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Network Reconfiguration to Improve Reliability and Efficiency in Distribution Systems

R. M. Vitorino, L. P. Neves and H. M. Jorge, *Member, IEEE*

***Abstract*-- This paper presents a new method to improve reliability and also 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 an historical data of the network such as the severity of the potential contingencies in each branch. Due to the greater number of possible configurations and the need of an efficient search, is also used an improved genetic algorithm (IGA), with adaptive crossover and mutation probabilities and with other new features. The method analyses the RDS in a perspective of optimization considering no investment, and a perspective of optimization where is given the possibility to place a limited number of 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.**

***Index Terms*-- Improved Genetic Algorithm, Loss Minimization, Network Reconfiguration, Reliability**

I. INTRODUCTION

THE existing distribution networks are actually growing with complexity more and more, due to the gradual increase of power demand and the existence of customers with more sensitive loads. An interruption has nowadays more severe impact in load equipment than in loads existing 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 distribution network.

An efficient operation of distribution networks can, therefore, be achieved by using reconfiguration techniques. Basically, the network reconfiguration is carried out by changing the on/off status of the sectionalizing (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 usual goals as the reduction of power loss, load balancing or voltage stability. The reconfiguration impacts on the system reliability indices usually aren't included.

The main aim of this paper is to present a methodology for network reconfiguration with the objective of finding the optimal configuration that minimizes losses and also improves reliability.

To evaluate distribution system's reliability two techniques have been used, including analytical and Monte Carlo simulation methods. Reference [1] used a Monte Carlo simulation to overall distribution system worth assessment. 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 [2] 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, also using an analytical method to estimate reliability, [3] adopted a simulated annealing approach for network reconfiguration with the objective of minimizing losses taking into account reliability constraints.

Distribution system reconfiguration for loss reduction was first proposed by [4]. They have used a branch and bound type optimization technique to determine the minimum loss configuration. While formulating the loss reduction and load balancing as an integer programming problem, [5] meanwhile proposed efficient load flow equations to calculate the power flow. Based in [4], many heuristic approaches have been suggested [6], [7], [8] where many approximations of [4] have been overcome.

Reconfiguration has received considerable interest in recent years. Most of the network reconfiguration 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 [9], [10], [11].

R. M. Vitorino (M.Sc.) is with the Polytechnic Institute of Leiria – School of Technology and Management, Department of Electrical Engineering, Leiria, Portugal (phone: +351 244-820-300; fax: +351 244-820-310; e-mail: romeu@estg.ipleiria.pt).

L. P. Neves (Ph.D.) is with the Polytechnic Institute of Leiria – School of Technology and Management, Department of Electrical Engineering, Leiria, Portugal (e-mail: lneves@estg.ipleiria.pt).

H. M. Jorge (Ph.D.) is with the University of Coimbra, Department of Electrical Engineering and Computers, Coimbra, Portugal (e-mail: hjorge@deec.uc.pt).

Authors are also with the R&D Institute INESC, Coimbra, Portugal (phone: +351 239-851-040; fax: +351 239-824-962).

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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 [12], [13]. 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 [14]. In this paper is proposed an improved genetic algorithm (IGA), with the ability to search global or near global optimal solutions. In this particular case, is also introduced some new features improving accuracy and the computational efficiency. IGA introduces a list of non-admissible solutions, a two-termination criterion and also dynamic adaptation of crossover and mutation probabilities according to the genetic diversity in the population.

The structure of the paper is the following: The next section will describe in more detail the improved genetic algorithm (IGA) and its main features. Section III is dedicated to the evaluation of distribution system reliability through Monte Carlo simulation. In Section IV is defined the fitness function in terms of losses and reliability. In Section V and VI the case study and test results will be presented. Finally, the conclusions and references complete the paper.

II. 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 approach, i.e. one bit for one branch. This kind of technique also allows, in a large scale, the generation of non-admissible solutions.

Also the most crucial aspect of the RDS reconfiguration is that important measures must be taken to guarantee the radiality of the network. In this particular case, using the IGA it is possible to ensure a chromosome with a small length and also that the network remains radial in every stage of the genetic evolution under the application of the genetic operators, i.e. mutation and crossover. For this, the IGA uses a suitable coding and decoding technique based on [10].

The generation gap represents the percentage of individuals to copy to the new population. In this paper, IGA uses a fixed size population of size (N_{ind}) and a fixed renewal rate (R_r) in all generations. After generating randomly the initial population, 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. IGA also adopts an elitist selection meaning that the best individual at generation *k* is maintained in the next generation *k*+1.

A. Genetic Operators

A new generation of individuals is produced as a result of genetic manipulation applied on parents. Crossover is the predominant operator and, therefore, with a higher probability of occurrence. This operation is made between pairs of parents randomly chosen and it consists in generating new individuals with characteristics of both parents. New points in the feasible space are generated. In this paper, 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 cutting points well defined.

Other genetic operator applied, but 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 and so, ensures 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 paper, the mutation operator is applied to each bit of the chromosome with a certain probability *pm*.

B. 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 and is used the vector distance [15]. Suppose individual *i* is represented as $Ind_i = [g_i(1), \dots, g_i(\mathrm{N})]$, and individual *j* is represented as $Ind_j = [g_j(1), \dots, g_j(\mathrm{N})]$. To define the distance between individuals *i* and *j* the following equation is used:

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

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

$$G_{div} = \left(\frac{\sum_{i=1}^{N_{ind}} \sum_{j=i+1}^{N_{ind}} 1_{\{d(i,j) > D_{th}\}}}{{}_{N_{ind}}C_2} \right) \times 100 \qquad (2)$$

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.

C. 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 [15]. 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 [12].

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

$$pc = \begin{cases} pc_{\min}, & if\ \ G_{div} < B_{\min} \\ pc_{\max}, & if\ \ G_{div} > B_{\max} \end{cases} \tag{3}$$

$$pm = \begin{cases} pm_{\max}, & if\ \ G_{div} < B_{\min} \\ pm_{\min}, & if\ \ G_{div} > B_{\max} \end{cases} \tag{4}$$

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:

$$pc = \left(\frac{pc_{\min} - pc_{\max}}{B_{\min} - B_{\max}} \right) G_{div} + \left(\frac{pc_{\max} B_{\min} - pc_{\min} B_{\max}}{B_{\min} - B_{\max}} \right) \tag{5}$$

$$pm = \left(\frac{pm_{\max} - pm_{\min}}{B_{\min} - B_{\max}} \right) G_{div} + \left(\frac{pm_{\min} B_{\min} - pm_{\max} B_{\max}}{B_{\min} - B_{\max}} \right) \tag{6}$$

D. Termination

In IGA the termination criterion is dependent either on the maximum number of generations (N_{pop}), or a convergence threshold (C_{th}). If the best fitness value in the population, during C_{th} generations, not suffers any changes then we may assume the convergence of IGA.

E. List of non-admissible solutions

An important feature of IGA, responsible for the increase of its efficiency, is the creation of a list with the identification of all the non-admissible 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 and transformers capacity and heat capacity of all the branches are satisfied. The non-admissible 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.

III. Evaluation of Distribution System Reliability

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 [2]. 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, 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 complex systems.

A. Monte Carlo Simulation Method

Various approaches can be followed when performing Monte Carlo simulation on electric power systems. In this study, is focused the branch reliability level, a fundamental element to assure continuity of service. To define the reliability level of each network branch it was considered four levels according to Table I.

TABLE I
Branch Reliability levels

Level	Failure
1	Very unlikely
2	Unlikely
3	Likely
4	Very likely

In order to better characterize the possible contingencies, were defined different degrees of severity based on historical data, each with different average interruption durations (D_{av}). Each branch of the network is also characterized according to probability of potential contingencies with the different degrees of severity. Here, past performance statistics provide a valuable reliability profile of the existing system.

The method considers (N_t) trials and, in each trial, an annual number of contingencies (N_{cont}), one by one, is simulated and analyzed their impact in the reliability indices. The interruption duration of each contingency is variable and is obtained through a normal density curve with a standard deviation (σ) and average. Finally are estimated the annual reliability indices in the considered network configuration. The total energy not distributed (*TEND*) is used as the reliability index to minimize in this study.

IV. Fitness Function Definition

Through IGA is possible to optimize the RDS in terms of losses and reliability. For this, a fitness function that we want to minimize is used to evaluate the performance of the solutions. The fitness function is defined using the equation (7) and basically considers the annual active energy loss (W_{Loss}) and total energy not distributed (*TEND*), obtained through Monte Carlo simulation.

$$\min \quad fitness = (\alpha_1 W_{Loss} + \alpha_2 TEND) \times 100 \qquad (7)$$

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).

It was also considered a daily representative loss profile in MV networks for each season, as shown in Fig. 1. The pattern of the loss profile in each season reflects the existence of typical types of consumers as residential, commercial and services.

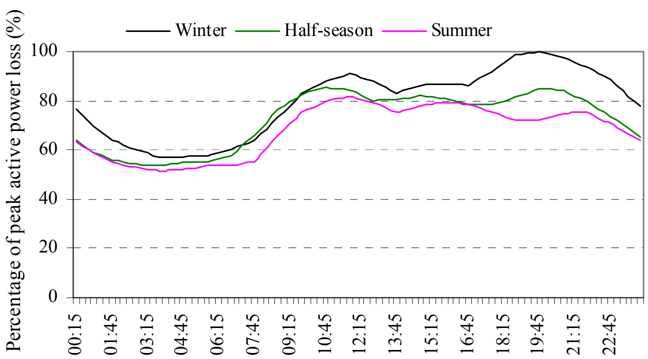

Fig. 1. Daily representative loss profile in MV networks.

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, is possible to estimate W_{Loss}. For this, the equation (8) is used:

$$W_{Loss} = 92 \times W_W + 90 \times W_S + 183 \times W_{HS} \qquad (8)$$

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.

V. Case Study

This study analyses network reconfiguration in two perspectives. Basically is given to the decision agent the opportunity to decide if we want to invest, or not, in new tie-switches according to the obtained results. I.e., a first perspective of optimization that considers no investment, where the benefits achieved are only due to the existing switches, and a second perspective that plans the optimal branches to be equipped with a 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 [10]. The network is formed by one substation, 73 branches (including 7 sectionalizing switches and 5 tie-switches) and 69 nodes of which 48 are transformation units, as shown in Fig. 2. 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].

A. IGA Control Parameters

In this study using the values shown in Table II, it was possible to achieve more promising results.

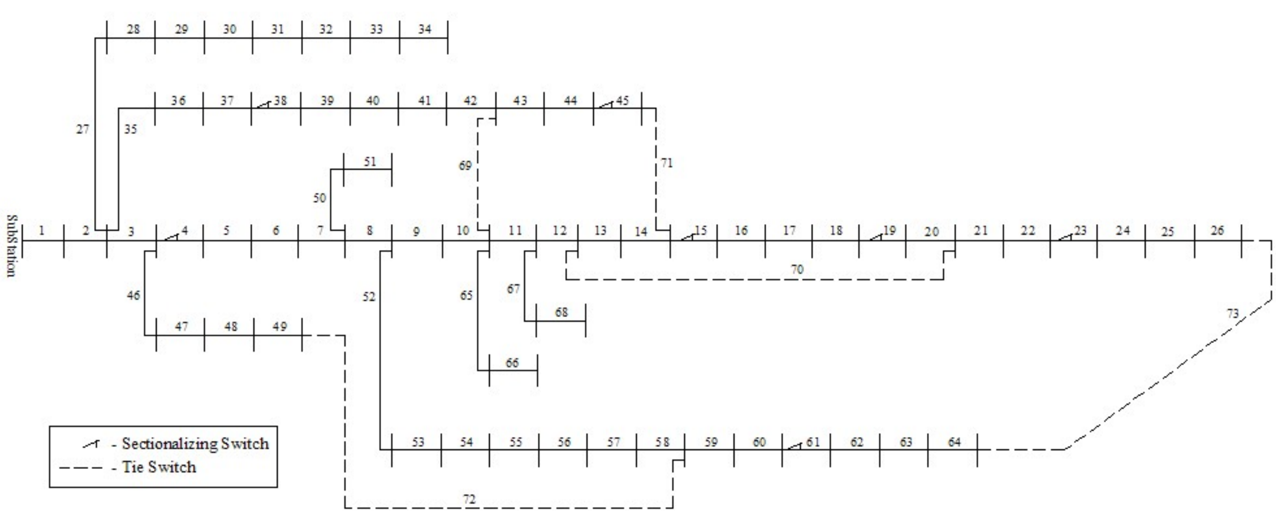

Fig. 2. Tested 69 bus radial distribution system.

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

B. 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 Fig. 3.

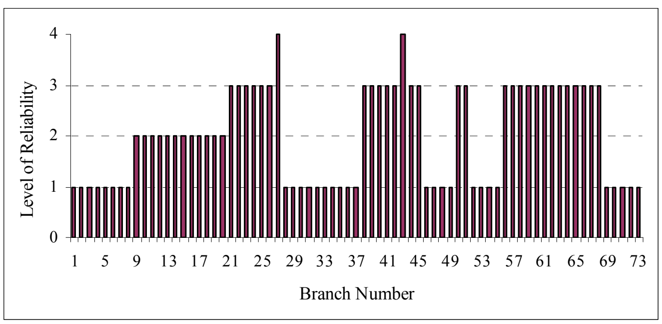

Fig. 3. Branch reliability levels of the 69 bus RDS.

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 POTENCIAL CONTINGENCIES

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

VI. 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 it was used a normalization method capable to reflect the importance of both objectives. Results demonstrate a first perspective of optimization (Table V) where it was considered the same weight to W_{Loss} and *TEND*, 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, a second perspective of optimization with the possibility to install a new tie-switch where it was considered, in a first case, the same weights (w_1 and w_2 equal to 0.5) and, in a second case, 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.

A. Performance of the proposed solutions

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 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 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

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

Note that it is also possible to maximize voltage stability and load balancing via loss minimization [16]. The solutions presented result in substantial improvements in these fields. As in [16], Fig. 4 demonstrates that there exists a direct relationship between voltage stability and losses by showing that voltage stability is improved when losses are reduced.

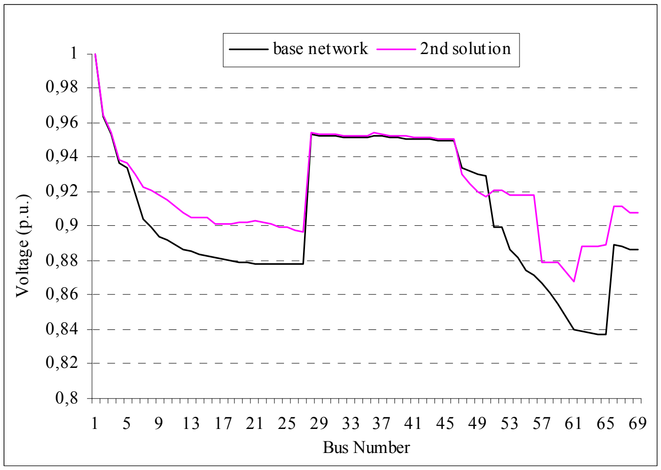

Fig. 4. Comparison voltage profile between base and reconfigured 69 bus RDS.

B. Behavior of the Improved Genetic Algorithm (IGA)

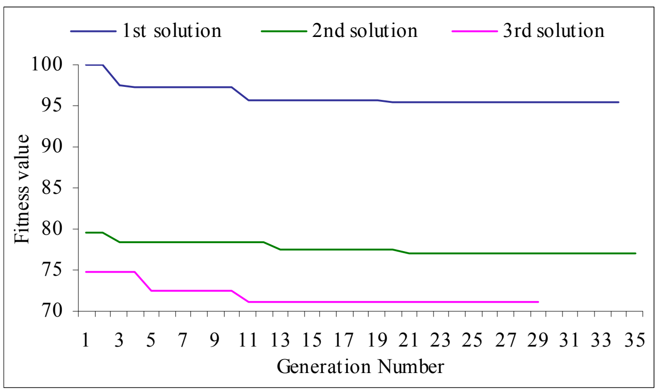

Fig. 5. Evolution of best fitness values using IGA.

Fig. 5 shows the convergence characteristic using IGA. Although the maximum number of generations was set to 50, all the runs 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.

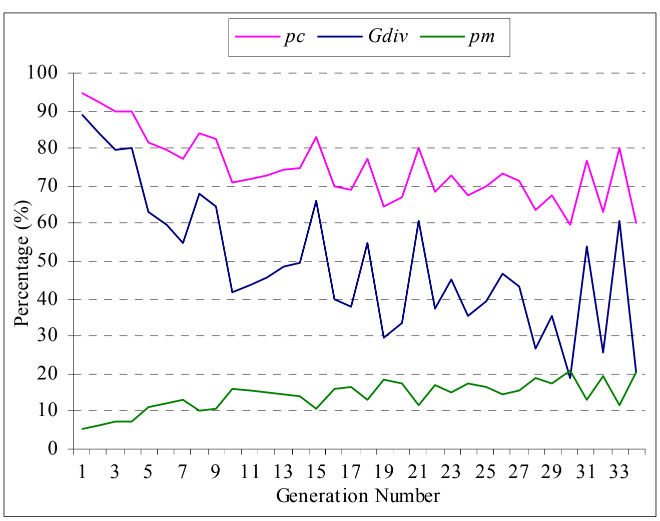

Fig. 6. Dynamic adjustment of genetic operator probabilities in search of the 1st solution.

The behavior of the curves shown in Fig. 6 indicates that the evolution of the crossover rate and mutation rate are both dependents 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.

VII. Conclusions

In this paper 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 reliability of the network configurations.

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 maintaining the genetic diversity in the population and thus preventing IGA to converge prematurely to a local optimum.

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 it is noted that the efficiency of the distribution system is achieved through the minimization of losses which is also responsible for the improvements in voltage stability and load balancing.

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IX. BIOGRAPHIES

Romeu M. Vitorino was born in Coimbra, Portugal on 14 December 1979. He is currently a Ph.D. student at Faculty of Sciences and Technology of the University of Coimbra (FCTUC). He received is M.S. degree in Electrical and Computer Engineering, specialization in Energy Systems, from FCTUC, in 2006. He is a researcher in Institute for Systems and Computers Engineering of Coimbra (INESCC), and also assistant professor since 2003 at the Department of Electrical Engineering in Polytechnic Institute of Leiria, School of Technology and Management, Portugal. His current research includes optimization and planning in distribution systems.

L. P. Neves - received his Electrical Engineering degree in 1992 and his PhD degree in 2005, both from the University of Coimbra. He is auxiliary Professor at the School of Technology and Management of the Polythecnic Institute of Leiria. His research areas include Demand-Side Management, Power Systems Planning and Analysis and Operational Research.

H. M. Jorge - received his Electrical Engineering degree in 1985 and his PhD degree in 1999, both from the University of Coimbra. He is auxiliary Professor at the Department of Electrical Engineering of University of Coimbra. His research areas include load research, load forecast, load profile, power quality, power distribution and energy efficiency. He is an IEEE member since 1992 (nº. 3181112).