Multiobjective Ant Colony Search Algorithm For Optimal Electrical Distribution System Strategical Planning

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Abstract- **In this paper, a dynamic MultiObjective, MO, algorithm based on the Ant Colony Search, the MultiObjective Ant colony Search Algorithm, MOACS, is presented. The application domain is that of dynamic planning for electrical distribution systems. A time horizon of H years has been considered during which the distribution system will be modified according to the new internal (loads) and external (market, reliability, power quality..) requirements. In this scenario, the objectives the Authors consider most important for utilities in strategical planning are: the quality requirement connected to the decrease of the expected number of interruptions per year and customer, in the considered time frame, and the choice for the lowest cost strategy. The Authors have formulated on purpose a new dynamic optimization algorithm to treat hard MO problems such as the one of strategical planning. The algorithm is a MO version of the Ant Colony Search based on the concept of Pareto optimality. Namely, it works with as many colonies of ants as many objectives the problem presents and it is conceptually divided in two different phases a forward phase, in which single objectives and local increments are prized and a backward phase in which Pareto optimal solutions are prized.**

I. INTRODUCTION

This paper deals with the problem of optimal dynamic strategical planning of distribution systems by means of a novel MO Ant Colony Search [1] algorithm. The implementation uses the notion of Pareto optimality and the sharing concept borrowed from the GA literature [2]. The problem here dealt with is indeed a dynamic planning problem in which the configurations through which the system can evolve are not known beforehand. Therefore a pre-processing phase is needed, in order to make the problem amenable to a minimum length problem. A NSGA algorithm has been used to define these intermediate solutions. In the considered application, the aim of the designer is that to generate an optimal expansion strategy for a distribution system, in terms of minimum cost and maximum quality of supply. Then, the objectives to be minimized are two and the strategy is optimal in a Pareto sense. This paper shows one of the parts of the research that is being carried out about strategical planning in distribution systems. In other papers, a distribution systems modelling methodology has been formulated based on the definition and implementation of particular 'functional modules' [3]. The idea was basically that to create a modular approach to the strategical planning problem. The use of such modules has indeed allowed the extensive application of mathematical, heuristic and meta-heuristic methodologies. Moreover, this formulation is well suited for the consideration of multiple objectives and of a dynamic framework. Some of the work that has been carried out till now, oriented towards the application of heuristics and meta-heuristics to this issue, has been addressed towards the static optimization. In particular, the Authors have first tried to find minimum cost design solution [4] then they have tried to optimize statically the system, both in terms of minimum cost and in terms of maximum quality of supply (minimum unavailability, minimum unbalance of the supply voltage, minimum expected of voltage dips)[5]. In this paper, the problem of strategical planning has been formulated as a dynamic and MO optimization problem. In this way, the problem is that to find the best expansion strategy of a system whose evolution is ruled by the load increase and by more strict requirements of power quality. A novel MO algorithm based on the ACS paradigm is therefore here proposed as a valuable tool to face this kind of problems. Other Authors have proposed MO versions of the ACS algorithm as Mariano and Morales. They have implemented the MO Ant-Q algorithm, MOAQ, [6] [7]. The proposed algorithm is different from the latter for many aspects. One of the most important is that it does not require a predefined priority among the considered objectives. On the other hand, as in the MOAQ, in the proposed algorithm it is necessary to use a number of colonies that equals the number of considered objectives. Iredi et al. [8] also propose a multi-colony approach to handle many objectives. The idea is to use heterogeneous colonies of ants, each of which weights the objectives differently. In [9] an extensive state of the art on the subject of MO optimization using the Ants paradigm is reported and well commented.

The paper is organized as follows. In Section II and III, the problem of optimal strategical planning of distribution systems is formulated in static and dynamic terms. Then, in

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Section IV, the proposed MO algorithm (MOACS) is described with reference to the considered application. Finally, in Section V and VI, results and conclusions are given.

II. THE PROBLEM OF OPTIMAL PLANNING OF DISTRIBUTION SYSTEMS

In this section, a brief description of the modular approach and of the 'functional modules' is given. They are adopted to build a mathematical system model suitable for optimization, as already demonstrated in previous work by the Authors [3][4], thus allowing to optimize the system configuration at both the Medium Voltage (MV) and Low Voltage (LV) levels.

A. Modular representation

A "functional module" is composed of an elementary power system module and a number of rules or constraints that define its operation and combination with other modules. The elementary system module is given by a supply node, a number of outgoing feeders and compensation devices, if present. In a multi-level distribution system, different types of modules may be used at different voltage levels. Here, a system with two voltage levels is considered. In this application, the same module, shown in figure 1, is used for both MV and LV levels. The figure shows a MV/LV substation, indicated with a circle, feeding ten lines, which bring the electrical energy to the customers supplied at LV. In the following, the subscript "a" denotes parameters related to the MV level and "b" to the LV level. The topological and electrical parameters of the module, as well as the operational constraints, are expressed mathematically. This makes it easy to create different configurations by inserting, removing or replacing modules, and to apply an optimization procedure analytically. The set of topological and electrical parameters that define a module are reported in Table I. Note that many of these parameters can only assume discrete values, e.g. depending on the sizes available on the market.

B. Operational constraints

Each module is subjected to operational constraints [3][4]. The voltage drop ΔUo on the feeder must be limited to a maximum admissible value ΔUx%

$$\frac{\Delta U_o}{U_s} = \frac{\sigma \cdot X \cdot a \cdot z}{U_s^2}\left(\frac{N_o \cdot a}{4} + \frac{X}{2}\right) \le \Delta U_x\% \quad (1)$$

where z is the feeder impedance per unit length and σ the load density per km^2. The current in the feeders Io must also be limited to a maximum admissible value that is the rated current Ix of the cable

$$I_o = \frac{\sigma \cdot X \cdot a}{\sqrt{3} \cdot U_s} \le I_x \quad (2)$$

Finally, the rating of the transformer must be sufficient to supply the power demand of the area that it serves, i.e.

$$S_n \ge 4\,\sigma\, X\, Y \quad (3)$$

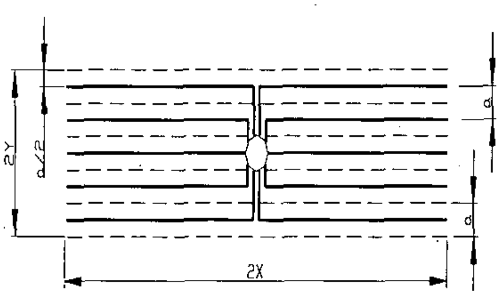

Figure 1. Elementary power system module

TABLE I – PARAMETERS AND SYMBOLS OF AN ELEMENTARY SYSTEM MODULE

Parameter	**Symbol**
Primary and Secondary transformer voltage	U_p, U_s
Transformer rated power	S_n
Number of MV feeders	N_o
Half-dimension of module on *x*-axis and *y*-axis (Fig.1)	X, Y
Feeder cross-section	s_o
Number of consumption points per feeder	n_n
Distance between two feeders (see Fig.1)	a

C. Interface functions

To link the modules together, correspondence among some "interface parameters" must be ensured [3][4]. These parameters can be either electrical or topological. The following relations between the topological parameters of the two modules can be written

$$Y_b = \frac{2Y_a}{N_{oa}} \quad X_b = \frac{2X_a}{N_{oa}} \quad a = \frac{4Y_a}{N_{oa}} \quad (4)$$

D. Cost functions

For the module in figure 1, the total cost, comprising installation costs, maintenance costs and losses costs, of the system is reported to the initial year of the time horizon H, by using an actualization rate a_{act}, as

$$C_{tot} = C_{inst} + C_{main} \cdot \left(\frac{1-e^{-a_{act}H}}{a_{act}}\right) + C_{loss} \cdot \left(\frac{e^{(2k_{load}-a_{act})H}}{(2k_{load}-a_{act})}\right) \quad (5)$$

where it is assumed that the load growth follows an exponential law $\sigma(t)=\sigma_0 e^{k_{load}}$ where k_{load} is the rate of change of the load.

E. Reliability and quality functions

A system performance index has been used in order to quantify the reliability of the distribution system. This index is the System Average Interruption Frequency Index (SAIFI)

$$\mathrm{SAIFI} = \frac{\text{Total number of customer interruptions}}{\text{Total number of customer served}} \tag{6}$$

This index and the quality indices have been evaluated using the methodology outlined in [11].

III. STATIC AND DYNAMIC OPTIMIZATION

To solve the dynamic MO problem, the total planning horizon H is divided into T sub-periods or time intervals TI_k, with $k = 1, \ldots, T$, each of which is $D = H/T$ years long. At the end of each sub-period, a static MO optimization is performed by using NSGA [10], and a set of optimal configurations for the load density expected in that year is found. The dynamic MO planning problem is now how to go from one initial configuration, which is optimal for the initial load density, to the optimal configuration at year H by moving along given optimal solutions identified for each sub-period. The MOACS is used to find the path having the minimum-cost and the maximum improvement in the System Average Interruption Frequency Index, SAIFI (see equation (12)).

A. Static optimization with NSGA

NSGA differs from the Simple Genetic Algorithm (SGA) [2], only in the way the selection operator is used. Crossover and mutation operators remain unchanged. Before selection is performed, the population is first ranked on the basis of the non-domination level of each individual, by comparing each individual with all others in the population for non-domination. All non-dominated solutions found are assumed to constitute the first non-dominated front in the population and assigned a large dummy fitness value. Thus, all these solutions have an equal reproductive potential. In order to maintain population diversity, these non-dominated solutions are then shared with their dummy fitness value.

In this application, the total cost per km^2, SAIFI and average expected number of voltage dips for the MV level (SAIFI_a, $n_{\mathrm{dips,a}}$) and for the LV level (SAIFI_b, $n_{\mathrm{dips,b}}$) are the five objective functions that have to be simultaneously optimized. By performing the optimization at the end of each interval TI_k, $k = 1, \ldots, T$, i.e. every D years, a set of Pareto-optimal solutions for the load density forecasted at the end of each TI is detected. In this way, a pre-processing phase in which the solutions for all the TIs are detected using the NSGA, is carried out. Then, a number of expansion strategies through these solutions can be identified. See example in figure 2.

IV. OPTIMAL EXPANSION STRATEGY WITH MOACS

In this section, the proposed Multi-Objective Ant Colony Search, MOACS, algorithm is presented. This procedure has been used to find the best expansion strategy. The algorithm is still inspired to the behaviour of ants and finds the 'minimum length' path going from a starting point to an arrival point, but this time the update of the pheromone is guided by local and global Pareto optimality conditions and 'sharing' procedures [2][9][10].

A. The ACS algorithm

The ACS algorithm has been proposed and first implemented for the Travelling Salesman Problem, TSP [1], which is the problem of finding, given a finite number of "cities" along with the cost of travel between each pair of them, the cheapest way of visiting all the cities and returning to the starting point. There is an obvious similarity between the 'tour length' in TSP and the path length of the ants. The key to the application of the ACS to a new problem is to identify an appropriate 'spatialization', which can be obtained by means of a graph representation. An appropriate expression of the distance between any two nodes of the graph must be determined. Any solution is represented by a tour through the edges of the graph. In the application here proposed, distances between different configurations of the electrical system in different TI are *'transition charges'* in terms of costs reported to the initial year in order to make them comparable, and of decrements of the SAIFI index.

The costs of the necessary modifications to expand the system from the current configuration at TI_k to another configuration to be reached at TI_{k+1} (as explained later) are the transition costs. The sets of MO optimal solutions $n_{\mathrm{S}i}$ ($i = 0, 1, \ldots, T$) have been previously determined for different values of the load density and the total number of possible configurations for the system therefore is $S = n_{\mathrm{S}0} + n_{\mathrm{S}1} + \ldots + n_{\mathrm{ST}}$. In figure 2, a representation of the search space is shown. Configuration 1 represents the system layout at the initial year ($n_{\mathrm{S}0} = 1$), while configurations 2, 3 and 4 (in this case, $n_{\mathrm{S}1}=3$), are the first class of Pareto-optimal solutions of the static MO problem, solved for the load density forecasted after D years, at TI_1. The configurations indicated as *S-1* and *S* ($n_{\mathrm{ST}}=2$) have been obtained for the load density forecasted at the end of TI_T, which also is the end of the horizon H. Note that it is always $n_{\mathrm{S}0} = 1$. Considering the possibility to delay or anticipate some modifications in the electrical system, the size of the search space increases as

$$\dim = \prod_{i=1}^{T} n_{\mathrm{S}i} \left\{ 1 + T \cdot \left[\sum_{k=2}^{T-1} \frac{1}{n_{\mathrm{S}k}} + \sum_{\substack{j,k=2 \\ j \neq k}}^{T-1} \frac{1}{n_{\mathrm{S}j} n_{\mathrm{S}k}} \right] \right\} \tag{7}$$

The possible strategies also include those obtained by keeping the same configuration for more than one TI.

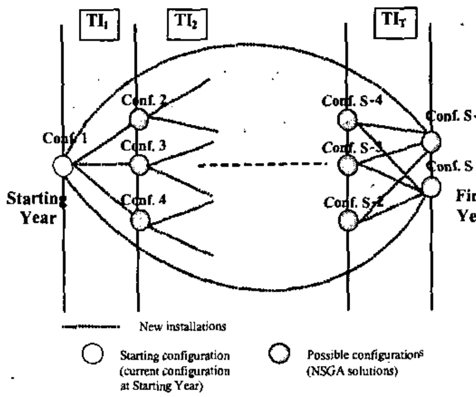

Figure 2. Graph representation of the search space for ACS algorithm.

B. Expressing the 'transition charges' in terms of costs and of variation of the reliability index

The cost of the expansion strategy C_{exp} is the sum of the costs of each modification to pass from one configuration to another in the following TI. These costs are associated to installation or removal of components, C_{mod}, and to change in the losses, thus in their cost, C_{loss}, when the configuration is changed. This results into

$$C_{exp} = C_{modH,a} + C_{lossH,a} + C_{modH,b} + C_{lossH,b} \tag{8}$$

where the subscript "H" indicates that the costs are related to the whole horizon H, while "a" and "b" again indicate the two voltage levels considered.

Within a module, changes can regard length, number and cross-section of feeders, as well as transformer rated power for each module. Costs of modifications (installation or removal) occur when the system changes to a new configuration at year j from a given one at year i ($i < j$). Note, however, that the configuration at year i has in general been built at the year x ($x < i$). The following reasoning is valid for both MV and LV modules.

The function $new\_inst\,(i,j,x)$ expresses the cost for the new installations and comprises installation costs and removal costs. Now, it is possible now to express the total cost modifications during H years as

$$C_{modH} = C_{inst,0} + \sum_{\substack{i,j=1 \\ i \neq j}}^{T-1} \frac{new\_inst(i,j,x)}{(1+a_{act})^{D_i}} \tag{9}$$

Finally, for each configuration, the cost of the losses during the corresponding TI with the proper value of the load density is calculated. This cost must also be reported to the initial year by using an actualization rate. The cost of the losses during each TI must be added up over the whole horizon. Finally, the '*transition charge*' in terms of costs to go from configuration r at year i (adopted at year x) to configuration s at year j can be expressed as:

$$\delta c(r,s) = (new\_inst(i,j,x)) + C_{loss}(r,s) \tag{10}$$

Where $new\_inst(i,j,x)$ is above defined, and $C_{loss}(r,s)$ is:

$$C_{loss}(r,s) = C_{loss_i} \left(\frac{e^{(2k_{load} - a_{act})(j-i)}}{(2k_{load} - a_{act})} \right) \tag{11}$$

Being $C_{loss\,i}$ the losses cost during year i.

The '*transition charge*' from one configuration at the year corresponding to the beginning of TI_i to another at year corresponding to the beginning of TI_{i+1} in quality terms, is evaluated by means of the difference between the relevant values of the SAIFI index defined in (6). Namely it can be written as:

$$\delta_{SAIFI}(r,s) = (SAIFI(r) - SAIFI(s)) \tag{12}$$

Where $SAIFI(r)$ and $SAIFI(s)$ respectively are the SAIFI indices for configurations r and s using expression (6).

C. The MOACS algorithm step by step

A more exhaustive formulation of any engineering problem generally requires the contemporary fulfilment of more than one objective. In this case, for example the planner would probably prefer a dynamic design solution along the years for which both costs are minimized and power quality is maximized. In this way, the network configurations through which the system evolves are ever more reliable and at minimum cost.

The algorithm uses two colonies of ants each devoted to the search in one of the two dimensions of the objectives space. All the interactions among the ants happen using the pheromone information which is locally and globally updated so as to encourage the attainment of Pareto optimal solutions. As in the traditional version of the ACS there is a forward phase and a backward phase. The forward phase is implemented in the classical way, but for each colony the driving objective is different. Then the local updating of the pheromone is carried out by taking into account for both families both objectives at the same time, using the concept of Pareto optimality on a local basis (elementary variations of the objectives). Later on, the law with which this updating has been carried out will be detailed. Once all the ants are arrived at the final year, a global updating of the pheromone is carried out. This procedure increases the pheromone trace of those tours that are ranked in the first class of non-dominated strategies. Before local and global updating of the pheromone is carried out, a sharing procedure is executed in order encourage a full exploration of the search space.

After a given number of iterations the two colonies, considered as a whole, include a group of solutions that are closer to the Pareto front, see the flow-chart in figure 3. The following quantities defined below are used in the algorithm:

- $\tau(r,s)$ is the pheromone amount between configurations r and s;
- M_k is the set of optimal configurations that have been identified for the year configuration r belongs to;
- 3β is the parameter weighting the importance of the transition 'cost' from configuration r to configuration s;

- α is the pheromone updating parameter, ruling its decay and its reinforcement;
- τ_0 is the pheromone initialization value which is given to any possible tuple such as *(r,s);*
- *n* is the number of ants constituting the artificial colonies (colony1 for the costs minimization and colony2 for the SAIFI index ionization).

Configuration *s* that has to substitute the starting configuration *r* is identified, for colony1, by means of the following laws:

$$s=\begin{cases}\arg\max_{u\in M_k}\left(\tau(r,u)\delta_c(r,u)^{-\beta}\right) & q\le q_0\\ s_{rand} & otherwise\end{cases} \quad (13)$$

where q is a random number between 0 and 1, whereas $q_0\in[0,1]$ is a parameter allowing to regulate the elitism of the algorithm, namely to establish a compromise between exploration and exploitation of the search space.

Indeed if q_0 is very close to the unity it is highly possible that the random parameter q is lower than q_0. In this case, configuration s is the argument giving the maximum value of the function $\tau(r,s)\delta_c(r,s)^{-\beta}$. If $q>q_0$, configuration s is chosen following the probabilistic law below:

$$p_{kc}(r,s)=\begin{cases}\dfrac{\tau(r,s)\cdot\delta_c(r,s)^{-\beta}}{\sum_{u\in M_k}\tau(r,u)\cdot\delta_c(r,u)^{-\beta}} & \text{if } s\notin M_k\\ 0 & \text{otherwise}\end{cases} \quad (14)$$

The probability that the k-th ant moves towards a configuration of the same year must be zero. In the same way, configuration *s* that has to substitute the starting configuration *r* is identified, for colony2, by means of the following laws:

$$s=\begin{cases}\arg\max_{u\in M_k}\left(\tau(r,u)\delta_c(r,u)^{-\beta}\right) & q\le q_0\\ s_{rand} & otherwise\end{cases} \quad (15)$$

$$p_{kSAIFI}(r,s)=\begin{cases}\dfrac{\tau(r,s)\cdot\delta_{SAIFI}(r,s)^{-\beta}}{\sum_{u\in M_k}\tau(r,u)\cdot\delta_{SAIFI}(r,u)^{-\beta}} & \text{if } s\notin M_k\\ 0 & \text{otherwise}\end{cases} \quad (16)$$

When each ant of colony1 and colony2 has arrived to the configurations in the first TI, TI_1, a ranking selection rule with dummy fitness, *dum_fit,* [10] is used to find the best local transitions in terms of costs and of System Average Interruption Frequency Index.

The local updating is performed to prevent premature convergence and simulate the natural phenomenon of evaporation of the pheromone. It also increases the pheromone of all those transitions in a way that is directly proportional to their dummy fitness.

The local updating is executed by means of the following law:

$$\tau(r,s)=\tau(r,s)+a\,\tau_0{}^{*}dum\_fit(r,s) \quad (17).$$

Where *dum_fit(r,s)* is the dummy fitness value related to the transition from configuration *r* to configuration *s*, and *a* is a heuristically chosen positive parameter lower than 1. As it can be noted, the local decay of the pheromone simulating evaporation is not performed, because the sharing represents a reduction of the pheromone trace even if performed on a different basis.

In this way, a tour from the starting year to the horizon year can be completed. The global pheromone updating is executed when all ants have completed an entire tour. This updating is aimed at the reinforcement of the pheromone of those transitions *(r,s)* belonging to first class of Pareto dominant tours. The global updating is performed by means of the following expression:

$$\tau(r,s)=\tau(r,s)+a\,\tau_0{}^{*}dum\_fit(r,s) \quad (18)$$

if *(r,s)* belongs to the first class of non-dominate solutions on a global basis. Here *dum_fit* is the dummy fitness value given to the first class of non-dominated tours. In this way, the pheromone of transitions *(r,s)* belonging to the best tour is increased whereas the pheromone of other transitions remains the same. No decrease in the pheromone trace is performed because of the global sharing procedure which produces a generalized reduction of the pheromone trace. Therefore, in the proposed algorithm, both local and global updating of the pheromone encourage the exploration of the search space and the exploitation of the most promising solutions. The exploitation property is evidenced in the reinforcement of those pheromone traces belonging to the first class of non-dominated solutions.

D. Local and Global sharing procedure

In this paper, two sharing procedures have been applied, one is the *Local Sharing* [9][10] and it deals with the dummy fitness assigned values for a transition from one TI to another subsequent TI, the other is the *Global Sharing* [9] [10], which deals with the dummy fitness assigned values for a global tour.

Local sharing

When a transition from one configuration, belonging to TI_i, to another configuration, belonging to TI_j (with j>i), a ranking of the solutions can be performed on the basis of the values of the elementary '*transition charge*' for the two objectives. The solutions are ranked in classes of non-dominance and suitably ordered [10]. Then a dummy fitness is assigned to each set of solutions representing a class of non-dominated solutions. Given a set of n_k solutions in the k-th non-dominated front all having a dummy fitness value f_k, the sharing procedure is performed in the following way for each solution $i=1,\ldots n_k$:

step 1: compute a normalised Euclidean distance measure with another solution j in the k-th non-dominated front, as follows:

$$d_{ij}=\sqrt{\sum_{p=1}^{P}\left(\frac{x_p^i-x_p^j}{x_p^u-x_p^l}\right)^2} \quad (19)$$

where P is the number of optimization variables. Parameters x^u_p and x^l_p are the upper and lower bounds of variable x_p., defined by the commercial available sizes of components.

step 2: distance d_{ij} is compared with a pre-specified parameter σ_{share} and the following sharing function value is computed:

$$\mathrm{Sh}(d_{ij}) = 1 - \left(\frac{d_{ij}}{\sigma_{share}}\right)^2 \quad \text{if } d_{ij} < \sigma_{share} \tag{20}$$
$$\mathrm{Sh}(d_{ij}) = 0 \quad \text{otherwise}$$

step 3: j = j+1. If $j \leq n_k$, go to step 1 and calculate $\mathrm{Sh}(d_{ij})$. If $j > n_k$, calculate the niche count for the i-th solution as follows:

$$m_i = \sum_{j=1}^{n_k} \mathrm{Sh}(d_{ij}) \tag{21}$$

step 4: degrade the dummy fitness f_k of the i-th solution in the k-th non-domination front to calculate the shared fitness, f_i', as follows:

$$f_i' = \frac{f_k}{m_i} \tag{22}$$

The procedure is repeated for all i = 1,..n_k, and the corresponding values of f_i' are found. Thereafter, the smallest value f'_{mink} defined as:

$$f'_{mink} = min_{i=1,\ldots nk} \{f_i'\} \tag{23}$$

is used to set the dummy fitness value of the next non-dominated front.

Indeed:

$$f_{k+1} = f_{mink} - \varepsilon_k \tag{24}$$

where ε_k is a small positive number. The value of σ_{share} is defined using empirical laws that can be found in literature, such as the one that follows:

$$\sigma_{share} \approx \frac{0.5}{\sqrt[P]{q}} \tag{25}$$

where q is the desired number of different Pareto-optimal solutions and P is the number of optimization variables.

Global Sharing

When an iteration is completed, all the tours can be classified into dominance classes. Again a dummy fitness assignment is executed and a sharing procedure similar to the above described local sharing is carried out. In this case, the tours are considered entirely and therefore the objectives are also related to entire tours performed by the ants of the two colonies. Performing the sharing procedure at global level allows the identification of solutions that are positioned close to the origin of the axis in the objectives bi-dimensional space, if both objectives are expressed in terms of a minimization problem. Local sharing instead helps the diversification and avoids premature convergence.

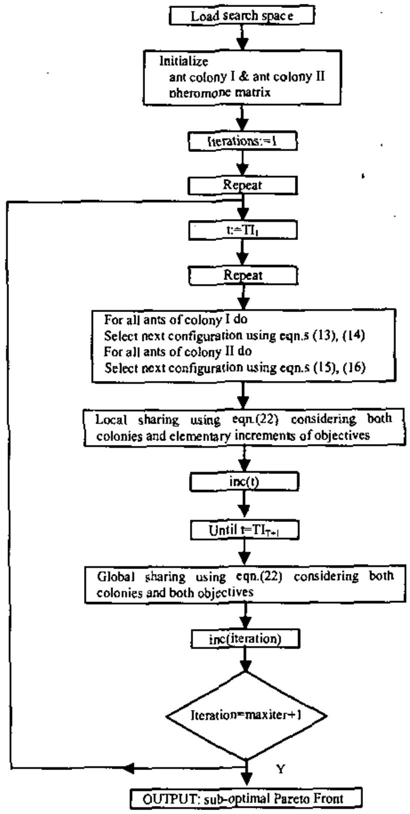

Figure 3. Pheromone matrix with σ_{share}=0.7.

V. RESULTS AND ANALYSIS

In this section, the algorithm has been tested with different control parameters, in order to set them. The initial configuration at year 0 has been detected using NSGA, optimizing with respect to the total cost per km^2 only for the load density forecasted after three years. The initial configuration represents a distribution system that has been designed and installed without making any specific power quality considerations. In this configuration, one "A" module supplies a surface of 9.888 km^2, and there are 112 modules at the LV level. By using MOACS, a set of Pareto-optimal expansion strategies in terms of minimum overall cost and maximum improvement of SAIFI have been detected. To evidence the potential of the algorithm to find good compromises in terms of the two objectives, the results of two single colonies ACS algorithms have also been considered. In figure 4 the results of one run of the MOACS algorithm are reported together with the solutions found by the same algorithm with single colonies and therefore objectives and namely cost and inverse of the value expressing the improvement of the SAIFI. As it can be observed the algorithm finds solutions that none of the two single objective algorithms could find. The set of solutions found indeed comprise both alternatives still keeping low costs and a low frequency of expected interruptions in the considered time frame. Namely it outputs a set of solutions that cover the entire best non-dominated front.

From the electrical engineering point of view it can be observed that the solutions found by the MOACS, of course, generally present higher values of the overall cost, as compared to the solutions found by the minimum cost criteria. This is justified by the increased required performance in terms of reliability. On the other hand the costs still remain at acceptable values, as compared to the solutions attained by simply improving the SAIFI.

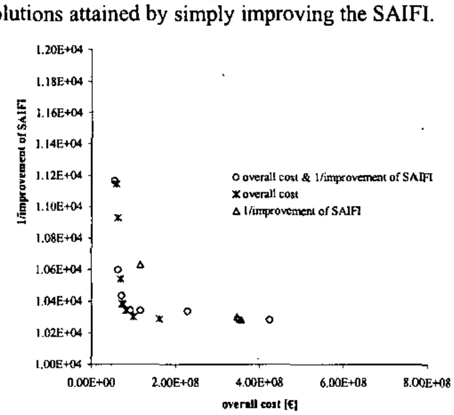

Figure 4. MOACS runs with single objectives and with multiple objectives

A single run with and without local and global sharing has also been reported in figure 5. σ_{share} has been set to 0.7. In this case, a good choice of the sharing parameter allows to find better and diversified solutions. Other runs have been executed with different values of the sharing parameter and it has been observed that local and global sharing help diversification. Sometimes, more diversity implies low elitism and therefore worst quality solutions. Other runs have been performed again without and with the sharing procedures and observing the pheromone matrix, respectively in figures 6 and 7. In the first case, the pheromone trails are more intense but more concentrated, whereas in the second case the pheromone trails are more flat, thus allowing a wider exploration of the search space.

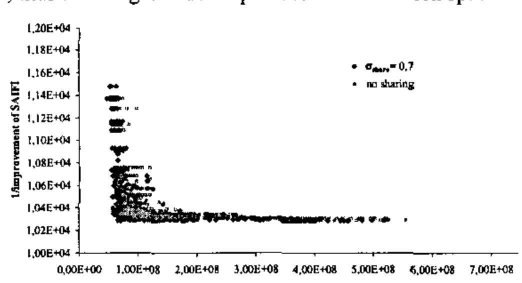

Figure 5. MOACS runs with and without sharing

The elements in the i^th row and j^th column of pheromone matrix indicate the pheromone trials for the transitions starting from configuration i and arriving to configuration j. In order to obtain a measure of exploration executed, the number of times in which the elements of pheromone matrix is different from the initial settled value, referred to the total number of pheromone matrix elements (n_e=901x901) is counted, either without sharing (n_0), and with the sharing procedure and σ_{share}=0.7 ($n_{0.7}$). Then the summation of the pheromone extended to each elements of pheromone matrix different from the initial settled value τ_0, both without sharing (S_0) and with σ_{share}=0.7 ($S_{0.7}$).

n_0=9287, $n_{0.7}$=10324, S_0 =13063, $S_{0.7}$ =11349,

$(n_0/n_e)\cdot S_0 = 0.0114\cdot 13063 = 149.44$;

$(n_{0.7}/n_e)\cdot S_{0.7} = 0.0127\cdot 11349 = 144.13$;

The expressions above show that when the sharing is present, there is a flattening of the pheromone intensity thus allowing a wider exploration in each front. Even though the number of explored solutions is larger, (pheromone different from the initial value) there is a larger number of different solutions in the first non-dominated front, as it is shown in figure 8. In figure 8 the influence of sharing in terms of different solutions in the first non-dominated sub-optimal front detected at the last iteration, for different values of σ_{share} is shown.

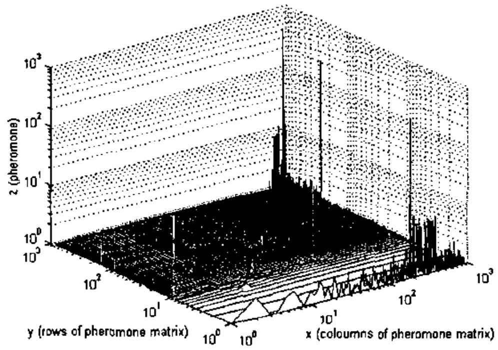

Figure 6. Pheromone matrix without sharing

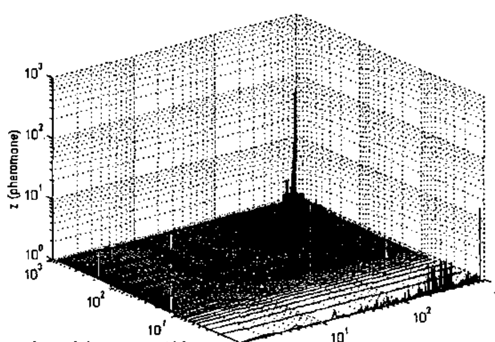

Figure 7. Pheromone matrix with σ_{share}=0.7.

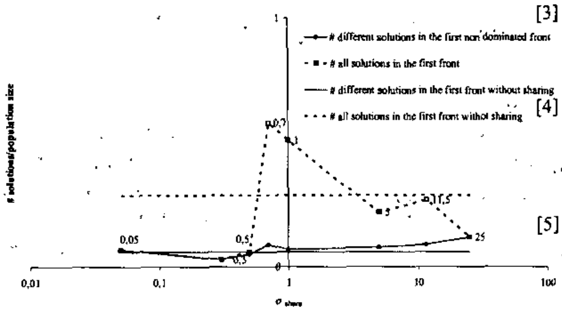

Figure 8. Influence of sharing procedure in terms of number of different solutions in the same front for different value of σ_{share}

VI. CONCLUSIONS

In this paper, a novel MO optimization technique called MOACS and based on the ACS paradigm and on the concept of Pareto optimality is proposed. The algorithm includes a sharing procedure on local and on global basis. It has been applied to a hard combinatorial dynamic optimization problem as the strategical expansion planning in electrical distribution systems. The spatialization of the problem has required first the identification of some states through which the system would evolve along the overall time horizon of 30 years.

This identification has been carried out using a Non dominated Sorting Genetic Algorithm (NSGA) statically finding the multi-objective optimal solutions for each sub-interval. The lowest-*charge* set of transitions bringing the system from the starting year up to the final year of the considered time horizon H, in terms of costs and high quality, is then found by using the MO Ant Colony Search (MOACS) algorithm. The optimization along the years is therefore again a MO problem where reliability (expected frequency of interruptions per year and customer) is considered together with the total cost. It is shown that the proposed algorithm outputs good and diversified solutions in terms of both objectives which are unobtainable with standard ACS and single objectives. Moreover the effect of the sharing procedure is shown by considering the solutions obtained with the sharing procedure and without it at local and at global level. Future work will be addressed towards the implementation of the same algorithm using the concepts of elitism and parameter-free diversification operators.

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