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MODIFIED ANT COLONY OPTIMIZATION TECHNIQUE FOR SOLVING UNIT COMMITMENT PROBLEM

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Abstract- Ant colony optimization (ACO) which is inspired by the natural behavior of ants in finding the shortest path to food is appropriate for solving the combinatorial optimization problems. Therefore, it is used to solve the unit commitment problem (UCP) and attain the minimum cost for scheduling thermal units in order to produce the demand load. In this paper modified ACO (MACO) is used to solve the UCP in which particle swarm optimization (PSO) is used to find the ACO parameters and genetic algorithm (GA) is used to solve economic dispatch and to minimize the generation cost in order to select the committed units appropriately. At first, all possible combinations that satisfy the demanded load and spinning reserve are calculated by means of genetic algorithm and the minimum economic generation cost of each state is calculated to make the ants search space (ASS). Then the artificial ants are allowed to search in this space. Problem formulation takes into consideration the minimum up and down time constraints, startup cost, shutdown cost, spinning reserve, and generation limit constraints. The feasibility of the proposed method in two systems is explained and the results are compared with the other methods. The results reveal that the suggested algorithm is more encouraging than the other ones.

Keywords: Unit Commitment, Modified Ant Colony Optimization, Genetic Algorithm, Constraints.

I. INTRODUCTION

The UCP is a difficult optimization problem that has enough potential to save millions of dollars annually in electrical industry and also, unit commitment in power systems refers to the optimization problem for determining the on/off states of generating units that minimize the operating cost for a given time horizon. The objective of problem is that minimize the all operation cost with considering security constraints [1-3].

This problem was proposed first by Lowery in 1966 through dynamic programming. Basically the most accurate way to solve this problem is enumeration method in which through testing all possible combinations of units in the studding time interval the optimal answer can be achieved. The problem of this method is its long solving time that increases exponentially as the size of the system grows [4]. The methods for solving the unit commitment problem are divided in three categories: classic, intelligent, and mixed. Some examples of the first category are as follows: enumeration, priority list, dynamic programming and Lagrange relaxation.

These methods are not so accepted in terms of convergence, calculation time and quality of answer. The widely used intelligent methods to solve this problem are: tabu search [5], neural network [6], genetic algorithm [7, 8], particle swarm optimization [9], mixed genetic algorithm and fuzzy logic [10], and ant colony search [11, 12].

The ACO which was first proposed by Dorigo to solve complex optimization problems, including traveling salesman's problem (TSP) attracted the researcher's attentions. The researchers understood the optimization potentials through the behavior of ants colony and during the analysis realized that the ants are able to find the shortest path to reach the food from the nest that can be used in solving complex problems.

The ACS algorithm was used to solve the problem of economic dispatch in a large-scale power system in reference [13]. In reference [14] the ACS was employed to improve productive scheduling of hydroelectric generation. In reference [15] ACS was used to reduce the loss in a reconfigured distribution network.

In reference [16] ACS was used to optimize the reactive power. To solve the UCP in this paper, firstly, the problem is formulated as a constraint optimization problem and then the ACO algorithm is applied to achieve minimum total generation cost. Genetic algorithm is also used to solve the economic dispatch problem. To show its feasibility, the proposed method was employed to two systems: one with 4 units for 8 hours and another with 10 units for 24 hours and the results are compared with the other methods. In this algorithm by means of PSO algorithm, the optimal parameters of ACO algorithm are achieved and at the end, a brief study is done about.

II. PROBLEM FORMULATION

The aim of solving the UCP is to reduce total generation cost for scheduling starting up and shutting down the units and will be defined as following:

$$Cost_{NH}=\sum_{h=1}^{H}[[FC_i(P_{ih})+STC_i(1-U_{i(h-1)})]U_{ih} + +SD_i(1-U_{ih})U_{i(h-1)}] \quad (1)$$

The Equation (1) represents a cost function in which the related costs to the consumed fuel for N units along with the cost of starting up and off for committed units during the whole determined period of time (H) is also considered [2, 3]. The cost of fuel is usually shown as following in which a_i, b_i and c_i are constants.

$$FC_i(P_{ih})=c_iP_{ih}^2+b_iP_{ih}+a_i \quad (2)$$

The starting up cost of the generators can be represented as an exponential function:

$$STC_{ih}=TS_{ih}+\left(1-e^{\left(\frac{-T_{ih}^{off}}{AS_{ih}}\right)}\right)BS_{ih}+MS_{ih} \quad (3)$$

Of course, to model the cost of starting up the following multiform function can be used in:

$$STC_i=\begin{cases}Hsc & X_i^{off}\leq MD_i+Cs\_hrs\\ Csc & X_i^{off}>MD_i+Cs\_hrs\end{cases} \quad (4)$$

where Cs_hrs is the number of hours by passing them after the minimum shutting down time, the cost of restarting up the units is Csc. Otherwise, the cost equals Hsc. Solving the UCP includes some constraints as follows [3]:

1. *Real power balance constraint*: it guarantees the equality of total generation power whit the total prediction load.

$$\sum_{i=1}^{N}P_{ih}U_{ih}=D_h \quad (5)$$

2. *Spinning reserve constraint*: is the difference between total active potential of the system and the sum of loads and losses. The spinning reserve constraint is 10% in this paper.

$$\sum_{i=1}^{N}P_{i(max)}U_{it}\geq D_h+R_h \quad (6)$$

3. *Generation limit constraint*:

$$P_{i(min)}\leq P_{ih}\leq P_{i(max)} \quad (7)$$

4. *Minimum up time constraint*:

$$X_i^{on}(t)\geq MU_i \quad (8)$$

5. *Minimum down time constraint*:

$$X_i^{off}(t)\geq MD_i \quad (9)$$

III. NATURAL BEHAVIOR OF ANTS

The ACO was first used by Dorigo and his colleague in 1991 to solve the complex optimization problems including TSP, attracts the researcher's attention and then in 1996 and 1997 the ant colony algorithm was proposed [11]. Ants are insects that live together. Investigating the behavior of these insects represents coordination among them. The ants are able to perform an organized task on their own, but in a colony there is a good coordination among the members in performing tasks such as finding the food and the shortest path to it. In natural world ants lay down a chemical trail on their passage during their search for food that is used to inform other ants. Those ants that travel the path leading to food also lay down this kind of chemical trail.

So each ant follows the path that more number of ants has passed through it means the shortest path to food [1]. In Figure 1 the distance between D and H, B and H; and B and D is one and C is placed in the center of B and D. evaluate what will happen in times 0, 1 and 2. Consider 30 new ants go from A to B and 30 from E to D with the speed of one unit per time unit.

In t=0 there is no pheromone in the path but there are 30 ants in B and 30 ants in D. They determine their path randomly. Therefore there are 15 ants traveling each path averagely (Figure 1-b). This process continues so long as all ants choose the shorter path. In nature the pheromone trail evaporate gradually over time. So the amount of pheromone in the paths that are traveled through less reduces gradually and they will be omitted from the search space.

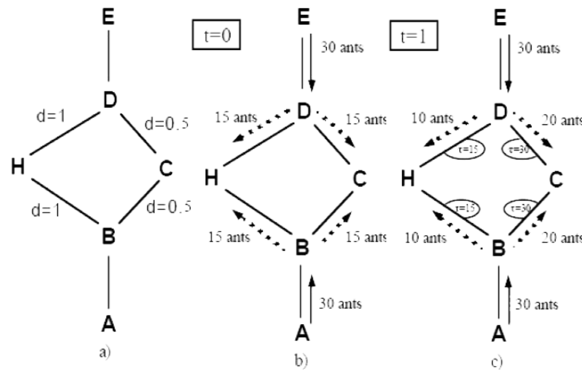

Figure 1. An example with artificial ants

IV. OPERATION OF MODIFIED ANT COLONY ALGORITHM

In this study, at first at each time all states that are able to provide the demanded load and spinning reserve are calculated and the minimum cost relating to each state by use of economic dispatch is calculated by applying genetic algorithm (GA). In fact, in each state for different values of U_i, the values of P_i should be found by considering generation limit constraint of each unit, and the following objective function should be minimized.

$$\sum_{i=1}^{N}FC_i(P_i)\times U_i=P_{sch} \text{ and } \forall i \ P_{min\,i}\leq P_i\leq P_{max\,i} \quad (10)$$

where P_{sch} is demanded power in each hour. In this case the ants searching space is formed. Now for the paths between each two hours a pheromone matrix is formed in which if the first hour has n states and the second one m states, the related matrix is an $m\times n$ one that the initial value for all the indices is 1. So for a system with 10 units in a 24-hour interval 24 pheromone matrices are formed. It is presented in Figure 2.

At first the artificial ants are released randomly in cities of the first hour and they are allowed to move in the search space to find the minimum cost. Each ant should start its journey from one of the cities at the first hour and ends it in a city at last hour. At this time the total path cost of each ant including production costs, starting up and shutting down cost for the units is calculated. It is also checked that whether the constraints relating to minimum up time and down time of the units are followed or not.

If the constraints is followed the cost of the path equals the calculated cost, otherwise the path cost is changed in to a big number so that it is omitted from the optimal paths. When all ants reach the end, the minimum cost among the calculated costs is identified. If this amount is less than the least amount in the previous repetitions it will be saved as the minimum cost, otherwise the amount of minimum cost won't change. This algorithm is dividing into three general sections of initializing, the passing strategy, and updating pheromone matrices.

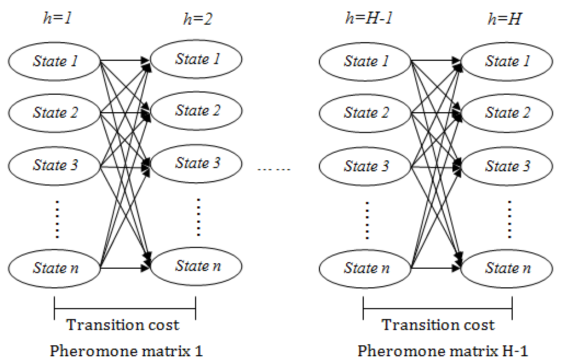

Figure 2. The searching space for finding the optimal path

A. Initializing

In this section the number of states (cities) relating to each hour is determined and initial parameters as number of ants (m), the relative importance of the pheromone trail (α), relative importance of the visibility (β) and pheromone evaporation coefficient (ρ) set according to Table 1 and the pheromone initial value of each path (τ_0) set as 1.

Table 1. Optimal parameters achieved from PSO algorithm

Parameters	4-unit system	10-unit system
Number of ants (m)	277	530
α	0.8079	1.6445
β	10.8376	28.5412
ρ	0.6892	0.1185

B. Passing Strategy

The Ants in traveling from one city (i) to another city (j) use the passing strategy law. In this law, the city that is nearer to the present city is more likely to be selected. Other cities have the possibility of being selected, though. In this law at first to travel from city ith to jth the selection probabilities of city jth is calculated through the following relation and all of these probabilities are saved in matrix $P(k)(t)$.

$$P_{ij}(k)(t)=\begin{cases}\dfrac{[\tau_{ij}(t)]^{\alpha}.[\frac{1}{L_{ij}}]^{\beta}}{\sum[\tau_{ij}(t)]^{\alpha}.[\frac{1}{L_{ij}}]^{\beta}} & j,s\in tabu(k)\\ 0 & \text{otherwise}\end{cases} \quad (11)$$

$$P=[P_{i1}\ P_{i2}\ \dots\ P_{in}] \quad (12)$$

where τ_{ij} is the amount of pheromone in the path between cities of ith and jth, the L_{ij} is the distance between the two cities of ith and jth (cost between states) and P_{ij} is the selection probability of city jth as the next city of ith.

The next city (jth) is achieved through solving in Equation (13) in which q is a random number between 0 and 1 that is produces randomly in each time of applying the law.

$$\sum_{k=1}^{j} P_{ik}\leq q \quad (13)$$

C. Pheromone Update

When all the ants have completed their tour, the pheromone matrix should be updated so the ants can be lead to shorter path in the next step. Updating each pheromone matrix is performing as following:
If the ant kth in hour nth is in city ith and at hour $(n+1)$th is in city jth the (i, j) and (j, i) indexes of nth matrix is updated according to the following:

$$\tau'_{ij}=\left(\tau_{ij}+\frac{1}{c\times L_t}\right)\times(1\text{-}\rho) \quad (14)$$

In which ρ is pheromone evaporation constant, L_t is the total cost of the tour from the first city to the last one and c is a constant that is multiplied by the denominator to reduce the size of it. (c=0/0001).

D. Implementation of MACO to Solve UCP

The process of the MACO algorithm for solving UCP can be summarized as follows (Figure 3):
Step 1: forming the search space of each ant for all hours;
Step 2: initializing the values of parameters and forming the pheromone matrices;
Step 3: ants are distributed in cities of 1st hour randomly;
Step 4: ants choose their next cities by using the passing strategy law to reach to the final city;
Step 5: the constraint of minimum up and down time of units are being checked, the total path cost is calculated and in case of not satisfying the constraints, the calculated cost will be changed in to a big number;
Step 6: pheromone matrices, and minimum cost are updated and in the case of not satisfying the ending condition, the algorithm goes to step 4.

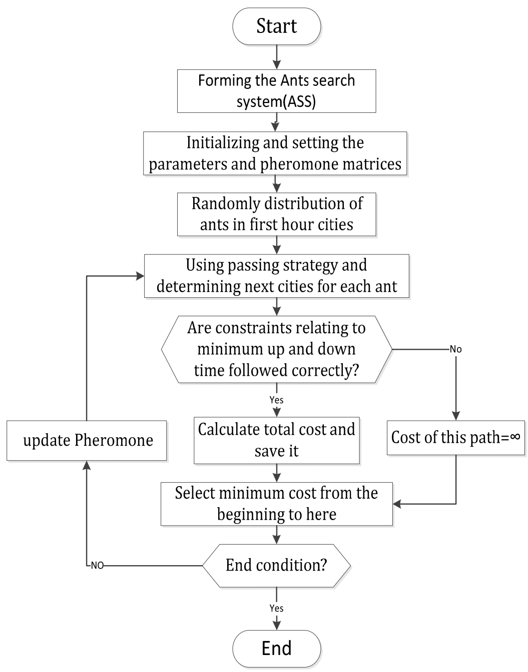

Figure 3. Flowchart for MACO method

V. SETTING THE MACO PARAMETERS

A good convergence is achieved through the appropriate selection of parameters so correct setting of parameters m, α, β and ρ influence the calculations and achieving the optimal solution greatly. Then, by conceding these parameters variable and determining their limits as $\alpha \in [0, 5]$, $\beta \in [0, 30]$, $\rho \in [0, 1]$ and $m \in [1, 300]$ for a system with 4 units and $m \in [1, 600]$ for a 10-unit system are considered as the parameters of PSO algorithm. The fitness function is used in PSO algorithm is total cost resulting from MACO algorithm in addition to the given repetition number for achieving that cost are also taken in to account.

In fact it is in order to determine by which class of parameters in a definite number of repetitions, ant colony algorithm reaches the minimum cost sooner. By keeping all the parameters constant, except one and changing that parameters in the limit mentioned above their roles will be investigated. This is one of the main contributions of this work. The result of these observations is presented in Table 2. The more the number of ants the less number of repetition it reaches minimum cost but calculation time and size increases. The exact values of these parameters that attained through PSO are shown in Table 1.

Table 2. Investigating the role of parameters in converging the answer of MACO

α	0	0.2	0.5	1	1.5	2	3	5	
Avg.TGC	74976.9	74593.2	74521.2	74520.3	74520.3	74522.8	74688.2	74862.2	
β	0	1	2	5	10	15	20	25	30
Avg.TGC	74664.4	74654.2	74577.1	74522.0	74520.3	74520.3	74520.3	74577.3	74570.4
ρ	0.1	0.2	0.5	0.7	0.9				
Avg.TGC	74719.0	74522.0	74520.3	74520.3	74521.2				
m	20	50	100	150	200	250	300		
Avg.TGC	75726.0	74856.7	74708.9	74520.3	74520.3	74520.3	74520.3		

Avg. TGC: average total generation cost in \$/day

VI. SIMULATION RESULTS

This algorithm is applied to a 4-unit system and a 10-unit system that their specifications are listed in Appendices (Tables 7, 8, 9 and 10). There are 24 pheromone matrices for the 10-unit system and 8 pheromone matrices for 4-unit one. All simulations are done by MATLAB. The repetition number for the 4-unit system is 10 and for the 10 unit system is 30.

In Table 3 that shows the simulation results for the 4-unit system, the starting up cost of the units and fuel costs are represented separately in each hour and the total cost for 8 hours is 74520.344 \$.

Table 4 represents the results from MACO with other methods. The numerical results affirmed the proficiency of proposed approach over other existing methods. Table 5 also includes the results of the 10-unit system with the related costs for each hour and the generators states in each. The total cost for 24 hours is 83051.1033 \$.

In Table 6 the results from this algorithm are compared with the results from other methods. Figures 4 and 5 show the graph of the amount of cost in terms of number of repetitions for the 4-unit and 10-unit systems respectively. These figures represent a good convergence speed for proposed algorithm.

Table 3. Results from simulation of the 4-unit system

Hour	Load (MW)	Unit number				Fuel cost (\$)	Starting up cost (\$)	Total cost (\$)
		1	2	3	4			
1	450	292.857	132.143	25	0	9389.038	150	9539.038
2	530	300	205	25	0	10856.240	0	10856.240
3	600	300	250	30	20	12534.54	0.02	12534.56
4	540	300	215	25	0	11043.80	0	11043.80
5	400	276.19	123.810	0	0	8205.788	0	8205.788
6	۲80	196.19	83.81	0	0	6067.148	0	6067.148
7	290	202.857	87.143	0	0	6243.828	0	6243.828
8	500	300	200	0	0	10030.360	0	10030.360
Total cost						74370.324	150.02	74520.344

Table 4. Comparing simulation results for the 4-unit system whit other references

Hour	Load (MW)	LR [9]				LR-PSO [9]				FL [10]				Proposed ACO			
		1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
1	450	1	1	1	0	1	1	0	0	1	1	0	0	1	1	1	0
2	530	1	1	1	0	1	1	1	0	1	1	0	0	1	1	1	0
3	600	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1
4	540	1	1	1	0	1	1	1	0	1	1	0	0	1	1	1	0
5	400	1	1	0	0	1	1	1	0	1	1	0	0	1	1	0	0
6	280	1	1	0	0	1	1	0	0	1	0	0	0	1	1	0	0
7	290	1	1	0	0	1	1	0	0	1	0	0	0	1	1	0	0
8	500	1	1	0	0	1	1	1	0	1	1	0	0	1	1	0	0
Total Cost		74808				75231.9				74683.6				74520.344			

Table 5. Results from simulation of the 10-unit system

Hour	Load (MW)	Units 1	2	3	4	5	6	7	8	9	10	Cost ($)
1	1170	1	1	1	1	1	1	1	1	1	1	2425.504
2	1250	1	1	1	1	1	1	1	0	1	1	2592.893
3	1380	1	1	1	1	1	1	1	0	1	1	2875.633
4	1570	1	1	1	1	1	1	1	1	1	1	3408.703
5	1690	1	1	1	1	1	1	1	1	1	1	3578.545
6	1820	1	1	1	1	1	1	1	1	1	1	3906.292
7	1910	1	1	1	1	1	1	1	1	1	1	4146.285
8	1940	1	1	1	1	1	1	1	1	1	1	4229.597
9	1990	1	1	1	1	1	1	1	1	1	1	4378.006
10	1990	1	1	1	1	1	1	1	1	1	1	4378.006
11	1970	1	1	1	1	1	1	1	1	1	1	4316.945
12	1940	1	1	1	1	1	1	1	1	1	1	4229.597
13	1910	1	1	1	1	1	1	1	1	1	1	4146.285
14	1830	1	1	1	1	1	1	1	1	1	1	3932.427
15	1870	1	1	1	1	1	1	1	1	1	1	4038.283
16	1830	1	1	1	1	1	1	1	1	1	1	3932.427
17	1690	1	1	1	1	1	1	1	1	1	1	3578.545
18	1510	1	1	1	1	1	1	1	1	1	1	3160.748
19	1420	1	1	1	1	1	1	1	1	1	1	2965.116
20	1310	1	1	1	1	1	1	1	0	1	1	2751.549
21	1620	1	1	1	1	1	1	1	0	1	1	2614.143
22	1210	1	1	1	1	1	1	1	0	1	1	2508.618
23	1250	1	1	1	1	1	1	1	0	1	1	2592.893
24	1140	1	1	1	1	1	1	1	0	1	1	2363.931
Total cost												83051.1033

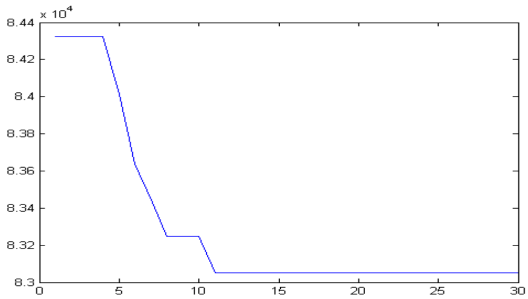

Figure 4. Answer convergence graph for the 10 unit system

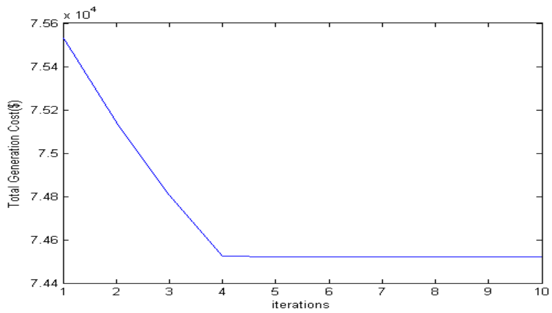

Figure 5. Answer convergence graph for the 4 unit system

Table 6. Comparing simulation results for the 10-unit system whit other methods

Hour	Load (MW)	Proposed ACO Cost	Proposed ACO Gen Status	Ant colony system [11] Cost	Ant colony system [11] Gen Status	Branch and bound [11] Cost	Branch and bound [11] Gen Status	Dynamic Programming [11] Cost	Dynamic Programming [11] Gen Status	EACO [17, 18] Cost	EACO [17, 18] Gen Status
1	1170	2425.5	1101111111	2849.6	1111111101	2725.8	1111111001	2638.1	1111101001	2593.5	1111111101
2	1250	2592.8	1101111111	2606.6	1111111101	2606.1	1111111001	2719.1	1111111001	2606.9	1111111101
3	1380	2875.6	1101111111	2887.0	1111111101	2981.7	1111111011	2889.4	1111111001	2981.4	1111111111
4	1570	3408.7	111111111	3396.8	1111111111	3409.8	1111111111	3426.0	1111111101	3295.8	1111111111
5	1690	3578.5	111111111	3578.7	1111111111	3578.7	1111111111	3607.4	1111111101	3578.7	1111111111
6	1820	3906.2	1111111111	3906.4	1111111111	3906.4	1111111111	3948.8	1111111101	3906.4	1111111111
7	1910	4146.2	1111111111	4146.4	1111111111	4146.4	1111111111	4247.4	1111111111	4146.4	1111111111
8	1940	4229.5	1111111111	4229.7	1111111111	4229.7	1111111111	4229.7	1111111111	4229.7	1111111111
9	1990	4378.0	1111111111	4378.2	1111111111	4378.2	1111111111	4378.2	1111111111	4378.2	1111111111
10	1990	4378.0	1111111111	4378.2	1111111111	4378.2	1111111111	4378.2	1111111111	4378.2	1111111111
11	1970	4316.9	1111111111	4317.1	1111111111	4378.2	1111111111	4378.2	1111111111	4317.1	1111111111
12	1940	4229.5	1111111111	4229.7	1111111111	4317.1	1111111111	4317.1	1111111111	4229.7	1111111111
13	1910	4146.2	1111111111	4146.4	1111111111	4146.4	1111111111	4146.4	1111111111	4146.4	1111111111
14	1830	3932.4	1111111111	3932.5	1111111111	3932.5	1111111111	3932.5	1111111111	3932.5	1111111111
15	1870	4038.2	1111111111	4038.4	1111111111	4038.4	1111111111	4038.4	1111111111	4038.4	1111111111
16	1830	3932.4	1111111111	3932.5	1111111111	3932.5	1111111111	3932.5	1111111111	3932.5	1111111111
17	1690	3578.5	1111111111	3578.7	1111111111	3578.7	1111111111	3578.7	1111111111	3578.7	1111111111
18	1510	3160.7	1111111111	3160.9	1111111111	3160.9	1111111111	3160.9	1111111111	3160.9	1111111111
19	1420	2965.1	1111111111	2996.2	1101111111	2996.2	1101111111	2968.5	1111111111	2965.2	1111111111
20	1310	2751.5	1101111111	2721.7	1101111111	2721.7	1101111111	2734.9	1111111111	2770.2	1101011111
21	1260	2614.1	1101111111	2614.3	1101111111	2614.3	1101111111	2633.2	1111111111	2610.7	1101011111
22	1210	2508.6	1101111111	2508.7	1101111111	2508.7	1101111111	2533.2	1111111111	2528.8	1101011111
23	1250	2592.8	1101111111	2593.0	1101111111	2593.0	1101111111	2612.9	1111111111	2589.5	1101011111
24	1140	2363.9	1101111111	2364.1	1101111111	2364.1	1101111111	2394.1	1101111111	2345.3	1101011111
Total cost		83051.1033		83491.42		83475.25		83652.4		83240.17	

VII. CONCLUSIONS

This paper deals with the UC problem and the necessity for an algorithm to solve it. Since ACO is appropriate for solving the mixed optimization problems and has enough potential to find the optimal solution, it is appropriate to solve UCP. Then by using the proposed method (MACO), UCP for two sample systems were solved. The results were compared with other related methods from different references. The algorithms optimal parameters were calculated by PSO technique and their roles were investigated. The findings represented that the suggested method is more economical than other methods and is able to save a large amount of cost annually. It is also encouraging in terms of convergence speed.

APPENDICES

Table 7. Unit data for 4-unit system

Unit	P_{max} (MW)	P_{min} (MW)	α ($/h)	β ($/MWh)	γ $/(MW^{2}h)	MU (h)	MD (h)	Hsc ($)	Csc ($)	Cs_hrs (h)	Initial state (h)
1	300	75	648.74	16.83	0.0021	5	4	500	1100	5	8
2	250	60	585.62	16.95	0.0042	5	3	170	400	5	8
3	80	25	213.00	20.74	0.0018	4	2	150	350	4	-5
4	60	20	252.00	23.60	0.0034	1	1	0	0.02	0	-6

Table 8. Unit data for 10-unit system

Unit	P_{max} (MW)	P_{min} (MW)	α ($/h)	β ($/MWh)	γ $/(MW^{2}h)	MU (h)	MD (h)	Shutdown cost ($)	Hsc ($)	Csc ($)	Cs_hrs (h)	Initial state (h)
1	200	80	82	1.2136	0.00148	3	2	50	70	176	3	4
2	320	120	49	1.2643	0.00289	4	2	60	74	178	4	5
3	150	50	100	1.3285	0.00135	3	2	30	50	113	3	5
4	520	250	105	1.3954	0.00127	5	3	85	110	267	5	7
5	280	80	72	1.3500	0.00261	4	2	52	72	180	3	5
6	150	50	29	1.5400	0.00212	3	2	30	40	113	2	-3
7	120	30	32	1.4000	0.00382	3	2	25	35	94	2	-3
8	110	30	40	1.3500	0.00393	3	2	32	45	114	1	-3
9	80	20	25	1.5000	0.00396	0	0	28	40	101	0	-1
10	60	20	15	1.4000	0.00510	0	0	20	30	85	0	-1

Table 9. Load demand for 8 hours

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

Table 10. Load demand for 24 hours

Hour	1	2	3	4	5	6	7	8	9	10	11	12
Load (MW)	1170	1250	1380	1570	1690	1820	1910	1940	1990	1990	1970	1940
Hour	13	14	15	16	17	18	19	20	21	22	23	24
Load (MW)	1910	1830	1870	1830	1690	1510	1420	1310	1260	1210	1250	1140

NOMENCLATURES

U_{ih}: Status of unit ith at hour h (on=1, off=0)
N: Total number of generation units
H: Total number of hours
$Cost_{NH}$: Sum of costs for H hours and for N units
$FC_i(P_{ih})$: Generation fuel cost of unit ith at hour hth for generating P_{ih}
STC_i: Start up cost of unit ith
SD_i: Shut down cost of unit ith
TS_{ih}: Generator start up cost
BS_{ih}: Boiler start up cost
MS_{ih}: Constant start up cost
T_{ih}^{off}: Continuously off time for unit i^{th} at hour H (h)
AS_{ih}: Boiler cold shutdown coefficient
D_h: Load demand at hour H (MW)
R_h: Spinning reserve at hour H (MW)
$P_{i(min)}$: Minimum real power generation of unit ith (MW)
$P_{i(max)}$: Maximum real power generation of unit ith (MW)
MD_i: Minimum down time of unit ith
Mu_i: Minimum up time of unit ith
$X_i^{on}(t)$: Continuously on time of unit ith (h)
$X_i^{off}(t)$: Continuously off time of unit ith (h)
a: Cost coefficient for generator ($)
b: Cost coefficient for generator ($/MW)
c: Cost coefficient for generator ($/MW^2)

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