Multiobjective Reconfiguration for Loss Reduction and Service Restoration Using Simulated Annealing

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Abstract - This paper presents an approach to the reconfiguration of radial distribution networks, for both loss reduction and service restoration, using the same meta-heuristic tool: the simulated annealing algorithm. Besides the main objective of each problem (minimizing losses or load not supplied) minimization of the total number of switching device operations is also included as a possible criterion. Due to these conflicting goals, the network reconfiguration is a multi-objective optimization problem. The paper shows how to generate efficient solutions for the problem and discusses the associated decision issues. A 52-bus distribution network is used to illustrate the methodology.

Keywords: Reconfiguration, loss reduction, service restoration, simulated annealing, distribution network, multiobjective.

I. INTRODUCTION

Electric distribution networks are usually explored in a radial topology, but they have a meshed structure (with open lines) that allows for several operating configurations. The reconfiguration of these networks by changing the switching devices status aims at optimizing the network configuration for a given load profile, by minimizing the power losses [1 - 5]. A related problem is the service restoration problem in the sequence of a fault situation, when one try to re-supply (at least part of) the loads [2, 5 - 9]. The combinatorial nature of the network reconfiguration problem (due to the switching operations) makes it difficult to solve in real cases. Many techniques have been proposed to solve these problems, vg mathematical programming, heuristic methods [7] and, more recently, expert systems [5] and non-convex optimization techniques such as genetic algorithms [1] and simulated annealing [3, 4].

In this paper, we address both problems using the same tool: the simulated annealing meta-heuristic [10]. This methodology has proven to be adequate to combinatorial problems like these ones, and is very flexible regarding the evaluation of each candidate configuration, allowing the inclusion of different criteria, operation and also electrical constraints (as penalty costs). Loss minimization was already addressed with this technique [3, 4] but in a perspective different from the one used in the present paper.

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The same basic procedure is used for both problems, although the main issue is active power losses in the losses minimization problem and load not supplied in the service restoration problem. Voltage drop constraints and line overload constraints are common to both problems.

In the service restoration problem, the preoccupation in finding a new configuration that minimizes the total load affected by a faulty situation is not the only evaluation criterion. It is also important to minimize the number of necessary switching operations, due to obvious technical reasons. So, in this case, we have a multiobjective decision problem, because minimizing the number of switching actions leads generally to a conflict with the process of restoring service. The same criterion may be used in the loss minimization case, where line load balance [4] and voltage drop are other possible criteria that an operator may wish to consider.

The paper includes the following sections: the formulation of the two problems (section II), the description of the Simulated Annealing methodology (section III) and the multiobjective approach (section IV). To illustrate the methodology, results with a test distribution network are presented in section V. The conclusions (section VI) and references complete the paper.

II. PROBLEM FORMULATION

In this section, both reconfiguration problems are formulated. A feasible solution is one that respects the network electrical constraints given by the power flow equations. Also, line loads and bus voltages deviation must lie within specified limits. Finally, the radial network topology must be maintained after the reconfiguration process:

$$\left|I_k\right| \le \left|I_k^{max}\right|, \forall k \in L_s$$

$$\left|V_i^{min}\right| \le \left|V_i\right| \le \left|V_i^{max}\right|, \forall i \in B_s$$

$$c_j \in R$$

where:
L_s is the set of the network lines
C_s is the set of consumer loads
C_{ns} is the set of loads not supplied

B_s is the set of buses
R is the set of radial configurations
I_k is the current flow in line k
I_k^{max} is the maximum current flow allowed in line k
V_i^{min} is the minimum voltage allowed in bus i
V_i^{max} is the maximum voltage allowed in bus i
c_j is the actual network configuration

Regarding the objective functions, the basic loss minimization problem is formulated as follows:

$$\min \sum_{k \in L_s} LOSS_k$$

Additional objective functions may be considered, as pointed out in the introduction. As for the service restoration problem, the formulation is the following:

$$\min \sum_{k \in C_{ns}} PNS_k \text{ (Power not supplied)}$$
$$\min NSO \text{ (No. of switching actions)}$$

The fact that this problem is multiobjective leads us to develop an integrated multiobjective methodology that deals with the basic loss reduction problem as a special case. Therefore, we are not talking about “optimal solutions” (as it were with a single objective) but nondominated (or efficient) solutions, i.e., configurations that cannot be improved simultaneously on both objectives. The operator may then chose his preferred alternatives, according to the values of the attributes (vg PNS, NSO) calculated by the methodology.

III. SIMULATED ANNEALING META-HEURISTIC

The idea of simulated annealing [10] comes from thermodynamics and metallurgy: when a melting metal is cooling slowly enough (annealing), it tends to solidify in a minimum energy structure. The same principle is used in simulated annealing: at the beginning of the process almost every actions are allowed (with a very high probability). This permits to jump from local minimum and visit other solutions eventually better than the present one. During the procedure the process temperature decreases, making the algorithm more selective (it accepts less solutions worst). Reaching the end of the procedure, almost only better solutions are accepted.

The simulated annealing algorithm is based on the Metropolis algorithm, which has fundamentally the following two phases:

- Initial increase of the temperature to a maximum energy state;
- Successive and slow decrease of temperature for reaching a minimum energy state.

Monte Carlo and successive state generation techniques are used for simulating the process evolution:

- Define an initial with cost C_i as present solution;
- Generate a new solution (neighbor of present solution)
- Evaluate the new solution (cost = C_j)
- If Cj<Ci accept the new solution as present solution, else the new solution will be accepted, with a given probability.

Next, a pseudo program for the algorithm is presented:

```
Procedure SIMULATED_ANNEALING
  initialize (i, cost(i),T)
  do
    for l=1 to L
      generate neighbor(j from i)
      calculate cost(j)
      d = exp( (cost(i)-cost(j))/(T*Kb) )
      if ( cost(j)<cost(i) OR d > RAND[0;1[ )
        then
          accept neighbor(j)
          i = j
        else
          reject neighbor(j)
     next l
     T = α.T
  while (stop criterion not reached)
```

For the simulated annealing algorithm development, some parameters must be defined:
T_o - initial process temperature
T_f - final process temperature
α - cooling rate
L - number of iterations per level of temperature

The acceptance ratio for the worst solution depends on the cost difference between the present and the new generated solution, as well as on the temperature parameter. This parameter is responsible for the success of the search process, allowing to escape from local minimum.

For the stop criterion, many implementations can be used:

- stop if optimal cost has not improved ε_1% for the last n_1 iterations
- stop if the number of accepted solutions if less than ε_2% of L
- stop if the process temperature is less than ε_3% of initial temperature
- stop if time exceed a specified value

In our implementation, a combination of the first and fourth criteria has been adopted.

Figure 1 represents the adopted temperature schedule in this work. The initial process temperature is T_o, and it is maintained for L iterations; after each L iterations the temperature is decreased proportionally to the cooling rate. Thus after K.L iterations the temperature will be:

$$T(KL) = T_k = T_0 . \alpha^k$$

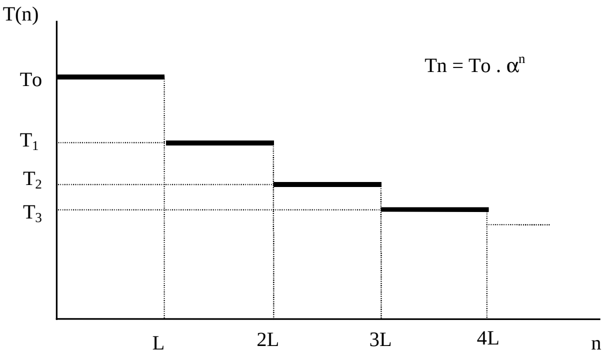

Fig. 1. Temperature schedule.

The acceptance factor provides a way of calculating a value between 0 and 1, which will be compared with a random generated value, to determine if a worst solution will or not be accepted:

$$e^{\left(\frac{E_i - E_j}{Kb.T}\right)} > \mathrm{RAND}[0..1[$$

where Kb (Boltzmann constant) regulates the acceptance ratio.

To implement the simulated annealing procedure, it is necessary to define, according to the problem being solved:

- cost function - quantifying the cost (or value) of a proposed solution. This is discussed in section IV.
- neighborhood structure - defining a new candidate solution from the present one, making the most elementary operation possible;

The neighborhood structure implemented in this work is very simple and elementary. For the loss minimization problem:

- Open a branch and close an other one, in such a way that the network remains radial and all the consumers stay served.

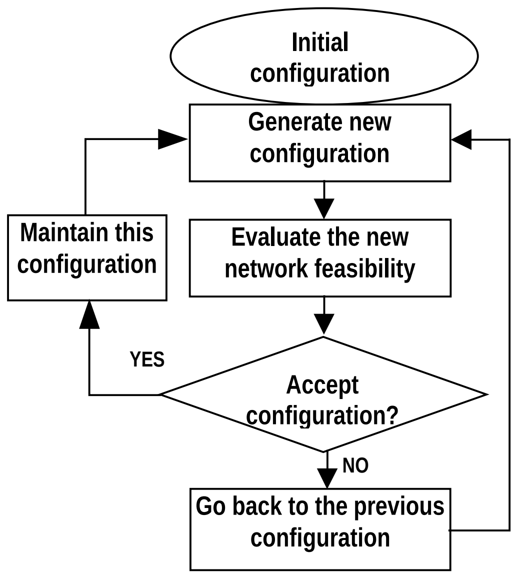

Fig. 2: The core of simulated annealing.

And for the service restoration problem:

- Close a branch that close no loops;
  or
- Open any branch.

As seen in the previous description, the two reconfiguration problems have a similar structure, with minor changes in the implementation of the simulated annealing procedure. Figure 2 shows the main cycle of the application of the simulated annealing algorithm. When restoring service, the **initial configuration** represents the distribution network with the fault isolated and some consumers not supplied. When minimizing losses, the initial configuration is the present status of the network.

IV. MULTIOBJECTIVE APPROACH

As mentioned before, these problems are usually multiobjective. In order to generate the efficient solutions, the simulated annealing process is repeated for different levels of satisfaction in one of the criteria, while minimizing the other one. Due to the characteristics of the simulated annealing method some dominated solutions may come out of this process, so multiple runs are performed, followed by a filtering process.

In the service restoration problem this leads to:

$$\text{Repeat for } N = n_1 \text{ to } n_2$$

$$\begin{cases} \text{min PNS} \\ \text{subj.} \\ \text{NSO} \le N \\ \left|I_k\right| \le \left|I_k^{max}\right|, \forall k \in L_S \\ \left|V_i^{min}\right| \le \left|V_i\right| \le \left|V_i^{max}\right|, \forall i \in B_S \\ c_j \text{ is a feasible solution} \end{cases}$$

where N is the maximum number of switching operations specified as the satisfaction level.

In both problems, the restrictions are implemented as penalties, as presented next:

- overload penalty (from power flow results):

$$\begin{cases} 0 & \text{if no overloaded lines} \\ N_0 & \text{if there are overloaded lines} \end{cases}$$

$$N_0 \text{ - number of overloaded lines}$$

- voltage drop penalty:

$$\begin{cases} 0 & \text{if no bus out of limits} \\ \left(N_v\right)^2 & \text{if there are bus deviations out of limits} \end{cases}$$

$$N_0 \text{ - number of buses with voltage deviation out of bounds}$$

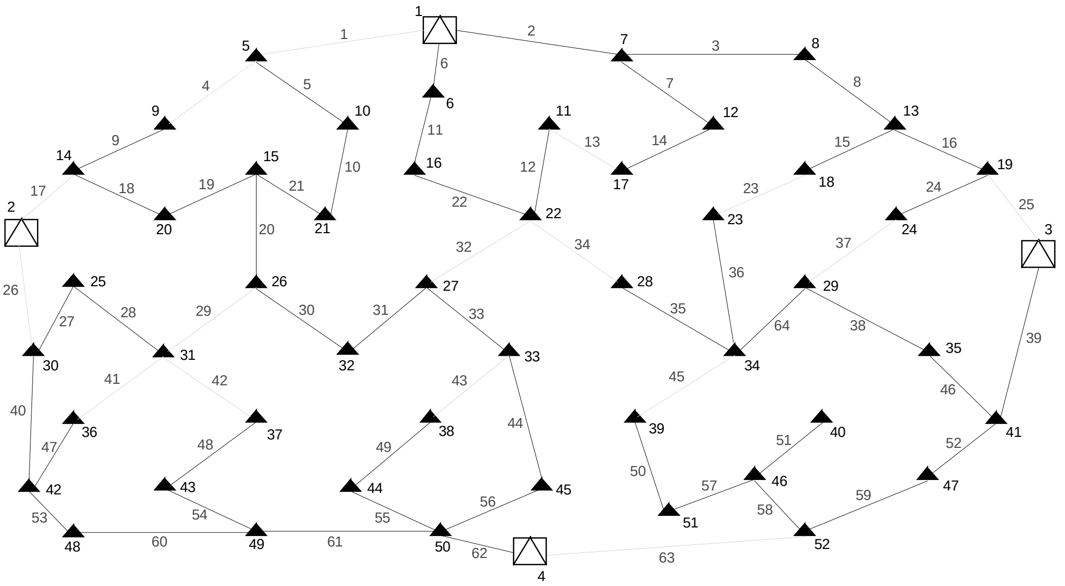

Fig. 3: test network (52 buses).

- the maximum number of switching operations penalty:

$$\begin{cases} 0 & N_k \le N \\ (N_k - N) & N_k > N \end{cases}$$

Due to the conflicting nature of the objectives, this approach will permit to generate a set of solutions, where the decision maker must choose a compromising point between the number of switching operations and the power losses/power not supplied.

V. NUMERICAL STUDIES

The 52-bus distribution network of figure 3 is used in the studies presented in this section. The total load system is 28.6 MW, 5.2 Mvar. All the lines have switches.

The reconfiguration process was implemented as a single program and, for each case presented in this section, each single efficient solution was obtained under 20 seconds on a Pentium II 300MHz. The output results include:

- initial network power losses/power not supplied
- final solution network power losses/power not supplied
- final list of switching operations of that solution
- final configuration power flow results

Next, the results obtained for the two reconfiguration studies are presented:

a) Loss minimization

The initial configuration is represented in figure 3, which has 1763 kW of active losses. In the first study, only overload constraints were considered, leading to a new value of losses of 371 kW. Several runs were made to obtain this configuration, as shown in figure 4, where the number of switching actions necessary to obtain each configuration is also shown.

A second study includes a limitation on the number of switching actions (24), and also the consideration of the minimization of this number as a second objective, as mentioned in the previous section. As expected, the results shown in figure 5 lead to more losses (394 kW) than in the previous case, and it is also patent the conflict between the two objectives (nondominated solutions are highlighted).

In the third study, a second objective related to voltage drop was considered (results in figure 6, for different limits of voltage drop).

Results show two interesting aspects: first, the best result of the first study is a local optimum (because a better solution - 341 kW - was discovered now), and second, including non-conflicting additional objectives seems to favor the optimization process. This conjecture is very promising to this kind of methods, and was confirmed in other studies.

b) Service Restoration

These results were obtained by simulating a fault in

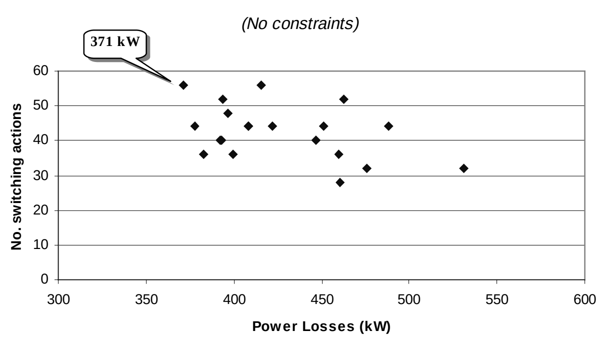

Fig 4 - Solutions of the first study

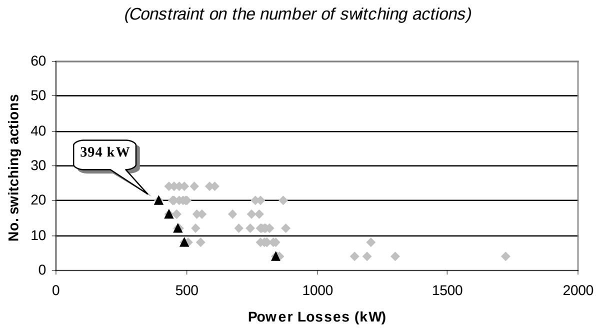

Fig 5 - Solutions of the second study

branch 62. After the isolation process, 24 consumers were not supplied (which corresponds to 11.4 MW and 2.4 Mvar). Applying the simulated annealing algorithm, several solutions were obtained which are summarized in table I:

TABLE I - Efficient Solutions (restoration)

Solution #	PNS	NSO
1	9.6	2
2	9.1	3
3	6.6	4
4	5.8	5
5	4.1	6
6	2.7	7
7	1.6	8
8	1.4	9

Figure 7 represents graphically the efficient solutions. Note that similar solutions in the attribute space may be very different in the decision space. As it can be observed, as the number of switching operations increases, the power not supplied decreases. The operator will have to choose among the given set for the most satisfying solution. Of course, limitations on the maximum number of switching actions can be included previously to save execution time.

As an example, in figure 8, is presented the final network configuration for the solution #8.

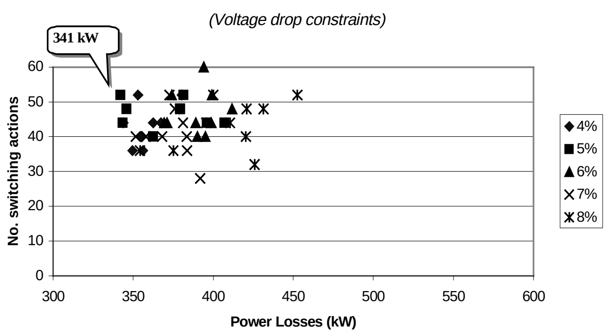

Fig 6 - Solutions of the third study

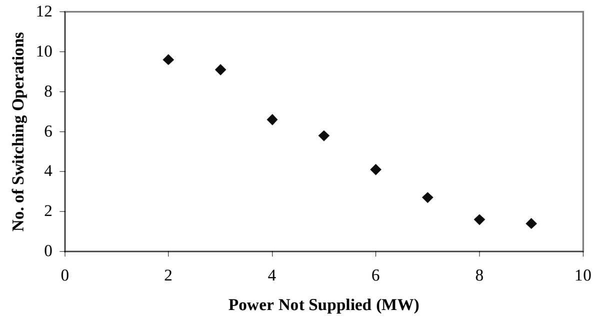

Fig. 7: Service restoration efficient solutions.

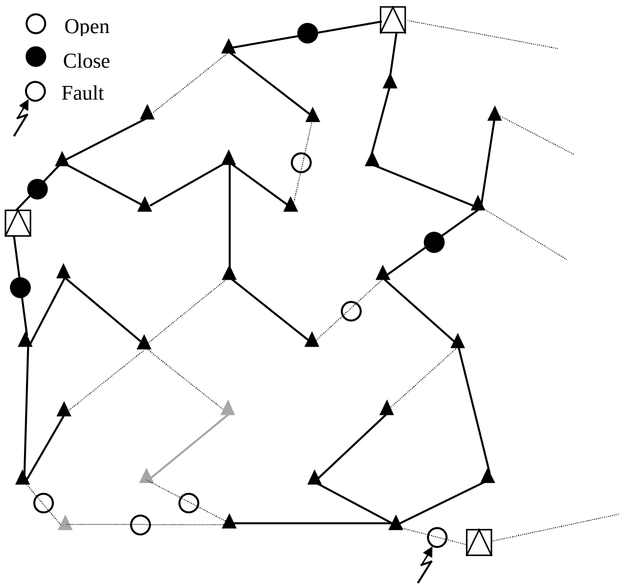

Fig. 8: Service restoration - Solution 8.

VI. CONCLUSIONS

The simulated annealing algorithm shows good characteristics to deal with reconfiguration problems in distribution networks, not only for the single criterion problems but also to generate a set of efficient solutions when multiple criteria are considered.

The methodology described in the paper is flexible enough to deal with different formulations of the reconfiguration problems, both for loss minimization and service restoration.

Further development of this work will include switching time data and energy not supplied calculation. Priority loads will also be considered.

VII. ACKNOWLEDGMENT

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X. BIOGRAPHIES

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