Genetic Algorithms and Treatment of Multiple Objectives in the Allocation of Capacitor Banks in an Electric Power Distribution System

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Abstract - Genetic Algorithm (GA) is a non-parametric optimization technique that is frequently used in problems of combinatory nature with discrete or continuous variables. Depending on the evaluation function used this optimization technique may be applied to solve problems containing more than one objective. In treating with multi-objective evaluation functions it is important to have an adequate methodology to solve the multiple objectives problem so that each partial objective composing the evaluation function is adequately treated in the overall optimal solution. In this paper the multi-objective optimization problem is treated in details and a typical example concerning the allocation of capacitor banks in a real distribution grid is presented. The allocation of capacitor banks corresponds to one of the most important problems related to the planning of electrical distribution networks. This problem consists of determining, with the smallest possible cost, the placement and the dimension of each capacitor bank to be installed in the electrical distribution grid with the additional objectives of minimizing the voltage deviations and power losses. As many other problems of planning electrical distribution networks, the allocation of capacitor banks is characterized by the high complexity in the search of the optimum solution. In this context, the GA comes as a viable tool to obtaining practical solutions to this problem. Simulation results obtained with a real electrical distribution grid are presented and demonstrate the effectiveness of the methodology used.

Key words – Genetic Algorithm, Multiple Objectives, Allocation of Capacitor Banks and Electric Distribution Grid

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I. Introduction

Genetic algorithm is a branch of the evolutionary algorithms and as such it can be defined as a search technique based in a metaphor of the biological process of natural evolution (LINDEN, 2006).

The GA may be applied to problems with one or more objectives. Each objective, in general, can be seen as a type of inherent evaluation of the individuals of a population. Such individuals (chromosomes) represent the solutions to the problem. The use of the GA with a single evaluation function (one objective) is very well understood and returns very good results in general. The use of GA with multiple evaluation functions, in other words, multiple objectives, in general, has not been an easy task (ZHU & LEUNG, 2002; LINDEN, 2006).

LIDEN (2006) comments in his book that there are several ways to work with multi-objective problems, when using GA as the optimization tool, as for example: *no-Pareto* optimization approach (ZEBULUM, 2002); the VEGA algorithm (Vector Evaluated Genetic Algorithm), (ZEBULUM, 2002; EIBEN, 2004); separation of objectives and making the selection by the comparison of individuals pairs in agreement with the chosen objective in a random way (FONSECA, 1995); separation of objectives for the division of the operation of the genetic algorithm in *t* phases, being *t* the number of existent objectives (ZITZER, 2003); method based on weights (NG *et al.*, 2000; AMAZONAS FILHO *et al.*, 2004), among others.

The difficulty in working with multiple objectives and, therefore, the need to simplify this process is one of the main motivators of this work. Another motivator is the improvement and transparency in the manipulation of the different evaluation functions used in the allocation of capacitor banks using GA.

II. Genetic Algorithms

To understand in a clear way the applied methodology for equally considering the different evaluation functions (objectives) in a multi-objective fitness function it is initially made use of the fundamental concepts of the basic GA for a single evaluation function and, subsequently, this same principles are used so that each evaluation function behaves in the selection process as if the others didn't exist.

The GA procedure is summarized by the steps illustrated in **Figure 1**.

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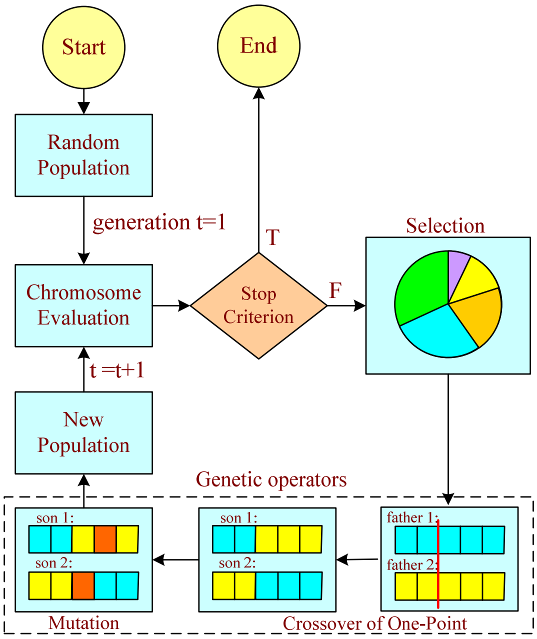

Figure 1 – Basic Genetic Algorithm.

The GA processing begins with an initial population in which the genetic material for each individual of the population is established randomly.

The Evaluation Process calculates the evaluation values for each chromosome (solution). To avoid problems related to super-individuals or when the evaluation values of the individuals of the population are very close amongst themselves and very distant from the reference, fitness evaluation techniques are adopted such as Linear Normalization and Windowing (GOLDBERG, 1989). For this work the Linear Normalization is used as the fitness evaluation technique. This avoids not only the two mentioned aspects as well as it allows the evaluation values to be negative. In other words, the Linear Normalization is equal to establishing fitness values uniformly distributed in an interval and linearly related with the rank of the best fit individuals. Therefore, what defines the selection frequency of each individual in the population is its position in the rank of the best fit individuals. In the end of the evaluation process, the fitness values are passed to the selection process.

The selection process characterizes the most important step of the GA, because it is this process that imitates the Natural Selection. The selection process is governed by selection techniques such as the Roulette-Wheel Selection, the Tournament Selection and the Stochastic Universal Sampling (GOLDBERG, 1989).

The genetic operators of crossover and mutation act after the selection process and they determine the balance among the exploitation and exploration elements during the evalution of the Genetic Algorithm. The crossover is commonly accomplished by techniques such as the crossover of One-Point, Two-Points and Uniform (DAVIS, 1991).

After the application of the genetic operators, a new population is obtained. According to **Figure 1**, all of the individuals of the population are changed by their descendants. But, with the purpose of adding components of memory of previous evolutions, individuals of the old population can be added to the new population. That is accomplished through techniques such as Elitism and Stead State (DAVIS, 1991).

The methodology proposed in this work doesn't interfere in the way of processing the phases of the basic GA, described previously. It just adds one more particularity to the process that will be presented in the next section. The *LabWASF* software, used to simulate the results presented in this paper, incorporate the basic GA configuration as well as the proposed methodology.

III. Calculation of The Total Fitness Value

In general, one aspect that distinguishes an evaluation function from another is its metric, such as *MW*, *Volts*, *$*, among others. It is common to join the values of each evaluation function in a multi-objective evaluation function. When the values of the different evaluation function are of the same metric, this combination becomes the more recommended. However, not being this the case, the multi-objective evaluation function cannot supply a fair balance among the values of the different evaluation functions. That is strongly evidenced when the order of the numeric values for each evaluation function is significant, which makes the total evaluation value of the chromosome to be characterized strongly by the value of the evaluation function with larger numeric values, because it causes larger impact on the value of the overall evaluation function. It is still common to observe the use of constant factors to penalize the values of the different evaluation functions. However, the values of these constants must be defined by the user in a trial and error approach and may cause additional difficulty in the interaction between the user and GA.

In the following analyses it is considered only the evaluation process without losing of view the impacts in the selection process. It is supposed a population with ***M*** chromosomes and that each chromosome of the population must be evaluated by ***N*** evaluation functions. The value corresponding to the evaluation function ***i*** of the chromosome ***k*** is defined as:

$$Evaluation\ _i^k \,, \qquad (1)$$

Where $1 \le k \le M$ and $1 \le i \le N$.

In this point, no effort should be made to join the evaluation functions. It is calculated the individuals aptitudes according to the adopted fitness evaluation technique (Linear Normalization). However, to apply this technique it is necessary to establish the *rank* values of the most capable individuals for each evaluation function. In this context, each one of the evaluation function ***i*** is used without considering the other functions, as what happens in a GA that makes use of a single evaluation function. Then, each evaluation function ***i*** will create a *rank* ***i***. **Figure 2** allows to observe the classification of the individuals of a hypothetical population for each rank ***i***. In this figure, ***j*** is the placement of the chromosomes in the *rank*, ***i*** indicates the evaluation function to which the rank is associated and ***k*** is the index of the chromosome. Then, **Figure 2** illustrates a rank matrix whose elements are the indexes ***k*** of the chromosomes, the lines are given by ***j*** and the columns by ***i***.

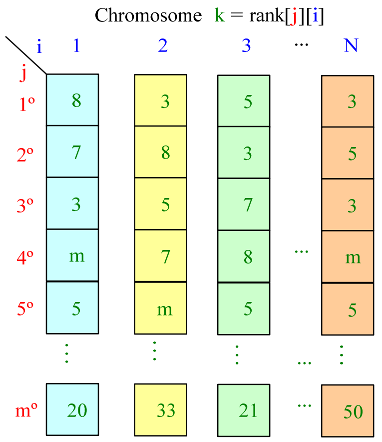

Figure 2 – Ranks associated to each evaluation function.

Each *rank* ***i*** creates a fitness value for each chromosome of the population and, therefore, for the **N** *ranks* there is, for each chromosome, ***N*** fitness values. Considering the technique of Linear Normalization the aptitude value of chromosome ***k*** with placement ***j*** in the *rank* ***i*** is given for:

$$Fitness_i^{\,k} = \max - \frac{(\max - \min)}{1 - M} \cdot (j-1) \qquad (2)$$

Where $k = rank[j][i]$, $1 \le j \le M$ and $1 \le i \le N$.

The values of *min* and *max* are defined by the user. However, if the selection method is the Roulette-Wheel Selection and the size of the population is not very big, a good choice would be *min=1* and *max=M*. This choice gives to the less fit chromosome a chance of survival equal to the difference among the chances of two any consecutive chromosomes. However, if the selection method is the Tournament, the less fit individual will be dead for any value *min*. In this case a convenient value would be *min=0* and *max=100*.

Figure 3 illustrates the graphic representation of **Equation (2)**.

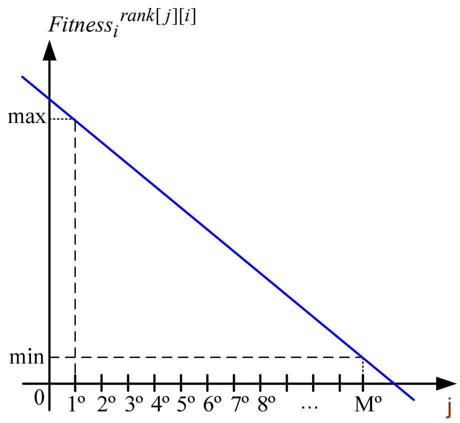

Figure 3 – Graphic representation of Equation (2).

To simplify this analysis, without loss of generality in relation to other selection methods, the use of the Roulette-Wheel Selection is adopted as selection method. Then, if each *rank* ***i*** is observed in an independent way of the other ones and, for any values chosen for *max* and *min*, it can be concluded that the fitness values of each *rank* ***i*** generate similar roulette, as it is illustrated in **Figure 4**. It can be observed in **Figure 4** that the proportionality among the slices of the roulettes that correspond to a placement **jº** is identical. Therefore,

$$\sum_{k=1}^{M} Fitness_1^k = \sum_{k=1}^{M} Fitness_2^k = \ldots = \sum_{k=1}^{M} Fitness_N^k \qquad (3)$$

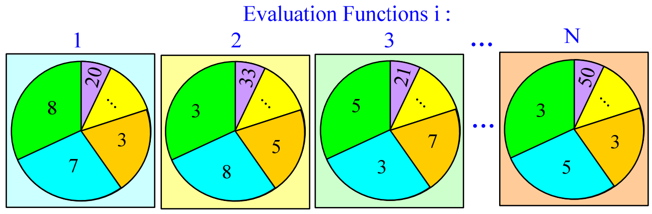

Figure 4 – One Roulette associated to each rank ***i*** shown in the **Figure 2**.

Under this aspect, the different fitness functions and, therefore, the different evaluation functions are normalized.

If the basic GA was performed for each one of those roulettes ***i*** in an independent way, each chromosome ***k*** would be selected as father with a frequency proportional to its slice. Therefore,

$$f_i^{\,k} = \frac{Fitness_i^{\,k}}{\sum_{k'=1}^{M} Fitness_i^{k'}} \qquad (4)$$

It is supposed now that basic GA, for each father to be selected, raffles one of the roulettes at random. Therefore, each roulette is chosen with a frequency $\frac{1}{N}$. Therefore, the chromosome would be selected as father with a frequency given for:

$$f^{\,k}total = \sum_{i=1}^{N} \left(\frac{Fitness_i^{\,k}}{\sum_{k'=1}^{M} Fitness_i^{k'}} \cdot \frac{1}{N} \right) \qquad (5)$$

Starting from the **Equations (5)** and **(3)**, it is obtained:

$$f^{\,k}total = \left(\frac{Fitness_{total}}{\sum_{k'=1}^{M} Fitness_i^{k'}} \right) \qquad (6)$$

Where,

$$Fitness^{\,k}total = \frac{\sum_{i=1}^{N} Fitness_i^{\,k}}{N} \qquad (7)$$

corresponds to the total fitness value of the chromosome **k**.

Applying the total fitness values (given by the **Equation (7)**) to the selection process of basic GA, it can be obtained the same effect suggested with the hypothetical raffle of the roulettes ***i***. The advantage, in relation to the hypothetical raffle, is that the bad luck is eliminated or the luck of a certain roulette to be raffled less or more times, what would generate a sampling mistake for a number not very big of raffles. In this context, the impact of each evaluation function ***i*** in the total fitness value is equivalent to the impact of any other evaluation function.

An interpretation of the presented methodology would be that, in the evolution process, a chromosome cannot improve its placement in the *rank* of one or more evaluation function in detriment to big placement falls in one or more *ranks* of other evaluation function. The effort of the GA is then in the sense of finding a chromosome that presents the best placement in all the *ranks* ***i***. If for a certain problem there is a chromosome which is the first in all of the ranks then, after an amount of enough generations, this chromosome represents the best solution of the problem.

Finally, it can be added a weight p_i to each $Fitness_i^k$ of **Equation (7)** to define how much an evaluation function ***i*** is important in relation to the others.

IV. Allocation of Capacitor Banks

The allocation of capacitor banks corresponds to one of the most important problems related to the planning of electrical distribution grids. This problem consists of determining the placement and the dimension of each capacitor bank in the distribution grid with the objective of minimizing the voltage deviations and power losses for example. As many other problems of planning electrical distribution networks, the allocation of capacitor banks is characterized by high complexity in the search of the optimal solution (AMAZONAS FILHO *et al.*, 2004). In this context, the GA comes as a viable tool for the determination of the best solution to the problem, because GA performs a process of parallel search on an enormous amount of *schemata*.

The proposed solution presents three different evaluation functions, namely: the Cost of CBs ($), the Total Voltage Deviation (p.u.) and the Total Power Losses (kW) of the Distribution Grid.

The first objective is to reduce the active power losses. This also relieves the stress of the system and, consequently, increases the useful life of their components.

The second objective is to reduce the voltage deviation between the actual bus voltage and the specified voltage.

The third objective is to reduce the cost and, therefore, the amount of capacitors banks kVAr's allocated to reduce losses and the total voltage deviation.

It is important to point out, that, in many problems with multiple objectives, one or more objectives may be conflicting amongst themselves. For example, in the allocation of the Capacitor Banks the reduction in the total voltage deviation and the reduction of cost of CBs are conflicting objectives. In other words, a decrease in the total voltage deviation value tends to increase the cost in the allocation of CBs.

Differently of the proposal of this work, it is common to observe for the problem of capacitor banks allocation, the use of a single evaluation function based on weights, according to Equation (8) (AMAZONAS FILHO *et al.*, 2004):

$$Evaluation = p_p \times P_{kW} + p_c \times (C_{actual} - C_{budget})^2 + p_t \times C_t \quad (8)$$

Where:

$$C_t = \sum_{b=1}^{N_b} \left(\frac{V_b - V_b^{espec}}{\Delta V_b^{\max}} \right)^2 \quad (9)$$

C_t : Evaluation function for the voltage deviation;

P_{kW} : Evaluation function for system active loss in kW;

C_{actual} : Actual cost of capacitor banks;

C_{budget} : Foreseen budget for allocation of capacitor banks;

V_b : voltage at bus ***b***;

V_b^{espec} : specified voltage at bus ***b***;

$\Delta V_b^{\max}$: maximum voltage deviation at bus ***b***.

$p_p, p_c\, e\, p_t$: weight constants in the interval [0,1] defined by the user.

It is observed in the **Equation (8)** that the user shall execute two tasks. The first, and the most difficult, is to define the values of the weights p_p , p_c e p_t which don't have transparency in their meanings. The second task is to define the foreseen budget for the purchase of capacitor banks. This decision can be critical, because the user can spend a much larger monetary value than the necessary to reach a good solution. If this budget value is to be obtained from **Equation (8)**, the GA will try to spend the whole resource, because the portion regarding the cost of the banks is a parabola with minimum in $C_{actual} = C_{\mathrm{budget}}$.

Applying the proposal of this work, these two tasks are eliminated and, therefore, the process becomes simpler. Then, each chromosome of the population will present three evaluation functions as objectives, which are given by:

$$Evaluation_1 = C_t = \sum_{b=1}^{N_b} |V_b - 1{,}0| \quad (10)$$

$$Evaluation_2 = P_{kW} \quad (11)$$

and

$$Evaluation_3 = C_{actual} \quad (12)$$

The equation for C_t was simplified making $V_b^{espc} = 1{,}0\, p.u.$ and $\Delta V_b^{\max}$ be constant for all buses. The exponentiation operation was substituted by the operator of absolute value $|\ |$. This allows calculating in percentage the gain in the total voltage deviation for the solution suggested by GA.

The value of C_{actual} is given as the reactive compensation suggested by the chromosome. For each reactive compensation value there is a cost ($) associated to the Capacitor Bank as shown in **Table 1** (AMAZONAS FILHO *et al.*, 2004).

Table 1 – Cost of the Capacitor Bank.

Tap	Reactive Compensation (kVAr)	Capacitor Banks' Cost ($)
1	150	1.797,00
2	300	1.925,00
3	450	1.944,00
4	600	2.1875,00
5	900	3.060,00
6	1200	3.546,00

Equations (10), **(11)** e **(12)**, after the process of Linear Normalization, are used in **Equation (7)** for the calculation of the total fitness value of each chromosome. **Equations (10)**, **(11)** e **(12)** show the simplicity of working with the objectives. However, it is important to point out, that in this case, all the objectives have the same degree of importance. But, in case it is necessary, it can be added, with total transparency, a weight p_i to each $Fitness_i^k$ in **Equation (7)** to define how much an evaluation function is important in relation to the other.

V. Genetic Representation

For each capacitor bank (CB) two variables are necessary: *tap* and busbar location at which the capacitor bank will be installed. The tap values presented in **Table 1** allow defining the reactive power compensation and the capacitor bank cost.

The chromosome codification is that shown in **Figure 5**, using a binary representation where the genes represent the busbars and the capacitor bank taps.

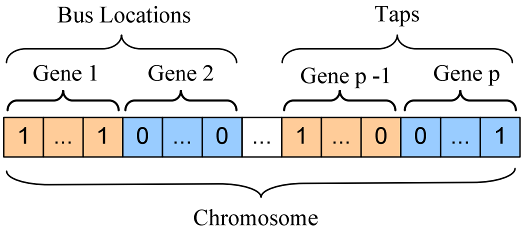

Figure 5 - Conceptual genetic representation approached in the LabWASF software.

VI. Results

The simulations are divided in three groups: (A), (B) and (C). In simulation (A) the minimization in the total voltage deviation is considered as the only objective, and in simulation (B) the objective is the active power loss minimization alone. In simulation (C) three simultaneous objectives are considered: reduction in the total voltage deviation, reduction in the active power losses and reduction in the cost of the capacitor banks allocation. This way, in case (C), the objective is to minimize the total fitness function.

A load flow program was used in all simulations to calculate the total voltage deviation and the real power losses. These calculated values are used in the chromosomes evaluation process.

The electrical distribution grid used in the simulation studies is a feeder with 222 distribution transformers (busbars) that is located in Belém City, capital of the State of Pará, in Brazil.

Finally, the following parameters of the Genetic Algorithm were adopted for simulations (A), (B) and (C):

Number of Generations: 100
Genetic operators: Together
Mutation Rate: 0,03
Generation Technique: Elitism
Fitness Evaluation Technique: Linear Normalization
Selection Technique: Tournament
Type of Crossover: One-Point

A. Minimization of the Total Voltage Deviation

In this simulation, the Genetic Algorithm allocated the nominal capacity of the capacitor banks, as shown in **Table** 2. In this case, the GA proposed a solution whose gain in the reduction of the total voltage deviation was of 99,95% and whose gain in the reduction of the power losses was of 13,29%. The cost of capacitor banks allocation was of $ 14.180,00 which is equal to 100% of the available resource.

Table 2 – Solution proposed by the GA when the objective is the minimization of the total voltage deviation.

Buses	**124**	**50**	**21**	**17**
Taps	6	6	6	6

Figure 6 shows the total voltage deviation evaluation of the best fit individual in the reduction of the total voltage deviation

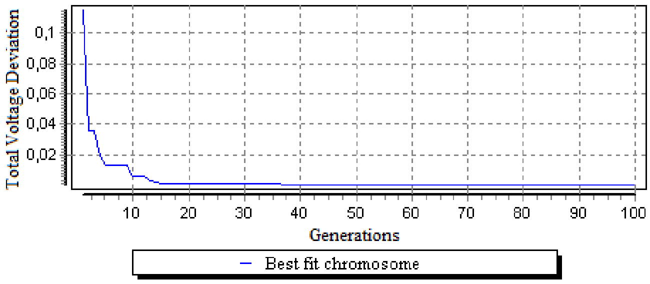

Figure 6 – Total voltage deviation evaluation of the best fit chromosome in the reduction of the **total voltage deviation**.

Figure 7 shows the power loss evaluation of the best fit chromosome in the reduction of the total voltage deviation. As it can be observed, the best fit chromosome in the reduction of the total voltage deviation worsened its profile in the reduction of the power losses when it improved its profile in the reduction of the total voltage deviation.

Figure 8 illustrates the Capacitor Banks' cost evaluation of the best fit chromosome in the reduction of the total voltage deviation. It is observed that the cost ($) reached maximum value.

Figure 9 shows the improvement in the voltage profile obtained with the solution of allocation of the Capacitor Banks proposed by GA. This improvement in the voltage profile can be considered excellent (gain of 99,95%). However, its cost is 100% of the available resource.

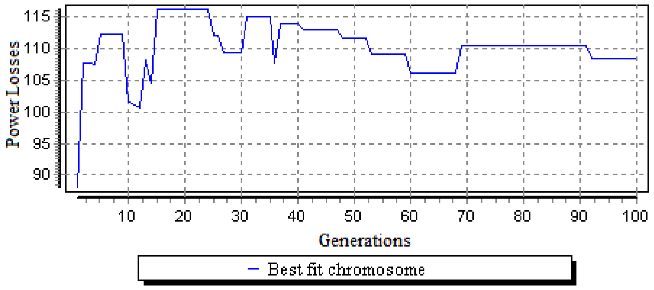

Figure 7 – Power loss evaluation of the best fit chromosome in the reduction of the **total voltage deviation**.

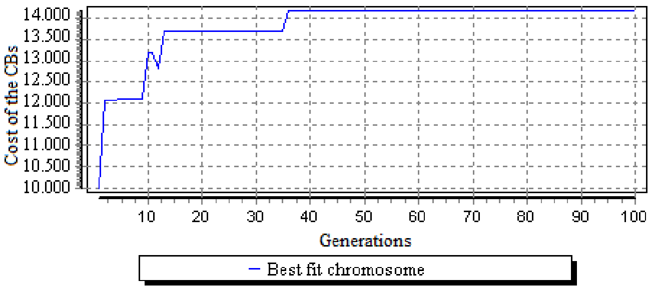

Figure 8 – Capacitor Banks' cost evaluations of the best fit chromosome in the reduction of the **total voltage deviation**.

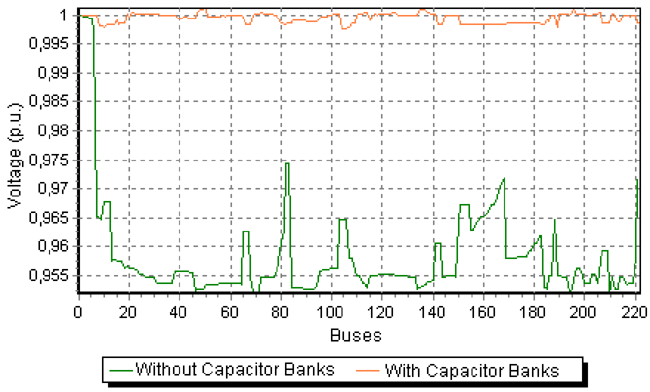

Figure 9 – Voltage profiles of the power distribution system with and without Capacitor Banks. The objective of the GA is the reduction of the total voltage deviation.

B. Reduction of Power Loss

In this simulation, GA allocated all of Capacitor Banks without however using the maximum reactive compensation available (**Table 3**). To this case GA proposed a solution whose gain in the reduction of the total voltage deviation was of **81,56%** and whose gain in the reduction of the power losses was of **33,42%**. The cost of the allocation of Capacitor Banks was of **\$ 10.834,00**, which is equal to **76,40%** of the available resource.

Table 3 – Solution proposed by GA.

Buses	**16**	**188**	**23**	**14**
Taps	6	1	3	6

Figure 10 shows the total voltage deviation evaluation of the best fit individual in the reduction of the power losses. As it can be observed, the best fit chromosome in the reduction of the power losses improved its profile in the reduction of the total voltage deviation as it improved its profile in the reduction of the power losses. The inverse, as mentioned in the simulation (A), it is not true.

Figure 11 shows the power loss evaluation of the best fit chromosome in the reduction of the power losses.

Figure 12 shows the Capacitor Banks' cost evaluation of the best fit individual in the reduction of the power losses. It can be observed that the total cost of the reactive compensation is reduced as compared with the previous simulation shown in **Figure 8**.

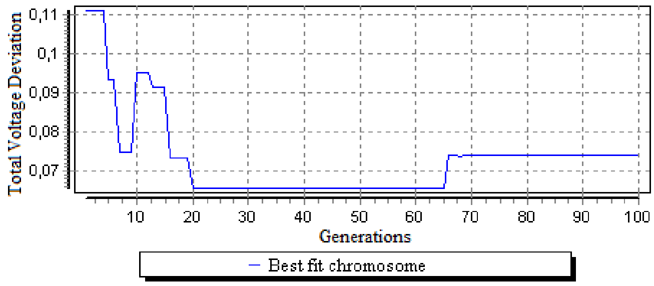

Figure 10 – Total voltage deviation evaluation of the best fit chromosome in **power losses**.

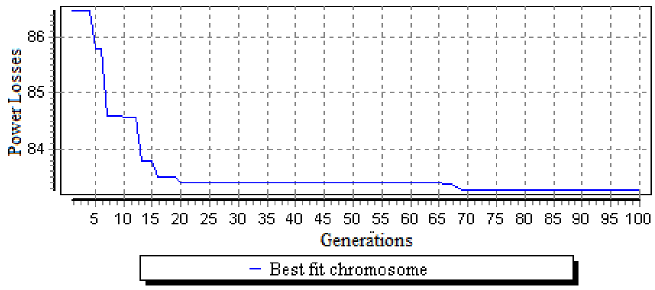

Figure 11 – Power loss evaluation of the best fit chromosome in the reduction of the **power losses**.

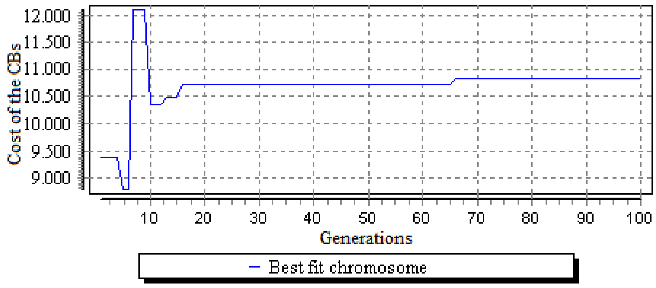

Figure 12 – Capacitor Banks' cost evaluation of the best fit chromosome in the reduction of the **power losses**.

Figure 13 shows the improvement in the voltage profile obtained with the solution of allocation of the Capacitor Banks proposed by GA, when the objective is the reduction of the power losses. This improvement in the voltage profile can be considered good (gain of **81,56%**) with cost also considered good (**76,40%** of the available resource).

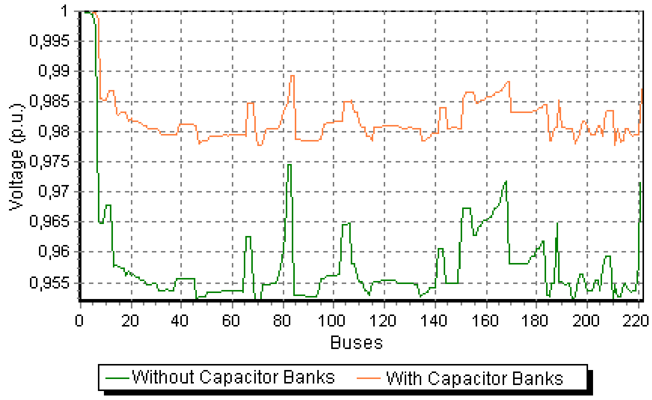

Figure 13 – Voltage profiles of the power distribution system with and without Capacitor Banks. The objective of the GA is the reduction of the power losses.

C. Minimization of the Total Voltage Deviation, Minimization of the Power Losses and Minimization of the Cost in the Allocation of the Capacitor Banks

In this simulation, the GA allocated only three of the four Capacitor Banks without however using of the maximum reactive compensation of the three Capacitor Banks (**Table 4**). In this case GA proposed a solution whose gain in the reduction of the total voltage deviation was of **88,44%** and whose gain in the reduction of the power losses was of **31,89%**. The cost of the allocation of the Capacitor Banks was of **$ 10.152,00**, which is equal to **71,59%** of the available resource.

Table 4 – Solution proposed by GA.

Buses	**28**	**23**	**58**	**14**
Taps	5	6	0	6

Figure 14 shows the total voltage deviation evaluation of the best fit chromosome in the reduction of the total fitness value (total fitness function).

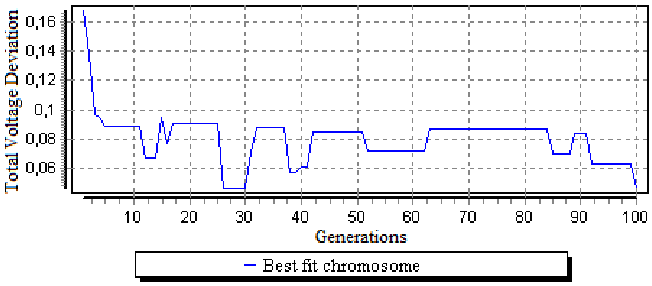

Figure 14 – Total voltage deviation evaluation of the best fit chromosome in the reduction of the **total fitness value**.

Figure 15 shows the power loss evaluation of the best fit chromosome in the reduction of the total fitness value.

Figure 16 shows the Capacitor Banks' cost evaluation of the best fit chromosome in the reduction of the total fitness value.

Figure 14 and **Figure 15** show the improvement in the total voltage deviation and in the power losses of the best fit chromosome in the reduction of the total fitness value. **Figure 16** shows a better use of the available financial resource as compared with the previous simulations shown in **Figure 8** and **Figure 12**. In most of the time during the GA evolution, the plausible improvement in one or more of the objectives resulted in a moderate reduction in one or more of the other objectives. This way, it is visible the effort of the GA in maintaining the balance among the evaluation functions with conflicting objectives.

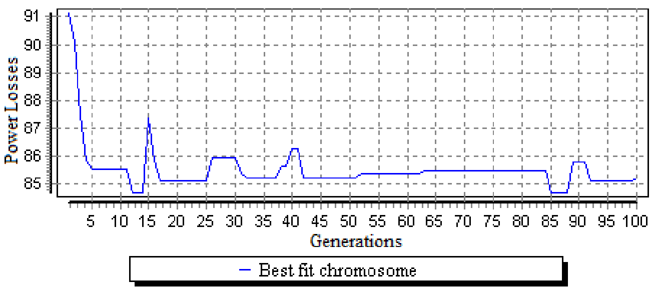

Figure 15 – Power loss evaluation of the best fit chromosome in the reduction of the **total fitness value**.

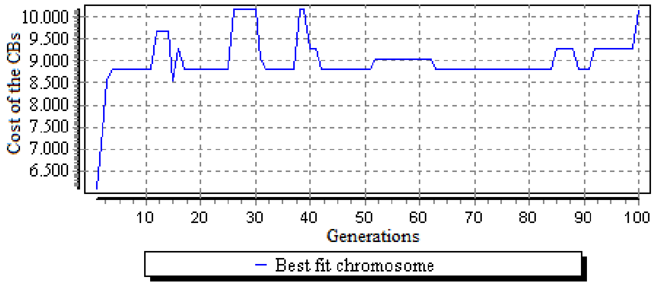

Figure 16 – Capacitor Banks' cost evaluation of the best fit individual in the reduction of the **total fitness value**.

Figure 17 shows the improvement in the voltage profile of the power distribution system obtained with the solution of allocation of the Capacitor Banks proposed by GA, when the objective is the reduction of the total fitness value. This improvement in the voltage profile can be considered good (gain of **88,44%**) with cost also considered good (**71,59%** of the available resource).

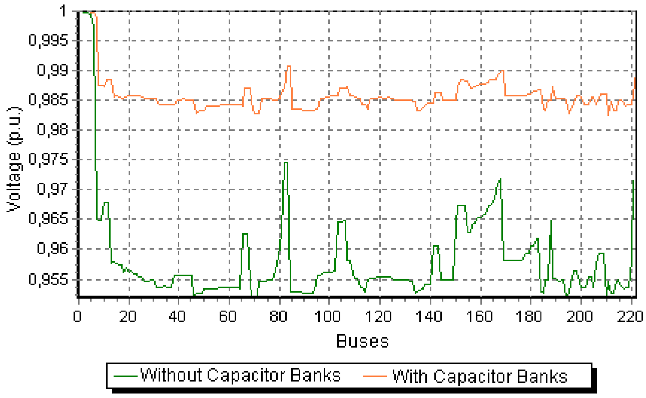

Figure 17 – Voltage profiles of the power distribution system with and without Capacitor Banks. The objective of the GA is the reduction of the total fitness value.

Table 5 shows a summary of the results obtained in the simulations: (A) Reduction of the total voltage deviation, (B) Reduction of the power losses and (C) Reduction of the total voltage deviation, reduction of the power losses and reduction of the cost in the allocation of the Capacitor Banks – for the reduction of the total fitness value.

Table 5 – Summary of the results of simulations (A), (B) e (C).

Simulation	Gain in the Reduction of the Total Voltage Deviation	Gain in the Reduction of Power Losses	Capacitor Banks Cost
(A)	99,95%	13,29%	100%
(B)	81,56%	33,42%	76,40%
(C)	88,44%	31,89%	71,59%

The solution in **(A)** is excellent in the reduction of the total voltage deviation however it presents the worst results for the other objectives. The solution in **(B)** is excellent in the reduction of the power losses however it presents the worst result in the reduction of the total voltage deviation and a good cost in the allocation of Capacitor Banks. The solution in **(C)** is excellent in the use of the available budget for purchasing of the Capacitor Banks; very good in the reduction of the power losses and good in the reduction of the total voltage deviation. Therefore, the solution suggested by the proposed methodology (calculation of the total fitness value) is the one that presents the best results in cost-benefit terms in the allocation of the Capacitor Banks.

VII. Conclusions

This work presented in an objective and concise way the fundamental principles of the Genetic Algorithms. Based in these principles, it was possible to formulate a methodology for treating problems with multiple evaluation functions (multiple objectives). The proposed methodology was applied to the allocation of Capacitor Banks and excellent results were obtained in the use of the available budget for purchasing the Capacitor Banks, very good in the reduction of the power losses and good in the reduction of the total voltage deviation. The methodology allows all the objectives to have transparency in the degree of importance of each objective. In this paper, the objectives had the same degree of importance (weights equals to one). In spite of the presented specific application, the use of the methodology is general and, therefore, it can be applied any problem with multiple objectives.

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IX. Biographies

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