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Ant Colony Search Algorithm for Solving Unit Commitment Problem

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Abstract

In this paper Ant Colony Search Algorithm is proposed to solve thermal unit commitment problem. Ant colony search (ACS) studies are inspired from the behavior of real ant colonies that are used to solve function or combinatorial optimization problems. In the ACSA a set of cooperating agents called ants cooperates to find good solution of unit commitment problem of thermal units. The UC problem is to determine a minimal cost turn-on and turn-off schedule of a set of electrical power generating units to meet a load demand while satisfying a set of operational constraints. This proposed approach is a tested on 10 unit power system and compared to conventional methods.

Keywords: Ant Colony Search Algorithm, unit commitment, cooperating agents.

1. INTRODUCTION

Unit commitment (UC) program is used to economically schedule generating units over a short-term planning horizon subject to the forecasted demand and other system operating constraints. In solving the UC problem, generally two basic decisions are involved, namely the "unit commitment" decision and the "economic dispatch" decision. The UC decision involves the determination of the generating units to be running during each hour of the planning horizon, considering the system each hour of the planning horizon, considering the system capacity requirements, including the spinning reserve, start up and shut down of units'

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constraints. The economic dispatch decision involves the allocation of the system demand and spinning reserve capacity among the operating units during each specific hour of operation. The electric power industry has been using optimization methods to help them solve the UC problem. The result has been saving of tens and perhaps hundreds of millions of dollars in fuel costs. Many optimization methods have been proposed to solve the UC Problem. These methods included priority list (PL) methods, dynamic programming (DP) methods, sequential method, and Lagrangian relaxation (LR) methods. More recently, meta-heuristic methods have been tested and used, such as genetic methods have been tested and used, such as genetic algorithms (GA), tabu search (TS) and simulated annealing (SA), along with expert systems and neural networks. Because electric markets are changing rapidly from a single buyer to a wholesale competition, how UC models are solved and what purposes they serve need reconsideration.

For the last few years, the algorithms inspired by the observation of natural phenomena to help solving complex combinatorial problems have been increasing interest. In this study, a new UC problem method, which was derived by the observation of the behavior of ant colonies, is proposed. In analyzing the behaviors of real ants, it was found that the ants are capable of finding shortest path from food sources to the nest without using visual cues.

In the application of this method to UC problem, the initial population of colony can be first randomly generated within the search space of problem. Then, the fitness of ants is individually assessed based on their corresponding objective function. With the selection of trail, the ant dispatch can be activated based on the level of pheromone and distance of the selected trail in order to find the best tout or the shortest path.

2. PROBLEM FORMULATION

The main objective of the UC problem is to determine a minimal cost turn-on and turn-off schedule of a set of electrical power generating units to meet a load demand while satisfying

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a set of operational constraints. Therefore the standard UC problem is to minimize the sum of two cost terms. The first term is the cost of the power produced by the generating units and the second term is the start up cost of the generating units.

Constraints include capacity reserve, minimum up/down time, and operating limits. The objective function of the unit commitment problem for N generating units and T hours can be written as follows:

$$Min\ F\left(P_i^t, u_i^t\right) = \sum_{t=1}^{T} \sum_{i=1}^{N} \left[Fi\left(P_i^t\right) + ST_i^t\left(1 \quad u_i^{t\ 1}\right)\right] \bullet u_i^t \tag{1}$$

Subject to the constraints:

(i) Power balance constraint

$$p_{load}^t - \sum_{i=1}^{N} p_i^t u_i^t = 0 \tag{2}$$

(ii) Generation limits constraint

$$P_i^{\min} \leq P_i^t \leq P_i^{\max} \tag{3}$$

(iii) Spinning reserve constraint

$$p_{load}^t + R^t - \sum_{i=1}^{N} p_i^{\max} u_i^t \leq 0 \tag{4}$$

(iv) Minimum up time constraint

$$u_i^t = 1\ for \sum_{h=t \quad T_i^{up}}^{t\ 1} u_i^t < T_i^{up} \tag{5}$$

(v) Minimum down time constraint

$$u_i^t = 0\ for \sum_{h=t \quad T_i^{down}}^{t\ 1} \left(1 \quad u_i^t\right) < T_i^{down} \tag{6}$$

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Where,

$F_i(p)$ is cost of producing p units of power by unit i

ST_i is start up cost of unit i

P^t_{load} is load at time t (demand)

R^t is power reserve at time t (unit failures case)

P_i^t is amount of power produced by unit i at time t

U_i^t is control variable of unit i at time t

t = 1, 2, 3, ……… N and i = 1, 2, 3, …….. N

3. ACSA PARADIGM

A. Behavior of Real Ants

Ant colony search (ACS) studies are inspired from the behavior of real ant colonies that are used to solve function or combinatorial optimization problems. Currently, most work has been done in the direction of applying ACS to combinatorial optimization. The first ACS system was introduced by Marco Dorigo [1], and was called "ant system". Ant colony search algorithms, to some extent; mimic the behavior of real ants.

As is well known, real ants are capable of finding the shortest path from food sources to the nest without using visual cues. They are also capable of adapting to changes in the environment; for example, finding a new shortest path once the old one is no longer feasible due to a new obstacle. The studies by ethnologists reveal that such capabilities are essentially due to what is called pheromone trails", which ants use to communicate information among individuals regarding path and to decide where to go. Ants deposit a certain amount of pheromone while walking, and each ant probabilistically prefers to follow a direction rich in pheromone rather than a poorer one. The process can he clearly illustrated by Fig. 1(a) ants are moving on a straight line that connects a food source to their nest. An ant:

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- Ants deposit pheromone while walking.
- Probabilistically prefers to follow a direction rich in pheromone.

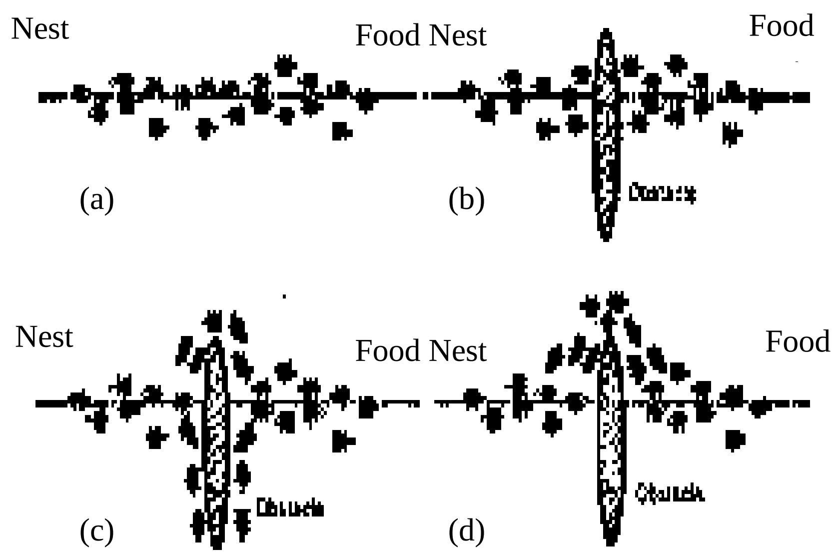

Fig.1: Behaviour of ants

(a) Real ants follow a path between nest and food source. (b) An obstacle appears on the path: ants choose whether to turn left or right with equal probability. (c) Pheromone is deposited more quickly on the shorter path. (d) All ants have chosen the shorter path.

This behavior can be explained how ants can find the shortest path that reconnects a line that is broken by an obstacle in Fig.1 (b). On introducing, those ants are just in front of the obstacle and they cannot to continue to go. Therefore they have to choose between turning right or left. Half the ants choose to turn right and the other half choose to turn left.

A similar situation arises on the other side of the obstacle Fig.1 (c). Ants choosing the shorter path will more rapidly reconstitute the interrupted pheromone trail compared with those choosing the longer path. Thus, the shorter path will receive a greater amount of

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pheromone per time unit and, in turn, a larger number of ants will choose the shorter path. Due to this positive feedback, all the ants will rapidly choose the shorter path Fig.1 (d). All ants move at approximately the same speed and deposit a pheromone trail at approximately the same rate. The time to go round the longer side of an obstacle is greater than the shorter. This makes the pheromone trail accumulate more quickly on the shorter side.

Ants prefer higher pheromone trail levels causing this accumulation to build up still faster on the shorter path. This behavior of ants can be used to solve optimization problems and in particular the Traveling Salesman Problem (TSP). This is the problem of finding a shortest closed tour, which visits all cities in a given set once. This was the first problem solved by using the ant colony metaphor. [1]

4. ANT COLONY SYSTEM

A. ACS State Transition Rule

In ACS the state transition rule is as follows: an ant positioned on node r chooses the city s to move to by applying the rule given by Eqn. (7).

$$S = \begin{cases} \text{Arg} \quad \max_{w \in J_{k(r)}} \{[\tau(r, u)].[\eta\,(r, u)]^{\beta}\}, & \text{if } q \leq q_0, \text{ (exploitation)} \\ S, & \text{otherwise (biased exploration)} \end{cases} \tag{7}$$

where

q is a random number uniformly distributed in [0 …1]

q_0 is a parameter ($0 \leq q_0 \leq 1$)

S is a random variable selected according to the probability distribution given in Eqn. (8)

The state transition rule used by ant system, called a random-proportional rule, is given by Eqn. (8), which gives the probability with which ant k in city r chooses to move to the city s.

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$$P_k(r,s) = \begin{cases} \dfrac{[\tau(r,s)]\bullet[\eta(r,s)]^{\beta}}{\sum\limits_{\mu\in J_k(r)}[\tau(r,u)]\bullet[\eta(r,u)]^{\beta}}, if\ s \in J_k(r) \\ 0, otherwise \end{cases} \tag{8}$$

where:

τ is the pheromone

$J_k(r)$ is the set of cities that remain to be visited by ant k positioned on city r (to make the solution feasible)

β is a parameter, which determines the relative importance of pheromone versus distance (β> 0)

η= I/δ is the inverse of the distance δ (r,s)

B. ACS Global Updating Rule

Global updating is performed after all ants have completed their tours. The pheromone level is updated by applying the global updating rule of Eqn. (9).

$$\tau (r ,s) \Downarrow (1 -a) .\tau (r , s) + \alpha.\Delta\tau (r , s) \tag{9}$$

where:

$$\Delta\tau(r,s) = \begin{cases} (L_{gb})^{-1}\ I\ f\ (r,s) \in \text{global-best -four} \\ 0, \text{otherwise} \end{cases}$$

α is the pheromone decay parameter (0<α 1) L_{gb} is the length of the globally best tour from the beginning of the trial.

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C. ACS Local Updating Rule

While building a solution of the UC, ants visit edges and change their pheromone level by applying the local updating rule of Eqn. (10).

$$\tau(r, s) \leftarrow (1 - p)\,\tau(r, s) + p.\Delta\tau(r, s) \qquad (10)$$

where

p is a heuristically defined coefficient ($O<p<1$)

$\Delta\tau(r, s) = \tau_0$,

τ_0 is the initial pheromone level

4. 4. ACS Parameter Setting

In this program of the following sections the numeric parameters, except when indicated differently, are set to the following values: $\beta = 2$, $q_o = 0.9$, $\alpha = p = 0.1$, and $\tau_0 = (nL_{nn})^{-1}$, where L_{nn}, is the tour length produced by the nearest neighbor heuristic and n is the number of cities.

5. COMPUTATION PROCEDURE

To solve UC by ACS, the search space of generation scheduling problem is established using multi-process decision making concept. Fig.2 depicts the computation procedure of the proposed method. The main computation blocks are discussed below:

Step 1: Ant Production Initiation

In the first step, the colonies of ants are first generated. Ants are positioned on initial state while the initial pheromone value is also given at this step. Fig. 2 plots a multi-stage search space. All the possible permutations constitute this search space. Each stage contains several states, while the order of state selected at each stage can be combined as an achievable tour that is deemed a feasible solution to the problem.

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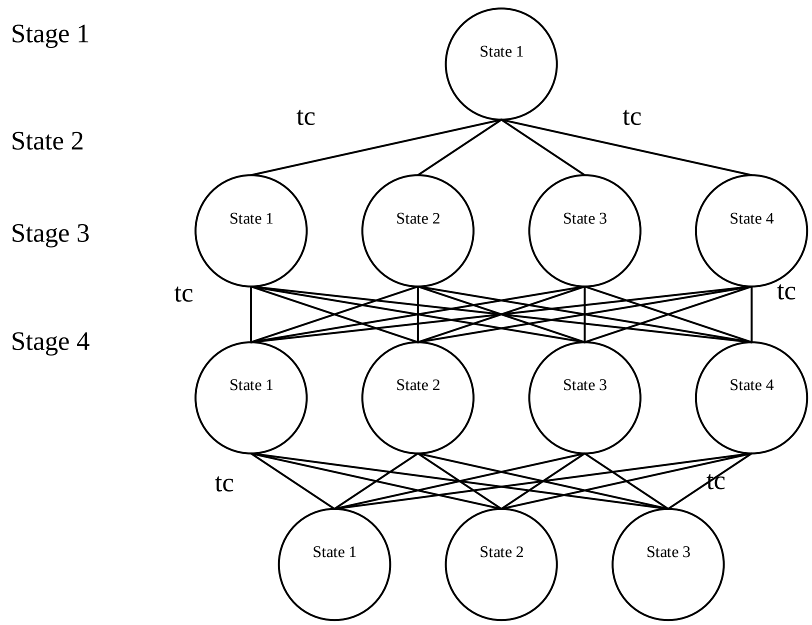

Fig. 2 : The Multi-state Search Space

Step 2: Fitness Evaluation

In this step, the fitness of all ants is assessed based on the corresponding objective function, which can be expressed as follows:

$$f(\mu) = \sum_{i=1}^{n} tc\left(S_{\mu(i),} S_{\mu(i+1)}\right) \tag{11}$$

where:

tc (S_i,S_j) is the transition cost between state S_i

and S_j

μ(i) for i = 1, …., ndefines a permutation.

With the evaluated fitness of the corresponding ants, the pheromone can be added to the particular direction in which the ants have selected.

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Step: 3 Ant Dispatch

In this step, the ants are dispatch based on the level of pheromone and distance. As shown in Eqns. (12) and (13), each ant chooses the next state to move taking into account of $t_{ij}\eta_{ij}$ and values. When the value of t_{ij} gets larger, there has been a lot of traffic on this edge; hence it is more desirable to reach the optimal solution.

When the value of η_{ij} increases, it represents that the closer state should be chosen with a higher probability. If an ant "k" positioned on state i chooses the next state j to move, then such movement can be expressed by:

If q>q_0 select the next state at random with probability as before.

$$P_{ij}^{k} = \frac{\lfloor \tau_{ij} \rfloor \lfloor \eta_{ij} \rfloor^{\beta}}{\sum_{u \in j^{k}_{i}} [\tau_{iu}][n_{iu}]^{\beta}} \tag{12}$$

If q>q_0 select the next state with best local pheromone-distance profile.

$$Maximum\,[\tau_{ij}][\eta_{ij}]^{\beta} \tag{13}$$

Now, if m is the number of ants, then for each iteration, these m ants will perform m movements within the time interval (t, t+1). While building a solution to the problem, the pheromone of visited path can be dynamically adjusted by Eq. (10) in order to broaden the search space, which this process is called "local pheromone-updating rule". After n iterations, all ants have completed a tour. The shortest path found by the ants is allowed to update its pheromone. This shortest path will be also saved as a record for the later comparison with the succeeding iteration.

Step 4: Stop Criteria

The computation process continues until the number of iterations reaches the predefined maximum threshold, or the iteration counter without improving the best objective function

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reaches the maximum allowable value. All the four visited by ants in each iteration should be evaluated. If a better path found in the process, it will be saved for later reference. The best path selected among all iterations implies the optimal scheduling solution to the problem.

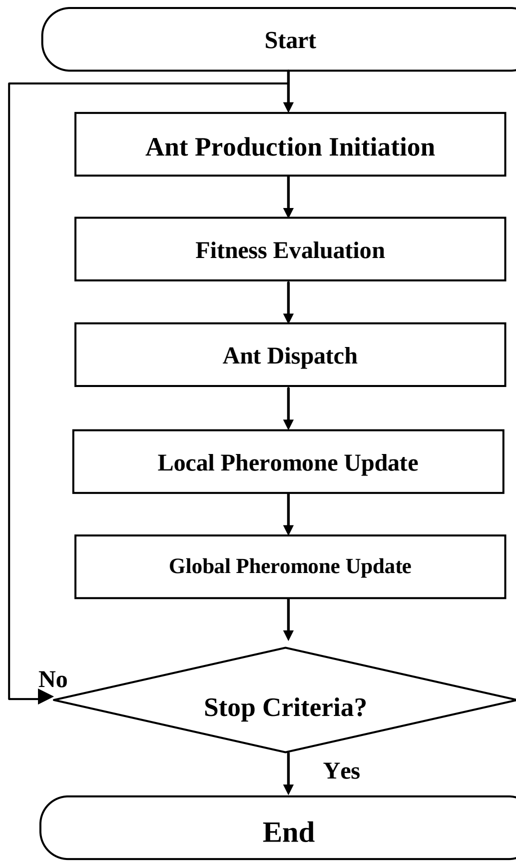

Fig. 3: The flowchart of the ACSA unit commitment program

6. SIMULATION RESULTS

The proposed method is tested on the 10 generator system over the 24 hour time horizon9. The system data and load data are given in appendix. The result of the generation scheduling

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is presented in Table .2 As shown in Table.1, the total production cost of ACSA is shown to be less expensive than those of LR[3], GA[3], EP[4], and LRGA[2] on the 10 unit system.

Table 1: Comparison of total production costs

Methods	Total production costs ($)
LR [3]	565,825
GA [3]	565,825
LRGA[2]	564,800
EP [4]	564,551
ACSA	564,049

Table2: Generation scheduling of the best solution obtained by ACSA method

Hr	PG1	PG2	PG3	PG4	PG5	PG6	PG7	PG8	PG9	PG10
1	455	245	0	0	0	0	0	0	0	0
2	455	292	0	0	0	0	0	0	0	0
3	455	370	0	0	25	0	0	0	0	0
4	455	455	0	0	40	0	0	0	0	0
5	455	260	130	130	25	0	0	0	0	0
6	455	360	130	130	25	0	0	0	0	0
7	455	410	130	130	25	0	0	0	0	0
8	455	455	130	130	30	0	0	0	0	0
9	455	455	130	130	85	20	25	0	0	0
10	455	455	130	130	162	33	25	10	0	0
11	455	455	130	130	162	25	25	10	10	0
12	455	455	130	130	162	80	25	43	10	0
13	455	455	130	130	162	33	25	10	0	0
14	455	455	130	130	85	20	25	0	0	0

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15	455	455	130	130	30	0	0	0	0	0
16	455	310	130	130	25	0	0	0	0	0
17	455	260	130	130	25	0	0	0	0	0
18	455	360	130	130	25	0	0	0	0	0
19	455	455	130	130	30	10	0	0	0	0
20	455	455	130	130	162	33	25	10	0	0
21	455	455	130	130	85	20	25	0	0	0
22	455	455	0	0	145	20	25	0	0	0
23	455	420	0	0	25	0	0	0	0	0
24	455	455	0	0	0	0	0	0	0	0

CONCLUSION

In this paper, the ACS is efficiently and effectively minimizing the total cost in a UC problem. The standard UC problem is to minimize the sum of two cost terms. The first term is the cost of the power produced by the generating units and the second term is the start up cost of the generating units. ACSA total cost over the 24 hour time horizon is less expensive than conventional LR, GA, EP and LRGA on the 10 unit system. And the results reveals about the effectiveness of the ACSA algorithm over other conventional methods.

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