different values for the mutation ratio have also been taken, including 0.01 and 0.02. All results are expressed in per unit system, with base voltage and base power of the network of 10 kV and 10 MVA, respectively.

The appropriate selection of the first population is affected on algorithm convergence. That is why the initial population in the algorithm is defined as a string containing all ones, meaning that all switches are closed. The power losses for the initial population are given in Table 1 and are 0.00493 (p.u.). Voltage deviation is 6.1062 (p.u).

**Table 2.** Parameters used

|  |  |
| --- | --- |
| **Population size** | 128 |
| **Selection function** | Tournament, 2 |
| **Crossover fraction** | 0.8 |
| **Mutation rate** | 0.01 |
| **Pareto fraction** | 0.35 |
| **Generations** | 100 |

For the algorithm, tournament selection was used as well as a single-points crossover. Parameters shown in Table 2 appeared to give the best possible solution for this network. For the parameters given in Table 2, a set of 10 Pareto optimal solutions is displayed in Figure 2. The total number of possible solutions obtained is 59.

**Figure 2.**  Pareto optimal solutions

Table 3 represents the values of the objective functions for the solutions that belong to the Pareto optimal set, as well as the change of the switch state, which are turned off, for each new topology of the network.

**Table 3**. Values of objective functions for Pareto solutions from Figure 2

|  |  |  |  |
| --- | --- | --- | --- |
| **Number** | **Switches turned off** | **Losses (p.u.)** | **Sum of voltage deviation (p.u.)** |
| 1. | 70,116 | 0.000444652 | 6.189822413 |
| 2. | 70,116,120 | 0.000445259 | 6.176039098 |
| 3. | 88,116,120 | 0.000445394 | 6.13121247 |
| 4. | 70,83,116 | 0.000445589 | 6.072566544 |
| 5. | 27,77,83,116 | 0.00046503 | 6.056944514 |
| 6. | 76,117 | 0.000494985 | 5.957068444 |
| 7. | 75,76 | 0.0004978 | 5.95393479 |
| 8. | 75,83 | 0.000497772 | 5.880102 |
| 9. | 29,75,83,88 | 0.000521528 | 5.779748676 |

In the optimization history, it can be observed that the evolution of the objective functions vs iteration is consistent for all algorithm runs thus confirming its robustness of the implemented algorithm. Among the solutions obtained, the optimal solution from the aspect of power loss is the solution for which the total losses are 0.000444652 (p.u). However, this solution gives poor voltage quality. From the aspect of voltage quality, the optimal solution is for which the sum of the voltage deviation is 5.77974876 (p.u), but in this case, the power losses are high (higher than the values obtained for the initial state). From the aspect of both target functions, the good solutions include the 4th and 5th. The best solution obtained is a solution with number 4. In this case, a new network configuration is obtained by turning off switches 70, 83 and 116. Power losses decrease from 0.00049335 to 0.000445589 (p.u) and voltage deviation from 6.1062 to 6.072566544 (p.u). In Figure 3, the voltage profile for the best combination of switches is shown. From Figure 4 and configuration obtained, we can see that if 70, 83 and 116 switches are opened, and the rest of switches are closed, the optimal power losses and voltage deviation are obtained.

**Figure 3.** Voltage profile for the 4th solution

**Figure 4.** The configuration of switches for the 4th solution



In Figure 5, a comparison between voltage profiles for initial configuration and configuration obtained after reconfiguration is shown. It can be seen that after reconfiguration, the voltage profile is nicely improved. The optimal solutions obtained for the NSGA-II show the properties of each solution from the Pareto front (single solution of Pareto front cannot be improved for one function without affecting others in the opposite way). However, for these two objective functions, power losses and voltage deviation, Pareto front is not a must. By changing the parameters of algorithm different results can be obtained which will not produce Pareto front. That is because these two functions do not depend each on another. They are not opposing functions.

**Figure 5.** The configuration of switches for the 4th solution

1. **Conclusion**

The paper shows the application of multi-objective genetic algorithm NSGA II on resolving the problem of reconfiguration of the distribution network with the aim to identify optimal topological solution taking into account the set of limitations. Proposed algorithm is tested on a part of a real network with 598 buses and 392 switches. The algorithms and solutions are implemented in the MATLAB environment with interactive graphical and tabular outputs. The implementation of the proposed methodology and the NSGA-II has demonstrated the ability to find multiple solutions through one algorithm. By comparing the obtained optimal solutions and sensitivity analysis, the influence of certain parameters on the distribution network planning process has been demonstrated.

The presented methodology can be efficiently used to reconfigure distribution networks to select the optimal distribution network topology in order to achieve savings in power losses and improve voltage profile. Although the proposed methodology does not guarantee that all solutions are optimal solutions, its application in solving reconfiguration problems of distribution networks provides good results. Future work and research can be linked to planning distribution networks using modern optimization methods and creating algorithms that consider more complex market models. Reconfiguration and eventual connection of new elements to the system, as well as distributed sources, can also be included in future work, as they offer some possibilities for reducing losses and improving the voltage profile.

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