

# A Novel Binary Ant Colony Optimization: Application to the Unit Commitment Problem of Power Systems

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**Abstract** - This paper proposes a novel binary ant colony optimization (NBACO) method. The proposed NBACO is based on the concept and principles of ant colony optimization (ACO), and developed to solve the binary and combinatorial optimization problems. The concept of conventional ACO is similar to Heuristic Dynamic Programming. Thereby ACO has the merit that it can consider all possible solution sets, but also has the demerit that it may need a big memory space and a long execution time to solve a large problem. To reduce this demerit, the NBACO adopts the state probability matrix and the pheromone intensity matrix. And the NBACO presents new updating rule for local and global search. The proposed NBACO is applied to test power systems of up to 100-unit along with 24-hour load demands.

**Keywords:** Binary ant colony optimization, Combinatorial optimization, Unit commitment, Swarm intelligence

## 1. Introduction

Ant Colony Optimization (ACO) is one of meta-heuristic and evolutionary approaches to find the optimal solutions of the combinatorial or binary search problems. ACO was first developed by Dorigo et al. inspired by ant colonies [1,2]. In ACO, artificial ants search for good solutions in a cooperative way. Artificial ants move randomly along paths and deposit chemical substance trails, called pheromone, on the ground when they move, then collect and store information in pheromone trails. This pheromone trails motivates them to follow the path and can choose the shortest path in their movement. The ACO method has been researched in various aspects and successfully applied to the various optimization problems [3-10].

Unit commitment (UC) is a mixed integer combinatorial optimization problem, of which the purpose is to schedule the turning on and off of generating units so that the operating cost, start-up cost and shut-down cost be minimized for a given time horizon under various operating constraints [11]. The number of combinations of 0-1 variables grows exponentially as the number of units grows. Over the past decades, many salient methods have been developed for solving the UC problems. The exact solution to the problem can be obtained by complete enumeration, which cannot be applied to the real power systems due to its computational burden [11]. The solution methods for

UC problems can be divided into two categories: One is the numerical optimization techniques such as priority list methods [12-13], dynamic programming [14], Lagrangian relaxation methods [15], branch-and-bound methods [16], and mixed-integer programming [17]. The other is the stochastic methods based on heuristic search such as genetic algorithms [18], evolutionary programming [19], simulated annealing [20], particle swarm optimization [21], and quantum evolutionary algorithm [22].

Conventional ACO shows reasonable performance for small problems with moderate dimensions and searching space. However, Conventional ACO is recognized as not suitable for large scale problems such as UC problem, because the size of pheromone matrix grows exponentially along with the problem size [10]. This paper proposes a novel binary ant colony optimization (NBACO) method. The proposed NBACO is developed to solve the large size binary and combinatorial optimization problems. To overcome the computational burden of conventional ACO, the NBACO adopts the state probability matrix and the pheromone intensity matrix in place of the pheromone matrix used in conventional ACO method. In addition, the NBACO presents new updating rule for local and global search. The proposed NBACO is applied to UC problem of test power systems of up to 100-unit along with 24-hour load demands.

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## 2. Ant Colony Optimization Algorithm

### 2.1 Framework of Ant Colony System

Entomologists have studied the ability of ants to find the

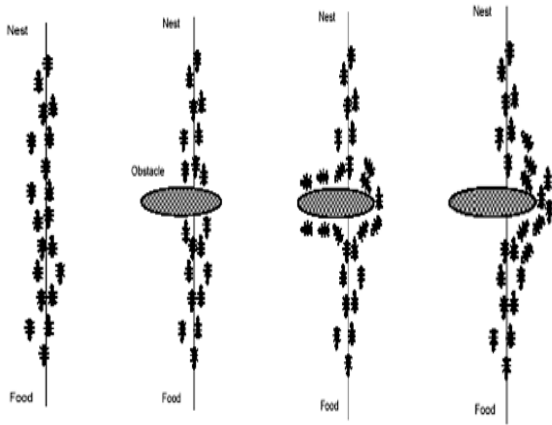


Fig. 1. An example of finding the shortest path.

shortest path between their nest and a food source. From these studies, Ant Colony Optimization (ACO) has been developed by Dorigo et al. [1,2] and successfully employed to solve various optimization problems. ACO is a meta-heuristic and evolutionary approach where several generations of artificial ants in a cooperative way search for good solutions. Initially artificial ants move randomly along paths and deposit chemical substance trails, called pheromone, on the ground when they move. And ants collect and store information in pheromone trails during their moving. This pheromone trails motivate them to follow the path with high intensity of pheromone. With time, the pheromone trail is reinforced or evaporated by the move of ants. Finally, all ants can choose the shortest path in their movement.

### 2.2 Ant Colony Optimization Algorithm

As shown in Fig. 1, the agents (i.e. ants) are guided by the intensity of pheromone trails. The path rich in pheromone becomes the best tour with time. This concept inspired the ACO algorithm. Initially, each agent is positioned on a starting node. Agents move to feasible neighbor nodes following the state transition rule. This rule indicates the preference of ants in choosing their paths that connect the current node to the next node. During the moving process, ants modify the level of pheromone on the paths they choose by applying the local updating rule. If the pheromone level on the chosen paths is lowered, these paths become less attractive to other agents. This property gives agents a higher probability to explore different paths and find an improved solution. Once all agents have reached the final node and have identified the best path which has the optimal value of the objective function, they update the pheromone level on the best path by applying a global pheromone updating rule. This is intended to allocate a higher level of pheromone on the best path. The rules to find the best path are detailed as below:

#### A. State Transition Rule

This rule guides the agents' search toward neighbor

nodes stochastically. The  $k$ -th agent at time  $t$  positioned on node  $r$  move to the next node  $s$  along the shorter path with higher intensity of pheromone  $\tau_{ru}(t)$ . This is achieved by a state transition rule (1) that utilizes both the inverse of the length of the path  $\eta_{ru}(t)$  and the amount of pheromone  $\tau_{ru}(t)$

$$s = \begin{cases} \arg \left\{ \max_{u \in allowed_{k(t)}} [\tau_{ru}(t)^\alpha \eta_{ru}^\beta] \right\} & \text{when } q \leq q_0 \\ S & \text{otherwise} \end{cases} \quad (1)$$

where,

- $\tau_{ru}(t)$  : The pheromone trail at time  $t$ .
- $\eta_{ru}(t) = 1/TC_{rs}(t)$ : the inverse of the transition cost  $TC_{rs}(t)$  with  $rs$  being the path from node  $r$  at the current stage to node  $s$  at the next stage
- $\alpha, \beta$  : parameters representing the relative importance
- $q$  : a random number uniformly distributed in  $[0,1]$
- $q_0$  : a pre-specified parameter ( $0 \leq q_0 \leq 1$ )
- $allowed_{k(t)}$ : the set of feasible nodes currently not assigned by the ant  $k$  at time  $t$
- $S$  : an index of node selected from  $allowed_{k(t)}$  according to the probability distribution given by (2)

$$P_{rs}^k(t) = \begin{cases} \frac{\tau_{rs}(t)^\alpha \eta_{rs}^\beta}{\sum_{u \in allowed_{k(t)}} \tau_{ru}(t)^\alpha \eta_{ru}^\beta} & \text{if } s \in allowed_{k(t)} \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

#### B. Local Updating Rule

An ant changes the pheromone level on the moved path (local updating) by applying the local updating rule (3). This rule has the effect of lowering the pheromone level on the search paths.

$$\tau_{rs} = (1 - \rho)\tau_{rs} + \rho\tau_0 \quad (3)$$

where,

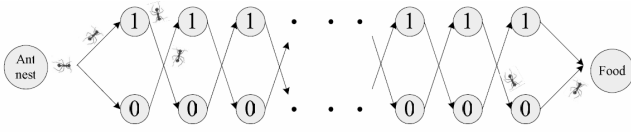
- $\rho$  : evaporation coefficient ( $0 < \rho < 1$ )
- $\tau_0$  : initial pheromone level,  $\tau_0 = 1/J$  where  $J$  is a rough approximation of the optimum value of the cost function.

#### C. Global Updating Rule

The global pheromone updating is performed only after all ants have completed their moving. The global pheromone updating rule (4) is intended to provide a greater amount of pheromone to shorter path.

$$\tau_{rs} = (1 - \alpha)\tau_{rs} + \alpha\Delta\tau_{re} \quad (4)$$

where,



**Fig. 2.** Feasible paths of a binary ant colony optimization.

$$\Delta\tau_{re} = \begin{cases} (J^*)^{-1}, & \text{if } (r,s) \in \text{global-path} \\ 0, & \text{otherwise} \end{cases}$$

$\alpha$  : pheromone decay coefficient ( $0 < \alpha < 1$ )

$J^*$  : the best value of the objective function

The capability of finding the optimal path can be enhanced through this rule in the search process. The pseudo code of Conventional ACO algorithm can be described as:

```

Initialize pheromone trails
Repeat until system convergence conditions satisfied
Generate agents ();
Move according to the transition Rules ();
Update Pheromone ();
End

```

### 3. A Novel Binary Ant Colony Optimization

#### 3.1 A novel Binary Ant Colony Optimization

Fig. 2 presents feasible paths of a binary ant colony optimization for an integer optimization problem. Although the framework of NBACO is similar to the conventional ACO, it adopts new rules and concepts to overcome the limit of conventional ACO. The new rules and concepts are described in the following subsections.

##### A. State Transition Rule

The proposed NBACO has a state probability matrix for all states. Using the state probability matrix, agents determine their own state. The state of each agent takes a value of 0 or 1 by the probability of  $P_i^k$  of the state probability matrix as follows:

$$\mathbf{P}^k = [P_1^k \dots P_i^k \dots P_H^k] \quad (5)$$

where,

$P_i^k$  : The probability that a state has value 1 at the stage  $i$  of  $k$ -trail

$H$  : The number of the stages

$Q_i^k$  : The probability that a state has value 0 at the stage  $i$ ,  $Q_i^k = 1 - P_i^k$

Initially, all states probability is  $1/2$  and the state of each agent is determined by the state transition rule (6).

$$S_i^k(RN, P_i^k) = \begin{cases} 1, & \text{if } RN \leq P_i^k \\ 0, & \text{otherwise} \end{cases} \quad (6)$$

where,

$RN$  : the random number ( $0 \leq RN \leq 1$ )

##### B. Pheromone Updating Rule

For pheromone updating, the relative Pheromone Intensity Matrix (7) is proposed as follows:

$$\mathbf{C}^k = [C_1^k \dots C_i^k \dots C_H^k], \quad C_i^k = \sum_{j=1}^N c_j^k \quad (7)$$

where,

$$c_j^k = \begin{cases} +\rho, & s_i^k = 1 \\ -\rho, & s_i^k = 0 \end{cases}, \quad \mathbf{C}_{initial}^k = 0$$

$N$  : the number of agents

$\rho$  : an ant's pheromone quantity

$H$  : the number of the stages

It is assumed all agents move at the same time and they make relative pheromone intensity on the state of 0 or 1. And pheromone intensity matrix is initialized to 0 at every trial (i.e.,  $\mathbf{C}_{initial}^k = 0$ ). As shown in equation (8), since relative pheromone intensity is divided by the number of the total agents (i.e.,  $N$ ), relative state selection probability (i.e.,  $C_i^k / N$ ) of  $k$ -trial is created. By a linear combination of both relative state selection probability and the best state, the state probability matrix is updated as follows:

$$P_i^{k+1} = P_i^k + C_i^k / N + \rho \times BState_i^k \quad (8)$$

where,

$$P_i^{k+1} = \begin{cases} P_i^{k+1}, & 0 < P_i^{k+1} < 1 \\ 1 \text{ or } 0, & P_i^{k+1} \geq 1 \text{ or } P_i^{k+1} \leq 0 \end{cases}$$

$BState_i^k$  :  $k$ -trail best state.

(the value of 0 state indicates -1.)

$N$  : the number of agents

The procedure of the proposed NBACO algorithm can be summarized as the following pseudo-code:

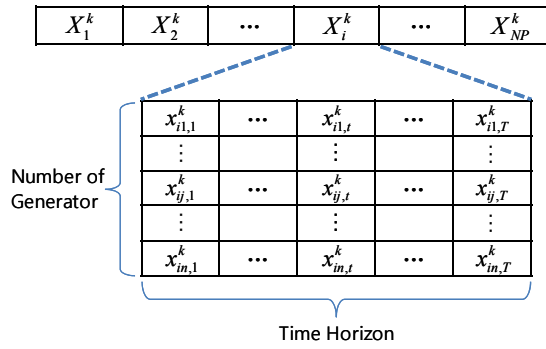
```

Begin
Create Initial State Probability Matrix
Repeat until system convergence conditions satisfied
Generate agents group ();
Generate Relative Pheromone Intensity Matrix ();
Update Best State and State Probability Matrix ();
End

```

#### 3.2 Application of NBACO to UC Problem

The UC problem determines the on/off status of generating units. So the decision variables are the on/off states of generating units. The structure of an agent state of the proposed NBACO for UC problems is depicted in Fig. 3. If the  $j$ -th generator in  $i$ -th agent at hour  $t$  of  $k$ -trial is ON, the



**Fig. 3.** The structure of an agent of NBACO for UC.

$x_{ij,t}^k$  is set to be 1. Otherwise,  $x_{ij,t}^k$  is set to be 0.

After determining the feasible commitment scheduling, the optimal power outputs of the units are determined through the conventional economic dispatch (ED). Since the fuel cost function of a generating unit is represented as the quadratic function, ED problem can be easily solved by numerical techniques. In the subsequent sections, the detail procedures of NBACO for scheduling the on/off states of generating units are described.

#### A. Creating Initial State Probability Matrix and Agents Group

For UC problem, the state probability matrix at  $k$ -th trial is defined as follows:

$$P_{jt}^k = \begin{bmatrix} P_{11} & \cdots & P_{1H} \\ \vdots & \ddots & \vdots \\ P_{N1} & \cdots & P_{NH} \end{bmatrix} \quad (9)$$

The element of the matrix  $P_{jt}^k$  represents the state probability that the  $j$ -th generator at hour  $t$  of  $k$ -th trial is 1 (ON). All elements of the state probability matrix are set to be 1/2 at initial stage. It means that all states have the same probability. The state matrix of agents group on the  $k$ -th trial is determined by the state probability matrix (9) and the state transition rule (6). After generating a random number  $RN_{ij,t}$ , the state at the hour  $t$  of the  $j$ -th generator at trial  $k$  (i.e.,  $x_{ij,t}^k$ ) takes a value of 0 if  $RN_{ij,t}$  is less than 1/2, otherwise it is set to 1. All agents' states are generated in the same way.

#### B. Creating Relative Pheromone Intensity Matrix

The relative pheromone intensity matrix is generated by (10), which is composed of all agents' state. If the  $x_{ij,t}^k$  is 1, the pheromone's quantity (i.e.,  $\rho$ ) is added to relative pheromone intensity. Otherwise, it is subtracted. If an element of the matrix is positive, it means that the number of 1 states is larger than that of 0 states.

$$C^k = [C_1^k \cdots C_{j,t}^k \cdots C_H^k], \quad C_{j,t}^k = \sum_{i=1}^N c_{ij,t}^k \quad (10)$$

where,

$$c_{ij,t}^k = \begin{cases} +\rho, & x_{ij,t}^k = 1 \\ -\rho, & x_{ij,t}^k = 0 \end{cases}, \quad C_{initial}^k = 0$$

#### C. Updating the Best State

If the state of  $i$ -th agent,  $X_i^{k+1}$ , yields a smaller cost function value than  $BState_i^k$ , then  $BState_i^{k+1}$  is set to  $X_i^{k+1}$ . Otherwise,  $BState_i^k$  is retained. The Rule Updating the best state can be formulated as (11).

$$BState_i^{k+1} = \begin{cases} X_i^{k+1} & \text{if } f(X_i^{k+1}) \leq f(BState_i^k) \\ BState_i^k & \text{otherwise} \end{cases} \quad (11)$$

#### D. Updating the State Probability Matrix

The state probability matrix is updated by (12), which is composed of the relative state selection probability matrix and the best state.

$$P_{jt}^{k+1} = P_{jt}^k + C_{j,t}^k / N + \rho \times BState_i^k \quad (12)$$

#### E. Stopping Criteria

The proposed NBACO algorithm is terminated if the iteration reaches a pre-specified maximum iteration or a pre-specified critical probability.

## 4. Numerical Test

The proposed NBACO is applied to the several test systems, which have 10-, 20- 40-, 80-, and 100-generating units, respectively. Time horizon is chosen along with 24-hour load demands. For each test case, 50 independent trials are conducted to compare the solution quality and convergence characteristics. Numerical tests have been executed on a Pentium IV 2.6GHz computer. In implementing the proposed algorithms, some parameters must be determined in advance. The number of agent and maximum iteration count are chosen same as those in the referred paper [22]. The value of pheromone quantity is obtained through a parameter tuning. When the pheromone quantity is more than 0.05, the cost is observed to increase. In other words, the solution's quality becomes worse with higher pheromone quantity. In this paper the parameters were set through experiments as follows:

- The number of Agent  $N = 30$ ;
- Maximum iteration count  $iter_{max} = 1,000$ ;
- Pheromone quantity  $\rho = 0.05$ .

Firstly, the proposed NBACO is applied to the simple 10-unit system with a 24-hour time horizon as a base case.

**Table 1.** The generating units data for the 10-Unit system

Unit	Unit1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6	Unit 7	Unit 8	Unit 9	Unit 10
$P_{max}$ (MW)	455	455	130	130	162	80	85	55	55	55
$P_{min}$ (MW)	150	150	20	20	25	20	25	10	10	10
$A$	1000	970	700	680	450	370	480	660	665	670
$B$	16.19	17.26	16.6	16.5	19.7	22.26	27.74	25.92	27.27	27.79
$C$	0.00048	0.00031	0.002	0.00211	0.00398	0.00712	0.00079	0.00413	0.00222	0.00173
$MUT$ (Hr)	8	8	5	5	6	3	3	1	1	1
$MDT$ (Hr)	8	8	5	5	6	3	3	1	1	1
$SU_{it}$ (\$)	4500	5000	550	560	900	170	260	30	30	30
$SU_c$ (\$)	9000	10000	1100	1120	1800	340	520	60	60	60
$T_{cold}$ (Hr)	5	5	4	4	4	2	2	0	0	0
Initial status(Hr)	8	8	-5	-5	-6	-3	-3	-1	-1	-1

**Table 2.** The demand with 24-hour time horizon

Hour	Demand (MW)	Hour	Demand (MW)	Hour	Demand (MW)
1	700	9	1,300	17	1,000
2	750	10	1,400	18	1,100
3	850	11	1,450	19	1,200
4	950	12	1,500	20	1,400
5	1,000	13	1,400	21	1,300
6	1,100	14	1,300	22	1,100
7	1,150	15	1,200	23	900
8	1,200	16	1,050	24	800

**Table 3.** The simulation results of NBACO for test systems

Units	Best Cost (\$)	Average Cost (\$)	Worst Cost (\$)	Standard Deviation	Execution Time(s)
10	563,977	563,977	563,977	0	39
20	1,124,531	1,125,320	1,126,251	384	77
40	2,246,022	2,247,272	2,248,710	654	267
80	4,487,254	4,488,535	4,489,890	786	995
100	5,609,583	5,611,105	5,612,892	962	1535

**Table 4.** The performance comparison of UC algorithms

Method	10-unit	40-unit	80-unit	100-unit
LR [15]	565,825	2,258,503	4,526,022	5,657,277
GA [18]	565,825	2,251,911	4,504,933	5,627,437
EP [19]	564,551	2,249,093	4,498,479	5,623,885
SA [20]	565,828	2,250,063	4,498,076	5,617,876
IPSO [21]	<b>563,954</b>	2,248,163	4,495,032	5,619,284
NBACO	563,977	<b>2,246,022</b>	<b>4,487,254</b>	<b>5,609,583</b>

The characteristics of the generators used in the 10-unit system and the demand are given in Table 1 and Table 2, respectively. Subsequently, the 20-, 40-, 80-, and 100-unit data are obtained by duplicating the base case, and the load

**Table 5.** Unit scheduling and corresponding costs for the 10-unit system

Hr	Generation Output										Total Power	Fuel Cost	Startup Cost
	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10			
1	455	245	0	0	0	0	0	0	0	0	700	13,683	0
2	455	295	0	0	0	0	0	0	0	0	750	14,554	0
3	455	370	0	0	25	0	0	0	0	0	850	16,809	900
4	455	455	0	0	40	0	0	0	0	0	950	18,598	0
5	455	390	0	130	25	0	0	0	0	0	1,000	20,020	560
6	455	360	130	130	25	0	0	0	0	0	1,100	22,387	1,100
7	455	410	130	130	25	0	0	0	0	0	1,150	23,262	0
8	455	455	130	130	30	0	0	0	0	0	1,200	24,150	0
9	455	455	130	130	85	20	25	0	0	0	1,300	27,251	860
10	455	455	130	130	162	33	25	10	0	0	1,400	30,058	60
11	455	455	130	130	162	73	25	10	10	0	1,450	31,916	60
12	455	455	130	130	162	80	25	43	10	10	1,500	33,890	60
13	455	455	130	130	162	33	25	10	0	0	1,400	30,058	0
14	455	455	130	130	85	20	25	0	0	0	1,300	27,251	0
15	455	455	130	130	30	0	0	0	0	0	1,200	24,150	0
16	455	310	130	130	25	0	0	0	0	0	1,050	21,514	0
17	455	260	130	130	25	0	0	0	0	0	1,000	20,642	0
18	455	360	130	130	25	0	0	0	0	0	1,100	22,387	0
19	455	455	130	130	30	0	0	0	0	0	1,200	24,150	0
20	455	455	130	130	162	33	25	10	0	0	1,400	30,058	490
21	455	455	130	130	85	20	25	0	0	0	1,300	27,251	0
22	455	455	0	0	145	20	25	0	0	0	1,100	22,736	0
23	455	420	0	0	25	0	0	0	0	0	900	17,685	0
24	455	345	0	0	0	0	0	0	0	0	800	15,427	0
Total	10,920	9,680	2,080	2,210	1,540	332	225	83	20	10	27,100	559,887	4,090

demands are adjusted in proportion to the system size. In all cases, the spinning reserve requirements are assumed to be 10% of the hourly demand.

In Table 3, the best, average, worst costs, standard deviation, and execution time for test systems obtained by the proposed NBACO algorithm are summarized.

The results of the proposed NBACO are compared with those of Lagrange relaxation (LR) [15], genetic algorithm (GA) [18], evolutionary programming (EP) [19], simulated annealing (SA) [20], and improved particle swarm optimization (IPSO) [21]. As shown in the Table 4, the results of the proposed algorithm are superior to those of other algorithms in most cases except the 10-unit case. Even in the 10-unit case, the proposed method provides the second best solution, of which the difference to the best solution is negligible.

The commitment schedules during the planning horizon obtained by the proposed NBACO for 10-unit and 100-unit systems are described in Table 5 and Table 6, respectively. The convergence characteristics of the NBACO for 40-unit



generation limits of unit  $j$ , respectively.

Spinning Reserve Constraints:

$$\sum_{j=1}^N P_{j,\max} u_{j,t} \geq PD_t + SR_t \quad (18)$$

where  $SR_t$  is the required spinning reserve at hour  $t$ .

Generation Ramping Constraints:

$$RD_j \leq P_{j,t} - P_{j,(t-1)} \leq RU_j \quad (19)$$

where  $RD_j$  and  $RU_j$  are the ramp-down and ramp-up limits of unit  $j$ , respectively.

Minimum Up-time/Down-time Constraints:

$$u_{j,t} = \begin{cases} 1 & \text{if } 1 \leq TON_{j,t-1} < MUT_j \\ 0 & \text{if } 1 \leq TOFF_{j,t-1} < MDT_j \\ 0 \text{ or } 1 & \text{otherwise} \end{cases} \quad (20)$$

where  $TON_{j,t}$  is the duration for which unit  $j$  remains on-line at hour  $t$  and  $MUT_j$  is the minimum up-time of unit  $j$ .

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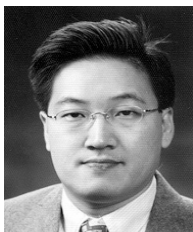
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