Ant Colony Optimization (ACO) Technique in Economic Power Dispatch Problems

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Abstract—Most of electrical power utilities in the world are required to ensure that electrical energy requirement from the customer is served smoothly in accordance to the respective policy of the country. Despite serving the power demands of the country, the power utility has also to ensure that the electrical power is generated within minimal cost. Thus, the total demand must be appropriately shared among the generating units with an objective to minimize the total generation cost for the system in order to satisfy the economic operation of the system. Economic dispatch is a procedure to determine the electrical power to be generated by the committed generating units in a power system so that the total generation cost of the system is minimized, while satisfying the load demand simultaneously. This paper presents the economic power dispatch problems solved using Ant Colony Optimization (ACO) technique. ACO is a meta-heuristic approach for solving hard combinatorial optimization problems. In this study, the proposed technique was tested using the standard IEEE 26-Bus RTS and the results revealed that the proposed technique has the merit in achieving optimal solution for addressing the problems. Comparative studies with other optimization technique namely the artificial immune system (AIS) were also conducted in order to highlight the strength of the proposed technique.

Keywords – Ant Colony Optimization, economic dispatch, meta-heuristic, power systems, optimization.

I. INTRODUCTION

The main role of electrical power utility is to ensure that electrical energy requirement from the customer is served. However in doing so, the power utility has also to ensure that the electrical power is generated with minimum cost. Hence, for economic operation of the system, the total demand must be appropriately shared among the generating units with an objective to minimize the total generation cost for the system. Economic Dispatch is a procedure to determine the electrical power to be generated by the committed generating units in a power system so that the total generation cost of the system is minimized, while satisfying the load demand simultaneously. To address this problem, optimization is a *priori* in solving the cost minimization problems. Power system optimization is an important field in the operation, planning and control of power systems. Many modern heuristic techniques to the solution of complex power system optimization problems have been proposed, each differing in their method of representation, implementation and solution procedure [1]. Economic power dispatch is one of the fundamental problems in power system operation and planning [2]. It is defined as the process of allocating generation levels to the generating units so that the system load is supplied entirely and most economically [3]. It concerned on the minimization of an objective function, usually the total cost of generation, while satisfying both the equality and inequality constraints [4]. Depending on load variations, the output of generators has to be changed to meet the balance between loads and generation power to make the system efficient. Recently, a new global optimization techniques known as Ant Colony Optimization (ACO) has become a candidate for many optimization applications. The ACO has solved several combinatorial optimization traveling salesman (ATSP), quadratic assignment problem (QAP), optimal design and scheduling problem of thermal units [5]. ACO has been used to address various optimization problems as reported by [6-12]. This paper presents the application of Ant Colony Optimization (ACO) in solving economic power dispatch problems. The objective function is cost minimization considering loss of transmission implemented on a 6 generating unit system. Comparison was implemented using AIS.

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II. 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 systemǿs power balance equation under various system and operational constraints. The Economic Dispatch problem can be formulated mathematically as follows

A. Objective Function

$$minimize\ cost = \sum_{i}^{Ng} Fi(Pi) \quad (1)$$

where *cost* is the operating cost of power system. N_g is the number of units. $F_i(P_i)$ is the cost function and P_i is the power output of the unit *i*. $F_i(P_i)$ is usually approximated by a quadratic function of its power output P_i as:

$$Fi(Pi) = a_i P_i^2 + b_i P_i + c \quad (2)$$

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 ñvalve-pointsò, a recurring rectified sinusoid contribution is added to the cost function. The result is:

$$Fi(Pi) = a_i P_i^2 + b_i P_i + c + g_i \sin[h_i(P_i - P_i^{min})] \quad (3)$$

where g_i and h_i are the valve-points coefficients. P_i^{min} is the lower generation limit of unit i. Ignoring valve point effects, some inaccuracy would be introduced into the resulting dispatch [3].

B. Constraint Equations

1: Unit Operation Constraints are given by:

$$P_i^{\min} \le P_i \le P_i^{\max} \quad i = 1,2,\ldots, N_g \quad (4)$$

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

2: Power Balance equation:

$$\sum_{i=1}^{N_g} P_i = P_L + P_D \quad (5)$$

where P_D is the demand and P_L is transmission loss. The transmission loss can be calculated bye the B-coefficients method or power flows analysis.

B-coefficients used in the power system is:

$$P_L = P^T B P + P^T B_0 + B_{00} \quad (6)$$

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

3: Line flow constraints:

$$\left|Lf_i\right| \le Lf_i^{\max} \quad i=1,2,\text{é} \;..N_L \quad (7)$$

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

4: System stability constraints:

$$\left|\partial_i - \partial_j\right| \le \partial_{ij}^{max} \quad i,j=1,2,\ldots..ND \quad (8)$$

where ∂_i, ∂_j are voltage angle of bus i and j. ∂_{ij}^{max} is the allowable maximum voltage angle.

C. Solution Coding:

Let X_i = $(x_1,x_2,\ldots.,xN_g)$ be a vector denoting the i^{th} individual of the ant colony, where Ng is the number of units and X_i is the generated output of unit $_i$. At initialization phrase, X_i is selected randomly from the selected region S.

D. Objective Function and Feasible Region:

In order to minimize the objective function of ED the constraints have to be obeyed. Penalty function was used to transform those constraints which have difficulties to deal with in the feasible region including power balance, etc. The feasible region S is determined by the unit operation constraints.

E. Parameter Setting:

The parameter used here are $N=5$, $\tau_0 = 1.0$, $\gamma_1 = \lambda_2 = 1$, $\rho=0.6$, $q_0=0.6$.

III. ANT COLONY OPTIMIZATION TECHNIQUE

Ant Colony Optimization (ACO) was first developed by Dorigo *et al.* [5]. It is proposed as a viable new approach to stochastic combinatorial optimization. The idea is based on the following observation. A colony of ants is able to succeed in a task to find the shortest path between the nest and the food source. It was found that ants deposit a chemical substance trail, called *pheromone* on the ground when they move. This pheromone can be observed by other ants and motivates them to follow the path with a high probability. The following example shows how over time, the shortest paths are found through this self-reinforcing process.

In Fig. 1a, suppose that ants move between food source *A* and nest *E* on a straight line. Then, as shown in Fig. 1b, suddenly an obstacle appears and the path was cut off. At position *B*, ants have to decide whether to turn right or left. Under this situation, they may choose to turn right *(BCD)* or left *(BHD).* For all that, due to path *BCD* is shorter than *BHD*, the first ant following path *BCD* will reach *D* before the first ant following path *BHD*. So, a higher level of pheromone intensity on the right will give information to the followers as a higher probability to turn right, which is shown in Fig. 1c. For a while, the shorter path will collect larger amount of pheromone trail than the longer path. Therefore, more ants will be increasingly guided to move on the shorter path. The result is that, very soon all ants will choose the shortest path in their movement.

Like neural networks, ACO is based on biological research ï in this case is the research into the foraging behavior of ant colonies. While individual ants essentially move at random, ant colonies can be seen as a system of collaborating agents pursuing a common goal: finding the quickest path to a food source. Ants communicate with the aid of a chemical called pheromone in a process referred to a ñstigmergyò. Pheromones are produced by ants and they deposit them on trails when walking in search of food [1]. ACO is based on the indirect communication of a colony of simple agents, called (artificial) ants, mediated by (artificial) pheromone trails. The pheromone trails in ACO serve as distributed, numerical information, which the ants use to probabilistically construct solutions to the problem being solved, and which the ants adapt during the algorithmôs execution to reflect their search experience.

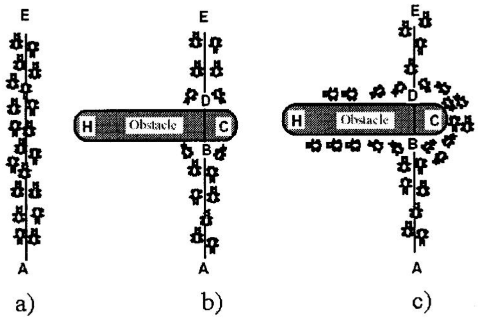

Fig. 1. Illustration of the real ant behavior.

IV. Ant Colony Optimization (ACO) Algorithm

ACO algorithm is inspired by the behaviour of real ant colonies used to solve combinatorial optimization problem [3]. The real ants lay down in some quantity an aromatic substance, known as pheromone, in their way to food. The pheromone quantity depends on the length of the path and the quality of the discovered food source. An ant chooses an exact path in connection with the intensity of the pheromone.

The pheromone trail evaporates over time if no more pheromone is laid down. Other ants are attracted to follow the pheromone trail. Therefore, the path will be marked again and it will attract more ants to use the same path. The pheromone trail on paths leading to rich food sources close to the nest be more frequented and will therefore grow faster. In this way, the best solution has more intensive pheromone and higher probability to be chosen. The described behaviour of real ant colonies can be used to solve combinatorial optimization problems by simulation: artificial ants searching the solution space by transiting from nodes to nodes. The artificial ants move usually associated with their previous action, stored in the memory with a specific data structure. The pheromone consistencies of all paths are updated only after the ant finished its tour from the first node to the last node. Every artificial ant has a constant amount of pheromone stored in it when the ant proceeds from the first node. The pheromone that stored in will be distributed average on the path after artificial ants finished its tour. The amount of pheromone will be high if artificial ants finished its tour with a good path. The pheromone of the routes progressively decreases by evaporation in order to avoid artificial ants stuck in local optima [8].

The overall steps of the ACO can be represented in the flow chart in Fig. 2. In this study, there is some modifications performed on the ACO algorithm in order to make it suitable for the application in power system. The following sections explain the ACO algorithms in detail.

Step 1: Initialization

In the beginning, the ACO parameters have to be specified during initialization process. The main difficulty with the ACO program is that; an appropriate choice of ACO control parameters is necessary before applying the ACO program. The choice of parameters has been obtained by trial and error. In order to get better result in the development of the ACOôs program; the parameters must be selected carefully.

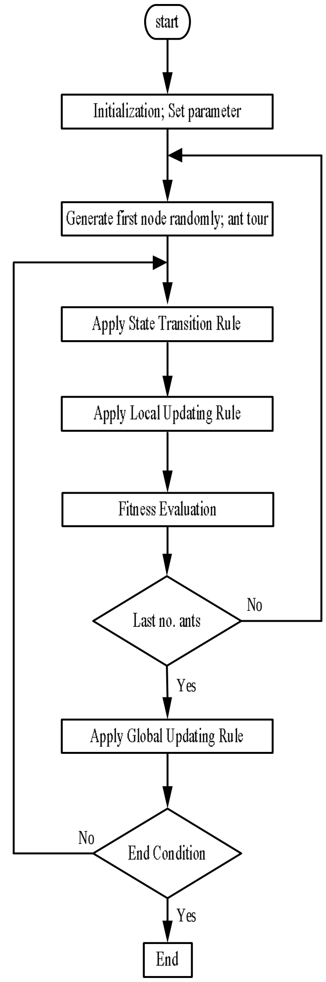

Fig. 2. Flow chart for ACO

On the other hand, every parameter requires to be set for limiting the search range in order to avoid large computation time. During initialization; the following parameters need to be initialized for the purpose of ACO implementation.

n : no. of nodes
m : no. of ants
t_{max} : maximum iteration
d_{max} : maximum distance for every ants tour
β : parameter, which determines the relative importance of pheromone versus distance ($\beta > 0$)
ρ : heuristically defined coefficient ($0 < \rho < 1$)
α : pheromone decay parameter ($0 < \alpha < 1$)
q_0 : parameter of the algorithm ($0 \le q_0 \le 1$)
τ_o : initial pheromone level

The maximum distance for every ants tour (d_{max}) can be calculated by using this formula:

$$d_{max} = \left[\sum_{i=1}^{n-1} d_i \right] \tag{9}$$

$$d_i = \left| r - \max(u) \right| \tag{10}$$

where:
r : current node
u : unvisited node
d_i : distance between two nodes

In order to determine d_{max}, every node in the list is required to be set as the first node. The node in the list can only be selected once for every tour of ant. Each ant will select the next node which has higher distance from the current node. This process will repeat until the end node in the list.

Step 2: Generate First Node

The first node will be selected by generating random number based on the uniform distribution, ranging from 1 to *n*.

Step 3: State Transition Rule

At each construction step, ant *k* applies a state transition rule in order to decide which node to be visited next. The ant *k,* which is currently positioned at current node (*r*) will move to the next node (*s*) by applying the state transition rule given by:-

$$s=\begin{cases} \arg\max_{u\varepsilon J_{k(r)}} \left\{ [\tau(r,u)][\eta(r,u)^{\beta}] \right\}, if\ q \le q_0\ (\exp loitation) \\ S,\ otherwise\ (biased\ \exp loration) \end{cases} \quad (11)$$

where:

- q : random number uniformly distributed in [0 to 1]
- q_0 : parameter of the algorithm ($0 \le q_0 \le 1$)
- S : random variable selected according to the probability distribution given in eq. (12)

The probability for an ant *k* at current node (*r*) to choose the next node (*s*) is calculated using the probability equation given by:-

$$P_k(r,s)=\begin{cases} \dfrac{[\tau(r,s)].[\eta(r,s)^{\beta}]}{\sum_{u\varepsilon J_{k(r)}}[\tau(r,u)].[\eta(r,u)^{\beta}]},\ if\ s\,\varepsilon\, J_{k(r)} \\ 0,\ otherwise \end{cases} \quad (12)$$

where:

- τ : pheromone
- $J_{k(r)}$: set of nodes that remain to be visited by ant *k* positioned on node (to make the solution feasible)
- β : parameter, which determines the relative importance of pheromone versus distance ($\beta > 0$)
- η : $1/d$, is the inverse of the distance $d(r,s)$

In equation (11) and (12) the pheromone on path $\tau(r,s)$ is multiplied by the heuristic value $\eta(r,s)$ in order to determine the selection of paths which are shorter and have a greater amount of pheromones. The parameter q_0 determines the relative importance of the exploitation versus exploration condition: an ant at node *r* (current node) has to choose a node *s* (next node) to move. This is determined by the value of *q* randomly where ($0 \le q \le 1$). If ($q \le q_0$) the best path will be determined based on equation (11), (i.e. in the exploitation mode). On the other hand, if (q Óq_0) the best path will be determined based on equation (12), (i.e. in the exploration mode). The process to determine the next node (*s*) starts by calculating the probability of choosing the next node using equation (12). After the calculation of probability, the value of *q* is then generated randomly. If ($q \le q_0$), node 4 was selected as next node (*s*) which has the highest probability (i.e. in the exploitation mode). On the other hand, if (q Ó q_0), the next node (*s*) will be selected randomly from the list of unvisited nodes (i.e. in the exploration mode).

Step 4: Local Updating Rule

Local updating rule is a process used to change the amount of pheromone to the visited paths during the construction of solution. The amount of pheromones can be updated based on the following equation:-

$$\tau(r,s) \text{ ũð } (1-\rho)\,\tau(r,s)+ \rho.\text{ɸ}\,\tau(r,s) \quad (13)$$

where:

- ρ = heuristically defined coefficient ($0 < \rho < 1$)
- $\Delta\ \tau(r,s) = \tau_o$
- τ_o = initial pheromone trail

This local updating rule will shuffle the tours, so that the early nodes in one antộs tour may be explored later in other antsô tours. The amount of pheromone on visited paths will be reduced so that the visited paths become less desirable and therefore will be chosen with lower probability by the other ants in the remaining steps of an iteration of the algorithm. When the new τ value is lower, the probabilities to select the same nodes also become lower.

Step 5: Fitness Evaluation

Fitness evaluation is performed after all ants have completed their tours. In this step, the control variable (*x*) is computed using the following equation:-

$$x=\frac{d}{d_{\max}}\times x_{\max} \quad (14)$$

where:

- d : distance for every ants tour
- $x_{\max}$: maximum x
- d_{max} : maximum distance for every ants tour

The values of variable *x* will be assigned for the fitness in the ACO algorithm.

Step 6: Global Updating Rule

Global updating rule is a process used to update the amount of pheromones generated by the ant which has constructed the shortest tour from the beginning of the tour. There will be only one ant is allowed to update the amount of pheromone which determines the best fitness. The amount of pheromones is updated after all ants have completed their tours by applying equation (15).

$$\tau(r,s) \text{ ũð } (1-\alpha)\,\tau(r,s)+ \alpha.\text{ɸ}\,\tau(r,s) \quad (15)$$

where:

$$\Delta(r,s)=\begin{cases} (L_{gb}),\ if\ (r,s)\,\varepsilon\ global-best-tour \\ 0,\ otherwise \end{cases}$$

- α : pheromone decay parameter ($0 < \alpha < 1$)
- L_{gb} : length of the globally best tour from the beginning of the tour

In this case, the paths belonged to the globally best tour (i.e. the best fitness) of current iteration will receive reinforcement. For the next iteration; the first node of globally best tour in the first iteration will be selected as first node by the each ant.

Step 7: End Condition

The algorithm stops the iteration when a maximum number of iterations (t_{max}) have been performed. Every tour that was visited by ants should be evaluated. If a better path is discovered in the process, it will be kept for the next reference. The best path selected between all iterations engages the optimal scheduling solution. As a consequence, ants never converge to common path. This is observed experimentally, and it is a desirable property. If ants explore different paths then there is a higher probability that one of them will find an improving solution. There are cases where solutions converge to same tour which would make the use the no. of ants (m) pointless.

V. RESULTS AND DISCUSSION

The results tabulated in Table I are obtained when the ACO parameter are set to the following values at the initialization process:

$n = 10$, $m = 5$, $t_{\max} = 5$, $d_{\max} = 49$, $\beta = 2$, $\alpha = 0.1$, $q_o=0.6$, $\rho = 0.6$ and $\tau_o= 1$.

The developed technique was employed to determine the economic dispatch for the IEEE 26-Bus RTS that has 6 generating units. The test was performed with bus 19 subjected to the load variation. The generatorŝ operating costs in \$/h, with P_i in MW are as follows [5]:

$$C_1 = 240 + 7.0P_1 + 0.0070P_1^2$$
$$C_2 = 200 + 10.0P_2 + 0.0095P_2^2$$
$$C_3 = 220 + 8.5P_3 + 0.0090P_3^2$$
$$C_4 = 200 + 11.0P_4 + 0.0090P_4^2$$
$$C_5 = 220 + 10.5P_5 + 0.0080P_5^2$$
$$C_{26} = 190 + 12.0P_{26} + 0.0075P_{26}^2$$

The total cost of generation is given by,

$$C_T = C_1 + C_2 + C_3 + C_4 + C_5 + C_{26}$$

In this study, C_T is taken as the fitness which was minimized during the optimization process. On the other hand, Table II tabulates the minimum generation cost obtained by ACO while varying the load (P_{load}) at a selected bus (i.e. bus 19) until it reaches the stability limit. The total loss increased accordingly as the load is increased. The constrains need to be considered are: $Vm \geq 0.95$ *p.u and* $Vm \leq 1.06$ *p.u.* and $T_{loss} \leq 20$. The developed ACO has successfully the generated power by each generating unit to minimize the total cost in the system. The minimization of total generation cost has also taken account the systemsô limits and constraints. Table II shows the minimum generation cost obtained by ACO while varying the load (P_{load}) at a selected bus (i.e. bus 19) until it reaches the stability limit. The total loss increased accordingly as the load is increased.

Table III tabulates the output power by all the generating units in the system with the optimized cost of \$15448.76 as highlighted in the table. In order to achieve this minimal cost, the amount of generating unit for each generator is given in the table.

TABLE I
GENERATING LIMIT OF GENERATING UNITS

Generating Unit	Minimum MW	Maximum MW
1	100	500
2	50	200
3	80	300
4	50	150
5	50	200
26	50	120

TABLE II
MINIMUM COST OF GENERATION WHILE VARYING THE LOAD AT BUS 19

Load at bus 19 (MW)	Load (MW)	Total Losses (MW)	Generated Power (MW)	Generation Cost (\$/h)
0	1199	10.9335	1209.934	14445.00
10	1209	11.1885	1220.189	15117.00
20	1219	11.4680	1230.468	14712.00
30	1228	11.6693	1239.669	14846.00
40	1240	11.9216	1251.922	14983.00
50	1250.2	12.3615	1262.562	15118.00
60	1260.5	12.5051	1273.005	15253.00
70	1270.8	12.7972	1283.597	15390.00
80	1270.8	13.0903	1283.89	15526.00
90	1291.4	13.4135	1304.814	15664.00
100	1301.8	13.7669	1315.567	15802.00
110	1312.1	14.1313	1326.231	15940.00
120	1322.5	14.5272	1337.027	16080.00

TABLE III
POWER OUTPUT BY GENERATING UNITS AT MINIMUM GENERATING COST

P_1 / MW	449.8322
P_2 / MW	170.2403
P_3 / MW	264.5261
P_4 / MW	124.3220
P_5 /MW	170.2403
P_{26} / MW	96.7710
P_D / MW	1275.9319
Fitness / \$$h^{-1}$	**15448.76**

TABLE IV
COMPARISON IN MINIMUM GENERATING COST

Optimization Technique	Fitness / \$$h^{-1}$	Execution Time / sec.
Artificial Immune System (AIS)	15481.74	113.14000
ACO	**15448.76**	**8.5230**

To realize the effectiveness of the proposed ACO technique, comparative studies were performed by reevaluating the process using AIS; with results given in Table IV. It is obvious that ACO outperformed AIS in terms of cost minimization, implemented with much faster execution time.

VI. CONCLUSION

Ant colony optimization has been proposed for solving economic dispatch problems with cost minimization as the objective function. In this study, the developed ACO engine is capable to implement the power to be generated by each generating unit at the minimum cost and meet the demand requirement. The results obtained are also compared with

AIS to investigate its computation capability. The comparison shows that ACO is versatile, robust and efficient. Further work is required to develop techniques for searching the neighborhood, and present more efficacious sufficient conditions for convergence.

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VIII. BIOGRAPHIES

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