Fault diagnosis of analogue circuits based on improved genetic algorithm and neutral-network

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Received 1 March 2014, www.cmnt.lv

Abstract

This paper proposes a novel method for optimization of BP neutral network using improved genetic algorithm to diagnose the circuit fault in power-supply system. First, BP neutral-network's structure is determined so that its threshold values and weight values can be optimized by GA. Second, stable threshold values and weight values are obtained via the calculation of GA's operators. Finally, the values are utilized in BP neutral network as initial parameters to conduct sample iteration training. The results show that, during fault diagnosis, BP neural network and genetic algorithm combined with each other to achieve complementary advantages between the two methods.

Keywords: improved genetic algorithm, BP neutral network, analogue circuits; fault diagnosis, power-supply system

1 Introduction

The common fault in power-supply system implies the situation when the system equipments cannot perform under formed scheme and indexes, or when the power-supply system cannot implement the various types of function it equips.

2 Common fault in power supply system

2.1 CLASSIFICATION OF THE COMMON FAULT

There are various faults in power system with the most destroying and severe one being short circuit. Short circuit fault means the phenomenon when access exists between phase-and-phase or phase-and-ground, besides, phase-and-phase, phase-and-ground is insulated. Neutral point is not insulated in run. Power-supply system fault occurs owing to access arising from insulation breakdown. Short circuit fault primarily results from the damage of the insulated layer's on the system's current carrying part. The power-supply system fault includes component short circuit and short line, etc. Among these faults, short circuit fault is the most dangerous and destructive one.

When power system normally runs, all the components are likely to give rise to faults, which can cause the system's irregular operation. Power-supply accident takes place if the fault not properly handled.

2.2 CHARACTERISTICS OF POWER SYSTEM FAULT

2.2.1 Layered characteristic

In general, the symptom of the power-supply system fault is layered and its occurrence is based on the one in another level. When fault occurs, each branch's current and voltage will alter instantly. In the meantime, the protector will send out automatic protection action signal to trigger the circuit breaker to shut down the circuit.

2.2.2 Redundancy characteristic

According to fault symptom's layered characteristic of the power system, the execution of action message to breaker is based on the protection action message. Therefore, the form of fault symptom message is different in different level with the identical system fault. However, redundancy exists in the fault content exhibited by the symptom message. Generally, information redundancy should be avoided in fault diagnosis, but when the fault is complex or data information loss occurs due to operation abnormity of power system, then the information redundancy can be utilized to conduct accurate location and detailed diagnosis on the components.

2.2.3 Intermittence characteristic

Recording of the fault's data information in power system is realized in detail through relay protection equipment and fault filtering equipment. When fault arises in power system, mass data is collected in short time. To transmit the data to command dispatching center accurately will cause information channel unusually busy. However, in most cases, the information channel is free and to some extent intermittent.

2.2.4 Irregularity characteristic

According to power system's operation, data communication of relay protection equipment and fault filtering equipment is conducted in closed environment, not open to outside. The relay protection equipments and fault filtering

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equipments produced in different factories have their unique software programs and communication schemes and equipped with different rules and format, which disable the data information share between power systems. To unify the data collection and data share, format transformation is needed, which is extremely trivial.

3 Genetic algorithm's characteristics and application

3.1 GENETIC ALGORITHM'S APPLICATION

GA is a type of bionic algorithm characterized by biological population and models the optimization process by combining biological population with intelligent technology. A binary string representing the chromosome is a solution of the problem to be optimized, and a feasible solution set is generated at random in this format. As to each individual, since greater fitness value means stronger fertility, by simulating the evolution process comprised of natural selection and other operators including selection, crossover and mutation, the global optimal solution can be obtained through population optimization [1,3]. As a searching method, GA has strong optimization ability and definite characteristics:

1) The object that GA optimizes is not certain concrete parameter but individuals of the parameter set coded, then it can directly impose operation on the structure.
2) The majority of the traditional search algorithm is single-point algorithm, and can easily falls into the local optimal. However, GA can simultaneously cope with all individuals in the population, then accomplish the evaluation one by one, causing the probability of falling into local optimal enormously reduced. Moreover, parallel processing can be easily implemented by GA.
3) GA generally needs no additional information, but evaluates certain individual by fitness value to accomplish genetic operation and process. The fitness function can be not constrained by consecutiveness and has a definitional domain set at random, which broadens GA's application.
4) GA employs probability transformation rules but not deterministic rules to direct the search.
5) GA is of fine adaptability, self-learning and self-organization. The self-organization search of information is achieved in the evolution process that the individual possessing a greater fitness value has a higher survival probability and will more easily win proper gene.

3.2 SOLUTION PROCEDURE

When applying GA to a concrete problem, a population is generated at first, then individuals in the population are exposed on selection, crossover and mutation operation according to the fitness function. With sufficient information exchange and recombination of each individual, their qualities can be improved and therefore global optimal solution is obtained.

3.2.1 Coding

In solving the problem using GA, once the objective function and variables are chosen, the variables need to be encoded. Since operators' operation in GA is accomplished in iteration, the coding method will have great effect on the operation of mutation operator and GA. In general, coding method includes binary coding and decimal coding.

The binary coding have obvious advantages. On the one hand, the binary coding is in line with computer coding, so this coding method is rather simple and easy to implement. On the other hand, the binary coding owns a broad variable range and is quite appropriate to discrete variable coding, but large population is required to ensure precision for consecutive variable. The decimal coding has a shorter number string, which enormously reduces the computation amount and time. However, the decimal coding depends on actual problem, with additional consideration of operation mode and coding presentation mode.

3.2.2 Initial population generation

As a searching algorithm of population optimization, GA is applied to multiple individuals. After the coding design, initial population is generated and set as the computation initial point. In most cases, GA generates the initial population at random, therefore, the global optimal solution cannot be determined in advance. According to the principles of GA, distributing the initial population uniformly in solution space will effectively enlarge the initial population's scope. However, the solution arising from this method has a low quality and will require quite a long searching time to obtain satisfying solution. Therefore, in general, multiple individuals are firstly generated at random, then optimal individual is selected and added into the initial population until population size arrives at given number through iteration.

3.3.3 Fitness function

In the course of solution search, GA usually needs not extern information but accomplishes the optimization process according to the individual's fitness value offered by fitness function. Therefore, the selection of fitness function will not only have effect on the search of optimal solution but also on the convergence speed. In general, fitness function is acquired from objective function.

3.3.4 Genetic operation

Genetic operation simulates biology evolution process and enforces certain operation on chromosomes by fitness values to achieve the process of survival of the fittest. In terms of optimizing search, genetic operation can generationally optimize the solution to approach the optimal solution. Genetic operation consists of three fundamental genetic operators: selection, crossover and mutation. Selection and crossover achieve the majority of GA's function, and mutation enhances its ability to obtain optimal solution.

The GA operation mainly comprises selection operator, crossover operator and mutation operator. Concretely, the optimization process is primarily accomplished by selection operator and crossover operator, while mutation operator reinforces the search capability for optimal solution.

3.3 IMPROVED GENETIC ALGORITHM

3.3.1 Dividing the optimization space.

Indicates the highest bit string $B_i^{n_i}$ (left-most) of each substring variable x_i can be 0 or 1 (indicated by b). Accordingly existence of a division, you can put a string of two sub-divided into pairs and other spaces. Assuming there are m variables, there are m division can be formed m subspace, with the set as follows:

$$A_i^b = \{S \mid B_i^{n_i} = b\}$$
$$i = 1,2,\cdots,m \quad .$$
$$b = 0,1$$

To divide the interval, in which the individual fitness value in descending order according to the following:

$$S_1^/, S_2^/, S_3^/, \cdots, S_{np}^/,$$

$$f(\varphi(S_i^/)) \geq f(\varphi(S_{i-1}^/))$$
$$i = 1,2,3,\cdots,np$$

3.3.2 Design the space degradation.

When evolution to a generation, if the highest fitness value before np_0 (proportional np_0 take a group of pre-determined size, here take $0.3np$) individuals are located in the same string subspace (such as A_k^b):

$$S_j^/ \in A_k^b,$$

$$i = 1,2,\cdots,np_0$$
$$b = 0,1 \quad .$$

The most advantageous can be considered as falling into A_k^b with great probability, as the next generation of optimization space. Corresponding variables are as follows:

$$\begin{cases} x_i \in \begin{cases} [x_i^L, x_i^U] & i \neq k \\ [x_i^{'L}, x_i^{'U}] & i = k \end{cases} \\ [x_i^{'L}, x_i^{'U}] = \begin{cases} [x_k^L, x_k^U] & b = 0 \\ [x_k^{'L}, x_k^{'U}] & b = 1 \end{cases} \end{cases}$$

$$x_k^m = \frac{1}{2}(x_k^L + x_k^U)$$

As in this space, expressed in the *i* variables' substring $S_i^/ = B_i^{n_i} B_i^{n_{i-1}} \cdots B_i^1$ highest bit same as the highest bit of standard genetic algorithm. In order to improve the coding efficiency, improve the accuracy of the variable expression, while ensuring that each gene locus theorem explained by mode meaning unchanged, the $S_i^/$ gene locus in you from the left to start the second position $B_i^{n_i-1}$, followed by the left one:

$$B_i^{j+1} \Leftarrow B_i^j,$$
$$j = n_i - 1, n_i - 2, \cdots, 1$$

The last one filled with a random number. In order to protect the best individual to the corresponding variables constant degradation during the interval, the best individual is consistent with the last bit before the first move. Due to the continuous degradation of the design space, string length of each variable n_i without too long, can take 4 to 6, does not affect accuracy.

3.3.3 Searching mobile optimization space.

If the current optimal solution is a component of x_k in the current boundaries of the design space, the variable corresponding substring you the same, are 0 or 1, it is considered the optimal solution may range beyond the current optimization. In this case, the direction of movement of the component optimization space to avoid optimization space reduction resulting from the loss of the optimal solution. You can take moving distance between two discrete points for $2d_k$, d_k adjacent direction along

$$x_k : d_k = \frac{x_k^U - x_k^L}{2^{n_k} - 1} .$$

Move method is to adjust the boundaries are as follows:

$$\left[x_i^L, x_i^U\right] = \begin{cases} \left[x_k^L - 2d_k, x_x^U - 2d_k\right], b = 0 \\ \left[x_k^L + 2d_k, x_x^U + 2d_k\right], b = 1 \end{cases} .$$

Then change the corresponding substring method is to change the sub-string as a binary number, when $b = 1$ minus 2; contrary plus 2. This operation ensures that the overlapping portion is moved back and forth in the space of two individuals at the same location on the design space. When there is a carry or borrow occurs, indicating that the points will be removed from the current optimization space, omitting carry or borrow, it will fall within that part of the new into the optimization space, can be understood as a new individual randomly generated.

In the improved genetic algorithm, the improved three operators usually GA algorithm crossover, two chromosomes are randomly selected single-point crossover (also available in other crossover operation, such as multi-point crossover, tree cross section cross matching, etc.), that is to take a little at a high fitness mode for ancestors "family", but this has emulated its one-sidedness. Proven, simple genetic algorithm in any case (crossover probability Pc, mutation probability Pm, arbitrary initialization, any crossover, arbitrary fitness function) are not convergent, that can not find the global optimal solution; through improved the genetic algorithm, that is, before selecting the role (or later) to retain the current optimal solution, is able to guarantee convergence to the global optimal solution [14].

While it is proved that the improved genetic algorithm eventually converge to the optimal solution, but the time required to converge to the optimal solution may be very long. In addition, the question is premature genetic algorithm phenomenon can not be ignored, and its specific performance:

1) Population all individuals caught in the same extremum evolution stopped.
2) An individual close to the optimal solution is always to be eliminated, the evolutionary process does not converge.

   You can use this method to solve the following:

1) To dynamically determine the mutation probability, can prevent good genes because the mutation who were destroyed, but also when the optimal solution for the population trapped Bureau to introduce new genes.
2) Improving the selection mode, abandon roulette wheel selection, in order to avoid an early high fitness individuals quickly occupied populations and populations due to late fitness or less the result of individual populations to stop evolution; roulette wheel selection method will make every an individual can obtain a copy of opportunity does not embody good individual competitiveness, survival of the fittest principle of genetic algorithms can not be achieved. In view of this, here in a press based on the size of individual fitness sorting algorithm to replace the population roulette wheel selection method. The procedure is described as follows:

first () {the population size of individual sorted by fitness;}
while the population has not yet been scanned
do {two copies of the top surface of the individual; intermediate copy; behind not copied;}

Merit cross in solving premature convergence problem, usually accustomed to using the best individual limit the competitiveness (high fitness individuals Copies) approach. This will undoubtedly reduce the speed of evolution of the algorithm, increasing the time complexity of the algorithm, reducing the performance of the algorithm. Because genetic diversity of the population could be reduced into a bureau optimal solution, and accelerate the speed of evolution of the population and can improve the overall performance of the algorithm. To resolve this contradiction, try one without destroying the genetic diversity under the premise of accelerating the speed of evolution population methods. This method is described as follows: In the random selection of male and female later, according to the crossover method (single point, multipoint, uniform crossover) n times the cross, generate 2n individuals, then individuals from 2n pick out the best of two individuals to join a new population. This will not only save the paternal and maternal genes, but also in the process of evolution greatly improve the average performance of individuals in the population.

Based on the above analysis, the improved genetic algorithm is described as follows:

1) In the initial population, individuals of all sizes are sorted according to their fitness, and then calculate the support and confidence of the individual.
2) By a certain percentage copy (current population is about two individuals to adapt to the highest degree of integrity of the structure to be copied with the population).
3) The individual is determined by the location of its mutation probability and mutation; 4 parts by copying the best individual, the individual does not replicate the principles of inferior copy individuals.
4) Randomly selected from the replication group, two individuals, these two individuals were repeatedly crossed, choose from one of the best individual results obtained in stores new populations.
5) If the termination condition is satisfied, then stop, otherwise, skip the first step (1), until you find all the qualifying rules.

The advantage of this algorithm is that every generation in the process of evolution, the progeny of the parent always retains the best individuals, with the "mode is a high degree of adaptation of the family ancestors direction" search of better sample to You can search to ensure that the final global optimal solution.

4 The characteristics and application of BP neural network

4.1 COMPARISON OF DIFFERENT NEUTRAL NETWORKS

As a type of feed-forward network, BP neutral network has good scalability and can be applied to fault diagnosis and identification. Being similar to RBF neutral network, BP neutral network possessing high operation efficiency and small space usage is quite applicable to online real-time monitoring and fault diagnosis, therefore, the training samples of BP neutral network can be representative and error-tolerant [2,4,6].

ART neutral network and SOM neutral network are the representatives of unsupervised neutral network. ART neutral network supports online learning to guarantee the synchronization of learning and memory, and automatically classifies the samples added in the network. When a sample cannot be categorized, a new classification mode arises automatically. To search corresponding data in certain stereotyped classification category, the input has to be incorporated into this category. SOM neutral network employs off-line learning to direct extraction of the object characteristic. In the field of power-supply fault diagnosis, ART neutral network and SOM neutral network are rarely used [5,7]. Though with a poor applicability, however, the adaptability and self-organization endow these neutral networks clear advantage in solving complex fault diagnosis problem.

SOM neutral network classification is accomplished primarily on distance theory and reaches request number of categories through selecting different training number. Besides, SOM neutral network is quite applicable to the situation when fault type is unknown[8,9]. Feed-forward neutral network can approach consecutive function and square function with different precision to achieve accurate fitting of training sample set. Therefore, in this paper, BP neutral network model is presented.

4.2 CONSTRUCTION OF BP NEUTRAL NETWORK MODEL

At present, the multiple-level sensor of BP neutral network is widely adopted in the field of neutral network. As the mostly used structure in multiple-level sensor, single-hidden neutral network consists of three levels, that is, input level, output level and hidden level, as shown in Figure 1, which shows the schematic of three-level BP neutral network structure.

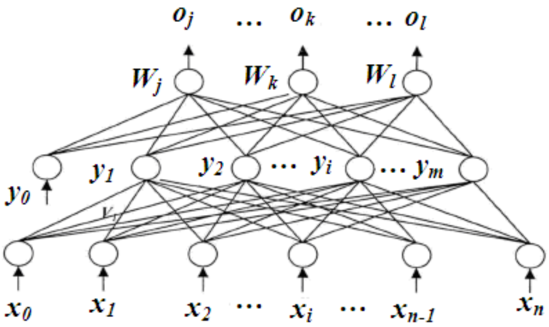


FIGURE 1 Schematic of three-level BP neutral network structure

5 Technical plan of optimization of BP neutral network with GA

At present, there are two methods in artificial neutral network optimization. The first one is to optimize initial threshold and weight; and the second is to optimize structure. In this paper, we conduct threshold and weight optimization while maintaining the structure unchanged.

At first, all the neurons of the artificial neutral network are listed and weight values and coefficients derived from possible connections between the neurons are encoded in binary or decimal coding to make each individual independent. Then multiple populations are generated to execute GA's search process in iteration [10]. At last, the parameters are utilized in the artificial neutral network to calculate the fitness value of each individual by mean error obtained from sample training [11-13]. Genetic algorithms to optimize BP neural network algorithm steps are as follows:

1) A set of threshold and weight of the BP neutral network in binary or decimal coding is generated, in the meantime, the initial population is built.
2) Taking minimal error as the evolution rule, individual fitness value can be obtained from the calculation of error function. It can be observed that the error increases with the fitness value's decrease.
3) Select individual with the greatest fitness value and add it into next generation directly. The remains are chosen by probability according to their fitness values and imposed on crossover and mutation operator to arrive at the next generation.
4) Repeat aforementioned procedure (2)-(3) until optimal solution is found. Through several iteration, a set of threshold and weight can be obtained, which has the minimal error to BP neutral network optimized by GA.

6 Simulation of the power-supply system fault diagnosis with BP neutral network optimized by GA

6.1 RECTIFICATION VOLTAGE WAVEFORM AND FAULT CLASSIFICATION

As shown in Figure 2, we take three-phase bridge rectifier circuit as an example, and apply GA to power-supply system fault diagnosis. Meanwhile, two hypotheses are provided as follows:

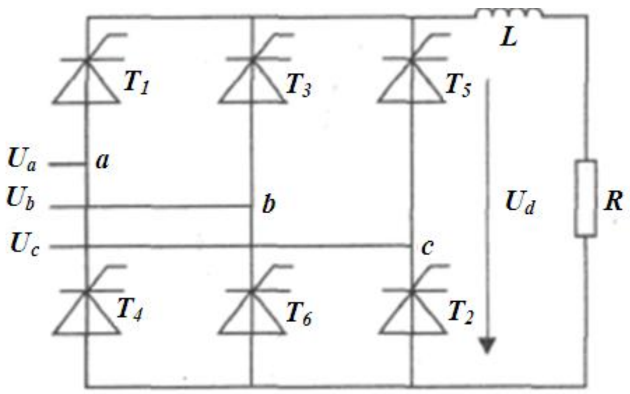


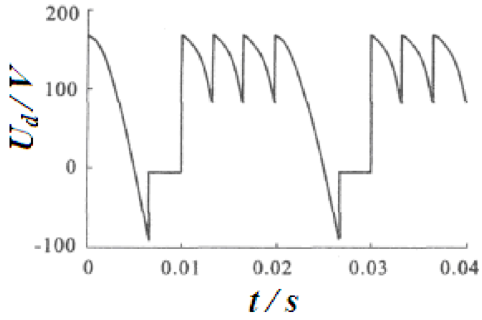
FIGURE 2 Three-phase bridge rectifier circuit

1) Take the thyristor's open-circuit fault as the actual problem.
2) There are at most two faults in thyristors simultaneously. The output of three-phase bridge rectifier circuit outputs direct voltage, denoted as U_d . Direct voltage which contains the thyristor's fault information is the key to detect the fault. Generally speaking, direct voltage U_d is easy to be detected, therefore, it is the primary object of fault diagnosis.

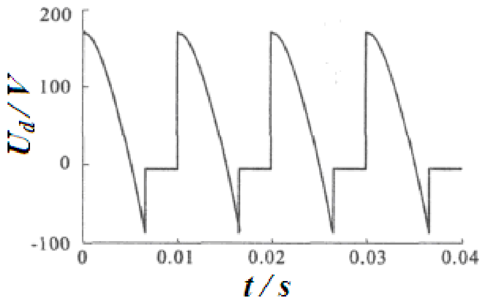
On the basis of the two hypotheses, take the normal condition as a special fault problem and the fault of three-phase bridge rectifier circuit falls into five categories roughly or twenty-two types in detail.

<u>Category 1:</u> Thyristor has no fault and it works normally;
<u>Category 2:</u> Fault arises in one thyristor and includes six types, which is denoted as $T_i = (i = 1,2,\ldots,6)$;
<u>Category 3:</u> Fault arises in two thyristors connected to the same voltage and includes three types, which is denoted as T_i and T_j , $i = 1,2,3\ j = i + 3$;
<u>Category 4:</u> Fault arises in two thyristors placed in the same half-bridge and includes six types, which is denoted as T_i and T_j , $i = 1,2,\ldots,6\ j = (i + 2) \bmod 6$;
<u>Category 5:</u> Fault arises in the two thyristors placed in different group and includes six types, which is denoted as T_i and T_j , $i = 1,2,\ldots,6\ j = (i + 1) \bmod 6$;

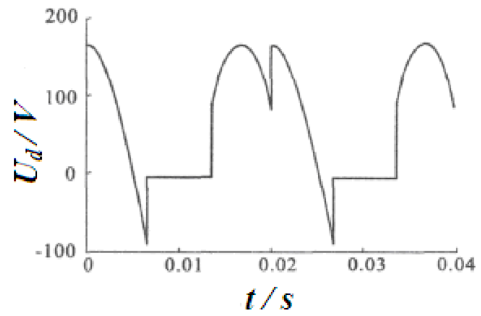
Typical waveform of circuit fault in each category is depicted in Figure 3.



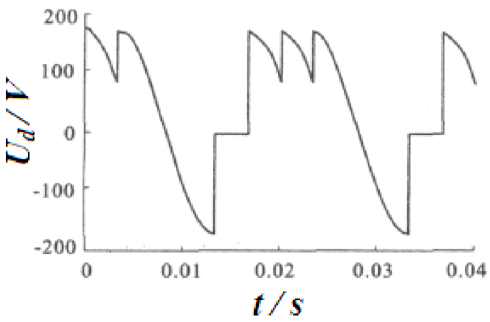
a) Class 2: T1 failure, the output waveform



b) Class 3: T1 and T4 failure, the output waveform



c) Class 4: T1 and T3 failure, the output waveform



d) Class 5: T2 and T3 failure, the output waveform

FIGURE 3 Typical voltage waveform of circuit fault

In the same category of fault, the waveform corresponding to different fault types can be virtually obtained through horizontal shift on the time axis under given triggering angle α to generate BP neutral network's training sample. In this paper, triggering angle is set as 30°.

6.2 CONSTRUCTION OF THE CIRCUIT FAULT MODE VECTOR

Impose Fourier transform on the output voltage of the twenty-two types of circuit fault and the five-dimension structure vector composed of first harmonic, second harmonic, fundamental current amplitude, phase can be obtained. Then we normalize the vector of each fault and take it as the training sample of BP neutral network, as detailed in Table 1.

TABLE 1 Characteristic vector of circuit fault

Faulty Unit	Characteristic Vector				
T1	91.41	81.6	150	47.73	29.98
T2	91.41	81.6	89.99	47.73	–89.98
T1,T3	67.59	100	120	0.045	131.9
T2,T4	67.60	100	60.01	0.008	–23.26
T1,T6	43.71	141.4	180	47.71	90.01
T2,T3	43.67	141.4	59.98	47.73	–150
T4,T5	43.67	141.3	–60.02	47.75	–30.06
T5,T6	43.67	141.3	–120	47.75	–150
T1,T4	43.67	0.001	51.10	95.45	29.98
T2,T5	43.66	0.001	56.01	95.45	–90.00

As we can see from Table 1, different circuit faults of the same category have the identical fundamental current amplitude, first harmonic amplitude and second harmonic amplitude, respectively, however, their fundamental current amplitude phases and second harmonic amplitude phases are different. Therefore, the harmonic amplitude can be utilized to identify the type of the fault and the harmonic amplitude phase is utilized to distinguish the thyristor.

In this paper, each fault ($X_i = 1,0$) is represented with six binary digit $X_6X_5X_4X_3X_2X_1$. Furthermore, the first three digits means fault type and the second three digits means fault component. The binary coding of the circuit faults is listed in Table 2:

TABLE 2 Type code of circuit fault

Faulty thyristor	Code	Faulty thyristor	Code
Normal	001000	T1,T5	011101
T1	010001	T2,T6	011110
T2	010010	T1,T6	100001
T3	010011	T1,T2	100010
T4	010100	T2,T3	100011
T5	010101	T3,T4	100100
T6	010110	T4,T5	100101
T1,T3	011001	T5,T6	100110
T2,T4	011010	T3,T6	101001
T3,T5	011011	T1,T4	101010
T4,T6	011100	T2,T5	101011

7 Conclusion

In summary, BP neutral network has simple structure as well as good identification ability, however, it may easily fall into local minimum and owns a slow convergence speed. It was found that these disadvantages can be complemented with GA which can search in global space but cannot be employed alone as a control method for its lack of self-organization and learning ability. Hence, in this study, we combine BP neutral network and GA to achieve their advantageous complementarities.

Acknowledgments

This work is supported by Aeronautical Science Fund of China No.20120196006.This work is supported by Electronic Information in Shaanxi Province Key Laboratory of System Integration Fund No.201113y14.

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