#### LOSS REDUCTION IN DISTRIBUTION SYSTEMS USING ANT COLONY ALGORITHMS

Ovidiu Ivanov, Technical University "Gh. Asachi", Iaşi, Romania Mihai Gavrilaş, Technical University "Gh. Asachi", Iaşi, Romania Călin-Viorel Sfinteş, EXIMPROD S:A Buzău, Romania

### 1. INTRODUCTION

The optimal planning and operation of distribution networks often implies solving of several optimization problems such as finding the optimum configuration, or the optimal reactive power compensation solution. At present, following the energy markets' rapid development, these problems have been analyzed from an economical and financial perspective, minimum energy losses being able to generate important savings in money and assets for an electricity utility. Over time, several traditional methods have been developed to solve these problems, but although in most cases they produce good results, this is achieved with the price of significant computation time. To address this issue and to improve the efficiency, new concepts were developed using artificial intelligence techniques such as genetic algorithms [1], expert systems [2] or intelligent maps [3].

This paper presents a new approach to the problem of loss reduction in distribution systems through network reconfiguration and reactive power compensation (NR-RPC). The proposed method uses an optimization technique that applies an Ant Colony Algorithm (ACA) [4] to search for the best solution.

The algorithm is used to solve the problem of loss reduction through network reconfiguration and reactive power compensation for a test-system, which consists of 73 load sections on 33 feeders, 61 buses, and a limited stock of capacitor banks of 5 kVArs each. The results describe power losses for the basic non-compensated configuration and the reconfigured compensated solutions generated by the algorithm. Convergence properties and other intrinsic characteristics of the computational method are described.

### 2. PROBLEM DESCRIPTION

The problem can be stated as follows: knowing the network characteristics (space co-ordinates of the consumers (transformers), their loads (as currents) the position of the supply sources, the line parameters, the available capacitor banks stock, the optimal path of the electrical network and the optimal capacitor banks placement must be determined so that a objective function (the network's power losses)

to be minimized. Several constraints apply (all the consumers must be supplied, the radial structure of the network, voltage and current limitations, reactive power injection limit).

For an electrical network with N nodes (NN consumer nodes and NS source nodes) and NT load sections, the stated problem can be expressed mathematically as follows:

The objective function to be minimized (the power losses):

$$F = \sum_{i=1}^{ND} \sum_{i=TI_1}^{TI_2} I_{ji} * r_{ij} = \min$$
 (1)

- Constraints:
  - all consumers must be supplied a condition test is performed on the network's nodebranch matrix
  - o the admissible thermal current:

$$\sum_{j=T}^{T} I_{ji} \leq I_{i}^{adm} \quad (i = 1,...,ND)$$

o the admissible voltage drop:

$$\sum_{k \in M_i} \sum_{j=T_{1_i}}^{T_{2_i}} I_{jk} * Z_{jk} \le \Delta U_{adm}$$

o the reactive power injection limit:

$$q_0 * N_K \le Q_k , \qquad (k = 1, ..., NT)$$

o the available capacitor banks stock:

$$\sum_{k=1}^{NT} N_k \le NC$$

where:  $I_{ji}$  – the current on the j-th load section of the i-th feeder;  $r_{ij}$  – the resistance of the j-th load section of the i-th feeder;  $I_i^{adm}$  – the admissible thermal current for the i-th feeder;  $Z_{jk}$  – the impedance of the j-th load section of the k-th feeder;  $\Delta U_{adm}$  – the admissible voltage drop;  $q_0$  – the rated power of capacitors;  $Q_k$  – the reactive load of the k-th transformer;  $N_k$  – the number of capacitor banks in the k node; NC – the capacitor banks stock; ND – the number of feeders;  $T1_i$ ,  $T2_i$  – the first and last load section of the i-th feeder;  $M_i$  – the set of feeders between the source node and the i-th feeder, including this one. A feeder is considered as a group of consecutive load sections between two branching points of the network.

# 3. THE ANT COLONY ALGORITHM

The classic ant colony algorithm proposed by Marco Dorigo in 1992 is inspired from the natural behaviour of ants, which are able to find their way using pheromone trails. The ants travel between two fixed points A and B on the shortest route, following the next procedure: a number of ants leave the A point, following random directions, leaving behind a pheromone trail that marks the chosen path. After the first ant reaches the B point, it returns in A following its own pheromone trail, thus doubling the pheromone layer intensity. As the first ant reaches back the A point and the pheromone trail grows, an increasing number of ants will follow the same path. For each ant, a taboo list is defined to memorize its path. The ants move between nodes i and j with probability  $P_{ii}$ , chosen with a roulette-type rule, defined as

$$P_{ij} = \begin{cases} \frac{(\tau_{ij})^{\alpha} \cdot (1/d_{ij})^{\beta}}{\sum_{p \in Tabu_k} (\tau_{ip})^{\alpha} \cdot (1/d_{ip})^{\beta}}, & j \notin Tabu_k \\ 0, & j \in Tabu_k \end{cases}$$

$$(2)$$

where  $\tau_{ij}$  –the pheromone intensity between nodes i and j,  $Tabu_k$  – the taboo list of the k-th ant,  $1/d_{ij}$  – the visibility between nodes i and j,  $\alpha$  and  $\beta$  are parameters that control the influence of pheromone intensity  $\tau_{ij}$  and the visibility  $1/d_{ii}$ .

After each ant completes its path (the taboo list is filled), the pheromone intensity of every edge is updated using the formula:

$$\tau_{ii} = \rho \cdot \tau_{ii} + \Delta \tau_{ii} \tag{3}$$

where  $\rho$  is a coefficient ( $\rho$  <1), so that  $(1-\rho)$  is the trail evaporation rate.  $\Delta \tau_{ij}$  is the pheromone intensity correction rate, determined according to the ant's performance.

#### 4. IMPLEMENTATION OF THE ANT ALGORITHM FOR THE NR-RPC PROBLEM

### 4.1 Implementation issues

To adapt the basic ACA algorithm to the NR-RPC problem, several changes and adaptations had to be made. The ants move in a search space defined by the network's parameters. Two search spaces were defined, one for the optimal reconfiguration problem, one for the optimal compensation problem. Those are rectangular spaces [5] that can be defined as matrices, with a number of rows equal to the number of affected network parameters and a number of columns equal to the possible values of the modified parameter. For the reconfiguration problem, the search matrix has as much lines as the number of load sections that need to be opened so the network can be operated in a radial configuration, and a number of columns equal to the number of load sections in the network that can be opened. A feasible solution will be represented by a vector consisting of the load sections that will be opened to obtain the radial configuration of the network, taking into account the problem's constraints (no consumer is to be disconnected and the thermal current and voltage drop meet the admissible limits).

For the optimal compensation problem, the matrix of the search space has a number of lines equal to the number of consumer nodes in the network and a number of columns equal to a positive multiple of the maximum number of capacitor banks that can be simultaneously placed in a node. A feasible solution will be a vector, which shows how many capacitor banks are placed in each node of the network. To be considered valid, the solution must meet the problem's constraints (the thermal current and voltage drop limits, the capacitor stock and the reactive injection limits).

These search spaces are modelled through the pheromone trails left by the ants as they move from a point to another. The ant k will move from point i to point j with a probability computed as:

$$P_{ij} = \frac{\tau_{ij}}{\sum_{m \in Tahu.}} \tau_{im} \tag{4}$$

After each ant completes its path, the pheromone intensity between the points visited by the ant is updated following the general rule (3), where the pheromone intensity correction is computed as

$$\Delta \tau_{ij} = \frac{1}{Q \cdot F} \tag{5}$$

where Q is a sub-unitary constant and F is the objective function to be minimized (the power losses in the network) computed for the solution described by each ant.

The main steps of the algorithm are those from Box 1.

Box 1. ACA algorithm for the NR-RPC problem

- 1. Input the network and algorithm data
- 2. The iterative process for the reconfiguration problem
  - 2.1. Define the taboo lists for the reconfiguration problem
  - 2.2. For every ant that solves the reconfiguration problem
  - 2.3. Choose a valid path in the search space
    - 2.3.1. Define the search space for the reactive power compensation problem
    - 2.3.2. The iterative process for the compensation problem
      - 2.3.2.1. Define the taboo lists for the compensation problem
      - 2.3.2.2. For every ant that solves the reactive compensation problem
        - 2.3.2.2.1. Choose a valid path
        - 2.3.2.2.2. Compute the objective function (the power losses)
        - 2.3.2.2.3. Update the pheromone trail of the ant
  - 2.4. Update the pheromone trail of the ant
- 3. The algorithm found an optimal solution for minimizing the power losses

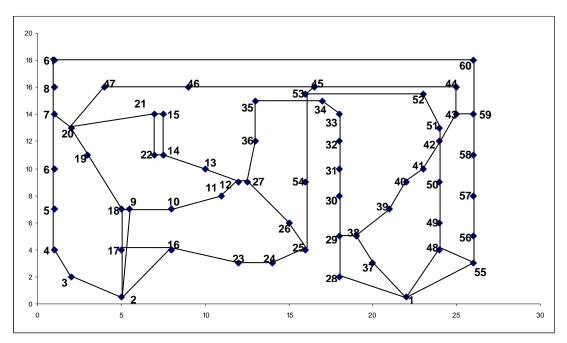


Figure 1. The test distribution network

# 4.2. Case study

The above algorithm was implemented in Matlab and tested with a real distribution network from Romania, presented in Figure 1 and Table 1. Node 42 is not a branching node (the load sections 41-42-43 and 50-51-52 are distinct).

The consumers were modelled as transformers with rated capacities of 400 or 630 kVA, loaded at 0.6 - 0.8 of their rated capacity. For the reconfiguration problem, in order to obtain a radial configuration a number of 14 load sections must be opened, and the remaining load sections must not form closed loops and no consumer must be left unsupplied.

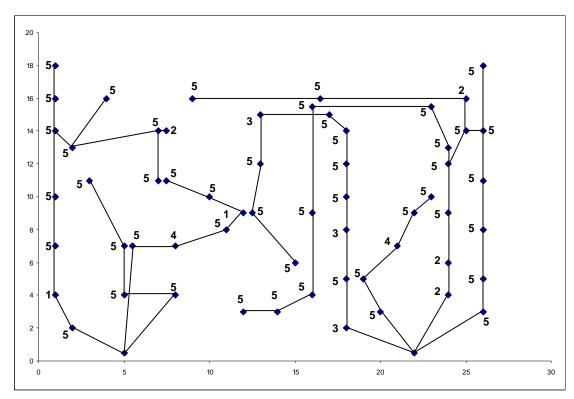


Figure 2. The best configuration obtained with the ACA algorithm

Table 1. Technical data for the distribution network from Fig. 1

Nominal voltage	20 kV	
Number of nodes	61 59 consumers 2 sources	
Number of load sections	73	
Number of feeders	33	
Admissible voltage drop	5%	
Admissible current	500 A	
Total active power	16.936 MW	
Line type	Cable	

Table 2. Power losses for the best configuration, with and without compensation

Iteration	ΔP [kW] (uncompensated)	ΔP [kW] (compensated)
1	153.73	131.02
2	149.60	127.25
3	144.50	123.31
4	144.50	123.31
5	144.50	123.31
6	141.70	121.27
7	114.72	98.07
8	114.72	98.07
9	114.72	98.07
10	114.72	98.07

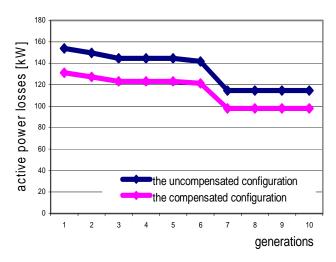
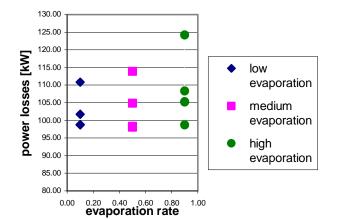


Figure 3. The evolution of power losses for the best configuration



Power losses [kW]			
ρ = 0.1	$\rho = 0.5$	ρ = 0.9	
98.79	98.19	124.22	
98.79	98.19	108.31	
98.79	98.07	98.70	
101.74	104.84	105.26	
110.78	113.82	105.19	

Figure 4. The influence of the trail evaporation rate on the optimization results

For the compensation problem, a maximal stock of 270 capacitor banks was provided; with the restriction that only a maximum of 5 banks can be installed simultaneously in one node, without violating the injection limit.

The best configuration was obtained as in Figure 2, in which are presented the optimal reconfiguration structure and the number of capacitor banks installed in each node. For this configuration, the power loss was of 114.72 kW for the basic, uncompensated configuration, and of 98.07 kW with compensation. The results of the iterative process are presented in Figure 3 and Table 2 for the uncompensated and compensated configurations.

The simulation process pointed out a few general tendencies:

- The power loss reduction depends rather on finding the best reconfiguration than an optimal compensation. As shown in Figure 3, the curves of the power losses reduction are following one-another closely, and the reduction of the available capacitor stock would increase this tendency.
- $\circ$  The best solutions were achieved using a medium or low evaporation rate ( $\rho$ <=0.5). For these settings, the algorithm generated solutions with lower power losses. High evaporation rates generated usually higher power losses The best five attempts for evaporation rates 0.1, 0.5 and 0.9 are presented in Figure 4. For  $\rho$  = 0.1 (low

- evaporation), the power losses value of 98.79 kW was obtained three times, and for  $\rho$  = 0.5, power losses of 98.19 kW were obtained twice.
- Using high values for the pheromone trails correction lowered the optimization performances. The best solutions were obtained with smaller corrections, which enabled the ants to perform a wider range search for a longer period. Heavy pheromone corrections usually blocked the search process in a local minimum, the obtained power losses being high.
- The best results were obtained with a small number of ants for the reconfiguration problem (1 ant for each load section included in the search space) and a higher number of ants for the compensation problem (2 ants for each node from the search space). Power loss values less than 100 kW were obtained only for these settings.

# 4. CONCLUSIONS

This paper presented a new approach to the problem of loss reduction in distribution systems through network reconfiguration and reactive power compensation. The proposed method used an optimization technique that applies an Ant Colony Algorithm to search for an optimal or suboptimal configuration of the power distribution network and a corresponding placement and settings of switched capacitors that minimizes the power losses.

The results describe power losses in a real distribution network. Power losses values are presented for the basic non-compensated configuration and the reconfigured compensated solutions generated by the AC algorithm. Also, the optimal settings for the algorithm's parameters are determined (low evaporation rate and pheromone trail intensity corrections).

#### References

- [1] Gavrilaş M., Filimon N. Tendinţe moderne în distribuţia energiei electrice, Editura Agir, Bucureşti, 2001, pp.124-127
- [2] Y.Y. Hsu, J.L. Chen Distribution Planning Using A Knowledge-Based Expert System; IEEE Trans. On Power Delivery, vol. 5, no.3 July 1990, pp. 1514-1519.
- [3] T. Rajakandhan, A.S. Meyer, B. Dwolatzky Smart Maps Streamline Distribution Design; IEEE Computer Applications In Power; vol.11, no.1, Jan. 1998, pp.48-53.
  - [4] Dorigo M, Stutzle T. Ant Colony Optimization; The MIT Press, 2004
- [5] Kwang Y. Lee, John G. Vlachogiannis Optimization of Power Systems based on Ant Colony System Algorithms: An Overview, Proceedings of the 13th International Conference on Intelligent Systems Application to Power Systems, Nov. 6-10, 2005, pp 22-35

#### Authors' contact information:

- O. Ivanov is with the Technical University of Iasi, Bd. D. Mangeron, nr. 51-53, Iasi, 700050, Romania (phone 402-32-237627; fax 402-32-237627; e-mail: ovidiuivanov@ee.tuiasi.ro).
- M. Gavrilas is with the Technical University of Iasi, Romania (mgavril@ee.tuiasi.ro).
- C. V. Sfintes is with Eximprod S.A. Buzău, Romania (e-mail: <u>calin.sfintes@eximprod.ro</u>).