Applied Intelligence 23, 139–152, 2005

Ant Colony Search Algorithm for Optimal Strategical Planning of Electrical Distribution Systems Expansion

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Abstract. Strategical planning is one of many research fields in the design of electrical distribution systems. The problem of strategical planning is a multiobjective combinatorial problem and the search space may often be quite large concerning to the options. The aim is to identify a strategy of expansion of a given distribution system in a given timeframe. For this problem, the search space is created beforehand by running a multiobjective optimisation algorithm for the optimal design of distribution networks for different load levels related to different years. The sets of Pareto-optimal solutions obtained for each load level at each year are equivalent in terms of the considered objectives, these being minimum losses, installation costs, and minimum unavailability. The problem of the identification of the optimal expansion strategy through these chronologically intermediate solutions leading to the final target configuration at the last year has been solved herein using an ACS (Ant Colony Search) algorithm. In order to verify the efficiency of the ACS algorithm, a small size application has been carried out and results have been compared to those obtained with enumeration. Then, a Simulated Annealing (SA) approach was used for a larger size test problem and results were compared to those obtained using the ACS. For this problem, the ACS demonstrated to be more robust than SA with higher quality results.

Keywords: ant colony search, adaptive behaviour, electrical distribution systems, strategical planning

1. Introduction

Electrical systems distributing energy from power plants to customers are composed of different parts. As the energy is generated by the plants, it is transformed in terms of voltage and current levels and then it is carried through High Voltage, HV, transmission lines, primary substations, and again transmission lines, up to the secondary substations, where the voltage level is decreased to the Medium Voltage, MV, level. At this section, the distribution system starts. The distribution system reaches the customers at MV or at Low Voltage, LV, through MV/LV substations. The most common way to deliver energy is at alternating current, a.c., medium or low voltage.

In order to improve the quality of supply and to reduce installation and operation costs, at the distribution level, many different configurations of the network at LV and MV can be adopted, each of which has topological and operational features that are well-suited to the geographical collocation and to the customers-related continuity of supply requirements. Given that the load grows over the years, it is necessary that electrical systems must be adapted to increasing loading requirements by customers, in order to guarantee a secure and rational management of available resources.

The problem of designing the medium and long term of these systems is quite complex since its formulation depends on a large number of geographical, electrical and economic parameters. On the other hand, as with any other engineering design problem, it is necessary to make some simplifying hypotheses in order to manage the problem and to get results that can be generalized.

The aim of electrical distribution systems planning is that of defining the plants expansion in a defined timeframe, in order to optimally face (costs, security, service quality, etc.) the growth of the loads and the renewal of obsolete plants.

With reference to distribution systems, design can be strategical or operational. The first is oriented to the identification, in a long term optimisation, of the general choices characterising the plants development. The latter is aimed at the definition of the operational plans, in the medium term, in agreement with the guidelines already defined in the strategical design.

In the field of strategical planning, new electrical energy distribution systems are being studied taking into account different assumptions concerning the number of voltage levels between the HV/MV station and the users (number of stages), values and voltage types (direct or alternating), new types of network structures, etc. These options are considered due to some specific problems concerning the MV and LV networks which have risen over the years depending on particular situations, such as the fast expansion of networks, especially in urban areas.

The main characteristics of the electrical systems in service in these days (alternating current at each voltage level, voltage levels values, rated size of the substation transformers, ...) are the result of strategical planning studies carried out some decades ago, at the beginning of a phase of development and economical growth, that brought the western countries to the present asset.

Once the general development guidelines have been identified, during the last decades, planning and design activities have more and more concerned specific intervention plans on limited areas, aimed at the optimization of the installation and management costs of the system in the medium term.

In agreement with the results of these activities, the electrical systems have developed in its different parts evolving through modifications and improvements. In this traditional context during the last decade some new elements assumed a growing importance giving rise to new research activities aimed at the evaluation and comparison of different development plans in the long term (30 years) containing strong innovations.

The new elements to be accounted for are the following:

(1) the full exploitation of the strategical guidelines and choices executed many years ago; new development perspectives also require the adoption of methodologies aiming at innovation instead than at modification or refinement;
(2) the growing electrical demand together with new electro-technologies that are radically modifying the features of the electrical components in distribution and utilization systems;
(3) the perspective of a growing penetration of small production plants (wind, photovoltaic, biomass, ...) connected to distribution systems;
(4) the liberalization of the energy market and the importance of quality in the supply of energy;
(5) the environmental constraints and requirements for a sustainable development plan for electrical systems.

In literature other authors have dealt with the problem of designing electrical systems. Most of them have formulated the problem as a combinatorial optimisation problem, since its realistic size and complexity is such that the application of heuristic techniques has proved to be convenient [1–4]. In [2] and [4], the authors deal with long-term planning problems in electrical distribution systems. The multi-year optimal planning problem is first divided into several static single-year optimization problems. The overall solution algorithm is a forward/backward path procedure, which proceeds by iteratively improving a single expansion plan, created in order to meet minimum cost and maximum reliability. In this case the domain knowledge is integrated into the operators that allow the generation or modification of a new expansion plan. In [5], the authors propose a planning model to solve the sizing, siting of distribution substations and the timing of their construction. A pseudo-dynamic procedure is adopted, which again splits the problem into two stages. First it is solved statically, with fixed loads, so at each loading level, the system is optimized. In the second phase, the advancement through the solutions found in the first phase details the timing of the installation of all the components. Heuristic methods do not prove the optimality, but those that are population-based allow the attainment of a set of good sub-optimal solutions among which the planner can choose the most suitable for the particular problem at hand. Often the requirement is not simply that to minimize costs, but also to ensure good quality and security. For this reason, design has also been formulated as a multiobjective optimisation problem, for which some authors have adopted weighting factors for the objective function creation [6]. The weak point of this approach is that the use of weights can greatly affect the solution, since it changes the objective function shape.

In all cases, there was no explicit reference to a general model for handling the planning problem. The authors have already studied the problem of electrical distribution networks planning and they have introduced and implemented a number of elementary models which can be combined in many different ways giving rise to a global model of the entire network.

To this purpose, this paper proposes a methodology which enables the development of strategical planning in a general form by means of a modular approach. In particular, in [7, 8] the concept of modularity has been introduced starting from the definition and implementation of particular 'functional modules', each of these, as it is shown in Section 2, is representative of the structure and of the operational trend of each stage composing the electrical system [9].

As shown in Section 2, this approach allows the identification of a mathematical model, for distribution systems, that is suitable for automation in order to solve optimal design problems in terms of topology and management policy.

From a methodological point of view, the strategical planning problem can be stated in two ways. If the entire expansion plan for the final year load level is built up at the starting year, then the optimisation approach is 'static' and the relevant model is 'non-evolutive'. If the optimisation of the entire electrical system aims at the identification of a network development plan, both in terms of its organisation along time and in terms of distribution and localization of the plants in the area, then the optimisation approach is 'dynamic' and the relevant model is 'evolutive'.

The first formulation, especially if the time-frame to which it refers is too long, may lead to an analysis not considering the time dimension for investments. Adapting the system to the future customers requirements at one time may be less efficient than executing many small interventions along the years so as to adjust the load growth as needed.

The second formulation aims at the identification of the less expensive sequence of configurations of the system in a predefined time interval (typically 20–30 years). This sequence must be coupled with an optimised expansion plan, articulated in a discrete number of years, which implements the network changes on the basis of the changing customer needs.

The results of a dynamic optimisation process generally do not match those related to a given number of static optimisations carried out in the sub-intervals in which the entire timeframe can be divided, due to non-linearities in the problem formulation. Therefore a dynamic strategical planning problem, for distribution systems reinforcement, can be divided into two parts. The first can be carried out by solving many static strategical planning problems at different times, the second is an optimal scheduling of investments problem. The latter is the object of this paper. In both cases, the optimisation can be carried out using different types of algorithms.

Dividing the problem in two steps not only analytically simplifies the problem. This measure indeed implies a reduction of the search space size and it is the approach commonly adopted in the literature for this kind of scheduling problems, [2, 4].

From the application point of view, it also allows an increased flexibility in the use of the proposed tool as a decision support system for those who plan and manage a system. Indeed:

(a) starting from the first transaction and then at each step, the planner can choose in a set of development plans, he can also integrate the set of solutions derived by the static optimization with other solutions derived by the human experience in the field;
(b) at any time of the evolution of the electrical system (i.e. after five or ten years), the planner can search (more easily and rapidly as compared to the case in which one uses a global optimization tool) other classes of solutions varying and differently weighting the objectives and evaluating different development perspectives, else than those initially identified.

Deterministic strategies are not generally suitable for planning studies mainly because the required simplifications and approximations intrinsic to the problem formulation would not justify the search for the absolute optimum. Moreover, they usually require huge computation times and since they identify a single solution, the designer has no alternative choices. Heuristic strategies are more suitable since the solution is searched by making a comparison among the costs of many different solutions (different plant expansion strategies); there is then the possibility to record a number of sub-optimal solutions.

With reference to a static optimisation, Genetic Algorithms (GAs) allow, with a limited computational effort, the attainment of good sub-optimal solutions by means of a process of evolution. As far as static strategical planning is concerned, in [10, 11], some GA-based optimisation procedures for a two or more level distribution system design have been implemented. In [10], a single objective optimisation strategy (minimum cost) has been implemented for a system organised on two voltage levels. In [11], a multiobjective strategy for a three levels system, two of which work in a.c. and one in direct current was implemented.

In this paper, a dynamic design strategy is developed. It is aimed at the optimisation of the expansion of a distribution system through a discrete number of interventions within a time frame of some years and related to a load increase in the served area. The solution of this problem requires the identification of an efficient expansion strategy of the system.

The problem is combinatorial and non-linear. It has been dealt with through the multiobjective solution of static planning sub-problems related to different values of the load density and then identifying the minimum cost path through the different design solutions. The multiobjective solutions of static planning are optimised on the basis of minimum cost attainment, minimum losses and maximum quality of supply (in terms of unavailability, medium average expected frequency of voltage sags and voltage unbalance rate).

The search for the minimum cost system's expansion strategy from the starting to the final year is a complex problem, due to the amplitude of the search space and to the inherent non-linearities. For this reason, the authors have preferred to use non-traditional optimisation algorithms based on heuristic criteria. The solution technique for the posed problem of dynamic strategical planning is based on the Ant Colony Search (ACS) algorithm adapted in order to make it suitable for the treatment of the specific problem, of which an application has been here carried out.

The same application has then been dealt with by means of a Simulated Annealing (SA) algorithm. SA has a comparable efficiency to ACS in similar test problems and in other engineering applications [12].

On the other hand, techniques typically adopted for scheduling problems, such as dynamic programming, for a successful and efficient appplication, require a limited search space. In the present application, the search space of the scheduling problem is large and any significant limitation would result in a strong pertubation of the problem formulation.

The ACS algorithm [13] is an algorithm simulating the behaviour of natural ant colonies. The algorithm uses a set of agents which cooperate for the research of new solutions acting simultaneously. This algorithm has been applied to different problems in engineering, in particular for those applications where a length measure must be optimised such as in the Travelling Salesman Problem, (TSP). This algorithm has rarely been applied for optimisation strategy problems. However, there are some papers regarding this aspect for different engineering fields [14, 15].

2. The Problem of Optimal Planning of Distribution Systems

In many engineering fields and, in general, in the production and management of resources, planning is one of the fundamental steps for a secure and economically convenient operation of a production process.

Planning interventions on any productive process also means planning the related investments. Therefore, identifying times and modes of the investments is essential for the characterisation of the actions to be taken in terms of profitability and efficiency.

Given the complexity of the problem of distribution systems strategical planning, the issue is currently solved using a two-stages approach:

1. a multiobjective optimization to solve static planning problems (using a Non-dominated Sorting Genetic Algorithm, NSGA, [11]) in which the solutions show minimum losses and installation costs and minimum unavailability;
2. a single objective optimization to find the minimum cost expansion strategies (using an ACS algorithm).

The largest inconvenience in adopting a two stages approach is that the reduction of the search space could be misleading. It could be argued that the adoption of a one-stage approach is necessary for which the solution string is the entire set of configurations composing the expansion plan, but this would increase the problem size proportionally to the presumed number of interventions. On the other hand, there are a few considerations supporting the two-stages approach. The problem is strongly constrained, both on a static basis and on a dynamic basis. The static problem is electrically constrained by voltage drops, currents in branches and topological constraints, the dynamic search adds to the up-cited terms even constraints concerning the correct expansion of the system. Another item of concern is the choice of the 'intermediate' stages. While in the one stage approach these intermediate stages are 'free' and are subjected only to the minimum overall cost requirement, in the two stages approach these intermediate stages are fixed in advance using Pareto optimal solutions in terms of costs and quality of service.

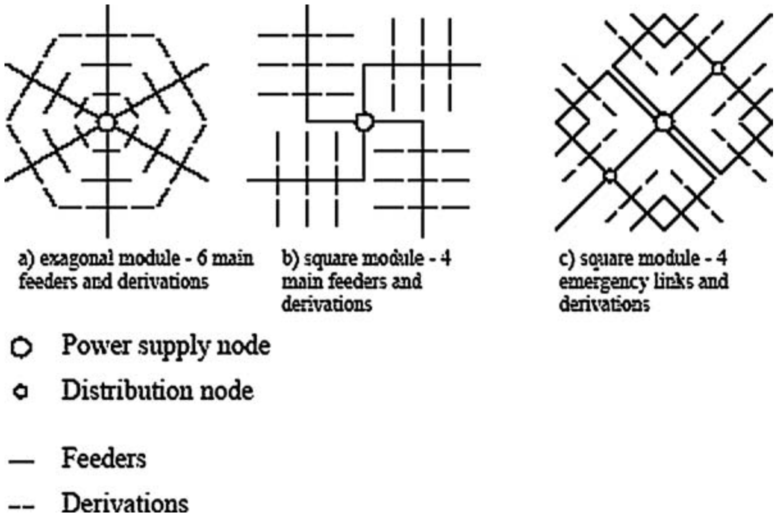

Figure 1. Some examples of vectoring modules.

This ensures that all these stages are certainly 'good' in terms of both objectives and enables the designer to add other 'heuristically' derived configurations. Besides, the set of configurations at each time interval is quite rich because obtained with minimum cost and minimum unavailability. Quality and cost are normally competing objectives and give rise to solutions that range from over-dimensioned (high quality) to strictly dimensioned for the required load (low cost).

The NSGA has been applied to a generic electrical distribution system, described in terms of functional modules, and a static planning problem has been solved for a considered year and relevant load level. This approach starts with the definition and implementation of particular functional modules, each of which is made up of a vectoring module and its management policy. The vectoring module is a part of the electrical system devoted to the vectoring of the electrical energy. In the present application, the term vectoring module (Fig. 1) indicates a stage of the distribution system made up of:

(1) a feed node;
(2) a network share which is homogeneous in relation to the used electrical vector (cable/overhead line) which plays the role of transmission and/or of distribution;
(3) eventual power compensation devices.

The management policy consists of the set of control actions exerted on the vectoring module in order to secure the preservation of the electrical vector quality, of the service continuity and the best efficiency. The parameters which contribute to the service quality are for example those defining the voltage level and waveform. It varies depending on the plant structural features. The service continuity level assured by a functional module depends on the effects produced at the customers level by a fault occurring in the vectoring module. For example, on the basis of the particular management policy adopted, the set of control actions taken by the grid operator, for the faults identification and location and the opening of the involved line section, strongly influences the service continuity levels. Therefore, a functional model indicates the set of parameters and relations which constitute the functional module analytical description, from the structural and electrical point of view and in terms of service quality, continuity and costs (Fig. 2).

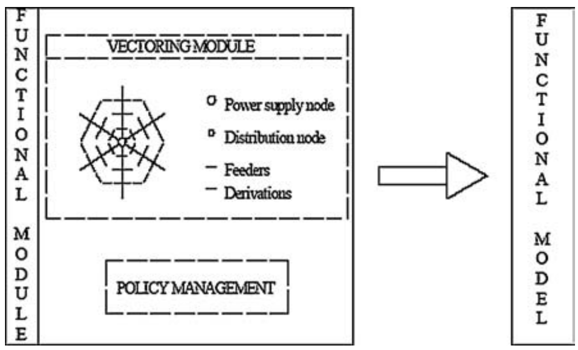

Figure 2. Functional module and functional model.

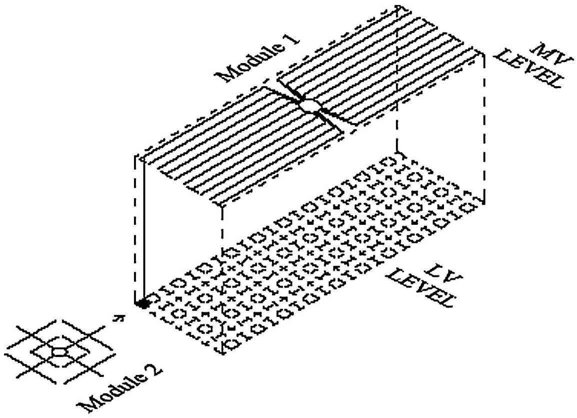

Figure 3. Schematic representation of a two voltage levels system.

The set of parameters and relations expressing the functional model are analytically organized in order to make easy module combinations. In this way, an optimisation algorithm is able to create any module combination by means of operations of replacement, insertion or removal of modules. The combination of a certain number of vectoring modules defines a possible configuration of the whole distribution system.

The energy distribution system is composed of elements having different voltage levels; each of these employs different types of vectoring modules. In Fig. 3, the electrical topology of the system supplying an area is illustrated. The two parts having different voltage are shown and the relevant electrical connections, for a module at one voltage level, Module 1, with another module at the other voltage level, Module 2, are also shown.

Each combination of modules is characterised by a set of functions expressing the installation cost and the operational cost per year and per unit area (km^2) [8], a set of quality indices [9, 16] and a set of constraint relations. The values of the definition parameters of each electrical vector cannot be chosen arbitrarily but, in general, they vary in the sphere of commercial availabilities. Some parameters belonging to the vectoring modules are subject to limitations derived from the design criteria (for example, supply node power, thermal limits and limits of voltage drop in the lines, etc.).

For each load level, sets of solutions can be obtained. These are classified into classes of dominance [17]. The solutions belonging to the first class of dominant solutions (Pareto-optimal), at the last iteration of the NSGA, constitute some possible optimal configurations of the distribution system for that year. These configurations are in terms of minimum installation cost and power losses and of minimum unavailability of supply and meeting some important technical constraints such as supply node power, thermal limits and limits of voltage drop in the lines.

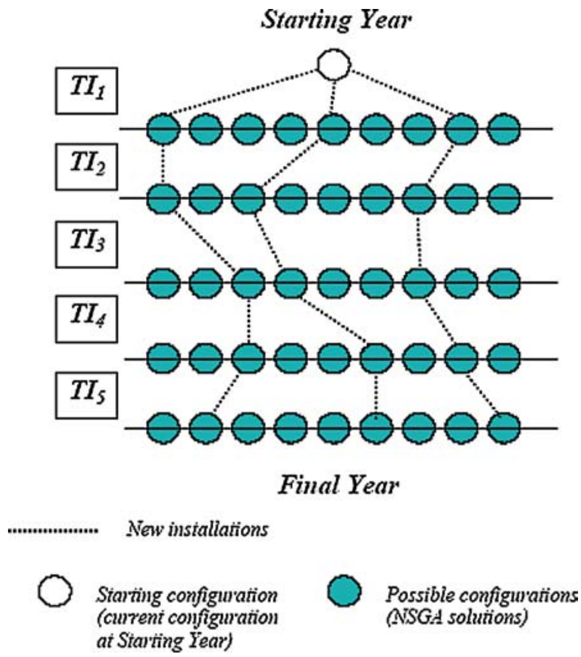

Figure 4. Expansion strategy for a distribution system, $T = 5$.

Iteratively applying this algorithm, for each of the time intervals in which the entire time frame of the planning problem can be divided, sets of optimal solutions for each year can be obtained. These constitute the possible states through which the development of a distribution system can evolve in the considered time frame. In Fig. 4, three possible expansion strategies of the distribution system considering a division of the time horizon in T Time Intervals, (TI), are represented.

A state identifies a particular configuration of the system's parameters. Therefore, going from one optimal configuration for a given year to another optimal configuration for one of the following years, means to modify one or more design parameters, keeping the same topology for the adopted vectoring module.

Executing a modification of the system's state may imply new installations or removals of components. In this study, the authors do not allow removals—a realistic hypothesis.

From a general point of view, there is no doubt that this choice puts constraints on the systems evolution. Analogous effects may one attain introducing the opportunity to remove components (following a more correct but even more complex formulation), and giving this operation high costs. In reality these costs are high, due to the following factors:

1. low residual value of the removed components;
2. impact of the removal works in the area.

It is therefore quite strong the requirement to limit this kind of interventions as much as possible. On the other hand, considering this issue in the planning procedure in a rational way requires the exact detemination of these costs.

The proposed formulation of the problem also allows to meet the requirement of executing the investment at the right time. Moreover, the ability to plan in advance the investments allows the utilities to suitably find the necessary economic resources only when they are needed. In this way, these resources can be rationally used along the years for other investments.

The procedure used to find the best expansion strategies is the ACS algorithm. Inspired by the behaviour of real ants, ACS finds the 'minimum length' path going from a starting point to the arrival point. In this paper, the best sequence of structural changes to be performed on a given system along the years for a given increase in the load level is searched.

3. The ACS Algorithm for Optimal Expansion Planning of Distribution Systems

Real ants find the shortest path from a food source to their nest, without using visual cues, by exploiting pheromone information [18, 19]. While the ants go towards the food, each ant deposits on the ground a certain quantity of pheromone, that can be recognised by the other ants, and continues its tour. At the beginning all the ants move randomly. When the pheromone evaporates, the traces that can still be recognised are those that have been left on the shortest paths since they can be followed more rapidly. In this way, the number of ants that choose to go through the shortest paths grows and the pheromone trace gets stronger as more ants follow it [13].

The ACS algorithm has been presented and first implemented for the TSP, since there is an explicit similarity between the 'tour length' in the problem and the ants path length. The TSP 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.

The key to the application of the ACS to a new problem is to identify an appropriate representation for the problem, namely an appropriate spatialization. The latter can be attained by means of a graph representation (when possible) of the considered engineering problem. Any solution must also be represented by means of a tour through the edges of a graph.

A suitable expression of the distance between any two nodes of a graph must be determined. Then, the probabilistic interaction among the artificial ants mediated by the pheromone trial deposited on the graph edges will generate good, and often optimal, solutions. However, some problems may arise when the 'spatialization' is not straightforward, namely, when physical measures have to be turned into 'distances'.

In our application, distances between different configurations of the electrical system at different years (with the relevant load factor) are transition costs, suitably actualised in order to make them comparable at year zero. The transition costs are the installation and operation costs to expand the system from the current configuration to another to be reached in the following time.

3.1. ACS Adapted Algorithm

The problem of identifying the best expansion strategy of distribution systems has been accomplished by identifying a graph representation of the considered engineering problem. The Pareto-optimal configurations identified are the edges of the graph grouped in sets (one per year available for an intervention). A solution strategy is therefore a path in the graph comprising at least two years (year zero and the final year) and the cost of a strategy is the summation of the transition costs in the considered time horizon. These costs have all been actualised in order to make different strategies comparable, with a different number of interventions at different years. The distance between two solutions, namely between configuration r, related to year i, and configuration s related to year j and executed at year i, with $(i < j)$, is given by $\delta(r, s)$ defined as follows:

$$\delta(r, s) = \frac{Cinst_s^{(j)} - Cinst_r^{(i)}}{(1 + a)^i} + Closs_s^{i,j} \qquad (1)$$

where $\mathrm{Cinst}_r^{(i)}$ and $\mathrm{Cinst}_s^{(j)}$ respectively are the installation costs for configuration r at year i and the installation costs for configuration s at year j, and a is the actualization rate. The term $Closs_s^{i,j}$ can be expressed as:

$$\sum_{k=i}^{j} Closs_s^k \frac{1}{(1+a)^k}$$

where $Closs_s^k$ is the yearly cost of power losses at year k with configuration s.

The following quantities 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;
- β 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 colony.

Configuration s that has to substitute the starting configuration r is identified by means of the following law:

$$s = \begin{cases} \arg\max\limits_{s \notin M_k}(\tau(r,s)\cdot\delta(r,s)^{-\beta}) & \text{if } q \le q_0 \\ S & \text{otherwise} \end{cases} \tag{2}$$

where $q \in [0, 1]$ is a random number and $q_0 \in [0, 1]$ 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, then it is highly possible that the random parameter q is lower than q_0 and therefore that configuration s is the maximum of the function $(\tau(r, s) \cdot \delta(r, s)^{-\beta})$.

If $q > q_0$ (condition S) then configuration s is chosen following the probabilistic law:

$$p_k(r,s) = \begin{cases} \dfrac{\tau(r,s)\cdot\delta(r,s)^{-\beta}}{\sum_{u\notin M_k}\tau(r,u)\cdot\delta(r,u)^{-\beta}} & \text{if } s \notin M_k \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

The probability that the k-th ant moves towards a configuration of the same year must be zero, whereas a Monte Carlo simulation has been used to select the configuration towards which the ant shall move.

As it can be noticed, low values of q_0 encourage a search guided by a probabilistic law, for which the transitions having a larger value of the product pheromone by a suitably weighted fitness have more chances to be selected. Higher values of q_0, instead, prize the search guided by elitism, since the transition having the highest value of the product pheromone by a suitably weighted fitness will be selected.

The local updating of the pheromone is performed to prevent premature convergence and simulate the natural phenomenon of evaporation (of the pheromone). It is executed by means of the function:

$$\tau(r,s) = (1-\alpha)\tau(r,s) + \alpha\tau_0 \tag{4}$$

the local updating of the pheromone maintains diversity in the population keeping low the elitism. In this expression, the reduction of the intensity of the pheromone trace occurs when the current value of the pheromone is greater than its initial value, otherwise this expression causes an increase of the pheromone.

Global updating is executed when all ants have completed an entire tour for exploration and it is aimed at the reinforcement of the pheromone of those transitions (r, s) belonging to the best tour, namely to the minimum cost strategy. The other transitions are instead penalized and the pheromone of their trail is reduced.

It is performed using the function:

$$\tau(r,s) = \begin{cases} (1-\alpha)\tau(r,s) + \alpha L_{gb}^{-1} & \text{if } (r,s) \in \text{global best tour} \\ (1-\alpha)\tau(r,s) & \text{otherwise} \end{cases} \tag{5}$$

where L_{gb} is the length namely the cost of the best strategy which has been identified up to that moment from the beginning of all iterations.

$$L_{gb} = \min_{k=1..n}\left\{ \sum_{l=1}^{n\_edges}\left(\frac{Cinst_k^{(l)} - Cinst_k^{(l-1)}}{(1+a)^{\alpha_l - 1}} + Closs_{\alpha_{l-1},\alpha_l}^{l-1,l}(k)\right)\right\} \tag{6}$$

where:

- $n_$edges is the total number of edges of the k-th path (ant);
- α_{l-1} is the year in which new installations related to the configuration l have been executed;

- n is the number of ants constituting the artificial colony.

Note that, when l equals the total number of edges of the considered path, the ant has reached the target configuration and the strategy is complete.

Therefore expression (6) gives the cost of the entire strategy actualised at the starting year as well as the objective function of the problem here dealt with. The global problem is combinatorial and also non linear mainly because the losses term refers to the Joule effect and therefore is a non-linear function of the optimization parameters.

In this way, the pheromone of the transitions belonging to the best tour is increased whereas the pheromone of other transitions is decreased. The local updating encourages the exploration of the search space because it prevents premature convergence, whereas global updating encourages the exploitation of the most promising solutions, namely the overall least costy solutions.

The algorithm works as follows:

(1) a set of ants starts all from the same state representing the initial configuration of the system;
(2) each of them chooses at each stage, or time interval, the following state to visit using equations (2) and (3),
(3) the local updating of the pheromone (4) is carried out for each of them;
(4) when all ants arrive at the final year one iteration is completed and the global updating of the pheromone is also executed, using Eq. (5).

When the maximum number of iterations is completed the algorithm ends and the strategy with the lowest cost in all iterations is chosen. Of course, as it happens in GAs, at the last iteration the average quality of the ants involved in the search is higher as compared to the first iteration, thanks to the'selection' mechanisms implemented by Eqs. (2) and (3).

3.2. Search Space

Hypothesizing a given variation of the load density related to a given load area, it is possible to determine what is the load density at each year in the considered time frame in which the strategical planning must be carried out. It may happen that the load density increase in one year is not relevant and the electrical system reinforcement becomes necessary in two or more years. In this way, it is possible to divide the time frame into a finite number of intervals each lasting two, three or more years depending on the load density course. Consider T of such intervals, all having the same duration, D years. The sets of multiobjective optimal solutions for each load level, n_{si} $(i = 0, 1, \ldots, T)$ have been previously determined and the total number of possible configurations for the system therefore is $S = n_{s0} + n_{s1} + \cdots + n_{sT}$. In Fig. 5, a general search space is shown.

Configuration 1 represents the layout of the electrical system at the starting year, configurations 2, 3 and 4 (in this case, $n_{s1} = 3$), are the first class of Pareto-optimal solutions of the static multiobjective optimization problem, attained for the load density forecasted after the first time interval. In the same way, configurations $S-1$ and S, for which $n_{sT} = 2$, have been obtained for the load density forecasted after T time intervals.

If a system update is required at each time interval, then the search space size (number of possible strategies) is:

$$\dim = n_{s0} \cdot n_{s1} \ldots n_{sT} \tag{7}$$

Considering the possibility to delay or anticipate some interventions in the electrical system, the search space size increases with the following law:

$$\dim = \prod_{i=0}^{T} n_{Si} \left\{ \mathbf{1} + T \cdot \left[\sum_{\mathbf{k}=1}^{T-1} \frac{\mathbf{1}}{\mathbf{n}_{S\mathbf{k}}} + \sum_{\substack{\mathbf{j},\mathbf{k}=1 \\ \mathbf{j}\neq\mathbf{k}}}^{T-1} \frac{\mathbf{1}}{\mathbf{n}_{S\mathbf{j}}\mathbf{n}_{S\mathbf{k}}} \right] \right\} \tag{8}$$

The allowable strategies also include those obtained keeping the same configuration for more than one time interval.

In Fig. 6 the search space of a small scale design problem is represented. The dotted lines represent the new installations required to attain the new configurations. For this application, an exhaustive search algorithm to identify the minimum cost solution has been carried out.

Consider a time horizon divided into three intervals ($T = 3$), all having the same duration ($D = 3$) , and $n_{s0} = 1, n_{s1} = 5, n_{s2} = 1, n_{s3} = 2$, are the number of Pareto-optimal solutions for each time interval. The search space dimension using Eq. (8) is: $\dim = 52$.

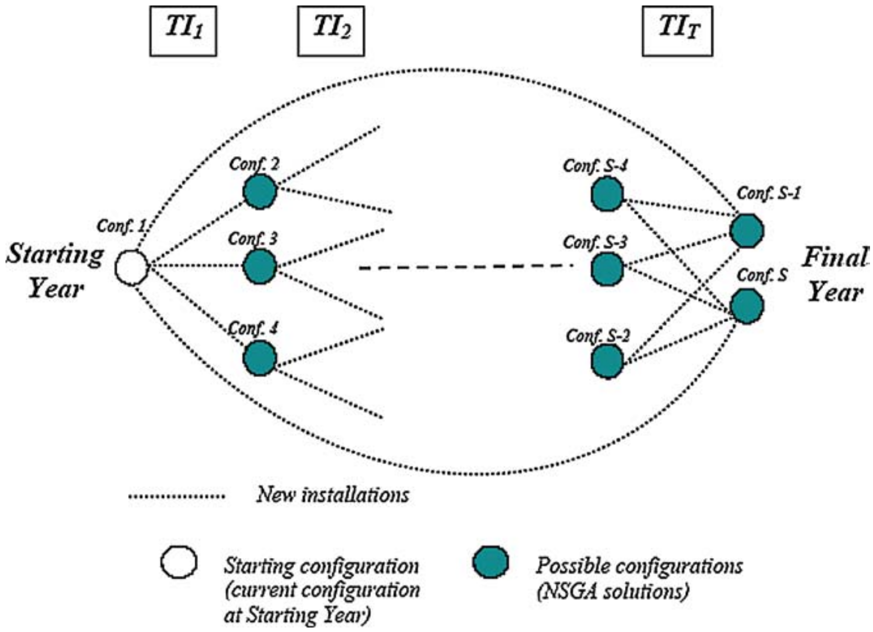

Figure 5. A general search space.

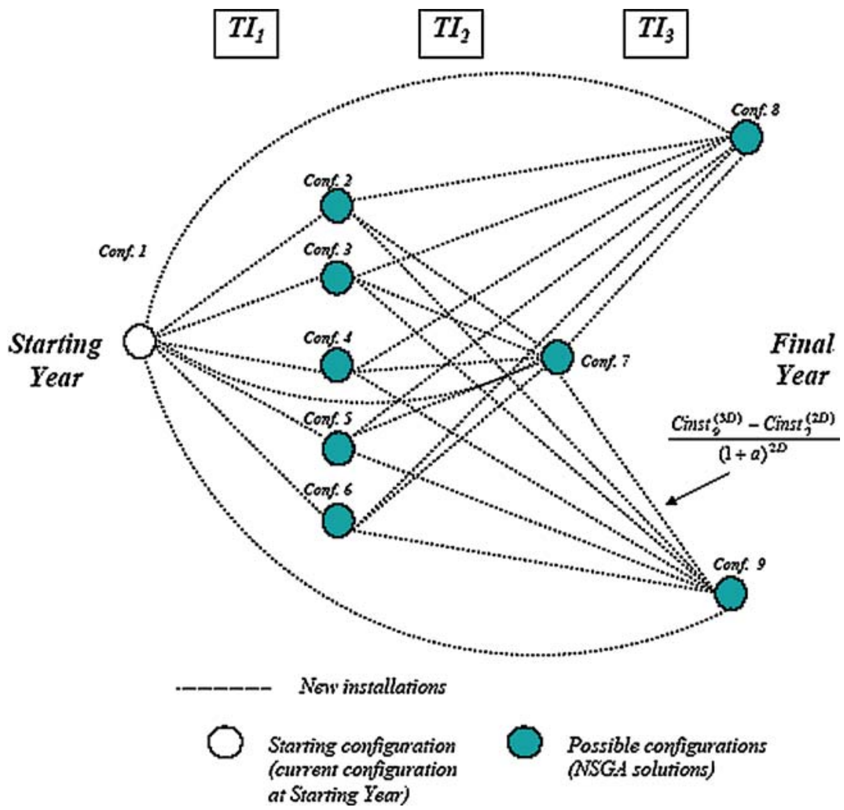

Figure 6. All allowable strategies for a small scale design problem.

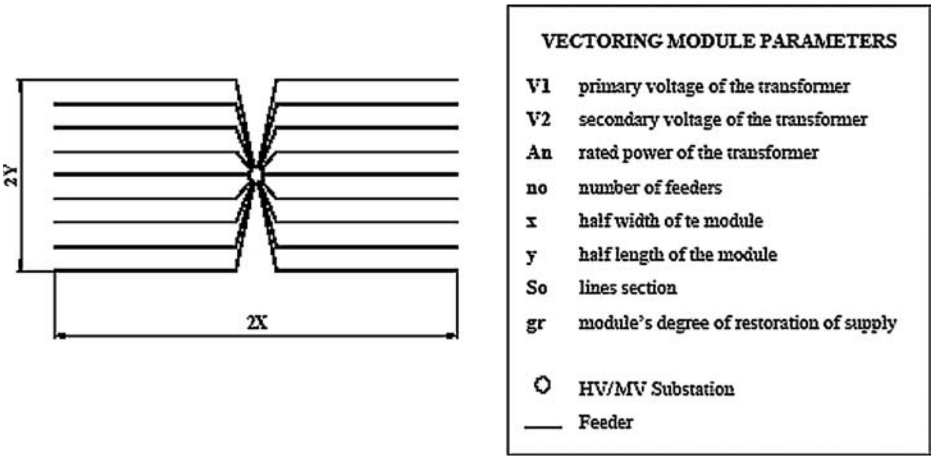

Figure 7. Vectoring module used to obtain the MV stage of electrical distribution system.

For this small scale design problem, an exhaustive search method has produced the same optimal solution of the ACS adapted algorithm.

4. Application

Consider the single medium voltage stage of a distribution system obtained by the interconnection of several vectoring modules (see Fig. 7). The electric load is uniformly distributed on each feeder according to a rectangular law. The planning study that has been considered for this system is related to a time horizon of 20 years in which the forecasted load density growth [MVA/ km^2] has this course:

$$\sigma(t) = \sigma_o(1 + r)^t \tag{9}$$

where:

$\sigma_o = 10$ [MVA/km^2] starting load density;
$r = 0.05$ yearly growth rate of load density;
$t = 0$–20 years.

Seven time intervals, each of three years, have been chosen. For each of these intervals the Pareto optimal configurations of the system have been obtained, these being optimal in terms of installation and operational costs, quality while meeting a set of technical, logical and economical constraints. The objective is to identify an efficient expansion strategy for the electrical system (in the considered time horizon), namely the minimum cost sequence of changes of configuration required to follow the load density growth.

The installation costs of the lines and of the transformation and/or compensation node of the functional module, are expressed by the following relations [8]:

$$C_L{=}(\textbf{Error!} + \textbf{Error!})\,(C_1 + c_2 V_2 + c_3 s_o) \quad [€/\text{km}^2] \tag{10}$$

$$C_{nt}{=}C_4 + c_5 A_n^d (V_1 + V_2)^b \quad [€] \tag{11}$$

where expression (10) is the overhead lines cost per km^2. This expression is made up of a fixed part, C_1 (fixed installations and accessories) which in this application is 40025.65 €/km, and a variable part made up of two terms, one depending on the voltage level, where c_2 is 774.49 €/km kV, and the other depending on the line section, where c_3 is 129.11 €/km·mm^2. Expression (11) is the installation cost of the HV/MV transformers. In this expression, C_4 is a constant 1549380 €, c_5, d and b are heuristically derived coefficients (respectively 0.205, 0.8 and 1).

The configurations are considered optimal in terms of the system's yearly and per area unity cost (Ctot) and the maximum yearly unavailability (Unav), namely to the maximum stationary probability that one node of the system is not supplied due to a fault above it.

The systems update do not consider the elimination of the existing elements, instead new elements having the same capacity are added in parallel to the existing ones (i.e.: transformers, lines,..) The rated power of the transformation node must be adapted to the power increase required, connecting in parallel more

Table 1. Installation cost (Cinst), losses cost (Closs), unavailability (Unav), parameters of functional module (see Fig. 7) and constraints: maximum voltage drop (ΔV), maximum current density in all the lines (ΔI), power balance at supply node (P_{SN}), for optimal strategy.

Yr	σ (MVA/km^2)	Cinsr (€/km^2)	Closs (€/km^2)	Unav (h/yr)	V_1 (kV)	V_2 (kV)	An (MVA)	n_a	X (km)	Y (km)	S_a (mm^2)	gr	ΔV	ΔI (A/mm^2)	P_{sv} (MVA)
0	11.57	327299	84524	1.10E-04	150	20	200	6	2.05	1.94	600	0	0.0169	1.476	193.36
3	13.3	375604	155604	1.00E-04	150	20	200	6	1.95	1.72	600	0	0.0159	1.441	188.7
6	15.5	454916	216518	8.54E-05	150	20	200	6	1.65	1.58	600	0.1	0.0192	1.427	186.84
9	17.69	461755	267270	8.84E-05	150	20	200	6	1.75	1.48	600	0	0.0137	1.492	195.35
12	20.69	516154	310269	8.24E-05	150	20	200	6	1.55	1.44	600	0.1	0.0127	1.488	194.88
15	24.01	601373	346862	7.50E-05	150	20	200	6	1.45	1.28	600	0	0.0188	1.432	187.60
18	27.08	680488	378426	7.04E-05	150	20	200	6	1.75	1.36	600	0	0.0102	1.397	183.00

transformers; the main feeders sections increase must be realised putting other cables of the same size in parallel with the existing ones. For these reasons, only the expansion strategies, including new installations that follow the above cited rules, are feasible.

If the starting solution is fixed, then $n_{s0} = 1$. The fist time interval contains $n_{s1} = 61$ solutions; the second, $n_{s2} = 63$, the third, $n_{s3} = 53$; the fourth, $n_{s4} = 41$; the fifth, $n_{s5} = 34$; the sixth, $n_{s6} = 13$. The search space amplitude, using Eq. (8) is: 6, 112, 187, 250.

Applying the ACS algorithm with the following control parameters: $\tau_0 = 0.001$, $\beta = 2$, $\alpha = 0.1$, $n = 10$, $a = 10\%$, $q_0 = 0.5$, iterations = 100, the minimum cost strategy identified most frequently by the algorithm is the following: [1, 49, 71, 177, 206, 235, 265], namely the system will have to be updated at each time interval and will be modified at each time interval (every three years) going through some of the configurations identified by the NSGA in the first phase. In Table 1, the most frequent optimal solution strategy (with a very low variance), obtained using the ACS, is reported.

Cinst and Closs respectively are the installation and losses costs for the considered year (not reported to the starting year), for this solution, the value of $L_{\rm gb}$ (global cost of the best strategy) is: 680.488 €/km^2 and the corresponding operation cost is: 476,817 €/km^2, both actualized at the starting year; the maximum voltage drop is 1.00% and the current in all the lines never exceeds the rated values. As it can be noted, the strategy tries to

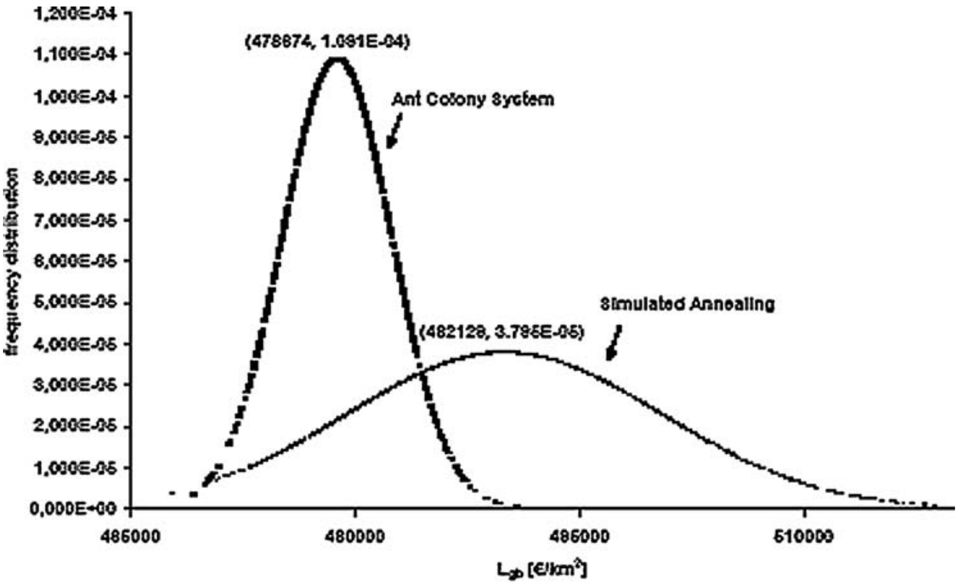

Figure 8. Frequency distribution of results vs. fitness value L_{gb} (cost of the best strategy) for 1000 runs.

minimize the overall cost by simply changing the size of the elementary module and never changing the other parameters. One of the main implications of the size reduction of each module concerns the reduction of the unavailability parameter (see fifth column of Table 1), thus producing an improvement of the service quality. A traditional planning approach would have simply minimized the overall installation and losses costs per square km^2, producing solutions with large modules, long lines and higher size substations. In this way, the system's reinforcement would be carried out keeping the costs at a low level, but not meeting the requirement of service quality which is nowadays a basic issue.

The results have been compared with results from a SA algorithm. Since neither the ACS nor the SA are deterministic, they do not result in the same final solution. For this reason, in order to prove their robustness, 1000 runs of both algorithms have been performed and the distribution of results are compared, as shown in Fig. 8. The ACS is more robust having a lower standard deviation, and the most frequent solution is more economical than the most frequent solution identified by SA.

5. Conclusions

A dynamic strategical planning problem for electric distribution systems has been solved with an Ant Colony Search (ACS) algorithm. This solution method has been compared to the Simulated Annealing technique and, for a very large sample test problem, the ACS was shown to be more efficient and robust. The entire solution approach proposed by the authors is made of two phases, the first identifies the sets of Pareto-optimal solutions (in terms of possible configurations) for each of the considered load densities; the second phase, finds a minimum cost path through these solutions. The proposed methodology allows the planner to include some other heuristically determined solution to those obtained in the first phase, or to modify some of these.

After the presentation of the general problem of strategical planning in dynamic terms, the optimization procedure used to solve it, the ACS algorithm, has been described in detail together with the necessary modifications for this kind of application. Then test results obtained for a medium voltage system, for which an expansion strategy in a time horizon of 20 years has to be planned, are reported and commented. Future developments of this work aim at the application of the ACS algorithm or other modified cooperative search methods to more complex systems with more than one voltage level and with dispersed generation nodes.

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