Test configuration optimization method based on NSGA2-MOPSO algorithm

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Abstract. Test configuration optimization is an important part in the process of testability design. In order to be close to the reality, this paper chooses to carry out the test optimization selection under the condition of unreliable test. Under this condition, Test configuration optimization is essentially a multi-objective optimization problem. Therefore, this paper establishes a mathematical model of the problem with test cost, test quantity and false alarm rate as optimization objectives. In this paper, the multi-objective particle swarm optimization algorithm and NSGA2 algorithm are comprehensively analyzed. According to the advantages and disadvantages of the two algorithms, NSGA2-MOPSO algorithm is proposed to solve the test optimization selection problem. The results show that the NSGA2-MOPSO algorithm has good performance and high practicability.

1. Introduction

The life cycle cost of equipment increases with the performance, one of the main reasons is the increase of maintenance support cost. How to reduce the cost of maintenance and support has become one of the most difficult problems for researchers. The most direct solution is to improve the speed and accuracy of equipment testing and diagnosis to meet the requirements. In the research and practice, it is found that in order to achieve rapid and accurate test and diagnosis, it is necessary to consider the future test and diagnosis problems in the early stage of equipment design and development, that is to carry out testability design in the early stage of development[1]. Test configuration optimization is an important part of testability design. Its basic idea is to meet the testability requirements of the system[2-6].

The Test configuration optimization problem is essentially a constrained multi-objective optimization problem when some indexes are set as constraints. The former two solutions are to solve the problem as or into a single objective optimization problem. In this paper, the Test configuration optimization problem is reduced to a multi-objective optimization problem to solve. Firstly, the mathematical model of the multi-objective optimization problem is established through the analysis of the problem. Secondly, the Bayesian network model is briefly introduced to evaluate the test scheme. Then, considering the defects of the multi-objective problem, such as the increase of calculation time and the decrease of global search ability. The combination algorithm of NSGA-2 and MOPSO is proposed to solve the problem. Finally, an example of a missile electronic system is used to verify the outstanding advantages of this method compared with the single objective optimization method. By comparing with MOPSO algorithm and NSGA-2 algorithm, it is proved that the algorithm in this paper has the characteristics of fast convergence speed and strong global search ability.
2. Test configuration optimization problem and testability model

2.1 Test configuration optimization
According to the introduction, Test configuration optimization problem is a multi-objective optimization problem. In this paper, fault detection rate and fault isolation rate are set as constraints, false alarm rate, number of test points and test cost are optimized objectives to solve test configuration scheme. Therefore, the mathematical model of Test configuration optimization problem can be expressed as formula (1) and (2)

\[
\begin{align*}
\text{min}(FAR) \\
\text{min}(D(x)) \\
\text{min}(C(x))
\end{align*}
\]

The constraints are as follows:

\[
\begin{align*}
FIR \geq FIR^* \\
FDR \geq FDR^*
\end{align*}
\]

2.2 Testability model
The basic elements of Bayesian network testability model are as follows [7]:

- Fault node set: \( F = \{f_1, f_2, \ldots, f_n\} \), \( f_i \) Indicates the fault node.
- Test node: \( T = \{t_1, t_2, \ldots, t_m\} \), \( t_j \) Represents the test node.
- Directed edge: \( E \), The fault node and signal node are connected to represent the correlation between them.
- Conditional probability information table: \( CPT \), It contains the parameter information of Bayesian network. The testability model of Bayesian network is shown in Figure 1.

2.3 Calculation of testability index
The testability index is calculated by the model in order to evaluate the performance of test options. The detection rate was as follows:

\[
FDR_j = 1 - p(\sum_{i=1}^{m} q_i = 0 | f_j)
\]

System failure detection rate :

\[
FDR = 1 - \prod_{j=1}^{q} FDR_j
\]

Fault isolation rate :

\[
FIR = \frac{\sum_{j=1}^{q} p(f_j) \times p(f_j | f_j)}{\sum_{j=1}^{q} p(f_j) \times FDR_j}
\]

The false alarm rate of the system is as follows :

\[
FAR = 1 - p(\sum_{j=1}^{m} t_j = 0 | \sum_{i=1}^{n} f_i)
\]
3. NSGA2-MOPSO algorithm
In this paper, NSGA2-MOPSO algorithm is proposed for the multi-objective optimization problem of Test configuration optimization.

3.1 Pareto solution and related concepts

For any two decision variables \( x_a, x_b \), the solution is feasible set

\[
\begin{align*}
(1) & \forall i = 1, 2, ..., k: f_i(x_a) \leq f_i(x_b) \\
(2) & \exists i = 1, 2, ..., k: f_i(x_a) < f_i(x_b)
\end{align*}
\]

Only if the above two conditions are satisfied, the \( x_a \) control \( x_b \). In the decision space, there is a set of decision vectors \( x \), \( x \) is not dominated by any decision vector, then \( x \) is called Pareto optimal solution.

Pareto optimal solution are shown in Fig. 2.

3.2 NSGA2 algorithm
The results are as follows: (1) generate the initial population with the scale of \( N \), and update the initial population with the cross mutation operator to generate the offspring population. (2) merge the offspring population and the initial population to make the non-dominated sorting, and calculate the crowding degree. When more than one solution is in the same level, the solutions are sorted according to the crowding degree. (3) using the selection operator, the tournament selection method is usually used. (4) repeat steps (1) ~ (3) until the required algebra is completed.

3.3 MOPSO algorithm
MOPSO algorithm is a multi-objective particle swarm optimization algorithm. The basic concepts of particle swarm optimization are as follows:

Current position of particle \( X_i = \{x_{i1}, x_{i2}, ..., x_{in}\} \).

The historical optimal location of particles themselves \( P_id = \{p_{i1}, p_{i2}, ..., p_{in}\} \).

The historical optimal position searched by particle swarm optimization \( G_id = \{g_{i1}, g_{i2}, ..., g_{in}\} \).

The speed and position update algorithm of binary particle swarm optimization is as follows:

\[
\begin{align*}
v_{id} &= \omega * v_{id} + c_1 * rand * (p_{id} - x_{id}) + c_2 * rand * (g_{id} - x_{id}) \\
s(v_{id}) &= \frac{1}{1 - \exp(-v_{id})} \\
x_{id} &= \begin{cases} 1, & rand \leq s(v_{id}) \\ 0, & \text{otherwise} \end{cases}
\end{align*}
\]

among \( \omega \) The default value is 8.0, \( c_1, c_2 \) Is a learning factor. Rand is a random number.

The principle of MOPSO algorithm is as follows: (1) generate the initial population randomly with the scale of \( N \), calculate the optimal position of the particle swarm and the particle itself, and save the
optimal position of the particle swarm in the file. (2) update the particle swarm according to the speed and position update algorithm. (3) update the historical optimal position of the file and the particle itself according to the rules. (4) repeat steps (2) ~ (3) until the required algebra is completed.

3.4 NSGA2-MOPSO algorithm
As mentioned above, hybrid algorithms are basically divided into three types: horizontal combination, vertical combination and cross combination. The basic principles of the hybrid algorithm are as follows:

1) The first n / 2 individuals are extracted according to the degree of non-dominance and crowding degree, and these n / 2 individuals are further evolved by MOPSO algorithm. (4) The last n / 2 individuals are merged into a population of N size by using NSGA2 algorithm. (6) repeat (1) ~ (4), complete the required algebra.

4. Case analysis
Taking the airborne radio altimeter of an anti-ship missile as an example, the test optimization and selection work is carried out. The structure of the Bayesian network model of the anti-ship missile is shown in Figure 3. The fault information is shown in Table 1. The test cost is shown in Table 2.

![Fig. 3. Bayesian network model of radio altimeter](image)

Table 1. fault information

| fault | Prior probability of failure (10^{-5}) |
|-------|---------------------------------------|
| $f_1$ | 5                                     |
| $f_5$ | 35                                    |
| $f_9$ | 7                                     |
| $f_{13}$ | 8                                 |
| $f_{17}$ | 17                                 |
| $f_{21}$ | 26                                 |

| fault | Prior probability of failure (10^{-5}) |
|-------|---------------------------------------|
| $f_2$ | 49                                    |
| $f_6$ | 5                                     |
| $f_{10}$ | 14                                 |
| $f_{14}$ | 67                                 |
| $f_{18}$ | 39                                 |
| $f_{20}$ | 13                                 |

Table 2. test cost

| test | $t_1$ | $t_2$ | $t_3$ | $t_4$ | $t_5$ | $t_6$ | $t_7$ | $t_8$ | $t_9$ | $t_{10}$ | $t_{11}$ | $t_{12}$ |
|------|-------|-------|-------|-------|-------|-------|-------|-------|-------|----------|----------|----------|
| cost | 5     | 7     | 10    | 11    | 3     | 11    | 3     | 6     | 4     | 7        | 5        | 5        |
| test | $t_{13}$ | $t_{14}$ | $t_{15}$ | $t_{16}$ | $t_{17}$ | $t_{18}$ | $t_{19}$ | $t_{20}$ | $t_{21}$ |
| cost | 4     | 3     | 9     | 6     | 6     | 5     | 4     | 5     | 6     |
The NSGA2-MOPSO algorithm proposed in this paper is used to optimize the test of radio altimeter. The fault detection rate is not less than 95%, and the fault isolation rate is not less than 70%. The optimization objectives are test quantity, test cost and false alarm rate. The parameter settings of the combined algorithm are shown in Table 3, and some of the Pareto optimal solutions obtained are shown in Table 4.

Table 3. Parameter setting

| Parameter            | Value | Parameter | Value | Parameter    | Value | Parameter | Value |
|----------------------|-------|-----------|-------|--------------|-------|-----------|-------|
| Inertia constant ω   | 0.8   | Population size | 50    | Number of iterations K | 5     | Crossover probability | 0.8   |
| Total iterations     | 20    | Number of iterations M | 5     | Mutation probability | 0.1   | Number of objective functions | 3     |
| Number of constraints | 2     | Individual length | 21    | Learning factors c₁ | 0.2   | Learning factors c₂ | 0.2   |

Fig. 4. Fitness curve

Table 4. Pareto solution set

| Serial number | Test configuration scheme | Test cost | Number of tests | False alarm rate |
|---------------|---------------------------|-----------|-----------------|-----------------|
| 1             | {000100000111101111011}   | 85        | 10              | 7.4%            |
| 2             | {000110000101011101111}   | 93        | 11              | 6.4%            |
| 3             | {10110001011111001110}    | 82        | 12              | 9.8%            |
| NSGA2         | {100111110011110011011}   | 95        | 14              | 10.1%           |
| NSGA2         | {101111000011110011011}   | 114       | 13              | 9.6%            |
| NSGA2         | {101101001110011011111}   | 105       | 13              | 9.8%            |
| NSGA2         | {1011001010011011110111}  | 106       | 13              | 9.8%            |
| NSGA2         | {0011111000111001101111}  | 115       | 13              | 8.9%            |
| MOPSO         | {1011000100111001101111}  | 87        | 12              | 8.7%            |

At the same time, NSGA2 algorithm and MOPSO algorithm are applied to optimize the object. The iteration times of the three algorithms are set to 20 times. The operation results are shown in Table 4 and compared with the algorithm in this paper. The change curve of the optimal fitness function of this algorithm, NSGA2 algorithm and MOPSO algorithm is shown in Fig. 4, where the fitness mainly refers to the Pareto non dominated sorting results of all schemes.

It can be seen from Table 4 and Figure 4 that the convergence speed of NSGA2 algorithm is slow, and the MOPSO algorithm is easy to fall into local optimum. The proposed hybrid algorithm of NSGA2 and MOPSO in this paper has the ability of global search with fast convergence speed.
5. Conclusion
In this paper, the problem of test selection under the condition of unreliable testing is deeply analyzed, and a new solution is proposed to solve the problems existing in previous studies. The protocol differs from previous studies in three aspects:

1) The problem of optimal test selection under unreliable test conditions is reduced to a multi-objective problem to solve, and a mathematical model is established with test cost, test quantity and false alarm rate as objectives and fault detection rate and isolation rate as constraints.

2) The Bayesian network model is introduced to calculate the testability index by Bayesian network reasoning, which makes the evaluation result more reliable.

3) The NSGA2-MOPSO algorithm is proposed to solve the problem. It is proved that the algorithm has fast convergence speed and is not easy to fall into local optimum.

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