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An AEALSCE-based optimization method of sequential diagnostic strategy generation

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Abstract：As an important part of testability design and fault diagnosis, sequential fault diagnostic strategy generation plays a crucial role in improving the efficiency of system fault diagnosis and reducing the cost of system maintenance support. With the system complexity increasing, it is extremely difficult to generate an optimal diagnostic strategy. The existing methods are easy to fall into the local optimal solution and the time complexity is high. Therefore, this paper proposes a method based on a covariance matrix adaptation evolution strategy (CMA-ES) variant, named AEALSCE, to obtain the optimal strategy. Firstly, the fault diagnosis strategy problem model based on AEALSCE is established, and the fault diagnostic strategy problem is transformed into a continuous optimization problem to adapt the algorithm solving. Then, based on the diagnostic objective of the minimum diagnostic steps and test cost, the fitness function of the algorithm is constructed. At last, the optimal diagnosis strategy is obtained by solving the transformed continuous optimization problem with AEALSCE algorithm. The experimental results proves that the proposed AEALSCE-based approach is reasonable and feasible in obtaining the optimal diagnostic strategy, and outperforms other traditional methods and evolutionary algorithms in terms of accuracy and time efficiency.

Keywords: Covariance matrix adaptation evolution strategy (CMA-ES), Testability design, Diagnostic strategy, Evolutionary computation

1. Introduction

With the advanced technologies widely applied in military equipment, the structure of weapons and equipment is becoming more and more complex. The requirements of good testability design and fault diagnosis scheme of weapon and equipment are increasing, due to the high requirements o mobility and fast maintenance support in modern war. As an important part of system testability design and fault diagnosis, sequential diagnostic strategy generation is to obtain a test sequence or sequential test set to realize the suspected fault detection and determine its location[1-2], and the ultimate goal of it is to find the optimal strategy to minimize the test cost which including fault isolation time[2,3] , which is a typical NP-Complete problem[4]. Generally, the diagnostic strategy can be divided into dynamic and static types[5]. The dynamic strategy refers to the generation of decision tree according to the test results during the test process[6-7]. It is easy to implement in engineering at present, but it takes more time to analyze the test results. The static strategy is independent of test results, and provides a global decision tree or test sequence before test, which is conducive to rapid maintenance and guarantee of equipment. Therefore, most studies have focused on static strategy[8-18], including this paper.

The earliest optimization method of diagnostic strategy is the dynamic programming (DP) [8]. DP finds the optimal solution by traversing the entire binary tree, which means a large amount of storage and computation. Then, information heuristic algorithm[9] is proposed with less storage and

computation based on information entropy theory, and the next optimal test is determined after calculating the information entropy increment of all available tests, which is one-step look-ahead algorithm also known as greedy algorithm[10] and easily fall into local optimality. The AO* algorithm[11] which is combined with AND/OR search graph and information entropy theory is proposed. Because of its backtracking and comparison at each node, the repeated calculation of redundant states is easy to cause the computation explosion. For this, the Rollout algorithm[2] is proposed to further reduced the computation and storage, based on combination of the AO* algorithm and Rollout strategy, for its backtracking is performed after several expansion of each node. Yang et al [14] proposed an improved heuristic algorithm based on quasi-depth-first search algorithm based on the greedy algorithm and AO* algorithm, which makes a trade-off between optimality and computational complexity. Yang et al [15] studied the implementation process of AO* algorithm deeply, and proposed to conduct subsequent diagnosis by finding the optimal child node of the original decision tree instead of the root node, which reduced the running time while ensuring the accuracy. Zhang [16] tried to improve AO* algorithm in different search widths and depths, but there is still a small deviation between its solution and the optimal solution. A bottom-up test sequence generation method[17] is also proposed to get the optimal solution, but its iterations may increase too sharply and lead to combinatorial explosion. Wang et al.[18] proposed a new bottom-up/top-down hybrid strategy-based method to avoid the redundant state, but this method is time-consuming when the number of faults and tests is over 40. In addition, the above traditional methods rely heavily on complex heuristic functions which determine the accuracy and computation amount of the algorithm, and the obtained solutions are usually the approximate global.

Recently, intelligent optimization algorithms have shown high efficiency in solving NP-complete problems, and have been introduced to solve the diagnostic strategy generation problem, such as genetic algorithm(GA)[19], ant colony algorithm(ACA)[20], particle swarm optimization(PSO) [21], discrete particle swarm optimization(DPSO)[22], growing algorithm[23] and so on. Zhang et al[24] used the tabu search algorithm(TS) which has strong ability to jump out of the local optimal to obtain the global optimal diagnosis strategy. An improved differential evolution (IDE) algorithm [25] is introduced to optimize the test sequence sets with a fitness function including the fault isolation rate and generate the diagnostic decision tree. Lei et al [26] proposed an improved quantum-inspired evolutionary algorithm(QEA) to solve the test selection optimization model under imperfect tests. The improved genetic simulated annealing algorithm(IGAS)[27] is introduced to solve the test selection optimization problem, with using a nonlinear accelerating fitness function to improve the searching speed. The above algorithms have good improvement in the efficiency and quality of solution, compared with the previous methods. However, some algorithms lack global search ability and are easy to fall into local optimal solutions, and many studies use information heuristic function that is usually complex to improve algorithm performance, which brings large computation and lower efficiency. And some algorithms have high time complexity, resulting in low efficiency and unsuitable for large-scale engineering systems.

Covariance matrix adaptation evolution strategy(CMA-ES)[28] is a well-known estimation of distribution algorithm(EDA)[29]. By capturing the characteristics of the objective function to find the optimal solution, it performs very well in solving ill-conditioned and inseparable problems, and is widely used in practical optimization applications[30]. As a variant of CMA-ES, an AEALSCE[31] algorihm combining CMA-ES with two search strategies is proposed, to achieve more efficient searching ability and stronger convergence ability. Hence, an optimization method based on AEALSCE

is proposed to solve the diagnostic strategy generation problem in this paper, which utilizes the excellent global optimization ability of the algorithm to directly optimize the problem without relying on the heuristic function. This paper is organized as follows. A generalized formulation of sequential fault diagnostic strategy problem is presented in Section 2. The AEALSCE algorithm is introduced in Section3, also with the AEALSCE-based diagnostic strategy problem model. A case study of the proposed method is discussed in Section 4, 5 classic algorithms are chosen, and their generation performance are compared. Section 5 gives a summary of this work.

2. Problem formulations

Generally, sequential fault diagnostic strategy generation is to build a test sequence to achieve specified fault diagnosis and accurate fault location with minimal test cost. It can be defined as a five-tuple $\left(\boldsymbol{F},\boldsymbol{P},\boldsymbol{T},\boldsymbol{C}^*,\boldsymbol{D}\right)$, where

(1) $\boldsymbol{F}=\{f_0,f_1,f_2,\cdots,f_m\}(m\geq 1)$ is a set of statistically independent failure sources of the system, where f_0 represents on fault state of the system, and $f_i\,(0<i\leq m)$ is the condition that only *i*-th failure occurred.

(2) $\boldsymbol{P}=\{p(f_0),p(f_1),\cdots,p(f_m)\}(m\geq 1)$ is a set of the priori probability distributions of failure source.

(3) $\boldsymbol{T}=\{t_1,t_2,\cdots,t_n\}(n\geq 1)$ is a set of *n* available tests with binary outcome, and each $t_j(0<j\leq n)$ checks a subset of $\boldsymbol{F}$.

(4) $\boldsymbol{C}^*=\{c_1^*,c_2^*,\cdots,c_n^*\}(n\geq 1)$ is a set of test cost measured considering time-consuming, manpower or some other factors, and each $c_j^*(0<j\leq n)$ represents the cost of applying test $t_j(0<j\leq n)$.

(5) $\boldsymbol{D}=\left[d_{ij}\right]_{(m+1)\times n}(m\geq 0,n\geq 1)$ is a binary matrix which represents the relationship between the failure state set $\boldsymbol{F}$ and test set $\boldsymbol{T}$, also called $\boldsymbol{FT}$ matrix, where $b_{ij}=1$ if test t_j can detect failure f_i, otherwise $b_{ij}=0$.

The ultimate goal of sequential fault diagnostic strategy generation is to build an optimal test sequencing with least test cost to achieve fast fault isolation, and it can be described as

$$J=\min\left\{\sum_{i=0}^{m}p(f_i)\left(\sum_{k=1}^{|\boldsymbol{D}_i|}c_{D_i[k]}\right)\right\} \qquad (1)$$

where, $\boldsymbol{D}_i$ is the test sequence used to isolate the fault state f_i, and $|D_i|$ is the capacity of the sequence $\boldsymbol{D}_i$, also is the length of the test sequence, and $C_{D_i[k]}$ is the cost of the *k*-th test in the sequence $\boldsymbol{D}_i$.

3. AEALSCE-based diagnostic strategy optimization model

3.1 AEALSCE optimization algorithm

The covariance matrix is very important in adjusting the solution distribution in CMA-ES, as given in the next subsection. Based on this, the anisotropic eigenvalue adaptation (AEA) strategy which adjusts the eigenvalues of the covariance matrix based on fitness value detection, and the local search (LS) strategy is introduced to enhances the exploration ability of CMA-ES and avoid convergence stagnation. This is the AEALSCE optimization algorithm, and it can be briefly summarized as: CMA-ES uses the first μ solution of high quality to calculated the mean points, and the covariance matrix, and uses the AEA strategy to modify the covariance matrix; then, the population is iteratively evolved using a modified distribution model or LS strategy.

3.1.1 CMA-ES algorithm

Since AEALESCE algorithm is a variant of CMA-ES algorithm, the basic CMA-ES is provided at first. As a variant of EDA, the most significant difference between CMA-ES and general EDA algorithm lies in the manner in which the mean $\boldsymbol{m}$ and covariance matrix $\boldsymbol{C}$ are updated. Besides, CMA-ES utilizes a step size of σ to control the search scope. The adjustment of the above 3 parameters has an important influence on the convergence performance of CMA-ES, which is the key to achieve the optimal solution. The search process can be divided into the following 3 steps:

- Sampling to produce a new solution;
- Calculating the value of the objective function;
- Updating the distributions of parameters $\boldsymbol{m}$, σ and $\boldsymbol{C}$.

In each iteration, the solutions of CMA-ES are updated as

$$\boldsymbol{x}_{t+1} = \boldsymbol{m}_t + \sigma_t \boldsymbol{y}_i, \quad \boldsymbol{y}_i \sim N\left(\boldsymbol{0}, \boldsymbol{C}_t\right) \tag{2}$$

where σ_t is the step size and $\boldsymbol{y}_i$ obeys a normal distribution with a mean value of 0.

The corresponding objective function values $f(x_i)$ of the newly generated solutions are calculated and sorted as

$$f(\boldsymbol{x}_{1:N}) \le f(\boldsymbol{x}_{2:N}) \le \ldots \le f(\boldsymbol{x}_{N:N})$$

where x_i is the i-th solution. Generally, the first $\mu=\lfloor N/2 \rfloor$ solutions are used to update the distribution parameters according to the order of the objective function values, and the weighted maximum likelihood estimation is used to update the $\boldsymbol{m}$ of multivariate normal distribution, as

$$\boldsymbol{m}_{t+1} = \sum_{i=1}^{\mu} \omega_i \boldsymbol{x}_{i:} = \boldsymbol{m}_t + \sum_{i=1}^{\mu} \omega_i \left(\boldsymbol{x}_i - \boldsymbol{m}_t\right) \tag{3}$$

and

$$\omega_i = \ln\left(\mu+1\right) / \left(\sum_{i=1}^{\mu} \left(\ln\left(\mu+1\right) - \ln\left(i\right) \right) \right) \tag{4}$$

The above Eq.(3) shows that the mean is shifted along the mean search direction. CMA-ES determines the mean of the next generation by combining selected high-quality solutions. For the weight coefficient ω_i, if $\omega_i=1/\mu$, the maximum likelihood estimation strategy is used in Eq.(3), which is the same in EDA. In the actual algorithm, $\omega_1>\omega_2>\ldots>\omega_\mu$, as given in Eq.(4).

The covariance matrix update principle is given as

$$\begin{cases} \arg\max\, p\left(p_{t+1} \mid \boldsymbol{m}, \boldsymbol{C}\right) \\ \arg\max \prod_{i=1}^{\mu} p\left(\dfrac{\boldsymbol{x}_{i:\lambda} - \boldsymbol{m}_t}{\sigma_t} \mid \boldsymbol{m}, \boldsymbol{C} \right) \end{cases}$$

Based on it, the covariance matrix is updated as

$$\boldsymbol{C}_{t+1} = \left(1-c_1-c_\mu\right)\boldsymbol{C}_t + c_1\boldsymbol{p}_{t+1}\boldsymbol{p}_{t+1}^{\mathrm{T}} + c_\mu\sum_{i=1}^{\mu}\omega_i\left(\frac{\boldsymbol{x}_i-\boldsymbol{m}_t}{\sigma_t}\right)\left(\frac{\boldsymbol{x}_i-\boldsymbol{m}_t}{\sigma_t}\right)^{\mathrm{T}} \tag{5}$$

where, the 2-th item is the "rank-1" update strategy which has better performance under the condition of small population, and it uses historical search information and describes shifts in the mean. The evolutionary path is constructed as follows:

$$p_{t+1} = \left(1-c\right)p_t + \sqrt{c\left(2-c\right)}\sqrt{\mu_w}\,\frac{\boldsymbol{m}_{t+1}-\boldsymbol{m}_t}{\sigma_t} \tag{6}$$

And the 3-th item in Eq.(5) is the "rank-μ" update strategy that plays an important role in the algorithm performance when the population size is large. The learning rate $c_1 \approx 2/D^2$ and $c_\mu \approx \mu_\omega/D^2$, that is, the learning rate is inversely proportional to the degree of freedom D.

CMA-ES uses the cumulative step size adjustment. Its principle is that the continuous search directions should be conjugate. If the continuous search directions are positively correlated, the step size is too small and should be increased. If the continuous search directions are negatively correlated, the step size is too large and should be reduced. Similar to the previous evolutionary paths, the conjugate evolutionary paths are calculated as

$$\boldsymbol{s}_{t+1} = \left(1-c_\sigma\right)\boldsymbol{s}_t + \sqrt{c_\sigma\left(2-c_\sigma\right)}\sqrt{\mu_\omega}\,\boldsymbol{C}^{-\frac{1}{2}}\frac{\boldsymbol{m}_{t+1}-\boldsymbol{m}_t}{\sigma_t} \tag{7}$$

$$\sigma_{t+1} = \sigma_t \exp\left(\frac{c_\sigma}{d_\sigma}\left(\frac{\left\|\boldsymbol{s}_{t+1}\right\|}{E\left(\left\|N\left(\boldsymbol{0},\boldsymbol{I}\right)\right\|\right)}-1\right)\right) \tag{8}$$

Under stationary conditions, $\boldsymbol{s}_{t+1}\sim N(\boldsymbol{0}, \boldsymbol{I})$, meaning that the search path is a random vector that follows a D-dimensional normal distribution, whose module length is a chi-square distribution $\| \boldsymbol{s}_{t+1} \| \sim \chi(n)$, $E(\| \boldsymbol{s}_{t+1} \|)=\sqrt{n}$ and $E(\| N(\boldsymbol{0}, \boldsymbol{I}) \|)= \sqrt{n}$. Therefore, if the length is larger than the average, the exponent is positive and the scaling factor increases. Otherwise, the exponent is negative and the step size is reduced. The cumulative step size adjustment is achieved.

3.1.2 AEA strategy

Based on CMA-ES, the AEA strategy is used to scale the corresponding eigenvalues according to the changing trend of the objective function values on different eigenvectors. This adjustment is anisotropic and different from the step size adjustment in CMA-ES. In AEA strategy, the distributed mean point is considered as the middle point, and the trial points are distributed on either side of the middle point, as shown in Fig.1. The distance between the middle point and a trial point is controlled by parameters δ which follows a normal distribution, given as

$$\begin{cases}\boldsymbol{x}_{\mathrm{L}} = \boldsymbol{m}_t + \delta\boldsymbol{\upsilon}_j \\ \boldsymbol{x}_{\mathrm{R}} = \boldsymbol{m}_t - \delta\boldsymbol{\upsilon}_j\end{cases},\quad \delta \sim N\left(0,\lambda_j\right) \tag{9}$$

where $\boldsymbol{\upsilon}_j$ is the j-th eigenvector of the covariance matrix, and λ_j is the j-th eigenvalue. The eigenvectors and eigenvalues can be obtained by the eigen decomposition of the covariance matrix, by

$$\boldsymbol{C} = \boldsymbol{B}\boldsymbol{D}\boldsymbol{B}^{\mathrm{T}} \tag{10}$$

where $\boldsymbol{D}$=diag(λ_1,λ_2,…,λ_j,…, λ_D) , $\boldsymbol{B}$= ($\boldsymbol{\upsilon}_1$,$\boldsymbol{\upsilon}_2$,…,$\boldsymbol{\upsilon}_j$, …,$\boldsymbol{\upsilon}_D$), and the subscript D represents the variate degree of freedom which also is the dimension of the problem.

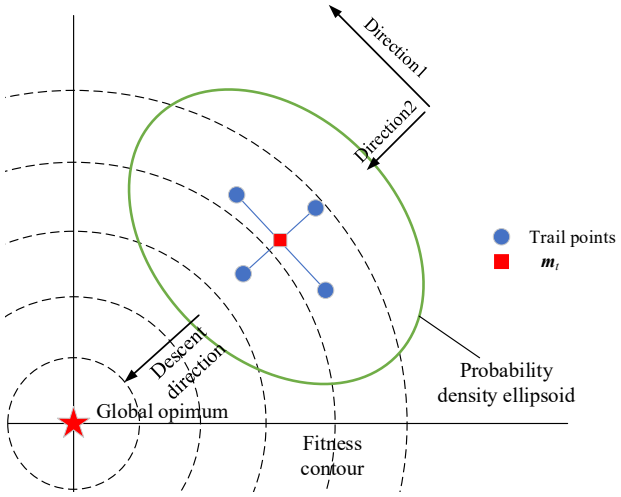


Figure 1 The trial points selection

When moving from one test point to the other side along a certain eigendirection, the objective function values of the three points show a monotonous trend, or slope, i.e. $\min(f(\boldsymbol{x}_L), f(\boldsymbol{x}_R)) \le f(\boldsymbol{m}_t) \le \max(f(\boldsymbol{x}_L), f(\boldsymbol{x}_R))$, and this direction is considered as the descent direction of the function value, such as the direction 2 in Fig.1. In this case, the corresponding eigenvalue should be increased to expand the distribution range, otherwise, the trend is considered as a valley and the eigenvalue remains unchanged. There are still two deficiencies. First, the test points on eigendirection are sampled based on the normal distribution $\boldsymbol{N}(0, \lambda_j)$. Once λ_j is large, the test point may exceed the input domain and cannot reflect the effective variation trend of the local objective function value. Second, the variation trend of the function value is divided into slope, valley and ridge, as shown in Fig.2, while the ridge shape is often ignored in most studies. For this, the AEA strategy is proposed with a new trail points sampling strategy, which can constrain the trail points in the input domain, and also considers three different variant trends of the objective function values.

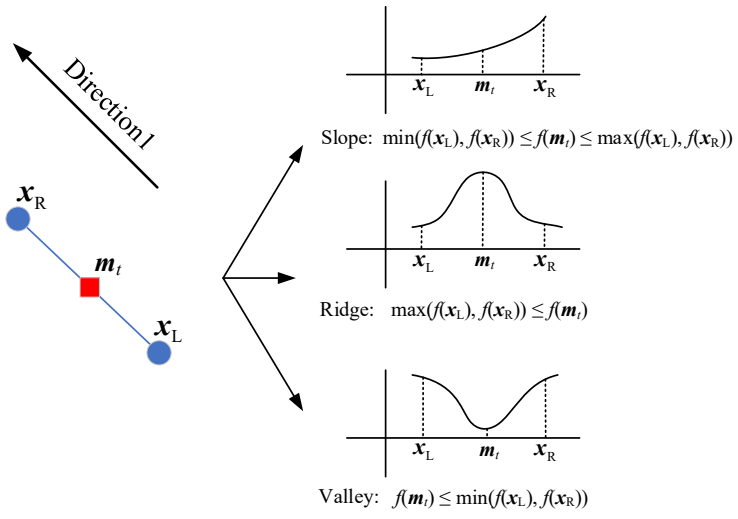


Figure 2 The three variation trends of the objective function value

Since the trail points are sampled along the eigenvector direction, the mean points and input domain boundaries are first converted from the standard coordinate system to the eigen coordinate system, that is

$$\begin{cases} \boldsymbol{m}_t^{\mathrm{E}} = \boldsymbol{B}^{\mathrm{T}} \cdot \boldsymbol{m}_t \\ \boldsymbol{UB}^{\mathrm{E}} = \boldsymbol{B}^{\mathrm{T}} \cdot \boldsymbol{UB} \\ \boldsymbol{LB}^{\mathrm{E}} = \boldsymbol{B}^{\mathrm{T}} \cdot \boldsymbol{LB} \end{cases} \tag{11}$$

where $\boldsymbol{UB}$ and $\boldsymbol{LB}$ represent the upper and lower boundaries of the problem respectively, and the superscript E indicates that the vector is located in the eigen coordinate system. In AEA, the control parameter δ in Eq.(9) is selected as

$$\delta = r \cdot \min\left[\boldsymbol{m}_{t(j)}^{\mathrm{E}} - \boldsymbol{LB}_{(j)}^{\mathrm{E}}, \boldsymbol{UB}_{(j)}^{\mathrm{E}} - \boldsymbol{m}_{t(j)}^{\mathrm{E}}, \lambda_j \right], \quad r \square U(0,1) \tag{12}$$

Therefore, trail points can be selected as

$$\begin{cases} \boldsymbol{x}_{\mathrm{L}} = \boldsymbol{m}_t + \delta \boldsymbol{\upsilon}_j \\ \boldsymbol{x}_{\mathrm{R}} = \boldsymbol{m}_t - \delta \boldsymbol{\upsilon}_j \end{cases} \tag{13}$$

This sampling method not only considers the characteristics of distribution, but also considers the boundary constraints to ensure that the trail points are located in the input domain. So AEALSCE can reflect the real situation of the objective function value variation characteristics. Meanwhile, the fitness value contains three measurable situations, namely the slope, ridge and valley mentioned above. According to Fig.2, if the variation trend of the slope or ridge is known, an enlarged eigenvalue in this direction can improve the exploration ability and convergence performance of the algorithm. For another, a shrinkage of a valley may contribute to the local development of the algorithm. Based on the above, using AEA strategy to adjust the anisotropy of the eigenvalues is summarized as

$$\begin{cases} \lambda_j = \alpha \cdot \lambda_j, & \text{if slope or ridge is detected} \\ \lambda_j = 0.7 \cdot \lambda_j & \text{if valley is detected} \end{cases} \tag{14}$$

where scaling parameter α which amplifies the eigenvalue of the descending direction should be greater than 1. And α is set to decrease from 4 nonlinearity to 1 as the iteration number increases, as shown in Eq.(15).

$$\alpha = \left(1 + \left(1 - iter / iter_{\max}\right)\right)^2 \tag{15}$$

In the initial stage of search, a larger α value can improve the search ability of the algorithm in the direction of decline, while a smaller α value in the later stage can help the algorithm focus more on development. As shown in Fig.3, after the eigenvalues of the covariance matrix are modified by AEA, the new individuals are more likely to generated in the dominant region with the improved covariance matrix. And new individuals are generated by

$$\boldsymbol{x}_{t+1} = \boldsymbol{m}_t + \boldsymbol{y}_i, \ \boldsymbol{y}_i \sim N\left(\boldsymbol{0}, \boldsymbol{C}_t^{AEA}\right) \tag{16}$$

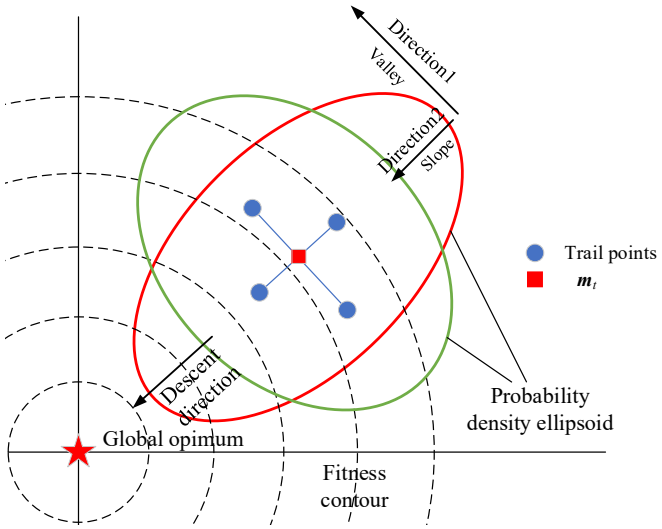


Figure 3 The modified distribution scope using AEA (in red)

3.1.3 LS strategy

As described in Section 3.1.1, the original CMA-ES algorithm is completely dependent on the covariance matrix, which results in a sharp decrease in the population diversity of the algorithm when the solution distribution becomes ill-shaped. Restart strategy is used to solve this problem, but there is insufficient guidance to produce good candidate solutions. In addition, the remaining N-μ inferior solutions of CMA-ES do not participate in building the distribution during iteration, as indicated earlier, which results in computational waste. Therefore, a new search strategy that does not depend on the covariance matrix is needed to make use of the neglected inferior solution information, and thus enhance the diversity of the population. This is the purpose of LS strategy.

The LS strategy is executed in the eigen coordinate system. There are two different forms of it. For the superior solutions, their children are generated around the current optimal solution according to the coordinate difference. For the inferior solutions, their children are sampled by the displacement mean method. First, the individuals of the population are sorted according to the fitness value, and P_{rank} is used to indicate the quality of the solution.

$$P_{\text{rank}}(i) = \left(N - rank\left(f\left(\boldsymbol{x}_i\right)\right) + 1\right) / N \tag{17}$$

If $0.5 < P_{\text{rank}}(i)$, the i-th solution is considered as a superior one and updated with Eq.(18).

$$\boldsymbol{x}_i^{\text{E}} = \boldsymbol{x}_{\text{Best}}^{\text{E}} + \left(\boldsymbol{x}_{\text{Best}}^{\text{E}} - \boldsymbol{x}_i^{\text{E}}\right) \cdot |\boldsymbol{z}_i|, \ \boldsymbol{z}_i \sim N(0,1) \tag{18}$$

where the superscript E indicates that the vector is located in the eigen coordinate system, and this can eliminate the correlation between different dimensions in the general coordinate system and make the adjusted distribution direction consistent with the downward direction, as shown in Fig.4.

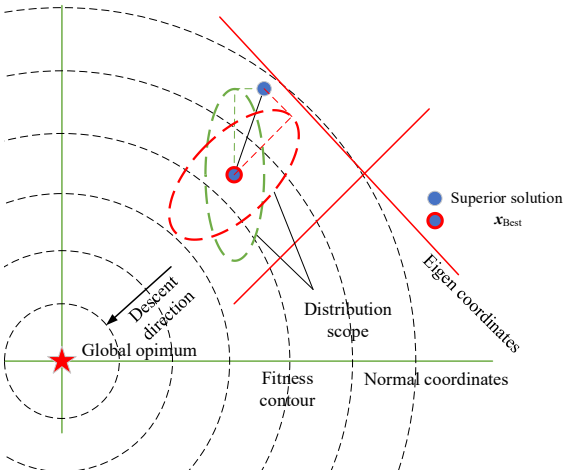


Figure 4 Distribution differences among different coordinate systems

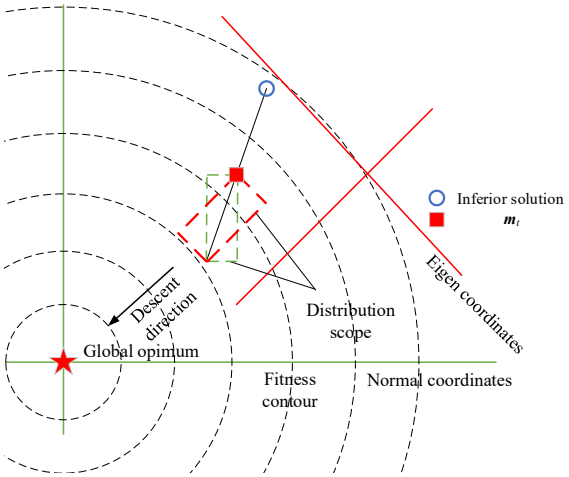


Figure 5 The vector direction pointed from the inferior solution to the mean point is the descent direction of the objection function

If $0.5 \geqslant P_{\text{rank}}(i)$, the new solutions are generated based on the inferior ones. It can be seen from Fig.5 that the direction of the guidance vector pointing from the inferior solution to the mean point is correlated with the descent direction of the objective function. Thus, the updates for inferior solutions in LS strategy are generated according to this guidance vector. Firstly, the individual is performed displacement operation according to the guidance vector as

$$\boldsymbol{x}_{i(j)}^{\mathrm{E}}{}' = \boldsymbol{m}_{t(j)}^{\mathrm{E}} + r \cdot \left(\boldsymbol{m}_{t(j)}^{\mathrm{E}} - \boldsymbol{x}_{i(j)}^{\mathrm{E}} \right), \ r \sim U(0,1) \tag{19}$$

where $\boldsymbol{m}_{t(j)}^{\mathrm{E}}$ represents the distributed mean point in the eigen coordinate system and the subscript j represents the j-th dimension. As shown in Fig.5, the possible distribution areas of this modified mean point in the two coordinate systems are different, and the possible distribution range in the eigen coordinate system is ideal. Then, a local search is performed near the modified mean point, as given by

$$\boldsymbol{x}_{i(j)}^{\mathrm{E}} = \boldsymbol{x}_{i(j)}^{\mathrm{E}}{}' + \left(\boldsymbol{m}_{t(j)}^{\mathrm{E}} - \boldsymbol{x}_{i(j)}^{\mathrm{E}} \right) \cdot z_j, \ \ z_j \sim N(0,1) \tag{20}$$

This strategy makes full use of the position information of the remaining N-μ inferior solutions, not only avoids computational waste, but also effectively enhances the local exploration performance of the algorithm.

Finally, the new solution vector in the feature coordinate is rotated to the general coordinate for fitness value evaluation, as given by

$$\boldsymbol{x}_i = \boldsymbol{B} \cdot \boldsymbol{x}_i^{\mathrm{E}} \tag{21}$$

Besides, compared with the basic CMA-ES, AEALSCE adopts the greedy strategy, which preserves the higher-quality solutions in the parents and children in each iteration to achieve the global convergence performance of the algorithm.

Based on the above, the pseudocode of AEALSCE is presented as following:

The search process of AEALSCE.

1: Initialization: the population N, the step size σ, the scale factor α, and maximum evaluation times MaxFEs;
2: Set FES=0, produce an initial population $\boldsymbol{X}$ and evaluate $FES=FES+N$;
3: Update the current best solution $\boldsymbol{x}_{\mathrm{Best}}$;
4: Output the optimal objective function value $f(\boldsymbol{x}_{\mathrm{Best}})$ when $FES \geqslant$ MaxFEs;
5: Update the distribution model with the pre-$\mu=\lfloor N/2 \rfloor$ solutions as in Eqs.(3) to (6); update the step size σ as in Eqs.(7) to (8);
6: Rotate the population vector to the eigen coordinates as Eq.(11); modify C using AEA described as Eqs.(12) to (15); $FES=FES+2D+1$;
7: For solution $\boldsymbol{x}_i$,
  Calculate $P_{\mathrm{rank}}(i)$ as Eq.(17);
  if $P_{\mathrm{rank}}(i) \geqslant FES/$MaxFEs, $\boldsymbol{x}_i$ is updated by Eq.(16);
  else
    if $P_{\mathrm{rank}}(i)>0.5$, $\boldsymbol{x}_i$ is updated by Eq.(18);
    else
      $\boldsymbol{x}_i$ is updated by Eq.(19) and (20);
    end if
  end if
 End for.
8: Rotate the new population to the normal coordinates with Eq.(21), and evaluate the population $FES=FES+N$;
9: Use the greedy strategy to preserve the best N solutions from sire and filial generation as a new population; Go to step 3.

3.2 AEALSCE-based diagnostic strategy problem model

Since AEALSCE is a continuous optimization algorithm, the focus of using AEALSCE algorithm to optimize the fault diagnostic strategy is how to build an effective problem model, and transform the discrete optimization problem of fault diagnosis into a continuous optimization problem for solving. Assuming a certain system under test has m faults in the failure set $\boldsymbol{F}$, and considering the realization of 100% fault diagnosis isolation, m independent tests are required, so the degree of freedom of the problem is m, that is, the individual dimension in AEALSCE algorithm is m. There are n tests in the available test set $\boldsymbol{T}$, so the population initialization boundary of the algorithm can be set to (0, n). The j-th dimension of any individual x in the population is initialized as

$$x_j = rand \cdot (n-0), \ \ rand \sim U(0,1) \tag{22}$$

At the same time, it is rounded up to $\lceil x_j \rceil$, and the continuous variable is transformed into a discrete variable. For example, set m=10, n=5, and individual x is initialized as [3.2787, 0.1786, 2.2456, 4.6700, 3.3937, 3.7887, 3.7157, 1.9611, 3.2774, 0.8559]. It can be obtained after rounding as $\lceil x \rceil$= [4, 1, 3, 5, 4, 4, 4, 2, 4, 1], and the corresponding test sequence is $\boldsymbol{T}$=[t_4, t_1, t_3, t_5, t_4, t_4, t_4, t_2, t_4, t_1]. After obtaining the corresponding test sequence of the individual, the fitness value of the individual can be calculated, and

the steps are as follows.

(1) The initial system state set is defined as $\boldsymbol{A}_1$, and it can be divided into the passed subset $\boldsymbol{A}_2$ and failed subset $\boldsymbol{A}_3$ after the first test $t_{[x_1]}$ is performed. The sum of the probabilities of system states contained in these two subsets can be calculated separately as

$$p_{\boldsymbol{A}_2} = \sum_{s_i \in \boldsymbol{A}_2} p(s_i) \tag{23}$$

$$p_{\boldsymbol{A}_3} = \sum_{s_i \in \boldsymbol{A}_3} p(s_i) \tag{24}$$

The sum of the probabilities of the two subsets is multiply by the corresponding cost of this test $c_{[x_1]}$, which denoted as cost1:

$$\text{cost1} = (p_{\boldsymbol{A}_2} + p_{\boldsymbol{A}_3}) \cdot c_{t_{[x_1]}} \tag{25}$$

(2) The state set $\boldsymbol{A}_2$ is divided into 2 subsets by the second test $t_{[x_2]}$, and the subsets obtained are further numbered as $\boldsymbol{A}_4$ and $\boldsymbol{A}_5$. The cost2 is calculated as

$$\text{cost2} = (p_{\boldsymbol{A}_4} + p_{\boldsymbol{A}_5}) \cdot c_{t_{[x_2]}} \tag{26}$$

(3) In a similar way, the third test $t_{[x_3]}$ is performed on the state set $\boldsymbol{A}_3$, and the subsets $\boldsymbol{A}_6$ and $\boldsymbol{A}_7$ are obtained, as well as cost3. The remaining state sets proceed in turn. After all tests are performed, the fitness value of the individual x can be calculated, that is, the sum from cost1 to cost$m$ as

$$J(\boldsymbol{x}) = \sum_{i=1}^{m} \text{cost}m \tag{27}$$

It should be emphasized that in this process, if there is a subset of $\boldsymbol{A}_z(z>1)$ that contains only one element, the subset is no longer numbered, and the other subset continues to be numbered. And if there is an empty set in the subsets of $\boldsymbol{A}_z$, neither subset is numbered anymore. Thereinto, only one element in the subset indicates that the corresponding failure source is successfully isolated, while the existing of empty subset indicates that the corresponding test $t_{[x_i]}$ cannot implement the new fault state isolation and is a duplicate and invalid test. For the invalid test, a penalty be added to its cost, that is, cost$i$= cost$i$+max(c_1, c_2,…,c_n).

4. Simulation and analysis

In this section, the example in Ref.[32] is selected to verify the effectiveness of the proposed method. The detailed information is given in Table 1, and 5 other algorithms that have been applied to solving the fault diagnostic strategy problem are selected as a comparison, namely the genetic algorithm(GA)[19], the improved genetic simulated annealing algorithm(IGSA)[27], the improved quantum-inspired evolutionary algorithm(IQEA)[26], the tabu search algorithm (TS)[24] and the fractal differential evolution algorithm(FDE)[33]. The initial parameter settings of each algorithm are given in Table 2. The dimension of this diagnostic strategy is 10, and the maximum evaluation times is set as 9000. Each algorithm is tested 10 times independently, and all the experimental results are analyzed statistically, as given in Table 3.

Table 1 The $\boldsymbol{D}$ matrix, probabilities and test costs

	t_1	t_2	t_3	t_4	t_5	**Prior probability**
f_0	0	0	0	0	0	0.66815
f_1	0	1	0	0	1	0.00949
f_2	0	0	1	1	0	0.01845

f_3	0	1	1	1	1	0.00026
f_4	1	0	0	1	1	0.09545
f_5	1	1	1	1	1	0.02029
f_6	1	0	1	1	1	0.00265
f_7	1	1	0	0	0	0.04875
f_8	1	1	0	0	1	0.00069
f_9	1	1	1	1	0	0.12731
f_{10}	1	1	0	1	1	0.00842
Test cost	1	1	1	1	1	—

Table 2 The initial parameter settings of 6 algorithms

Algorithm	Initial parameters
GA	N=80, l=10, p_c=0.8, p_m=0.01, N_c=5
OGASA	N=20, p_c=0.8, p_m=0.01, λ=0.9, μ=1, α=β=1
IQEA	N=30, θ_{max}=0.05π, θ_{min}=0.01π
TS	N=40, ω=0.9 to 0.2, c=1.496, I=1, E=1
FDE	N=100, λ=1.123, c=0.1, μ_{CR}=μ_F=0.5, p_0=0.35, a_1=0.00011, a_2=0.00067
AEALSCE	N=12D, σ=1, α_0=4

Table 3 The experiment result of 6 algorithms

Algorithm	Minimum value	Maximum value	Mean value	Average time consumption	Optimal rate
GA	2.5316	3.5585	3.1465	0.5214 s	0 %
OGASA	2.5316	3.2290	2.9866	0.6770 s	0 %
IQEA	2.4024	3.1476	2.7971	1.2411 s	0 %
TS	2.5964	2.5964	2.5964	0.7335 s	0 %
FDE	2.4013	2.4782	2.4199	0.8359 s	50 %
AEALSCE	2.4013	2.4024	2.4017	0.5314 s	90 %

As shown in Table 3, the experiment results of 6 algorithms are statistically analyzed. Among these 10 experiments, only FDE and AEALSCE obtain the minimum test cost of 2.4013. And AEALSCE obtains the minimum cost for 9 times, so the optimal rate is 90%. The only non-optimal value is 2.4024 which is not much different from 2.4013, and this gap could be ignored in some situations. Moreover, FDE obtains the optimal value for 5 times, and the optimal rate is 50%, which is much lower than AEALESCE. And the other 4 algorithms do not get the optimal value in 10 experiments, which shows that the optimal rate of them are very low. It is easy to see that AEALSCE has excellent optimization ability and accuracy in solving diagnostic strategy problems, which is due to its excellent ability to balance exploration and development. In terms of execution time, AEALSCE and GA are the two algorithms of highest computational efficiency, with the average time consumed for each experiment is about 0.5 seconds. IQEA takes the longest execution time due to its complex algorithm framework. Thus, the proposed method based on AEALSCE has excellent performance in optimality of solution and time consuming.

The average convergence curves of 6 algorithms are shown in Fig.6. As shown, TS converges quickly, but falls into local optimization, because the diagnostic strategy obtained through the isolation matrix is locally optimal. This fast convergence obviously has no practical advantage of solving. Furthermore, AEALSCE has faster convergence speed and optimal search accuracy, compared with the other 4 algorithms, and the expectation test cost of its optimal solution is also the least.

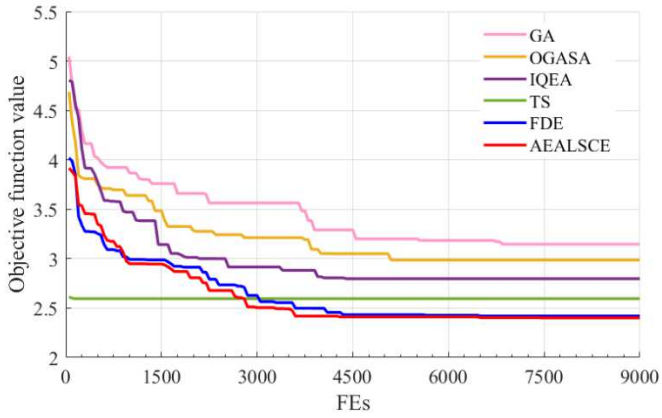


Figure 6 The average curves of 6 algorithms

At last, the optimal diagnostic strategy obtained by AEALSCE is further analyzed. There are totally 14 different optimal solutions obtained in the search process using AEALSCE. After classifying those 14 optimal solutions, 3 optimal fault diagnostic trees are obtained as shown in Fig.7~Fig.9, and their expected test costs all are 2.4013. The optimal diagnostic strategies in Fig.7 are $[\boldsymbol{x}]$=[2,4,3,3,5,5,1,1,1,4] and $[\boldsymbol{x}]$=[2,4,3,3,5,5,5,1,1,4]. The optimal diagnostic strategies in Fig.8 are $[\boldsymbol{x}]$=[2 4 5 3 3 1 1 3 3 4], $[\boldsymbol{x}]$=[2 4 5 3 4 1 1 3 3 4], $[\boldsymbol{x}]$=[2 4 5 3 3 1 5 3 3 4], $[\boldsymbol{x}]$=[2 4 5 3 4 1 5 3 3 4], $[\boldsymbol{x}]$=[2 4 5 3 3 1 1 4 3 4], $[\boldsymbol{x}]$=[2 4 5 3 4 1 1 4 3 4], $[\boldsymbol{x}]$=[2 4 5 3 3 1 5 4 3 4] and $[\boldsymbol{x}]$=[2 4 5 3 4 1 5 4 3 4]. The optimal diagnostic strategies in Fig.9 are $[\boldsymbol{x}]$=[2 4 5 3 3 3 1 1 1 4], $[\boldsymbol{x}]$=[2 4 5 3 4 3 1 1 1 4], $[\boldsymbol{x}]$=[2 4 5 3 3 3 5 1 1 4] and $[\boldsymbol{x}]$=[2 4 5 3 4 3 5 1 1 4]. Compared with the optimal solutions obtained by other 4 methods, which can only construct one optimal diagnostic tree, the AEALSCE-based method has better global search ability. In Fig.7, $A_1=\{f_0,f_1,\ldots,f_{10}\}$, and the fault states of other nodes are given in Table 4. And the fault states A_1, A_2 and so on in Fig.8 and Fig.9 can be deduced with the chosen tests and the $\boldsymbol{D}$ matrix in Table 1, which are no longer listed here.

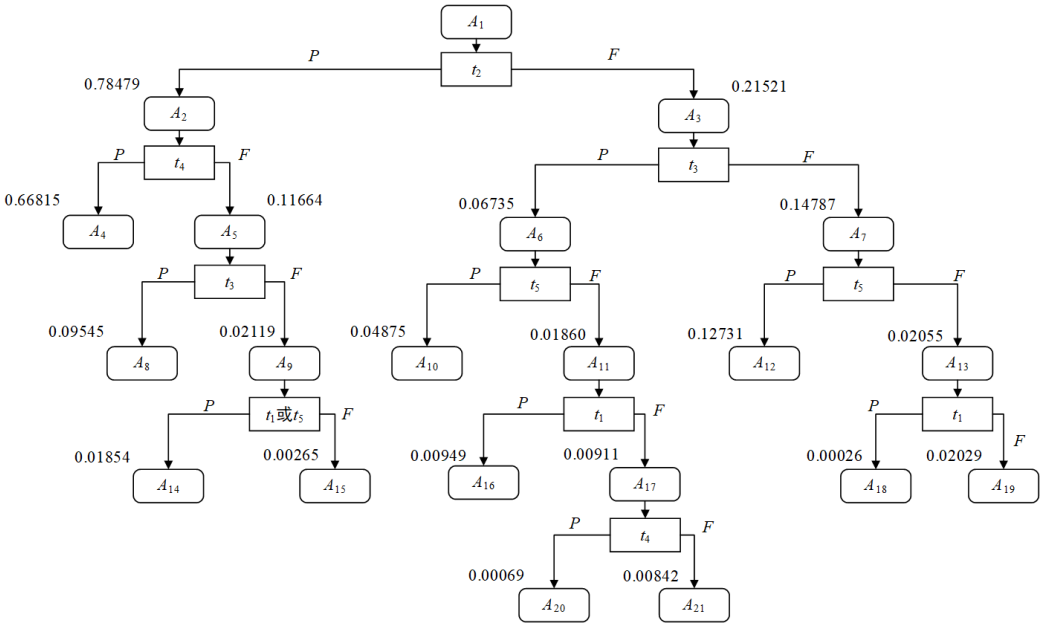


Figure 7 The optimal diagnostic tree I

Table 4 The fault states of each nodes in Fig.7

Node	Fault state	Node	Fault state	Node	Fault state

A_1	$f_0f_1f_2f_3f_4f_5f_6f_7f_8f_9f_{10}$	A_8	f_4	A_{15}	f_6
A_2	$f_0f_2f_4f_6$	A_9	f_2f_6	A_{16}	f_1
A_3	$f_1f_3f_5f_7f_8f_9f_{10}$	A_{10}	f_8	A_{17}	f_5f_9
A_4	f_0	A_{11}	$f_1f_5f_9$	A_{18}	f_3
A_5	$f_2f_4f_6$	A_{12}	f_{10}	A_{19}	f_7
A_6	$f_1f_5f_8f_9$	A_{13}	f_3f_7	A_{20}	f_9
A_7	$f_3f_7f_{10}$	A_{14}	f_2	A_{21}	f_5

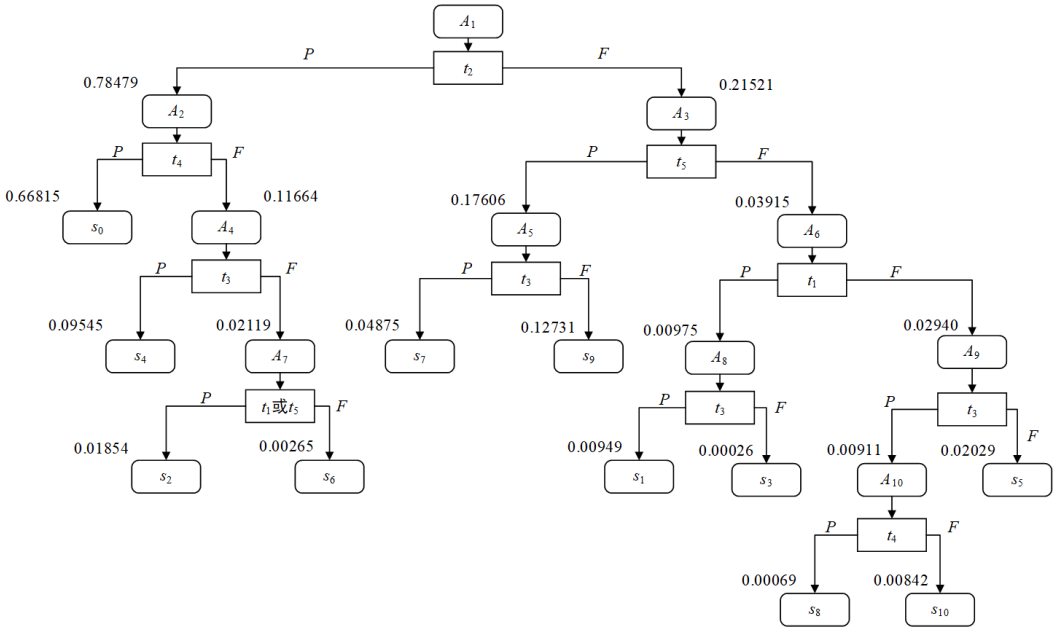


Figure 8 The optimal diagnostic tree II

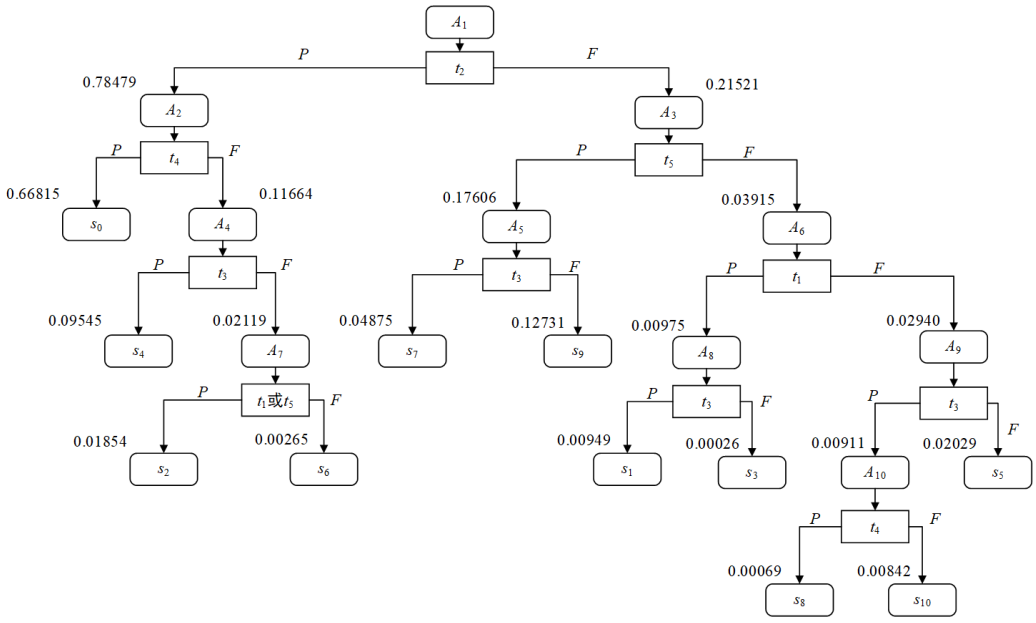


Figure 9 The optimal diagnostic tree III

Compared with the results based on Rollout algorithm proposed in Ref.[32], the optimal test sequences obtained by it draws the diagnostic tree as given in Fig.8. Only 1 optimal diagnostic tree means that some other optimal solutions are not found. That is, the expected test cost of the optimal

solutions obtained based on AEALSCE in this paper is the same as that obtained by the Rollout algorithm based on information entropy, but more different optimal solutions are found in this paper. This further verifies that the optimality of solution obtained by the proposed method in this paper is better than most existing methods, which benefits from the excellent global search ability of AEALSCE. The proposed method can provide better practical and reference value for diagnostic strategy in engineering practice.

5. Conclusions

In the end, the complexity of using AEALSCE to get the optimal diagnostic strategy is discussed. It includes 2 aspects, the time consumption of the search mechanism of AEALSCE algorithm and the consumption of evaluating the population fitness value by using the objective function. Assuming that the system has m failure sources and n available tests, the time complexity of AEALSCE algorithm execution is $O(m^3)$ according to Ref[31]. The complex information theory and backtracking method are not used to solve the fitness value of the individual, so the calculation time complexity is $O(m\log_2 m)$. For the population size is related to the problem dimension, the fitness evaluation of the population is $O(m^2\log_2 m)$. Therefore, the time complexity of AEALSCE to get the optimal diagnostic strategy is $O(m^3)$. The time complexity of using FDE in Ref.[33] to solve this problem is $O(m^2n^3)$, and the time complexity of using Rollout in Ref.[32] is $O(n^2 2^{n-1})$. Because $n>\log_2(m+1)$ is required, AEALSCE has higher computational efficiency when the number of available tests n is relatively large.

Aiming at the NP-complete problem of fault diagnosis strategy construction, this paper introduces an advanced evolutionary algorithm AEALSCE to solve it and proposes a diagnostic strategy optimization method based on AEALSCE. The discrete optimization problem of fault diagnostic strategy is transformed into a continuous one and the fitness function is constructed according to the diagnostic process and test cost, to adapt the algorithm solving. The simulation example and comparison show that the proposed method can effectively solve the diagnostic strategy optimization problem, and obtain more optimal diagnostic strategies with its excellent global search ability, in steading of relying on heuristic equation to optimize. And the comparison further indicates that the proposed method has obvious advantages in precision and time efficiency in solving this problem, which could provide a new and effective tool for fault diagnosis problem in engineering.

Declarations

The authors did not receive support from any organization for the submitted work.

The authors have no competing interests to declare that are relevant to the content of this article.

Data availability statements

Data sets generated during the current study are available from the corresponding author on reasonable request.

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