Ant Colony Optimization For Solving Economic Dispatch of Power System

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Abstract—**This technical paper presents an ant colony optimization (ACO) method for solving the economic dispatch (ED) problem in power systems. Ant Colony Optimization (ACO) is model for bio-simulation due to their relative individual simplicity and their complex group behaviors. An economic dispatch problem, consisting of six generating units is applied to compare the performance of the proposed method with those of genetic algorithm (GA) and simulated annealing (SA).**

Keywords- - **Economic Dispatch (ED), ant colony optimization (ACO), simulated annealing (SA), genetic algorithm (GA).**

1.0 INTRODUCTION

Over the past few years, application of soft computing techniques has been focused much attention in the electric power industry particularly in the area of optimal operation of generation schedule. An area of the ED is also one of the optimization problem and an important daily activity in power system operation. The main objective of ED problem is to find the generation schedule that minimizes the cost subject to meeting a specified load demand and other system operating constraints. The Lagrangian multiplier method[1], which is generally used in the ED problem, is no longer directly applicable. Whereas, an approach based on global search techniques like genetic algorithm (GA), evolutionary programming (EP) and simulated annealing (SA) appear to be very efficient in solving highly non-linear ED problems without any restriction on the shape of cost curves. Genetic algorithms (GA) maintain a pool of solutions rather than just one[2]. The process of finding superior solutions mimics that of evolution, with solutions being combined or mutated to alter the pool of solutions, with solutions of inferior quality being discarded while simulated annealing (SA) is a related global optimization technique which traverses the search space by generating neighboring solutions of the current solution[3]. A superior neighbor is always accepted. An inferior neighbor is accepted probabilistically based on the difference in quality and a temperature parameter. The temperature parameter is modified as the algorithm progresses to alter the nature of the search. In 1991, Marco Dorigo with his phd thesis "Optimization, learning, and Natural Algorithms", modeling the way real ants solve problems using pheromones, and, since then, many diverse variants of the basic principle have been reported in the literature. Real ants are capable of finding the shortest path from a food source to their nest. While walking ants deposit pheromone on the ground and follow pheromone previously deposited by other ants, the essential trait of ACO algorithms is the combination of a priori information about the structure of a promising solution with a posteriori information about the structure of previously obtained good solutions. In ACO, a number of artificial ants build solutions to an optimization problem and exchange information on their quality via a communication scheme that is reminiscent of the one adopted by real ants. To find a shortest path, a moving ants lay some pheromone on the ground, so an ant encountering a previously trail can detect it and decide with high probability to follow it. As a result, the collective behavior that emerges is a form of a positive feedback loop where the probability with which an ant choose a path increases with the number of ants that previously chose the same path. Ant colony optimization is an iterative distributed algorithm. At each iteration, a set of artificial ants (cooperating agents) are considered. Each of them builds a solution by walking from vertex to vertex on the graph with the constraint of not visiting any vertex that it has already visited in her walk. At each step of the solution construction, an ant selects the following vertex to be visited according to a stochastic mechanism that is biased by the pheromone: when in vertex i, the following vertex is selected stochastically among the previously unvisited ones. In particular, if j has not been previously visited, it can be selected with a probability that is proportional to the pheromone associated with edge (i, j). At the end of an iteration, on the basis of the quality of the solutions constructed by the ants, the pheromone values are modified in order to bias ants in future iterations to construct solutions similar to the best ones previously constructed[4]. In this study, an ant colony optimization (ACO) for solving six unit system economic dispatch problems is proposed.

2.0 THEORY

2.1 THE ECONOMIC DISPATCH PROBLEM

The purpose of the conventional economic dispatch problem is to solve the optimal allocation of generation powers in a power system. The power system balance condition for system demand, power losses and entire generator power, as well as the some generating power constraints for all units, should be satisfied. The objective of the economic dispatch is to minimize the total generation cost of a power system over some appropriate period while satisfying various constraints[5]. The economic dispatch problem can be mathematically described as follows:

$$\min_{P_i} \sum F_i(P_i) = \min_{P_i} \sum (a_i + b_i P_i + c_i P^2) \qquad (1)$$

Where
i: index of dispatchable units
Fi: fuel cost function of unit i
Pi power generation of unit i
$a_i, b_i\ c_i$: fuel cost coefficients of unit i

The cost function is subjected to the following constraints:

A) Power balance constraint

$$\sum (P_i) = P_D + P_L \qquad (2)$$

$$P_L = \sum_{i=1}^{n}\sum_{j=1}^{n} P_i\, \beta_{ij} P_j + \sum_{i=1}^{n} \beta_{0i} P_i + \beta_{00} \qquad (3)$$

where
P_D: total load demand
P_L: power losses
β_{ij}: power loss coefficient

B) Generating limit

$$P_{i,min} \leq P_i \leq P_{i,max} \qquad (3)$$

where
$P_{i,min}$: minimum generation limit of unit i
$P_{i,max}$: maximum generation limit of unit i

To solve the above-mentioned system, the ant colony optimization is described as follows.

2.2 THE ANT COLONY OPTIMIZATION ALGORITHM

Step 1. Initialization

The system data is input, and the initial population is generated. The initial population is chosen randomly in an attempt to cover the entire parameter space uniformly. The uniform probability distribution for all random variables as follows is assumed

$$X^0 i = X_{,min} + \zeta_{ii} (X_{i\ max} - X_{i,min}),\ i = 1\ldots\ldots Np \qquad (4)$$

Where $\zeta_i\ \varepsilon\ (0,1]$ is a random number. The initial process can produce Np individuals of X_i° randomly.

Step 2. Ant direction search

In every generation, each of Np ants selects a mutation operator according to heuristic information and pheromone information. Different from [6-10], the difference between the objective function value in the next generation and the best objective function value of the present generation constructs a fluctuant pheromone quantity. The fluctuant pheromone quantity is defined as follows:

$$\Delta\tau_i = \begin{cases} Q/LK \text{ ,if the proper mutation operator is chosen } i=1\ldots N_p \\ 0, \text{ otherwise} \end{cases} \qquad (5)$$

In (5), the proper mutation operator is chosen when the objective function value of the next generation is better than the best objective function value of the present generation. Where Q is a constant, LK is defined as follows:

$$LK = \left| \ object_{new} / (best_{present} - object_{new}) \ \right| \qquad (6)$$

Where $best_{present}$ expresses the best objective function value of the present generation and $object_{new}$ expresses the objective function value of the next generation. The pheromone updating employs the following rule:

$$\tau_i^{New} = \rho\ \tau_i^{Old} + {}_{\Delta}\tau_i \qquad (7)$$

The coefficient p must be fixed to a value < 1 to avoid an unlimited accumulation of traces. The magnitude of the new pheromone is updated by vaporizing (1- ρ) percentage of pheromones from the previous iteration and fluctuant pheromone quantities in the current iteration. It is observed that the probability of selecting a mutation operator is proportional to the pheromone quantity ri and the information η_i, i = 1,...,Np. The information η_i, is defined as follows:

$$\eta_i = (\sum_{j=1} ((X_{ij}^{G+1} - X_{bj}^{G}) / X_{ij}^{G+1})^2)^{0.5} \qquad (8)$$

Where X_{ij}^{G+1} denotes the j-th gene of the i-th individual in a population in the (G+1)-th generation, n is the number of units, and X_{bj}^{G} denotes the j-th gene of the best individual in a population in the G-th generation. Hence, the probability of choosing a mutation operator is defined as follows:

$$\rho_i (t) = ((\tau_i^{\alpha} (t) . \eta_i^{\beta}) / \sum \tau_i^{\alpha} (t) . \eta_i^{\beta}) \qquad (9)$$

Where α and β are parameters to regulate the influence of τ_i and η_i respectively. At the same time, the probabilities are arranged in ascending order. The initial value of probability for choosing a mutation operator is first defined as

$P = [P_1, P_2, P_3, P_4, P_5] = [0.2\ 0.4\ 0.6\ 0.8\ 1.0]$.

Subsequently, the five integers 1, 2, 3, 4, and 5 are randomly arranged. For example, if the resultant arrangement is [2 4 1 5 3], then by relating this arrangement to P, we have the probabilities of choosing mutation operators for operator 2 = 0.2, operator 4 = 0.4, operator 1 = 0.6, operator 5 = 0.8,

Step 3. Estimation and selection

The evaluation function of a child is one-to-one competed to that of its parent. This competition means that the parent is replaced by its child if the fitness of the child is better than that of its parent. On the other hand, the parent is retained in the next generation if the fitness of the child is worse than that of its parent, i.e.

$$X_i^{G+1} = \arg\min\{f (X_i^{G}), f (X_i^{G+1})\} \qquad (10)$$

$$X_b^{G+1} = \arg\min \{f (X_i^{G+1})\} \qquad (11)$$

where arg min means the argument of the minimum.

Step 4. Repeat step 2 to step 3 until the maximum iteration quantity or the desired fitness is reached.

This computational process of the ACO algorithm for solving optimal economic dispatch problem is stated using a flowchart, shown in Figure 1.

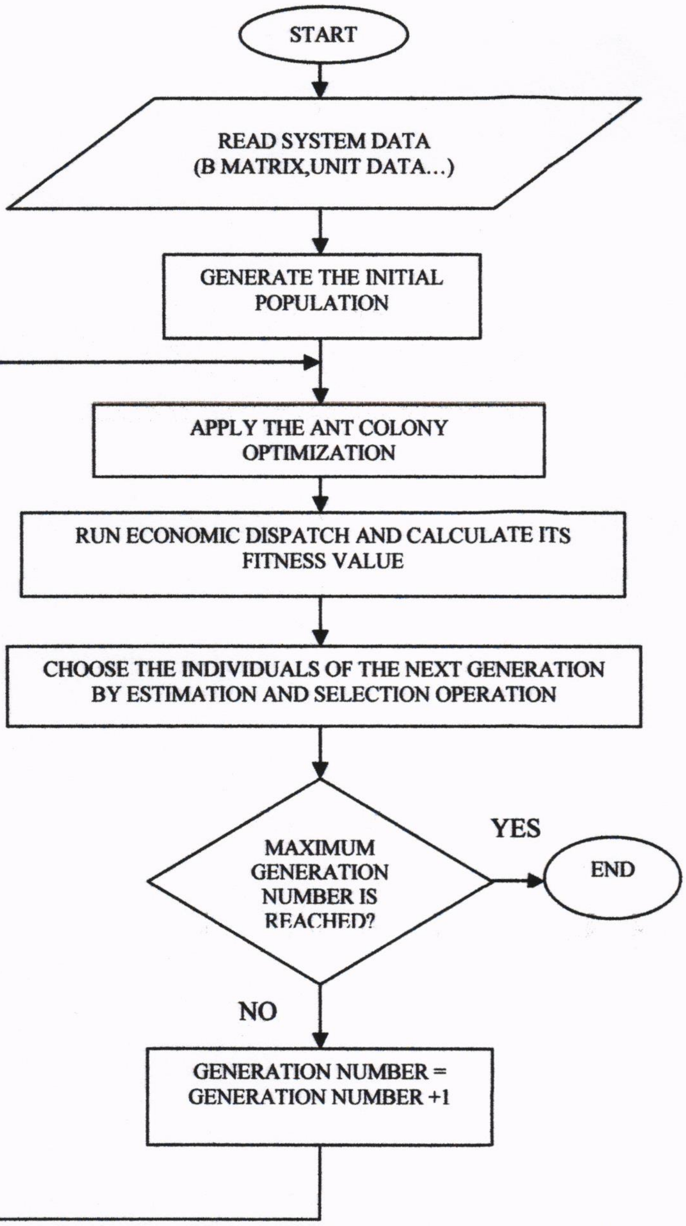

Figure 1. Main calculation procedures of the proposed method.

3.0 RESULT AND DISCUSSION

The system considered in this study has 6 generating units and loss coefficients B matrix [11] is given as

$$B_{ij} = \begin{bmatrix} 0.0017 & 0.0012 & 0.0007 & -0.0001 & -0.0005 & -0.0002 \\ 0.0012 & 0.0014 & 0.0009 & 0.0001 & -0.0006 & -0.0001 \\ 0.0007 & 0.0009 & 0.0031 & 0.0000 & -0.0010 & -0.0006 \\ -0.0001 & 0.0001 & 0.0000 & 0.0024 & -0.0006 & -0.0008 \\ -0.0005 & -0.0006 & -0.0010 & -0.0006 & 0.0129 & -0.0002 \\ -0.0002 & -0.0001 & -0.0006 & -0.0008 & -0.0002 & 0.0150 \end{bmatrix}$$

$$B_{0i} = 1.0e^{-03} * [-0.3908 \; -0.1297 \; 0.7047 \; 0.0591 \; 0.2161 \; -0.6635]$$

$$B_{00} = 0.0056$$

The computational results of best fuel costs, unit The total load demand of the system is 1,263 MW. The computational results of unit generations, power loss and total generation are also shown in Table 2. From the computational results of Table 2, the fuel cost obtained by the ACO is 15,449.90$/h, which is slightly lower than those of the GA and SA methods[12].

Unit	ai	bi	ci	Pimin	Pimax
	($/WM)	($/MW)	($/MW)	(MW)	(MW)
1	240	7.0	0.0070	100	500
2	200	10.0	0.0095	50	200
3	220	8.5	0.0090	80	300
4	200	11.0	0.0090	50	150
5	220	10.5	0.0080	50	200
6	190	12.0	0.0075	50	120

Table 1 Input data of the 6-unit system

Unit Power	GA	SA	ACO
PI (MW)	447.7654	446.3127	447.5067
P2 (MW)	169.2718	172.1813	173.3135
P3 (MW)	266.6757	264.3262	263.4567
P4 (MW)	139.8564	138.9105	139.0738
P5 (MW)	166.9084	166.8225	165.4703
P6 (MW)	85.49942	87.42288	87.13700
Power loss (MW)	12.97701	12.97627	12.95805
Total generation (MW)	1,275.97	1,275.97	1,275.958
Cost ($/h)	15,450.20	15,449.94	15,449.89

Table 2 Computational results of the application system for 6-unit system

4.0 CONCLUSION

Research in the area of heuristics has made possible the development of optimization methods that have the goal of providing high-quality solutions to complex systems. As modern electrical power systems become more complex, planning, operation and control of such systems using conventional methods face increasing difficulties. Intelligent systems have been developed and applied for solving problems in such complex power systems to obtain minimized the total fuel cost of generation. The result obtained show that the ACO method can used to solve ED problems.

5.0 RECOMMENDATION

For the future development ACO method can be applied to minimize the cost in an environmental objective power system. This method may also used together with hybrid differential evolution (HDE) method to accelerate the search for the global solution.

6.0 ACKNOWLEDGEMENT

The author would like to thank P.M Bibi Norasiqin Sheikh Rahimullah for her guidance, suggestion, and constant encouragement. She always kept her student do their project. The weekly meeting kept her student in correct way. Also thanks to persons who involved in this project.

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