APEM journal

Advances in Production Engineering & Management
Volume 16 | Number 3 | September 2021 | pp 372–384
https://doi.org/10.14743/apem2021.3.407

ISSN 1854-6250
Journal home: apem-journal.org
Original scientific paper

A multi-objective selective maintenance optimization method for series-parallel systems using NSGA-III and NSGA-II evolutionary algorithms

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A B S T R A C T

Aiming at the problem that the downtime is simply assumed to be constant and the limited resources are not considered in the current selective maintenance of the series-parallel system, a three-objective selective maintenance model for the series-parallel system is established to minimize the maintenance cost, maximize the probability of completing the next task and minimize the downtime. The maintenance decision-making model and personnel allocation model are combined to make decisions on the optimal length of each equipment's rest period, the equipment to be maintained during the rest period and the maintenance level. For the multi-objective model established, the NSGA-III algorithm is designed to solve the model. Comparing with the NSGA-II algorithm that only considers the first two objectives, it is verified that the designed multi-objective model can effectively reduce the downtime of the system.

A R T I C L E   I N F O

Keywords:
Maintenance;
Series-parallel system;
Maintenance decision model;
Multi-objective optimization;
Selective maintenance;
Evolutionary algorithms;
Non-dominated sorting genetic algorithm;
NSGA-II;
NSGA-III

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Article history:
Received 1 July 2021
Revised 22 October 2021
Accepted 25 October 2021

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1. Introduction

The safe and reliable operation of equipment is the primary condition for enterprises to ensure production efficiency. Reasonable maintenance methods can effectively guarantee the reliable operation of equipment and reduce the maintenance cost of enterprises. Effective, reliable and economical equipment maintenance plays an increasingly important role in enterprise production and operation [1]. In the manufacturing environment, manufacturing systems often contain multiple devices, forming a multi-device system, and there are often complex dependencies between them. How to make reasonable maintenance and maintenance decisions is the research focus of predictive maintenance. Common maintenance decision-making methods include mathematical model analysis method, Markov decision model method, simulation model method, etc. [2].

Mathematical analytic method is generally based on the knowledge in the field of operations research to study the application and planning of various maintenance resources, establish the corresponding model and solve it. Rashidnejad *et al.* proposed a dual-objective model and solution to the geographically dispersed asset maintenance plan based on NSGA-II (Non-Dominated Sorting Genetic Algorithm II) algorithm, and evaluated the effectiveness and performance of the proposed model through the actual case of bank ATM (Automatic Teller Machine) maintenance [3]; Pandey *et al.* made decisions about the selection of equipment to be maintained and the level of maintenance to be performed by the maintenance equipment during the fixed downtime of the continuous generation system [4]; Dao *et al.* established a maintenance optimization model of multi-state serial-parallel system based on resource availability and component maintenance time and cost dependence, and used genetic algorithm to solve the optimization problem [5]. Khatab and Khatab assumed that the duration of the next task and the duration of rest were random variables with known distribution, and modeled the final selective maintenance optimization problem as a mixed integer nonlinear stochastic programming [6-7]; Chaabane proposed a selective maintenance planning (SMP) model to optimize maintenance and allocation decisions in systems running multiple tasks[8]; Cheng *et al.* conducted joint modeling and Optimization on output, product quality and predictive maintenance of series parallel multi-stage production system, and reasonably allocated maintenance resources according to the importance of equipment [9]; Lu *et al.* optimized the preventive maintenance problem of multi equipment series production system with buffer zone by using genetic algorithm [10]; For the Series production system without buffer, Leng *et al.* made decisions and optimized the production lot size and the imperfect preventive maintenance of the equipment under the conditions of both shortage and inventory [11]. According to the resource demand priority of each process in the production system, Li *et al.* established the opportunity maintenance strategy of multi-resource constrained serial-parallel system. Apart from the above example, a different structure of manuscript may be accepted if it is the most suitable and effective style for the contents of the manuscript [12].

Markov decision model is a mathematical model to simulate the Random Strategy and Return of agents in the environment, and the state of environment has Markov property, which is widely used in dynamic programming, random sampling, decision optimization and other fields. Bousdekis *et al.* proposed a main event-driven model for joint maintenance and logistics optimization in the Industrial Internet environment, which combines the Markov decision process (MDP) and embeds the model into the event driven information system to make maintenance and logistics optimization decisions [13]; Gerum *et al.* proposed a new method to predict rail defects, and determined the best maintenance strategy through Semi-Markov decision process model [14]. Xu *et al.* Proposed a Dynamic state maintenance decision model based on Markov, which was used to make maintenance decisions for the Major components of equipment [15].

Pei *et al.* constructed an imperfect maintenance stochastic degradation model based on the Wiener process, and established a maintenance decision model to decide variables by the inspection intervals and maintenance threshold, and solved the model through numerical simulation [16]; Nguyen *et al.* proposed a predictive maintenance strategy with multi-level decision, which considers respectively system level and component level maintenance decision-making process, and uses Monte Carlo simulation technique to evaluate the maintenance cost rate [17]; Dao and Zuo studied the selective maintenance problem of a multi-state series system working under variable load conditions in the next task, and simulated the degradation of multi-state components through Monte Carlo simulation methods and evaluated the system reliability to determine the best choice maintenance strategy to maximize the expected reliability of the system for the next task within the range of available resources [18].

Studies have shown that the shutdown time is usually assumed to be constant, most scholars only consider the two optimization objectives of minimizing maintenance cost and maximizing the probability of completing the next task. However, in the enterprise continuous production line, the maintenance decision-making model and personnel allocation model are not considered together, when making maintenance decisions for the common series-parallel system of multiple devices. In each decision-making cycle, it is not only to solve the problems of which equipment needs to be maintained, the maintenance level of each equipment and the task assignment, but also to obtain the optimal downtime of the system. Therefore, we take the minimizing downtime as the third objective of the decision scheduling model. Then, we design a NSGA-III algorithm to solve the three-objective model. Compared with the NSGA-II algorithm of two objectives, the three objective decision model can achieve optimal downtime of system maintenance and detailed dispatch of maintenance tasks, and effectively reduce the downtime of the system.

2. Description of selective maintenance problem for series-parallel system

In the continuous production process, the production line is generally composed of multiple devices in series and parallel. In the multi equipment system, there are complex relationships among the equipment, such as economic dependence, structural dependence, random fault dependence and resource dependence. Economic dependence refers to the maintenance or inspection of multiple equipment at the same time under the condition of limited budget. This moment, there is an economic dependence among the equipment. Random dependence means that the deterioration process or failure time of various equipment has random correlation to some extent. Structural dependence refers to that the failure of one equipment may lead to the deterioration or failure of other equipment, and the maintenance of one component in the unit also means the maintenance of other components. Resource dependence refers to that the maintenance personnel are responsible for the maintenance activities of various units or systems, the limited spare parts inventory is used to replace multiple equipment, or selectively maintain the multi-equipment system in a limited time window.

Therefore, it is necessary to consider various dependence relationships between equipment in maintenance decision-making. The structure of series-parallel system is shown in Fig. 1. Series-parallel system usually performs continuous production tasks. Selective maintenance of equipment in the time interval between two continuous tasks can improve the reliability of the system when new tasks start. Due to the limited resources to complete maintenance activities, it is particularly important to determine the maintenance strategy based on the system requirements.

In the maintenance of series-parallel system, not only the loss cost of each equipment, but also the probability of the overall failure system should be considered. Therefore, it is necessary to determine the system shutdown time and the length of shutdown time during the maintenance of series parallel system, because the shorter the shutdown time, the smaller the impact on production. In order to solve the problem that traditional maintenance decision-making model of series-parallel system does not consider task dispatch and the system downtime is usually assumed to be constant, a multi-objective maintenance decision-making model of integrated maintenance assignment system is established by taking the shortest system downtime as one of the optimization objectives, and genetic algorithm is designed to solve the model.

Suppose that a production system is composed of n independent subsystems in series, each subsystem i is composed of m_i independent identical subsystems in parallel. Each device in the system can be expressed as E_{ij}, where i is the sub-system index and j is the sub-device index.

Each device in the system has two possible states, denoted by 0 (Complete failure state) and 1 (normal operation state). Since the whole system is composed of several subsystems in series, the whole system can work when all subsystems are running normally, and the device parallel structure in the subsystem, at least one device can work when they are all in normal operation.

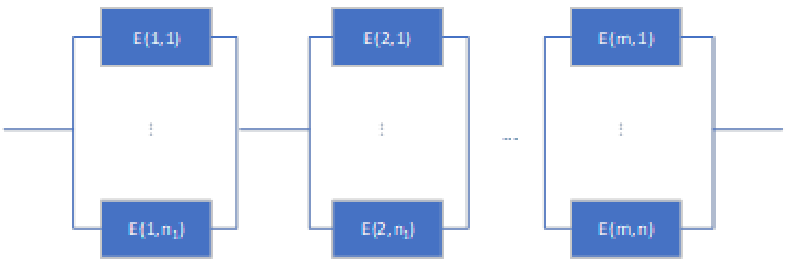

Fig. 1 Series parallel system structure

Within a given time period, the system needs to perform a series of consecutive identical tasks, and maintenance activities are performed only during the rest time between adjacent tasks. In order to facilitate future discussion, it is assumed that the amount of maintenance resources (budget, time, etc.) required for a maintenance activity is determined, and the reliability of components, subsystems or systems is given in advance, which is the possibility of successful completion of a given task.

Question hypothesis:

1. The system is composed of multiple independent repairable binary state devices, that is, the device is in a normal working state or a failure shutdown state. The life of each device in the initial state is different, and the life distribution parameters are known.
2. Maintenance activities (imperfect maintenance, preventive replacement, corrective maintenance) are performed at most once for each equipment during each rest cycle, in which corrective maintenance and preventive replacement are both perfect maintenances.
3. System components will not be aging during rest, that is, the life of components depends on the operation.
4. The cost of corrective maintenance is higher than that of preventive maintenance, and the mean time for corrective maintenance on each device is longer than the average time for preventive maintenance.
5. During the mission, the system does not perform any maintenance activities. When the faulty components are repaired to a minimum degree, the failure rate remains unchanged.
6. When necessary, all essential maintenance resources (maintenance personnel, tools and rest hours) are available. If the maintenance resource constraints are exceeded, the corresponding parameters should be punished, and the model is still holding.

3. Modeling of series-parallel maintenance system

In order to establish the selective maintenance model of series-parallel system, the following symbols are defined:

- A_{ij} is the effective service age of each equipment at the beginning of maintenance period;
- B_{ij} is the effective service age of each equipment at the ending of maintenance period;
- Y_{ij} is the state of each equipment at the ending of maintenance period;
- X_{ij} is the state of each equipment at the beginning of maintenance period (if the equipment works normally at the beginning of maintenance X_{ij} = 1, otherwise it is 0. if the equipment works normally when the maintenance ends Y_{ij} = 1, otherwise it is 0);
- l_{ij} is the level of maintenance performed by the equipment in the current rest cycle (0 indicates that no maintenance is performed, 1 indicates preventive imperfect maintenance, 2 indicates preventive substitution, and 3 indicates corrective maintenance);
- K is the number of maintenance personnel;
- k is the index of maintenance personnel;
- $P_{ij,t}$ is the cumulative failure probability of equipment at time, which is given by the prediction model;
- DT_{ij} is the expected downtime for unexpected equipment failure;
- δ_{ij} is the unit downtime cost for equipment;
- T_{IJkL} is the time it takes for maintenance personnel k to perform maintenance level l on equipment E_{ij};
- C_{IJkL} is the cost it takes for maintenance personnel k to perform maintenance level l on equipment E_{ij};
- when equipment E_{ij} is maintained at level l by maintenance personnel k, w_{ijlk} is 1, otherwise it is 0;
- T_{stop} is the length of downtime for maintenance;
- $f(t)$ is the downtime cost of the system over time;

Assuming that the life of each device E_{ij} in system obeys Weibull distribution, and the distribution of its shape parameters and scale parameters are β_{ij} and α_{ij}, then the reliability $R_{ij}(t)$ of equipment E_{ij} is:

$$R_{ij}(t) = \exp\left(-\left(\frac{t}{\eta_{ij}}\right)^{\beta_{ij}}\right) \tag{1}$$

The total reliability of the whole system at time t is:

$$\Re(t) = \prod_{i=1}^{m} R_i(t) = \prod_{i=1}^{m}\left(1 - \prod_{j=1}^{n}(1 - R_{ij}(t))\right) \tag{2}$$

The probability that device E_{ij} can still run normally after performing the next task with length u is as follows:

$$R_{ij}^{c} = \frac{R_{ij}(A_{ij} + U)}{R_{ij}(A_{ij})} \tag{3}$$

The reliability of the whole system to successfully complete the next task with length u is as follows:

$$\Re^{c} = \prod_{i=1}^{m}\left(1 - \prod_{j=1}^{n}(1 - R_{ij}^{c})\right) \tag{4}$$

The cost of maintenance:

$$C_{mt} = \sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{K}\sum_{l=0}^{L_{ij}} C_{IJkL} \cdot w_{tijlk} \tag{5}$$

The maintenance personnel cost:

$$C_{hire} = K \cdot c_p \cdot T_{stop} \tag{6}$$

The maintenance time:

$$T_{stop} = max\left(\sum_{i=1}^{m}\cdot\sum_{j=1}^{n}\cdot\sum_{l=1}^{L_{ij}} t_{ijkl} \cdot w_{tijlk}\right) \quad k \in K \tag{7}$$

Objective function 1: Minimize maintenance costs

$$\text{Min } C_{total} = C_{mt} + C_{hire} \tag{8}$$

Objective function 2: Maximize the probability of the system successfully executing the next task

$$\text{Max } \Re^{c} = \prod_{i=1}^{m}\left(1 - \prod_{j=1}^{n}(1 - R_{ij}^{c})\right) \tag{9}$$

Objective function 3: Minimize maintenance time

$$\text{Min } T_{stop} \tag{10}$$

Constraint condition:

- Maintenance activities are performed at most once for each equipment during shutdown:

$$\sum_{k}^{K}\sum_{l=0}^{L_{ij}} w_{ijkl} \leq 1, \quad \forall i,j \tag{11}$$

- Maintenance duration cannot be greater than system downtime:

$$\sum_{i=1}^{N}\sum_{j=1}^{N_i}\sum_{l=0}^{L_{ij}} t_{ijkl}\cdot w_{ijkl} \leq T_{stop}, \quad \forall k \tag{12}$$

- If the equipment is faulty at the start of the rest, correction must be performed:

$$\sum_{k}^{K}\sum_{l=0}^{L_{ij}} w_{ijkl} = 3\,, \qquad X_{ij} = 0, \forall i,j \tag{13}$$

- The constraint of Maintenance decision and failure probability:

$$w_{ijkl} \in \{0,1\}, 0 \leq R_{ij}(t) \leq 1, \quad \forall i,j,k,l,t \tag{14}$$

4. Designing of multi-objective genetic algorithm

The traditional genetic algorithm is only suitable for the single-objective optimization problem, and cannot solve the optimization model similar to the selective maintenance of series-parallel system.

Srinivas and Deb proposed a Non-Dominated Sorting Genetic Algorithm (NSGA), using the characteristics of genetic algorithm parallel batch to obtain as many Pareto solutions as possible, but in the later use process there are high computational complexity, lack of elite and need to share parameters [19]. Therefore, Deb *et al.* proposed a Non-Dominated Sorting Genetic Algorithm II, which solved the above problems of NSGA, and could find the non-dominated solution set with good convergence and dispersion in the two-objective optimization problem [20].

Zhao *et al.* [21] proposed a time-dependent and bi-objective vehicle routing problem with time windows (TD-BO-VRPTW). The non-dominated sorting genetic algorithm II (NSGA-II) is adopted to obtain the Pareto optimal solution set. Through comparing these results with solutions in the Pareto front, the results in Pareto front are competitive because there is a trade-off between two objectives. Liu and Zhang [22] established a multi-objective planning model. This model can solve the dual uncertainty demand problems of number and delivery time when orders are emergent or are modified for equipment manufacturing enterprises. The NSGA-II genetic algorithm is used to solve the model. Targeting at the problems existing in the multi-objective scheduling of traditional flexible job shop and the complexity of multi-resource allocation, Zhong *et al.* [23] established an improved calculation model considering the optimization of such four targets as completion time, labour distribution, equipment compliance and production cost. The multi-objective integrated constraint optimization algorithm was designed and the Pareto solution set following different rules based on the NSGA-Pi algorithm was finally obtained.

However, when the optimization objectives increase, the multi-objective optimization algorithm encounters new challenges: 1) the proportion of non-dominated solutions in the target vector set increases exponentially; 2) the calculation quantity of diversity protection operator is huge;3) surface visualization is difficult to achieve. In order to solve the above problems, Deb *et al.* proposed a multi-objective algorithm based on the framework of NSGA-II, which is called NSGA-III [20]. This algorithm has obtained good results in solving the multi-objective optimization problem with 3-15 objectives. Therefore, we select the three objectives in the NSGA-III algorithm to solve the multi-objective selective maintenance problem.

The NSGA-III algorithm flow is shown in Fig. 2. In essence, NSGA-III adopts a similar framework of NSGA-II, the difference is mainly the change of selection mechanism. NSGA-II mainly uses crowding to sort, its effect in high-dimensional target space is not obvious, and NSGA-III maintain population diversity by introducing widely distributed reference points.

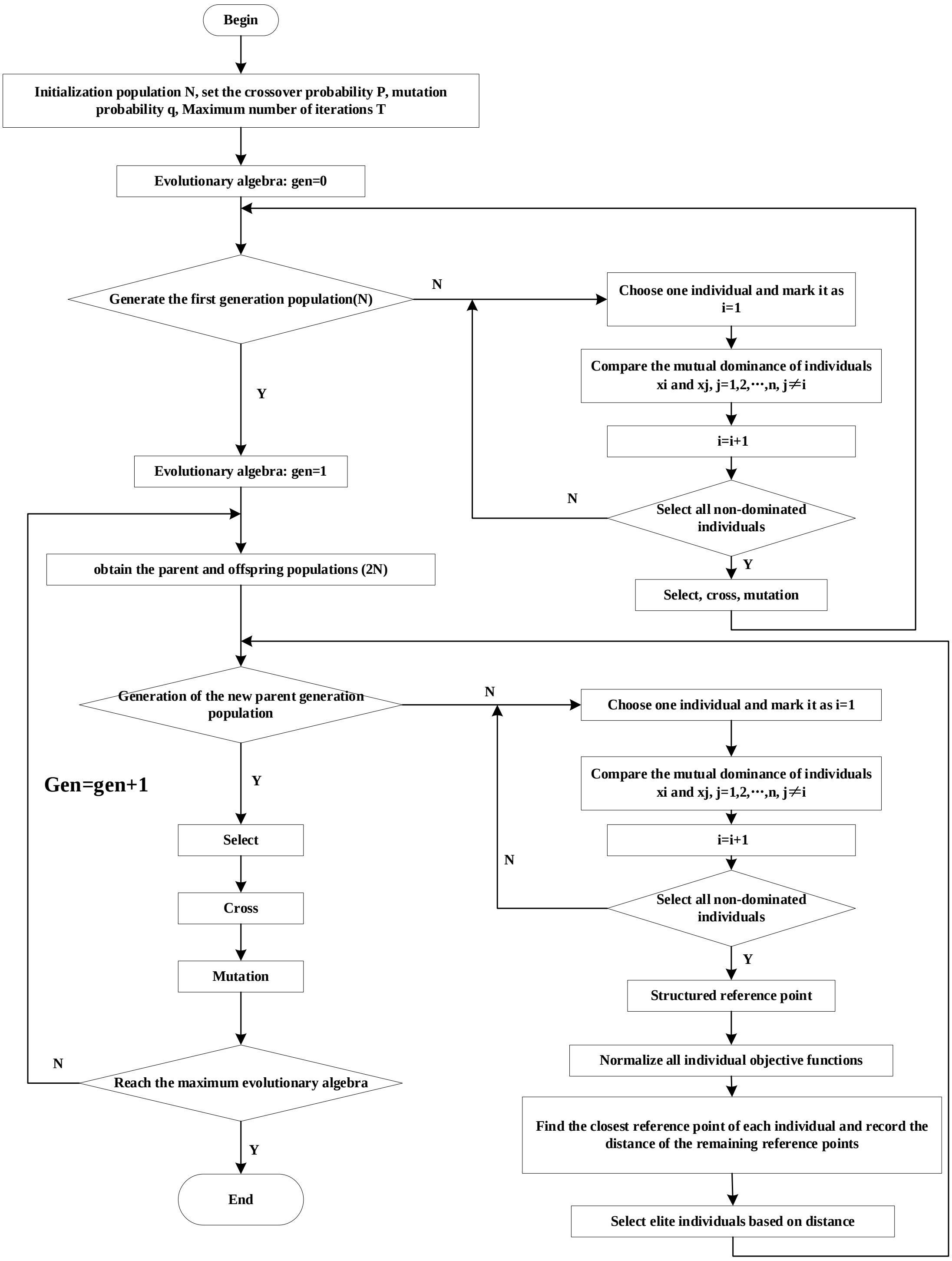

Fig. 2 NSGA-III algorithm flow

Aiming at the multi-objective optimization model for series-parallel system, the coding, crossover and mutation operators of NSGA-III algorithm are designed as follows.

4.1 Encoding

For the multi-objective optimization problem of selective maintenance in series-parallel system, each chromosome needs to determine three problems: 1) the equipment that needs to perform maintenance operation during rest period; 2) The level of maintenance operations performed by the equipment to be maintained; 3) Maintenance task assignment issues, so three issues need to be covered when encoding. Assuming there are N devices in the system, the chromosome is represented by a matrix of $2N$ rows. Among them, the first N columns of the chromosome correspond to the equipment in the system, and the coding of the corresponding position represents the maintenance operation level that needs to be performed during the current rest period (0 indicates that no maintenance is performed, 1 indicates preventive imperfect maintenance, 2 indicates preventive substitution, and 3 indicates corrective maintenance). The latter N is the distribution of the corresponding equipment maintenance tasks. If the equipment i decides not to perform any maintenance operation, the corresponding position is 0. If the maintenance personnel 2 decides to perform preventive replacement, the corresponding position is 2, indicating that the maintenance operation is performed by the maintenance personnel 2. Therefore, Fig. 3 shows an example of chromosome encoding.

Fig. 3 Encoding

4.2 Crossover operator

The crossover operation adopts the double-cut point crossover method. First, two positions are generated in the chromosome part that determines the maintenance level of the equipment. Then, the fragments of the two chromosome crossover intervals are exchanged, and the corresponding task assignment gene fragments are exchanged in the same time. This crossover method ensures the feasibility of generating new offspring. The crossover operation is shown in Fig. 4.

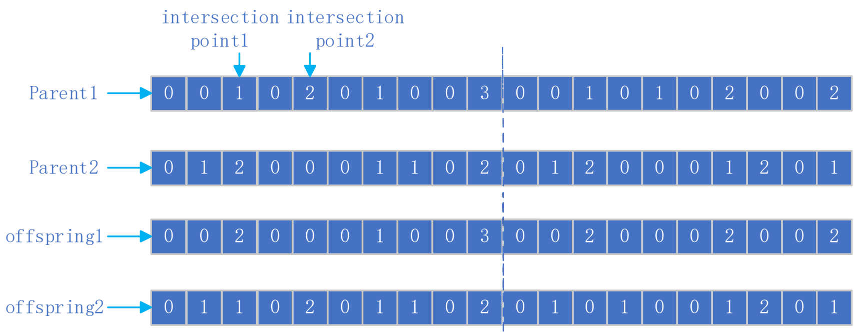

Fig. 4 Crossover operator

4.3 Mutation operator

In this paper, two types of mutation operators are used, and one is randomly selected from the two mutation operators for mutation operation each time. The first mutation operator performs mutation operation on the chromosome part which determines the equipment maintenance level, and the second mutation operator performs mutation operation on the chromosome part of equipment maintenance allocation.

The first mutation operator generates two arbitrary points in the first half of the chromosome, cross the encoding of the corresponding position, and exchange the encoding of the corresponding dispatching chromosome region, as shown in Fig. 5.

The second mutation operator randomly generates two non-zero gene positions in the second half of the chromosome, and then cross codes the corresponding positions, as shown in Fig. 6.

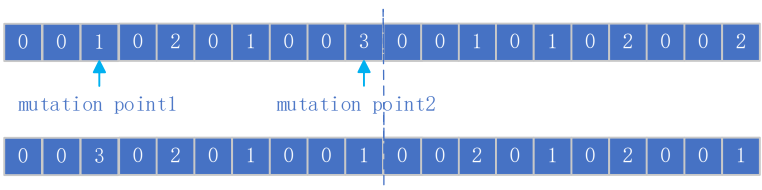

Fig. 5 Mutation operator 1

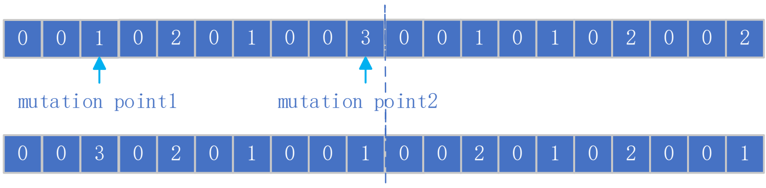

Fig. 6 Mutation operator 2

The above two mutation methods ensure the feasibility of chromosome after mutation, so it is not necessary to verify the rationality of coding.

5. A case study and a comparative analysis of NSGA-II and NSGA-III

The equipment composition of a production line is shown in Fig. 7, which is consisted of five subsystems composed of 14 components. The Weibull distribution life of each equipment and the shape and scale parameters represented have been given. PM represents the implementation of preventive replacement, IPM represents the implementation of imperfect maintenance, and CM represents the implementation of corrective maintenance. In addition, other parameters are given in Table1, in which the units of various maintenance costs are all yuan, and the unit of maintenance duration is day. Suppose the downtime cost of the system is RMB500 per day and the hiring cost of a single maintenance worker is RMB50 per day.

In order to verify the validity of the model in this paper, NSGA-II algorithm and NAGA-III algorithm are used to solve the model respectively. The goal of NSGA-II is to minimize maintenance costs and maximize the success rate of the next task, the goal of NAGA-III algorithm increases the minimum downtime maintenance time on the basis of NSGA-II. In both algorithms, the population is 500, the crossover probability is 0.8, the mutation probability is 0.1, and the number of iterations is 500.

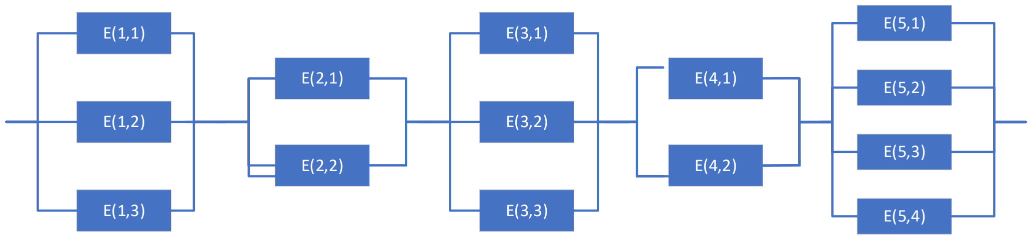

Fig. 7 System structure

Table 1 Example parameter table

Serial number	α	β	PM cost	PM time	CM cost	CM time	Operating time	IPM cost	IPM time
E11	1.5	250	476	1	952	1.5	110	158	0.5
E12	2.4	380	653	3	1306	4.5	150	217	1
E13	1.6	280	962	2	1924	3	170	320	1
E21	2.5	400	323	2	646	3	120	107	1
E22	1.5	280	185	3	370	4.5	180	61	1
E31	2.4	340	639	2	1278	3	100	213	1
E32	2.5	260	812	2	1624	3	130	270	1
E33	2	280	391	3	782	4.5	170	130	1
E41	1.2	260	672	1	1344	1.5	150	224	0.5
E42	1.4	350	188	1	376	1.5	120	62	0.5
E51	2.8	400	294	3	588	4.5	180	98	1
E52	1.5	350	297	1	594	1.5	130	99	0.5
E53	2.4	300	394	2	788	3	100	131	1
E54	2.2	450	712	1	1424	1.5	150	237	0.5

The running time of NSGA-II algorithm is 460 s, and the number of Pareto solutions is 500. The calculation results are shown in Fig. 8. The surface formed by the optimal set in space is called Pareto fronts. All solutions in Pareto front are not dominated by other solutions outside or within the Pareto front curve. Therefore, these non-dominated solutions have the least goal conflict than other solutions, which can provide a better choice space for decision makers. So, after calculation, the number of Pareto front solutions is 26.

The running time of NSGA-III algorithm is 474 s, and the number of Pareto solutions obtained is 496. The results of NSGA-III algorithm are shown in Fig. 9. After calculation, the number of Pareto front solutions is 19.

The Pareto optimal solution set obtained by the algorithm only provides the non-inferior solution of the problem to three objectives, and there is no single objective optimal. Therefore, it is necessary to select according to the expected degree of each objective of the decision maker. Assuming that the decision maker is most concerned about the probability of the system successfully completing the next phase of the task and the maintenance cost, the chromosome with the smallest maintenance cost can be selected from the solution set with the reliability of completing the next task greater than 0.85.

The maintenance scheduling decision scheme solved by NSGA-II algorithm is shown in Fig. 10. The equipment that performs maintenance is selected as E11, E12, E22, E31, E33 and E42. The maintenance level is preventive replacement, and the final maintenance cost is 3182. The probability of the system successfully completing the next task is 0.853. The shutdown maintenance time of the system is 5 days, and the number of maintenance personnel enabled is 1.

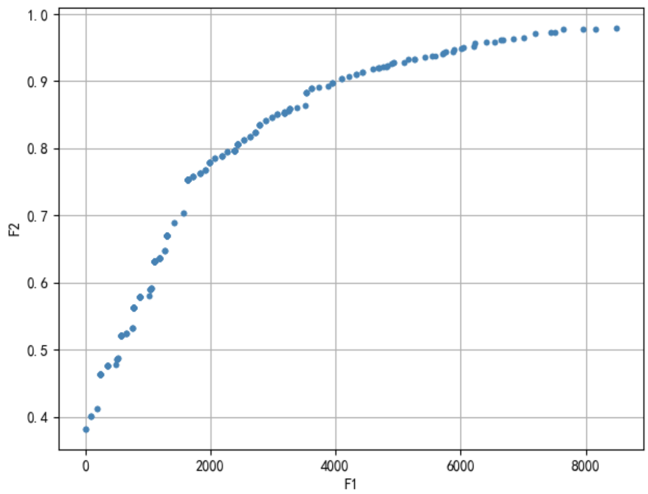

Fig. 8 NSGA-II algorithm results

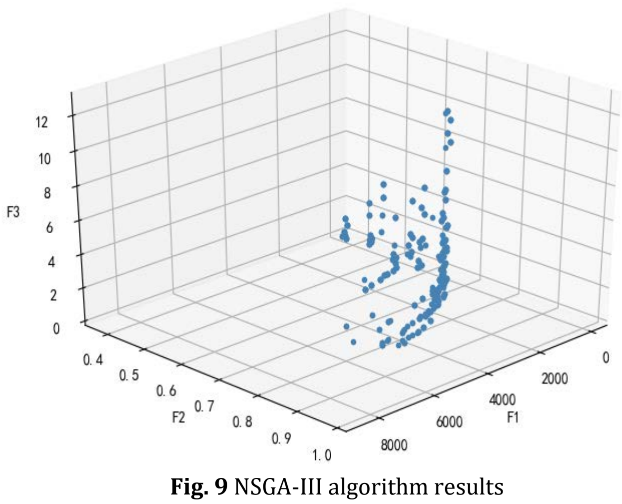

Fig. 9 NSGA-III algorithm results

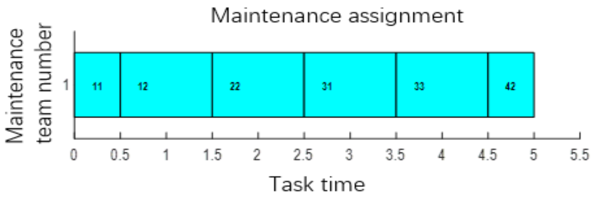

Fig. 10 NSGA-II algorithm maintenance scheduling scheme

The maintenance scheduling decision scheme solved by NSGA-III algorithm is shown in Fig. 11. The equipment that performs maintenance is selected as E11, E12, E22, E31, E33, E42, and E52. The machine E33 performs imperfect maintenance, and the other equipment performs preventive replacement maintenance. The final maintenance cost is 3168. The probability of the system successfully completing the next task is 0.850. The system shutdown maintenance time is 2 days, and the number of maintenance personnel enabled is 3.

The comparison of the two algorithms is shown in Fig. 12. It can be seen that when the maintenance cost is close to the probability of completing the next task, the downtime of the maintenance scheduling result solved by NSGA-III algorithm is less than that of NSGA-II algorithm.

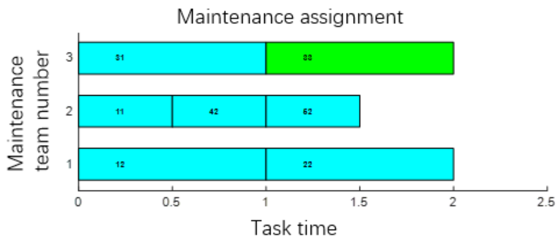

Fig. 11 NSGA-III algorithm maintenance scheduling scheme

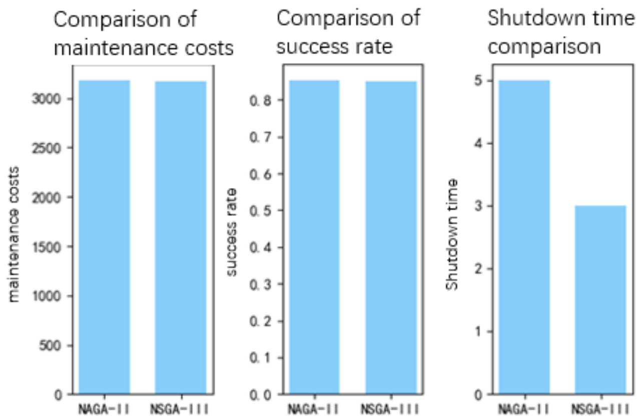

Fig. 12 Comparison of two algorithms

6. Conclusion

Aiming at the problems of selective maintenance for series-parallel systems, including simply assuming downtime and not considering resource maintenance dispatch, firstly, we establish a multi-objective selective maintenance model with the purpose of minimizing downtime, minimizing maintenance cost and maximizing the probability of completing the next task. Then, the genetic algorithm is selected to solve the model, and the coding method, crossover operator and mutation operator are designed in detail. Finally, in order to verify the effectiveness of the designed strategy, we design NSGA-II and NSGA-III algorithms with specific examples. These two algorithms are respectively used to solve the two objective maintenance decision-making model which only considers minimizing maintenance and maximizing the probability of the system completing the next task, and the three objective maintenance decision-making model which additionally considers minimizing the downtime of the system. By comparing the results of the two schemes, the decision-making scheme of NSGA-III is better than that of NSGA-II, which verifies that the three-objective decision-making model considering minimizing downtime can effectively reduce the downtime of the system.

Acknowledgement

This research is supported by Doctoral innovation fund of Xi'an University of Technology (No. 310-252072013), National Natural Science Foundation of China (Grant No. 52005404) and China Postdoctoral Science Foundation (No. 2020M673612XB).

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