OPTIMAL OPERATIONAL PLANNING OF LARGE DISTRIBUTION SYSTEMS WITH ANT COLONY SEARCH

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Abstract – This paper illustrates and discusses an original technique based on the Ant Colony Search (ACS), applied to the optimal location of remote controllers for the switches in the substations of large MV distribution systems. Starting from the basic concepts of ACS, the solution strategy of the proposed method has been specifically formulated in order to take into account the reliability aspects that make the installation of new remote controllers convenient. Results obtained on a large real MV distribution system are presented.

Keywords: Ant Colony Search, distribution systems, operational planning, heuristic methods.

1 INTRODUCTION

The introduction of the competitive electricity markets has changed several aspects in the regulation of the electricity distribution sector. In some countries, as in Italy, the electricity business restructuring has partitioned the territory into several areas, allowing only the presence of a single distributor inside each area. As such, areas where the distribution networks of different companies were coexisting are experiencing a transition for merging the existing distribution networks into a unique network. From the technical point of view, the completion of this transition process will take several years and has opened a number of activities for effectively supporting it. A significant part of the transition can be performed by means of *operational planning* activities, aimed at assessing the economical convenience of making investments for rationalizing the network structure, typically assuming *constant loads*. The basic planning actions include construction of new branches, removal of existing branches, remote control of the switches in a node, and variation of the characteristics of branches or nodes. Some of these actions, such as the installation of backup circuits and of remote-controlled switching in a node, may exhibit a major impact on the distribution system reliability, even without changing the current configuration of the distribution system [1-8]. Other *expansion planning* activities [9-11], aimed at taking into account foreseen developments of the territorial areas, could require radical revisiting of the techniques adopted to fit the needs of restructured distribution systems and services.

This paper deals with *optimal* operational planning, which consists in selecting, among a pre-specified set of short-term planning actions, the ones that should be activated in order to reach the optimal value of a given objective function. More specifically, this paper addresses as planning actions the installation of remote-controllers for the switches in the distribution system nodes (substations). A set of candidate locations for remote-controllers installation is identified a priori. The objective function is given by the variation of the total annual cost resulting from the activation of a subset of the candidate planning actions. The objective function components are the cost of activation of the planning actions selected and the *variations* in the reliability, maintenance and investment cost components with respect to the costs corresponding to the initial configuration of the system. In addition, a *budget limit* may be included for limiting the number of planning actions activated, by constraining the variation of the total investment cost.

The optimal operational planning problem can be solved by using a deterministic *exhaustive search*, or *heuristic* algorithms [12], such as *genetic* algorithms, *evolutionary* algorithms, the *Simulated Annealing* method, and others [13][14]. For large distribution systems, where the number of planning actions to be processed is relatively high, the combinatorial nature of the problem makes exhaustive search practically inapplicable, so that searching for an efficient heuristic is worthwhile.

The authors have developed, implemented and tested on large real distribution systems a new promising technique by using Ant Colony Search (ACS) optimisation [15,16]. ACS is a numerical technique aimed at simulating the behaviour of the ants while searching for food. Each ant leaves a pheromone trail in its path from nest to food, that evaporates with time. The pheromone trail may be reinforced by the ants going back to the nest to inform that food has been found. The successive ants will tend to follow the pheromone trail corresponding to the “shortest” path, marked with strong pheromone quantities. The basic concepts of the ACS technique are rather general, so that ACS has been applied to solve different classes of optimisation problems in various contexts [17,18]. Concerning distribution systems optimisation, ACS has been applied to optimal reconfiguration [19], capacitor placement [20], optimal restoration [14] and expansion planning [21,22]. This paper illustrates how the original ACS concepts have been adapted to address the optimal selection of the planning actions to be activated for enhancing the remote-controlled switching of a large radial MV distribution system. In the implementation of the ACS heuristic, the pheromone trail provides a "memory" of the planning actions that provided the best values of the objective function found in the previous phases of the search. Starting from the basic concepts of ACS, the solution strategy of the proposed method has been specifically formulated in order to take into account the reliability aspects that make the installation of new remote controllers convenient.

Section 2 of this paper illustrates the application of ACS to the optimal operational planning problem. Section 3 shows the effectiveness of the proposed approach, by presenting the numerical results obtained on large real 6.3 kV distribution system.

2 ANT-COLONY SEARCH APPLIED TO THE OPTIMAL OPERATIONAL PLANNING

2.1. Objective function and constraints

The planning actions considered concern the substitution of on-site switching with remote-controlled switching at one or more nodes belonging to a predefined set $\boldsymbol{J}$. However, installing a new remote controller in a node is not always convenient, since the benefits in terms of reliability improvements could not be high enough to compensate for the costs of installing and maintaining the remote controller. Let's indicate with $\boldsymbol{R} \subset \boldsymbol{J}$ the subset of the remote controllers activated at a specified stage of the solution process.

The cost evaluation is performed on an annual basis. The total annual cost is

$$C_{tot} = C_R + C_M + C_V \tag{1}$$

and is composed of the following terms:

- *reliability* cost, expressed by
$$C_R = \rho_P \, P + \rho_W \, W \tag{2}$$
where P is the power not served, W is the energy not served, ρ_P and ρ_W are respectively the cost coefficients related to power and energy not served;
- *maintenance* cost C_M ;
- *annual investment* cost C_V , computed from the total investment cost C_V^{tot} and the discount rate r_q in the q-th period (year) of investment (with Q total periods), as
$$C_V = C_V^{TOT} \left(\sum_{q=1}^{Q} \frac{1}{\left(1 + r_q\right)^q} \right)^{-1} \tag{3}$$

In the definition of the objective function, it is not necessary to introduce the total annual costs. The cost to be considered is given by summing up, for each planning action activated, the cost of activation $C_A(\boldsymbol{R})$ and the *variations* $\Delta C_R(\boldsymbol{R})$, $\Delta C_M(\boldsymbol{R})$ and $\Delta C_V(\boldsymbol{R})$ of the cost components with respect to the corresponding values related to the initial system. For instance, the reliability cost variation is only formed by the term depending on the duration of the interruptions, since the installation of new remote controllers does not affect the frequency of the interruptions, so that

$$\Delta C_R(\boldsymbol{R}) = \rho_W \; \Delta\bar{d}(\boldsymbol{R}) \; P \tag{4}$$

The resulting objective function is

$$f(\boldsymbol{R}) = C_A(\boldsymbol{R}) + \Delta C_R(\boldsymbol{R}) + \Delta C_M(\boldsymbol{R}) + \Delta C_V(\boldsymbol{R}) \tag{5}$$

The budget limit B, applied to the variation of the investment cost, may be introduced as a constraint depending on the management strategy of the distribution company.

The constrained optimization problem becomes

$$\min_{\boldsymbol{R}} \{ f(\boldsymbol{R}) \} \tag{6}$$

subject to

$$\Delta C_V(\boldsymbol{R}) \le B \, . \tag{7}$$

Any solution for which the variation of the investment cost exceeds the *budget limit B* is rejected during the solution process. Furthermore, when the budget limit is not specified the effectiveness of the results obtained is assessed by means of the *performance factor*

$$\zeta(\boldsymbol{R}_{best}) = 100 \, \frac{C_{tot}(\boldsymbol{0}) - C_{tot}(\boldsymbol{R}_{best})}{C_{tot}(\boldsymbol{0}) - C_{tot}(\boldsymbol{J})} \tag{8}$$

where $C_{tot}(\boldsymbol{0})$ is the total annual cost in the initial condition, $\boldsymbol{R}_{best} \subset \boldsymbol{J}$ is the subset of the remote controllers activated to obtain the best objective function found so far, and $C_{tot}(\boldsymbol{J})$ is the total annual cost obtained with *all* the planning actions included in the set $\boldsymbol{J}$ activated. Larger performance factor values correspond to better solutions.

2.2. Algorithm structure and parameters

The algorithm includes three loops (Figure 1). Initially all nodes $j \in \boldsymbol{J}$ are associated to the same quantity of pheromone φ_0. During each iteration of the external loop, M ants are sent to insert a number of remote controllers in some of the nodes $j \in \boldsymbol{J}$. Each ant places the remote controllers in a number of nodes chosen at random from 1 to J[1]. The selection of the nodes is performed by using a random extraction among a set of alternatives characterised by their fitness values. The fitness definition depends on a local heuristic function built on the basis of specific reliability concepts (Section 2.4). At the end of each iteration, part of the pheromone evaporates. However, the nodes at which the new remote controllers have been positioned to obtain the best objective function found during the iteration are marked by increasing their quantity of pheromone (Section 2.6). The external loop continues

[1] Among the options of the program there is the possibility of requiring a given number of remote controllers. In this case, all the ants are forced to locate exactly the given number of remote controllers. An additional possibility is to set minimum and maximum limits to the number of remote controllers positioned by each ant. During the tests, a first analysis was carried out in order to explore the characteristics of the system without such additional limits. Then, the successive application of this technique to limit the search within a desired range of values for the number of nodes allowed for drastically reducing the computation time.

until no improvement of the objective function (5) is detected for a specified number of iterations K_C. The stop criterion also includes the maximum number of iterations K_M, to be used as a last-resource option to avoid excessively long duration of the iterative process.

The input parameters of the algorithm are:

B budget limit (default: none)
K_M maximum number of iterations
K_C maximum number of iterations without improvement in the objective function
M number of ants
N_S given number of remote controllers (default: none)
α exponent for pheromone update (local heuristic)
β exponent for the local heuristic function
γ_b pheromone amplification factor (global best)
γ_c pheromone amplification factor (local best)
δ pheromone evaporation rate
φ_0 initial pheromone quantity

2.3. Feeder selection

Any iteration of the ant colony loop sends a colony of M ants. In the same iteration, the ants are sent in parallel to modify the same system, so that the changes introduced by a single ant are not immediately applied. The process for which each ant locates a random number of new remote controllers is composed of successive searches (one for each controller to be positioned). In principle, each ant could select the next remote controller among the candidate nodes belonging to the set $\mathbf{J}$ and not yet activated. However, this would require updating the fitness of *all* these candidate nodes at each search, and for large systems this process would be excessively time consuming. Hence, the system partitioning into *feeders* has been taken into account. Each feeder corresponds to the portion of the distribution system supplied by a specified circuit breaker. Each search is then performed in two steps. The first step consists of the feeder selection, whereas the second step locates the new remote controller in a node belonging to the candidate nodes inside the selected feeder. For the first step, each h-th feeder is assigned a *fitness*, computed by taking into account the number N_h of remote controlled nodes already installed in the feeder and the potential benefit, in terms of reduction of the energy not served, given by the installation of an additional remote control in the feeder. By using the equivalent failure rate of the feeder λ_h and the power not served in the feeder P_h, the feeder fitness ξ_h is expressed by

$$\xi_h = \frac{\lambda_h P_h}{1 + N_h} \tag{9}$$

At each iteration of the solution procedure, the feeder selection is performed by associating each feeder to its fitness value and randomly extracting the number of the feeder with the biased roulette wheel mechanism described in the Appendix. The fitness of the selected feeder is then updated with N_h increased by one.

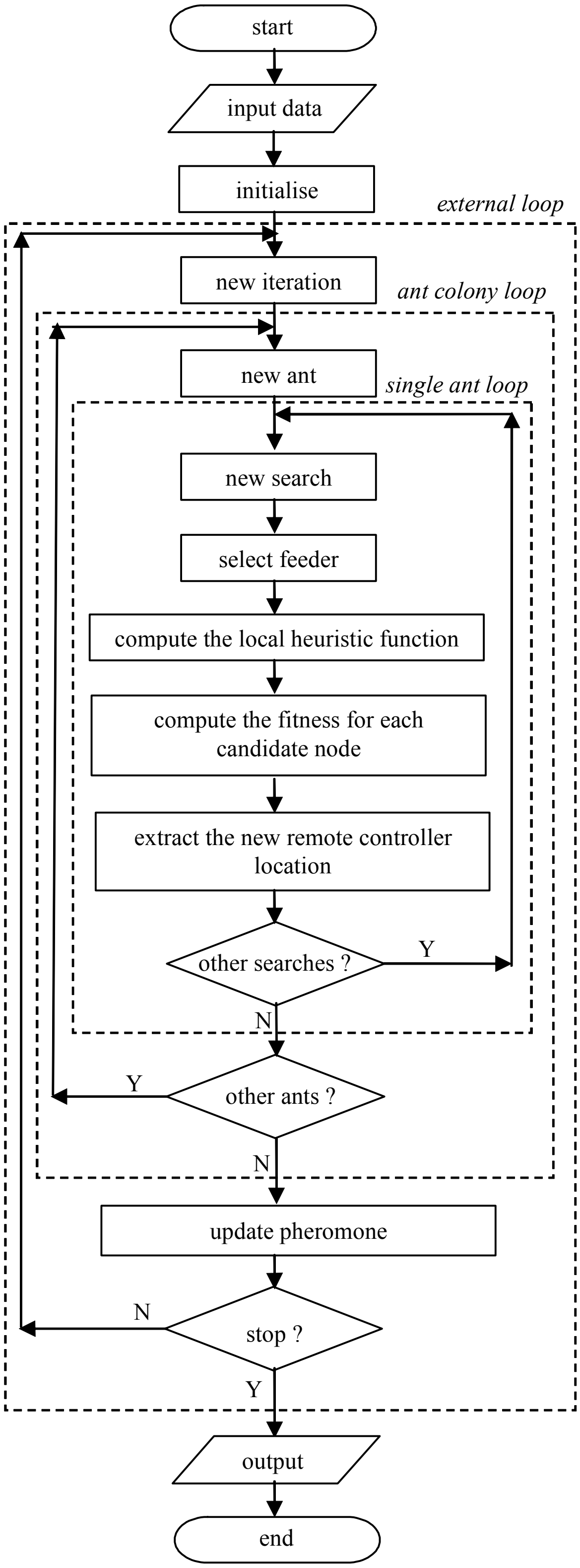

Figure 1: Flow-chart of the proposed algorithm.

2.4. The local heuristic function

The key benefit of performing remote-controlled switching lies in reducing the duration of identification of the faulted branch in case of *permanent* faults, with subsequent reduction of the energy not supplied.

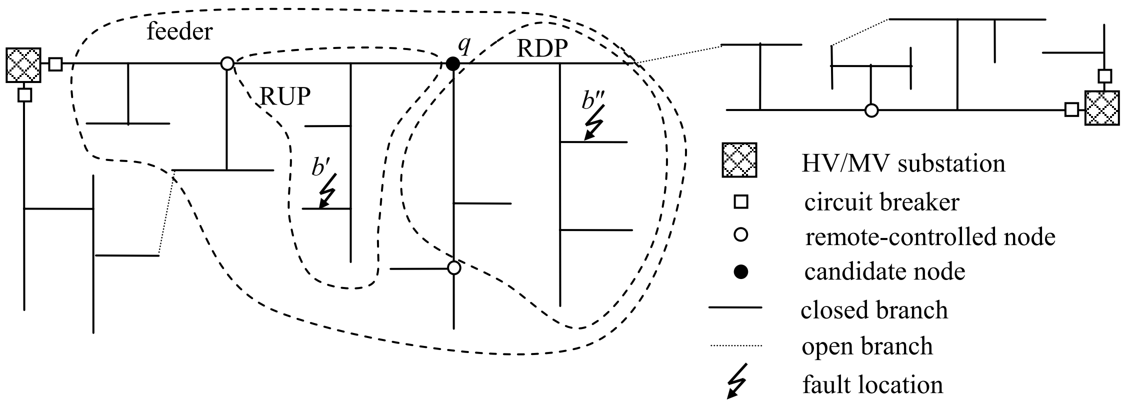

Figure 2: Schematic distribution system structure for illustration of the local heuristic function terms

Reducing the energy not supplied is used as a criterion for defining the *local* heuristic function, associated to each node candidate for inserting a new remote-controller. For each candidate node, the location of other remote controllers already in place in the neighbouring portion of the feeder is also taken into account. The local heuristic function is formulated in such a way that its higher values correspond to the most convenient locations for installing the new controllers.

Let's consider a given configuration of the distribution system, in which a number of remote controllers is already active. For a candidate node $q \in \boldsymbol{J}$ belonging to a specified feeder (Figure 2), it is possible to identify the *Reduced Upstream Portion* (RUP) of the feeder, containing the set $\boldsymbol{U}_q$, of the nodes located in the path found starting from node q and moving upward to the first remote-controlled node or to the node with circuit breaker protection, and all their ramifications up to any remote-controlled node. In the same way, it is possible to identify the *Reduced Downstream Portion* (RDP) of the feeder, formed by the set $\boldsymbol{D}_q$, containing all the nodes located in the path found starting from node q and moving downward along all the ramifications, up to any remote-controlled node. Installing a remote control in node q would reduce the energy not supplied for two reasons:

a) for a permanent fault in the RDP of the feeder (e.g., branch b'' in Figure 2), the presence of the remote controller in node q allows for speeding up the re-energisation of the RUP of the feeder, with a benefit in terms of reduction in the energy not supplied expressed as

$$\Delta W_{\boldsymbol{U}_q} = P_{\boldsymbol{U}_q} \lambda_{\boldsymbol{D}_q} \left(\tau_s - \tau_r\right) \tag{10}$$

where τ_r and τ_s are the average restoration times corresponding to remote-controlled and on-site switching, respectively, whose values can be assessed from operational practice [23], $P_{\boldsymbol{U}_q}$ is the total power not served in the RUP of the feeder and $\lambda_{\boldsymbol{D}_q}$ is the equivalent failure rate for the RDP of the feeder;

b) for a permanent fault in the RUP of the feeder (e.g., branch b' in Figure 2), the presence of the remote controller in node q could speed up the re-energisation of the RDP of the feeder. However, this benefit may occur *only* if there is at least one open branch connecting the RDP to another feeder (i.e., a feeder protected by another circuit breaker and able to supply the RDP load during the restoration process). In this case, the reduction in the energy not supplied would be

$$\Delta W_{\boldsymbol{D}_q} = P_{\boldsymbol{D}_q} \lambda_{\boldsymbol{U}_q} \left(\tau_s - \tau_r\right) \tag{11}$$

where $P_{\boldsymbol{D}_q}$ is the total power not served in the RDP of the feeder and $\lambda_{\boldsymbol{U}_q}$ is the equivalent failure rate for the RUP of the feeder.

The local heuristic function corresponding to the candidate node q then depends on the sum $\Delta W_{\boldsymbol{U}_q} + \Delta W_{\boldsymbol{D}_q}$ and, being the term $\left(\tau_s - \tau_r\right)$ constant and thus not affecting the selection mechanism, is formulated as

$$\eta_q = P_{\boldsymbol{U}_q} \lambda_{\boldsymbol{D}_q} + P_{\boldsymbol{D}_q} \lambda_{\boldsymbol{U}_q} . \tag{12}$$

2.5. Fitness calculation and selection of the node for remote control

At iteration k, for each candidate node $j \in \boldsymbol{J}$ belonging to the selected feeder, the fitness is calculated as

$$\psi_j^{(k)} = \left(\varphi_j^{(k)}\right)^{\alpha} \left(\eta_j^{(k)}\right)^{\beta} \tag{13}$$

The set of candidate nodes and their associated fitness values are then sent to the biased roulette wheel mechanism (described in the Appendix) for selecting the node in which the next remote controller will be positioned.

2.6. Update pheromone

At the end of iteration k, the pheromone level corresponding to each planning action $j \in \boldsymbol{J}$ is updated according to the expression

$$\varphi_j^{(k)} = \breve{\varphi}_j^{(k)} + \Delta\varphi_j^{(k)} \tag{14}$$

where the term $\breve{\varphi}_j^{(k)}$ represents the pheromone decay applied to each planning action, with evaporation coefficient δ (e.g., δ = 0.01÷0.2):

$$\breve{\varphi}_j^{(k)} = (1-\delta)\varphi_j^{(k-1)} \quad (15)$$

and the term $\Delta\varphi_j^{(k)}$ represents the pheromone reinforcement, applied only to the planning actions belonging to the subset $\boldsymbol{R}_{best}^{(k)} \subset \boldsymbol{J}$ activated in the case corresponding to the best objective function $f\left(\boldsymbol{R}_{best}^{(k)}\right)$ found during the iteration *k*. A further refinement has been included in the pheromone reinforcement, by using different amplification factors ($\gamma_b > \gamma_c > 1$) to distinguish the case in which the objective function $f\left(\boldsymbol{R}_{best}^{(k)}\right)$ is the best solution found so far (factor γ_b) from the case in which it is "only" the best solution obtained at the current iteration (factor γ_c). Then, the amplification factor used at iteration *k* is

$$\gamma_a^{(k)} = \begin{cases} \gamma_b & \text{if } f\left(\boldsymbol{R}_{best}^{(k)}\right) > f\left(\boldsymbol{R}_{best}^{(k-1)}\right) \\ \gamma_c & \text{if } f\left(\boldsymbol{R}_{best}^{(k)}\right) \le f\left(\boldsymbol{R}_{best}^{(k-1)}\right) \end{cases} \quad (16)$$

and the pheromone reinforcement term is expressed by

$$\Delta\varphi_j^{(k)} = \left(\frac{f\left(\boldsymbol{R}_{best}^{(k-1)}\right)}{f\left(\boldsymbol{R}_{best}^{(k)}\right)} \varphi_j^{(k-1)} - \breve{\varphi}_j^{(k)} \right) \frac{\gamma_a^{(k)}}{N^{(k)}}, \quad (17)$$

$N^{(k)} = \dim\left\{\boldsymbol{R}_{best}^{(k)}\right\}$ being the number of remote controllers activated in the solution corresponding to $f\left(\boldsymbol{R}_{best}^{(k)}\right)$. If $f\left(\boldsymbol{R}_{best}^{(k)}\right) > f\left(\boldsymbol{R}_{best}^{(k-1)}\right)$, the last operation of the iteration *k* is the assignment of $f\left(\boldsymbol{R}_{best}^{(k-1)}\right)$ to $f\left(\boldsymbol{R}_{best}^{(k)}\right)$, in order to avoid losing the best solution found so far.

3 APPLICATION TO LARGE REAL MV DISTRIBUTION SYSTEMS

The proposed method has been applied to various large real MV distribution systems [2,23]. The results presented in this paper refer to a 6.3 kV urban distribution system with 33 supply nodes, 2135 load nodes, 89 nodes with circuit breaker, no remote-controlled node (in the initial system), 1832 nodes with on-site switching, 2669 branches (of which 2135 closed and 534 open), total line length 761 km and total power 370 MW. The number of nodes belonging to the set $\boldsymbol{J}$ has been chosen in such a way to avoid the nodes connected without redundant paths, resulting in 1330 nodes selected as candidates for placement of the remote controllers. The dimension of the set $\boldsymbol{J}$ makes the problem intractable by using exhaustive search techniques.

In the solution process, the two-step selection of the node to install the remote controller, with a first selection of the feeder and a successive selection of the node belonging to the set $\boldsymbol{J}$ and located inside the feeder, has led to reducing the computation times of about 10 times, with respect to the case in which the node selection is always open to all the nodes belonging to the set $\boldsymbol{J}$ and not yet selected.

In order to gain deeper insights on the characteristic of the proposed method, several tests have been carried out with different values of the input parameters. The parameters δ, α, β, K_C and M have been varied within pre-defined ranges. The performance factor (8) and the duration of the iterative process have been observed. For any given δ, the values of γ_b and γ_c have been tuned by checking the evolution of the maximum and minimum pheromone during the iterations. While the minimum pheromone tends to follow an exponential decay, due to the fact that at least one node never belongs to the best set of nodes, an inaccurate choice of the maximum pheromone could lead to very high pheromone values. If the same node would always belong to the best set found at all the iterations, the maximum pheromone would grow exponentially, leading to an even higher probability of selecting always the same nodes during the successive iterations. The occurrence of this behavior could trap the solution of the iterative process into a local minimum. A careful tuning of the parameters governing the pheromone decay and reinforcement can prevent excessive growth of the maximum pheromone, increasing the probability of finding alternative paths. Figure 3 shows an example of reasonable evolution of the maximum and minimum pheromone during the iterations.

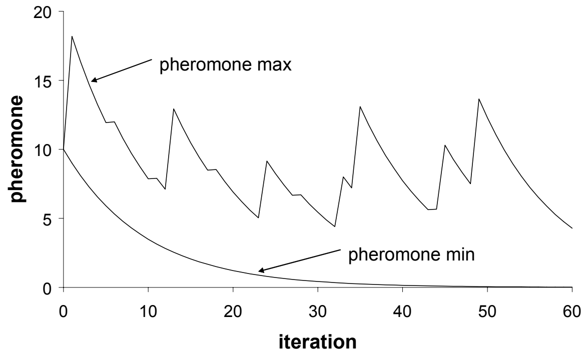

Figure 3: Evolution of the maximum and minimum pheromone during the iterations.

A selection of significant results is shown in the sequel. For the sake of comparison, some results are represented by using their Cumulative Distribution Functions (CDFs).

A first test concerned the impact of the number of ants *M* on the solution. The CDFs of the performance factor obtained by varying δ, γ_b and γ_c within the same set of values for different numbers of ants *M*, with α = β = 1, φ_0 = 10 and K_C = 10, are shown in Figure 4. For the 6.3 kV system under test, the performance factor exhibits an increasing trend when *M* increases, but the improvements become less and less effective for increasing values of *M*. The results of Figure 4 suggest limiting *M* to a value not greater than 500÷600. A further information is given by Figure 5, concerning the computation time required, where it is clear that relatively good solutions in terms of performance factor can be reached for $M = 600$, but also for $M = 300$ in a much shorter computation time[2], since the number of solutions per unit time has a small variation with respect to the number of ants (Figure 6).

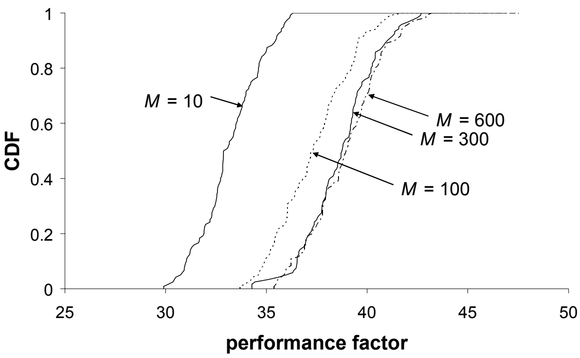

Figure 4: Performance factor for different numbers of ants.

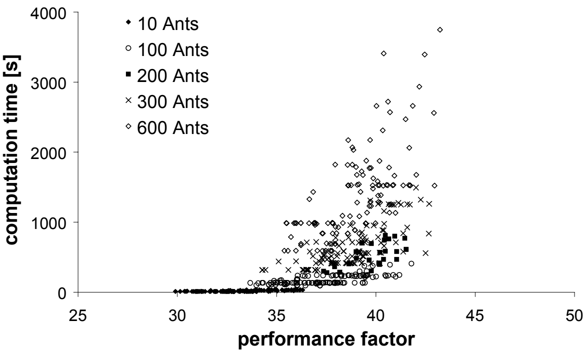

Figure 5: Computation time vs. performance factor for different numbers of ants.

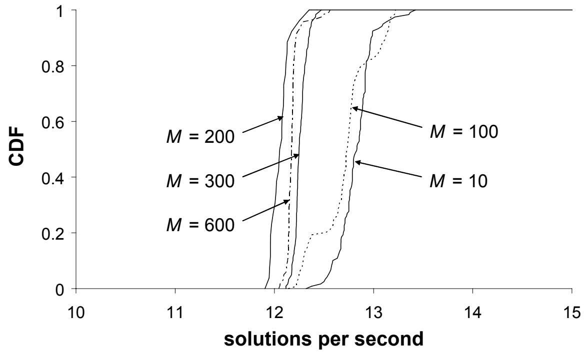

Figure 6: Number of solutions per unit time for different numbers of ants.

The impact of the exponents α and β on the performance factor is shown in Figure 7, from which $\alpha = 1$ and $\beta = 1$ is considered to be an acceptable setting for the case under study.

A specific analysis has been carried out by fixing the number N of remote controllers to specified values. Extensive testing has been performed with N variable from 10 to 1000 with a step of 10, by changing the parameters δ, K_C and M within pre-defined ranges. Some of the best solutions found during the analysis for selected values of N are shown in Table 1. The optimal number of remote controllers found in the 6.3 kV system is 100, corresponding to the performance factor of 46.5% and to a total duration of the calculations of 2434 seconds[3]. This number is in line with the operational practice, that suggests to install the remote controllers in about 10% of the total number of nodes. For $N > 100$, the performance factor decreases.

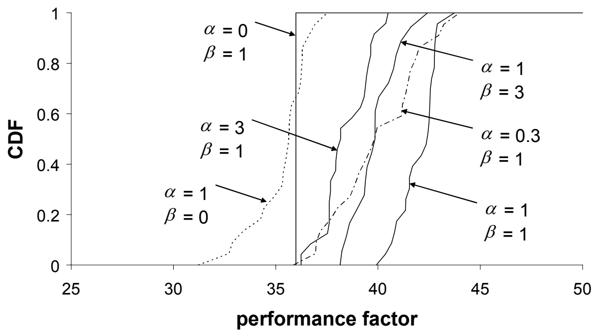

Figure 7: Impact of the exponents α and β on the performance factor (with $M = 600$, $\delta = 0.1$, $\varphi_0 = 10$ and $K_C = 10$)

fixed number of remote controllers	best performance factor found (%)
10	10.9
50	29.1
100	46.5
200	35.5

Table 1: Best performance factors found in the 6.3 kV system with fixed numbers of remote controllers.

The results obtained on the 6.3 kV system by using the proposed ACS method have been compared to the ones reached by using genetic algorithms (GAs), traditionally adopted by the authors for solving the operational planning problems of various large real distribution systems [2]. In the distribution system under test, the performance factor values resulting from ACS method were comparable to those obtained from GAs in many years of experience. However, the ACS method resulted to be faster than GAs both in terms of number of solutions per unit time (for the GAs, the value comparable to the results of Figure 6 was around 10 solutions per second) and in terms of the total duration of the optimisation process (the average duration computed from over a thousand GA calculations for a comparable value of K_C for the stop criterion was up to four times higher than the average duration resulting from the proposed ACS method). In addition, the ACS method implemented has shown interesting behaviour

[2] The numerical calculations have been performed on a Pentium IV 1.7 GHz personal computer.

[3] This solution has been obtained with $M = 600$, $\varphi_0 = 10$, $\delta = 0.1$, $\gamma_b = 210$, $\gamma_c = 35$ and $K_C = 20$.

in terms of converting specific adaptation of the solution strategy into performance factor improvements, so that searching for further refinements is worthwhile.

4 CONCLUSIONS

A new technique based on ACS has been presented for remote controller location in large distribution systems. The technique developed embeds reliability concepts in the solution strategy and has shown interesting performance in terms of reducing the total annual costs by properly selecting a suitable number of remote controllers to be installed in a subset of the selected set of distribution system nodes. The authors are working towards improving the solution strategy, with special focus on finding suitable alternatives for implementing the two steps of the search performed by each ant. The authors are also working to extend the proposed ACS method in order to include appropriate local heuristics for handling other planning actions, with the aim of developing a comprehensive ACS-based optimal operational planning strategy for large distribution systems.

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APPENDIX

A.1. The biased roulette wheel mechanism.

Several parts of the algorithm described in Section 3 require the random selection of a subject from a set of $z = 1,\dots, Z$ subjects, each of which is associated to a fitness value. This selection is performed by means of the *biased roulette wheel* mechanism, implemented as shown in Figure A1. The fitness values are first normalised to obtain the heights ζ_z of the steps of the cumulative staircase, for $z = 1,\dots, Z$. The selection of the subject is then performed by extracting a random number r from a uniform distribution in (0,1) and interpreting this number as a cumulative value, from which the corresponding subject is selected (e.g., the subject #4 in the example of Figure A1).

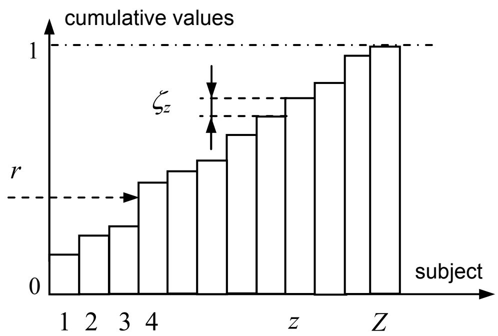

Figure A1: Random extraction of a subject from a set of subjects associated to fitness values.