A GENETIC ALGORITHM APPLIED TO THE POWER SYSTEM RESTORATION PLANNING PROBLEM

A Metaheuristic Approach for a Large Combinatorial Problem

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Abstract: This work reports the use of a Genetic Algorithm (GA) to solve the Power System Restoration Planning Problem (PSRP). The solution to the PSRP is described by a series of operations or a plan to be used by the Power System operator immediately on the occurrence of a blackout in the electrical power supply. Our GA uses new initialization and crossover operators based on the electrical power network, which are able to generate and maintain the plans feasible along GA runs. This releases the Power Flow program, which represents the most computer demanding component, from computing the fitness function of unfeasible individuals. Results for three different electrical power networks are shown: IEEE 14-Bus, IEEE 30-Bus and a large realistic system.

1 INTRODUCTION

The Power System Restoration Planning Problem (PSRP) can be defined as the search for an optimal sequence of control actions leading a faulty electrical power system from a restoration state of operation to a secure state. The secure state is defined by a normal energy supply with all operational limits observed. The transition of one state to the other is performed through a series of commands sent by the power system operator to the power system. Each faulty situation demands a specific sequence of commands to bring, as fast as possible, the power system back to the secure state. These operations include the connection and disconnection of line sections without overloading the electrical system components.

Further, the PSRP is a multistage problem, being the objective of each stage the reestablishment of the service to a group of priority loads. The solution must obey additional constraints such as those placed by a priority chain in the energy supply. For instance, first hospitals must be attended, then public services, and so on, if distribution context is considered.

However, the main constraint is the time gap while consumers are without energy, which must be kept as small as possible.

The Power System Restoration Planning may be carried out *off* or *on-line*. *Off-line* plans are typically based on previous operator experiences in restoring a faulty system. The efficiency of this process rests on the ability of the restoration program (or operator) in finding a similar network state and in applying the corresponding plan. However, if a new contingency occurs, a new plan (*on-line*) has to be generated. In the simplest case, this can be achieved by shooting down some part of the network and bringing it back to a known state, for which a plan exists. The other solution, certainly better, starts directly from the actual network state.

Two main classes of algorithms have been used to solve this problem: deterministic and stochastic ones. One of the first efforts for treatment of the PSRP with deterministic techniques was the work of (Sakaguchi and Matsumoto, 1983), who had created a Knowledge Based System (KBS) based on the knowledge of the power system operator. This was followed by other works using an expert system approach, such as (Komai *et al*, 1988) and Kojima *et al* (1989). As the size and complexity of electrical power systems surpassed the capacity of human control and therefore of rules based on human knowledge, other methods were developed, such as (Aoki *et al*, 1987) using the classical integer programming approach, (Huang *et al*, 1991) using optimization techniques (Nagata *et al*, 1995) using a

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hybrid system of rules and mathematical programming. For a review on these methods, see (Curcic *et al*, 1997). Even for these methods, the determination of hundreds of discrete variables in time is a complex task. Therefore, stochastic methods combined with power flow simulation tools became an interesting alternative to the deterministic approaches (Matos et al, 2004).

Stochastic approaches such as Neural Networks (Hsu and Huang, 1995) (Bretas, 2003) and Genetic Algorithms (Bretas, 1998) (Luan *et al*, 2002) are relatively new and have received some criticisms such as that they typically use a fixed length string to represent the solution plan, high computing times and the low confidence of the power system operator on the generated plans (Susheela, 2000). In order to solve these problems, we propose a variable length solution representation (chromosome) with new mutation and crossover operators. In relation to the computing time, first, only feasible solutions are generated and second, our crossover operator maintains the feasibility of the plan. This spares time because the computation of the power flow along the plan represented in the chromosome does not end in an unfeasible solution and therefore must not be immediately discarded. A plan in the population may have a low score but is rarely discarded because of unfeasibility. The crossover cut occurs only at network states in each plan submitted to the crossover operator.

The third criticism, the confidence of the power system operator on the obtained solution, can be partially solved by exhaustively testing and by carrying out demonstrations on previous cases with the planner and power flow simulator. However, we propose in this work that sound solutions may be obtained if this aspect is considered in the fitness function already, for instance, by requiring a good quality solution along the plan and not just at the last stage of the restoration. Finally, the increase in computer performance will certainly turn those methods now just used for the composition of a restoration plan into *on-line* solutions with a response time from seconds to minutes.

This paper is organized as follows: after the introduction, section 2 presents the restoration system and its components. Section 3 shows the Genetic Algorithm component with a description of the GA operators and section 4 presents results for three different power systems, the IEEE 14-Bus system and IEEE 30-Bus (Freris and Sasson, 1968) and finally the CEEE 146-Bus. Section 5 presents our conclusions.

2 THE RESTORATION SYSTEM

The main components of the restoration system are shown in Figure 1. The GA component obtains information about the network topology by reading the Electrical Network Topology file. This file describes the buses with their connected generators and loads as well the transmission lines among buses. As an illustration, the upper part of Figure 3 shows a schematic view of the IEEE 14-Bus topology file. The topology and the actual network state are used to create an initial population of feasible solutions. The actual state of the electrical network is defined by the actual pattern of connections and activity/inactivity of buses and must be read from the real network through sensors and state observers.

Then, during a GA generation, each chromosome (restoration plan) is used to drive the whole power system through a series of states, from the actual state to an end state, hopefully with all loads restored. Further, the intermediate states of the network must obey the component limits and available power for the loads. Each such state is computed by the Power Flow Program (PFP), whose results are turn back to the GA. Then, the fitness function is used to evaluate the restoration plan.

The PFP is called many times for the evaluation of a chromosome. If the plan in the chromosome is composed of N stages, then the PFP is called N times. For example, if a GA needs a population of size 25 and 25 generations to find a good plan, then the PFP will be executed $25\times25\times N$ times. Our work spares this time by generating and processing feasible solutions and leaving a small margin for unfeasible solutions only in the case of mutated chromosomes, and only for intermediate solutions (before the last generation).

The PFP implements the classical fast decoupled Power Flow method of Stott and (Alsaç, 1974) and was developed by (Canto dos Santos *et al*, 2006) In that work, another approach to the .problem, based on Linear Programming, was presented.

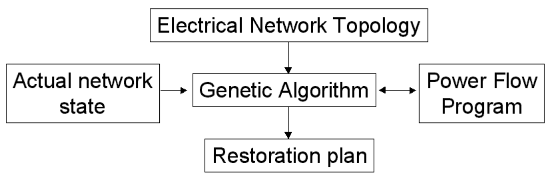

Figure 1: Restoration system components.

3 GENETIC ALGORITHM COMPONENT

The design of the chromosome format is crucial in quickly finding an optimal solution. First, the mutation operator must have a small impact on the chromosome performance (big random jumps should be avoided) and second, the crossover operator should transfer whole functional blocks avoiding any rough breaking of these functional blocks. In this work, the time axis is mapped on the linear chromosome structure.

3.1 Chromosome Representation

Different of the classical GA approach (Goldberg, 1989), the new chromosome representation has a variable size, consisting of a sequence of stages, each containing a group of commands sent to the electrical power system. As the commands are sent, lines and buses change their state. As will be shown in the next section, these states are used to define the crossover points.

For this new proposed representation, each chromosome codes a sequence of operations or stages and has a variable size. Not only the whole sequence has a variable size, but also each stage is composed of a variable number of operations, which are executed simultaneously during the restoration process. Further, the different chromosome sizes and the requirement for feasibility of the restoration plans demanded a new crossover operator different from the classical ones.

Figure 2 shows two different illustrative representations of the chromosomes. The stages are shown as discrete elements (white boxes) inside each chromosome and they contain a group of operations. Each operation in turn is represented by a pair of identifiers using the format "<address>: <operation>". The operations are divided into two groups: operations on lines and operations on buses. The <address> identifies the bus or line on which the <operation> will be executed. If the operation is executed on a bus *n*, its <address> is expressed as B*n*. If it is executed on a transmission line *n*, its <address> is L*n*. The other identifier represents the operation. Operations on transmission lines include the connection of one of its end points (the origin point or operation O+ and destiny point or operation D+). Operations on buses may be a load connection to the bus (operation L+), connection of the power supply (operation Ger) and the connection of synchronous compensators to the bus (operation C+). The system was designed so as to enable simple additions of other operations as well new equipment types.

For instance, the second stage in Figure 2 represents the connection of the origins of transmission line L1 and L2 at the same time.

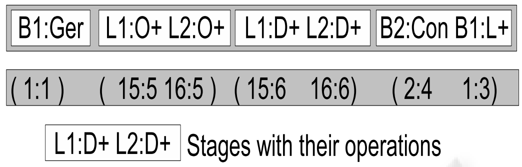

Figure 2: Chromosome representation as a vector of stages with discrete operations. The operations are indicated by mnemonic and numeric codes. The first line shows a chromosome in a mnemonic format and the second line, in a numeric format.

3.2 Genome Initialization

The highly flexible representation of the chromosome demanded the inclusion of specific program modules for the generation of feasible chromosome initializations.

In order to obtain feasible initializations, first a graph is generated in which buses are represented by nodes and transmission lines by edges. Also, the buses associated with black start generators (capable of restarting with no external power source) are at the root of the graph and are connected with other buses in a tree-like way. The graph represents the topology of the power system.

Then, a Random Search (RS) is carried out on the graph from the root nodes where components attached to buses are randomly selected. For each selected component an operation is chosen. Since many components may be chosen at the same stage, not only an operation is created, but a whole operation set may be created and added to the current chromosome. This way, different operation sequences are placed in the initial population.

An example of the genome initialization process is shown in Figure 3 for the IEEE 14-Bus power system topology composed of 14 buses, 18 transmission lines, 2 generators and 11 loads (arrows). In this example, the objective is to find a sequence of operation sets, which should lead the power system from an initial state characterized by total blackout to a final state with all loads supplied. The nodes in the topology graph represent the buses and the links the transmission lines. In the real operation, these data are obtained from a supervisory system. In the first step (topology graph (1)), only the bus 1 (node 1) is activated, fed by the generator (black start capable generator) connected to the bus. Then (graph (2)), the algorithm computes which are the nodes linked to already activated nodes such as in a Random Search. From the nodes allowed to be activated, the algorithm chooses randomly if they shall be activated or not generating different individuals. In the next steps, the algorithm proceeds considering all the nodes directly linked to the already activated nodes and determines if and which ones shall be activated. Note that the algorithm may activate more than one bus at the same time. For instance, from graph (4) to graph (5), both buses 3 and 4 (nodes 3 and 4) were activated simultaneously.

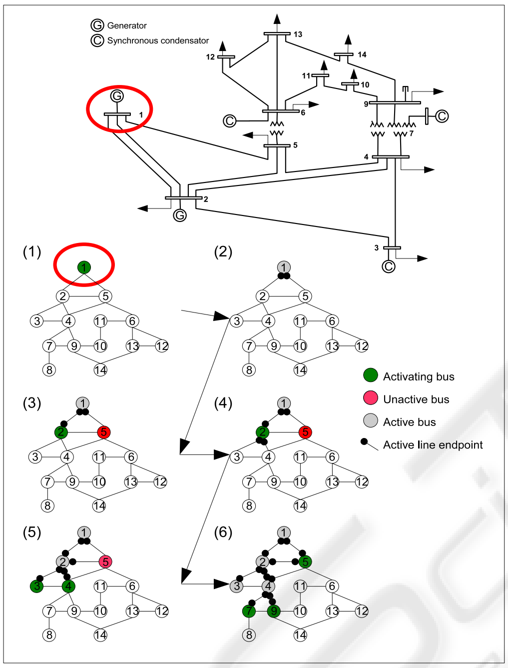

Figure 3: Demonstration of the genome initialization process for the IEEE 14-Bus system. The graph is searched and the corresponding buses are randomly activated. At each step, inactive buses have a renewed opportunity to be activated by the algorithm. Buses are indicated by numbers, transmission lines by solid lines and loads by arrows.

The resulting activations during these steps are accordingly indexed in the genome in the form of operations, and the initialization process continues until all the nodes are connected to active buses and the number of inactive nodes reaches a previously chosen random limit. Therefore, different solutions are generated, all of them considering possible pathways described in the topology graph. For instance, there is no sense in connecting bus 14 before bus 9 or bus 13 is activated. The randomness of the bus activation creates chromosomes with diverse solution strategies ensuring a good coverage of the solution space.

3.3 Crossover Operator

Due to the more flexible representation of the chromosome, a new crossover operator was developed, which avoids improper operations, such as the connection of a load or generator (not the black start capable generator) to a bus without power.

The classical GA crossover cuts two chromosomes at the same position because there is an exact correspondence between both left and right sides of the chromosomes. However, the flexibility of the operation positioning inside the variable size chromosome demands the computation of synchronization states in the parents' chromosomes. Each stage in a chromosome is associated with a network state, which is used by the crossover operator. This state is the result of all operations of all stages to the left side (before) of the respective chromosome stage and of the operations in the stage.

Lines may be in one of four states:

- not connected;
- origin point connected;
- end point connected;
- totally connected.

Each end of a transmission line was modeled by a different connection for two reasons: first, this is more realistic, resulting in solutions that can be readily understood by the system operator and second, if the line model had included just one connection, then the activation of the line would automatically activate both connected buses at the same time.

Figure 4 shows an example how a line is activated, depending on the sequence of bus activation and end connections.

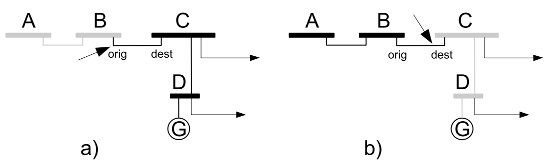

Figure 4: Example of how a line may be activated from different sides. In case a) the line is activated by the bus B if it is activated and the "orig" end of the line is connected. In the case b), the line is activated if the bus C is activated and the "dest" end is connected.

For the buses, the allowed states are:

- inactive bus (disconnected);
- bus activated - when the bus has power from a transmission line or generator;
- generator connected;
- load connected;
- synchronous compensator connected.

The states of the buses in both chromosomes are compared, and if the network state is the same, they are equivalent.

All the equivalent state pairs are stored in a list, and a position in the list is randomly chosen, which represents the stage at which the two sequences will be cut and where the crossover occurs.

A consequence of the use of this operator is that the resulting sequences (children) have a different number of operations reaching the same state, which means that some of them will be smaller and, possibly, more efficient than the others.

This process is illustrated in Figure 5. In this case, a new chromosome generated by crossover of the left side of the upper chromosome and the right side of the lower chromosome may be better than both parent chromosomes in terms of number of stages. The left side of the upper chromosome takes a smaller number of stages to reach the same state than the lower chromosome and it will be transmitted to the children chromosome.

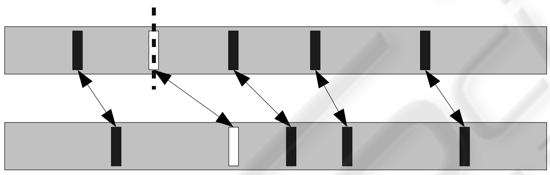

Figure 5: Determination of equivalent stages in two chromosomes of the genome. Different pairs of equivalent stages are stored in a list and one of them (the white one, for instance) is randomly chosen. Dotted lines show the stages in the chromosomes where the two sequences are divided for the crossover operation.

3.4 Mutation Operator

There are three types of mutations: inclusion and exclusion of an operation in one stage and permutation of operations in two stages. As an illustration of the steps performed by the mutation operator, see Figure 6. Because these are unrestricted operations on the chromosome, these may generate unfeasible solutions with respect to the delivered and consumed power. Unfeasible solutions are tolerated only at intermediate generations of the GA and intermediate stages of the chromosome because this increases the diversity of solutions and helps the GA to escape local minima. For instance, a certain load requiring more power than available may be connected during intermediate generations. However, only feasible plans are considered in the end generation.

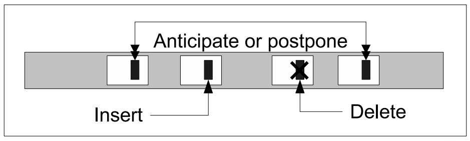

Figure 6: Representation of possible mutations. The white rectangles represent stages and the black ones, possible operations in the stages. The operations can be included, excluded or transferred from one stage to another by the mutation operator.

3.5 Fitness Function

In order to compute the fitness function, the operations described in the chromosome are used by the PFP to compute the power flow at each stage.

In this work, the flexibility of the fitness function was maintained by the use of parameters (A, B and C in the following equations) allowing a detailed analysis of the influence of each system variable on the solution obtained by the GA. The fitness function FF is defined by:

$$FF = \frac{\overline{L_{At}}(L_{At_N} - A \cdot \overline{Fl_{At}}) + \overline{L_{Re}}(L_{Re_N} - B \cdot \overline{Fl_{Re}})}{1 + C \cdot N}$$

$$\overline{L_{At}} = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{M} L_{At_{ij}}$$

$$\overline{L_{Re}} = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{M} L_{Re_{ij}}$$

$$\overline{Fl_{At}} = \frac{1}{N}\sum_{i=1}^{N} R(\sum_{j=1}^{M} L_{At_{ij}} - \sum_{j=1}^{M} Ge_{At_j})$$

$$\overline{Fl_{Re}} = \frac{1}{N}\sum_{i=1}^{N} R(\sum_{j=1}^{M} L_{Re_{ij}} - \sum_{j=1}^{M} Ge_{Re_j})$$

$$R(x) = \begin{cases} 0, & ifx < 0 \\ x, & \text{otherwise} \end{cases}$$

where M is the number of buses in the power system, N is the number of stages, L_{At} and L_{Re} are the active and reactive loads respectively, Ge_{At} and Ge_{Re} are the generated active and reactive power respectively, and A, B and C are trimming constants. i and j denote the stage and bus respectively and $R(x)$ is the ramp function.

The main component of the fitness function is the supplied active and reactive loads at the last stage *N*, L_{At_N} and L_{Re_N}. However, tests with just these variables presented solutions which were not balanced along the stages and are difficult to be accepted by the system operator. The inclusion of the mean of the loads along the stages intends to meet, at each stage, the highest possible number of active and reactive loads, a good distribution of supplied loads along the stages and a sound solution to the system operator.

Parameters *A* and *B* decrease the fitness function of individuals in case the generated power is lower than the total load of the system and therefore help to discard any unfeasible solution generated during the GA runs by the mutation operator. The inclusion of the supply power failure in the fitness function intends to obtain solutions whose power generation is sufficient to attend all the connected loads. The parameters *A* and *B* control how tolerant is the GA to unfeasible solutions during runs. This allows suboptimal solutions to remain in the population and thus contributing to maintain the diversity of the population. Both parameters may be increased in the last few generations leaving only feasible solutions in the population.

Since the quick evaluation of the PFP is the main concern for a practical use of the GA, the PFP needs only to compute the state of the connected part of the network. Then, as the restoration program goes through each stage in the chromosome, only the buses and lines necessary to the execution of the current stage are transferred to the PFP, reducing the number of nodes and edges the PFP has to consider during the calculations. As the electrical network gets more and more connected with each new stage, its size increases and the computations in the PFP become harder to carry out.

Other fitness functions were designed. However, the previous fitness function resulted in the best solution plans, with a quick attendance of the needed power while maintaining the power generation restrictions.

4 RESULTS

In this section, results of experiments performed with three different power systems, the IEEE 14-Bus system, IEEE 30-Bus and finally the CEEE 146-Bus, three power systems with increasing degree of complexity are shown. Each experiment used a different population initialization and all electrical parameters of the systems were monitored, such as the active and reactive powers of the best genome in each generation. After running each experiment, the best genome in the population is shown in a graphic representation. As each stage corresponds to a group of operations executed on the power system and the execution of each such operation spends time, a correspondence can be made between the consecutive execution of those stages and the restoration elapsed time. It will be assumed that each stage takes one unit of time to be executed.

It was considered the occurrence of a general blackout in the IEEE 14-Bus (Freris and Sasson, 1968) system and that only the generator at bus 1 is black start able. Also, all the 20 branches are available for the restoration.

In Figure 7, the evolution of the GA with three different initializations is presented. Typically, the GA starts with 40-50 stages (dashed lines) and a fitness function of 0.75 (solid lines) of the maximum value, showing that many solutions generated by our method have a high fitness function (and feasible) at the GA initialization already. As the GA computes new solutions, the fitness function increases and the number of stages needed to reach it decreases.

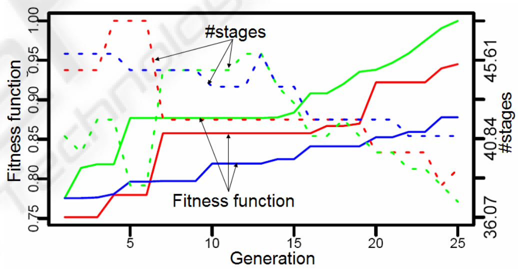

Figure 7: Three GA runs for the IEEE 14-Bus System, with a population size=25 chromosomes and fitness function *FF* with parameters *A*=1, *B*=5 and *C*=1. Solid lines represent the value of the normalized fitness function for the three runs (scale at the left side of the graph) while dashed lines represent the number of stages (scale at the right side of the graph) of the best solution in the population.

Figure 8 shows the corresponding plan obtained. The generated and delivered power of the best individual in the population is shown along the restoration stages. Results for the power system IEEE 30-Bus using the same GA parameters are shown in Figure 9. It can be observed that the GA obtained an efficient solution in terms of used power. For instance, once the difference between generated and consumed reactive power reaches zero, there is an increase in the power generated so as to supply the new loads. Afterwards, the loads are connected to the system until that margin reaches zero again, and so on. Further, as expected, the plan for a larger power system such as the IEEE 30-Bus demands more stages, for instance, 37 for the IEEE 14-Bus and 78 for the IEEE 30-Bus .

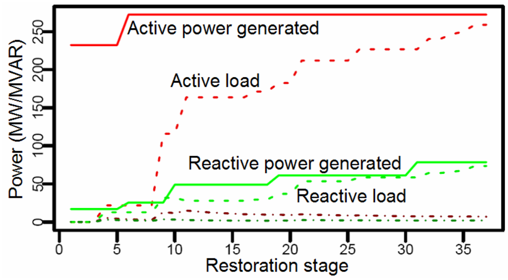

Figure 8: Restoration of the IEEE 14-Bus. Solid lines represent the active and reactive power generated while the dashed ones represent the power consumed or the total loads.

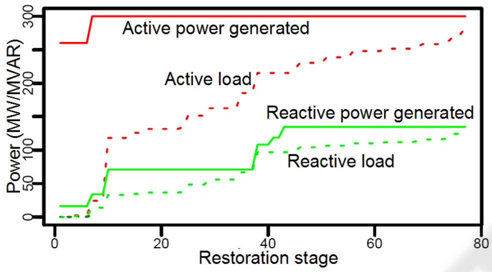

Figure 9: Restoration of the IEEE 30-Bus power system. Solid lines represent the active and reactive power generated while the dashed ones represent total loads.

Finally, we tested the GA algorithm with the CEEE (a real life Brazilian system) power system composed of 146 buses and 196 transmission lines in south Brazil. Figure 10 shows one of the obtained plans. Approximately 130 stages are needed to restore the full system from a complete blackout.

Certainly, the set of experiments presented in this section represents only part of all test performed with our approach. Other tests varying the number of generations, population size, fitness function and parameters were performed too.

5 CONCLUSIONS

The objective of this work was to show a restoration system based on a GA that presents efficient plans to the power system operator when a blackout or any other serious lacks occurs. The use of GA for the generation of operation sequences, or strategies is only possible with the careful codification of the operation sequences in the chromosome taking into account the electrical power network topology. If the task of determining the feasibility of the solutions is entirely left to the PFP, then the GA generates many unfeasible solutions with a direct impact on the performance of the GA. Also, there must be a limit on the number of allowed generations if the system is to be used in an *on-line* modus. For example, in this work, this number was set to 25 generations. All this enable the GA to quickly find a solution without wasting of time computing the power flow for unfeasible individuals.

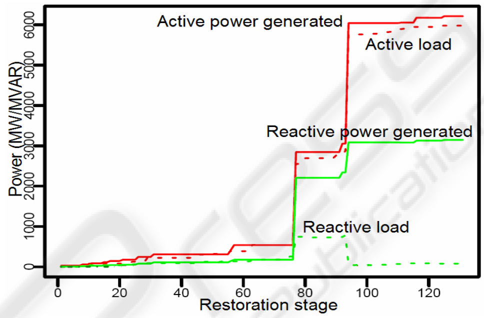

Figure 10: Power system restoration plan for the CEEE System, obtained with a GA with a population size=25, number of generations=25, and parameters A=1, B=5 e C=1.

The choice of the fitness function is important to define the quality of the obtained solution. In this work, a parameterized function was chosen as a good compromise among user priorities, flexibility and complexity of the function. Also, a good distribution of connection operations along the plan represents a sound solution for the operator. In this respect, we observe that there are no works considering the quality of operation stages along the plan in terms of soundness for the system operator, as proposed in this article. Certainly, this is one of the causes for the low confidence level of system operators on solutions obtained by stochastic algorithms.

However, some care must be kept in relation to a solution found by stochastic algorithms. A GA may find a good solution in terms of fitness function but it may be unfeasible. The stochastic freedom of GA solutions may be kept at the intermediate generations with the risk of reaching the last generation with unfeasible plans in the whole population. For example, if the best individual is good but unfeasible, its genes may propagate along the population making all of them unfeasible. This is called *lost of diversity* in the GA area. Therefore, there must be a compromise between keeping all the time all the solutions feasible (for example, making the parameters *A* and *B* very high) and maybe loosing a good solution, and leaving the GA completely free to generate and process any solution plan. We think that in this respect we could attain a good compromise by allowing only the mutation operator to generate unfeasible solutions at intermediate generations and also by considering only feasible end solutions in the last generation.

Finally, researches in progress point out to the need of inclusion of more complex and realistic simulations, such as the dynamical behavior of the electrical power system. For example, the simulation of voltage and current overshooting during switching operations, which can cause the breaking of lines by limiting current and voltage devices, could preview an instable system reaction leading the power system to a complete blackout. Since this analysis increases the processing time of the PFP, any such addition makes the feasibility analysis presented in this work even more important. Currently, the use of other metaheuristics, specifically Tabu Search, is being studied and will be published in the future.

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