An Ant Colony Search Algorithm (ACSA) Approach

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Abstract **– The unit commitment problem aims at minimizing the cost of operation subject to fulfillment of demand by determine a minimal cost turn-on and turn-off schedule of a set of electrical generating units to meet a load demand while satisfying a set of operational constraints which include fuel, startup, shutdown, and no load costs. This paper applies Ant Colony Search Algorithm (ACSA) technique which can be extended up to 'N' numbers of generators.**

Index Terms **– Unit commitment Problem, ant colony technique, operational cost**

I. Introduction

The Unit Commitment (UC) involves ON/OFF status of the generators and also the output to meet forecast load by related it with economical scheduling [2] and the problem typically involves technological and economic constraints. Usually, proof of concept application is applied by researcher in order to optimize the new methaheuristic. Researchers try to deepen their understanding of the method's functioning not only through all the sophisticated experiments but also by means of an effort to build a theory and it is only after experimental work has shown the practical interest of the method [1]. Finding an answer will help in improving its applicability by tackling questions such as "how and why the method works'' is important. This experimental objective is to maximize the profit and in the same time will reduce the operational cost.

Ant colony optimization (ACO), which was introduced in the early 1990s by M. Dorigo and colleagues as a novel technique for solving hard combinatorial optimization problems, finds itself currently at this point of its life cycle. With this article we provide a survey on theoretical results on ACO. ACO belongs to the class of metaheuristics, which are approximate algorithms used to obtain good enough solutions to hard CO problems in a reasonable amount of computation time. Other examples of metaheuristics are tabu search, simulated annealing , and evolutionary computation. The inspiring source of ACO is the foraging behavior of real ants. When searching for food, ants initially explore the area surrounding their nest in a random manner. Once an ant finds a food source, it evaluates the quantity and the quality of the food and carries some of it back to the nest. During the return trip, the ant deposits a chemical pheromone trail on the ground. The quantity of pheromone deposited, which may depend on the quantity and quality of the food, will guide other ants to the food source. As it has been shown in figure 1, indirect communication between the ants via pheromone trails enables them to find shortest paths between their nest and food sources. That is why ACO model is more suitable for solving combinatorial optimization problem, and has been applied to the hard combinatorial Unit commitment problem (UCP). Here, a parallel can be drawn of ants finding the shortest path from source (nest) to its destination (food) and solving UCP to obtain the minimum cost path (MCP) for scheduling of thermal units for the demand forecasted. Multi-stage decisions give ant search a competitive edge over other conventional approaches like dynamic programming (DP) and branch and bound (BB) integer programming techniques. Before the artificial ants starts finding the MCP, all possible combination of states satisfying the load demand with spinning reserve constraint are selected for complete scheduling period which is called as the ant search space (ASS). Then the artificial ants are allowed to explore the MCP in this search space.

ACO is characterized used to generate solutions to the problem under consideration by the use of a (parameterized) probabilistic model. The probabilistic model is called the pheromone model. The pheromone model consists of a set of model parameters, also known as the pheromone trail parameters. The pheromone trail parameters have values, called pheromone values. At run-time, ACO algorithms try to update the pheromone values in such a way that the probability to generate high-quality solutions increases over time. The pheromone values are updated using previously generated solutions. The update aims to concentrate the search in regions of the search space containing high-quality solutions. In particular, the reinforcement of solution components depending on the solution quality is an important ingredient of ACO algorithms. It implicitly assumes that good solutions consist of good solution components. To learn which components contribute to good solutions can help to assemble them into better solutions.

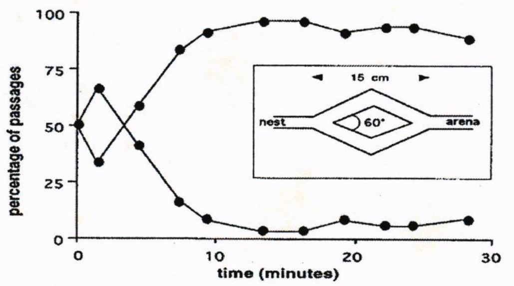

Fig. 1. - Experimental setting: nest and food are connected by two paths of different length

II. UNIT COMMITMENT PROBLEM FORMULATION

As is true for many systems, an electric power system experiences cycles. The demand for electricity is higher during the daytime and lower during the late evening and early morning. This cyclical demand requires that utility companies plan for generation of power on an hourly basis. The problem is first to decide which of the available units to turn on, and then to determine an economical dispatch schedule of the units. Determine an optimal economical dispatch schedule of a set of generating units to meet a load demand while satisfying a set of operational constraints is called the unit commitment problem (UCP). The following notation is used:

System parameters:
CFi(p) : Cost of producing p units of power by unit i
SUi : Start up cost of unit i
u(t) : Load at time t (demand)
r(t) : Power reserve at time t (in case of unit failures)

Decision variables:

Pi(t) : Amount of power produced by unit i at time t
vi(t) : Control variable of unit i at time t

$$v_i(t) = \begin{cases} 0 & \text{if unit } i \text{ is off at time } t \\ 1 & \text{if unit } i \text{ is on at time } t \end{cases} \quad (1)$$

Auxiliary variables:

xi(t) : Consecutive time that unit i has been up (+) or down (-) at time t
I(x) : Logic function defined by

$$I(x) = \begin{cases} 0 & \text{if } x \text{ is false} \\ 1 & \text{if } x \text{ is true} \end{cases} \quad (2)$$

The objective of the standard UCP is to minimize the sum of two cost terms. The first term is the cost of the power produced by the generating units, which depends on the amount of fuel consumed. The second term is the start-up cost of the generating units, which for thermal units, depends on the prevailing temperature of the boilers.

2.1 Fuel Cost

For a given set of N committed units at hour, t, the total fuel cost, at that particular hour, is minimized by economically dispatching the units subject to the following constraints:

a) The total generated power must be equal to the demand (also called load).

b) The power produced by each unit must be within certain limits (minimum and maximum capacity).

This problem is called Economic Dispatch (ECD) and it can be stated as follows (the subscript t is omitted for simplicity):

$$\min CF = \sum_{i=1}^{N} CF_i(P_i) \quad (3)$$

Subject to

1) $\sum_{i=1}^{N} P_i = u$

2) $P_i^{min} \le P_i \le P_i^{max} \qquad i=1,2,\dots,N$

2.2 Start-up Cost

The start-up costs relate to turning a unit on. If the thermal unit has been off for a long period, a cold start-up cost will be incurred. If the unit has been recently turned off (temperature of the boiler is still high), a hot start-up cost is applied. Two functions are commonly used to model start-up costs as a function of the temperature: two-step (Kazarlis et al. 1996) and exponential functions (Bard 1988, Turgeon 1978).

a) Two-step function

$$S(t) = \begin{cases} S_c & if \; -x(t) \le t_{cold\ start} \\ S_h & otherwise \end{cases} \qquad (4)$$

t_{cold} start is the number of hours that it takes for the boiler to cool down. The S_c and S_h costs are the start-up costs incurred for a cold and hot start, respectively.

b) Exponential function

$$S(t) = b_0\left(1 - e^{-\frac{\max(0,-x(t-1))}{\tau}}\right) + b_1 \qquad \text{----- (5)}$$

Start-up costs are incurred only when a transition from state off to on occurs, which can be expressed as follows:

$$CS(t) = S(t)v(t)(1 - v(t-1)) \qquad \text{----- (6)}$$

2.3 Objective function

Consequently, the objective function of the unit commitment problem for N generating units and T hours can be written as follows:

$$\min \sum_{t=1}^{T}\sum_{i=1}^{N}\left[CF_i(P_i(t))v_i(t) + CS_i(t)\right] \qquad \text{--- (7)}$$

Subject to the constraints

a) Demand: $\sum_{i=1} v_i(t)P_i(t) = u(t) \qquad t=1,\ldots,T$

b) Capacity limits : $v_i(t)P_i^{min} \le P_i(t) \le v_i(t)P_i^{max} \quad t=1,\ldots,T;\; i=1,\ldots,N$

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c) Minimum uptime and minimum downtime

$$v_i(t) \ge I(1 \le x_i(t-1) \le t_{up} - 1) \qquad t=1,\ldots,T;\; i=1,\ldots,N$$

$$v_i(t) \le 1 - I(-t_d + 1 \le x_i(t-1) \le -1) \qquad t=1,\ldots,T;\; i=1,\ldots,N$$

d) Power reserve:

$$\sum_{i=1}^{N} v_i(t)P_i^{max} \ge u(t) + r(t) \qquad t=1,\ldots,T$$

e) Spinning reserve

Spinning reserve is the total amount of generation capacity available from all units synchronized (spinning) on the system minus the present load demand. This is necessary due to certain outage of equipment. Spinning reserve requirement may be specified in terms of excess generation capacity or some form of reliability measure equipment. Spinning reserve requirement may be specified in term excess generation capacity or some form of reliability measure.

$$\sum_{i=1}^{N} X_{i,t} P\max_i \ge (D_t + R_t) \quad 1 \le t \le T \qquad \text{-- (8)}$$

III. METHADOLOGY

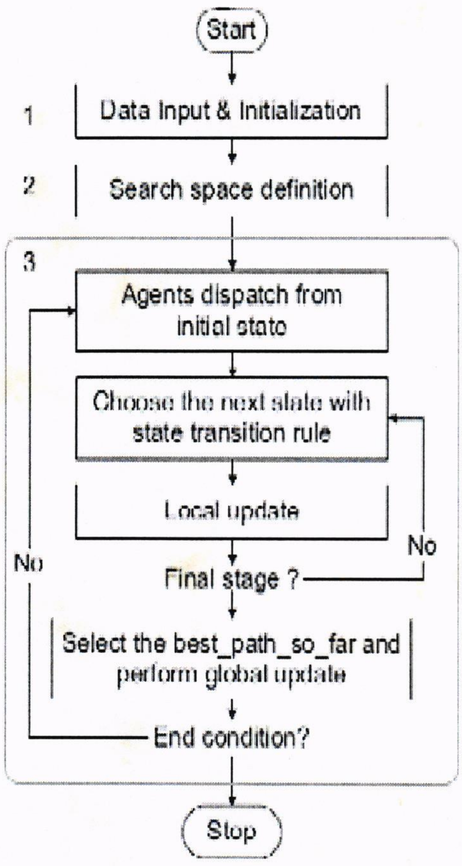

Figure 2. Overall flowchart of the proposed ACO topology

Initialize parameters and search space

As started respected to the proposed algorithms, the input data of generators including forecasted load demand are assigned to the program. and the bit strings consist of the status ON/OFF for each generating unit during the UC hour horizon represented as '1' or '0', respectively. The length of the bit strings in the columns is equal to the number of generating units. The 24 bits strings are given for the rows of UC solution format after considering a future 24 hour of UC problem. Then, the initial parameters of pheromone trail intensity, transition probability, and the initial of ant populations are also declared at this step and the number of ant populations can be adaptively changed during the search.

Fig. **2** illustrates the computational flow of the **ACSA** to solve the unit commitment problem. The main computational processes are discussed as follow:

Step 1. Initialize Stage

Setup the set of parameters and capture the data.

Step 2. Define Search space

Establishing the multi-stage search space. All the possible permutations form this search space. Every stage contains several states, at which economic dispatch incorporates the system and unit related constraints.

Step 3. The cycle of ACSA

Once the search space is created, the **ACSA** is applied. This procedure has several main activities:

a) Define the number of agents and place and dispatch them at the initial state,

b) Each agent uses state transition in order to choose the next state,

c) Local update will be performed by every agent for the chosen path.

d) All the agents perform the two processes (b and c) until they reach the final stage (inner loop),

e) Select the best-so-far path and apply the global updating for the trail which belongs to the best selected path,

f) One full cycle is completed and the process starts the next cycle, the process will end if "end condition" is satisfied, otherwise repeat the outer loop.

IV) Results and discussion

The previous chapters that have been studied provide the complete knowledge of unit commitment problem and its formulation using particle swarm optimization and dynamic programming. The algorithms of Ant Colony optimization, which is presented in chapter 2 and chapter 3 respectively, have been applied for solving unit commitment. The performance has been studied for three generator and four generator test data. The results for the respective systems are discussed as –

Case A: Three unit generators are to be committed to serve a 24-h load pattern.

Three units are to be committed to serve 24-hours load pattern. Data on the units and load pattern are contained in the given Table 5.1. The details of fuel cost components, initial conditions and load pattern are given in Table 1, 2 and 3 respectively.

Units	Max MW	Min MW	No Load Cost RM/MWh	Full Load Ave. Cost RM/MWh	Min. Up Time h	Min. Down Time h	Fuel Cost Component		
							Ai RM/h	Bi RM/MWh	Ci RM/MW²h
1	600	150	213.00	9.79	4	2	561	7.92	0.001562
2	400	100	585.62	9.48	5	3	310	7.85	0.00194
3	200	50	684.74	11.188	5	1	93.6	9.564	0.005784

Table 1 Fuel cost components

Unit	Initial condition	Start up Cost Hot	Start up Cost Cold	Cold Start Time (h)
1	-5	150	350	4
2	8	170	400	5
3	8	500	1100	5

Table 2 Initial conditions

Hour	1	2	3	4	5	6	7	8
Load	1200	1150	1100	1050	1000	950	900	850
Hour	9	10	11	12	13	14	15	16
Load	800	750	700	650	600	550	500	600
Hour	17	18	19	20	21	22	23	24
Load	700	750	800	800	850	900	1000	1100

Table 3 Load pattern

Hour h	Load MW	Unit Commitment Selected	Distribution of load among the units			Total Operating cost× 10^4 (RM)
1	1200	111	600	400	200	13848.96
2	1150	111	600	400	150	25152.48
3	1100	111	600	400	100	35938.69
4	1050	111	600	400	50	46225.05
5	1000	110	600	400	0	55915.61
6	950	110	550	400	0	65401.29
7	900	110	500	400	0	74520.47
8	850	110	450	400	0	83401.31
9	800	110	400	400	0	91591.83
10	750	110	350	400	0	99437.15
11	700	110	350	400	0	106581.62
12	650	110	250	400	0	112981.24
13	600	110	200	400	0	118996.72
14	550	110	150	400	0	124632.96
15	500	110	150	350	0	128832.41
16	600	110	250	350	0	138668.10
17	700	110	300	400	0	142867.55
18	750	110	350	400	0	150012.02
19	800	110	400	400	0	157857.34
20	850	110	400	400	0	166047.86
21	950	110	550	400	0	184047.88
22	1000	111	500	400	50	193533.56
23	1050	111	600	400	50	203224.12
24	1100	111	600	400	100	213510.48
Total operating Cost						213510.48

Table 4 Result of 3-units, unit commitment problem using ACSA

Table 1-3 shown units characteristics, load pattern, and initial status of the unit. The results obtained from ACSA are detailed in Table 4 for three generator system. The total operating cost is calculated, the unit combination selected in each hour and the distribution of load among each unit it is concluded that at first there is variation in the operating cost and after some iteration the operating cost is set to its optimal point and the operating cost will minimized.

Case B: Four unit generators are to be committed to serve an eight-h load pattern.

Results are coming according to given data for the four generator unit commitment problem. Here the total operating cost is calculated, the unit combination selected in each hour and the distribution of load among each unit. Four units are to be committed to serve 8-hours load pattern. Data on the units and load pattern are contained in the given Table 8. The details of fuel cost components, initial conditions and load pattern are given in Table 5, 6 and 7 respectively.

Units	Max MW	Min MW	Incremental Cost RM/MWh	No Load Cost RM/MWh	Full Load Ave. Cost RM/MWh	Min. Up Time (h)	Min. Down Time (h)	Fuel Cost Component		
								Ai RM/h	Bi RM/MWh	Ci RM/MW^{2}h
1	80	25	20.88	213.00	23.54	4	2	684.74	16.83	0.0021
2	250	60	18.00	585.62	20.34	5	3	585.62	16.95	0.0042
3	300	75	17.46	684.74	19.74	5	1	213	20.74	0.0018
4	60	20	23.80	252.00	28.00	1	1	252	23.60	0.0034

Table 5 Unit characteristics

Unit	Initial condition	Start up Cost Hot	Start up Cost Cold	Cold Start Time (h)
1	-5	150	350	4
2	8	170	400	5
3	8	500	1100	5
4	-6	0	0.02	0

Table 6 Fuel cost component

Hour	1	2	3	4	5	6	7	8
Load	450	530	600	540	400	280	290	500

Table 7 Load pattern

Hour h	Load MW	Unit Commitment Selected	Distribution of load among the units (MW)				Total Operating cost× 10^4 (RM)
1	450	0110	0	150.614	298.96	0	10645.3544
2	530	0110	0	230.154	299.804	0	21274.5187
3	600	0111	0	253.054	306.635	40.06	35938.69
4	540	0110	0	239.714	300.635	0	44539.7219
5	400	0110	0	125.007	274.863	0	52781.5693
6	280	0010	0	0	274.863	0	58343.343
7	290	0010	0	0	290.006	0	64085.3994
8	500	0110	0	199.497	299.852	0	74551.818
Total operating Cost							74551.818

Table 8 Result of 4-units, unit commitment problem using ACSA

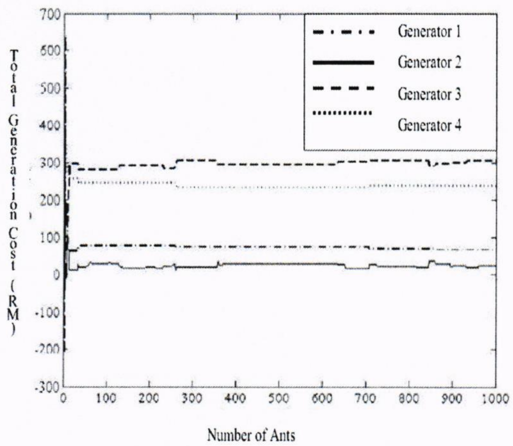

Figure 3 Total generation cost taken by each ant (four unit system).

V) CONCLUSION

The paper described an algorithm using a meta heuristic approach known as Ant Colony Search Algorithm (ACSA) for solving the unit commitment problem. Ant Colony application to price based unit commitment problem has been presented here and has been implemented for small four-generator. Developed algorithms provide optimal unit commitment and also optimal MW values for energy, spinning reserve and non-spin. Proposed algorithm can be applied to 'n' generators system.

VI) FUTURE DEVELOPMENT

In future, presented algorithm and analysis could be beneficial to industries when it been applied to big number of generators in order to maximize the profit and bid in competitive electricity market.

VIII. Appendix

Table A1 Numerical four unit systems

Unit (no.)	Max. (MW)	Min. (MW)	Ramp level (MW/h)	Minimum up-time (h)	Minimum down-time (h)	Shut-down cost ($)	Start-up cost		Cold start (h)	Initial unit status
							Hot ($)	Cold ($)		
1	80	25	16	4	2	80	150	350	4	−5
2	250	60	50	5	3	110	170	400	5	8
3	300	75	60	5	4	300	500	1100	5	8
4	60	20	12	1	1	0	0	0.02	0	−6

Fuel cost equations

$C_1 = 25 + 1.5000P_1 + 0.00396P_1^2$

$C_2 = 72 + 1.3500P_2 + 0.00261P_2^2$

$C_3 = 49 + 1.2643P_3 + 0.00289P_3^2$

$C_4 = 15 + 1.4000P_4 + 0.00510P_4^2$

Unit characteristics (four unit system). Initial unit status: hours off (−) line or on (+) line

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