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RESEARCH ARTICLE

An Integrated Flow Shop Scheduling Problem of Preventive Maintenance and Degradation With an Improved NSGA-II Algorithm

YANG LIU, XIAOFENG WANG, YUN ZHANG, AND LI LIU
School of Intelligent Manufacturing, Changchun Sci-Tech University, Changchun 130600, China
Corresponding author: Xiaofeng Wang (289799164@163.com)

ABSTRACT The main objective of this research is to establish and solve a scheduling model for the degraded flow shop taking completion time and average device idle time as optimization objectives. Therefore, considering the interaction among schedule, production, maintenance and degradation, a mathematical model with completion time as well as average device idle time is constructed. Based on the NSGA-II algorithm, a local search strategy is first proposed to obtain junction points and sparse points according to the non-dominated sorted results. Subsequently, the comparative experiments are conducted utilizing NSGA-II-ALS, NSGA-II, and PSO algorithms. The optimal solution sets and Pareto diagrams of the three algorithms are obtained. The Gantt charts of the optimal solutions are drawn. Eventually, the multi-objective evaluation indexes of each algorithm are calculated and compared. Using statistical experiments and analysis, it can be found that NSGA-II-ALS exhibit excellent performance compared with other algorithms. The scheduling model proposed in this paper is able to effectively coordinate and balance the relationship among production, equipment maintenance and degradation, thus improving the efficiency of manufacturing systems, saving production costs, and realizing the optimal utilization of resources.

INDEX TERMS Workshop scheduling, preventative maintenance, degeneration, multi-objective optimization, NSGA-II, pareto front.

I. INTRODUCTION

In actual production systems, with continuous operation of the manufacturing system, the equipment degradation and equipment failure are peculiarly prone to occur in the production and processing [1]. Therefore, it is necessary to carry out preventive maintenance on the equipment so as to reduce the failure rate and ensure the stable operation of the equipment [2]. Nonetheless, preventive maintenance activities will occupy the production time, which can lead to additional consumption of production resources. It can be seen that production scheduling, equipment degradation and equipment maintenance are interrelated. Thus, coordinating and balancing the relationship among production scheduling, equipment degradation, and equipment maintenance can be a way to improve the efficiency of the manufacturing system and effectively protect equipment, thus reducing production costs and realizing the optimal utilization of resources as well as energy can be achieved.

The actual machining time in the production process is not constant. More and more scholars have paid attention to the processing penalties caused by equipment performance degradation or processing delay. Some scholars have further studied the production scheduling model considering degradation effects. Alidaee and Womer [3] and Cheng et al. [4] provided detailed reviews of the production scheduling where the actual processing time is a linear or non-linear time function. Cheng and Ding [5] studied two linear formulas of processing time and successfully applied them to production scheduling. Besides, considering the limitations of single-function expression, some scholars began to apply piecewise functions to describe the degradation effects [6], [7], [8], [9].

Through combining with actual production, many scholars have studied the single-machine scheduling problems taking

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into account the effect of man-hour degradation [10], [11], [12]. As the actual production scheduling problem and single machine scheduling problem become increasingly complex, some scholars have studied the parallel machine scheduling problem thereupon accordingly. These parallel machine scheduling studies are modeled by minimizing a certain objective, including costs, completion time, delay time, waiting time, delayed processing times and so on [13], [14], [15], [16]. Cheng et al. [17] designed a variable neighborhood search operator during the process of solutions in view of the step degradation effect of parallel machines. Guo et al. [18] devised a cuckoo search algorithm for the purpose of dealing with the parallel machine scheduling problems given that the effect of working-hour degradation.

In the aforementioned researches, when studying the joint optimization of production and preventive maintenance, the researches mostly reckon that the processing time is fixed, or only consider the effect of equipment degradation on the processing time. However, there are few studies on the influence of equipment degradation on the maintenance time and maintenance period. To this end, aiming at the aforementioned problems and deficiencies, this paper considers the linear degradation models of machining time and preventive maintenance time are established respectively in terms of the influence of equipment degradation on machining time and preventive maintenance time. The failure function obeying Weibull distribution is applied to describe the degradation and failure of equipment. The reliability threshold value is used as constraints to perform preventive maintenance. Moreover, minimizing the completion time and minimizing the average idle time of equipment are used as joint optimization goals.

In recent years, the intelligent algorithm has developed rapidly and been widely used in engineering fields. In particular, the advantages of intelligent algorithms in dealing with multi-objective optimization problems are very distinct. Thus, intelligence algorithm has become a significant solution method for work shop scheduling with multi-objective optimization as the core [19], [20], [21], [22]. Musharavati and Hamouda [23] designed and utilized four simulated annealing algorithms so as to solve the process planning problems in reconfigurable manufacturing systems. Zarrouk et al. [24] proposed a bi-level particle swarm optimization algorithm for dealing with flexible job-shop scheduling. Azadeh et al. [25] put forward a stochastic scheduling algorithm for operating plants based on computer simulation and artificial neural network. Qin et al. [26], [27], [28] proposed a mathematical model of blocking constraints and designed a collaborative iterative greedy algorithm.

The genetic algorithm is a representative one of intelligence algorithms. Holland and Reitman [29] first created the Genetic Algorithm (GA), which adopted the theory of species evolution in biology to solve the job-shop scheduling problems in a randomized manner. The core of the algorithm is the description of ''survival of the fittest, elimination of the unfit'' in the theory of evolution. It is worth mentioning that Deb [30] proposed the Non-dominated Sorted Genetic Algorithm II (NSGA-II) algorithm based on NSGA, which uses a fast non-dominated sorted multi-objective optimization algorithm with an elite retention strategy. Owing to its low computational complexity, it is considered as a multi-objective optimization algorithm for Pareto optimal solutions. In recent years, several relevant scholars have carried out a great deal of research on the application of NSGA-II in flow shop scheduling [31], [32], [33], [34], [35]. To evaluate the effectiveness of the introduced mechanism, Basseur et al. [36] progressed a dynamic mutation Pareto Genetic Algorithm (GA), a combined diversification mechanism that integrates target space sharing and decision space sharing, and a hybrid algorithm that combines Pareto genetic algorithm and local search. In addition, they applied it to the flow shop scheduling. Seng et al. [37] proposed an improved NSGA-II for flexible job-shop, which reduced the no-load and total energy consumption. Hu et al. [38] proposed NSGA-II-EDSP, NSGA-II-KES, and NSGA-II-QKES heuristic rule algorithms to solve the problem of unbalanced workload of employees in parallel flow shop scheduling.

The present review of the above-mentioned literatures reveals that despite the increasing complexity of scheduling problems, NSGA-II is more suitable for finding efficient solutions or near-optimal solutions. Moreover, the NSGAII algorithm has been widely used to solve the job-shop scheduling problems because of its advantages, such as high efficiency to optimize the complex problems and the ability to gain widespread Pareto-optimal solutions [32]. Therefore, this paper chooses NSGA-II to solve the job-shop scheduling problem. However, the crowded distance exclusion mechanism adopted by NSGA-II to maintain population diversity has the defect of uneven distribution of Pareto optimal solution set. Besides, the crowded distance exclusion mechanism has high computational complexity. In this regard, an adaptive local search-based NSGA-II algorithm is propsed, which changes the search and sorted rules in the traditional NSGA-II algorithm, effectively maintains the diversity of the population and simplifies the computational complexity.

The main contributions of this research are as follows:

(1) Considering the influence of equipment degradation on machining time and preventive maintenance time, a linear degradation model of machining time and preventive maintenance time is established simultaneously.

(2) The scheduling model proposed in this paper can effectively coordinate and balance the relationship among production, equipment degradation and equipment maintenance, which can improve the efficiency of manufacturing system and save production costs.

(3) The local search strategy of NSGA-II-ALS approximates the Pareto front more effectively, while the uniformity of the solution distribution and the range of the solution distribution are improved.

(4) The boundary points and sparse points in NSGA-II-ALS can be obtained directly from the results of non-dominated sorting, without calculating density and gradient,

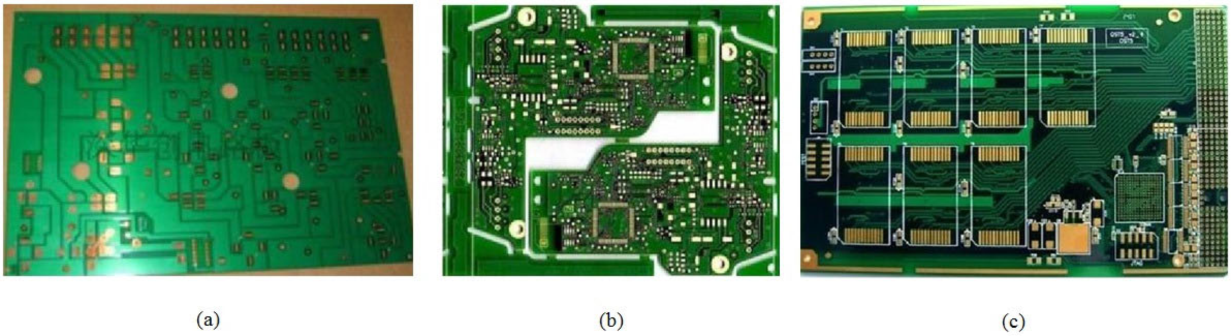

FIGURE 1. The types of workpieces (a) single layer board, (b) doubling layers board, (c) six layers board.

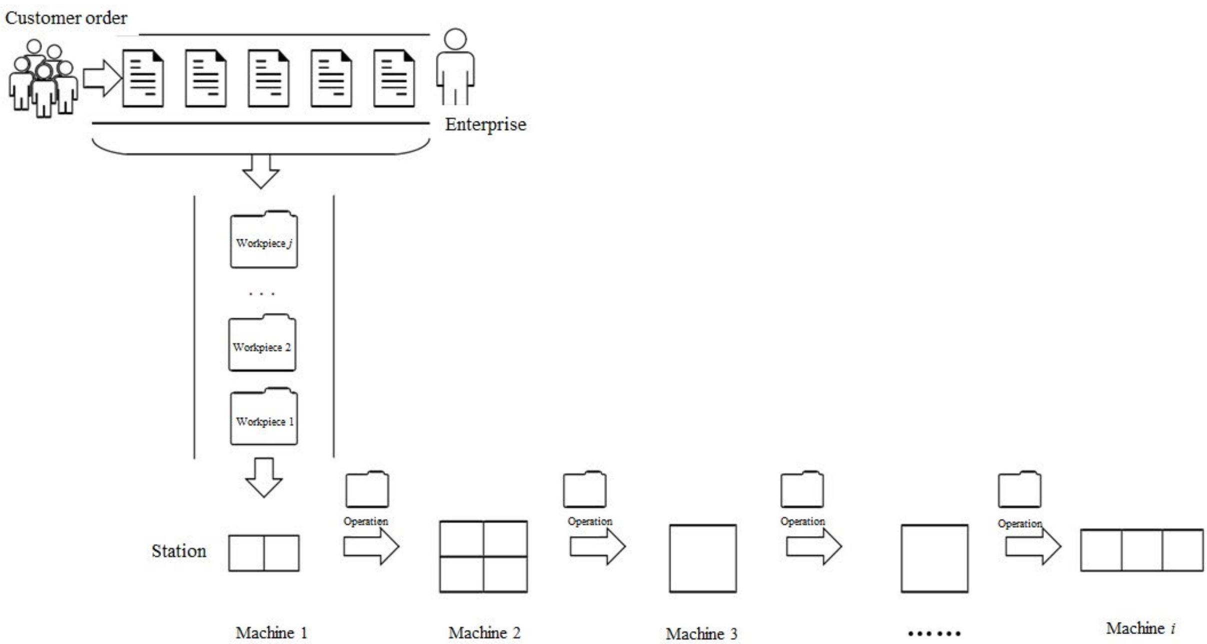

FIGURE 2. The schematic diagram of scheduling problem.

which leads to less calculated amount, more efficient solution and better search capability.

The remaining segments of this paper are organized as follows. In Section II, the flow shop scheduling problem is presented. The mathematical model that minimizes the completion time and the average equipment idle time is established. In Section 6, the reliability model and failure model of the equipment are clarified. The preventive maintenance theory and preventive strategy of workshop scheduling are introduced. The Section IV expounds the degradation model of workpiece processing time and preventive maintenance time. The estimation method of residual degradation coefficient of machining time is studied. In Section V, the application of NSGA-II and NSGA-II algorithm based on adaptive local search (NSGA-II-ALS) in flow shop scheduling is explained, and in Section VI, an experimental comparison and analysis is carried out using NSGA-II-ALS, NSGA-II, PSO with regard to flow shop scheduling problem. Finally, some concluding remarks are proposed in Section VII. The scheduling model displayed in this paper is able to improve the efficiency of manufacturing systems, save production costs, and realize the optimal utilization of resources.

II. PROBLEM DESCRIPTION

A. DESCRIPTION OF THE FLOWSHOP SCHEDULING PROBLEM

Printed circuit board (PCB) manufacturers accept personalized orders from customers. These orders can be divided into several types of workpiece operations, such as single-layer board, double-layer board, six-layer board, etc, as shown in Figure 1. Each operation corresponds to a machine, and these operations have different durations. The goal of scheduling is to minimize the total completion time of these jobs. The schematic diagram of this scheduling problem as sketched in Figure 2.

TABLE 1. Processing schedule.

Serial number of workpieces j	Processing time $p_{[k],i}$		
	M_1	M_2	M_3
1	6	8	6
2	7	5	7
3	5	5	8
4	4	4	5
5	5	6	4
6	8	6	7

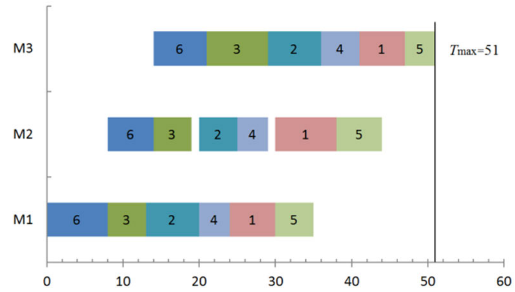

FIGURE 3. The scheduling gantt chart of example.

The flow shop scheduling problem studied in this paper is described as follows: during the scheduling period there are n workpieces $J = \{1, 2, 3, \ldots, n\}$, which are processed by m machines $M_1, M_2, \ldots, M_m$ in turn, the workpieces are processed in the same order on each machine, they can only be processed once on each machine, and each machine can only process one workpiece at the same time with infinite buffer space between the machines. The problem studied in this paper is based on the following assumptions: all workpieces are independent and can be machined at zero time; machining preparation time, minor repair preparation time and maintenance preparation time are not counted.

The following is an example of a flow shop. The scheduling target is the maximum completion time. All machines have the same sequence of workpieces and the scheduling target is the maximum completion time $T_{\max}$. There are three machines and six workpieces. The processing times of workpieces on each machine are shown in Table 1. The processing sequence is $\{6-3-2-4-1-5\}$. The scheduling Gantt chart for this problem is shown in Figure 3. The maximum completion time $T_{\max}$ is 51.

B. MATHEMATICAL MODEL

1) NOTATION DESCRIPTION

(1) Parameters

- n The number of workpieces.
- m The number of equipment.
- j Serial number of workpiece $j = \{1, 2, \ldots, n\}$.
- i Serial number of the equipment $i = \{1, 2, 3, \ldots, m\}$.
- k Serial number of the workpiece's position on the machine $k = \{1, 2, 3, \ldots n\}$.
- $p_{j,i}$ The processing time of workpiece j on machine i.
- $p^0_{[k],i}$ The standard processing time for the kth workpiece to be processed by machine i.
- tr Minor repair time after failure.
- tp^0 Standard preventive maintenance time.
- $\delta_{[k],i}$ The processing time degeneration factor for machine i when processing the kth workpiece.
- δ Basic processing time degeneration factor.
- γ Preventive maintenance time degeneration factor.
- R_L Critical value of reliability.
- t_L The service age of the equipment corresponding to the threshold reliability value.

(2) Decision variable

- $T_{[k],i}$ The completion time of the kth workpiece processed by equipment i.
- $S_{[k],i}$ The start time of the kth workpiece on equipment i.
- $S_{[1],i}$ The start time of the first workpiece on equipment $iS_{[1],1} = 0$.
- $p_{[k],i}$ The actual processing time of the kth workpiece on equipment i.
- $tp_{[k],i}$ The actual maintenance time for equipment i after processing the kth workpiece.
- $t_{[k],i}$ The service age after equipment i finishes processing the kth workpiece;$t_{[0],i} = 0$,the service age of all equipment before commencement is 0.
- $y_{[k],i}$ 0/1 preventive maintenance decision variable, if the equipment i is maintained after processing k workpiece, it is 1. Otherwise, it is 0.

2) MATHEMATICAL MODEL

$$F_1 = \min E(T_{[n],m}) \tag{1}$$

$$F_2 = \min \frac{1}{m}\sum_{i=1}^{m}\left(E(T_{[n],i}) - \sum_{k=1}^{n} p_{[k],i} - S_{[1],i}\right) \tag{2}$$

$$s.t: \ S_{[1],i} = E(T_{[1],i-1}),\ i = 2, \ldots, m \tag{3}$$

$$E\left(T_{[1],i}\right) = S_{[1],i} + p_{[1],i} + tr\left[u\left(t_{[1],i}\right) - u(0)\right],\ i = 1, \ldots, m \tag{4}$$

$$S_{[k],1} = E\left(T_{[k-1],1}\right) + y_{[k-1],1} tp^0,\ k = 2, \ldots, n \tag{5}$$

$$E\left(T_{[k],1}\right) = S_{[k],1} + p_{[k],1} + tr\left[u\left(t_{[k],1}\right) - u\left(t_{[k-1],1}\right)\right],\quad k = 2, \ldots, n \tag{6}$$

$$S_{[k],i} = \max\left[E\left(T_{[k-1],i}\right) + y_{[k-1],i} \cdot tp_{[k-1],i}, E\left(T_{[k],i-1}\right)\right],\ k = 2, \ldots, m;\ i = 2, \ldots, n \tag{7}$$

$$E\left(T_{[k],i}\right) = S_{[k],i} + p_{[k],i} + tr\left[u\left(t_{[k],i}\right) - u\left(t_{[k-1],i}\right)\right],\ k = 2, \ldots, m;\ i = 2, \ldots, n \tag{8}$$

$$t_{[k],i} = t_{[k-1],i}\left(1 - y_{[k-1],i}\right) + p_{[k],i}, \times k = 1, \ldots, m; i = 1, \ldots, n \quad (9)$$

$$y_{[k-1],i} = \begin{cases} 1 & t_{[k-1],i} + p_{[k],i} \geq t_L \\ 0 & t_{[k-1],i} + p_{[k],i} < t_L \end{cases} \quad (10)$$

Equation (1) indicates that the optimization objective is to minimize the maximum completion time. It is meant to minimize the expected completion time of the last workpiece processed on the last equipment. Equation (2) indicates that the optimization objective is minimize the average idle time of the equipment, and the idle time of the equipment is the time that the equipment does not process the workpiece from the start time to the completion time. Equation (3) indicates that any equipment the start time of the first position workpiece. Equation (4) represents the expected completion time of the first workpiece processed on any equipment. Equation (5) represents the start time of the workpiece processed at any location on the first equipment. Equation (6) represents the expected completion time of the workpiece processed at any location on the first equipment. Equation (7) represents the start time of the workpiece processed at any location on any equipment. Equation (8) represents the completion time of the workpiece processed at any location on any equipment. Equation (9) represents the equipment's service life as the accumulation of the processing time, but after preventive maintenance the service life goes to zero. Equation (10) represents the preventive maintenance strategy. Whether equipment i performs preventive maintenance after processing the k-1th workpiece depends on the equipment service age at the completion of the kth workpiece. If the equipment service age at the completion of the kth workpiece is greater than or equal to the equipment service age corresponding to R_L, then $y_{[k-1],i} = 1$, perform preventive maintenance. Otherwise $y_{[k-1],i} = 0$, process the next workpiece without preventive maintenance.

III. RELIABILITY AND PREVENTIVE MAINTAINABILITY OF EQUIPMENT

A. EQUIPMENT RELIABILITY

Reliability is defined as the ability of a product to perform a specified function under specified conditions and within a specified period of time. The reliability of general mechanical products follows two-parameter Weibull distribution.

The failure rate function of the two-parameter Weibull distribution is as follows.

$$f(t) = \frac{\beta}{\alpha}\left(\frac{t}{\alpha}\right)^{\beta-1} \exp\left[-\left(\frac{t}{\alpha}\right)^{\beta}\right], t \geq 0 \quad (11)$$

where, β is the shape parameter of the Weibull distribution, $\beta > 0$; α is the size parameter, $\alpha > 0$.

The cumulative failure distribution function.

$$F(t) = 1 - \exp\left[-\left(\frac{t}{\alpha}\right)^{\beta}\right], t \geq 0 \quad (12)$$

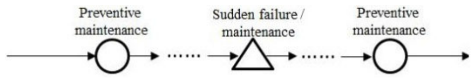

FIGURE 4. The sequence relationship diagram of the breakdown maintenance strategy.

B. RANDOM FAILURE

Random failures may occur during the working cycle of the equipment. Random failures are concentrated in the random failures period of the equipment, which is uncertain and makes it difficult to accurately predict the moment of failure. The uncertainty of the equipment can be reasonably described by the integral of the probability and statistics failure rate function over the dispatch period as the expected number of failures, where the failure rate function is expressed as λ(t).

$$\lambda(t) = \frac{f(t)}{1 - F(t)} = \frac{\beta}{\alpha}\left(\frac{t}{\alpha}\right)^{\beta-1} \quad (13)$$

$u(t)$ is the expected number of failures occurring in $0 \sim t$.

$$u(t) = \int_0^t \lambda(x)dx = \int_0^t \frac{\beta}{\alpha}\left(\frac{x}{\alpha}\right)^{\beta-1} dx = \left(\frac{t}{\alpha}\right)^{\beta} \quad (14)$$

$E(N)$ is the expected number of failures of the equipment during preventive maintenance cycles $t_1 \sim t_2$.

$$E(N) = \int_{t_1}^{t_2} \lambda(t)dt = u(t_1) - u(t_2) = \left(\frac{t_2}{\alpha}\right)^{\beta} - \left(\frac{t_1}{\alpha}\right)^{\beta} \quad (15)$$

C. PREVENTIVE MAINTENANCE

Preventive maintenance (PM) is defined as the operation of detection and maintaining equipment before the failure. Thus reduce the probability of accidents and ensure the efficient and stable operation of the equipment. Time-based preventive maintenance is to perform preventive maintenance on a device when the accumulated running time reaches a certain level. According to different maintenance periods, preventive maintenance can be divided into fixed period preventive maintenance and variable period preventive maintenance

This paper focuses on the time-based variable period preventive maintenance. The sequence relationship diagram of the breakdown maintenance strategy is shown in Figure 4. It can be seen that several preventive maintenances are required during the life cycle. If random failure occurs, a breakdown maintenance is carried out immediately after the random failure.

1) PREVENTIVE MAINTENANCE STRATEGY

For production scheduling system, when to carry out maintenance is a vital concern to ensure the stable operation of equipment and reduce production resources. If there are too many maintenance steps during the processing of the equipment, the maintenance period will preempt the processing time of the workpiece, therby leading to the delay of the completion of the task. Whereas, if there are too few maintenance

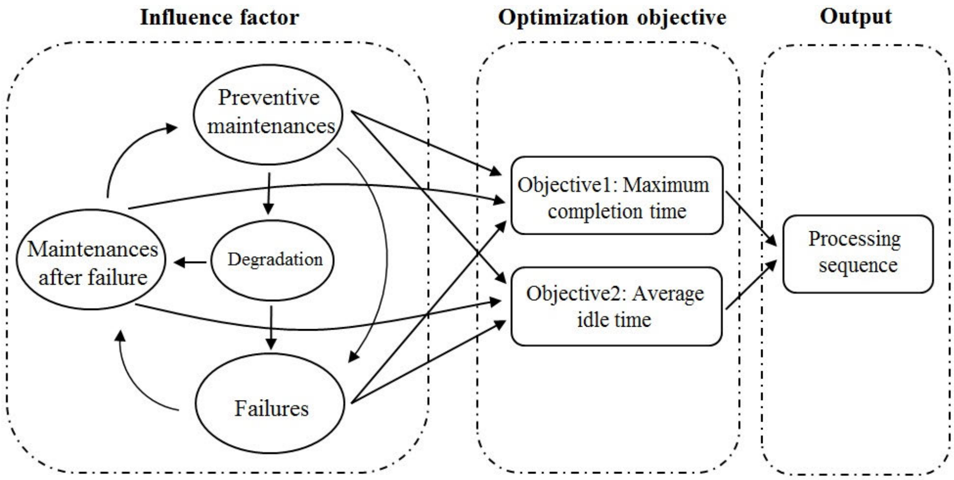

FIGURE 5. Diagram of relationship between influencing factors and scheduling.

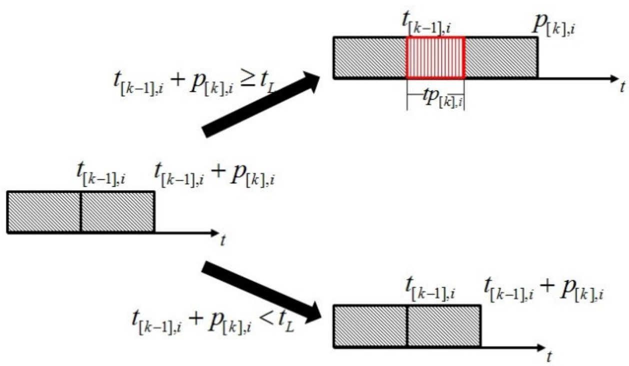

FIGURE 6. The diagram of preventive maintenance strateg.

steps, due to the accumulation of service time, the equipment will degraded seriously and failures will occur frequently during the machining process so that the project cannot be accomplished as planned. There are complex interactions among production, maintenance, preventive maintenance and degradation, where the correlation diagram among factors is shown in Figure 5. Therefore, scientific and reasonable maintenance strategy is indispensable in production scheduling.

In this paper, the reliability of equipment is taken as a limit condition for preventive maintenance. When the equipment finishes the current processing, the current reliability of equipment is compared with the critical value of reliability as a basis for whether to carry out preventive maintenance steps. In order to display the maintenance decision method, the schematic diagram of preventive maintenance strategy is drawn, as shown in Figure 6.

The precomputation of service age $t_{[k],i}$ of the equipment is carried out, when the kth workpiece is completed. $t_{[k],i} = t_{[k-1],i} + p_{[k],i}$. If $t_{[k],i} < t_L$, then $y_{[k-1],i} = 0$, preventive maintenance is not inserted, the next workpiece is processed directly. If $t_{[k],i} > t_L$, then $y_{[k-1],i} = 1$, preventive maintenance is inserted, after k-1th workpiece is processed by equipment i, the specific preventive maintenance time is $tp_{[k],i}$. After preventive maintenance, the service age of the equipment is zero, and then the next workpiece is inserted.

IV. EQUIPMENT DEGRADATION MODEL

In reality, as the time increases, the equipment itself degrades in performance. This paper focuses on the impact of equipment degradation on processing time, preventive maintenance cycle and preventive maintenance time. The linear degradation models of processing time and preventive maintenance time are established.

A. DEGRADATION MODEL OF PROCESSING TIME

1) LINEAR DEGRADATION MODEL OF PROCESSING TIME

The equipment degrades during the scheduling period within the scheduling cycle, relative degradation of component functions. Such as passivation of machining tools can lead to an increase in the actual processing time of the equipment. The greater the age of the equipment at the time the workpiece is processed, the greater the effect on the degradation of the machining time. In this paper, the following expression for the machining time degradation function is given on the basis of the standard machining time:

$$p_{[k],i} = p^0_{[k],i} + \eta t_{[k-1],i} \tag{16}$$

where, $p_{[k],i}$ is the actual machining time of equipment i at the k workpiece; $p^0_{[k],i}$ is the standard machining time; $t_{[k-1],i}$ is the service life of equipment i after machining the $k-1$ workpieces; η is the residual degradation coefficient of the equipment machining time.

2) RESIDUAL DEGRADATION COEFFICIENT OF MACHINING TIME

Let the residual degradation of processing time is $X = \{x_1, x_2, \cdots x_n\}$ after the n times preventive maintenance. According to Equation (16), the residual degradation coefficient of machining time after the j times preventive maintenances is

$$\eta_j = x_j / t_{[k-1]} \tag{17}$$

where, η_j is residual degradation coefficient after j maintenance and $\eta_j \sim N(1-\exp(-aj), b)$.

Based on measurement, residual degradation coefficient of machining time is $\eta = \{\eta_1, \eta_2, \cdots \eta_n\}$. Furthermore, the maximum likelihood estimation method can be used to estimate parameters a and b. The likelihood function can be expressed as follow.

$$L(a, b) = \left(\frac{1}{\sqrt{2\pi b}}\right)^n \prod_{j=1}^{n} \exp\left(-\frac{(\eta_j - (1-e^{-aj}))^2}{2b}\right) \tag{18}$$

Take the log of equation (18).

$$\ln L(a, b) = -\frac{n}{2}\ln 2\pi - \frac{n}{2}\ln b - \frac{\sum_{j=1}^{n}(\eta_i - (1-e^{-aj}))^2}{2b} \tag{19}$$

The partial derivative of equation (19) with respect to b.

$$\frac{\partial \ln L}{\partial b} = -\frac{n}{2b} + \frac{\sum_{j=1}^{n}(\eta_i - (1-e^{-aj}))^2}{2b^2} \tag{20}$$

Let the above formula be equal to 0.

$$b = -\frac{1}{n}\sum_{j=1}^{n}(\eta_i - (1-e^{-aj}))^2 \tag{21}$$

By substituting Equation (21) into Equation (19), a logarithmic likelihood function only about a can be obtained.

$$\ln L(a) = -\frac{n}{2}\ln 2\pi + \frac{n}{2}\ln\left(n\sum_{j=1}^{n}(\eta_i - (1-e^{-aj}))^2\right) + \frac{n}{2} \tag{22}$$

Maximizing $\ln L(a)$, The maximum likelihood estimate of parameter a can be obtained. According to the properties of normal distribution, the expected residual degradation coefficient of machining time can be expressed as.

$$E(\eta_j) = 1 - \exp(-aj) \tag{23}$$

B. DEGRADATION MODEL OF PREVENTIVE MAINTENANCE TIME

With the increase of the service age of the equipment, the failure rate increases and the reliability decreases gradually. Therefore, preventive maintenance activities should be carried out before equipment reliability reduced to a set reliability threshold. Preventive maintenance time varies with the service age of the equipment, the damage degree of the equipment. Referring to linear degradation of processing time, maintenance time is an increasing function of equipment service age, expressed as follows.

$$tp_{[k],i} = tp^0 + \gamma t_{[k-1],i} \tag{24}$$

where, $tp_{[k],i}$ is the actual maintenance time of equipment i after processing the kth workpiece; tp^0 is the standard maintenance time; γ is maintain time degradation factors.

V. PROPOSED GENETIC ALGORITHM

A. NSGA-II

The non-dominated Sorting Genetic Algorithm (NSGA) solve multi-objective problems using a small habitat density comparison operator, but it requires users to define their own shared radius and has a high time complexity. So, Deb et al. addressed the shortcomings of NSGA and designed NSGA-II, which uses the crowdedness comparison operator instead of the original small habitat sharing density. NSGA-II improved the operability of the algorithm.

1) CODING SCHEME

This paper involves two parts: the production order of the workpieces and the maintenance of the equipment. The production part uses an integer code of (1∼n) to represent the processing order of the workpieces. Since the replacement shop scheduling problem is characterised by the fact that all workpieces pass through each machine in the same order, the production order is coded the same on all machines. 1∼n non-repeating integer sequence is randomly generated, this sequence represents the workpiece processing order on the equipments. Take the workpiece processing sequence 2-4-1-7-3-5-6 as an example, represent as $P = 2\ 4\ 1\ 7\ 3\ 5$.

Preventive maintenance decision matrix is used to represent the location of preventive maintenance. The maintenance of a flow shop with n workpieces and m equipment can be represented by the 0/1 matrix D_{pm} of $m \times n$.

$$D_{pm} = \begin{bmatrix} y_{1,1} \cdots & y_{k,1} \cdots & y_{n,1} \\ \cdots & \cdots & \cdots \\ y_{1,i} \cdots & y_{k,i} \cdots & y_{n,i} \\ \cdots & \cdots & \cdots \\ y_{1,m} \cdots & y_{k,m} \cdots & y_{n,m} \end{bmatrix} \tag{25}$$

The decision variables are all initialised to zero. Determine the processing sequence of the workpiece on the equipment in accordance with the process chromosome. According to Equation (9), calculates the service age of the equipment. According to Equation (10), decision whether to perform preventive. The preventive maintenance matrix is finally generated.

2) INITIAL SOLUTION GENERATION

Considering the characteristics of the same processing order of workpieces on each equipment in the flow shop, the initial solution generation is done by random generation. The random generation can make the solution distributed in the target space as uniformly as possible and expand the search range. A random sequence of 1∼n random integers of a certain size

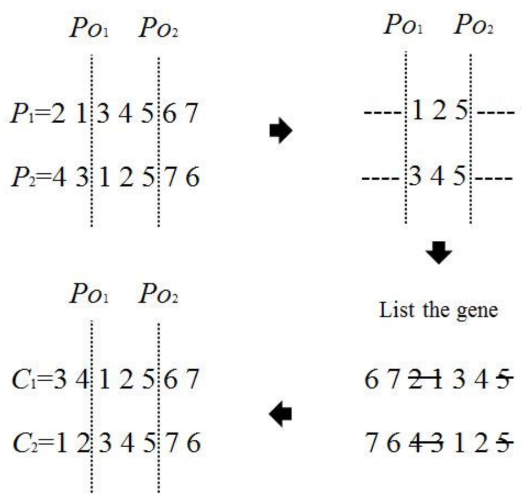

FIGURE 7. The flow of NSGA-II algorithm.

without repetition is generated to represent the initial population. Any random sequence represents the individuals within the population and participates in the competitive selection process.

3) CROSSOVER AND MUTATION

Crossover and mutation are the basic ways in which genetic algorithms generate a large number of diverse solutions. Crossover is the process of re-generating two completely new chromosomes from two segments of chromosomes in a certain crossover pattern, where the chromosomal characteristics of the previous generation are retained to some extent. For the flow shop scheduling problem, Order Crossover (OX) can better preserve the sequential position relationship of workpiece processing and ensure the generation of feasible solutions, so the crossover method uses OX.

As an example of a sequential crossover of seven workpieces, the steps are as follows:

(1) Select the entry points Po_1, Po_2

(2) Exchange the middle part.

(3) List the original order from the first gene after the second cut point Po_2 and remove the existing genes.

(4) Starting from the first position after the second cut point Po_2 fill in the obtained repeat-free order.

The above steps can be illustrated in Figure 7.

Exchange Mutation (EM) is used for mutation. The EM principle is that two gene locations are randomly selected on a chromosome and exchanged to form a new chromosome.

4) SELECTION OPERATIONS BASED ON NON-DOMINATED SORTING AND CROWDING

In contrast to GA, NSGA-II can be thought of as replacing the fitness selection step of traditional genetic algorithms with a nondominated sorting and crowding degree operator. Before selection, all individuals in the population are subjected to a fast non-dominance ranking, and the ranked individuals have

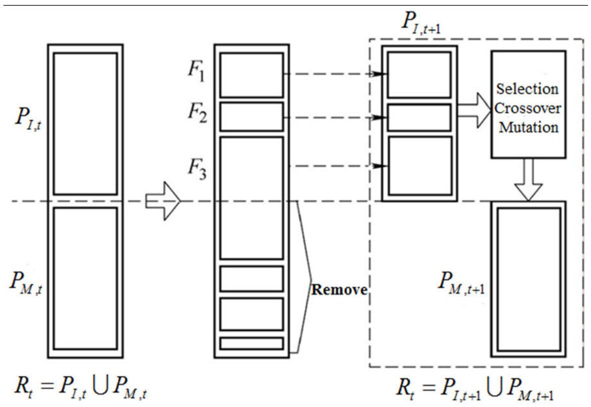

FIGURE 8. The flow of NSGA-II algorithm.

a rank level. The individuals are then stratified according to the rank level, with a smaller rank representing a lower number of dominated individuals in that stratum. In this way, all individuals in the population are given both rank and distance, and individuals with a high rank are selected in preference to those with a high degree of crowding. In this way, a multi-objective selection optimization method is achieved.

5) NSGA-II ALGORITHM EXECUTION FLOW

The traditional NSGA-II algorithm uses an implicit elite solution retention strategy. First a combined population $R_t = P_{I,t} \cup P_{M,t}$ is generated, where $P_{I,t}$, $P_{M,t}$ are the parent and offspring populations respectively, and the number of R_t is 2N; The population R_t is then sorted according to the partial order relationship until the number of individuals reaches N to form a new parent population $P_{I,t+1}$, on the basis of which genetic operations are carried out to produce the offspring population $P_{M,t+1}$, The flow of the NSGA-II implementation is shown in Figure 8. Algorithm 1 presents the main steps of NSGA-II.

Algorithm 1 NSGA-II Procedure

1: input data
2: initialise Population Size, Number of iterations
3: randomize *parentpopulation*$P_{I,t}$
4: **for** t = 1 :Number of iterations
5: non-dominated sorting$R_t$until the number reaches Population Size and
form a new parent population $P_{I,t+1}$
6: generate childpopulation $P_{M,t+1}$from $P_{I,t+1}$using: order crossover and exchange mutation
7: $R_{t+1} = P_{I,t+1} \cup P_{M,t+1}$
8: **end**
9: **return**$P_{I,t}$

B. NSGA-II ALGORITHM BASED ON ADAPTIVE LOCAL SEARCH

In this paper, NSGA-II algorithm based on adaptive local search (NSGA-II-ALS) is proposed to address the computationally intensive issue of NSGA-II. Firstly, all the current populations are sorted non-dominantly, and the junction points and sparse points are obtained according to the sorted results, which are defined as the junction region and sparse region center. Secondly, the local search is conducted around the junction and sparse points. NSGA-II-ALS algorithm has the advantages of outstanding convergence speed and excellent solution quality because of the extreme optimization and random search strategies.

1) REGIONAL CENTER

In the traditional local search, the center is determined by clustering and density calculation, and the Euclidean distance between any two solutions needs to be calculated, which increases the computational effort of the algorithm. Therefore, in this paper, the center of the search region can be directly obtained by non-dominated sorting and crowded distance sorting, both of which are inherent steps of the NSGA-II algorithm. This search area center method does not increase computational complexity.

The specific method of obtaining the regional center is as follows. The number of objective functions is m. The level 1 non-dominated solution set P_1 is the non-dominated solution set of the current population. The number of boundary points is equal to the number of objective functions. The crowding distance of the first m individuals in the population P_1 is infinite, and the crowding distance of the $(m+1)$ th individual is the largest point except the boundary point. The density of solutions around the $(m+1)$ th individual is the lowest. Therefore, the first m individuals in P_1 are boundary points, and the $(m+1)$ th individual is a sparse point, corresponding to m boundary regional centers and one sparse regional center.

The local search of this paper focuses on the boundary points and the sparse points. The boundary point is the maximum value or the minimum value in in the direction of at least one target vector, so the search centered on the boundary points is a measure to ensure the distribution range of population. The crowding distance of the sparse point is the lowest, and the solutions around the sparse point is the sparsest. The local search around the sparse point can increase the uniformity of population distribution, so it makes sense to focus on boundary points and sparse points with the smallest crowding distance in this paper.

Taking the two-objective optimization problem as an example, Figure 9 depicts the population evolution process of NSGA-II-ALS algorithm.

2) LOCAL SEARCH

After setting the boundary point and sparse point, NSGA-II-ALS uses two mutation strategies to generate local solutions simultaneously, firstly, the limit optimization strategy is used to generate new populations, and the limit optimization mutation method changes only one controlled variable of solution for each local solution when generating local solutions. The limit optimization strategy improves the local search ability when the population is close to the Pareto optimal solution, and effectively improves the accuracy of the solution. The specific method as follows: let the central solution of the currently searched region be $X = (x_1, x_2, \cdots, x_n)$, n is the number of decision variables, and the total number of populations be N. Then the number of local solutions is generated as n. The variation formula of local solutions is as follows.

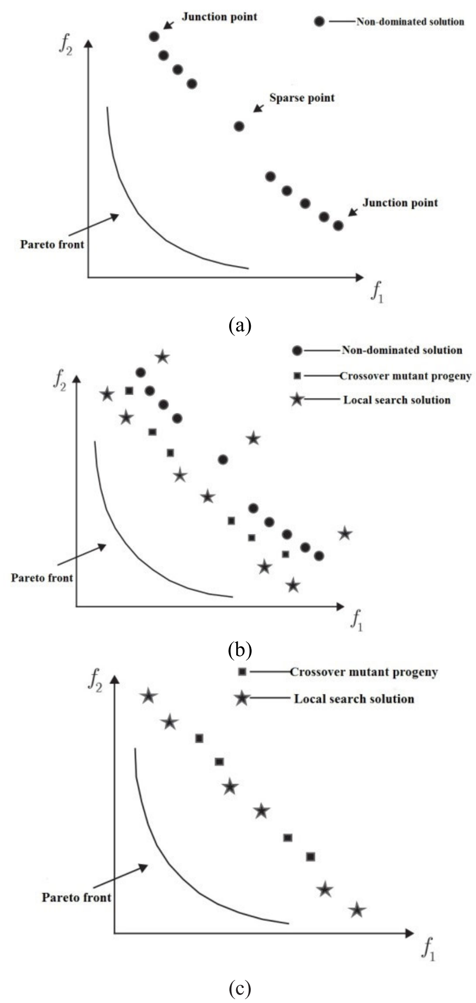

FIGURE 9. Population evolution process diagram of NSGA II-ALS algorithm (a) The population of generation t and its boundary points and sparse points, (b) The offspring generated by crossover, mutation and local search, (c) Obtained the t+1 generation population by non-dominated sorting and crowded distance sorting.

$$X_i = (x_1, \cdots, x_i', \cdots, x_n), \ 0 < i \le n \tag{26}$$

$$x_i' = x_i + \alpha \cdot \beta_{\max}(x_i), \quad 0 < i \le n \tag{27}$$

$$\alpha = \begin{cases} (2h)^{(1/(q+1))} - 1 \\ 1 - [2(1-h)]^{(1/(q+1))} \end{cases} \tag{28}$$

$$\beta_{\max}(x_i) = \max[x_i - l_i, u_i - x_i], \quad 0 < i \le n \tag{29}$$

where, x_i is the decision variable; h is a random number between 0 and 1; q is a positive real number, called the shape parameter, and in this paper q is taken as 11. l_i is the lower bound of the i th controlled variable; u_i is the upper bound of the i th controlled variable. $\beta_{\max}(x_i)$ is the maximum changed range for x_i. The limit optimization variation method changes only one controlled variable at a time, which has a strong fine-tuning capability but a small search range.

In order to increase the convergence speed of the algorithm, while using the second mutation strategy, let the central solution of the current search region be $X = (x_1, x_2, \cdots, x_n)$, n is the number of controlled variables, and the total number of populations be N. The number of local solutions generated is 20% of the total number of populations (rounded if not divisible). The mutation formula is follow.

$$X_k^j = (x_1, \cdots, x_i', \cdots, x_n) \quad (30)$$

$$x_k' = rand(\gamma)x_k, \quad k = 1, 2, \cdots, [0.2N];$$
$$j = 1, 2, \cdots, [0.2N/n] \quad (31)$$

where, γ is the search range parameter, which is used to determine the size of the search range; $rand(\gamma)$ denotes the random number of values between $(0, \gamma)$, and in this paper γ =1.2. The above mutation strategy generates $(m + 1)(n + [0.2N])$ local solutions, and m is the number of objective functions.

3) NSGA-II-ALS ALGORITHM FLOW

The parameters of the algorithm are set according to the actual MOP problem: the initial population size is N. Maximum optimization time $T_{\max}$;The number of decision vector dimensions n; the upper and lower bounds $u = (u_1, u_2, \cdots, u_n)$ and $l = (l_1, l_2, \cdots, l_n)$;Number of objective functions m; shape parameter q; crossover probability p_c and mutation probability p_m; crossover parameter η_c and mutation parameter η_m. The specific algorithm flow of NSGA II-ALS is as follows.

Step 1. Randomly initialize the population $P_I = \{X^1, X^2, \cdots, X^N\}$ in the range of values, Among them, $X^i = (x_1', x_2', \cdots, x_n')$, i =1,2,…,n.

Step 2. Sort P_I by non-dominated, crowded distance, and all non-dominated solutions in the current population are recorded as P_C, Determine the junction region center and sparse region center based on the sorting results.

Step 3. Cross mutation of populations in P_I according to the standard NSGA-II algorithm to form offspring P_M.

Step 4. A local search around the junction center and the sparse region center generates a total of $(m + 1)(n + [0.2N])$ local solutions, and the set is set as the population P_N.

Step 5. Combine P_I, P_M and P_N and rank all solutions in terms of non-dominated, congestion distance, from which the optimal N solutions are selected to form the next generation population P_O, and set $P_I = P_O$.

Step 6. Repeat steps 2-5 and proceed to step 7 when the maximum optimization time $T_{\max}$ or target accuracy is reached.

Step 7. The current non-dominated solution in is the obtained optimal solution.

The specific algorithm flowchart of NSGA-II-ALS is shown in Figure 10.

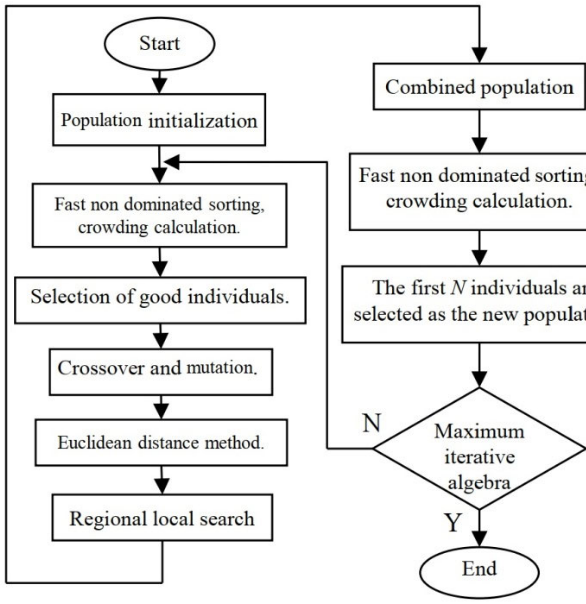

FIGURE 10. The flow chart of NSGA-II-ALS algorithm.

Algorithm 2 presents the main steps of NSGA-II -ALS.

Algorithm 2 NSGA-II-ALS Procedure

1: input data
2: initialise Population Size, Number of iterations
3: randomize $parentpopulationP_{I,t}$
4: **for** $t = 1$:Number of iterations
5: $P_C =$ non-dominated sorting($P_{I,t}$)
6: Determine the junction region center and sparse region center by P_C
7: generate childpopulation P_M from P_I using: order crossover and
exchange mutation
8: Apply local search around the junction
center and the sparse region center, generates local solutionsP_N
9: $P_O =$ non-dominated sorting $(P_I \cup P_M \cup P_N)$
10: $P_I = P_O$ (1: Population Size, :)
11: **end**
12: **return** P_I

Compared with other improved NSGA-II algorithms, the NSGA-II-ALS algorithm only performs local search in the boundary and sparse regions, which is significantly less computationally intensive and can ensure the convergence speed and population distribution of the algorithm; two local search strategies are used to make the algorithm have better search efficiency in both the early and late stages of the search; the local search method proposed in this paper does not need to know the Pareto front in advance, and requires fewer parameters to be set, which meets the requirements of practical engineering applications.

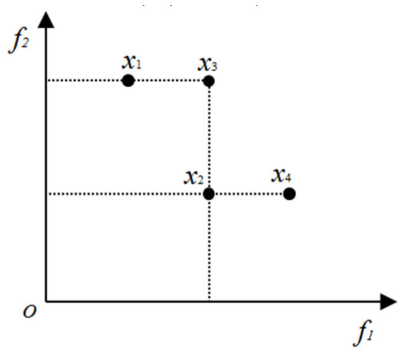

FIGURE 11. **Dual objective Pareto dominance relationship.**

C. MULTI-OBJECTIVE OPTIMIZATION

1) MULTI-OBJECTIVE OPTIMIZATION

In reality, engineering and economic fields both contain multi-objective optimization problems. Multi-objective optimization refers to the simultaneous optimization of multiple objectives. These objectives may be conflicting or coupled, and optimizing one of them may lead to the deterioration of other objectives, so all objectives must be optimized in a coordinated manner. Such kind of problem is called a Multi-objective Optimization Problem (MOP), which cannot find a solution that makes multiple objectives satisfy the maximum or minimum values at the same time, but finds a compromise solutions set that considers multiple objectives. The solution set is called the Pareto front. As the number of objectives increases, the solution will also become more difficult.

The concept of multi-objective optimization is as follows

Definition 1 (Pareto Dominance): for any two decision variables x_1 and x_2.

(1) x_1 dominates b: $x_1 \prec x_2$, if and only if $\forall i = \{1, 2, \ldots, k\}$, make $f_i(x_1) \leq f_i(x_2)$(x_1 is not worse than x_2 in all sub-objectives) and $\exists i = \{1, 2, \ldots, k\}$, make $f_i(x_1) < f_i(x_2)$(there exists at least one sub-objective such that a is better than b).

(2) x_1 no difference from x_2: $x_1 \sim x_2$, if and only if $x_1 \not\prec x_2$ and $x_2 \not\prec x_1$.

If there is a pareto dominance relationship between decision vectors x_1 and x_2, then all objective function values of decision vector x_1 are less than or equal to the respective objective function values corresponding to decision variable b.

Definition 2 (Pareto Optimal Solution): controlled variable $x_1 \in X_f$ is said to be the Pareto optimal solution. if and only if $\nexists x_2 \in X_f : \ x_2 \prec x_1$.

Definition 3 (Pareto Optimal Set): the set of all Pareto optimal solutions POS= $\{x_1 \mid \nexists x_2 \prec x_1\}$.

In Figure 11, the solutions x_1 and x_3 have $f_2(x_1) = f_2(x_3)$, but $f_1(x_1) < f_1(x_3)$, so $x_1 \prec x_3$. Similarly, it follows that $x_2 \prec x_4$. But the solutions x_1 and x_2, $f_1(x_1) < f_1(x_2)$, $f_2(x_2) < f_2(x_1)$, these two cannot determine the dominance relationship, they are in the same dominance layer. If there are no solutions in the target space that can dominate x_1 and x_2, then the layer of x_1 and x_2 becomes a non-dominance layer.

2) EVALUATION INDEX FOR MULTI-OBJECTIVE OPTIMIZATION ALGORITHMS

The optimization process of multi-objective optimization algorithm can be regarded as the continuous approach to Pareto front. The optimal front is found by iterative search. However, only the approximate solutions can be found because the optimal front solution is difficult to determine.

Coupled with that in most cases, the approximate solutions found by different algorithms cannot form a clear demarcation, and the dominance relationship cannot be identified. Thus, it is impossible to compare the merits of the algorithms. To this end, the uniformity and the extensiveness of the distribution should be reflected in the evaluation of solution set. For the uniformity of the solution distribution, this paper uses the spacing distribution degree assessment index which has been proposed by Scoot to represent the uniformity of the solution set in the target space. The spacing distribution degree calculation function is as follows.

$$SD = \sqrt{\frac{1}{N-1}\sum_{g=1}^{N}(\bar{d} - d_g)^2} \tag{32}$$

$$d_g = \min_h(\left|f_1(s_g) - f_1(s_h)\right| + \left|f_2(s_g) - f_2(s_h)\right|) \tag{33}$$

where, SD denotes the spacing distribution between adjacent solutions in the Pareto front solution set. N is the number of solutions on the Pareto front, and s_h is an arbitrary solution on the Pareto front, $g, h = 1, 2, 3\ldots, N$. d_g is the Manhattan distance, which means the nearest distance between any solution s_g and s_h except s_g. $\bar{d}$ is the average value. The smaller SD, the closer the resulting solution is to a uniform distribution.

For the extensive degree of the distribution of the Pareto solutions. spread scope (SS) index which is proposed by Zitzler is used in this paper. SS represents the distance between two extreme solutions in the solution space. The larger SS, the wider the spread of the resulting solution and the larger the search space. The formula is as follows:

$$SS = \sqrt{(\max f_1 - \min f_1)^2 + (\max f_2 - \min f_2)^2} \tag{34}$$

where, max / minf_i is the maximum or minimum of the i th objective value in the Pareto front.

VI. EXPERIMENTAL RESULTS

In order to test the feasibility and effectiveness of the algorithm in this paper, NSGA-II-ALS was compared with several other genetic algorithms in experiments to analyze the performance of multiple groups of different algorithms. The specific experimental parameters are as follows:

The minor repair time tr=5min, the standard preventive maintenance time tp^0 =15min, reliability threshold values R_L =0.8, Weibull shape parameter β =2, Weibull dimension parameter α =150, the preventive maintenance time degradation factor γ =0, 0.05, 0.1, 0.2, the scale of the scheduling problem $n \times m$ is 10 × 6. The standard processing times for workpieces on machines are shown in Table 2.

TABLE 2. Standard processing schedule.

Workpiece serial number j	Standard processing time $p^0_{[k],i}$					
	M_1	M_2	M_3	M_4	M_5	M_6
1	20	20	20	25	24	19
2	18	24	26	15	24	16
3	24	27	27	27	21	19
4	16	17	18	15	18	18
5	27	22	22	24	28	22
6	25	18	28	18	27	17
7	19	27	17	23	16	19
8	17	19	17	28	16	18
9	15	16	20	21	26	16
10	15	26	18	27	27	16

TABLE 3. Observed value of η_j.

j	η_j			
1	0.00355	0.00365	0.00635	0.00705
2	0.00527	0.00627	0.01327	0.01627
3	0.01136	0.00736	0.01836	0.02436

TABLE 4. Parameter value of level.

Factor level	PS	NI	PC	PM
1	10	50	0.5	0.05
2	30	100	0.7	0.1
3	50	200	0.9	0.2

The observed value of residual degradation coefficients after j maintenance as shown in Table 3. According to the research in Section IV, the maximum likelihood estimated parameters $\hat{a} = 0.00516$ and $\hat{b} = 2.22 \times 10^{-5}$. According to Equation (23), $E(\eta_1) = 0.05147, E(\eta_2) = 0.010267$ are obtained.

A. PARAMETERS SETTING

The NSGA-II-ALS algorithm has four parameters: PS (population size), NI (number of iterations), PC (crossover probability) and PM (mutation probability). According to the value range of parameters in the relevant literature, each parameter is set to three levels, as shown in Table 4.

According to parameter values of level, the orthogonal experiments are performed to optimize parameter combinations. A total of 3^4 experiments were conducted. The optimal parameter combination is selected according to the SD index. Therefore, the algorithm with the best performance is obtained by taking $PS = 20$, $NI = 100$, $PC = 0.9$, PM=0.1.

B. RESULTS AND ANALYSIS

In order to demonstrate the experimental results of this scheduling problem, and show the effectiveness of the algorithms studied in this paper. NSGA-II-ALS, NSGA-II and Particle Swarm Optimization (PSO) algorithms are applied to optimize this scheduling problem.

When γ =0, preventive maintenance degradation is not considered. According to NSGA-II-ALS to find the solution set, the scheduling order of the sparse solution is 9-10-1-4-5-8-2-3-7-6 and the preventive maintenance decision matrix D_{pm1} is shown below. The Gantt chart is shown in Figure 12(a).

$$D_{pm1} = \begin{bmatrix} 0\,0\,0\,0\,0\,0 \\ 0\,0\,0\,1\,1\,0 \\ 0\,1\,1\,0\,0\,0 \\ 1\,0\,0\,0\,1\,1 \\ 0\,0\,0\,1\,0\,0 \\ 0\,1\,1\,0\,0\,0 \\ 1\,0\,0\,1\,1\,1 \\ 0\,1\,1\,0\,0\,0 \\ 0\,0\,0\,0\,0\,0 \\ 0\,0\,0\,0\,0\,0 \end{bmatrix}$$

When γ =0.05, NSGA-II-ALS finds the solution set. The scheduling sequence of sparse solutions is 9-10-1-4-5-2-8-3-6-7, and tD_{pm2} is shown below. The Gantt chart is shown in Figure 12(b).

$$D_{pm2} = \begin{bmatrix} 0\,0\,0\,0\,0\,0 \\ 0\,0\,0\,1\,1\,0 \\ 1\,1\,1\,0\,0\,1 \\ 0\,0\,0\,0\,1\,0 \\ 0\,0\,0\,1\,0\,0 \\ 1\,1\,1\,0\,0\,1 \\ 0\,0\,0\,0\,1\,0 \\ 0\,0\,1\,1\,0\,0 \\ 1\,1\,0\,0\,0\,1 \\ 0\,0\,0\,0\,0\,0 \end{bmatrix}$$

When γ =0.01, NSGA-II-ALS finds the solution set. The scheduling sequence of sparse solutions is 9-4-10-1-5-8-2-3-7-6, and D_{pm3} is shown below. The Gantt chart is shown in Figure 12(c).

$$D_{pm3} = \begin{bmatrix} 0\,0\,0\,0\,0\,0 \\ 0\,0\,0\,0\,1\,0 \\ 0\,1\,1\,1\,0\,0 \\ 1\,0\,0\,0\,1\,1 \\ 0\,0\,0\,1\,0\,0 \\ 0\,1\,1\,0\,0\,0 \\ 1\,0\,0\,1\,1\,1 \\ 0\,1\,1\,0\,0\,0 \\ 0\,0\,0\,0\,0\,0 \\ 0\,0\,0\,0\,0\,0 \end{bmatrix}$$

When γ =0.02, NSGA-II-ALS finds the solution set. The scheduling sequence of sparse solutions is 9-10-1-4-8-6-3-5-2-7, and D_{pm4} is shown below. The Gantt chart is shown in

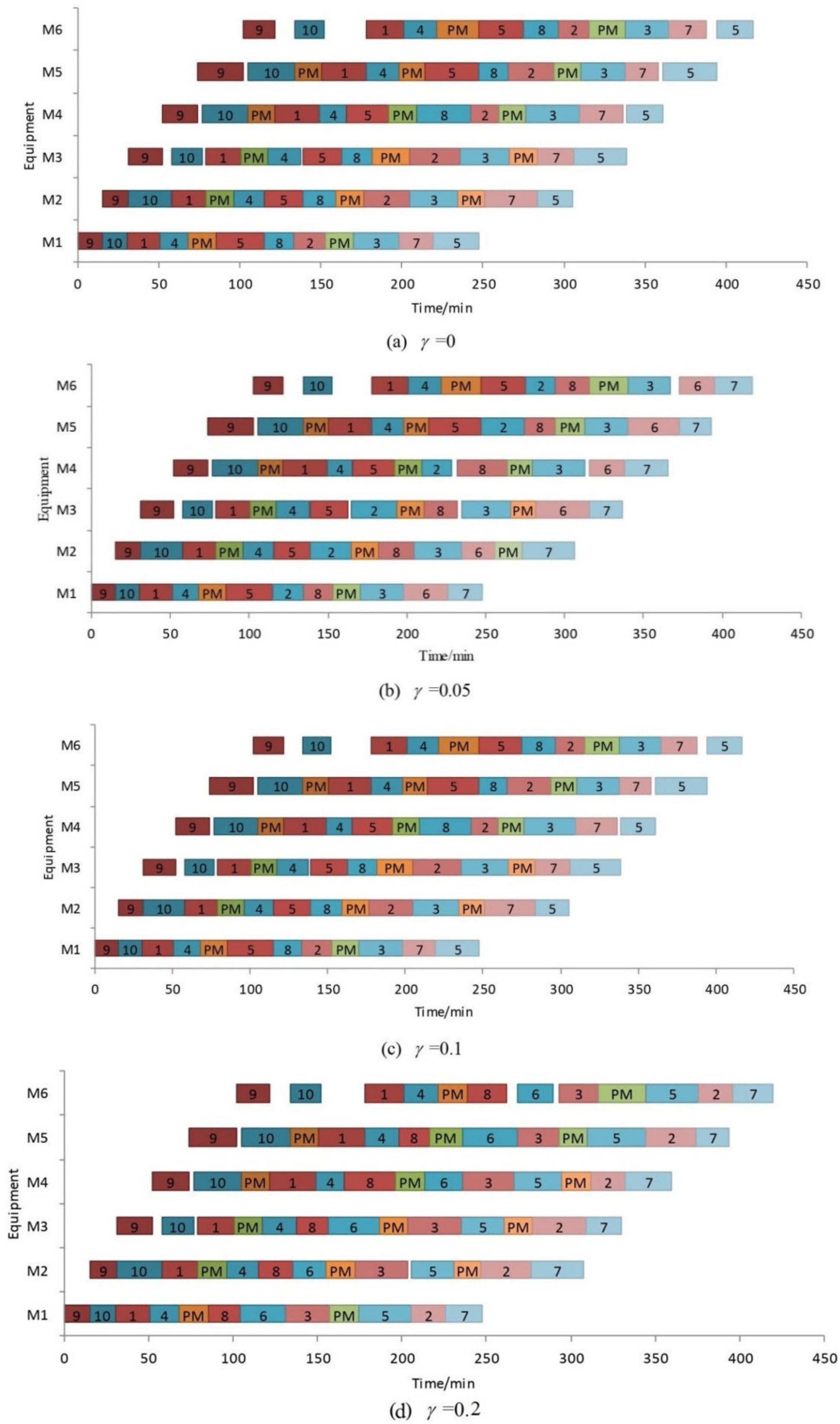

FIGURE 12. Scheduling Gantt chart obtained by NSGA-II-LS. (a)γ =0, (b)γ =0.05, (c)γ =0.1, (d)γ =0.2.

Figure 12(d).

$$D_{pm4} = \begin{bmatrix} 0\,0\,0\,0\,0\,0 \\ 0\,0\,0\,1\,1\,0 \\ 0\,1\,1\,0\,0\,0 \\ 1\,0\,0\,0\,0\,1 \\ 0\,0\,0\,1\,1\,0 \\ 0\,1\,1\,0\,0\,0 \\ 1\,0\,0\,0\,1\,1 \\ 0\,1\,1\,1\,0\,0 \\ 0\,0\,0\,0\,0\,0 \\ 0\,0\,0\,0\,0\,0 \end{bmatrix}$$

Based on the above analysis, the scheduling sequence of sparse solutions is 9-10-1-4-5-2-8-3-6-7 for γ =0.05. According to the mathematical model established by Equation (1) to (10), under different i and k, start time $S_{[k],i}$, processing completion time of the workpiece $E(T_{[k],i})$, preventive maintenance time $tp_{[k],i}$ can be obtained, as shown in Table 5. The correctness of the mathematical model established is verified by Table 5. Further, Gantt chart of γ =0.05 can be obtained as shown in Figure 12(b).

The objective function values and scheduling order of sparse points obtained by the three algorithms are shown in Table 6. The different scheduling sequences obtained by the three algorithms for different γ are shown in Figure 13. It can be seen from the above table and figure that F_1 and F_2 obtained by NSGA-II-ALS are optimal when $\gamma = 0.2$, F_1 obtained by NSGA-II-ALS is optimal and F_2 obtained by NSGA-II-ALS is second optimal when γ =0.1,0.05,0.

The Pareto fronts obtained by using the three algorithms for different values of γ is shown in Figure 14. Taking $\gamma = 0.05$ as an example, as shown in Figure 14(b), the five groups of Pareto front solutions obtained by NSGA-II-ALS are (430.95,81.56), (425.66,81.69), (425.57,81.85), (418.95,86.34), (416.45,89.24). There are 430.95>425.66>425.57>418.95> 416.45 for F_1, while there are 81.56<81.69<81.85<86.34 <89.24 for F_2. This demonstrates that makespan objective get better while the average idle time objective get worse. In other words, the objectives are contradictory when using multi-objective Pareto based optimization algorithms.

The following conclusions can be drawn from the analysis of Figure 14.

(1) As the number of degradation factor γ increases, all objective dimensions obtained by the three methods increase. This indicates that the increase of the degradation factor leads to the increase of the maximum completion time and average equipment idle time, making the efficiency of the production system worse.

(2) It is more possible for the Pareto solutions from NSGA-II and PSO to yield multiple similar solutions within a local area. In contrast, the solutions of NSGA-II-ALS are distributed more equally and spread more widely, which facilitates the availability of a wide range of different preference options.

TABLE 5. Calculation result of mathematical model when $\gamma = 0.05$.

j	k		i = 1	2	3	4	5	6
9	1	$S_{[k],i}$	0	15.05	31.26	51.85	74.03	102.25
		$E(T_{[k],i})$	15.05	31.26	51.85	74.03	102.25	121.36
		$tp_{[k],i}$	0	0	0	0	0	0
10	2	$S_{[k],i}$	15.05	31.26	57.94	76.85	105.28	134.22
		$E(T_{[k],i})$	30.35	57.94	76.85	105.28	134.22	152.30
		$tp_{[k],i}$	0	0	0	16.05	16.30	0
1	3	$S_{[k],i}$	30.35	57.94	79.00	121.33	150.52	177.96
		$E(T_{[k],i})$	51.02	79.00	100.28	149.20	177.96	200.91
		$tp_{[k],i}$	0.00	17.11	16.91	0	0	0
4	4	$S_{[k],i}$	51.02	96.10	117.19	149.20	177.96	200.91
		$E(T_{[k],i})$	67.97	115.24	137.68	165.67	197.95	221.47
		$tp_{[k],i}$	17.52	0	0	0	16.23	25.66
5	5	$S_{[k],i}$	85.49	115.24	138.74	165.67	214.18	247.13
		$E(T_{[k],i})$	114.99	138.74	162.58	192.10	247.13	275.31
		$tp_{[k],i}$	0	0	0	17.04	0	0
2	6	$S_{[k],i}$	114.99	138.74	164.85	209.14	247.13	275.31
		$E(T_{[k],i})$	134.37	164.85	193.64	227.99	274.71	294.25
		$tp_{[k],i}$	0	16.99	17.04	0	0	0
8	7	$S_{[k],i}$	134.37	181.84	210.67	231.80	274.71	294.25
		$E(T_{[k],i})$	153.01	204.59	231.80	263.75	293.71	315.47
		$tp_{[k],i}$	17.30	0	0	15.78	19.18	25.14
3	8	$S_{[k],i}$	170.30	204.59	234.71	279.53	312.89	340.61
		$E(T_{[k],i})$	198.26	234.71	265.54	312.89	340.61	367.30
		$tp_{[k],i}$	0	0	15.88	0	0	0
6	9	$S_{[k],i}$	198.26	234.71	281.42	315.97	340.61	373.02
		$E(T_{[k],i})$	226.16	255.48	315.97	338.13	373.02	395.22
		$tp_{[k],i}$	0	17.34	0	0	0	0
7	10	$S_{[k],i}$	226.16	272.82	315.97	338.13	373.02	395.22
		$E(T_{[k],i})$	247.97	306.30	336.59	365.81	393.16	418.95
		$tp_{[k],i}$	0	0	0	0	0	0

(3) The average equipment idle time from NSGA-II-ALS becomes shorter when the maximum completion time targets are the same. Also, the maximum completion time from NSGA-II-ALS becomes shorter when average equipment idle time of the average equipment is the same. Thus, NSGA-II-ALS approximates Pareto front more effectively, having better searching ability and higher solving efficiency.

C. COMPARISONS OF THE EMPLOYED ALGORITHMS

1) COMPARATIVE OUTCOMES

In order to evaluate the optimization effect of algorithms, the spacing distribution SD and the scattering range index SS of three algorithms were calculated according to Equation (32) to Equation (34). T_{sim} is simulation time.

According to Table 2, 8 workpieces were randomly selected from 10 workpieces, and 20 instances were randomly

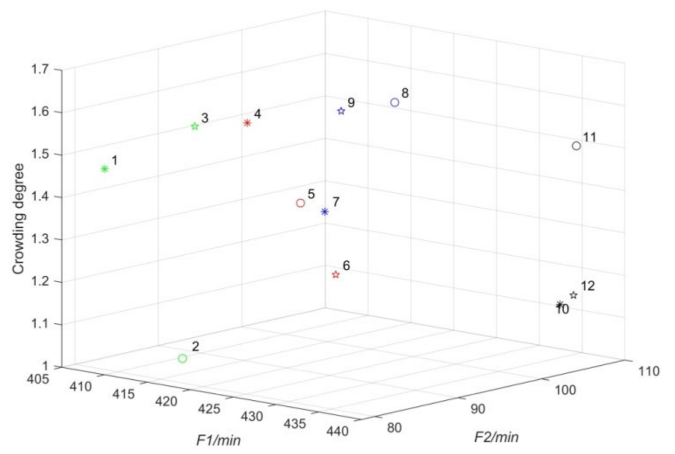

FIGURE 13. Optimization results of different scheduling sequence.

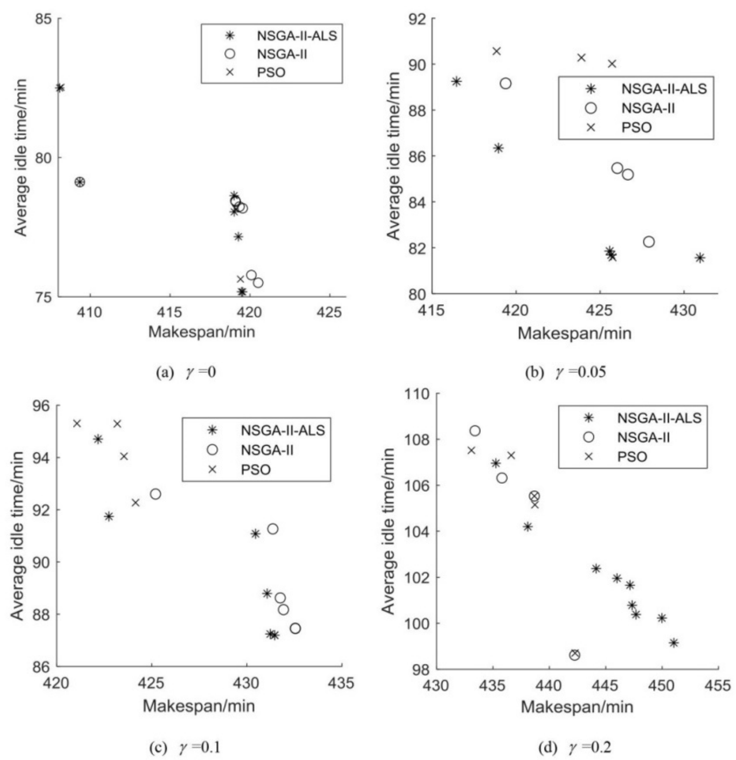

FIGURE 14. Pareto fronts obtained by the three algorithms. (a)$\gamma = 0$, (b)$\gamma = 0.05$, (c)$\gamma = 0.1$, (d) $\gamma = 0.2$.

generated. Taking γ =0.05 as an example, the evaluation indexes obtained by the three algorithms are shown in Table 7.

SD denotes the spacing distribution between adjacent solutions in the Pareto front solution set. When its value is zero, it means that all members of the Pareto front are spread equidistantly. Obviously, the lower *SD* value, the better distribution uniformity of the solutions. *SS* represents the distance between two extreme solutions in the solution space. The larger *SS*, the wider the spread of the resulting solution and the larger the search space.

According to the results obtained from Table 8, one can observe that for different degradation influence factors γ, the proposed NSGA-II-ALS outperforms the other two employed algorithms in all indicators.

According to the above analysis, it can be found:

(1) Under the same γ, NSGA-II-ALS yields the smallest *SD* compared to the other two algorithms. This indicates that the Pareto front solutions obtained by the NSGA-II-ALS algorithm are more evenly distributed in space.

TABLE 6. The optimal solutions obtained by different algorithms.

No	γ	Algorithm	Scheduling sequence	F_1	F_2	Crowding degree
1	0	NSGA-II-ALS	9-10-1-4-5-8-2-3-7-6	409.35	79.12	1.48
2		NSGA-II	10-6-9-7-4-5-1-3-8-2	419.08	78.45	1.07
3		PSO	1-4-10-9-5-3-7-6-8-2	419.01	80.01	1.61
4	0.05	NSGA-II-ALS	9-10-1-4-5-2-8-3-6-7	418.95	86.34	1.59
5		NSGA-II	10-9-4-1-7-6-5-8-3-2	426.02	85.47	1.43
6		PSO	10-6-4-8-9-5-1-3-7-2	425.71	90.02	1.24
7	0.1	NSGA-II-ALS	9-4-10-1-5-8-2-3-7-6	422.74	91.74	1.37
8		NSGA-II	10-9-1-4-3-5-6-8-7-2	431.37	91.27	1.66
9		PSO	9-10-1-4-5-8-2-3-7-6	424.15	92.27	1.61
10	0.2	NSGA-II-ALS	9-10-1-4-8-6-3-5-2-7	438.09	104.20	1.15
11		NSGA-II	9-10-4-1-5-8-2-3-7-6	438.68	105.53	1.52
12		PSO	9-4-10-8-2-5-1-3-6-7	438.72	105.15	1.17

TABLE 7. Results of evaluation indicators for γ=0.05.

No	*SD*			*SS*		
	NSGA-II-ALS	NSGA-II(2002)	PSO(2000)	NSGA-II-ALS	NSGA-II(2002)	PSO(2000)
1	3.2667	4.0445	3.4780	16.9900	9.8833	9.2957
2	2.9103	5.0417	2.3591	15.4868	10.4656	10.9520
3	2.8806	4.9038	2.8102	17.0266	11.1167	11.5598
4	3.3199	4.3565	2.9412	17.7570	10.6575	12.4051
5	2.5638	3.8793	3.2355	16.8439	11.2932	10.9260
6	3.0383	4.2761	2.3565	17.2806	11.3982	13.6057
7	3.0820	4.3840	3.2561	17.0343	9.9743	10.6247
8	2.7411	4.5455	2.5486	16.2100	10.7807	11.7962
9	2.8863	4.3447	3.0858	16.6879	8.6872	12.2848
10	2.4496	4.6081	3.3320	15.8230	12.1963	11.4450
11	2.4553	4.5888	3.1954	17.1635	10.2964	12.5981
12	2.8512	3.9748	3.5127	15.5351	9.6810	11.7899
13	3.0464	4.0880	3.4806	15.5977	10.6981	10.1854
14	3.6352	4.1653	2.7846	15.8052	9.4403	8.7056
15	2.6073	4.2525	3.1660	14.0974	10.9477	14.0147
16	2.8773	4.3225	2.6614	17.6035	10.3697	10.4456
17	2.7920	4.4470	2.5028	16.7130	13.3017	11.4714
18	2.2072	3.3100	3.4464	15.8489	12.1890	12.1376
19	2.6794	4.2715	3.0580	17.5490	8.2966	11.4862
20	2.2509	4.9067	3.0349	15.0836	11.4425	10.0107
Avg	2.8270	4.3355	3.0123	16.4068	10.6558	11.387

TABLE 8. Average values of evaluation indicators.

γ	index	NSGA-II-ALS	NSGA-II(2002)	PSO(2000)
0	SD	2.0530	3.8137	5.5638
	SS	13.5888	11.7319	13.1729
	T_{sim}	25.2	30.6	33.5
0.05	SD	2.8270	4.3355	3.0123
	SS	16.4068	10.6558	11.387
	T_{sim}	25.2	31	33.8
0.1	SD	1.5132	2.9352	4.6929
	SS	11.9459	8.9776	11.1860
	T_{sim}	25.2	31.2	33.6
0.2	SD	1.8929	3.3059	3.9112
	SS	17.6057	13.1653	12.7326
	T_{sim}	25.3	31.3	33.7

(2) Under the same γ, NSGA-II-ALS yields the largest *SS* compared to the other two algorithms. This indicates that the Pareto front solutions obtained by the NSGA-II-ALS algorithm have a wider distribution.

(3) For different degradation influence factors γ, the solution time T_{sim} of NSGA-II-ALS is smaller than the other two algorithms. Therefore, NSGA-II-ALS has the highest solving efficiency.

(4) The change of degradation factor γ has little influence on T_{sim} values of the three algorithms.

(5) According to Figure14, it can be found that under different γ, the number of Pareto solutions of NSGA-II-ALS are more than that of the other methods. Therefore, NSGA-II-ALS provides decision makers with greater choice space.

2) STATISTICAL ANALYSIS

In order to statistically test whether the differences in the data in Table 6 are significant or not, The Kolmogorov–Smirnov (K-S) procedure is employed to examine the normality of the obtained data [39], [40].

In order to examine statistically whether the dissimilarities are significant or not, analysis of variance (ANOVA) should be conducted. The ANOVA, as a parametric statistical

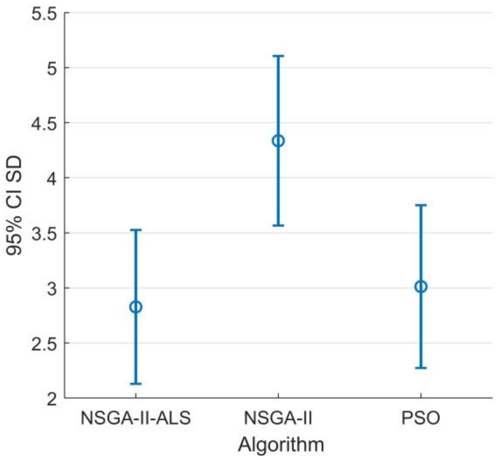

FIGURE 15. The algorithms' performance (at the 95% confidence level) of $\gamma = 0.05$ for SD.

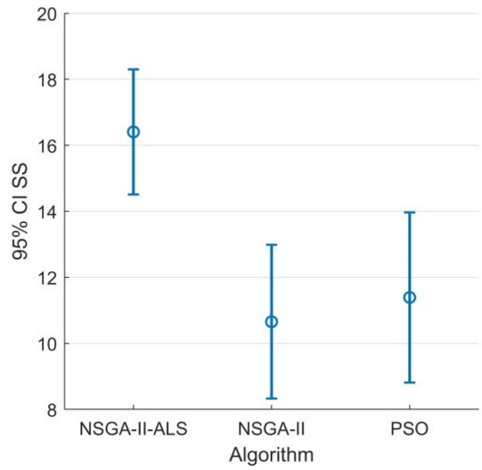

FIGURE 16. The algorithms' performance (at the 95% confidence level) of $\gamma = 0.05$ for SS.

TABLE 9. The P-value (sig. value) of statistical analyses for $\gamma = 0.05$.

	SD	SS
K-S test (P-value)	0.012	0.000732
Kruskal-Wallis(Asymptotic significance)	3.1×10^{-9}	1.1×10^{-9}

test, has three requisites to be done, named homoscedasticity, residuals independence, and normality, as well. The Kolmogorov–Smirnov (K-S) procedure is employed for every metric to examine the normality of the obtained data. If the obtained P-value or sig. be greater than the significance level (which is considered 5% in this research), the attained results are dispersed normally. And then, ANOVA can be performed. If the obtained P-value or sig. be lesser than the significance level, the attained results are not dispersed normally. In this circumstance, one cannot apply the parametric tests such as ANOVA, and the Kruskal–Wallis test might be employed.

Taking γ =0.05 as an example, K-S test is conducted on the data in Table 6. For SD, the P-values of the K-S test results is 0.012<0.05, so Kruskal-Wallis test should be performed. The asymptotic significance value of the Kruskal-Wallis test results is 3.1×10^{-9} <0.01, consequently there is statistically significant differences among the applied techniques. Similarly, k-s test and Kruskal-Wallis test can obtain the same result for SS. This result is proved by Figure 15 and Figure 16 since there is no overlapping between NSGA-II-ALS and NSGA-II in a 95% confidence interval. Figures 15–16 exhibit the confidence interval and responding means plot at the 95% confidence level for $\gamma = 0.05$.

According to the mean value obtained results from Figure15-16, it could be seen that the proposed NSGA-II-ALS has the smallest *SD* and the largest *SS* compared to the other two algorithms. So the solutions of NSGA-II-ALS are more evenly distributed and wider.

Similarly, the statistical parameters of SD and SS indexes corresponding to different degradation influence factors γ and employed algorithms are obtained as shown in Table 10. The proposed NSGA-II-ALS outperforms the other two employed algorithms in all indicators.

D. MANAGERIAL AND PRACTICAL IMPLICATIONS

Some managerial and practical insights are proposed in response to this study that may be helpful to practitioners, managers, and decision makers, as shown below.

(1) In the actual production systems, with the continuous operation of the manufacturing system, the production and processing are peculiarly prone to equipment degradation and equipment failure. Hence, production scheduling, equipment degradation and equipment maintenance are interrelated. Therefore, the method proposed in this study can coordinate and balance the relationship among production scheduling, equipment degradation and equipment maintenance. The proposed method can be a way contributes to the improvement of the efficiency of the manufacturing system and protection equipment, thus reducing costs and realizing the optimal utilization of resources as well as energy.

(2) With the outbreak of COVID-19, several industries such as printed circuit board manufacturing have been affected. In this case, workpiece batch size and scheduling problems are of great importance. For PCB factory and other degenerate flow shop manufacturing industries, the model proposed in this study can be applied as a basic model of such systems to provide managers with an effective management method.

(3) From the technical point of view, the local search strategy of NSGA-II-ALS proposed in this study approximates the Pareto front more effectively, while the uniformity and the range of the solution distribution are improved. The boundary points and sparse points in NSGA-II-ALS can be obtained directly from the non-dominated sorted results, without the need to calculate density and gradient, which leads to less calculated amount, more efficient solution and better search

TABLE 10. Statistical comparison of employed algorithms.

γ	index	Algorithm	Mean	*Std. error*	*95% confidence interval*	
					L limit	U limit
0	SD	NSGA-II-ALS	2.0530	0.6077	0.8619	3.2441
		NSGA-II[2002]	3.8137	0.7277	2.3874	5.2400
		PSO[2000]	5.5638	0.8777	3.8435	7.2841
	SS	NSGA-II-ALS	13.5888	0.2703	13.0591	14.1185
		NSGA-II[2002]	11.7319	0.3103	11.1238	12.3400
		PSO[2000]	13.1729	0.3603	12.4668	13.8790
0.05	SD	NSGA-II-ALS	2.8270	0.3560	2.1292	3.5248
		NSGA-II[2002]	4.3355	0.3924	3.5664	5.1046
		PSO[2000]	3.0123	0.3772	2.2730	3.7516
	SS	NSGA-II-ALS	16.4068	0.9672	14.5111	18.3025
		NSGA-II[2002]	10.6558	1.1875	8.3283	12.9833
		PSO[2000]	11.3870	1.3149	8.8098	13.9642
0.1	SD	NSGA-II-ALS	1.5132	0.6599	0.2197	2.8067
		NSGA-II[2002]	2.9352	0.7299	1.5045	4.3659
		PSO[2000]	4.6929	0.7949	3.1348	6.2510
	SS	NSGA-II-ALS	11.9459	0.6961	10.5816	13.3102
		NSGA-II[2002]	8.9776	0.7211	7.5643	10.3909
		PSO[2000]	11.1860	0.7421	9.7315	12.6405
0.2	SD	NSGA-II-ALS	1.8929	0.4046	1.0999	2.6859
		NSGA-II[2002]	3.3059	0.4646	2.3953	4.2165
		PSO[2000]	3.9112	0.5046	2.9222	4.9002
	SS	NSGA-II-ALS	17.6057	0.9683	15.7079	19.5035
		NSGA-II[2002]	13.1653	1.0683	11.0715	15.2591
		PSO[2000]	12.7326	1.2183	10.3448	15.1204

capability. This will provide a new algorithm means for managers to solve the scheduling problems.

VII. CONCLUSION

In actual production systems, production scheduling, equipment degradation and equipment maintenance are interrelated. Based on this, this paper takes the scheduling of a degraded flow shop as the research object, considers the interaction among scheduling, production, maintenance and degradation, and establishes a mathematical model with completion time and average equipment idle time. Finally, a reasonable scheduling solution is obtained in accordance with the characteristics of the problem. In this paper, the application of flow shop scheduling in PCB factory is introduced and a mathematical model is established deeming minimizing the completion time, as well as the average idle time of equipment as the optimization objectives. Considering the influence of equipment degradation on actual processing time and preventive maintenance time, a degradation model of workpiece processing time and the degradation model of equipment preventive maintenance time are constructed. Moreover, the estimation method of residual degradation coefficient of machining time is studied as well. The relationships among failure, maintenance, preventive maintenance and schedule are introduced and the preventive maintenance strategy is studied.

The coding, crossover and mutation operations are performed according to NSGA-II algorithm. On this basis, a local search strategy is proposed, in which boundary points and sparse points are obtained according to non-dominated sorted results. Through limit optimization strategy and random search strategy, local search is carried out near boundary points and sparse points. This method not only ensures the diversity and uniformity of population, but also improves the quality of solution and convergence speed.

The comparative experiments are conducted through NSGA-II-ALS, NSGA-II, and PSO, and the optimization results are compared and analyzed. Optimal sparse solutions are obtained for different degradation factors γ respectively. Gantt charts and Pareto front diagrams are drawn. The multi-objective assessment indicators for each algorithm are calculated and compared to verify the effectiveness of the proposed algorithm.

Multiple sets of randomized experiments are performed on the employed algorithms, SD and SS indicators are statistically analyzed. The statistical analysis show that the proposed NSGA-II-ALS algorithm outperforms the other two employed algorithms in all indicators. Finally, the following conclusions are drawn:

(1) The scheduling model proposed in this paper can effectively coordinate and balance the relationship among production, equipment degradation and equipment maintenance, which is able to improve the efficiency of the manufacturing system, effectively protect the equipment, so as to save production costs and achieve the optimal use of resources and energy.

(2) As the maintenance time of degradation factor γ increases, all objective dimensions of the solutions obtained by the three methods increase, reflecting that the increase of the maintenance degradation factor leads to the increase of the maximum completion time, average cost ratio. and the decrease in the efficiency of the production system.

(3) The local search strategy of NSGA-II-ALS approximates the Pareto front more effectively, while the uniformity of the solution distribution and the range of the solution distribution are improved.

(4) The boundary points and sparse points in NSGA-II-ALS can be obtained directly from the non-dominated sorted results without the need to calculate density and gradient, which leads to less calculated amount, more efficient solution and better search capability.

Based on the aforementioned analysis, managerial and practical insights are proposed. For PCB factory and other degenerate flow shop manufacturing industries, the model proposed in this study can be applied as a basic model for such systems to provide managers with an effective management method and a new algorithm means.

The research gap and prospect are as follows:

(1) In this study, only completion time and average device idle time are taken as the optimization objectives. In practice, the performance of production systems is influenced by many complex factors. Therefore, in the follow-up study, more optimization objectives are considered at the same time, and several alternatives are provided for managers, so that they can freely choose one of several options according to the situation and make correct decisions.

(2) With the development of genetic algorithm, the performance of the algorithm will continue to improve, so more effective algorithms should be sought and applied to a wider range of flow shop scheduling problems.

The future trends in this field:

NSGA-III is the successor of NSGA-III, so it is a trend to use NSGA-III algorithm to solve multi-objective scheduling problems with more than three objectives. In addition, most current studies use deterministic methods, and how to provide more robust methods to solve uncertainties in scheduling problems is becoming another development trend. Finally, the application of scheduling in the field of energy conservation is also a future research trend.

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YANG LIU received the master's degree in mechanical engineering from the Changchun University of Technology. He is currently a Professor at Changchun Sci-Tech University. He has published more than ten academic articles. His research interests include vibration analysis of complex systems and numerical simulation. He has won three national competition awards.

XIAOFENG WANG received the Ph.D. degree in mechanical engineering from Jilin University. He is currently a Postdoc at Jilin University. He has published more than 20 academic papers and received five invention patents. His research interests include manufacturing equipment reliability, vibration analysis of complex systems, and numerical simulation.

YUN ZHANG received the master's degree in computer application from the Changchun University of Technology. She is an Associate Professor at Changchun Sci-Tech University. Her research interests include artificial intelligence technology and computer vision.

LI LIU graduated in agricultural engineering and information technology from Jilin Agricultural University. She received the master's degree in agronomy. She is currently a Lecturer at Changchun Sci-Tech University. Her main research interests include vibration analysis of complex systems and numerical simulation.