

Applications of Genetic Algorithm in Power System Control Centers

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1. Introduction

Nowadays, modern operation control centers have managed electrical power systems, accomplishing functions such as automatic generation control, state estimation, topology analysis, etc. In these centers, operators handle the system using several computational programs to help them in the problem solving.

Usually, these programs are based on traditional numerical computation. However, recently, some applications based on intelligent systems have started to be used in control center. This chapter will present three new developments/applications of these programs based on genetic algorithms: power flow calculation, system restoration process and economic dispatch/unit commitment.

The chapter starts with an introduction about the structure of modern control centers, their relations with the power system, their management structure, and the computational programs available. And then, an overview about the new intelligent computational program applications is presented with focus in genetic algorithm techniques.

After this introductory part, the three applications, power flow, system restoration and unit commitment, will be presented in details. It means, how to use genetic algorithm techniques to solve these problems is presented with illustrative examples and with the possibility to readers reproduce the results.

2. Overview of the modern power control centers

Electric power systems are the structures that have the purpose of generating, transporting and distributing electricity. These structures are composed of energy generating plants, transmission lines, distribution systems and elevating and distribution substations. The biggest challenge of this type of system is that the electrical energy is not a material that can be stored. That is, so it is required by the load (which can be a driver in an industry or the mere light of a lamp in a residence) this energy must be generated, transported and delivered to the user instantly.

Another problem is regarding to a systematic increase of demand and consumption of electric energy, observed mostly in large urban centers and regions where focus greater industrial activity. This also conducts to the growth of complexity to the management, supervision and control in meeting these demands.

There are several ways to design a control system to an electrical system. The hierarchical form is the form most widely used. It holds a system operation center that is responsible for controlling generation of large blocks of energy in the power plants and by monitoring of interconnection transmission lines between the areas. The electrical system is then operated by areas of operation, where each area has its own center for the operation, named area operation center or regional operation center. These area operation centers are responsible for the operation of power plants in their area of control, by the operation of transmission lines and substations into their control areas. They are also responsible for the energy supply of large consumers of electricity in their area. Operation centers receive information from distribution operation centers, coordinate this information and deliver to the system operation centers.

Within an area, there is another division of the electrical system in power distribution centers, which are controlled by distribution operation centers. These centers are responsible for the operation of the lines of sub-transmission, distribution networks and distribution substations. These centers are also responsible for the supply of energy for industrial consumers and small and medium industries and residential consumers of electrical energy existing in your distribution sub-area. Figure 1 shows a possible structure of a power system control with a system operation center (SOC), three area operation centers (AOC), and many distribution operation centers (DOC).

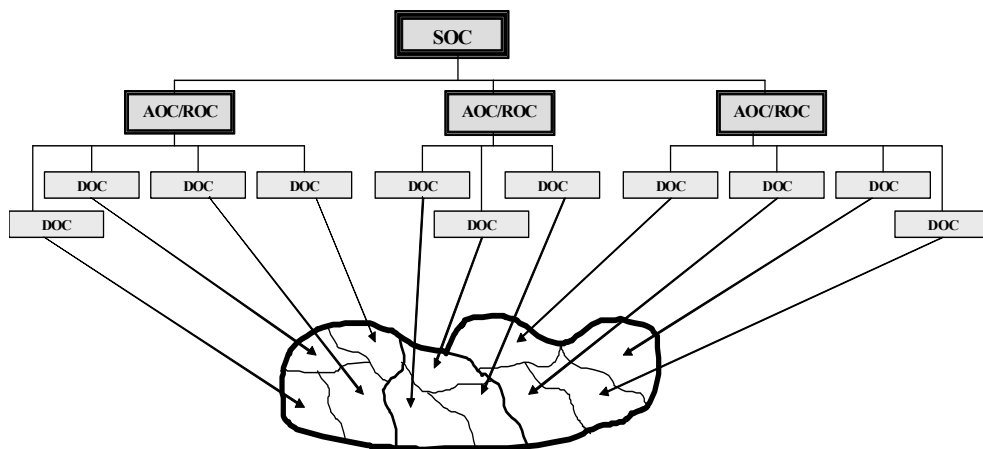


Fig. 1. Hypothetical power system control structure with system operation center (SOC), three area operation centers (AOC), and many distribution operation centers (DOC)

The operation centers, regardless of their type, have structures that are very similar. They are equipped with computers that have two main functions. The first one is to receive the information from the electric system. The size of flow of this information depends on the type of the monitored equipment and the type of measurement that is being monitored. For example, the power flow in a transmission line can have a read performed every second,

while the status of operation of a circuit breaker can be read and sent to the operation center each minute. However, with increasingly reduced cost of measurement and telecommunication systems, more measuring points are created and the number of data read has increased a lot. Currently, a mid-size operation center receives something around 3000 to 5000 values per minute.

The second function of computers is to save a set of computer programs for analysis and assistance to the operation of the system. Several existing programs are in operation center computers. For example, one of them is responsible for the reception, validation and delivery of this large volume of data received per minute by control centers, namely SCADA (Supervisory Control and Data Acquisition). Figure 2 shows the structure of an Operating Centre. The path of operation in a control center is the following. The center receives the measurements from the system. These measurements are validated and presented to the operator. He/she runs computational programs in order to obtain the status of the system, and then, if necessary, he/she sends action control commands to the system also by some computational programs. In order to support the power system management, operation and control, the SCADA systems can be integrated with computational tools composing what is usually named EMS (Energy Management System). These systems comprise functions such as state estimator, power flow, optimal power flow, fault calculation, network sensitivity, security analysis, economic dispatch, etc (Wood & Wollenberg, 1996). Some of these applications can be implemented in real-time, and some of them are performed in study modes.

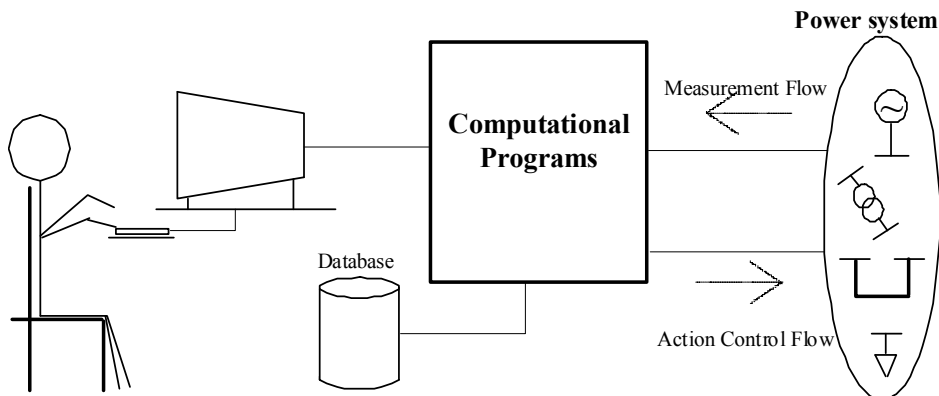


Fig. 2. Structure of a control center with the measurement flow and action control flow (Lambert-Torres et al., 1999)

3. Problem statement

The present section provides an overview on three common activities performed in power system control centers, the power flow studies, the power system restoration after contingencies, and economic dispatch of generator units and their commitment. These mentioned activities will be approached in coming sections through genetic algorithm based methodologies.

3.1 Power flow analysis in electrical power systems

The achievement of many power flow studies is required by most functions performed in power system control centers. Power flow is an electrical engineering known problem which determines the power system operation point in the steady-state. The power flow – or load flow – problem consists in the obtainment of the buses voltages and then in the calculation of the amount of power in the system generation buses as well as the power flow in the system branches. A set of non-linear equations is applied to model this kind of problem, which is commonly solved by numerical computational methods (Stott & Alsac, 1974). Among the traditional numerical methods, the usually applied method in the power flow computation is the Newton-Raphson method, as well as its variations, because it presents a better and a faster convergence. However, such method implies some difficulties because of the complex Jacobian matrix calculation and inversion, and also the dependence on good initial estimated values to guarantee the convergence.

In fact, a power bus in the system has 4 variables, where two of them can be controlled and the other two are related to be system conditions. These variables are: P expresses the values of active power in the bus; Q expresses the values of reactive power in the bus; $|V|$ represents the magnitude of the bus voltage; and, δ represents the phase angle of the bus voltage. The values of P and Q are positive if the active power is injected in the bus – it means, for generation buses, and negative if the active power is taken from the bus – it means, for load buses.

The power system buses are classified according to the variables previously known, in three types:

- a. Type 1 or Type PQ: P_i and Q_i are specified and $|V_i|$ and δ_i are calculated – usually, this type represents the load buses of the system.
- b. Type 2 or Type PV Bus: P_i and $|V_i|$ are specified and Q_i and δ_i are calculated – usually, this type is used to represent generation buses.
- c. Type 3 or Type V δ (namely “Slack Bus”): $|V_i|$ and δ_i are specified and P_i and Q_i are calculated – this type is a representation of the strongest generation bus of the system.

The buses type 1 usually represents the load buses because the values of P and Q are known by the load. An example is the power required to a motor runs. The user knows these values and can control it. If he/she put more motors in a bus, it is quite simple to know the power. However, it is impossible to the user control the voltage values ($|V|$ and δ). It also occurs in our homes, we know the power required but we don't have any kind of control about the voltage levels.

The buses type 2 usually represents the generation buses because in a power plant the values of P and $|V|$ can be controlled by the operator. If the operator increases the primary source of energy, the value of P increases together, and, vice-versa, it means, if the operator decreases the primary source of energy, the value of P decreases. The same occurs with the value of $|V|$ but in this case the operator changes the excitation system of the generator. However, for this type of bus, the operator can not have any kind of control of the Q and δ values.

Finally, the bus type 3 is generally only one in the power flow calculation. Usually, this bus is the strongest power generation in the system. This bus gives a reference for the system

(the values of $|V_i|$ and δ) and receives all balance power required from the system, it means, this generator needs supply all power not given by the other generators to the system.

The power flow study provides the system status in the steady-state; it consists in the determination of the possible power system operational states through the previous knowledge of some variables of the system buses. This study aims to obtain the system buses voltages in order to determine later the power adjustments in the generation buses and the power flow in the system branches. After the system steady-state is calculated, it is possible to obtain the amount of power generation necessary to supply the power demand plus the power losses in the system branches. Besides, the voltage levels must remain within the boundaries and overloaded operations added to those in the stability limit must be prevented (Anderson & Fouad, 2003).

The main idea behind the power flow computation, which is made by iterative form, is to find equilibrium of the known values (controlled values) and the calculated values. For instance, let's a system with 2 buses with voltages V_1 and V_2 and supplying a load with values P and Q , the power flow computation between two buses is given by the following equation:

$$P - jQ - yV_1V_2^* = 0 \quad (1)$$

Or, in general form of the static power flow equations is given by (2):

$$P_i - jQ_i - y_{i1}V_1V_i^* - y_{i2}V_2V_i^* - \dots - y_{in}V_nV_i^* = 0 \quad (2)$$

Where: $i = 1, \dots, n$, and it represents the bus number; P_i is the active power generated or injected in the bus i ; Q_i is the reactive power generated or injected in the bus i ; $|V_i|$ represents the voltage magnitude of the bus i ; δ_i is the voltage phase angle of the bus i .

And more, $V_i = |V_i|e^{j\delta_i}$, i. e., the voltage in the polar form; $V_i^* = |V_i|e^{-j\delta_i}$, i. e., the conjugate voltage; y_{ik} = element of the nodal admittance matrix Y_{bus} .

The nodal admittance matrix can be computed as follows: if $i = k$, y_{ik} is the sum of the admittances that come out from the bus i ; else y_{ik} is the admittance between the buses i and k , multiplied by -1.

A complex and non-linear equations system is represented by (1), so its solution is obtained through approximations using numeric methods. These methods make the assumption of the initial estimate values to the bus voltages and in the application of the static power flow equations in successive iterations, looking for better approximations. The required accuracy determines the stop criterion.

3.2 Restoration of electrical energy distribution systems

Modern society depends increasingly on power supply, which conducts to the growth in demand and consumption of electrical energy. Therefore, in order to supply this amount of power, electrical power systems have been presenting a natural expansion. The described phenomenon is more evident in large urban centers and in regions of greater industrial concentration. As consequence of the development of the system, the complexity of its

supervision, control, and energy demand supply management have been increasing. These mentioned factors highlight the importance of high quality power supply as well as its continuity, low cost and reliability.

At the same time we point out the power system current scenario, the possibility of faults along the line is inherent to the system or even greater due to the rise in electrical system complexity and natural factors. Thus, after system contingencies, it is extremely important that the electric power system restoration be quick to guarantee the power demand supply and the customer's satisfaction. The longer it takes, the greater the loss for the company as well as for the customer. This situation becomes worse when the fault reaches an industrial area (Chiang, et al. 2001). The reconfiguration is a switch shifting (open/closed), loss reduction, load balancing, and restoration process (Lambert-Torres et al., 1997).

Electrical energy transmission systems usually adopt structured procedures to restore a faulted system, following pre-defined rules established by standardization agencies. So the operator has a limited decision power and its main function is to proceed according to the operation steps sequence pre-determined for the system given contingency. Moreover, it is usual the employment of the "N-1" criterion, in which, the whole power system, must be restored after a single contingency occurrence. In some particular cases, more rigorous restoration criteria can also be applied (Esmín et al., 2005).

Introducing this problem to electrical energy distribution systems, which usually have less regulation to perform these processes, we will face some peculiarities. The system operator has more decision power in a network reconfiguration process, because of the mentioned difference regarding to less standardization or even lack of network procedures. Each distribution company can adopt a different philosophy to perform a restoration process and the computer programs which support the system operator can play an important role. These computer programs can assist in the choice for a better solution and even reduce time required by the operator for its decision-making (Lambert-Torres et al., 2009).

Moreover, there are differences regarding to the system structure and topology. Electrical energy distribution systems generally present a radial topological structure. In other words, in this kind of system is not usual the presence of meshes. These systems often comprise switches that can be classified in general as NO - Normally Open switches and NC - Normally Closed switches. In the case of all the present switches are closed, so there will be formation of meshes. Then, in order to preserve the radial structure of the topology, for a system composed by k meshes, k switches must to be open. That is, there must be at least one normally open switch in each mesh (Salomon et al., 2011).

Resuming the system restoration process issue, the restoration is defined as the process of changing the open/closed status of switches, loss reduction, load balancing and restoration (Lambert-Torres et al, 1997). This is a decision-making problem of combinatory nature, subject to optimization and system building characteristics constraints. The reconfiguration of the system is performed by closing NO switches in order to restore the system in an optimized way, however retaining the radial topology inherent of electrical distribution systems. Moreover, NC switches may also be opened, providing a network reconfiguration without overloaded branches.

Generally electrical distribution systems comprise lines with NO switches, lines with NC switches and lines without switches. For an optimized reconfiguration, the decision-making involving switching is done so as to maximize the power supply, minimize the switching maneuvers and avoid overloaded branches. This process must happen fast and dynamically. It should provide a simple, objective, and efficient solution to the operator (Lambert-Torres et al., 1997). Considering a single contingency in the distribution system, meeting the characteristics mentioned above, the closing of a single NO switch is enough to restore the system. To avoid overloaded branches, one or more NC switches may also be opened, depending on the contingency consequences for the given system. And, in this case, other NO switches can be closed. This fact generates a new path for energy transmission, to supply the greatest possible power supply after the system contingency.

3.3 Economic dispatch and unit commitment

One of the principal operators' activities in system operation centers is to dispatch the demand and generated energy. However, to accomplish this task the operators need to know different type of information from the system, such as: location of the load demand, situation of the energy generation among the power plant, power flows in the transmission system, and so on. Also they receive some studies previously prepared about the available capacity of each power plant, and the better situation of power dispatch, this study is named economic dispatch and unit commitment.

The economic dispatch study has the aim to establish the better division among the power plants to supply the load demand for a period of time t_j . This study takes into account the cost of primary energy for electric power generation, the cost of transmission system (to take the energy between the power plant and the place where the load is required), and other possible costs related to the dispatch of a generation unit. The main idea behind this study is to minimize all these costs. It can be expressed by (3)

$$F_T = F_1 + F_2 + \dots + F_N = \sum_1^N F_i(P_i) \quad (3)$$

Where F_i represents all the generation costs to produce and transport until the load a power P_i by the power unit i , and F_T is the total generation cost the supply a required load in a period t .

The problem is to minimize the value of F_T , subject to the constraint that the sum of each power unit must equal to the required load, expressed in (4).

$$\phi = 0 = P_{Load} - \sum_1^N P_i \quad (4)$$

P_{Load} represents the total required load during the period t_j . The most traditional method of optimization to solve this problem involves Lagrange function, and it can be expressed by (5), where the Lagrange multiplier λ appears.

$$L = F_T + \lambda\phi \quad (5)$$

And to minimize the Lagrange function must be derivative with respect to the power produced, as expressed in (6).

$$\frac{\partial L}{\partial P_i} = \frac{dF_i(P_i)}{dP_i} - \lambda = 0 \quad (6)$$

So, the conditions and inequalities are completed by the capacity of each power unit expressed by (7). At this time, for N generation units, there are N equations (eq. (6)), $2N$ inequalities (eq. (7)), and one constraint (eq. (4)).

$$P_{\min,i} \leq P_i \leq P_{\max,i} \quad (7)$$

Where $P_{\min,i}$ and $P_{\max,i}$ express the minimum and maximum capacity of generation of unit i .

Different gradient methods have been applied to solve this problem, in special, Newton's method (Wismer, 1971). Also, dynamic programming has been used to solve this problem. In all cases the problem is the computational cost for real-life problems, and some non-convex regions appear in the feasible region.

If the economic dispatch is a "snapshot" of the power generation, the unit commitment can be considered by a "movie", because unit commitment study makes many economic dispatch studies for a period of time t (it involves many periods t_i). Figure 3 shows a hypothetical unit commitment study to supply the required load for three generation units. The largest line represents the required load during the period of study t , and each block represents the generation power P_1 , P_2 , and P_3 necessary to supply the load.

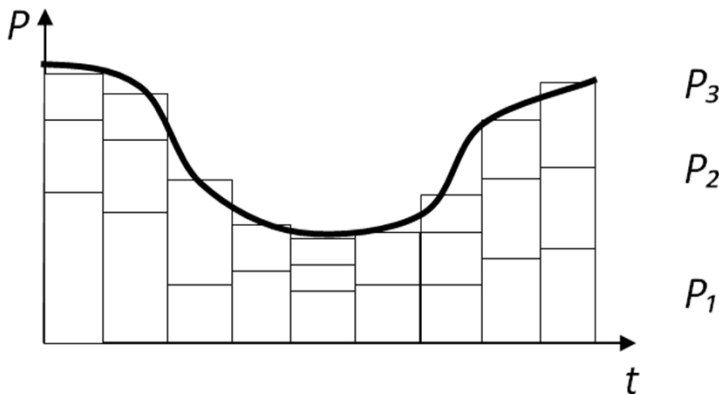


Fig. 3. Hypothetical unit commitment study result for three power units

Of course, unit commitment studies have other elements to take into account to process the economic dispatch. For example, in thermal units, new constraints must be care such as: minimum operational time, minimum time to restart the machine, and so on. And more, aspects such as spinning reserves and fuel reserves are also presented in these studies. Usually, dynamic-programming methods are used to solve this problem (Larson, 1978). The major problems found here are the same of the economic dispatch: computational cost for real-life problems and some non-convex feasible region.

4. Types of genetic algorithm applications in power system problem-solution

The application of modern meta-heuristic methods, in special genetic algorithms, in power system problem-solution can be divided in three types, namely: stand-alone systems, integrated systems, or fused systems.

The first type, stand-alone systems, is where the genetic algorithms run completely alone. It is possible in three ways. The first one is to get the input data, run the genetic algorithm, and give a final answer for the problem. The second way to build stand-alone systems is to help other methodologies to get a final answer. It occurs in two paths: the first one is to run the methodology and then to get the answer of this methodology and to run the genetic algorithm in order to have the final answer. The second path is to run the genetic algorithm from the initial input data and to have a partial answer and then the methodology runs from these data in order to have the final answer. Figure 4 shows these two types of stand-alone integration system. To be classified as stand-alone system it is important that there is any type of integration between the helped methodology and the genetic algorithm. Example of this type of application is presented below in the chapter for restoration system.

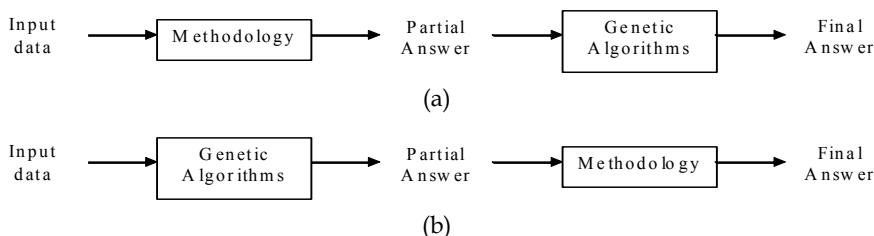


Fig. 4. Two types of stand-alone integration system

Another type of stand-alone systems is a concurrent strategy where helped methodology and genetic algorithm run in parallel, getting the same input data, run each system alone (methodology and genetic algorithm) and each one give their own answer independently. Figure 5 shows this type of stand-alone system. This type of system is applied when sometimes the helped methodology fails to get an answer or gives an incorrect answer for the input data. Example of this type of application is presented below in the chapter for load-flow problem.

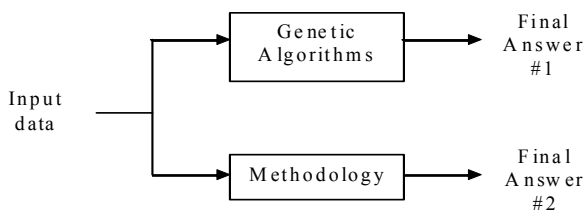


Fig. 5. Two types of stand-alone integration system

The second type is namely integrated systems. In this type, the helped methodology and the genetic algorithms run together, one after other, in cycles. For example, genetic algorithms get some data, run the crossovers and mutations for some generations and give more

refined data to the helped methodology. Then, this methodology gets these data, runs its algorithm, and provides an answer. And then, the genetic algorithms get these data, and the process restarts. It occurs many times until to achieve a final answer. An example of this type of integration is when genetic algorithm training a neural network. A good example of this application in power system control is presented in (Farag et al., 1998, Farag et al., 1999). In this example, a genetic algorithm training system is used in a fuzzy-neural model shown in Figure 6. The fuzzy memberships of the fuzzy-neural model are setting by a genetic algorithm strategy to control synchronous generators in power plant. The proposed control can be used for multi-machines and to control the flows in the transmission lines between the areas of the system.

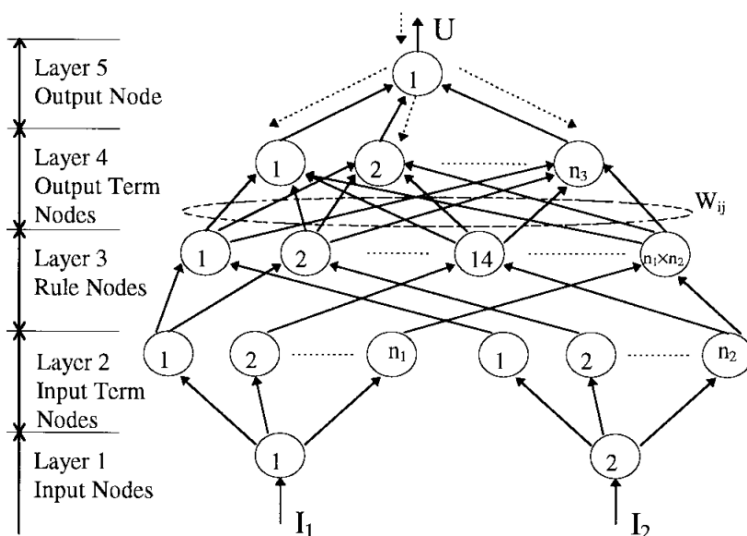


Fig. 6. Example of fuzzy-neural model training by genetic algorithms (Farag et al., 1998)

The third type is named fused systems. In this type, the helped methodology and the genetic algorithms run completely together. It means, it is impossible to have a separation where one methodology finishes and the other methodology starts. It is exactly the difference between fused systems and integrated systems. In the second one, it is possible to change the genetic algorithms for other methodology, meta-heuristic or not, without any kind of compromise of the entire system. For example, in the case presented in Figure 6, the training process could be performed by other meta-heuristic technique, as such, particle swarm optimization (Eberhart & Kennedy, 2001) or ant colonies (Dorigo & Stützle, 2004). In fused systems, this change is impossible without lost of identity of the system. An example of this third type of integration is, for instead, a genetic algorithm with fuzzy parameters, it means where the chromosomes have a fuzzy means and the genetic evaluation has also made by fuzzy arithmetic. An example of this procedure is presented in (de Carvalho et al., 2011). This application for power system operation center has been developed to evaluate the current status of the operational point. This approach reads the operation center database and establishes a set of rules for operation status classification. Then the current

measurements from the system are evaluated by this set of rules. The genetic algorithms are used to provide a previous classification of the attributes. Figure 7 shows the chromosomes a_1 , a_2 , a_3 , and a_4 , with the ranges of fuzzy memberships and how the crossover is made.

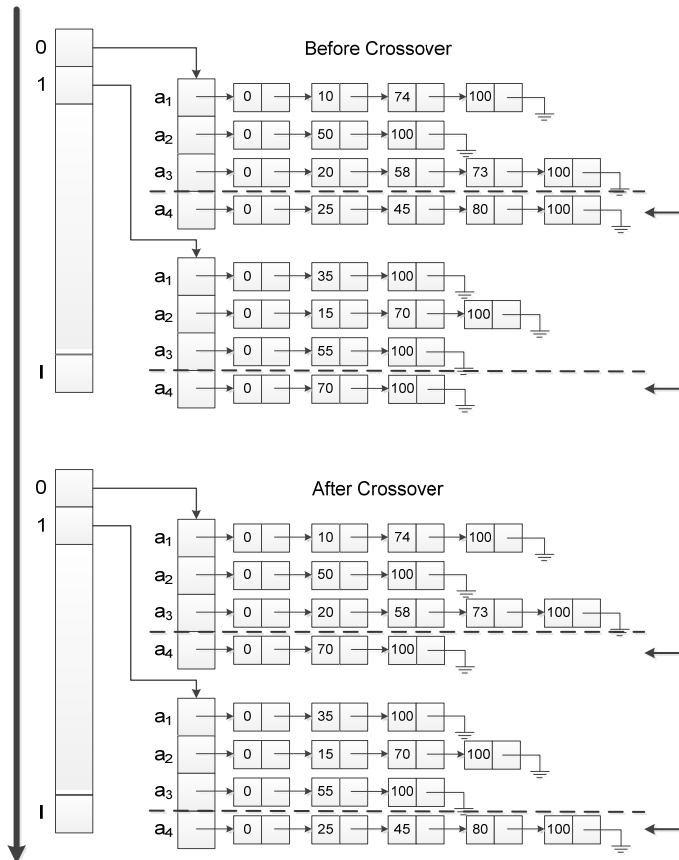


Fig. 7. Example of genetic-fuzzy chromosomes and crossover (de Carvalho et al., 2011)

Another type of classification can be expressed by the kind of the current possible solution for a problem. There are three possible types of classifications: (a) problems with traditional methodologies to solve it but these methodologies have a high computational cost; (b) problems with traditional methodologies to solve it but with some constraints in their application; and (c) problems without any traditional methodologies to solve it. In the first type of classification, a problem has been solved with traditional techniques; however, these techniques have a high computational cost in time or in memory space. Usually, these techniques are not very well scalable, it means, when the size of the problem increases the cost for the solution increases much more. An example of this type of problem is the load-flow. Newton full, Newton-Raphson, and Gauss-Seidel are some traditional methods used to solve load-flow problems. In the second type of classification, we can find problems solving by traditional methodologies; however, these methodologies present some problems

to be applied in all possible situations or they don't have an expected performance in all situations.

In the second type of this classification, certain solutions are very-well applied if certain conditions and constraints available. For example, some of them work in convex feasible regions such as the solution of unit commitment problem by dynamic programming. However, when this condition is not satisfied some areas can leave to be explored. The third type of classification occurs when a problem doesn't have any type of traditional numerical solution. The power restoration system is an example of this kind of problem. Usually, only intelligent methods, in special meta-heuristic methods, have been applied to solve this problem.

5. Power flow computation using genetic algorithms

This section presents a methodology using genetic algorithm for accomplishing power flow studies of electrical power systems. The intent of this chapter is to present a novel approach for power flow calculation, providing an easier and more flexible implementation comparing with the traditional methods, and also being potential to overcome some limitations found when executing power flow studies using current computational routines.

The presented genetic methodology is based on the minimization of the power mismatches in the power system buses. The principle of the proposed algorithm consists in adopting the chromosomes as the power system buses voltages, phase angles and magnitudes. The computational routine starts with estimated initial values for the chromosomes parameters, and these values are updated in each iteration process through the genetic operators, and the rule function, which comprises the problem modeling. The chromosome structure model is given as:

$$x_i = \{\delta_2, \delta_3, \dots, \delta_k, \dots, \delta_n, |V_2|, |V_3|, \dots, |V_k|, \dots, |V_n|\} \quad (8)$$

Where i represents the chromosome index, related to the population size; n is the number of buses of the system; k is the system bus index, δ_k is the voltage angle at the bus k ; and, $|V_k|$ is the voltage magnitude at the bus k . The bus with $k = 1$ is taken as swing bus and it does not compose the chromosome structure.

Let's the test IEEE power system shows in Figure 8. This system contains 14 buses, 15 transmission lines, and 3 transformer branches. The IEEE 14-Bus Test System represents a part of the Midwestern US Electric Power System as of February, 1962. The Bus #1 is chosen as swing bus. The Buses #2, #3, #6, and #8 are buses with generation, and they are the type 2, where P and $|V|$ are known and the values of Q and δ are calculated. The Buses #4, #5, #7, #9, #10, #11, #12, #13 and #14 are load buses and they are type 1, where P and Q are known and the values of $|V|$ and δ are calculated.

In this case the chromosome for the system shown in Figure 8 has the following form:

$$x_i = \{\delta_2, \delta_3, \delta_4, \delta_5, \delta_6, \delta_7, \delta_8, \delta_9, \delta_{10}, \delta_{11}, \delta_{12}, \delta_{13}, \delta_{14}, \\ |V_4|, |V_5|, |V_7|, |V_9|, |V_{10}|, |V_{11}|, |V_{12}|, |V_{13}|, |V_{14}|\} \quad (9)$$

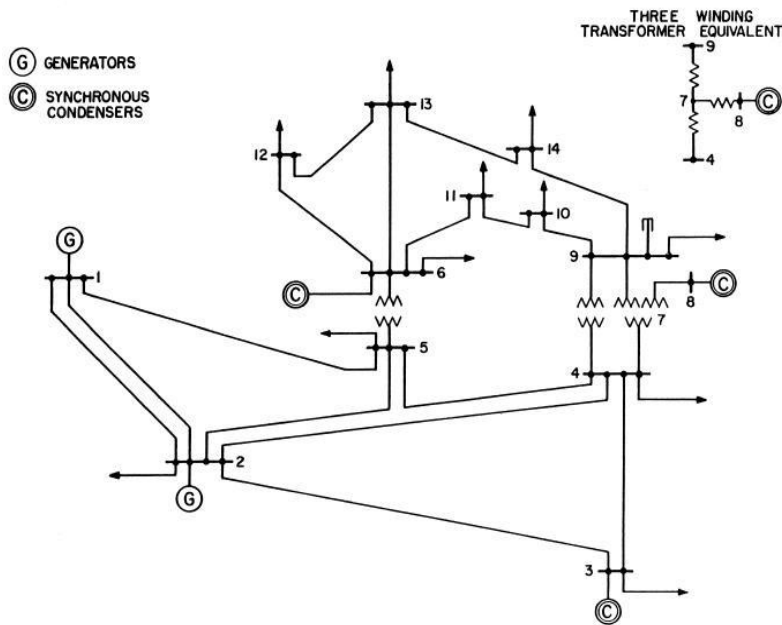


Fig. 8. IEEE 14-bus test system, with all system buses, branches and elements

The definition of the population parameters is made according the power flow problem particular features. The chromosomes are defined as the system buses voltages, so they assume continuing values within the boundaries specified in the system input data. The rule function parameters to be minimized during the genetic algorithm procedure are defined as *scores*. The scores are computed as the arithmetic mean of the buses apparent power. Each chromosome has a *personal score*, and it uses during the creation of individuals in the mating pool.

The algorithm begins with the generation of the initial estimated values for each chromosome. The voltage angle begins with a random initial value within the specified boundary. The voltage magnitude initial value depends on the nature of the bus that the parameter is associated with. In the case of a PQ bus, the voltage magnitude begins with a random value within the specified boundary. On the other hand, in the case of a PV bus, the voltage magnitude receives the related value specified in the input data and this value remains the same during the process iterations, it means, this is a fixed value.

Once all the parameters of the population have the initial estimated values, the iterations are initiated. The procedure detailed as follows is performed for all iterations and for each chromosome.

1. The system buses voltages are assigned with the chromosome values.
2. The reactive power of the PV buses is computed applying the equation (2).
3. The active and reactive power of the $V\delta$ bus is computed applying equation (2).
4. The power flow in the system branches is calculated using the equation (10):

$$S_{ij} = P_{ij} + jQ_{ij} = V_i(V_i^* - V_j^*)Y_{ij}^* + V_iV_i^*Y_{sh,i} \quad (10)$$

Where S_{ij} represents the complex apparent power between the buses i and j ; P_{ij} is the active power between the buses i and j ; Q_{ij} is the reactive power between the buses i and j ; V_i is the bus i voltage; V_j is the bus j voltage; $V_i^* = |V_i| e^{j\theta_i}$, i. e., the conjugate voltage; $V_j^* = |V_j| e^{-j\theta_j}$, i. e., the conjugate voltage; Y_{ij} is the admittance between the buses i and j ; $Y_{sh,i}$ is the shunt admittance of the bus i .

5. The active and reactive power mismatches of each bus are calculated as the sum of the injected power in the approached bus. The apparent power mismatches are calculated using the equation (11):

$$\Delta S_k = \sqrt{(\Delta P_k)^2 + (\Delta Q_k)^2} \quad (11)$$

Where k is the system bus index; ΔP_k is the active power mismatch at bus k , ΔQ_k is the reactive power mismatch at bus k ; ΔS_k is the apparent power mismatch at bus k .

6. The buses apparent power mismatches arithmetic mean is calculated.
7. The performance index is computed for each chromosome. The performance index is related to the power mismatch obtained by the chromosome. All mismatches produced by each chromosome are summed producing a total mismatch value. Then each mismatch is divided by this total mismatch value producing the individual mismatch degree. After that, all degrees are multiplied by the number of individuals resulting in the final degree of each chromosome.
8. It is obtained the chromosome which has the worst - the bigger - power mismatch until now. This chromosome index is kept and it is used in the mutation operation.

Once all chromosomes have passed through the described routine, it proceeds through the steps described as follows.

9. The elements of the mating pool are composed according the degree of each chromosome. Initially, the entire part of each chromosome contains the number of individuals in the mating pool. For example, if a degree of a chromosome is 4.27, this chromosome has 4 copies in the mating pool. The other chromosomes are chosen by the roulette wheel rules according the not entire value. In the case of the previous chromosome, it has 0.27 to be chosen.
10. The mutation operation is then applied. This operation aims to coverage better the problem domain and to obtain a new chromosome, avoiding a premature convergence to a local best point. The mutation is applied to the worst chromosome of the current iteration, i. e., the chromosome which has the bigger power mismatch value, and because of this philosophy it is called Biased Mutation. The procedure consists in changing random values to the chromosome voltage module and angle, according the minimum and maximum value of the attribute.

Finally, in the end of the iterations, it is obtained the best solution, which is adopted as the power flow study solution. It is important to notice that the genetic algorithm methodology can achieve several acceptable results for the same power flow study, depending on the simulation. It occurs because each chromosome has a random initial estimated value and the genetic operators also make use of random values, so several solutions that are very similar

can be achieved for the same initial estimative. However, numeric traditional methods start with the same initial estimative values and achieve the same final results, regardless of the program simulation.

6. Power system restoration computation using genetic algorithms

This section presents a genetic algorithm based decision support tool applied to electrical power system restoration after an incident. The power system restoration is based on the system reconfiguration, which is accomplished by changing switches statuses. This is a NP-hard problem, involving operational optimization constraints and decision-making of combinatorial nature. The purpose of the proposed methodology is to support the power system operator providing an optimal solution for system restoration after the occurrence of a single contingency, similar to an N-1 criterion applied to electrical energy distribution systems.

As mentioned previously, electric distribution systems present a radial topological structure that must remain after the system restoration process. The present approach supposes that for each line there must be one switch, and if in the initial configuration it is not on, then, its normal operation status is open. For an optimized reconfiguration, the decision-making involving the switches, which must be closed, is done so as to maximize the power supply and minimize the number of closed switches. Moreover, network configurations with overloaded branches are prevented. Considering fault occurrence on a single line of the distribution system, with the characteristics described above, the closing of a single switch is enough to restore the system. There are contingencies which result in a single possibility for the system restoration, and contingencies which result in several possibilities for the system restoration. Besides, a peculiarity occurs in case the faulted line is of the kind which has normally open switches, because fault occurrence on the line does not compromise the distribution of the system, therefore, the loads supply. In this case the only solution is repairing it, providing necessary technical support.

In the solution provided by genetic algorithm methodology for this problem, each gene of chromosomes presents the information of a switch that composes just one transmission line of system. This switch is normally opened (NO) in the original configuration. The normally closed (NC) switches don't compose the chromosome. If the original configuration of system presents N lines NO then each chromosome will have N genes. The gene is a binary number, 0 or 1. The value 0 means that the switch state is open or without energy. The value 1 means that the switch state is closed or with energy. Now it is necessary to structure the information of power system. Each line of the system is represented by two consecutive nodes, according to Figure 9. In this scheme, the full lines are switches NC, the hatched lines are switches NO, and there are three circuits.

The chromosomes require an evaluation procedure for their feasibility. Several functions are presented in order to identify the chromosomes potentially and its validation.

- a. *Unsupplied Loads Function* - This function identifies the amount of loads without energy along the system after a contingency.
- b. *Loop Function* - A radial topological structure can't present meshes or *loops*. Then the Loop Function identifies the number of loops formed during the restoration process.

- c. *Overload Factor Function* - Each system line possesses a transmission capacity, that is, a maximum power. The Overload Factor Function deals with maximum and current power.

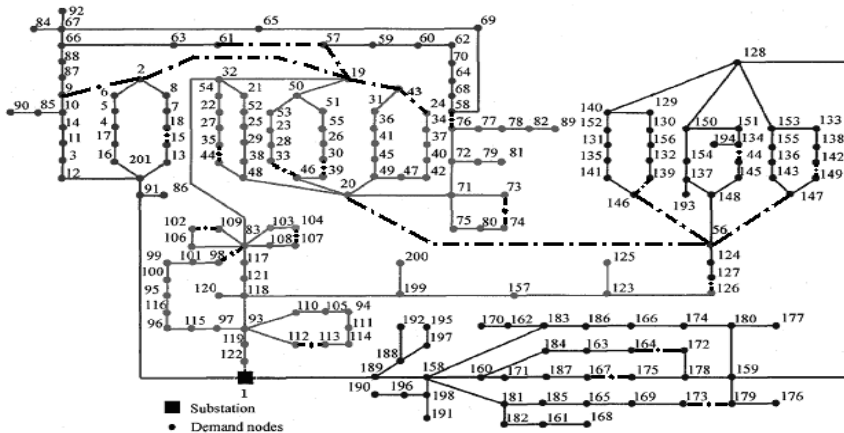


Fig. 9. Distribution test system (Ramírez-Rosado & Bernal-Agustín, 1998)

The maximum power parameter is in the data base but the current power parameter must be calculated from *Power Flow Program*, which is adapted for distribution network analysis. The Overload Factor is determined by (12):

$$OF_i = \frac{\sum_{m=1}^N (MP_m - CP_m)}{N} \tag{12}$$

Where i represents the i th chromosome; N is the number of transmission lines closed; OF_i is the Overload Factor for the chromosome i ; MP_m is the maximum power of transmission line m ; and, CP_m is the current power of transmission line m .

- d. *Overload Lines Function* - This function is a sub-product of Overload Factor Function. It determines the number of overload transmission lines. If the current power value is great than maximum power value then this transmission line is overload line.

The proposed genetic algorithm is composed of the following steps:

1. *Fitness Function Computation* - In this stage each individual receive a *value*. Therefore, how much bigger is the individual value it is better. In other words, how much bigger is the individual value it has more possibility of being the potential solution of restoration. The individual value is determined by (13):

$$\text{Value}(\text{individual}) = 0.5 \times f_1(x) + 0.1 \times f_2(x) + 0.3 \times f_3(x) + 0.1 \times f_4(x) \tag{13}$$

Where:

$f_1(x)$ = Total of supplied loads/ Total of unsupplied loads

$f_2(x)$ = 1/(amount of loops + 1)

$f_3(x)$ = 1/(overload factor)

$$f_i(x) = 1 / (\text{total of overload lines})$$

According to (13), the weights can be chosen empirically. For this approach, the criterion of judgment is based on unsupplied loads with the weight of 0.5, followed by overload factor of system with the weight of 0.3, overload transmission line number with the weight of 0.1, and number of created loops with weight of 0.1.

2. Composition of the Mating Pool - In this stage the better individuals are chosen for constitute the mating pool. To determinate the individuals that will compose the mating pool is necessary to calculate the weight of each one in the group. Therefore, the value of each individual is already applied the fitness function then it is divided by the average of the group value.

If the individual value gets a weight bigger than 1 then it goes directly to the mating pool, and its weight is deducted by 1, and this operation is repeated until that its weight becomes less than 1. If still exist vacant in the mating pool, it is necessary to use the roulette wheel to decide which individual will compose the mating pool randomly. The roulette wheel needs a straight line composed by the weights of each individual. Therefore, if the random number is between 0 and the first individual weight, then the first individual gets the vacant, else: if the random number is bigger than the first individual weight and smaller or equal than the first individual weight added by the second individual weight, the second individual goes to the mating pool.

3. Crossover Operator - The crossover operator combines the features of two parent structures to form two similar offspring. Two good chromosomes share their good quality; therefore it is possible to produce better chromosomes than before. An arbitrary crossover position along two individuals is selected, beyond which the crossover takes place. They exchange their parts.

The resulting crossover yields two new individuals where the chromosomes have parts of parent's genetic information. This crossover operation occurs if the random parameter is inferior to crossover rate (probability of crossover).

4. Mutation Operator - In the same way, this mutation operation occurs if the random parameter is inferior to mutation rate (probability of mutation). Mutation is an alteration of a value at a particular position in the individual. This particular position is selected randomly and the gene value is changed. For example, if the gene value is 1 then it is changed to 0.
5. Determination of the New Population - After all this steps, a new population is created. Therefore, the best individuals from previous generations appear in the new population. All steps are executed for the new population again, creating another genetic iteration. The process stops when a pre-defined stopping rule is satisfied.

The restoration system solution provides a switch (or a set of switches) that must have the status changed. Besides, the proposed methodology applies the maximization of power demand supplied, minimization of switching operations, and avoids the overload lines.

7. Economic dispatch and unit commitment studies using genetic algorithms

Initially, this section presents a strategy to use genetic algorithms in economic dispatch studies. The main problem of this study is to get the best composition of generations according some criteria. Usually, these criteria are generation cost and transmission cost. However, in nowadays, another criterion is also taking into account: the environment cost.

This criterion is hard to be express in numbers, and traditional techniques have problems to include this factor in the equation solution.

The economic dispatch problem is a classical optimization problem; it means some elements must to be optimized according some criteria (here expressed by the fitness function). The chromosome for this study is composed by all generated power of each unit, represented by P_i , minus the generation of the swing bus (in our case $index = 1$). The chromosome is shown in (14) for n generator.

$$x_i = \{P_2, P_3, \dots, P_n\} \quad (14)$$

The generation of the swing bus is not in the chromosome because it promotes the balance between the required load and the power produced by the other generations, in (15).

$$P_1 = P_{Load} - \sum_{j=2}^n P_j \quad (15)$$

The fitness function could be expressed by also traditional cost involved (generation and transmission) but also environment cost, political cost, and others aspects required by the system or by the companies, such as: security operation point, maintenance program, fuel constraints. Many of these costs are not necessarily expressed only by equations, but they can be used algorithms or some heuristics.

$$value(P_i) = F_{g,i} + F_{t,i} + F_{o,i} \quad (16)$$

Where $F_{g,i}$, $F_{t,i}$, and $F_{o,i}$ represent the cost of generation, transmission and others for the unit i to produce the power P_i .

The proposed genetic algorithm is composed of the following steps:

1. Fitness Function Computation - In this stage each individual receive a *value*, computing by (16). However, the economic dispatch is a minimization problem. Therefore, how much bigger is the individual value it is worst. In other words, how much bigger the individual value is, less possibility of being the potential solution of economic dispatch has. Then, the fitness function is computed by (17):

$$f_{fitness}(i) = 1 / value(P_i) \quad (17)$$

The only exception of this fitness function computation process is when the constraints of the swing bus are extrapolated. In this case, the generation of the swing bus can't support generate the required power, and the value of the fitness function is zero.

2. Composition of the Mating Pool - The best individuals are chosen for constitute the mating pool. The strategy describes in the power flow mating pool composition is used here. Use all fitness function to calculate the weight of each individual. The individuals with entire values are represented in the mating pool. The decimal part goes to the roulette wheels.
3. Crossover Operator - By a random process two individuals are chosen to be combined, and another random process decides where they will change their material. And then,

they exchange their parts. This crossover operation occurs if the random parameter is inferior to crossover rate (probability of crossover).

4. Mutation Operator - The mutation operation occurs if the random parameter is inferior to mutation rate (probability of mutation). When one power generator is selected randomly and the gene value is changed for a new value inside of its generation limits, expressed by (7).

This process is repeated until a predefined number of iterations. The best solution found (it means the minimum *value*) until in moment is the solution of the problem.

The unit commitment process uses the economic dispatch shown above. The idea is to start the economic dispatch for the first period of time, t_1 . The three best solution are selected, denoted by $S_{1,A}$, $S_{1,B}$, and $S_{1,C}$. Each solution has its own total cost, denoted by $C_{1,A}$, $C_{1,B}$, and $C_{1,C}$.

For the second period of time, t_2 , another economic dispatch is run. The three possible best solutions are selected for each best solution selected in the previous period of time. It is important to note that the three possible best solution in the second period for the solution $S_{1,A}$ could not be the same, for example, for the solution $S_{1,B}$. It occurs because there are some constraints to be analyzed such as start-up generator time or minimum time to restart the generator. In Figure 10, the three best solutions for $S_{1,A}$, have been denoted by $S_{2,AA}$, $S_{2,AB}$, and $S_{2,AC}$. For $S_{1,B}$, the selected best solutions are $S_{2,BA}$, $S_{2,BB}$, and $S_{2,BC}$. And, for the solution $S_{1,C}$, the selected solutions are $S_{2,CA}$, $S_{2,CB}$, and $S_{2,CC}$. In this example, the solutions $S_{2,AB}$ and $S_{2,BA}$ are the same solution. The same occurs to $S_{2,AC} - S_{2,BB} - S_{2,CA}$, and $S_{2,BC} - S_{2,CB}$.

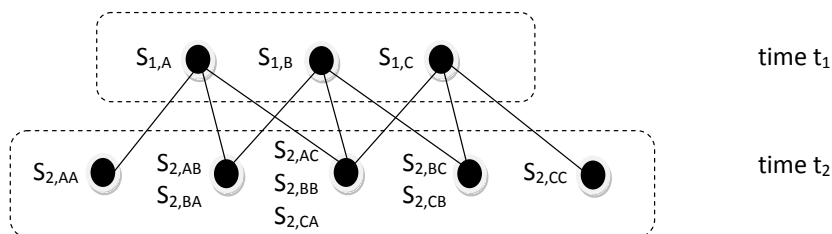


Fig. 10. First and second iteration of the unit commitment process

Each solution of time t_2 also has its own total cost, denoted by $C_{2,AA}$, $C_{2,AB}$, and so on. Of course, the cost of the solutions $S_{2,AB}$ and $S_{2,BA}$ are the same.

For the third period of time t_3 , another economic dispatch is run. The three possible best solutions are selected for each best solution selected in the previous period of time, in this case t_2 . And the process continues until the last period of time. In this procedure, a search tree is created. There are two possibilities to break one of the possible paths in the search. One possibility is when there is no solution available in the next step of the economic dispatch study for a previous selected state. The other possibility is when the total cost exceeds a predefined value. The total cost is the sum of all previous cost in the path. Figure 11 shows a possible search tree with 6 periods of times (t_1, t_2, \dots, t_6). Two special remarks have been made in this figure. The first one is the case where there is no solution available in the next period, and then the path is cut. The second one shows a situation where there are only two possible solutions in the next period of time. The search continues for these two solutions.

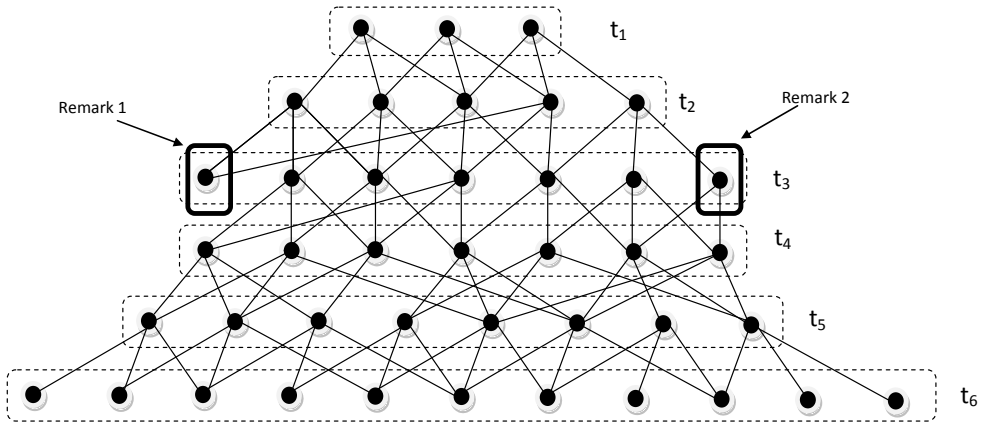


Fig. 11. Complete search tree for unit commitment problem-solving

When the search tree is complete each path has its own total cost which is composed by the sum of each individual solution existed along the path. Figure 12 shows in highlight one possible path (possible solution) for the unit commitment problem. The total cost of this solution is computed by the sum of each individual costs of each solution (C_{1B} , C_{2C} , C_{3D} , C_{4D} , C_{5E} , and C_{6F}) and denoted by $C_{path,k}$, shown in (18). The best solution is that with lowest total cost.

$$C_{path,k} = C_{1B} + C_{2C} + C_{3D} + C_{4D} + C_{5E} + C_{6F} \tag{18}$$

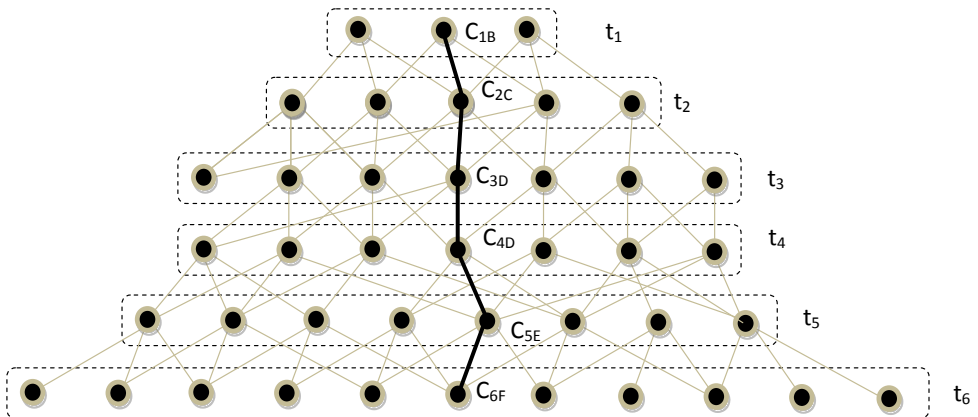


Fig. 12. One possible solution of unit commitment problem with individual costs

Finally, a hint. If the problem requires many periods of time the number of possible paths can be enormous. In this case, intermediary evaluations can occur and a predefined maximum number of paths can continue the search tree.

8. Conclusion

This chapter presented the genetic algorithm application to three functions commonly executed in power control centers – power flow, system restoration and unit commitment. The genetic algorithm based techniques are potential to solve problems whose traditional methodologies to solve them have a high computational cost, problems whose traditional methodologies to solve them hold some constraints in their application, and problems without any traditional methodologies to solve them. This has been well represented by these typical power system control centers applications, and the explanation on how to perform genetic algorithms to compute them.

It is expected that this chapter provided the reader with a comprehensive view of the use of genetic algorithms to solve control center problems and supports them in developing new genetic algorithms based methods for applications of their interest.

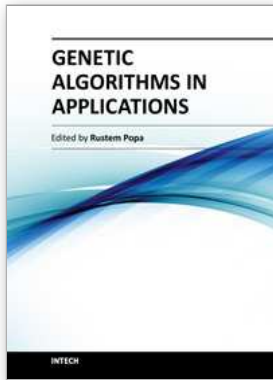
9. Acknowledgment

The authors would like to express their thanks to the financial support of this work given by the Brazilian research agencies: CNPq, CAPES, and FAPEMIG.

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Genetic Algorithms in Applications

Edited by Dr. Rustem Popa

ISBN 978-953-51-0400-1

Hard cover, 328 pages

Publisher InTech

Published online 21, March, 2012

Published in print edition March, 2012

Genetic Algorithms (GAs) are one of several techniques in the family of Evolutionary Algorithms - algorithms that search for solutions to optimization problems by "evolving" better and better solutions. Genetic Algorithms have been applied in science, engineering, business and social sciences. This book consists of 16 chapters organized into five sections. The first section deals with some applications in automatic control, the second section contains several applications in scheduling of resources, and the third section introduces some applications in electrical and electronics engineering. The next section illustrates some examples of character recognition and multi-criteria classification, and the last one deals with trading systems. These evolutionary techniques may be useful to engineers and scientists in various fields of specialization, who need some optimization techniques in their work and who may be using Genetic Algorithms in their applications for the first time. These applications may be useful to many other people who are getting familiar with the subject of Genetic Algorithms.

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Camila Paes Salomon, Maurílio Pereira Coutinho, Carlos Henrique Valério de Moraes, Luiz Eduardo Borges da Silva Germano Lambert-Torres and Alexandre Rasi Aoki (2012). Applications of Genetic Algorithm in Power System Control Centers, Genetic Algorithms in Applications, Dr. Rustem Popa (Ed.), ISBN: 978-953-51-0400-1, InTech, Available from: <http://www.intechopen.com/books/genetic-algorithms-in-applications/applications-of-genetic-algorithm-in-power-system-control-centers>

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