Vehicle Routing Optimization Problem with Time-windows and its Solution by Genetic Algorithm

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ABSTRACT: *Vehicle Routing Problem (VRP) is a hot issue in the field of logistics. Furthermore, the Vehicle Routing Problem with Time-Windows (VRPTW) is an additional constraint of the customer access time windows based on the VRP. It becomes a noticeable problem with the development of logistics distribution and the just-in-time distribution demand from customers, which increases a visiting window to traditional VRP. This paper firstly analyzes the distribution vehicle scheduling optimization problem with time-windows. Subsequently, through transforming the capacity and soft time-windows constraint into objective constraint, the authors establish a non-full loaded VSP model. Moreover, genetic algorithm is used to solve this problem, where natural number is adopted to realize problem coding and the maximum reservation crossover and improved inverse mutation technology are used to generate new individuals. Finally through the simulation experiment, the results verify its feasibility and effectiveness.*

Categories and Subject Descriptors:
B.4.1 [Data Communications Devices] Receivers; **H.4.2 [Types of Systems]** Logistics

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1. Introduction

Modern logistics is regarded as the third important factor of making profit besides reducing material loss and improving labor productivity in enterprises. Logistic distribution and delivery are much important procedures in the modern logistics, connected with a distribution center and a customer, which is a material circulation mode integrating collection, dispatch, distribution, loading and shipping. Since the distribution network scale expands dramatically along with the rapid development of logistics industry and increasing customer service point, the traditional distribution mode has been unable to meet the service demand. How to realize the rapid and accurate delivery is an essential prerequisite to improve the competitiveness of enterprises, to reduce administration cost, and to promote the quality of service demand.

Logistics distribution routing optimization problem was firstly proposed by Dantzig and Ramser [1] in 1959. And it soon attracted the attention of various discipline experts, transport planning makers and managers from logistics research, applied mathematics, combinatorial mathematics, graph theory and network analysis, logistics science, computer applications, which became the popular issues of logistics research and combination optimization field. Various discipline experts had made great progress in this research via a series of theoretical and experiment analysis. Worldwide scholars mainly focused on the aspects of mathematics models and intelligent algorithms for solving this problem. For instance, Cao and Lai [2] considered the open vehicle routing problem with fuzzy demands (OVRPFD) and a fuzzy chance-constrained program was designed based on fuzzy credibility theory. They also used stochastic simulation and an improved differential evolution algorithm to solve the OVRPFD model. Pop et al. [3] provided two new models of the generalized vehicle routing problem (GVRP) based on integer programming. The first model was the node formulation produced a stronger lower bound. The second one was the flow formulation. The authors showed that under specific circumstances the proposed models of the GVRP reduced to the well known routing problems. In addition, others focused on artificial intelligent algorithms for vehicle routing problems. For instance, Pisinger and Ropke[4] presented a unified heuristic which was able to solve five different variants of the vehicle routing problem and the outcome of tests was promising as the algorithm was able to improve 183 best known solutions out of 486 benchmark tests. Marinakis et al.[5] introduced a new hybrid algorithmic nature inspired approach based on particle swarm optimization, for successfully solving one of the most popular supply chain management problems, the vehicle routing problem.

Moreover, Chinese scholars mainly focused on the aspects of Traveling Salesman Problem (TSP), Chinese Postman Problem (CPP), Directed Chinese Postman Problem (DCPP). For instance, Rao et al.[6] constructed recent field algorithm and insert algorithm in a heuristic algorithm for solving TSP problem, and the experiment results are shown that this hybrid algorithm is superior to the most other intelligent algorithms. Fei et al.[7] proposed a new algorithm called CPDPA (Chinese postman decision process algorithm) towards the undirected Chinese postman problem, which firstly resolved the CPP problem of dynamic decision process. Han et al.[8] established a new DNA encoding scheme for the Chinese postman problem, which represented weights on a weighted graph. This encoding scheme had characteristics of easy encoding, easy generalizing and low error rate, which was helpful to improve the capability of representing and dealing with data and extended the range of solving numerical optimization problems in DNA computing.

This paper firstly analyzes the distribution vehicle scheduling optimization problem with time windows. Subsequently, through transforming the capacity and soft time windows constraint into object constraint, we establish a non-full loaded VSP (Vehicle Routing Problem) model. Furthermore, genetic algorithm is used to solve this problem, where natural number is adopted to realize problem coding and the maximum reservation crossover and improved inverse mutation technology are used to generate new individuals. Finally through the simulation experiment, the results verify its feasibility and effectiveness.

The paper is organized as follows: related mathematic model associated with non-full loads vehicle routing problem with time windows is set up in section 2; the genetic algorithm is proposed to solving this problem in order to find out the optimal solution in section 3; a case study is applied to verify the efficiency and effectiveness of the model and algorithm presented in this paper in section 4; section 5 is the conclusions of this paper.

2. Mathematic model of non-full loads vehicle routing problem with time windows

As every task demand point like grocery and chain store endeavors to sell fast selling merchandises, not too much inventory and not out of stock, current distribution is now generally operated via the economic activities of the small scale, close distance, more variety, small amount, multiple batches and multi user. At this point, the quantity of cargo in each task is less than its capacity. Using one car loaded with cargo of different task demand points to perform a single task is a matter of delivery vehicle scheduling, also called non-full loads vehicle scheduling problem.

Vehicle scheduling optimization problem with time-windows constraint could be summarized as depot service problem of single parking, single vehicle types, non full-loads, multiple constraints (including the time-windows constraints) multi-objectives, close vehicle. The problem is a NP-hard[9] problem in combination optimization field. This paper deploys a genetic algorithm to find out the optimal or approximate optimal solution towards this problem.

2.1 Problem description

Usually vehicle scheduling optimization problem can be described as a task of several same load vehicles completing several cargo demand points in one distribution center. The demand quantity (supply quantity) of every demand point (supply point) is given and less than the load of each vehicle. The distance of distribution center and each demand point is given or can be calculated. The task of one demand point can only be operated by one single vehicle at one time. Every vehicle starts from the distribution center and returns to it after finishing the task. How to identify the vehicle route of minimum cost so as to meet the requirements of cargo demand and vehicle load is the key issue needing to be considered. This can be applied to solve the problems in daily life and production. For example, products from a number of manufacturers need to be transported to the distribution center. Vehicles start from the distribution centre, load the goods of every manufacturer and then return to it. In this case, the minimum cost route that meets the delivery requirements of manufacturers is also called vehicles scheduling optimization.

2.2 Mathematical model

VSP with time-windows requires each task i being completed within time interval $[a_i, b_i]$, based on the general vehicle routing optimization problem. Whether the time constraint is strict or not, the problem could be divided into VSP with soft time windows and with hard time windows accordingly. This paper mainly concentrates on that with soft time windows. Because VSP with time windows is a typical NP-hard problem, it would lead to combination proliferating phenomenon [10] as the nodes increases.

Mathematical model of VSP is established as follows: the distribution center has enough vehicles with load q. There exists n task demand points for cargo transportation, denoting with $1,\ldots,n$. Given cargo demand at the i demand point is g_i $(i = 0, 1, \ldots, n)$, and satisfies $g_i < q$. Usually, the more problem constraints are, the more difficult the routing scheduling problems are, and consequently the less the tasks are in which one vehicle could satisfy all the constraints. Under such circumstances, if the less task capacity one vehicle has, then the more vehicles the demand point should use. In order to make the routing flexible, it can estimate the vehicle number m, which could complete the tasks:

$$m = \left[\sum_{i=1}^{n} g_i \Big/ aq \right] + 1 \tag{1}$$

Where [.] denotes the largest integer not greater than the figures in parentheses. The parameter *a* $(0 < a < 1)$ is an estimation of the complexity loading or unloading and of constraint quantity. Generally speaking, the value of *a* should be small when there are more complex loading (unloading) and more constraints, which indicates that one vehicle could load less cargo quantity. This algorithm adjusts the value of *a* via the man-machine interaction.

For the mathematical model of this problem, the number of distribution center is 0, and those of demand points are $1, \ldots, n$, then the distribution center and demand points could be denoted as i $(i = 0, 1, \ldots, n)$. Given the total vehicle number *m* required to accomplish the distribution task; each vehicle load q; demand g_i $(i = 0, 1, \ldots, n)$ at each demand point; any two point distance between distribution center and the demand points d_{ij} $(i = 1, \ldots, n;\ j = 1, \ldots, n)$; k routing path of k vehicle routing, which goes through the n_k demand points; p_k denotes the set of n_k demand points at k routing path, where element p_{ki} $(i = 0, 1, \ldots, n)$ denotes the i demand point at k routing path; p_{k0}, $p_{k(n_k+1)}$ both denote the distribution center and only $p_{k0}, p_{k(n_k+1)} = 0$. It proposes the vehicle scheduling optimization mathematical model as follows:

$$\min z = \sum_{k=1}^{m} \sum_{i=1}^{n_k+1} d_{p_{k(i-1)} p_{ki}} \tag{2}$$

$$\sum_{i=1}^{n_k} g_{p_{ki}} \leq q \; (1 \leq n_k \leq n, k = 1, 2, \ldots, m) \tag{3}$$

$$\sum_{k=1}^{m} n_k = n \tag{4}$$

$$P_k = \{ p_{ki} \mid p_{ki} \in \{1, 2, \ldots, n\}, i = 1, 2, \ldots, n_k \} \; (k = 1, 2, \ldots, m) \tag{5}$$

$$P_{k_1} \cap P_{k_2} = \phi \, (\forall\, k_1 \neq k_2;\ k_1 = 1, 2, \ldots, m, k_2 = 1, 2, \ldots, m) \tag{6}$$

In addition, the VSP problem with time windows requires task i start time locating at a certain time range of $[a_i, b_i]$, where a_i is the task i allowed the earliest start time, b_i is task i allowed the latest start time. If the time of vehicle arriving at the task i is earlier than a_i, then the vehicle has to wait at the task i. If the time of vehicle arriving at the task i is later than b_i, then the task i has to delay. Given s_i denotes the time of vehicle arriving at point i, the following formulation is established:

$$s_0 = 0,\ a_i \leq s_i \leq b_i \,(i = 1, 2, \ldots, n) \tag{7}$$

3. Genetic algorithm for solving the non-full load vehicle routing problem with time windows

Genetic algorithm is a kind of search algorithm referring biological natural selection and natural genetic mechanisms. It is firstly proposed by professor Holland of the United States in one book of "*The fitness of combination of nature and artificial intelligence system*". It uses the method developed by the biological evolution characteristics. Firstly, population produces the next generation through random mating. Then, it uses Crossover and Mutation to operate the gene evolution, and determines the next population numbers through the Selection mechanism, in order to obtain a larger probability of fitness passed to the next generation, for the sake of the optimization solution of the problem. At present, this method has been widely and successfully deployed in the engineering application of clustering[11], project scheduling[12], system matching[13], assembly line balancing[14]. This paper adopts the method to obtain VSP solution through the chromosome structure design and genetic operators design.

3.1 Design of chromosome structure

This paper applies the natural number coding method towards the VSP for the efficiency improvement. The single-depot vehicle scheduling problem can be compiled into a feasible route length of chromosome $n + m$, $(0, i_{11}, i_{12}, \ldots i_{1s}, 0, i_{21}, i_{22}, \ldots, i_{2t}, 0, \ldots i_{m1}, \ldots, i_{mw})$, where i_{kj} denotes a demand point, via natural number. The chromosome structure can be understood that the first vehicle traverses from the distribution center 0, through the demand points $_{11}$, $i_{12}, \ldots i_{1s}$, back to the distribution center 0, producing the sub path 1. The second vehicle traverses from the distribution center 0, through the non visited demand points $i_{21}, i_{22}, \ldots, i_{2t}$, back to the distribution center 0, producing the sub path 2. Accordingly, all of the n demand points are traversed, producing sub path m. For example, chromosome 021304605870 represents the following routing:

Sub path 1: distribution center → demand point → demand point → demand point → distribution center 0

Sub path 2: distribution center → demand point → demand point → distribution center 0

Sub path 3: distribution center → demand point → demand point → demand point → distribution center 0

When the interior of sub path in chromosome structure is sequential, if demand point 1 and demand point 3 of Sub path 1 exchange location, it will make the objective function value changed. When interior of sub path is not sequential, if demand point 1 and demand point 2 exchange location, it will not make the objective function value changed. If the sub path is reversal, i.e. 0460 reversed to 0640, it will not make the objective function value changed.

3.2 Disposal of constraints in model

There is the need for constraint processing through the genetic algorithm towards VSP of constraint complicated optimization problem. Generally there are the following methods:

(1) The problem constraint appears in chromosomes. Designing special genetic operators, it will make the solution of chromosomes feasible in the process of genetic algorithm.

(2) The constraint is not considered during the coding process. Chromosome corresponding solution is detected in the calculation process of the genetic algorithms. If feasible, then pass it into the next generation, otherwise discard it.

(3) Process the constraint by the penalty function method to. If a chromosome corresponding solution violates a constraint, depend on its degree to give certain penalty tomake it a little fitness. Under the circumstance, some infeasible solutions may also enter the group, to ensure chromosome number, so that the genetic algorithm can continue. After several generations, the infeasible solution proportion in groups is smaller and smaller, whereas feasible solution held dominant position gradually, and tends to the optimization solution[15].

3.2.1 The constraint of load process

As mentioned above, the first one is a method of processing constraint directly, but with the limited application. And the design of specialized chromosome and genetic operator are more difficult, and hence the method application depends on the problem features very much. The second one is a method which can only be applied to the optimization problem of simple constraints, feasible solution, without very high value. This paper adopts the penalty function method to deal with the constraints.

It would adopt the following transformation to change constraint of load to one part of objective function towards the general VSP.

$$\min z = \sum_{k=1}^{m} \sum_{i=1}^{n_k+1} d_{p_{k(i-1)} p_{ki}} + M \sum_{k=1}^{m} c_k \times \max path \tag{8}$$

Where $M \sum_{k=1}^{m} c_k \times \max path,$ denotes the penalty value if the solution violates the constraint of load. c_k is the overload of k vehicle. $\max\ path$ is the largest distance between any two points. M is the penalty coefficient with the overload, i.e. objective function plus the maximum distance ratio.

3.2.2 The constraint of time windows process

This paper processes soft time windows constraint, in which d denotes the loss of opportunity cost of unit time of the vehicle waiting in the task point, and e denotes the given penalty value of unit time of the vehicle arriving after the required time. In other words, if the vehicle arrives at demand point j before a_j, it results in cost $d\,(a_j - s_j)$. If the vehicle arrives at demand point j after b_j, it results in penalty $e\,(s_j - b_j)$. It processes time windows constraint via the penalty function method, resulting in the soft time windows VSP objective function:

$$\begin{aligned} \min z = & \sum_{k=1}^{m} \sum_{i=1}^{n_k+1} d_{p_{k(i-1)} p_{ki}} + M \sum_{k=1}^{m} c_k \times \max path \\ & + d \sum_{j=1}^{n} \max(a_j - s_j, 0) + e \sum_{j=1}^{n} \max(s_j - b_j, 0) \end{aligned} \tag{9}$$

3.3 Fitness function

In the vehicle scheduling optimization problem with time windows, it is better for the objective function value tending to be smaller.(i.e. It is better for the total routing distance value tending to be smaller, on the basis of meeting the constraints of load and time.) But in the genetic algorithm, the greater fitness represents the better individual performance, and therefore there is a need to change the objective function into the fitness function. This algorithm adopts the following method to change the objective function to the fitness function.

$$f_k = \frac{\max path \times n^2}{z_k} \tag{10}$$

Where z_k denotes the corresponding objective function value of k chromosome in the population, which represents the transportation cost of k chromosome. $\mathrm{Max}path$ denotes the maximum distance. f_k denotes the fitness of k chromosome, the value of which determines the probability of the chromosome producing offspring.

3.4 Design of Genetic Operators

The algorithm adopts the optimal reserved roulette wheel method for chromosome duplication, and adopts optimal reserved sequent crossover operator to achieve the chromosome, whereas mutation operator adopts the improved inversion mutation operator. In accordance with an inversion mutation probability p_m, the sub string between the two positions is reversed. For example: it would produce the following two problems, if the algorithm adopts that directly in chromosome structure.

(1) When both of the haphazard two points are 0, an inversion mutation is invalid, as it makes sub path reversed only.

(2) When either of the haphazard two points is 0, the other's neighbor is 0, an inversion mutation would produce invalid chromosome, where two zero are neighbors in the chromosome, which is demonstrated in Figure 1.
Accordingly, there must be an identification process before the mutation process, in order to avert the two situations above. The improved inversion mutation operator procedure is demonstrated in Figure 2 below.

3.5 The control parameters and termination conditions

The control parameters selection (including population size $popsize$, crossover rate p_c, mutation rate p_m) has a large influence on genetic algorithm. To achieve the optimal

0	3	8	0	6	7	2	0	1	5	4	0
0	3	8	2	7	6	0	0	1	5	4	0

Figure 1. An original inversion mutation producing invalid chromosome

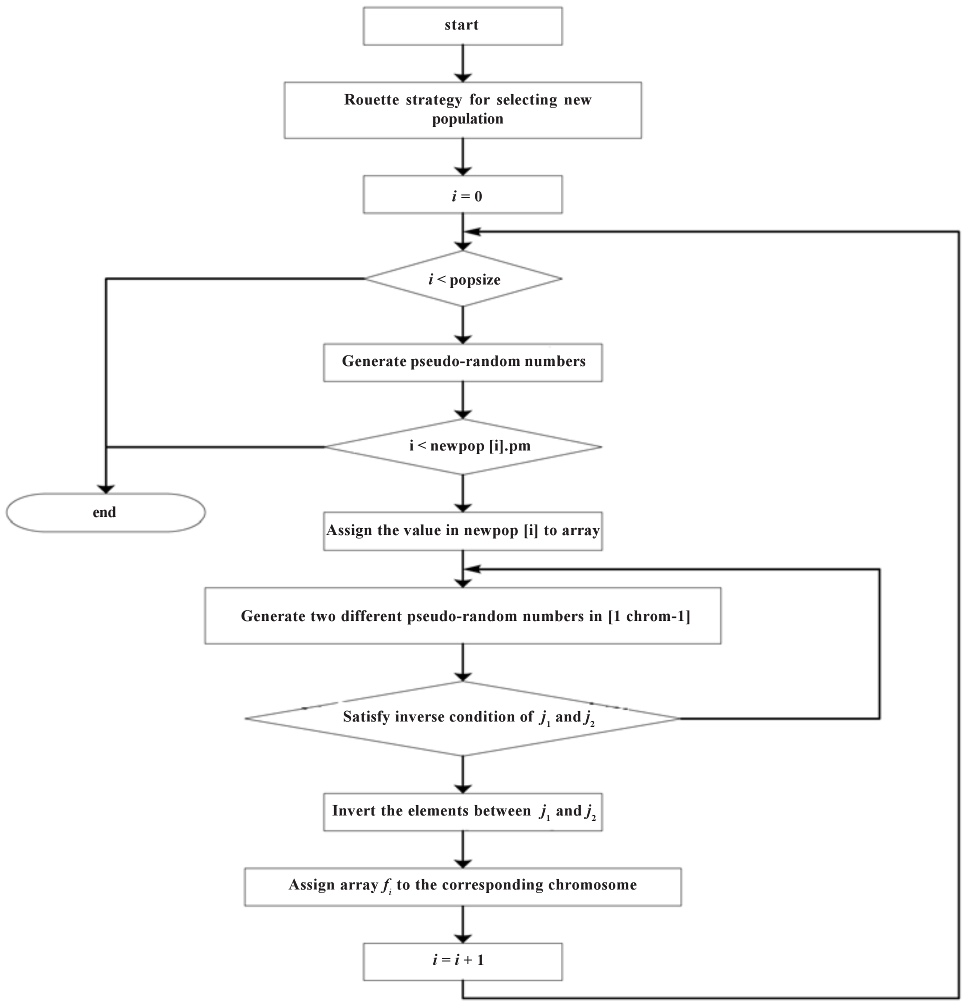

Figure 2. The improved inversion mutation operator procedure graph

performance of genetic algorithm implementation, it must determine the optimal parameter selection. General control parameter selection is determined according to the problem attribute.

In addition, due to the genetic algorithm with random, there are some heuristic termination conditions. The algorithm could be regarded as convergence, as long as it satisfies any given parameters λ, X, Y.

(1) Calculate average fitness value of each generation group, when the ratio of average value and the best chromosome fitness is greater than λ, it is regarded as convergence.

(2) Record every generation of the best chromosome, if best chromosome continuous until X generation, then the algorithm is termination.

(3) Due to the limited computational time and machine capacity, iterative generation cannot be infinite. As a result, when the generation number is Y, stop the calculation.

The algorithm flow diagram is demonstrated in Figure 3.

4. Case study

This section deploys one example to verify the proposed model and algorithm, analyzes and discusses key factors which have the influence on the algorithm.

4.1 Simulation experiment

The general VSPTW problem is usually composed of the input and output data. The input data includes the following four categories: (1) the input parking location coordinate; (2) input demand point number; (3) input demand point coordinate, cargo demand, task execution time, task start execution time range; (4) the system control parameters.

In addition, the output data includes the following six categories: (1) parking position coordinate and the demand of the vehicle number; (2) demand point coordinate, cargo demand, the task execution time, task start execution time range; (3) the system control parameters; (4) the chromosome maximum fitness, the minimum fitness, average fitness in each generation of genetic process; (5) the best individual fitness, chromosome constitution of each generation in the algorithm solution; (6) the final chromosome constitution and fitness value.

4.2 Analysis and discussion

The main control parameters in genetic algorithm includes: length of chromosome l, population size n, crossover rate p_c, mutation rate p_m. In order to select the appropriate population size n, crossover rate p_c, mutation rate p_m, select different value to assess the influence on fitness in the experiment, the results are as shown in figure 4-6.

As can be seen from Figure 4, population size has less influence on fitness.

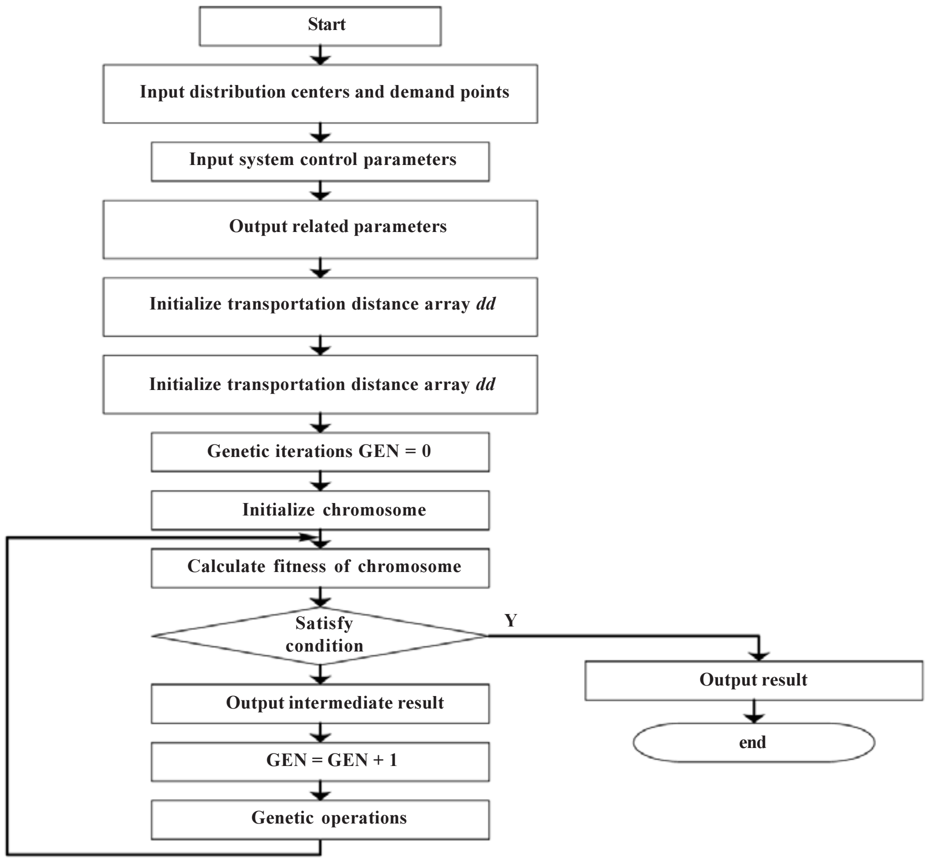

Figure 3. The genetic algorithm solution to VSPTW

In this case, set the demand point number is 8, the demand information of which is shown in Table 1. In addition, based on the input parking and demand point coordinates in the formulation (11) calculation, it could produce the any two point distance, the information of which is shown in Table 2.

$$d_{ij} = \sqrt{(X_i - X_j)^2 + (Y_i - Y_j)^2} \qquad (11)$$

Table 1 can obtain the demand, the load time and set time-window of any corresponding demand quantity of the 8 tasks. In addition, the definition of Vehicle Rate = 0.95; Vehicle Load = 8 (Ton); speed = 50 (km/h); max generation = 500; early arrival = 3; late = 6.

Through genetic algorithm, we can find out the optimal solution. The vehicle optimal path is: 0 8 5 7 0 1 3 2 0 6 4 0, the fitness value is 247.678.

As the maximum and minimum fitness curve fluctuate dramatically according to the crossover rate, but average fitness curve is stable in Figure 5, it indicates that crossover rate has less influence on fitness, which tends to be a constant.

As the maximum fitness tends to be a constant no matter how the mutation rate changes in Figure 6, it indicates that mutation rate has less influence on maximum fitness. In contrast, the minimum and average fitness fluctuate dramatically, it indicates that mutation rate has more influence on minimum and average fitness.

According to the experiment results, it can draw a conclusion that the influence of crossover rate p_c on fitness is not stable, which may be due to less number of vehicles, resulting in fewer gene segments in the chromosome, thereby inhibiting the crossover effect. Consequently,

Task i	1	2	3	4	5	6	7	8
demand volume g	2	1.5	4.5	3	1.5	4	2.5	3
Load time T	1	2	1	3	2	2.5	3	0.8
[ET, LT]	[1,4]	[4,6]	[1,2]	[4,7]	[3,5.5]	[2,5]	[5,8]	[1.5,4]

Table 1. Demand point demand information

d_{ij}	0	1	2	3	4	5	6	7	8
0	0	40	60	75	90	200	100	160	80
1	40	0	65	40	100	50	75	110	100
2	60	65	0	75	100	100	75	75	75
3	75	40	75	0	100	50	90	90	150
4	90	100	100	100	0	100	75	75	100
5	200	50	100	50	100	0	70	90	75
6	100	75	75	90	75	70	0	70	100
7	160	110	75	90	75	90	70	0	100
8	80	100	75	150	100	75	100	100	0

Table 2. Distance between demand point and distribution centre (*km*)

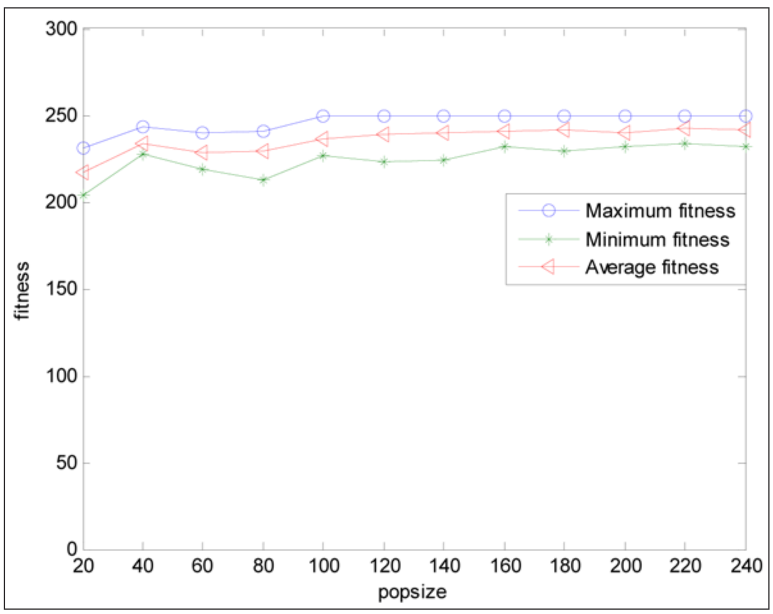

Figure 4. The influence of population size on fitness

increase the demand of some demand points (new demand is shown in Table 3), in order to increase the number of vehicles, for the sake of experiment outcomes once more, which are shown in Figure 7.

According to the above results, it can draw the conclusion that the crossover operation will improve the algorithm performance as the problem is large scale. To sum up, using genetic algorithms to solve the VRP problem with time windows of the third party logistics enterprise, it can obtain better feasible solution, reduce freight, save the logistics cost and improve the various resource utilization for the third party logistics enterprise transportation. Experimental results show that the algorithm is feasible to solve the vehicle routing problem, and has good performance.

6. Conclusions

Since VRPTW problem has been a typical NP-hard problem, there has been great practical value to study on this problem, along with the rapid development of logistics industry. On the basis of the analysis and research of distribution vehicle optimum scheduling problem, there is a further study on the vehicle optimum scheduling problem with time windows. This paper designs a genetic algorithm

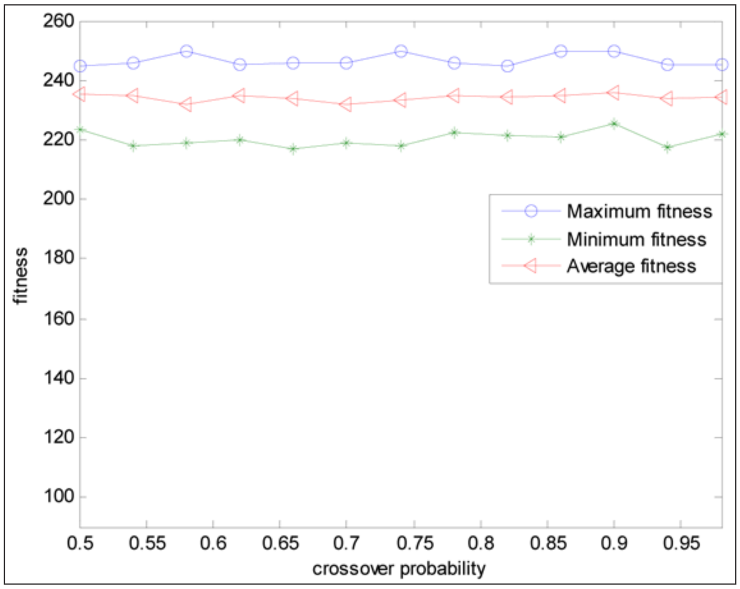

Figure 5. The influence of crossover rate on fitness

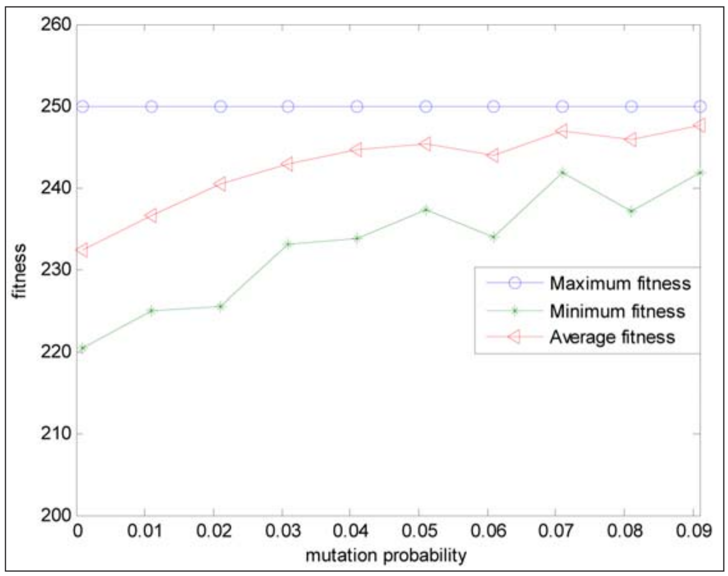

Figure 6. The influence of mutation rate on fitness

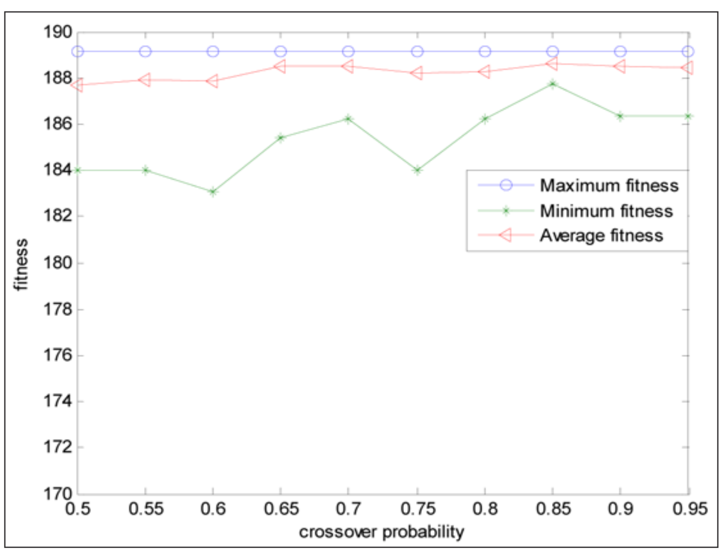

Figure 7. The influence of crossover rate on fitness

Task i	1	2	3	4	5	6	7	8
Demand volume g	4	3	4.5	3	3	4	5	3

Table 3. Demand variation situation of demand point

towards this problem, and carries out experimental simulation. The algorithm deploys selection operation based on the linear ordering of the roulette wheel method, which effectively prevents the search from local optimization. It adopts optimum reserved strategy to pass a better solution to the next generation by a greater probability. Meanwhile, it improves inversion mutation operator, resulting in an inhibition of the chromosome by selection and crossover operation caused by effective gene deletion, and to prevent illegal chromosome appearing. The algorithm is verified by experiment, and has sound searching performance and the rapid convergence speed, which is more suitable for vehicle scheduling problem with time windows.

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