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Capacitor Placement for Economical Electrical Systems using Ant Colony Search Algorithm

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Abstract— **The optimal capacitor placement problem involves determination of the location, number, type and sizes of capacitor to be placed in a distribution system in the most efficient manner. The main objective of optimal capacitor allocation is to reduce the peak power losses of the system while striving to minimize the cost of the capacitors in the system. This paper describes an approach to minimize the active losses in electrical distribution systems with the help of the optimal capacitor bank placement. Ant Colony Optimization (ACO) technique along with the gradient method is employed in order to have the perfect placement of the Capacitor Banks. We have used the gradient method along with the metaheuristic so as to accelerate the convergence of the ACO algorithm. The optimization algorithm described here has been applied successfully in two real systems. Results obtained by simulation of real systems, are presented to validate the proposed solution method.**

Key Words — **ACO metaheuristic, Capacitor Placement, Algorithm**

I. INTRODUCTION

The complex social behaviors of insects have been intensively studied in science and in research of computer technology. The attempt is to develop algorithms inspired by insect behavior to solve optimization problems. These behavior patterns can offer models for solving difficult combinatorial (distributed) optimization problems. Real ants which can indirectly communicate by pheromone information without using visual cues are able of finding the shortest path between food sources and their nest. Artificial ants imitate the behavior of real ants how they forage the food [1], but can solve much more complicated problem than real ants can. One of search algorithms with such concept is Ant Colony Optimization (ACO) [3]. Ant algorithm has been inspired by the behavior of real ant colonies, in particular, by their foraging behavior. ACO has been widely applied to solving various combinatorial optimizations problems such as Travelling Salesman Problem (TSP) [2, 4, 5], Quadratic.

Assignment Problem (QAP) [3], Weapon-Target Assignment problems (WTA) [16, 17], etc. Since 1970s, researchers are working towards the goal of producing computational methods in order to optimize power systems. In the late 80s and early 90s, work oriented to distribution systems became more common, after the emergence of efficient computational methods, such as, the power summation load flow method [1] used for simulating electricity distribution radial systems. At that time, also began to emerge general purpose heuristics, called metaheuristics, applied successfully in many optimization problems. For capacitor placement optimization, it is emphasized the Tabu Search [2], [3], Genetic Algorithms [4], [5] and Ant Colony [6], [7], [8], due to the frequency with which they are addressed in technical literature and survey.

The capacitor placement problem consist of finding places to install capacitor bank in an electrical distribution network aiming to reduce losses due to the compensation of the reactive component of power flow. The capacitor placement is hard to solve in sense of global optimization due to the high non linear and mixed integer problem.

The current work presented here helps in the minimization of the active losses in distribution systems, with the help of placement of capacitor banks. In [9], the solution of this problem was formulated by the gradient method combined with a clustering algorithm that, may be fast, but does not guarantee to find the global optimized solution. The algorithm proposed here combines the gradient method with the ACO metaheuristic. The gradient vector provides a measure of the impact caused by the injection of reactive power losses in the system. The metaheuristic uses this measure to guide and accelerate the search. The final result is a method which is able to find the global optimum solution very easily.

This paper is organized as follows. Section II describes the problem of optimal capacitor placement. In Section III, it presents a brief introduction to the ACO metaheuristic. In Sections IV and V, it describes the proposed ACO algorithm for capacitor bank placement. In Section VI, it shows the various experimental results of the proposed algorithm. Finally, it presents the conclusions in Section VII.

II. PROBLEM FORMULATION

Capacitor placement problem basically determines the location and sizes of capacitors in order to minimizing the active losses. An Alternate, application can be correction of the power factor, increase the capacity of transmission lines. In this work, the function to be optimized is defined as the total active losses of the system. In the form of the mathematical equation the problem can be written as:

Reduce $L_t = \sum L_i$ where i ranges from 1 to n

………………1

where n is the number of lines and Li is the active losses in line i.

III. Ant Colony Optimization

A. Basic ACO

Initially ants wander randomly, and upon finding food source return to their colony while laying down a pheromone trails. During the return trip, the quantity of pheromone that an ant leaves on the ground may depend on the quantity and quality of the food. When other ants find such a path, they are likely to follow the trail, rather than keep travelling at random.

On the passage of some time, the pheromone trail starts to evaporate, which reduces its attractive strength. If an ant takes more time to travel down and come back to colony, it gives more time to pheromones to evaporate. A shortest path, by comparison, gets marched over more frequently, and thus the pheromone density grows heavily on shortest path as compared to the other longer paths. With the help of the pheromone evaporation convergence to a locally optimized solution can be converged which is the main advantage of pheromone evaporation. This makes the ACO algorithm more accurate in finding the shortest and the most reliable path for the journey. If there were no evaporation at all, the paths chosen by the first ants would tend to be excessively attractive to the following ones. In that case, the exploration of the solution space would be constrained.

So when one ant finds a good or shortest path from the colony to a food source, other ants are more likely to follow that path, and this positive feedback eventually leads all the ants following a single path. The idea of the ant colony algorithm is to mimic this behavior with "simulated ants" walking around the graph which represents a method to solve a given problem.

B. Basic ACO Methodology

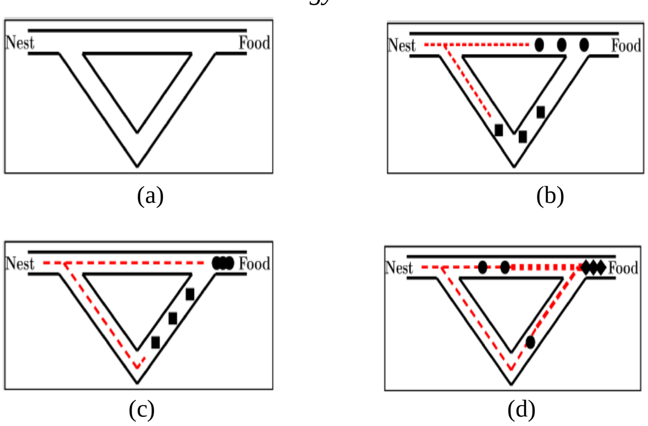

Figure 1 – Natural ACO

1. In Figure 1 (a), initially all ants are in the Nest. There is no pheromone in the environment.
2. In Figure 1 (b) the foraging starts. 50% of the ants take the short path (symbolized by circles), and 50% of the ants take the long path to the food source(symbolized rhombus).
3. As shown in figure 1 (c), the ants that have taken short path have arrived earlier than the ants which followed the longer path.. So while returning the probability to take short path is higher.
4. As shown in figure 1 (d), the pheromone trail on the short path receives in probability a stronger reinforcement and thus the probability to follow this path grows.
5. Finally due to the evaporation of the pheromone on the longer path, the whole colony will, in probability, use the short path.

C. ACO metaheuristic Algorithm

ACO metaheuristic is briefly described in this section. Further details can be found in [10].

In nature, after finding the food source an ant returns to its nest or colony. Ant leaves a trail of pheromone (a chemical) between the food source and its colony. If other ants manage to find this trail, they will be attracted by the pheromone as it is attractive in nature. So the other ants will mostly follow the same path with some probability. As a result these new ants reinforce the pheromone trail. Future ants choose to follow the same trail with higher probability, due to the increase in the percentage of pheromone on the trail. The final result is a strong pheromone scent on the trail connecting the colony to the food source, which attract even more ants. The ACO metaheuristic algorithm mimics this behavior of ants to build the solution of search and optimization problems.

```
1: initialize
2: while termination condition not met do
3: for all ant k do
4: repeat
5: add a bank to a node for ant k by rule of Eq. (3)
6: until there is no more improvement in Lt(k) , Eq.(1)
7: compute Lt(k) by Eq.(1)
8: if Lt(k)  < L* then
9: x* = x(k)
10: L* = Lt(k)
11: end if
12: end for
13: update the pheromone by Eq. (5) and (6)
14: end while
15: return x* (the best solution found)
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Figure 2 – ACO Algorithm

Artificial ants basically implement constructive algorithms. Generally, these algorithms start with a partial solution. With the help of step by step addition of a component (e.g., capacitors banks) to this partial solution, the algorithm builds a complete solution. At each step, the ant takes a decision which is probabilistic in nature, for the choice of the next component (capacitor bank) to be **a**dded to partial solution. This decision depends on two types of information:

1. The pheromone percentage which represents the desirability of a solution component.
2. The heuristic information which represents a prior information about the problem statement.

As soon as artificial ant builds a solution (finds a path), it deposits pheromones on the path that lead the ant to the final solution. The amount of the pheromone deposited depends on the nature and quality of the food source. This procedure is repeated until it satisfies some predetermined criteria.

IV. THE PROPOSED APPROACH

This section describes the proposed algorithm for the efficient capacitor placement.

A. Representation of Solution

A solution for the capacitor placement problem statement is represented by a vector x of size n. The component x_i of the vector x represents the number of capacitor banks in node i of the system (e.g., if there are Seven capacitor banks in node i, then $x_i = 7$).

B. Constructing the Solution

Artificial ant builds a solution in a step by step manner. In each step, artificial ant selects a node where the capacitor bank is to be deposited and add a capacitor bank to this selected node. The ant stops addition of capacitor banks to the nodes, when there is no more improvement in the objective function value.

In the current work, ACO metaheuristic uses a probabilistic rule involving pheromone and heuristic information for the selection of the node in order to add capacitor bank. More specifically, an ant k with $x_j^{(k)}$ capacitor banks in node j, has probability p_j of selecting the node j. The value p_j is calculated by the following equation:

$$P_j^{(k)} = \frac{(\Gamma_{j,zj})^{\alpha} (\eta_j)^{\beta}}{\sum^{n}_{w=1} (\Gamma_{i,zw})^{\alpha} (\eta_w)^{\beta}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 2$$

where

Γ is the performance matrix.

η_j is the heuristic information associated with node j.

α and β are the scaling factors defined by user.

z_j refers to the next bank to be added.

C. The Pheromone

The pheromone τ is a n × 7 matrix. The row i of the matrix refer to node i and the column j refer to the number of capacitor banks in each node. The maximum number of capacitor banks in a node is limited to the seven banks. The matrix element τ_{ij} is a pheromone level representing the desirability of adding the jth capacitor bank to the node i.

D. Heuristic Information

The Heuristic Information is denoted as η_j and it represents the desirability of adding a capacitor bank of the node j. In the current work, η_j is defined as jth component of gradient vector

η_j helps to provide a measure of the impact caused by the injection of reactive power losses in the system.

With the help of a mathematical equation η_j can be written as:

$$\eta_j = \frac{\delta L_t}{\delta Qc_{,i}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3$$

here $\delta Qc_{,j}$ is the capacitive reactive power at node j.

E. Updating status of Pheromone Trails

After the completion of tasks of all the artificial ants, the pheromone trail needs to be updated. There are two important events which affects this process, the evaporation of pheromone and the deposition of pheromone.

Evaporation reduces the level of pheromone in the pheromone matrix г as follows:

$$\Gamma_{ij} = (1 - \rho) \Gamma_{ij} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 4$$

for i = 1 to 7 and j = 1 to n. Γ is the pheromone evaporation rate, whose value ranges in between 0 to 1. The evaporation process avoids the pheromone level to grow rapidly. Thus it avoids convergence to suboptimal solutions.

After the evaporation process, pheromone deposition process continues. During the deposition process the pheromone matrix is updated as per the following equation:

$$\Gamma_{ij} = \Gamma_{ij} + \sum \Delta г_{ij}^{(k)} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 5$$

Here k is the constant which takes values from 0 to m.(m is the ant population)

for i = 1 to 7 and j = 1to n, the term $\Delta г_{ij}^{(k)}$ is the amount of pheromone that the ant k deposits on the element Γ_{ij}.

V. IMPLEMENTATION PF THE PROPOSED APPROACH

In the case of analytical method the computation of the, Eq. (1), demands the expensive analysis of a power flow. But the ACO algorithm requires a computation of the objective function in each simple step of the solution formation. As a result, much processing time would be needed to run the ACO algorithm. In the current work in order to reduce the processing time, it was implemented a memory to save the N last power flow computations. This approach significantly reduced the processing time.

VI. EXPERIMENTAL ANALYSIS

To analyze the performance of the algorithm proposed here we have used two distributed real time systems.

1. System I - 55 nodes with total load of 2.5 MVA;
2. System II - 27 nodes with total load of 1.4 MVA;

The proposed ACO algorithm uses populations of 55 and 27 ants, respectively, and a maximum of 25 iterations. For computation of power flow, we have used the algorithm given in [1].

Table 1 – Active Losses for different systems

	Initial State	100kVAr	200kVAr	300kVAr
System 1	0.6793	0.5743	0.6791	0.6795
System 2	4.3017	3.5361	3.6223	4.3027

Second column of Table 1, shows the value of total losses for the initial configuration without the addition of the capacitor banks. The last three columns indicates the resultant losses obtained by proposed ACO algorithm using units of capacitor banks of 100, 200, and 300 kVAr, respectively.

Table 2 – Capacitor Banks Added

	100kVAr	200kVAr	300kVAr
System 1	1	0	0
System 2	3	1	0

Table 2 specifies the number of capacitor banks added in each system. From the results it can be said that the ACO algorithm worked perfectly in its task of placement as it has not added capacitors of 200 MVA and 300 MVA to the system 1, since these capacitors have high powers for the system 1 and its addition would lead to the increase in the losses.

Table 3 – Iterations for the optimal solution

	100kVAr	200kVAr	300kVAr
System 1	7	0	0
System 2	5	1	0

In Table 3, shows the number of iterations performed by the proposed ACO algorithm for obtaining the optimal solution. While the simulation, in all the cases, the best solution was found with few iterations only.

Table 4 – Gradient influence to the result

	With Heuristic	Without Heuristic
System 1	22	31
System 2	11	17

In Table 4 specifies a different experimental study results to know the influence of the gradient. In this study we have used heuristic information of the ACO algorithm, as per the according to Equation 3. The algorithm was applied to the systems using two different methods: with information heuristic and without information heuristic. Table 4 shows the number of iterations to find the optimal solution. While using the heuristic information the number of iterations is less in both the cases.

VII. CONCLUSION

The ACO metaheuristic algorithm is proved to be efficient to find the optimal solution in the capacitor placement problems studied in this work. The proposed algorithm described here, which uses the gradient vector as heuristic information to the colony of artificial ants, was effective, efficient and promising in the experiments studied here. Also in this current work the ACO approach is implemented with innovations like method of finding solution and the use of the pheromone matrix.

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