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An immune-tabu hybrid algorithm for thermal unit commitment of electric power systems*

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Abstract: This paper presents a new method based on an immune-tabu hybrid algorithm to solve the thermal unit commitment (TUC) problem in power plant optimization. The mathematical model of the TUC problem is established by analyzing the generating units in modern power plants. A novel immune-tabu hybrid algorithm is proposed to solve this complex problem. In the algorithm, the objective function of the TUC problem is considered as an antigen and the solutions are considered as antibodies, which are determined by the affinity computation. The code length of an antibody is shortened by encoding the continuous operating time, and the optimum searching speed is improved. Each feasible individual in the immune algorithm (IA) is used as the initial solution of the tabu search (TS) algorithm after certain generations of IA iteration. As examples, the proposed method has been applied to several thermal unit systems for a period of 24 h. The computation results demonstrate the good global optimum searching performance of the proposed immune-tabu hybrid algorithm. The presented algorithm can also be used to solve other optimization problems in fields such as the chemical industry and the power industry.

Key words: Immune algorithm (IA), Tabu search (TS), Optimization method, Unit commitment
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INTRODUCTION

The thermal unit commitment (TUC) problem has been an active research topic in the field of power systems for several decades because of its potential economic benefits. The efficiency of a power plant can be improved by 1% to 2.5% through optimization of TUC (Cai and Cai, 1997). In newly deregulated electric power markets, this problem is one of the key elements in determining the market clearing prices for optimizing bidding strategies for electric power suppliers (Fan *et al*., 2002). The TUC problem is a non-linear combinatorial optimization problem. The objective of this TUC problem is to find the optimal unit combination and power output to meet the varying demand for electricity, taking into consideration some system and operational constraints that must be satisfied during a scheduling period. Specifically, it involves the scheduling of thermal units and their most economical production levels over a set period of time.

Various methods, such as priority listing, dynamic programming (Pang *et al*., 1981), integer and mixed-integer programming (Dillon, 1978), linear programming, the Lagrangian relaxation method (Bard, 1988) and the enhanced adaptive Lagrangian relaxation method (Ongsakul and Petcharaks, 2004), have been proposed to solve the TUC problem. Recently, artificial intelligence techniques have been used widely for solving this optimization problem. Genetic algorithms (GAs) (Kazarlis *et al*., 1996), neural networks (NNs) (Ouyang and Shahidehpour, 1992), simulated annealing (SA) (Zhuang and Galiana, 1990), and rule-based expert systems (Kothari and Ahmad, 1995) approaches have become increasingly popular and are applied to tackle the TUC

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problem. These methods have different requirements for memory consumption and/or computation time. Some research results have covered the solutions of the TUC problem using the GA. Yang *et al.*(1996) solved the TUC problem with the GA through a constraint satisfaction technique. Swarup and Yamashiro (2003) proposed a new encoding and representation strategy based on the GA to solve the TUC problem considering the constraints of minimum up-time and minimum down-time. Mantawy (2004) used the GA to solve the new fuzzy unit commitment model. However, by using the GA it is easily trapped in local optima due to its poor diversity and premature convergence. Tabu search (TS) has been successfully applied to a number of combinatorial optimization problems as a meta-heuristic local improvement method (Mantawy *et al*., 1998; El-Amin *et al*., 2000). It has the ability to avoid being trapped in local optima by a short-term memory procedure. The search performance of a TS algorithm depends on the initial solutions. Good initial solutions help to find the best or near best solution quickly, while bad initial solutions will decrease the convergence speed. Besides, the TS algorithm is a serial operation, which slows down the search. Huang (1999) and lately, Li *et al*.(2006), employed the immune algorithm (IA) to solve the TUC problem. With the embodiment of affinity computation, the possibility of stagnation in the iteration process was decreased and the computational performance was enhanced.

To reduce the search space in large-scale optimization problems, hybrid methods or improved methods have been used widely. Mantawy *et al.*(1999) used a hybrid algorithm to solve the TUC problem, and this hybrid algorithm is mainly based on the GA incorporating the TS method to generate new population members in the reproduction phase of the GA. Victoire and Jeyakumar (2006) used TS, particle swarm optimization (PSO), and sequential quadratic programming techniques to solve the TUC problem and used fuzzy logic to address various uncertainties. Chen *et al*.(2006) developed a refined immune algorithm (RIA) to perform the optimal generation expansion planning of the utility. RIA is conducted by an improved crossover and mutation mechanism with a competition and auto-adjust scheme to avoid prematurity. Tabu lists with heuristic rules are also employed in the searching process to enhance the performance. Recently, Dieu and Ongsakul (2007) proposed an improved merit order (IMO) and an augmented Lagrange Hopfield network (ALHN) for unit commitment. Arroyo and Conejo (2002) proposed a parallel repair GA conducted through heuristics to solve the unit commitment problem, and the developed GA has been successfully applied to realistic case studies. Saber *et al.*(2007) used a two-fold SA method that consists of decomposed- and coupling-SA to generator scheduling. These hybrid methods and improved methods are more efficient than the single methods, due to less production cost and better convergence performance.

In this paper, a new hybrid algorithm based on the combination of an IA and TS is proposed to solve the TUC problem. The IA is a global search method and has the capability of pattern recognition, memorization, and good convergence. The objective function is viewed as an antigen and the feasible solutions as antibodies, in the IA. This is followed by the production of antibodies in a feasible space through the genetic operators including selection, crossover, and mutation. The antibody that most fits the antigen is considered as the optimal solution to this problem (Huang, 1999; Gao, 2001; Sun and Wei, 2002; Liao, 2006). TS is a meta-heuristic local improvement method that uses the history of the search process. The essence of the method is the use of adaptive memory, which prevents convergence to local optima by driving the search to different parts of the search space (El-Amin *et al*., 2000). In this paper, the TS algorithm is applied to generate new antibodies in the reproduction phase of the IA. Each feasible individual in the IA is used as the initial solution of the TS algorithm after certain generations of IA iteration. Thus, the IA can provide good initial solutions for TS, and the population quality can be improved to accelerate the search. Our examples verify that the proposed hybrid algorithm can achieve a near optimal solution to the TUC problem more easily and has good convergence performance. In addition, a new encoding method is employed to denote the antibody by considering the constraint of the start-up and shut-down frequency of the generating unit. The code length of an antibody is shortened by encoding the continuous operating time and consequently the search speed of the algorithm can be improved.

The rest of the paper is organized as follows. The next section describes the TUC problem formulation including the objective function and the constraints. The proposed immune-tabu hybrid algorithm and its computation procedure are discussed in detail in Section 3. Examples to illustrate the proposed hybrid algorithm and some calculation results can be found in Section 4. The last section concludes the paper with the summary and future work.

FORMULATION OF THE TUC PROBLEM

In the following discussion, first the objective function of the TUC problem is formulated, and then a set of possible constraints are listed.

Objective function of the TUC problem

In electric power systems, the objective of the TUC problem is to minimize the total production cost of the power generating units including the fuel cost and the start-up and shut-down cost while satisfying the load demand, spinning reserve requirement and other operational constraints. For a given set of G committed thermal units during a schedule period of T, the objective function can be mathematically described as

$$\begin{aligned}\min F(U_{it},P_{it}) &= \sum_{t=1}^{T}\sum_{i=1}^{G}\left(U_{it}F_i(P_{it})+U_{it}(1-U_{i(t-1)})ST_i\right)\\ &\quad+\sum_{t=1}^{T}\sum_{i=1}^{G}U_{i(t-1)}(1-U_{it})SD_i,\end{aligned} \tag{1}$$

where $F(U_{it}, P_{it})$ (\$) is the total production cost of all units, T (h) is the total number of hours, G is the total number of all thermal units, i is the index of the thermal unit (i=1,2,…,G), t is the index of the time period (t=1,2,…,T), U_{it} is the on/off status of unit i at time t (0: off; 1: on), P_{it} (MW) is the generation output power of unit i at time t, and $F_i(P_{it})$ (\$/h) is the fuel cost function of unit i at time t. The objective is a quadratic polynomial with coefficients a_i (\$/(MW^2·h)), b_i (\$/(MW·h)), and c_i (\$/h):

$$F_i(P_{it}) = a_iP_{it}^2 + b_iP_{it} + c_i\,.$$

SD_i (\$) is the shut-down cost of thermal unit i. ST_i (\$) is the start-up cost of thermal unit i, and

$$ST_i = S_{0i} + S_{1i}(1-\mathrm{e}^{-T_{i,\mathrm{off}}/\tau_i}),$$

where S_{0i}, S_{1i}, and τ_i are the coefficients of the start-up cost function. $T_{i,\mathrm{off}}$ (h) is the continuous off-time of unit i.

Constraints of the TUC problem

Based on the power system analysis, the TUC problem is subject to the following constraints:

(1) Electric power balance equation:

$$\sum_{i=1}^{G}P_{it} = P_{\mathrm{D}t},\quad t=1,2,\ldots,T, \tag{2}$$

where $P_{\mathrm{D}t}$ (MW) is the system load demand at time t.

(2) Output limits of generating units:

$$U_{it}P_{i\min} \le P_{it} \le U_{it}P_{i\max},\quad i=1,2,\ldots,G;\ t=1,2,\ldots,T, \tag{3}$$

where $P_{i\min}$ (MW) and $P_{i\max}$ (MW) are the minimum and maximum outputs of thermal unit i, respectively.

(3) Spinning reserve considerations:

$$\sum_{i=1}^{G}U_{it}P_{i\max} \ge P_{\mathrm{D}t} + R_t,\quad t=1,2,\ldots,T, \tag{4}$$

where R_t (MW) is the system spinning reserve requirement at time t. The total amount of power available at each hour must be greater than the load demand.

(4) Limits of ramp rates:

$$-\tau_{\mathrm{d}i}\times 60 \le P_{it} - P_{i(t-1)} \le \tau_{\mathrm{g}i}\times 60,\quad i=1,2,\ldots,G;\ t=1,2,\ldots,T, \tag{5}$$

where $\tau_{\mathrm{d}i}$ (MW/min) and $\tau_{\mathrm{g}i}$ (MW/min) are the ramp-down and ramp-up rate limits of unit i, respectively.

(5) Generating unit start-up and shut-down frequency:

$$\sum_{t=1}^{T}\left|U_{it}-U_{i(t-1)}\right| \le M_i,\quad i=1,2,\ldots,G, \tag{6}$$

where M_i is the maximum start-up and shut-down frequency of unit i.

(6) Minimum up/down-time:

$$T_{i,\mathrm{on}}\geq T_{1i},\ \ T_{i,\mathrm{off}}\geq T_{2i},\ \ i=1,2,\ldots,G, \tag{7}$$

where $T_{i,\mathrm{on}}$ (h) and $T_{i,\mathrm{off}}$ (h) are the continuous on-time and off-time of unit i, respectively; T_{1i} (h) and T_{2i} (h) are the minimum up-time and down-time of unit i, respectively.

(7) Transmission constraints:

$$F_{lt}=\left|\sum_{i=1}^{G}\Gamma_{l,i}P_{it}-\sum_{k=1}^{K}\Gamma_{l,k}P_{\mathrm{D}kt}\right|\leq\overline{F}_l, \tag{8}$$

where l is the index of the transmission line (l=1,2,…,L), L is the total number of the transmission lines, $\overline{F}_l$ is the real power flow limit on transmission line l, $\boldsymbol{\Gamma}_l$ is the matrix relating generator output to power flow on transmission line l, K is the total number of buses with loads, and $P_{\mathrm{D}kt}$ (MW) is the load at bus k at time t.

(8) Initial status of units.

At the beginning of the schedule, the initial status of units must be taken into account.

There still exist some other constraints such as the prohibited operating zone, crew constraints, must-run or unavailability constraints, fuel constraints, and minimum generation output of a unit at the first hour and the last hour. Practically, these constraints may be considered in different scenarios.

IMMUNE-TABU HYBRID ALGORITHM

In the following discussion, the proposed immune-tabu hybrid algorithm and its computation procedure are described in detail.

Overview of the immune-tabu hybrid algorithm

The IA is a general-purpose search technique based on principles inspired by the immune mechanisms. Different from other probabilistic optimization based algorithms, the IA operates on the feasible antibodies that guarantee fast convergence. The diversity is embedded by means of affinity calculation. The self-adjustment of the immune response is accomplished by the promotion or suppression of antibody generations (Huang, 1999; Liao, 2006).

The TS algorithm is a higher-level method or strategy for solving optimization problems. It uses a local or neighborhood search procedure to iteratively move from a solution x to another x' in the neighborhood of x, until some stopping criteria have been met (Mantawy *et al*., 1999; Victoire and Jeyakumar, 2006). It can be imposed on any procedures whose operations produce a sequence of moves that lead from one trial solution to another. Each move is obtained from a set of available alternatives that are evaluated by one or more functions that measure their attractiveness in some local sense (El-Amin *et al*., 2000).

In the proposed hybrid algorithm, the objective functions and constraints of the TUC problem are considered as antigens. The feasible solutions are considered as antibodies. The affinity computation is embedded to determine the promotion or suppression of the production of antibodies. Therefore, the diversities of the feasible antibodies can be better kept and the global optimum can be more easily achieved. If an antibody fits the antigen best, this antibody is considered as the optimal solution to the optimization problem. Moreover, TS is incorporated in the production phase of the IA, as a tool for escaping from the local optima and improving the search performance. And the IA provides good initial solutions for TS after certain generations of IA iteration.

Overall procedure of the immune-tabu hybrid algorithm

The proposed hybrid algorithm based on the IA and TS can be described as follows (Fig.1).

Step 1: Initialization.

Input some setting parameters of the IA and TS, such as the population size, the total number of memory cells, the concentration threshold value, the viability threshold value, crossover rate, mutation rate, and tabu list length.

Step 2: Generation of initial antibodies.

The initial antibodies are generated according to the encoding method. Each antibody represents a feasible solution to the optimization problem. In this work, the binary code is adopted to represent antibodies.

Step 3: Affinity calculation.

Two affinity calculation forms are considered in the proposed approach. One is to describe the relationship between an antibody and the antigen, where

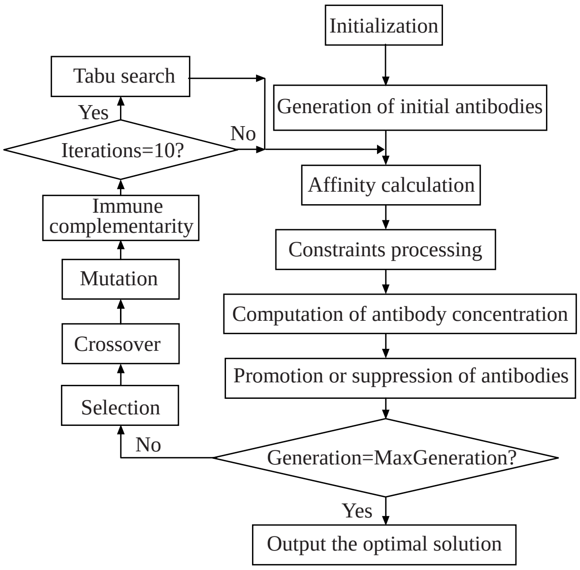

Fig.1 Flowchart of the proposed immune-tabu hybrid algorithm

the combination intensity between the objective and the solution is investigated. The other accounts for the degree of association between antibodies, and thus the mutual diversity of antibodies can be evaluated (Huang, 1999).

An antibody pool is composed of N antibodies, each of which has M genes. The entropy $H_j(N)$ of the jth gene can be expressed as

$$H_j(N) = -\sum_{k=1}^{N} p_{kj} \log p_{kj}, \quad j=1,2,\ldots,M, \tag{9}$$

where p_{kj} is the probability that the kth allele comes out of the jth gene.

Then the average information entropy can be expressed as

$$H(N) = \frac{1}{M}\sum_{j=1}^{M} H_j(N). \tag{10}$$

The affinity between antibodies can evaluate the mutual diversity of antibodies. If antibodies are more similar, the affinity between antibodies is higher. The computing formulation can be represented as

$$\alpha_{v,w} = 1/(1+H(2)), \tag{11}$$

where $H(2)$ is the information entropy between antibody v and antibody w.

Step 4: Computation of antibody concentration.

Antibody concentration is the proportion of some similar antibodies in the whole population. It can be expressed as

$$c_v = \frac{1}{N}\sum_{w=1}^{N} S_{v,w}, \quad S_{v,w} = \begin{cases} 1, & \alpha_{v,w} \ge T_{\mathrm{ac1}}, \\ 0, & \alpha_{v,w} < T_{\mathrm{ac1}}, \end{cases} \tag{12}$$

where c_v is the concentration of antibody v, and T_{ac1} is the threshold value of concentration.

Step 5: Promotion or suppression of antibodies.

In this step, the antibody viability is computed, which can be expressed as

$$\begin{aligned} e_v &= A_v \prod_{s=1}^{S} \left[(1 - L_{v,s}^{k}) \Big/ \left(c_v \sum_{j=1}^{N} A_j \right) \right], \\ L_{v,s} &= \begin{cases} \alpha_{v,s}, & \alpha_{v,s} \ge T_{\mathrm{ac2}}, \\ 0, & \alpha_{v,s} < T_{\mathrm{ac2}}, \end{cases} \end{aligned} \tag{13}$$

where e_v is the viability of antibody v, A_v is the sufficiency of antibody v, S is the total number of the suppressor cells, k is the suppressor index, and T_{ac2} is the viability threshold value.

Eq.(13) shows that an antibody with high affinity and low concentration will most likely be retained for the next generation. When the antibody has a high affinity with the suppressor cells, its viability will be low. The similar antibodies can excite each other to promote their viabilities, which can improve the convergence close to the optimal solution.

Step 6: Generation of new antibodies.

Based on the predetermined crossover rate and mutation rate parameters, new antibodies will be generated after selection operation, crossover operation, mutation operation, immune complementarity, and TS. Immune complementarity means that the antibody with low viability will be replaced with a new antibody generated randomly to improve the diversity of antibodies. In this step, TS is employed after certain generations of IA iteration. The values of IA iterations are considered as 5, 10, and 20 respectively. Based on the pilot tests and the sensitivity study, an iteration value of 10 was adopted, because it yields enough reasonably good solutions and requires relative short computation time. For other values, the system cannot generate enough feasible solutions in the case of 20 and wastes the computation time in the case of 5. The optimum antibody and several near optimal antibodies in each generation are reserved for the next generation to guarantee that enough feasible solutions are used as initial solutions for the TS method.

Step 7: Termination condition.

The computation process will stop if the maximum number of iterations has been reached. Otherwise, the computation will iterate from Step 3 to Step 7.

Step 8: Output the best heuristic solution.

At last, the best heuristic solution is achieved based on the antibody with the highest affinity with the antigen.

Encoding strategy of the hybrid algorithm

In the hybrid algorithm, a new method is proposed to encode the continuous operating time of each unit. If a thermal unit is 'on' during the whole schedule period, the continuous time is 24 h, which can be represented by a 5-bit binary code. For example, if the maximum start-up and shut-down frequency of unit i is 3, then there are four continuous time period statuses altogether. We need only to encode the first three continuous time periods T_0, T_1, and T_2 (Fig.2), and then the 4th continuous time period is equal to 24 h$-T_0-T_1-T_2$. Other cases may be deduced by analogy. This encoding method not only shortens the code length, but also releases the start-up and shut-down frequency constraints. Supposing that the maximum start-up and shut-down frequency of unit i is 3 and that the initial status is 'on', we can give the encoding method of an antibody, as shown in Fig.2.

On (1) T_0	Off (0) T_1	On (1) T_2
A 5-bit binary	A 5-bit binary	A 5-bit binary

Fig.2 An example illustrating the encoding method of an antibody
This example shows the former three continuous time period statuses of a four-continuous-time period, when the maximum start-up and shut-down frequency is 3

In this case, a 15-bit binary code is needed to indicate the operating status of each unit in 24 h. For example, assume that the initial status of one unit is 1 (on) and that the antibody code is 00101 00110 00100 (in decimal numbers, 5-6-4), which denotes that the operating status in the first 5 h for this unit is 1 (on), in the following 6 h 0 (off), in the next 4 h 1 (on), and in the last 9 h in a 24-h cycle 0 (off). During the decoding process, if it happens that $T_0+T_1+T_2>24$ h and $T_0+T_1\le 24$ h, we can make $T_2=24$ h$-T_0-T_1$. If one continuous time period, for instance T_1, is less than the minimum down-time, we can make $T_1=0$ h. The decoding disposal method can consider the minimum up/down-time constraint. With this encoding strategy, the search speed of the hybrid algorithm can be improved.

A heuristic method is adopted to generate the initial antibodies (mapped to solutions) to avoid infeasible solutions when they are generated randomly. First, the base load units in the system will be selected using the priority list method, and they are set as 'always on' during the schedule time. Meanwhile, the fault units in the system will be set as 'always off' during the schedule time. By doing this, we can reduce the solution search space. Then let us decide the initial status of each unit at the first hour in the schedule. If the continuous on-time of unit i is less than the pre-determined minimum up-time, the status of unit i at this hour will be set as 'on'. Similarly, if the continuous off-time of a unit is less than its minimum down-time, the unit status at this hour will be set as 'off'. We will then need to determine the statuses of undetermined units in the 24-h period. Without loss of generality, we can assume that at a certain hour t, the statuses of the undetermined units are set as 'off' initially. Under this condition, if it turns out that the current distribution scheme can satisfy the power constraints, the calculation will move on to the next iteration. On the other hand, if it turns out that the scheme cannot satisfy the power constraints, one of the undetermined units should be selected and turned on based on the probability of a roulette wheel according to the unit efficiency. If it turns out that with this additional unit running, the system still cannot meet the constraints, and then another unit should be picked and turned 'on'. This procedure will continue until all the constraints are met. By doing this, a feasible initial solution can be generated.

Sufficiency function of the antibody

The affinity between an antibody and the antigen is represented by the sufficiency function. The higher the value of antibody sufficiency is, the higher the affinity between the antibody and the antigen will be. So the antibody with the highest sufficiency value is considered as the best heuristic solution. As the target of the TUC problem is to obtain the minimum total production cost, we can adopt the value of $C_{\max}$ divided by the total production cost as the sufficiency function:

$$A_v = \frac{C_{\max}}{F(U_{it}, P_{it})}, \tag{14}$$

where A_v is the sufficiency of an antibody v, and $C_{\max}$ is a big constant. The smaller the antibody objective value is, the higher the antibody sufficiency will be. The antibodies are selected and generated according to their sufficiency values.

Processing of constraints in the hybrid algorithm

By encoding the continuous operating time of units, two constraints of the unit start-up and shut-down frequency and the minimum up/down-time are released. To guarantee that the limits of ramp rate constraints are satisfied, the strategy of load distribution is employed. The calculation method is

$$P_{it} = \begin{cases} \min(P_{i\max},\ P_{i(t-1)} + \tau_{gi} \times 60), & P_{it} > P_{i(t-1)}, \\ \max(P_{i\min},\ P_{i(t-1)} - \tau_{di} \times 60), & P_{it} < P_{i(t-1)}. \end{cases} \tag{15}$$

The penalty factor is used for processing the constraints of output limits of generating units and spinning reserve considerations. Fig.3 shows the process, which will reduce the antibody sufficiency if the antibody violates the constraints. Therefore, this antibody is easier to eliminate during the evolution. In other words, antibodies that violate the constraints are not easily retained for the next generation.

Generation of new antibodies in the hybrid algorithm

The new population is generated by selection, crossover, mutation, immune complementarity, and TS in a feasible search space. In the selection operation, the roulette wheel mode is employed. In addition, the optimal antibody and several near optimal antibodies in each generation are reserved to the next generation to guarantee a higher-quality generation. In the crossover operation, multiple-point crossover is adopted (Fig.4). The 5-bit binary string, which represents one continuous operating time of each parent, is operated as a whole to avoid violating the constraint of the minimum up/down-time. In the mutation operation, antibodies mutate according to a given mutation rate. In the immune complementarity operation, some antibodies will be eliminated at a certain rate if their viability is lower than the viability threshold value, and new individuals will be generated randomly to be the replacement. This method helps improve the convergence near the local optimal solution.

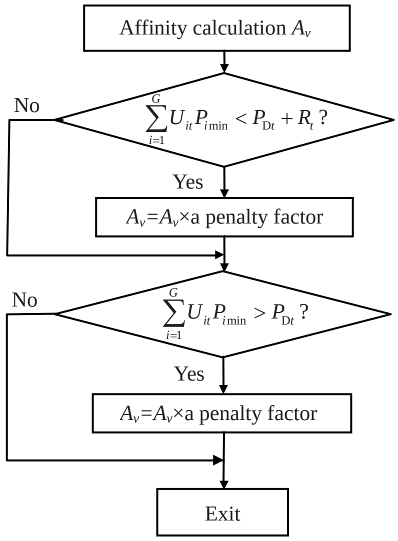

Fig.3 Flowchart of constraints processing in the hybrid algorithm

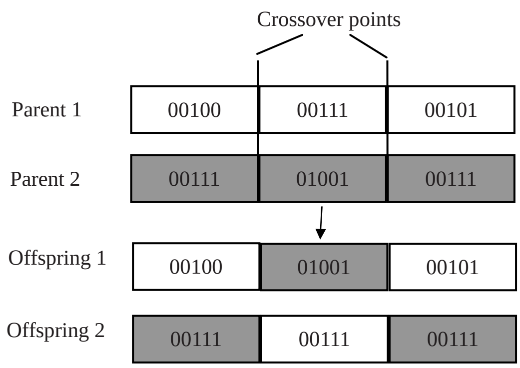

Fig.4 Multi-point crossover

The TS algorithm is a higher-level method or strategy for solving optimization problems. In the hybrid algorithm, TS is applied to seek the optimum solution in the reproduction phase of the IA. This algorithm starts at some initial solution and then moves to a neighboring solution. The feasible antibodies in the IA are used as the initial solutions of the TS algorithm after certain generations of IA iteration. Then the population quality can be improved to accelerate the search. A neighborhood solution is generated by a set of admissible moves on the neighbors. For example, a string 00100 00111 00101 denotes a current solution of 15 bits in Fig.5. The new gene strings form the neighborhood of the current solution by moving the 0-1 boundary. There are six neighbors (Fig.5). The list of neighboring solutions considered, called the tabu list, consists of feasible solutions, each differing from the current solution. At each iteration, the best solution in the neighborhood of the current solution will be found. The distinguishing characteristic of this technique is that it keeps a list that prevents the method from moving to solutions that have certain attributes. In order to override the tabu list when there is a good tabu move, the following aspiration criterion is used: the tabu move is accepted if it produces a better solution than the best obtained so far (El-Amin *et al*., 2000). The TS operation will be terminated if the number of steps exceeds the maximum step.

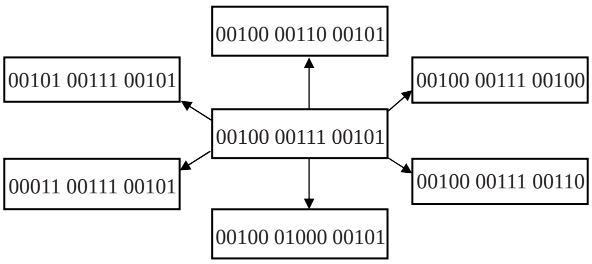

Fig.5 Current antibody and its neighborhoods

IMPLEMENTATION AND RESULTS

The proposed immune-tabu hybrid algorithm program for the TUC problem has been implemented with Visual C++ running on a Sony SZ13C laptop with 1.66 GHz CPU and 512 MB memory in the School of Mechanical and Energy Engineering at Zhejiang University, China. The results of computation examples are narrated as follows.

Example 1: A 10-unit power system

This example shows the computation results with a power system consisting of 10 thermal power units. Their characteristic data are listed in Table 1. In this example, the start-up and shut-down frequency of each generating unit is set as 3. And the reserve is required to be 7% of the load demand. Table 2 lists the computation results using different optimization methods and some parameters of each method from the literature (Han and Liu, 1994; Cai and Cai, 1997; Pei *et al*., 2001; Shi *et al*., 2002). Fig.6 shows the system load demand and the output levels of all units. In the algorithm, the number of generated antibodies and the number of iterations were experimentally determined. The population size is 100, the maximum generation is 50, the crossover rate is 0.75, the mutation rate is 0.05, the concentration threshold value is 0.9, the viability threshold value is 0.85, and the selection rate is 0.8. The length of the neighborhood list is 100.

The calculated coal consumption using the hybrid algorithm is 78970.3 t of standard coal. It is less than the calculation result using the modified GA by 27.7 t and less than the calculation result using the heuristic GA by 836.7 t. The near optimal solution can be achieved after several generations, whereas other algorithms need tens of generations and sometimes even more than 100 generations. For comparison, we applied the immune-tabu hybrid algorithm, IA, TS and GA to solve the TUC problem, respectively. Fig.7 shows the convergence process of the four algorithms. From the results, the hybrid, IA, and GA algorithms can all find the optimal solution while the TS algorithm cannot. The convergence processes of these algorithms are quite different. The figure shows that the immune-tabu hybrid algorithm can achieve a better solution more quickly than the IA, GA and TS. The IA provides good initial solutions for the TS algorithm, which can improve the population quality. TS can accelerate the local searching near the local optimal solution. In this way, a better heuristic solution can be achieved more easily. The computation time and the number of feasible solutions of these four algorithms are listed in Table 3. The computation time of the immune-tabu hybrid algorithm is much shorter than that of the GA, TS and close to that of the IA, because the TS can improve the convergence rate of the hybrid algorithm though it will slow down the

Table 1 Characteristic data of the 10 units in an example power systems

Unit i	$P_{i\max}$ (MW)	$P_{i\min}$ (MW)	a_i ($\times10^{-3}$ t/(MW^2·h))	b_i (t/(MW·h))	c_i (t/h)	S_{0i} (t)	S_{1i} (t)	τ_{di}, τ_{gi} (MW/min)	T_{1i}, T_{2i} (h)	Initial status
1	60	15	5.10	2.2034	15	0	85	0.300	2	0
2	80	20	3.96	1.9101	25	0	101	0.400	2	0
3	100	30	3.93	1.8518	40	0	114	0.500	2	0
4	120	25	3.82	1.6966	32	0	94	0.600	3	0
5	150	50	2.12	1.8015	29	0	113	0.750	3	1
6	280	75	2.61	1.5354	72	0	176	1.400	5	1
7	320	120	2.89	1.2643	49	0	187	1.600	5	1
8	445	125	1.48	1.2130	82	0	227	2.225	8	1
9	520	250	1.27	1.1954	105	0	267	2.600	8	1
10	550	250	1.35	1.1285	100	0	280	2.750	8	1

Table 2 Computation results using different optimization methods

Optimization method	Population size	Maximum generation	Crossover rate	Mutation rate	Total fuel consumption (t)
Lagrangian relaxation (Han and Liu, 1994)	–	–	–	–	80766.0
Heuristic genetic algorithm (Cai and Cai, 1997)	91	60	–	–	79807.0
Dynamic programming (Shi *et al*., 2002)	–	–	–	–	79349.0
Modified genetic algorithm (Pei *et al*., 2001)	100	50	0.60	0.005	78998.0
Genetic algorithm (Shi *et al*., 2002)	–	–	–	–	79004.0
Immune-tabu hybrid algorithm (This paper)	100	50	0.75	0.050	78970.3

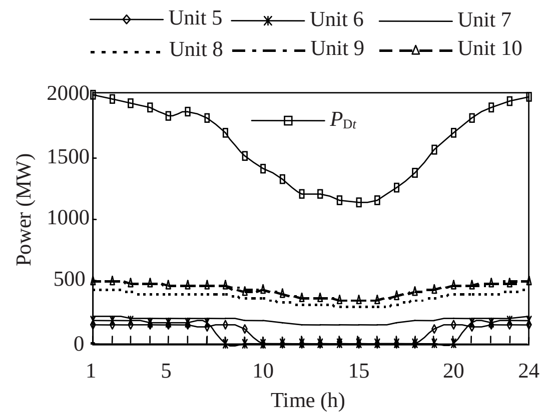

Fig.6 Load distribution of all the power units (the loads of units 1~4 are zero)

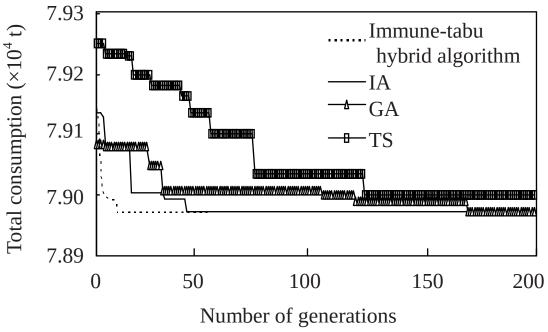

Fig.7 Convergence process of the immune-tabu hybrid algorithm, IA, TS, and GA

Table 3 Computation time of the algorithms

Method	Computation time (s)	Number of feasible solutions
Immune-tabu hybrid algorithm	8	28
Immune algorithm	11	23
Tabu search	65	15
Genetic algorithm	53	18

calculation procedure. The numerical results demonstrated that this immune-tabu hybrid algorithm is a new and efficient method for solving the TUC problem.

Example 2: A 10-unit benchmark power system and larger systems based on the scaled duplication of the benchmark system

The proposed method was tested in another benchmark system for comparison with other recent methods published in widely identified international journals. The data of this 10-unit benchmark system is from (Kazarlis *et al*., 1996). The population size is 200, the maximum number of generations is 100, the crossover rate is 0.8, the mutation rate is 0.05, the concentration threshold value is 0.9, the viability threshold value is 0.85, and the selection rate is 0.85. The length of the neighborhood list is 80. Table 4 lists the immune-tabu hybrid algorithm solution and load demands of this 10-unit benchmark system. This proposed algorithm was also tested in larger-scale systems (20, 40, and 80 units) to demonstrate the feasibility of this algorithm. The 20-, 40-, and 80-unit data were obtained by duplicating the base case (10-unit benchmark system), and the load demands were adjusted in proportion to the system size. In the computation, the reserve is required to be 10% of the load demand. The total production cost and computation time using different methods are listed in Table 5. The total production cost over the schedule time using the proposed hybrid algorithm is less than that of adaptive Lagrangian relaxation (ALR), enhanced adaptive Lagrangian relaxation (ELR), Lagrangian relaxation (LR), GA, evolutionary programming (EP), Lagrangian relaxation & GA (LRGA) and GA of unit commitment (GAUC), except for two-fold SA. The computation time increases greatly as the number of units increases. Hence, our future work will focus on how to remarkably improve the search speed for large-scale systems.

Table 4 Immune-tabu algorithm solution of the benchmark system and load demands*

Time t	Power (MW)										P_{Dt} (MW)
	Unit 1	2	3	4	5	6	7	8	9	10	
1	455	245	0	0	0	0	0	0	0	0	700
2	455	295	0	0	0	0	0	0	0	0	750
3	455	370	0	0	25	0	0	0	0	0	850
4	455	455	0	0	40	0	0	0	0	0	950
5	455	390	0	130	25	0	0	0	0	0	1000
6	455	360	130	130	25	0	0	0	0	0	1100
7	455	410	130	130	25	0	0	0	0	0	1150
8	455	455	130	130	30	0	0	0	0	0	1200
9	455	455	130	130	85	20	25	0	0	0	1300
10	455	455	130	130	162	33	25	10	0	0	1400
11	455	455	130	130	162	73	25	10	10	0	1450
12	455	455	130	130	162	80	25	43	10	10	1500
13	455	455	130	130	162	33	25	10	0	0	1400
14	455	455	130	130	85	20	25	0	0	0	1300
15	455	455	130	130	30	0	0	0	0	0	1200
16	455	310	130	130	25	0	0	0	0	0	1050
17	455	260	130	130	25	0	0	0	0	0	1000
18	455	360	130	130	25	0	0	0	0	0	1100
19	455	455	130	130	30	0	0	0	0	0	1200
20	455	455	130	130	162	33	25	10	0	0	1400
21	455	455	130	130	85	20	25	0	0	0	1300
22	455	455	0	0	145	20	25	0	0	0	1100
23	455	425	0	0	0	20	0	0	0	0	900
24	455	345	0	0	0	0	0	0	0	0	800

* Data from (Kazarlis *et al*., 1996)

Table 5 Total production cost and computation time using different methods for 10, 20, 40, and 80 units

Method	Total production cost ($)				Computation time (s)			
	10	20	40	80	10	20	40	80
ALR*	565 508	1 126 720	2 249 790	4 494 487	3	12	34	111
ELR*	563 977	1 123 297	2 244 237	4 485 633	4	16	52	209
LR**	565 825	1 130 660	2 258 503	4 526 022	–	–	–	–
GA**	565 825	1 126 243	2 251 911	4 504 933	221	733	2697	10 036
EP***	564 551	1 125 494	2 249 093	4 498 479	100	340	1176	3584
LRGA#	564 800	1 122 622	2 242 178	4 501 844	518	1147	2165	3383
GAUC##	563 977	1 125 516	2 249 715	4 505 614	85	225	614	1975
Two-fold SA###	563 872	1 122 178	2 242 350	4 477 833	6	13	25	72
IA+TS†	563 937	1 122 356	2 247 754	4 500 632	9	18	40	134

* Ongsakul and Petcharaks (2004); ** Kazarlis *et al*.(1996); *** Juste *et al*.(1999); # Cheng *et al*.(2000); ## Senjyu *et al*.(2002); ### Saber *et al*. (2007); † This paper. The computation time of LR is not given in the reference

Example 3: A 16-unit power system

The immune-tabu hybrid algorithm program was also applied to solve the unit commitment of a 16-unit power system. The characteristic data of all units are listed in Table 6 (Fan and Wei, 2004). Table 7 tabulates the system load demand and the optimal unit power for a 24-h period using the hybrid algorithm.

The calculated coal consumption of the 16 units in 24 h is 19499.2 t of standard coal, while the calculation result using the modified GA is 22372 t in (Fan and Wei, 2004). Similar further data analysis can be conducted as in Example 1. The optimum solution can be achieved after 30 generations with quicker convergence and high quality solutions.

Table 6 Characteristic data of the 16 units in a power system

Unit i	$P_{i\max}$ (MW)	$P_{i\min}$ (MW)	a_i ($\times10^{-4}$ t/(MW^2·h))	b_i (t/(MW·h))	c_i (t/h)	S_{0i} (t)	S_{1i} (t)	τ_{di}, τ_{gi} (MW/min)	T_{1i}, T_{2i} (h)
1	100	30	7.86	0.2700	8.0	9.8040	12.9960	0.20	2
2	80	20	7.92	0.3000	5.0	8.2012	11.9988	0.20	2
3	120	25	7.92	0.2800	6.4	6.5800	12.2200	0.18	3
4	150	50	7.92	0.2657	20.0	14.1564	42.2436	0.09	3
5	150	50	4.24	0.3080	5.8	8.1586	14.4414	0.18	3
6	150	50	2.70	0.2657	20.0	14.1564	40.2436	0.09	3
7	150	50	4.24	0.3080	5.8	8.1586	14.4414	0.18	3
8	60	15	1.02	0.2800	3.0	7.0040	9.9960	0.20	3
9	120	40	7.86	0.2700	8.0	14.1564	42.2436	0.09	2
10	150	55	2.96	0.2427	16.4	14.1564	42.2436	0.09	3
11	220	75	5.22	0.2700	14.4				
12	320	120	5.78	0.2529	9.8				
13	220	75	2.96	0.2427	16.4				
14	550	200	2.54	0.2791	21.0				
15	550	200	2.54	0.2791	21.0				
16	445	125	5.22	0.2700	14.4				

Note: units 11~16 are base load units

Table 7 Power sharing of all the 16 units using the hybrid algorithm

Time	Power (MW)												P_{Dt}
t	Units 1~5	6	7	8	9	10	11	12	13	14	15	16	(MW)
1	0	0	150	60	120	150	217	211	220	428	428	217	2200
2	0	0	150	60	120	150	214	208	220	422	422	214	2180
3	0	0	150	60	120	150	220	216	220	440	440	223	2240
4	0	0	150	60	120	150	217	211	220	428	428	217	2200
5	0	0	150	60	120	150	191	197	220	378	378	196	2040
6	0	0	150	60	120	150	220	210	220	365	365	210	2070
7	0	150	150	0	120	150	203	178	220	334	334	181	2020
8	0	150	150	0	120	150	215	180	220	323	323	169	2000
9	0	150	0	0	0	150	220	180	220	320	320	150	1710
10	0	150	0	0	0	0	220	176	220	344	344	156	1610
11	0	150	0	0	0	0	220	154	220	350	350	176	1620
12	0	150	0	0	0	0	220	168	220	343	343	156	1600
13	0	150	0	0	0	0	220	183	220	329	329	169	1600
14	0	150	0	0	0	0	220	180	220	354	354	182	1660
15	0	150	0	0	0	0	220	194	220	348	348	160	1640
16	0	150	0	0	0	0	220	188	220	365	365	152	1660
17	0	150	0	0	0	0	220	180	220	355	355	180	1660
18	0	150	150	0	0	0	205	178	220	315	315	147	1680
19	0	150	150	0	0	0	215	194	220	350	350	131	1760
20	0	150	150	0	0	150	178	180	177	368	368	179	1900
21	0	150	150	0	0	150	192	190	198	397	397	197	2020
22	0	150	150	0	0	150	207	202	220	407	407	207	2100
23	0	150	150	0	120	150	197	193	220	387	387	197	2150
24	0	150	150	0	120	150	220	184	220	398	398	201	2190

CONCLUSION

The proposed immune-tabu hybrid algorithm has some distinct features, such as good diversity, a promotion or suppression mechanism between antibodies and the memorization function. The code length of the antibody was shortened by encoding the continuous operating time period, and the optimum search speed of the algorithm was improved. Each individual in the IA was used as the initial solution of the TS algorithm after certain generations of IA iterations. Thus the population quality can be improved to accelerate the search.

Our contributions are the appropriate use of TS to seek the optimum solution in the reproduction phase of the IA and the encoding strategy of its algorithm, which encapsulates two constraints and speeds up the convergence. The method could be considered as one kind of improvement of the IA, and this encoding strategy is worthy of being used in other problems of this type. The examples show that the hybrid algorithm has good global search ability and convergence performance, and can tackle the TUC problem efficiently. The testing and validation of this approach in other commitment problems is in progress. It should be promising to use the proposed algorithm to solve other optimization problems in fields such as the chemical industry and the power industry.

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