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A Hybrid Whale Optimization Algorithm for Plane Block Parallel Blocking Flowline Scheduling Optimization With Deterioration Effect in Lean Shipbuilding

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ABSTRACT Plane block parallel blocking flowline is a special parallel blocking flowline, which can also be called incomplete hybrid flowline. However, the existing scheduling work has less research on this problem and lacks the constraint of considering the deterioration effect. Therefore, this paper studies the plane block parallel blocking flowline scheduling problem considering the deterioration effect (PBFSP-DE). This is a typical NP hard problem, so this paper proposes a Hybrid Whale Optimization Algorithm (HWOA) for this problem. In the HWOA, tent map of chaotic map is introduced to initialize the population, to improve the diversity of the initial population and effectively improve the optimization performance of the algorithm. Then, a hybrid strategy combining adaptive weight factor and Gaussian random disturbance is used to update the whale's position, to provide strong global exploration ability and avoid falling into local optimum. In addition, Levy flight mechanism is applied to the current optimal individuals to improve the efficiency of local search. Finally, the results show that the HWOA proposed in this paper has strong engineering practicability.

INDEX TERMS Lean shipbuilding, parallel blocking flowline scheduling problem, deterioration effect, hybrid whale optimization algorithm.

I. INTRODUCTION

Lean manufacturing, as an important part of Industry 4.0, has been widely used in manufacturing industry since it was first introduced by Toyota in Japan [1]. As the ship market weakness, how to enhance the core competitiveness, establish the advantage, strive for the order, improve the quality of ship construction and profitability, has become the urgent demand of ship manufacturing, it is with lean manufacturing ''use to eliminate waste and continuous partial and queuing process rather than a'' thought is consistent. Based on lean manufacturing, the concept of lean shipbuilding was put forward. Lean shipbuilding is the application of lean manufacturing concepts in shipbuilding industry. By constantly eliminating waste in shipbuilding design, construction, management, etc., value-added flows are created to reduce costs, shorten shipbuilding cycles, and improve product quality and customer satisfaction [2].

For the shipbuilding industry, process planning and shop scheduling are important links in the production and construction, and play an important role in the enterprise production efficiency and competitiveness [3]. Over the years, with the application of modern shipbuilding models, the plane block flowline has been introduced into most shipyards to improve the efficiency of ship section construction. However, due to the fact that most enterprises still use the traditional on-site scheduling method in the application of planar blocked flowline, the applied scheduling scheme is not optimal, resulting in the low production efficiency of planar blocked flowline [4].

Although plane block flow- line has the characteristics of general flowline, it is different from any other flowline model.

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Due to the heavy and bulky hull blocks, there is no buffer station between stations in the flowline, so various factors should be considered when scheduling. For the parallel flowline, different blocks also need to consider the selection of flowline. Sometimes with the continuous advancement of the project, there will be urgent need to insert some sections for processing, or due to processing errors caused by bad parts need to interrupt and exit the urgent flow and other change problems, which makes the scheduling problem of plane block flowline more complex [5]. If the scheduling cannot be carried out reasonably, it will cause serious delay of the project, waste of resources and increase the cost of the enterprise.

In the traditional flowline scheduling problem, the processing time of jobs is usually set as a constant, but in the actual workshop production, the actual processing time of some jobs is variable. For the ship blocked assembly line, because some stations need manual operation, the operator's proficiency, fatigue, and equipment wear will cause the change of blocked processing time, which is called deterioration effect. Gupta and Gupta [6] have introduced the deterioration effect into the scheduling problem of production process. They believe that in the actual production process, with the processing of workpiece, the machine gradually produces wear aging, unplanned emergency parts insertion or the passage of the workpiece start processing time, which leads to the increase of the actual processing time of the workpiece. According to the above description, the deteriorating effect scheduling problem can be described as: assuming that there are n jobs to be processed, the starting processing time of job j is defined as s_j, so the actual processing time of job j is $p_j = a_j+b_jf\left(s_j\right) j = (1, 2, 3, \ldots, n)$, where a_j is the basic processing time of job j, b_j is the deteriorating coefficient of job j, and $f\left(s_j\right)$ is the correlation function of the starting time of job j. As this scheduling problem is closer to the actual production, it has become a research hotspot of many scholars as soon as it is proposed.

At present, the research on flowline scheduling problem, because of its own characteristics, the ship plane block flowline is not deep enough as a special type of related research, and few studies have been made considering the deterioration effect. Therefore, in the context of lean shipbuilding, this paper studies the ship plane block parallel flowline scheduling problem considering deterioration effect (PBFSP-DE). In view of the characteristics of PBFSP-DE with many constraints and high difficulty, a mathematical model is established, and the improved optimization algorithm is used to solve the problem. The effectiveness of the model and algorithm is verified by numerical experiments and comparative analysis, to improve the efficiency of plane section construction.

In the following context, Section 2 introduces the most related literature. In Section 3, we describe the problem and set up a mathematical model. The HWOA is presented in Section 4 and experimental Verification in Section 5. Section 6 concludes the paper and proposes several directions for the future work.

II. LITERATURE REVIEW

In recent years, flowline scheduling problem [7] has become a research hotspot. Scholars have carried out in-depth research on a variety of different types of flowline, and made breakthrough progress in theory [8]–[10] and algorithm [11]–[14], and solved many problems in flowline scheduling. The classical flowline scheduling problem (FSP) assumes that there are buffers with unlimited storage capacity between processing machines [15], but in some practical production environments, due to the constraints of conditions or processing technology requirements, the storage capacity of buffers is limited or even does not exist [16].

However, for the large-scale engineering of ships, the volume and weight of plane blocks are very large, and it is inconvenient to move. After one station is completed, it cannot be stored. The blocks can only be processed after the next station is free, which results in the blocking time in the processing of each block. Because there is no buffer station between the stations in the plane blocked flowline, the block flow shop scheduling problem (BFSP) is a kind of block flow shop scheduling problem (BFSP) [17]. If a shipyard is equipped with two or more planar blocked flowlines, the scheduling problem is a parallel blocking flow shop scheduling problem (PBFSP) [18]. PBFSP studies the scheduling problem of workpieces to be processed in multiple flow shop (flowline).

For the PBFSP problem, He *et al.* [19] first studied the PFSP with glass production line as the object, and proposed a heuristic algorithm to solve the corresponding problem. Ribas *et al.* [20] proposed an iterative greedy algorithm to solve the job scheduling problem in parallel flowline. For the first time, it tried to solve the parallel blocking flow shop problem or distributed blocking flow shop problem with the goal of minimizing the total tardiness. However, it did not consider the existence of the transverse moving station, which could not meet the needs of the parallel flowline problem of ship plane segmentation. Han *et al.* [21] established a multi-objective optimization model for blocked flow shop scheduling problem with completion period and energy consumption criteria and proposed a discrete evolutionary multi-objective optimization (Demo) algorithm. Due to the characteristics of assembly line and the imprecision and fuzziness of time parameters in practical production, Yang *et al.* [22] proposed a multi-objective meme algorithm (MOMA). The scheduling of panel block assembly on parallel production lines was expressed as a fuzzy parallel blocking flow shop scheduling problem with fuzzy processing time and fuzzy due date. Wang *et al.* [23] established a multi-objective model of blocking flow shop scheduling, which considers the machine energy and idle time consumed by blocking. Then, a multi-objective parallel variable neighborhood search algorithm (MPVNS) is proposed and its superiority is proved. These scholars used different methods to solve PBFSP and got the relatively optimal scheduling scheme to a certain extent. However, the optimization goal is to minimize the maximum completion time, only considering the economic benefits, while ignoring the energy consumption caused by flowline congestion.

At present, the research on parallel blocking flowline scheduling mostly adopts intelligent algorithm for optimization and improves the performance of the algorithm and the accuracy of the solution by optimizing the basic optimization algorithm. According to the above analysis, most of the current research is only aimed at the ordinary parallel blocking flowline scheduling, and there is still less research on the special case of planar segmented flowline. Due to the lateral shift of stations, the problem model of planar segmented flowline is more complex than that of ordinary parallel flowline, which has great research value. Moreover, most studies take the processing time as a constant without considering the deterioration effect, which leads to a certain difference between the problem model and the actual situation. The aging of equipment and the difference of workers' proficiency are common in actual production. Therefore, considering the deterioration effect, the model is more suitable for the actual production situation.

For the deteriorating flowline scheduling problem, most of the current researches focus on the single machine and flow shop environment. For a more complex and special kind of ship plane blocked parallel blocking flowline scheduling problem, the research on deteriorating characteristics is relatively less. At present, researches on deterioration characteristics are mainly divided into two categories: linear deterioration (LD) [24]–[27] and step deterioration (SD) [28]–[31]. Fu *et al.* [32] studied the flow shop scheduling problem considering multi-objective, processing time, learning and deterioration effects. Cheng *et al.* [33] studied a two machine flow shop scheduling problem with time-varying deteriorating jobs, that is, the processing time of jobs is an increasing function of the start time of jobs. The goal is to minimize the total completion time on the premise of minimum completion time. Wang *et al.* [34] studied the interference management problem of the arrival of many new unplanned jobs in the execution of the initial plan in the single machine environment with deteriorating processing time. Taking the processing cost as the initial goal and the delay of jobs relative to the initial completion time as the disturbance goal, a multi-objective interference management model was constructed.

At present, the research on deterioration effect mostly exists in job shop or flow shop. For parallel pipeline scheduling, the relevant research is still less, but it is also very worth studying.

The idea of precise algorithm is to establish a specific mathematical model, and then solve it by mathematical method according to the mathematical model. Typical accurate algorithms include branch and bound method [35], dynamic programming method [36] and so on. However, as the scale of the problem continues to grow, the computation of this method is also increasing exponentially. In the actual workshop production, the scheduling process is more complex, so the exact algorithm is used less. Therefore, the significance of accurate algorithm mainly lies in providing a solution idea, while heuristic algorithm is different from accurate algorithm. Its main idea is to develop an algorithm that can search or approach towards the optimal solution according to intuition and experience. Therefore, this paper mainly uses heuristic algorithm to optimize.

At present, many algorithms are used to solve flowline scheduling problems, such as genetic algorithm [37], particle swarm optimization algorithm [38], simulated annealing algorithm [39] and so on. The whale optimization algorithm (WOA) is a new meta heuristic optimization algorithm which simulates the hunting behavior of humpback whales by Mirjalili in 2016 [40]. It has excellent performance in solving optimization problems, and has been widely used in feature selection [41], machine learning [42], clustering [43], [44], power dispatching [45], [46] and other aspects. As a new swarm intelligence optimization algorithm, whale optimization algorithm has been gradually used in job shop scheduling problem [47]–[49]. This paper will verify the feasibility and effectiveness of its application in this field.

All of the above studies are aimed at ordinary flowline scheduling problems. For the special flowline scheduling problems such as plane sections of ships, there are few studies that take deterioration effect into account. However, this scheduling problem is of great significance for the ship block flowline. This paper focuses on the special flowline scheduling problem of plane block flowline, according to the characteristics of plane block, a scheduling problem model considering the deterioration effect was established to minimize the maximum completion time. On this basis, a HWOA is designed and verified by an example to prove the effectiveness of the improved algorithm, to achieve the improvement of economic benefits.

III. PROBLEM DESCRIPTION AND FORMULATION

A. PROBLEM DESCRIPTION

The hull structure is mainly composed of various blocks and steels. Block is the partial structure of hull made up of hull parts and components and is the intermediate product of the whole hull. The whole hull structure is the product of the combination of single blocks into a block or ring, and then combined again. The general process of plane block is to assemble and weld the structure first. Generally, according to the different assembly and welding methods of the structure, the construction methods of the plane block are divided into two categories: frame method and longitudinal first installation method. Since the longitudinal first assembly method is more convenient for the application of automatic welding and semi-automatic welding technology, most shipyards use this method to build the plane block assembly line. However, due to the large volume and weight of the plane section of the ship, there is no buffer to store after the processing is completed at the station, and it can only wait at the station until the next station is idle, which will cause blocking, increase the time cost. Therefore, this scheduling problem can be regarded as a special kind of blocking flow shop scheduling

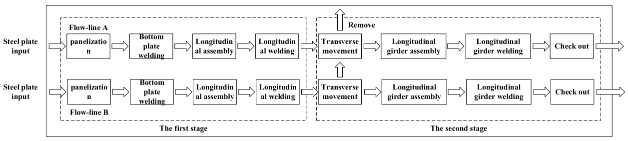

FIGURE 1. **Schematic diagram of a shipyard's parallel flowline.**

problem (BFSP). To improve the production capacity, some shipyards have set up a parallel block flow shop scheduling problem (PBFSP) [50].

Different from the traditional parallel blocking flowline scheduling problem, the ship plane block parallel flowline scheduling problem also has some unique features:

(1) No buffer. Due to the influence of the volume and weight of the plane block, and there is no buffer station in the parallel flowline, it will cause the blocking phenomenon.

(2) Transverse work station. For the plane block parallel flowline, the station setting of each flowline is roughly similar to that of single flowline, but the transverse work station is set in the middle of the flowline, which is the only buffer area in the flowline, which is convenient for the removal of blocks and the transfer between flowlines.

(3) Blocks do not necessarily need to pass through all stations. Some piecewise blocks only need to be processed by several necessary workstations. After manufacturing, they need to be moved out of the flowline through the transversal workstation, but there is only one flowline moving station out of the outlet, so the constraints between the blocks are not only tight before and after operation constraints, but also due to the operation sequence constraint caused by the blocks.

The following figure 1 is the schematic diagram of a shipyard's parallel flowline. The parallel assembly line has a total of two flowlines, and the station layout of each flowline is the same. The whole processing process starts from the steel plate input and is processed in turn through each station of the flowline. The sheet block is only processed in four positions from the panel assembly to the longitudinal welding and is moved out from the transverse moving station after being made. The plane block passes through all stations of the assembly line and is processed in the corresponding position. Except the bottom welding station, longitudinal assembly station and longitudinal welding station are semi-automatic stations, other stations are manual operation. After the assigned work on each workpiece is completed, the workers need to move the next workpiece to continue the operation. The proficiency of the operator and the moving speed of the operator will lead to the increase of the actual processing time, resulting in deterioration effect. Therefore, a linear function is used to describe the processing time. $\alpha_{i,j}$ represents the deterioration rate of block i in station j, and $S_{i,j}$ represents the starting time of block i in station j. then the actual processing time of block i in station j can be expressed as $P'_{i,j} = P_{i,j} + \alpha_{i,j}S_{i,j}$.

The PBFSP-DE problem studied in this paper is represented by a triple of $\alpha|\beta|\gamma$, which can be defined as: $F\left|block, P'_{i,j} = P_{i,j} + \alpha_{i,j}S_{i,j}\right| C_{max}$. Therefore, PBFSP-DE can be described as: n blocks of s types are processed at M stations on N flowlines with the same production capacity and production speed, the processing time of the block on the working position changes linearly with the starting time, the k-th station is buffer traverse station, and the k-th station of all production lines is provided with conveyor belt, among which, the buffer traverse station of the n-th flowline is provided with a removal outlet to facilitate the removal of blocks from the transverse work station. It should be noted that no matter which flowline is processed, if the processing is completed before the k-th station, it can only be transferred to the k-th transverse work station on the n-th flowline through the conveyor belt between the k-th stations.

B. ASSUMPTIONS

To better establish the mathematical model, the following assumptions are made for the problem:

(1) The processing time of the blocks on the transverse shift station is 0.

(2) At the same time, a station can only process a block, and a block can only be processed on a station.

(3) The movement time of blocks between stations is not considered.

(4) The moving time of blocks between transverse stations is not considered.

(5) Block is not adjusted between the assembly line, only in the same assembly line processing

(6) The machines at the station are ready to use without trouble.

C. MATHEMATICAL MODEL

According to the above content, establish the mathematical model. The required parameters are listed as Table 1.

To sum up, the mathematical model established in this problem is as follows:

$$C_{i,j} = \begin{cases} \sum_{h=1}^{i} x_{hi}L_{h,j} + P'_{i,j}, & j = 1 \\ max\left(C_{i,j-1}, \sum_{h=1}^{i} x_{hi}L_{h,j}\right) + P'_{i,j}, & 1 < j \leqslant k \\ x_i \cdot \left[max\left(C_{i,j-1}, \sum_{h=1}^{i} x_{hi}L_{h,j}\right) + P'_{i,j}\right], & j > k \end{cases} \tag{1}$$

$$L_{i,j} = \begin{cases} C_{i,j},\ i \leq 2, j = m \\ max\left(C_{i,j}, \sum_{h=1}^{i} x_{hi}L_{h,j+1}\right), & i > 2, \\ & j < k, j \neq m \\ x_i max\left(C_{i,j}, \sum_{h=1}^{i} x_{hi}L_{h,j+1}\right), & i > 2, j > k, \\ & j \neq m \\ x_i\left(max\left(L_{i,j-1}, L_{i-1,j+1}\right)\right) & \\ +(1-x_i)\left[x_{iB}L_{i,j} + (1-x_{iB}) \cdot C_{i,j}\right], & j = k \end{cases} \tag{2}$$

$$P'_{i,j} = P_{i,j} + \alpha S_{i,j} \tag{3}$$

$$L_{i,j} = max\left(C_{i,j}, maxL_{f,j} \mid f < i \in n\right), \quad j = k \tag{4}$$

$$T_i = x_iC_{i,m} + (1 - x_i)\,C_{i,h} \tag{5}$$

TABLE 1. Variable and Meaning.

Variable	Meaning
i	Blocks index, $i = (1,2,\ldots,n)$
j	Processing station index, $j = (1,2,\ldots,m)$
$S_{i,j}$	Start processing time of block i at station j
$P_{i,j}$	Basic processing time of block i in station j
$P'_{i,j}$	Actual processing time of block i in station j
$C_{i,j}$	Completion time of block i on station j
$L_{i,j}$	Time for block i to leave station j
T_i	Time for completion of block i
C_{max}	Maximum block completion time
$\alpha_{i,j}$	Deterioration rate
Decision variables	Meaning
x_{hi}	When block h is processed in front of block i, $x_{hi} = 1$, otherwise $x_{hi} = 0$
x_{iB}	When block i enters from flowline B, then $x_{iB} = 1$, otherwise, $x_{iB} = 0$
x_i	When the block i moves out from the last station, $x_i = 1$, if it moves out from k station, then x_i=0

Therefore, the objective function can be expressed as follows:

$$F = minC_{max} \tag{6}$$

The constraints are as follows:

$$\sum_{h=1}^{i} x_{hi} = 0 \mid i \leqslant N \tag{7}$$

$$\sum_{h=1}^{i} x_{hi} = 1 \quad i < 2,\ h \neq i \tag{8}$$

$$\sum_{i=h+1}^{n} x_{hi} \leqslant 1 \quad i \geq 2,\ i > h \tag{9}$$

$$x_{iB} = \sum_{f=1}^{i} x_{fi} \cdot x_{fB} \quad i > f \tag{10}$$

where: Equation (1) respectively represents the completion time of block i at the first station, each station before traverse station k, and each station after traverse station k; Equation (2) represents the time when block i leaves each station. When $i \leq 2$, it represents the first processing block on the two flowlines A and B. since they have no immediate front block, the time when block I leaves each station is equal to its completion time in that station. When $i > 2, j \neq k, j \neq m$, it means the rest of the blocks. Since the rest of the blocks have tight front blocks, it is necessary to judge whether it is necessary to wait for the tight front block to leave. When $j = h$, it means the time for block i to leave the traverse station, which can be discussed in three cases: 1) the block enters from line B and moves out directly from traverse station k; 2) The block i does not move out from the traverse station, but needs to pass through all stations; 3) The block i enters from line A and moves out from the traverse station without passing through all stations. Equation (3) shows the linear deterioration relationship between the actual processing time and the starting time; Equation (4) represents the departure time when the block enters from line B and directly moves out from the traverse buffer station k. When block i completes processing on line-B, if there is a block stop in station k on line A, block i must wait. Equation (5) shows the completion time of the block. Equation (6) expresses the objective of optimization; Equation (7) shows that at 0, all the production lines start to process in blocks, and there is no tight front block at this time; Formula (8) indicates that each block has only one immediate front block; Equation (9) indicates that each block has at most one tight back block. Equation (10) indicates that if there is a pre tight and post tight relationship between two blocks, then they enter from the same flowline.

IV. HYBRID WHALE OPTIMIZATION ALGORITHM

A. ENCODING MECHANISM

In this paper, the coding method of block number random full permutation is adopted. The coding order represents the order of being processed, and the first two bits of coding represent the first processed block on two flowlines respectively. For example, $L = \{4, 2, 6, 7, 3, 1, 5, 8\}$ means that block 4 is processed at the first station on line-A, block 2 is processed at the first station on line-B, and block 6 starts processing when there is an idle station, and so on. As shown in the figure, x_l represents the position vector of whales.

x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8
4	2	6	7	3	1	5	8

FIGURE 2. Coding form.

Since the individual location of whales in the whale optimization algorithm is a continuous value, but the scheduling scheme is a discrete value, this paper adopts the Ranked Order Value (ROV) rule based on random key coding to transform the individual location of whales and the scheduling scheme. The specific ROV transformation mechanism is shown in the Figure 3.

In the same way, it is necessary to convert the individual position vector of the whale to the blocked scheduling scheme, which also adopts the ROV rule. Firstly, each position element is assigned a unique ROV value in ascending order, and then the operation arrangement scheme can be constructed according to the ROV value. As shown in the Figure 4, the final sequence of the processes is $L = \{4, 2, 6, 7, 3, 1, 5, 8\}$.

B. POPULATION INITIALIZATION OF CHAOTIC MAP

For swarm intelligence optimization algorithm, the quality of initial population will have a great impact on the global convergence speed and the quality of the optimal solution. Therefore, improving the diversity of the initial population can effectively improve the optimization performance of the algorithm. However, the standard whale optimization algorithm

Random Number	0.15	0.34	0.95	0.24	0.31	0.75	0.08	0.56
ROV Value	2	5	8	3	4	7	1	6
Scheduling Scheme	4	2	6	7	3	1	5	8

Location Element	0.31	0.15	0.56	0.75	0.24	0.08	0.34	0.95

FIGURE 3. **Conversion of scheduling scheme into individual location process.**

Location element	0.31	0.15	0.56	0.75	0.24	0.08	0.34	0.95
ROV value	4	2	6	7	3	1	5	8

Scheduling scheme	4	2	6	7	3	1	5	8

FIGURE 4. **Process of converting location elements into scheduling schemes.**

uses random method when initializing the population, which cannot guarantee the uniform distribution of the population in the whole search space, which will cause the algorithm to search less efficiently. Chaos mapping has the characteristics of ergodicity and randomness and can explore search space more comprehensively in a certain range. By using this feature, the population initialization of whale optimization algorithm can make up for the disadvantage of basic whale optimization algorithm. Kaur and Arora [51] combines chaos theory with whale algorithm and optimizes whale algorithm by using a variety of chaos mapping. The results show that tent map greatly improves the performance of WOA in all chaotic maps.

The initial solutions can be obtained as follows:

Step1. The initial whale position variable is mapped to the definition field (0,1) of the Tent chaos map, and the formula is as follows:

$$z_i = \frac{x_0 - l_b}{u_b - l_b} \tag{11}$$

Step2. Using the Tent map to generate chaotic variables:

$$z_{i+1} = \begin{cases} \dfrac{z_i}{0.7} & z_i < 0.7 \\ \dfrac{10}{3}(1 - z_i) & z_i \geqslant 0.7 \end{cases} \tag{12}$$

Step3. Transforming the chaotic variable into the whale position variable by inverse mapping:

$$x_i = l_b + (u_b - l_b)\, z_i \tag{13}$$

where l_b and u_b are the minimum and maximum values of the optimization variable interval, x_i is the whale position variable, and z_i is the chaotic variable.

C. LOCATION UPDATING MECHANISM OF INDIVIDUAL WHALE BASED ON HYBRID STRATEGY

The parameter a in the standard WOA algorithm is used to adjust the global exploration and local development ability of the algorithm. The convergence factors a decrease linearly in the iterative process, which makes the convergence speed of the algorithm too slow to adapt to the actual situation. According to the iterative principle of WOA algorithm, larger convergence factor can provide strong global exploration ability and avoid falling into local optimum, while smaller convergence factor makes the algorithm have strong local development ability and can accelerate the convergence speed of the algorithm. If the algorithm is in the early stage of iteration, using a larger a will make the algorithm have a stronger ability to jump out of local extremum; in the middle stage of the algorithm, to ensure a faster convergence speed, the convergence factor should be designed to rapidly reduce a to a smaller value with the increase of iteration times. To improve the final convergence accuracy of the algorithm, a smaller m value is selected, and the decreasing speed is slow. Therefore, this paper adopts a piecewise updating formula of convergence factor:

$$\begin{cases} a = 2 - e^{-\frac{t}{Max_{iter}}} & t \leq \dfrac{1}{2}Max\_iter \\ a = 1 - e^{\left(\frac{t}{Max_{iter}} - 1\right)} & t > \dfrac{1}{2}Max\_iter \end{cases} \tag{14}$$

In the global search process of the basic whale optimization algorithm, it is not considered that there may be differences in the guiding force of the prey to guide the whale to update the position in the iterative process. To prevent the algorithm from falling into premature maturity, combined with the idea of inertial weight guiding the population optimization in the PSO algorithm, an adaptive weight factor is introduced into the position update formula, so that the optimal solution can be more fully utilized, thereby improving the optimization accuracy of the algorithm. Most research usually used linear adjustment of inertia weights. Although simple and intuitive, they cannot fully coordinate the global and local search performance of the algorithm. To increase the search ability of whales, this paper proposed an adaptive dynamic inertia weight factor and introduced it into the whale position update method. The specific formula is as follows:

$$\vec{X}(t+1) = w\vec{X}(t) - \vec{A}\cdot\vec{D}, \quad p < 0.5, \ |A| \leq 1 \tag{15}$$

$$\vec{X}(t+1) = w\vec{D}\cdot e^{\omega t}\cdot cos(2\pi l) + \vec{X}^{*}(t), \quad p \geqslant 0.5 \tag{16}$$

$$\vec{X}(t+1) = w\vec{X}_{\text{rand}}(t) - \vec{A}\cdot\vec{D}_{\text{rand}} p < 0.5, \quad |A| > 1 \tag{17}$$

$$w = e^{\frac{-4.5*i}{Max\_iter}} \tag{18}$$

where: i is the current number of iterations, and Max_iter is the maximum number of iterations. As can be seen from the Figure 5 below, the adaptive weight factor has a larger value at the beginning of the iteration, which is helpful for the global search. At the end of the iteration, the curve declines slower, and the weight is smaller, which enhances the ability of local search and improves accuracy.

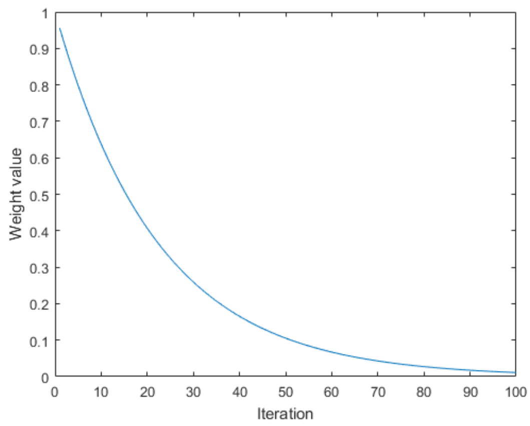

FIGURE 5. Adaptive weight factor iterative curve.

In the iterative process, to avoid the algorithm falling into the local optimal solution which may appear in the process of optimization, this paper introduces the random number operator based on the original algorithm to improve the population diversity. The random number operator is obtained by adding a disturbance term to the initial individual. The perturbation term obeys the normal distribution with the mean value of μ and the variance of σ. In the process of global search, we can get the required Gaussian mutation whale individuals through the improved random mutation operator.

The formula for updating the position of individual whale with random number disturbance is as follows:

$$X(t+1) = X(t) + X(t) \cdot \lambda \cdot \delta \tag{19}$$

where: $\delta \sim N(0, 1)$ satisfies the Gaussian distribution of mean value 0 and variance 1.

$$\lambda = 1 - \frac{t}{Max\_iter - 1} \tag{20}$$

In the formula: when λ value is 1, the mutation effect is the most significant, while when λ value is 0, there is almost no variation phenomenon.

D. LEVY FLIGHT

To solve the problem that WOA is easy to fall into local convergence and the global search ability is insufficient, Levy flight mechanism is introduced into WOA. However, Levy flight is a random step size operation mode, that is, the combination of short distance motion and long-distance motion. Affected by the step size factor, although the global search ability of the algorithm is increased, it will still fall into local optimum. Therefore, this paper proposes a Levy flight mechanism with dynamic step size factor, which changes the fixed step size α to the dynamic step size factor with the number of iterations.

$$\alpha' = 2e^{0.2\left[-ln\left(\frac{10T}{T_{max}}\right)^4\right]} \tag{21}$$

$$Levy(u, v) = \frac{u}{|v|^{\frac{1}{\beta}}} \tag{22}$$

Procedure 1 Hybrid Strategy

Calculation of nonlinear convergence factor a, inertia weight w
for $i = 1{:}\ n$
    Calculate the fitness function value f
    Calculate the values of the coefficient vectors A and C
    if $p < 0.5$
        if $|A| >= 1$
            using formula (15)
        else
            using formula (17)
    else
        using formula (16)
        end if
    end if
    using formula (19)
end for
Output X

TABLE 2. Hybrid whale optimization algorithm flow.

Set the algorithm parameters
Random generation of whale populations
Initialization of population position by chaotic map
while （t<=*Max_iter*）
    Calculation of nonlinear convergence factor *a*, inertia weight *w*
    for *i*=1: *n*
        Calculate the fitness function value *f*
            Calculate the values of the coefficient vectors *A* and *C*
            if *p*<0.5
                if |*A*|>=1
                    Under the hybrid strategy, updating the position of the whale by formula (15)
                else
                    Under the hybrid strategy, formula (17) is used to contract and surround the prey
            else
                Under the hybrid strategy, the formula (16) is used for spiral predation
            The adaptive Gaussian mutation operator is calculated, and the position of the individual is updated by formula (19)
            Update the optimal position by using Levy flight formula (25)
            Calculate the new fitness function *f*
            Update current optimal value and optimal value position
    end for
end while

$$u \sim N\left(0, \sigma_u^2\right) v \sim N(0, 1) \tag{23}$$

$$\sigma_u = \left\{ \frac{\Gamma(1+\beta) sin\left(\pi \frac{\beta}{2}\right)}{\Gamma\left[\left(\frac{1+\beta}{2}\right)\beta 2^{\frac{\beta-1}{2}}\right]} \right\}^{\frac{1}{\beta}} \tag{24}$$

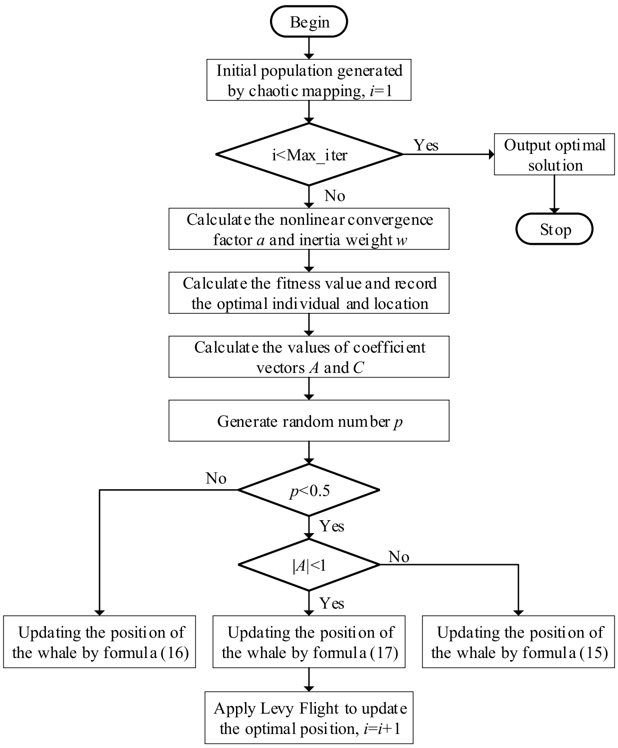

FIGURE 6. Flowchart of the HWOA.

TABLE 3. Description of unimodal benchmark functions.

Formula	Dim	Range	f_{min}
$F_1 = \sum_{i=1}^{Dim} x_i^2$	30	[-100,100]	0
$F_2 = \sum_{i=1}^{Dim}\lvert x_i\rvert + \prod_{i=1}^{Dim}\lvert x_i\rvert$	30	[-10,10]	0
$F_3 = \sum_{n=1}^{m}(\sum_{i=1}^{k} x_i)^2$	30	[-100,100]	0
$F_4 = maxi\,\{\lvert x_i\rvert, 1 \le i \le D\}$	30	[-100,100]	0
$F_5 = \sum_{i=1}^{Dim-1}[100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$	30	[-30,30]	0

TABLE 4. Description of multimodal benchmark functions.

Formula	Dim	Range	f_{min}
$F_6 = \sum_{i=0}^{n-1} x_i^4 + N(0,1)$	30	[-1.28,1.28]	0
$F_7 = \sum_{i=1}^{Dim} - x_i \, sin(\sqrt{x_i})$	30	[-500,500]	-12569.5
$F_8 = \sum_{i=1}^{Dim}[x_i^2 - 10\,cos(2\pi x_i) + 10]$	30	[-5.12,5.12]	0
$F_9 = -20\,exp\left(-0.2\sqrt{\frac{1}{Dim}\sum_{i=1}^{Dim} x_i^2}\right) - exp\left(\frac{1}{Dim}\sum_{i=1}^{Dim} cos\,(2\pi x_i)\right) + 20 + e$	30	[-32,32]	0
$F_{10} = \frac{1}{4000}\sum_{i=1}^{Dim} x_i^2 - \prod_{i=1}^{Dim} cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	30	[-600,600]	0
$F_{12}(x) = \frac{\pi}{Dim}\{10\sin\,(\pi y_1) + \sum_{i=1}^{Dim-1}\,(y_i - 1)^2[1 + 10\sin^2\,(\pi y_{i+1})] + (y_{Dim} - 1)^2\} + \sum_{i=1}^{Dim}\,u(x_i, 10, 100, 4)$	30	[-50,50]	0

where: the value of β is usually 1.5, which decreases slowly at the beginning of the iteration, and decreases rapidly at the end of the iteration in an exponential manner, so it can jump out of the local optimum for global search.

TABLE 5. Description of fixed-dimension multimodal benchmark functions.

Formula	Dim	Range	f_{min}
$F_{12} = \sum_{i=1}^{11}\left[a_i - \frac{x_1(b_i^2+b_i x_2)}{b_i^2+b_i x_3+x_4}\right]^2$	30	[-5,5]	0.00030

TABLE 6. Performance comparison of unimodal benchmark functions with classical intelligent algorithms.

Function	algorithms	Mean	std.dev
F1	WOA	4.42E-72	2.42E-71
	PSOWOA	1.06E-268	0.00E+00
	PSO	1.45E-04	2.27E-04
	GSA	2.48E-16	1.15E-16
	MSWOA	0.00E+00	0.00E+00
	HWOA	0.00E+00	0.00E+00
F2	WOA	2.33E-51	8.57E-51
	PSOWOA	5.86E-142	2.71E-141
	PSO	3.40E-02	5.84E-02
	GSA	2.20E-01	5.10E-01
	MSWOA	7.17E-203	1.64E-203
	HWOA	0.00E+00	0.00E+00
F3	WOA	4.94E+04	1.42E+04
	PSOWOA	1.49E-191	0.00E+00
	PSO	8.17E+01	3.91E+01
	GSA	1.04E+03	3.11E+02
	MSWOA	0.00E+00	0.00E+00
	HWOA	0.00E+00	0.00E+00
F4	WOA	4.86E+01	2.65E+01
	PSOWOA	2.22E-102	8.68E-102
	PSO	1.12E+00	2.72E-01
	GSA	7.57E+00	2.32E+00
	MSWOA	4.59E-139	2.51E-138
	HWOA	0.00E+00	0.00E+00
F5	WOA	2.81E+01	4.84E-01
	PSOWOA	2.78E+01	2.81E-01
	PSO	9.75E+01	8.52E+01
	GSA	1.31E+02	2.07E+02
	MSWOA	2.81E+01	2.76E-01
	HWOA	2.82E+01	3.83E-01

Therefore, the whale position updating formula based on adaptive step size Levy flight is as follows:

$$X\,(t+1) = X\,(t) + \alpha' * Levy\,(u, v) \tag{25}$$

E. HYBRID WHALE OPTIMIZATION ALGORITHM FLOW

The specific process of the hybrid whale optimization algorithm proposed in this paper is as Table 2.

The steps of HWOA are illustrated in Figure 6.

V. EXPERIMENTAL VERIFICATION

To verify the usability of the mathematical model and the hybrid whale optimization algorithm, this paper uses two methods to test the algorithm: numerical experiment and example verification. Through numerical experiments, the effectiveness of HWOA is verified by comparing with other optimization algorithms, and the practicality of the algorithm is verified by optimizing the actual data of the shipyard's actual plane block parallel flowline.

The experiment is set up on a computer with an Intel Core i7-4790 3.60GHz CPU, a Intel(R) HD Graphics 4600, and 8GB memory running on Windows 10.

TABLE 7. Performance comparison of multimodal benchmark functions with classical intelligent algorithms.

Function	algorithms	Mean	std.dev
F6	WOA	2.04E-03	2.07E-03
	PSOWOA	1.01E-04	8.08E-05
	PSO	1.76E-01	7.52E-02
	GSA	4.94E+00	3.40E+00
	MSWOA	1.94E+00	2.49E+00
	HWOA	6.46E-05	8.07E-05
F7	WOA	-1.03E+04	1.90E+03
	PSOWOA	-1.18E+04	1.29E+03
	PSO	-5.39E+03	1.22E+03
	GSA	-2.66E+03	4.63E+02
	MSWOA	-1.25E+04	7.08E+01
	HWOA	-1.16E+04	9.62E+02
F8	WOA	3.79E-15	1.44E-14
	PSOWOA	0.00E+00	0.00E+00
	PSO	5.47E+01	1.20E+01
	GSA	2.83E+01	4.88E+00
	MSWOA	0.00E+00	0.00E+00
	HWOA	0.00E+00	0.00E+00
F9	WOA	4.80E-15	3.14E-15
	PSOWOA	2.43E-15	1.79E-15
	PSO	2.63E-01	5.33E-01
	GSA	1.20E-08	3.17E-09
	MSWOA	0.00E+00	0.00E+00
	HWOA	0.00E+00	0.00E+00
F10	WOA	0.00E+00	0.00E+00
	PSOWOA	0.00E+00	0.00E+00
	PSO	8.14E-03	8.84E-03
	GSA	2.84E+01	6.57E+00
	MSWOA	0.00E+00	0.00E+00
	HWOA	0.00E+00	0.00E+00
F11	WOA	3.18E-02	3.25E-02
	PSOWOA	2.46E-02	1.15E-02
	PSO	1.38E-02	3.58E-02
	GSA	1.44E+00	1.03E+00
	MSWOA	8.54E-03	2.97E-03
	HWOA	6.04E-02	6.35E-02

TABLE 8. Performance comparison of fixed-dimension multimodal benchmark functions with classical intelligent algorithms.

Function	algorithms	Mean	std.dev
F12	WOA	8.14E-04	6.19E-04
	PSOWOA	4.85E-04	1.42E-04
	PSO	8.59E-04	1.77E-04
	GSA	4.44E-03	3.46E-03
	MSWOA	4.11E-04	1.00E-04
	HWOA	4.59E-04	1.43E-04

A. NUMERICAL EXPERIMENT

To verify the performance of HWOA algorithm, 12 typical benchmark functions are selected. Table 3 for unimodal benchmark functions, Table 4 for multimodal benchmark functions, and Table 5 represents fixed-dimension multimodal benchmark functions. Test functions with different forms can effectively verify the optimization performance of the algorithm.

In order to verify the performance of HWOA algorithm and classical intelligent algorithm, the population size was set as 30 and the maximum number of iterations was 500. WOA, PSOWOA, PSO, GSA, MSWOA [52] and HWOA were run independently for 30 times. The mean and standard deviation of the optimal target value (std.dev) were used as the performance evaluation basis, and the test results were shown in Table 6 - Table 8.

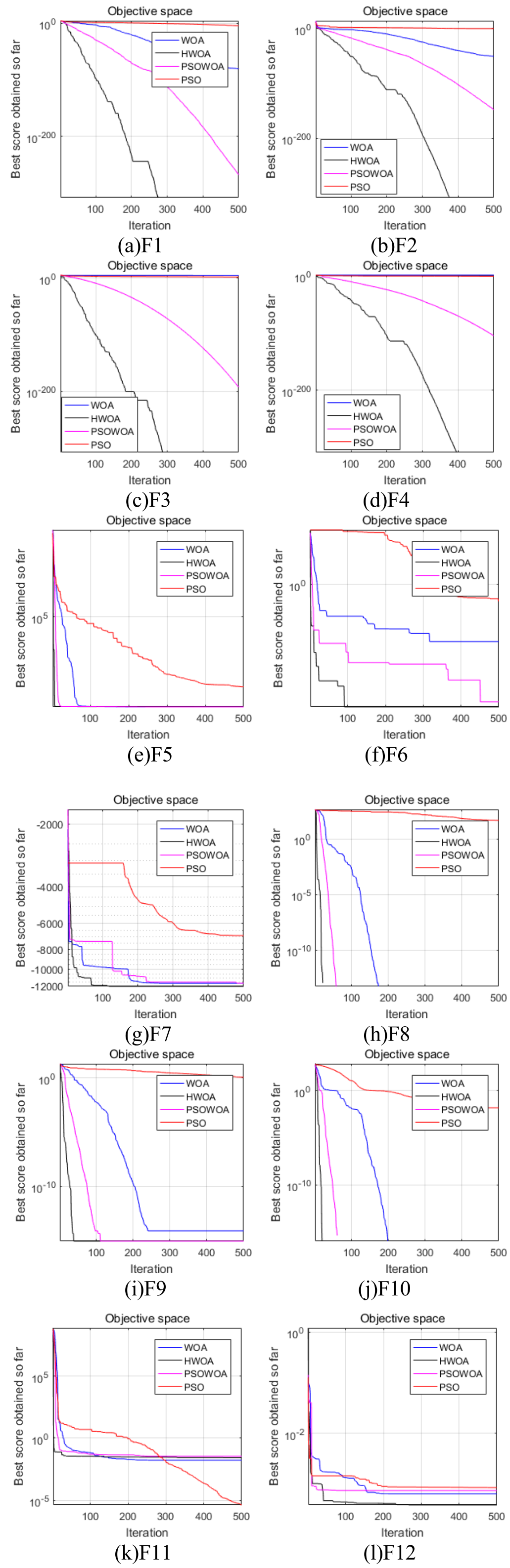

FIGURE 7. Algorithm convergence graph.

It can be seen from Table 4 that among the 12 test functions, the HWOA algorithm proposed in this paper has the best index results among the 12 test functions. Taking the average

TABLE 9. Processing time of waiting to be scheduled block in each station.

Block	Block type	J_1	J_2	J_3	J_4	J_5	J_6	J_7	J_8
1	G_1	3	2	4	1	0	2	3	5
2	G_1	3	2	4	1	0	2	3	5
3	G_1	3	2	4	1	0	2	3	5
4	G_1	3	2	4	1	0	2	3	5
5	G_1	3	2	4	1	0	2	3	5
6	G_2	5	4	6	3	0	0	0	0
7	G_2	5	4	6	3	0	0	0	0
8	G_2	5	4	6	3	0	0	0	0
9	G_2	5	4	6	3	0	0	0	0
10	G_2	5	4	6	3	0	0	0	0
11	G_3	6	3	5	1	0	1	4	2
12	G_3	6	3	5	1	0	1	4	2
13	G_3	6	3	5	1	0	1	4	2
14	G_3	6	3	5	1	0	1	4	2
15	G_3	6	3	5	1	0	1	4	2
16	G_4	2	5	1	4	0	0	0	0
17	G_4	2	5	1	4	0	0	0	0
18	G_4	2	5	1	4	0	0	0	0
19	G_4	2	5	1	4	0	0	0	0
20	G_4	2	5	1	4	0	0	0	0

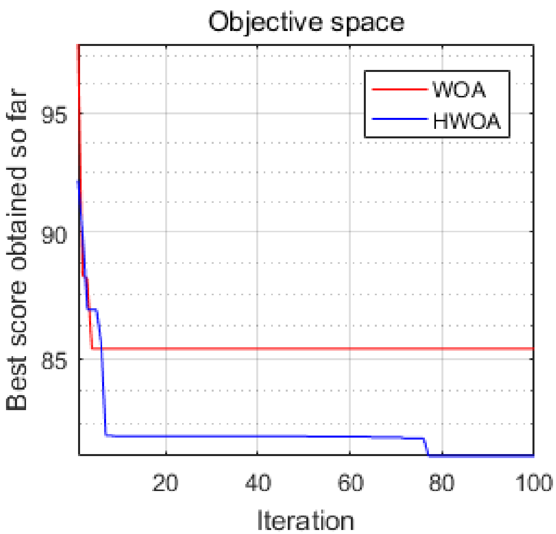

FIGURE 8. Comparison Chart of algorithm iteration.

value and standard deviation of the optimal solution as the evaluation criteria, it can be seen that the solution accuracy of HWOA algorithm is obviously better than other intelligent algorithms and has strong robustness. In order to more intuitively reflect the convergence speed and the ability to jump out of the local optimal value of HWOA algorithm, the convergence curves of each algorithm are shown in Figure 6.

From the convergence curve in Figure 7, we can see that HWOA has the fastest convergence speed and can save the optimization time effectively compared with the standard WOA, PSO and GSA in the 12 benchmarks function optimization process. The decline of convergence curve of HWOA algorithm is abrupt, which proves that the ability

TABLE 10. Parameter values of deterioration rate.

Block	Type	$\alpha_{i,j}$ J_1	J_2	J_3	J_4	J_5	J_6	J_7	J_8
1	G_1	0.07	0.02	0.04	0.07	0.03	0.03	0.06	0.08
2	G_1	0.08	0.03	0.06	0.08	0.08	0.03	0.02	0.02
3	G_1	0.03	0.09	0.02	0.05	0.05	0.05	0.03	0.09
4	G_1	0.07	0.03	0.01	0.02	0.09	0.01	0.04	0.08
5	G_1	0.07	0.08	0.06	0.03	0.03	0.09	0.08	0.05
6	G_2	0.02	0.03	0.08	0.09	0.03	0.10	0.01	0.05
7	G_2	0.02	0.09	0.09	0.02	0.02	0.05	0.01	0.05
8	G_2	0.05	0.04	0.02	0.08	0.02	0.05	0.03	0.04
9	G_2	0.10	0.03	0.06	0.06	0.09	0.04	0.07	0.06
10	G_2	0.04	0.03	0.05	0.10	0.06	0.09	0.08	0.06
11	G_3	0.06	0.07	0.01	0.02	0.06	0.04	0.07	0.08
12	G_3	0.03	0.05	0.04	0.05	0.02	0.02	0.05	0.08
13	G_3	0.08	0.04	0.02	0.02	0.09	0.08	0.06	0.07
14	G_3	0.03	0.08	0.08	0.10	0.07	0.05	0.04	0.04
15	G_3	0.06	0.06	0.04	0.01	0.04	0.03	0.08	0.08
16	G_4	0.07	0.06	0.06	0.08	0.06	0.05	0.03	0.06
17	G_4	0.09	0.09	0.02	0.08	0.05	0.02	0.07	0.04
18	G_4	0.10	0.04	0.06	0.09	0.02	0.02	0.03	0.09
19	G_4	0.06	0.08	0.03	0.02	0.03	0.09	0.04	0.09
20	G_4	0.02	0.08	0.07	0.05	0.02	0.10	0.07	0.06

of the algorithm to jump out of local optimal is effectively enhanced. Therefore, HWOA algorithm has a stronger ability to jump out of local optimal than other intelligent algorithms.

The test functions are divided into unimodal functions and multimodal functions. For unimodal functions, the search speed is an important indicator of the performance of the detection algorithm. As can be seen from Fig. 7 (a) - Fig. 7 (f), HWOA has faster search speed than other algorithms under the condition of ensuring to find the best global optimization. For multimodal functions, since there are many local optimal solutions, it is very important to jump out of the local optimal solution and get the global optimal solution. From Fig.7(g) - Fig.7(l), it can be seen that most of the optimization results of HWOA are better than other comparison algorithms. For function F8-F10, HWOA can jump out of the local optimal solution and find the global optimal solution 0.

TABLE 11. A better scheduling scheme.

Flowline	One Scheduling scheme	One Optimal solution
Flowline A	[1 20 3 5 13 18 2 11 10 7]	81.3086
Flowline B	[16 4 17 6 15 14 9 12 8 19]	

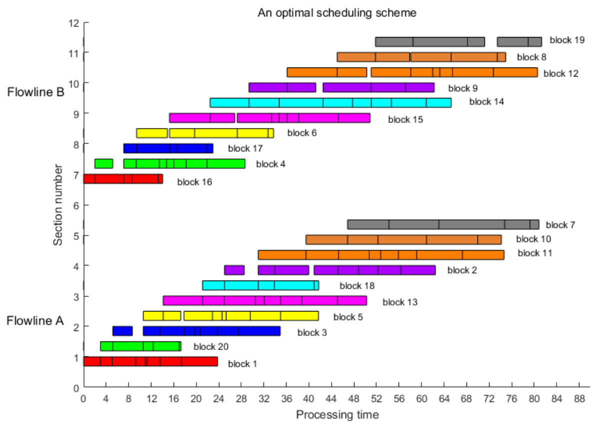

FIGURE 9. Gantt chart of dispatching scheme.

When optimizing different test functions, compared with other algorithms, HWOA has higher accuracy. Therefore, it can be concluded that HWOA algorithm shows certain advantages in solution accuracy, convergence speed and robustness.

B. CASE VERIFICATION

To verify the correctness of the model, this paper takes a shipyard a straight centre block assembly line data as an example. There are three types of a-plane block products in a shipyard: 1) double layer block (block G_1, block G_2). It includes an inner bottom block G_1 which is transported out of the workshop from the last station through all stations, and an outer bottom block G_2 which is transported out of the workshop from the transverse station only through some stations. 2) A class of single-layer block G_3. An insole block is transported out of the workshop from the last station through all stations. 3) The second type is single-layer block G_4. Only one block is transported out of the workshop from the traverse station through some stations.

The processing time of the same type of block in each station is different from that of the station. Station J_5 is the buffer traverse station. If the block is moved out of the buffer traverse station, it does not need to be processed in the subsequent station, and the processing time is recorded as 0.

Taking 20 blocks of a shipyard as an example [53], the deterioration rate a is defined as the uniform distribution between the intervals [0.010, 0.100] [54]. The processing time and deterioration rate of the blocks to be scheduled in each station are shown in Table 9 and Table 10 respectively. By applying HWOA and WOA to calculate respectively, we can get the algorithm comparison chart as shown in Figure 8, and the optimal scheme is shown in Table 11, the corresponding Gantt chart is shown in Figure 9.

In the process of optimization, the original WOA tends to be stable after finding the local optimal solution; The HWOA finds the local optimal solution faster than the original WOA and can jump out of the local optimal solution in time to find the global optimal solution. The HWOA has significantly improved the optimization ability and convergence speed compared with the original whale algorithm. To sum up, it can be concluded that the HWOA proposed in this paper also has good applicability to the practical problems of shipyards.

VI. CONCLUSION AND FUTURE WORK

The purpose of this paper is to solve the problem of ship plane block parallel flowline scheduling considering deterioration effect. Based on the traditional optimization objective of flowline scheduling, the deterioration effect is considered. In this study, we propose a hybrid whale optimization algorithm to solve the problem. The applicability of the proposed hybrid whale optimization algorithm to the problem is proved by numerical verification and example verification, and the influence of the results in actual production is analysed. The main conclusions of our work are as follows.

(1) At present, there are few studies on the problem of parallel blocking flow flowline scheduling with deteriorating effect. This paper has a certain reference value for the related research.

(2) Aiming at combinatorial optimization problem, a HWOA is proposed, which extends the application scope of whale optimization algorithm.

(3) The applicability and performance of the HWOA proposed in this paper are proved by numerical experiments and examples.

In the follow-up research, the problem model should be closer to the actual production, to further improve the applicability of the research. As the next research direction, we will consider the insertion and removal of emergency blocks, the damage of equipment, and the selection of different flowlines through the buffer station to ensure that the problem model is more practical, to improve the application value of the research.

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