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Ant colony optimization algorithm with random perturbation behavior to the problem of optimal unit commitment with probabilistic spinning reserve determination

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Abstract

In this paper, a novel ant colony optimization algorithm with random perturbation behavior (RPACO) based on combination of general ant colony optimization and stochastic mechanism is developed for the solution of optimal unit commitment (UC) with probabilistic spinning reserve determination. In general, the purpose of UC is to enhance the economical efficiency as could as possible while simultaneously satisfying physical and operation constraints of individual unit. Consider the possibility of generating unit failure, the requirement, the sufficient spinning reserve capacity to ensure adequate reliability levels, must be satisfied by the commitment schedule. The security function approach is applied to evaluate the desired level of system security, and the proposed method in this paper, RPACO, is adopted to solve the UC problems. The effectiveness of the proposed method has been demonstrated on the corresponding numerical results. Further, the sensitivity of the desired security level to the optima during optimization is investigated in this paper.

Keywords: Unit commitment; Reliability; Ant colony optimization algorithm; Transition strategy

1. Introduction

The unit commitment (UC) problem is to determine an optimal schedule which should minimize the system production cost during a considered period while simultaneously satisfying the load demand, spinning reserve, physical and operation constrains of the individual unit. In view of the uncertainty of load forecast and likelihood of generating unit failure, a very important requirement that must be satisfied by the commitment schedule is the preservation of sufficient spinning reserve to ensure adequate reliability levels. At present, there are mainly two kinds of approaches for the evaluation of spinning reserve requirement, deterministic methods and probability methods. In general, spinning reserve evaluation is carried out via using deterministic criteria. This approach has resulted in high operating reliability, but experience seems to suggest that the deterministic criteria may be more conservative than necessary. Furthermore, the major limitation of this approach is that it cannot adequately consider the probabilistic characteristics of component failure. While on the contrary, the probability methods can effectively simulate the stochastic action of system components, and combine all components to evaluate the spinning reserve. Various probability methods, such as PJM [1], Frequency and Duration approach (F&D) [1], security function approach [1], have been employed in the past with varying degree of success. Considering that the application of probability methods in operations gradually receives some attention, and the “security function” method is a practical approach in the engineering application due to its simplicity and liability to use, this method is applied to maintain a desired level of system security in this paper.

It is well known that UC problem is commonly formulated as a nonlinear, large scale, non-convex, discrete, mixed-integer combinatorial optimization problem with constrains. It is very difficult for large-scale power systems

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to obtain a real solution. Research endeavors, therefore, have been focused on efficient UC algorithms which can be applied to realistic power systems. Various approaches such as priority list method [2], dynamic programming [2], mixed-integer programming [3], branch-and-bound methods, and Lagrangian relaxation methods [3,4], have been proposed for solving UC problem with success in varying degree. However, most of the techniques are inadequate and insufficient to the UC problem due to its inherent complexity. At present, computational intelligence techniques, such as Genetic Algorithms [5,6], Simulated Annealing [7], Artificial Neural Network [8], Basic Ant Colony Algorithm [12,13], have also been applied to UC problem, and bring about some good results in solving more complicated constrains and obtaining global or near global optima. In this paper, a novel ant colony optimization algorithm with random perturbation behavior (RPACO) is first proposed in accordance with the stagnation behavior in basic ant colony algorithm [9] (BACO), and at the same time, the new method is applied to the solution of UC under reliability. Some technical problems, such as model conversion, handling of constraints et al., are further studied. The mechanism of this new approach and its applications will be discussed in detail in the section to follow.

2. Ant colony optimization algorithm with random perturbation behavior

2.1. Mechanism of RPACO

In order to easily understand the optimization mechanism of the proposed algorithm, all descriptions in the following section are based on the traveling salesman problem (TSP).

2.1.1. Transition strategy

The operational mechanism of basic ant colony algorithm is based on the combination of positive feedback principle and a certain heuristic search technique. It can be brought to light from the transition probability formula (1) [9] formulated as follows:

$$P_{ij(k)}(t) = \begin{cases} \dfrac{\tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}}{\sum \tau_{is}^{\alpha}(t)\eta_{is}^{\beta}}, & j, s \notin \mathrm{tabu}_{(k)} \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

where $\tau_{ij}(t)$ is the amount of pheromone trail on the path ij at time t; $\eta_{ij} = 1/d_{ij}$ is the heuristic value of moving from node i to node j; $\mathrm{tabu}(k)(k = 1, 2, \ldots, m)$ is the set of states that remain to be visited by ant k positioned on state i; α and β are two parameters that control the relative weight of pheromone trail and heuristic value.

Eq. (1) implied a fact that the more the amount of pheromone presented on a shorter branch, the higher the transition probability with the branch, the more the ants that use the shorter path. In view of this physical meanings, a more concise transition strategy is developed in this paper.

$$C_{ij(k)}(t) = \begin{cases} \tau_{ij}(t)\eta_{ij}, & j \notin \mathrm{tabu}_{(k)} \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

Let $s(t)$ be the cities visited by ants according to $\max(C_{ij}(k))$. In Eq. (2), the physical meanings of $\tau_{ij}\ \eta_{ij}$ is the pheromone of unit length on path ij. Here, it must be noted that $C_{ij}(k)$ in Eq. (2) is no longer represented the transition probability with stochastic characteristics, but the transition coefficient with deterministic selection on path ij. Ants always select the path with maximal transition coefficient to move. Furthermore, $C_{ij}(k)$ has the dimensions of pheromone divided by path length. Considering that only the size of $C_{ij}(k)$ is applied during computation, there is not any influence on the results.

2.1.2. Magnifying factor

τ_{ij} in Eq. (1) represents the pheromone on path ij, and it plays an important role during optimization. In order to enhance the effect that more pheromone should be deposited on the shorter path at the initial stages of iteration, a parameter γ, called magnifying factor, is introduced in this paper. How to effectively formulate the magnifying factor γ, the following two aspects must be considered: (1) The ant always chooses the path with the maximal transition coefficient to move. If the population size is very large, it is difficult for the algorithm to find the best closed tour from many disordered tours at short notice, so in order to improve the convergence of algorithm, the value of γ should be relatively larger at the initial stages of iteration. This can make the intensity of the best paths obviously greater than of the others. (2) If γ is all along held fixedness, it will lead the search to premature convergence (stagnation), that is, the situation in which some not very good individual takes over the population just because of a contingent situation impeding further exploration of the search space. Therefore, reducing γ gradually during iteration, on the one hand, can strengthen diversity of the selected tour, on the other hand, can asymptotically converge to the optimum.

According the ideas described above, the following experimental formula to formulate γ is presented in this paper.

$$\gamma = e^{b/r}\ (r = 1, 2, \ldots I_{\max} \quad b > 0) \quad (3)$$

where $I_{\max}$ is the maximal number of iterations; b the scaling factor. The curve is shown in Fig. 1.

Fig. 1 shows that magnifying factor γ approaches 1 finally, and the rate of timing approaching 1 is determined by size of b.

Thus, transition coefficient can be further described as

$$C_{ij(k)}(t) = \begin{cases} [\tau_{ij}(t)]^{\gamma}\eta_{ij} & j \notin \mathrm{tabu}_k \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

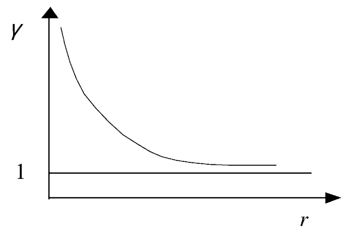

Fig. 1. Inverse exponent curve.

2.1.3. Random perturbation strategy

In view of the stagnation behavior existed in BACO, a random perturbation strategy is introduced into transition coefficient $C_{ij}(k)$:

$$C_{ij(k)}(t) = \begin{cases} [\tau_{ij}(t)]^{\alpha}\eta_{ij}\; U \leq p_{\mathrm{m}} & j \notin \mathrm{tabu}_k \\ [\tau_{ij}(t)]^{\gamma}\eta_{ij}\; U > p_{\mathrm{m}} & j \notin \mathrm{tabu}_k \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

where γ is the magnifying factor; α is a coefficient, it can be viewed as a constant magnifying factor; U, $p_{\mathrm{m}} \sim R$ [0,1] (R[0,1]) denotes the uniform distribution. Here, p_{m} is called mutation rate. The introduction of the mutation rate p_{m} brings the perturbation characteristics into the evolutionary process. In general, p_{m} is set to a very small value, naturally, the second item in Eq. (5) is easily satisfied. The first item in Eq. (5), moreover, represents the concrete perturbation degree.

From Eq. (5), when p_{m} is set to a very small value, Eq. (5) will retrogress the status the same as Eq. (4). However, when p_{m} is set to a value properly, the search process can be prevented from being in local optima due to perturbation behavior of p_{m}.

Ultimately, the model of ant colony optimization algorithm with random perturbation behavior is formulated as follows:

$$C_{ij(k)}(t) = \begin{cases} [\tau_{ij}(t)]^{\alpha}\eta_{ij}\; U \leq p_{\mathrm{m}} & j \notin \mathrm{tabu}_k \\ [\tau_{ij}(t)]^{\gamma}\eta_{ij}\; U > p_{\mathrm{m}} & j \notin \mathrm{tabu}_k \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

$s(t) =$ the cities visited by ants according to $\max_{ij}(C_{ij(k)})$
where

$$\gamma = \mathrm{e}^{b/r}\ (r = 1, 2, \ldots I_{\max} \quad b > 0)$$

$$\tau_{ij}(t+n) = \rho \cdot \tau_{ij}(t) + \Delta\tau_{ij}$$

$$\Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\tau_{ij}(k)$$

$$\Delta\tau_{ij}(k) = \begin{cases} \dfrac{Q}{L_k}, & \text{if } k\text{th ant uses path}(i, j)\text{in its tour} \\ 0, & \text{otherwise} \end{cases}$$

where m is the number of ants; Q is the heuristically defined parameter; L_k is the length of the tour performed by ant k.

In a nutshell, RPACO is based on the combination of deterministic and stochastic selection. On the one hand, ants move toward the optimal path under the lead of deterministic selection, and on the other hand, the search process of ants can be effectively avoided local minimums under the operation of stochastic selection. It is observed that RPACO possesses stronger global optimization capability of escaping local optimum as a result of combination of the two strategies.

2.2. Parameter setting

As with a lot of nature inspired problem solving techniques in AI, parameter setting is a key issue in the performance of such a system. In RPACO, the selection of parameters α, ρ, Q, ρ_{m} and β affect directly or indirectly the computation efficiency and convergence of algorithm. It is difficult to set the optimal combination of parameters via using analysis method currently. Here, the empirical method of finding optimal parameter settings via simulating a large number of trials is used in this paper. The details are described as follows:

(1) One found such a rule through running a set of experiments that the numeric area of parameters α and Q was larger, and ρ, $p_{\mathrm{m}} \in [0, 1]$. Based on the rule, one randomly sets a set of values of ρ and p_{m} first, and then regulates α and Q in accordance with the given ρ and p_{m} until an ideal solution is obtained.
(2) When next one will regulate ρ and p_{m} as soon as the α and Q is attained according to (1).
(3) Repeating (1) and (2) until a set of better combinations of parameters are achieved.

Finally, one can obtain the following optimal numeric area of parameters:

(1) $\alpha \in [0.1, 5]$.
(2) Considering that the physical meanings of $\rho \times \tau$ represents the remanent pheromone, suggesting $\rho \in [0.5, 0.8]$.
(3) Here, the numeric area of Q is obtained through the following formula can be constructed as:

$$Q = \rho L_k \tau_{ij}(0) \quad (7)$$

From (7), the numeric area of Q can be confirmed according to the path length in which any one ant moved as soon as the first iteration is completed. In this paper, suggesting $Q \in [50, 100]$:
(4) Scaling factor $b \in [0.5, 2]$.
(5) Mutation rate $p_{\mathrm{m}} \in [0, 0.1]$.

It should be noted that the numeric area of parameters described above possesses a certain universality, that is, the numeric area of parameters heuristically defined in this paper is suitable for the solution of different problems.

Table 1
The environmental parameters

TSP	BACO				RPACO				
	α	β	ρ	Q	α	ρ	p_m	b	Q
24	1.0	5.0	0.5	100	0.5	0.8	0.1	2	100
29	1.5	4.0	0.6	100	0.2	0.8	0.1	2	100
48	1.5	4.0	0.6	100	0.5	0.8	0.1	2	100

Table 2
Simulation results of various algorithms

TSP	BACO		RPACO	
	Time (s)	The length of tour	Time (s)	The length of tour
24	100	1298	61	1264
29	160	2040	96	2020
48	600	5494	367	5256

2.3. Experimental testing

To verify the computational efficiency and the convergent performance of RPACO, one takes a set of examples based on TSP problems, such as gr24 (24 towns and 276 edges), bayes29 (29 towns and 406 edges), gr48 (48 towns and 1128 edges). (Note: These examples can be found from the web site TSPBIB provided by Pablo Moscato—a scholar of Universided Nacional university in Argentina.) And the numerical results of the RPACO are compared with those from the BACO. All the programs are developed using C++ and run on a Pentium-400 MHz computer. The environmental parameters are given in Table 1. The number of maximal iteration times is 1000.

Testing results obtained from the proposed RPACO and the BACO are summarized in Table 2. It can be seen that the proposed method—RPACO expresses the strong global optimization capability of escaping stagnation behavior, and reduces the CPU time. The dynamic optimization curves of the two algorithms, BACO and RPACO based on the bayes29 TSP, are given in Fig. 2.

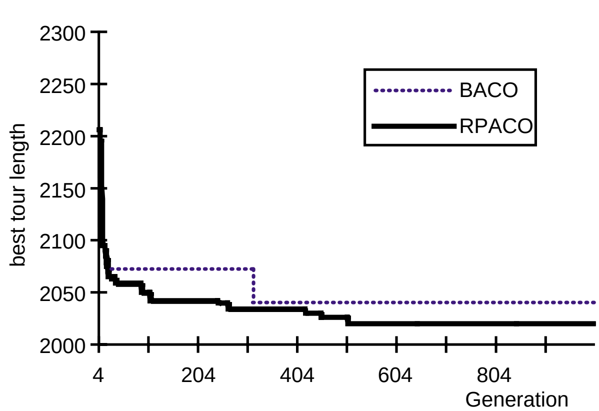

Fig. 2. Dynamic optimization curves of two algorithms.

3. Resume of formulation of the UC problem

UC problem has become increasingly important in the power industry, specially under the competitive electricity markets, because significant savings can be accrued from sound commitment decisions. A dispatcher to do this must indicate which of the generating units are to be committed (on or off) in every time interval during the scheduling time horizon. This decision must take into account load forecast information and the economic implications of the startup or shutdown of various units. The transition between their commitment states must satisfy the operating constraints. In order to maintain a certain degree of reliability, the amount of spinning reserve is an important factor in ensuring an uninterrupted power supply. The UC problem can be formulated as the following mixed-integer programming problem:

Objective function [10–15]

$$\min\sum_{t=1}^{T}\sum_{i=1}^{n}[Fi(P_i^t)u_i^t + F_{si}(\tau)u_i^t(1-u_i^{t-1})] \tag{8}$$

For each committed unit, the cost included is the fuel cost (F_i) and the *start-up* cost (F_{si}). P_i^t is a real power output of the ith unit in the tth stage; u_i^t is the status index of the ith unit at the tth hour (1 for up and 0 for down).

Due to operational requirements, the objective function is subjected to the following constrains [10–15]:

(1) Real power balance constraint

$$\sum_{i=1}^{n}P_i^t = P_D^t + P_L^t \quad (t=1,\ldots,T) \tag{9}$$

where P_D^t and P_L^t are the load demand and transmission losses at the tth hour, respectively.

(2) Real power operating limits of generating units

$$u_i^t\underline{P}_i \le P_i^t \le u_i^t\bar{P}_i \quad (i=1,\ldots,n;\ t=1,\ldots,T) \tag{10}$$

(3) Minimum up/down time of generating units

$$(u_i^t - u_i^{t-1})(w_i^{t-1} - w_i^{\min}) \le 0$$
$$(i=1,\ldots,n;\ t=1,\ldots,T) \tag{11}$$

where $w_i^t = u_i^t(w_i^{t-1}+1)$. w_i^{t-1} is the length of time the ith unit was up consecutively at the $t-1$ h; $w_i^{\min}$ is the minimum up time of the ith unit.

$$(u_i^t - u_i^{t-1})(q_i^{t-1} - q_i^{\min}) \le 0$$
$$(i=1,\ldots,n;\ t=1,\ldots,T) \tag{12}$$

where $q_i^t = (1-u_i^t)(q_i^{t-1}+1)$. q_i^{t-1} is the length of time the ith unit was down consecutively at the $t-1$ h; $q_i^{\min}$ is the minimum down time of the ith unit.

(4) Ramp-rate limits of generating units

$$P_i^{t+1} < P_i^t + \Delta\omega_i$$

$$P_i^{t+1} > P_i^t - \Delta\omega_i \quad (i=1,\ldots,n;\ t=1,\ldots,T) \tag{13}$$

where $\Delta\omega_i$ is the maximum sustained change in the average generation from period to period for unit i;

(5) Transmission line capacity limits

$$P_l \leq P_{l\,\max} \tag{14}$$

(6) Spinning reserve constraint

For the purpose of maintaining a certain degree of reliability, some stand-by capacity is necessary that can immediately take over when a running unit breaks down or unexpected load occurs. There are several spinning reserve policies that have usually been adopted: the deterministic based methods, such as a fixed percentage of the forecast peak demand at every time period, a variable reserve, a reserve slightly greater than the output of the most heavily loaded unit, and the probability based methods described above. In this paper, the corresponding constraint based on the deterministic methods is formulated as follows:

$$\frac{\sum_{i=1}^{n} u_i^t P_i^{\max} - P_{\mathrm{D}}^t}{P_{\mathrm{D}}^t} \geq R^t \quad (t = 1, \dots, T) \tag{15}$$

where R^t is the spinning reserve rate.

For the probability methods, the "security function" approach is applied to evaluate the system spinning reserve in this paper. The details are discussed in this section to follow.

3.1. *Security function based method for evaluating spinning reserve*

The security function provides a means for assessing system security in hour-to-hour operation on a probabilistic basis. Thus, the security function can be used as a control criterion in the generating unit scheduling process to assure that some pre-selected acceptable risk of system insecurity is not exceeded. The mathematical model of security function is given as follows:

$$S(t) = \sum_i P_i(t) Q_i(t) \tag{16}$$

where $P_i(t)$ is probability in state i at time t; $Q_i(t)$ the probability which state i constitutes a breach of security at time t. $S(t)$ is the insufficient generating capacity probability at time t. Suppose a system has n generators which behave independently of each other. Assuming that the status of a generator can be characterized as a two-state (on forced outage and totally unavailable or fully available) Markov process, the probabilities of finding the ith generator in the 'up' or 'down' state at time t given the generator up at time zero are

$$P_{\mathrm{upm}}(t) = \frac{\mu_{\mathrm{m}}}{\mu_{\mathrm{m}} + \lambda_{\mathrm{m}}} + \frac{\lambda_{\mathrm{m}}}{\mu_{\mathrm{m}} + \lambda_{\mathrm{m}}} \mathrm{e}^{-(\mu_{\mathrm{m}} + \lambda_{\mathrm{m}})t} \tag{17}$$

$$P_{\mathrm{dnm}}(t) = \frac{\lambda_{\mathrm{m}}}{\mu_{\mathrm{m}} + \lambda_{\mathrm{m}}} [1 - \mathrm{e}^{-(\mu_{\mathrm{m}} + \lambda_{\mathrm{m}})t}] \tag{18}$$

where λ_{m} and μ_{m} represent the forced outage rate and repair rate of unit i, respectively. Assuming no stand-by generators or t less than the time required to start a stand-by generator, the probability of a system state can be found as follows:

$$P_i(t) = \prod_{j \in X_{\mathrm{d}}} P_{\mathrm{dn}\,j}(t) \cdot \prod_{k \in X_{\mathrm{u}}} P_{\mathrm{up}k}(t) \tag{19}$$

where X_{d} and X_{u} are set of generators which are down in state i and up in state i, respectively.

The values of $Q_i(t)$ will depend on the load forecasting method. Here, assuming that the load forecasts are exact, then

$$Q_i(t) = \begin{cases} 1 & \text{system load} > \text{available capacity} \\ 0 & \text{otherwise} \end{cases} \tag{20}$$

The $S(t)$ at time t can be obtained from carrying out all possible system states. Then, the spinning reserve constraint based on security function is described as follow:

$$S(t) \leq \mathrm{MTIL} \quad t = 1, \dots, T \tag{21}$$

here, MTIL is expressed as 'Maximum Tolerable Insecurity Level', 1-MTIL represents the desired security level. If the value of the security function does not exceed MTIL during interval, it can be concluded that the combination of units provides adequate security.

4. RPACO algorithm for the UC problem

4.1. *ACO computation schema of the UC problem*

UC is essentially a complex multi-period optimal decision-making process. ACO is also a multistage optimal decision process for solving TSP. For UC, different combinations of generating units can be committed in every time interval. Similarly, for TSP using ACO, only towns that were not visited by ants in the preceding steps will be selected in every time interval. In view of the similarity between them, it is possible to solve UC via using ACO. In order to construct a solving context similar to that of TSP, the concepts of state and decision defined in dynamic programming (DP) should be introduced first.

State: The commitment of generating units along with on/off decision constitutes a state.

Decision: The process which a state in a time interval transits another state in the next time interval constitutes a decision.

Considering that a tour (i.e., all towns have been visited) completed by an ant in TSP using ACO is closed, the definition of a path similar to the tour, which is applied to UC, is proposed in this paper. It can be described as:

Path: The set of decisions, which consists of states chosen arbitrarily at each time period t in all time intervals from 1 to T, is called a path. It must be noted that there is not any closed path existed in the UC problem.

Fig. 3 shows the multistage search process for UC in accordance with the description above.

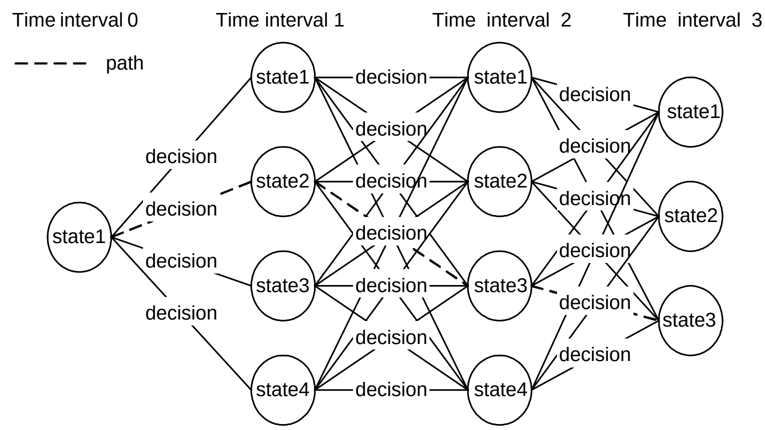

Fig. 3. States transition space.

Considering that the UC problem can be modeled in a form of dynamic process as follows:

$$F_t(U_t^l) = \mathrm{Min}\{\phi_t^l(U_{t-1}^k, U_t^l)\}, \quad t \in T \tag{22}$$

s.t. the constraints (9)–(14), (15) or (21)
where

$$\phi_t^l(U_{t-1}^k, U_t^l) = \sum_{i\in G} F_i(P_i^t) + \sum_{i\in G} F_{si}(q_i^{t-1}) + C_{\mathrm{P}}(k,l) + F_{t-1}(U_{t-1}^k) \tag{23}$$

Eq. (22) is the minimal total operational cost to arrive at the state k of stage $t-1$ from the state l of stage t. In Eq. (23), the first and second terms represent the total production fuel costs and start-up costs of units in stage t, respectively. The third term represents the penalty cost imposed when any of constrains are violated, and the last term is the total accumulated cost from stage 0 to stage t.

Ultimately, the UC problem to be minimized, as in the TSP, is given as:

$$\min \sum_{i=1}^{n-1} \mathrm{tc}(s_{\pi(i)}, s_{\pi(i+1)}) \tag{24}$$

where $\mathrm{tc}(s_i, s_j)$ denotes the total transition cost from state i to state j, which is a counterpart of path length in TSP; and $\pi(i)$ is the set of all states which can be selected in stage i.

4.2. *Handling of equality and inequality constraints*

UC model could be rewritten as.

$$\begin{cases} \min\ F(x) \\ \text{s.t. } H(x) = 0 \\ G(x) \geq 0 \end{cases} \tag{25}$$

where equality constraint is real power balance constraint, which can be calculated directly. The calculation for network losses is based on DC **B** coefficient method [2]. The inequality constraints of real power operating limits and ramp rate limits of generating units are dealt with during solving economic dispatch problem. The spinning reserve constraint based on the deterministic approach and the minimum up/down time of generating units are handled via the *tabu list* at time t.

For the spinning reserve constraint based on the security function, if the value of the security function for one state which is satisfied with the operating constraints in any time interval does not exceed MTIL mentioned above, the flag existed in the tabu list will be changeless, otherwise the flag is to be set to zero.

The transmission line capacity limits are brought in the objective function by means of the penalty factor C_{E}. Finally, the equivalent unconstrained optimization problem can be stated as:

$$\min \sum_{t=1}^{T}\sum_{i=1}^{n}[Fi(P_i^t)u_i^t + F_{si}(\tau)u_i^t(1-u_i^{t-1})] + C_{\mathrm{E}}\left[\max\left(0, \sum_{k\in NL}(P_{lk} - P_{l\max k})\right)\right] \tag{26}$$

Here, the other equality and inequality constraints can be treated as the mode described above. The overall flow of the proposed RPACO-based approach for UC is briefly given in Fig. 4.

4.3. *Application example*

The proposed method for UC problem is examined with three test systems by the c++ language on a Pentium-400 MHz computer. The details will be discussed in this section to follow. (Note: The power is based on per unit, and the base power is 100 MW.)

The environmental parameters of optimal algorithms for three test systems are given in Table 3.

4.3.1. *Test system 1*

A simple test system with three generating units is used first to demonstrate the optimization ability of the RPACO. The numerical data and parameters are taken from [4] and

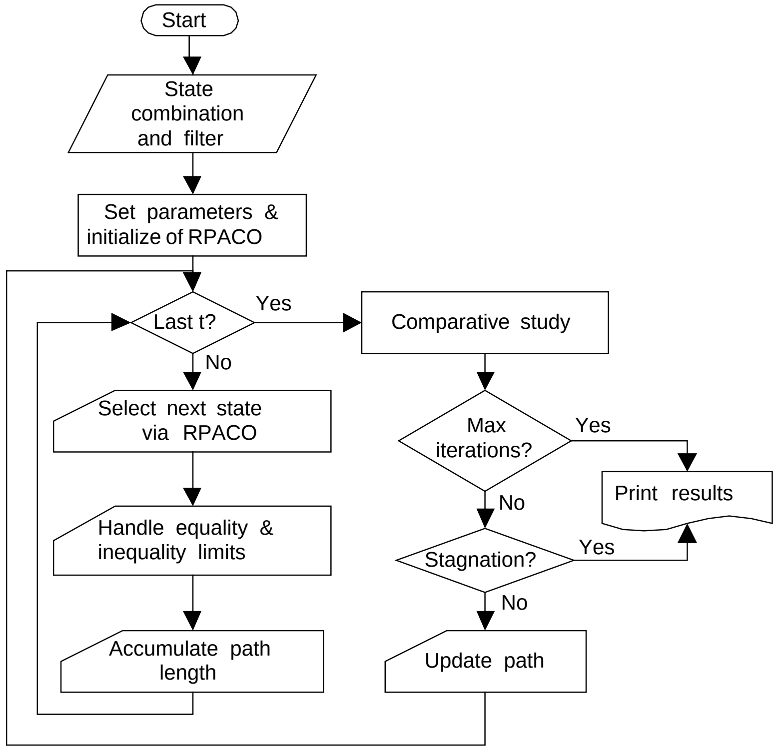

Fig. 4. Flow of RPACO-based approach for UC.

Table 3
The environmental parameters of optimal algorithms for three test systems

Test systems	N security	Network losses	Probabilistic spinning reserve	BACO			RPACO				
				α/β	ρ	Q	α	ρ	p_m	b	Q
1	✓	✓	–	0.2	0.5	100	1.0	0.8	0.1	2	100
2	×	×	–	0.5	0.4	100	1.0	0.8	0.1	2	100
3	–	–	×	0.2	0.5	100	1.0	0.8	0.1	2	100
	–	–	✓	0.2	0.4	100	2.0	0.8	0.1	2	100

Note: The maximal iteration and stagnation times are 300 and 10, respectively.

[14]. The load in every time interval is given in Table 4, and at the same time, the commitment schedules obtained by RPACO are also given in Table 4. The results calculated by BACO and RPACO are summarized in Table 5.

Table 4
Unit commitment schedules determined by RPACO

Time in (h)	Load demand	Committed output	State of units		
			Unit 1	Unit 2	Unit 3
1	2.10	2.18596	1	1	1
2	2.00	2.06125	1	1	0
3	1.80	1.85582	1	1	0
4	2.50	2.58932	1	1	1
5	2.30	2.42629	0	1	1
6	2.35	2.47959	0	1	1
7	1.95	2.00983	1	1	0
8	1.75	1.80456	1	1	0

4.3.2. *Test system 2*

The second test system deals with a 10 generating units system [5]. Table 5 lists the results obtained by BACO, RPACO and [5]. The commitment schedules calculated by RPACO are given in Table 6.

Fig. 5 shows that a good solution can be obtained when the number of ants is set to be from 80 to 100, especially we found during optimization that a good solution can be acquired if the number of states selected by ants in every time interval is close to the number of ants. This conclusion is consistent with that of Ref. [9], i.e. the optimal number of ants is close to the number of cities ($m \approx n$).

4.3.3. *Test system 3*

A test system containing a set of 10 generators [15] is used to illustrate the performance of RPACO. Table 5 shows the results solved by BACO, RPACO and [15] (Dynamic programming). The commitment schedules obtained by RPACO are summarized in Table 7. Fig. 6

Table 5
Simulation results of various algorithms for three test systems

Test systems		BACO			RPACO			Ref. [5]	Ref. [15]
		Generating cost	Total cost	Time (s)	Generating cost	Total cost	Time (s)		
1	–	24009	24199	0.8	24009	24199	0.55	–	–
2	–	568471	571518	809	563312	565302	512	565825	–
3	×	77074	79425	808	77028	78631	510	–	–
	✓	78399	80495	865	78083	79087	560	–	79471

Note: (✓) and (×) are the flags of considering probabilistic (✓) and deterministic (×) spinning reserve. MTIL is set to 0.0005.

Table 6
Unit commitment schedules determined by RPACO for test system 2

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Unit 1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Unit 2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Unit 3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
Unit 4	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
Unit 5	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0
Unit 6	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1
Unit 7	0	0	1	1	1	1	1	1	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0
Unit 8	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	1	1	1	1	0	0	0
Unit 9	0	0	0	1	1	1	1	1	1	1	1	1	1	1	0	0	0	1	1	1	1	0	0	0
Unit 10	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0

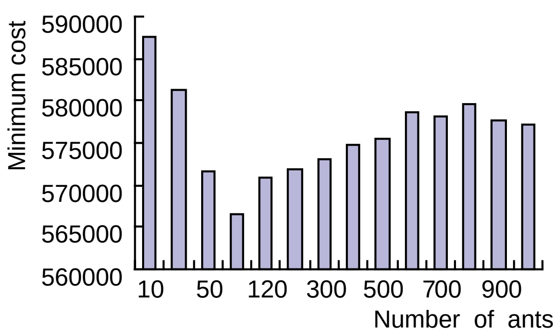

Fig. 5. Minimum total cost with increasing number of ants.

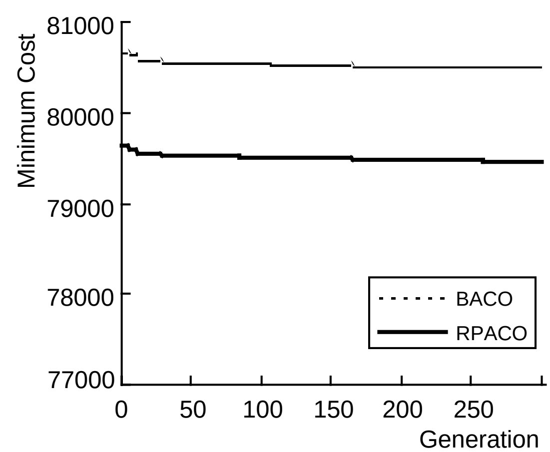

Fig. 6. Dynamic optimization curves of BACO and RPACO.

Table 7
Unit commitment schedules determined by RPACO for test system 3

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Unit 1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
Unit 2	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
Unit 3	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
Unit 4	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1	1	1
Unit 5	1	1	1	0	0	0	0	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0
Unit 6	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1	1	1
Unit 7	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Unit 8	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Unit 9	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Unit 10	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

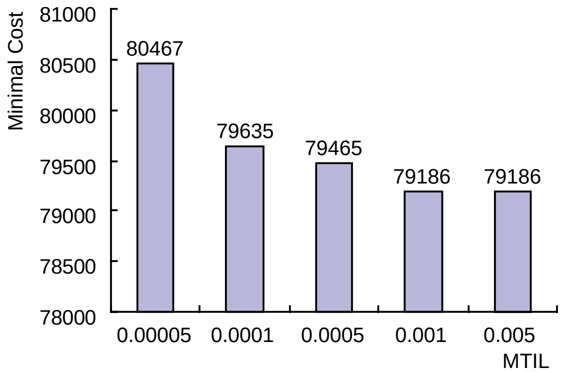

Fig. 7. Influence of MTIL on minimum cost.

illustrates the dynamic optimization behavior of BACO and RPACO.

Consider the influence of level of system security on optimization results, the sensitivity analysis of the desired security level to the optima is studied in this paper. The details are given in Fig. 7. Fig. 7 shows that the smaller the value of MTIL, the higher the system reliability, the more the total cost, vice versa. So in a physical system, a reasonable level of system reliability must be established in order to realize the satisfied trade-off between reliability and economical efficiency.

From the results illustrated above, it can be seen that the proposed method for solving UC problem can bring about some good results on agilely handling constraints, reducing the computing complexity, and effectually preventing the search from being in stagnation behavior. Furthermore, it should be noted that the results obtained by RPACO based on many experiments run under the same environmental parameters are identical. It is observed that the mechanism of positive feedback has decisive effect on the rapid discovery of good solutions and avoiding premature convergence.

5. Conclusion

This paper presents a new approach based on combination of general ant colony optimization method and random search technique, called the RPACO, and applied to the unit commitment to achieve minimum operating costs while simultaneously providing sufficient spinning reserve capacity to satisfy a given security level. Consider the uncertainty of load forecast and probability of component failure, the probabilistic technique based on security function method is applied to evaluate the spinning reserve requirements of system.

The proposed method can effectively avoid being in stagnation behavior due to the introduction of random perturbation strategy. Furthermore, the optimal parameter setting is further studied in this paper. In order to apply the proposed approach to solve the UC problem, the computation schema of ACO for unit commitment is discussed in detail. Some corresponding technical problems, such as the handling of equality and inequality constraints, et al., are investigated. Albeit the proposed method has obtained good solutions in solving UC problem, the further studies still needs to be done, specially for the solution of large scale systems with more complicated constraints. On the whole, the research into the RPACO in practical UC problem is in prospect, particularly under the competitive electricity market environment.

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References

[1] R. Billinton, R.N. Allan, Reliability Evolution of Power Systems, Longman, 1984.
[2] W. Li, The Models and Methods of Security Economic Operation on Electric Power Systems, Chongqing University Press, Chongqing, 1989.
[3] S.K. Tong, S.M. Shahidehpour, Z. Ouyang, A heuristic short-term unit commitment, IEEE Trans. PAS 6 (1991) 1210–1216.
[4] S. Ruzic, N. Rajakovic, A new approach for solving extended unit commit problem, IEEE Trans. PAS 6 (1991) 269–277.
[5] C.-P. Cheng, C.-W. Liu, C.-C. Liu, Unit commitment by Lagrangian relaxation and genetic algorithm, IEEE Trans. PAS 15 (2000) 707–714.
[6] D. Dasgupta, D.R. McGregor, Thermal unit commitment using genetic algorithm, IEE Proc-Gener, Trans. Distrib. 141 (1994) 459–465.
[7] K.P. Wong, Suzannah, Y.W. Wong, Combined genetic algorithm/simulated annealing/fuzzy set approach to short-term generation scheduling with take-or-pay fuel contract, IEEE Trans. PAS 11 (1996) 128–136.
[8] Z. Ouyang, S.M. Shahidehpour, A multi-stage intelligent system for unit commitment, IEEE Trans. PAS 7 (1992) 639–646.
[9] M. Dorigo, V. Maniezzo, A. Colorni, Ant system optimization by a colony of cooperating agents, IEEE Trans. Syst. Man Cybernetics—Part B 26 (1996) 29–41.
[10] S.J. Wang, S.M. Shabidehpour, D.S. Kirchen, Short-term generation scheduling with transmission and environmental constraints using an augmented Lagrangian relaxation, IEEE Trans. PAS 10 (1995) 1294–1301.
[11] L. Shi, G. Xu, Self-adaptive evolutionary programming and its application to multi-objective optimal operation of power systems, Electr. Power Syst. Res. 57 (2001) 181–187.
[12] Y.H. Song, C.S. Chou, T.J. Stonham, Combined heat and power economic dispatch by improved ant colony search algorithm, Electr. Power Syst. Res. 52 (1999) 115–121.
[13] S.-J. Huang, Enhancement of hydroelectric generation scheduling using ant colony system based optimization approaches, IEEE Trans. PAS 16 (2001) 296–301.
[14] A.J. Wood, B. Wollenberg, Power System Operation and Control, Power Technologies Inc., Schenectady, New York, 1984.
[15] A.K. Ayoub, A.D. Patton, Optimal thermal generating unit commitment, IEEE Trans. PAS 90 (1971) 1751–1756.