VAR Planning in Distribution Systems via Genetic Operators

F. Salgado, Student Member, IEEE, E. López, and H. Rudnick, Fellow, IEEE

Abstract -- A new solution for VAR planning in distribution systems is proposed. It is based on Genetic Algorithms (GAs). Allelic Alphabet and Hamming Distance concepts are efficiently exploited under real coding. The model's robustness is demonstrated through a 69-node system. The effect of the genetic operators is quantified (mutation probability and mutation radius, crossover probability) regarding the convergence of the solution. The procedure allows obtaining a realistic solution for the VAR planning problem.

Keywords -- VAR planning, Genetic Algorithms, Hamming Distance, Allelic alphabet, Mutation radius.

I. INTRODUCTION

There are many publications that refer to the reactive power planning. According to [1], usually the planning problem is divided in two sub-problems: the operation planning problem and the investment planning problem. In the operation planning problem, the reactive power sources are dispatched and the transformer tap values explored to ensure minimum costs. The last one is recognize as a control problem. In the investment planning problem, the optimal location of new reactive power sources is explored over a long-term planning horizon for a minimum total cost (operation and investment). As the latter problem contains total costs, it has been enhanced to include the modeling of the demand variability through time.

The main lack in the methods used "initially" to plan reactive power is the continuous representation of the variables involved in the problem and the long CPU times. Since the 90s until today, the treatment of the reactive power planning problem has included heuristics [2], artificial intelligence techniques such as: Simulated Annealing [3], Tabu Search [4], Evolutive Programming [5], Fuzzy Logic and Evolutive Programming [6], Fuzzy logic and micro-GA [7] and Genetic algorithms [8]-[12]. These techniques have been used recently to locate capacitor banks [13]. The ones based on evolutive algorithms are worth noting. Reference [14] carries out a comparative study on them. They have two fundamental advantages that make them different regarding the classic Linear and Non-linear programming algorithms: they have the capacity to represent a large number of discrete variables and to converge to a global optimum that theoretically occurs with a probability equal to 1. That is one of the reasons why they are used in this work.

In the problem of reactive power planning, the objective function "to be minimized" is formed by two major components: Operating Costs (costs for peak power and energy loss; the latter one is only present when considering the load variation through time) and Investment Costs (installation and purchase of new reactive power sources expenses).

This work contributes to the solution techniques for the reactive power planning problem in the phase of investment planning, exploiting the characteristics of the GAs to solve non linear problems with a broad space for solutions containing local optima. The implemented GA allows to easily obtain a solution that indicates the location and size of the capacitor banks to be installed. The treatment of the problem considered is such that these two concerns are solved simultaneously, considering the capacitor banks available in the market.

This paper has 5 sections. Section II presents the solution model based on genetic algorithms, Section III depicts the application to a system of 69 nodes, Section IV analyzes the results, sensitizing the solutions regarding the GA parameters and costs. Finally, Section V establishes the conclusions.

II. PROPOSED MODEL

A. Presentation and assumptions for the problem

The investment planning problem presented intends to answer the concerns about the location and size of fixed new capacitor banks in order to ensure minimum total costs (investment plus operation).

The following assumptions are made:
1.- It is assumed that the distribution system is balanced.
2.- Transformer tap settings are consider as fixed values.
3.- No reactive power injection associated to the distribution substation is considered.

B. Presentation of the objective function

The objective function represents investment and operating costs (1). The latter ones consider the costs produced by the branch peak power losses and power losses produced at the capacitor banks to be installed. The peak power losses costs reflect the cost associate to the use of the system’s capacity, as it is done in [15] and [16]. To minimize them implies increasing the branch capacity and improving the voltage profile.
\[ C_T = C_I + C_O \]  

Where,  
\( C_T \) : Total costs.  
\( C_I \) : Investment costs.  
\( C_O \) : Operating costs.

Regularly, investment costs have three components: the purchasing capacitor cost, their installation costs and the additional protection devices costs. In our case, a unique value that includes these three components will be considered \( (K_c) \). This cost is proportional to the injection of reactive power, as shown in (2).

\[ C_I = \sum_{i=1}^{N_q} K_c \cdot Q_i \]  

Where,  
\( K_c \) : Purchasing cost of the capacitor bank \([\text{US$/kVAR}]\).  
\( Q_i \) : Nominal reactive power of the \( i \)-th capacitor bank to be installed \([\text{kVAR}]\).  
\( N_q \) : Total capacitor banks to be installed.

Operating costs (3) take into account the operation power losses cost of the capacitor banks. (in the worst case, they are equivalent to 0.5 \([\text{W/kVAR}] [17]\)) and the cost of peak power losses at the distribution system’s feeders. The cost associated to the capacitor losses is insignificant compared to the cost of the system’s losses. However, it is included to have a more accurate estimate of the costs involved.

\[ C_O = K_p \cdot \sum_{i=1}^{N} R_i \cdot I_i^2 + \frac{K_p}{1000} \sum_{i=1}^{N} 0.5 \cdot Q_i \]  

Where,  
\( Q_i \) : Nominal capacity in kVAR of \( i \)-th capacitor bank to be installed.  
\( K_p \) : Costs of peak power losses \([$/kVAR/year]\).  
\( N \) : Total amount of branches in the distribution system.  
\( R_i \) : Resistance of the \( i \)-th branch of the distribution system.  
\( I_i \) : Current at the \( i \)-th branch of the distribution system.

C. Implemented GA

The two major needs are location and sizing of the new fixed capacitor banks to be installed. They are variables that we propose to determine. Thus, a chromosome is defined with discrete integer variables.

1) Chromosome

In our case, each gene will correspond to one node in the system; therefore the length of the chromosome is equal to the number of nodes to be analyzed. For each gene we propose the use of an allelic alphabet constituted by the possible capacitor sizes to be installed. The structure of the individuals is shown in Fig. 1. The non-injection of reactive power in any busbar is implemented considering the value of zero to the allelic alphabet.

An example of the use of integer discrete variables in a GA can be found in [10]. However, it does not exploit the use of an allelic alphabet as in this work.

2) Initial population

The initial population is generated randomly. All individuals are feasible.

3) Crossover

Crossover is applied with a probability of \( P_c \). The selection of individuals for the crossover is based on the concept of maximum Hamming distance \( d_h \), i.e., two most different individuals are chosen (see Fig. 2). This helps preventing obtaining local optima, achieving a broader range of exploration in the solution space. The crossover is made in double points.

4) Mutation

Mutation is made randomly over each gene with a small probability \( P_m \). Each gene mutates within the possibilities presented by the allelic alphabet and the mutation radius \( r \).

5) Selection

The selection method known as Ranked-Based Selection
[18],[19] is used with a selective pressure of 2.

6) Reinsertion
   The reinsertion process keeps the best individual among parents and offspring.

7) Fitness function
   The objective function (1) is used to measure the fitness of individual. The intent is to minimize that function.

8) Stopping criterion
   The criterion to stop the algorithm corresponds to the running of an arbitrary number of generations that has been considered as 600.

   The esquematic flow diagram for the planning of reactive power is indicated in Fig. 4.

III. APPLICATIONS

In order to measure the algorithm’s performance, it has been applied to a 69 nodes test system whose data and description can be found in [20]. Fig. 14 of the annex shows the numbering used for each node. The capacitor banks considered for the reactive power planning were 300, 600, 900 and 1200 kVAR. Table II of the annex gives details of the ten cases, regarding the GA parameters and costs.

The best one (Case 3) localizes reactive power as indicated in Table I. Fig. 5 shows a broad view of the voltage profiles compared to the ones presented before the reactive power injection. The value of the objective function is 36.20 (thousand US dollars), for 590 generations. Losses associated to this solution are 150 kW.

Fig. 6 shows the effect of the mutation parameter in the convergent of the algorithm proposed, Fig. 7 the effect of the crossover parameter, Fig. 8 the influence of the mutation radius in the convergence toward a solution and Fig. 9 the voltage profile for the definite solution.

<table>
<thead>
<tr>
<th>Node</th>
<th>Voltage</th>
<th>a priori module (p.u.)</th>
<th>a posteriori module (p.u.)</th>
<th>kVAR</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>0.95660</td>
<td>0.96803</td>
<td>300</td>
<td></td>
</tr>
<tr>
<td>25</td>
<td>0.99895</td>
<td>1.00230</td>
<td>600</td>
<td></td>
</tr>
<tr>
<td>38</td>
<td>0.97855</td>
<td>0.98577</td>
<td>900</td>
<td></td>
</tr>
<tr>
<td>44</td>
<td>0.91267</td>
<td>0.93596</td>
<td>1200</td>
<td></td>
</tr>
<tr>
<td>55</td>
<td>1</td>
<td>1.00070</td>
<td>1200</td>
<td></td>
</tr>
<tr>
<td>62</td>
<td>0.99841</td>
<td>1.00220</td>
<td>300</td>
<td></td>
</tr>
<tr>
<td>69</td>
<td>1</td>
<td>1.00070</td>
<td>300</td>
<td></td>
</tr>
</tbody>
</table>

Fig. 5. Comparison of busbar voltages: cases 1 and 3.

Fig. 6. Comparison of convergences: cases 2 and 3.
IV. RESULTS ANALYSIS

A. Influence of the mutation probability

This parameter gives randomness to the search, helping to get the global optimal. Fig. 6 shows that for case 2 there is convergence at an optimal point near to generation 300. For case 3 the optimal point is reached around generation 600. The latter case, as observed in Table II of the annex, shows the most desirable objective function value. It has been verified that $P_m$ probability must be small to assist in the effectiveness of the algorithm.

B. Influence of the crossover probability

The effect of high and low crossover probabilities can be seen in Fig. 7. It is verified that a high crossover probability, regarding the mutation probability, is desirable for a good convergence of the algorithm. An excessively high value can be detrimental for the algorithm’s performance.
C. Influence of the mutation radius

Figures 8 and 9 show similarities, for the convergence and the voltage profiles for the final solution, between cases 4 and 5 with a mutation radius higher than 1.

The three cases have similar convergence characteristics during the first generations. Then a convergence with better characteristics, for the case of the smaller mutation radius, is attained. This is related to the way in which the capacitor sizes are arranged within the allelic alphabet, from smallest to largest. The mutation to close reactive power values helps the convergence.

The voltage profile for the final solution is better shown for cases 4 and 5. However, its losses and costs are higher, as can be verified in Fig. 8 and Table II (annex).

D. Influence of $K_p$

Fig. 10 shows similar convergence characteristics. The $K_p$ values are 120, 125 and 115. The final values of the objective function are: 36.20, 55.63 and 46.53 (thousand US dollars), respectively. The losses associated to each case are 150, 178 and 167 kW. Fig. 11 shows the best voltage profile for case 8 ($K_p = 125$) while case 9 is perceived as deficient. Clearly, $K_p$ acts as a weighting factor that gives relevance to the voltage profile improvement. This is explained by the relationship existing between the voltage profile and the losses.

E. Influence of $K_c$

There are no big differences between cases 3, 6 and 7 regarding the convergence pattern shown in Fig. 12. A similar behavior is observed in Fig. 10.

The best values obtained for the objective function are: 36.20, 45.16 and 47.09 (thousand US dollars) in 590, 480 and 573 generations, respectively. Losses for these cases are 150, 163 and 165 kW.

Fig. 13 does not show an influence of this parameter on the voltage profiles, as it happens with the $K_p$ parameter.

V. CONCLUSIONS

A Genetic Algorithm has been proposed to solve the investment reactive power planning problem. This takes advantage of allelic alphabet and the Hamming distance concepts. The parameters used for genetic operators: crossover probability, mutation probability and mutation radius were sensitized in order to obtain a satisfactory solution.

The algorithm achieves a solution with minimum total costs.

It is verified that the mutation probability is a parameter that has a strong incidence on the convergence of the proposed method and on the optimal values achieved. A high mutation probability increases the risk of reaching local minima.

The second important parameter is the mutation radius. The results show that as smaller its value, better its performance, when the allelic alphabet has arranged the capacitor banks in descending order. In addition, the effect of the mutation radius is important when the GA is reaching the optimal value, i.e., in the first GA generations, the simulations with different mutation radius have similar convergence speeds.

The effects of both parameters: mutation probability and mutation radius on the GA convergence prove that techniques assisted by search mechanisms will be more effective that random search techniques in a solution for reactive power planning.

When analyzing the results obtained, it can be verified that the proposed solution of the reactive power planning problem takes advantage, in a practical manner, of the strengths of Genetic Algorithms. This happens due to the application of an allelic alphabet and the use of the Hamming distance concept under real coding. The adequate exercise of this elements mentioned in our work enable discrete and realistic-character solutions.

VI. ANNEX

Table II describes the different cases analyzed. The system’s loss calculation is obtained through an N-R power flow. The number of generations, where the objective function reaches an optimal value, is shown in parenthesis.

VII. REFERENCES


**VIII. ACKNOWLEDGEMENTS**

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Mr. Fabricio Salgado is a scholarship holder from CONICYT for his PhD studies.
IX. BIOGRAPHIES

**Fabricio Salgado**, IEEE Student, was born in Concepción, Chile. He has an Electrical Engineering degree and M.Sc. at Universidad de Concepción, Concepción, Chile. He is a Ph.D. student in Electrical Engineering. He is an associate of IEEE Industry Applications Society, Power Engineering Society and IEEE Computational Intelligence Society. His areas of interest are optimization, planning, quality and continuity of electrical supply.

**Enrique López** was born in Lota, Chile. He is an associate professor at the Electrical Engineering Department at Universidad de Concepción, Concepción, Chile. He has an Electrical Engineer degree at Universidad Técnica del Estado, Chile, and a Ph.D. at INPG, France. His interest areas are planning, optimization, control, reliability and quality of electrical systems.

**Hugh Rudnick**, IEEE Fellow, is a professor of electrical engineering at Universidad Católica de Chile, Santiago, Chile. He graduated from Universidad de Chile, later obtaining his M.Sc. and Ph.D. from Victoria University of Manchester, UK. His research and teaching activities focus on the economic operation, planning and regulation of electric power systems. He has been a consultant with utilities and regulators in Latin America, the United Nations and the World Bank.