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Research Article

An Improved Test Selection Optimization Model Based on Fault Ambiguity Group Isolation and Chaotic Discrete PSO

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Sensor data-based test selection optimization is the basis for designing a test work, which ensures that the system is tested under the constraint of the conventional indexes such as fault detection rate (FDR) and fault isolation rate (FIR). From the perspective of equipment maintenance support, the ambiguity isolation has a significant effect on the result of test selection. In this paper, an improved test selection optimization model is proposed by considering the ambiguity degree of fault isolation. In the new model, the fault test dependency matrix is adopted to model the correlation between the system fault and the test group. The objective function of the proposed model is minimizing the test cost with the constraint of FDR and FIR. The improved chaotic discrete particle swarm optimization (PSO) algorithm is adopted to solve the improved test selection optimization model. The new test selection optimization model is more consistent with real complicated engineering systems. The experimental result verifies the effectiveness of the proposed method.

1. Introduction

High technologies contribute a lot to the improvement of the performance of complex equipment. However, new challenges are also brought into testing, diagnosis, and maintenance stages of the equipment because the system structure is more and more complicated [1–3]. In order to improve the testing efficiency and diagnosis ability, as well as to reduce the test cost, the design for testability (DFT) should be carried out simultaneously during the design of the equipment [4]. Test optimization selection is a process of selecting the proper test set from all the available test set under the constraints including minimum test cost, test cycle, fault detection rate (FDR) index, fault isolation rate (FIR) index, test resources, and engineering-oriented constraint rules [5]. Test optimization selection is a nondeterministic polynomial-time hard (NP-hard) problem [6], which is a challenging problem related to the combination problem and the permutation problem.

In general, two categories of methods have been applied to solve the test optimization selection problem: sequential fault diagnosis methods [7–11] and direct searching algorithms [12–15]. Sequential fault diagnosis methods include dynamic programming (DP) algorithm, information entropy method, graph search method, and heuristics method. These methods model the test optimization selection problem as a binary identification problem [7, 16]. Direct searching algorithms are intelligent optimization algorithms, including evolution algorithms and particle swarm optimization (PSO) algorithm. The direct searching method with artificial intelligence searching method can directly find the optimal test set, for example, the multidimensional discrete PSO algorithm [17, 18], the genetic algorithm (GA) [13], and so on [19]. With these methods, although the optimal solution can be found, some faults with low probability cannot be detected and isolated, which means information loss for the system.

In the process of test selection optimization, among the alternative test sets, if the test cost of each test is equal to each other, the test set corresponding to faults of high fault rate is usually chosen. This may lead to failure in fault detection and isolation of those faults with low probability. More seriously for the complex system, the losing of some fault information may lead to increasing of the maintenance costs of equipment system. In addition, if all those faults with low probability are taken into consideration by increasing the FDR, the test cost will increase significantly. In real engineering practice, it is unreasonable and uneconomical to realize the unique isolation of all the faults. Thus a process of fault detection and isolation that can isolate the fault into a specific replacement unit or some fault ambiguity groups is consistent with real applications. In this paper, an improved test selection optimization model is proposed. Firstly, a fault is isolated to a fault ambiguity group with a number of L replacement unit (in real applications, L is usually chosen to be 3). After that, the maintenance methods such as replacement are adopted to isolate the fault to a specific replacement unit. The proposed strategy is different from the methods in [20, 21], where the fault ambiguity degree of FIR is 1. A more flexible model for test selection optimization model will be proposed in this paper, which can be more compatible with real engineering applications.

Computational intelligence (CI) theories such as evolutionary algorithms [22, 23], artificial neural networks [24], cognitive map analysis [25], Physarum solver [26–28], fuzzy sets [29–31], belief function [32–34], PSO [35–37], and so on [38], have been widely used to cope the complex problems including the permutation flow shop problem [39], supply chain network [40, 41], traveling salesman problem [42], pattern recognition [43–46], power system [47], product design and manufacturing [48], and so on [49–52]. Recently, based on this progress in CI, many nature inspired approaches have been proposed to solve test selection optimization problem, such as the greedy strategy [53], the genetic algorithm [54, 55], the evolutionary algorithm [56, 57], and so on [58]. The PSO has some advantages in comparison with some other methods; for example, it requires less parameters and has a fast convergence rate. In this paper, the improved chaotic discrete PSO (ICDPSO) algorithm is applied to deal with the improved test selection optimization model. The indexes including FDR and FIR are handled simultaneously to solve the improved test selection optimization model. While modelling the fitness function, the fault ambiguity group with different ambiguity degree is taken into consideration. The reasonableness of the improved test selection optimization model as well as the effectiveness of the ICDPSO algorithm is verified according to the experiment. In addition, the computational performance of the proposed method is better than that of GA.

The rest of this paper is organized as follows. The preliminaries are introduced in Section 2. In Section 3, a new evidential sensor fusion method is proposed. The method of solving the improved test selection optimization model is introduced in Section 4. An application example in fault diagnosis is illustrated to show the efficiency of this method in Section 5. Finally, the conclusion is presented in Section 6.

2. Preliminaries

2.1. Fault Test Dependency Matrix. Fault test dependency matrix is a Boolean matrix describing the correlation between the system fault and test. Assume that the fault set is $F = \{f_1, \dots, f_m\}$, the alternative test set is $T = \{t_1, \dots, t_n\}$, and the dependency matrix is a Boolean matrix with $m \times n$ dimensions, denoted as follows [59, 60]:

$$FT_{m\times n} = \begin{bmatrix} ft_{11} & ft_{12} & \cdots & ft_{1n} \\ ft_{21} & ft_{22} & \cdots & ft_{2n} \\ \vdots & \vdots & & \vdots \\ ft_{m1} & ft_{m2} & \cdots & ft_{mn} \end{bmatrix}, \tag{1}$$

where ft_{ij} is generally defined as a Boolean variable, which represents the correlation between the fault mode f_i and the test t_j.

If a fault mode f_i can be detected by the test t_j, then $ft_{ij} = 1$; otherwise $ft_{ij} = 0$. In the matrix, the vector $F_i = [ft_{i1}, ft_{i2}, \dots, ft_{in}]$ in the ith row represents the correlation of the fault mode f_i with all the tests. F_i is called the symptom of the fault mode f_i. The vector $T_j = [ft_{1j}, ft_{2j}, \dots, ft_{mj}]^T$ in the jth column represents the correlation of the test t_j with all the fault modes. T_j is called the symptom of the test t_j.

A test set that can be affected by the fault mode f_i is defined as $T(f_i) = \{t_j \mid ft_{ij} = 1, \ \forall t_j\}$. Similarly, a fault set that can be detected by the test t_j is defined as $F(t_j) = \{f_i \mid ft_{ij} = 1, \ \forall f_i\}$.

2.2. Testability Index. Testability index includes fault detection rate (FDR) and fault isolation rate (FIR).

2.2.1. Fault Detection Rate. Fault detection rate (FDR) is generally defined as, within the prescribed time, the ratio of the total fault rate of the fault modes to the total fault rate of the units under test. The condition of a fault mode f_i which can be detected by the test set T_s is that, in the fault test dependency matrix, at least one element of the row vector corresponding to the f_i is 1. Mathematically, the condition can be denoted as follows:

$$\bigcup_{t_j \in T_s}^{N_s} ft_{ij} = 1, \tag{2}$$

where $\bigcup$ is the OR operation of Boolean variable and N_s is the element number in the set T_s. Then, all the fault modes detected by T_s can be denoted as a set F_D, shown as follows:

$$F_D = \left\{ f_i \mid f_i \in F, \bigcup_{t_j \in T_s}^{N_s} ft_{ij} = 1 \right\}. \tag{3}$$

Thus, FDR is defined as follows:

$$\gamma_{FD} = \frac{\sum_{f_i \in F_D} \lambda_i}{\sum_{f_i \in F} \lambda_i}, \tag{4}$$

where λ_i is the fault rate of the ith fault mode.

2.2.2. Fault Isolation Rate. Fault isolation rate (FIR) is generally defined as, within the prescribed time, with the specified method, and under the constraint that the number of the replacement unit is no more than the requested replacement number L, the ratio of the total fault rate that can be isolated correctly to the detected total fault rate. The replacement number L represents the ambiguity of fault isolation. If $L = 1$, it is called the unique isolation. If $L > 1$, it is called ambiguity isolation.

Assume that $T(f_i)$ and $T(f_j)$ are the symptom sets of the fault modes f_i and f_j, respectively; then the condition that a fault mode f_i can be isolated can be shown as follows:

$$T(f_i) \oplus T(f_j) = 1, \quad \forall f_j \in F_D,\ i \neq j, \tag{5}$$

where $\oplus$ is the exclusive OR operator of two sets. If two sets are the same, the calculation result with $\oplus$ is 0; otherwise, the result is 1. Define an operator for two sets, denoted as $\otimes$, satisfying the following condition: if $T(f_i) \oplus T(f_j) = 0$, then $T(f_i) \otimes T(f_j) = 1$; that is, the fault modes f_i and f_j belong to the same fault ambiguity group.

For a given ambiguity of fault isolation L, the fault set, denoted as F_I, that can be isolated by a test set T_s is defined as follows:

$$F_I = \left\{ f_i \mid f_i \in F_D, \sum_{f_j \in F_D} T(f_i) \otimes T(f_j) \leq L,\ \forall f_j \in F_D,\ i \neq j \right\}. \tag{6}$$

FIR is defined as follows:

$$\gamma_{FI} = \frac{\lambda_L}{\lambda_D} = \frac{\sum_{f_i \in F_I} \lambda_i}{\sum_{f_i \in F_D} \lambda_i}, \tag{7}$$

where λ_D represents the total fault ratio of all the detected fault modes and λ_L represents the total fault ratio of the fault modes that can be isolated under the constraint that the number of the replaced units is no more than the replacement number L.

3. The Improved Test Selection Optimization Model

In real applications, the value of ambiguity of fault isolation (L) is generally not bigger than 3. Without lose generality, we define FIR as follows:

$$\gamma_{FIL} = \frac{\sum \lambda_{1i} + \sum \lambda_{2j} + \sum \lambda_{3k} + \cdots + \sum \lambda_{Lp}}{\lambda_D}, \tag{8}$$

where L represents the ambiguity of fault isolation and $\Sigma\lambda_{Lp}$ is the fault rate of the pth fault mode with the isolated replacement unit number of the fault being L. Equation (8) contains the following conditions:

(1) $L = 1$: in this case, $\gamma_{FI1} = \sum \lambda_{1i}/\lambda_D$, where λ_{1i} is the fault rate of the ith fault mode while the isolated replacement unit number of the fault is 1.

(2) $L = 2$: in this case, $\gamma_{FI2} = (\sum \lambda_{1i} + \sum \lambda_{2j})/\lambda_D$, where λ_{2j} is the fault rate of the jth fault mode while the isolated replacement unit number of the fault is 2.

(3) $L = 3$: in this case, $\gamma_{FI3} = (\sum \lambda_{1i} + \sum \lambda_{2j} + \sum \lambda_{3k})/\lambda_D$, where λ_{3k} is the fault rate of the kth fault mode while the isolated replacement unit number of the fault is 3.

The aim of the improved test selection optimization model is selecting the optimized test set from the alternative test sets of the system to meet the requirements of the system testability index as well as to minimize the test cost corresponding to the selected test set. Assume that $\lambda = [\lambda_1, \ldots, \lambda_m]^T$ is the vector of prior probability of fault modes, $C = [c_1, \ldots, c_n]$ is the vector of test cost, and the selected test set is T_s, where $T_s \subseteq T$. The total test cost of the test set T_s is defined as follows:

$$C_{T_s} = \sum_{t_j \in T_s} c_j. \tag{9}$$

Based on the constraint of testability index and the objective function, the proposed test selection optimization model is defined as follows:

$$\begin{aligned} \min \quad & \{C_{T_s}\}, \\ \text{s.t.} \quad & \gamma_{FD} \geq \gamma_{FD}^*, \\ & \gamma_{FI1} \geq \gamma_{FI1}^*, \\ & \gamma_{FI2} \geq \gamma_{FI2}^*, \\ & \gamma_{FI3} \geq \gamma_{FI3}^*, \\ & \vdots \\ & \gamma_{FIL} \geq \gamma_{FIL}^*, \end{aligned} \tag{10}$$

where γ_{FD}^*, γ_{FI1}^*, γ_{FI2}^*, γ_{FI3}^*, and γ_{FIL}^* are the desired fault detection rate of the system, the fault isolation rate with an ambiguity degree 1, the fault isolation rate with an ambiguity degree 2, the fault isolation rate with an ambiguity degree 3, and the fault isolation rate with an ambiguity degree L, respectively. The fault isolation rate of the ambiguity degree L enables the proposed test selection optimization model to be more flexible in real applications.

4. Solving the Improved Test Selection Optimization Model

The process of test selection optimization is a multiobjective optimization problem. The ICDPSO algorithm has been adopted to solve the improved test selection optimization model.

4.1. Chaos Initialization. The chaotic motion seems to be random, but it has a hidden exquisite structure such as the characteristics of ergodicity, randomness, and regularity. The basic idea of this algorithm is, firstly, to generate a set of chaotic variables, which has the same number as the optimization variables; secondly, to introduce the chaos into the optimization variables with a way similar to carrier and to amplify the search scope of chaotic motion to the range of the value of the optimization variables simultaneously; finally, to search for and optimize the chaotic variables directly.

The improved Tent map has better ergodic uniformity and is beneficial to global optimization of chaos; thus, it is adopted to generate the chaotic variables. The Tent map is shown as follows:

$$z_{k+1} = T(z_k) = \begin{cases} 2z_k, & 0 \le z_k \le 0.5, \\ 2(1 - z_k), & 0.5 < z_k \le 1. \end{cases} \quad (11)$$

The Tent map may iterate to a fixed point, for example, 0, 0.25, 0.5, 0.75; to avoid this situation, a small disturbance is added to the sequence to enable the Tent map to go back to chaos. The added disturbance is shown as follows:

$$\begin{aligned} &\textit{if } Z_k = 0, 0.25, 0.5, 0.75 \text{ or } Z_k = Z_{k-m}, \\ &\textit{then } Z_{k+1} = T(Z_k) + 0.1\,\mathrm{rand}(0,1), \\ &\textit{else } Z_{k+1} = T(Z_k), \end{aligned}$$

where Z_k is a chaotic variable, $z_k \in [0,1]$, $m = 1, 2, 3, 4, 5$. The improved Tent map enables the ergodic process of Z_k to cover the whole range among $[0,1]$. The iterative results starting from an arbitrary initial value of $z_0 \in [0,1]$ can be a deterministic chaotic time sequences: z_1, z_2, z_3, etc.

4.2. Calculation of Fitness Function. The fitness value aims to evaluate the pros and cons of each particle in the group, of which the calculation method has an important influence on the performance of a particle swarm. To solve the test selection optimization model in (10), the FDR and the penalty function are adopted to define the fitness function; the fitness degree of the test set T_i is defined as follows:

$$\begin{aligned} \text{Fitness} = {} & \frac{\sum_{t_i \in T} c_i}{\sum_{t_i \in T_i} c_i + \sum_{t_i \in T} c_i} - \alpha \cdot \max\left(0, \gamma_{FI1}^{*} - \gamma_{FI1}\right) \\ & - \beta \cdot \max\left(0, \gamma_{FI2}^{*} - \gamma_{FI2}\right) - \theta \\ & \cdot \max\left(0, \gamma_{FI3}^{*} - \gamma_{FI3}\right) - \cdots - \tau \\ & \cdot \max\left(0, \gamma_{FIL}^{*} - \gamma_{FIL}\right), \end{aligned} \quad (12)$$

where α, β, θ, and τ are penalty factors and they are constants, the penalty function aims to correct the particle that crossed the boundary, and the heuristic strategy is used to process the FDR to get the feasible particle.

According to the fitness degree defined in (12), if a particle in the group meet all the L requirements of FIR, its fitness is defined by the first term of (12); thus, the particle has a bigger fitness degree; if a particle in the group does not meet the 3 requirements of FIR, a penalty function is used to penalize the corresponding fitness degree; thus, its fitness degree is much more smaller than the first term of (12); in this way, the chance of this particle entering the next generation can be decreased.

4.3. Inertia Weight Adaptive Adjustment. In the discrete particle swarm algorithm, the purpose of the inertia weight ω is to control the effect of the former speed on the current speed, which is also for balancing the exploration and exploitation ability of the algorithm. After the initialization of the particle, in the early stage, the movement of the particle is not objective, the searching range is the whole solution space, and, thus, the value of ω should be bigger than the other cases. With the ongoing of the search, the searching range becomes smaller and will finally determine the range of search at the vicinity of the optimal solution; in this case, the value of ω should be small until the optimal solution is got. In this paper, the adjustment strategy is based on the degree of premature convergence of the particle, and the inertia weight of the particle is self-adaptively adjusted. The degree of premature convergence of the particle can be assessed with the following equation:

$$\Delta = \left| f_g - f_{ap} \right|, \quad (13)$$

where f_g is the fitness value of the global optimum particle and f_{ap} is the average fitness value of the particle whose fitness value is higher than the average fitness value of the current particle swarm (denoted as f_{ag}). The assessment rule is that the smaller the Δ is, the easier the particle swarm gets premature.

If the fitness value of a particle is f_i, the adjustment strategy is defined as follows:

(1) If $f_i > f_{ap}$, which means that the corresponding particle has a good fitness in the whole population and it is near the vicinity of the optimal solution, then a small inertia weight should be assigned on the particle to enhance its local search ability. In this case, the adjustment strategy is defined as follows:

$$\omega(t) = \omega_s - \left(\omega_s - \omega_{\min}\right) \cdot \left| \frac{f_i - f_{ap}}{\Delta} \right|, \quad (14)$$

where $\omega_{\min}$ is chosen as the minimum of ω_s while doing parameter initialization and ω_s is the median of the value range of ω; that is to say, $\omega_s = (\omega_{\max} + \omega_{\min})/2$.

(2) If $f_{ag} < f_i < f_{ap}$, which means that the corresponding particle has a proper fitness in the whole population and it has a good global search ability as well as the local search ability, then the adjustment strategy is defined as follows:

$$\omega(t) = \omega_{\max} - \left(\omega_{\max} - \omega_{\min}\right) \cdot \left(\frac{T - t}{T}\right)^2, \quad (15)$$

where T is the maximum iterations of the algorithm and t is the current number of iterations.

(3) If $f_i < f_{ag}$, which means that the corresponding particle has bad fitness in the whole population and it is far from the vicinity of the optimal solution, then, a big inertia weight should be assigned on the particle

to enhance its global search ability. In this case, the adjustment strategy is defined as follows:

$$\omega(t) = \omega_{\max} - \frac{1}{1 + k_1 \cdot \exp(-k_2 \cdot \Delta)}, \qquad (16)$$

where k_1 is the controlling parameter ($k_1 > 1$) and k_2 is the adjusting parameter ($k_2 < 0$).

4.4. Algorithm Implementation. The ICDPSO algorithm for test selection optimization is implemented as in the following steps.

Step 1 (parameter initialization). The initial value is assigned to the following parameters, respectively: the size of the population denoted as *Popsize*, the learning factors denoted as c_1 and c_2, the inertia weights denoted as $\omega_{\max}$ and $\omega_{\min}$, the maximum iteration denoted as $N_{\max}$, and the constants such as α, β, θ, and τ.

Step 2 (generation of an initial population). The iteration counter of the population is set as $i = 0$. The initial population with a size M, which is denoted as $X(i) = \{x_1^i, x_2^i, \dots, x_M^i\}$, is generated based on chaos initialization.

Step 3 (calculation of fitness function). The fitness degree of each individual in the population $X(i)$ is calculated based on (12). Simultaneously, the individual extremum, denoted as P_{bestid}, and the global extremum, denoted as G_{bestid}, are updated.

Step 4 (inertia weight adjustment). The update of the population speed and location is based on the strategy of the inertia weight adaptive adjustment presented in Section 4.3. The next generation of population is $X(i+1)$. The counter should be updated, which means $i \leftarrow i + 1$.

Step 5 (determination of the number of iteration). If the number of iterations has reached the maximum number, which is denoted as $i > N_{\max}$, then, jump to the next step (Step 6); else, go back to Step 3.

Step 6 (output). Output the results of test selection optimization.

The procedure of the algorithm solving the improved test selection optimization model is presented in Figure 1.

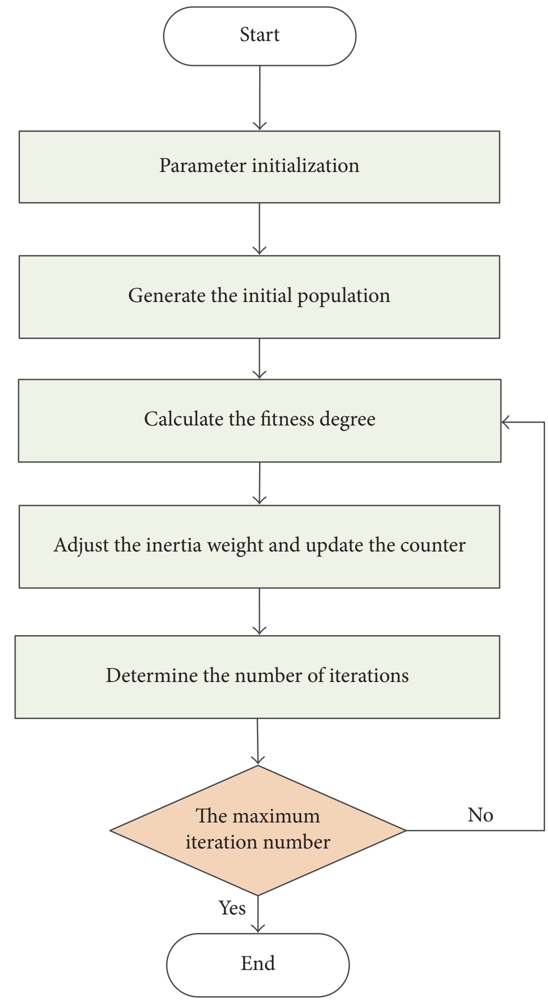

Figure 1: The procedure of the algorithm solving the proposed test selection optimization model.

Table 1: The testability indicators for the superheterodyne receiver.

Indicator	Minimum
FDR	95%
FIR with an ambiguity degree of 1	95%
FIR with an ambiguity degree of 2	98%
FIR with an ambiguity degree of 3	99%

5. Application

The improved test selection optimization model is applied to a superheterodyne receiver system, which is adopted from [8]. There are 36 different alternative tests denoted as t_a ($a = 1, 2, 3, \dots, 36$) and 22 fault modes denoted as f_m ($m = 1, 2, 3, \dots, 22$) in the system. The fault probabilities, denoted as λ_i ($i = 1, 2, 3, \dots, 22$), of all the 22 fault modes are $10^{-3} \times [1.85, 9.23, 185, 1.85, 1.85, 9.23, 1.85, 9.23, 185, 185, 185, 1.85, 9.23, 185, 9.23, 1.85, 9.23, 1.85, 1.85, 1.85, 1.85, 1.85]$. The cost of each test is assumed to be a standard unit. The testability indicators for the system are shown in Table 1.

The ICDPSO algorithm has been applied to solve the improved test selection optimization model of the superheterodyne receiver system. The values of the parameters are as follows: the size of the population is Popsize $= 40$, the maximum iteration number is $N_{\max} = 200$, the inertia weights is $\omega_{\max} = 1.2$, the learning factors are $\omega_{\min} = 0.4$, $c_1 = 1.3$, $c_2 = 1.5$, and the penalty factors are $\alpha = \beta = \theta = 0.5$.

After 30 times of independent calculation with 200 iterations for each independent calculation, the fitness convergence curve of the particle can be got, as is shown in Figure 2. The optimal solutions for all the independent calculation can be got after about 45 to 95 iterations, which shows the convergence performance of the proposed method.

The optimal solutions of simulation are [0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 1, 1, 0, 1, 0, 0], which means that the optimal complete test set is $[t_8, t_9, t_{26}, t_{28}, t_{31}, t_{32}, t_{34}]$. The corresponding fault set of the optimal complete test set is $[f_1, f_2, f_3, f_5, f_6, f_8, f_9, f_{10}, f_{11}, f_{13}, f_{14}, f_{17}, f_{18}, f_{19}, f_{20}, f_{22}]$, as is shown in Table 2.

The FDR of the system is

$$\begin{aligned}\gamma_{FD} &= \frac{\sum_{f_i \in F_D} \lambda_i}{\sum_{f_i \in F} \lambda_i} \\ &= \frac{\lambda_1 + \lambda_2 + \lambda_3 + \lambda_5 + \lambda_6 + \lambda_8 + \lambda_9 + \lambda_{10} + \lambda_{11} + \lambda_{13} + \lambda_{14} + \lambda_{17} + \lambda_{18} + \lambda_{19} + \lambda_{20} + \lambda_{22}}{\lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 + \lambda_5 + \lambda_6 + \lambda_7 + \lambda_8 + \lambda_9 + \lambda_{10} + \lambda_{11} + \lambda_{12} + \lambda_{13} + \lambda_{14} + \lambda_{15} + \lambda_{16} + \lambda_{17} + \lambda_{18} + \lambda_{19} + \lambda_{20} + \lambda_{21} + \lambda_{22}} \\ &= 0.9815.\end{aligned} \tag{17}$$

The fault set with an ambiguity degree of 1 is $[f_3, f_9, f_{10}, f_{11}, f_{14}, f_{17}, f_{20}]$; thus, the FIR with an ambiguity degree of 1 is

$$\gamma_{FI1} = \frac{\sum \lambda_{1i}}{\lambda_D} = \frac{\lambda_3 + \lambda_9 + \lambda_{10} + \lambda_{11} + \lambda_{14} + \lambda_{17} + \lambda_{20}}{\lambda_1 + \lambda_2 + \lambda_3 + \lambda_5 + \lambda_6 + \lambda_8 + \lambda_9 + \lambda_{10} + \lambda_{11} + \lambda_{13} + \lambda_{14} + \lambda_{17} + \lambda_{18} + \lambda_{19} + \lambda_{20} + \lambda_{22}} = 0.9530. \tag{18}$$

The fault set with an ambiguity degree of 2 is $[f_2, f_6, f_8, f_{18}, f_{19}, f_{22}]$; thus, the FIR with an ambiguity degree of 2 is

$$\begin{aligned}\gamma_{FI2} &= \frac{\sum \lambda_{1i} + \sum \lambda_{2j}}{\lambda_D} = \frac{\lambda_2 + \lambda_3 + \lambda_6 + \lambda_8 + \lambda_9 + \lambda_{10} + \lambda_{11} + \lambda_{14} + \lambda_{17} + \lambda_{18} + \lambda_{19} + \lambda_{20} + \lambda_{22}}{\lambda_1 + \lambda_2 + \lambda_3 + \lambda_5 + \lambda_6 + \lambda_8 + \lambda_9 + \lambda_{10} + \lambda_{11} + \lambda_{13} + \lambda_{14} + \lambda_{17} + \lambda_{18} + \lambda_{19} + \lambda_{20} + \lambda_{22}} \\ &= 0.9868.\end{aligned} \tag{19}$$

The fault set with an ambiguity degree of 3 is $[f_1, f_5, f_{13}]$; thus, the FIR with an ambiguity degree of 3 is

$$\begin{aligned}\gamma_{FI3} &= \frac{\sum \lambda_{1i} + \sum \lambda_{2j} + \sum \lambda_{3k}}{\lambda_D} \\ &= \frac{\lambda_1 + \lambda_2 + \lambda_3 + \lambda_5 + \lambda_6 + \lambda_8 + \lambda_9 + \lambda_{10} + \lambda_{11} + \lambda_{13} + \lambda_{14} + \lambda_{17} + \lambda_{18} + \lambda_{19} + \lambda_{20} + \lambda_{22}}{\lambda_1 + \lambda_2 + \lambda_3 + \lambda_5 + \lambda_6 + \lambda_8 + \lambda_9 + \lambda_{10} + \lambda_{11} + \lambda_{13} + \lambda_{14} + \lambda_{17} + \lambda_{18} + \lambda_{19} + \lambda_{20} + \lambda_{22}} = 1.\end{aligned} \tag{20}$$

The experimental result shows that (1) the FIRs with the ambiguity degrees of 1, 2, and 3 are 95.3%, 98.68%, and 100%, respectively; (2) the optimal complete test set is $[t_8, t_9, t_{26}, t_{28}, t_{31}, t_{32}, t_{34}]$, which means the test cost is 7; (3) there are 6 fault modes that cannot be detected and isolated by the optimal test set, including f_4, f_7, f_{12}, f_{15}, f_{16}, f_{21}. In comparison with the experimental results in [20], the number of fault modes that cannot be detected and isolated decreases from 9 to 6, which can be a marked improvement because 3 more fault modes in the system have been addressed. In addition, the FDR increases from 96.86% to 98.15%. This improvement should not be ignored especially for a core system or some big systems, in which each tiny improvement may lead to a more safe or more economical system. The comparison of the experimental results between the proposed method and the method in [20] is shown in Table 3. In general, it is complicated to judge which method is better. The judgement should be dependent on the specific needs. However, two things are for sure: on the one hand, the effectiveness of the proposed method has been verified; on the other hand, the proposed method has a better performance than the method in [20], including a higher FDR and more detected fault modes. Last but not least, the proposed method can handle the FIR with a complicated ambiguity degree.

Table 2: The testability indicators for the superheterodyne receiver.

Fault mode	t_8	t_9	t_{26}	t_{28}	t_{31}	t_{32}	t_{34}	Fault probability ($\times 10^{-3}$)
f_1	0	1	0	0	0	0	0	1.85
f_2	1	1	0	1	1	1	1	9.23
f_3	0	0	1	0	0	0	0	185
f_4	0	0	0	0	0	0	0	1.85
f_5	0	1	0	0	0	0	0	1.85
f_6	1	1	0	1	1	1	1	9.23
f_7	0	0	0	0	0	0	0	1.85
f_8	0	1	0	0	0	1	0	9.23
f_9	0	1	0	1	0	1	0	185
f_{10}	0	1	0	0	1	0	0	185
f_{11}	0	1	0	0	0	0	1	185
f_{12}	0	0	0	0	0	0	0	1.85
f_{13}	0	1	0	0	0	0	0	9.23
f_{14}	0	1	0	1	1	1	1	185
f_{15}	0	0	0	0	0	0	0	9.23
f_{16}	0	0	0	0	0	0	0	1.85
f_{17}	1	1	0	0	0	0	1	9.23
f_{18}	0	1	0	0	0	1	0	1.85
f_{19}	1	1	1	1	1	1	1	1.85
f_{20}	0	1	0	0	1	1	0	1.85
f_{21}	0	0	0	0	0	0	0	1.85
f_{22}	1	1	1	1	1	1	1	1.85

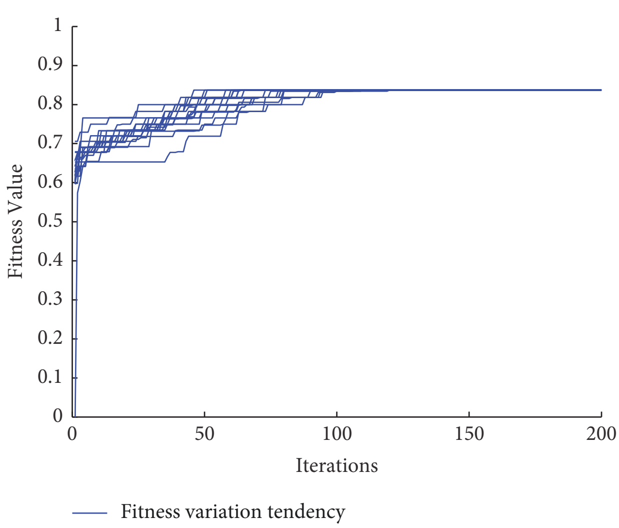

Figure 2: The fitness convergence curve of the superheterodyne receiver system.

Figure 3 presents the average convergence time of solving the test selection model in the application with ICDPSO algorithm, as well as the average convergence time with GA. In the aforementioned application, with GA, define that the population size is $Popsize' = 40$, the maximum iteration number is $N'_{\max} = 200$, the length of the chromosome is $Chrsize = 22$, the probabilities of crossover and mutation are $P_c = 0.7$ and $P_m = 0.01$, respectively, and the penalty factors are $\alpha' = \beta' = \theta' = 0.5$.

The curves of the fitness values with respect to the running time of ICDPSO and GA presented in Figure 3 show that, regarding the running time, ICDPSO has a significantly better performance in solving global optimization solution in comparison with GA. The running time of GA is about twice the cost of ICDPSO. After 30 times of independent experiments of the test selection optimization model for the superheterodyne receiver system, the statistical results of GA and ICDPSO are shown in Table 4. Although both ICDPSO and GA have the same minimum test cost of 7 and the success rates of searching out optimal solution are both 100%, the average running time of GA is more than 2 times that of ICDPSO. The priority of the proposed method in running time is not that significant while dealing with small scale test selection problem. However, with the increasing of test size, for example, in complex equipment or systems, the proposed method with ICDPSO can have a significant improvement in working performance than GA.

6. Conclusions

A proper selection of the appropriate test set plays an important role in measuring the testability level, which is related to the test cost of the diagnostic for a system or equipment as well as the subsequent maintenance costs. An improved test selection optimization model based on fault ambiguity group isolation and chaotic discrete PSO is proposed in this paper, which considers the ambiguity FIR index constraint. The main contribution of this paper is the modelling and mathematical expressions of the FIR with a complicated

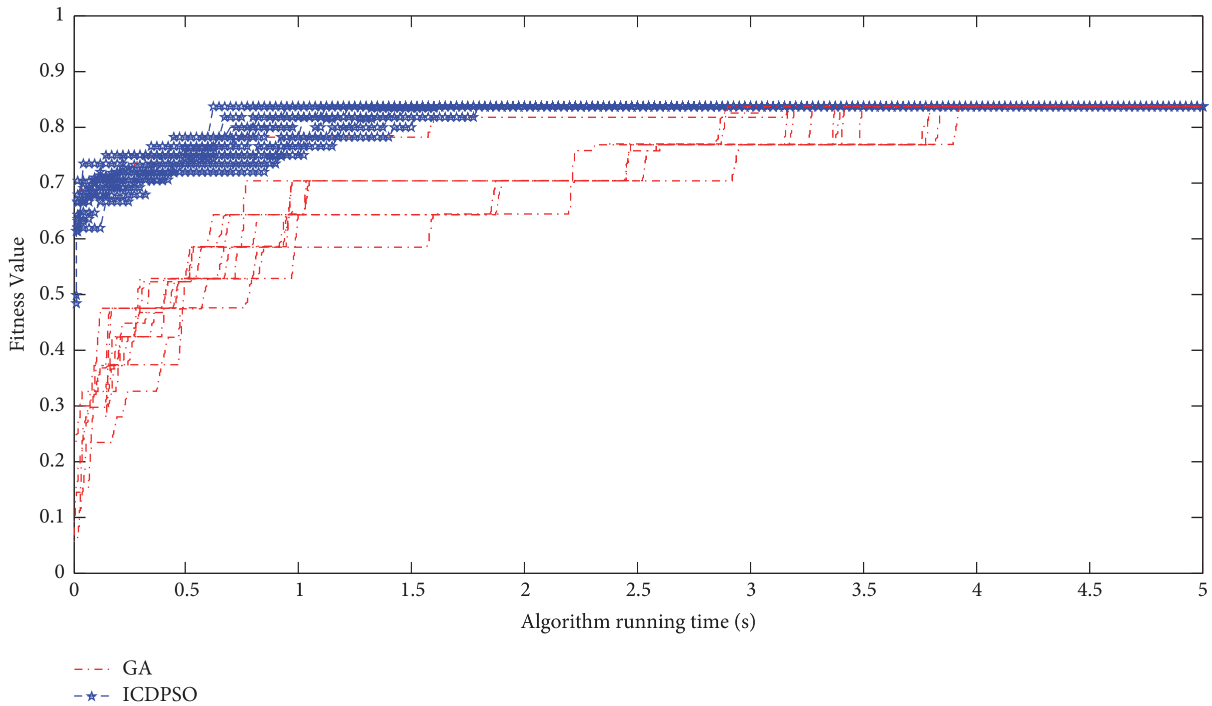

Figure 3: Comparison of the average convergence time of GA and ICDPSO.

Table 3: The experimental results of different methods.

Indicator	The method in [20]	The proposed method
FDR	96.86%	98.15%
FIR with an ambiguity degree of 1	96.57%	95.30%
FIR with an ambiguity degree of 2	100%	98.68%
FIR with an ambiguity degree of 3	N/A	100%
Test cost	6	7
Number of undetected fault modes	9	6

Table 4: The statistical results of GA and ICDPSO.

Algorithm	Minimum test cost	Success rate	Average running time
GA	7	100%	3.526
ICDPSO	7	100%	1.497

ambiguity degree, as well as the corresponding solving algorithm based on the chaotic discrete PSO algorithm. The FDR and FIR indexes are handled simultaneously while solving the improved test selection optimization model. The simulation result shows the feasibility and effectiveness of the proposed method, as well as the superiority in convergence.

The following work will be focused on combining the selection of test set with the designing of the diagnosis strategy, which is quite a complicated open issue related to the combination problem and the permutation problem. In addition, some new developed optimization techniques like differential evolution should be taken into consideration in the ongoing work.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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