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Institute for Systems and Computers Engineering
INESC – Coimbra

Romeu M. Vitorino, Humberto M. Jorge, Luís P. Neves

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Instituto de Engenharia de Sistemas e Computadores de Coimbra
INESC – Coimbra
Rua Antero de Quental, 199; 3000 - 033 Coimbra; Portugal
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NETWORK RECONFIGURATION USING AN IMPROVED GENETIC ALGORITHM FOR LOSS AND RELIABILITY OPTIMIZATION IN DISTRIBUTION SYSTEMS

Romeu M. Vitorino [(1)], Humberto M. Jorge [(2)], Luís P. Neves [(1)]

[(1)] Dept. of Electrical Engineering, Campus 2, Polytechnic Institute of Leiria,
2411-901 Leiria, Portugal

[(2)] Dept. of Electrical Engineering and Computers, Polo II, University of Coimbra,
3030-290 Coimbra, Portugal

[(1), (2)] Institute for Systems and Computers Engineering – Coimbra (INESCC), Rua Antero de Quental, 199, 3000-033 Coimbra, Portugal

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Abstract: This study presents a new method to improve simultaneously reliability and minimize active power losses in radial distribution systems (RDS), through a process of network reconfiguration. The methodology adopted to enhance reliability uses the Monte Carlo (MC) simulation and historical data of the network, such as the severity of the potential contingencies in each branch. Due to a large number of possible configurations and the need of an efficient search, the optimization is made through an improved genetic algorithm (IGA) with adaptive crossover and mutation probabilities, and with other new features. The method analyses the RDS considering in a first step, the absence of investment, and in a second step, the possibility of placing a limited number of new tie-switches, defined by a decision agent, in certain branches. The effectiveness of the proposed method is demonstrated through the analysis of a 69 bus RDS.

Keywords: Improved Genetic Algorithm, Loss Minimization, Network Reconfiguration, Reliability.

1. Introduction

The existing distribution networks are actually growing in complexity, due to the gradual increase of power demand and the existence of customers with more sensitive loads. The impact of an interruption is nowadays more severe than a few years ago. This fact combined with the analysis of customer failure statistics, causing also financial loss for utility companies, reinforces the need to be concerned with reliability evaluation of the distribution network.

An efficient operation of distribution networks can be achieved by using reconfiguration techniques. The network reconfiguration is carried out by changing the on/off status of the sectionalizing switches (normally closed) and tie-switches (normally open). The switching must be performed in such a way that the radiality of the network is maintained and all the loads are energized. Obviously, the greater the numbers of switches, the greater are the possibilities for reconfiguration and better are the effects.

Traditionally, network reconfiguration has been implemented to achieve goals as the reduction of power loss, load balancing or voltage stability, in normal operating conditions (Baran and Wu (1989); Shirmohammadi and Hong (1989); Borozan *et al.* (1995); Kashem and Moghavvemi (1998); Sahoo and Prasad (2006)). The reconfiguration impacts on the system's reliability indices usually aren't included.

The main aim of this study is to present a methodology for network reconfiguration with the objective of finding, in normal operating conditions, the optimal configuration for the distribution system that minimizes losses and simultaneously improves reliability by reducing the impact of potential contingencies.

In the emergency state caused by contingency situations, some research has been made to ensure in a shorter time, service restoration reducing the quality of service index figures and causing financial losses for utility companies. Shin *et al.* (2004) presented an approach using a genetic-tabu algorithm to find the optimal service restoration and optimal reconfiguration in the distribution network. More recently, Garcia and França (2007) used a local search based heuristic which considers the minimization of the load not supplied and the number of switching operations involved.

To evaluate the distribution system's reliability, two techniques have been used, including analytical methods and Monte Carlo simulation methods. Ou and Goel (1999) used a Monte Carlo simulation to assess the overall distribution system. The study is focused on the impacts of various probability distributions for restoration times on load point expected cost and interrupted energy assessment.

To improve reliability, Brown (2003) used an analytical simulation method to predict reliability and an annealed local search for feeder reconfiguration. The search adjusts switch positions until an optimal solution is identified. More recently, Coelho *et al.* (2004) adopted a simulated annealing approach for network reconfiguration with the objective of minimizing losses taking into account reliability constraints, also using an analytical method to estimate reliability.

The use of distribution system reconfiguration for loss reduction was first proposed by Merlin and Back (1975). They have used a branch and bound type optimization technique to determine the minimum loss configuration. Baran and Wu (1989) proposed efficient load flow equations to calculate the power flow formulating the loss reduction and load balancing as an integer programming problem. Many other heuristic approaches have been suggested, based in the method proposed by Merlin and Back (1975) (Shirmohammadi and Hong (1989); Borozan *et al.* (1995); Das (2006)).

Network reconfiguration has received considerable interest in recent years. Most approaches proposed so far use some sort of heuristics, mathematical programming or approximate techniques. Thus, the computation results are rather approximate or only local optimal solutions. Network reconfiguration using simulated annealing and genetic algorithms (GA's) based approaches have also been used (Huang (2002); Sahoo and Prasad (2006); Lin *et al.* (2000)).

Conventional genetic algorithms easily get stuck at a local optimum, and often have slow convergence speed. In order to overcome these shortcomings, many researchers have made great efforts to improve the performance of GA's (Vasconcelos and Saldanha (1997), Vasconcelos *et al.* (2001)). The significance of the probabilities of crossover (*pc*) and mutation (*pm*) in controlling GA's has been acknowledged in GA research, since *pc* and *pm* greatly determine whether the algorithm will find a near optimum solution or whether it will find a solution efficiently (Zhang *et al.* (2004)). This study proposes an improved genetic algorithm (IGA) with the ability to search global or near global optimal solutions. It also introduces some new features improving accuracy and the computational efficiency, including a black list of infeasible solutions, a two-termination criterion and also the dynamic adaptation of crossover and mutation probabilities according to the genetic diversity in the population.

The next section will describe in more detail the improved genetic algorithm (IGA) and its main features. Section 3 is dedicated to the evaluation of the distribution system reliability through Monte Carlo simulation. Section 4 defines the fitness function in terms of losses and reliability. In Section 5 and 6 the case study and the test results will be presented. Finally, the conclusions and references complete the research report.

2. Improved Genetic Algorithm (IGA)

In a typical RDS, the number of branches is quite large, resulting, with the use of GA's, in a chromosome of very large length with the binary coding technique, i.e. one bit for one branch, as in Huang (2002). This kind of technique also results easily in the generation of a large number of infeasible solutions, leading to a large computational effort.

The most crucial aspect of the RDS reconfiguration approaches, using genetic algorithms is that proper measures must be taken to ensure the radiality of the network at every stage of the genetic evolution, under the application of the genetic operators, i.e. crossover and mutation. If not, invalid solutions will probably appear, therefore, prompting the need to make changes to satisfy the radial structure constraint (Lin and Tsay (2000); Huang (2002)).

In this particular case, using the IGA it is possible to ensure the use of a chromosome with a small length and also to keep the network radial during the optimization process. For this, the IGA uses a suitable coding and decoding technique based on Sahoo and Prasad (2006).

2.1 Coding and Decoding Technique

To maintain the radiality of the network in the process of network reconfiguration, the number of open branches should always be equal to the number of tie-switches (N_{ts}). This could be obtained through expression (1) where (N_b) represents the number of branches, (N_n) the number of nodes and (N_{ss}) the number of substations in the distribution system.

$$N_{ts} = N_b - (N_n - N_{ss}) \quad (1)$$

The coding technique depends, on a first step, of the analysis of the network structure, to find the branches participating in each loop that is formed as each tie-switch gets closed. In a perspective of optimization without investment, it is only considered, in each loop, the branches equipped with a sectionalizing switch. In the other perspective of optimization, candidate branches for a tie-switch installation are also considered.

The chromosome consists of N substrings of binary values ('0' and '1'). Each tie-switch is represented by one substring that when decoded, allow the determination of the branch in the loop to be opened, guaranteeing the radiality of the network. The number of bits in a substring (N_{bit}) is decided by the number of participating branches in each loop (N_{loop}) and can be obtained through the expression (2) , where $\lfloor\ \rfloor$ stands for the mathematical "floor" function.

$$N_{bit} = \left\lfloor \log_2 N_{loop} + 1 \right\rfloor \quad (2)$$

When decoding of each substring, the binary number is converted to its equivalent decimal number (D_n), which is used to show which branch should be opened. Three conditions are considered: If (D_n) is equal to '0' then the tie-switch is not considered as a candidate to be closed, else if (D_n) is less then or equal to (N_{loop}) , then (D_n) is used as index to define the branch that should be opened with the correspondent tie-switch being closed. If not, is used as index the result of (D_n) – (N_{loop}).

2.2 Generation of the initial population

The initial population is randomly generated considering a specified number of individuals (N_{ind}), with bits being either '0' or '1'. This will assure a higher genetic diversity in the beginning of the optimization process. To avoid the creation of a bigger loop the genetic algorithm gives the guarantee that, during the decoding process, the same branch isn't detected more than once.

The IGA, if specified, also allows the insertion of the individual that represents the base network in the initial population (Ind_{BN}). This will assure that the better fitness value, in the initial population, is at least equal to the fitness attributed to (Ind_{BN}).

2.3 Selection mechanism

The generation gap represents the percentage of individuals to copy to the new population. In this study, the IGA uses a fixed size population of size (N_{ind}) and a fixed renewal rate (R_r) in all generations. This represents that at least we will have always two solutions in order to allow the reproduction process.

After generating a random initial population and evaluating the solutions performance, a selection mechanism is applied based on the "*Roulette Wheel Parent Selection*" technique in which there is a larger probability of the best fitness individuals being chosen to participate in the next generation and where each solution is represented proportionally to its performance. The IGA also adopts an elitist selection meaning that the best individual at generation (k) is maintained in the next generation (k+1).

2.4 Genetic Operators

A new generation of individuals is produced as a result of genetic manipulation applied on parents. The crossover is the predominant operator and, therefore, with a higher probability of occurrence (*pc*). This operation is made between pairs of parents randomly chosen and it consists in generating new individuals with characteristics of both parents. This also adds new points in the feasible space. In this study, due to the coding technique used, and in order to achieve the best performance of the IGA, it was applied a multi-point crossover with well defined cutting points, as demonstrated in Figure 1. This will assure that descendents inherit characteristics (after decoded) from both parents and with a probability (*pc*).

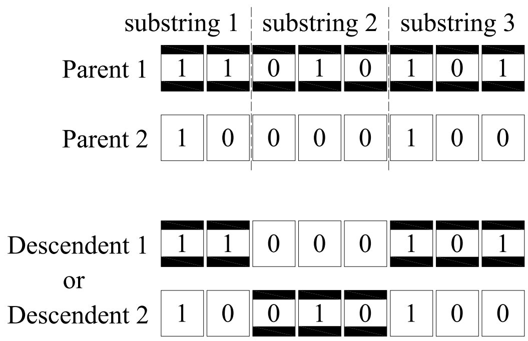

Figure 1 – Example of the Multi-point crossover technique.

Another genetic operator applied with a low probability consists in cloning one of the parents to generate a new individual with the same characteristics.

The genetic manipulation ends with the application of the mutation operator to all the new individuals generated through crossover or cloning. Mutation is the most important operator responsible to introduce new genetic characteristics in the population and thus, maintain the genetic diversity. This is possible by randomly changing some characteristics of the individual to which is applied, ensuring that the probability of reaching any point in the search space is never zero. In addition, mutation will avoid the problem of premature convergence to local optimum. In this study, the mutation operator is applied to each bit of the chromosome with a certain probability (*pm*) of occurrence. Mutation will change the selected bit from ‘0’ to ‘1’ or vice versa as shown in Figure 2.

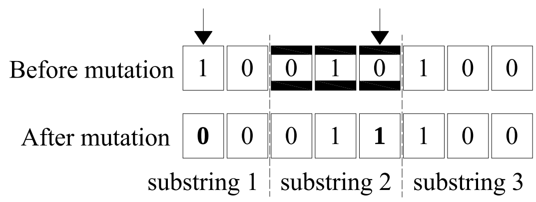

Figure 2 – Example of the Mutation process in a descendent.

After the new population is generated, all individuals are submitted to a process of evaluation and selection. The selected individuals will be responsible for the generation of other individuals through genetic manipulation. The genetic manipulation process can be described by Figure 3.

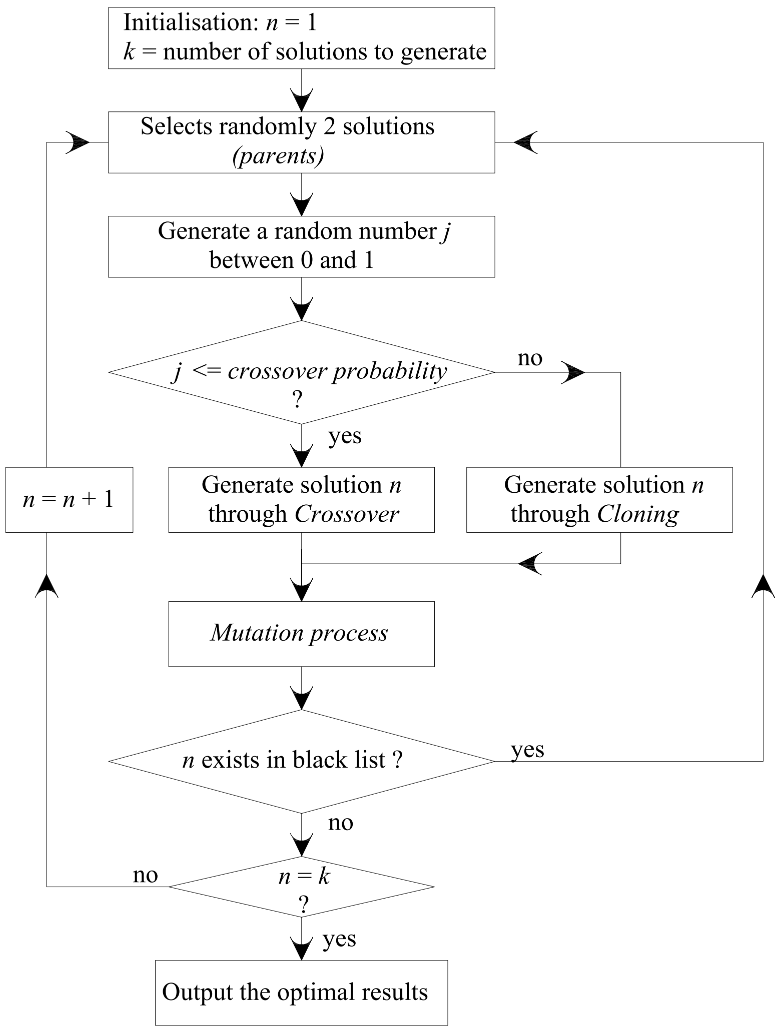

Figure 3 – Flowchart of the genetic manipulation approach (IGA).

2.5 Genetic Diversity in the Population

The genetic diversity in the population is related with the genetic variability of individuals and is responsible for the scattering of solutions in the feasible space. To measure the similarity of individuals, they must be regarded as a multidimensional vector. The measure is the vector distance, as in Tang *et al.* (2008). Suppose individual i is represented as $Ind_i = [g_i(1), \dots, g_i(N)]$, and individual j is represented as $Ind_j = [g_j(1), \dots, g_j(N)]$. To define the distance between individuals i and j the following equation is used:

$$d(i,j) = \sqrt{(g_i(1) - g_j(1))^2 + \dots + (g_i(N) - g_j(N))^2} \tag{3}$$

If the distance is below a predefined threshold (D_{th}), we may assume the two individuals are similar; else, the two individuals are dissimilar. The genetic diversity (G_{div}) is measured using the following equation:

$$G_{div} = \left(\frac{\sum_{i=1}^{N_{ind}} \sum_{j=i+1}^{N_{ind}} 1_{\{d(i,j) > D_{th}\}}}{{}_{N_{ind}}C_2} \right) \times 100 \tag{4}$$

G_{div} is a variable in the range [0,100]. When the value of G_{div} is zero, this indicates that all individuals are similar. On the other hand, if all the individuals in the population are dissimilar, G_{div} assumes the value 100.

2.6 Adaptive Crossover and Mutation Probabilities

It is known that the choice of the crossover and mutation probabilities critically affect the behavior and the performance of the GA. In most studies these probabilities remain unchanged in the course of GA execution. Instead of using fixed crossover and mutation probabilities, IGA dynamically changes these values during the optimization process and according to the genetic diversity. This feature will maintain the genetic diversity in the population and thus prevents IGA to converge prematurely to local optimum.

The heuristic updating principals are; using large *pc* and small *pm* when G_{div} in the current generation is large. The increase of *pc* leads to rich information exchange between individuals, while the decrease of *pm* avoids random search (Tang *et al.* (2008)). In the other case, to avoid premature convergence, *pc* and *pm* must be changed in such a way to introduce new genetic characteristics and to reduce the loss of genetic material. So, *pc* must be reduced and *pm* augmented (Vasconcelos *et al.* (2001)).

The IGA control parameters pc and pm are adjusted according to the following conditions and considering bounds B_{min} and B_{max}:

$$pc = \begin{cases} pc_{\min}, & if\ G_{div} < B_{\min} \\ pc_{\max}, & if\ G_{div} > B_{\max} \end{cases} \tag{5}$$

$$pm = \begin{cases} pm_{\max}, & if\ G_{div} < B_{\min} \\ pm_{\min}, & if\ G_{div} > B_{\max} \end{cases} \tag{6}$$

On the other hand, if the genetic diversity in the population is between the considered bounds, i.e., $B_{min} \leq G_{div} \leq B_{max}$, then pc and pm are calculated through linear interpolation defined by the following equations:

$$pc = \left(\frac{pc_{\min} - pc_{\max}}{B_{\min} - B_{\max}} \right) G_{div} + \left(\frac{pc_{\max} B_{\min} - pc_{\min} B_{\max}}{B_{\min} - B_{\max}} \right) \tag{7}$$

$$pm = \left(\frac{pm_{\max} - pm_{\min}}{B_{\min} - B_{\max}} \right) G_{div} + \left(\frac{pm_{\min} B_{\min} - pm_{\max} B_{\max}}{B_{\min} - B_{\max}} \right) \tag{8}$$

2.7 Termination

Being the genetic algorithm a stochastic search method, it is difficult to formally specify a convergence criterion. In IGA the termination criterion is dependent either on the maximum number of generations (N_{pop}), or a specified convergence threshold (C_{th}). If during C_{th} generations the best fitness value in the population, doesn't suffer any changes, then we may assume the convergence of IGA.

2.8 Black List of infeasible solutions

An important feature of IGA, responsible for the increase of its efficiency, is the creation of a black list with the identification of all the infeasible solutions obtained during the optimization process. This list also can remain after the process so that the solutions search, in future simulations using the same network, can be more effective.

All the generated solutions must pass through an admissibility test. A solution is considered admissible if, in addition to being radial (condition always guaranteed), the network configuration reveals that all the loads are energized, the bus voltage magnitude is between predefined limits and transformers capacity and heat capacity of all the branches are satisfied. The infeasible solutions are then converted to its equivalent decimal number and added to the list. The same procedure is used in the perspective of investment, if the solution reveals a number of tie-switches superior than a specified value.

3. Evaluation of Distribution System Reliability

Reliability assessment models are needed to allow feeder configurations to be optimized for reliability. These models must be able to predict reliability at each consumer based on system topology and component reliability data.

There are two main categories of reliability worth evaluation methods: Monte Carlo simulation method, applied in this study, and analytical methods. The analytical methods are highly developed and have been used in practical applications for several decades (Brown (2003)). This method represents the system by mathematical models and evaluates the reliability indices from these models using mathematical solutions. The exact mathematical equations can become quite involved and approximations may be required when the system is complex.

On the other hand, the Monte Carlo simulation method currently receiving considerable attention, computes the reliability indices by simulating the actual process and random behavior of the power system, and can include any system effects or system processes which may have to be approximated in analytical methods due to the complexity of the system (Billinton and Wang (1999); Ou and Goel (1999)).

3.1 Monte Carlo Simulation Method

When applied to a distribution system reliability assessment, a Monte Carlo simulation typically analyses system behavior for a specific period of time (such as a year) (Brown, 2002). Because each simulation will produce different results, many simulations are typically needed. Theoretically, the expected value of the simulation ($\overline{X}$) is equal to the average of the results of each simulation (x_i) as the number of simulations or trials (N_t), approaches infinity:

$$\overline{X} = \lim_{N_t \to \infty} \left(\frac{1}{N_t} \sum_{i=1}^{N_t} x_i \right) \quad (9)$$

A Monte Carlo simulation has several advantages when compared to an analytical method. One, as previously mentioned, is the ability of a Monte Carlo simulation to produce a distribution of possible results rather than the expected value alone. Another is the ability to easily model component parameters as random variables characterized by probability distribution functions, rather than as constant values. A Monte Carlo simulation can also more easily model complex system behavior such as nonexclusive events, cascading failures, conditional probabilities and so forth.

Various approaches can be followed when performing Monte Carlo simulation on electric power systems. In this study, there is a focus on the branch reliability level, a fundamental element to assure the continuity of service. If a branch suffers an unexpected event such as a fault or an open circuit (contingency situation) this can affect the power distribution system and lead to a blackout state, which is caused by the interruption of the power supply for a portion of the network.

To define the reliability level of each network branch it was considered four levels according to Table I.

Table I: Branch reliability levels

Level	*Probability of Failure*
1	Very unlikely
2	Unlikely
3	Likely
4	Very likely

As the system behavior does not depend upon past events, contingency situations caused by branch failures can be probabilistically selected (according to Table I) and simulated in any arbitrary order. Since this process does not necessarily simulate contingencies in order of occurrence, it is referred to as a non-sequential Monte Carlo simulation (Brown, 2002). The non-sequential Monte Carlo simulation starts with a pool of network branches (Figure 4), i.e., each branch can fail and cause a contingency with a certain probability.

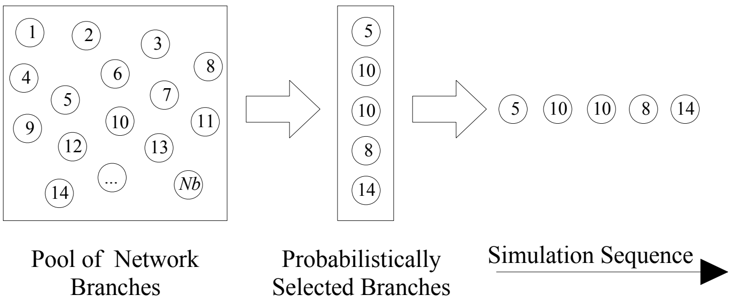

Figure 4 – Monte Carlo simulation determines all branch failures that will occur before the simulation begins.

Contingencies caused by branch failures are randomly selected from a pool of candidate network branches based on contingency probabilities (the same branch can be selected to fail more than once).

After the branches and their number of failure occurrences being selected, it is necessary to determine the associated interruption durations. So, in order to better characterize the possible contingencies, various degrees of severity were defined based on historical data, each with different average interruption durations (D_{av}). Each branch of the network is also characterized according to a certain probability of failure, with the different degrees of severity. Here, past performance statistics provide a valuable reliability profile of the existing system.

The interruption duration associated with each contingency is variable, and follows a normal distribution, whose density function (f) is obtained through a normal density curve, characterized by standard deviation (σ) and the average (μ).

The density function (f) is defined as follows:

$$f(x;\mu,\sigma)=e^{\frac{-(x-\mu)^2}{2\sigma^2}} \tag{10}$$

The method considers (N_t) trials. In each trial, an annual number of contingency situations (N_{cont}), are simulated and their impact analyzed in terms of number and duration of the interruptions that occur in each transformation unit of the RDS. There was no distinction between permanent faults and open circuits, i.e., faults are restricted and correctly isolated, and therefore only affect downstream.

Finally, the expected value of the Monte Carlo simulation ($\overline{X}$) is obtained according to expression (9) allowing the estimation of the annual reliability indices in the considered network configuration of the distribution system. The total energy not distributed (*TEND*) is used as the reliability index to minimize in this study.

4. Fitness Function Definition

Through IGA it is possible to optimize the RDS in terms of losses and reliability. The objective function to minimize is the fitness function used to evaluate the performance of the solutions. The fitness function is defined using the equation (11) considering the annual active energy loss (W_{Loss}) and total energy not distributed (*TEND*), obtained through Monte Carlo simulation.

$$\min \quad fitness=(\alpha_1 W_{Loss}+\alpha_2 TEND)\times 100 \tag{11}$$

Here, parameters α_1 and α_2 are calculated in order to reflect the importance of both objectives to the decision agent.

To estimate the annual active energy losses in order to better model seasonal effects and to achieve more precise results, the year was considered to have three seasons, summer (July, August and September), winter (December, January and February) and half-season (remaining months).

A daily representative loss profile in MV networks was also considered for each season (provided by ERSE[1]), as shown in Figure 5. The loss profile in each season reflects the existence of different types of consumers: residential, commercial and other tertiary activities.

[1] ERSE – Energy Services Regulatory Authority

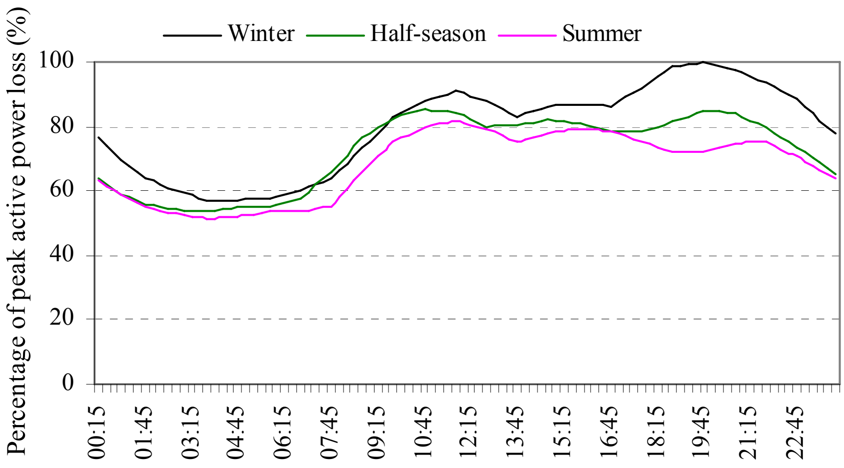

Figure 5 – Daily representative loss profile in MV networks by ERSE.

Mathematically the total active power loss on a distribution system can be calculated by summing up the power loss of each line through the following equation:

$$\sum_{i=1}^{B_i} r_i \frac{P_i^2 + Q_i^2}{|V_i|^2} \tag{12}$$

B_i is the total number of lines; r_i the resistance of the i-th line; P_i is the active power flow of the i-th line; Q_i is the reactive power flow of the i-th line; $|V_i|$ is the ending voltage of the i-th line.

The energy loss, W_{Loss}, is estimated after calculating the peak value of the active power loss through a power flow simulation in the distribution system, and also using the patterns of the loss profile (Figure 5). For this, the equation (13) is used:

$$W_{Loss} = 92 \times W_W + 90 \times W_S + 183 \times W_{HS} \tag{13}$$

Here, variables W_W, W_S and W_{HS} represent the daily active energy losses in winter, summer and half-season, respectively. Finally, the parameters α_1 and α_2 are calculated in order to reflect the importance of both objectives in the fitness function.

5. Case Study

This study analyses network reconfiguration in two perspectives. Basically the opportunity is given to the decision agent to decide if we want to invest or not in new tie- switches. The first perspective of optimization considers no investment, and the benefits achieved are only due to the existing switches. The second perspective identifies the optimal branches to be equipped with a new tie-switch. The maximum number of tie-switches that can be placed in the network is defined by the decision agent as well as the list of candidate places for a tie-switch installation.

The tested case is a 12.66 kV RDS based on Sahoo and Prasad (2006). The network is formed by one substation, 73 branches (including 7 sectionalizing switches and 5 tie-switches) and 69 nodes of which 48 are transformer units with the total load of 3.8 MW and 2.69 MVAr, as shown in Figure 6. In the case study analysis it was also considered a restricted number of branches without constraints in tie-switch placement including [9-11-13-17-26-36-40-47-49-53-56-64].

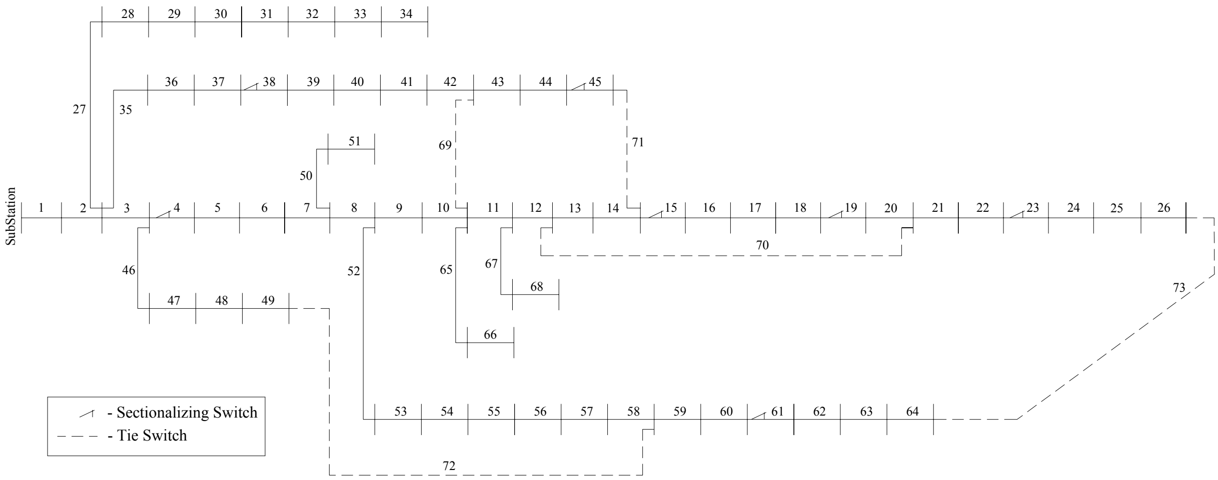

Figure 6 – Tested 69 bus radial distribution system.

5.1 IGA Control Parameters

The genetic control parameters were carefully determined due to its influence in the efficiency of IGA. In this study it was possible to achieve more promising results using the values shown in Table II.

Table II: Improved Genetic Algorithm (IGA) Control Parameters

Control Parameters	*Considered Value*
N_{ind}	20
R_r	50%
N_{pop}	50
B_{min}	0
B_{max}	100
pc_{min}	50%
pc_{max}	100%
pm_{min}	3%
pm_{max}	25%
D_{th}	3
C_{th}	15

5.2 Monte Carlo Simulation Parameters

In the case study, the Monte Carlo Simulation method considers 3000 trials, and, in each trial, the occurrence of 15 annual contingencies in predefined locations according to the reliability level assigned to each branch, as shown in Figure 7.

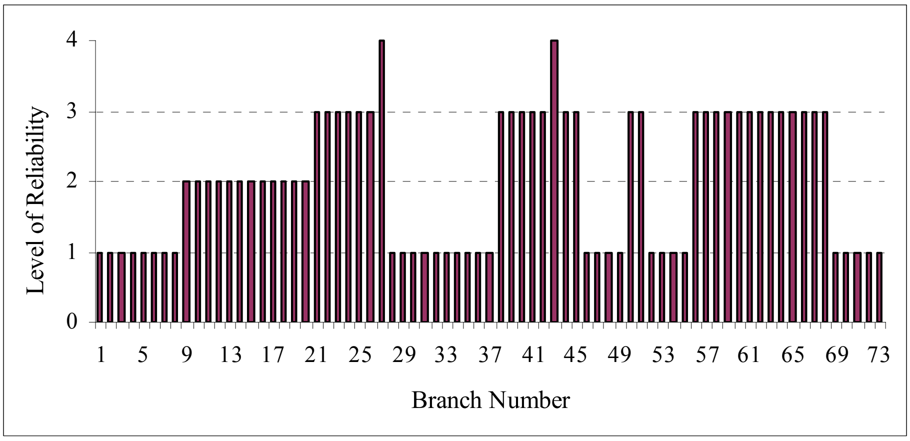

Figure 7 – Branch reliability levels of the 69 bus RDS.

The parameters that had been considered to characterize the severity of the contingencies are mentioned in Table III. Also, according to the reliability level of each branch, were assigned different probabilities to the several degrees of failure severity, as shown in Table IV.

Table III: Degrees of failure severity

Degree	*D_{av} (min.)*	*Standard deviation (σ)*
1	60	3
2	40	3
3	15	3

Table IV: Probability (%) of each degree of failure severity

Level of reliability	*Degree of failure severity*		
	1	2	3
1	60	40	0
2	40	50	10
3	20	40	40
4	0	20	80

6. Results

After analyzing the base network, the annual study revealed an annual active energy loss of 3157.5 MWh and a total energy not distributed of 4.2924 MWh, according to Table V. Due to the difference between these values a normalization method was used capable to reflect the importance of both objectives. Results demonstrate a first perspective of optimization (Table V) where the same weight to W_{Loss} and *TEND* were considered, i.e., w_1 and w_2 equal to 0.5. Parameter α_1 assumes the value 1.5835×10^{-4} and α_2 the value 0.1165 in the fitness function. On the other hand, in the second perspective of optimization, the possibility to install a new tie-switch was considered, in a first case, with the same weights (w_1 and w_2 equal to 0.5) and, in a second case, with different weights ($w_1 = 0.3$ and $w_2 = 0.7$) (Table VI). In this last case, parameters α_1 and α_2 are adjusted respectively to 0.9501×10^{-4} and 0.1631.

6.1 *Performance of the proposed solutions*

From Table V, using only the sectionalizing and tie-switches already installed in the network, we can obtain a first solution with W_{Loss} reduction of 6.5% and *TEND* reduction of 2.6%.

Table V: Optimization without investment

	Base network	*1st Solution*
Open Branches	[69-70-71-72-73]	[19-61-69-71-72]
W_{Loss} (MWh)	3157.5	2953.1
TEND (MWh)	4.2924	4.1801
Fitness value	100	95.45

From Table VI, installing a new tie-switch in branch 56 causes a more significant impact. In the first case, W_{Loss} reduction achieved 17.2% and *TEND* 28.5%. In the second case a higher priority to reliability was assumed at the expense of efficiency. Thus, a W_{Loss} reduction of 8.2% and *TEND* reduction of 37.3% were obtained.

Table VI: Optimization with investment (one new tie-switch)

	2nd Solution ($w_1 = 0.5$; $w_2 = 0.5$)	3rd Solution ($w_1 = 0.3$; $w_2 = 0.7$)
Open Branches	[15-**56**-61-69-71]	[19-45-**56**-69-73]
W_{Loss} (MWh)	2613.19	2898.69
TEND (MWh)	3.0706	2.6758
Fitness value	77.15	71.17

Note that it is also possible to maximize the voltage stability and the load balancing via loss minimization (Kashem and Moghavvemi (1998)). The solutions presented result in substantial improvements in these fields (Figure 8 and Figure 9). As in Kashem and Moghavvemi (1998), Figure 9 demonstrates that there exists a direct relationship between voltage stability and losses by showing that voltage stability is improved when losses are reduced.

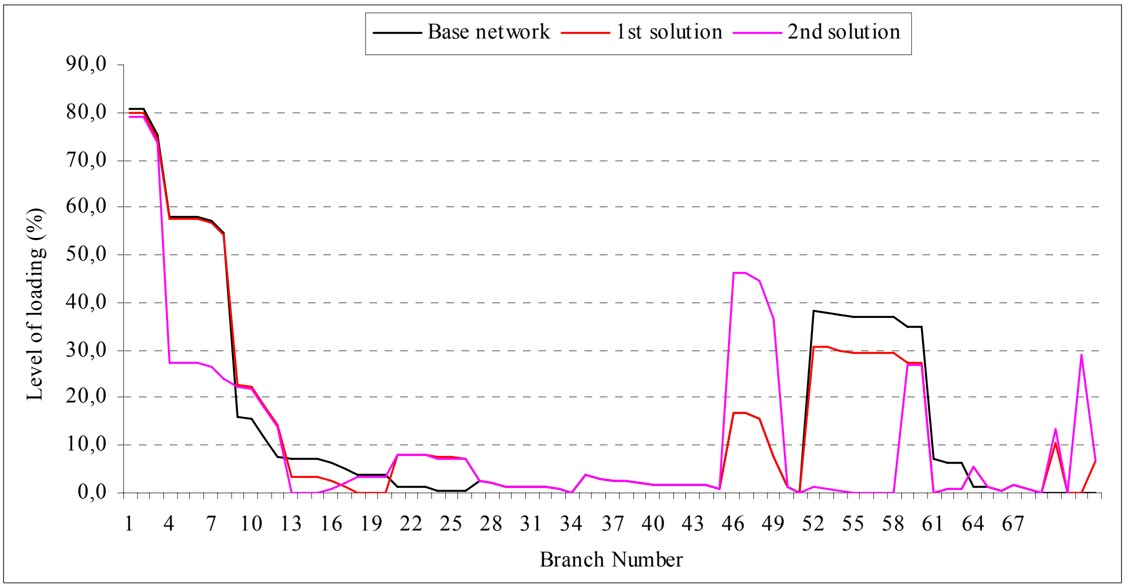

Figure 8 – Comparison load balancing between base and reconfigured 69 bus RDS.

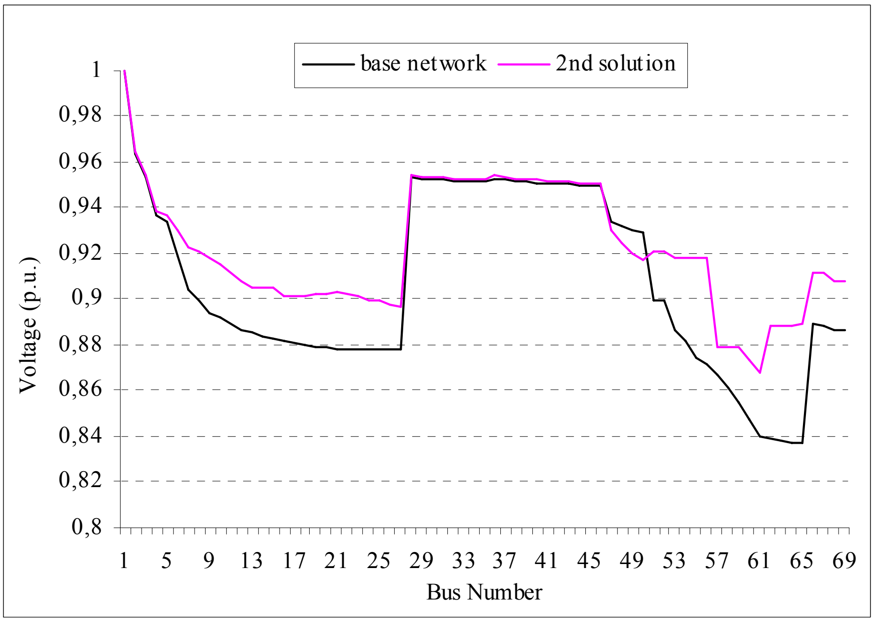

Figure 9 – Comparison voltage profile between base and reconfigured 69 bus RDS.

6.2 Behavior of the Improved Genetic Algorithm (IGA)

Figure 10 shows the convergence characteristic using IGA. Although the maximum number of generations was set to 50, all the runs were terminated under the convergence threshold. It also can be observed a fast convergence capability avoiding some considerable time to arrive at the best possible solution.

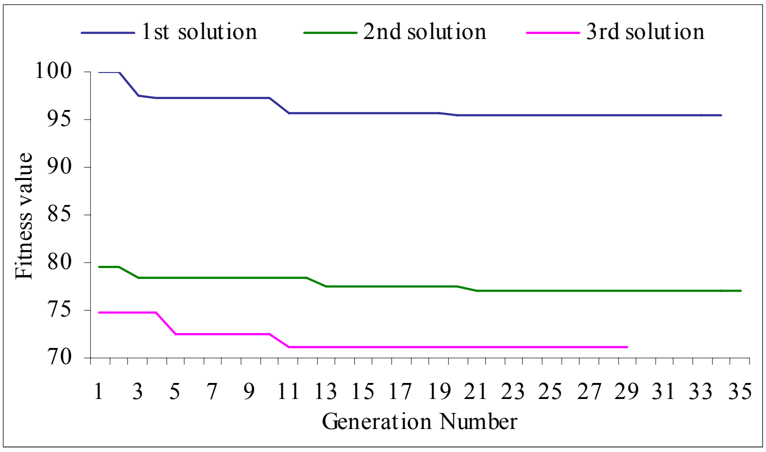

Figure 10 – Evolution of best fitness values using IGA.

The behavior of the curves shown in Figure 11 indicates that the evolution of the crossover rate and mutation rate are both dependent on each other. This behavior was expected since these operators are defined to maintain the genetic diversity in the population. When the values of a probability operator change, the values of the other operator must also change to obtain a good genetic diversity in the population. Thus, the learning of the crossover and mutation probabilities is dependent on the genetic diversity implied in the problem considered.

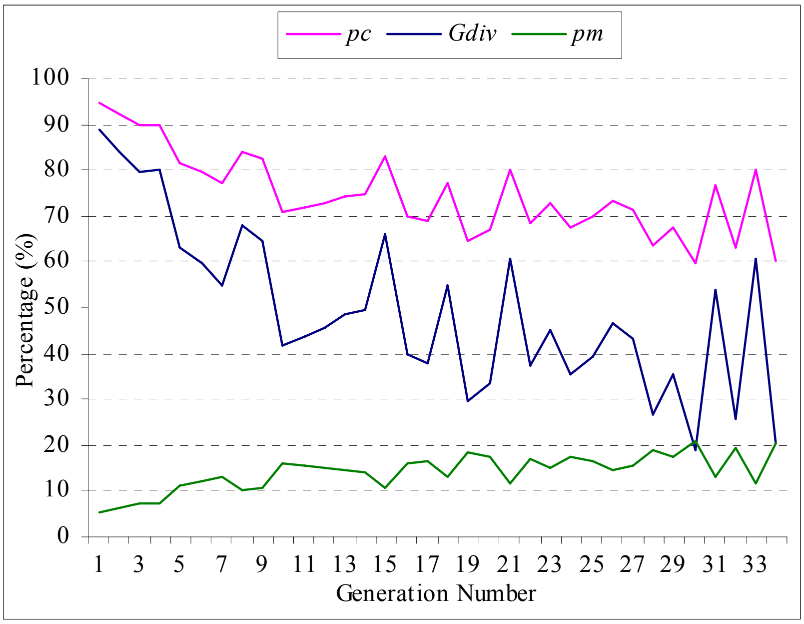

Figure 11 – Dynamic adjustment of genetic operator probabilities in search of the 1^{st} solution.

7. Conclusions

In this study an improved genetic algorithm (IGA) has been suggested in a two-perspective approach for network reconfiguration with the aim of improved reliability and efficiency. A Monte Carlo simulation method, based on the branch reliability, was used to predict the reliability of the network configurations.

The IGA uses a suitable coding technique ensuring a chromosome with a small length. This feature is responsible for a lower computational effort, when compared with other techniques. Other important feature of IGA, responsible for the increase of its efficiency, is the creation of a black list with the identification of all the infeasible solutions obtained during the optimization process.

The results demonstrate the good performance of IGA when applied to network reconfiguration problems (convergence speed and stability increased). The introduced features, namely dynamic crossover and mutation probabilities, allow the maintenance of the genetic diversity in the population thus preventing IGA to converge prematurely to a local optimum.

The optimization method allows considering different weights to both the objectives according to the preferences of the decision agent. In this study a 69 bus radial distribution system was considered. The results are encouraging, and future work should be directed to the inclusion of new objectives in the field of reliability and also to the dynamic variation of other GA parameters.

Finally this study demonstrates the direct relationship between losses, voltage stability and load balancing. It is noted that the efficiency of the distribution system is achieved through the minimization of losses which are also responsible for the improvements in voltage stability and load balancing.

8. References

Baran, M.E. and Wu, F.F. (1989), “Network reconfiguration in distribution systems for loss reduction and load balancing”, IEEE Transactions on Power Delivery, 4 (2), 1401–1407.

Borozan, V., Rajicic, D. and Ackovski, R. (1995), “Improved method for loss minimization in distribution networks”, IEEE Transactions on Power Systems, 10 (3), 1420-1425.

Billinton, R. and Wang, P. (1999), “Teaching distribution system reliability evaluation using Monte Carlo simulation”, IEEE Transactions on Power Systems, 14 (2), 397-403.

Brown, R.E. (2002), “Electric Power Distribution Reliability”, Marcel Dekker, Inc., New York.

Brown, R.E. (2003), “Network reconfiguration for improving reliability in distribution systems”, IEEE Power Engineering Society General Meeting, 4, 2419–2424.

Coelho, A., Rodrigues, A.B. and Da Silva, M.G. (2004), “Distribution network reconfiguration with reliability constraints”, 2004 International Conference on Power System Technology - PowerCon 2004, 2, 1600–1606.

Das, D. (2006), "Reconfiguration of distribution system using fuzzy multi-objective approach", International Journal of Electrical Power and Energy Systems, 28 (5), 331–338.

Garcia, V.J. and França, P.M. (2007), "Multiobjective service restoration in electric distribution networks using a local search based heuristic", European Journal of Operational Research, doi:10.1016/j.ejor.2006.07.048.

Huang, Y.C. (2002), "Enhanced genetic algorithm-based fuzzy multi-objective approach to distribution network reconfiguration", IEE Proceedings - Generation, Transmission and Distribution, 149 (5), 615–620.

Kashem, M.A. and Moghavvemi, M. (1998), "Maximizing radial voltage stability and load balancing via loss minimization in distribution networks", Proceedings of the International Conference on EMPD'98, 1, 91-96.

Lin, W.M., Cheng, F.S. and Tsay, M.T. (2000), "Distribution Feeder Reconfiguration with Refined Genetic Algorithm", IEE Proceedings – Generation, Transmission and Distribution, 147 (6), 349–354.

Merlin, A. and Back, H. (1975), "Search for a minimal-loss operating spanning tree configuration in an urban power distribution system", Proceedings of the fifth power system computation conference (PSCC), Cambridge, UK, 1–18.

Ou, Y. and Goel, L. (1999), "Using Monte Carlo simulation for overall distribution system reliability worth assessment", IEE Proceedings-Generation, Transmission and Distribution, 146 (5), 535–540.

Sahoo, N.C. and Prasad, K. (2006), "A fuzzy genetic approach for network reconfiguration to enhance voltage stability in radial distribution systems", Energy Conversion and Management, 47, 3288–3306.

Shin, D.-J., Kim, J.-O., Kim, T.-K., Choo, J.-B. and Singh, C. (2004), "Optimal service restoration and reconfiguration of network using Genetic-Tabu algorithm", Electric Power Systems Research, 71 (2), 145-152.

Shirmohammadi, D. and Hong, H.W. (1989), "Reconfiguration of electric distribution networks for resistive line losses reduction", IEEE Transactions on Power Delivery, 4 (2), 1492-1498.

Tang, Z., Zhu, Y., Wei, G. and Zhu, J. (2008), "An Elitist Selection Adaptative Genetic Algorithm for Resource Allocation in Multiuser Packet-based OFDM Systems", Journal of Communications, 3 (3), 27-32.

Vasconcelos, J.A., Ramírez, J.A., Takahashi, R.H.C. and Saldanha, R.R. (2001), "Improvements in Genetic Algorithms", IEEE Transactions on Magnetics, 37 (5), 3414-3417.

Vasconcelos, J.A. and Saldanha, R.R. (1997), "Genetic Algorithm Coupled with a Deterministic Method for Optimization in Electromagnetics", IEEE Transactions on Magnetics, 3 (2), 1860-1863.

Zhang, J., Chung, H.S.H. and Hu, B.J. (2004), "Adaptive Probabilities of Crossover and Mutation in Genetic Algorithms Based on Clustering Technique", Congress on Evolutionary Computation, CEC2004, 2, 2280-2287.