A New Sustainable Scheduling Method for Hybrid Flow-Shop Subject to the Characteristics of Parallel Machines

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ABSTRACT Sustainable production for hybrid flow shop scheduling problem (HFSP) has attracted growing attention due to the environment and economy pressure in industry. As the major source of energy-consumption and cost, the selection of parallel machines for various jobs quite affect the sustainability in HFSP. However, the characteristic of parallel machines in job shops have not been addressed in current research, which hinder its practical application. Thus, in this work a novel sustainable HFSP model considering the characteristics of the machines is proposed through evaluation of the power, production efficiency and cost of the parallel machines. To solve this model, an improved genetic algorithm is developed, in which the matching distance between the parallel machines and the weights of the optimization objectives is introduced and integrated into iterations to accelerate the convergence. Finally, a case study is adopted to verify the proposed model and algorithm. Based on the optimization results, three kinds of typical scheduling modes, i.e., efficiency, energy-saving, and economic, are put forward to provide guidance for the sustainable production of hybrid flow-shop scheduling.

INDEX TERMS Green manufacturing, hybrid flow-shop scheduling, characteristics of parallel machines, improved genetic algorithm.

NOMENCLATURE

| Notation | Description |
|----------|-------------|
| f        | objective function |
| f_{norm}(x) | normalized objective function |
| T        | makespan |
| E        | energy consumption |
| C        | cost |
| \alpha   | weight of makespan |
| \beta    | weight of energy consumption |
| \gamma   | weight of cost |
| k        | the selected machine number |
| k'       | the selected machine number for next stage |
| T_0      | the maximum of makespan |
| E_0      | the maximum of energy consumption |
| C_0      | the maximum of cost |

\[ ST(n, h, l) \] start time for the lth job of the nth process at machine h
\[ FT(n, h, l) \] completion time for the lth job of the nth process at machine h
\[ PT(n, h, l) \] processing time for the lth job of the nth process at machine h
\[ PT_{unit}(n, h, l) \] processing energy consumption per unit time for the lth job of the nth process at machine h
\[ WT_{unit}(n, h, l) \] waiting energy consumption per unit time for the lth job of the nth process at machine h
\[ D_{nh} \] matching distance
\[ p_{machine} \] the characteristics of parallel machines
\[ s_{machine} \] process time of the selected machine
\[ c_{machine} \] production cost per unit time of the selected machine
\[ w \] the weight vector of the optimization objective

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I. INTRODUCTION

With the pressure of economy and environment, sustainable production has been pay much attention both in the industrial production and academic [1]–[3]. The sustainable production is generally defined as: the creation of goods and services using processes and systems that are non-polluting, conserving of energy and natural resources and economically viable. Sustainable production has non-polluting conserving of energy and natural resources; economically viable; safe and healthful for employees, communities and consumers; and socially and creatively rewarding for all working people. From the point view of industrial practice, the sustainability can be evaluated with three criterions, i.e., environmental impact, production efficiency and cost. Generally, the most environmental impact was owing to the energy consumption [4], which result in the Energy-related CO2 emission. Production efficiency is closely related to processing time. Recently, researches on reduce energy consumption can be summarized into three aspects: the machine level, the product level, and the manufacturing level [5], [6]. At the machine level, the energy-saving machines or reasonable parameters for processing were developed to reduce the power and energy demands [7]–[10]. Unfortunately, it indicated that the share of energy demand for removal of metal material is quite small [11]. At the product level, the specific energy frameworks of product are developed [12], [13], which cannot be easily applied in small or medium enterprises because of the enormous investment of the simulation software. At the manufacturing level, optimal production planning and scheduling are developed to achieve energy conservation apparently [14], it is feasible in application and requires much less financial investment than other methods.

Hybrid flow-shop scheduling problem (HFSP) refers to the optimal arrangement of production plan and resources to satisfy the requirements of specific goals, by means of adjusting of jobs processing sequence and allocating the parallel equipment reasonably [15], [16]. To this end, in this work, we proposed a sustainable production model for hybrid flow shop to reduce the production time, energy consumption and production cost in the scheduling, that is consistent with the current definition.

The parallel machines are the core equipment in HFSP and the main energy source in machining. Improving the energy efficiency of machines in production was an important strategy to improve the sustainability of job-shops. Reference [16], [17] found that the non-bottleneck machines consumed a considerable amount of energy when left idle. A turn-on and turn-off scheduling framework was proposed to control the machines so as to reduce the idle energy consumption. However, the frequent turn on and off switches led to a large amount of energy consumption and damage to the life of machines. To solve this problem, a new machine speed scaling framework was introduced, in which the machines were allowed to work at different speed when processing various jobs [18], [19]. Based on this new framework, reference [20] leveraged the variable speed of machining operations corresponding to different energy consumption levels to explore the potential for energy saving. Moreover, switching between different states of the machines can also realize energy-saving. For instance, reference [21] proposed an emergency stop circuit methods for servo device on NC machines, which can save 20% of energy consumption of standby state by shutting down the servo system. In addition, reference [22] presented an ultra-low idle state of machines by turning off some auxiliary parts in idle state, and a hybrid algorithm was developed by adjusting the state of various NC machines. In summary, the existing studies have mainly focused on reducing energy consumption through active control of the processing state of machine tool. Note that the process of machine tool state switching neglected the influents of time and cost, a trade-off must be made between all the objectives.

From the perspective of sustainable production demand and multi-objective scheduling optimization, reference [23] considering the production efficiency and electric power cost with the presence of time-of-use electricity prices simultaneously in HFSP, a new ant colony optimization meta-heuristic was developed to reduce the energy consumption. Meanwhile, reference [24] developed a heuristic-search genetic algorithm aiming at minimizing the maximum completion time and minimizing the total weighted tardiness, respectively. Moreover, a large amount of improved algorithms developed to improve the efficiency, e. g. backtracking search algorithm [5], teacher’s teaching-learning-based method [28], [29], ant colony optimization [23], [30], improved genetic algorithm [19], [31]. However, the selection of machines for various jobs in HFSP was passively in current studies. It is noted that most of the researches focused on the accuracy model or the modified algorithm, they mostly have lost sight of the relevant among them, which enlarge the scheduling solution space. To address this problem, few local search methods were designed, for instance, a forward scheduling decoding method considering idle time [24], [25], an extended NEH-Insertion procedure with an energy-saving capability [26], strategy for improving the total weighted tardiness under fixed machine speeds, strategy for improving the total energy consumption under a fixed schedule [27]. Apparently, local search methods mostly optimized from the perspective of single objective, which not applicable to sustainable production.

According to the No free lunch theorem [32], it indicated the importance of utilizing problem-specific information to guide the search process of general-purpose algorithms. Inspired by the local search methods and the characteristics of machine tools, a sustainable production scheduling method was developed considering the goal of sustainable production, which can accelerate the convergence speed. Specifically, in the scheduling process of HFSP, the information of the characteristics of parallel machines can be exacted and incorporated into the selected meta-heuristic as a specialized local search module. To this end, this work established a sustainable model of HFSP and proposed an improved genetic
algorithm method integrating the characteristics of parallel machines. It can realize active selection of machines. The improved meta-heuristic algorithm could narrow the search scope to improve the efficiency of scheduling. Compared with the existing work, we make three contributions:

(1) A new sustainable scheduling mathematical model considering makespan, energy consumption, and cost reduction was proposed for the hybrid flow shop.

(2) The characteristics of parallel machines were defined by the process time, process power and production cost. By evaluating the matching distance between the characteristics of parallel machines and the weights of optimization objectives to realize active selection of machines.

(3) To solve the multi-objective model of HFSP, an improved genetic algorithm was presented to integrate the matching distance into each stage of genetic algorithm including the mutation operations and elite strategy, which can accelerate the convergence.

The framework of the following work is organized as: Section II elaborated the sustainable production model of HFSP and described the characteristics of parallel machines. Section III gave a solution for multi-objective problem of HFSP sustainable production based on improved genetic algorithm. Section IV presented the case study and comparison results, and three types scheduling schemes were analyzed to verify the model’s validity and practicability. Finally, a conclusion was drawn in section V.

II. PROBLEM FORMULATION

A. HYBRID FLOW SHOP SCHEDULING PROBLEM

The hybrid flow shop scheduling problem (HFSP) is one of the typical NP-Hard problems in combinatorial problem. It can be briefly described as follows: a set of jobs has to be processed at several stages in series. Each job consists of a chain of operations, which are processes in the same order. The operation should be processed at each stage with one machine, as shown in Fig.1. It should be point out that the parallel machines were not identical in this work, which means that the parallel machines at each stage may perform differently for the same job operation. Besides, without loss of generality, the following assumptions are considered for a better description of the problem.

(1) All machines and jobs are simultaneously available at time zero.

(2) All jobs are processed following the same production flow.

(3) There is no precedence constraint among the operations of different jobs.

(4) The machine cannot be turned off completely until it has finished all operations assigned to it.

B. SUSTAINABLE MODEL OF HFSP

This work proposed a multi-objective sustainable optimization problem in hybrid flow shop. The process of production can be divided into two parts: (1) processing, (2) waiting. Each part involved the corresponding consumption of makespan, energy and cost. In this work, the assignment of machines and the sequence of operations on all the machines were taken as variables to be solved. The makespan $T$, energy consumption $E$ and cost $C$ were taken as optimization objectives to realize sustainable production. Intuitively, the jobs were prioritized according to the weights $(\alpha, \beta, \gamma)$ of each objective. The optimization model equations are as follows:

$$
\min f = \alpha \cdot f_{\text{norm}}(T) + \beta \cdot f_{\text{norm}}(E) + \gamma \cdot f_{\text{norm}}(C) \quad (1)
$$

where $f_{\text{norm}}(x)$ is the normalized function of makespan, energy consumption and cost; $\alpha, \beta, \gamma$ means the weight of each objective, the sum of each objective is 1.

The multi-objective model in HFSP was also subject to the following constraints to ensure its integrity during the schedule optimization.

$$
X_{lk} = \begin{cases} 
1, & \text{if machine } k \text{ is selected for operation } l \\
0, & \text{otherwise} 
\end{cases} \quad (2)
$$

$$
FT(n + 1, k^*, l) - FT(n, k, l) \geq PT(n + 1, k^*, l) \quad (3)
$$

FIGURE 1. Work flow of hybrid flow-shop sustainable production.
\( ST(n+1,k^*,l) - FT(n,k,l) \geq 0 \) \hspace{1cm} (4)
\( FT(n,k,l) - FT(n,k,l-1) \geq PT(n,k,l) \) \hspace{1cm} (5)
\( 1 \leq k \leq m, \quad k \neq k \) \hspace{1cm} (6)
\( PT(n,k,l) \neq PT(n,k^*,l) \) \hspace{1cm} (7)
\( T \leq T_0 \quad E \leq E_0 \quad C \leq C_0 \) \hspace{1cm} (8)

where constraint (2) defines the assignment of jobs and the sequence of machines. Constraint (3) and Constraint (4) ensures that workpieces are processed according to sequence constraints. Constraint (5) governs that at one time a machine can execute one operation and it becomes available for other operations only if the previous operation is completed. Constraint (6) and Constraint (7) implies that the processing time of workpiece varied in different machines. Constraint (8) guarantees that the production processed meet the constrains of makespan, energy consumption and cost.

The makespan, energy-consumption and cost of production were elaborated in the following.

1) PRODUCTION MAKESPAN

The makespan of machining include processing time and waiting time. Generally, the processing time performed on each machine was a constant value which was initially given by the HFSP. The waiting time \( WT \) means the idle time of machines, which was determined by the completion time of the workpiece and the start time of the next workpiece on the same machine, as shown in Eq. (9).

\[ WT = ST(n,k,l) - FT(n,k,l-1) \] \hspace{1cm} (9)

where \( n \) implies the stage \( (n = 1,2,\ldots,s) \), \( k \) means the selected machine. \( l \) represents the job \( (l = 1,2,\ldots,w) \).

The makespan was the maximum completion time of each parallel machine in the last operation. It can be described in detail as shown in Eq. (10).

\[ T = \max \{ FT(s,k,l) \} \quad (l = 1,2,\ldots,w) \] \hspace{1cm} (10)

Completion time of the selected machine depended on the machining process. Noted that the first operation has no waiting time, start time is equal to machine completion time. For the following operation, start time is equal to the maximum value of the machine completion time and the last operation completion time of the workpiece. Consequently, the model was provided as follows: 1) The first operation of machines \( (n=1) \)

\[ ST(1,k,l) = FT(1,k,l-1) \] \hspace{1cm} (11)
\[ FT(1,k,l) = ST(1,k,l) + PT(1,k,l) \] \hspace{1cm} (12)

2) \( n \)th operation of machines \( (n \geq 2) \)

\[ ST(n,k,l) = \max \{ FT(n-1,k^*,l) , FT(n,k,l-1) \} \] \hspace{1cm} (13)
\[ FT(n,k,l) = ST(n,k,l) + PT(n,k,l) \] \hspace{1cm} (14)

2) PRODUCTION ENERGY CONSUMPTION

Energy consumption in job-shops was generally viewed as the impact of the environment indirectly. The total amount of energy consumption can be obtained by summing up the processing energy of all operations as Eq. (15).

\[ E = E_w + E_p \] \hspace{1cm} (15)

where \( E \) means the energy consumption. \( E_p \) refers to the energy consumption in machining. It was determined by processing time and the processing power per unit time of machine. \( E_w \) indicates the idle energy consumption of machines. It was determined by waiting time and the waiting power per unit time of machine. Details are as follows:

\[ E_p = \sum_{h=1}^{m} \sum_{l=1}^{w} \sum_{n=1}^{s} X_{inh} \cdot PT(n,h,l) \cdot P_{unit}(n,h,l) \] \hspace{1cm} (16)
\[ E_w = \sum_{h=1}^{m} \sum_{l=1}^{w} \sum_{n=1}^{s} X_{inh} \cdot (ST(n,h,l) - FT(n,h,l-1)) \cdot W_{unit}(n,h,l) \] \hspace{1cm} (17)

3) PRODUCTION COST

Cost is an important factor to obtain benefits for the sustainable development of enterprise. It included the consumption of electricity, this type of cost is ignored in most existing studies. Thus, the cost was composed of the using cost of machines \( C_U \) and energy consumption cost \( C_E \).

\[ C = C_U + C_E \] \hspace{1cm} (18)

where \( C_U \) refers to the cost of material, labor, equipment depreciation and management, which is mainly consists of the process time and the cost per unit time of the selected machine. \( C_E \) is generally means the electricity cost of total energy consumption. The value of the cost per unit energy consumption was set as 0.75 RMB/kW-h in calculation. The equations are defined below.

\[ C_U = \sum_{h=1}^{m} \sum_{l=1}^{w} \sum_{n=1}^{s} X_{inh} \cdot FT(n,h,l) \cdot c_{machine} \] \hspace{1cm} (19)
\[ C_E = E \cdot 0.75 \] \hspace{1cm} (20)

C. CHARACTERISTICS OF PARALLEL MACHINES

For the HFSP, there are a series of production stages, and each stage consists of several parallel machines. Machines at each stage can be identical, somewhat related, or unrelated at all. The scheduling problem is to assign each operation to a proper machine among a set of given parallel machines, whereas the scheduling sub-problem is to sequence the assigned operations on all machines with a satisfactory objective value. The selection of machine for operations from all parallel machines is an important decision-making process for scheduling optimization. Hereby, a matching distance method was developed to guide the selection of machines for various jobs assignment. The matching distance means the similarity between two individuals. In this work, the characteristics of parallel machines were matched with the weights of optimization objectives. By evaluating the matching degree between machines and production requirements to achieve
efficient selection and scheduling optimization of HFSP. In general, the closer matching distance indicated that the machine is more suitable for the production requirement.

There were two main aspects to determining the matching distance: (1) definition of the characteristics of parallel machines, (2) evaluation of matching distance.

1) DEFINITION OF THE CHARACTERISTICS OF PARALLEL MACHINES
According to the proposed model of makespan, energy consumption and cost, as well as the research on the characteristics of machines by Sutherland and other scholars [33], [34], machines show different characteristics in machining. In order to correlate the characteristics of parallel machines with optimization objectives effectively, a multi-level characteristic model of process time, process power and production cost were established to describe the parallel machines: $machine_c = \{t_{machine}, p_{machine}, c_{machine}\}$. In addition, the normalized evaluation matrix $f_{norm}(machine_c)$ is obtained by eliminating the influence of parameter dimension.

$$f_{norm} = (machine_c) = (f_{norm}(t_{machine}), f_{norm}(p_{machine}), f_{norm}(c_{machine}))$$  \hspace{1cm} (21)

2) EVALUATION OF MATCHING DISTANCE
Based on the normalized evaluation matrix $f_{norm}(machine_c)$, Euclidean distance was used to calculate the matching distance between the characteristics of parallel machines and the objectives, as shown in Eq. (22). For the sake of convenience in the computation, the weights of optimization objectives are expressed as matrix $w = [\alpha, \beta, \gamma]$.

$$d_{nh} = \|f_{norm}(machine_c) \times w\|$$  \hspace{1cm} (22)

where $d_{nh}$ represents the matching distance of $h$th machine for the $n$th stage with the objectives.

As shown in Fig. 2, the matching distances for all the parallel machines in HFSP can be formed an vector represented as $d_{nh} = \{d_{n1}, d_{n2}, \ldots, d_{nm}\}$, which would be used in the following genetic algorithm iteration processes.

### III. AN IMPROVED GENETIC ALGORITHM BASED ON MATCHING DISTANCE

Inspired by the matching distance between the characteristics of parallel machines and the weights of optimization objectives, an improved genetic algorithm (IGA) was developed to solve the hybrid flow-shop sustainable scheduling. In this approach, the matching distance was integrated into iterations of the genetic algorithm to improve the convergence.

The specific process can be described as follows:

#### A. THREE-LAYER ENCODING

The encoding representation of the HFSP is consist of three-layer. As shown in Fig. 3, the first layer means the sequence of workpiece, which adopts integer encoding to represent the order of workpiece entering the manufacturing system. The processing sequence of the workpiece is 2, 1, 3. The second layer represents the job operation. By scanning the chromosome from left to right, the appearance of a job number refers to the operation sequence of this job. The third layer is the machine selected by each operation. It is noted that the machines in the third layer could be encoded by the matching distance order. In Fig. 3, the matching distance order of the
parallel machines M12, M11, M13 for the first operation is 3,1,2.

**B. HEURISTIC MUTATION BASED ON MATCHING DISTANCE**

A heuristic mutation method was proposed based on the matching distance. The mutation operation mainly focused on the third layer of the chromosome. As shown in Fig.4, several mutation points were randomly selected in the chromosome, then the matching distance of the selected machines were calculated according to Eq. (22). The mutation operation of the machine tends to happen for the minimum value of the matching distance in the parallel machines. The improvement machine-selection process following the matching distance is described on Algorithm 1. This operation could force the GA to select the most suitable machine in the mutation process according to the scheduling objectives.

**C. ELITE STRATEGY BASED ON MATCHING DISTANCE**

An elite strategy was proposed according to the matching distance, which reserves the optimal individual. The evaluation criteria were set as follows: on the basis of the matching distance of all the selected machines, the offspring and parental individuals were re-selected into the next generations. It can be seen in Fig.5, in the third layer of chromosome, the matching distance of each gene was accumulated to calculate the score of the whole chromosome shown in Eq. (23). The chromosome with low score means more suitable for machining, which can enter the next generation population. Algorithm 2 describes how to obtain reasonable ones via screening all populations.

\[
G = \sum_{i=1}^{L} \sum_{h=1}^{m} X_{ih} \cdot d_{ih}
\]  

(23)

where \( G \) means the total score of chromosome. \( i \) is the gene on chromosomes. \( L \) ensures the number of chromosome genes.

**D. STOPPING CONDITION**

Meeting one of the following conditions can exit the iterations.
Algorithm 1 Improved Machine-Selection Process Following the Matching Distance

Input: \((n, l)\), \(mp/(n, l)\) represents the \(n\)th job of the \(l\)th stage; \(mp\) is the mutation points.
Output: \(M_{\text{select}}(n, l)\); \(M_{\text{select}}(n, l)\) means the selected machine for the \(n\)th job of the \(l\)th stage in the mutation process.

1) For \(mp=1\) To \(h\)
2) For \(n = 1\) To \(s\)
3) \(l = 1;\)
4) While \((l \leq w)\) Do
5) Calculate the parallel machines’ matching degree for the \(n\)th job of \(l\)th stage \(d_{nh}(n, l)\) via Eq.(22) respectively;
6) \([~, M_d] = \text{sort}(d_{nh}(n, l));\)
7) \(M_{\text{selected}}(i, j) = M_d(1);\)
8) \(l++;\)
9) End While
10) \(n++;\)
11) End For
12) \(mp++;\)
13) End For

Algorithm 2 Elite Strategy Based on Matching Distance

Input: \(M_{\text{select}}(n, l)\), \(\text{pop}(\text{gen})\), \(r\); \(\text{pop}(\text{gen})\) means the populations after genetic operation; \(r\) represents the number of all individuals.
Output: \(\text{pop}(\text{gen}+1);\) \(\text{pop}(\text{gen}+1)\) is the populations which can enter next generation.

1) For \(r = 1\) To \(p\)
2) Calculate the matching degree of the selected machine for the \(n\)th job of \(l\)th stage \(d_{nh}(n, l)\) via Eq.(22)
3) Calculate the score of the individuals \(\text{Score}(r)\) via Eq.(23).
4) \([~, \text{Rank}] = \text{sort}(\text{Score}(r));\)
5) \(S_{\text{seq}} = \text{Rank}(1:r/2);\)
6) \(\text{pop}(\text{gen}+1) = \text{Score}(r)(S_{\text{seq}});\)
7) \(p++;\)
8) End For

1) Maximum iterations.
2) There is no improvement in continuous iteration results. It can be expressed as: \(\|\Delta f\| \leq \epsilon.\)

\[\|\Delta f\| = \sqrt{\frac{1}{v} \sum_{i=1}^{v} (f_i - \bar{f})^2} \tag{24}\]

where \(v\) means the iterations, \(f_i\) refers to the fitness value of the \(i\)th generations, \(\bar{f}\) is the average fitness value.

In summary, the improved GA entails several key steps shown in Fig. 6:

Step1: Initialize the population, i.e., workpieces and machines.

Step2: Genetic operation was carried out orderly based on three-layer encoding.

Step3: Heuristic mutation of the selection of machine was implemented based on matching distance.

Step4: An elite strategy based on the evaluation chromosome matching distance was carried out.

Step5: Repeat steps 2-4 for a predefined stopping condition.

Step6: Report the best individual outcome as the optimal solution.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

An example was presented to testify the feasibility and effectiveness of the proposed methodology. In this case, 12 machines and 5 workpieces were prepared for production. Each workpiece require 4 steps operations. There were 3 parallel machines in each process. To increase the problem scale,
TABLE 1. The parameters of HFSP.

| process | machines | process time (min) | process power (kW) | waiting power (kW) | using cost per unit time (RMB/min) |
|---------|----------|--------------------|--------------------|--------------------|-----------------------------------|
|         | M1       | 5                  | 9                  | 9                  | 5                                 |
| n1      | M2       | 29                 | 16                 | 21                 | 24                                |
|         | M3       | 37                 | 36                 | 45                 | 25                                |
|         | M4       | 29                 | 17                 | 35                 | 20                                |
| n2      | M5       | 23                 | 13                 | 32                 | 16                                |
|         | M6       | 16                 | 9                  | 20                 | 10                                |
|         | M7       | 26                 | 19                 | 14                 | 23                                |
| n3      | M8       | 22                 | 15                 | 12                 | 16                                |
|         | M9       | 16                 | 10                 | 7                  | 10                                |
|         | M10      | 32                 | 26                 | 35                 | 16                                |
| n4      | M11      | 30                 | 21                 | 26                 | 14                                |
|         | M12      | 19                 | 16                 | 18                 | 10                                |

FIGURE 8. Gantt chart for different modes.

each workpiece was processed twice. So, it forms the 10 × 12 hybrid flow shop scheduling problem. All the data were listed in Table 1. The process time and process power was measured by Yokogawa, Japan CW240. The using cost per unit time was determined by the cost accounting of the industry.

The program was implemented in MATLAB 2010 on a computer with intel core i5, 2.39 GHz, 4 GB RAM, and a windows 8 operating system. The range of the three indicators were respectively set as follows: makespan [100,300], energy consumption [150,330], cost [700,1200]. The parameters of the IGA were set listed in Table 2.

TABLE 2. Parameters of the IGA.

| parameters | constraint |
|------------|------------|
| Initial population size | 100         |
| Range of crossover probability | [0.1, 1]    |
| Range of mutation probability | [0.01, 0.2] |
| Stopping condition | Maximum number of iterations 150 or convergence condition $\|\mathbf{v}\| \leq 10^{-3}$ |

Simplex lattice method [35] was used to distribute the weights of the HFSP reasonably and evenly in the design space. In this work, 5-order lattice points were selected to determine the 21 sets of data. The matching distance of different machines for the 21 weights were shown in Table 3. For each instance, we ran the algorithm 50 times independently and took the average value. The solutions obtained by the IGA was shown in Table 4. It can be seen that the variation of weights agrees with the trend of the objectives, which denoted the effectiveness of the proposed IGA.

To further assess the versatility of the proposed sustainable model and algorithm, this work defined three production mode, that is, economic mode, energy-saving mode and efficiency mode. The corresponding data were set as case 1, case6 and case21. The Gantt chart of each mode were generated respectively shown in Fig.8.

The economic mode was illustrated in Fig.8(a). For this instance, the machines were selected with different probabilities in parallel machines. Besides, it was noted that the machines M1, M5, M7 and M10 were allocated with more tasks. Those machines were generally defined as economic machine based on its machining features described in Table 1. Similar conclusions can be drawn for the other production modes solved with the proposed IGA. To demonstrate the details of matching methods, the selected machines with high utilization rate for 3 production modes were listed in Table 5. It can be seen that the selected machines with high utilization rates were quite agree with the matching distance order. In other words, if the machine features were coincident with the objectives of HFSP, the machines would be selected with
high probability. It could be explained that the IGA could perform intelligently in the machine selection of HFSP based on the matching method. What’s more, to further test the performance of the proposed method, this work compared the quasi-optimal solutions (in brief, q-o-s), convergence time (in brief, c-t),
TABLE 5. Selected machines with high utilization rates for different modes.

| Production mode (objective weights) | The matching distance orders of machines | The selected machines with high utilization rates by IGA |
|-------------------------------------|------------------------------------------|-------------------------------------------------------|
| economic mode (0,0,1)               | M1-M2-M3, M5-M4-M6, M7-M8-M9, M10-M11-M12 | M1-M5-M7-M10 |
| energy-saving mode (0,1,0)          | M1-M2-M3, M6-M5-M4, M9-M8-M7, M12-M10-M11 | M1-M6-M9-M12 |
| efficiency mode (1,0,0)             | M1-M2-M3, M6-M5-M4, M9-M8-M7, M12-M11-M10 | All machine were selected, but M1, M6, M9 and M12 with high utilization rates |

TABLE 6. Simulation results.

| Algorithms | IGA | GA | PSO |
|------------|-----|----|-----|
| q-o-s | σ(E-03) | C-t | Iteration | q-o-s | σ(E-03) | C-t | Iteration | q-o-s | σ(E-03) | C-t | Iteration |
| case 1    | 0.309 | 1.717 | 19.48 | 45.12 | 0.325 | 2.074 | 69.84 | 61.36 | 0.359 | 5.934 | 19.80 | 52.12 |
| case 2    | 0.338 | 2.153 | 19.82 | 30.23 | 0.308 | 2.675 | 66.39 | 59.24 | 0.348 | 8.091 | 20.45 | 41.56 |
| case 3    | 0.339 | 7.362 | 19.35 | 32.10 | 0.356 | 7.652 | 44.71 | 83.58 | 0.364 | 3.320 | 20.09 | 53.72 |
| case 4    | 0.278 | 0.994 | 19.27 | 22.62 | 0.303 | 1.009 | 31.78 | 60.74 | 0.298 | 5.236 | 19.53 | 48.47 |
| case 5    | 0.264 | 0.461 | 19.37 | 42.24 | 0.297 | 0.478 | 42.76 | 45.50 | 0.273 | 5.548 | 19.70 | 44.62 |
| case 6    | 0.216 | 6.037 | 19.02 | 37.67 | 0.205 | 6.713 | 50.53 | 70.20 | 0.225 | 6.213 | 19.53 | 47.13 |
| case 7    | 0.314 | 2.671 | 19.20 | 35.14 | 0.369 | 2.972 | 25.33 | 49.73 | 0.299 | 7.521 | 19.80 | 40.35 |
| case 8    | 0.325 | 2.640 | 19.06 | 35.32 | 0.355 | 3.124 | 55.37 | 74.21 | 0.347 | 5.975 | 19.32 | 39.57 |
| case 9    | 0.311 | 4.352 | 19.20 | 34.72 | 0.315 | 4.576 | 31.69 | 80.18 | 0.351 | 4.397 | 19.50 | 52.29 |
| case 10   | 0.296 | 5.371 | 19.73 | 30.43 | 0.302 | 5.608 | 54.35 | 57.62 | 0.297 | 8.631 | 20.30 | 42.43 |
| case 11   | 0.237 | 7.059 | 19.46 | 35.02 | 0.283 | 7.843 | 47.01 | 45.35 | 0.242 | 5.404 | 19.46 | 46.26 |
| case 12   | 0.273 | 2.750 | 19.49 | 32.85 | 0.256 | 2.997 | 65.61 | 95.68 | 0.286 | 3.328 | 19.87 | 50.87 |
| case 13   | 0.261 | 1.861 | 19.25 | 52.91 | 0.254 | 2.084 | 29.41 | 80.19 | 0.274 | 8.292 | 19.75 | 51.94 |
| case 14   | 0.237 | 1.650 | 19.21 | 36.12 | 0.243 | 1.724 | 56.44 | 52.43 | 0.260 | 4.651 | 19.32 | 46.62 |
| case 15   | 0.191 | 3.591 | 19.63 | 28.25 | 0.201 | 3.632 | 34.14 | 69.27 | 0.228 | 6.825 | 19.53 | 50.72 |
| case 16   | 0.229 | 1.767 | 19.17 | 30.56 | 0.265 | 2.522 | 48.70 | 85.30 | 0.230 | 5.456 | 19.58 | 51.15 |
| case 17   | 0.226 | 3.531 | 19.15 | 35.86 | 0.268 | 3.790 | 27.96 | 52.27 | 0.217 | 4.590 | 20.45 | 44.41 |
| case 18   | 0.165 | 2.703 | 19.22 | 27.48 | 0.185 | 2.851 | 60.45 | 74.86 | 0.174 | 4.776 | 21.93 | 35.63 |
| case 19   | 0.187 | 2.091 | 19.28 | 29.64 | 0.176 | 2.217 | 41.34 | 76.61 | 0.159 | 7.031 | 19.42 | 49.51 |
| case 20   | 0.113 | 6.387 | 19.26 | 50.24 | 0.125 | 6.614 | 30.99 | 82.17 | 0.117 | 7.872 | 19.33 | 51.21 |
| case 21   | 0.050 | 7.612 | 19.13 | 37.37 | 0.098 | 8.292 | 28.00 | 68.56 | 0.071 | 8.263 | 20.30 | 47.19 |

The standard deviation (σ), and iterations of the proposed method with traditional genetic algorithm and particle swarm optimization (PSO). Each experiment conducted 20 independent runs and the average value was selected for each case. The comparison results were shown in Table 6. According to the simulation tests in Table 6, it can be seen that the IGA superior to the PSO and traditional GA in terms of the evaluation of q-o-s, c-t, σ and iterations. Although, the quasi-optimal solutions of all algorithms were consistent and close. The IGA performs better in convergence time and iterations than the traditional GA. The quasi-optimal solutions of all algorithms were consistent and close. The IGA performs better in convergence time and iterations than the traditional GA. The standard deviation of IGA is significantly better than PSO, which showed strong robustness. Therefore, the proposed method based on machining distance can ensure the effective of the solution and improve the convergence rate efficiently. In summary, according to the simulation tests, Gantt chart for different modes, and comparison study, it is demonstrated that the proposed IGA base on the matching distance is effective, efficient, and robust in solving the HFSP. It could provide more candidate scheduling schemes for decision-makers. In addition, the scheduling schemes can be reasonably...
adjusted according to actual production requirements and changes in production targets to better guide production.

V. CONCLUSION

This work addressed an IGA based on the matching distance, which firstly considered the correlation between the characteristic of parallel machines and the weights of optimization objectives. The goal is to achieve HFSP sustainable production on the premise of production-efficiency, environment and economy. The main contributions of this work were described as follows.

(1) A new multi-objective mathematical model for HFSP considering the makespan, energy consumption and cost was developed. It can realize the sustainable production through the optimization of machines-selection and process sequence.

(2) The characteristics of parallel machines were defined by process time, power and cost. The matching distance was proposed according to the Euclidean distance between characteristics of parallel machines and the weights of optimization objectives. It aimed to evaluate the correlation degree between machines and production requirements.

(3) Based on the matching distance, an IGA was carried out. Matching distance is integrated into each stage of genetic algorithm including the mutation operations and elite strategy. The proposed method was capable to solve the HFSP effectively, efficiently, and robustly, which was demonstrated by simulation tests and compared to several existing algorithms. Moreover, three kinds of typical production modes are proposed to verify the versatility of the model.

It is hoped that the proposed IGA should be employed to effectively solve the problem of sustainable production in HFSP. The characteristics of parallel machine tools are influenced by time, energy consumption and cost, which may have limited generalization. More indicators, such as social impact, quality, function, etc., should be further improved the definition of the characteristics of machine tools. In future work, the sustainable production model should be further perfected to evaluate the effectiveness of the method. Another area to be investigated is that the improved algorithm should be applied in wider set of job-shops to validate its more general applicability.

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