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ANT COLONY ALGORITHM APPLICATION IN ECONOMIC LOAD DISTRIBUTION

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Abstract- In this paper we try to introduce the Ant Colony Optimization (ACO) and its application in Economic Dispatch ED). In the step one we present theory and performance of ant colony and its history and its application in various applications and how work the ant colony algorithm. In step two we present ant colony optimization include Basic Concept, Ant Searching Behavior, Path Retracing and Pheromone Updating, Pheromone Trail Evaporation, and in the overall view we present theory of Ant Colony completely. In step three we present general Ant Colony Algorithm step by step for solving any problem, but each problem will have specific formulation. In step four we have "Economic Dispatch Problem Formulation" that we present how this formulation for ED problems do, so by study this section you can do ED problem with Ant Colony Optimization and expand it for big problems. In step five we have present of simple ED problem and it's simulating and comparing with Genetic Algorithm result and Lagrangian method result with Matlab programing tool that this program presented in this paper attachment. To end we have "Conclusion" and references that can be useful for more study about ACO.

Keywords: Ant Colony Optimization (ACO), Economic Dispatch (ED), Optimization Algorithms.

I. INTRODUCTION

Optimization problems are of high importance both for the industrial world as well as for the scientific world. Examples of practical optimization problems include train scheduling, time tabling, shape optimization, telecommunication network design, power systems or problems from computational biology [2]. Ant Colony Optimization (ACO) is one of met heuristic and evolutionary approaches to find the optimal solutions of the combinatorial or binary search problems [2].

ACO was first developed by Dorigo et al. inspired by ant colonies. In ACO, artificial ants search for good solutions in a cooperative way. Artificial ants move randomly along paths and deposit chemical substance trails, called pheromone, on the ground when they move, then collect and store information in pheromone trails. This pheromone trails motivates them to follow the path and can choose the shortest path in their movement. The ACO method has been researched in various aspects and successfully applied to the various optimization problems [1, 2]. Conventional ACO shows reasonable performance for small problems with moderate dimensions and searching space. However, Conventional ACO is recognized as not suitable for large scale problems such as unit commitment (UC) problem, because the size of pheromone matrix grows exponentially along with the problem size, so to solve complex problems using a method called novel binary ant colony optimization (NBACO) method [5, 6].

II. ANT COLONY OPTIMIZATION

A. Basic Concept

Ant colony optimization is based on the cooperative behavior of real ant colonies, which are able to find the shortest path from their nest to a food source. The ant colony optimization process can be explained by representing the optimization problem as a multi-layered graph as shown in Figure 1, where the number of layers is equal to the number of design variables and the number of nodes in a particular layer is equal to the number of discrete values permitted for the corresponding design variable. Thus each node is associated with a permissible discrete value of a design variable. Figure 1 denotes a problem with six design variables with eight permissible discrete values for each design variable [1].

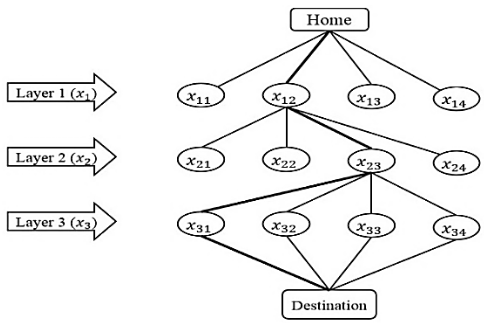

Figure 1. Graphical representation of the ACO process in the form of a multi-layered network [1]

The ACO process can be explained as follows. Let the colony consist of N ants [2, 10]. The ants start at the home node, travel through the various layers from the first layer to the last or final layer, and end at the destination node in each cycle or iteration. Each ant can select only one node in each layer in accordance with the state transition rule given by Equation (1). The nodes selected along the path visited by an ant represent a candidate solution. For example, a typical path visited by an ant is shown by thick lines in Figure 1. This path represents the solution (x_{12}, x_{23}, x_{31}). Once the path is complete, the ant deposits some pheromone on the path based on the local updating rule given by Equation (2). When all the ants complete their paths, the pheromones on the globally best path are updated using the global updating rule described by Equations (1) and (2) [2, 10].

In the beginning of the optimization process (i.e., in iteration 1), all the edges or rays are initialized with an equal amount of pheromone. As such, in iteration 1, all the ants start from the home node and end at the destination node by randomly selecting a node in each layer. The optimization process is terminated if either the pre-specified maximum number of iterations is reached or no better solution is found in a pre-specified number of successive cycles or iterations. The values of the design variables denoted by the nodes on the path with largest amount of pheromone are considered as the components of the optimum solution vector. In general, at the optimum solution, all ants travel along the same best (converged) path [2, 10, 12, 13].

B. Ant Searching Behavior

An ant k, when located at node i, uses the pheromone trail τ_{ij} to compute the probability of choosing j as the next node:

$$p_{ij}^{(k)} = \begin{cases} \dfrac{\tau_{ij}^{\alpha}}{\sum_{j \in N_i^{(k)}} \tau_{ij}^{\alpha}} & \text{if} \quad j \notin N_i^{(k)} \\ 0 & \text{if} \quad j \notin N_i^{(k)} \end{cases} \tag{1}$$

where α denotes the degree of importance of the pheromones and $N_i^{(k)}$ indicates the set of neighborhood nodes of ant k when located at node i. The neighborhood of node i contains all the nodes directly connected to node i except the predecessor node (i.e., the last node visited before i). This will prevent the ant from returning to the same node visited immediately before node i. An ant travels from node to node until it reaches the destination (food) node [10].

C. Path Retracing and Pheromone Updating

Before returning to the home node (backward node), the kth ant deposits $\Delta\tau^{(k)}$ of pheromone on arcs it has visited. The pheromone value τ_{ij} on the arc (i, j) traversed is updated as follows:

$$\tau_{ij} \leftarrow \tau_{ij} + \Delta\tau_{ij} \tag{2}$$

Because of the increase in the pheromone, the probability of this arc being selected by the forthcoming ants will increase [10].

D. Pheromone Trail Evaporation

When an ant k moves to the next node, the pheromone evaporates from all the arcs ij according to the relation:

$$\tau_{ij} \leftarrow (1-\rho)\tau_{ij} \; ; \; \forall (i, j) \in A \tag{3}$$

where $\rho \in (0, 1]$ is a parameter and A denotes the segments or arcs travelled by ant k in its path from home to destination. The decrease in pheromone intensity favors the exploration of different paths during the search process. This favors the elimination of poor choices made in the path selection. This also helps in bounding the maximum value attained by the pheromone trails. An iteration is a complete cycle involving ant's movement, pheromone evaporation and pheromone deposit.

After all the ants return to the home node (nest), the pheromone information is updated according to relation:

$$\tau_{ij} = (1-\rho)\tau_{ij} + \sum_{k=1}^{N} \Delta\tau_{ij}^{(k)} \tag{4}$$

where $\rho \in (0, 1]$ the evaporation is rate (also known as the pheromone decay factor) and $\Delta\tau_{ij}^{(k)}$ is the amount of pheromone deposited on arc ij by the best ant k. The goal of pheromone update is to increase the pheromone value associated with good or promising paths. The pheromone deposited on arc ij by the best ant is taken as:

$$\Delta\tau_{ij}^{(k)} = Q / L_k \tag{5}$$

where Q is a constant and L_k is the length of the path traveled by the kth ant (in the case of the travel from one city to another in a traveling salesman problem). Equation (5) can be implemented as:

$$\Delta\tau_{ij}^{(k)} = \begin{cases} \dfrac{\zeta f_{best}}{f_{worst}} & \text{if} \quad (i, j) \in \text{Global Best Tour} \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

where f_{worst} is the worst value and f_{best} is the best value of the objective function among the paths taken by the N ants, and ζ is a parameter used to control the scale of the global updating of the pheromone. The larger the value of ζ, the more pheromone deposited on the global best path, and the better the exploitation ability. The aim of Equation (6) is to provide a greater amount of pheromone to the tours (solutions) with better objective function values [1, 2, 10].

III. ACO ALGORITHM

The steps of procedure of ACO algorithm for solving a minimization problem can be summarized as follows:

• Step1: Assume a suitable number of ants in the colony (N). Assume a set of permissible discrete values for each of the n design variables. Denote the permissible discrete values of design variable x_i as x_{i1}, x_{i2}… x_{ip} ; i=1, 2,…, n. Assume equal amounts of pheromone τ_{ij}^{l} initially along all the arcs or rays (discrete values of design variables) of the multilayered graph shown in Figure 1. The superscript to τ_{ij} denote the iteration number. For simplicity $\tau_{ij}^{l}=1$ can be assumed for all arcs ij. Set the iteration number $l = 1$ [1, 2, 10].

• Step 2:

a. Compute the probability p_{ij} of selecting the arc or ray (or the discrete value) x_{ij} as:

$$p_{ij} = \frac{\tau_{ij}^{(l)}}{\sum_{m=1}^{p} \tau_{im}^{(l)}} \quad ; \quad i = 1,2,...,n \ , \ j = 1,2,..., p \qquad (7)$$

which can be seen to be same as Equation (1) with α=1. A larger value can also be used for α.

b. The specific path (or discrete values) chosen by the kth ant can be determined using random numbers generated in the range (0, 1). For this, we find the cumulative probability ranges associated with different paths of Figure 1 based on the probabilities given by Equation (7). The specific path chosen by ant k will be determined using the roulette-wheel selection process in step 3a [1, 2, 10, 12, 13].

• Step 3:

a. Generate N random numbers r_1, $r_2 \ldots r_N$ in the range (0, 1), one for each ant. Determine the discrete value or path assumed by ant k for variable i as the one for which the cumulative probability range (found in step 2b includes the value r_i [1, 2, 10].

b. Repeat step 3a for all design variables i=1, 2… N.

c. Evaluate the objective function values corresponding to the complete paths (design vectors X^k or values of x_{ij} chosen for all design variables i=1, 2…N by ant k, i=1, 2… N.

$$f_k = f(X^{(k)}) \quad ; \quad k = 1,2,..., N \qquad (8)$$

Determine the best and worst paths among the N paths chosen by different ants:

$$f_{best} = \min\{ f_k ; k = 1,2,..., N\} \qquad (9)$$

$$f_{worst} = \max\{ f_k ; k = 1,2,..., N\} \qquad (10)$$

• Step 4: Test for the convergence of the process. The process is assumed to have converged if all N ants take the same best path. If convergence is not achieved, assume that all the ants return home and start again in search of food. Set the new iteration number as $l = l + 1$, and update the pheromones on different arcs (or discrete values of design variables) as:

$$\tau_{ij}^{(l)} = \tau_{ij}^{(old)} + \sum_{k} \Delta \tau_{ij}^{(k)} \qquad (11)$$

where $\tau_{ij}^{(old)}$ denotes pheromone amount of the previous iteration left after evaporation, which is taken as:

$$\tau_{ij}^{(old)} = (1-\rho)\tau_{ij}^{l-1} \qquad (12)$$

and $\Delta\tau_{ij}^{(k)}$ is the pheromone deposited by the best ant k on its path and the summation extends over all the best ants k (if multiple ants take the same best path). Note that the best path involves only one arc ij (out of p possible arcs) for the design variable i. The evaporation rate or pheromone decay factor ρ is assumed to be in the range 0.5 to 0.8 and the pheromone deposited $\Delta\tau_{ij}^{(k)}$ is computed using Equation (6) [1, 2, 10].

With the new values of $\tau_{ij}^{(l)}$, go to step 2. The steps 2, 3, and 4 are repeated until the process converges, that is, until all the ants choose the same best path. In some cases, the iterative process is stopped after completing a pre specified maximum number of iterations ($l_{\max}$). To better study of algorithm steps Figure 2 can be useful [1, 2, 10, 12, 13].

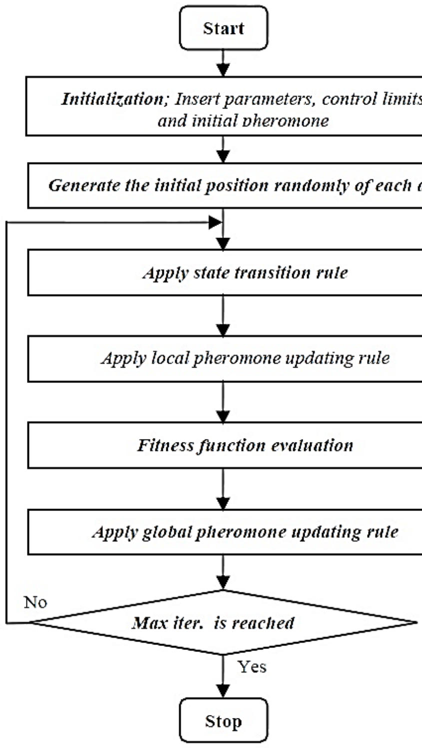

Figure 2. Flowchart of proposed algorithm [10]

IV. ECONOMIC DISPATCH PROBLEM FORMULATION

Economic Dispatch problem can be solved by minimizing the cost of generation in the system. The solution gives the optimal generation output of the online generating units that satisfy the system's power balance equation under various system and operational constraints. The Economic Dispatch problem can be formulated mathematically as follows:

A. Objective Function

The objective function for this action is same as follow:

$$\text{minimize} \quad Cost = \sum_{i=1}^{N} F_i(P_{Gi}) \qquad (13)$$

where $Cost$ is the operating cost of power system, N is the number of units, $F_i(P_{Gi})$ is the cost function and P_{Gi} is the power output of the unit i. The $F_i(P_{Gi})$ is usually approximated by a quadratic function of its power output P_{Gi} as:

$$F_i(P_{Gi}) = a_i P_i^2 + b_i P_i + c_i \qquad (14)$$

where a_i, b_i and c_i are the cost coefficients of unit i. Wire drawing effects occurs when each steam admission valve in a turbine starts to open, and at the same time a rippling effect on the unit curve is produced. To model the effects of valve points, a recurring rectified sinusoid contribution is added to the cost function. The result is:

$$F_i(P_{Gi}) = a_i P_i^2 + b_i P_i + c_i + g_i \sin(h_i(P_{i-}P_i^{\min})) \qquad (15)$$

where g_i and h_i are the valve points coefficients. $P_i^{\min}$ is the lower generation limit of unit i. Neglecting valve point effects, some inaccuracy would be introduced into the resulting dispatch [11, 12, 13].

B. Constraint Equations

1. Unit operation constraints are given by:

$$P_i^{\min} \le P_i \le P_i^{\max} \quad ; \quad i = 1,2,...,N \tag{16}$$

where $P_i^{\min}$ and $P_i^{\max}$ are the lower and upper generation limit of unit *i*.

2. Power balance equation:

$$\sum_{i=1}^{N} P_i = P_D + P_{loss} \tag{17}$$

where P_D is the demand and P_L is transmission loss. The transmission loss can be calculated by the *B*-coefficients method or power flows analysis. *B*-coefficients used in the power system is:

$$P_L = P^T B P + P^T B_0 + B_{00} \tag{18}$$

where *P* is a-dimensional column vector of the power output of the units.

3. Line flow constraints:

$$\left| Lf_i \right| \le Lf_i^{\max} \quad ; \quad i = 1,2,...,N_L \tag{19}$$

where Lf_i is the line flow MW, $Lf_i^{\max}$ is the allowable maximum flow of line *i* (line capacity), and N_L is number of transmission lines subject to line capacity constraints.

4. System stability constraints:

$$\left| \partial_i - \partial_j \right| \le \partial_{ij}^{\max} \quad ; \quad i,j = 1,2,...,N_D \tag{20}$$

where ∂_i, ∂_j are voltage angle of bus *i* and *j*. The $\partial_{ij}^{\max}$ is the allowable maximum voltage angle [11, 12, 13].

5. ACO based ED solution:

The classic economic dispatch problem can be stated as:

$$\phi = \sum_{i=1}^{N} P_{Gi} - P_D - P_{loss} = 0 \tag{21}$$

Adding penalty factor h_1 to violation of power outputs, we can combine Equations (13) and (21) as below:

$$F_A = \sum_{i=1}^{N} F_i(P_{Gi}) + h_1 \sum_{i=1}^{N} (P_{Gi} - P_D - P_{loss})^2 \tag{22}$$

The value of the penalty factor should be large so that there is no violation for unit output at the final solution. Since ACO is designed for the solution of minimization problems, the ACO fitness function is defined same as Equation (22):

$$F_{fitness} = F_A \tag{23}$$

In the economic dispatch problem, the problem variables correspond to the power generations of the units. So we start simulation recently presented subject [5-7, 3, 11-13].

V. SIMULATION AND RESULTS

We assume a system that has 2 power generators which fuel cost functions by $/h is as follow:

$$F_1 = 500 + 5.3P_1 + 0.004P_1^2$$
$$F_2 = 500 + 5.3P_2 + 0.006P_2^2 \tag{24}$$

The powers are determined by MW and total load is 600MW which the losses and other constraints are neglected. Generators constraints (by MW) are as follow:

$$200 \le P_1 \le 450 \quad ; \quad 200 \le P_2 \le 450 \tag{25}$$

In this paper we use Matlab software programing tool for write a program based ACO for solve this simple problem. The results are as follow:

$$P_1 = 374.6425 \text{ MW} \quad ; \quad P_2 = 225.3525 \text{ MW} \tag{26}$$

and the optimum fuel cost is equal to 4991.2 $/h. The distribution of ants position, Initial random distribution of the ants and the convergence of the algorithm iterations are shown in Figures 3, 4 and 5.

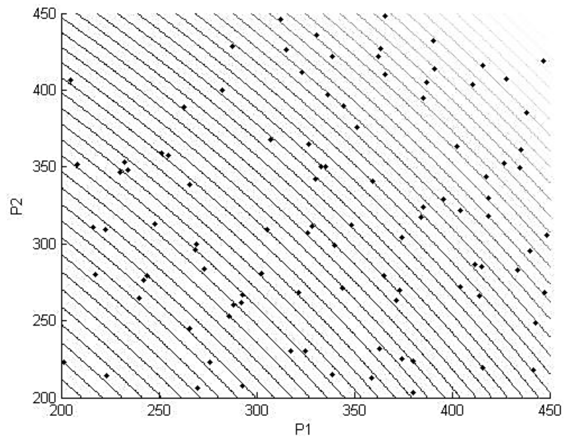

Figure 3. Distribution of ants position after algorithm end

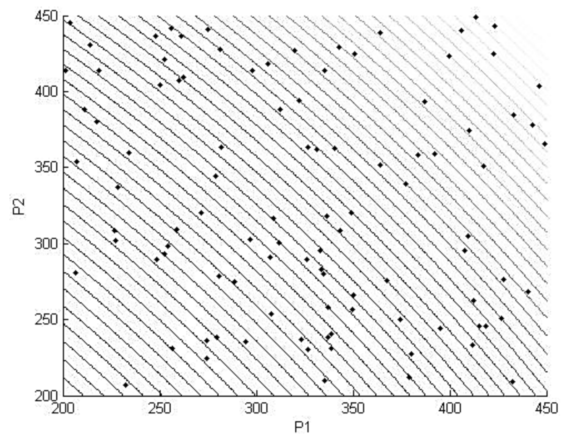

Figure 4. Initial random distribution of the ants

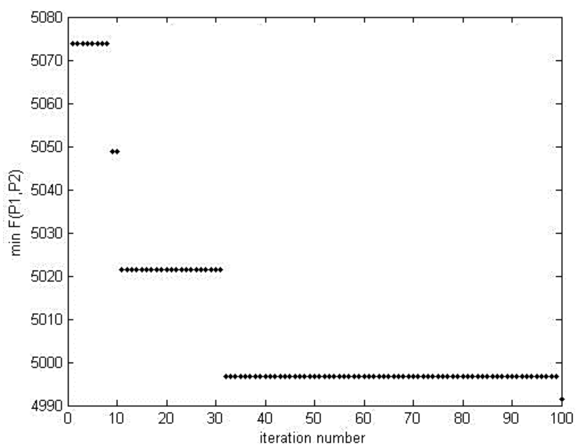

Figure 5. Demonstrate how the convergence of the algorithm iterations

The comparison results of ant colony algorithm and genetic algorithm and Lagrangian method for three methods are shown as Table 1.

Table 1. Results of three algorithms for solving assumed economic dispatch [4]

Parameters	ACO	GA	Lagrangian	P_{load} (MW)
P_1 (MW)	374.6425	369.7192	370	600
P_2 (MW)	225.3525	230.2808	230	600
Cost ($/h)	4991.2	4991	4991	600

For solving this problem we use ρ = 0.6, ζ = 10 that experimentally obtained by trial and error. For understand about ρ and ζ go to step two of this paper. But note that the value of above parameters is very important to convergent algorithm.

Note that the ant colony algorithm is probabilistic and might we can't obtain the best result in first run of program, so for obtain best result we should run program for some time and if need, change parameters of ant colony algorithm and try again [2-6].

VI. CONCLUSIONS

Thus, by comparing three results of three algorithms for Economic Dispatch problem we can see Ant Colony Algorithm will have good performance and accuracy if we choose parameters appropriate, so again note that in the ACO algorithm parameters of ρ and ζ is very important. The ant colony has many good properties for searching global optimization can include below items:

a. In the case of Economic dispatch, ACO is able to solve complicated, non-convex, nonlinear problems.

b. It achieves good convergence and provides accurate dispatch solutions in reasonable time.

c. The results show ACO is robust, accurate and efficient.

d. Further work is required for searching the neighborhood, and present more efficacious sufficient conditions for convergence.

The field of ACO algorithms is very lively, as testified for example by the successful biannual workshop, where researchers meet to discuss the properties of ACO and other ant algorithms, both theoretically and experimentally. From the theory side, researchers are trying either to extend the scope of existing theoretical results, or to find principled ways to set parameters values.

From the experimental side, most of the current research is in the direction of increasing the number of problems that are successfully solved by ACO algorithms, including real world, industrial applications.

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BIOGRAPHIES

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