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Kumamoto University
Application of Intelligent Techniques for Voltage Management of Power Transmission Systems

Kumamoto University

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Graduate School of Science and Technology
Kumamoto University

A thesis submitted for the degree of
Doctor in Electrical Engineering
2010 March
To my loving parents
Acknowledgements

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I would like to express my sincere gratitude to my supervisor Dr. Takashi Hiyama for guiding me and his support especially in the most difficult moments.
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Last but not least, I would like to express my ultimate gratitude to my dear parents, my family and friends in Cuba, for their endless support and love.

Yoel Raul Rosales Hernandez

Kumamoto, Dicember 2009
Abstract

This thesis presents a group of algorithms for the voltage and reactive power control (Vol/Var control) in transmission systems. The first algorithm is a rule-based technique. Transformers with a tap changer installed in the system are selected by the proposed technique as control devices. For each bus under voltage violation, the most effective control device is selected by using the minimum electric distance criteria. In order to demonstrate the efficiency of the method, several simulations were performed using an IEEE 30-bus network as a model system. The distance measure technique is compared with classic voltage regulation approach and a genetic algorithm based.

The second algorithm is a hybrid algorithm. The objective is to minimize the number of manipulations of control devices within a 24 hours period, while the voltages at all buses are kept within the limits of a normal operation. A genetic algorithm is combined with two rule-based statements. Load behavior is analyzed by a first rule: The more acutely load varies, the more required manipulations in control devices will become. And, a second rule is implemented in order to estimate the ability of the controllable devices to decrease voltage violations.

A study of different genetic algorithms (GA) applied to Voltage/VAr optimization was made. Notable works are compared and critiqued in terms of common features of GA, such as encoding format, local convergences, genetic operators, evaluation functions, and processing speed. Some thoughts and suggestions for future research are given.
Finally, a multi-objective genetic algorithm, based on NSGA-II, is implemented to find an optimal condition of minimum voltage deviations, minimum power losses and minimum number of control actions of a transmission network system. Generators and transformers with off-nominal tap ratio are the devices to be controlled. Different probabilities of mutation factors are compared and it is proved that a more important mutation factor can improve the velocity of convergence without getting into a random search.
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Chapter 1

Introduction

1.1 Background

Reactive power and voltage control is a task which guarantee that voltages at buses in the system are within acceptable limits. Thus, enhances utilization of the transmission system and reduce the power losses. The task is accomplished by controlling the generation, absorption and flow of reactive power. The devices used for this propose can be classified as:

- Source or sinks of reactive power.
- Line reactance compensators.
- Regulating transformers.

The reactive power and voltage control is not an easy task due to a vast number of load are everywhere and the system is fed from many generators. As loads vary, the reactive power requirement of the system vary. Reactive power and voltage control is a large-scale nonlinear optimization problem with a large number of variables and uncertain parameters. Various mathematical optimization algorithms have been developed for the Volt/Var control, which in most cases, use nonlinear, linear, or mixed integer programming, and decomposition methods. In these conventional algorithms, many mathematical assumptions, such as analytic and differential properties of the objective functions have to be given to simplify the problem.
1.2 Objective

Electric power system is a very old system with an old philosophy of operation. Until now just small technical-patches have been inserted to try to keep alive a more than 100 years old system. Smart grid seems to be the rational substitution for this obsolete way of generate and transmit electricity. This is the ideal time to developing more powerful and accurate optimization algorithms for the Volt/Var control.

1.2 Objective

The main objective of this thesis is to study and developing effective algorithms for the Volt/Var control problem in transmission systems.

1.3 Outline of the Thesis

Chapter 1 is the introduction to the thesis.
Chapter 2 a rule-based algorithm is proposed to reduce voltage deviations in a transmission system.
Chapter 3 a hybrid algorithm is presented for the optimization of the Volt/Var control.
Chapter 4 discusses Volt/Var control methods by using genetic algorithms.
Chapter 5 a multi-objective genetic algorithm is illustrated. Three objectives are optimized and the method is based in a pareto approach.
Chapter 6 presents conclusions and recommendations for future works.
Chapter 2

Distance Measure Algorithm. A Rule-based Algorithm for Minimization of Voltage Deviations

2.1 Introduction

Current approaches to the operation of a modern distribution network demand high operational performance of the system and consequently require highly effective control strategies. Although voltage deviation control is one of the problems that has been extensively investigated, it still remains as an important topic to deal with. Voltage control algorithms may be classified into two categories: rule-based and network model-based. Rule-based algorithms use rules that control switched capacitors and transformer tap changers based on real-time measurements and past experience. Network model-based systems use network topology, impedance, real-time measurements and statistical information to establish the current state of the system. It then applies optimization techniques to get the best possible solution. Within the network models-based systems there are many different approaches. A simulated annealing technique for global optimal solution is presented in [1]. The authors propose a knowledge-based expert system which detects buses with maximum voltage deviations and operates the nearest
available transformer control unit to correct the problem. Then, a simulated annealing algorithm is utilized to solve the problem of capacitors manipulation. The paper shows a very good result in terms of power loss reductions but does not guarantee an economical use of transformers operations. Restriction in the number of switching operation is the focus in [2]. Here, dynamic programming and fuzzy logic algorithms are combined to control voltages and reduce power losses. The problem is decomposed into two sub-problems: first, the control of the load tap changers (LTC) and capacitor banks at substation level and second, the control of the capacitor banks installed at the feeder level. Dynamic programming is used in sub-problem 1 and fuzzy logic is adopted for the second sub-problem. Simulation results show the excellent performance of the proposed approach. The use of genetic algorithms is another approach to the control of voltage and reactive power in the system. The approach in [3] combines the benefits of a linearized system model and genetic algorithms (GA). Whenever a voltage correction is demanded, an initial calculation of the sensitivity matrix is done in order to identify an initial population for the GA. Then the GA finds a proper set of control actions to execute. The method offers good solutions to the voltage/reactive power problem and also reduces the number of control actions. Authors in [4] use a method based on an artificial neural network to find the suitable capacitor switching regime for every load state. The main objective is to reduce power losses and the only constraint considered is bus voltage. The advantage of this method is the short calculation time. However, in real applications, it might be difficult to use because the system requires training sessions every time any small change is made to the network topology.

The approach presented in this paper is rule-based and is a new decision-making tool for centralized control of voltage. When the system lacks automatic function control the task has to be performed manually by the supervisor in the dispatch center. Due to the complexity of a modern power system and the severe consequences to the economy of power failures, reliable algorithms have to be part of the daily support tools in the dispatch center. This research was motivated by the necessity to design a simple and effective support algorithm for the voltage control process. The algorithm is based on the identification of a bus having the worst voltage violations and the nearest bus where a voltage control
2.2 Case Study System

The modeled system is an IEEE 30-bus scheme. The system bus data is given in Table 2.1, and with figure 2.1 showing the single line diagram. Shunt capacitor banks are located at bus 10 and 24. The capacitor bank found at node 10 contains up to 10 units with a reactive power capacity of 1.9 Mvar for each unit. In the case of bus 24, banks have been installed containing up to 3 units of 0.8 Mvar each one. The tap changer settings ranges are modeled at settings from 0.9 to 1.1 with a step of 0.01 per unit. Four synchronous condensers are also considered at buses 5, 8, 11 and 13.

2.3 Proposed Method

Usually, the system is exposed to overload and under-load conditions in 24 hour intervals. When the system is in the overload condition, transferred power through lines and transformers might cause excessive voltage drops and consequently appear bus voltages below the minimum limit. In the case of an under-load condition, shunt capacitance of the lines inject an excessive reactive power into the network and the voltage in some buses might be above the maximum limit. A safe voltage operation range is considered to be from 0.95 to 1.05 per unit. A rule-based approach is proposed to bring the system to a normal point of operation, with rules being presented in Table 2.2. The ranking list order is based on the electrical distance criteria between every voltage control device and the target...
2.3 Proposed Method

Figure 2.1: 30-bus IEEE scheme
### Table 2.1: IEEE-30 Bus Data

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bus. Once the nearest voltage control device is selected, the device settings have to be modified using a minimum number of steps in order to avoid unnecessary control actions.

Table 2.2: Voltage control procedure

| Step1: Perform the power flow calculation. If there is any violation of voltage then move to step 2. If not then move to step 4. |
| Step2: Identification of the bus under the worst voltage condition as target bus. Creation of a ranking list of voltage control devices. |
| Step3: Identification of the device located at the first position of the ranking as optimal control device. If is not available, due to settings reaching upper/lower limits, then the device in the next ranking position is selected as the optimal control device. If is available, then perform setting modifications at the optimal control device. Return to step 1. If there is not any more control action possible and the target bus remains as same bus, then move to step 4. |
| Step4: The calculation is stopped. |

2.4 Distance Measure Algorithm

The shortest route from the bus under worst voltage condition to a corresponding control device location is calculated using Dijkstra’s algorithm [5]. The basic operation of this algorithm uses edge relaxation. In this case, the edges are the electrical distance $L_{ij}$ of the transmission line between buses $i$ and $j$. The electrical distance is defined in (1).

$$L_{ij} = \sqrt{R_{ij}^2 + X_{ij}^2}$$  \hspace{1cm} (2.1)

where:

$R$: is the resistance of i-j brach

$X$: is the reactance of i-j brach

Once the minimum paths are found, a ranking of distance measures is established in order to develop a decision strategy to solve the problem of voltage violation.
2.5 Simulation Results

For the controllable devices to have a long operating life it is vital to avoid unnecessary control actions. Therefore, only strictly necessary actions are allowed. A control effort index, CEI, is defined to count the number of control actions used in every simulation. The CEI definition is presented below.

\[
CEI = \sum_{i=1}^{n} |tap_i^s - tap_i^{ref}|
\]

(2.2)

where:
\(i\): is the \(i\)-th controllable device
\(s\): actual tap position of the \(i\)-th controllable device
\(ref\): is the reference tap position of the \(i\)-th controllable device

In the initial state of the system, the voltage violations are under the minimum voltage limit. It was for this reason that the shunt capacitors were not adjusted in these simulations. Also, it is important to note that the minimum tap modification is 0.01 in per unit so that if the CEI value is 0.36, it means that 36 operations of the tap were made. The simulation results are shown in three parts. The first part is a comparison between a local control strategy, an evolutionary search based on a genetic algorithm and the distance based method. The second part illustrates the performance of the proposed method under a load variation during a period of 24 hours. In the last section, there is also a power losses analysis.

2.5.1 A comparison of voltage local control, genetic algorithm based correction, and the proposed voltage control algorithm

Voltage local control is a classic method based on the local monitoring and operation of each control device. It means that at every node where a control device is installed, a local and independent control strategy is followed, and control actions are executed exclusively where voltage problems appear. Fig. 2 illustrates
an initial voltage profile of the network under a hypothetical load scenario which is assumed to be the maximum load scenario. The voltage profile shows several nodes violating the minimum voltage limit. Buses which are under violation and where a control device is installed are marked with a circle. In this initial condition only transformer operations are available because all capacitor banks are already connected.

![Voltage profile of the network obtained for initial conditions](image)

**Figure 2.2**: Voltage profile of the network obtained for initial conditions

Table 2.3 lists the positions of transformer taps in the initial state, during two partial solutions and for the final solution. The final solution is reached when the four buses highlighted in Fig. 2 are out of the violation zone. The final solution, shown in Fig. 3, does not solve the problem of voltage at nodes other than those where the control devices are installed.

Also the proposed algorithm is compared with a genetic algorithm (GA). GAs are considered more flexible and robust than most of deterministic optimization methods because it requires only information concerning the quality of the solution produced by each parameter set. This is unlike many traditional methods.
### 2.5 Simulation Results

Table 2.3: Operation of the controllable devices using the control method of local voltage

<table>
<thead>
<tr>
<th>Bus Number</th>
<th>Tap (p.u)</th>
<th>Name</th>
<th>Sending</th>
<th>Receiving</th>
<th>Initial</th>
<th>1</th>
<th>2</th>
<th>Final</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>T1</td>
<td>6</td>
<td>9</td>
<td>0.97</td>
<td>1.00</td>
<td>1.00</td>
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<tr>
<td></td>
<td></td>
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<td>10</td>
<td>0.96</td>
<td>0.99</td>
<td>1.01</td>
<td>1.02</td>
</tr>
<tr>
<td></td>
<td></td>
<td>T3</td>
<td>11</td>
<td>9</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td></td>
<td></td>
<td>T4</td>
<td>9</td>
<td>10</td>
<td>1.00</td>
<td>1.00</td>
<td>0.91</td>
<td>0.91</td>
</tr>
<tr>
<td></td>
<td></td>
<td>T5</td>
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<td>12</td>
<td>0.93</td>
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<td>0.93</td>
<td>0.93</td>
</tr>
<tr>
<td></td>
<td></td>
<td>T6</td>
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<td>1.00</td>
<td>1.03</td>
<td>1.05</td>
<td>1.06</td>
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<tr>
<td></td>
<td></td>
<td>T7</td>
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<td>1.02</td>
<td>1.04</td>
</tr>
<tr>
<td></td>
<td>CEI</td>
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<td></td>
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<td>0.13</td>
<td>0.15</td>
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<tr>
<td></td>
<td>Total CEI</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.36</td>
</tr>
</tbody>
</table>

Figure 2.3: Voltage profile of the network obtained after execution of voltage local control
2.5 Simulation Results

that require derivative information or worse yet, completed knowledge of the problem structure and parameters [6]. For this GA, decision variables are expressed as integers. Each gene represents the tap position of a transformer. Integer variables are used in order to avoid unnecessary coding and decoding. By using this non-binary coding, which is a closer representation of real system parameters, it is expected that there should be an increment in the velocity of convergence [7]. The representation of one individual is shown in Fig. 4. The initial population is generated randomly.

<table>
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<tr>
<th>+1</th>
<th>0</th>
<th>-5</th>
<th>+8</th>
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<td>T5</td>
<td>T6</td>
<td>T7</td>
</tr>
</tbody>
</table>

Figure 2.4: Integer representation of one individual

Then, chromosomes are evaluated through a fitness function (see equations 3 and 4) where the objective function is the minimum number of adjustments to the tap changers. The voltage deviation at each bus, the reactive limit violation at each generator and maximum line current limit are considered as constraints. The evaluation is based on Newton-Raphson power flow calculations, provided by the MatPower package [8]. The genetic operators are tournament selection, one-point crossover, and uniform mutation. The stopping criterion is the number of generation being 60 with the probability of mutation being 15%.

\[
Fit = \min \left( \sum \left| tap_i^s - tap_i^{ref} \right| + R \right) \quad (2.3)
\]

\[
R = a \cdot vd + b \cdot ql + c \cdot cl \quad (2.4)
\]

where

- \( s \): actual tap position.
- \( i \): ith-tap transformer.
- \( ref \): index of tap position.
- \( vd \): index of voltage deviation.
- \( ql \): index of violation for reactive generation.
In order to get a clear solution with the GA, a total of 45 independent simulations were executed with a common initial condition, (the conditions being as shown in Fig. 2). Fig. 5 shows the mean value of voltage deviation factor at each generation. The mean value of number of control actions are shown in Fig. 6, where most of the simulations reach a common solution with fewer than 43 operations. The mean value of fitness for each generation are illustrated in Fig. 7. In these three figures each curve represent one of the 45 simulations. The superposition of the curves demonstrates the similarity of the solutions for each simulation. The best solution at each simulation are shown in Fig. 8. With 41 control operations being the minimum value that can be reached by the GA. The best solution for each simulation has no constraint violations. For example, Fig. 9 shows the best solution for the voltage profile simulation number 45.

![Figure 2.5: Mean value of voltage deviation factor for the 45 simulations](image)

In the case of the proposed rule-based method, the initial state is the same as that showed in Fig. 2. The worst voltage is located at node 30 and transformer T7 is the best control device to solve the problem. The tap position in transformer 7 was moved from 0.96 to 1.00 and the voltage problem in node 30 was solved. Then bus 19 appeared as the worst bus and the most effective control device was transformer 2. The process was repeated several times until a final
2.5 Simulation Results

Figure 2.6: Mean value of the number of operations for the 45 simulations

Figure 2.7: Mean value of fitness for the 45 simulations

Figure 2.8: Number of control action for the best solution at each simulation
2.5 Simulation Results

solution was reached. Table 2.4 shows the initial conditions of tap positions, two partial solutions and the final solution. Values in boldface font represent a new modification of the tap position. In Fig. 10, 11 and 12 the voltage profile for the two partial solutions and the final result are presented respectively. Final voltage profile shows the capacity of the rule-based method to find a suitable solution, and the total CEI=0.42, means that the number of control actions is 42, which is very close to the optimal solution of the GA-based method.

![Figure 2.9: Voltage profile for the best solution at simulation number 45](image)

Table 2.4: Operation of the controllable devices using the distance measure method

<table>
<thead>
<tr>
<th>Name</th>
<th>Bus Number</th>
<th>Tap(p.u)</th>
<th>CEI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Sending</td>
<td>Receiving</td>
<td>Initial</td>
</tr>
<tr>
<td>T1</td>
<td>6</td>
<td>9</td>
<td>0.97</td>
</tr>
<tr>
<td>T2</td>
<td>6</td>
<td>10</td>
<td>0.96</td>
</tr>
<tr>
<td>T3</td>
<td>11</td>
<td>9</td>
<td>1.00</td>
</tr>
<tr>
<td>T4</td>
<td>9</td>
<td>10</td>
<td>1.00</td>
</tr>
<tr>
<td>T5</td>
<td>13</td>
<td>12</td>
<td>0.93</td>
</tr>
<tr>
<td>T6</td>
<td>28</td>
<td>27</td>
<td>0.96</td>
</tr>
<tr>
<td>T7</td>
<td>0.00</td>
<td>0.11</td>
<td>0.10</td>
</tr>
<tr>
<td>Total CEI</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
2.5 Simulation Results

Figure 2.10: Voltage profile of the network obtained in sub-solution 1

Figure 2.11: Voltage profile of the network obtained in sub-solution 2
2.5 Simulation Results

Figure 2.12: Voltage profile of the network obtained in the final solution

2.5.2 Performance of the new method applied for a load variation over a 24 hour interval

It is well known that power demand in a real system is changing continually during the day, and consequently state variables are varying as well. Thus, it is necessary to study the effectiveness of the proposed method for this typical behavior. Load variation was modeled as coincident in time. In figure 2.13 it is shown the variation of load at every bus in 24 hours and the voltage at buses 19, 23, 24, 25, 26 and 30 after application of the distance measure method. Other than the buses shown in figure 2.13 are kept within the non-violating voltage zone. The variations in the transformer taps are illustrated 2.14. In the case of capacitor bank adjustment, none were executed because all the banks were connected in the initial state and the voltage violations that appeared were of the under-voltage type.
Figure 2.13: Load rate at every bus in 24 hours and voltage at buses 19, 23, 24, 25, 26 and 30 as a result of the distance measure method
Figure 2.14: Variation of tap positions at transformers as a result of the distance measure method
2.6 Analysis of Power Loss Reduction

In addition to voltage correction, power losses were also monitored and analyzed. This new control method yields a very flat voltage scenario which is very important in order to reduce power loss. Figure 2.15 illustrates how the power losses are reduced gradually in each partial solution obtained by the proposed method.

![Power Losses Graph](image)

Figure 2.15: Total power losses for intermediate solutions and for the final solution of the distance measure method

2.7 Conclusions

In this chapter a Rule-based method was presented for regulating voltage deviations and to reduce power losses of a transmission system. The control method is based on simple rules. Which allow to operate only the most effective devices to solve voltage violations. Thus, control actions were executed under the principle of imposing the fewest number of operations of control devices. Several simulations were done to compare a local voltage control strategy and GA-based method with the new method. The results proved that:
2.8 References

1. The new method achieves the goal where the local voltage control strategy fails. The most important issue, which is voltage correction, is not successfully accomplished with the approach based on local control.

2. The rule-based method was compared with several simulations of a GA-based method and the results are very similar. The number of control actions from GA-approach is 41 while for the rule-based method is 42. There are no constraint violations in the solutions provided by both methods.

3. The rule-based method significantly reduces power losses of the system under maximum load condition and under a load variation period of 24 hours. Voltages at all buses were maintained out of the voltage violation zone.

4. Although the proposed method is based on very simple rules, where significant approximations are used to determine a ranking list of effective controllable devices, this approach can be used as a useful, simple and fast tool for dispatcher engineers in a situation requiring correction of voltages.

2.8 References


Chapter 3

A Hybrid Algorithm for Correction of Voltage Deviation Considering the Time-Varying Load

3.1 Introduction

In this chapter a hybrid algorithm is introduced and compared with a rule-based algorithm. The main goal of this work is to prove the advantage of this new approach in a more complex load scenario. In chapter 1 it was introduced a rule-based algorithm for solving the voltage deviation. Such rule-based algorithm is able to find acceptable solutions by using a very simple approach. However, some weak points in this algorithm need to be highlighted:

- Low probability of obtaining the minimum number of operation control.
- It is not considered the variation of load.

The problem of voltage correction and dispatch of reactive power is known as an optimization problem due to the complexity and behavior of the power system. The rule-based algorithm contains approximations which facilitate fast and good solutions, but precisely due the approximation of the distance of impedance it
is very difficult to reduce the voltage deviation with a global or a near-global minimum number control actions.
In the case of the load, is usual to consider a fixed load scenario. In the algorithm presented in chapter 1 is assumed a constant load condition for all buses. This assumption does not allow taking a wider perspective of the correction of the voltages for a complete day of operation.
In this chapter is presented a hybrid algorithm able to overcome the weakness mentioned before. The hybrid algorithm is a combination of a genetic algorithm and a rule-based approach. By using simple rules, a time-varying load analysis is made and this information is introduced in the optimization process in order to speedup the computation time. The objective function is to minimize the required number of control actions.

\section{3.2 Proposed Method}

Basically the method contains three main tasks. One is the reading of variables of state, control and disturbance of the system at each hour. Then, two rules are used to analyze the trend of the load during an interval of three hours and then this information is used to modify the mutation process of the genetic algorithm. The third one is the genetic algorithm which is the core of the method. In figure 3.1 it is shown the structure of the method.

Figure 3.1: Flow chart of the voltage and reactive power control method proposed.
3.3 Mathematical Formulation

Objective function is reducing of the number of control actions within 24 hours. Power flow equations and voltage limits in each bus are constraints of this optimization problem.

O.F:

$$\text{Fit} = \min \left( \sum \left| \text{tap}^*_i - \text{tap}^{ref}_i \right| \right) \quad (3.1)$$

Subject to:

$$V_{\min} \leq V_k \leq V_{\max} \quad (3.2)$$

$$f(x, u, d, z) = 0 \quad (3.3)$$

where:

Setting: tap position of i-th controllable device at h-th hour
V: voltage at k-th bus
x: state variables
u: control variable
d: disturbance variables
z: constants

In order to mapping the O.F and constrains to fitness form, a cost-to-fitness transformation [4] is used.

$$f(x) = C - w_1 \times V_d - w_2 \times N_{ca} \quad (3.4)$$
3.4 Reading System Condition Data

Where:
C: constant
w1 and w2: weighs
Vd: voltage deviation index
Nca: number of control action index

The variables of control, state and disturbance of the system are read. Then, the control areas of the system are identified. A control area is defined an area where necessarily is installed a controllable device like an off-nominal tap transformer or shunt capacitor. Each bus is identified with one of the control area. For each bus, it is computed the electrical distance from the bus to the controllable device of each control area. Each bus is identified with the area where the corresponding electrical path is the shorter one. Conformation of control areas is aimed by the idea of reducing unnecessary control efforts. A controllable device, with the highest influence on adjacent buses, will be considered as a first candidate for any control action.

3.5 Genetic Algorithm

The genetic algorithm is basically a classic genetic algorithm, but there are some modifications introduced in the crossover and mutation stages. First, the initial population is generated randomly. A NR-based power flow is used to compute the fitness value of each individual. Then, a crossover process is launched. The crossover is based on the multiple control areas generated previously. Next, the mutation task is started. Here, the mutation process is influenced by external information received from the analysis of load behavior. Finally, a convergence condition is checked. If the convergence condition has not been met then a new iteration begins, otherwise the algorithm ends.
3.5 Genetic Algorithm

Figure 3.2: Structure of the proposed GA
3.5 Genetic Algorithm

3.5.1 Sub-system crossover

Using the same approach presented by [1] the crossover operation is a partial string exchanging which are related to operation conditions of each control area in the network. Suppose a network is decomposed into four control areas (1, 2, 3 and 4) as shows figure 3.3. From three individuals a new individual will be created. A selection of potentially better control area is done by using roulette wheel method. The control areas 1 of each individual are competing through the roulette wheel mechanism, the same idea for control area 2 and so on. The winners of each control area will be part of the new individual.

![Figure 3.3: Sub-System Crossover approach](image)

3.5.2 Mutation and manipulation

Mutation is a genetic operator which in a classical GA follows strictly a stochastic law. Here, the mutation will be conditioned by a rule-based strategy besides the
3.5 Genetic Algorithm

stochastic nature. Figure 3.4 illustrates how stochastic law (mutation) and the rules based on knowledge (manipulation) are combined. A uniform random value is generated. Then, the value is compared with a specific threshold and from that comparison either mutation or manipulation will be executed. The random values generated are between limits 0 and 1. The threshold value is fixed in 0.5.

![Mutation & Manipulation Diagram](image)

Figure 3.4: Link between the mutation and the manipulation

The rule-based strategy contains two rules, which are related to load conditions and position of buses with voltage violations in the system.

**Rule 1**: “If a controllable device is the closest to voltage violation position, then the device will be selected as candidate for setting modification”.

This rule is implemented by locating a gene which represents the candidate device. In order to estimate the closest bus, a calculation of the shortest “electrical distances” between bus under violation and controllable devices is done. The shortest route, from the bus under the worst voltage condition to a corresponding control device location, is calculated by using Dijkstra’s algorithm [5]. Basic operation of this algorithm is edge relaxation. In this case, the edges are the electrical distance $L_{ij}$ of the transmission line between buses i and j. The electrical distance is defined below.

$$L_{ij} = \sqrt{R_{ij}^2 + X_{ij}^2} \quad (3.5)$$

where:
- $R$: is the resistance of i-j brach
- $X$: is the reactance of i-j brach
3.5 Genetic Algorithm

**Rule 2**: “If load variation increases, then probability of setting modification of the candidate device will be increased”.

A load trend is estimated based on load conditions of each bus at three different moments. Those are: a previous hour (h1), present (h2) and a next hour (h3). The load condition in a future scenario is estimated by a load forecasting procedure. Figure 3.5 and equations below illustrate relations between load factors (Lf) of the system and probability of mutation factors (Pm).

![Figure 3.5: Representation of relation between the time and the load factors in the system.](image)

\[ m_1 = \frac{L_{f3} - L_{f2}}{h_2 - h_1} \]  \hspace{1cm} (3.6)

\[ m_2 = \frac{L_{f1} - L_{f3}}{h_3 - h_2} \]  \hspace{1cm} (3.7)

\[ M = m_1 + m_2 \]  \hspace{1cm} (3.8)

For a situation with under voltage violation, the figure 3.6 shows the distribution of the mutation rate (Pm). This distribution is defined in equation 3.9, 3.10 and 3.11.

\[ if \ -0.5 < M < 0.5 \ then \ Pm = 0.5 + M \]  \hspace{1cm} (3.9)
3.5 Genetic Algorithm

\hspace{1cm} if \ M \geq 0.5 \ then \ Pm = 1 \quad (3.10)

\hspace{1cm} if \ M \leq -0.5 \ then \ Pm = 0 \quad (3.11)

Figure 3.6: Representation of relation between the M and Pm for under voltage violation.

Similar rules are applied in the case of over voltage violation. Figure 3.7 and equations 3.12-3.14 illustrate the relations between M and the mutation rate.

\hspace{1cm} if \ -0.5 < M < 0.5 \ then \ Pm = 0.5 - M \quad (3.12)

\hspace{1cm} if \ M \geq 0.5 \ then \ Pm = 0 \quad (3.13)

\hspace{1cm} if \ M \leq -0.5 \ then \ Pm = 1 \quad (3.14)
Figure 3.7: Representation of relation between the M and Pm for over voltage violation.
Where
Lf: Mean value of load factor for all buses
Pm: Probability of mutation factor
Uwb: Voltage at bus under the worst voltage condition in per unit (p.u)

3.6 Study Case System

The modeled system is an IEEE 30-bus scheme. The system bus data is given in Table 3.1, and figure 3.8 shows the single line diagram. Shunt capacitor banks are located at bus 10 and 24. Bank capacitor found at node 10 contains up to 10 units with a reactive power capacity of 1.9 Mvar for each unit. In the case of bus 24, banks have been installed up to 3 units per 0.8 Mvar. The tap changer settings ranges are modeled from -0.1 to 0.1 with a step of 0.01 per unit. Four synchronous condensors are also considered at buses 5, 8, 11 and 13.

Figure 3.8: 30-bus IEEE scheme
### Table 3.1: IEEE-30 Bus Data

<table>
<thead>
<tr>
<th>Name</th>
<th>Type</th>
<th>V(^{(\text{p.u})})</th>
<th>Pg(^{(\text{p.u})})</th>
<th>Qg(^{(\text{p.u})})</th>
<th>Pd(^{(\text{p.u})})</th>
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3.7 Simulation Results

3.6.1 Load modeling

Load modeling is based on the assumption of the conforming nature of kW and kvar loads [6]. Individual curves of load factor for each bus were created. In figure 3.9, shapes of 30 curves in 24 hours are illustrated. Load factors are per unit values, based on active load data which are showed in table 3.1.

Figure 3.9: Load factor for each bus within 24 hours.

3.7 Simulation Results

Several simulations were executed in order to compare results of the proposed method with a rule-based method shown in chapter 2. Initial conditions of voltage in the system are showed in figure 3.10. Curves represent the voltage situation for each hour in every bus. The system without any control action presents at many hours voltage values below the minimum limit which is 0.95 in per unit (p.u)

If the Rule-based method is applied, voltage situation of network improves considerably, see figure 3.11. Also, as shows figure 3.12, by applying the hybrid algorithm, the voltage condition is acceptable for a normal operation.
3.7 Simulation Results

Figure 3.10: Voltages in the system for each hour.

Figure 3.11: Voltages in the system after applying Rule-based method.
3.7 Simulation Results

Figure 3.12: Voltages in the system after applying the hybrid algorithm.

Number of control actions was calculated for each method as well. Figure 3.13 and 3.14 illustrate number of action by using the Rule-based and the Hybrid GA respectively.

Figure 3.13: Number of control actions by applying Rule-based method.

Last results prove a superior performance of the proposed method. By using
3.7 Simulation Results

![Graph showing simulation results.]

Figure 3.14: Number of control actions by applying the hybrid algorithm.

The hybrid algorithm, the number of control actions was reduced from 54 to 31. Twenty five simulations were made by using the proposed method with 300 generations and a population size of 40 individuals. From that group of simulations, see figure 3.15, the minimum amount of control actions obtained was 31. Most of solutions offer 32 control actions executed and some solutions require 39 operations, which is the maximum value.

![Bar chart showing minimum, mean, and maximum number of operations.]

Figure 3.15: Amount of operations obtained by running 25 simulations of the hybrid algorithm.
3.8 Conclusions

In this chapter, a genetic algorithm with a hybrid approach was presented for regulating voltage deviations and to minimizing the number of required control actions in the study system during its one day operation. The genetic algorithm includes non-conventional operations of crossover and mutation. The crossover is based on a different treatment of chromosomes. At each chromosome, a group of genes are distinguished and they are compared and crossed with their homologous genes of the other chromosomes. Mutation is accomplished by including some rules based on experiences. This means that mutations may have a deterministic nature in specific occasions and the law followed is not purely stochastic. This approach brings more rapid convergence to the searching process of a globally optimal solution.

A power system with 30 buses was selected as a study system. A hypothetical load scenario was used to represent the load variation during a 24 hours period. Proposed method with the hybrid approach was tested to demonstrate the efficiency of the proposed scheme. The results clearly indicate that the proposed scheme gives a better solution. The required number of control actions was reduced considerably by applying the proposed approach.

3.9 References


Chapter 4

A Wide View of Genetic Algorithms Applied to Volt/Var Optimization

4.1 Introduction

As it is said in previous chapters, the new economic and technical environments in the power system demand more accuracy and effectiveness in the Voltage/Var control task. Usually, such actions are implemented by changing the operating parameters of the transformers, shunt capacitors, shunt reactors, generators and others devices installed in the system. Typical goals of these actions include the reduction of power losses, voltage deviations, operating costs, etc. The nature of the power systems, their objectives and constraints lead to a complex optimization problem. To solve such problem, many algorithms have been designed. In chapter 2 and 3 two algorithms with strong components of rule-based approaches have been shown. The obtained results up to now are good enough for a reduced voltage deviation and even for less number of operations. But, as it is mentioned before, the voltage and reactive power control is multi-dimensional optimization problem and it is necessary to employ more powerful tools to solve this problem.

This chapter covers an extended analysis of one of those tools that may be very useful for this challenge. The genetic algorithms (GAs) are the alternative
4.2 Genetic Algorithm. General Structure

GAs are stochastic search algorithms based on the principles of natural selection and genetics [43]. GAs attempt to find an optimal solution by making modifications to a population of candidate solutions. The candidates, which are called chromosomes, contain information of the settings of the controllable devices in the system. Generally, the initial population is generated randomly. The chromosomes are evaluated through a fitness function and those with better performance are selected as parents of the next generation. Then adjustments of the population are executed in order to explore and exploit the search space of the problem. Again the new individuals thus obtained are evaluated and the cycle is repeated until a termination criterion is satisfied. Figure 4.1 illustrates the structure of a typical genetic algorithm [45].

4.3 Coding

While it may appear that coding format is a trivial issue in the application of GA to the Voltage/VAr optimization problem, it is actually an important starting point in designing a fast and effective algorithm. In the surveyed literature, the coding format could be grouped into two broad categories: Binary and non-binary format.

Binary format offers an easier way to implement classic and novel genetic operators like Gene Swap Operator (GSO), Gene Cross-Swap Operator (GCSO), Gene Copy Operator (GCO) among others. In [13], these genetic operators are implemented using a binary representation (see figure 4.2). In [42], a comparison...
4.3 Coding

Figure 4.1: Structure of a typical genetic algorithm
between a binary and a non-binary format is presented, where it is evident that the binary format offers a natural association between high fitness and coding similarities among strings in the population [42]. In addition, it is shown that binary coding gives the largest number of schemata per bit of information of any coding. This feature allows a larger search space to be covered.

![Image of binary coding format](image)

**Figure 4.2:** Representation of controllable devices with a binary coding format

On the other hand, other authors point out some drawbacks of the binary coding. For example, in [19], a string with a length of 5-bits, which represents ULTC transformers, is analyzed. Typically, a ULTC has 23 discrete positions. The consequence is that the number of possible states is larger than the number of tap positions. It may, therefore, be possible for states to be generated that do not correspond to any actual tap positions and which are considered forbidden. These states must therefore be eliminated from the search process, adding complexity to the evaluation stage, thereby reducing the effectiveness of the GA. The non-binary coding approach group can be divided into mixed coding and integer coding approaches. In [32] and [16], floating and integer values are used (see figure 4.3). The floating values are used to represent the voltage set point of the controlled voltage buses with the integer values coding the transformer tap positions or the capacitor units. In [14], binary coding is used for the position of the taps in the transformers the connected capacitors, while the voltages at PV nodes are expressed as real values. In the case of [4], the binary format is used for representing capacitor size while the integer values indicate the location of the installed capacitors.

An integer coding approach is implemented in [1], [10], [11], [15], [18], [21], [26] and [31]. Shunt reactive units, transformer tap positions, and other controllable devices are expressed as integer value. Even generators voltages are coded as integers because the set point voltages specified by digital controllers are discrete.
4.3 Coding

parameters in many real cases [1].
In general, the non-binary approach is justified by the goal of avoiding unnessessary coding and recoding. The non-binary coding format, which is closer to the format of real system parameters, should increase the rate of convergence.
For any type of coding format, it is very important to reduce the string length while keeping it long enough to not impair the solution space search.
In order to find a global optimal solution it is necessary that the string representations cover a wide search space. This is possible if the number of combinations of strings is large enough, that is, if their lengths are sufficiently great. While this goal is achievable, long string codings introduce low convergence rates into the algorithm. This is one of the classic problems of the coding representation. The pure binary-coding is the most prone approach to this problem.

\[
\begin{array}{cccccccc}
0.981 & 0.970 & \ldots & 1 & 4 & 3 & \ldots & 4 & -2 & +1 & \ldots & +3 \\
U_1 & U_2 & U_n & Qc_1 & Qc_2 & Qc_n & T_1 & T_2 & T_n
\end{array}
\]

Figure 4.3: Representation of controllable devices with mixed floating and integer format.

4.3.1 Avoiding locally optimal solutions

In the earliest stages of the genetic algorithm, there is a tendency for a few super-individuals to dominate the selection process [42]. Although this will bring a fast convergence, there is the risk of obtaining only local solutions. To address this problem, is necessary to scale back the fitness function in order to stop the super-individuals from running away with the population. Scaling is a classical technique for avoiding local solutions. Some of the popular scaling functions are linear scaling, sigma truncation and power law scaling.

4.4 Genetic Operators

In the literature reviewed, dynamic modification of mutation and crossover probability factors is the most commonly used technique for reducing the risk of local solutions. References [7], [13], [15], [19], [20] and [26] use different criteria for changing genetic operator factors. For example, in [19], [20] and [15] a modification of genetic operator factors based on the number of generations processed is proposed. Authors in [19] and [20] argue that in the early stages of the evolution, the crossover probability factor must be large while the mutation probability factor is small. In later stages, the magnitudes of the factors must reverse. It is argued by [20], that once the population has reached fair solutions, mutation will help the search jump out of local optimization. Nevertheless, [15] has presented a criterion which is exactly the opposite of that in the approach published in [20]. On the other hand, [7], [13] and [26] suggest a strategy based on the statistics of fitness evaluation. If fitness value is lower than average fitness, large crossover and mutation factors are applied. Otherwise, if the fitness value is near the maximum fitness, then the crossover and mutation factors are assigned the minimum values.

This spectrum of approaches indicates the great diversity of proposed solutions to this problem. In the search for more effective strategies, other researchers include new genetic operators in the algorithms. Details about new genetic operators will be presented in next section.

4.4 Genetic Operators

Selection, crossover and mutation are the three basic genetic operators most used in the literature surveyed. Even though these operators are very simple, they have the ability to make the population evolve toward the optimal solution. By a careful design of these three important operators, it is possible to get very good results.

4.4.1 Selection

Selection provides the driving force in a genetic algorithm, and therefore it is the critical component. Typically, a low selection pressure should be present in the
initial stages of the GA. This condition allows the GA to evolve into a wide area of the search space. Subsequently, high selection pressure is recommended near the end of the search in order to exploit the most promising regions of the search space [44].

The sampling mechanism is one of the issues to consider when establishing a suitable selection pressure. It can be classified into three groups: stochastic, deterministic and mixed sampling. A large number of published algorithms use stochastic sampling, more specifically, the roulette wheel [1], [2], [5], [8], [10], [13], [25] and [30]. The roulette wheel is quite a simple scheme although it is inferior relative to deterministic and mixed schemes.

Researchers who deal with combinatorial optimization problems prefer deterministic sampling because it is easier to implement, it eliminates the probability of bad selections, and accelerates convergence. Chromosomes are ranked according to their fitness and the best ones are selected as parents for the next generation [16], [9] and [24].

The mixed sampling scheme contains random and deterministic features simultaneously. The most representative example is tournament selection. Tournament selection chooses a set of chromosomes randomly. Then, a comparison is established between them, with the best ones being selected to be part of the next generation. Although the method gives very good results, it is poorly used in the literature surveyed. Implementation of Tournament selection can be seen in [21] and [32].

4.4.2 Crossover

Crossover provides a method whereby information for differing solutions can be melded to allow the exploration of new parts of the search space [40]. This operator chooses a random position (crossing point) in a pair of parents and then swapping of bits occurs between them [6] (see figure 4.4). According to the number of random positions used, it is possible to distinguish four types of crossover: single-point, two-point, multiple-point, and uniform crossover.

Single-point crossover was the first approach published and still is the most popular; see [2], [3], [6], [7], [8], [10], [14], [19], [22], [25], [26], [28] and [32]. Two-
4.4 Genetic Operators

Figure 4.4: Single-point crossover

point crossover is implemented in [9], [11], [27] and [30]. Few works exploit the potential of multi-point crossover: [4] and [31]. In the case of uniform crossover, the number of reported results is minimal: [13], [17] and [23].

Single and two-point crossovers are very commonly used due to their low disruptive effect. However, it has been proven that multiple-point and uniform crossovers, in spite the higher disruption rates, can attain a superior recombination behavior [39]. Disruption did not seem to be a negative feature of the evolutionary process. Disruption contributes to finding a proper balance between exploration and exploitation in the algorithm. Empirical studies carried out by [39], show that uniform crossover, with a variable crossing probability value during the evolutionary process, can control disruption effects and keep a promising level of crossover productivity throughout the generations.

Adaptive uniform crossover can be a very effective crossing technique when implementing an algorithm with non-constant parameters like population size.

4.4.3 Mutation

The mutation operation is defined by [42] as a mechanism to compensate for the loss of information that can occur during selection and crossover. Author in [42] considers that mutation plays a secondary role in the algorithm and is unable to contribute to exploring new solution areas. According to that concept, he suggests the low value for the frequency of mutation of one mutation per thousand bits. On the other hand, [38] gives more weight to the mutation arguing that mutation is very useful for searching new solutions.
Most of the authors in the survey employ a low fixed value for the mutation probability factor. In [2], [3], [9], [12], [14], [16], [18], [21], [23], [27], [28], [29], [30], [31], [32] and [33] the mutation factors have been assigned values between 0.008 and 0.35. Such low levels of mutation are linked to the idea that if the mutation factor is increased too much, the GA performance will be approach that of a simple random search [42]. Such an assumption is true in the case of encodings with low cardinality alphabets like the binary format. However, many of the previously cited references, which use more complex encoding formats, also use that conservative strategy of having a very low mutation factor. In the case of encodings with higher cardinality alphabets, [38] has proved that it is possible to avoid the undesirable random behavior if the new generation contains both mutated and unmutated offspring. Even if the mutation rate is high, it is possible to keep the conservative recombination essentials and the necessary exploration potential.

Others support the idea of a mutation based on the relative fitness of the old population: [7] and [26]. Mutation with a dynamic behavior linked to fitness values should be a more frequent practice to obtain a continued improvement of average fitness.

### 4.5 Evaluation Function

Some important issues have to be considered when an evaluation function is designed. First, there should be a strong correlation between the quality of the proposed solution and its corresponding value of fitness. Second, it is advisable that small variations in the individual genes do not lead to large changes in the output of the evaluation function. This will ensure that at least locally optimal solutions can be reached. These two basic features, recommended by [41], are present in all the cited works. However, there is another issue on which the authors do not seem to agree. The divergence of opinions is centered on the question of whether it is enough to formulate the Voltage/VAr optimization problem using a constrained single function, which includes the weighted sum of several objectives, or whether it is more effective to implement a true multi-objective function approach.
Most of the papers reviewed use evaluation functions, which are the weighted sums of various objectives and constraints. Usually, the formulated objectives are the minimization of power loss, operating cost, number of control actions, among others.

An example of the weighted sum of two objectives, voltage deviation and power loss reduction, are shown in (1). Equations (2) and (3) are the constraints on the voltage and tap positions, respectively.

\[
\min \left( w_1 \sum | V_{n,ref} - V_n | + w_2 \cdot \text{Loss} \right) \tag{4.1}
\]

\[
V_{o,min} \leq V_o \leq V_{o,max} \tag{4.2}
\]

\[
t_{min} \leq t_o \leq t_{max} \tag{4.3}
\]

where:
- \(V_{n,ref}\): is n-th node voltage target value
- \(V_n\): is n-th node voltage
- \(V_o\): sending voltage
- \(V_{o,min}\) and \(V_{o,max}\): are min and max values of sending voltage
- \(t\): transformer tap ratios
- \(t_{min}\) and \(t_{max}\): are min and max of the transformer tap ratio
- \(w_1\) and \(w_2\): are weighting values

In the case of multi-objective GA, there are few published results. In [29] a non-dominated sorting genetic algorithm II (NSGAII) was applied to a multi-objective reactive power-planning problem (RPP). Two objectives are optimized, the minimization of shunt compensation investment costs and the average load bus voltage deviation. A numerical case study was carried out using a modified IEEE 30-bus test system and the results show good performance in finding the non-dominated solutions.

A similar approach is proposed in [21]. The reduction in reactive power cost, deviation voltage and limit violation measure are the objectives. The last objective
4.6 Limitation in the Applicability of GAs

includes all violation constraints like tap settings, generator capacity, bus voltages, among others. The GA is compared with a LP-based method (SCORPION) and it was found that solutions given by the GA are cheaper than the solution obtained through SCORPION. In addition, a decrease in real and reactive power mismatches, and a reduction in MVAr installation costs and utilization were observed.

Supporters of the multi-objective approach point out several weak points in single function based approaches. The optimal solution may be highly dependent on how the weights are set [41]. In addition, the single solution may border one or more operating constraints violations. In such a case, an unexpected system perturbation may push the system into an undesirable operating state [29].

Why are weighted sum approaches still popular? An explanation is that it is easier to implement a GA using a simple weighted approach than a Pareto-optimality [46] one. In addition, a weighted sum approach converges to a unique optimal solution while a Pareto-optimality approach yields many trade-off solutions. Actually, for dispatching reactive power, only one solution is required, so apparently the weighted sum approach is more convenient. However, the question remains regarding the selection of suitable weights. Adjustment of the weights may demand a lot of processing time. On the other hand, given a number of trade-off solutions, the unique solution may be chosen among the solutions in the non-dominated front. An expert can then, using superior information and criteria, make the final decision. It is evident that in terms of results, the Pareto-optimality approach brings a more flexible and complete tool to the dispatchers.

4.6 Limitation in the Applicability of GAs

The application of genetic algorithms has a high probability of achieving the best solution. However, as in every engineering problem, where there are no perfect approaches, and GAs are no different. The proposed GAs have some important problems that need to be addressed. Uncertainties in the computational load and the processing speed are two factors that can limit the applicability of GA-based approaches to real-world system control.
4.6 Limitation in the Applicability of GAs

4.6.1 Uncertainties for load conditions

In [34], a widespread communication infrastructure, allowing for accurate data acquisition in the distribution system was considered. However, this is not necessarily true in practice, and therefore a more realistic scenario is desirable. Under real-world conditions, just 20 to 30 % of the necessary data are available from real time measurements [36] of the distribution system. The lack of sufficient real time measurements combined with failures in the real time data transmission lead to inevitable uncertainties in the load information. It is necessary to design a GA-based approach allowing for the uncertainty and which is capable of linking to real DMS functions. Among the published results, the uncertainty has not yet been treated with the required consideration. Very few authors have paid attention to this topic. A notable suggestion to this problem has been proposed by [19]. The author proposes an Integrated GA-Fuzzy Multi-Objective Model which can integrate some of the functions of a real DMS. The model takes historical data as input and combines this with the limited set of real-time measurements. Then, fuzzy set theory is used to assign different reliability levels to the input data, and finally, the optimization process is executed in the GA module.

4.6.2 Speed considerations

Calculation time is the historical limitation of GA-based approaches to Voltage/Var control and therefore is used mainly for planning applications. The reason for the long calculation time is the large number of function evaluations during the algorithm processing.

In order to speed up the calculations, many ideas have proposed. The most interesting ones can be classified into three groups: hybrid algorithms, off-line GA applications, and parallel GA.

4.6.3 Hybrid algorithms

It is clear that GAs are very good at spanning large, complex solution search spaces within a realistic time interval. For a real time application, the GA probably will reach a near-optimum solution. However, if the GA is combined with a
classic optimization algorithm, a good result should be achievable within a reason-
able processing time. The GA will locate the “hills” while the classic algorithm
will climb them. Such a combination allows the strengths of both algorithms to
complement each other.

In [8], a GA is implemented to define the location of a new reactive power source
and then a linear programming method (Simplex) is used to calculate the mag-
nitude of reactive sources. Authors in [2] make use of a combination of a simple
GA and a successive linear programming technique (Benders’ cut). The approach
has two levels of hierarchy. In the first level, the SGA is used to select the loca-
tion and the amount of reactive power sources to install. The result obtained in
the first level is passed on to the second level, where an operation optimization
sub-problem is solved through the Benders’ cut linear programming technique.

4.6.4 Off-line GA applications

The off-line GA applications are implemented in order to avoid the constraint
of processing time. For example, [35] proposed a system comprising a GA op-
timization block, a knowledge data base, and multiple criteria decision making
(MCDM) block. A number of typical disturbance are repeatedly simulated trig-
gering the GA to find a new optimal system operating point. Each new solution
is stored in the knowledge database. Up to this point, the process is off-line.
However, in case of emergency, the MCDM is activated and the suitable control
actions are taken using the data from the knowledge database.

Authors in [33] propose another interesting idea in which the control system is
divided in two stages. During the first stage a GA is used to define the capaci-
tor operation dispatch schedule. Then, in the second stage, the under-load tap
changers are controlled in real time based on the previous capacitor schedule.

4.6.5 Parallel GA

The basic idea behind a parallel GA (PGA) is to divide a large problem into
smaller tasks and solve the tasks simultaneously using multiple processors. This
concept has been applied successfully to different engineering problems, although
4.6 Limitation in the Applicability of GAs

it has not yet been sufficiently explored in the Voltage/VAr optimization problem. The classification of PGAs given by [43] includes four types.

- Single-population master-slave GAs
- Multiple-population GAs
- Fine-grained GAs
- Hierarchical hybrids GAs

master-slave GA has a single population. The master executes selection, crossover and mutation, and the slaves perform the fitness evaluations.

The multiple-population GA consists of several subpopulations that perform genetic operations and exchange individuals under a controlled mechanism.

The fine-grained GA is a two dimensional grid structure that represents the population. Each node of the grid represents an individual. Ideally, there is one processor per individual, so the fitness evaluations are performed simultaneously. Individuals involved in the same genetic operations are defined geographically.

Hierarchical hybrids are a combination of multiple-population GA and either the master-slaves GA or the fine-grained GA. By using such structure, the hybrid model can get the benefits of each individual system. Figure 4.5 shows a schematic representation of these four types of parallel GA.

The results in [14] are the outcome of multiple-population GA. The population is divided in subpopulations and a simple GA is executed at each subpopulation. The multiple-population GA presented here is called stepping-stone because only the best individuals are exchanged between specific subpopulations. The results in the paper show that a good performance is achievable by using such sophisticated algorithms. Notwithstanding, this GA design introduces new problems, such as the appropriate sub-population size, the sub-populations that need to be connected, and the timing of the execution of the emigration.

A very interesting idea is presented by [37], where the master-slave structure is used. However, it is not used as described by other authors. The slaves not only do the fitness evaluations, but they also execute the genetic operations. The master layer is responsible for monitoring the process, gathering the solutions
from the slaves, choosing the optimum solutions, coordinating communications and finally assigning the individuals of the new optimal solutions to the next generation of each slave.

Figure 4.5: Schematic representation of four types of parallel GA. a) Master-Slave. b) Multiple-population. c) Fine-grained. d) Hierarchical GA

Implementation of parallel concepts can considerably speed up the performance of GAs, although it is necessary to explore and better understand the effect of several new parameters that have to be included in the algorithm. This tool can potentially bring very promising results to the Voltage/VAr optimization task.

4.7 Conclusions

This chapter was focused in a study of GA approaches for the optimization of Voltage/VAr operations. Some significant points of the GA, such as coding format, genetic operators, objective functions and speed problems are studied. The coding format encountered in the published literature is diverse. Full binary coding allows easier schema representation but may slow down the fitness
4.7 Conclusions

evaluation process. The floating and integer formats provide a more natural representation of the problem and as well as assisting in the fitness evaluation.

The strategies most used to avoid local convergences are the dynamic modification of mutation and the crossover probability factors, with some works showing good and interesting results. However, more frequent implementation of scaling would yield better results.

The review also highlighted the genetic operator. Stochastic, deterministic, and mixed sampling selection operators were reviewed. The most popular operators are the deterministic ones. The mixed sampling strategy is more attractive, but until now it has been poorly implemented. Mixed sampling makes use of the best characteristics of deterministic and stochastic selection operators.

In the case of crossover operators it is observed that the single-point crossover is the most frequent one with uniform crossover almost never being used in order to avoid undesired disruption. However, it has been shown that with an intelligent strategy of crossing probability factor variation, it is possible to control the disruption allowing for the adaptive uniform crossover to be very effective.

The mutation operator is subject to disagreement among authors. This study proposes the dynamic modification of the probability factor value.

Another key feature addressed in the analysis is the formulation of the evaluation functions. Both the single function with weighted sum of factors and the multi-objective function based on Pareto-optimality are examined. Pareto-optimality is still not very popular but it will be, because it yields more diverse solutions and its setup is less time-consuming.

Finally, some of the implementation problems of GA based algorithms in a real control system are discussed. For GA algorithms to be used effectively, the uncertainties in the data load must be integrated into the processing stages. In addition, the issue of speed requires more attention. Some of the approaches to mitigate this problem are described: off-line GA applications, hybrid algorithms, and parallel GA. These are very interesting solutions which offer a wide spectrum of possibilities for developing new algorithms.
4.8 References


Chapter 5

A Multi-Objective Genetic Algorithm Applied on Voltage/Var Control

5.1 Introduction

Based on the analysis in the previous chapter, the developing and implementation of evolutionary concepts has became the main route for the creation of new algorithms in this work. The potential of GAs to reach optimal or near-optimal solutions is very significant and is already a fact that the GAs can be very useful for the voltage correction in power systems. But still there are many dark areas relate to the application of such approaches. For example, most of the problem related with voltage and Var control involve multiple objectives but it is common to see GA-based approaches where the problem is modeled as a single objective function. Until today most of the authors are trying to deal with dispatching issue, which is a multi-objective problem, by using in the GA a single objective function with some assigned weighs [1], [2], [3] and [4]. One major problem associated with these proposals is that an optimal solution may be highly dependent on how the weighs are set. In this chapter the main objective is to prove that is possible to eliminate this drawback by applying a multi-objective GA. The algorithm finds the Pareto-optimal front, where power losses voltage deviations
and number of control actions are minimal. The algorithm is based on the Non-
-dominated Sorting Genetic Algorithm II [5].
In this chapter the basic concepts of the non-dominated sorting genetic algo-
rithm are exposed, and an example of application in a power transmission system
is illustrated.

5.2 Problem Formulation

The problem to solve here is very similar to those exposed previously in chap-
ter 2 and 3. A typical power system network is exposed to several changes of
conditions in one-day operation. From the control center, reactive dispatch con-
ditions and voltages are modified seeking for a better performance of the network
with minimum power losses, voltage deviations and reduce as much as possible
the number of control actions. These objectives are considered very important
indicators of quality of delivered energy (voltage deviation), efficient operation
(losses and number of control actions). In the case of the number of control ac-
tions, the life of devices like tap changers and capacitors could be extended if its
number of actions is reduced to a minimum. This is the motivation to provide
an efficient computation algorithm capable of find the suitable levels of reactive
power at generators, tap position of transformers and connected capacitors. The
multi-objective algorithm NSGA-II is a very good candidate for this complex
optimization problem.

5.2.1 Mathematical formulation

Equations below define the three objectives to evaluate. The evaluation task is
made by using the an efficient Newton-Raphson power flow method which is pro-
vided by MatPower package [9].

Power loss:
5.2 Problem Formulation

\[ P_{\text{loss}} = \sum_{k=1}^{l} g_k \left[ V_i^2 + V_j^2 - 2 \cdot V_i \cdot V_j \cdot \cos (\delta_i - \delta_j) \right] \]  \hspace{1cm} (5.1)

where:
- \( l \) is the number of lines
- \( g_k \) is the conductance of the \( k \)-th line
- \( V_i \) and \( V_j \) are the absolute values of the voltage at nodes \( i \) and \( j \) of the \( k \)-th line respectively
- \( \delta_i \) and \( \delta_j \) are the angle values of the voltage at nodes \( i \) and \( j \) of the \( k \)-th line respectively

Voltage deviation:

\[ Vd = \sum_{k=1}^{b} |V_k - V_{\text{ref}}^k| \]  \hspace{1cm} (5.2)

where:
- \( b \) is the number of load busses
- \( V_{\text{ref}} \) is the prespecified voltage at the \( k \)-th bus. In this case voltage of reference is 1 pu

Number of control actions:

\[ N_{\text{Ctrl}} = \sum_{n=1}^{d} |S_n - S_{n_{\text{ref}}}| \]  \hspace{1cm} (5.3)

where:
- \( d \) is the number of controllable devices installed in the system
- \( S \) is the tap position of the \( n \)-th device
- \( S_{\text{ref}} \) is the initial tap position of the \( n \)-th device

The constraints of this problem are:

- Power flow equations constraints.

- Operation limits of tap-transformers, bus voltages, generated reactive power and current flowing through the lines.
5.2.2 Coding format of individuals

It seems that coding format is a trivial issue of GA applied into Volt/VAr optimization, but actually is an important start point to designing a fast and effective algorithm [6]. Other authors have proven the advantages of using a non-binary coding format [7] and [8]. In our case, non-binary format is supported by the idea of avoid unnecessary processes of coding and recoding. By using this non-binary coding format, which is closer to the format of real parameters of the system, might bring an increment of the velocity of convergence. Figure 5.1 shows the genetic information format of one individual. The first five gens represent the voltage value at terminals of generators and synchronous condensers. Next three values represent tap position of transformers and the last position shows the number of connected capacitors units.

![Figure 5.1: Representation of controllable devices by using floating and integer format](Image)

5.3 Multi-Objective Genetic Algorithm

A multi-objective genetic algorithm is quite similar to any classic GA except the selection process. In the selection stage occurs the selection of a group of best solutions based on the multi-objective philosophy. In figure 5.2 is shown the flow chart of the implemented GA.

Initially, a random population Po is created. The population is sorted into different non-domination levels. Each solution is assigned a fitness equal to its non-domination level (1 is the value for the best level). Thus, minimization of the fitness is assumed. Binary tournament selection, crossover and mutation operators are used to create a offspring population Qo of size N. The complete
Figure 5.2: General structure of the implemented genetic algorithm
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procedure is outlined in the following.

Step1 Combine parent and offspring population and create \( R_t = P_t \cup Q_t \). Perform a non-dominant sorting to \( R_t \) and identify different fronts: \( \Phi_i, i = 1, 2, ... \), etc.

Step2 Set new population \( P_{t+1} = 0 \). Set a counter \( i = 1 \). Until \(|P_{t+1}| + |\Phi_i| < N\), perform \( P_{t+1} = P_{t+1} \cup \Phi_i \) and \( i = i + 1 \).

Step3 Perform the Crowding-sort procedure and include the most widely spread \((N - |P_{t+1}|)\) solutions by using the crowding distances values in the sorted \( \Phi_i \) to \( P_{t+1} \).

Step4 Create offspring population \( Q_{t+1} \) from \( P_{t+1} \) by using the crowded tournament selection, crossover and mutation operators.

5.3.1 Concept of domination

Identification of non-dominated fronts is a fundamental step for the selection process in any multi-objective GA. The definition is given in following.

A solution \( x^{(1)} \) is said to dominate the other solution \( x^{(2)} \), if both conditions 1 and 2 are true:

1. The solution \( x^{(1)} \) is not worst than \( x^{(2)} \) in all objectives.

1. The solution \( x^{(1)} \) is strictly better than \( x^{(2)} \) in at least one objective.

Let us consider a two-objective optimization problem with five different solutions shown in the objective space, as illustrated in figure 5.3. Let us also assume that the objective function 1 needs to be maximized while the objective function 2 needs to be minimized. Five solutions with different objective function values are shown in this figure. Since both objective function are of importance to us, it is usually difficult to find one solution which is best with respect to both objectives. However, we can use the above definition of domination to decide which solution is better among any two given solution in terms of both objectives. For example, if solution 1 and 2 are to be compared, we observe that solution 1 is better than solution 2 in objective function 1 and solution 1 is also better than
5.3 Multi-Objective Genetic Algorithm

solution 2 in objective function 2. Thus, both of the above conditions for domination are satisfied and we may write that solution 1 dominates solution 2. We take an other instance of comparing solutions 1 and 5. Here, solution 5 is better than solution 1 in the first objective and solution is not worst (in fact, they are equal) than solution 1 in the second objective. Thus, both the above conditions for domination are also satisfied and we may write that solution 5 dominates solution 1.

![Figure 5.3: A population of five solutions](image)

5.3.2 Pareto-optimality

If we compare solutions 3 and 5 in figure 5.3 we observe that solution 5 is better than solution 3 in the first objective, while solution 5 is worst than solution 3 in the second objective. Thus, the first condition is not satisfied for both of these solutions. Then we cannot say that solution 5 dominates solution 3, nor can we say that solution 3 dominates solution 5. When this happens, it is customary to say that solution 3 and 5 are non-dominated with respect to each other. When both objective are important, it cannot be said which of the solutions 3 and 5 is better. We can conclude that solution 3 and 5 constitutes the non-dominated set.
Non-dominated set: Among a set of solutions $P$, the non-dominate set of solutions $P'$ are those that are not dominated by any member of the set $P$.

Pareto-optimal set: The non-dominated set of the entire search space $S$ is the Pareto-optimal set.

The procedure to identifying the Non-Dominated Set is proposed by Kung [11]. This approach first sorts the population according to the descending order of importance to the first objective function value. Thereafter, the population is recursively halved as top (T) and bottom (B) subpopulations. Knowing that the top half of the population is better in terms of the first objective function, the bottom half is then checked for domination with the top half. The solutions of B that are not dominated by any member of T are combined with member of T to form a merged population $M$. The merging and the domination check starts with the innermost case (when there is only one member left in either T or B in recursive divisions of the population) and proceeds in a bottom-up fashion.

- **Step 1** Sort the population according to the descending order of importance in the first objective function and rename the population as $P$ of size $N$.

- **Step 2** Front $(P)$ If $|P| = 1$, return $P$ as the output of Front($P$). Otherwise, $T = \text{Front}(P^{(1)} - P^{(|P|/2)})$ and $B = \text{Front}(P^{(|P|/2+1)} - P^{(|P|)})$. If the $i$-th solution solution of $B$ is not dominated by any solution of $T$, create a merged set $M = T \cup \{i\}$. Return $M$ as the output of Front ($P$).

For the solutions in figure 5.3 a non-domination sorting is executed. The entire population is sorted and the pareto fronts are shown in figure 5.4.

### 5.3.3 Crowded tournament selection

A solution $i$ wins a tournament with another solution $j$ if any of the following condition are true:

1. If solution $i$ has a better rank, that is, $r_i < r_j$. 

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2. If they have the same rank but solution \( i \) has a better crowding distance than solution \( j \), that is, \( r_i = r_j \) and \( d_i > d_j \).

The first condition makes sure that chosen solutions lies on a better non-dominated front. The second condition resolves the tie of both solution being on the same non-dominated front. The crowding distance is an index that express the distance between the solutions on the same front. Crowding of solutions anywhere in the search space is discouraged, thereby providing the diversity needed to maintain multimple optimal solutions.

### 5.3.3.1 Crowding distance

To get an estimated of the density of solutions surrounding a particular solution in \( i \) in the population, we take the average distance of two solutions on either side of solution \( i \) along each of the objective. This quantity \( d_i \) serves as an estimate of the perimeter of the cuboid formed by using the nearest neighbors as the vertices (we call this the crowding distance) in the figure 5.5, the crowding distance of the \( i-th \) solution in its frot (marked with solid circles) is the average side-length of the cuboid (shown by a dashed box). The following algorithm is used to calculate
5.3 Multi-Objective Genetic Algorithm

the crowding distance of each point in the set \( \Phi \).

- **Step C1** Call the number of solutions in \( \Phi \) as \( l = |\Phi| \). For each \( i \) in the set, first assign \( d_i = 0 \).

- **Step C2** For each objective function \( m = 1, 2, ..., M \), sort the set in worst order of \( f_m \) or, find the sorted indices vector: \( I^m = \text{sort}(f_m, >) \)

- **Step C3** For \( m = 1, 2, ..., M \), assign a large distance to the boundary solutions, or \( d_{I^m_1} = d_{I^m_l} = \infty \), and for all other solutions \( j=2 \) to \((l-1)\), assign:

\[
  d_{I^m_j} = d_{I^m_j} + \frac{f_{I^m_{j+1}} - f_{I^m_{j-1}}}{f_{\text{max}} - f_{\text{min}}} \quad (5.4)
\]

The index \( I_j \) denotes the solution index of the \( j \)-th member in the sorted list. Thus, for any objective, \( I_1 \) and \( I_l \) denote the lowest and highest objective function values, respectively. The second term in the right side of the last equation is the difference in objective function values between two neighboring solutions on either side of solution \( I_j \). Thus, this metric denotes half of the perimeter of the enclosing cuboid with the nearest neighboring solutions placed on the vertices of the cuboid (figure 5.5).

### 5.3.4 Considering constraints in the multi-objective GA

The problem of constraints usually is handled by most of the authors in the simplest way, ignoring any solution that violates any of the assigned constraints. Another very popular method is the penalty function approach. The penalty method is basically a calculation of the total constraint violation and then it is added to each objective function as penalty.

In our case it is used a more effective approach. The tournament selection operator is transformed to a *Constrained tournament selection operator*
5.3.4.1 Constrained tournament selection operator

Before comparing two solutions for domination, they are checked for their feasibility. If one solution is feasible and the other is not, the feasible solution dominates the other. If two solutions are infeasible, the solution with the smaller normalized constraint violation dominates the other. On the other hand, if both solutions are feasible, the usual domination principle is used (see definition of domination in 5.3.3).

For instance, two of the constraints of our problem can be defined in the following equations.

Constraint for the limit of tap position of the transformers.

\[
t_{\text{min}} \leq t_o \leq t_{\text{max}}
\]  

(5.5)

Constraint for the limit of the reactive power from the generators.

\[
Q_{\text{min}} \leq Q_o \leq Q_{\text{max}}
\]  

(5.6)
In our case all constraints are defined as hard constraints. This condition makes it more difficult to find feasible solutions but increases the accuracy of the algorithm. The new Pareto front will be different from the ideal Pareto front. It is evident that the new solutions may be more conservative because the constraints are included in the searching process. In Figure 5.6 is shown an example of how the Pareto front could look.

![Pareto front with a constrained tournament selection operator](image)

**Figure 5.6: Pareto front with a constrained tournament selection operator**

The constrained tournament selection provides more diversity in the solutions because the infeasible solutions have more opportunities to survive and at the same time the infeasible solutions are forced to be always dominated by feasible solutions. There is no need for any extra constraint handling strategy.

### 5.4 Simulations I

A first group of simulations were made by using the IEEE-14 bus model, see Figure 5.7. Controllable devices are two generators, three synchronous condenser, three tap-transformers and one shunt capacitor.

*The initial condition of voltage in the system:*  
The voltages at terminals of generators are all equal to 0.95 (per unit). The
Figure 5.7: IEEE 14 bus scheme
tap position of all transformers is cero and none connected capacitor. The non-violation voltage range is between 0.95 and 1.05. For this initial condition, voltages at each node are showed in Fig. 5.8 and it is clear that most of the buses are under voltage violation. Total power loss is 16.11 MW.

![Figure 5.8: Voltages at initial conditions](image)

A total of 60 independent simulations were executed and the average values of those simulations are showed in each generation. The averages of the minimum and maximum voltage deviation in the first front for all simulations are showed in figure 5.9. In figure 5.10 it is showed the average of minimum and maximum power losses of all simulations and the figure 5.11 illustrates a similar analysis for the case of the number of control actions.

One of the several simulations is showed in a three dimensions. See in figure 5.12 how the best solutions are located in the pareto optimal front. From this group of solutions anyone is optimal.
Figure 5.9: a) Minimum voltage deviation in the first front for all simulations. b) Maximum voltage deviation in the first front for all simulations.

Figure 5.10: a) Minimum power loss in the first front for all simulations. b) Maximum power loss in the first front for all simulations.
Figure 5.11: a) Minimum number of control actions in the first front for all simulations. b) Maximum number of control actions in the first front for all simulations.
5.5 Analysis of Mutation Factors

Mutation operation is defined by [11] as a mechanism to compensating loss of information that might occur during selection and crossover. Author in [11] considers that the mutation plays a secondary role in the algorithm and is unable to contribute to exploring new solution areas. According to that concept, he suggests a low value of frequency of mutation, one mutation per thousand bits. Such low level of mutation is linked to the idea that if mutation factor increases too much, GA performance will be closer to a simple random search [11]. Such criterion is true in case of encodings with low cardinality alphabets like binary format. However, in case of encoding with higher cardinality alphabets, which is our case, is possible to avoid the undesirable random behavior with the application of elitism. Even if mutation rate is high, it is possible to keep the conservative recombination essentials and the necessary exploration potential.

Figure 5.12: Three dimension view of one simulation result with mutation probability = 0.90
5.6 Simulations II

The modeled system is an IEEE 30-bus scheme. Detailed data of buses and branches are given in [12]. The system has six generators at bus 1, 2, 5, 8, 11, and 13 and four transformers with off-nominal tap ratio in lines 6-9, 6-10, 4-12, and 27-28. The limits of voltage for all busses are 0.95 pu and 1.05 pu. The lower and upper limits of the transformer tappings are 0.9 and 1.1pu respectively. The initial condition of the system is showed in table 5.1.

Table 5.1: Initial Condition in the System

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
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<tbody>
<tr>
<td>( V_{G1}(pu) )</td>
<td>1.05</td>
</tr>
<tr>
<td>( V_{G2}(pu) )</td>
<td>1.045</td>
</tr>
<tr>
<td>( V_{G5}(pu) )</td>
<td>1.01</td>
</tr>
<tr>
<td>( V_{G8}(pu) )</td>
<td>1.01</td>
</tr>
<tr>
<td>( V_{G11}(pu) )</td>
<td>1.05</td>
</tr>
<tr>
<td>( V_{G13}(pu) )</td>
<td>1.05</td>
</tr>
<tr>
<td>( T_{6-9}(pu) )</td>
<td>0.978</td>
</tr>
<tr>
<td>( T_{6-10}(pu) )</td>
<td>0.969</td>
</tr>
<tr>
<td>( T_{4-12}(pu) )</td>
<td>0.932</td>
</tr>
<tr>
<td>( T_{27-28}(pu) )</td>
<td>0.968</td>
</tr>
<tr>
<td>Voltage Deviation (pu)</td>
<td>0.834</td>
</tr>
<tr>
<td>Power Losses (MW)</td>
<td>5.4356</td>
</tr>
</tbody>
</table>

Several simulations were made in order to find crossover and mutation factors that can improve the speed performance of the algorithm. Also, some plots show the group of best solutions which are part of the calculated optimal pareto front.

Voltage deviation, power losses and the number of control actions. A comparison of results with different mutation factors:

This comparison was made in order to prove that a more important mutation factor can bring a faster convergence of the algorithm without getting into a pure random search. The mutation probability factors (M.F) used for the comparison
are 5%, 10% and 25%. A total of fifty independent simulations were executed for each mutation factor. Voltage deviation factor, power losses and number control actions are shown in figure 5.13, 5.14 and 5.15 respectively. It is observed that a lower mutation factor do not necessarily guarantee better performance results.

Figure 5.13: Mean value of voltage deviation for each mutation probability

Figure 5.14: Mean value of power losses for each mutation probability

*Final solutions of the multi-objective algorithm:*
Figure 5.15: Mean value of number of control actions for each mutation probability

Figure 5.16: Result1. 3D view of the optimal solutions
5.6 Simulations II

Figure 5.17: Result 1. 2D view of the optimal solutions

Figure 5.18: Result 2. 3D view of the optimal solutions
### Table 5.2: Initial and Final Conditions in the System

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Initial Value</th>
<th>Final Value</th>
</tr>
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</tr>
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<td>$V_{G5}(pu)$</td>
<td>1.01</td>
<td>1.00</td>
</tr>
<tr>
<td>$V_{G8}(pu)$</td>
<td>1.01</td>
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<tr>
<td>$V_{G11}(pu)$</td>
<td>1.05</td>
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</tr>
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<td>1.05</td>
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<td>$T_{27-28}(pu)$</td>
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<td>1.04</td>
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<td>Voltage Deviation (pu)</td>
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<td>0.38</td>
</tr>
<tr>
<td>Power Losses (MW)</td>
<td>5.4356</td>
<td>5.3513</td>
</tr>
</tbody>
</table>

Figure 5.19: Result2. 2D view of the optimal solutions
5.7 Conclusions

A multi-objective genetic algorithm, based on NSGA-II, was implemented in order to find minimum voltage deviations, minimum power losses and minimum number of control actions. Several simulations were made and the exposed results show the robustness of the algorithm. Thus, a comparison analysis of different mutation factors was made and the results give a clear indication that it is possible to increase the mutation factor without losing the conservative recombination essentials and increasing the exploration potential of the algorithm. With a 25% of mutation probability it is possible to reach the convergence with an important reduction of the number of iterations.

5.8 References


Chapter 6

Conclusions and Future Work

6.1 Conclusions

Voltage and reactive power control in power transmission systems is not a new problem and it has been studied for many decades, but this issue should be faced in a new context. Consumer behaviors are changing, new reactive controllers are gaining more and more spaces in the power system and penetration of renewable power sources is growing exponentially. The future scenario in power system requires a more intelligent and robust power system able to solve the new problems that already exist and those that will come. One of the areas to work on it is the creation control algorithms which have to be able to met the new demands of this ever-improving-system that we all need.

The aim of this thesis is to investigate and develop new algorithms for the control of voltage and reactive in a steady state frame. The main result is a group of algorithms that are based on rules, pure evolutionary approach and a combination of both. These algorithms are able to solve important problems of voltage deviations, reduce the number of switching operations of the controllable devices and the power losses as well.

An algorithm based on rules has been presented in Chapter 2. Here, a simple approach is shown. The idea is basically that a group of rules leading to a search of the most suitable controllable device for any voltage violation that appear. Remarkable points here are the simplicity and the reduced time consuming of computation. In case of a 30 bus system is aproximately 10 seconds. The voltage
correction is effective and is notable the reduction of power losses and the number of control actions.

A design of hybrid algorithm has been proposed in Chapter 3. The approach is a combination of a genetic algorithm and some rules based of the algorithm of Chapter 2. The component of evolutionary searches are introduce in order to get solutions more close to the global optimal ones. The used rules have the role of accelerating in the selection, crossover and mutation process. The hybrid algorithm was compared to the previously designed, and the results show a better performance when the best features of the GA and simple rules are used coordinately.

Motivated by the great potentiality of the genetic algorithms, a study and analysis of several genetic algorithms applied to the Volt/Var control has been carried out in Chapter 4. Several issues of the GAs were discussed. Coding format for instance is a key point. Floating and integer formats provide a more natural representation of the problem and as well as assisting in the fitness evaluation. Ideas most used to avoid local convergences are the dynamic modification of mutation and the crossover probability factors, with some works showing good and interesting results. In the case of crossover operators it is observed that the single-point crossover is the most frequent one with uniform crossover almost never being used in order to avoid undesired disruption. However, it has been shown that with an intelligent strategy of crossing probability factor variation, it is possible to control the disruption allowing for the adaptive uniform crossover to be very effective. Another important aspect is the speed of convergence in GAs. This issue of speed requires more attention. Some of the approaches to mitigate this problem are described: off-line GA applications, hybrid algorithms, and parallel GA. These are very interesting solutions which offer a wide spectrum of possibilities for developing new algorithms.

Finally, in Chapter 5 is proposed a multi-objective genetic algorithm. It is a common to see the solution of optimization of the voltage and reactive power, which is a multi-objective by using a approaches based on single-objective functions. This type of solutions do not guarantee global optimal solutions because some parameter in the fitness functions have to be tuned by trial and error. This problem is overcome by applying a multi-objective based on Pareto principles.
The results show a successful performance of the algorithm with a minimum values on voltage deviation, power losses and number of control actions. With this type of solutions, the dispatcher counts with several solutions that are in the group of the best solutions. Such flexible conditions brings better possibilities to the especialist to chose the suitable control actions for each scenario.

6.2 Future Works

In Chapter 4 some weak points of the GA applied to Volt/Var have been exposed. The speed convergence still is one of those weak points. For future condition of the system is absolutely necessary to work with algorithms in real time and able to find optimal solutions. One of the way to explore will be developing GA-based approaches much more faster to control voltages and reactive power flow. Using the potencialities of GAs is posible to implement robust parallel systems. Further studies will be done in order to reduce at a minimum the evaluation time of the algorithms. This is the bottle-neck of most of the algorithms. Solutions may be reached by inserting powerful neural networks. Thus, it will not be necessary many power flow calculations.

Other issue to work on it is the insertion of FACTs in new controlling algorithms. The FACTs will play a very important role in the future network and their powerful features have to be used to get more intelligent control actions.

The new concepts for operation of the system, like trading of energy amount consumers will bring more congestions in transmission and distributions lines. For that reason also in the future work, security and stability will be include in the optimization of the system.