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Collaborative Planning Method for Flexible Production Workshop Equipment and AGV Trolley Based on Artificial Intelligence Algorithms

Jin-Ping Du[1,2], Xiao-Fei Wu[3], Jian Wang[1*], Dong-Liang Fan[1,2], Qian-Han Zhang[1]

[1] Department of Electrical Engineering, Hebei Institute of Mechanical and Electrical Technology,
Xingtai City 054000, Hebei Province, China
{dujinping232756, wangjian11587, fandongliang25432, qianhan202555}@163.com

[2] Xingtai Technology Innovation Center for Intelligent Sensing and control of mechanical and electrical equipments,
Xingtai City 054000, Hebei Province, China
[3] Hebei Institute of Mechanical and Electrical Technology,
Xingtai City 054000, Hebei Province, China
xiaowei2323@126.com

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Abstract. This article proposes a multi-objective function that includes AGV running time, production workshop energy consumption, and machine running efficiency, in response to the problems of path conflicts, single planning objectives, and isolation of planning stages in the current flexible production workshop AGV car planning. Then, the flying mouse algorithm is used to solve the problem using multiple functions. In order to avoid falling into local optima during the solving process, a simulated annealing strategy is incorporated into the flying mouse algorithm. Finally, taking the production of new energy vehicle on-board batteries as an example, a collaborative planning analysis was conducted using the method proposed in this paper. The results showed that the algorithm proposed in this paper can save 30% of running time and improve machine operating efficiency by 22.7%.

Keywords: AGV, flying mouse search algorithm, collaborative planning

1 Introduction

With the development of digital workshop and unmanned factory technology, flexible manufacturing systems have become an important direction for the development of modern workshops in enterprises. Its characteristics are that each process does not affect each other and each process is separated from each other. In modern flexible workshop, the material flow between various functional modules mainly depends on AGV technology.

By utilizing integrated AGVs, more flexible operations can be performed, resulting in a more flexible manufacturing system, greatly improving production efficiency and intelligence. In order to operate the integrated AGV stably and effectively, a scheduling system is needed for decision management. However, the current AGV scheduling has the following problems:

(1) Insufficient consideration of path conflict issues in AGV scheduling process

(2) Simply planning AGV paths without integrating the scheduling of processing machines

(3) Considering AGV and production machines comprehensively, but dividing scheduling into two stages, namely AGV allocation stage and AGV scheduling stage, did not achieve a more precise unified scheduling.

Therefore, in response to the above issues, this article takes a flexible production workshop as the carrier, and studies the production machines and AGVs in the workshop as a whole to achieve collaborative scheduling. Therefore, the work done is as follows:

(1) Combining AGV operation time with workshop energy consumption and machine operation efficiency as the objective function based on production practice;

(2) Incorporating simulated annealing strategy into the flying mouse algorithm enables the improved solving algorithm to avoid falling into local optima when solving the objective function;

(3) Taking the battery production of new energy vehicle enterprises as an example, collaborative planning between AGV and production equipment is carried out, and the planning results are used to guide production.

* Corresponding Author

In order to better elaborate on the investigation strategy of this article, the following chapters will be discussed. Chapter 2 mainly lists some research achievements of relevant researchers, providing research ideas for this article. Chapter 3 establishes a multi-objective optimization function model, Chapter 4 uses the flying mouse search algorithm to solve the optimal solution of the objective function, Chapter 5 takes the battery production of new energy vehicle enterprises as a case simulation and analyzes the results. Chapter 6 is the conclusion section.

2 Related Work

Moshayedi believes that the main factor affecting the performance of AGV is its control strategy, and then uses the existing AGV design to build a simulation structure. In the simulation, he analyzes the particle swarm optimization algorithm and the beetle antenna algorithm. Finally, he compares and analyzes the results of the two algorithms. The establishment of simulation model and the selection of algorithm have reference significance [1]. Singh takes battery power as a constraint condition, minimizes operating costs as the goal, and uses adaptive large neighborhood search algorithm as the solution method. The effectiveness of the algorithm has been proven through real cases and industry cases, but the battery as a constraint condition is slightly singular [2]. Reith proposed a lane concept to solve the problem of routing conflicts during AGV operation, and used heuristic methods to improve the accuracy of algorithm solving. The problem model establishment has reference significance, but the algorithm selection is not scientific enough and the convergence speed is slow [3]. Kaituan Feng studied the issue of inaccurate real-time task allocation in discrete workshop AGV and proposed an improved scheduling strategy based on water injection algorithm. After verification, the improved scheduling strategy can provide a reasonable running plan for temporary scheduling and dynamic allocation, but the algorithm convergence time is high and needs to be improved [4]. Qianhui Ma takes multiple AGVs and production machines as integration goals, with the optimization goals of minimizing time and equipment load. He uses multiple group binary tournament selection and segmented cross mutation strategies, as well as Pareto level de duplication elite retention strategies, to complete the search for the optimal solution [5]. Kunpeng Li divided AGV scheduling into two stages, namely task allocation and scheduling. Considering actual semiconductor production cases, an accurate mathematical model was used to solve the allocation strategy, and then priority and weighting methods were used to solve the path conflict problem between various AGV groups [6].

3 Establishment of A Multi-objective Mathematical Model

Multi objective is a characteristic of workshop scheduling problems. Due to the relative difficulty of considering optimization for multiple objectives, many studies only consider optimization for one objective, often considering completion time. However, in practical situations, only considering one goal often results in other indicators being very negative. The AGV and processing machine studied in this article are core equipment, which are expensive and have high maintenance costs. Therefore, the impact of AGV and processing machine losses during production cannot be ignored. The running time of AGV and the maximum load of the processing machine can to some extent reflect the losses of both [7].

3.1 Establishment of Time Function Model

In a flexible workshop, time performance indicators include completion time, processing time, transportation time, preparation time, and delivery time. According to the operational characteristics of the flexible workshop, the actual time composition is integrated into processing time, transportation time, and adjustment time. The allocation diagram of each time is shown in Fig. 1.

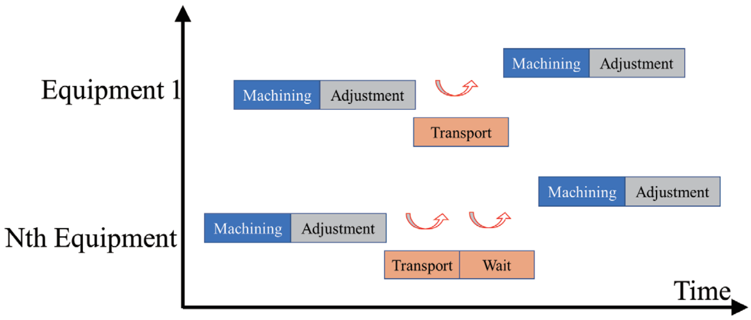

Fig. 1. Schematic diagram of time allocation

Driven by tasks, the shorter the running time for n AGV cars to complete tasks, the higher the production efficiency of the workshop. Considering the two processes including machining equipment processing time and AGV transportation time, with the goal of minimizing the collaborative time between transportation and processing, the time-based objective function is represented as follows:

$$f_T = C_{T\min} = \min[\max_{i=1}^{m}(C_i)]. \tag{1}$$

In the equation, f_T represents the time function, $C_{T\min}$ represents the shortest completion time, m represents the number of workpieces, and C_i represents the total time of processing and transportation for the i -th workpiece. Therefore, the machine processing time is represented as follows:

$$C_{MT} = \sum_{i=1}^{m}\sum_{j=1}^{M_i}\sum_{k=1}^{n}(T_{i,j,k}). \tag{2}$$

In the formula, C_{MT} is the machine processing time, $T_{i,j,k}$ is the processing time of process $O_{i,j}$ in machine N_k , m is the number of workpieces, M_i is the number of processes of workpiece J_i , and n is the number of machines. The machine adjustment time is represented as follows:

$$C_{AT} = \sum_{i=1}^{m}\sum_{j=1}^{M_i}\sum_{k=1}^{n}(t_{i,j,k}). \tag{3}$$

In the formula, C_{AT} is the machine processing time, $t_{i,j,k}$ is the adjustment time of process $O_{i,j}$ in machine N_k, m is the number of workpieces, M_i is the number of processes of workpiece J_i, and n is the number of machines. The transportation time of AGV is expressed as:

$$C_{ATT} = \sum_{i=1}^{n}\sum_{j=2}^{M_i}(T_{i,j-1,w,k}) \big| w,k \in [1,n]. \tag{4}$$

In the formula, C_{ATT} is the AGV transportation time, and $T_{i,j-1,j,w,k}$ is the transportation time between the continuous process ($O_{i,j-1}$, $O_{i,j}$) of workpiece J_i and the required processing machine (N_w, N_k).

3.2 Establishment of Energy Consumption Target Model

Energy consumption mainly includes the energy consumption of the workshop during production, waste emissions, carbon emissions, energy utilization efficiency, etc. The main goal is to minimize energy consumption. The composition of workshop energy consumption is shown in Fig. 2.

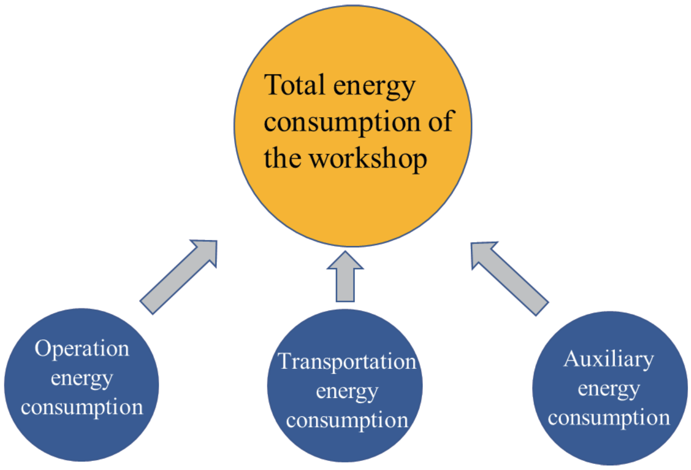

Fig. 2. Schematic diagram of energy consumption composition

Therefore, the minimum energy consumption of the workshop is expressed as follows:

$$f_C = \min(OC + TC + AC)\,. \tag{5}$$

In the formula, OC represents processing energy consumption, TC represents transportation energy consumption, and AC represents auxiliary energy consumption. Among them, processing energy consumption represents the comprehensive energy consumption of various processing equipment in the workshop. Generally, a machine involves four states during operation: startup, processing, no-load, and shutdown. Among them, processing consumes the most energy consumption, expressed as:

$$OC = E_1 + E_2 + E_3 + E_4\,. \tag{6}$$

Among them, E_1 is the startup energy consumption, E_2 is the processing energy consumption, E_3 is the no-load energy consumption, and E_4 is the shutdown energy consumption.

$$E_1 = \sum_{i=1}^{m}\sum_{j=1}^{M_i}\int_0^{t_{i,j}^{start}} P_{i,j}^{start}(t)dt\,. \tag{7}$$

$$E_2 = \sum_{i=1}^{m}\sum_{j=1}^{M_i} P_{i,j}^{cut} \times t_{i,j}^{cut}\,. \tag{8}$$

$$E_3 = \sum_{i=1}^{m}\sum_{j=1}^{M_i} t_{i,j}^{idle} \times P_{i,j}^{idle}\,. \tag{9}$$

$$E_4 = \sum_{i=1}^{m}\sum_{j=1}^{M_i}\int_0^{t_{i,j}^{stop}} P_{i,j}^{stop}(t)dt\,. \tag{10}$$

$$t_{i,j}^{idle} = t_{i,j}^{all} - t_{i,j}^{cut} - t_{i,j}^{start}\,. \tag{11}$$

The meanings of each parameter in the above formula are shown in Table 1.

Table 1. Explanation of the meanings of each parameter in the energy consumption formula

Parameter symbols	Parameter meaning
m	Number of workpieces
M_i	Workpiece J_i sequence number
$t_{i,j}^{start}$	Start time of equipment processing process $O_{i,j}$
$P_{i,j}^{start}(t)$	Process $O_{i,j}$ processing time at time t
$P_{i,j}^{cut}(t)$	Electrical power during process $O_{i,j}$
$t_{i,j}^{cut}$	The consumption time of equipment processing process
$P_{i,j}^{idle}(t)$	The power of the machine during process $O_{i,j}$
$t_{i,j}^{idle}$	Equipment idle time in process $O_{i,j}$
$t_{i,j}^{all}$	The total time from device startup to shutdown
$P_{i,j}^{stop}(t)$	Power during shutdown of processing machinery and auxiliary equipment
$t_{i,j}^{stop}$	Equipment shutdown time in process $O_{i,j}$

Transportation energy consumption refers to the energy consumed by AGV during the interspersed transportation of workpieces between different machines, collectively referred to as transportation energy consumption. Therefore, the transportation energy consumption function is expressed as:

$$TC = \sum_{i=1}^{m}\sum_{j=2}^{M_i}(P_e \cdot T_{i,j-1,w,k} \cdot X_{i,j})\big|(w,k \in (1,m)) \text{ .} \quad \textbf{(12)}$$

In the formula, P_e is the average rated power of AGV, $T_{i,j-1,j,w,k}$ is the transportation time between the required processing machine (M_w, M_k) for continuous process $(O_{i,j-1}, O_{i,j})$ of workpiece J_i , and $X_{i,j}$ is the allocation decision variable. Auxiliary energy consumption refers to the energy consumed by auxiliary equipment required to support the entire production workshop. Auxiliary energy consumption is relatively fixed, so the use of auxiliary energy consumption is proportional to time. The calculation function of auxiliary energy consumption is:

$$AE = P_0 \times C_{\max} \text{ .} \quad \textbf{(13)}$$

3.3 Establishment of an Objective Function Model for Machine Utilization

Machine utilization rate is an important reference for workshop energy consumption. The higher the machine utilization rate, the higher the utilization rate of workshop resources, the shorter the idle rate of machines, and the more reasonable the workshop scheduling. The formula for workshop equipment utilization rate is expressed as:

$$f_L = \max\{[\sum_{i=2}^{n}\sum_{j=1}^{M_i}\sum_{k=1}^{m}(C_{i,j,k} - S_{i,j,k})] \div nC_l\} \quad \textbf{(14)}$$

In the formula, $C_{i,j,k}$ is the completion time of process $O_{i,j}$ on machine M_k , $S_{i,j,k}$ is the start time of process $O_{i,j}$ on machine N_k , C_l is the completion time of the last workpiece produced, and M_i is the total number of processes for workpiece J_i . If process $O_{i,j}$ has not been processed on machine N_k, then $C_{i,j,k}$ and $S_{i,j,k}$ are both 0.

4 Improving the Flying Mouse Algorithm to Solve the Objective Function

This article incorporates a greedy strategy based on the flying mouse algorithm to generate a locally optimal initial population to improve search ability [8]. The search steps are as follows:

4.1 Greedy Strategy Integrated into The Flying Mouse Algorithm

M flying mice exist in the forest, and a greedy strategy is used to iterate the initial population in sequence. Firstly, the initial population is randomly generated. When the number of iterations is greater than 2, a ranking mapping is established between the fitness values of the flying mice in the previous iteration and the fitness values of the flying mice in the current iteration [9]. The optimal solution of the excellent flying mouse individuals in the previous and next generations is recorded, and the search process is shown in Fig. 3.

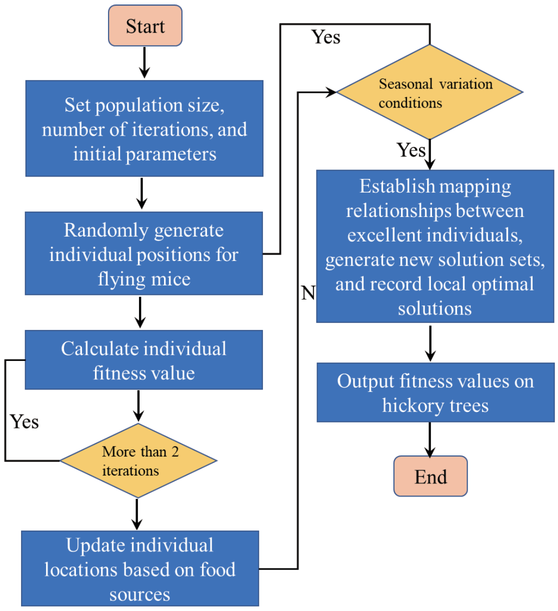

Fig. 3. Search process diagram

The initial value of the flying mouse search algorithm directly affects the quality of the optimal solution, and generating the initial population using a completely random method cannot guarantee the quality and speed of the initial solution. In order to effectively ensure the diversity of the flying squirrel population, it is necessary to expand the population size. Therefore, this article adopts a greedy strategy to initialize the flying mouse search population. Part of the pseudocode incorporated into the strategy is as follows:

```
fitness=zeros (1,pop) ;
fori=1:pop
fitness (i) =fob j (FS (i,:) ) ;
end
[~,index]=sort (fitness) ;
GBestF=fitness (index (1) ) ;
GBestX=FS (index (1) ,:) ;
curve=zeros (Max_iter,1) ;
curve (1) =GBestF;
FS0=x_ini;
FS1=Tent Initialization (pop,dim,ub,lb)
```

4.2 Integrating Simulated Annealing Strategy into Flying Mouse Algorithm

The initial population of the initial solution after the greedy strategy is too large, so it is necessary to determine the new and old individuals. The improvement criteria are revaluated during the comparison and screening of the new and old populations after the greedy strategy optimizes the population.

$$P = e\left(-\frac{f(x_n(j)) - f(x_0(j))}{kT}\right). \tag{15}$$

Where, x_n and x_0 are new and old optimal solutions, $f(x_n(j))$ and $f(x_0(j))$ are new and old population individuals respectively, j is the fitness value, T is the current temperature, and k is the coefficient of change.

The algorithm process is:

(1) Compared with the fitness value of the individuals in the old and new populations, if the fitness value of the individuals in the new population is better, they will accept the update as offspring;

(2) The corresponding individual of the old population is greater than the fitness value of the new population. For individuals in the new population, variable neighborhood search is used to improve the local optimal ability of the flying squirrel search algorithm.

4.3 Variable Neighborhood Search

The neighborhood search method adopts a variable neighborhood search with a neighborhood structure of two moving processes [10]. The principle is to remove one key process and then increase the insertable position of the removed key process by removing another process. Firstly, it is necessary to determine the first critical process and determine its critical path. The critical path refers to the path that starts from the first process until the completion of all processes, and the processing time is continuously combined for the longest time. Fig. 4 is a case Gantt chart chart.

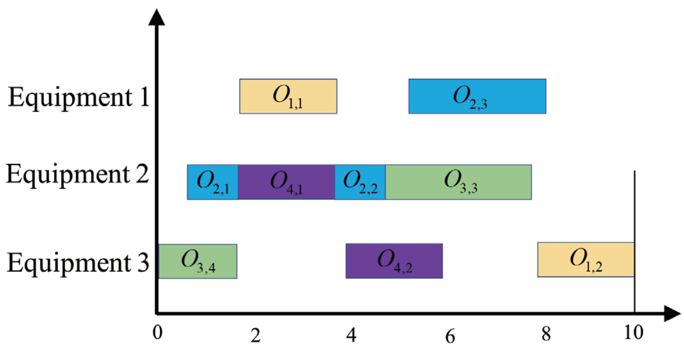

Fig. 4. Case Gantt chart chart

As shown in the above figure, Route A is the key route in scheduling, and the various processes in the route are also key processes. Therefore, the improved flying mouse algorithm is used to solve the objective function, and the solving process is as follows:

Step 1: Set parameters for algorithms such as the population size M, maximum number of iterations T, and predation probability P of flying mice;

Step 2: Calculate the fitness values of all individual flying mice, sort them according to their fitness values, and select the individual positions where flying mice are located at each food source;

Step 3: According to Fig. 3, select the optimal solution by retaining some individuals and continuing the loop operation, supplementing them with the initial population;

Step 4: Anneal the population after updating the greedy strategy, and compare and screen the individual fitness values of the new and old populations;

Step 5: Perform sine cosine or glide search operations for individuals located in oak trees and ordinary trees in the population based on control parameters P and season S_c;

Step 6: Judge the seasonal changes, and if it meets the criteria, randomly allocate the positions of flying mice on ordinary trees. Otherwise, follow the steps

Step 7: judge whether the algorithm has completed iteration T, if it has completed outputting the optimal fitness value and the location of the optimal solution, otherwise, execute step 2 to continue the cycle.

5 Case Simulation Results and Analysis

New energy vehicle on-board batteries are mass-produced in the battery welding workshop. The main processes include cell assembly, end plate side plate welding, wire harness partition laser welding, and module testing, with a maximum of 2 machines available for each process. The transportation of semi-finished and finished batteries between machines is completed by 2 AGVs. The processing data of 5 batches of batteries are shown in Table 2.

Table 2. Battery processing data

Production processes	Machine	$job1$	$job2$	$job3$	$job4$	$job5$
Cell assembly	M_1	3.9min	4.2min	4.1min	3.6min	3,7min
	M_2	2.6min	2.9min	3.3min	3min	2.8min
Plate welding	M_3	3.1min	2.8min	4.0min	2.9min	3.6min
	M_4	4.2min	3.9min	3.8min	3.5min	4.2min
Welding of wire harness partition	M_5	4.1min	2.6min	3.7min	4.3min	3.3min
Performance testing	M_6	2.9min	3.7min	4.8min	4.2min	2.9min

Use the improved flying mouse algorithm to solve the solution sets of each objective function. For the convenience of description, the improved flying mouse algorithm is called I-FMSA, and the distribution of the solution sets is shown in Fig. 5.

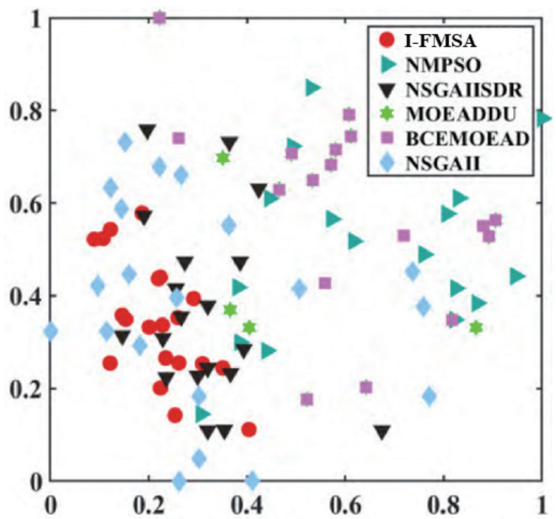

Fig. 5. Comparison of Algorithm Solution Sets

To verify the effectiveness of this algorithm, the convergence curve of this algorithm was analyzed, as shown in Fig. 6.

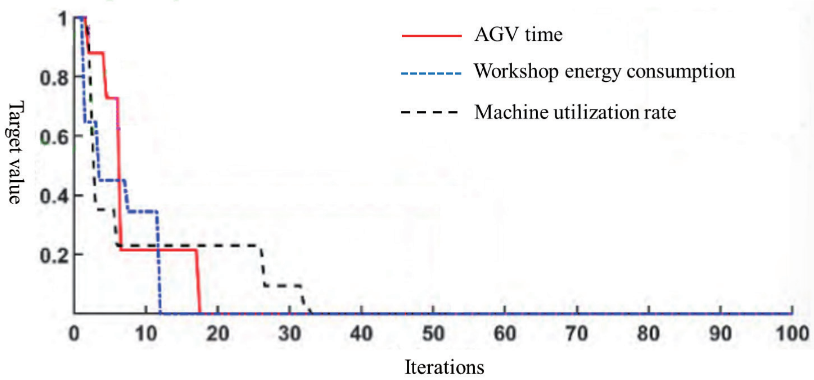

Fig. 6. Convergence curve

After optimization, the optimal solutions for each objective function are shown in Table 3.

Table 3. Optimal results

Algorithm	f_T	f_c	f_L
I-FMSA	57.7h	3980.2kW.h	79.1%

After the above analysis, as shown in Fig. 5, the method proposed in this article solves closer to the zero point and has good convergence. At the same time, the solution distribution is uniform. As shown in Fig. 6, the algorithm proposed in this article converged before the 60th generation. From Table 3, it can be seen that after optimization, the total running time of the AGV car has been reduced to 57.7 hours, and the utilization rate of the AGV has been increased to 79.1%. The calculated total energy consumption of the workshop has also been reduced from the initial value of 4572.7 kWh to 3980.2 kWh.

6 Conclusion

After the above analysis, this article establishes a multi-objective function targeting AGV running time, workshop energy consumption, and machine efficiency, and then solves it using an improved flying mouse algorithm, so that the solution process can avoid local optima and obtain ideal values. Finally, the feasibility of the algorithm proposed in this paper was verified through real cases, and significant improvements were achieved in AGV runtime, energy consumption, and efficiency values.

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