IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received August 5, 2020, accepted August 24, 2020, date of publication August 28, 2020, date of current version September 10, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3020056

Research on Many-Objective Flexible Job Shop Intelligent Scheduling Problem Based on Improved NSGA-III

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This work was supported by the National Key Research and Development Program of China under Grant 2018AAA0101703.

ABSTRACT With the development of intelligent manufacturing and the customized product demand of customers, manufacturing enterprises are urgently required to carry out high-efficiency, high-quality, flexibility and low-cost manufacturing to enhance the competitiveness of enterprises. Intelligent job shop scheduling problem is the core decision of intelligent manufacturing production management. Many-objective job shop scheduling algorithms can effectively solve this problem. However, existing optimization algorithms cannot effectively solve many-objective flexible job shop scheduling problem. This paper establishes the many-objective job shop intelligent scheduling model with complex constraints, and proposes an improved intelligent decision optimization algorithm named NSGA-III-APEV based on NSGA-III. This algorithm uses the penalty-based boundary intersection distance that takes into account both convergence and diversity simultaneously to define the distance between the population individual and the reference vector in the association operation. This paper exploits the penalty-based boundary intersection distance-based elimination mechanism to preserve individuals and reduce the computational cost in the individual preservation strategy. Meanwhile, the adaptive mutation strategy based on consanguinity is employed in genetic operators. The presented method effectively improves the convergence and diversity of the population. Finally, NSGA-III-APEV with other algorithms was compared through benchmarks. Experimental results demonstrated the effectiveness and superiority of the improved method. The feasibility of the improved method in solving the many-objective flexible job shop scheduling problem are verified by engineering examples.

INDEX TERMS Adaptive mutation strategy, elimination mechanism, many-objective flexible job shop scheduling problem, many-objective optimization, NSGA-III.

I. INTRODUCTION

With the development of artificial intelligence technologies such as big data and machine learning, global manufacturing is turning to be intelligent. Intelligent manufacturing is a major trend and a key topic of manufacturing development [1]. Its related technologies are not limited to the manufacturing process but cover the whole process of market analysis, production management, sales and after-sales. Intelligent manufacturing can optimize products, their production and service process, and obtain high quality, flexibility, high efficiency and low consumption of the product manufacturing process. Intelligent job shop scheduling is the core decision of intelligent manufacturing production management and the basis of the intelligent manufacturing system.

The intelligent manufacturing system under the multi-variety and small-batch production model becomes more complicated. In order to realize high-quality, flexibility, high-efficiency and low-consumption of the product manufacturing process, traditional job shop scheduling methods are not suitable for solving the current scheduling problem. It is necessary to comprehensively consider and optimize multiple objectives in the scheduling process. A reasonable multi-objective flexible job shop scheduling scheme can reduce cost, improve production efficiency, reduce energy consumption, improve product quality, and improve the

The associate editor coordinating the review of this manuscript and approving it for publication was Nagarajan Raghavan.

intelligent manufacturing level of enterprises. The research on the multi-objective flexible job shop scheduling problem (MOFJSP) under the new intelligent manufacturing mode has high theoretical significance and practical application value.

The intelligent job shop scheduling problem belongs to a multi-objective optimization problem (MOP), which is a typical NP-hard problem. Due to its high complexity, it is difficult to solve this issue [2]. Flexible job shop scheduling problem (FJSSP) was proposed by Brucker and Schlie. So far, there are various ways to solve the FJSSP. MOFJSP in engineering is characterized by complexity, dynamics, and randomness [3]. Generally, the algorithms for the MOFJSP can be divided into two types: traditional methods and intelligent methods. Traditional methods include optimization methods (mathematical programming, gaussian elimination, etc.), simulation methods and heuristic rule scheduling methods [4], [5]. This type of methods is inefficient and can only solve small-scale scheduling problems. Due to the advancement of computer science, intelligent methods can well perform the optimization process of MOFJSP. Compared to traditional methods, intelligent methods can solve the large-scale scheduling problems more effectively.

There are many intelligent computing methods such as the artificial neural network (ANN), evolutionary computation (EC) and swarm intelligence (SI). Intelligent computing methods provide new ideas for solving complex problems and their rise is closely related to the formation of computational complexity theory.

Particle swarm optimization (PSO), invented by Dr. Eberhart and Dr. Kennedy, is a random search algorithm based on group collaboration developed by simulating the foraging behavior of birds. It is considered to be a type of SI. Based on PSO method, Singh *et al.* [6] established a multi-objective shop scheduling model including completion time, delay and operation time, and applied a multi-objective PSO algorithm (MOPSO) to optimize the model. The results outperform NSGA-II and MOEA. Carvalho *et al.* [7] proposed the diversity PSO (DIPSO) for the problem of local convergence in PSO. This algorithm not only improves the diversity of the algorithm but also ensures convergence.

Ant colony optimization (ACO) was proposed by Marco Dorigo in his doctoral thesis in 1992. It was inspired by the behavior of ants in finding paths during the process of finding food. Huang et al [8] established a flexible workshop scheduling model including the objectives of earliness and delay time. They improved the ant colony algorithm and proposed the 2PH-ACO algorithm to solve the scheduling model. The experimental results showed that this method is superior to ACO.

Artificial bee colony (ABC) is an optimization method proposed by imitating the behavior of bees. It is a specific application of cluster intelligence. Its main feature is that it does not need to understand the special information of the problem. Yuguang *et al.* [9] established a flexible job shop scheduling model with completion time, machine workload and the weighted agreement index and proposed a modified artificial bee colony algorithm (MABC) based on local search operator.

Another intelligent computing method is variable neighborhood search (VNS), the main idea of which is to use multiple different neighborhoods for system search. Zheng *et al.* [10] established a fuzzy job shop scheduling model with completion time and maximum machine workload, and proposed a hybrid PSO algorithm and variable neighborhood search algorithm (MOSNS). Li *et al.* [11] established a job shop scheduling model with the completion time, total workload of machines and critical machine workload. The improved hybrid genetic algorithm and VNS algorithm (VNS + GA) can better optimize scheduling model.

Tabu search, proposed by Fred Glover in 1986, is a modern heuristic algorithm. Tabu search is a search method used to escape the local optimal solution. Jia *et al.* [12] established a job shop scheduling model including the maximum completion time, total workload of machines and critical machine workload, and proposed a path relinking algorithm based on the Tabu search (PRMOTS). This method has better computing performance. The above algorithms are shown in Table 1.

TABLE 1. **The recent and popular algorithms.**

Algorithms	Objective functions
MOPSO	Completion time, mean delay and flow time
2PH-ACO	Maximum earliness, maximum tardiness
DIPSO	Completion time, mean delay and flow time
MABC	Completion time, the weighted agreement index and the maximum fuzzy machine workload
MOSNS	Completion time the maximum machine workload
NSGA-II	Total equipment load, completion time, and equipment maximum load
VNS+GA	Completion time, total workload of machines, Critical machine workload
PRMOTS	Completion time, total workload of Machines, critical machine workload
HPTSA	Completion time, total workload of Machines, critical machine workload, the earliness/tardiness (E/T)

Evolutionary Algorithm (EA) is a kind of population-based algorithm, with the characteristics of self-organization, self-adaptation and self-learning. It can obtain multiple Pareto optimal solutions in a single operation without the limitation of problem properties. Therefore, it is often widely used to solve MOFJSP [13], [14].

Because genetic algorithms have relatively strong global search capabilities, they show good performance in solving large-scale complex optimization problems. Genetic algorithms not only show better performance in solving continuous problems, but also have more mature applications in discrete problems. Typical discrete problems include the workshop scheduling problem studied in this paper. It is not constrained by problem continuity and derivability.

In 2002, a multi-objective optimization algorithm (MOEA) named NSGA-II was proposed by Deb. It can better solve the MOFJSP and show superior performance compared to the NSGA algorithm [15]. By considering the transportation constraints, Dai *et al.* [16] established a model of MOFJSP with two objectives, i.e., minimization of energy consumption in job shop and minimization of completion time. The model was optimized by an improved NSGA-II approach. Gen *et al.* established a multi-objective job shop scheduling model that minimized the total equipment load, completion time, and equipment maximum load. The improved genetic algorithm based on the fitness allocation mechanism can better optimize the MOFJSP [17]. Yuan *et al.* [18] established a flexible job shop scheduling model with objectives of critical workload, completion time and total machine load. Meanwhile, a new memetic algorithm was proposed to optimize the scheduling model. Dai *et al.* [19] established a workshop scheduling model that optimizes workshop energy consumption and completion time. A genetic-simulated annealing algorithm was proposed to optimize the scheduling model, and a reasonable scheduling scheme was finally obtained.

The above-mentioned literatures mainly focus on low-dimensional MOFJSP and the number of optimization objectives in the scheduling model is generally either 2 or 3. Moreover, the objectives of scheduling optimization are generally completion time and equipment load. In the multi-variety and small-batch production mode, intelligent manufacturing production scheduling also involves some realistic goals. The management expects to reduce production cost and make the best use of existing resources. The manufacturing department wants to improve production efficiency and reduce energy consumption while the sales department wants to meet the customer's delivery date requirements. Different scheduling objectives indicate the decision criteria of each department for the scheduling reference scheme, and the many-objective flexible job shop scheduling problem (Ma-OFJSSP) contains the optimization of four or more objectives [20]. It is of great theoretical and engineering significance to study the Ma-OFJSSP.

The common used MOEAs based on Pareto advantage can effectively deal with low-dimensional MOFJSP, but there are still some other problems in solving Ma-OFJSSP. Firstly, the search capability is degraded. With the increase of the optimization objective, the number of non-dominated individuals increases exponentially. Consequently, it reduces the selection pressure in the evolutionary process. Secondly, the number of non-dominated solutions covering the entire Pareto front increases exponentially. Therefore, the method to deal with the low-dimensional MOFJSP is not suitable for solving Ma-OFJSSP.

For the many-objective optimization problem (MaOP), in 2014, Deb *et al.* [21] proposed the NSGA-III based on the framework of NSGA-II. The difference between the two algorithms is mainly the change of selection mechanism. The diversity of the population is maintained by reference points, and the effectiveness of NSGA-III for the MaOP is demonstrated by solving the benchmark test. This approach can effectively maintain the capability of diversity but ignores convergence toward the Pareto front. At the same time, the computational complexity of environmental selection can also be minimized [22], [23]. Because NSGA-III is a centralized optimization algorithm, the computational time cannot meet the requirements of online real-time scheduling for large-scale industrial many-objective scheduling problem. Especially in complex production environments where multiple disturbances often occur, online scheduling needs to be adjusted in real time. Therefore, the application of NSGA-III is limited for large-scale industrial real-time scheduling problem.

To sum up, the NSGA-III is proved to be suitable for solving the MaOP. However, firstly, it needs to improve in terms of convergence and diversity since the balance between convergence and diversity is not effectively taken into account in NSGA-III. Secondly, the computational complexity of its environmental selection is quite high. Thus, NSGA-III cannot directly and effectively solve the Ma-OFJSSP. As far as we know, how to improve NSGA-III to solve the Ma-OFJSSP is still an open problem.

For the many-objective optimization problem, so far, the performance of the new MOEAs is mainly verified through benchmark problems, but the theory is rarely applied to specific fields to solve practical engineering problems. In theory, the Ma-OFJSSP is a many-objective optimization problem. To solve the Ma-OFJSSP, we propose an improved decision optimization algorithm (named NSGA-III-APEV). The main contributions are as follows:

1) This paper establishes a high-dimensional many-objective job shop intelligent scheduling model with complex constraints.

2) Based on NSGA-III, we propose an improved intelligent decision optimization algorithm (named NSGA-III-APEV). This proposed algorithm uses the penalty-based boundary intersection distance (PBI distance) that can take into account both convergence and diversity to define the distance between the population and the reference vector in the association operation. We use a PBI distance-based elimination mechanism to preserve individuals and reduce the amount of computation in the individual preservation strategy. The adaptive mutation strategy based on consanguinity is applied to genetic operators. This presented method improves diversity and convergence of the population efficiently.

3) We apply the proposed NSGA-III-APEV algorithm to solving the practical Ma-OFJSSP. Compared with existing methods, experimental results demonstrate the superiority and feasibility of the proposed algorithm in solving the Ma-OFJSSP.

The remainder of this paper is organized as follows. Section 2 introduces the related work. Section 3 introduces the model of many-objective flexible job shop scheduling. In Section 4, we present the proposed method NSGA-III-APEV in detail. In Section 5, we employ the proposed NSGA-III-APEV algorithm to solve the practical Ma-OFJSSP. The conclusions are drawn in Section 6.

II. RELATED WORK

Ma-OFJSSP belongs to the many-objective optimization problem. Compared with other methods, EA has better performance for the Ma-OFJSSP. In general, EAs can be divided into three categories, i.e., Pareto dominance based EAs, performance indicators based EAs and decomposition based EAs.

For the Pareto dominance based EAs, Hadka *et al.* [24] proposed the Borg multi-objective evolutionary algorithm (MOEA) including ε-dominance. He *et al.* [25] used fuzzy domination to modify the Pareto dominance relationship. This improved method increased the selection pressure in the solution process and improved the convergence. Li *et al.* [26] introduced a density estimation strategy to evaluate the diversity and increase the selection pressure in the solution process under the condition that the Pareto dominance relationship remains unchanged. Zhang *et al.* [27] introduced the evolution algorithm based on the Knee point, which improves convergence and computational efficiency. Although the above methods have good convergence, the lack of population diversity protection mechanism usually results in local optimization and cannot obtain excellent scheduling schemes in solving Ma-OFJSSPs.

The performance indicators based EAs indicate that various evaluation indicators are added to the MOEA. Tian *et al.* [28] introduced a new MOEA on the basis of the inverted generational distance indicator. Cai *et al.* [29] proposed a unary diversity indicator based on reference vectors (DIR) to reveal the diversity of the Pareto Front, and the experiment verified the superiority of the method. These methods can effectively balance diversity and convergence. However, such methods lead to a sharp increase in the computational complexity of the many-objective evolutionary algorithm, and cannot efficiently solve the Ma-OFJSSPs.

Decomposition based EAs transform the MOP into a series of single-objective optimization sub-problems. Zhao *et al.* [30] designed a new decomposition-based evolutionary algorithm which constructed a high-quality initial population and adaptive select mechanism for the MOFJSP. Li *et al.* [31] proposed an improved EA based on decomposition which merged dominance and decomposition for many-objective optimization. Zhang *et al.* [32] added the DE operator to MOEA / D, effectively improving the quality of Pareto Front. Asafuddoula *et al.* [33] proposed an improved EA(I-DBEA)on the basis of decomposition. The decomposition technology can effectively enhance the convergence, but its distribution is largely dependent on the contour characteristics of the aggregation function, and different types of problems are sensitive to the selection of the aggregation function.

Yuan *et al.* [34] enhanced the convergence and diversity of the NSGA-III algorithm by applying a new dominance relationship ($\theta-DEA$). Bi *et al.* [35], [36]introduced a many-objective EA (NSGA-III-OSD) based on objective space decomposition by combining MOEA/D-M2M space decomposition and NSGA-III. Masood *et al.* [37] proposed an hybrid algorithm on the basis of Genetic Programming (GP) and NSGA-III for Ma-OFJSSP. Li *et al.* [38] proposed an hybrid Ts algorithm based on pareto (HPTSA) for Ma-OFJSSP. Gao et al [39]presented non-dominated sorting on the basis of dominance degree for NSGA-III.

III. FORMULATION OF MANY-OBJECTIVE FLEXIBLE JOB SHOP SCHEDULING PROBLEM MODEL

The many-objective flexible job shop scheduling problem (Ma-OFJSSP) of the intelligent manufacturing system can be described as: n jobs$J = \{J_i\}\,(i \in [1, n])$ in the job set J are processed on m machines in the machine set M. Each job J_i contains q_i operations, and each operation can be processed on p_{ij} machines among m machines. There is a technological constraint relationship between all the operations of each job. Let O_{ij}^k represent the jth operation of the jobJ_i processed on the kth machine, and t_{ij}^k represent the processing time of operationO_{ij} in machineM_k. The scheduling goal of the intelligent manufacturing system is to determine a suitable processing machine for each operation, and to arrange all the operations allocated on each machine, and finally to make the set optimization goal optimal.

The production scheduling problem in this study simultaneously considers the optimization of five objective functions, expressed as f_1 to f_5, namely maximum completion time, delivery delay time, total equipment load, total energy consumption and processing quality, respectively. The notations in the mathematical model have been pre-defined in Table 2.

TABLE 2. The notations information.

Notation	Representation
f_1	Completion time
f_2	Total equipment load
f_3	Energy consumption
f_4	Delay time
f_5	Processing quality
C_i	The completion time of the last operation for the ith job
a_{ij}^k	Whether the operation O_{ij}^k is processed on machine M_k
t_{ij}^k	The processing time of operation O_{ij}^k on machine M_k
E_k^J	The processing energy consumption of the machine M_k
E_k^K	The no-load energy consumption of the machine M_k
P^k	The processing power of the machine M_k
PD^k	The no-load power of the machine M_k
C_k	The completion time of the machine M_k
S_k	the start time of the machine M_k
DD_i	The delivery date of job i
L_{ijk}	The failure rate of the operation O_{ij}^k processed by equipment M_k
S_{ijk}	The start processing time of the operation O_{ij}^k
T_{ijk}	The processing time of the operation O_{ij}^k
F_{ijk}	The completion time of the operation O_{ij}^k

The specific definition of the high-dimensional flexible job shop scheduling model with the five optimization objectives can be expressed as:

$$\min F = (f_1, f_2, f_3, f_4, f_5)^T \tag{1}$$

1) Completion time f_1. The maximum completion time is the embodiment of the production efficiency of the manufacturing system and one of the important performance indexes of the FJSSP.

$$f_1 = \max\,(C_i\,|i = 1, 2, \cdots n) \tag{2}$$

2) Total equipment load f_2. The scheduling goal of the equipment load is to uniformly distribute the processing

process of all the jobs on each equipment, and improvethe probability of equipment utilization. The total equipment load is defined as the sum of the processing time of all equipment.

$$f_2 = \sum_{k=1}^{m} \sum_{i=1}^{n} \sum_{j=1}^{q_i} a_{ij}^k \times t_{ij}^k \tag{3}$$

3) Energy consumption f_3. Energy consumption in intelligent manufacturing system mainly includes equipment processing energy consumption and equipment no-load energy consumption. The energy-based scheduling goal is to lower the energy consumption in manufacturing process and achieve green manufacturing.

$$f_3 = \sum_{k=1}^{m} E_k = \sum_{k=1}^{m} (E_k^J + E_k^K) \tag{4}$$

Processing energy consumption is expressed as follows:

$$E_k^J = \sum_{i=1}^{n} \sum_{j=1}^{q_i} \left(a_{ij}^k \times t_{ij}^k\right) \times P^k \tag{5}$$

No-load energy consumption is expressed as follows:

$$E_k^K = \left(C_k - S_k - \sum_{i=1}^{n} \sum_{j=1}^{q_i} \left(a_{ij}^k \times t_{ij}^k\right)\right) \times PD^k \tag{6}$$

4) Delay time f_4. The delay time for job processing is the backward delay time in the specified job delivery time. The scheduling goal based on the delay time is to reduce latency and deliver on time based on delivery time.

$$f_4 = \sum_{i=1}^{n} \max\left(C_i - DD_i, 0\right) \tag{7}$$

5) Processing quality f_5. When the same operation of a job is processed on different equipment, the processing quality is different. The scheduling goal based on processing quality is to reduce the failure rate of all jobs. Processing quality can be written as

$$f_5 = \sum_{i=1}^{n} \sum_{j=1}^{q_i} O_{ij}^k L_{ijk} \tag{8}$$

The constraints can be expressed as follows:

$$S_{ijk} + T_{ijk} \leq S_{ij+1p} \tag{9}$$

$$S_{ij} + M \times F_{ijk} \geq S_{jk} + T_{jk} \tag{10}$$

$$S_{ij} + M \times \left(1 - F_{ijk}\right) \geq S_{jk} + T_{jk} \tag{11}$$

$$\sum_{k=1}^{m} X_{ijk} = 1 \tag{12}$$

$$S_{ijk} \geq 0, \quad T_{ijk} \geq 0, \ tr_{i,j-1,j} \geq 0 \tag{13}$$

Eq.(9) indicates that the last operation can only be started after the previous operation is finished. Eq.(10) and Eq.(11) indicate that the same machine can only process one job at a time. Eq.(12) indicates that a job can only be processed on one machine at a time. Eq.(13) represents a positive constraint.

IV. IMPROVED NSGA-III TO MANY-OBJECTIVE FLEXIBLE JOB SHOP SCHEDULING PROBLEM

Firstly, overview of NSGA-III was introduced. NSGA-III has been proposed based on the framework of NSGA-II, and the difference between the two algorithms is mainly the change of selection mechanism. Finally, NSGA-III-APEV was introduced in detail.

A. OVERVIEW OF NSGA-III

A set of uniformly distributed reference points is generated, and the scale of the reference points is H. A parent population P_t with size N is initialized. Operating population P_t with genetic operators (selection, mating, mutation) can obtain an offspring population Q_t with size N. Merging the population P_t and the population Q_t can obtain the population U_t with size 2N. We want to choose N individuals from the population U_t such that the population U_t via non-dominated sorting can obtain different non-dominated layers F_1, F_2, etc. Individuals with non-dominated layers are added to the new population S_t until the size of S_t is greater than or equal to N. If the last non-dominated layer is F_l, the individuals in S_t/F_l are directly added to the next generation parent populationP_{t+1}. The remaining individuals need to be selected from F_l until the size of S_t reaches N according to the diversity preservation strategy.

Individuals are selected by reference point-based niche technology in NSGA-III. The specific process is as follows: Normalizing the objective values of the population can solve the problem of inconsistent dimensions of different objective functions. At this time, the reference point becomes the origin, and a reference point vector is constructed. Individuals in a population S_t are associated with various reference points by calculating the vertical distance of each individual to all reference vectors. Then, Niche Preservation Operation can be employed to choose individuals from F_l until the number of individuals in P_{t+1} reaches N.

The niche preservation operation is given as follows: the individuals in S_t/F_l are associated with each reference point, and the number of individuals associated with the jth reference point is recorded as p_j. The reference point with the least number of associations is found. The following two situations are discussed:

case 1: (1)If $p_j = 0$, there are some individuals associated with this reference vector in F_l, then the individual with the smallest distance can be found, it is extracted from F_l and added to P_{t+1}, we add one to the number of p_j. (2)If $p_j > 0$, from the individuals associated with the reference point in the F_l, we randomly select one individual that is added to P_{t+1}.

case 2: If no individual is associated with the reference point in F_l, the reference point is deleted.

The operation is performed repeatedly until the requirement of the population size is met.

B. THE PROPOSED ALGORITHM NSGA-III-APEV

In this subsection, the proposed algorithm(NSGA-III-APEV) is presented in detail. Firstly, we introduce the overall structure of the proposed algorithm, and then the encoding method of the scheduling problem, the normalization operation, the adaptive penalty distance, the adaptive elimination mechanism, adaptive mutation strategy and fuzzy decision, are introduced separately.

1) FRAMEWORK OF THE PROPOSED ALGORITHM

First, H uniformly distributed reference points are generated. We define the encoding method of production scheduling problems. A parent population P_t with size N is initialized. Operating population P_t with genetic operators (selection, mating, mutation) can obtain an offspring population Q_t with size N. The mutation operation in the genetic operator uses an adaptive mutation strategy based on consanguinity. Merging the population P_t and the population Q_t can obtain the population U_t with size 2N.

We need to choose N individuals from the population, so the population via non-dominated sorting can obtain different non-dominated layers F_1, F_2, etc. For the Ma-OFJSSP, after several iterations, the number of individuals in the first dominating layer of the population will exceed N. Therefore, if the number of individuals in the first dominating layer is not more than N, we use environmental selection of NSGA-III to get N individuals of the next generation parent population P_{t+1}. Otherwise, we use an elimination mechanism to obtain N individuals of the next generation parent population. The distance between the individual and the reference vector is calculated by using the PBI distance in association operation. When the correlation operation is carried out, the operation is conducted repeatedly until the requirement of iterations is met. Finally, we obtain a scheduling solution set, and use fuzzy decision method to select the appropriate scheduling solution. The flowchart of NSGA-III-APEV is illustrated in Fig.1.

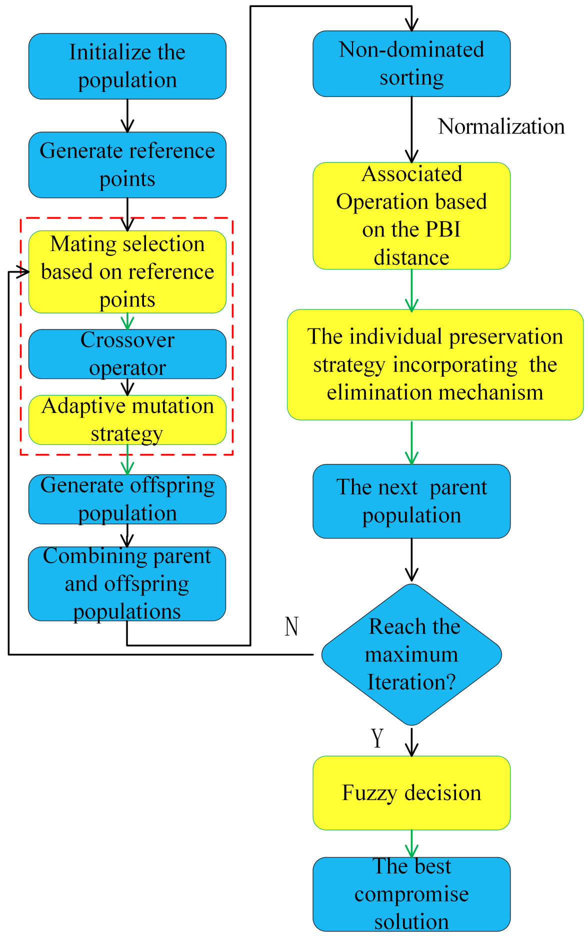


FIGURE 1. The flowchart of NSGA-III-APEV.

2) THE ENCODING AND DECODING METHOD

In the intelligent manufacturing system scheduling problem, considering the emergence of process sequencing and equipment allocation, this paper adopts a double integer encoding method based on process and equipment, as depicted in Fig.2.

Encoding based on process: the length of chromosome x in each process is the total number of all processes to be processed. Each gene of the chromosome represents the ith workpiece number, and the occurrence number of the workpiece numberq_i represents the q_ith operation of the workpiece$i$.

Encoding based on equipment: the length of each equipment chromosome y is equal to the length of the process chromosome. Each gene of the equipment chromosome indicates the optional equipment serial number of the corresponding process chromosome.

Decoding procedure can transform chromosomes into scheduling schemes based on coding information and coding rules. The scheduling schemes are generally represented by Gantt charts. Decoding is not a simply reverse coding operation. Different decoding methods produce different scheduling solutions. The decoding process of the optimization method mentioned in this article can be divided into two steps. The first step is to determine the processing equipment corresponding to each process according to the equipment encoding of the chromosome, and to convert the equipment-based encoding into a machine matrix and a time matrix; The second step is to determine the processing order of different processes on each equipment, and to convert the process-based encoding into the sequence of the process.

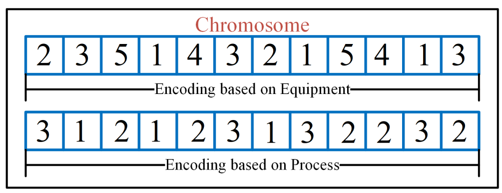


FIGURE 2. Double integer encoding method.

3) ADAPTIVE NORMALIZATION

Adaptive normalization is used to solve the problem of inconsistent dimensions belonging to different objective functions. Firstly, we need to calculate the minimum of each objective dimension I, and the corresponding minimum on the ith objective is Z_i. The set of Z_i is the ideal point set.

Extreme points can be obtained by using the following the achievement scalarizing function:

$$ASF\,(x,\omega)=\max_{i=1}^{M} f_i'(x)\big/\omega_{ji} \tag{14}$$

where $\omega_{ji}=\left(\omega_{j1},\omega_{j2},\omega_{j3},\cdots\omega_{jM,}\right)^T$ is the axis direction of the objective axisf_j. Then ω_{ji} satisfies the following formula:

$$\omega_{ji}=\begin{cases}10^{-6}, & i\neq j;\\ 1, & i=j.\end{cases} \tag{15}$$

The corresponding intercept can be calculated by constructing M-dimensional hyperplanes based on M-dimensional extreme points. For each individual x in the population, the ith dimension of the normalized objective function is expressed as:

$$f_i^n\,(x)=\frac{f_i\,(x)-Z_i^{\min}}{a_i-Z_i^{\min}},\, i=1,2,\cdots M \tag{16}$$

4) ADAPTIVE PENALTY DISTANCE

NSGA-III ignores the convergence of the population in the environment selection. Therefore, when we define the distance between population and reference vector, this paper uses the penalty-based boundary intersection distance (PBI distance) that can take into account both convergence and diversity. Let $f^n\,(x)=\left(f_1^n\,(x)\,,f_1^n\,(x)\,,\cdots f_M^n\,(x)\right)^T$ is the normalized vector of individual objective values, L be the reference direction, $d_{j,1}(x)$ denote the projection distance of $f^n\,(x)$, and $d_{j,2}(x)$ denote the vertical distance of $f^n\,(x)$, as indicated in Fig.3. Their mathematical expression can be expressed as follows:

$$d_{j,1}(x)=\left\|\left(f^n(x)^T\omega_{ji}\right)\right\|\big/\left\|\omega_{ji}\right\| \tag{17}$$

$$d_{j,2}(x)=\left\|f^n\,(x)-d_{j,1}(x)\left(\omega_{ji}\big/\left\|\omega_{ji}\right\|\right)\right\| \tag{18}$$

Then, the PBI distancecan be expressed by $d(x)=d_{j,1}(x)+\theta d_{j,2}(x)$, where $d_{j,1}$ is used to evaluate the convergence, $d_{j,2}$ is used to evaluate the diversity, and θ is a preset penalty parameter.

5) ADAPTIVE ELIMINATION MECHANISM

Due to the large number of optimization objectives, the number of non-dominant solutions in the population increases exponentially in the process of solving the Ma-OFJSSP. After several iterations, the number of non-dominated solutions in the first layer will exceed N. In NSGA-III, the environment selection operator is repeated N times, it results in a decrease of computing efficiency. In order to improve computing efficiency in environment selection, the adaptive elimination mechanism is proposed as shown in Algorithm 1.

Case 1: If the population size of the non-dominated layer F_1 <N. The environment selection operator utilizes the selection mechanism of NSGA-III.

Case 2: If the population size of non-dominated layer F_1 >N, the number of individuals associated with reference point j is expressed as p_j. Firstly, we need to find the reference point associating with the largest number of population individuals. In the population individuals associated with this reference point, we find the individual with the largest PBI distance and delete it. Then, the count of p_j is decreased by 1. The operation is cycled continuously until the requirement of the population size is met. Compared with the NSGA-III, the calculation efficiency is greatly improved in environment selection.

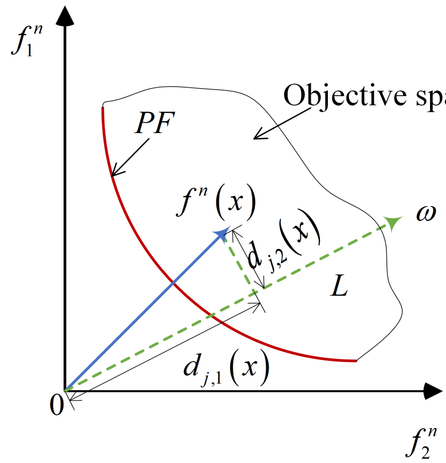


FIGURE 3. The schematic of distance $d_{j,1}$ and $d_{j,2}$.

Algorithm 1 Adaptive Elimination Mechanism

Input: U_t, S_t, H reference points
Output: the parent population P_{t+1}

```
if |S_t|=N then
    P_{t+1} = S_t
else
    if |F_1|>N then
        repeat
            Associate individuals with reference points
            Find the reference point j with maximal p_j
            Eliminate i with the largest PBI distance from
    I_j
        until |S_t|=N
        P_{t+1} = S_t
    else|F_1|<N
        repeat
            Use the selection mechanism of NSGA-III
        until |S_t|=N
        P_{t+1} = S_t
    end if
end if
return P_{t+1}
```

6) ADAPTIVE MUTATION STRATEGY

Due to the continuous crossover and reproduction of closely related genes, the population converges too quickly. In order to increase the diversity of the population and avoid converging on local optima, the genetic operator adopts the adaptive mutation strategy which can obtain the close relative index of the crossed chromosomes and the mutation rate of individuals by calculating the consanguinity of two crossed individual chromosomes. We can improve the diversity of the population effectively by mutation operation based on the mutation rate. Calculation method of the adaptive mutation strategy is shown in Algorithm 2.

Algorithm 2 Adaptive Mutation Strategy

Input: two crossed individual chromosomesP_1, P_2 and initial mutation probability M

Output: the mutation probability m

```
float t =0
for i = 0 → n − 1 do
    if P1[i] == P2[i] then
        t ++
    end if
end for
s=t/n
m = M*s
return m
```

(1) Mutation operation of process gene segment. We randomly select a process gene on the process gene segment and insert it in other positions, as indicated in Fig.4.

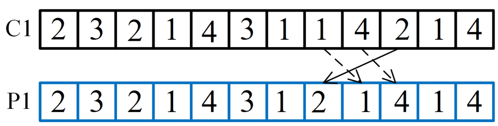


FIGURE 4. Mutation operation of process gene segment.

(2) Mutation operation of equipment gene segment. We randomly select 3 gene positions and change the corresponding optional equipment numbers.

7) FUZZY DECISION

In an intelligent manufacturing system, the number of optimization objectives for Ma-OFJSSP is usually no less than 4. The NSGA-III-APEV algorithm in solving Ma-OFJSSP ends up with the Pareto Set. The decision-maker needs to find the appropriate production scheduling solution from Pareto Set. We apply fuzzy decision to find the best compromise solution of Ma-OFJSSP and use the fuzzy subordinating degree function to deal with each objective function. The mathematical expression of the subordinate degree u_i for the ith objective function is expressed as follows:

$$u_i = \frac{F_i^{\max} - F_i}{F_i^{\max} - F_i^{\min}} \tag{19}$$

where $F_i^{\max}$ and F_i^{min} represent the maximum and minimum of the ith function respectively.

According to Eq.(20), the subordinate degree of the ith non-dominant solution is normalized, and the non-dominant solution with the maximum subordinate degree is the best compromise solution (BCS).

$$u^{opt} = \frac{\sum_{i=1}^{objs} u_i^n}{\sum_{n=1}^{N} \sum_{i=1}^{objs} u_i^n} \tag{20}$$

where $objs$ represents the number of all optimization objectives, N represents the number of all non-dominated solutions.

V. EXPERIMENT RESULTS AND ANALYSIS

In this section, we apply the proposed NSGA-III-APEV algorithm to the Ma-OFJSSP of FJSSP benchmarks and discrete machine tool component production line and machining production line. We verify the effectiveness and superiority of the proposed algorithm in engineering practice.

A. FJSSP BENCHMARKS

1) CASE INTRODUCTION AND PARAMETER SETTING

We choose 10 BRdata FJSSP benchmarks(Mk01-Mk10) to test the performance of the algorithm. NSGA-III-APEV, NSGA-III, Discrete MOPSO and NSGA-II are used for optimization, and each algorithm runs independently 30 times. We used Wilcoxon rank sum test to evaluate performance of the algorithms. The confidence level was set at 0.05. Due to lack power data in the benchmark example, Table 3 shows the equipment power information. The workshop fixed power is set to 20. The calculation formula for the delivery date of each job is as follows:

$$D_i = \delta \sum_{j=1}^{q_i} \max \left\{ t_{ij}^k \right\} \tag{21}$$

TABLE 3. The equipment power information.

Machine number	Operating power/kW	No-load power/kW
M_1	20	3.45
M_2	15	2.82
M_3	6	0.84
M_4	12	1.58
M_5	10	1.41
M_6	5.5	0.55
M_7	7.5	1.02
M_8	10	1.80
M_9	12	3.45
M_{10}	14	2.82
M_{11}	16	0.84
M_{12}	9	1.58
M_{13}	17	1.41
M_{14}	8	0.55
M_{15}	13	1.02

Table 4 shows the operating parameter settings of each intelligent optimization algorithm.

Because the visualization of Pareto Front is difficult for Ma-OFJSSP, two performance metrics are selected

TABLE 4. Parameters setting.

Parameters	Value
Population size	126
Maximum iteration	100
Crossover probability	0.8
Mutation probability(NSGA-III-APEV/ NSGA-III/ NSGA-II)	$0.5/0.1/0.1$

to evaluate performance of intelligent scheduling decision algorithms. IGD can evaluate convergence and diversity simultaneously. The smaller is the IGD value, the better is the comprehensive performance of the algorithm. Hypervolume (HV) can evaluate convergence and diversity simultaneously. The larger is the HV value, the better is the comprehensive performance of the algorithm.

The scheduling optimization experiment are run on MatlabR2016b software at a computer with Windows 10, Intel (R) Core (TM) i7-7700HQ and 8G RAM.

2) RESULTS AND ANALYSIS

Table 5 and Table 6 show that the performance metrics value obtained by the NSGA-III-APEV are better than NSGA-III, MOPSO and NSGA-II. The NSGA-III-APEV algorithm can improve the convergence and diversity of the population when we solve Ma-OFJSSP. The utilization of NSGA-III-APEV is beneficial to obtain a reasonable scheduling scheme.

It can be seen from the analysis of the above results that the convergence and diversity of the population are improved though the use of NSGA-III-APEV. NSGA-III focuses on diversity and ignore population convergence in environment selection. Furthermore, as the objective dimension increases, the selection pressure of NSGA-III based on Pareto dominance is not enough. Considering the two factors, NSGA-III-APEV uses the penalty-based boundary intersection distance (PBI distance) that can take into account both convergence and diversity to define the distance between the population individual and the reference vector in the association operation. Since NSGA-II uses crowded distance to select individual and the obtained solution is not uniformly distributed on the non-dominated layer for the many-objective scheduling optimization problem, the population converges to local optima.

For the population diversity, based on NSGA-III, NSGA-III-APEV adds an adaptive mutation strategy, which calculates the individual mutation rate based on the close relative index of the crossed chromosomes. Therefore, it can effectively avoid the rapid convergence caused by the continuous crossover of the close relative genes and improve the population diversity. For the many-objective scheduling problem, the selection operation of the crowded distance in the NSGA-II algorithm cannot effectively maintain the population diversity. Because the reference points set by the NSGA-III algorithm are widely distributed on the hyperplane, the selected population also is widely distributed on the really Pareto surface and the NSGA-III algorithm can improve the population diversity.

TABLE 5. Statistical results of IGD.

Algorithms	NSGA-II		NSGA-III		MOPSO		NSGA-III-APEV
	Mean	p value	Mean	p value	Mean	p value	Mean
Mk01	81.3238	3.0199e-11	25.7975	3.1589e-10	26.9293	1.0702e-09	12.5427
Mk02	60.8325	3.0199e-11	27.5395	3.8202e-10	27.7728	1.1023e-08	16.6352
Mk03	338.8447	6.6955e-11	136.1138	2.0023e-06	180.8075	1.6947e-09	79.9001
Mk04	119.0831	3.0199e-11	47.5849	8.9934e-11	53.1214	8.1014e-10	18.5910
Mk05	310.9173	3.0199e-11	98.5249	1.4643e-10	105.5516	8.1527e-11	26.4535
Mk06	220.4932	3.0199e-11	114.7429	2.4386e-09	89.3118	9.5332e-07	47.7113
Mk07	339.5531	3.0199e-11	114.8447	2.8314e-08	121.9311	1.4733e-07	56.8063
Mk08	1053.363	3.0199e-11	404.3522	4.6159e-10	457.161	3.4742e-10	155.5852
Mk09	760.8753	3.3384e-11	210.359	7.0881e-08	395.5859	6.6955e-11	82.8211
Mk10	532.1969	3.0199e-11	125.5077	6.0104e-08	186.7019	3.8249e-09	71.3986

TABLE 6. Statistical results of HV.

Algorithms	NSGA-II		NSGA-III		MOPSO		NSGA-III-APEV
	Mean	p value	Mean	p value	Mean	p value	Mean
Mk01	5.94E-04	3.0180e-11	0.002049	3.0199e-11	0.002348	4.5043e-11	0.005409
Mk02	9.99E-04	3.0199e-11	0.002548	3.0199e-11	0.003023	4.9752e-11	0.00708
Mk03	4.46E-04	3.0199e-11	0.000912	3.1589e-10	0.000986	2.4386e-09	0.001638
Mk04	0.000211	3.0199e-11	0.000562	3.0199e-11	0.00067	1.0937e-10	0.00157
Mk05	1.33E-05	3.0142e-11	4.51E-05	2.0676e-11	5.74E-05	3.6874e-11	0.000147
Mk06	5.42E-04	3.0199e-11	1.60E-03	6.0621e-11	2.45E-03	3.3505e-08	0.0046
Mk07	4.40E-05	3.0199e-11	1.96E-04	3.0161e-11	2.89E-04	4.5015e-11	0.00087
Mk08	8.79E-05	3.0199e-11	1.76E-04	3.0085e-11	1.91E-04	3.3280e-11	0.000375
Mk09	4.98E-05	3.0199e-11	1.39E-04	2.3688e-10	1.05E-04	3.3342e-11	0.000309
Mk10	2.18E-04	3.0180e-11	4.79E-04	6.6874e-11	4.71E-04	1.6132e-10	0.000886

B. ENGINEERING CASE 1

1) CASE INTRODUCTION

Consider that a factory provides high-quality optical machines for high-precision CNC machine tools [40]. This factory which belongs to the production mode of multiple varieties and small batches mainly produces various tables, vertical columns, pedestals of machine tools, etc. We choose the core process of five typical components produced in the workshop to verify the proposed algorithm. The scheduling objectives are the maximum completion time, energy consumption, delay time, machine load and processing quality. This scheduling problem is a typical Ma-OFJSSP. The original data obtained in the manufacturing process includes equipment information and operation information of the jobs, as shown in Table 7 and Table 8.

TABLE 7. Operation information of the jobs.

job	workstage	Process operation	Processing machines	Processing time /min	Processing quality
machine tool bed	O_{11}	Milling benchmark	M_1/M_{10}	110/100	0.11/0.23
	O_{12}	Milling guide	M_2/M_{11}	45/55	0.1/0.2
	O_{13}	Drilling tapping	M_3	120	0.15
	O_{14}	coarse grinding guide surface	M_4	120	0.18
	O_{15}	paint spraying	M_5/M_9	25/35	0.22/0.02
Vertical column	O_{21}	Milling benchmark	M_1/M_{10}	30/25	0.12/0.18
	O_{22}	high-frequency quenching	M_6	30	0.08
	O_{23}	Boring and milling	M_7	20	0.15
	O_{24}	Drilling tapping	M_3	120	0.09
	O_{25}	coarse grinding guide	M_4	210	0.2
	O_{26}	paint spraying	M_5/M_9	240/250	0.11/0.15
Table	O_{31}	Milling benchmark	M_1/M_{10}	40/50	0.3/0.15
	O_{32}	high-frequency quenching	M_6	30	0.12
	O_{33}	laser cutting	M_8	100	0.23
	O_{34}	Roughing table	M_4	150	0.01
	O_{35}	finish-milling	M_2/M_{11}	37/49	0.23/0.2
	O_{36}	paint spraying	M_5/M_9	15/25	0.13/0.02
Headstock	O_{41}	Milling guide	M_2/M_{11}	38/52	0.01/0.35
	O_{42}	Drilling tapping	M_3	120	0.15
	O_{43}	Boring and milling	M_7	70	0.25
	O_{44}	paint spraying	M_5/M_9	23/17	0.12/0.18
Saddle	O_{51}	Milling benchmark	M_1/M_{10}	49/36	0.2/0.18
	O_{52}	laser cutting	M_8	120	0.08
	O_{53}	coarse grinding guide surface	M_4	120	0.12
10	O_{54}	Finish milling panel	M_2/M_{11}	34/41	0.25/0.15
	O_{54}	paint spraying	M_5/M_9	13/20	0.06/0.26

TABLE 8. The equipment information.

Machine name	Machine number	Operating power/kW	No-load power/kW
Semi-automatic planer milling machine	M_1 M_{10}	27.6 21.3	3.7 3.0
CNC planer milling machine	M_2 M_{11}	34.2 32.6	4.5 4.3
radial drilling machine	M_3	7.5	0.6
CNC vertical horizontal double head gantry grinder	M_4	20.1	2.9
spray robot	M_5 M_9	8.9 8	0.8 0.7
High-frequency quenching machine	M_6	28.5	3.9
boring lathe	M_7	22	3.2
laser cutting machine	M_8	15.5	2.1

TABLE 9. Objective values obtained using four algorithms.

Algorithms	Objectives	Min value	Mean value
NSGA-II	Completion time	783	905.0384
	Delay time	**0**	201.1538
	Total equipment load	**2010**	2035.6538
	Energy consumption	658.9050	684.8499
	Processing quality	3.5100	3.7808
MOPSO	Completion time	**781**	**862.1200**
	Delay time	**0**	57.9800
	Total equipment load	**2010**	2039.9200
	Energy consumption	646.1900	671.6193
	Processing quality	3.6100	3.8421
NSGA-III	Completion time	**781**	873.5300
	Delay time	**0**	64.8100
	Total equipment load	2019	2042.0700
	Energy consumption	650.0133	671.1022
	Processing quality	**3.4000**	3.8418
NSGA-III-APEV	Completion time	**781**	890.1900
	Delay time	**0**	**32.8200**
	Total equipment load	2012	**2030.8900**
	Energy consumption	**645.8683**	**664.5610**
	Processing quality	3.4400	**3.7579**

2) RESULTS AND ANALYSIS

In the intelligent scheduling problem of discrete machine tool component production line, because NSGA-III-APEV, NSGA-III, MOPSO and NSGA-II, are run once randomly, we get the minima and means of five objectives, as shown in Table 9. The better result in Table 9 is shown in bold. It can be found from Table 9 that the means of four objective functions obtained by the NSGA-III-APEV algorithm are superior to those of the other three methods, and the minima of three objective functions obtained by NSGA-III-APEV are superior to those of the other three methods. The above results show that the convergence of NSGA-III-APEV is improved and the utilization of NSGA-III-APEV can obtain a reasonable scheduling scheme.

Fig.5 shows the evolutionary trajectory of the two performance metrics with respect to function evaluations when the four algorithms are exploited to solve the machine tool component production line scheduling problem. The HV indicators of the four algorithms gradually increase with the increase of the functional evaluation time, while the IGD indicator gradually decrease with the increase of the functional evaluation time. Fig.5 shows that the convergence performance of these three algorithms is stable. In Fig.5, the HV evolution curve of the NSGA-III-APEV is higher than the

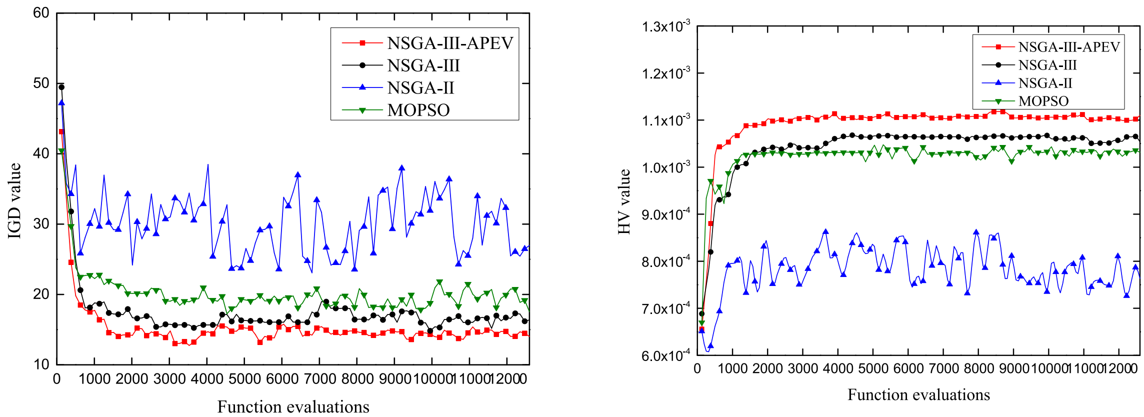


FIGURE 5. The evolutionary trajectory of the two performance metrics.

other curves. The IGD evolution curve of the NSGA-III-APEV are lower than other curves. The above results show that the optimization effectiveness of NSGA-III-APEV is better.

Table 10 shows the best compromise solution obtained by the four algorithms. The best result in Table 10 is shown in bold. Fig.6 shows the Gantt chart of scheduling scheme for each algorithm. It can be found from Table 10 that the best compromise solution obtained by NSGA-III-APEV is superior to other algorithmsin terms of all objectives except one. It has a slightly lower processing quality. Note that it is important to optimize multiple objective functions simultaneously and find the best compromise scheduling scheme in actual flexible job shop production.

TABLE 10. The best compromise solution.

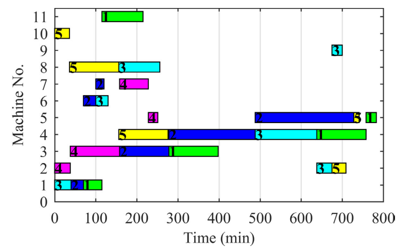
Algorithms	NSGA-II	MOPSO	NSGA-III	NSGA-III-APEV
Completion time	**783**	**783**	794	**783**
Delay time	141	**0**	**0**	**0**
Total equipment load	2016	676.5966	2016	**2015**
Energy consumption	683.1883	676.5966	667.8483	**660.2916**
Processing quality	3.8600	3.8600	**3.7800**	3.8200

Fig.6 shows the scheduling gantt chart obtained by each algorithm. It can be found that the scheduling scheme obtained by NSGA-III-APEV is superior to NSGA-III, MOPSO and NSGA-II. The scheduling scheme obtained by NSGA-III-APEV can effectively shorten the completion time and the delay time, reduce the energy consumption and equipment load of processing, and can better guide production operation in Fig.6 demonstrates the effectiveness and superiority of NSGA-III-APEV.

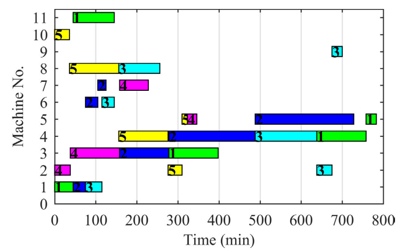
The computational time in the environment selection operator is shown in the Table 11.

We run 30 times and do statistical test (Wilcoxon rank sum test) for comparing the performance of each algorithm. Table 12 shows the mean of the two metrics.

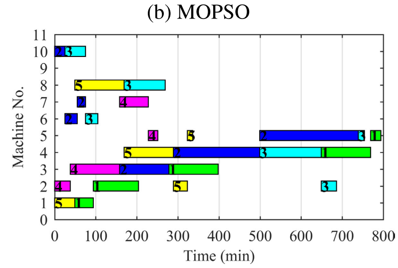
Table 12 shows that the performance metrics obtained by the NSGA-III-APEV are better than NSGA-III, MOPSO and NSGA-II.



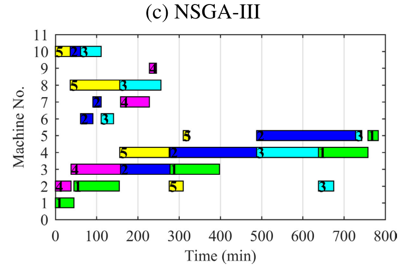
(a) NSGA-II



(b) MOPSO



(c) NSGA-III



(d) NSGA-III-APEV

FIGURE 6. The scheduling Gantt chart obtained by each algorithm.

In one word, the NSGA-III-APEV algorithm can improve the convergence and diversity of the population for

TABLE 11. The computational time.

Algorithms	NSGA-III	NSGA-III-APEV	p value	Improved ratio
Mean time(s)	0.00556	0.00342	1.7849e-13	39.21%

TABLE 12. Statistical results of two metrics.

Algorithms	Indicators	IGD	HV
NSGA-II	Mean	27.6665	9.1542e-4
	p value	7.3803e-10	4.6856e-08
NSGA-III	Mean	22.0732	10.3911 e-4
	p value	0.0392	0.0271
MOPSO	Mean	21.4574	10.1734e-4
	p value	3.0199e-11	0.0031
NSGA-III-APEV	Mean	18.7444	11.2928e-4

the Ma-OFJSSP. This improved optimization algorithm strengthens the balance between convergence and diversity, and improves the quality of Pareto Set.

For computing efficiency, it is difficult for Ma-OFJSSP to calculate the crowded distance in NSGA-II. The crowded distance is not suitable for solving Ma-OFJSSP. Therefore, NSGA-III no longer uses the crowded distance, but utilizes a reference point-based selection mechanism, which increases the calculation efficiency. Due to a large number of optimization objectives, the number of non-dominant solutions in the population increases exponentially in the process of solving the Ma-OFJSSP. After several iterations, the number of non-dominated solutions in the first layer will exceed N. In NSGA-III, the environment selection operator is performed N times, resulting in a decrease of computing efficiency. The adaptive elimination mechanism is used to improve computing efficiency in environment selection.

At the same time, we also analyze the computational complexity of the proposed algorithm. Assuming that the number of population is N and the number of objectives is M. There are mainly the following four operations for the population, which are genetic operator, chromosome decoding, non-dominated sorting and environment selection. Environmental selection includes calculation of ideal points, calculation of extreme points, population normalization, association operations, and niche preservation operation. The computational complexity of non-dominated sorting, calculating the ideal point, calculating the extreme points and population normalization are $O\left(N\log^{M-2}N\right)$, $O\left(MN\right)$, $O\left(M^2N\right)$ and $O\left(N\right)$, respectively. During the association operation, the number of reference points is $H(H=N)$, so the computational complexity of the association operation is $O\left(MN^2\right)$. The computational complexity of genetic operator is $O\left(N\right)$. The computational complexity of chromosome decoding is $O\left(N\right)$. According to the above computational complexity analysis, the worst computational complexity of the proposed algorithm is $O\left(MN^2\right)$.

C. ENGINEERING CASE 2

1) CASE INTRODUCTION AND PARAMETER SETTING

A machining production line has the characteristics of multiple varieties and small batches. Each component contains multiple processes. The process route of each workpiece is different. Each process can be processed on multiple equipment and each equipment can process multiple processes. The number of optimization goals is more than 4, so the scheduling problem of machining production line is a typical high-dimensional flexible workshop scheduling problem. The operation information of machining jobs in the machining production line is shown in the Table 13, and the processing equipment information is shown in the Table 14. The transfer energy of each operation is 2Kw. Energy consumption included transfer energy. The operating parameters and experimental conditions of the decision optimization algorithm are the same as those benchmarks.

TABLE 13. Operation information of the jobs.

Job	workstage	Processing machines	Processing time /min	Processing quality	Delivery date
J_1	O_{11}	$M_4/M_6/M_7$	12/1/9	0.1/0.09/0.11	60
	O_{12}	M_1/M_5 M_6/M_8	17/17/10/15	0.07/0.15 0.12/0.05	
	O_{13}	$M_2/M_4/M_7$	24/11/10	0.2/0.1/0.13	
J_2	O_{21}	$M_3/M_4/M_5$ M_6/M_8	$11, 10, 21, 14, 17$	0.05/0.10/0.11 0.14/0.11	100
	O_{22}	M_1/M_2 M_5/M_6	$8, 12, 19, 11$	0.08/0.15, 0.09/0.1	
	O_{23}	$M_2/M_4/M_6/M_7$	$15, 21, 25$	0.05, 0.12, 0.15	
	O_{24}	M_5/M_7	$18, 9$	0.1, 0.09	
	O_{25}	$M_1/M_2/M_4$ M_5/M_6	$12, 15, 14, 9, 10$	0.12/0.05/0.1 0.09/0.12	
	O_{26}	M_2/M_4 M_5/M_6	$9, 7, 10, 8$	0.09, 0.08 0.10, 0.09	
J_3	O_{31}	M_2/M_7	14/17	0.1/0.12	120
	O_{32}	M_2/M_3 M_4/M_6	23/23/17/18	0.13/0.08 0.07/0.15	
	O_{33}	M_3/M_4 M_5/M_8	20/9/22/21	0.20/0.09 0.1/0.11	
	O_{34}	$M_1/M_3/M_5$ M_6/M_7	7/10/8/11/9	0.07/0.12/0.18 0.11/0.12	
J_4	O_{41}	$M_2/M_6/M_7$	18/17/18	0.1/0.07/0.08	80
	O_{42}	M_4/M_7	10/12	0.10/0.08	
	O_{43}	$M_2/M_3/M_4$ M_7/M_8	8/11/8/9/20	0.08/0.1/0.18 0.1/0.20	
J_5	O_{51}	$M_3/M_4/M_5$	24/10/16	0.14/0.10/0.11	60
	O_{52}	M_4/M_8	18/19	0.12/0.14	
J_6	O_{61}	M_2/M_7	20/22	0.08/0.2	80
	O_{62}	M_3/M_7	18/19	0.11/0.19	
	O_{63}	$M_1/M_3/M_4$ M_5/M_8	19/17/16/16/18	0.09/0.1/0.12 0.06/0.1	
J_7	O_{71}	$M_3/M_5/M_6$	16/17/16	0.12/0.07/0.12	200
	O_{72}	$M_1/M_6/M_7$	22/20/22	0.2/0.13/0.12	
	O_{73}	M_6/M_7	18/23	0.08/0.11	
	O_{74}	M_6/M_8	10/24	0.12/0.14	
J_8	O_{81}	$M_1/M_7/M_8$	11/21/21	0.07/0.11/0.09	100
	O_{82}	M_1/M_2	25/11	0.2/0.09	
	O_{83}	M_1/M_2 M_6/M_8	24/18/25/20	0.14/0.13 0.09/0.15	

2) RESULTS AND ANALYSIS

In the intelligent scheduling problem of machining production line, NSGA-III-APEV, NSGA-III, MOPSO and NSGA-II, are run once randomly, we get the minima and means of five objectives, as shown in Table 15. The better result in Table 15 is shown in bold. From the comparison results, we can find that the means of five objective functions obtained by the NSGA-III-APEV algorithm are superior to those of the other three methods, and the minima of three

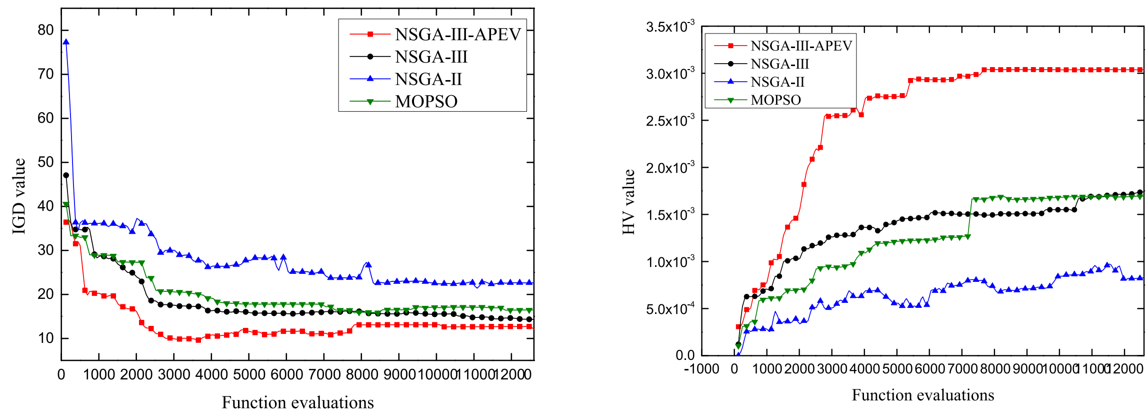


FIGURE 7. The evolutionary trajectory of the two performance metrics.

TABLE 14. The equipment information.

Machine number	Operating power/kW	No-load power/kW
M_1	20	3.45
M_2	15	2.82
M_3	6	0.84
M_4	12	1.58
M_5	10	1.41
M_6	5.5	0.55
M_7	7.5	1.02
M_8	10	1.80

TABLE 15. Objective values obtained using four algorithms.

Algorithms	Objectives	Min value	Mean value
	Completion time	93	115.1200
	Delay time	**0**	49.7300
NSGA-II	Total equipment load	384	404.6000
	Energy consumption	178.1905	186.6464
	Processing quality	**2.6300**	2.8274
	Completion time	88	105.8500
	Delay time	**0**	14.4100
MOPSO	Total equipment load	398	414.7200
	Energy consumption	172.0740	189.3731
	Processing quality	2.6600	2.8600
	Completion time	85	98.8100
	Delay time	**0**	16.1300
NSGA-III	Total equipment load	385	396.2900
	Energy consumption	172.6291	179.9686
	Processing quality	2.7100	2.8910
	Completion time	**82**	**90.7200**
	Delay time	**0**	**3.2100**
NSGA-III-APEV	Total equipment load	**379**	**395.8200**
	Energy consumption	**169.1225**	**174.3933**
	Processing quality	**2.6300**	**2.7241**

objective functions obtained by NSGA-III-APEV are superior to those of the other three methods. The above results show that the convergence of NSGA-III-APEV is improved and the utilization of NSGA-III-APEV is beneficial to obtain a reasonable scheduling scheme.

TABLE 16. The best compromise solution.

Algorithms	NSGA-II	MOPSO	NSGA-III	NSGA-III-APEV
Completion time	100	89	104	**85**
Delay time	15	7	4	**0**
Total equipment load	398	412	**388**	389
Energy consumption	178.1905	177.9106	178.3816	**172.6880**
Processing quality	2.9300	2.7400	**2.7100**	2.7300

TABLE 17. The computational time.

Algorithms	NSGA-III	NSGA-III-APEV	p value	Improved ratio
Mean time(s)	0.00593	0.00326	1.9529e-13	45.03%

Fig.7 shows the evolutionary trajectory of the two performance metrics with respect to the number of function evaluations when the four algorithms are exploited to solve the machine tool component production line scheduling problem. The HV indicators of the four algorithms gradually increase with the increase of the functional evaluation time, while the IGD indicator gradually decrease with the increase of the functional evaluation time. Fig.7 shows that the convergence performance of these three algorithms is stable. In Fig.7, the HV evolution curve of the NSGA-III-APEV is higher than the other curves. The IGD curve of the NSGA-III-APEV are lower than other curves. The above results show that the optimization effectiveness of NSGA-III-APEV is better.

Table 16 shows the best compromise solution obtained by the four algorithms. The best result in Table 16 is shown in bold. Fig.8 shows the Gantt chart of scheduling scheme for each algorithm. It can be found from Table 16 that the best compromise solution obtained by NSGA-III-APEV is superior to other algorithms, with only slightly lower processing quality and equipment load, and other objective values are better than other algorithms. It is important to optimize multiple objective functions simultaneously and find the best compromise scheduling scheme in actual flexible job shop production.

Fig.8 shows the scheduling gantt chart obtained by each algorithm. It can be found that the scheduling scheme

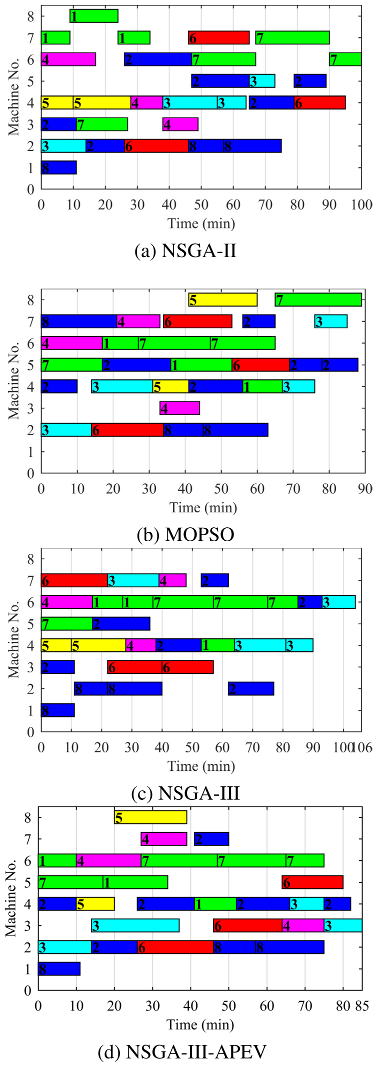


FIGURE 8. The scheduling Gantt chart obtained by each algorithm.

TABLE 18. Statistical results of two metrics.

Algorithms	Indicators	IGD	HV
NSGA-II	Mean	18.4055	18.5780e-4
	p value	4.4440e-07	0.0030
NSGA-III	Mean	15.4391	19.5439 e-4
	p value	0.0364	0.0207
MOPSO	Mean	16.9793	0.001863
	p value	1.6132e-10	3.4971e-09
NSGA-III-APEV	Mean	13.7176	22.6181 e-4

obtained by NSGA-III-APEV is superior to NSGA-III, MOPSO and NSGA-II. The scheduling scheme obtained by NSGA-APEV can effectively shorten the completion time and the delay time, and reduce the energy consumption, and can better guide production operation in practice. Fig.8 demonstrates the effectiveness and superiority of NSGA-III-APEV. The computational time in the environment selection operator is shown in the Table 17.

We run 30 times and do statistical test (Wilcoxon rank sum test) for comparing the performance of each algorithm. Table 18 shows the mean of the four metrics. Table 18 shows that the performance metrics obtained by the NSGA-III-APEV are better than NSGA-III, MOPSO and NSGA-II. The NSGA-III-APEV algorithm can improve the convergence and diversity of the population for the Ma-OFJSSP. This improved optimization algorithm strengthens the balance between convergence and diversity, and improves the quality of Pareto Set.

VI. CONCLUSION

In order to realize the high-efficiency, high-quality, high-flexibility and low-consumption of the product manufacturing process, this paper studies the Ma-OFJSSP of intelligent manufacturing systems and establishes the many-objective flexible job shop scheduling model with complex constraints. We propose an improved intelligent decision optimization method (named as NSGA-III-APEV) based on NSGA-III. This algorithm uses the penalty-based boundary intersection distance (PBI distance), which takes into account both convergence and diversity, to define the distance between the population and the reference vector in the association operation. We use a PBI distance-based elimination mechanism to preserve individuals and increase the computational efficiency in the individual preservation strategy. The adaptive mutation strategy based on consanguinity is applied to genetic operators. We obtain excellent scheduling schemes in solving two practical Ma-OFJSSPs. Compared with other methods, the proposed NSGA-III-APEV algorithm improves the convergence and the diversity of the population, strengthens the balance between convergence and diversity, and improves the quality of Pareto set. The NSGA-III-APEV algorithm can ensure that the decision-maker obtains a more suitable production scheduling scheme. Experiment results demonstrate the feasibility and superiority of the proposed method in solving the Ma-OFJSSP of intelligent manufacturing systems.

The occurrence of interference events, such as the insertion of emergency orders and machine failure, makes the original scheduling scheme unfeasible. Therefore, in future research, we will study how to carry out dynamic scheduling in the presence of interference events. As the scale of scheduling problem increases, the requirement for scheduling decision-making optimization algorithm increases, so it is necessary to study how to obtain Pareto front with good convergence and uniform distribution under the premise of ensuring the computational efficiency.

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