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EFFICIENT OPERATION OF POWER DISTRIBUTION NETWORKS USING EVOLUTIONARY ALGORITHMS

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Dedicated to my wife,

who has always been with me in happiness and sadness.

FOREWORD

Power system operation is a complex constrained task. It has to be performed fast and reliably. Evolutionary algorithms (EAs) are expert in solving very complex problems. However, they are slow if they are not well-designed for a specific problem.

Performance of EAs is significantly affected by modeling of the problem and employed operators. This work proposes an efficient modeling of the power distribution network, new sets of operators, and an integrated framework for EAs in order to make them fast and more effective for solving distribution networks' operational problems.

ABSTRACT

Power distribution network operation is a complex constrained optimization problem. A high quality of continuous service to the customers should be guaranteed while satisfying operational and structural constraints. Introduction of evolutionary algorithms (EAs) to the power distribution network operation has opened many new opportunities. However, many applications of these methods suffer from high computational burden. Performance of EAs is significantly affected by modeling of the problem and employed operators.

Among the distribution network's operational problems, network reconfiguration and service restoration are studied in this work. A branch-based object-oriented modeling is employed in order to represent the network which offers a natural representation of the network and allows for the use of graph concepts for modifying its configuration. Based on this modeling, an integrated EA framework is proposed employing three sets of operators which:

i) reconfigure the network,

ii) minimize amount of the loads that are excluded from recovery,

iii) optimize settings of the network's existing compensators in order to support the restoration process.

In addition, three techniques are proposed in order to introduce more intelligence to the operators and guide the search to more productive areas of the search space by using more information about status of the network. Furthermore, a new technique is proposed for liming the search space without losing the global search capability of EAs. Simulations show efficiency of the proposed methods in terms of speed and the quality of results.

PUBLICATIONS AND AWARD

- ISI Journal paper:

[1] Saeed RamezanJamaat, Youhei Akimoto, Hernan Aguirre, and Kiyoshi Tanaka, "Efficient reconfiguration of distribution networks using extended pruning-grafting operators," *IEEJ Trans. on Electrical and Electronic Engineering*, vol. 10, no. 2 (2015) (to appear).

- International Conference papers:

[2] Saeed RamezanJamaat, Hernan Aguirre, Youhei Akimoto, and Kiyoshi Tanaka, "Smart EA operators for effective service restoration of compensated distribution networks," *Proc. IEEE Innovative Smart Grid Technologies - Asia (ISGT ASIA)*, pp. 1–6, Kuala Lumpur, Malaysia (2014).

[3] Saeed RamezanJamaat, Hernan Aguirre, and Kiyoshi Tanaka, "A fast and effective EA for service restoration of compensated distribution networks," *Proc. IEEE PES Asia-Pacific Power and Energy Engineering Conf. 2013 (APPEEC)*, in CD-ROM (no. 0108, 6 pages), Hong Kong, China (2013).

[4] Saeed RamezanJamaat, Youhei Akimoto, Hernan Aguirre, and Kiyoshi Tanaka, "Extended pruning-grafting operators for efficient distribution network reconfiguration," *Proc. 3rd Int. Conf. on Electric Power and Energy Conversion Systems*, pp. 92–97, Istanbul, Turkey (2013).

- Demestic Conference papers:

[5] Yohei Eda, Saeed RamezanJamaat, Youhei Akimoto, Hernan Aguirre, and Kiyoshi Tanaka, "A study on test network generation for power distribution system including dispersed power generators," *Proc. IEICE Student Branch Conf.*, p. 11, Shinshu University, Nagano, Japan (2013).

[6] Yuta Nakajima, Saeed RamezanJamaat, Youhei Akimoto, Hernan Aguirre, and Kiyoshi Tanaka, "A study on dynamic optimization of power distribution system by evolutionary algorithms," *Proc. Evolutionary Computation Symposium*, no. 4–2 (6 pages), Kogoshima, Japan (2013).

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[11] Yuta Nakajima, Saeed RamezanJamaat, Hernan Aguirre, and Kiyoshi Tanaka, "A basic study on power flow calculation for radial distribution networks using sweep method," *Proc. IEICE Shin-etsu Session*, no. P–5 (1 page), Niigata University, Niigata, Japan (2012).

- Award:

[1] IEEE Power & Energy Society (PES) Best Student Paper Award, in *IEEE PES Asia-Pacific Power and Energy Engineering Conf. 2013 (APPEEC)*, Hong Kong, China (2013).

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Part I

GENERAL WORDS

1

INTRODUCTION

Electrical distribution networks are always subject to continuous extension due to the development of society. This has led to complex spider-net urban distribution networks. Distribution network operation is a complex constrained optimization problem. A high quality of continuous service to the customers should be guaranteed while satisfying many constraints. Some of them include:

1. Structural constraints: distribution network configuration has to be maintained radial for ease of protection and fault location. In addition, electrical service has to be provided to as many customers as possible.

2. Operational constraints: loading of the lines and transformers have to lie below the permissible ranges in order to avoid irreversible effect on the network equipment. In addition, for maintaining an acceptable quality of service to the customers, nodal voltage amplitudes have to be in predefined margins.

Among the network operational problems, network reconfiguration and service restoration of compensated distribution networks are studied in this work. Introduction of evolutionary algorithms (EAs) to the distribution network operation has opened many new opportunities for solving these complex problems. However, many applications of these methods suffer from high computational burden. Performance of EAs is significantly affected by modeling of the problem and employed operators.

EA's conventional binary representation and crossover/mutation operators can contribute to solve the problem. However, they have generally an average convergence response, since they are defined for a general application. In order to have an efficient EA for solving the power distribution networks' operational problems, it has to be problem specific in terms of the problem representation and operators. Therefore, it should fulfill special requirements such as:

i) maintain the search in the space of radial configurations,

ii) serve all loads (for the network reconfiguration problem) or as much loads as possible (for the service restoration problem),

iii) be flexible for considering distribution network's more equipment such as compensators in the optimization,

iv) have a global search capability,

v) have a fast and reliable response.

1.1 NETWORK RECONFIGURATION

Network reconfiguration means to alter the status of open and closed switches of the network. Switches could be located inside a feeder or between two different feeders. Inside-feeder reconfiguration is mainly performed in order to reduce loss and/or to balance loading inside the feeders. On the other hand, inter-feeder load transfer is commonly utilized in order to restore service in contingencies following a fault and/or to balance loading amongst different feeders. Consequently, solving distribution network's operational problems such as loss reduction, load balancing, and service restoration is highly influenced by performance of the reconfiguration optimization plans.

Network reconfiguration involves incorporation of many candidate switching combinations. Meanwhile, Structural and Operational constraints have to be fulfilled. Therefore, it is a complicated combinatorial multi-constrained optimization problem.

1.1.1 *Literature review*

Merlin et al. [7] propose the first approach to the distribution network reconfiguration problem. They employ *branch-exchange* method that alters the topological structure of the network by successively altering the status of normally open and normally closed switches in the neighborhood. However, their method is capable of finding only local optima and the final solution heavily depends on the initial configuration [8].

Murai et al. [9] propose an advanced branch-exchange method that closes N switches and thus creates N intermediate loops in each iteration, where N is not necessarily equal to the total number of loops. Then, the loops are opened by opening N switches while performing a local search for finding the proper switches to open in each iteration. Although this method improved the traditional one, it still inherits the branch-exchange method's local search problem.

Other approaches such as heuristic algorithms [10]-[14] and expert systems [15]-[18] are suggested for the network reconfiguration problem. However, they sometimes produce poor suboptimal solutions [19]. Some researchers employ methods based on mathematical programming [20]-[23]. They formulate the reconfiguration problem using one of the standard techniques, such as linear programming. The main disadvantage of these methods is their high computational burden [24].

Several evolutionary algorithms (EAs) are developed in order to address this problem with encouraging results [8], [24]-[35]. However, the majority of them still demand high running time which is essentially affected by modeling of the problem and employed operators. Besides, EA's conventional crossover/mutation operators cannot guarantee producing only radial configurations [36], [37] which imposes extra computational burden for checking the radiality and possible repairs. In addition, evaluation of the individuals who contain loops commonly takes more time.

In order to improve the performance of EAs in the reconfiguration problem, Delbem et al. [38] propose a tree encoding based on graph chains, called Graph Chain Representation (GCR), and its corresponding genetic operators that exclusively produce radial configurations. However, their method suffers from high burden of numerical modeling and relevant orderings (called properly grouping) as well as the processing required for implementation of the reconfiguration.

Santos et al. [24] employ the concept of node-depth encoding and similar operators called Preserve Ancestor Operator (PAO) and Change Ancestor Operator (CAO), and tackled the high computation burden problem of the numerical modeling in [38]. However, their method still demands extra analysis such as processing intermediate representations due to the employed numerical node-based modeling. In addition, PAO/CAO operators' application is basically limited to inter-feeder load transfer [39].

1.1.2 *Motivation*

In order to provide an integrated solution to the network reconfiguration problem, an approach is required that can address both inside-feeder reconfiguration and inter-feeder load transfer, simultaneously. In addition, it has to maintain the search in the space of radial configurations and mitigate the high computational burden, which is a discouraging feature for the application of EAs to this problem, providing a solution in reasonable time.

1.2 SERVICE RESTORATION

Service quality improvement of electric power delivery is one of the permanent tasks of modern distribution companies. The ever-increasing demand of electric power has led to larger and more complex power distribution networks, which in turn, has increased the likelihood of occurrence of faults and size of the affected area. Therefore, an effective post-fault supply restoration strategy plays a key role in improving service reliability and enhancing customers' satisfaction.

The main objective of a service restoration (SR) plan is to provide a base level of service to maximum number of customers during emergencies. SR is mainly performed using network reconfiguration. The number of switching operations should be minimized due to its required time and sequence [40] in addition to operation and maintenance costs. Meanwhile, Structrual and Operational constraints have to be fulfilled.

Sometimes it is not possible to restore the whole out-of-service area since it cannot be served without violating the operational constraints. Consequently, some loads should be excluded from recovery in a process called *load shedding*.

Furthermore, if the network's existing compensators are optimally operated (Volt/Var control), they could effectively contribute in the SR plan and help to minimize the amount of load shedding [40]-[43]. Therefore, SR of a compensated distribution network is a complex multi-constraint combinatorial optimization problem.

1.2.1 *Literature review*

Several EAs have been developed in order to deal with the SR problem [41]-[51]. They provide better results than mathematical programming and traditional artificial intelligence approaches [44].

However, EA's conventional crossover-mutation operators cannot guarantee producing only radial configurations [36]. In addition, improper modeling of the problem could lead to a high computational burden of the EA [36], [45], [46].

Mansour et al. [44] employ node-depth encoding and two operators in order to address these problems. However, their method still demands extra numerical analysis such as processing intermediate representations. Moreover, the operators are limited to inter-feeder load transfer [39].

Luan et al. [47] employ an integer representation, improve the conventional EA operators using graph analysis techniques, and try to produce only radial configurations. However, their method requires checking radiality of each newly created individual that imposes an extra computational burden.

Methods in [44]-[51] do not include network compensators in the SR plan. Their inclusion for optimization makes the EA's problems even worse by extending the search space. There are not many papers reported in the literature that consider compensation in the SR simultaneously with reconfiguration and load shedding. This might be due to complexity of the problem and large size of the search space.

Some papers try to limit the search space by considering only feeder capacitors with only on/off status [40]-[43] or considering the capacitors only in the out-of-service area when the reconfiguration fails to restore the whole loads [40].

Augugliaro et al. [41] perform the reconfiguration and Volt/-Var control iteratively which has been time consuming [42]. They extend their work to include simultaneously optimization of the network configuration and Volt/Var control in normal operating conditions [52]. However, their method limits the search space by confining the transformers' tap changes to a maximum of ± 1 step around analytically calculated preset values. They admit that this assumption might produce different results for the same loading conditions. Besides, their method still does not include voltage regulators (VRs).

Actually, using such simplifying assumptions could lead to focusing on a partial part of the problem or converting the optimization to a local search.

1.2.2 *Motivation*

An integrated framework for solving the SR problem using EA is required in order to simultaneously optimize the network configuration, amount of load shedding and settings of the compensators. In addition, if it is enabled to limit the search space without sacrificing the quality of results, it can have a global search capability while accelerating the final response.

1.3 DISSERTATION STRUCTURE

This work is organized as follows:

PART I is dedicated to the general words including an introduction to Evolutionary Algorithms (EAs) in Chapter 2 and methods of network modeling and evaluation in Chapter 3.

PART II is on the contribution of this work for solving the distribution network reconfiguration problem. The proposed method is explained in details in Chapter 4, and test results and discussions are presented in Chapter 5.

PART III is about the second contribution of this work for solving the service restoration problem in compensated distribution networks. The proposed method and test results & discussions are presented in Chapter 6 and 7, respectively.

APPENDIX A presents detailed data regarding three test cases.

APPENDIX B provides an example of the input data file and its detailed description.

2 EVOLUTIONARY ALGORITHMS

Evolution by natural selection is one of the most compelling themes of modern science and it has revolutionized the way we think about biological systems [1]. The Darwinian theory of evolution depicts biological systems as the product of the ongoing process of natural selection. Evolutionary algorithms (EAs) employ similar concepts and allow engineers to evolve solutions in a computer program. Although the computational setting is highly simplified compared to the natural world, EAs are capable of evolving surprisingly complex and interesting structures.

A variety of EAs have been proposed which differ based on the way they represent the problem, operators they use in order to make variations in the population, their selection method, and so on [2]. However, all of them share the following general and basic properties:

i) Evolutionary algorithms utilize the collective learning process of a population of individuals. Each individual represents and encodes a search point in the space of potential solutions to a given problem,

ii) By means of evaluating individuals in their environment, a measure of quality or fitness can be assigned to the individuals. According to the quality measure, a selection process favors fitter individuals to reproduce more often than those that are relatively less qualified,

iii) Descendants of individuals are generated by randomized process intended to model mutation and recombination. Mutation corresponds to an erroneous self-replication of individuals and recombination interchanges information between two or more individuals.

Genetic algorithms (GAs) are specific types of EAs which are commonly implemented in a binary representation and employ the conventional crossover / mutation operators in order to evolve a population of solutions. In this chapter, GAs are used in order to introduce the main concepts and associated terminology of the evolution based methods [3]-[5]. In the contribution of this work a tree representation is employed and new operators are proposed in order to manipulate this representation, thus it is called in a general term as an EA and will be explained with details in Chapter 4 and 6.

2.1 FUNDAMENTAL CONCEPTS

GAs are search methods based on principles of natural selection and genetics. GAs encode the decision variables of a search problem into finite-length strings of alphabets of certain cardinality. The strings which are candidate solutions to the search problem are referred to as *chromosomes*, the alphabets are referred to as *genes* and the values of genes are called *alleles*. For example, in a problem such as the traveling salesman problem, a chromosome represents a route, and a gene may represent a city. In contrast to traditional optimization techniques, GAs work with coding of parameters, rather than the parameters themselves.

To evolve good solutions and to implement natural selection, we need a measure for distinguishing good solutions from bad solutions. The measure could be an *objective function* that is a mathematical model or a computer simulation, or it can be a *subjective function* where humans choose better solutions over worse ones. In essence, the fitness measure must determine a candidate solution's relative fitness, which will subsequently be used by the GA to guide the evolution of good solutions.

Another important concept of GAs is the notion of population. Unlike traditional search methods, genetic algorithms rely on a population of candidate solutions. The population size, which is usually a user-specified parameter, is one of the important factors affecting the scalability and performance of genetic algorithms. For example, small population sizes might lead to premature convergence and yield substandard solutions. On the other hand, large population sizes lead to unnecessary expenditure of valuable computational time.

Once the problem is encoded in a chromosomal manner and a fitness measure for discriminating good solutions from bad ones has been chosen, GA can start to *evolve* solutions to the search problem using the following steps:

1. *Initialization*: The initial population of candidate solutions is usually generated randomly across the search space. However, domain-specific knowledge or other information can be easily incorporated.

2. *Evaluation*: Once the population is initialized or an offspring population is created, the fitness values of the candidate solutions are evaluated.

3. *Selection*: Selection allocates more copies of those solutions with higher fitness values and thus imposes the survival-of-the-fittest mechanism on the candidate solutions.

   The main idea of selection is to prefer better solutions to worse ones, and many selection procedures have been proposed to accomplish this idea, including roulette-wheel selection, stochastic universal selection, ranking selection and tournament selection, some of which are described in the next section.

4. *Recombination*: Recombination combines parts of two or more parental solutions to create new, possibly better solutions (i.e. offspring). There are many ways of accomplishing this (some of which are discussed in the next section), and competent performance depends on a properly designed recombination mechanism.

   The offspring under recombination will not be identical to any particular parent and will instead combine parental traits in a novel manner.

5. *Mutation*: While recombination operates on two or more parental chromosomes, mutation locally but randomly modifies a solution. Again, there are many variations of mutation, but it usually involves one or more changes being made to an individual's trait or traits. In other words, mutation performs a random walk in the vicinity of a candidate solution.

6. *Replacement*: The offspring population created by selection, recombination, and mutation replaces the original parental

population. Many replacement techniques such as elitist replacement, generation-wise replacement and steady-state replacement methods are used in GAs.

Steps 2–6 are repeated until a terminating condition is satisfied.

2.2 MAIN COMPONENTS

In this section, some of the selection methods, recombination and mutation operators, and convergence criteria commonly used in GAs are described.

2.2.1 *Selection*

Selection procedures can be broadly classified into two classes as follows.

FITNESS PROPORTIONATE SELECTION This includes methods such as roulette wheel selection and stochastic universal selection. In roulette wheel selection, each individual in the population is assigned a roulette wheel slot sized in proportion to its fitness. That is, in the biased roulette wheel, good solutions have a larger slot size than the less fit solutions. The roulette wheel is spun to obtain a reproduction candidate.

The roulette wheel selection scheme can be implemented as follows:

1. Evaluate the fitness, f_i, of each individual in the population,
2. Compute the probability, p_i, of selecting each member of the population: $p_i = f_i / \sum_{j=1}^{n} f_j$, where n is the population size,
3. Calculate the cumulative probability, q_i, for each individual: $q_i = \sum_{i}^{j=1} p_j$,
4. Generate a uniform random number, $r \in (0, 1]$,
5. If $r < q_1$, then select the first chromosome x_1, else select the individual x_i such that $q_{i-1} < r \leqslant q_i$.

Steps 4–5 are repeated n times to create n candidates in the mating pool.

To illustrate, consider a population with five individuals ($n = 5$), with the fitness values as shown in the table below. The total fitness $\sum_{j=1}^{n} f_j = 28 + 18 + 14 + 9 + 26 = 95$. The probability of selecting an individual and the corresponding cumulative probabilities are also shown in Table 2.1.

Table 2.1: Probability of selecting an individual and corresponding cumulative probabilities

Chromosome #	1	2	3	4	5
Fitness, f	28	18	14	9	26
Probability, p_i	28/95 = 0.295	0.189	0.147	0.095	0.274
Cumulative probability, q_i	0.295	0.484	0.631	0.726	1.000

Now if a random number $r = 0.585$ is generated, then the third chromosome is selected as $q_2 = 0.484 < 0.585 \leqslant q_3 = 0.631$.

ORDINAL SELECTION This includes methods such as tournament selection, and truncation selection. In tournament selection, s chromosomes are chosen at random (either with or without replacement) and entered into a tournament against each other. The fittest individual in the group of k chromosomes wins the tournament and is selected as the parent. The most widely used value of s is 2.

Using this selection scheme, n tournaments are required to choose n individuals. In truncation selection, the top $(1/s)^{th}$ of the individuals get s copies each in the mating pool.

2.2.2 *Operators*

Two types of operators are commonly applied in order to make variations in the individuals of the population (parents) and create a new generation of individuals (offspring). These operators are briefly introduced here.

2.2.2.1 *Recombination (crossover) operators*

After selection, individuals from the mating pool are recombined (or crossed over) to create new, hopefully better, offspring. In the GA literature, many crossover methods have been designed and some of them are described in this section.

In most recombination operators, two individuals are randomly selected and are recombined with a probability p_c, called the crossover probability. That is, a uniform random number, r, is generated and if $r \leqslant pc$, the two randomly selected individuals undergo recombination. Otherwise, that is, if $r > p_c$, the two offspring are simply copies of their parents. The value of p_c can either be set experimentally, or can be set based on schema-theorem principles.

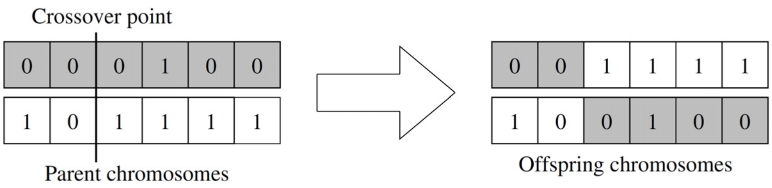
K-POINT CROSSOVER One-point, and two-point crossovers are the simplest and most widely applied crossover methods. In one-point crossover, illustrated in Figure 2.1a, a crossover site is selected at random over the string length, and the alleles on one side of the site are exchanged between the individuals.

In two-point crossover, two crossover sites are randomly selected. The alleles between the two sites are exchanged between the two randomly paired individuals. Two-point crossover is also illustrated in Figure 2.1b. The concept of one-point crossover can be extended to k-point crossover, where k crossover points are used, rather than just one or two.

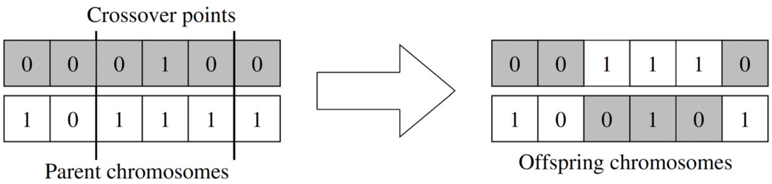
UNIFORM CROSSOVER Another common recombination operator is uniform crossover. In uniform crossover, illustrated in Figure 2.2, every allele is exchanged between the a pair of randomly selected chromosomes with a certain probability, p_e, known as the swapping probability. Usually the swapping probability value is taken to be 0.5.

2.2.2.2 *Mutation operators*

If we use a crossover operator, such as one-point crossover, we may get better and better chromosomes but the problem is, if the



(a) One point crossover



(b) Two point crossover

Figure 2.1: k-point crossover

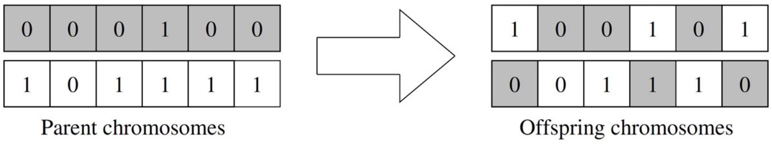


Figure 2.2: Uniform crossover

two parents (or worse, the entire population) has the same allele at a given gene then one-point crossover will not change that. In other words, that gene will have the same allele forever. Mutation is designed to overcome this problem in order to add diversity to the population and ensure that it is possible to explore the entire search space.

In evolutionary strategies, mutation is the primary variation/ search operator. Unlike evolutionary strategies, mutation is often the secondary operator in GAs, performed with a low probability. One of the most common mutations is the bit-flip mutation. In bitwise mutation, each bit in a binary string is changed (a 0 is converted to 1, and vice versa) with a certain probability, p_m, known as the mutation probability.

Mutation performs a random walk in the vicinity of the individual. Other mutation operators, such as problem-specific ones, can also be developed and are often used in the literature.

2.2.3 *Replacement*

Once the new offspring solutions are created using crossover and mutation, we need to introduce them into the parental population. There are many ways we can approach this. Bear in mind that the parent chromosomes have already been selected according to their fitness, so we are hoping that the children (which includes parents which did not undergo crossover) are among the fittest in the population and so we would hope that the population will gradually, on average, increase its fitness.

Some of the most common replacement techniques are outlined below.

DELETE-ALL This technique deletes all the members of the current population and replaces them with the same number of chromosomes that have just been created. Canonical GA uses this type of replacement.

This is probably the most common technique and will be the technique of choice for most people due to its relative ease of implementation. It is also parameter-free, which is not the case for some other methods.

STEADY-STATE This technique deletes n old members and replaces them with n new members. The number to delete and replace, n, at any one time is a parameter to this deletion technique. Another consideration for this technique is deciding which members to delete from the current population.

Do you delete the worst individuals, pick them at random or delete the chromosomes that you used as parents? Again, this is a parameter to this technique.

STEADY-STATE-NO-DUPLICATES This is the same as the steady-state technique but the algorithm checks that no duplicate chromosomes are added to the population. This adds to the computational overhead but can mean that more of the search space is explored.

2.2.4 *Convergence*

Generally, there are two methods for evaluating the convergence of GA [6]. Either one of these methods or their combination could be used to stop the evolution process. They include:

PASSIVE CONDITION This is defined as stopping the evolution after passing a pre-defined maximum number of evaluations,

ACTIVE CONDITION If changes of the average fitness of the individuals in the population becomes less than a pre-defined precision value, the process is considered to be converged and stops.

Commonly, Active condition is more reliable than Passive condition. However, obtaining a minimal distance to the global optimum is not guaranteed. Furthermore, if the precision value is not properly tuned, GA might go to a premature convergence. Another solution is using a combination of Active and Passive conditions. It means that Active condition could be checked until n evaluations. If it is fulfilled, GA stops. Otherwise, GA will continue until the pre-defined maximum number of evaluations is reached (Passive condition).

2.3 NUMBER OF ITERATIONS VS NUMBER OF EVALUATIONS

In order to avoid ambiguity, the difference between the number of *iterations* and the number of *evaluations* in GA is clarified. In a general genetic algorithm with population size n, the number of evaluations is equal to the number of iterations times the population size. This is because in each iteration, n individuals are created and need to be evaluated.

The computational burden of GA is proportional to the number of required evaluations, especially when evaluating the objective function is time-consuming.

3 NETWORK MODELING AND EVALUATION

The method used for modeling and evaluation of the network is presented in this chapter. Graph Theory with some adaptations to the electricity network concepts has been employed for the modeling of distribution network.

3.1 GRAPH MODELING CONCEPTS

A graph G is a pair $(N(G), E(G))$, where $N(G)$ is a finite set of elements called vertices and $E(G)$ is a finite set of elements called edges. A graph without loops is a tree. One of the tree vertices is usually named the root that is the vertex where the tree initiates. Main chain of an edge is the set of edges that connect the edge to the source on a unique path in the tree. More details on the fundamentals of the Graph Theory are available in [38].

Some adaptations of the graph concepts to the electricity network terms are:

i) using term *node* instead of vertex,

ii) using term *branch* instead of edge,

iii) using term *source* instead of root, and

iv) *feeder* concept that is a set formed by a branch directly connected to a source and all of its downstream branches.

3.2 NETWORK MODELING

Distribution network is modeled like a tree using the Graph modeling concepts. Consequently, a radial distribution network will resemble an inverted tree whose root is located in the top part and serves as the source of electrical energy. A general representation of a radial MV distribution network is illustrated in Figure 3.1.

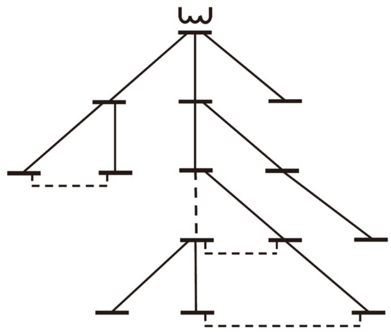


Figure 3.1: A general representation of MV distribution network

The main focus of this work is on MV (Medium-Voltage) distribution networks with voltage levels 12.66kV, 11kV, and 11.4kV. MV distribution networks commonly have the following attributes:

a) are commonly operated under radial configuration for ease of protection and fault location,

b) have almost balanced loads.

Single line diagram has been used in order to model the network which has an acceptable accuracy in balanced loading conditions. Nonetheless, the proposed method can be easily extended to a 3Φ unbalanced network model.

3.2.1 *Branches*

In the model, branches are models of the lines of the network. They connect two nodes called sending and receiving nodes. This naming is due to the direction of energy flow in the branch from the sending toward the receiving node.

3.2.2 *Switches*

Two types of switches have been considered on branches:

i) sectionalizing switch that is a normally closed switch, and

ii) tie switch that is a normally open switch with both end-nodes as energized.

Normally open switches with one or two de-energized end-nodes isolate a part of the network or are located in isolated parts, respectively, and are out of the scope of the proposed method. Sectionalizing and tie switches are shown by bold and dashed lines in Figure 3.1, respectively.

Vicinity set defined for each sectionalizing switch is the set of tie switches that are directly connected to the receiving node of the sectionalizing switch.

3.2.3 *Loops*

Two types of loops are considered in this work:

i) simple loop that is formed by branches of a single tree,

ii) extended loop that is formed by branches of two different trees assuming the sources to be connected to infinite bus.

A *fundamental loop*, that can be a simple or an extended loop, is assigned to each tie switch. It is defined as the set of sectionalizing switches that connect both ends of the tie switch together or to the source(s). Therefore, each tie switch opens a fundamental loop. The number of fundamental loops is calculated using the following equation:

$$N_{fl} = N_{br} - N_{no} + N_{src} \tag{3.1}$$

where, N_{fl}, N_{br}, N_{no}, and N_{src} are the number of fundamental loops, branches, nodes, and sources, respectively.

3.2.4 *Loads*

Loads are connected to the receiving nodes of the branches. In MV distribution networks, they are mainly related to the MV-LV distribution substations or large industrial customers. An advanced modeling of the loads has been employed [53]. It considers each load as a composition of three contributions: a) constant power, b) constant current, and c) constant impedance, using the following formulation:

$$\begin{aligned} P &= P_0 * (a_0 + a_1 V + a_2 V^2) \\ Q &= Q_0 * (b_0 + b_1 V + b_2 V^2) \end{aligned} \tag{3.2}$$

and

$$a_0 + a_1 + a_2 = 1$$
$$b_0 + b_1 + b_2 = 1$$

where,
P and Q are active and reactive power consumptions of the load in the actual voltage, respectively,
P_0 and Q_0 are active and reactive power consumptions of the load in the nominal voltage (V_0), respectively,
(a_0, b_0), (a_1, b_1), and (a_2, b_2) are the coefficients related to constant power, constant current, and constant impedance contributions of each load, respectively. Note that these coefficients are typically set to $(1, 1)$, $(0, 0)$, and $(0, 0)$, respectively, for all loads in this work modeling them as constant power.

In this modeling of the loads, two types of data are required for completely identifying each load:

1. P_0 and Q_0 measured at the node location in the nominal voltage that are noted as network loading data in app. Table A.4-A.6,
2. load's composition.

The first part is obtained using network loading data recorders. For the second part, a test has to be performed on the load by small variations of the voltage in the substation in the permissible range, then recording the changes of the P and Q consumptions, and finally interpolation of the results.

3.3 NETWORK EVALUATION

Each candidate configuration has to be evaluated using a power flow analysis. An efficient power flow method called sweep method has been employed [55] that is a fast and reliable branch-based method capable of compensation for loops and PV nodes.

3.3.1 *Sweep method*

This method is implemented in two sweeps:

i) backward sweep: to sum up the loads' currents from the last to the first layer[1],

ii) forward sweep: to update the nodal voltages from the first to the last layer.

It starts with a flat assumption for nodal voltages (in each feeder, equal to their source voltage) and calculates current injection in each node at the beginning and after each nodal voltage update. When the difference between the injected apparent powers in two successive iterations becomes less than a predefined precision value for all nodes (1e-15 pu), the method is considered as converged.

Based on the experiments, the sweep method converges very fast, commonly in less than 3 iterations when no loops and PV nodes are involved. Santos el al. [24] claim that for the EA applications, merely a single iteration of the sweep method is adequate that makes this power flow method even faster. In this work, it runs until convergence.

In addition, this method has potential of parallel processing such as calculation of nodal current injections for all nodes or performing the sweeps for branches of the same layer, in parallel [55]. Furthermore, it is stable and reliable for power flow analysis of ill-conditioned (high R/X ratio) distribution networks.

On the other hand, sweep method needs to inverse a $n * n$ matrix when analyzing a configuration with n loops. Although the inversion is performed just once at the beginning, it could be time-consuming when the network is heavily looped. Fortunately, this is not troublesome for the proposed method, since it exclusively produces radial configurations.

1 Layer index of a branch is equal to the number of transitions required to traverse from the branch (including the branch) to the source through a unique path in the tree.

Part II

CONTRIBUTION I – NETWORK RECONFIGURATION

4 THE PROPOSED METHOD

The main contribution of this work for the network reconfiguration problem is to propose an extension and redefinition of PAO/CAO operators. The extension enables them to address the inside-feeder reconfiguration of densely tied urban distribution networks in addition to the inter-feeder load transfer, while retaining their merit on exclusively producing radial configurations. The new set of operators is called PG (Pruning-Grafting) operators and includes Extended-PAO (EPAO) and Extended-CAO (ECAO).

In addition, representation of the network has been upgraded from a numerical node-based modeling [24] to an object-oriented branch-based modeling. This representation can be used as it is for more complicated network operation applications, such as service restoration. This allows solving several problems associated to distribution networks, simultaneously and with the same framework. Moreover, the new modeling is compatible with the employed branch-based power flow method.

4.1 REPRESENTATION

A modeling that mainly stores data in branches of the network, called branch-based modeling, is employed in order to represent the network. In this modeling, a network is represented as a set of one or more trees. Each tree is composed of the feeders sharing a same source. Impedances, connection data of branches, and links to the sending and receiving nodes are stored as attributes of the branches in the tree.

There is a switch associated to each branch. Status of the switch is also stored as *Enable* attribute in the corresponding branch. In addition, information about transformers, loads, generators, and compensators are stored and linked to the sending and receiving nodes of the branches.

The employed branch-based tree modeling offers a natural representation of the actual power network and allows for the use of graph concepts in the optimization of its configuration. Some additional benefits of this modeling are:

- An easy access through each branch to the main chain and all of its downstream branches. This facilitates application of the same network modeling to more sophisticated analyses necessary for other optimization tasks related to the operation of a network, such as service restoration;

- Providing a compatible model with the adopted branch-based power flow method that is the evaluation core of the proposed method, introduced in section 3.3;

The evolutionary algorithm evolves population(s) of individuals. In this work, an individual is a network, which *phenotype representation* is given by the branch-based modeling described above. The *genotype representation* of the individual, that is the representation that the proposed operators manipulate to create new individuals, is a pair of lists of switches that are candidates for pruning and grafting named *p candidates* and *g candidates*.

These lists are constructed dynamically from status of the switches after parsing the branch-based representation of the network. In the following, a set of two operators is described which manipulate the genotype representation and create new individuals in the evolution process. Each operator implements a different definition of *p* and *g* candidates. Details of how these lists are created are as follows.

4.2 OPERATORS

The proposed set of operators called Pruning-Grafting (PG) operators includes Extended-PAO (EPAO) and Extended-CAO (ECAO). These operators are an extension and redefinition of the node-based PAO/CAO operators introduced by Santos et al. [24] that have been only applicable to inter-feeder load transfer.

The extension is performed by adopting the concept of fundamental loops and enables the operators to perform inside-feeder reconfiguration as well as inter-feeder load transfer, offering a wider application in the network operation. Therefore, the optimization process can find an integrated solution to the network reconfiguration problem in a single run.

In the same time, PG operators maintain the merit of PAO/-CAO operators on exclusively producing radial configurations. PG operators guarantee this by selecting both closing/opening switches from a same fundamental loop. Therefore, a single loop is created and opened in each application. On the other hand, PAO/CAO operators perform this by selecting their candidates from different feeders [24], which has limited their application to merely inter-feeder load transfer.

By maintaining the radial configuration of the individuals, checking the radiality of each newly created individual and possible correctional actions are not necessary anymore, resulting in the acceleration of the whole process. Details on the implementation of PG operators are presented here.

Figure 4.1 illustrates a graphical representation of pruning-grafting operations on a natural tree.

Figure 4.1: A graphical representation of pruning-grafting operations

4.2.1 *EPAO operator*

This operator prunes a part of a feeder (thus creates a sub-feeder) and grafts it to a feeder. The pruned node remains the root of the sub-feeder. In addition, the destination feeder can be the same as the source feeder, which is a new feature compared to PAO operator.

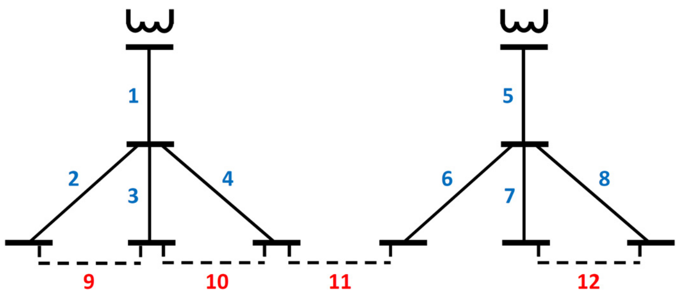
EPAO requires two switches for implementation:

1. a pruning switch (p) to be opened,
2. a grafting switch (g) to be closed.

By new definition, a p candidate is a sectionalizing switch which has at least one vicinity in the same fundamental loop. For each p, g candidates are its vicinities that are in the same fundamental loops with p. Application of EPAO results in a minor change in the network's configuration, since:

i) by definition, p and g candidates are directly connected to each other, thus the sub-feeder is moved to a nearby location,

ii) since the root of the sub-feeder does not change, direction of energy does not alter in any branch.



(a) A general representation of the network

All branches:	1	2	3	4	5	6	7	8	9	10	11	12
Enable:	*T*	*T*	*T*	*T*	*T*	*T*	*T*	*T*	*F*	*F*	*F*	*F*
***p* candidates:**	*F*	*T*	*T*	*T*	*F*	*T*	*T*	*T*				
***g* candidates:**		9	9, 10	10, 11		11	12	12				

(b) For EPAO

All branches:	1	2	3	4	5	6	7	8	9	10	11	12
Enable:	*T*	*T*	*T*	*T*	*T*	*T*	*T*	*T*	*F*	*F*	*F*	*F*
***p* candidates:**	*T*	*F*	*F*	*F*	*T*	*F*	*F*	*F*				
***g* candidates:**	11				11							

(c) For ECAO

Figure 4.2: Selection of p and g candidates

4.2.2 *ECAO operator*

This operator prunes a part of a feeder (thus creates a sub-feeder) and grafts it to a feeder, similar to the previous operator. However for ECAO, the root of the sub-feeder changes before being grafted. To imagine, it is similar to spinning the sub-feeder before grafting. Again, the destination feeder can be the same as the source feeder, which is a new feature compared to CAO operator.

ECAO requires a p switch and a g switch for implementation, too. However this time, a p candidate is a sectionalizing switch which has another sectionalizing switch x in its downstream with at least one vicinity in the same fundamental loop with p. For each p, g candidates are those vicinities of x that are in the same fundamental loops with p. Application of ECAO results in a more substantial change in the network's configuration, since:

i) by definition, p and g candidates are located far from each other, thus the sub-feeder is moved to a distant location,

ii) since the root of the sub-feeder changes, direction of energy alters in some branches that follows new requirements for the network operation such as re-setting the directional protection relays.

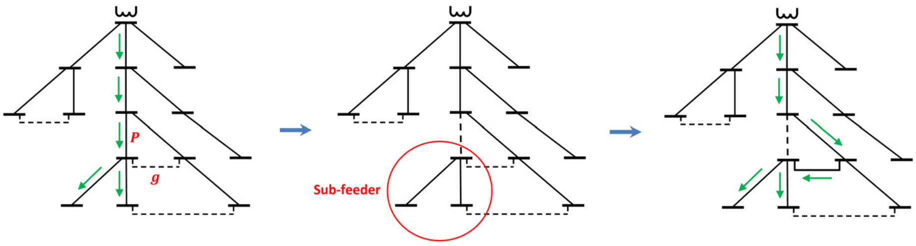
4.2.3 *Selecting* p *and* g *candidates*

In order to create lists of p and g candidates for EPAO and ECAO, a set of *True* / *False* questions are asked from the branches. In other words, a set of filters are created which first, detect sectionalizing and tie switches (bold and dashed lines in Figure 4.2a, respectively) by checking their *Enable* attributes.

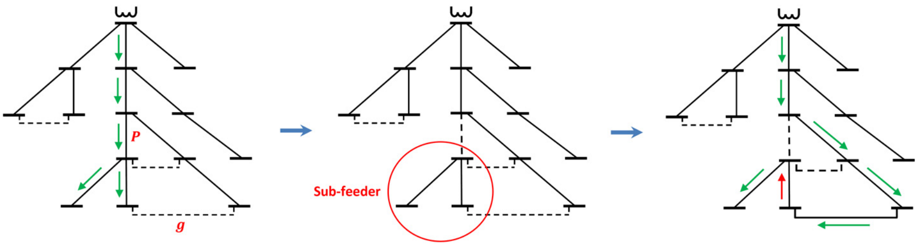
Then, a subset of sectionalizing switches is selected as p candidates and subsets of tie switches are selected as g candidates for each p candidate using the criteria discussed in the previous two subsections and illustrated in Figure 4.2b and 4.2c for EPAO and ECAO, respectively. In these figures, T represents a True and F represents a False response of the branches.

A subroutine in the network setup function creates the lists of network's p and g candidates when the individual is being created. This is simply performed due to the easy and broad access to downstream of all branches, as an advantage of the employed object-oriented branch-based modeling. This knowledge cannot be easily obtained by the numerical node-based representation in [24].

In order to run an EPAO or ECAO operation, a p is selected randomly among the network's p candidates and one of its g candidates is selected, randomly. Then, p is opened and g is closed, as illustrated in Figure 4.3.



(a) Using EPAO



(b) Using ECAO

Figure 4.3: Steps of network reconfiguration using EPAO and ECAO operators

4.3 FEASIBILITY

Feasibility concept in the network reconfiguration problem is defined as follows. A feasible configuration has to fulfill two sets of constraints, simultaneously:

1. *Structural constraints*: includes maintaining the radial structure of the network and serving all nodes. For this set, Lavorato et al. [54] prove that two conditions have to be fulfilled:

   i) the number of open switches has to be equal to the number of fundamental loops in Eq. 3.1,

   ii) all nodes have to be served.

   According to [54], fulfillment of the first condition is necessary but not sufficient for this constraint and both should hold, simultaneously.

2. *Operational constraints*: includes transformer and branch loading constraints and nodal voltage margins.

Individuals who violate one or more constraints are unfeasible and those who do not violate any constraint are feasible.

For EAs using Conventional, Enhanced Conventional, and Integer operators, the unfeasible individuals who violate Structural constraints are discarded. This is performed in order to avoid running the power flow method for these individuals since if they have loops, this could be sometimes very time-consuming, as discussed in section 3.3. PG and PAO/CAO operators never produce individuals who violate Structural constraints.

4.4 POPULATION

EAs using PG, PAO/CAO, Conventional, and Enhanced Conventional operators have two subpopulations (SPs): feasible SP and unfeasible SP. Unfeasible individuals who violate Operational constraints try to enter the unfeasible SP. A SP of these individuals is maintained in order to diminish the possibility of being trapped in local optima. On the other hand, each individual in the feasible SP is a potential solution to the reconfiguration problem and the final solution is the best individual in this SP at the last evaluation.

According to [37], in EA using Integer operators, unfeasible individuals who violate Operational constraints and feasible individuals evolve in a single population.

4.5 OBJECTIVE FUNCTION

In the network reconfiguration problem, active power loss of the network is considered as the objective function which has to be minimized through evolution of the network configuration.

After running the power flow method as discussed in section 3.3, parameters of the network including currents of all branches and voltages of all nodes are identified. These data are used to compute the sending and receiving active powers of each branch. The difference between these two powers is the active power loss in the branch. The total active power loss of the network is the summation of the active power losses in all branches, as calculated using the following equation:

$$P_{total} = \sum_{i=1}^{n_b} (P_i^S - P_i^R) \tag{4.1}$$

where P_i^S and P_i^R are the sending and the receiving active powers in branch i, and n_b is the total number of branches.

This formula assumes a lumped load modeling in which loads are compact energy sinks at nodes. This modeling inflates the calculated power loss compared to a distributed load model [56]. However, due to the focus of this work on MV distribution networks that commonly have lumped loads, this modeling still remains accurate.

For the unfeasible individuals, the objective function in Equation 4.1 is multiplied by a penalty term in order to favor those who less violate Operational constraints:

$$Penalty = 10 + w_1 * TOL + w_2 * BOL + w_3 * VV \tag{4.2}$$

where:
TOL: transformer overloading index that is the summation of overload apparent power $|S_{OL}|$ in all overloaded transformers;
BOL: branch overloading index that is the summation of overload current modulus $|I_{OL}|$ in all overloaded branches;
VV: nodal voltage violation index that is the summation of absolute differences of modulus of the nodal voltages $|V_n|$ and high ($|V_{max}| = 1.1pu$) or low ($|V_{min}| = 0.9pu$) margins in over-voltage and under-voltage nodes, respectively;

Note, TOL, BOL, and VV are normalized respect to their maximum values in order to have equal contributions in the penalization. The maximum values are updated in each evaluation. In addition, using the weights $w_i = 0.33, i = 1, 2, 3$, the maximum value of their summation is bounded to 1.

The constant number is added to the $Penalty$ term in order to penalize unfeasible individuals at least 10 times, even when they violate Operational constraints very lightly. This is vital for EA using Integer operators in order to differentiate between feasible and unfeasible individuals in a single population.

Since the individuals who violate Structural constraints are discarded in EAs using Conventional, Enhanced Conventional, and Integer operators and they are never produced in EAs using PG and PAO/CAO operators, no term is considered in $\mathtt{Penalty}$ regarding Structural constraints.

4.6 EA IMPLEMENTATIONS

In order to evaluate performance of the proposed method, five EAs have been implemented using:

i) PG operators,

ii) the original PAO/CAO operators,

iii) Conventional operators,

iv) Enhanced Conventional operators, and

v) Integer operators [37].

Details on the implementation of five EAs are as follows.

4.6.1 *EA using PG operators*

This EA performs a single evaluation per iteration. It means that a parent is selected, one of the PG operators is randomly selected and applied to the parent, and an offspring is created in each iteration. Main steps of the EA are presented here.

STEP 1: INITIALIZATION The initial configuration is added to the proper SP as the first individual.

STEP 2: PARENT SELECTION In each iteration, a SP is selected randomly and one of its individuals is selected as parent using tournament selection method, where two randomly selected individuals compete and the winner (the individual with less objective value) becomes the parent.

Obviously, when a SP is empty, the other is selected deterministically, and when a selected SP has only one individual, it will be the parent.

STEP 3: VARIATION One of the PG operators is selected randomly and applied to the parent in order to create an offspring. In order to determine the probability of selecting one of the PG operators, a fixed or adaptive probability adjustment strategies can be used.

In the fixed strategy, the probability is tuned and remains constant during the evaluations. In the adaptive strategy, evolution process starts with an equal probability (of 50%) for both operators. Then, if one of them creates an offspring that survives, its probability increases and other's decreases by a step (for example 1%) [24]. Both strategies have been examined and one is selected in a tuning process of the parameters.

STEP 4: SURVIVAL SELECTION The created offspring is evaluated using the method discussed in section 3.3. Then, it tries to enter the proper SP. If the SP is not full, it enters without any comparison. However when the SP is full, if the new individual is better than the worst individual of the SP, it replaces the worst. Otherwise, the new individual is discarded.

Steps 2 to 4 are repeated until a predefined number of evaluations are performed. Then, the best individual in the feasible SP at the last evaluation is introduced as the final solution. Flowchart of the EA using PG operators is presented in Figure 4.4.

4.6.2 *EA using PAO/CAO operators*

In order to evaluate the benefits of the extension applied to the original PAO/CAO operators, they are also implemented and applied to the same problem with the same objective function, steps, and the number of evaluations as the previous EA.

4.6.3 *EA using Conventional operators*

In this EA, a binary representation is used in order to encode the status of switches in which, each 1 represents a closed and each

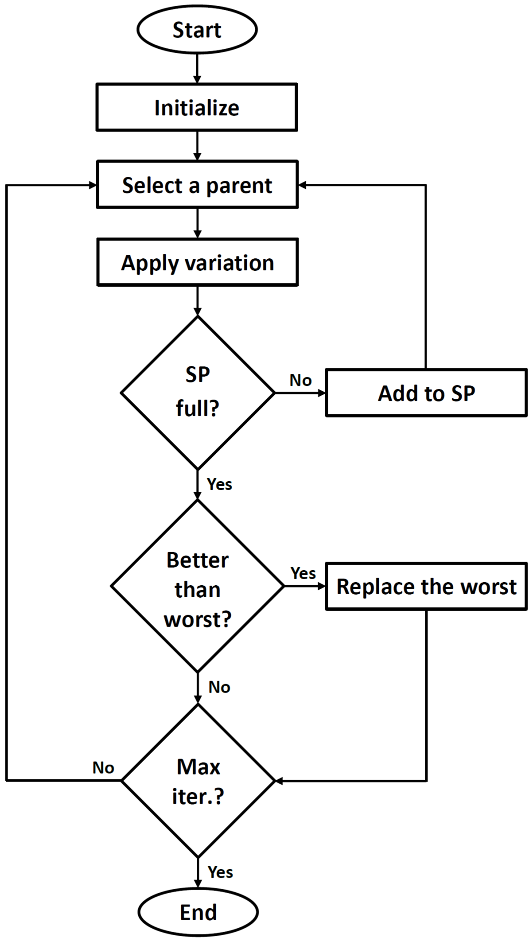


Figure 4.4: Flowchart of the EA using PG operators

0 represents an open switch. The resulting chromosome has the length n, equal to the total number of switches. The conventional EA operators including single-point crossover and bit-flipping mutation are used for this implementation. Main steps of the EA are as follows.

STEP 1: INITIALIZATION This EA needs two initial individuals. The current configuration is used as the first individual. Then, the mutation operator is applied to this individual in order to create a second individual. These individuals enter the proper SPs.

STEP 2: PARENT SELECTION For selecting each of two required parents, a SP is selected randomly and one of its individuals is selected by the tournament method.

STEP 3: VARIATION Single-point crossover operator is applied to the parents with a probability P_c. It selects an equal point in the range of 2 to $n-1$ for both parent chromosomes. Then, the bits of parents are exchanged from the selected point to the end of chromosomes in order to create two offspring.

Finally, bit-flipping mutation operator is applied with a probability P_m to every bit of each offspring in order to toggle their values.

STEP 4: SURVIVAL SELECTION One of the offspring is selected randomly and passes the same process as Step 4 of the EAs using PG and PAO/CAO operators.

The evaluation of both offspring is avoided in order to maintain an equal number of evaluations compared to the previous implementations (single evaluation per iteration) and to have a fair comparison.

Steps 2 to 4 are repeated until a predefined number of evaluations are performed. Then, the best individual in the feasible SP at the last evaluation is introduced as the final solution.

4.6.4 *EA using Enhanced Conventional operators*

In this EA, the conventional crossover/mutation operators are enhanced in order to adapt the requirements of the network reconfiguration problem. The enhancement aims to maintain a constant number of open switches (zeros) in the created offspring that has to be equal to the number of fundamental loops in Equation 3.1.

This technique tries to keep the search close to the feasible space, since the new individuals will have at least one feature in common with the feasible ones: the number of open switches. However, it cannot guarantee the fulfillment of Structural constraints, based on the discussions of section 3.2, since the second condition (serving all nodes) is not considered yet. Nonetheless, the size of the search space is significantly reduced from 2^n to $\binom{n}{m} = \frac{n!}{m!(n-m)!}$ where n is the total number of switches and m is the number of open switches.

The conventional single-point crossover is enhanced to a point-to-point crossover that receives the offspring's each bit from one of the parents, randomly. In addition, a masking technique is applied to the crossover operator. This is because if all bits of both offspring are initially set to 1, and zeros randomly come from two parents until the required number of zeros is fulfilled, the resulting individuals might have bits that do not exist in any of the parents. This is a crossover that sometimes could have a sort of mutation inside called a more explorative crossover, as illustrated in Figure 4.5. In order to have a pure and controllable crossover, it is masked before start.

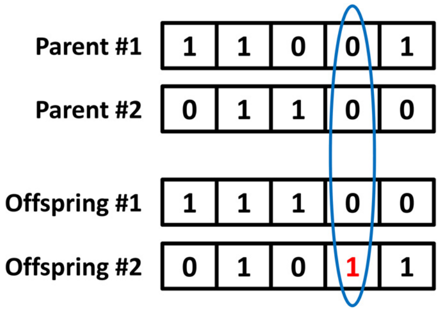


Figure 4.5: A more explorative crossover

For this, first, all bits of both offspring are initially set to 1, equal bits of two parents are copied directly to both offspring, and a mask is closed at these locations, as shown in Figure 4.6. Then, for each offspring, the first parent is used in order to fill the open-mask locations with a permutation and a predefined probability P_{fp-c}.

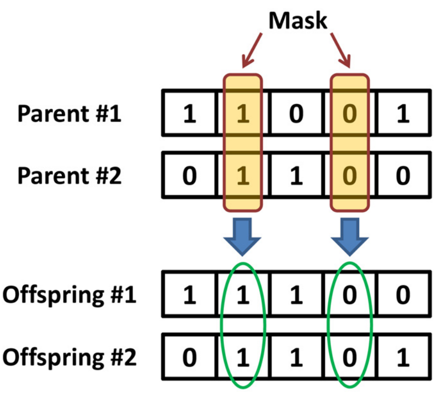


Figure 4.6: Masking technique

Finally, if the number of zeros in the offspring is not still enough, the second parent is used to fill the open-mask non-zero locations with a permutation but without considering any probability this time.

For enhancing the mutation operator, after each bit change, a random different bit is toggled. For instance, when a 0 is changed to 1 randomly, a random different 1 is selected and is changed to 0 in order to keep a constant number of zeros.

The same steps as the implementation of Conventional operators are used for this EA.

4.6.5 *EA using Integer operators*

The method in [37] employs an integer representation in order to encode the network using only its open switches. This helps to reduce length of the chromosomes in EA. For the EA operators, a single-point crossover and a directed mutation is utilized (Integer operators).

For the crossover operator, a single equal point is selected in both parent chromosomes with a probability (P_c) and open switches in two chromosomes are exchanged after this point in order to create two offspring. The crossover operator does not necessarily produce individuals who fulfill Structural constraints.

The mutation operator changes one or more open switches in the chromosome of each offspring with a probability (P_m). Each selected open switch for mutation is exchanged with a closed switch in the same fundamental loop. If the number of changes in each chromosome is more than one, fulfillment of Structural constraints for the resulting individual is not guaranteed again [37].

5 TEST RESULTS

The proposed method has been implemented using Visual C++ programming language on an Intel Pentium IV 3.4GHz desktop PC.

5.1 TEST CASES

Tests have been performed on the following MV distribution networks:

CASE I A network of PG&E company [57] with 70 nodes, 74 branches composed of a single feeder, operated in 12.66kV. It has 5 inside-feeder and no inter-feeder tie lines;

CASE II A hypothetic network [58] with 70 nodes, 76 branches composed of 4 feeders, operated in 11kV. It has 3 inside-feeder and 5 inter-feeder tie lines;

CASE III A variation of a Taiwan Power Company's network [59] with 94 nodes, 103 branches, operated in 11.4kV.

By the variation, seven new tie lines are added in order to model a densely tied urban distribution network. These new lines are located between nodes 4-9, 19-23, 65-70, 87-92, 19-26, 55-59, and 75-80 called branches number 97 to 103, respectively. Consequently, it has 8 inside-feeder and 12 inter-feeder tie lines;

All cases have automatic switches on all branches. Base power has been 5MVA. Detailed data regarding the test cases are presented in Appendix A. The proposed method's performance has been compared to the original PAO/CAO, Conventional, Enhanced Conventional, and Integer operators.

5.2 PARAMETER TUNING

Before commencing the experiments, settings of the EAs in five implementations are tuned and the settings used for generating the results are presented in Table 5.1.

For tuning the population sizes in EAs using PG, PAO/CAO, Conventional, and Enhanced Conventional operators, 28 experiments with sizes {1, 2, ..., 10, 15, 20, ..., 100} have been performed using 20000 evaluations and 30 trials for different seeds of the random number generator. For EA using Integer operators, only even population sizes are acceptable [37]. Thus, 23 experiments with sizes {2, 4, 6, 8, 10, 14, 20, 24, ..., 100} are performed.

For tuning the probability of selecting EPAO or ECAO operators, 12 experiments are performed using the settings {0, 10, 20, ..., 100} in addition to checking the adaptive probability, as introduced in subsection 4.6.1, where the fixed probabilities with different values had the best performance in terms of speed and quality of results in all test cases. The same procedure is applied to tuning the probability of selecting PAO or CAO operators.

Note that EA using PG operators has less tunable parameters compared to EAs using Conventional, Enhanced Conventional, and Integer operators, which shows the lower tuning requirement of the proposed method. In addition, based on the experiments, PG operators are robust to a wide range of parameter settings. For instance, when the population size setting varies in Case III, all simulations converge to a single solution and only the convergence speed is different. Furthermore, if a minor compromise is accepted, adaptive EPAO or ECAO selection probability can be considered for all test cases which in turn reduces one tunable parameter of the proposed method.

For tuning the mutation rates, 11 experiments are performed around $1/N$ by $\pm 25\%$ changes with the steps of 5%, where N is equal to:

i) total number of switches for EAs using Conventional and Enhanced Conventional operators,

ii) number of open switches in the initial configuration for EA using Integer operators.

Crossover probabilities for EAs using Conventional, Enhanced Conventional, and Integer operators as well as the first parent Crossover probability for EA using Enhanced Conventional operators are tuned by 11 experiments using settings {0, 10, 20, ..., 100}.

Table 5.1: Tuned settings of EA implementations

Method	Case	Settings		
		Probability		*Pop. Size*
		Title	*Value*	
PG (proposed)	Case I	EPAO (fixed)	40%	85
		ECAO (fixed)	60%	
	Case II	EPAO (fixed)	30%	75
		ECAO (fixed)	70%	
	Case III	EPAO (fixed)	100%	5
		ECAO (fixed)	0%	
PAO/CAO	Case I	PAO (fixed)	50%	5
		CAO (fixed)	50%	
	Case II	PAO (fixed)	80%	5
		CAO (fixed)	20%	
	Case III	PAO (fixed)	100%	85
		CAO (fixed)	0%	
Conventional	Case I	Crossover (P_c)	40%	40
		Mutation (P_m)	1.49%	
	Case II	Crossover (P_c)	70%	80
		Mutation (P_m)	1.58%	
	Case III	Crossover (P_c)	50%	20
		Mutation (P_m)	1.21%	
Enhanced Conventional	Case I	Crossover (P_c)	40%	65
		First parent crossover (P_{fp-c})	70%	
		Mutation (P_m)	1.69%	
	Case II	Crossover (P_c)	90%	50
		First parent crossover (P_{fp-c})	50%	
		Mutation (P_m)	1.39%	
	Case III	Crossover (P_c)	50%	50
		First parent crossover (P_{fp-c})	50%	
		Mutation (P_m)	1.12%	
Integer	Case I	Crossover (P_c)	50%	50
		Mutation (P_m)	17%	
	Case II	Crossover (P_c)	40%	50
		Mutation (P_m)	13.75%	
	Case III	Crossover (P_c)	50%	14
		Mutation (P_m)	3.75%	

5.3 EXPERIMENTS

Tests have been performed for 50000 evaluations and 30 trials. The average active power losses of the best individuals in each evaluation are presented in Figure 5.1, using logarithmic x-axis. A numerical summary of the final results in 30 trials and their production frequency are presented in Table 5.2.

In addition, a statistical report regarding the average number of evaluations required for convergence of five methods in 30 trials as well as their average response time (the average number of evaluations for convergence multiplied by the average time per evaluation) in three test cases are presented in Table 5.3.

5.3.1 *Convergence speed and computational time*

For all cases in Figure 5.1, Conventional operators present a poor convergence response. They require more than 10000 evaluations to converge, becoming worse when complexity and size of the network increases. In Case II and III, the large diversity among the final results produced by EA using these operators even after 50000 evaluations shows their convergence difficulty, as reported in Table 5.2.

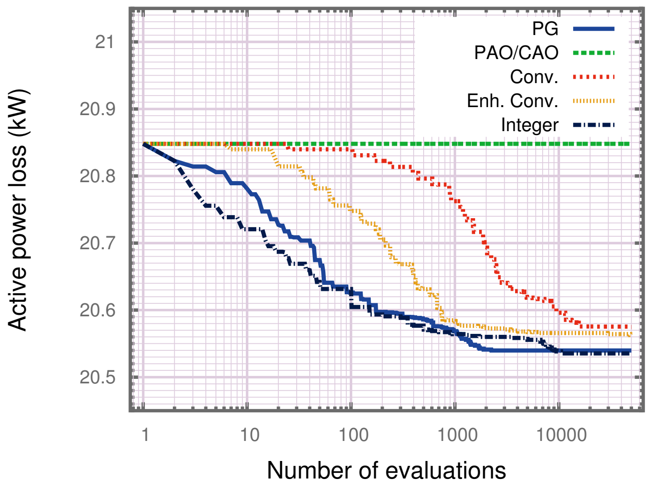
Enhanced Conventional operators try to mitigate the convergence problem of Conventional operators. However, they still converge slowly, especially in the largest test case (Case III) and they are much too slower than PG operators in all test cases (see Figure 5.1 and Table 5.3).

Integer operators have a better convergence behavior than Conventional and Enhanced Conventional operators. However, the average number of required evaluations for their convergence is more than PG operators in all cases (see Table 5.3).

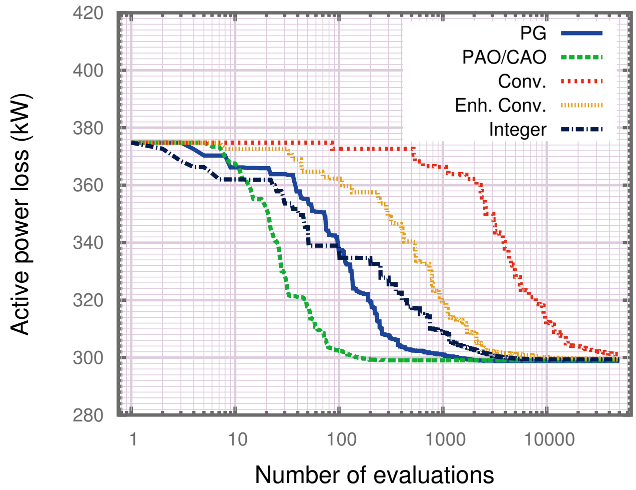
PAO/CAO operators are incapable of reconfiguring the network in Case I, as shown in Figure 5.1a, since they are limited to inter-feeder load transfer and this case has a single feeder. In Case II, PAO/CAO operators exhibit a better convergence speed than PG operators owing to their limitation that results in less switching options.

PG operators extend the application of PAO/CAO operators to inside-feeder reconfiguration as well as inter-feeder load transfer and by an excellent behavior, fast and successfully converge in all cases.

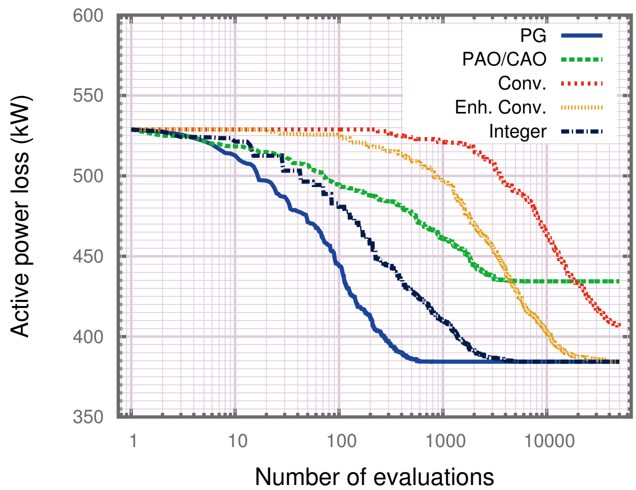
A reason for slow convergence rate of Conventional and Enhanced Conventional operators is the larger percentage of unfeasible



(a) Case I



(b) Case II



(c) Case III

Figure 5.1: Performance of EAs using different operators

Table 5.2: Statistical results at final evaluation in 30 trials

Case	**Method**									
	PG		*PAO/CAO*		*Conv.*		*Enh. Conv.*		*Integer*	
	Result	*Fr.*	*Result*	*Fr.*	*Result*	*Fr.*	*Result*	*Fr.*	*Result*	*Fr.*
Case I	20.54	27	20.85	30	20.54	3	20.54	12	20.54	30
	20.58	3	-	-	20.58	23	20.58	18	-	-
	-	-	-	-	20.59	4	-	-	-	-
Case II	298.88	30	299.06	30	298.88	5	298.88	23	298.88	25
	-	-	-	-	298.95	2	301.71	7	301.71	5
	-	-	-	-	299.06	3	-	-	-	-
	-	-	-	-	299.33	1	-	-	-	-
	-	-	-	-	299.54	1	-	-	-	-
	-	-	-	-	301.04	2	-	-	-	-
	-	-	-	-	301.2	1	-	-	-	-
	-	-	-	-	301.71	7	-	-	-	-
	-	-	-	-	301.89	1	-	-	-	-
	-	-	-	-	302.36	1	-	-	-	-
	-	-	-	-	302.37	1	-	-	-	-
	-	-	-	-	303.87	2	-	-	-	-
	-	-	-	-	304.46	2	-	-	-	-
	-	-	-	-	305.28	1	-	-	-	-
Case III	384.44	30	430.77	2	384.44	1	384.44	29	384.44	30
	-	-	430.82	5	384.51	1	384.51	1	-	-
	-	-	431.07	2	385.33	1	-	-	-	-
	-	-	431.24	2	386.14	1	-	-	-	-
	-	-	431.29	12	387.41	2	-	-	-	-
	-	-	432.3	2	388.11	1	-	-	-	-
	-	-	432.77	1	388.67	1	-	-	-	-
	-	-	445.14	3	388.95	1	-	-	-	-
	-	-	482.64	1	389.02	1	-	-	-	-
	-	-	-	-	390.41	1	-	-	-	-
	-	-	-	-	391.81	1	-	-	-	-
	-	-	-	-	393.13	1	-	-	-	-
	-	-	-	-	393.63	1	-	-	-	-
	-	-	-	-	396.55	1	-	-	-	-
	-	-	-	-	402.43	1	-	-	-	-
	-	-	-	-	403.53	1	-	-	-	-
	-	-	-	-	406.9	1	-	-	-	-
	-	-	-	-	412.92	1	-	-	-	-
	-	-	-	-	416.35	1	-	-	-	-
	-	-	-	-	418.4	1	-	-	-	-
	-	-	-	-	421.51	2	-	-	-	-
	-	-	-	-	423.93	1	-	-	-	-
	-	-	-	-	430.74	1	-	-	-	-
	-	-	-	-	430.93	1	-	-	-	-
	-	-	-	-	430.99	1	-	-	-	-
	-	-	-	-	432.52	1	-	-	-	-
	-	-	-	-	436.25	1	-	-	-	-
	-	-	-	-	454.4	1	-	-	-	-

individuals that are created by these operators compared to the other operators, especially in Case III as the largest network, as reported in Table 5.4. In this table, for each set of operators, three

Table 5.3: The average convergence and response time

Case		Method				
		PG	*PAO/CAO*	*Conv.*	*Enh. Conv.*	*Integer*
Case I	Required evaluations	1062	-	11117	6114	4643
	Response time [Sec]	1.13	-	5.70	3.98	4.25
Case II	Required evaluations	2428	166	35089	7965	4591
	Response time [Sec]	2.63	0.17	17.45	5.09	4.32
Case III	Required evaluations	548	4747	41803	23232	3180
	Response time [Sec]	0.68	5.85	27.80	17.06	3.37

Table 5.4: Produced unfeasible individuals in 50000 evaluations

Method		Case					
		Case I		*Case II*		*Case III*	
		Absolute	*Relative*	*Absolute*	*Relative*	*Absolute*	*Relative*
PG	Str.	0	0%	0	0%	0	0%
	Op.	38521	77.0%	41237	82.5%	34182	68.4%
	Unfeas.	38521	77.0%	41237	82.5%	34182	68.4%
PAO/CAO	Str.	-	-	0	0%	0	0%
	Op.	-	-	35153	70.3%	36448	72.9%
	Unfeas.	-	-	35153	70.3%	36448	72.9%
Conv.	Str.	36066	72.1%	36050	72.1%	38674	77.3%
	Op.	7059	14.1%	7620	15.2%	5776	11.6%
	Unfeas.	43124	86.2%	43669	87.3%	44449	88.9%
Enh. Conv.	Str.	28863	57.7%	27832	55.7%	34867	69.7%
	Op.	14210	28.4%	13279	26.6%	8513	17.0%
	Unfeas.	43072	86.1%	41110	82.2%	43379	86.8%
Integer	Str.	5443	10.9%	4756	9.5%	6523	13.0%
	Op.	20014	40.0%	27214	54.4%	13726	27.5%
	Unfeas.	25457	50.9%	31970	63.9%	20241	40.5%

rows appear regarding the individuals who violate Structural constraints, Operational constraints, and the total unfeasible individuals, respectively.

Note that for EAs using Conventional, Enhanced Conventional, and Integer operators, individuals who violate Structural constraints are discarded before running the power flow method. Consequently, fulfillment of Operational constraints is not examined for these individuals and thus, not reported in Table 5.4. Therefore, in the "Op" rows for these operators, only number and percentage of the individuals who fulfill Structural constraints and violate Operational constraints are reported.

Producing the individuals who violate Structural constraints has postponed the convergence and the final response of EAs using Conventional, Enhanced Conventional, and Integer operators. This is because some moves in the search space are wasted for exploring the areas that will not directly produce a solution to the problem. In other words, creating and then discarding the individuals who violate Structural constraints in some moves decelerates the convergence of these methods, as reported in Table 5.3.

On the other hand, PG operators exclusively produce individuals who fulfill Structural constraints, as discussed in section 4.2 and could be observed in Table 5.4. This leads to the better convergence speed and response time of PG operators compared to Conventional, Enhanced Conventional, and Integer operators.

Low time requirement of PG operators especially in the largest test case (Case III) and their almost flat time response for all cases in Table 5.3 suggests that they will scale up better on more complex and larger urban distribution networks.

5.3.2 *Quality of results*

In Case I, PG and Integer operators produce very close average results (see Figure 5.1a). Although Integer operators produce slightly better average results in this case, the difference in terms of kilowatts is insignificant. Besides, they require about 4 times more number of evaluations to converge compared to PG operators.

Conventional and Enhanced Conventional operators produce average results that are slightly worse than PG and Integer operators in Case I. This shows that when the network under study is not large and complex, Conventional and Enhanced Conventional operators could produce acceptable results, although they require many evaluations. PAO/CAO operators are totally incapable of contributing in the optimization in this case, as discussed before.

Case II has an initial configuration that violates Operational constraints by under-voltages in six nodes (#62~#67). An example of such cases is when the network reconfiguration is used to restore the healthy out-of-service loads after isolation of the fault(s). The proposed method is under extension by the authors in order to be applied to the service restoration of compensated distribution networks [60]. Note here that for the illustration purpose in Figure 5.1b, the objective values in the evaluations before producing the first feasible individual are filled with the maximum objective value of the feasible individuals obtained by five methods in Case II.

In this case, five EAs have to start from the unfeasible search space, enter the feasible search space (produce the first feasible individual), and find optimum solutions there. Actually, the methods need different number of evaluations in order to enter the feasible search space, as reported in Table 5.5. This number is quite large in the worst trial for Conventional, Enhanced Conventional, and Integer operators compared to PG operators, as could be seen in this table.

Table 5.5: The evaluation numbers of entering the feasible search space in Case II

Method	**Iteration number**	
	Best trial	*Worst trial*
PG	4	369
PAO/CAO	6	72
Conventional	86	15268
Enhanced Conventional	8	2099
Integer	2	1151

In Case II, PAO/CAO operators exhibit a good optimization behavior by having all trials converged to a single value (see Table 5.2) and finding the first feasible individual in 72 evaluations for the worst trial (see Table 5.5). Although the best result produced by these operators is worse than the other methods, the average value is competitive. The outstanding behavior of PAO/-CAO operators in this case comes from two possible reasons:

1. These operators are limited to inter-feeder load transfer and thus, search in a smaller space compared to PG operators, which increases the possibility of obtaining better local optima;

2. While Case II has inside-feeder tie lines that are out of the scope of PAO/CAO operators, some of them could be accessed after some steps of the network reconfiguration due to the short length of the feeders;

Therefore, when the limited search space of PAO/CAO operators contains good local optima, they could efficiently find them.

However, they are not applicable when this space is empty, such as Case I, since they do not have access to a part of the search space related to the inside-feeder reconfiguration.

PG operators have eliminated this limitation and produce encouraging results for all cases while maintaining PAO/CAO operators' benefit in exclusively producing radial configurations.

In Case II, Enhanced Conventional and Integer operators produce good average and absolute results, while PG operators are about twice faster in terms of total response time, as could be observed in Table 5.3. In this case, although Conventional operators could find the best result produced by PG operators in 5 trials, they are substantially slower.

Case III is the largest network with a feasible initial configuration. In this case, all trials of PG and Integer operators converge to a single solution that is better than the best result found by PAO/CAO operators. Conventional operators can find this result in only one trial. Enhanced Conventional operators produce acceptable average and absolute final results in this case. However, compared to PG operators, Integer operators are slower and Conventional and Enhanced Conventional operators are substantially slower (see Table 5.3).

A summary of the best results produced by the proposed method as well as the percentage reduction in the active power loss is presented in Table 5.6.

Table 5.6: The best results produced by the proposed method

Test case	*Active power loss*		*Percentage reduction*
	Initial	Final	
Case I	20.85	20.54	1.49%
Case II	374.82	298.88	20.26%
Case III	528.87	384.44	27.31%

5.3.3 *Reliability*

The original PAO/CAO operators are incapable of reconfiguring the network when it has a single feeder (such as Case I). Conventional, Enhanced Conventional, and Integer operators require many more evaluations than PG operators for finding the first feasible individual in the worst trial when the network is heavily loaded and the initial configuration violates Operational constraints (such as Case II). In addition, they are considerably slower than PG operators for producing the final results in all test cases.

Therefore, the proposed method is the most reliable method across the various test cases used in this study. It is capable of producing fast and high quality solutions for various networks with different complexity and initial loading conditions, which cannot be done by the other methods.

5.3.4 *Voltage profile*

The voltage profiles before and after the optimization are examined, noticing that they have been maintained or improved in all cases. The minimum voltages have stayed unchanged or improved from initial 0.973, 0.885, and 0.929 pu to 0.973, 0.916, and 0.959 pu for Case I, II, and III, respectively.

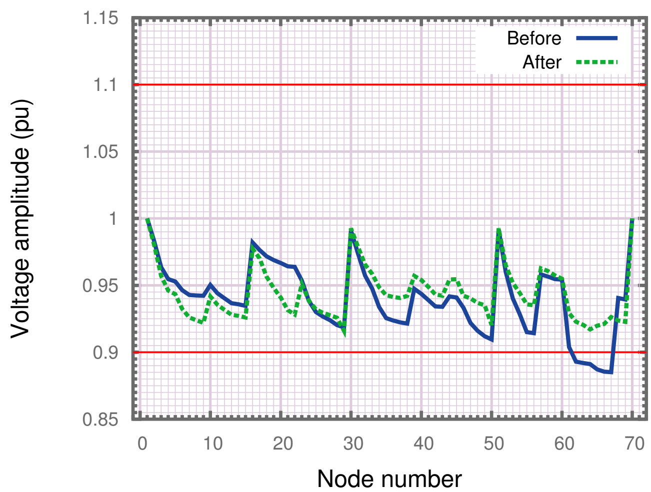


Figure 5.2: Nodal voltage profiles before and after the reconfiguration of Case II using the proposed method

Figure 5.2 shows the nodal voltage amplitudes for Case II before and after the reconfiguration using the proposed method, where red lines show the high and low margins. As it could be observed, a smoother profile of the nodal voltages is obtained using the network reconfiguration. In addition, the under-margin voltages are pulled up and thus the low voltage problem of this case is resolved.

5.3.5 *Load profile variation*

In this step of research, loads are assumed to be constant over 24 hours. They could indeed vary from daytime to nighttime. In the networks that are a composition of industrial, commercial and residential customers, this could lead to a variation in the balance of the network loading. The variation comes from the life pattern of people in the area who go to work in day and return back to home at night.

Here, a brief study on Case III is presented in order to illustrate the effect of variation in the balance of the network loading from one profile in day to another profile at night. Assume that data provided for Case III in Table A.6 are related to daytime.

At night, loads in feeders B and C decrease by 30% and loads in feeders D and E increase by 20%. This models a transition from day to night profiles which follows the reduced energy consumption of the industrial area and move of the workers to the residential area. Table 5.7 lists the open switches in the optimal daytime and nighttime configurations.

Table 5.7: List of open switches in the optimal daytime and nighttime configurations

Time	*Open switches*
Day	7, 8, 19, 23, 39, 52, 61, 63, 69, 80, 84, 86, 87, 88, 89, 90, 91, 92, 94, 95
Night	7, 8, 14, 19, 23, 39, 52, 61, 63, 69, 72, 80, 84, 86, 88, 90, 91, 92, 94, 95

As it is marked using the red colored (and underlined) numbers in Table 5.7, in order to have the optimal configuration in terms of active power loss in daytime and nighttime, two sets of switches should change their status, including (14-89) and (72-87).

5.4 CONCLUSION

The proposed method for the network reconfiguration problem employed a branch-based modeling scheme in order to represent the network. Based on this representation, two extended operators called PG operators were proposed that manipulate lists of candidate switches for pruning and grafting, dynamically constructed from the status of the switches in the network, to provide an efficient approach to the network reconfiguration problem.

In order to evaluate efficiency of the proposed method, five EAs using PG operators, the original PAO/CAO operators, two sets of operators in a binary representation (conventional crossover and mutation and an enhanced version of them), and a set of operators in an integer representation (conventional crossover and directed mutation operators) [37] were implemented.

Experimental results in three test cases with different complexity and initial loading conditions showed that PG operators overall outperform the original PAO/CAO operators in the quality of results. This is because they have broader access to the network's reconfiguration possibilities namely, inside-feeder reconfiguration as well as inter-feeder load transfer, while PAO/CAO operators are limited to inter-feeder load transfer. This is a key feature when reconfiguring the more densely tied urban distribution networks with many inside-feeder as well as inter-feeder tie lines.

In addition, PG operators had a significantly better performance than Conventional and Enhanced Conventional operators considering the quality of final results and the total response time. Integer operators could produce good final results in all cases. However, they were slower than PG operators in terms of the convergence speed and the total response time. Conventional, Enhanced Conventional, and Integer operators waste some moves in the search space by producing and then discarding individuals who violate Structural constraints, while PG operators never produce such individuals.

Performance achievement of the proposed method and its scalability is very promising since it facilitates the application of EAs to the reconfiguration of larger and more densely tied urban distribution networks, where the computational burden of the EAs used to be a discouraging feature. Furthermore, it is reliable for reconfiguration of the networks with different size, complexity, and initial loading conditions.

Part III

CONTRIBUTION II - SERVICE RESTORATION

6 THE PROPOSED METHOD

The main contribution of this work for the service restoration problem of compensated distribution networks is to employ an efficient modeling of distribution network and propose an integrated framework for the EA in order to solve the SR problem with the global search capability which applies:

1. Reconfiguration using PG operators,
2. Optimal load shedding in the out-of-service area by two new operators,
3. Compensation using two new operators in order to optimally control the compensators for an effective contribution in the SR process.

All of these functions are applied simultaneously in a single run of the optimization program. In addition, an intelligence is applied to the operators using more information about status of the network.

6.1 REPRESENTATION

The same object-oriented branch-based representation of the network used for the network reconfiguration problem discussed in section 4.1 is employed in this problem.

6.2 SEARCH SPACE LIMITING TECHNIQUE

Feeder-set (FS) is introduced as a set of feeders which are direct or indirect neighbors. Two feeders are direct neighbors when there is at least one tie switch between them, and indirect neighbors when they are neighbors through one or more medium feeders. It is assumed that substations are fed through an infinite bus.

Consequently, changing the settings of compensators or reconfiguring the network inside a FS will not influence others. A FS is called faulty when there is at least one fault on one of its feeders. The proposed method for liming the search space employs this concept and is called *FS technique*.

It confines the space of optimal reconfiguration and compensator setting search to only the faulty FSs and aims to increase the convergence speed and provide better local optima by searching in a smaller space.

6.3 BASIC OPERATORS

Three sets of operators are used for reconfiguration, load shedding, and compensation which create new individuals in the EA. Details of these operators are as follows.

6.3.1 *Reconfiguration*

PG operators introduced in section 4.2 are employed in order to reconfigure the network. PG operators are fast, always maintain the search in the space of radial configurations, and integrate both inside-feeder reconfiguration and inter-feeder load transfer compared to the operators of [24] which are limited to inter-feeder load transfer. In addition, they inherently entail the multi-tier (system-wide) switching capability of the method in [40] using a different approach.

6.3.2 *Shedding-Recovery*

These operators try to find a minimum set of loads to be excluded from recovery. They are defined as:

- Shedding operator: randomly selects and opens a switch in the initially out-of-service area which has been already energized,
- Recovery operator: neutralizes the shedding operator by selecting and closing one of the switches opened by that operator.

6.3.2.1 *Compensation*

These operators optimize the settings of compensators in order to support the SR in minimizing the amount of load shedding. They include:

- Volt operator: for changing the tap settings of transformers and VRs,
- Var operator: for changing the steps of substation and feeder capacitors.

Once one of these operators is selected, it randomly picks a proper compensator in a faulty FS and randomly increases or decreases its tap or step by 1 unit, each time.

For each individual, the application probabilities of the operators have to be determined. For this, first, applicable operators to the selected FS in that individual are identified and receive initial equal probabilities while inapplicable ones receive zero. This is based on a fundamental rule in the EAs: "each operator application has to make a move in the search space."

Then, if both EPAO and ECAO operators are applicable, their probabilities are adjusted so that 80% of the accumulated initially assigned probability to both is given to EPAO and 20% to ECAO. It is verified that this fixed ratio for PG operators works best for the network under study [39].

As an example, when a FS has no shed load, recovery operator should not be selected. Thus, the probability for each of other five operators is initially set to 20%. Then, it is adjusted to 32% for EPAO and 8% for ECAO. Note that Reconfiguration and Compensation operators are applied to only faulty FSs and Shedding-Recovery operators work on the out-of-service area.

6.4 Smart Operators

In this section, more intelligence is introduced to the operators in order to guide the search to more productive areas of the search space by directing the moves based on feasibility status and voltage profile of the network. In addition, an early start pattern for some operators is shown to be effective for enhancing the EA. The new set of operators is called *Smart operators*.

Three techniques are proposed in order to introduce more intelligence to the EA operators. Detailed explanations of these techniques are presented here.

6.4.1 *Smart Shedding-Recovery*

The fundamental concept used for extension of Shedding-Recovery operators comes from a judgment based on feasibility status of the parent.

For Shedding operator, when the parent is feasible, it is more likely to be able to accept more loads (less load shedding). On the other hand, when the parent is unfeasible, it is more likely to require cutting more loads (more load shedding). Thus, based on the feasible/unfeasible status of the parent, Shedding operator is pushed toward less/more load shedding, respectively.

The same logic is applied to Recovery operator. It means that based on the feasible/unfeasible status of the parent, Recovery operator is pushed toward more/less load recovery, respectively.

In order to implement this logic, for instance in the case of Shedding operator, instead of a single random shedding candidate, a set of shedding candidates is randomly selected and the amount of total apparent power of loads $|S_L|$ that each one cuts is calculated.

Then, a probability is assigned to each candidate proportional/counter-proportional to the amount of the load that each one cuts in order to favor more/less load shedding, respectively. Finally, one of the candidates is randomly selected based on the assigned probabilities. An analogous method is applied to Recovery operator.

6.4.2 *Smart Compensation*

The main objectives of the extension applied to Compensation operators are to:

i) avoid wasting the moves on irrelevant compensators,

ii) avoid the moves that are likely to create or deteriorate the violation of operational constraints, and

iii) encourage more compensation.

In order to achieve these objectives, two methods are proposed that are explained here in details.

6.4.2.1 *Locking method*

When some compensators are located in upstream of the fault(s) and there is no tie line connected to this path, they cannot contribute in restoring the out-of-service loads. Thus, they are totally locked and excluded from the optimization.

In addition, the nodal voltage profile is examined in order to determine whether step-up and step-down operations of each compensator are permitted or not. If one of these operations of a compensator is locked, only the other operation is permitted, deterministically. If both operations are locked, the compensator is totally locked.

Substation transformers and VRs only directly influence the voltage levels of their downstream nodes. Therefore, when there is at least one node in downstream of each one whose voltage amplitude is less than minimum permitted value or its difference to the minimum value is less than tap size of the transformer or VR, its step-down operation is locked.

On the other hand, when there is at least one node in the downstream whose voltage amplitude is more than the maximum permitted value or its difference to the maximum value is less than tap size of the transformer or VR, its step-up operation is locked.

Substation and feeder capacitors influence the voltage profile of the whole feeder. Therefore, all nodes of the feeder related to each capacitor are examined. When there is at least one node whose voltage amplitude is equal or less than the minimum permitted value, the capacitor's step-down operation is locked.

Besides, when there is at least one node whose voltage amplitude is equal or more than the maximum permitted value, the capacitor's step-up operation is locked.

6.4.2.2 *Push-up method*

Regarding the nature of the SR problem, it is more likely that under-voltage rather than over-voltage problem appears. Therefore, encouraging the step-up operation of the compensators aiming to increase the voltage levels would possibly improve the final results.

This is implemented by assigning more probability to step-up compared to step-down operation. Besides, the over-voltage problem also might occur due to the over-compensation. Thus, the chance of step-down for the compensators is not totally removed, but weakened.

6.4.3 *Early Shedding-Recovery*

When the size of out-of-service area is large or the pre-fault network is heavily loaded, the SR's solution could entail load shedding. In Early Shedding-Recovery technique, the EA starts by the application of only Shedding-Recovery operators for specific evaluations and then, the other operators are activated too. The pioneer initial individuals offering various load shedding options are expected to improve the EA's performance.

On the other hand, when the size of out-of-service area is small or the pre-fault network is lightly loaded, all loads could probably be restored using only reconfiguration and compensation. Thus, Early Shedding-Recovery technique might lead to a local convergence before activation of the other operators. However, when the number of evaluations used for the activation is small and the program is fast enough, this technique only will slightly delay the final response.

6.5 feasibility

Feasibility concept in the service restoration problem is defined in a slightly different way than section 4.3. Here, a feasible configuration has to fulfill three sets of constraints, simultaneously:

1. *Operational constraints*: includes transformer and branch loading constraints and nodal voltage margins.

2. *Shedding constraint*: shedding only the loads of already energized out-of-service area.

Individuals who violate one or more constraints are unfeasible and those who do not violate any constraint are feasible.

Shedding constraint is considered since in the absence of priority customers, shedding has to be limited to the out-of-service area. Although Shedding operator always selects its candidates from switches of this area, it might lead to cutting some loads of healthy area due to the effect of reconfiguration operators which could cause feeding healthy loads through already energized out-of-service area.

Therefore, in order to avoid cutting healthy loads to restore out-of-service ones, this constraint has to be fulfilled. Note that checking the radiality of individuals is unnecessary which accelerates the EA. This owes to the benefit of PG operators in exclusively producing radial configurations [39].

Note, when a fault occurs, the program goes to the emergency state. It means that loading limits and voltage margins are relaxed by $+10\%$ and $\pm 5\%$, respectively. This is because in contingencies, network equipment are permitted to operate in emergency loading conditions and wider voltage margins are justifiable, both for limited periods of time.

6.6 Population

The EA is implemented using two subpopulations (SPs): feasible SP and unfeasible SP.

Individuals who violate one or more constraints are unfeasible and those who do not violate any constraint are feasible. Each newly created individual tries to enter the proper SP. Unfeasible individuals aid to diminish the possibility of an immature convergence.

Besides, each individual in the feasible SP is a potential solution to the SR problem and the final solution is the best individual of this SP in the last evaluation. SPs are bounded to a maximum size.

6.7 OBJECTIVES

Two objectives are considered: primary and secondary. Priority is given to the primary objective. Only when two individuals have the same primary objective values, their secondary objectives are compared.

6.7.1 *Primary objective*

The primary objective function (F_1) is composed of five terms aggregated using equal weights $w_i, i = 1, 2, ..., 5$ all set to 0.2. It is expressed using the following formula:

$$F_1 = w_1 * TOL + w_2 * BOL + w_3 * VV + w_4 * E + w_5 * DE \quad (6.1)$$

where:
TOL: transformer overloading index which is the summation of overload apparent power $|S_{OL}|$ for all overloaded transformers and VRs;
BOL: branch overloading index which is the summation of overload current modulus $|I_{OL}|$ for all overloaded branches;
VV: nodal voltage violation index which is the summation of absolute differences of the nodal voltage modulus $|V_N|$ and high ($V_{max} = 1.05pu$) or low ($V_{min} = 0.95pu$) margins for over-voltage and under-voltage nodes, respectively;
E: energized shed which is the summation of apparent power of shed loads in the healthy area $|S_{Shed,E}|$;
DE: de-energized shed which is the summation of apparent power of shed loads in the out-of-service area $|S_{Shed,DE}|$;

For individuals of the unfeasible SP, all terms could have non-zero values, while for those in the feasible SP, only DE could be non-zero. All of the above terms are normalized respect to their maximum values. For TOL, BOL, and VV, the maximum values are updated in each evaluation. While for E and DE, the maximum values are constant and equal to the sum of apparent power of all loads in the healthy $|S_E|$, and the out-of-service $|S_{DE}|$ areas, respectively.

6.7.2 *Secondary objective*

The secondary objective (F_2) is the number of required switching operations. For each individual, it is equal to the number of switch status alterations between the initial healthy condition and that individual. Changes in the status of switches that isolate the faults are not counted.

6.8 EA STEPS

It is assumed that all faults are already located and isolated. Before commencing the evolution process, faulty FSs are identified and initially restored. Initial service restoration (ISR) means that a tie switch with an energized end node (tie line) in downstream of each fault is randomly selected and closed. Therefore, an initial configuration is obtained which feeds all out-of-service loads.

This individual is likely to violate some operational constraints. Random selection of the tie switches for ISR is adequate in that PG operators have access to change these selections to other possible choices. Faults with no chance of ISR (no tie line in downstream) are left unrestored and reported. ISR is capable of initially restoring single, multiple, and cascaded faults.

A graphical representation of the ISR process for initially restoring single fault, double faults[1], and cascaded faults are presented in Figure 6.1 to 6.3.

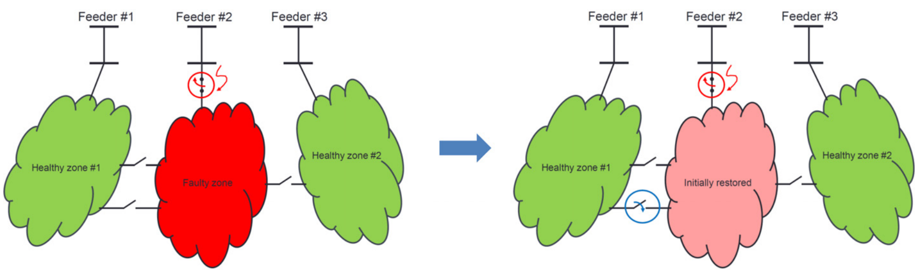


Figure 6.1: Initial service restoration for a single fault

EA performs a single evaluation per iteration. It means that a parent is selected, an operator is applied and an offspring is created in each iteration. After ISR, EA continues with the following steps:

1 Two faults occurring at the same time

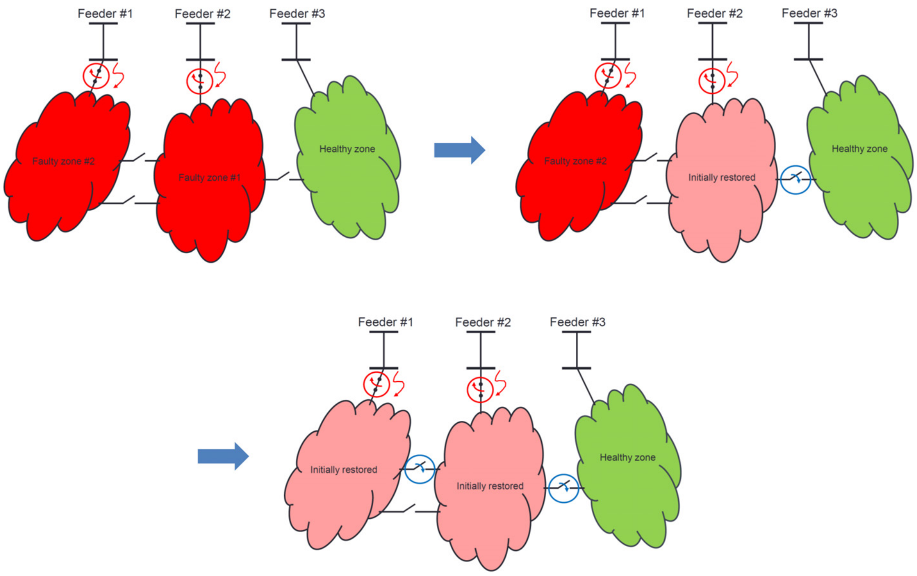


Figure 6.2: Initial service restoration for double faults

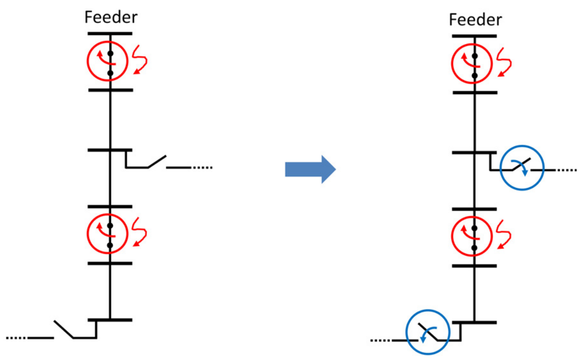


Figure 6.3: Initial service restoration for cascaded faults

STEP 1: INITIAL POPULATION CREATION Output of ISR described above is added to the proper SP. In addition, for trying to produce at least one feasible individual, the network configuration before ISR (100% shedding) is used and enters the proper SP.

If the network has been operating normally before occurrence of the fault(s) and it does not experience over-voltage due to the effect of compensators (over-compensation) after removal of some loads by isolation of the fault(s), this individual would be feasible.

STEP 2: PARENT SELECTION An individual in one of the SPs should be selected in this step. A SP is randomly selected and one of its individuals is selected using tournament selection method. It means that two individuals in that SP are selected randomly and compete considering their primary (and probably secondary) objective values. The winner becomes the parent.

Note, when a SP is empty, the other is selected deterministically. In addition, when there is only one individual in the selected SP, there is no need to the tournament selection.

STEP 3: VARIATION Applies one of the operators to the parent in order to create an offspring. For selecting the operator, one of the faulty FSs of the parent is selected, randomly. Then, one of the operators is randomly selected and applied based on the probability determination method described in section 6.3.

STEP 4: SURVIVAL SELECTION The created offspring is evaluated. If it is better than the worst individual of the related SP, it replaces the worst. Otherwise, the offspring is discarded.

Steps 2 to 4 above are repeated until a predefined number of evaluations are performed. Then, the best individual of the feasible SP is introduced as the final solution. Flowchart of the EA steps is presented in Figure 6.4.

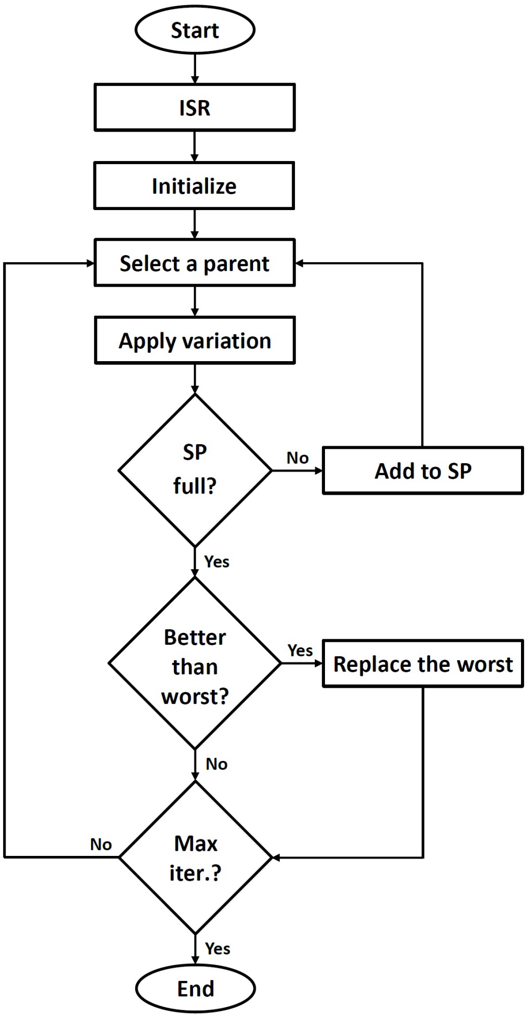


Figure 6.4: Flowchart of the EA steps for service restoration

7 TEST RESULTS

In this chapter, the test results in the service restoration using the basic service restoration operators and Smart operators are presented and discussed.

7.1 TESTING THE BASIC OPERATORS

The proposed method is implemented using Visual C++ programming language on a Pentium IV 3.4GHz desktop PC. All simulations are performed using 20000 evaluations and 30 trials for different seeds of random number generator.

7.1.1 *Test case*

A 94-bus network of Taiwan Power Company [59] has been used for testing the method. It has 96 branches with automatic switches on all branches operated at 11.4kV. Base power is 5MVA.

The following conventional compensators are considered in the SR plan:

1. substation transformer tap changers on all substation transformers,
2. feeder VRs at the middle of all feeders,
3. substation capacitors on all substations feeding 50% of Q requirement of the substation, and
4. feeder capacitors at $\frac{2}{3}$ length of all feeders, feeding all Q requirements of its node and downstream.

Items i and ii implement the volt compensation and items iii and iv the var compensation. Tap changing units in transformers and VRs have 17 taps (±8 in addition to neutral) for changing the voltage in the range of ±10% and capacitor banks have 5 steps of 0, 25%, ...,100% of the reactive power (Q) generation.

Locations and attributes of the compensators have been considered as typical. Sizing and siting of compensators for optimal volt/var control of distribution networks are out of the scope of this work.

The proposed method's performance is evaluated in the following conditions:

i) including and not including the compensators,

ii) including and not including the FS technique.

This results in four sets of simulations. Single and multiple faults in different locations have been tested. Three cases are presented and discussed here, including:

i) single fault on branch #18 (Case I),

ii) double faults on branches #16, #32 (Case II),

iii) triple faults[1] on branches #12, #18, #34 (Case III).

These cases are tested for (a) normal (50%), and (b) heavy (75%) loading conditions.

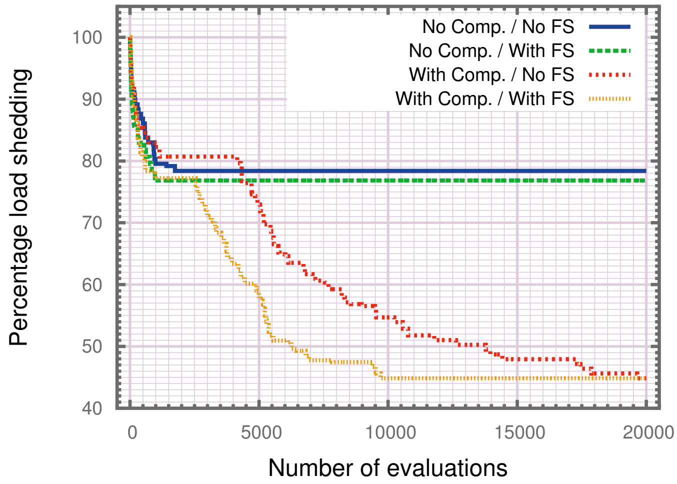
Note, the maximum size of each SP is set to 100 individuals. This selection was made by testing the method for sizes in the range of 5 to 1000 individuals where 100 had the best performance considering the quality of results and the convergence speed.

7.1.2 *Experiments*

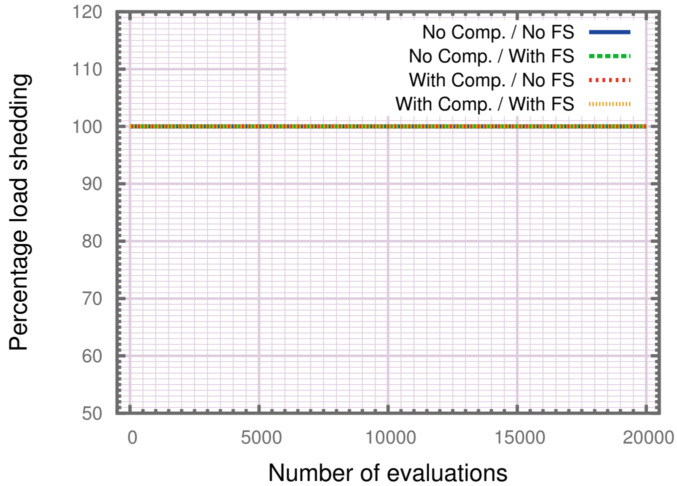
Averages of the best results of each evaluation for 30 trials and 20000 evaluations are presented in Figure 7.1 to 7.3. In addition, a numerical statistics of the tests including the final results for 30 trials and frequency of their production is presented in Table 7.1.

First, the effect of optimizing the compensators' settings simultaneously with reconfiguration and load shedding in the SR is discussed. Considering the data provided in Table 7.1, the best result found by the application of compensators is mostly equal or better than the condition of without compensation. For instance

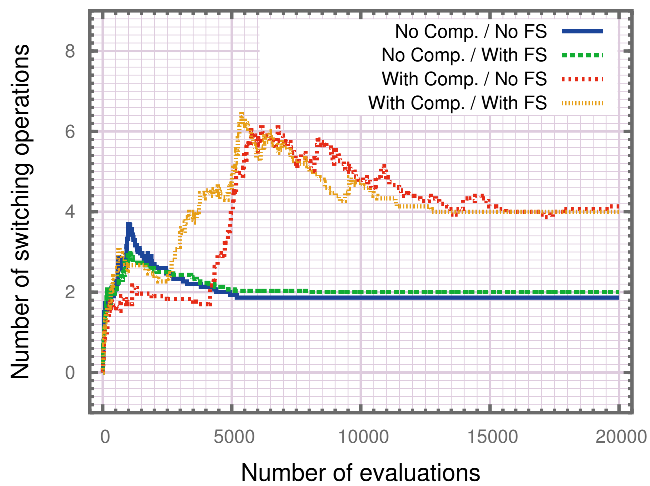
1 Three fault occurring at the same time



(a) 50% loading



(b) 75% loading



(c) 50% loading

Figure 7.1: Effect of contribution of compensators and FS technique in Case I

Table 7.1: Statistical results at final evaluation for 30 trials

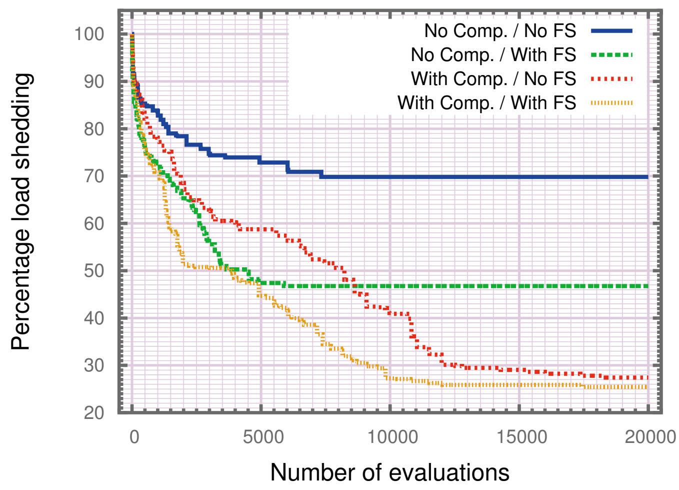
Case	**No Comp. / No FS**		**No Comp. / With FS**		**With Comp. / No FS**		**With Comp. / With FS**	
	Result	*Fr.*	*Result*	*Fr.*	*Result*	*Fr.*	*Result*	*Fr.*
Case I a (50%)	76.9%	28	76.9%	30	44.9%	30	44.9%	30
	100%	2	-	-	-	-	-	-
Case I b (75%)	100%	30	100%	30	100%	30	100%	30
Case II a (50%)	40.9%	11	40.9%	23	23.9%	16	23.9%	23
	53.3%	1	53.3%	3	24.4%	3	24.4%	2
	67.7%	3	66.7%	2	29.4%	1	32.3%	4
	73.2%	4	67.7%	1	31.3%	1	36.2%	1
	94.9%	1	100%	1	32.3%	5	-	-
	100%	10	-	-	36.2%	4	-	-
Case II b (75%)	85.5%	10	81.7%	1	73.2%	1	73.2%	2
	92.8%	2	85.5%	12	85.5%	9	85.5%	10
	94.9%	3	91.4%	1	94.9%	3	92.8%	2
	100%	15	92.8%	1	100%	17	94.9%	2
	-	-	94.9%	3	-	-	96.2%	2
	-	-	96.2%	2	-	-	99.3%	4
	-	-	99.3%	1	-	-	100%	8
	-	-	100%	9	-	-	-	-
Case III a (50%)	95.0%	1	95.0%	1	100%	30	86.8%	3
	99.5%	1	99.5%	1	-	-	95.0%	1
	100%	28	100%	28	-	-	100%	26
Case III b (75%)	100%	30	98.9%	2	95.0%	4	94.4%	1
	-	-	99.5%	3	100%	26	95.0	3
	-	-	100%	25	-	-	99.2%	1
	-	-	-	-	-	-	100%	25

Table 7.2: Optimal settings of compensators for Case I(a)

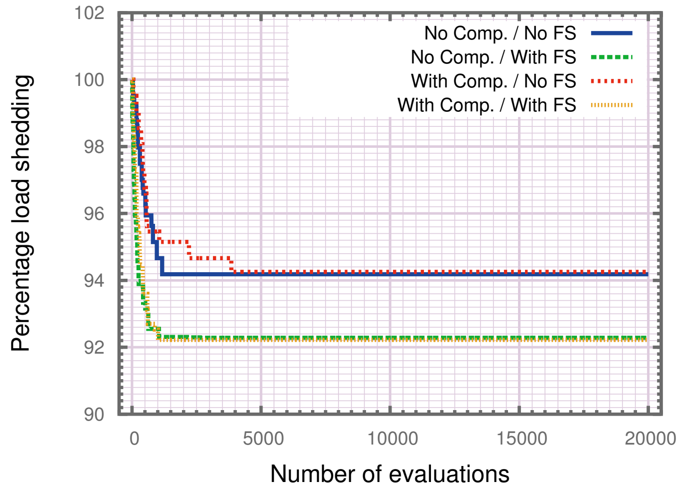
Compensators	**Settings**
Transformers' taps	0, 2, -1, 1, 1, 1, 0, 0, 2, 3, 2
VRs' taps	0, 2, 4, 1, 0, 2, 0, 0, 2, 1, 0
Substation capacitors' steps	0, 2, 0, 0, 1, 3, 0, 0, 2, 1, 1
Feeder capacitors' steps	0, 0, 4, 0, 1, 0, 0, 0, 0, 0, 1

in Case I(a), the best result obtained without compensation is 76.9% shedding, regardless of including the FS technique. However, this improves to 44.9% by effective operation of the compensators. For this case, optimal settings of the compensators as an output of the optimization program are presented in Table 7.2.

Then, the effect of FS technique for liming the search space in the SR is considered. If Figure 7.1 to 7.3 are observed, except for Case I(b) which has no option for recovery, including FS technique has improved or accelerated the results of the SR. This was expected since the FS technique limits search to only the faulty



(a) 50% loading



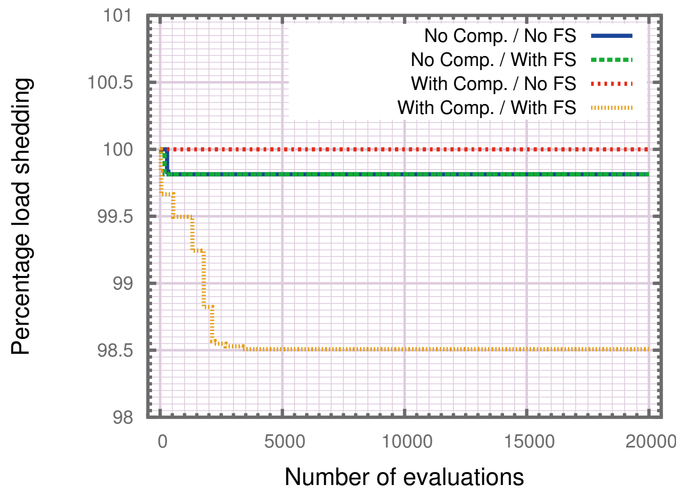
(b) 75% loading

Figure 7.2: Effect of contribution of compensators and FS technique in Case II

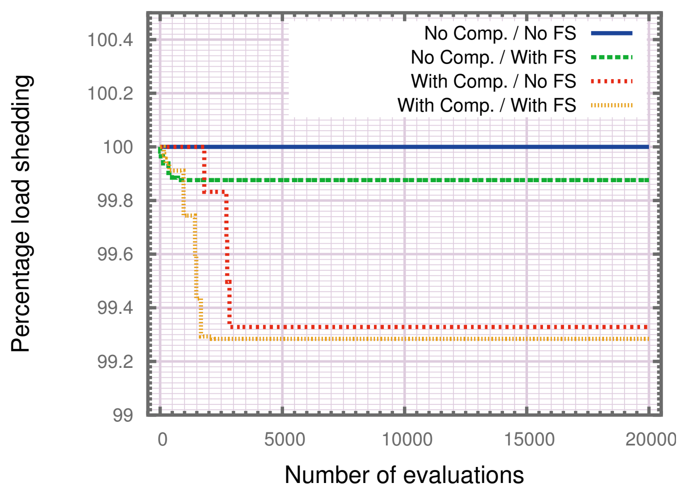
FSs. This technique helps to avoid wasting the moves in regions of the search space which are not correlated to the fault(s) and thus, explores better only the regions which could contain solutions to the SR problem.

Note that FS technique does not include simplifying assumptions such as the methods in [40]-[43], [52] and hence, keeps the global search capability of the optimization program.

As it could be observed in Figure 7.1c, the number of switching operations is not always decreasing in that it is the secondary and low importance objective. Actually, only when the primary objective (load shedding) is stabilized, the secondary objective has chance to be minimized.



(a) 50% loading



(b) 75% loading

Figure 7.3: Effect of contribution of compensators and FS technique in Case III

In addition, reducing the amount of shedding happens by the cost of more number of switching operations. This could always be justified when all switches are automatic. Because, restoring service to more customers is more important than switches' operation and maintenance costs. However, when some switches are manual with significant switching time, there should be a compromise between time and the amount of load recovery. In this case, distance to the switch(es) location from the nearest manned substation and the driving traffic pattern of the road at the fault time also become important [40].

An extension of the proposed method could consider the above terms in the optimization process under a new objective called switching cost including the switching time as well as the operation and maintenance costs and perform a multi-objective optimization.

Computation time related to the evolution process has been 2.72 milliseconds per evaluation which is promising and makes the application of the proposed method suitable for online operation of distribution networks.

Note a variance among the results in 30 trials as shown in "Fr." columns of Table 7.1, especially for Case II. This happens regardless of including the FS technique and thus, should be related to the behavior of operators.

For instance, shedding operator could cut a big portion of the already energized out-of-service area. If the parent is replaced, the produced individual has to wait for recovery operator in order to regain the removed portion. If this individual could survive after recovery, it needs to wait for a softer shedding in order to have less shed loads.

An advanced analysis of the operators should increase granularity of the search which would probably lead to smaller variance of the results in different trials.

In Case II(b), not including the compensators has produced good average results. Although including the compensators still provides better quality for the best results as shown in Table 7.1, averages are very close. This comes from two possible reasons:

a) the diversity among the results discussed above,

b) the need for coordination of shedding and compensation operators.

Shedding operator could remove some compensators when it cuts a portion of already energized out-of-service area which neutralizes the effect of these compensators. Thus, upgrading the shedding operator to give more priority to keeping the compensators in operation, or assigning more probability to the application of compensation compared to shedding operator might remedy this phenomenon.

7.2 testing smart operators

For testing Smart operators, simulations are performed using 50000 evaluations and 30 trials for different seeds of random number generator.

7.2.1 *Test case*

The variation of Taiwan Power Company's network (used in testing the network reconfiguration approach in section 5.1) is employed in this test. In addition, the same compensators introduced in section 7.1.1 are added to the network.

The proposed method's performance is evaluated using various single, double, and triple faults. Three sample cases are discussed here, including:

1. single fault on branch #18 in normal loading (Case I),
2. double faults on branches #5, #61 in heavy loading (30% increase of the |S| of all loads) (Case II),
3. triple faults on branches #12, #18, #34 in heavy loading (Case III).

Before commencing the experiments, a tuning process of the EA parameters is performed. The tuned settings used for producing the final results are presented in Table 7.3.

Table 7.3: Tuned settings of the EA parameters

Subject	Setting	Value
Reconfiguration	EPAO (fixed)	80%
	ECAO (fixed)	20%
Smart Shedding-Recovery	Max/Min candidate probability	5
	Number of candidates	10
Smart Compensation	Step-up/Step-down probability	3
Early Shedding-Recovery	Reconfig. & Comp. activation iter.	100
Population	Max SP size	1250

7.2.2 *Experiments*

Averages of the best results in each evaluation for 30 trials and 50000 evaluations for EAs using the original and Smart operators are presented in Figure 7.4 using logarithmic x-axis. In addition, numerical statistics of tests including the final results for 30 trials and frequency of their production are presented in Table 7.4.

Table 7.4: Statistical results at final evaluation for 30 trials

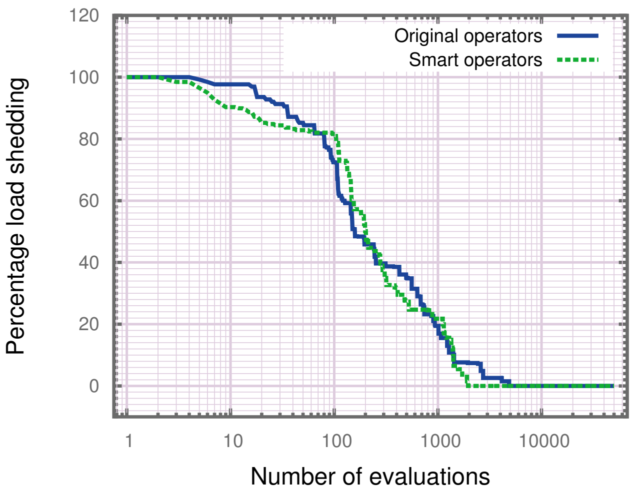
Case	**Original operators**		**Smart operators**	
	Final result	*Freq.*	*Final result*	*Freq.*
Case I	0	30	0	30
Case II	37.6%	27	37.6%	30
	67.9%	3	-	-
Case III	67.7%	2	67.2%	1
	68.2%	9	67.7%	5
	86.0%	1	68.2%	22
	86.8%	2	86.8%	2
	98.8%	1	-	-
	98.9%	1	-	-
	99.5%	6	-	-
	100%	8	-	-

For all cases in Figure 7.4, Smart operators have been able to improve the convergence behavior of the EA. For instance in Case I, the EA using Smart operators requires less than 2000 evaluations to converge while it is about 5000 evaluations for the original operators (see Figure 7.4a).

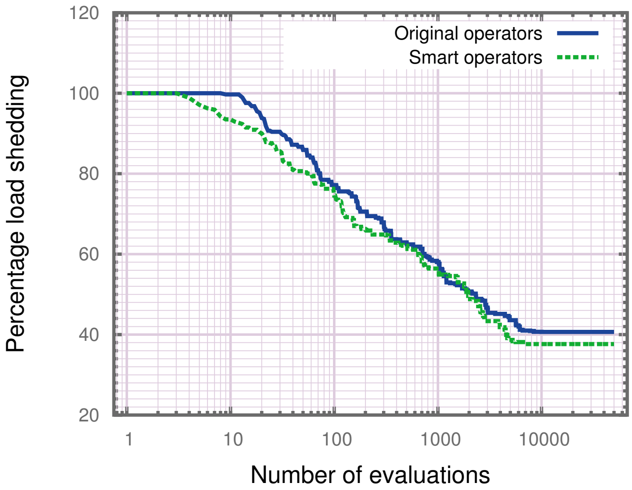
It is interesting to note that in this case, due to the application of Early Shedding-Recovery technique, the method locally converges before the evaluation number 100 and waits until the other operators start to work. Then, the obtained results improve again, significantly. Early Shedding-Recovery technique will be discussed more, later in this section. Note that when the number of faults increases, EA requires more evaluations to converge due to the increased number of combinations for the load shedding and recovery.

Considering the quality of results, Smart operators produce equal or better average results for all cases in Fig 7.4. In addition, absolute values of the final results produced by Smart operators are equal or better than the original operators in all cases (see Table 7.4). For instance, in Case III the best and the worst results produced in different trials as well as the diversity among the final results in 30 trials are improved.

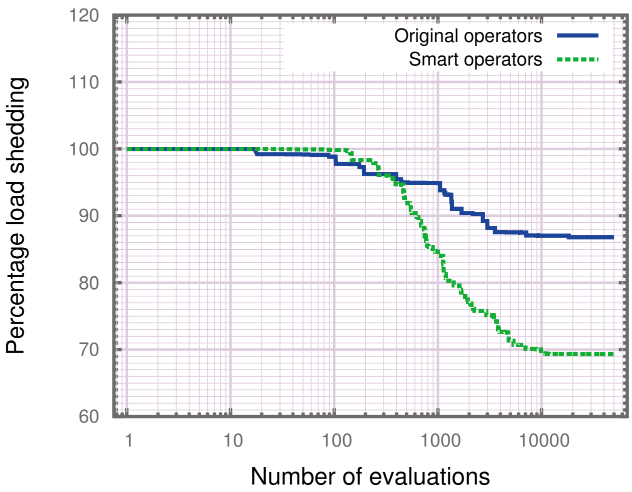
Based on the performed experiments, separate application of each technique slightly improves the performance of the method in many cases and produces competitive results in few ones.



(a) Case I



(b) Case II



(c) Case III

Figure 7.4: Obtained results by EAs using the original and Smart operators

However, when all techniques are applied simultaneously, the improvement is significant for all experiments.

Note that Case I does not require load shedding in the final solution while Case II and III require it. As examples of the effect of solely Early Shedding-Recovery technique with various activation evaluations of other operators, Case I and III are selected and presented in Figure 7.5.

In Case I, Early Shedding-Recovery technique provides a faster declining pattern before the activation point for all settings. However, the EA locally converges before these points. Then, Reconfiguration and Smart Compensation operators contribute in the optimization and lead to a fast response (see Figure 7.5a).

Considering the selected activation evaluation (that is 100) and the low computational requirement of the method (1.79 mSec per evaluation in an average of 50000 evaluations), the total delay is negligible. However, in this case the faster convergence of Smart operators is not obtained by only using Early Shedding-Recovery technique.

In Case III, for all activation points in Figure 7.5b, Early Shedding-Recovery technique significantly improves the quality of final results. Although 500 has the best performance in this case, 100 is selected considering all experiments as well as the incurred delays.

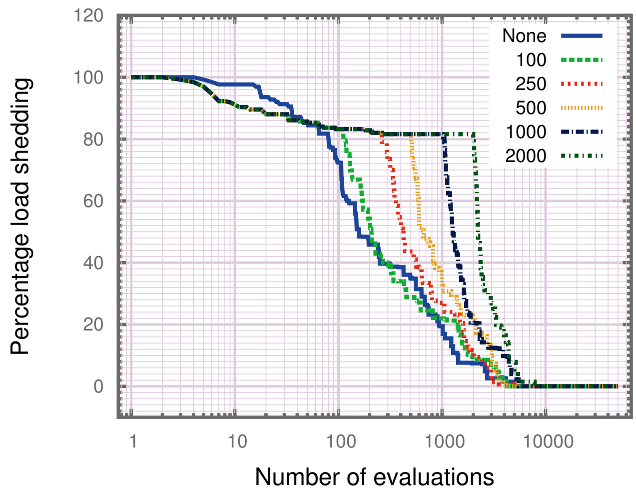
Referring again to Table 7.4, application of Smart operators has improved the variance among the final results in 30 trials, but still requires more work. Some possible reasons for this phenomenon are:

i) behavior of Shedding-Recovery operators which alter the amount of load shedding sometimes with large steps,

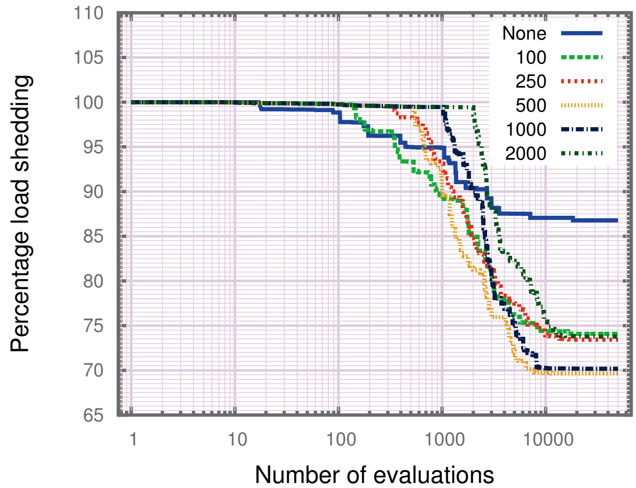
ii) leaving some areas of the search space undiscovered for some random number generation patterns,

iii) nature of EAs that are prone to be trapped in local optima, and

iv) combinatorial SR problem that leads the search to various difficult-to-return paths producing different local optima.



(a) Case I



(b) Case III

Figure 7.5: The effect of Early Shedding-Recovery technique

7.3 CONCLUSION AND FUTURE WORK

An integrated EA framework for optimal service restoration of compensated distribution networks was proposed. It considered an effective modeling of distribution network and optimally operated the compensators simultaneously with reconfiguration and load shedding in the SR plan. Three techniques were proposed in order to introduce more intelligence to the operators and guide the search to more productive areas of the search space.

In addition, the search space was limited using the FS technique while keeping the global search capability of the method. Effective operation of the compensators improved the quality of results. Furthermore, application of the FS technique provided faster and better results by searching in a smaller space. Low computational burden of the method encourages its application to the online operation of distribution networks.

As a future work, efforts will be performed on more effectively exploring the search space regardless of the random path by improving the granularity of the search and coordination of compensation and shedding operators aiming to reduce the variance among the results. In addition, switching cost could be incorporated in the method in order to perform a multiobjective optimization. The proposed methods would be tested on larger networks with more FSs which could provide more evidence on the benefits of the FS technique.

Finally, the proposed methods will be applied to more extent optimization requirements of the distribution network operation in order to integrate various aspects for a smarter control of the power system into a single framework.

Part IV

APPENDICES

A

APPENDIX: TEST CASES

Data regarding the test cases are presented here. Note that transformers' tap data in app. Table A.1-A.3 are not used in this step of research and they are presented for the future reference.

Furthermore, P_0 and Q_0 data in app. Table A.4-A.6 are related to the loads connected to the receiving nodes of branches.

Table A.1: Transformer data for Case I

Node	R [Ω]	X [Ω]	Step Size	Positive Steps	Negative Steps	Current Step	Capacity [kVA]
1	0	0	0.0125	8	8	0	2895.320

Table A.2: Transformer data for Case II

Node	R [Ω]	X [Ω]	Step Size	Positive Steps	Negative Steps	Current Step	Capacity [kVA]
1	0	0	0.0125	8	8	0	3478.061
70	0	0	0.0125	8	8	0	4751.290

Table A.3: Transformer data for Case III

Node	R [Ω]	X [Ω]	Step Size	Positive Steps	Negative Steps	Current Step	Capacity [kVA]
1	0	0	0.0125	8	8	0	8808.735
12	0	0	0.0125	8	8	0	6748.404
17	0	0	0.0125	8	8	0	9036.647
28	0	0	0.0125	8	8	0	5605.508
34	0	0	0.0125	8	8	0	9268.720
48	0	0	0.0125	8	8	0	2710.632
53	0	0	0.0125	8	8	0	6675.688
63	0	0	0.0125	8	8	0	3692.703
73	0	0	0.0125	8	8	0	7001.413
82	0	0	0.0125	8	8	0	3820.933
87	0	0	0.0125	8	8	0	9202.142

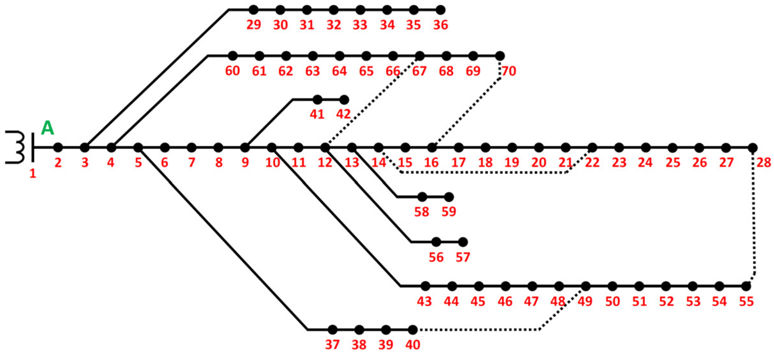


Figure A.1: Schematic of Case I

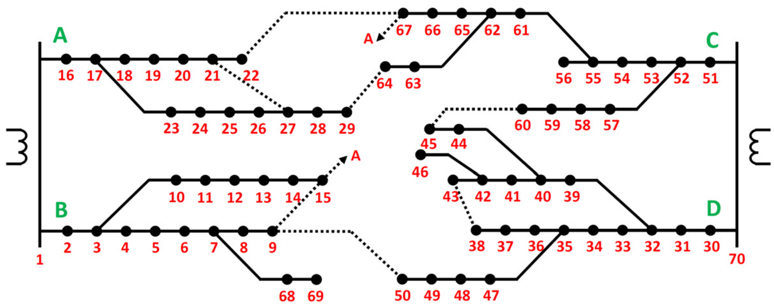


Figure A.2: Schematic of Case II

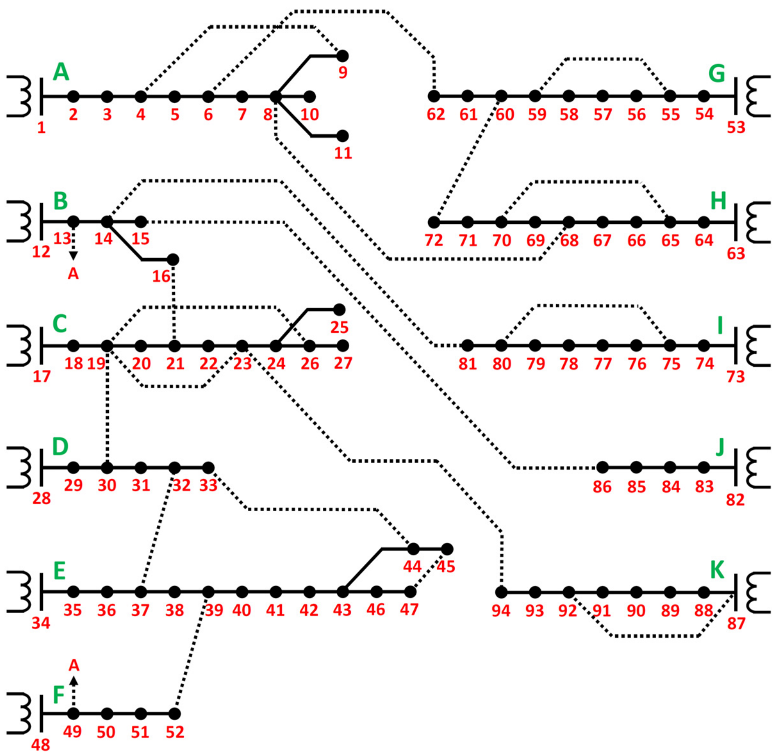


Figure A.3: Schematic of Case III

Table A.4: Branch, node, load, and ampacity data for Case I

Br	Sd Nd	Rc Nd	R [Ω]	X [Ω]	P_0 [kW]	Q_0 [kVar]	Ampacity [A]
1	1	2	0.0005	0.0012	0.00	0.00	132.0
2	2	3	0.0005	0.0012	0.00	0.00	132.0
3	3	4	0.0000	0.0000	0.00	0.00	128.7
4	4	5	0.0015	0.0036	0.00	0.00	123.2
5	5	6	0.0251	0.0294	0.00	0.00	98.8
6	6	7	0.3660	0.1864	0.88	0.72	98.8
7	7	8	0.3811	0.1941	13.46	9.98	98.6
8	8	9	0.0922	0.0470	24.89	17.81	97.1
9	9	10	0.0493	0.0251	10.00	7.21	92.7
10	10	11	0.8190	0.2707	9.33	6.67	28.2
11	11	12	0.1872	0.0619	48.50	34.61	27.1
12	12	13	0.7114	0.2351	48.50	34.61	20.3
13	13	14	1.0300	0.3400	2.71	1.82	12.7
14	14	15	1.0440	0.3450	2.71	1.82	12.4
15	15	16	1.0580	0.3496	0.00	0.00	12.1
16	16	17	0.1966	0.0650	15.18	10.20	12.1
17	17	18	0.3744	0.1238	16.50	11.78	10.4
18	18	19	0.0047	0.0016	16.50	11.78	8.5
19	19	20	0.3276	0.1083	0.00	0.00	6.7
20	20	21	0.2106	0.0696	0.32	0.21	6.7
21	21	22	0.3416	0.1129	37.98	27.10	6.6
22	22	23	0.0140	0.0046	1.76	1.18	2.3
23	23	24	0.1591	0.0526	0.00	0.00	2.1
24	24	25	0.3463	0.1145	9.39	6.67	2.1
25	25	26	0.7488	0.2475	0.00	0.00	1.1
26	26	27	0.3089	0.1021	4.67	3.33	1.1
27	27	28	0.1732	0.0572	4.67	3.33	0.5
28	3	29	0.0044	0.0108	8.67	6.19	3.4
29	29	30	0.0640	0.1565	8.67	6.19	2.4
30	30	31	0.3978	0.1315	0.00	0.00	1.4
31	31	32	0.0702	0.0232	0.00	0.00	1.4
32	32	33	0.3510	0.1160	0.00	0.00	1.4
33	33	34	0.8390	0.2816	4.58	3.26	1.4
34	34	35	1.7080	0.5646	6.50	4.55	0.9
35	35	36	1.4740	0.4873	1.92	1.29	0.2
36	4	60	0.0044	0.0108	8.67	6.19	5.5
37	60	61	0.0640	0.1565	8.67	6.19	4.5
38	61	62	0.1053	0.1230	0.00	0.00	3.6
39	62	63	0.0304	0.0355	8.00	5.71	3.6
40	63	64	0.0018	0.0021	8.00	5.71	2.7
41	64	65	0.7283	0.8509	0.39	0.33	1.9
42	65	66	0.3100	0.3623	0.00	0.00	1.9
43	66	67	0.0410	0.0478	2.00	1.43	1.9
44	67	68	0.0092	0.0116	0.00	0.00	1.7
45	68	69	0.1089	0.1373	3.08	8.79	1.7
46	69	70	0.0009	0.0012	3.08	8.79	0.8
47	5	37	0.0034	0.0084	0.00	0.00	24.9
48	37	38	0.0851	0.2083	26.35	18.80	24.9

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Table A.4 – Continue

Br	Sd Nd	Rc Nd	R [Ω]	X [Ω]	P_0 [kW]	Q_0 [kVar]	Ampacity [A]
49	38	39	0.2898	0.7091	28.23	91.49	22.0
50	39	40	0.0822	0.2011	128.23	91.49	14.4
51	9	41	0.0928	0.0473	13.51	9.44	1.7
52	41	42	0.3319	0.1114	1.20	0.89	0.1
53	10	43	0.1740	0.0886	1.45	1.16	63.3
54	43	44	0.2030	0.1034	8.79	6.32	63.2
55	44	45	0.2842	0.1447	8.00	5.71	62.2
56	45	46	0.2813	0.1433	0.00	0.00	61.3
57	46	47	1.5900	0.5337	0.00	0.00	61.3
58	47	48	0.7837	0.2630	0.00	0.00	61.3
59	48	49	0.3042	0.1006	0.67	24.03	61.3
60	49	50	0.3861	0.1172	0.00	0.00	59.9
61	50	51	0.5075	0.2585	414.67	295.91	59.9
62	51	52	0.0974	0.0496	10.67	7.61	12.2
63	52	53	0.1450	0.0738	0.00	0.00	11.0
64	53	54	0.7105	0.3619	75.67	53.87	11.0
65	54	55	1.0410	0.5302	19.67	13.91	2.3
66	12	56	0.2012	0.0611	6.00	4.28	1.4
67	56	57	0.0047	0.0014	6.00	4.28	0.7
68	13	58	0.7394	0.2444	9.33	6.66	2.1
69	58	59	0.0047	0.0016	9.33	6.66	1.1
70	12	67	0.5000	0.5000	-	-	128.7
71	14	22	0.5000	0.5000	-	-	12.7
72	16	70	1.0000	1.0000	-	-	128.7
73	40	49	2.0000	2.0000	-	-	123.2
74	28	55	1.0000	1.0000	-	-	92.7

Table A.5: Branch, node, load, and ampacity data for Case II

Br	Sd Nd	Rc Nd	R [Ω]	X [Ω]	P_0 [kW]	Q_0 [kVar]	Ampacity [A]
1	1	2	1.097	1.074	120.0	108.0	324
2	2	3	1.463	1.432	72.0	48.0	324
3	3	4	0.731	0.716	180.0	156.0	324
4	4	5	0.366	0.358	90.0	60.0	324
5	5	6	1.828	1.790	21.6	13.0	324
6	6	7	1.097	1.074	21.6	17.0	324
7	7	8	0.731	0.716	15.6	12.0	324
8	8	9	0.731	0.716	19.0	13.0	324
9	4	10	1.080	0.734	24.0	12.0	250
10	10	11	1.620	1.101	19.2	11.0	250
11	11	12	1.080	0.734	60.0	48.0	250
12	12	13	1.350	0.917	126.0	108.0	250
13	13	14	0.810	0.550	30.0	18.0	250
14	14	15	1.944	1.321	48.0	30.0	250
15	7	68	1.080	0.734	120.0	72.0	250
16	68	69	1.620	1.101	48.0	36.0	250
17	1	16	1.097	1.074	72.0	36.0	324
18	16	17	0.366	0.358	48.0	30.0	324
19	17	18	1.463	1.432	18.0	11.0	324
20	18	19	0.914	0.895	15.6	8.4	324
21	19	20	0.804	0.787	36.0	24.0	324
22	20	21	1.133	1.110	108.0	60.0	324
23	21	22	0.475	0.465	60.0	36.0	324
24	17	23	2.214	1.505	72.0	48.0	250
25	23	24	1.620	1.110	120.0	96.0	250
26	24	25	1.080	0.734	96.0	78.0	250
27	25	26	0.540	0.367	120.0	72.0	250
28	26	27	0.540	0.367	120.0	66.0	250
29	27	28	1.080	0.734	144.0	84.0	250
30	28	29	1.080	0.734	126.0	84.0	250
31	70	30	0.366	0.358	96.0	60.0	324
32	30	31	0.731	0.716	72.0	48.0	324
33	31	32	0.731	0.716	15.6	9.6	324
34	32	33	0.804	0.787	19.2	11.8	324
35	33	34	1.170	1.145	60.0	36.0	324
36	34	35	0.768	0.752	48.0	33.6	324
37	35	36	0.731	0.716	72.0	48.0	324
38	36	37	1.097	1.074	48.0	36.0	324
39	37	38	1.463	1.432	36.0	30.0	324
40	32	39	1.080	0.734	180.0	120.0	250
41	39	40	0.540	0.367	72.0	42.0	250
42	40	41	1.080	0.734	144.0	84.0	250
43	41	42	1.836	1.248	108.0	72.0	250
44	42	43	1.296	0.881	21.6	12.0	250
45	40	44	1.188	0.807	19.2	12.0	250
46	44	45	0.540	0.367	120.0	60.0	250
47	42	46	1.080	0.734	72.0	48.0	250
48	35	47	0.540	0.367	108.0	84.0	250

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Table A.5 – Continue

Br	**Sd Nd**	**Rc Nd**	**R** $[\Omega]$	**X** $[\Omega]$	$\mathbf{P_0}$ $[kW]$	$\mathbf{Q_0}$ $[kVar]$	**Ampacity** $[A]$
49	47	48	1.080	0.734	122.4	79.2	250
50	48	49	1.080	0.734	120.0	84.0	250
51	49	50	1.080	0.734	168.0	108.0	250
52	70	51	0.366	0.358	72.0	48.0	324
53	51	52	1.463	1.432	24.0	13.2	324
54	52	53	1.463	1.432	48.0	36.0	324
55	53	54	0.914	0.895	43.2	28.8	324
56	54	55	1.097	1.074	36.0	24.0	324
57	55	56	1.097	1.074	51.6	36.0	324
58	52	57	0.270	0.183	96.0	60.0	250
59	57	58	0.270	0.183	288.0	144.0	250
60	58	59	0.810	0.550	150.0	132.0	250
61	59	60	1.296	0.881	30.0	12.0	250
62	55	61	1.188	0.807	12.0	6.0	250
63	61	62	1.188	0.807	180.0	156.0	250
64	62	63	0.810	0.550	60.0	36.0	250
65	63	64	1.620	1.101	36.0	24.0	250
66	62	65	1.080	0.734	156.0	144.0	250
67	65	66	0.540	0.367	180.0	156.0	250
68	66	67	1.080	0.734	30.0	18.0	250
69	22	67	0.381	0.245	-	-	281
70	67	15	0.454	0.363	-	-	281
71	21	27	0.254	0.203	-	-	281
72	9	50	0.681	0.545	-	-	281
73	29	64	0.681	0.545	-	-	281
74	45	60	0.254	0.203	-	-	281
75	43	38	0.254	0.203	-	-	281
76	9	15	0.454	0.363	-	-	281

Table A.6: Branch, node, load, and ampacity data for Case III

Br	Sd Nd	Rc Nd	R [Ω]	X [Ω]	P_0 [kW]	Q_0 [kVar]	Ampacity [A]
1	1	2	0.1944	0.6624	0	0	446
2	2	3	0.2096	0.4304	100	50	446
3	3	4	0.2358	0.4842	300	200	435
4	4	5	0.0917	0.1883	350	250	396
5	5	6	0.2096	0.4304	220	100	351
6	6	7	0.0393	0.0807	1100	800	325
7	7	8	0.0405	0.1380	400	320	178
8	8	9	0.1048	0.2152	300	200	39
9	8	10	0.2358	0.4842	300	230	41
10	8	11	0.1048	0.2152	300	260	43
11	12	13	0.0786	0.1614	0	0	342
12	13	14	0.3406	0.6944	1200	800	342
13	14	15	0.0262	0.0538	800	600	104
14	14	16	0.0786	0.1614	700	500	89
15	17	18	0.1134	0.3864	0	0	458
16	18	19	0.0524	0.1076	300	150	458
17	19	20	0.0524	0.1076	500	350	424
18	20	21	0.1572	0.3228	700	400	361
19	21	22	0.0393	0.0807	1200	1000	278
20	22	23	0.1703	0.3497	300	300	115
21	23	24	0.2358	0.4842	400	350	71
22	24	25	0.1572	0.3228	50	20	6
23	24	26	0.1965	0.4035	50	20	11
24	26	27	0.1310	0.2690	50	10	5
25	28	29	0.0567	0.1932	50	30	284
26	29	30	0.1048	0.2152	100	60	278
27	30	31	0.2489	0.5111	100	70	266
28	31	32	0.0486	0.1656	1800	1300	254
29	32	33	0.1310	0.2690	200	120	24
30	34	35	0.1965	0.3960	0	0	469
31	35	36	0.1310	0.2690	1800	1600	469
32	36	37	0.1310	0.2690	200	150	220
33	37	38	0.0262	0.0538	200	100	194
34	38	39	0.1703	0.3497	800	600	171
35	39	40	0.0524	0.1076	100	60	67
36	40	41	0.4978	1.0222	100	60	55
37	41	42	0.0393	0.0807	20	10	42
38	42	43	0.0393	0.0807	20	10	40
39	43	44	0.0786	0.1614	20	10	5
40	44	45	0.2096	0.4304	20	10	2
41	43	46	0.1965	0.4035	200	160	33
42	46	47	0.2096	0.4304	50	30	6
43	48	49	0.0486	0.1656	0	0	137
44	49	50	0.0393	0.0807	30	20	137
45	50	51	0.1310	0.2690	800	700	134
46	51	52	0.2358	0.4842	200	150	25
47	53	54	0.2430	0.8280	0	0	338
48	54	55	0.0655	0.1345	0	0	338

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Table A.6 – Continue

Br	Sd Nd	Rc Nd	R [Ω]	X [Ω]	P_0 [kW]	Q_0 [kVar]	Ampacity [A]
49	55	56	0.0655	0.1345	0	0	338
50	56	57	0.0393	0.0807	200	160	338
51	57	58	0.0786	0.1614	800	600	312
52	58	59	0.0393	0.0807	500	300	208
53	59	60	0.0786	0.1614	500	350	147
54	60	61	0.0524	0.1076	500	300	83
55	61	62	0.1310	0.2690	200	80	23
56	63	64	0.2268	0.7728	0	0	187
57	64	65	0.5371	1.1029	30	20	187
58	65	66	0.0524	0.1076	600	420	183
59	66	67	0.0405	0.1380	0	0	107
60	67	68	0.0393	0.0807	20	10	107
61	68	69	0.0262	0.0538	20	10	105
62	69	70	0.1048	0.2152	200	130	103
63	70	71	0.2358	0.4842	300	240	78
64	71	72	0.0243	0.0828	300	200	38
65	73	74	0.0486	0.1656	0	0	355
66	74	75	0.1703	0.3497	50	30	355
67	75	76	0.1215	0.4140	0	0	349
68	76	77	0.2187	0.7452	400	360	349
69	77	78	0.0486	0.1656	0	0	292
70	78	79	0.0729	0.2484	0	0	292
71	79	80	0.0567	0.1932	2000	1500	292
72	80	81	0.0262	0.0528	200	150	27
73	82	83	0.3240	1.1040	0	0	194
74	83	84	0.0324	0.1104	0	0	194
75	84	85	0.0567	0.1932	1200	950	194
76	85	86	0.0486	0.1656	300	180	36
77	87	88	0.2511	0.8556	0	0	466
78	88	89	0.1296	0.4416	400	360	466
79	89	90	0.0486	0.1656	2000	1300	410
80	90	91	0.1310	0.2640	200	140	159
81	91	92	0.1310	0.2640	500	360	133
82	92	93	0.0917	0.1883	100	30	67
83	93	94	0.3144	0.6456	400	360	57
84	6	62	0.1310	0.2690	-	-	446
85	8	68	0.1310	0.2690	-	-	446
86	13	49	0.1310	0.2690	-	-	342
87	14	81	0.3406	0.6994	-	-	355
88	15	86	0.4585	0.9415	-	-	342
89	16	21	0.5371	1.0824	-	-	458
90	19	30	0.0917	0.1883	-	-	458
91	23	94	0.0786	0.1614	-	-	466
92	32	37	0.0524	0.1076	-	-	469
93	33	44	0.0786	0.1614	-	-	469
94	39	52	0.0262	0.0538	-	-	469
95	45	47	0.1965	0.4035	-	-	469
96	60	72	0.0393	0.0807	-	-	338
97	4	9	0.1356	0.3126	-	-	446

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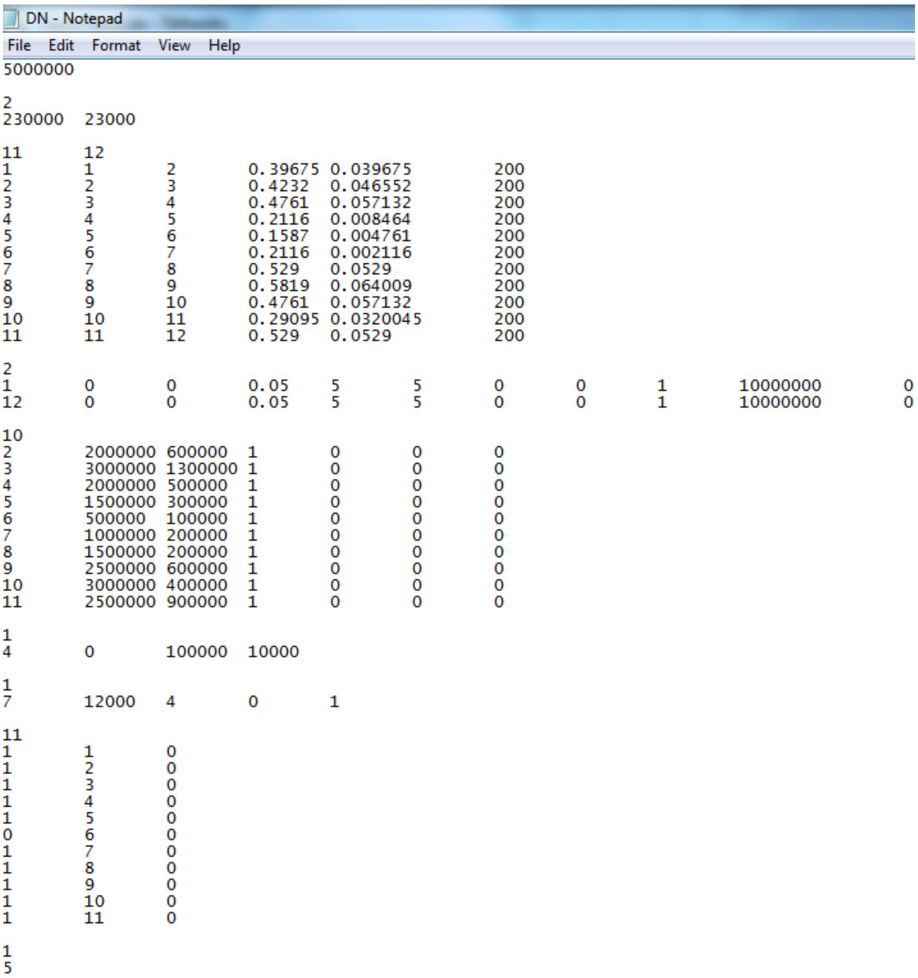
Table A.6 – Continue

Br	**Sd Nd**	**Rc Nd**	**R** [Ω]	**X** [Ω]	**P_0** [kW]	**Q_0** [$kVar$]	**Ampacity** [A]
98	19	23	0.1356	0.3126	-	-	458
99	65	70	0.1356	0.3126	-	-	187
100	87	92	0.1356	0.3126	-	-	466
101	19	26	0.1356	0.3126	-	-	458
102	55	59	0.1356	0.3126	-	-	338
103	75	80	0.1356	0.3126	-	-	355

Appendix: Input Data File

B

Network data are loaded into the program using a .txt input file. Input data file for a sample 12-node distribution network is presented in Figure B.1.



```
DN - Notepad
File  Edit  Format  View  Help
5000000

2
230000  23000

11      12
1       1       2       0.39675 0.039675        200
2       2       3       0.4232  0.046552        200
3       3       4       0.4761  0.057132        200
4       4       5       0.2116  0.008464        200
5       5       6       0.1587  0.004761        200
6       6       7       0.2116  0.002116        200
7       7       8       0.529   0.0529          200
8       8       9       0.5819  0.064009        200
9       9       10      0.4761  0.057132        200
10      10      11      0.29095 0.0320045       200
11      11      12      0.529   0.0529          200

2
1       0       0       0.05    5       5       0       0       1       10000000        0
12      0       0       0.05    5       5       0       0       1       10000000        0

10
2       2000000 600000  1       0       0       0
3       3000000 1300000 1       0       0       0
4       2000000 500000  1       0       0       0
5       1500000 300000  1       0       0       0
6       500000  100000  1       0       0       0
7       1000000 200000  1       0       0       0
8       1500000 200000  1       0       0       0
9       2500000 600000  1       0       0       0
10      3000000 400000  1       0       0       0
11      2500000 900000  1       0       0       0

1
4       0       100000  10000

1
7       12000   4       0       1

11
1       1       0
1       2       0
1       3       0
1       4       0
1       5       0
0       6       0
1       7       0
1       8       0
1       9       0
1       10      0
1       11      0

1
5
```

Figure B.1: Input data file for a sample 12-node distribution network

Details regarding contents of the input file are as follows:

i) base apparent power:
   – line 1: S_{base} `[VA]`

ii) voltage levels:
   – line 1: `no. of voltage levels`
   – line 2: V_1 `[V],` V_2 `[V], ...`

iii) branch, node, and connection data:
– line 1: `no. of branches, no. of nodes`
– line 2: `branch index, sending-node index, receiving-node index, R [`Ω`], X [`Ω`], ampacity [A]`
– line 3: `...`

iv) transformer and voltage regulator (VR) data:
– line 1: `no. of transformers and VRs`
– line 2: `node index, R [`Ω`], X [`Ω`], tap size [pu], no. of positive taps, no. of negative taps, current tap, primary voltage level index, secondary voltage level index, capacity [VA], adjust (0: lock, 1: adjust)`
– line 3: `...`

v) load data:
– line 1: `no. of loads`
– line 2: `node index, P [W], Q [Var], `$a_0(b_0)$`, `$a_1(b_1)$`, `$a_2(b_2)$`, priority (0: no, 1: yes)`
– line 3: `...`

vi) generator data:
– line 1: `no. of generators`
– line 2: `node index, operation mode (0: PQ mode, 1: PV mode), P [W], Q [Var] if operation mode is PQ or `V_{set}` [V] if operation mode is PV`
– line 3: `...`

vii) capacitor data:
– line 1: `no. of capacitors`
– line 2: `node index, Q [Var], no. of non-zero steps, current step, adjust (0: lock, 1: adjust)`
– line 3: `...`

viii) switch data:
– line 1: `no. of switches`
– line 2: `status (0: open, 1: closed), branch index, permanently open (0: no, 1: yes)`
– line 3: `...`

ix) fault data:
– line 1: `no. of faults`

– line 2: `faulty branch index`
– line 3: `...`

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