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Application of BPSO with GA in Model-based Fault Diagnosis of Traction Substation

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Abstract—**In this paper, a hybrid evolutionary algorithm based on Binary Particle Swarm Optimization (BPSO) and Genetic Algorithm (GA) is proposed to compute the minimal hitting sets in model-based diagnosis. And a minimal assurance strategy is proposed to ensure that the final output of algorithm is the minimal hitting sets. In addition, the logistic mapping of chaos theory is adopted to avoid the local optimum. The high efficiency of new algorithm is proved through comparing with other algorithms for different problem scales. Additionally, the new algorithm with logistic mapping could improve the realization rate to almost 100% from 96%. At last, the new algorithm is used in the model-based fault diagnosis of traction substation. The results show that the new algorithm makes full use of the advantages of GA and BPSO and finds all the minimal hitting sets in 0.2369s, which largely meet the real-time requirement of fault diagnosis in the traction substation.**

Keywords—model-based diagnosis; minimal hitting set; BPSO; GA; traction substation

I. INTRODUCTION

At present, the fault diagnosis systems of traction substation are mostly expert systems based on experts' experience [1]. For example, an expert system was constructed to diagnose the fault of relay protection equipment and breakers in reference [2]. The experience knowledge is used to analyze and judge the fault of traction equipment in substation in [3]. Although the expert system has been widely used, there are still some shortcomings, such as the difficulty of gaining expert experience.

In order to overcome the drawbacks of expert systems, model-based diagnosis (MBD) was proposed in 1970s, and then it quickly became an active branch of artificial intelligence [4]. Now, MBD has been widely applied in many fields [5-6].

Computing minimal hitting sets is an essential problem of MBD, and it is also a NP-Hard problem. According to Reiter's theory, the minimal hitting sets (*MHS*) are the diagnosis of the system [7]. After HS-tree was put forward by Reiter [4], many scholars have studied and improved this method, such as HST-Tree [8], BHS-Tree [9], HSSE-Tree [10], Boolean algebra [11], Genetic algorithm (GA) [12], binary article swarm optimization (BPSO) algorithm [13] and so on. The main disadvantages of these approaches are listed as follows: (1) a tree or graph is needed to be constructed, which will produce too many nodes; (2) partial MHS will be lost when the tree is pruned; (3) the algorithm is complex and inefficiency.

The rapid and effective diagnostic solution for solving the minimal diagnosis with MBD is always a significant research area, especially for the fault diagnosis of traction substation, which emphasizes the real-time diagnosis. So in this paper, a hybrid evolutionary algorithm with an assurance strategy and logistic mapping is proposed to meet the need of real-time diagnosis of traction substation.

This paper is structured as follows: Part II provides the introduction of model-based diagnosis, BPSO and GA. Part III introduces a new method combined with BPSO and GA to compute minimal hitting sets. In part IV, the performance of the novel algorithm is compared with other algorithms, and the novel algorithm is used in the diagnosis of traction substation. In part V, the conclusion of the new algorithm is given.

II. RELEVANT KNOWLEDGE

A. Model-Based Fault Diagnosis

Firstly some chief definitions and theorems corresponding with model-based diagnosis are introduced as follows [4].

Definition 2.1 A diagnosis system can be expressed by a triple (*SD, COMPS, OBS*).

(1) *SD* (the system description) is a set of first order sentences.

(2) *COMPS* (the system component) is a set of constants.

(3) *OBS* (the system observation) is a finite set of first order sentences.

Definition 2.2 A conflict set (*CS*) for system (*SD, COMPS, OBS*) is a set$\{c_1, c_2, \ldots, c_n\} \subseteq COMPS$, when $SD \cup OBS \cup \{\neg ab\ (c_1), \neg ab\ (c_2) \ldots \neg ab\ (c_n)\}$ is inconsistent. Where, "ab" means "abnormal". If $c \in COMPS$ is abnormal, ab(c) is true, otherwise $\neg$ab(c) is true. If no proper subset of a *CS* is a conflict set for (*SD, COMPS, OBS*), this *CS* for (*SD, COMPS,*

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OBS) is called a minimal conflict set (*MCS*).

Definition 2.3 A set H is called a hitting set (*HS*) for a collection of conflict sets (*CSs*), if: $H \subseteq \bigcup_{CS \subseteq CSs} CS$ and $H \bigcap CS \neq \Phi, (CS \subseteq CSs)$.

If no proper subset of a *HS* is a hitting set for *CSs*, then the *HS* is called a minimal hitting set (*MHS*) for *CSs*.

Theorem 2.1 Only if Δ is a *MHS* of the *CSs* of a system (*SD, COMPS, OBS*), Δ⊆*COMPS* is a candidate diagnosis of the system.

Based on the above definitions and theorems, it is apparently that we can derive the diagnosis of the system by computing the *MHS* of the *MCS* [4].

B. Binary Particle Swarm Optimization

In order to solve the discrete problem existed in practical engineering, Kennedy and Eberhart put forward a discrete binary version of particle swarm optimization in 1997 [14]. In their model a particle is represented by 0 or 1, which means "include" or "not include". The major difference between BPSO and traditional particle swarm optimization (PSO) is that the velocities of particles are defined as the probabilities that a bit of one particle will change to 1. According to the definition, the velocity must be limited in [0, 1] with a sigmoid function as follows [13].

$$sig(x_{id}^{t+1}) = 1/[1+exp(-v_{id}^{t})] \quad (1)$$

The new position and velocity of the particle is obtained by using the equation below.

$$v_{id}^{t+1} = wv_{id}^{t} + a_1 r_1 (P_{bestid}^{t} - x_{id}^{t}) + a_2 r_2 (G_{bestid}^{t} - x_{id}^{t}) \quad (2)$$

$$x_{id}^{t} = \begin{cases} 0 & rand \geq sig(x_{id}^{t+1}) \\ 1 & rand < sig(x_{id}^{t+1}) \end{cases} \quad (3)$$

Where a_1, a_2 are learning factors. r_1^t, r_2^t are the random variables with uniform distribution between 0 and 1. w is the inertia weight which shows the effect of previous velocity vector on the new vector. v_{id}^t, x_{id}^t are the d-th dimensional velocity and position of the particle i at the t-th iteration respectively. $P_{bestid}^t, G_{bestid}^t$ are the personal and the global best position of the particle i at the t-th iteration respectively.

The inertia weight could keep the balance of the ability of local and global search and BPSO with a bigger inertia weight will have better global search ability. On the contrary, a smaller inertia weight can enhance the local search ability of BPSO. So in this paper, linear decrement inertia weight is obtained by equation (4) [15], which can enhance the global search ability in the early process to find the probable range of the best solution with a fast speed and enforce the local search ability in the later process to quickly locate the accurate position of the best solution.

$$w^t = (w_{ini} - w_{end}) \times \frac{T_{max} - t}{T_{max}} + w_{end} \quad (4)$$

Where, $w_{ini}, w_{end}, T_{max}$ are the initial inertia weight, the final inertia weight and the max number of the iteration, respectively.

C. Genetic Algorithm

Genetic algorithm (GA) is a search heuristic which mimics the process of natural selection [16]. GA is an iterative process with the start of a population of individuals generated randomly. In each iterative process, the fitness of each individual of the population is calculated and more suitable individuals will be selected from the current population to form a new generation by modifying the genome of each individual. The new generation of candidate solutions is then used in the next iteration until the best solution has been found. This method has been applied in many different fields, such as neural networks, expert systems, fuzzy logic control and multi-disorder diagnosis [17]. And GA also has been used for Multi-objective computation, such as [18, 19].

III. An Improved Binary Particle Swarm Optimization with Genetic Algorithm

A. Fitness Function

It is critical to construct a proper fitness function, which is the only index to evaluate the quality of the particles. A suitable fitness function can not only judge a particle whether it is a minimal hitting set, but also, to some extent, can improve the efficiency of the algorithm. The fitness function used in this paper is as follows.

$$f_i = h_{num}^i / x_{num}^i \quad (5)$$

h_{num}^i is the number of *CS* in *CSs*, which has intersection with the current particle i. h_{num}^i indicates the probability that a particle i becomes a hitting set, and particle i is a hitting set only when h_{num}^i equals the total number of *CS* ($CS_{total-num}$). x_{num}^i is the number of element 1 the current particle i has, which indicates the probability that a particle i becomes a minimal hitting set.

For example:

There is a *CSS*={{1,2,3},{2,3,4},{3,4,5}}. For the particle a = [1 0 0 1 0], h_{num}^a = 3 (all *CS* in *CSS* have intersection with a) and x_{num}^a = 2 (sum for i), so f_a =1.5. For the particle b = [1 1 0 1 0], h_{num}^b =3, x_{num}^a =3, f_b =1. The above results show that $h_{num}^a = h_{num}^b = CS_{total-num}$, so both particles a, b are hitting sets for the *CSS*. But $f_b < f_a$, a is the *MHS* of the *CSS*, b is a superset of a yet.

B. The Combination of BPSO and GA

BPSO and *GA* are much similar in their inherent parallel characteristics and in the population-based representation of the parameters. BPSO is a very promising evolutionary method and it seems to have a faster convergence rate than GA in the early run. Especially each particle of BPSO can keep a memory to trace its previous best position, and its velocity is adjusted according to its historical behavior and its neighbors. However, with the increase of iterative number, particles converge to a single point, which is not guaranteed to be even a local optimum [20]. That is to say, the swarm may prematurely converge. On the contrary, the GA can emphasize on global as opposes to local optimum. The main drawback of GA is that, if a chromosome is not selected, the information contained by that individual will be lost. However, without a selection operator used in GA, BPSO may waste resources of inferior individuals [21].

In order to make full use of the qualities and uniqueness of GA and BPSO, a hybrid technique called BPSO-GA is proposed in this paper. The new approach combines the standard velocity and update rules of BPSO with the ideas of selection, crossover and mutation of GA.

In each iterative process, the upper half of the best-performing individuals in a population is selected as elites. And then genetic algorithm is applied to those elites to generate offspring. Finally, the elites and offspring are recombined and updated by using the equations (2), (3) and (4).

C. *Assurance Strategy for Minimal Hitting Set*

In order to improve the efficiency of the algorithm and ensure that the final outputs are all minimal hitting sets, we present a novel assurance strategy. The novel strategy consists of two parts:

Part A.

Step 1. In each iterative process, judging whether the particle i is a hitting set ($h_{num}^{i} = CS_{total-num}$). If so, go to step 2, otherwise go on to the next iteration.

Step 2. Testing the particle i and judging if it has already existed in the collection of candidate minimal hitting sets (*CMHSs*). If so, go on to the next iteration, otherwise put the particle i into *CMHSs* as a candidate minimal hitting set (*CMHS*).

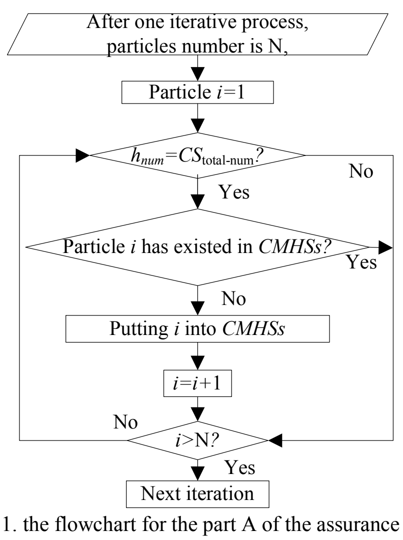

Fig.1. the flowchart for the part A of the assurance strategy

Part B.

After the process of BPSO-GA, there are many candidate sets in the *CMHSs*. All of the sets are hitting sets, but not all are minimal hitting sets. So some strategies should be used to delete the supersets. Each candidate minimal hitting set in the *CMHSs* should be disposed as follows.

Step 1: Testing the *CMHS* if it is a superset for anyone in the final minimal hitting sets (*MHSs*). If so, let the CMHS minus the subset in MHSs to become a new *CMHS*, and then return to step 1 and go on the testing, until the new *CHMS* couldn't be a superset for any *CHMS* of the *CHMSs*.

Step 2: Scanning each *CMHS*, if one bit of *CHMS* values 1, then change it to 0 and test if *CMHS* is still a minimal hitting set. If so, keep the change and scan its next bit.

Step 3: Testing the *MHS* if it has already existed in the collection of minimal hitting sets (*MHSs*). If it is not, put the *MHS* into the *MHSs*.

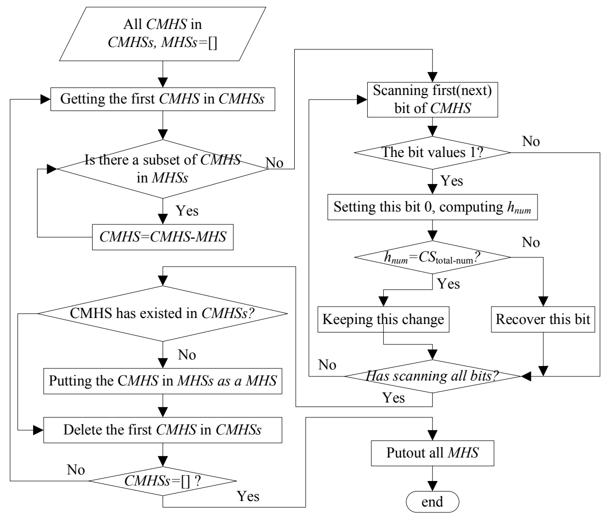

Fig.2. the flowchart for the part B of the assurance strategy

We can ensure all of the final outputs are minimal hitting sets, and all of their subsets are not minimal hitting sets via the insurance strategy.

D. *The Application of Chaos Theory*

The termination condition of the algorithm is important for the performance of the algorithm and affects the iterative numbers and the running time. Two kinds of termination conditions are given as follows.

TABLE 1
THE FIRST KIND OF TERMINATION CONDITION

N is the iterative number.
IF N>5
IF global best(N) equals global best (N-5)
Stop process of algorithm
ENDIF
ENDIF

The first kind of termination condition is used to compare the convergence rate of several algorithms, which means that when global best can't change better with the increasing iteration, the process of the algorithm will be stopped. But sometimes the algorithm will fall into the local optimum in finding minimal hitting sets. So the second kind stop condition is adopted by using the logistic mapping of chaos theory to make better performance of the algorithm in finding more hitting sets.

Chaos optimization algorithm could avoid local optimum and it is superior to random search algorithm [22]. The logistic mapping is applied to generate chaotic variables as follows.

$$c_j^{k+1} = \beta c_j^k (1-c_j^k), k=1,2,....,c_j \in (0,1)$$
$$c_j \neq 0.25, 0.5, 0.75, \beta \in (2,4] \quad (6)$$

Where k is the number of iteration, c_j is the j-th chaotic variable of particle i.

When the global best keeps the same in 5 iteration, the algorithm may fall into local optimum, so do chaos operation to the particles to avoid the local optimum. The pseudo code is shown in Tab.2.

TABLE 2
THE SECOND KIND OF TERMINATION CONDITION

```
Times of chaos operation: M=0， N is the iterative
number.
IF N<5 and global best(N) equals global best (N-5)
  IF M<3
    Chaos operation to current particles
    M=M+1;
    ENDIF
    ELSE Stop process of algorithm
ENDIF
```

E. Algorithm Flow

According to the analysis above, the flow chart of the new algorithm is shown in Fig.3. The algorithm includes a strong co-operation of GA, BPSO, the minimal assurance strategy and the logistic mapping of chaos theory. In fact, this kind of updating technique yields a particular evolutionary process where individuals improve their score for natural selection of the fitness and for good-knowledge sharing. And the minimal assurance strategy ensures all of the final outputs are *MHS*, which would be benefit for real-time system.

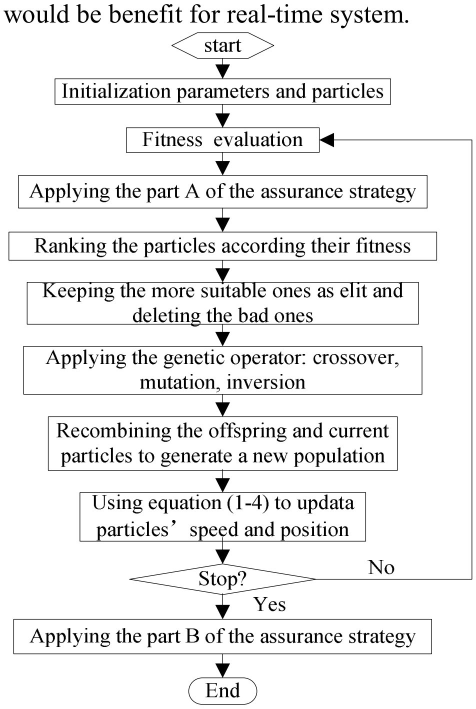

Fig.3 Flowchart of algorithm

IV. EXPERIMENT AND ANALYSIS

A. Comparison

In order to verify the efficiency of the proposed method, six algorithms (GA, BPSO, Boolean algebra, HS-Tree, BHS-Tree, and MGA) are employed for comparison.

Supposing the number of conflict sets is n. There are l elements in each conflict set. The conflict sets are{1,2,⋯,m},{2,3,⋯,m+1},⋯,{n,n+1,⋯,n+l-1}, and n+m-1 is the problem scale [11].

Experiment 1:

Let n=9, m=11. Parameters of the three algorithms (GA [12], BPSO [13], and BPSO-GA) are the same and are set as follows. Particle number is 40, learning factor a_1=2.5, a_2=1; crossover rate is 0.7 and mutation rate is 0.1. The fitness value and iteration numbers of the three algorithms is obtained with running 20 times, showed in Fig. 4-6, in which each line represents a result of one running.

BPSO seems to have faster convergence rate than others with less than 5 iterations in average, but it always fall into local optimum, as many fitness values of running are less than the best value. On the contrary, the convergence of *GA* is much slower than BPSO, while it always finds the global optimal finally. BPSO-GA, a hybrid technique of the two methods, dramatically utilizing the features and advantages of the two algorithms, is more likely to find the better solution with less iteration.

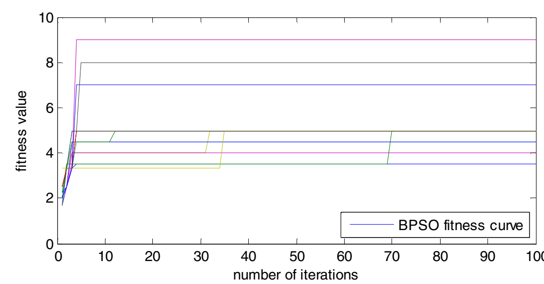

Fig.4 The convergence of BPSO (20 realizations)

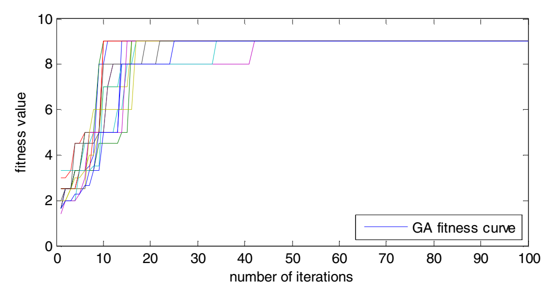

Fig.5 The convergence GA (20 realizations)

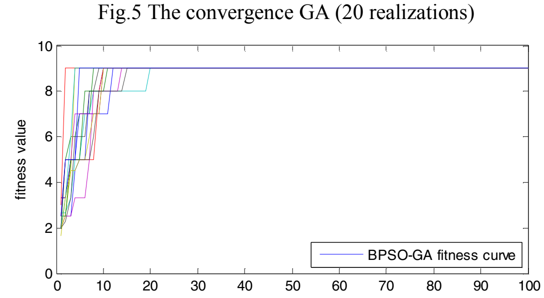

Fig.6 The convergence of BPSO-GA (20 realizations)

Experiment 2:

Let n=10, and the problem scale=20, 30, 40, 50, 60, 70, 80, 90. The average result with 50 realizations is shown in Fig.7, Fig.8. Compared with BPSO and GA, BPSO-GA is more feasible and effective and can find the minimal hitting sets more quickly. BPSO-GA finds out about 96% minimal hitting sets with the least time. The running time of GA is the longest but it also could find 96% minimal hitting sets.

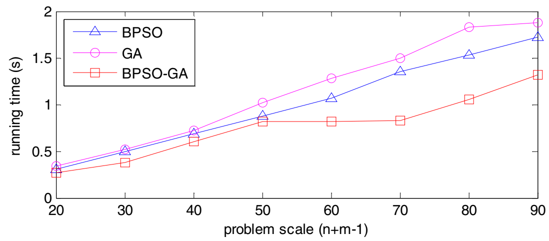

Fig.7 The running time of tree methods (average results of 50 realizations)

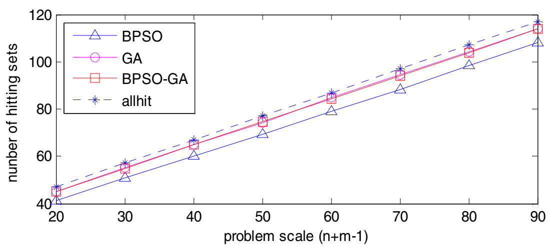

Fig.8 Hitting sets number of tree methods (average results with 50 realizations)

Experiment 3:

Let n=10, and the problem scale=20, 30, 40, 50, 60, 70, 80, 90. In order to prove the efficiency of the logistic mapping in avoiding local optimum and finding more *MHS*, we realize two kinds of BPSO-GA. One BPSO-GA is the normal without logistic mapping of chaos theory and the other one with it to enhance the ability of finding more hitting sets. The average results with 50 realizations are shown in Fig.9. From Fig.9, we can see that the algorithm with logistic mapping could jump out the local optimum and the realization rate rise from 96% to almost 100%.

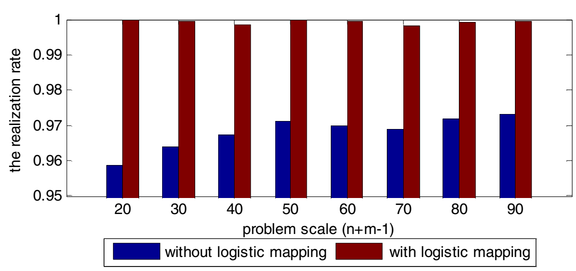

Fig.9 The realization rate of BPSO-GA (average results of 50 realizations)

Experiment 4:

Let n=10, and the problem scale=20, 30, 40, 50, 60, 70, 80, 90. The search efficiencies of the five algorithms are shown in Fig.10. The BPSO-GA is not sensitive for the problem scale, so it is more suitable for solving large-scale problems. With the increase of the problem scale, the efficiency of BPSO-GA would be higher compared with other algorithms. For instance, when the problem scale is large, the running time of BPSO-GA is 5% of the HS-Tree and Boolean algebra. Specifically when the problem is 70, Boolean algebra and HS-Tree could not compute because of memory out, but BPSO-GA can find almost all minimal hitting sets in 5s.

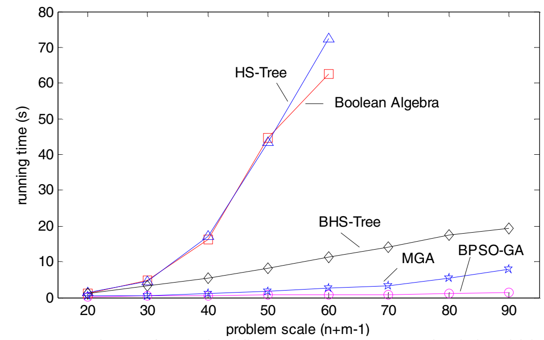

Fig.10 Comparison of search efficiency among several minimal hitting set algorithms

B. *Fault Diagnosis of Electric Railway Substation*

In this section, the algorithm proposed in this paper is used to diagnose the fault of the traction substation.

A simple structure diagram of the electric railway substation is shown in Fig.11. Where the connector wire L2 and traction transformer T2 work as the auxiliary equipment for L1 and T1 respectively, so they don't be included in our diagnosis system.

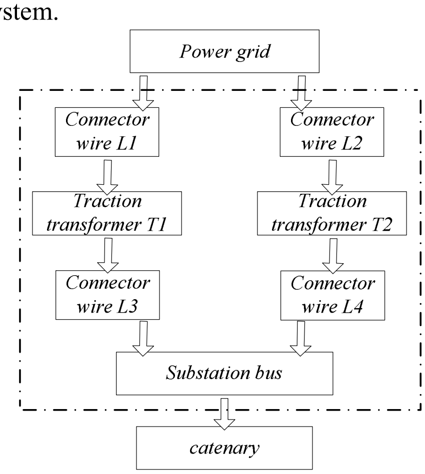

Fig.11 The frame diagram of electric railway substation

The traction transformer T1 is a V/V transformer with two single-phase transformers, which are represented as T1_T1F1 and T1_T2F2. L1_A, L1_B and L1_C represent the three-phase wires (A, B, C) of L1. As the connect wire between transformer and substation bus, L3 has to connect the two single-phase transformers through L3_T1, L3_F1 (connecting one single-phase transformer) and L3_T2, L3_F2 (connecting the other one). L3_N is the neutral line of L3. Similarly, there are B_T1, B_F1, B_T2, B_F2 and B_N in the substation bus, which are connected with L3. So there are 15 elements in the diagnosis system: COMPS = {T1_T1F1, T1_T2F2, L1_A, L1_B, L1_C B_T1, L3_T1, L3_F1, L3_T2, L3_F2, B_F1, L3_N, B_T2, B_F2, B_N}.

Assume both B_T1 and L1_B are shorted to ground. The fault data can be obtained by simulating the fault in Simulink, and all minimal conflict sets can be obtained by the approach proposed in reference [23, 24] as follows.

CSs={{L1_A,L1_B,L1_C,T1_T1F1,T1_T2F2}, {B_T1}, {B_N, B_T1, L1_A, L1_C, L3_N, L3_T1, T1_T1F1},{B_N, B_T2, L1_A， L1_B, L3_N, L3_T2, T1_T2F2},{L1_A, L1_B, L3_F2, L3_T2, T1_T2F2}}.

Several algorithms are used to find the HMS of the fault system and the results are shown in Tab.3.

TABLE 3
COMPARION OF PERFORMANCE AMONG THREE ALGORITHMS

Algorithm	MHS	CMHS	Time(s)
GA	11	492	0.2837
BPSO	10	305	0.2546
BPSO-GA	11	378	0.2369
HS-Tree	11	-	1.9654
Boolean Algebra	11	-	1.5214

From Tab.3, we can see that, BPSO doesn't find all *MHS* with the least *CMHS*, which means that BPSO quickly fall into local optimum in the process. And GA finds all of the MHS with a long time and the most *CHMS*. Instead, BPSO-GA finds all MHS in the least time. The validity of the assurance strategy is also proved in Tab.3. From tab.3 we can see that MHS decreased sharply from *CMHS*, that is to say, the assurance strategy ensure all of the output being minimal hitting sets. All of the minimal hitting sets are shown in Tab. 4.

TABLE 4
ALL OF THE MINIMAL HITTING SETS

Minimal hitting set	number
{L1_A, B_T1}	***2***
{L1_B, B_T1}	***2***
{T1_T2F2, B_T1}	***2***
{L1_C, L3_T2, B_T1}	3
{T1_T1F1, L3_T2, B_T1}	3
{L1_C, L3_F2, L3_N, B_T1}	4
{L1_C, L3_F2, B_T1, B_T2}	4
{L1_C, L3_F2, B_T1, B_N}	4
{T1_T1F1, L3_F2, L3_N, B_T1}	4
{T1_T1F1, L3_F2, B_T1, B_T2}	4
{T1_T1F1, L3_F2, B_T1, B_N}	4

Then we need to use the theory of model-based diagnosis to infer the specific fault components. Based on the probability statistics principle, the probability of two faults happens at the same time is far less than that of three. So, we will do the inspection and maintenance of the equipment which is in the hitting sets with less equipment in real diagnostic process. They are {L1_A, B_T1}, {L1_B, B_T1} and {T1_T2F2, B_T1}, in which the shorted components B_T1 and L1_B are contained. Of course we also can detect and repair B_T1 which appears three times in the sets at first according to the probability statistics principle.

V. CONCLUSION

In this paper, a new algorithm combining BPSO and GA is proposed to compute minimal hitting sets, which can utilize the qualities and uniqueness of the two algorithms to realize a better performance. Meanwhile, an insurance strategy is proposed to reduce the superset and ensure all of the outputs are minimal hitting sets. The experiments show that the realization rate of the new algorithm rises from 96% to 100% using logistic map of chaos theory. Additionally, the hitting sets can be solved within 1.5s by the new method even when the problem scale grows up to 80, which can satisfy the need of the real-time diagnostic system. At last, the new algorithm is applied in the fault diagnosis of traction substation, and the results show that the new method is accurate and efficient. Compared with other algorithms, it can solve all 11 *HMS* in the shortest time.

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