Ant Colony Systems Application for Electric Distribution Network Planning

J.M. Alvarado, E.V. Alvarado, M.A. Arévalo, S.P. Quituisaca, J.F. Gomez and P.M. De Oliveira-De Jesus

***Abstract*— This paper presents an application of Ant Colony System Algorithm (ACS) to solve electrical distribution planning problems. This model constitutes an improved version of the ant system algorithm, permitting to generate food routes from their nest, and where a set of artificial ants are cooperating in order to find a good route through the data exchange contained by the pheromone deposits in several trajectories. This algorithm is applied to choose the best network plan that satisfies all demand requirements. Objective function includes fixed and variable costs associated to future investments and power losses subject to network constraints, The algorithm has been applied into a real 139-node network located in Cuenca, Ecuador.[1]**

***Index Terms*— Circuit optimization, optimization methods, power distribution planning.**

I. Introduction

DISTRIBUTION network are suffering fundamental changes where economic efficiency and power quality are becoming critical issues. In the last forty years, several optimization models have been developed to deal with the planning problem.

The electric distribution planning problem has been extensively stated in Literature as a mixed integer linear programming problem (MILP), where an objective function that includes both the fixed and the variable costs of the network, is minimized subject to network constraints like power balance at nodes and capacity in lines and substations [7]. The MILP formulation includes binary variables linked to the investment costs associated to decision variables as well as linear approximations to represent the variable costs.

By contrast, several heuristic search methods as Genetic Algorithms[2], Branch Exchange[3], Simulated Annealing[4], Tabu Search[5] or Particle Swarm[6] have been applied showing in some cases faster performance than the traditional optimization methods based upon linear programming but with some limitations in the kindness of the solutions.

Most of them have been formulated as a combinatorial optimization problem, since its realistic size and complexity is such that the application of heuristic procedures has proved to be appropriate.

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Heuristic methods are typically based upon a pseudo-dynamic strategy where time and location of new lines is solved in two stages. The first one is solved statically, with fixed demands, so at each loading level, the system is optimized. In the second one, the progress through the solutions found in the first stage details the timing of new lines. Heuristic methods do not demonstrate to optimality. However, population-based heuristic methods permit the achievement of a set of good and efficient solutions among which the planner can choose the most suitable for the particular problem at hand.

Then, the problem is not only to minimize costs, but also to ensure good quality and reliability. To do this, the planning problem could be formulated as a multiple objective optimization problem, where a trade-off strategy should seek and identify non-dominated solutions. Population-based heuristic methods lead to sufficient solutions suitable to be filtered under this trade-off approach

In [7], a new population-based heuristic method denominated Ant Colony System (ACS) algorithm was strictly applied to solve electric distribution planning problems. This contribution is an improvement of the AS algorithm developed by Dorigo [8].

The idea behind ACS optimization is summarized as follows. Ants are members of a family of insects with socialized behavior living in an organized colony. These families of ants are able to find the best way into a very complex set of mazes using these features to establish food collection routes from the nest. Even though learning capabilities are very limited, the complexity of the organization of the colony allows a very efficient communication among individuals, based upon tactile and chemical media. Every expedition in searching of food sources liberates chemical secretions called pheromones in order to establish all paths used in the collection process. This allows other ants to follow-up all the food sources. It is established that shorter paths will tend to have a higher magnitude of the secretion deposits and, therefore, these routes will be preferred by new explorers.

This paper presents am application based upon the Ant Colony System algorithm to solve a real-world energy distribution planning problem. The methodology permits to obtain the location and the characteristics of the feeders minimizing the investment and operational cost while enforcing the technical constraints such as the transmission capabilities and the limits on the voltage magnitudes, allowing the consideration of a very complete and detailed model for the electric system.

The methodology was successfully applied to a real-world test case: a 139-node distribution system showing adequate results.

II. Statement of the Problem

The optimization problem has been stated by the minimization of an objective function representing the fixed costs correspondent to the investment in lines and substations and the variable costs associated to the operation of the system, expressed y the following equation

$$\min \sum_{i \in \Theta} \{(FC_i)(R_i) + (VC_i)\} \tag{1}$$

$$VC_i = \frac{8760 L_f L_i \, k_e}{CRF} \tag{2}$$

where

FC_i	fixed cost of branch *i* ($);
R_i	binary variable associated to branch *i*;
VC_i	levelized operational cost of branch *i* ($);
L_f	annual loss factor;
L_i	power losses of branch *i* (kW);
k_e	energy cost ($/kWh);
CRF	capital recovery factor;
Θ	set of all branches *i*;

The constraints are given by

.- *Global active power balance:*

$$P_{SE} - \sum_j D_j - \sum_i L_i = 0 \tag{3}$$

where

P_{SE}	active power delivered by substation (MW);
D_j	load demand at node *j* (MW);

.- *Circuit capacity:*

$$0 \le S_i \le S_i^{\max} \tag{4}$$

where

S_j	apparent power flow at branch *i* (MW);
$S^{max}{}_j$	maximum apparent power flow at branch *i* (MW);

.- *Voltage constraint:*

$$V_j^{\min} \le V_j \le V_j^{\max} \tag{5}$$

where

V_j	operational voltage at node *j* (kV);
$V^{min}{}_j$	minimum operational voltage at node *j* (kV);
$V^{max}{}_j$	maximum operational voltage at node *j* (kV);

.- *Radial network restriction*

The network is enforced to be operated in a radial form. No loops are allowed

Checking branch capacities and voltage drops requires the application of a distribution system load-flow algorithm. In this case we used a standard back-forward sweep load flow suitable to be applied to large distribution networks [9].

III. Proposed Methodology

The Ant Colony System method is based upon ants' behavior. Ants are insects with extraordinary abilities to locate the shortest paths to their food sources by using a substance called pheromone that is deposited as they walk clearly indicating a route. Initially, a set of individuals explores the surface without a predetermined direction. Since food is found, all individuals go back to the colony. Taking into account that all of the individuals travel approximately at the same speed; shorter paths have a tendency to contain a higher levels of pheromone because more individuals have used the same route. The differences among the pheromone levels in the routes are big enough to persuade the decision of the new individuals, which will decide toward the shorter paths. This situation produces a feedback that contributes and promotes the use of the best paths.

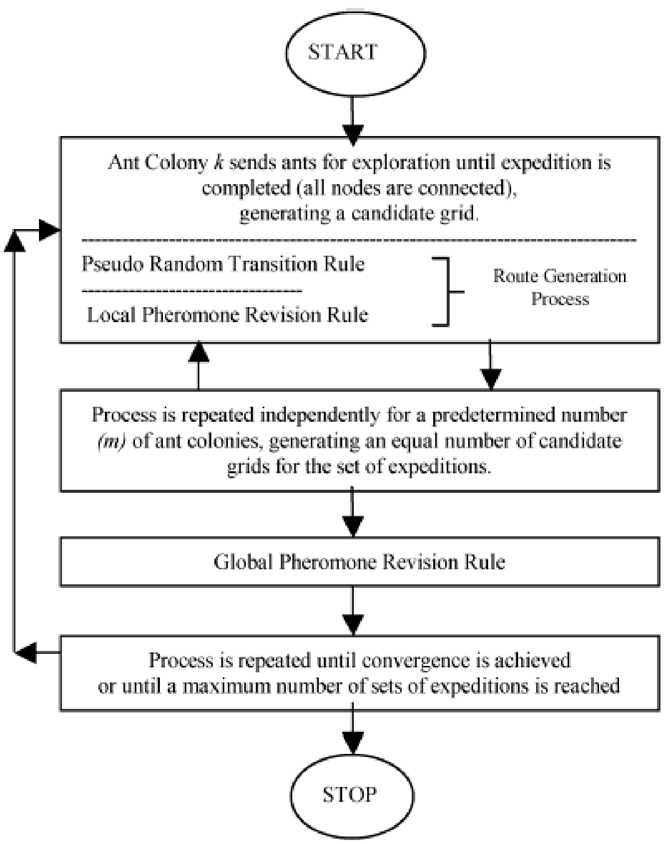

Fig. 1 Simplified Flow Chart [7]

A. Formulation of the Classic ACS Algorithm

The basic Ant System (AS) model [8] basically applies two functions to guide a search toward the optimum.

1) First by setting a function which is proportional to the amount of pheromone deposited;

2) Second by selecting a heuristic guide function, also referred to as the incremental cost function and generally defined as the inverse of the distance, which constitutes an auxiliary function that helps to generate better grids.

The mathematical formulation of the Ant Colony System (ACS) algorithm can be reviewed in detail in [7]. A simplified flow chart of the ACS algorithm is shown in Fig. 1 This proposal improves the AS [8] in three basic features:

i) by using a proportional pseudo-random transition rule, that weights the priorities of the exploration of new paths with the use of the accumulated knowledge of the problem, in order to improve the selection of the "best route."

ii) global pheromone level revision rule is applied only to those branches that belong to the best networks found so far. Pheromone is deposited only in those branches that belong to the best network. This change aims to make a more direct search, orienting the explorations toward the best one found so far. This modification is somehow similar to the elite strategies of the genetic algorithms or evolutionary programming approaches.

iii) local pheromone level revision rule in which these levels are updated during the route generation process.

B. Formulation of the Modified ACS Algorithm

The flow chart of the modified Ant Colony System (ACS) algorithm is shown in Fig. 2.

.- Mathematical Formulation

Optimal solution of the problem is stated as follows: It is considered a number n of nodes and a number m of ants. In order to guarantee an ant reach all nodes under a unique round up it is important to associate each ant k into a tabu list. This list contains all nodes reached by each ant. Since all nodes are reached, the route is completed and then the list is empty. At this point, the ant is free to begin a new route. Then a s- element of is given by Tabu(s). The initial point is given by a matrix of distances between nodes i and j. The visibility is give by the inverse of all distances,

On the other hand, τ represents a matrix with pheromone levels user to consolidate all information collected by all ants. In other word, t matrix represents the amount of pheromone in each route between nodes i and j. Under each iteration each ant choose to go to the following node according to the following probabilistic function

$$P_t(i,j) = \begin{cases} \frac{[\tau(i,j)]^\alpha [\eta(i,j)]^\beta}{\sum_j \{[\tau(i,j)]^\alpha [\eta(i,j)]^\beta\}} & \text{if } j \notin Tabu \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

where

$\tau_j(i,j)$ pheromone level deposited between nodes i and j;

$\eta(i,j)$ heuristic function i and j;

α decay rate of the pheromone level due to evaporation.

β parameter that determines the relative importance of the pheromone level τ and the heuristic search function η;

At the time t, ant is moving from i to j (this movement is called iteration). Then, when the ant reaches the n-1 iteration, all nodes have been explored and the ant is ready to go to the origin.

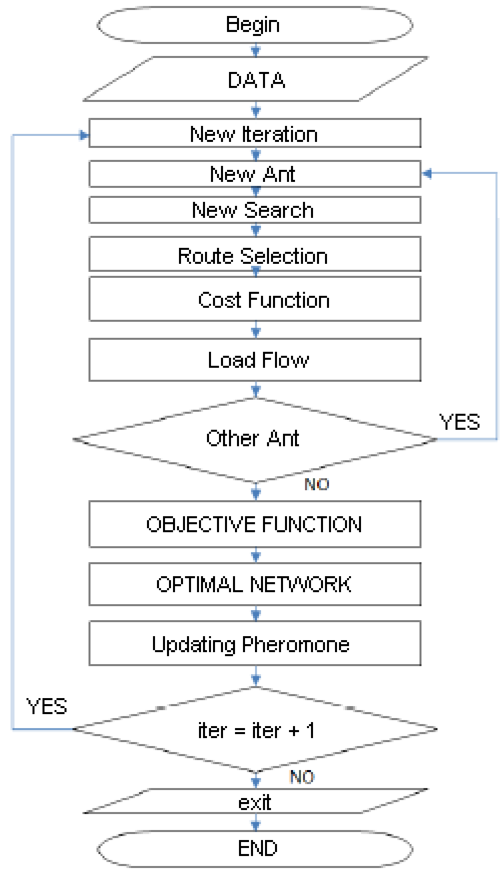

Fig. 2 Modified Flow Chart

Matrix τ is updated by specifying the level of pheromone between nodes i and j:

$$\tau^{t+1}(i,j) = \rho\tau^{t}(i,j) + A\tau^{t,t+1}(i,j) \quad (7)$$

where ρ is a coefficient that denotes pheromone persistence and 1-ρ represents pheromone evaporation between iteration t and $t+1$. The amount of pheromone deposited between i and j is given by:

$$A\tau^{t,t+1}(i,j) = \sum_k \{A\tau_k^{\,t,t+1}(i,j)\} \quad (8)$$

where k denotes the k-ant moving between i and j. The process stops when a convergence criterion is reached (i.e. minimal losses).

C. Planning of Distribution Systems with ACS

The *ACS* algorithm requires the definition of the objective function to be maximized, as well as a heuristic guide function in order to be applied in power system planning problems.

1) Objective Function: The objective function of the problem was defined as the sum of the total costs, considering the fixed and operational loss costs required for each solution, which are calculated with the available information from the power flow.

2) Heuristic Guide Function: The heuristic guide function plays a fundamental role during the first stages of the optimization process because it allows the generation of lower cost networks with good voltage performance. Nevertheless, as the algorithm progress, the levels of pheromone accumulated in the branches get higher, and the decisions of which branch to take is less dependent on the heuristic guide function. In the AS algorithm [8], the heuristic function is defined as the inverse of the length, giving in this way preference to the selection of shorter paths.

In this case, the *ACS* algorithm applied to solve the distribution system planning problem, the following variables were also included in the heuristic guide function: the length, the incremental cost of the network, and the magnitude of the demand at the end of the path. It was defined as the weighted sum of two terms.

IV. Case Study

The modified Ant Colony System method was tested in a distribution network owned by Empresa Electrica Regional Centro Sur C.A. that serves three provinces in Ecuador: Azuay, Cañar y Morona Santiago. The A0324 feeder under study corresponds to a future 139-bus network (16/24MVA, 69/22kV) that will serve urban sectors in Cuenca City.

All users are foreseen to be mainly residential and commercial.

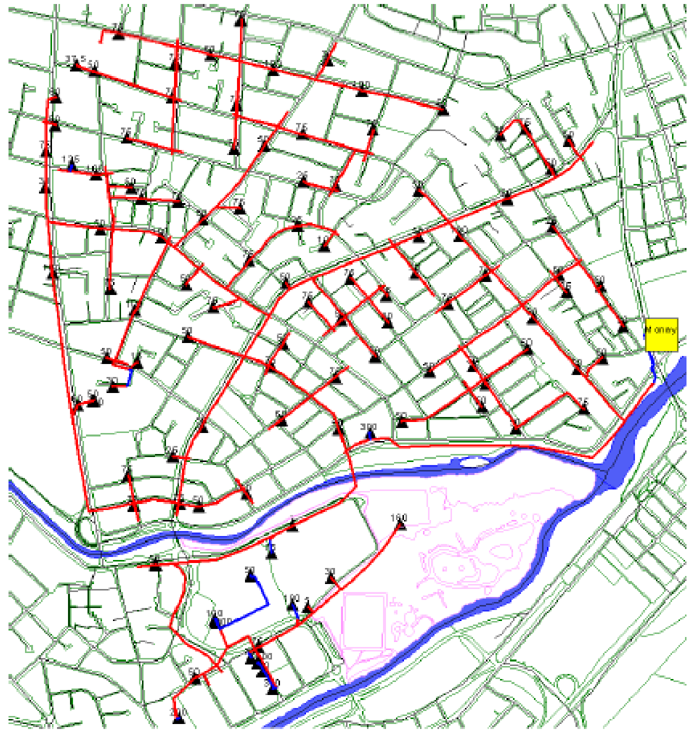

Fig. 3. Base Case - Originally planned configuration of A0324 feeder

Fig. 3 shows the original configuration of A0324 feeder, planned using other planning strategy. Fig. 4 displays all possible interconnections between nodes.

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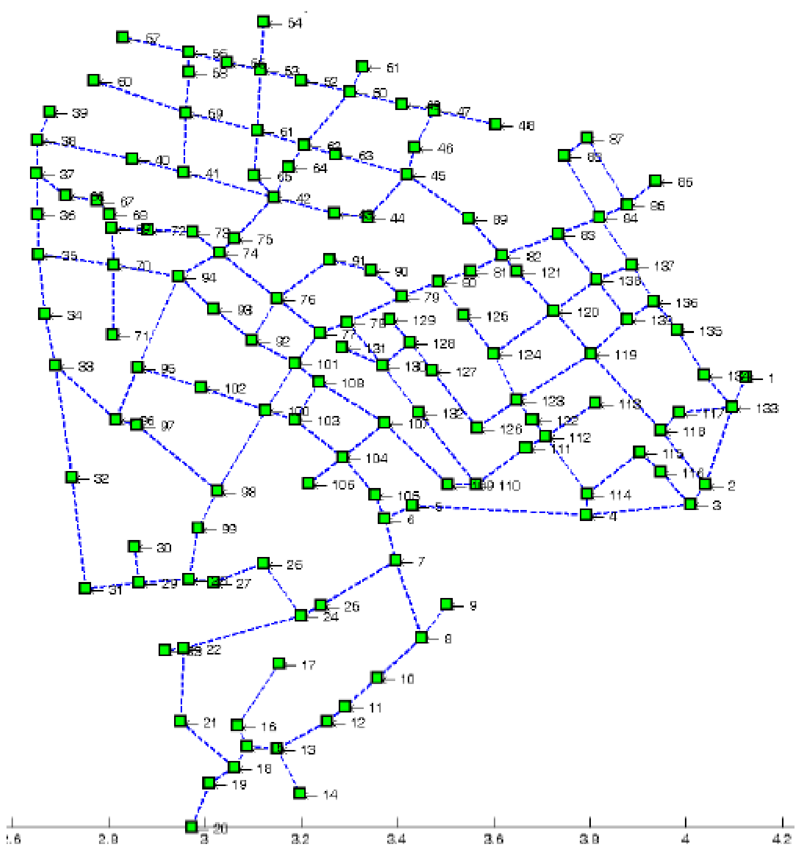

Fig. 4 Feasible routes

TABLE I
GENERAL SYSTEM DATA

Parameter	Value
Installed Load [kVA]	8.961,50
Demand [kVA]	3.097,83
Utilization factor [%]	35
Voltage [kV]	22
Power Factor	0,92
Load Factor	0,6917
Loss Factor	0,5066
Investment cost Cu3/0, 3phases [$/km]	14500
Dicount rate [%]	10
Enegy cost [$/kWh]	0,05
Period [years]	20

Table I shows the general system data of A0324 system. Network system data can be requested to the authors. All simulations considered an evaporation rate of 0.2, a decay rate of the pheromone level due to evaporation (α) equal to 1. The parameter that determines the relative importance of the pheromone level (β) is set in 0.5

Characteristics of this case study allows to consider multiple new routes and interconnections with lower investment an operational costs representing important savings

In this sense, the objective the algorithm attempts to reach minimal costs at present worth taking into account load and voltage profiles at horizon demand.

First, the base case (displayed in Fig. 3) is analyzed according to losses and investments required by the planner. Base case solution (with no optimization) is shown in Table II.

TABLE II
BASE CASE - SOLUTION

Power Losses [kW]	8,9544
Fixed Cost [$]	204.291
Operational Cost [$]	17.029
Total Cost [$]	221.320

Further, all feasible connections among nodes are identified (Fig. 4). Three simulations were performed as indicated in Table III

TABLE III
SIMULATION DATA

	Sim. 1	Sim. 2	Sim. 3
Number of Iterations	500	500	700
Number of Ants in the Colony	150	200	200

Number of iterations varies from 500 to 700 and number of ants varies from 150 to 700. All simulations were performed in MATLAB suite using a PC computer Core 2 Duo processor with 2,7Ghz, 2MB RAM.

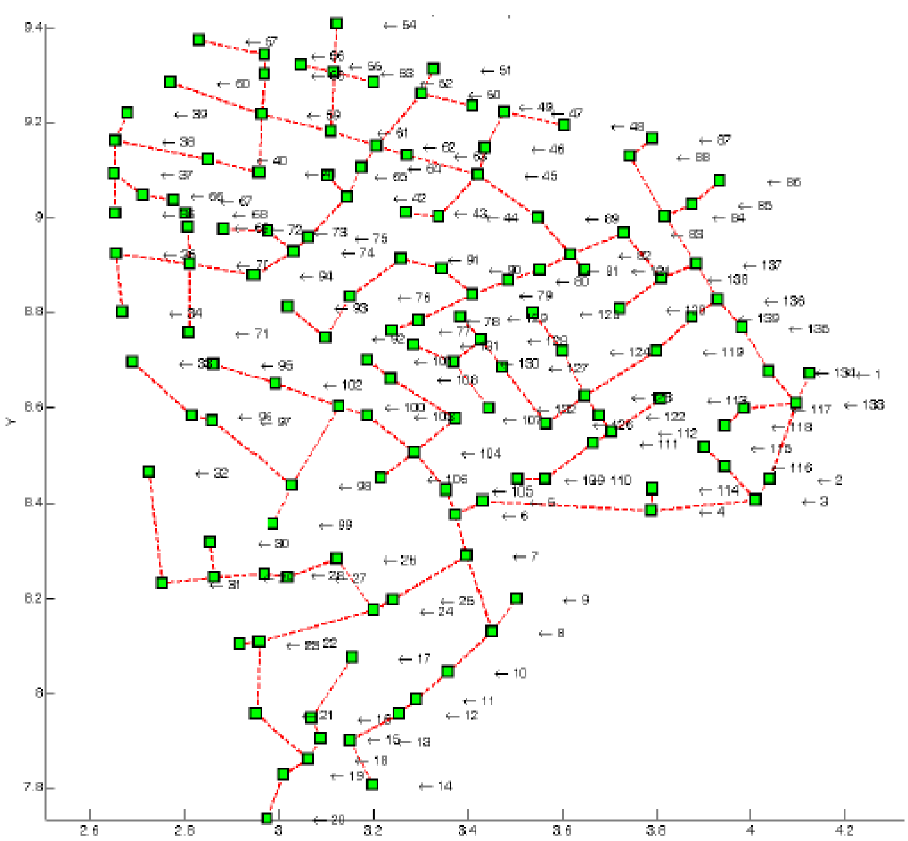

Fig. 5. Optimal Solution for the A0324 feeder (simulation with 200 ants and 700 iterations)

Table IV show solutions obtained in the three simulations performed. The best solution is achieved using 200 ants and 700 iterations, with more computational burden. Resultant network topology is shown in Fig. 5

TABLE IV
OPTIMAL (EFFICIENT) SOLUTIONS

	Sim. 1	Sim. 2	Sim. 3
Simulation Time [seg]	49.431	52.702	87.554
Power Losses [kW]	4,7584	4,6971	4,7594
Fixed Cost [$]	207.630	207.680	207.386
Operational Cost [$]	9.049	8.933	9.051
Total Cost [$]	216.679	216.613	216.437

According to these results, all solutions improve the original plan depicted in Fig. 3 and economically valuated in Table II. Power losses correspond to 50% of original estimated values. Also we can see that these solutions are nondominated because investment cost is higher when power losses diminish as shown in Fig. 5.

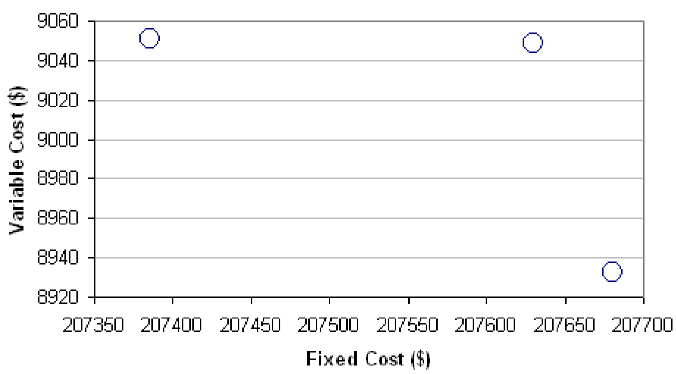

Fig. 6. Pareto Set- Efficient Solutions for the A0324 feeder

However, the overall best solution (considering that economic forecast: discount-rate, and energy prices will be stable during 20 years) corresponds to simulation 3, when total cost achieved is 216.437$.

V. CONCLUSION

A methodology based upon the Ant Colony System algorithm has been applied to solve a real-world energy distribution planning problem. The methodology permits to obtain the location and the characteristics of the feeders minimizing the investment and operational cost while enforcing the technical constraints such as the transmission capabilities and the limits on the voltage magnitudes, allowing the consideration of a very complete and detailed model for the electric system.

The methodology was successfully applied to a real-world test case: a 139-node distribution system showing adequate results. The proposal is shown as a flexible and useful tool for distribution system planning engineers permitting to identify several compromise solutions (Pareto solutions). The results encourage the use and further improvement of the methodology.

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