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Research Article

A Dynamic Scheduling Method for Logistics Tasks Oriented to Intelligent Manufacturing Workshop

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Aiming at the logistics dynamic scheduling problem in an intelligent manufacturing workshop (IMW), an intelligent logistics scheduling model and response method with Automated Guided Vehicles (AGVs) based on the mode of "request-scheduling-response" were proposed, and they were integrated with Internet of Things (IoT) to meet the demands of dynamic and real time. Correspondingly, a mathematical model was developed and integrated with a double-level hybrid genetic algorithm and ant colony optimization (DLH-GA-ACO) to minimize the finish time with the minimum AGVs and limited time. The mathematical model optimized the logistics scheduling process on two dimensions which include the sequence of tasks assigned to an AGV and the matching relation between transfer tasks and AGVs (AGV-task). The effectiveness of the model was verified by a set of experiments, and comparison among DLH-GA-ACO, hybrid genetic algorithm and particle swarm optimization (H-GA-PSO), and tabu search algorithm (TSA) was performed. In the experiments, the DLH-GA-ACO ran in a distributed environment for a faster computing speed. According to the comparisons, the superiority and effectiveness of DLH-GA-ACO on dynamic simultaneous scheduling problem were proved and the intelligent logistics scheduling model was also proved to be an effective model.

1. Introduction

Intelligent manufacturing (IM) is a new driving force that can drive the further development of the manufacturing industry and the engine of future economic growth [1]. Under the background, a lot of development strategies about IM were put forward by many countries to improve the competitiveness of manufacturing industry; IM has become the key of manufacturing industry development at present [2, 3]. For this topic, many scholars carried out a lot of studies on IM and come to a lot of valuable results [4–10].

Packaging is the middle reaches of light emitting diode (LED) production, and it is also a bridge between chip manufacturing and application of product [11]. Its production process is a typical discrete process; the characteristics of it are large quantities and high quality requirement. A typical LED packaging workshop in South China is shown in Figure 1. Although the automation of machines and informationization has been developed for some years, there are still problems as follows:

(1) Each operation is independent of each other; it leads to transportation of materials among the operations which are executed manually.

(2) It is not real-time and integrated on management and monitoring of production process, resulting in the information island.

(3) The logistics and operation time control are mainly done by manual work. It leads to the increase of uncertainty factors that affect the quality of products and cause huge loss of quality, so tasks of transferring materials should be responded in time.

To solve the problems above, IM has been developed in the industry. In intelligent manufacturing workshop (IMW) of LED packaging, logistics is the most important part of it [12, 13]. Aiming at the application of IMW in LED packaging

Figure 1: A typical LED packaging workshop in South China.

enterprise, an intelligent logistics scheduling model was proposed in this paper. In the IMW, logistics tasks are constantly generated and responded in the production process, and there are often multiple tasks to be responded at a certain time. Therefore, the process of logistics scheduling in the IMW is a dynamic, real-time, combinational, and concurrent process. Considering the characteristics and demands of the problems, Internet of Things (IoT) and automated guided vehicles (AGVs) which are the important part of IMW were introduced.

IoT was initially proposed in a research about resource identification and tracking system based on radio frequency identification (RFID) [14], and it has been researched in a lot of studies [15–20]. Zhong et al. extended the Physical Internet (PI) concept into manufacturing shop floors using IoT and wireless technologies to create a RFID-enabled intelligent shop floor environment [21]. Lin et al. proposed a heat treatment IM Execution System based on IoT in view of the complexity of the discrete production model and heat treatment process [22]. Tao et al. designed and presented a five-layered structure resource intelligent perception and access system based on IoT [23]. Liu et al. proposed the concept of IoT-enabled intelligent assembly system for mechanical products (IIASMP) [24]. To deal with the dynamics occurring in production logistics (PL) processes, Qu et al. investigated a dynamic PL synchronization (PLS) of a manufacturer adopting public PL services [19]. Li et al. concluded the relationship and associations among parameters after the research of the physical model and object model based on IoT [25]. To solve the smart interconnection issue for implementing smart manufacturing, Tao et al. proposed industrial Internet-of-Things hub (IIHub), which consists of customized access module (CA-Module), access hub (A-Hub), and local service pool (LSP) [26].

AGV is an automatic transport vehicle which can navigate along a planned route with different guidance ways and systems [27]. It is widely used to transfer materials in modern production system and enhance effectiveness of it [28–30], and all AGVs in flexible manufacturing system (FMS) can be unified scheduling using a center computer control system, so all the shop floor operations are controlled through AGVs system.

In summary, logistics scheduling in IMW is the real-time scheduling of AGVs to control the production process by computers. Aiming at the problem, some related studies have been carried out. Literature has shown tendency about multitask scheduling of AGV systems and FMS; minimizing makespan and several other criteria are introduced to meet the demands of actual-practice scheduling [31–33]. Udhayakumar and Kumanan addressed tasks scheduling of AGVs in a flexible manufacturing environment using nontraditional optimization algorithms and made an attempt to find the near-optimum schedule for two AGVs based on the balanced workload and the minimum traveling time for maximum utilization [34]. Lacomme P et al. introduced a framework based on a disjunctive graph to model the joint scheduling problem and on a mimetic algorithm for machines and AGVs scheduling with the objective of minimizing the completion time [35]. Mehrabian et al. proposed a mathematical model based on two metaheuristic algorithms of Nondominated Sorting Genetic Algorithm-II (NSGAII) and multiobjective particle swarm optimization (MOPSO) to solve the problem of integrating flow shop scheduling and AVG routing in FMS [36]. Demesure et al. proposed a decentralized motion planning and scheduling of AGV in a FMS, and a motion planner is combined with a scheduler allowing each AGV to update its destination resource during navigation based on a two-step strategy in order to complete the transported product [37]. In addition to these studies on AGVs static scheduling, some researches on AGVs dynamic scheduling have also made a lot of results [38–41]. But the dynamic in these studies is mainly reflected on the conflict resolution of AGV running, and these studies are not applicable to the model proposed in this paper.

Many scholars have done a lot of research on AGVs scheduling and obtained a lot of valuable results which provide good references for this study. However, in the IMW of LED packaging, the traditional logistics scheduling model is not appropriate on the following aspects:

(1) Studies and applications of intelligent logistics model on LED packaging industry based on AGV technology are few; targeted approach needs to be further studied.

(2) The existing mode of responding tasks of transferring materials is difficult to adapt to the uninterrupted production mode of the LED packaging workshop.

(3) Studies on dynamic optimization scheduling of AGVs model for responding to concurrent tasks in the process of manufacturing are few; establishing a reasonable mathematical model is of great significance for improving the efficiency of the workshop.

To address the above concerns, a response method of logistics tasks with the mode of "request-scheduling-response" was developed in this paper. In the model, the logistics scheduling problem is manufacturing resource combinatorial optimization (MRCO) problem which is often solved by evolutionary algorithms (EAs) [42]. A mathematical model was developed and integrated with a double-level hybrid genetic algorithm and ant colony

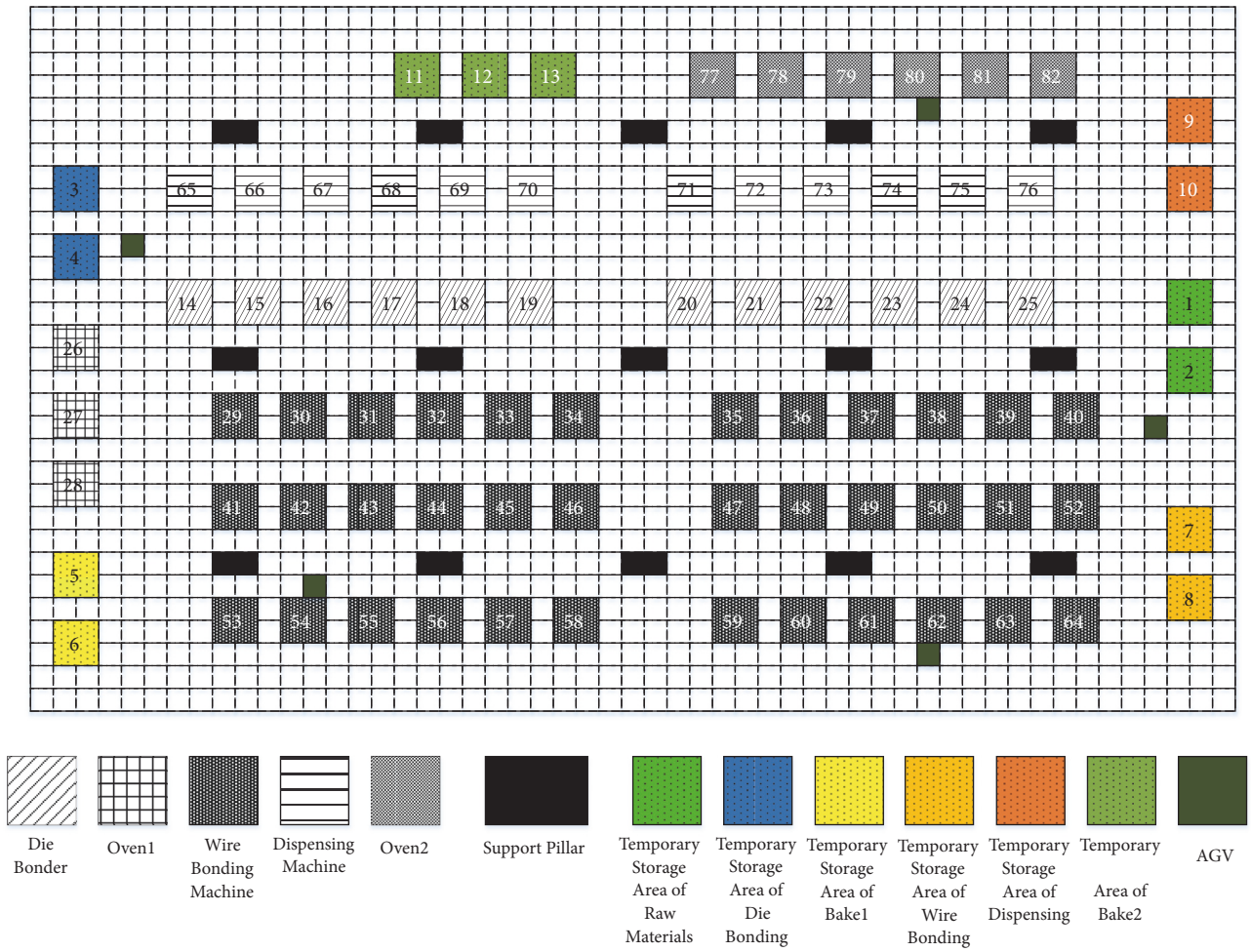


Figure 2: An IMW layout model of LED packaging.

optimization (DLH-GA-ACO). In the IMW, the finish time of transferring materials affects the quality of product and continuity of production process to a great extent. Besides, the number of AGVs heavily influences the profitability in manufacturing workshop [43–45]. Therefore, the objective of the mathematical model is to minimizing the finish time with the minimum AGVs and limited time. A set of experiments were carried out to verify the effectiveness of DLH-GA-ACO; it optimized the logistics scheduling process on two dimensions which include the sequence of tasks assigned to an AGV, the matching relation between transfer tasks and AGVs (AGV-task). The DLH-GA-ACO ran in a distributed environment for a faster computing speed, and some other methods were also applied to improve the running speed of it.

The rest of this paper is organized as follows. The model, problem description, and mathematical model are detailed in Section 2. The algorithm design is explained in Section 3. The simulation experiments and discussions are presented in Section 4. Particularly, a comparison is performed to prove the superiority of the DLH-GA-ACO proposed in this paper over other algorithms which include hybrid genetic algorithm and particle swarm optimization (H-GA-PSO) and tabu search algorithm (TSA). Finally, Section 5 concludes this paper and directs future research.

2. Problem Description and Intelligent Logistics Scheduling Model

2.1. Logistics Scheduling Model. The production process of LED packaging mainly includes die bonding (DB), baking (Bak1), wire bonding (WB), dispensing (Disp), and baking (Bak2). Define its operations set $WS = \{\text{DB, Bak1, WB, Disp, Bak2}\}$. The characteristics of it are as follows:

(i) It takes material box as the minimum unit of transferring materials, so the state of material can be tracked according to the state of material box.

(ii) The irregular requests of transferring materials in the process of production should be responded in time to ensure the production continuity and the quality of product.

(iii) The operations and machines are discrete, and logistics control is very important.

An IMW layout model of LED packaging is shown in Figure 2. To ensure the production beat and avoid a large

Figure 3: Execution method of transferring materials by AGV in an IMW of LED packaging.

amount of backlog of materials, the capacity matching has been done according to the capacity of different machines in this model. In the model, a temporary storage area is a storage equipment of materials after an operation is completed; it is used to establish the transfer center of materials. Manipulator is equipped on AGV for handling materials as shown in Figure 3.

To ensure real-time and effectiveness of logistics, a dynamic scheduling model of logistics base on IoT and AGVs was proposed for the IMW. It took the dynamic scheduling platform of logistics as the control center and AGVs are the responding agents. In the model, the control center collects the real-time states and positions of material boxes, so the request of transferring materials can be responded by scheduling multiple AGVs dynamically. Considering the production characteristics of LED packaging and the model, a mode of "request-scheduling-response" was introduced to deal with the tasks of transferring materials. IoT in the model is mainly composed of sensors, RFID tags, RFID reader and writer, and multisource real-time data acquisition network. In this model, the scheduling goal is to ensure that all tasks can be finished in the shortest time with the minimum AGVs and limited time. Therefore, a reasonable scheduling method of AGVs is important to improve the performance of the IMW.

Figure 4 shows the framework of intelligent logistics scheduling model. It can be described as follows:

(i) This model integrated with Ethernet technology and OPC technology to collect real-time data. The data mainly include states and positions of material boxes, machines, and AGVs.

(ii) If the logistics scheduling platform determines that there are new requests of transferring materials and free AGVs, the platform deals with all the requests which are not allocated, and all of AGVs are involved in scheduling by taking their free time into account.

(iii) Control center of AGVs receives instructions from dynamic scheduling platform to control AGVs for responding to requests of transferring materials.

2.2. Problem Description. On the basis of the dynamic scheduling model of logistics, the scheduling process was defined in this section. Let us define the AGVs set $Ag = \{Ag_1, Ag_2, \ldots, Ag_n\}$; current tasks to be allocated set $Ta=\{Ta_1, Ta_2, \ldots, Ta_m\}$. An AGV responds one or more tasks of transferring materials. The AGV-task set is defined as $TaAg=\{TaAg(1,i_1), TaAg(2,i_2), \ldots, TaAg(\mathrm{m},i_m)\}$; here, $TaAg(j,i_j)$ represents the AGV which responds task j. Tasks allocated to AGV i is represented by $ExcPath(i)=\{ExcTa(i,1),ExcTa(i,2), \ldots, ExcTa(i,N_i)\}$; here, $ExcTa(i,z)$ represents task z which is assigned to AGV i. $Route_{ij}=\{Eqs_{ij}, Eqm_{ij}, Eqe_{ij}\}$ defines the best route of AGV i executing task j; here, Eqs_{ij}, Eqm_{ij}, and Eqe_{ij} represent the starting position, the transfer position, and the end position of the task, respectively. The positions of machines are shown in Figure 2. The objectives of the model are minimum the finish time and number of AGVs aiming at the IMW, and the maximum finish time of all tasks should be less than the threshold. To explain, a schematic diagram of 5 tasks responded by 2 AGVs is shown in Figure 5. T_f and Tfr_1 are the finish time and the free time of Ag_1, respectively. The assumptions in the model are as follows:

(i) All AGVs have unit-load capacity and manipulator.

(ii) There is no battery charge problem on AGVs.

(iii) The maximum number of concurrent tasks is preknown.

(iv) If all the tasks of an AGV are responded, AGV stays at the place.

(v) There are no traffic problems, collision, deadlock, or conflict.

(vi) The operating time of loading and unloading on a machine is fixed.

(vii) The operating time of loading and unloading on a temporary storage area is fixed, and there are one or more temporary storage areas for each operation to load and unload materials.

(viii) The velocity of AGV is fixed and preknown.

(ix) The distances among machines and temporary storage areas are preknown.

(x) The capacity of material workbench of each machine is at least two material boxes or two operation units.

To formulate the mathematical model of the problem, the related parameters and variables are summarized as follows:

n: number of AGVs

m: number of tasks to be allocated

i: index of AGVs

j: index of tasks

k: index of machines and temporary storage areas

p: index of operations

s: type of tasks

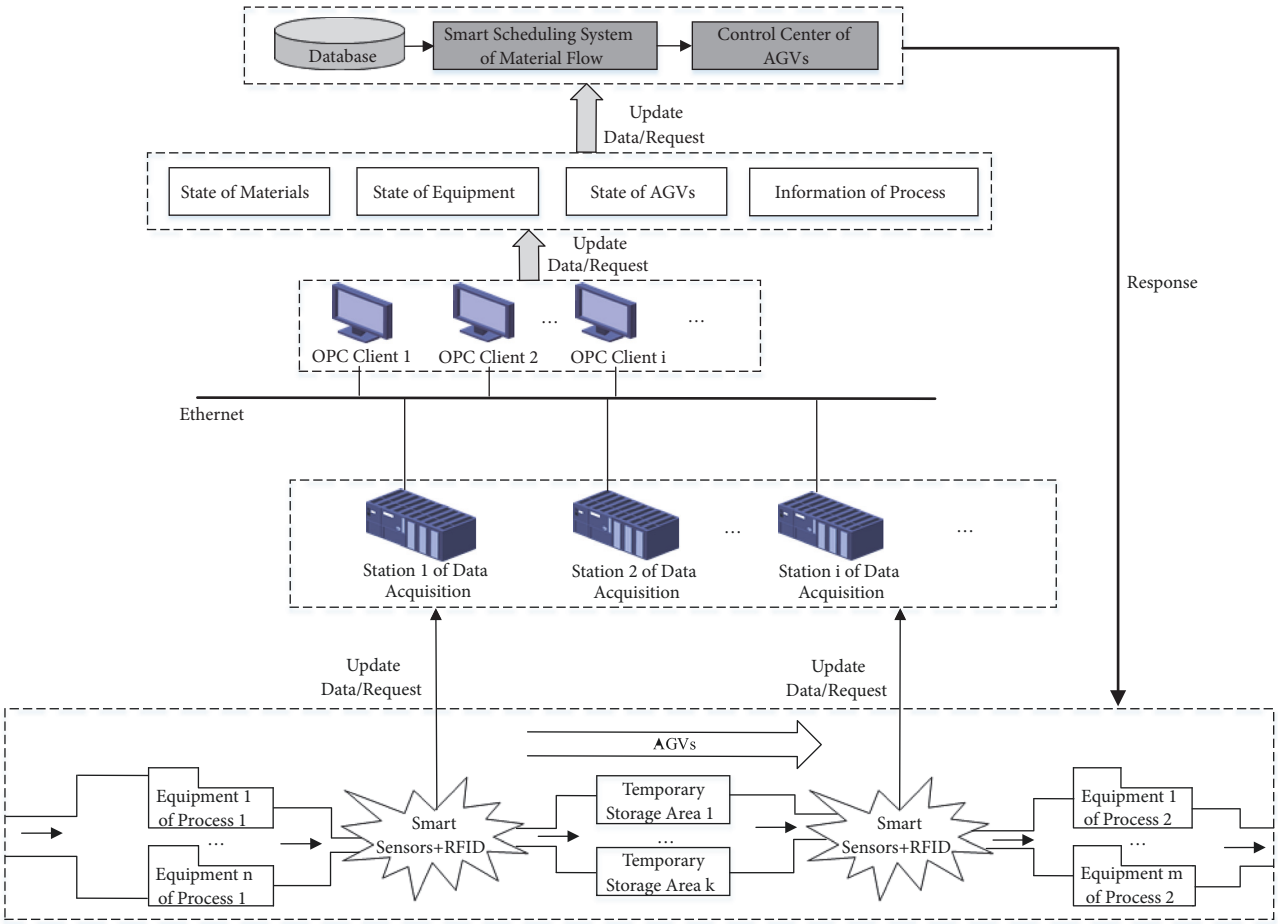


Figure 4: Framework of intelligent logistics scheduling model.

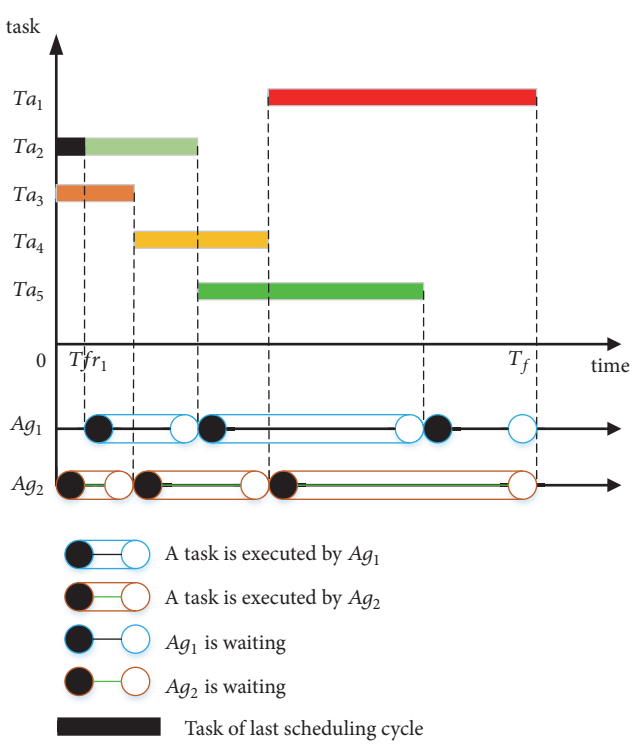


Figure 5: Schematic diagram of 5 tasks responded by 2 AGVs.

q: index of temporary storage areas

z: index of tasks assigned to an AGV

N_i: number of tasks assigned to AGV i

I_j: index of AGV that responds task j

$Tp(k)$: type of machines (excl. temporary storage area)

$TakRoute_{ij}$: the path of taking materials in $Route_{ij}$

$DownRoute_{ij}$: the path of adding materials in $Route_{ij}$

$L(Eq(k_1), Eq(k_2))$: distance between $Eq(k_1)$ and $Eq(k_2)$

$LRoute_{ij}$: the length of $Route_{ij}$

$LTakRoute_{ij}$: the length of $TakRoute_{ij}$

$LDownRoute_{ij}$: the length of $DownRoute_{ij}$

$TimeRoute_{ij}$: the length of time for AGV to travel $LRoute_{ij}$

$TimeTakRoute_{ij}$: the length of time for AGV to travel $LTakRoute_{ij}$

$TimeDownRoute_{ij}$: the length of time for AGV to travel $LDownRoute_{ij}$

T_{mop}: the length of time of loading and unloading by the manipulator of an AGV on a machine (excl. oven and temporary storage area)

T_{bakop}: the length of time of loading and unloading by the manipulator of an AGV on an oven

T_{stguop}: the length of time of loading and unloading by the manipulator of an AGV on a temporary storage area

$Type(q)$: type of temporary storage area q

$StoFlag(q)$: state of temporary storage area q

Tfr_i: the free time of AGV i

$Trpt_j$: the response time of task j

v: velocity of AGVs (m/s)

$Route(Eqs, Eqm, Eqe)$: it is the route that the starting point machine is Eqs, the transfer point machine is Eqm and the terminal device is Eqe

$T(i, j)$: the length of time that the AGV i responding the task j

$T_z(i)$: the length of time that AGV i responding task z assignd to it

$T(i)$: the time that AGV i has responded all of the tasks assigned to it

T_f: the time that all tasks have been responded (finish time)

$WS(p)$: operation p

$TsRT$: the threshold of finish time

$N(p)$: number of machines of operation p

$TaUT(WS(p))$: the operating time of materials in a material box (or an operation unit which is suitable for describing Bak1 and Bak2) of operation p

2.3. Mathematical Model. The objective of scheduling is to respond all the tasks in minimum time with minimum number of AGVs. In particular, the responding time of any task should be restricted in a reasonable range. It means that the value of T_f should be minimum and $T_f < TsRT$.

The discrete variables are expressed by

$$WS = \{\text{DB}, \text{Bak1}, \text{WB}, \text{Disp}, \text{Bak2}\} \tag{1}$$

$$WS(p), Tp(k) = \begin{Bmatrix} \text{DB}, & p = 0 \\ \text{Bak1}, & p = 1 \\ \text{WB}, & p = 2 \\ \text{Disp}, & p = 3 \\ \text{Bak2}, & p = 4 \end{Bmatrix} \quad p = 0, 1, \ldots, 4, \forall k \in N \tag{2}$$

$$TsRT = \frac{TaUT(WB)}{2} = \frac{TaWB(WS(2))}{2} \tag{3}$$

$$Type(q) = \begin{Bmatrix} \text{DB}, & q = 3, 4 \\ \text{Bak1}, & q = 5, 6 \\ \text{WB}, & q = 7, 8 \\ \text{Disp}, & q = 9, 10 \\ \text{Bak2}, & q = 11, 12, 13 \\ \text{Init}, & q = 1, 2 \end{Bmatrix} \tag{4}$$

$$s = \begin{cases} 0, & \text{If a machine needs to add materials from a temporary storage area} \\ 1, & \text{Processed materials need to be transfered to a temporary storage area} \end{cases} \tag{5}$$

$$StoFlag(q) = \begin{cases} 0, & \text{AGVs can take and add materials} \\ 1, & \text{AGVs can take materials from it} \\ 2, & \text{AGVs can add materials on it} \end{cases} \tag{6}$$

Here, $TaWB(WS(2))$ is the shortest in all of the operations, so the value of $TsRT$ is set to $TaWB(WS(2))/2$ for ensuring continuous operation of each machine and production efficiency of the IMW. The calculation method is explained as follows.

According to the definition of $TaWB(WS(2))$, it can be seen as an operation cycle on wire bonding machine; the output of it is represented by $OutP$. Assumed $TaWB(WS(2))$ is divided into two subcycles $Sc1$ and $Sc2$, and both of them have a corresponding output of $OutP/2$, so the values of $Sc1$

and $Sc2$ are both $TaWB(WS(2))/2$. If $Sc1$ is finished and the material box is the last one of the machine, then materials should be supplemented and a request of transferring materials will be generated. To ensure continuous operation of the machine, the request of transferring materials should be executed before finishing $Sc2$ which means the request should be responded in $TaWB(WS(2))/2$. If all of the tasks of transferring materials in the IMW can be responded in $TaWB(WS(2))/2$, then continuity of all the machines can be ensured. Therefore, $TaWB(WS(2))/2$ is a reasonable value of the threshold of finish time ($TsRT$).

$Type(q)$ corresponds to an operation, and it represents the temporary storage area of raw materials when $Type(q)$=Init. The value of $StoFlag(q)$ of a temporary storage area determines the availability of it, and the value also provides information for AGVs to choose the best way to respond a task.

Minimizing the finish time (T_f). It is the main objective of the mathematical model; the expression of T_f can be expressed by

$$T_f = \max\{T(i)\}, \quad n \in N \tag{7}$$

$$T(i) = Tfr_i + \sum_{z=1}^{N_i} T_z(i), \quad \forall j \in N,\ 1 \le j \le m \tag{8}$$

$$T(i,j), T_z(i) = \begin{cases} T_{mop} + T_{stguop} + TimeRoute_{ij}, & WS(p) = \{\text{DB, WB, Disp}\} \\ T_{bakop} + T_{stguop} + TimeRoute_{ij}, & WS(p) = \{\text{Bak1, Bak2}\}, \end{cases} \quad \forall i, j \in N,\ 1 \le i \le n,\ 1 \le j \le m \tag{9}$$

$$TimeRoute_{ij} = TimeTakRoute_{ij} + TimeDownRoute_{ij}, \quad \forall i, j \in N,\ 1 \le i \le n,\ 1 \le j \le m \tag{10}$$

$$TimeTakRoute_{ij} = \frac{LTakRoute_{ij}}{v}, \quad \forall i, j \in N,\ 1 \le i \le n,\ 1 \le j \le m \tag{11}$$

$$TimeDownRoute_{ij} = \frac{LDownRoute_{ij}}{v}, \quad \forall i, j \in N,\ 1 \le i \le n,\ 1 \le j \le m \tag{12}$$

$$LRoute = LTakRoute_{ij} + LDownRoute_{ij} = L\left(Eqs_{ij}, Eqm_{ij}\right) + L\left(Eqm_{ij}, Eqe_{ij}\right), \quad \forall i, j \in N,\ 1 \le i \le n,\ 1 \le j \le m \tag{13}$$

$$LTakRoute_{ij} = L\left(Eqs_{ij}, Eqm_{ij}\right), \quad \forall i, j \in N,\ 1 \le i \le n,\ 1 \le j \le m \tag{14}$$

$$LDownRoute_{ij} = L\left(Eqm_{ij}, Eqe_{ij}\right), \quad \forall i, j \in N,\ 1 \le i \le n,\ 1 \le j \le m \tag{15}$$

subject to

$$T_f = \max\{T(i)\} < TsRT, \quad \forall i \in N,\ 1 \le i \le n \tag{16}$$

$$m = \sum_{i=1}^{n} N_i \tag{17}$$

Here, (1) defines the finish time of all the tasks, and constraint number (16) defines the demand on the maximum finish time. Equations (8)-(15) define the calculation method of related distance and time which determine the result of the finish time. The calculation equations of $T_z(i)$ and $T(i,j)$ are the same as shown in (9). $LRoute_{ij}$ is the best route for AGV i to respond task j by choosing a reasonable and available temporary storage area.

Minimizing the number of AGVs. In the IMW as shown in Figure 2, the number of machines is limited which lead to the maximum number of concurrent tasks which is also limited. To improve the profitability of IMW, minimizing the number of AGVs on the basis of constraint number (16) and the result of T_f is valuable. Therefore, the objective of minimizing the number of AGVs is to configure minimum AGVs for the IMW and meet the demands of concurrent tasks of transferring materials. It is expressed by

$$MCT = \eta \times \sum_{p=0}^{4} N(p) \times \frac{TsRT}{TaUT(WS(p))}, \quad \eta > 1 \tag{18}$$

$$AT = \sum_{p=0}^{4} N(p) \times \frac{TsRT}{TaUT(WS(p))} \tag{19}$$

Here, AT as shown in (19) is the average number of tasks in $TsRT$. η is a stability coefficient which is designed to improve the designed response ability of AGVs scheduling platform. MCT is the designed maximum number of concurrent tasks; it is calculated by (18). The calculation methods of AT and MCT are explained as follows.

According to the above description of $TaWB(WS(\text{p}))$ and assumptions of the IMW, on average, there will generate no more than 1 task of transferring materials by a machine in $TaWB(WS(\text{p}))$. Here, we assume that there will be 1. It means that the number of tasks generated by a machine in unit time is $1/TaWB(WS(\text{p}))$. If the number of machines which correspond to $TaWB(WS(\text{p}))$ is $N(p)$, then the number of tasks generated by these machines in $TsRT$ should be $N(p)\times TsRT/TaWB(WS(\text{p}))$. Therefore, the total number of tasks of transferring materials generated by all of the machines of the IMW in $TsRT$ can be calculated by (19). To improve the designed logistics capacity of the IMW, the stability coefficient is proposed in this study by applying the concept pf safety factor in mechanical design. Thus the designed maximum number of concurrent tasks can be calculated by (18).

3. Algorithm Design

Makespan which corresponds to the finish time in this paper is the main objective in existing researches, some effective models of AGVs scheduling and corresponding evolutionary algorithms (EAs) have been developed. Zheng et al. developed a mixed integer linear programming (MILP) model with the objective of minimizing makespan and then a

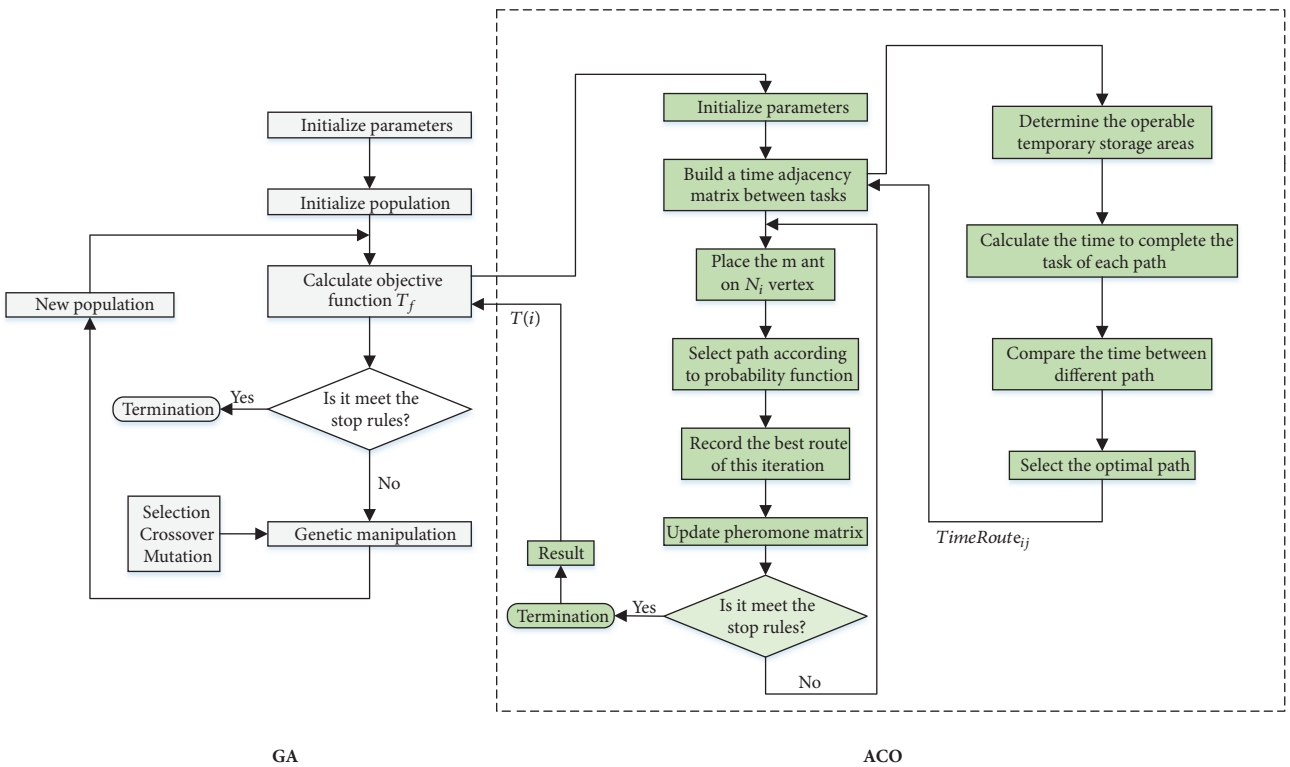


Figure 6: Flowchart of DLH-GA-ACO.

tabu search algorithm (TSA) was proposed for simultaneous machine/AGV scheduling problem [46]. Mousavi et al. proposed a AGVs scheduling method using a hybrid of genetic algorithm and particle swarm optimization (H-GA-PSO) by optimizing the sequence of operations [47]. However, the former just take the sequence of operations into account and the result of the latter depends to a great extent on the quality of the initial solution; besides, both the models have not been applied to the problem in this paper before, so an applicable algorithm should be further researched aiming at the problem in this study.

A DLH-GA-ACO which contains two levels was developed as follows: (1) The outer level algorithm is GA. It is used to optimize the AGV-task matching relation. (2) The inner level algorithm is ACO. It is used to optimize the sequence of the tasks assigned to an AGV. To improve the calculation speed of the algorithm, the DLH-GA-ACO ran in a distributed environment with 3 computers. Besides, some other methods as follows are also applied to improve the computation effectiveness of it.

(i) Prefiltering chromosomes. In a chromosome, if too many tasks are assigned to an AGV, it is considered to be a bad solution. For instance, there are 3 AGVs to respond 12 tasks; if more than 6 tasks are assigned to an AGV in a chromosome, the fitness of chromosome will be set to a large value without optimizing by ACO.

(ii) Applying result record set. All of the chromosomes and corresponding fitness are recorded, if another chromosome is in the record set, the fitness of the chromosome will be set to the value in record set without optimizing by ACO.

(iii) Applying the mixed programming method. For instance, because loop statements run faster in C language than in Matlab, part of the code is written in C language; it is compiled into a Matlab executable file (.mexw64) and invoked in Matlab 2018a.

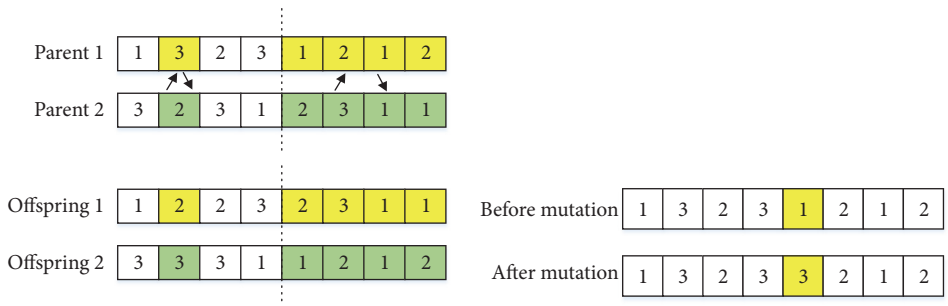
Table 1: General schematic for reading data.

GA	Chromosome(C_r)						C_r					
	Gene(G_j)	G_1	G_2	.	.	.	G_j	.	.	.	.	.	G_m
	Gene code(i)	1	3	.	.	.	i	2	.	3	.	n	i+1

The DLH-GA-ACO optimizes the logistics scheduling process on two dimensions which correspond to the content of Sections 3.1 and 3.2, respectively. The main steps of DLH-GA-ACO algorithm are shown in Figure 6 and detailed in Sections 3.1 and 3.2.

3.1. Genetic Algorithm

Step 1 (initializing parameters). It involves setting the parameters of GA which include crossover rate (CR), mutation rate (MR), population size (PS), length of a chromosome (LC), and maximum number of iterations ($NCMax\_GA$). The general schematic for reading data is presented in Table 1. The encoding of a chromosome is presented in the 3th row; it will be discussed later.



(a) Example of two-point crossover

(b) Example of mutation operator

Figure 7: Example of crossover and mutation in this paper.

Step 2 (initializing population). A set of chromosomes are generated in this step.

Chromosome encoding. The encoding used in this paper is real number coding according to the needs of the problem. As it is show in Table 1, the sequence of genes represents the indexes of tasks from left to right, and each gene code represents the index of an AGV related to a corresponding task. A chromosome (C_r) is expressed by

$$\begin{aligned} C_r &= \left\{\left(I_j\right) \mid \forall I_j, j \in N, 1 < I_j < n, j = 1, 2, \ldots, m\right\} \\ &= \left\{I_1, I_2, \ldots, I_m\right\} \end{aligned} \tag{20}$$

Here, j is the index of tasks; j=1, 2, ..., m and I_j represent that task j is responded by AGV I_j.

Chromosome encoding and generating are explained by an example of 8 tasks (Ta_1, Ta_2, Ta_3, Ta_4, Ta_5, Ta_6, Ta_7, and Ta_8) and 3 AGVs (Ag_1, Ag_2, and Ag_3). A chromosome could be [13231212]. Here, from the left, the first "1" represents that the first task is responded by Ag_1, the first "3" represents that the second task is responded by Ag_3, and so on.

Step 3 (fitness evaluation). Each chromosome is evaluated by T_f with (7).

Step 4 (new population). New population is generated by selection, crossover, and mutation; elitism is also be applied.

Elitism. The first three best chromosomes from each generation are transferred directly to the next generation for maintaining a good fitness value in some generations.

Selection. The roulette method which is a probability random selection method is used in this study for selection operator.

Crossover. A two-point crossover based on partial strings exchange and single-gene exchange is employed to increase the search scope of the algorithm. The two-point crossover is illustrated in Figure 7(a) based on the example in Step 2. In this operator, the first crossover point is generated by a random integer. Partial strings of the two parent chromosomes after the first crossover point exchange. Another crossover point is generated by a random integer before the first crossover point in the parent chromosomes and the corresponding genes exchange.

The number of crossovers is calculated based on the crossover rate (CR) and population size (PS) by

$$Number\ of\ crossovers = \frac{CR \times PS}{2} \tag{21}$$

Mutation. Mutation is another important operator of GA to create and maintain the diversity [46]. The number of mutations is calculated by (22) based on the mutation rate (Pm) and population size (PS).

$$Numer\ of\ mutations \cong PS \times Pm \tag{22}$$

In the algorithm, mutation is an auxiliary operator; considering this characteristic, one-point mutation is used in this study and it is shown in Figure 7(b). Since each gene can be valued as an integer between 1 and n; there are n-1 mutation choices on each gene. The mutation point is generated by a random integer.

Step 5 (termination). The loop of chromosome generation is terminated when the number of generation reaches its maximum, then the best chromosome is returned as the best solution.

3.2. Ant Colony Optimization. ACO is the inner level algorithm which optimizes the response sequence of tasks assigned to an AGV according to the chromosome of GA. It is a Traveling Salesman Problem (TSP). Considering the routing characteristic of ACO, it is proposed to solve the problem. In ACO, the foraging process of an ant is an independent process of constructing a route. A number of ants exchange information through pheromone to solve the problem together. The steps of the ACO are detailed as follows.

Step 1 (initializing parameters). The parameters include the number of tasks assigned to each AGV(N_i), maximum iterations($NCMax$), the number of ants (Am), the heuristic factors ($Alpha$ and $Beta$), pheromone volatilization coefficient (Rho), and pheromone enhancement coefficient (Q). To improve the performance of ACO, if $N_i < 5$, then Am=10, otherwise Am=2$*N_i$, and if $N_i < 10$, then $NCMax$=20, otherwise $NCMax$=2$*N_i$.

Table 2: The values of the parameters about the IMW.

v	T_{mop}	T_{bakop}	T_{stguop}	$N(0)$	$N(1)$	$N(2)$	$N(3)$	$N(4)$
0.4m/s	25 s	45 s	20 s	12	3	36	12	6
$TaUT(WS(0))$	$TaUT(WS(1))$	$TaUT(WS(2))$	$TaUT(WS(3))$	$TaUT(WS(4))$				
60 min	120 min	20 min	60 min	240min				

In TSP of this study, a task represents a city, and the distances among the tasks assigned to AGV i are defined by a matrix D_i as shown in

$$D_i = \begin{bmatrix} 0 & d_{12} & \cdots & d_{1N_i} \\ 0 & 0 & \cdots & d_{2N_i} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & d_{N_i 2} & \cdots & 0 \end{bmatrix} \tag{23}$$

In D_i, d_{ab} represents the length of time for AGV i responding the task $ExcTa(i,a)$ after responding the task $ExcTa(i,b)$. If b=1, then d_{ab}=0. If a=1, then d_{ab} represents the length of time for AGV i responding the task b from the initial position of AGV i. According to D_i, the visibility matrix of tasks assigned to AGV i is defined by Eta as shown in (24). Elements in Eta describe the visibility of task a to task b.

$$Eta = \frac{1}{D_i} \tag{24}$$

Step 2 (searching route). Within the maximum iterations, ants search routes according to the pheromone concentration and Eta in Step 1.

Step 2.1 (initializing the position of the ants). The m ants are randomly placed in the initial position of the AGVs.

Step 2.2 (selecting the next reachable node). The selected probability of each node is calculated according to pheromone concentration and Eta of the route as shown in (25), and a roulette method is applied in this paper.

$$p_{ab}^{h} = \begin{cases} \dfrac{[Tau_{ab}(t)]^{Alpha}[Eta_{ab}]^{Beta}}{\sum [Tau_{ab}(t)]^{Alpha}[Eta_{ab}]^{Beta}}, & b \notin \{tabu_h\} \\ 0, & \text{Others} \end{cases} \tag{25}$$

Here, h is the index of an ant; $tabu_h$ defines the tabu nodes of ant h.

Step 2.3 (updating the route and length of it). The route of ant h is recorded in $tabu_h$, and the length of it is also recorded in a matrix.

Step 2.4 (finishing the tour of ant h). Steps 2.2 and 2.3 are repeated until the ant h finishes all the tasks.

Step 2.5 (finishing the tour of all ants). Steps 2.2, 2.3, and 2.4 are repeated until all the ants finish all the tasks.

Step 3 (recording the results). The records include the best route of the iteration, length of the best route, the average length, and the responding time of each task. To get a better result, 3 shortest routes are selected directly to the next iteration after each iteration.

Step 4 (update the pheromone). The global pheromone updating rule is applied to update the pheromone in this study. The updating method of pheromone of the route between task a and task b is shown in

$$\Delta Tau_{ab} = \Delta Tau_{ab} + \frac{Q}{T_{ab}^{h}} \tag{26}$$

$$Tau_{ab} = (1 - Rho) \times Tau_{ab} + \Delta Tau_{ab} \tag{27}$$

Here, ΔTau_{ab} is the pheromone increment of the route between task a and task b; Q/T_{ab}^{h} is the increment of pheromone of the route between task a and task b of ant h.

Step 5 (termination). The algorithm is terminated when the number of iteration reaches its maximum, then the shortest route which meet the constraint number (16) is returned as the best solution.

4. Experiments Simulation and Discussion

4.1. Initial Data. To verify the effectiveness of the model and algorithm, aiming at the IMW as shown in Figure 2, a set of experiments were provided in this study. The values of the parameters about the IMW are shown in Table 2; constraints are defined by them. The positions of machines and temporary storage areas are shown in Table 3; they are the basis for the mathematical model to get the intermediate data and final results.

The value of $TaUT(WB)$ is about 20 min, and the threshold of finish time ($TsRT$) is calculated with (3), so $TsRT$ is set to 600 s. The maximum number of concurrent tasks (MCT) and the average number of tasks (AT) are calculated by (18) and (19), respectively, according to the data in Table 2. Here, the stability coefficient (η) is set to 1.15, so the values of MCT and AT are set to 25.875 and 22.5, respectively.

Besides, the initial positions of AGVs ($Pos(i)$) and the state of temporary storage areas ($StoFlag(q)$) in the experiments are shown in Table 4.

4.2. Experiment Results. Compared with other algorithms, the calculation process of DLH-GA-ACO is more complex for its two levels. To improve the performance of DLH-GA-ACO, a distributed computing method was applied with 3 computers. A set of experiments were performed to optimize the configuration of the number of AGVs and verify the

Table 3: The positions of machines and temporary storage areas.

Index of machines and temporary storage areas (k)									
1	2	3	4	5	6	7	8	9	10
(36,14)	(36,12)	(2,18)	(2,15)	(2,6)	(2,4)	(36,7)	(36,5)	(36,18)	(36,20)
11	12	13	14	15	16	17	18	19	20
(12,21)	(14,21)	(16,21)	(5,14)	(7,14)	(9,14)	(11,14)	(13,14)	(15,14)	(20,14)
21	22	23	24	25	26	27	28	29	30
(22,14)	(24,14)	(26,14)	(28,14)	(30,14)	(2,9)	(2,11)	(2,13)	(6,11)	(8,11)
31	32	33	34	35	36	37	38	39	40
(10,11)	(12,11)	(14,11)	(16,11)	(21,11)	(23,11)	(25,11)	(27,11)	(29,11)	(31,11)
41	42	43	44	45	46	47	48	49	50
(6,8)	(8,8)	(10,8)	(12,8)	(14,8)	(16,8)	(21,8)	(23,8)	(25,8)	(27,8)
51	52	53	54	55	56	57	58	59	60
(29,8)	(31,8)	(6,4)	(8,4)	(10,4)	(12,4)	(14,4)	(16,4)	(21,4)	(23,4)
61	62	63	64	65	66	67	68	69	70
(25,4)	(27,4)	(29,4)	(31,4)	(5,18)	(7,18)	(9,18)	(11,18)	(13,18)	(15,18)
71	72	73	74	75	76	77	78	79	80
(20,18)	(22,18)	(24,18)	(26,18)	(28,18)	(30,18)	(21,21)	(23.21)	(25.21)	(27,21)
81	82								
(29,21)	(31,21)								

Table 4: The initial positions of AGVs and the state of temporary storage areas in the experiments.

Index of AGVs (i)	1	2	3	4	5	6	7	8					
$Pos(i)$	(12,11)	(31,11)	(24,14)	(16,11)	(21,11)	(2,4)	(10,4)	(2,18)					
Index of temporary storage areas (q)	1	2	3	4	5	6	7	8	9	10	11	12	13
$StoFlag(q)$	0	0	0	1	0	0	0	1	0	0	0	0	2

effectiveness of DLH-GA-ACO in the IMW, and comparisons among H-GA-PSO, TSA, and DLH-GA-ACO were also performed. The details are shown in the following sections.

In this study, the hardware and software platform are list as follows: Windows 10, Intel® Core™ i7-4790K CPU, 3.6 GHz, 16 GB of RAM, and Matlab 2018a.

4.2.1. Minimizing the Number of AGVs and Algorithm Analysis. Minimizing the number of AGVs is important for IMW to improve the profit of it. Therefore, to optimize the configuration, five experiments with 26 tasks were performed. Here, the number of tasks is chosen to ensure the logistics capability of the IMW according to the value of MCT which is calculated in Section 4.1. The information of the request machines and the free time of each AGV are shown in Table 5. The j represents the index of a task, and the k represents the index of the corresponding machine. The value of i represents the index of an AGV, and the Tfr_i represents the corresponding free time (s) of it.

The initial parameters of DLH-GA-ACO in these experiments are shown in Table 6. According to the Step 1 of ACO, the values of $NCMax$ and Am are determined by the value of N_i.

In these experiments, each algorithm with n AGVs is run 20 times; the T_f of it is the average of results of them. The running results of the algorithms are shown in Table 7.

In Table 7, the T_f decreases along with the increase of the number of AGVs. Here, $TsRT$ is 600 s. Therefore, the minimum number of AGVs in experiment 1 corresponding to H-GA-PSO is 8 by considering the maximum value, and both the corresponding values of TSA and DLH-GA-ACO are 6 which is the minimum among the optimal solutions of the three algorithms. In other experiments, the minimum among the optimal solutions is also 6 which can be obtained by DLH-GA-ACO in every experiment, while other algorithms are not. Therefore, the minimum number of AGVs in the IMW should be set to 6 according to the optimization solution of DLH-GA-ACO. The number is the smallest one among the solutions obtained by the three algorithms which proves the superiority of DLH-GA-ACO over H-GA-PSO and TSA.

Figure 8 shows the comparison of finish time among H-GA-PSO, TSA, and DLH-GA-ACO with different number of AGVs. It can be obviously observed that almost all of the optimization results of DLH-GA-ACO are better than other two algorithms except when the number of AGVs is 1. So the DLH-GA-ACO is concluded to be more effective than others.

Figure 9 shows the comparison of stability among H-GA-PSO, TSA, and DLH-GA-ACO with different number of AGVs. The value in Figure 9 represents the difference between T_f and the maximum value of each algorithm in Table 7 with different numbers of AGVs. It reflects the stability of an algorithm. It can be obviously observed that

Table 5: The information of the request machines and the free time of each AGV in the five experiments.

Experiment 1	j	1	2	3	4	5	6	7	8	9	10	11	12	13
	k	57	18	27	67	25	49	28	43	30	60	82	44	34
	j	14	15	16	17	18	19	20	21	22	23	24	25	26
	k	59	20	45	81	15	62	16	69	55	75	64	61	46
	i	1	2	3	4	5	6	7	8					
	Tfr_i	0	6	13	22	27	33	34	42					
Experiment 2	j	1	2	3	4	5	6	7	8	9	10	11	12	13
	k	38	34	46	26	61	74	50	47	59	53	71	28	73
	j	14	15	16	17	18	19	20	21	22	23	24	25	26
	k	21	55	27	57	60	23	43	51	31	80	36	82	40
	i	1	2	3	4	5	6	7	8					
	Tfr_i	0	2	10	13	18	22	27	31					
Experiment 3	j	1	2	3	4	5	6	7	8	9	10	11	12	13
	k	57	48	73	40	41	42	47	32	26	45	33	18	64
	j	14	15	16	17	18	19	20	21	22	23	24	25	26
	k	71	38	21	17	14	34	23	62	46	44	65	29	61
	i	1	2	3	4	5	6	7	8					
	Tfr_i	0	11	12	19	23	30	33	38					
Experiment 4	j	1	2	3	4	5	6	7	8	9	10	11	12	13
	k	28	43	60	82	69	55	64	30	15	27	61	50	36
	j	14	15	16	17	18	19	20	21	22	23	24	25	26
	k	80	46	41	51	48	38	21	71	14	44	29	18	73
	i	1	2	3	4	5	6	7	8					
	Tfr_i	0	7	9	14	18	27	33	36					
Experiment 5	j	1	2	3	4	5	6	7	8	9	10	11	12	13
	k	21	25	37	43	52	78	80	27	53	58	63	59	16
	j	14	15	16	17	18	19	20	21	22	23	24	25	26
	k	19	66	70	74	75	39	47	68	31	32	46	55	22
	i	1	2	3	4	5	6	7	8					
	Tfr_i	0	3	11	17	20	22	30	37					

Table 6: The initialization parameters of DLH-GA-ACO.

GA	*CR*	*MR*	*PS*	*LC*	*NCMax_GA*	
	0.5	0.2	25	26	200	
ACO	*Alpha*	*Beta*	*Rho*	*Q*	*NCMax*	*Am*
	1.4	2.2	0.15	10^3	-	-

the stability of DLH-GA-ACO is the best among the three algorithms.

4.2.2. Experiment Simulation and Analysis. To further verify the performance of the three algorithms and superiority of DLH-GA-ACO over the other two algorithms, an experiment with 20 tasks was performed. Here, the number of tasks is close to the average value (*AT*) which corresponds to the general state of the IMW; besides, the number of tasks is enough. Therefore, it is a typical experiment to verify the performance of the proposed algorithms. It means that there are 20 tasks of transferring materials to respond in a certain time. The information of the request machines and the free time of each AGV is shown in Table 8.

The finish time of the 20 tasks before optimization is 593, and the Gantt chart of the tasks is shown in Figure 10. In the solution, each task is always responded by the earliest free AGV.

The optimization results of the three algorithms are shown in Table 9. Compared with the result before optimization as shown in Figure 10, the three algorithms are proved to be effective. Besides, no matter the maximum number of iterations is 100 or 200, the result of DLH-GA-ACO is better than H-GA-PSO and TSA. Although the computational time of DLH-GA-ACO is the longest for its two levels, DLH-GA-ACO is also proved to be an effective method on optimizing the logistics process in IMW. Additionally, the computational time can be controlled in a reasonable range with the methods

Table 7: The running results of H-GA-PSO, TSA, and DLH-GA-ACO.

Index of experiments	Algorithms	Data item	Number of AGVs (NA)							
			1	2	3	4	5	6	7	8
1	H-GA-PSO	T_f	3027.8	1682.8	1185	918.7	767.9	672.6	604	546.4
		Maximum value	3070	1735	1212	955	789	710	627	565
	TSA	T_f	3147.8	1584.2	1093.2	839.1	683.3	580	501.9	447.9
		Maximum value	3192	1605	1111	846	697	590	510	461
	DLH-GA-ACO	T_f	3148.3	1497.4	1012	766.6	631	548.7	478.2	433.3
		Maximum value	3166	1517	1017	769	647	554	483	442
2	H-GA-PSO	T_f	3101.8	1710.1	1172	926.1	769.3	662.4	584.9	539.2
		Maximum value	3152	1791	1209	952	797	703	616	568
	TSA	T_f	3224.7	1642.3	1094.1	839.5	687.3	571.9	497.4	439
		Maximum value	3259	1652	1119	852	697	582	509	445
	DLH-GA-ACO	T_f	3220.4	1566.5	1045	784	635.6	538.2	485.3	429.4
		Maximum value	3241	1569	1050	788	643	549	490	436
3	H-GA-PSO	T_f	3326.6	1786.2	1249.2	970.6	808.9	699	624.8	572.2
		Maximum value	3368	1827	1279	1002	830	722	649	591
	TSA	T_f	3399.6	1739.7	1182.2	895.6	733.8	615.3	538.5	479.5
		Maximum value	3443	1754	1205	907	751	625	552	489
	DLH-GA-ACO	T_f	3415.7	1668	1118	844.3	704.1	582	520.2	472.8
		Maximum value	3433	1672	1126	849	710	588	530	484
4	H-GA-PSO	T_f	3168.6	1736.2	1204.2	946.5	784.7	684.3	607.7	546.2
		Maximum value	3236	1765	1236	985	805	718	625	580
	TSA	T_f	3277	1652.1	1128.9	854.6	694.6	582.4	506.4	449.1
		Maximum value	3324	1673	1146	868	714	598	521	457
	DLH-GA-ACO	T_f	3262	1583.4	1050.4	798.2	658.8	560.4	490.6	446.6
		Maximum value	3284	1591	1058	810	664	565	495	455
5	H-GA-PSO	T_f	3151.1	1737.7	1215.7	935.9	790.2	675	611	565.1
		Maximum value	3271	1789	1233	969	817	710	630	591
	TSA	T_f	3249.7	1647.1	1122.5	857.4	702.6	588.3	511.4	457.6
		Maximum value	3315	1678	1139	874	717	597	525	462
	DLH-GA-ACO	T_f	3271.6	1563	1040.4	790	648.8	555.2	485.6	447
		Maximum value	3301	1572	1048	800	656	566	493	450

Table 8: The information of the request machines and the free time of each AGV in experiment 6.

j	1	2	3	4	5	6	7	8	9	10	11	12	13
k	82	56	68	54	15	33	66	52	73	72	59	30	62
j	14	15	16	17	18	19	20						
k	42	77	20	49	36	16	31						

i	1	2	3	4	5	6
Tfr_i	0	9	16	23	33	37

Table 9: The optimization results of the three algorithms in experiment 6.

Items	Maximum number of iterations					
	100			200		
Name of algorithms	H-GA-PSO	TSA	DLH-GA-ACO	H-GA-PSO	TSA	DLH-GA-ACO
T_f	552	484	470	533	476	464
Computational time	3.1 Sec	3.6 Sec	15.3 Sec	4.7 Sec	5.4 Sec	24.6 Sec

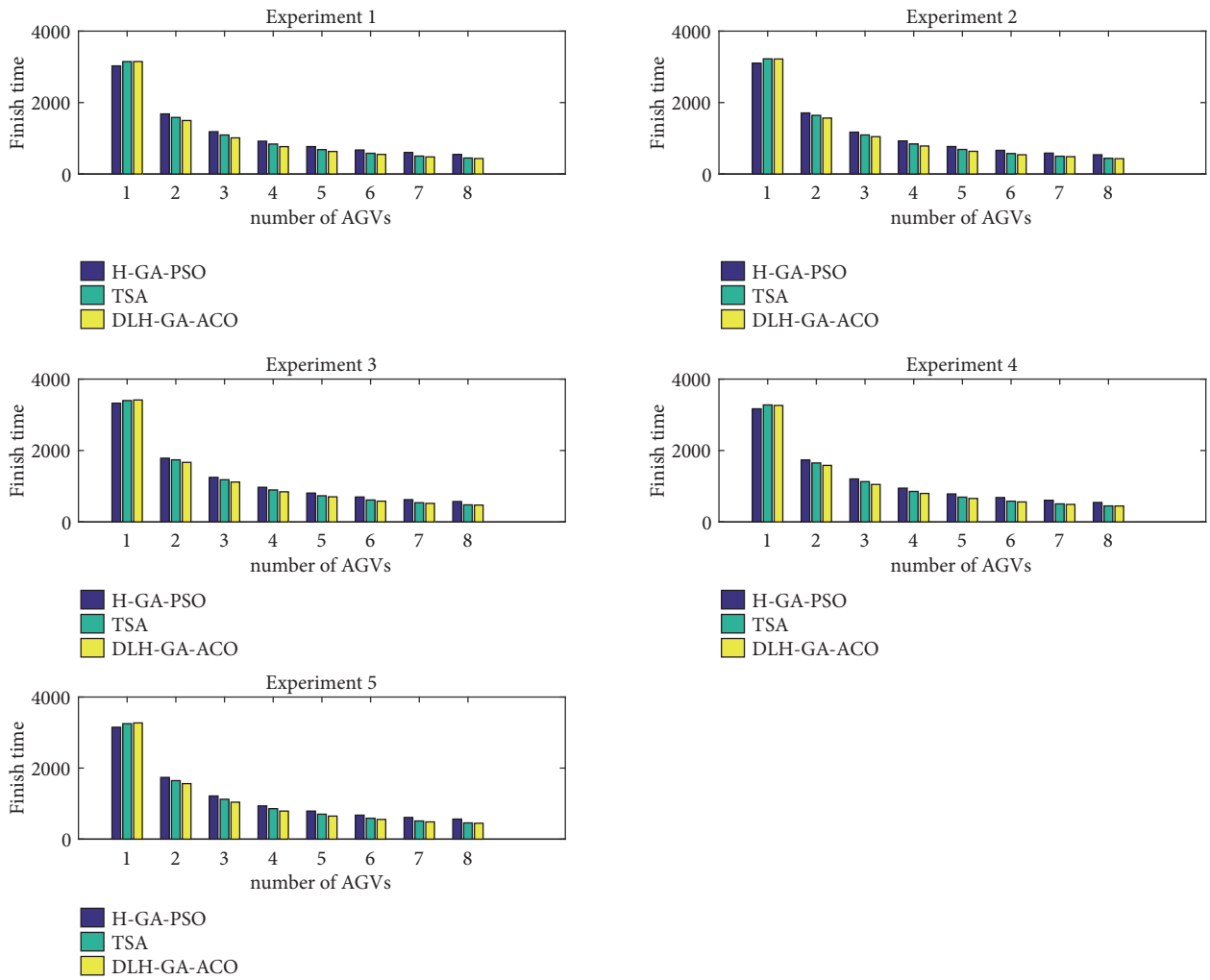


Figure 8: Comparison of finish time among H-GA-PSO, TSA, and DLH-GA-ACO with different number of AGVs.

proposed in Section 3 of this study, and it can also be further optimized by these methods or other technical means.

Figures 11(a) and 11(b) show the evolutionary curves of finish time with 100 iterations and 200 iterations respectively. It can be observed that TSA and DLH-GA-ACO have better convergence results and rate than H-GA-PSO; therefore, optimizing the logistics responding process on two dimensions is more effective than it on just one dimension. Compared with TSA, DLH-GA-ACO is more effective on minimizing finish time.

Figures 12(a) and 12(b) show the Gantt chart of the experiment after optimization by DLH-GA-ACO. The finish time is shorter than it in Figure 10 for the reasonable response sequence and matching relation of AGV-task.

5. Conclusions and Future Work

Aiming at the dynamic scheduling problem of logistics in an IMW, an intelligent logistics scheduling model and execution method with AGVs based on the mode of "request-scheduling-response" were proposed, and they were integrated with Internet of Things (IoT) to meet the demands of dynamic and real time. Correspondingly, a mathematical model was developed and integrated with a DLH-GA-ACO. In the model, the objectives of it were minimizing the finish time with the minimum AGVs and limited time.

To verify the effectiveness of the model, a set of experiments were applied. The first five experiments which include the preset maximum number of tasks of transferring materials were applied to determine the minimum number of AGVs in the IMW. Compared with H-GA-PSO and TSA, DLH-GA-ACO had a better optimization solution on minimizing the finish time and number of AGVs in limited time, and it is also more stable. Besides, another experiment simulation was provided to verify the effectiveness of the model and a comparison was also given in this experiment. The model and algorithm proposed in this study were proved to be effective, and the number of AGVs can finish all of the tasks in limited time. The superiority over other algorithms and performance of DLH-GA-ACO were intuitively shown in the experiment. To reduce the computational time, the DLH-GA-ACO was configured in a distributed environment and

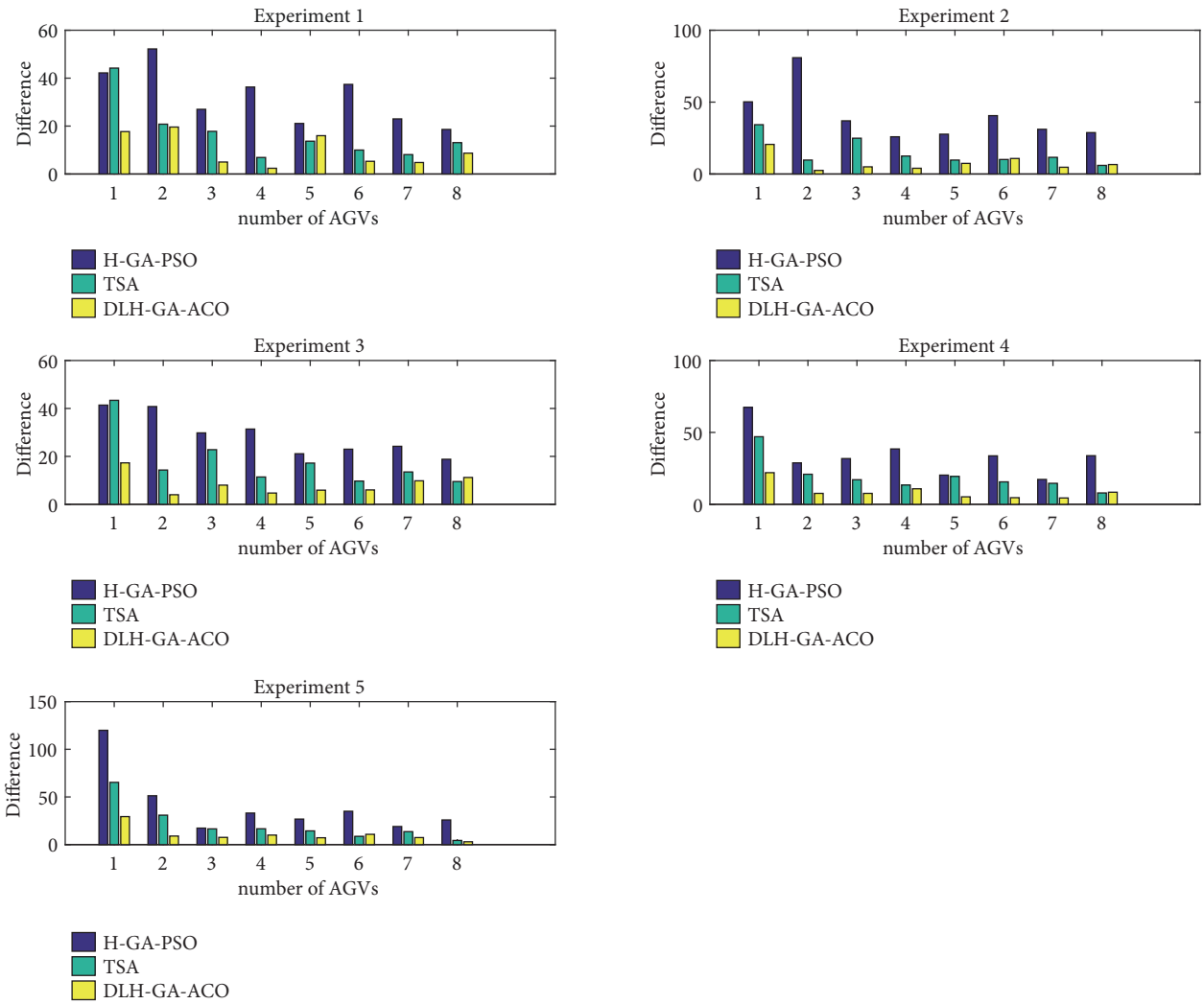


Figure 9: Comparison of stability among H-GA-PSO, TSA, and DLH-GA-ACO with different number of AGVs.

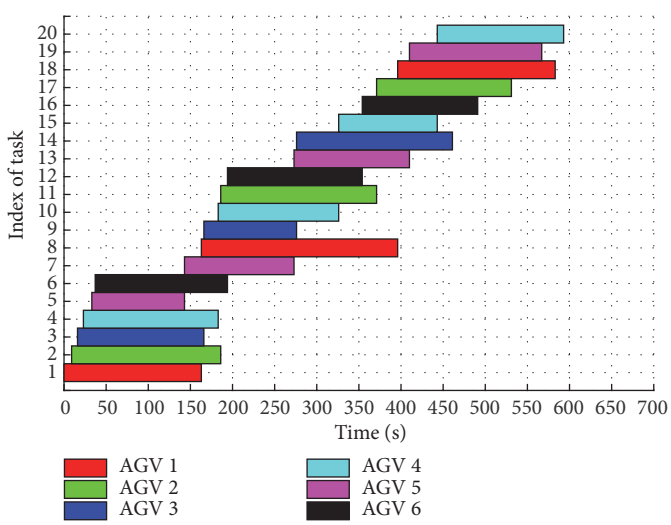
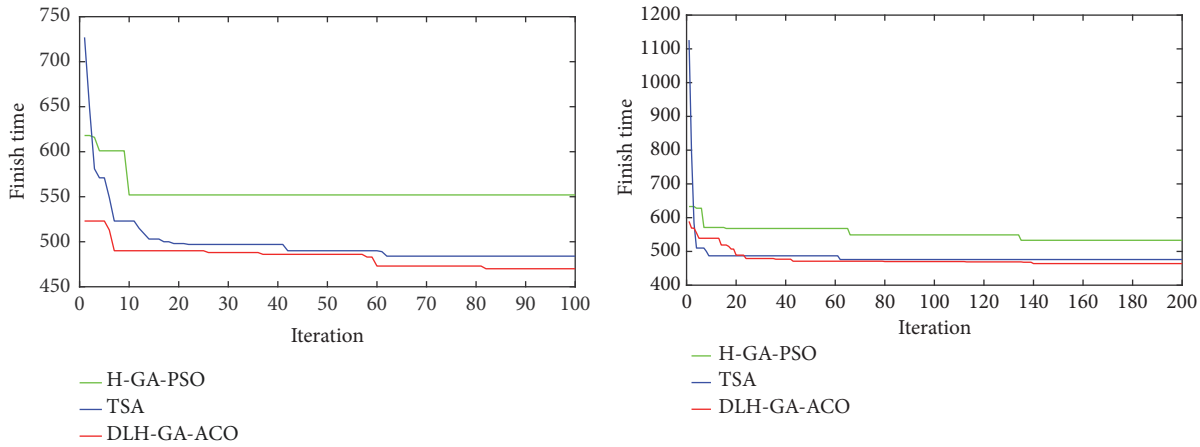


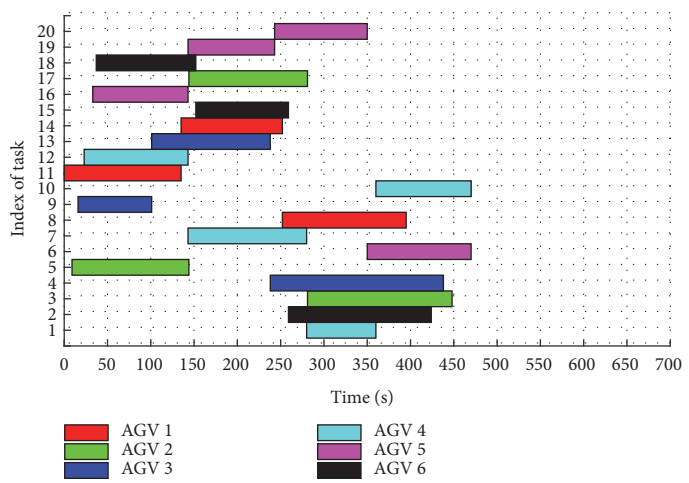
Figure 10: Gantt chart before optimization.



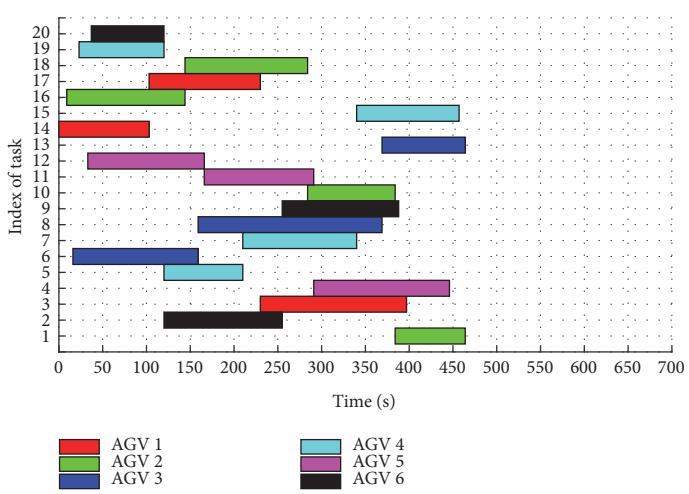
(a) Evolutionary curves of finish time with 100 iterations

(b) Evolutionary curves of finish time with 200 iterations

Figure 11: Evolutionary curves of finish time.



(a) Gantt chart of the experiment after optimization by DLH-GA-ACO with 100 iterations



(b) Gantt chart of the experiment after optimization by DLH-GA-ACO with 200 iterations

Figure 12: Gantt chart of the experiment after optimization by DLH-GA-ACO.

some other methods were also applied. In summary, the simulation results of the experiments proved the effectiveness and superiority of the DLH-GA-ACO over H-GA-PSO and TSA. The logistics dynamic scheduling model proposed in this study could be applied to more industries.

In the future, it will be interesting to investigate the following issues:

(1) To ensure the dynamic and real time of the model, the DLH-GA-ACO should run in short time; some other methods can be applied to further reduce the computational time of DLH-GA-ACO.

(2) More other factors, such as task priority and quality level, should be taken into account for more reasonable operation and logistics time control.

(3) The dynamic scheduling method should be extended to other industry and provides a new way to optimize the logistics process for them.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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