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A Dynamic Task Assignment Optimization Method for Multi-AGV System Based on Genetic Algorithm

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Abstract. Aiming at the influence of AGV without considering the working state on task assignment decision in multi-AGV system task assignment, a dynamic task assignment decision method with task completion prediction based on genetic algorithm. When assigning the arrived tasks at each stage, the decision method brings the working AGVs and the idle AGVs into the set of schedulable vehicles at the same time, which expands the scope of the optimal decision, makes the available AGV resources more fully mobilized in the dynamic scheduling process, and improves the efficiency of the whole scheduling system. First, this paper establishes a prediction model for task completion. On this basis, the task assignment decision model of multi-AGV system based on task completion prediction is established, and the coding, fitness function and genetic operation of the genetic algorithm suitable for this problem are designed. Finally, a univariate factor analysis is carried out on the task assignment time interval and the number of AGVs by using an example, which verifies the effectiveness of the task assignment strategy of the multi-AGV system based on task completion prediction. The results show that the genetic algorithm can better solve the task assignment problem with task completion prediction, and can schedule the available AGV resources to a greater extent, which effectively increase the number of tasks completed by the multi-AGV system in one production cycle.

Keywords: multi-AGV system, task assignment, decision model, genetic algorithm

1. Introduction

As an important part of intelligent storage [1], intelligent workshop [2], wharf [3] and other systems, Automatic Guided Vehicle (AGV) is widely used in goods handling, material transportation, semi-finished product transfer and other occasions, which improves the handling capacity and efficiency of such systems. Usually, in this kind of system, multiple AGVs undertake the transportation task, and different task assignment strategies will affect the transportation efficiency and transportation cost of multi-AGV systems. When researching the problem of task assignment among workers, Hassin et al. proposed that the first-in-first-out assignment method is inefficient, and rational design of task assignment rules is necessary to increase production efficiency and reduce production costs [4]. In the problem of computer resource assignment, Wei et al. [5] and Jiang et al. [6] effectively reduced the cost and execution time of computer systems by effectively assign computer resources. The essence of the problem is the efficient assignment of resources, which is consistent with the task assignment problem of multi-AGV system. The task problem is a common resource planning problem [7], and it is different according to its goals, but the AGV in the idle state is used as the feasible solution set for optimization [8]. For example, Wang et al. took the shortest task completion time as the goal, solved the problem of task assignment in the warehousing and logistics environment, and achieved the shortest total task completion time for scheduling [9]. Zhou et al. aimed at task balance, so as to minimize the task balance of shuttle vehicles and the minimum time to complete all tasks in a dense warehousing and logistics environment [10]. With the goal of minimizing the cost of path, time and task balance, Yang et al. used the variable neighborhood simulated annealing algorithm to effectively solve the task assignment problem [11]. In the above studies, by selecting different task assignment goals and designing assignment strategies, the task assignment problem in practical application scenarios can be solved. But in these strategies, tasks can only be assigned to idle vehicles, ignoring the situation where working vehicles are the optimal solution. These strategies have the problem of wasting schedulable AGV resources, resulting in higher transportation costs and lower vehicle utilization.

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Depending on the type of task assignment of the multi-AGV system, it can be divided into dynamic task assignment and static task assignment. The time periods of the two assignments are different, and the goals of task assignment optimization are also different. Static task assignment does not consider the time state of task arrival. The system scheduling center will process the received tasks in a centralized manner at a specified time. The optimization objectives of task assignment include the shortest time spent on completing all tasks, the smallest sum of path distances, or the least number of AGVs. For example, aiming at the limitations of the traditional flexible workshop scheduling problem, Liang et al. considered multiple constraints such as workpiece transportation time, delivery date, processing time and workpiece arrival time, a scheduling model aiming at maximizing machine efficiency and minimizing maximum completion time is constructed [12]. Li et al. established a multi-objective AGV scheduling model and took the total path distance of AGV, the standard deviation of AGV workload and the standard deviation of the difference between the latest delivery time and the predicted time as the scheduling objectives, and used the harmonious algorithm to better solve the task assignment problem [13]. Vivaldini et al. studied the minimum number of AGVs required in task assignment to save transportation costs [14]. Under the static task assignment strategy, the information of all tasks can be grasped, so the problem can be better solved by taking the shortest completion time, the shortest completion distance, and the minimum number of AGVs as the optimization goals. However, in the case of dynamic task assignment, task information is unpredictable, so there are certain limitations in selecting these indicators as optimization goals.

Dynamic task assignment considers the time state of task arrival. The system scheduling center dynamically processes the arrived tasks. When studying the task assignment of online service platforms, Hsu et al. randomized the timing of customer service arrivals and the number of tasks brought [15]. The time and number of tasks arriving in the actual manufacturing workshop are also more in line with this random approach. The goal of task assignment is to minimize the resource consumption of AGV within a production cycle (one working day or one week, etc.), minimize the task timeout, or relatively balance the number of tasks of each AGV. For example, Sun et al. took the minimum task completion time as the optimization target, which can better respond to the emergent orders and dynamic events [16]. Peng et al. used the Grey Wolf algorithm to solve the task assignment problem of unmanned aerial vehicle (UAV) with task assignment as the background and resource balance as the target of task assignment [17]. Fauadi et al. used the combined auction method to minimize the time-out of task transportation. The results showed that this method has a better performance on task assignment [18]. Duan et al. improved the performance of UAV task assignment using a hybrid “two-stage” auction algorithm with resource constraints [19]. Bai et al. compared the advantages and disadvantages of time triggering and event triggering to assign tasks with the goal of minimizing the total travel of tasks [20]. When studying dynamic task assignment strategies for electric fleets, Y. Dong et al. aimed at minimizing customer waiting costs and demand losses, and considered the vehicle’s power consumption and customer’s driving distance to judge the customer service of vehicle pickup [21]. This problem is essentially the same as the shop floor task assignment problem. Under the dynamic task assignment strategy in a certain production cycle, the shortest completion time and the shortest completion distance of all AGVs are affected by the number of tasks and task attributes. Comparing the shortest completion time or the shortest completion distance is not accurate. However, this paper aims at the maximum number of completed tasks in the production cycle. By comparing the number of completions of different strategies in a production cycle, the advantages and disadvantages of different assignment strategies are measured.

This paper summarizes past research and finds that there is a waste of schedulable resources in existing assignment strategies. Aiming at this problem, a multi-AGV system task assignment mathematical model based on task completion prediction is established. The model includes two parts: task completion prediction model and task assignment model. The model aims at maximizing the number of tasks completed by the AGV system during the production cycle, and incorporates both idle and working AGVs into the dispatchable vehicles. It expands the scope of optimal decision-making, makes the dispatching system more fully utilize AGV resources, and improves the utilization rate of vehicles and the execution efficiency of the entire multi-AGV system. Then, this paper redesigns the fitness function, coding, genetic operation, etc. in the genetic algorithm to make it suitable for this problem. In this paper, an example is designed to analyze the model, and the task assignment time interval, the number of vehicles in the multi-AGV system and other factors are compared with the task assignment strategy without completion prediction. The results show that more tasks can be completed in the same production cycle based on the completion prediction strategy, which effectively improves the transportation efficiency of the multi-AGV system. Finally, the article summarizes the work and looks forward to future research.

The existing task assignment scheme does not consider the influence of the working state of the AGV on the decision-making, resulting in the optimal task assignment scheme not in the schedulable set. In view of this problem, this paper proposes a dynamic task assignment method, which incorporates the AGV in working state into the scheduling model, pre-assigns the task to the working vehicle, and expands the optimal decision-making range. In this paper, the idea of combinatorial optimization is applied, and a mathematical model is established. Then a genetic algorithm is designed to solve the problem. Finally, the effectiveness of the task assignment strategy and the feasibility of the designed algorithm are verified by example simulation. The results show that the improved genetic algorithm can well solve the task assignment problem of dynamic multi-AGV system. The dynamic task assignment strategy based on completion prediction improves the number and utilization of tasks completed by the multi-AGV system in the production cycle, and also reduces production costs.

2. Multi-AGV System Task Assignment Model

2.1 Problem Description

Suppose a manufacturing workshop needs multiple AGVs to transport workpieces to multiple stations to complete the processing tasks of multiple processes. There are total of w cars in the workshop, and the handling tasks arrive randomly, but the probability distribution obeyed is known. The scheduling center dynamically assigns the arriving handling tasks to the AGVs in the system. The time of a production cycle is T. The triggering interval of two task assignment events in multiple AGV systems is Δt (Δt is the time interval of task assignment). The task should be transported from the starting point to the ending point, and then unloaded, and cannot be abandoned during the process. When the AGV is assigned a task, the AGV needs to complete the unfinished tasks in the previous stage first, and then it can reach the starting position of the task assigned in this stage and transport the task to the final position. After the task has completed, if others tasks are not assigned, it will stop in the same place and wait for the next task assignment.

Based on the above questions and analysis, the following assumptions are made for the convenience of research.

i. The weight and size of the task to be transported are known, and they do not exceed the load and volume limits of the AGV, and only one task can be transported at a time.
ii. The AGV is always driving at a constant speed, regardless of the process of acceleration and deceleration.
iii. When the AGV transport the task, the charging time is ignored, and the attributes of the AGV only have two states: the working state and the idle state.
iv. AGV loading and unloading times are fixed and equal.
v. The Euclidean distance is used in task assignment, regardless of the actual walking path. The workshop road is two-way and double-pass, and AGV collision is not considered.
vi. In the same time period, regardless of task priority.
vii. The scheduling center assigns tasks every fixed time Δt , and will not assign tasks in the middle.

2.2 Variable Symbols and Meanings

The variable symbols and their meanings used in this paper are as follows:

Z : The number of tasks completed in a production cycle.
N : The total number of task assignment stages in the production cycle.
n : Current task assignment stage n.
i : Number of AGVs.
j : Number of tasks.
W : Collection W (i = 1, 2, …w) of AGVs.
K : Collection K (j = 1, 2, …k) of tasks.
s_i : The distance required by the vehicle i to complete the assigned task.
s_{ni} : In the task assignment stage n, the distance of vehicle i to complete the task.
S_n : In the task assignment stage n, the total distance of all vehicles to complete the task.
P_i : The position of vehicle i.
PS_j : The starting position of task j
PF_j : The end position of task j.

d_{ijf} : The distance from vehicle *i* to the end of task *j*.

d_{ijs} : The distance from vehicle *i* to the start of task *j*.

d_j : The distance from the start point to the end point of the task *j*.

λ : The time required for AGV unloading.

v : The driving speed of the AGV.

c_{ij} : State variable, indicating that vehicle *i* is in the state of transport task *j*. If the value is 1, the vehicle *i* is in the transport task *j*, and if the value is 0, it means that vehicle *i* not in the transport task *j*.

x_{ij} : Decision variable, which represents the decision of vehicle *i* to transport task *j*. If the value is 1, it means that the vehicle *i* transports the task *j*, and if the value is 0, it means that it is not executed.

x_{ijt} : Represents the state of the decision variable at time *t*.

2.3 Task Assignment Model

Since tasks arrive in multiple time periods, only the tasks that have already appeared can be known, and the tasks that will appear in the future cannot be predicted. When assigning tasks, only the best task assignment scheme in the current stage can be obtained, and the global optimal in the entire production cycle cannot be obtained. Therefore, the idea of dynamic programming in Operations Research cannot be used to solve the problem. In each task assignment stage, in order to improve the utilization rate of vehicles, the shortest completion distance is used as the optimization index, and the optimal assignment scheme of the current stage is obtained. The total number of tasks transported in each stage is the whole tasks transported in a production cycle.

When calculating the completion distance of tasks in each assignment stage, the assignment strategy of multi-AGV system based on the prediction of completion of tasks included two parts. The first part was to estimate the distance that a vehicle in the previous stage would need to complete an unfinished task, and the second part was the distance that an AGV would need to transport the tasks assigned in the current stage. During the whole production cycle, formula (1) is used to calculate the total number of completed tasks. $\sum_{i=1}^{w}\sum_{j=1}^{k} x_{ij}$ is the total number of tasks completed in each task assignment stage, $\sum_{n=1}^{N}\sum_{i=1}^{w}\sum_{j=1}^{k} x_{ij}$ is the sum of all the tasks that had been completed in all the assignment stages, and it is also the number of tasks that had been completed in a production cycle.

$$Z = \sum_{n=1}^{N}\sum_{i=1}^{w}\sum_{j=1}^{k} x_{ij}. \tag{1}$$

Model for Task Completion Prediction. AGV and task information diagrams show in Fig. 1. Solid line *a* represents the distance that has been traveled, dashed lines *b*, *c*, *d*, *e* represent the distance that has not been traveled. Task k_1 has been assigned to vehicle w_1 and is already in transit. Task k_2 has not been assigned yet. If the vehicle w_1 completes the task k_2, the distance to be taken is $b+d+e$, and the unloading time is converted into a travel distance of $v\lambda$. If the vehicle w_2 completes the task k_2, the distance to be travelled is $c+e$. If $b+d+e+v\lambda < \mathrm{c+e}$, the vehicle w_1 transport the task k_2 is the better solution, otherwise w_2 is better. Therefore, predicting the task completion distance $b+v\lambda$ of a working vehicle is the sum of the distance *b* required to complete the current task and the distance $v\lambda$ converted from the unloading time.

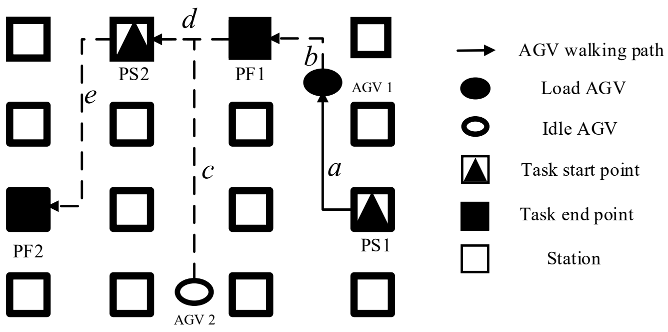


Fig. 1. Schematic diagram of AGV and task information

According to the calculation method of task completion distance prediction, the model is established as follows:

$$s_{ni}=\begin{cases}d_{ijf}+v\lambda, C_{ij}=1\\ 0, C_{ij}=0\end{cases}. \tag{2}$$

$$P_i=\begin{cases}PF_j, C_{ij}=1\\ P_i, C_{ij}=0\end{cases}. \tag{3}$$

$$s_{(n-1)i}=0, n=1. \tag{4}$$

$$C_{ij}=1, x_{ij}=1. \tag{5}$$

$$C_{ij}=0, x_{ij}=1, P_i=PF_j. \tag{6}$$

$$s_{ni}<d_j+d_{ijs}. \tag{7}$$

$$C_{ij}=\{0,1\}, \forall i, \forall j. \tag{8}$$

Formula (2) indicates that the predicted task completion distance, which is divided into two cases. When $C_{ij}=1$, it means that when the vehicle is in working state, the predicted distance for vehicle *i* to complete task *j* is $d_{ijf}+v\lambda$. When $C_{ij}=0$, predicted task completion distance is 0. Formula (3) indicates that the predicted vehicle location will be updated. Formula (3) also contains two cases. If the vehicle is in working state, the predicted vehicle location after completion is the end point of task *j*. If the vehicle is idle, the vehicle location will not be changed. Formula (4) indicates that all AGVs have a predicted task completion distance is 0 before the start of the first task assignment stage. Formula (5) indicates that when the AGV is assigned a task and the task start to be transported, the AGV becomes a working state. Formula (6) represents that when task *j* is assigned to vehicle *i* and the task are delivered to the end point of the task, the state of AGV becomes idle. Formula (7) indicates that the predicted task completion distance should be less than the transportation distance of task *j*, and the vehicle is already in the working state of transportation task *j*. This constraint restricts the AGV to only assign one more task in the transportation task. Formula (8) indicates that the value of state variable can only be 0 or 1.

Model of Task Assignment. After predicting the task completion distance of the AGV in the working state, the predicted completion distance in the previous stage and the completion distance in current stage are combined to form the shortest completion distance. Taking the shortest completion distance as the goal, the optimal task assignment scheme is selected.

$$S_n = \min(\sum_{i=1}^{w} s_{ni}). \tag{9}$$

s.t.

$$s_i = \sum_{j=1}^{k} x_{ij}(d_{ijs} + d_j), \forall i \in W, \forall j \in K. \tag{10}$$

$$s_{ni} = s_i + s_{(n-1)i}, \forall i \in W. \tag{11}$$

$$\sum_{j=1}^{w} x_{ijt} = 1, \forall i, \forall t. \tag{12}$$

$$\sum_{i=1}^{k} x_{ijt} = 1, \forall j, \forall t. \tag{13}$$

$$x_{ijt} = \{0,1\}, \forall i, \forall j, \forall t. \tag{14}$$

Formula (9) is the objective function, which indicates that under different task assignment schemes, the completion distance based on task completion prediction strategy is the shortest in each task assignment stage, and $\sum_{i=1}^{w} s_{ni}$ is the sum of the completion distances for each AGV in the current cycle. Formula (10) is the constraint condition, which represents the completion distance of all tasks required by AGV in the current stage, x_{ij} is the decision variable, and if $x_{ij} = 1$, it means that task *j* is transported by vehicle *i*. $d_{ijs} + d_j$ represents the sum of the no-load travel distance and the load travel distance of the vehicle *i* to complete the task *j*, which is the total transportation distance of the vehicle *i* to complete the task *j*. Formula (11) indicates the completion distance of vehicle *i* under the task completion prediction strategy. $s_{ni} + s_{(n-1)i}$ is the sum of the completion distance of the AGV in the current stage and the predicted completion distance of the previous stage. Formula (12) indicates that any vehicle can only transport one task at any time. Formula (13) indicates that any task can only be transported by one vehicle at any time. Formula (14) indicates that the value of decision variable can only be 0 or 1. If it is 1, it means that vehicle *i* receives task *j*.

3. Design of Multi-AGV System Task Assignment Algorithm

3.1 Design of Algorithm Flow

According to the mathematical model, a dynamic task assignment algorithm based on task completion prediction is designed to solve the dynamic task assignment problem. The genetic algorithm is used to solve the optimal task assignment scheme for each task assignment stage. Finally, the total number of tasks completed in each task assignment stage is calculated, which is the number of tasks completed under the production cycle *T*. The algorithm flow chart is shown in Fig. 2.

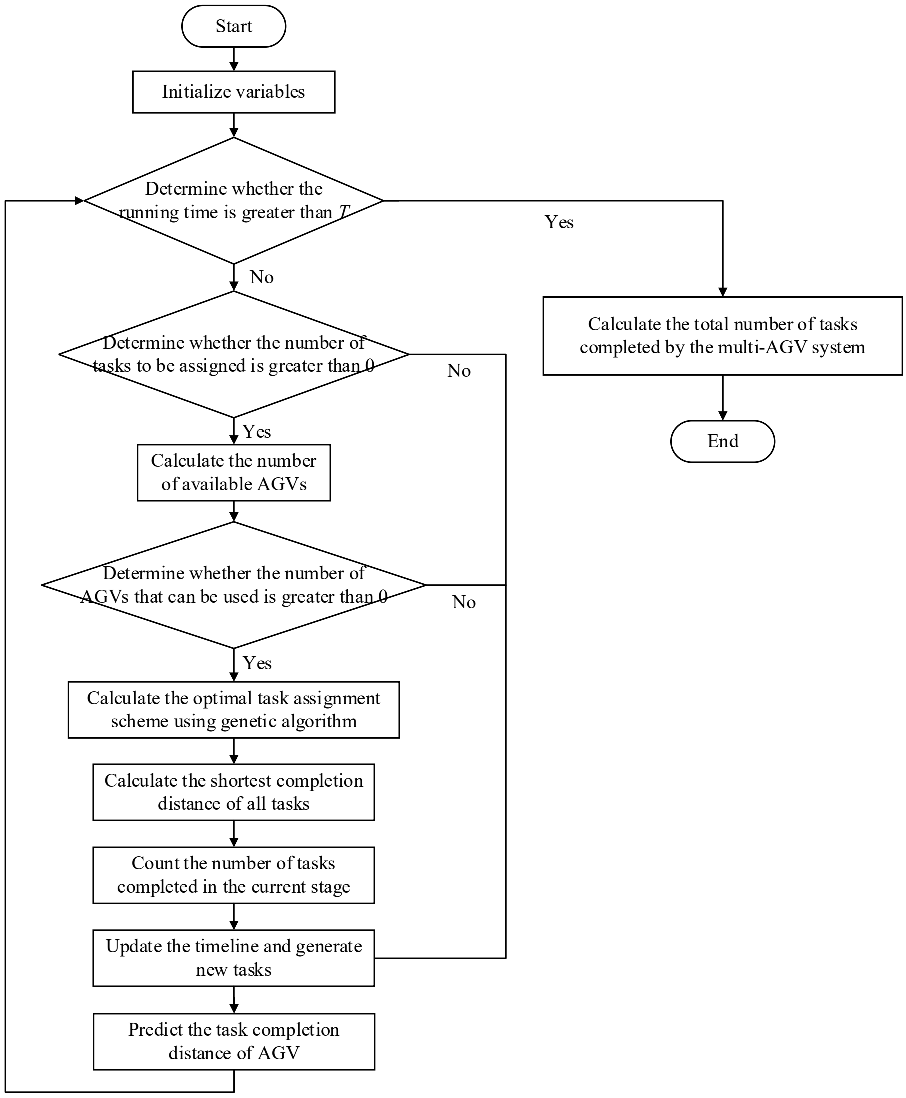


Fig. 2. Algorithm flowchart

Step 1. Initialize variables such as AGV position, initial task information, and station position.

Step 2. Determine whether the running time of the current scheduling system is greater than the specified production cycle time. If the conditions are met, the task assignment program stops running and outputs the total number of completed tasks. If not, the program continues to run.

Step 3. Determine whether there are currently tasks to be assigned. if so, go to the next step, if not, go to Step 8.

Step 4. Calculate the number of available AGVs.

Step 5. Determine whether the number of available AGVs is greater than 0. If the conditions are met, go to the next step. If not, go to Step 8.

Step 6. Use the genetic algorithm to calculate the optimal task assignment scheme.

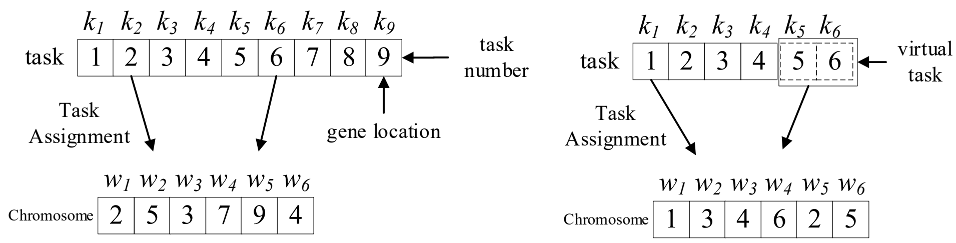
Step 7. According to the optimal AGV task assignment scheme, calculate the completion distance required for the vehicle to complete the assigned task.

Step 8. Update the task assignment timeline and generate new tasks.

Step 9. Predict the distance required by the AGV to complete the task. Go to Step 2.

3.2 Design of Genetic Algorithm

Coding Design. The task assignment problem is similar to the combinatorial optimization problem [22]. Since each task can only be completed by a unique vehicle, the use of real number coding has better results. In each chromosome, the number of genes represents the number of AGVs available. The locus represents the number of the AGVs, 1-6 in order. The numerical value in the locus represents the task number assigned to that AGV. As shown in Fig. 3(a), there are 9 tasks and 6 AGVs in total. After tasks are randomly assigned to AGVs, the assignment relationship between tasks and vehicles can be represented on the chromosome. For example, task k_2 is assigned to vehicle w_1, k_5 is assigned to w_2, and k_5 is assigned to w_3, and so on. This encoding method can effectively assign tasks to AGVs, but when the number of tasks is less than the number of AGVs, this encoding method cannot complete task assignment. Because some AGVs cannot be assigned tasks, they cannot form a complete chromosome. To solve this problem, a virtual task is introduced, whose start position is the same as the end position. As shown in Fig. 3(b), the number of actual tasks is 4, but the number of AGVs is 6, and tasks cannot be assigned. However, after the introduction of virtual tasks numbered 5 and 6, tasks can be easily assigned to AGVs.



(a) Num of task>Num of AGV (b) Num of task<Num of AGV

Fig. 3. Genetic algorithm coding

Fitness Function Design. Fitness function is an index used to evaluate genotypes. The evaluation index of fitness function in this paper is that the total completion distance of the assigned tasks completed in each task assignment stage is the shortest. The evaluation index specifically includes the sum of three parts, predicting the distance of vehicle completion in the previous stage (if the vehicle is already idle, the predicted completion distance is 0), and the no-load distance from AGV position to the starting point of the task, and the load distance of AGV transporting the assigned task from the starting position to the terminal position. The distance composition relationship of these three parts is shown in Fig. 4.

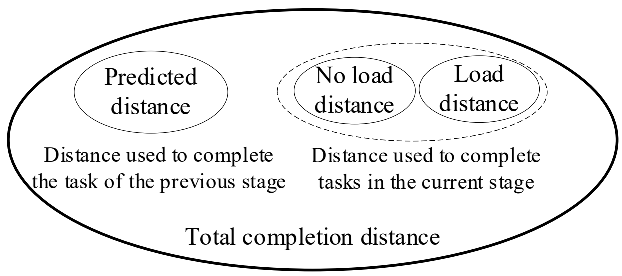


Fig. 4. Components of total completion distance

According to the components of the total completion distance, the fitness function formula based on task completion prediction is designed as follows. Formula (15) represents the shortest transport distance for all vehicles to complete all tasks in the current task assignment stage. Because the starting position of the virtual task is the same as the end position, transportation is not required. The cost calculation should be calculated according to formula (16), and the total transportation distance should be 0.

$$z_i = \sum_{i=1}^{w}\sum_{j=1}^{k} X_{ij}(d_{ijs} + d_j + s_{(n\text{-}1)i}), \forall i \in W, \forall j \in K. \quad \textbf{(15)}$$

$$d_{ijs} + d_j + s_{(n\text{-}1)i}, d_j = 0. \quad \textbf{(16)}$$

Genetic Manipulation.

a. Copy

The selection operation is to select the optimal task assignment scheme. The selected optimal scheme is directly inherited to the next generation, or a new task assignment scheme is generated through pairing and crossover to the next generation. This paper adopts the roulette wheel selection method. First, the fitness value of the shortest completion distance of each task assignment scheme is calculated and normalized. The greater the fitness value, the greater the probability of being selected, and the easier it is to select a better task assignment scheme.

b. Cross

Chromosome crossover is to replace and recombine the selected task assignment scheme chromosomes to form a new task assignment scheme. Since an AGV can only transport one task during task assignment, the elements in the chromosome cannot be repeated. The mapping relationship is established according to the elements in the exchange interval, and the duplicated genes are replaced to obtain two completely new arrays with non-repetitive elements [23]. The schematic diagram of the chromosome crossover process and results is shown in Fig. 5(a). The crossover position in the randomly selected chromosome is gene position 3, which represents task k_3 and task k_4 in two chromosomes. The tasks of k_3 and k_4 in the two chromosomes are exchanged to form two new chromosomes after crossover.

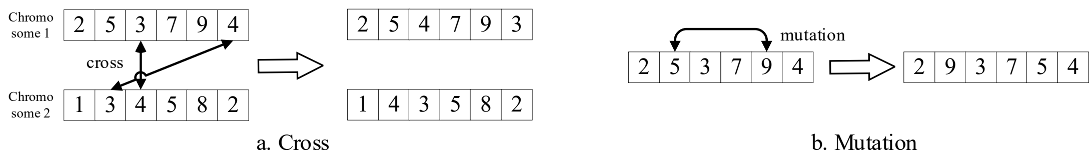


Fig. 5. Schematic diagram of genetic algorithm crossover and mutation

c. Mutation

The mutation operation of chromosomes is to mutate the task assignment scheme. The mutation operation used in this paper is to exchange the positions of elements in the same chromosome to realize the mutation operation. The specific mutation operation process and results are shown in Fig. 5(b). The tasks in position 2 and position 5 in the chromosome are exchanged with each other to form a new chromosome.

4 Analysis of Examples

This paper simulates a multi-process manufacturing workshop, its layout can be regarded as a two-dimensional plane, therefore, the calculation example sets the workshop layout as a rectangular area of $100m \times 100m$. In the workshop area, all position information is represented by coordinate points (x, y). The workshop stations are distributed in a matrix, with a total of 100 stations. The horizontal and vertical intervals between stations are both $11.1m$. The layout of the stations is shown in Fig. 6. Before task scheduling, it is assumed that there is a certain backlog of tasks, and it is set as initial task. Tasks are generated every fixed time Δt, and the number of tasks arriving follows a normal distribution. Because the AGV transports task from station to station, the position of the station is randomly selected as the start and end positions of the generated tasks. After each task transported and arrives, it takes 2s of unloading time, and the AGV driving speed *v* is 1m/s. The initial parking positions of the AGV are all at (0, 0).

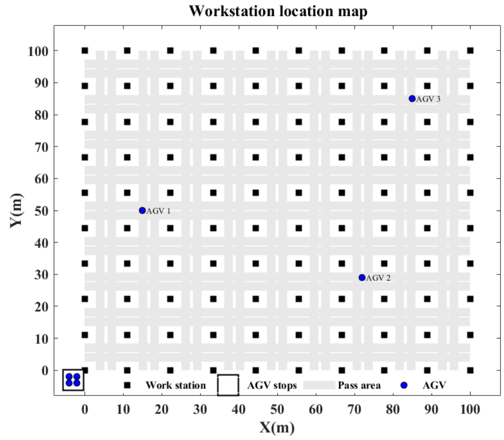


Fig. 6. Position of station

4.1 The Impact of AGV in Working State on Task Assignment Results

According to the initial conditions of appeal, a task assignment simulation experiment is designed to study the effect of AGV execution state on the task assignment result. First, five tasks are initialized, as shown in Table 1. Then set the time interval of task assignment to 80s. And tasks will be generated before task assignment. The number of task generation obeys a normal distribution with $\mu = 5$, $\sigma = 2$. The number of AGVs is set to 5. The generated task information is shown in the generated tasks section in Table 1. The task assignment strategy based on task completion prediction and the task assignment strategy without completion prediction use the same task attributes and initial conditions to study the time required for the two strategies to complete all tasks.

Table 1. Task information

Initialize tasks			Generated tasks		
Task number	Starting position	Target position	Task number	Starting position	Target position
1	(22.2,100)	(55.6,0)	6	(22.2,44.4)	(11.1,33.3)
2	(0,0)	(77.8,88.9)	7	(55.6,22.2)	(11.1,11.1)
3	(100,100)	(77.8,77.8)	8	(22.2,88.9)	(22.2,66.7)
4	(77.8,66.7)	(11.1,66.7)	9	(55.6,44.4)	(11.1,66.7)
5	(55.6,88.9)	(77.8,33.3)	10	(44.4,11.1)	(11.1,100)

After task assignment, two task assignment strategies are used according to the above initial conditions. Five AGVs are idle before the scheduling system runs. During multiple task assignment stages until the tasks are fully assigned. The status and the predicted completion distances are shown in Table 2 and Table 3.

Table 2. Implementation of AGV without completion predict

AGV	Task assignment stage 1			Task assignment stage 2			Task assignment stage 3			Task assignment stage 4		
	Number	State	Distance (m)	Number	State	Distance (m)	Number	State	Distance (m)	Number	State	Distance (m)
1	1	work	129.9	\	work	49.9	\	Idle	0	4	work	32.7
2	3	work	94.9	\	work	14.9	\	Idle	0	3	work	11.8
3	5	work	86.7	\	work	6.7	\	Idle	0	2	Idle	0
4	4	work	91.1	\	work	11.1	\	Idle	0	\	Idle	0
5	2	work	40.1	\	Idle	0	3	Idle	0	1	Idle	0

***Remark.**\ represents unassigned tasks*

Table 3. AGV Implementation under completion predict

AGV number	Task assignment stage 1			Task assignment stage 2		
	Assign task number	State at the end of the cycle	Predicted distance to completion (m)	Assign task number	State at the end of the cycle	Predicted distance to completion (m)
1	4	work	91.1	6	work	53.7
2	1	work	129.9	10	work	162.5
3	5	work	86.7	7	work	79.3
4	3	work	94.9	9	work	106.6
5	2	work	40.1	8	work	39.9

If the influence of the working state AGVs on the result of task assignment is not considered, only tasks are assigned to the AGVs in the idle state, and the results are shown in Table 2. When the previous two task assignment states are over, and most of the vehicles are in working condition. At the end of the task assignment state 2, only the vehicle $w5$ is in an idle state, so the number of vehicles that can be dispatched in the task assignment state 3 is only 1. If the AGVs in the working state is included in the dispatchable vehicle, the results of task assignment are shown in Table 3. In the task assignment stage 2, all vehicles are in working state, but the location and time of arrival after completing the task can be predicted, and the task is pre-assigned to the vehicle. When the AGV completes the tasks of the previous stage, it will execute the tasks assigned in the current stage. The number of vehicles that can be dispatched by this strategy is 5. Comparing the AGVs that consider the working state or not, it can be seen that the set of schedulable vehicles is all AGV vehicles when consider the working state are scheduled each time. But when only the AGVs in the idle state are considered, the range of the set of schedulable vehicles is small. Therefore, the scheduling scheme of AGVs considering the working state can increase the feasible solutions, make full use of the schedulable resources, and reduce logistics costs. Calculate the task completion time according to the task assignment and AGV driving speed. Considering the time required by the work state strategy to complete all the tasks, the time required for the two tasks to assign the stage is 160s and the time required to complete the tasks outside the two cycles is 162s, and the total is 332s.Only considering that the idle AGV needs four stages to complete all tasks, and after 320s of the four stages, it will take 32.7s to complete all tasks, and the total is 354s. It can be seen that after considering the AGV in the working state based on the task completion prediction strategy, a total of 22s is saved, and the optimization effect is 6.2%.

It can be seen from the Gantt chart of vehicle scheduling, as shown in Fig. 7. Under the strategy of considering the working state during scheduling, the vehicle can execute the next task if there is a pre-assigned task after the previous task ends. In the case of only considering idle vehicles, the vehicle will also have a certain downtime before the next task assignment. Therefore, the scheduling strategy of AGV considering the working state can not only increase the optimal decision-making range during scheduling, but also can efficiently transport tasks and improve the utilization rate of vehicles.

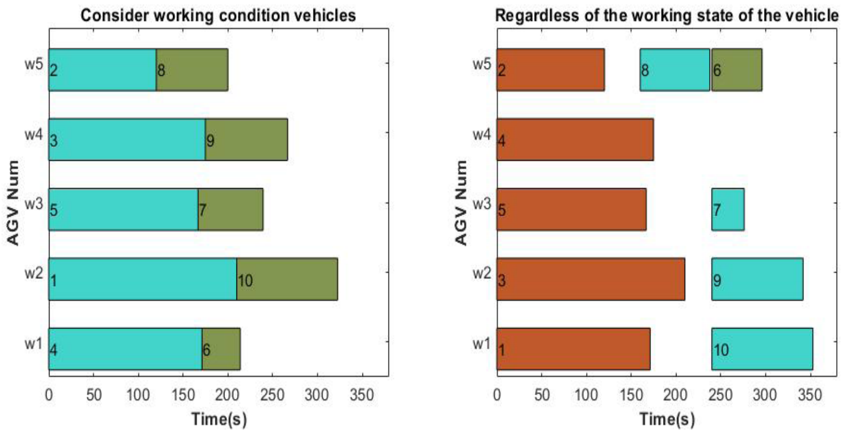


Fig. 7. AGV resource scheduling Gantt chart

4.2 The Effect of Task Assignment Time Interval on Task Assignment Results

In order to verify the effect of the task assignment time interval Δt on the two task assignment strategies, the number of AGVs is set to 5, and the number of task arrivals obeys the normal distribution of $\mu = 5$, $\sigma = 2$. Under the same other initial conditions, the total running time of the AGV is set to 5000 seconds. Calculating the number of completed tasks under two different task assignment strategies by changing different task assignment intervals Δt . Each experiment was repeated 10 times, and the mean values were recorded in Table 4.

Table 4. Comparison of finish time under different task arrival intervals

Time interval (s)	Quantity with prediction completion	Quantity without prediction completion	Optimized effects (%)	Time interval (s)	Quantity with prediction completion	Quantity without prediction completion	Optimized effects (%)
10	268	251	6.9	90	255	180	41.8
20	268	239	12.5	100	241	174	38.9
30	268	227	18.2	110	229	173	32.6
40	266	217	22.6	120	210	167	25.8
50	266	208	27.5	130	195	169	15.2
60	266	200	33.2	140	180	164	9.7
70	266	196	36.0	150	170	158	7.7
80	261	186	40.3				

According to the data in Table 4, the number of completed tasks and the optimization rate under different task assignment time intervals Δt are plotted, as shown in Fig. 8. It can be seen that when Δt does not reach 70s, the multi-AGV system completes a large number of tasks under the task assignment strategy based on task completion prediction, and the number of completed tasks changes little. When Δt is greater than 70s, the number of completed tasks decreases and changes greatly. For the task assignment strategy without completion prediction, as Δt increases, the overall trend is declining. It can be seen by its optimization rate, when Δt is small, the strategy considering vehicles in working state is better than the traditional one, because more vehicles can be dispatched and the optimal decision set is larger. When Δt increases, the strategy pre-assigns tasks to vehicles before the vehicle state becomes idle, and does not need to wait for the next task assignment stage to assign tasks. Therefore, compared with the traditional strategy, the time for the vehicle to wait for the task is reduced, which improves the utilization rate of the vehicle. Based on the above reasons, the optimization effect is more obvious, up to 41.83% under the given conditions. However, when Δt is greater than 90s, the task arrival time is longer, and due to the limitation of the workshop size, most vehicles can complete the task within Δt , so there are more idle vehicles under the two strategies, and the utilization rate decreases. Under the same circumstances, the decision-making range of vehicles considering working status is always larger than only considering idle vehicles when assigning tasks. Therefore, the task assignment strategy based on task completion prediction is still better than the traditional task assignment strategy.

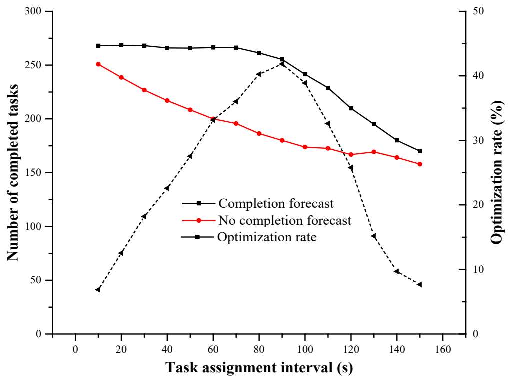


Fig. 8. Number of tasks completed at different task assignment intervals

4.3 Impact of Different AGV Numbers on Task Assignment

To explore the effect of different AGV quantities on task assignment in multi-AGV system, an experiment was designed to investigate the effect of AGV quantities on task assignment results. The task assignment time interval is set to 80s. The number of tasks generated obeys a normal distribution with $\mu = 5$, $\sigma = 2$, and the starting and ending positions are random. The number of AGVs ranged from 2 to 10. And each experiment was repeated 10 times, and the mean values were recorded in Table 5.

Table 5. Comparison of completion time and optimization rate

Number of AGVs	Quantity with prediction completion	Quantity without prediction completion	Optimized effects (%)	Number of AGVs	Quantity with prediction completion	Quantity without prediction completion	Optimized effects (%)
2	106	78	35.4	9	469	322	45.8
3	157	114	38.0	10	500	361	38.7
4	210	150	39.9	11	503	397	26.8
5	261	187	39.9	12	503	433	16.2
6	311	223	39.5	13	503	470	6.9
7	361	257	40.2	14	503	490	2.6
8	414	288	43.9	15	503	493	2.1

According to the data in the Table 5, the completion quantity and optimization rate under different AGV numbers are plotted, as shown in Fig. 9. When the number of AGVs increases, the number of tasks completed by both strategies increases. From the rate of change of the two completed task quantity curves, it can be seen that the strategy based on task completion prediction has a faster growth rate, while the other strategy has a slower growth rate. However, when the number of AGVs reaches a certain threshold, due to the limitation of the number of tasks arriving, the number of tasks completed by the two strategies tends to be stable. When the number of AGVs is greater than 9, the task assignment strategy based on task completion prediction is less effective than the strategy without completion prediction. As the number of AGVs increased by 14, the two strategies completed a similar number of tasks. When there are few vehicles, the strategy based on completion prediction includes both working and idle vehicles into the scheduling set during task assignment. When the number of vehicles increases, the decision-making range of the strategy also increases with the number of vehicles. For the strategy without completion prediction, when the number of vehicles increases, the number of idle AGVs increases is small, and the range of decision-making increases is also small. Comparing the two strategies, the assignment strategy based on completion predict has obvious advantages when there are fewer vehicles. When the number of vehicles continues to increase, the vehicles will be in a saturated state. In this case, the number of tasks will be significantly smaller than the number of vehicles, and the number of vehicles in the idle state will increase. At this point, the decision-making range of the two strategies is close. At the same time, the change rule of the optimization rate is to increase first and then decrease. When the optimization rate is at the highest, the number of vehicles in the corresponding multi-AGV system is 9. Therefore, according to the actual production situation, selecting the appropriate number of AGVs can greatly increase the number of tasks completed by multiple AGVs and improve vehicle utilization.

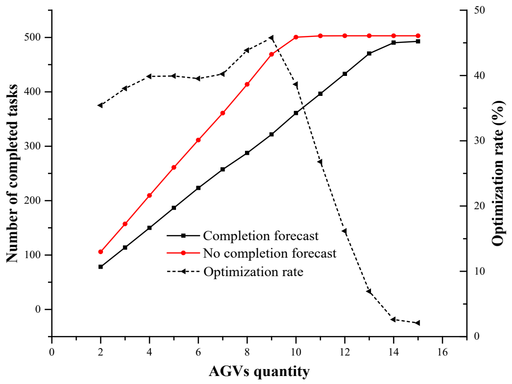


Fig. 9. Comparison of completion quantity and optimization rate

5. Conclusion

In this paper, the dynamic task assignment decision-making problem of multi-AGV system with task completion prediction based on genetic algorithm is studied. When assigning the arrived tasks at each stage, the AGVs in working state and in idle state are included in the assignment range, which expands the search range of feasible solutions. In this paper, the coding, fitness function and genetic operation of genetic algorithm are designed to make it more suitable for solving the optimal task assignment scheme. Through the analysis of the simulation results of the numerical example, it is found that this strategy can effectively solve the task assignment problem of the multi-AGV system. Compared with the task assignment strategy without completion prediction, this strategy can complete the task in a shorter time under the same situation. At the same production cycle, different task assignment time intervals and the number of vehicles in the multi-AGV system are discussed. The results show that under different values of Δt , the task assignment strategy based on task completion prediction can complete more tasks, which is better than the strategy without completion prediction. If the task assignment time interval is short or the task assignment interval is long, the assignment strategy based on task completion prediction is slightly better. When a suitable task assignment interval is selected, the task assignment efficiency can be greatly improved. When the number of vehicles in the multi-AGV system small, the task assignment strategy based on task completion prediction is significantly better than the strategy without task completion prediction. Therefore, the strategy with completion prediction is especially suitable for workshops with a small number of AGVs. In this paper, by changing the scheduling strategy and designing a genetic algorithm suitable for this strategy, the scheduling system can expand the dispatchable vehicles without adding hardware facilities, and effectively increase the number of tasks completed in the production cycle. And this strategy can reduce the transportation cost of enterprises and improve the utilization rate of vehicles.

The dynamic task assignment model proposed in this paper can effectively increase the number of transportation tasks in the production cycle of multiple AGV systems. In the model, the AGV has sufficient power and the charging time is neglected. The power of the AGV in the model is sufficient and the charging time is ignored. In future research, the state of the vehicle during the charging process and whether the power of the vehicle to complete the assigned task should be considered. At the same time, in this study, the AGV runs smoothly by default without considering the vehicle failure. In the actual production environment, vehicles may have accidental failures. Therefore, in future research, it is necessary to consider the impact of vehicle failures and adjust the task assignment scheme in time.

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