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A hybrid genetic algorithm used in vehicle dispatching for JIT distribution in NC workshop

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Abstract: Aiming at the characteristics of the vehicle dispatching problem for JIT distribution in NC workshop, a two-stage strategy was used, and a new hybrid genetic algorithm was put forward based on traditional heuristic algorithm and modern intelligent algorithm. Firstly, a greedy matrix sweep algorithm was designed to allocate the distribution mission for vehicles, which significantly optimized the population of the genetic algorithm. Then, the traditional genetic algorithm was improved to solve the best distribution order for every vehicle. Thus, a new hybrid genetic algorithm used for vehicle dispatching for JIT distribution in NC workshop is constructed. Computational results of an application instance shows that the algorithm is effective and feasible, which also has higher efficiency and better optimization result than the single genetic algorithm.

Keywords: NC workshop; JIT distribution; vehicle dispatching; sweep algorithm; genetic algorithm

1. INTRODUCTION

The vehicle dispatching problem in modern logistics and distribution, is to assign the fewest vehicles, appoint their distribution missions, departure times and the least-cost routes, to meet the customers' given demand.

As NC (Numerical Control) machining takes a significant role in modern manufacturing, the increasing application of JIT (Just in Time) production modem demands the optimal dispatching of tools distribution vehicles for cost reduction and efficiency improvement in NC workshop (B.Mursec et al., 2011; Xingqiu Ren et al., 2012).

The vehicle dispatching problem was raised at 1959, also named as the VRP (Vehicle Routing Problem). As a typical NP (Non-deterministic Polynomial) problem, it's usually solved by heuristic algorithm or modern intelligent algorithm (Garey M.R, 1989), which shows great advantage by the rapid development of computer technology.

After decades of research, lots of solutions have been brought forward to solve VRP. For example, CW algorithm (Clarke G and Wright J.W, 1964), sweep algorithm (Wren A, 1971) and Tabu search (Glover F, 1989) were all popular for a period. And recently, the modern bionic algorithm has become the mainstream, including the ant colony algorithm (Mazzeo S, Loisear I, 2004), the neural network algorithm (Renfa Yang, 2009) and also the genetic algorithm (Chung-Ho Wang and Jiu-Zhang Lu, 2009).

However, each algorithm has its own disadvantage, with the expansion of the problem's scale, it's really difficult for any algorithm to solve VRP alone. Moreover, most researches of this topic are mainly aimed at the urban logistics distribution problem. So the algorithm is usually inefficient and can't lead to the best solution, as the specialty of vehicle dispatching problem in NC workshop are not taken into account in these researches.

Based on the above analysis and past researches, this paper studies the particularity of this problem, combines the genetic algorithm and sweep algorithm to propose a new hybrid algorithm, which is especially applicable for the vehicle dispatching problem in NC workshop.

2. PROBLEM ANALYSIS AND MODEL BULIDING

2.1 Analysis of the problem

In this paper, the NC workshop in Chinese aviation industry is studied as a typical environment for VRP (Nan Di, 2007), which usually consists of numbers of production stations and a distribution centre. As the NC machine at every station need different cutting tools for different parts, the distribution centre uses vehicle to achieve the automatic distribution.

Against this background, the vehicle dispatching problem in this paper has the following features compared to the ones in normal logistics distribution problem:

(1) Distribution vehicles' quantity is limited, so it's better to carry more tools in every distribution mission, to achieve the maximum utilization of vehicles. Meanwhile, if vehicles are forced to be fully loaded, the potential distribution mission combinations will be greatly decreased, which may lower the quality of solution and the efficiency of algorithm.

(2) As the demand of cutting tools is large and rapidly changing, it's better to finish every distribution mission as

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fast as possible, so that there will be enough vehicles for the next mission. Since the vehicles are always running with a certain velocity, the fastest speed means the shortest distance, which is the mainly optimization goal of this problem.

(3) Since the punctuality of distribution is highly demanded in NC workshop, tool's using time of different stations must be considered as one constraint. As the consequence of slight unpunctuality is bearable, the soft time window constraint, containing given punishment, can make algorithm more flexible and will lead to a better solution.

(4) The distribution vehicle in NC workshop is AGV (Automated Guided Vehicle), driven and navigated in a unique method. So the travel distance is strongly affected by the distribution order in this problem, which makes it more pivotal. Also, a special calculation way of AGV's travel distance is demanded to ensure the accuracy of algorithm.

Therefore, this problem is essentially a not-fully loaded vehicle dispatching problem with single depot and soft time windows, which is obviously a special VRPTW (Vehicle Routing Problem with Time Windows).

2.2 Construction of the mathematical model

Based on the above analysis, this problem can be described as below: There are 1 distribution centre and n stations in NC workshop (numbered as i=0, 1, 2… n, i=0 stands for the distribution centre). All stations' locations are known, and the distribution vehicle is AGV with the capacity of q. Moreover, each station has proposed a tool distribution requirement, with gi as the quantity demand and $[a_i, b_i]$ as the time demand. Assuming that the time punishment of early and late arrival of tool distribution is d and e, and AGV's distribution cost is proportional to its travel distance, figure out the best optimal vehicle dispatching solution with the goal of the least distribution cost including time punishment.

The mathematical model can be expressed as the follow:

$$\min z = \sum_i \sum_j \sum_k c_{ij} x_{ijk} + d \sum_i \max(s_i - b_i, 0) + e \sum_i \max(a_i - s_i, 0) \qquad (1)$$

$$\sum_i g_i y_{ki} \le q \quad (\forall k) \qquad (2)$$

$$\sum_i y_{ki} = 1 \qquad (i = 1, \cdots, n) \qquad (3)$$

$$\sum_i x_{ijk} = y_{kj} \qquad (i = 1, \cdots, n; \forall j; \forall k) \qquad (4)$$

$$\sum_j x_{ijk} = y_{ki} \qquad (j = 1, \cdots, n; \forall i; \forall k) \qquad (5)$$

$$\sum_j x_{0jk} = 1 \qquad \sum_i x_{i0k} = 1 \qquad (\forall k) \qquad (6)$$

$$\sum_i x_{ihk} - \sum_j x_{hjk} = 0 \qquad (\forall h, \forall k) \qquad (7)$$

In this model, x_{ijk} can be 1 or 0, 1 means vehicle k travels from station i to station j, 0 means the opposite; y_{ijk} can be 1 or 0, 1 means the distribution mission of station i is or will be finished by vehicle k, 0 means the opposite; c_{ij} stands for the distribution cost from station i to j; h stands for any possible station; s_i stands for the time when vehicle arrives at station i.

In the above model, (1) is the object function; (2) is the vehicle capacity constraint; (3) ensures that every station's demand is meet; (4) and (5) constraints that every station's demand is distributed by only one vehicle; (6) and (7) ensures that vehicle returns to distribution centre when the current mission is completed.

3. GENERAL DESIGN OF THE ALGORITHM

When using traditional GA (Genetic Algorithm) to solve vehicle dispatching problem, the chromosome present not only vehicle's distribution missions, but also its distribution order. As a result, during the iteration process, it must be checked that whether the distribution missions meet the constraints of the model before the optimization of the distribution order. Therefore, the algorithm is very complex and inefficient. On the other hand, the chromosome in GA's first population is completely randomly generated, which doesn't correspond to the theoretical optimal situation where a vehicle's distribution stations should be relatively near to each other in space. This irrationality has a great chance to lower the solution's quality.

Aiming at the above defect of GA, a two-stage strategy is brought into this paper to solve this problem (Qianqian Qu, 2008). The basic flow of the hybrid algorithm in this paper is shown in Fig.1.

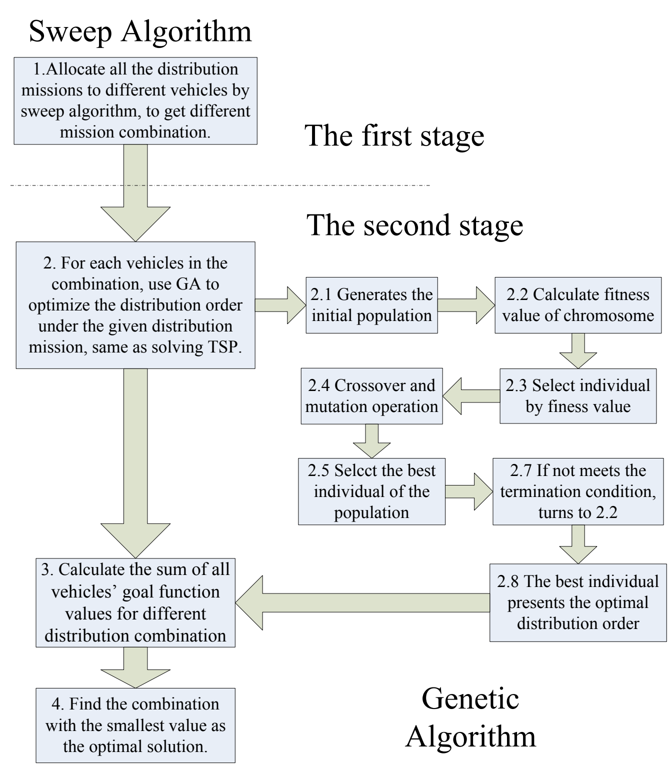


Fig.1 Basic flow of the hybrid algorithm

As shown in Fig.1, this problem is divided into two parts: the distribution mission allocation and the distribution order optimization.

Firstly, the distribution missions are allocated to vehicles by the sweep algorithm, according to stations' demand, locations and vehicles' capacity. Thus, the mission combinations are obtained. Secondly, for every vehicle in the combination, GA is used to optimize its distribution order under its given distribution missions. This part is actually the same as solving TSP (Travelling Salesman Problem). Finally, calculate the sum of all vehicles' distribution cost of all the mission combinations, and then find the smallest one. The distribution missions and order presented by this combination is exactly the optimal solution of this problem.

4. DESIGN OF MATRIX SWEEP ALGORITHM

Sweep algorithm is a traditional heuristic algorithm with the basic principle as allocating the distribution missions of the nearby customers to one vehicle by the rotation of radial (Byungsoo Na et al., 2011), to improve vehicle's efficiency in every distribution process.

The traditional sweep algorithm is often used in urban logistics and distribution problem, as the customers are approximately uniformly scattered around the distribution centre under this circumstance (Mo Zeyao and Fu Lianxiang, 2004). However, according to specific producing process, machine combination and winding placement demand, the machining stations are usually distributed like a matrix in the NC workshop, leaving the distribution centre in the corner. Therefore, the traditional sweep algorithm is no longer applicable in this situation.

Focusing on the above problem, this paper makes some improvement upon the traditional sweep method. Similar to the radial rotation route, two sweep routes for a 4*5 station matrix of this problem are shown in Fig.2.

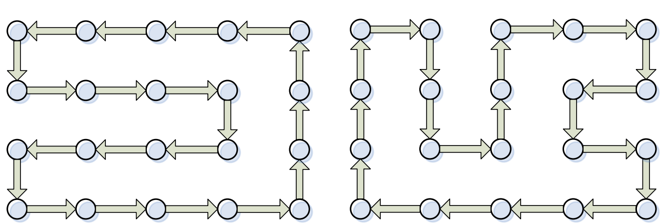


Fig.2 Sweep routes for 4*5 matrixes

Based on the above sweep route and greedy algorithm, the matrix sweep algorithm is designed with following steps:

(1) Sweep process for the first vehicle starts from any station in NC workshop, until it meets another station on the given sweep route.

(2) Calculate whether it will beyond the vehicle's capability if the demand of this station is added into the current route. If no, turn to (1) making current station the start point and continues; if yes, rule out the current station and the distribution mission is determined for current vehicle.

(3) Starts from the last station in (2), and continues the sweep process for the next vehicle.

(4) Repeat step (2) and (3) until all stations' demand have been allocated, a new distribution mission combination is then acquired.

(5) Starts from different stations in current sweep routes and repeat steps (1) ~ (4) to get more distribution mission combinations, and other sweep routes can also be used for sweep if necessary.

Thus, the matrix sweep algorithm is developed to allocate distribution missions for different vehicles by a rational and flexible method, simplifying the problem's solving process. Moreover, the chromosomes and initial generation in the following GA is remarkably optimized, which can improve GA's efficiency and enhance the quality of GA's result.

5. DESIGN OF GENETIC ALGORITHM

After getting the different mission combinations, the optimal distribution order for each vehicle in the combinations can be solved as TSP by GA. This part can be designed by reference to the existing studies of vehicle dispatching problem (Yuan Qu et al., 2010). Based on that, some further improvement is also need to be made according to this problem's specialty, so as to develop a more suitable algorithm. Some pivotal details will be introduced in the following sections.

5.1 AGV's travel distance calculation

As explained in section 2, there will be error if the vehicle's (AGV in this problem) travel distance is simply calculated by the straight-line distance between stations, which may affect the solution. Therefore, a coordinate method with direction is presented in this paper to calculate AGV's accurate travel distance. The specific method will be introduced with Fig.3.

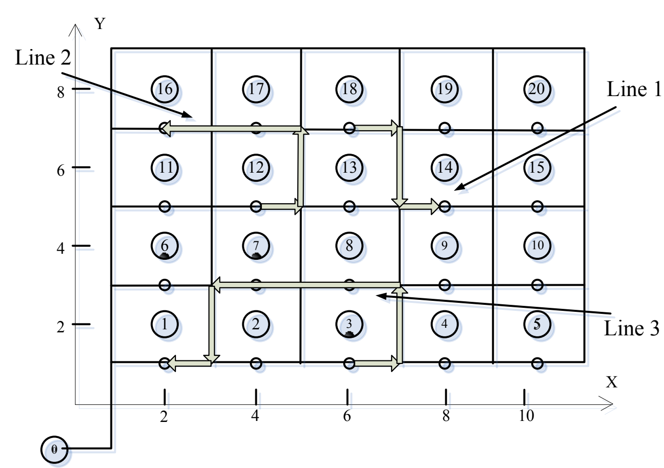


Fig.3 AGV's travel distance calculation

As shown in Fig.3, the location of distribution centre and each station (empty circles) are known, the coordinate of station i is presented as (X_i, Y_i). AGV travels along the given route (gridlines) and stops by the station (solid dots) for operators to pick up tools. The variable A is set to present the vehicle's current driving direction, for instance, the value of 1 means toward left and 0 means right. Assuming that AGV currently stops at station *i*, its next distribution target is station *i+1*, consider three different situations as below to calculate the travel distance $_{Li}$.

I $(X_{i+1} - X_i) \times A > 0$. Such as line 1 in Fig.3.

$$L_i = |X_{i+1} - X_i| + |Y_{i+1} - Y_i| + 1$$, A remains the same.

II $(X_{i+1} - X_i) \times A \le 0$ $Y_{i+1} \ne Y_i$. Such as line 2 in Fig.3.

$$L_i = |X_{i+1} - X_i| + |Y_{i+1} - Y_i| + 1,\ A = -A.$$

III $(X_{i+1} - X_i) \times A < 0$ $Y_{i+1} = Y_i$. Such as line 3 in Fig.3.

$$L_i = |X_{i+1} - X_i| + |Y_{i+1} - Y_i| + 3,\ A = -A.$$

5.2 The best departure time calculation

To get the chromosome's highest fitness value of the given distribution order, the best departure time must be calculated to minimize the sum of time punishment for the vehicle at all stations. Thus, by reference to the urban logistics distribution problem (S.R.Balseiro and J.Ramonet, 2011), the golden section algorithm is used in this paper with the following steps:

Firstly, the time for each mission can be calculated according to the travel distance algorithm and vehicle's given velocity. As the vehicle's stop time at stations is specified in advance, the time of the whole distribution process is known.

Select a time period [a, b], in consideration of the vehicle's distribution time, as the initial interval of the golden section.

Vehicle's arrival time at each station of this period can then be acquired, also the early and late arrival time according to the given time window. As the time punishment factor is also known, the total time punishment value can be calculated.

A new section [a', b'] can be got with the goal of minimizing the time punishment value, and the iteration continues.

As the golden section process constantly repeats in this way and the time period gets smaller and smaller, the vehicle's best departure time can be finally acquired.

5.3 Design of genetic operators

The genetic operators can be selected and designed by reference of the relative research.

The roulette wheel method is used in this paper as the selection operator, which can ensure both the randomness and the evolution of GA. The fundamental is that the probability for the chromosome to be selected is in proportion to its fitness value.

The OX (order crossover) operator is select and transformed, which selects a length of gene from one parent and keeps gene's relative order of the other parent, and then generates the offspring by combining the original parents.

For example, for the following two parents:
P1 :(1 2 3 4 5 6 7 8)   P2: (3 7 2 1 8 5 6 4)

Usually there will be two fixed cut points set in the original OX operator to achieve crossover. In this paper, there is no such fixed cut points but randomly generated ones (presented as "|") in the crossover process, so as to improve the diversity of the crossover's results.

Copy the genes between the cut points from the parents into the offspring:
P1: (* * * |4 5 6|* *)   P2: (* * * |1 8 5| * *)

Starting from the second cut point of either parent, copy the genes from the other parent in the same order. The copying process should jump back to the start of the chromosome when reaching the tail. The new offspring are ten generated:
P1: (2 1 8 |4 5 6| 3 7)   P2: (4 6 7 |1 8 5| 2 3)

The inversion mutation operator is selected in this paper, generating new offspring by listing genes between cut points in reverse order and keeping the others the same. Like the OX generator, the cut points are also randomly generated to improve the diversity of mutation.

6. CASE STUDY

In the NC workshop, there are 20 machining stations need to be distributed, with the given code and location (refer to Fig.3). The distribution vehicle is AGV, with the maximum capacity of 20 tools and the transportation cost of 1 every unit distance (distance in the coordinates). For the soft time window constraint, the time punishment factors for vehicle's early and late arrival at stations are 0.2 and 0.5 every unit time. At some point, the distribution information of all stations are shown in Table 1, the optimal vehicle dispatching solution is demanded.

Table 1 Distribution information

Station	1	2	3	4	5
Location	(1,1)	(2,1)	(3,1)	(4,1)	(5,1)
QD	2	3	2	5	1
TW	[25,35]	[40,50]	[37,47]	[15,25]	[32,42]
Station	6	7	8	9	10
Location	(1,2)	(2,2)	(3,2)	(4,1)	(5,1)
QD	3	4	2	1	4
TW	[28,38]	[50,60]	[6,16]	[34,44]	[22,32]
Station	11	12	13	14	15
Location	(1,3)	(2,3)	(3,3)	(4,3)	(5,3)
QD	3	3	2	4	2
TW	[47,57]	[15,25]	[30,40]	[29,39]	[33,43]
Station	16	17	18	19	20
Location	(1,4)	(2,4)	(3,4)	(4,4)	(5,4)
QD	3	5	2	4	1
TW	[5,15]	[40,50]	[19,29]	[24,34]	[49,59]

In table 1, stations' locations are presented by coordinates; "QD" stands for quantity demanded of tools; "TW" stands for time window, which is presented by abbreviators, for instance [25, 30] stands for [9:25, 9:35].

GA's several parameters can be determined by single factor experiment. In this problem, the algorithm can achieve both high solution quality and fast convergent rate when setting population size as 60, crossover probability as 0.9 and mutation probability as 0.08.

6.1 Solution and analysis

The best optimal solution of this problem can be solved by the hybrid algorithm in this paper, which is shown in Table 2.

Table 2 The optimal solution

Vehicle ID	Distribution mission and order	Departure time	Cost
1	1-4-5-10-9-3-2-6	9:04	24
2	14-18-7-12-13-19-20-15-8	8:58	47.8
3	11-16-17	9:01	17
	Total cost	24+47.8+27 = 88.8	

As shown in Table 2, the minimum distribution cost, same as the objective function of the problem, is 88.8. The vehicle's distribution mission is presented by a sequence of natural numbers, take vehicle 1 as an example: it starts from the distribution centre, distributes tools to eight stations in the sequence of 1, 4, 5, 10, 9, 2, 3, 6, and then returns back.

To analyze the distribution order optimizing function of the genetic algorithm, take vehicle 2's TSP for further research. The iteration process of the population and individuals can be reflected from two aspects, as shown in Fig.4 and Fig.5.

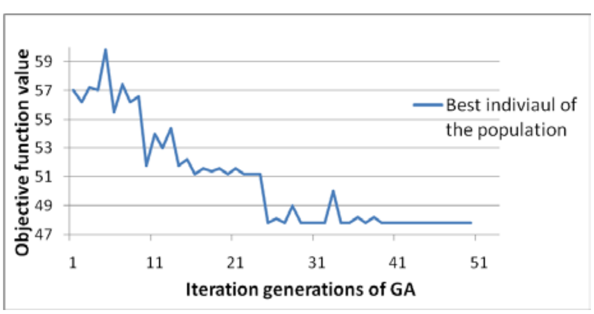
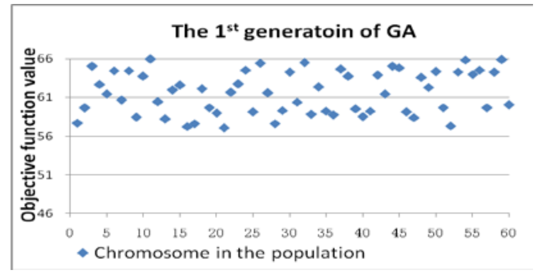


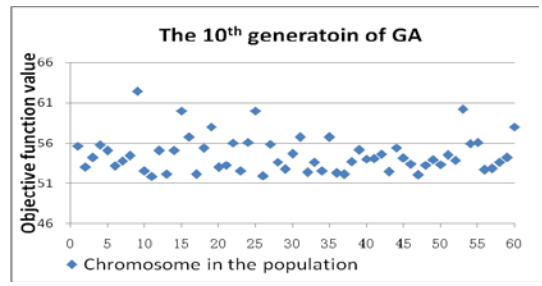
Fig.4 Evolution of the best individual

As shown in Fig.4, the objective function value of the best individual is approaching the final optimal value, which meets the iteration process of the classic evolution algorithm. The genetic algorithm automatically terminates at the 50th generation when the value of the best individual has not been changed for 10 consecutive generations, which is exactly the best optimal solution.

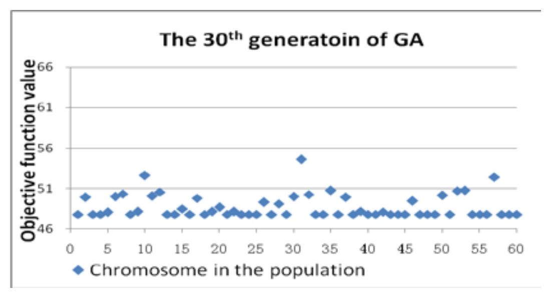
And as shown in Fig.5, the distribution of individuals is also optimized along with the iteration process. For the randomly generated 1st generation, the values of individuals are large and disperse. As the generation continuously evolving, values of individuals move towards the optimal solution and tend to be close to each other. At the 50th generation, most of the individuals are stabilized at one level, which also proves that the best optimal solution has been got.



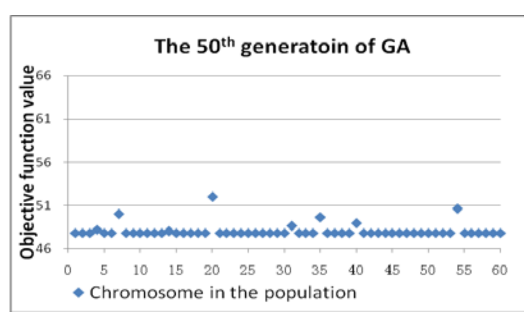
(a)



(b)



(c)



(d)

Fig.5 Individuals distribution in the population

6.2 More tests and analysis

After proving the hybrid algorithm's effectiveness, it's also need to be tested whether the matrix sweep method improves the total efficiency of the algorithm. Therefore, the genetic algorithm is also used to solve the problem alone, the compare between them is shown in Table 3.

Table 3 Compare of two algorithms

Solving method	Distribution cost	Iteration generations	Calculation time
Hybrid algorithm	128.8	50	7s
Genetic algorithm	162.6	81	24s

As shown in Table 3, the hybrid algorithm does not only get the better optimal solution (lower cost), but also takes less iteration generations and calculation time than the genetic algorithm, which means the sweep method does improve the algorithm's efficiency.

For the further analysis of the algorithm's performance, it's then applied for more such cases with larger data scale (more stations in this problem), the result is shown in Table 4.

Table 4 Algorithm performance with more cases

Number of machining stations	Genetic algorithm		Hybrid algorithm	
	Average generations	Average time	Average generations	Average time
30	96	30s	63	12s
40	117	38s	78	20s
50	131	43s	109	31s

As shown in Table 4, even with the larger problem scale, the hybrid algorithm still shows great superiority to GA for the faster computing time. Meanwhile, the test result also proves that the algorithm has good convergence, which will not be affected by the increasing amount of data.

7. CONCLUSIONS

This paper studies the specialty of the vehicle dispatching problem for JIT distribution in NC workshop, proposes a hybrid algorithm based on a two-stage strategy.

The hybrid algorithm uses a newly-designed matrix sweep method to allocate distribution missions to different vehicles. Then each vehicle's TSP can be solved by the improved GA, to achieve the optimal distribution order of vehicles. Finally, the best optimal solution is acquired from the result of the above process.

The case study improves that the algorithm is really effective and efficient, improving the defect of classical GA by the introduction of sweep algorithm. Therefore, the allocation of distribution mission is more rational and the initial population of GA is optimized. As a result, the hybrid algorithm shows greater superiority in both quality of solution and computing time.

This paper offers a new method for the vehicle dispatching problem in NC work shop, which has broad application in industrial production. But the research should not be stopped in the future, as the practical problem is more complex than the model in this paper. In real manufacturing field, tool demand maybe unexpectedly raised because of the accidents during producing process. Therefore, the algorithm needs the ability to handle these demands instead of the static distribution information. So in the next step, the dynamic vehicle dispatching will be involved into the research of this paper.

ACKNOWLEDGEMENT

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