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# Soft Time Windows Associated Vehicles Routing Problems of Logistics Distribution Center Using Genetic Simulated Annealing Algorithm

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The objective function of the vehicle routing problem with time windows (VRPTW) considered here is to achieve the minimization of total cost in a single distribution, which includes the travel costs and the penalty coefficient of time, under the constraints of time limits, volume and capacity. There are two main lines of development in relation to the exact algorithms for the VRPTW. One is concerned with the general decomposition approach and the solution to certain dual problems associated with the VRPTW. Another, more recent direction is concerned with the analysis of the polyhedral structure of the VRPTW. The algorithm to solve this model is a new stochastic approach called Genetic Simulated Annealing Algorithm (GSAA), which added both memory function and annealing operation to the algorithm. The result was compared to the former which operated by genetic algorithm, and showed that the approach to solve the VRPTW is very competitive.

*Keywords:* vehicle routing problem, logistics distribution center, time-window, mathematical mode, genetic simulated annealing algorithm

## 1. Introduction

Vehicle Routing Problem (VRP) was defined as determining the appropriate delivery routes for a series of given customers [1], so that the vehicles can depart from the distribution center and return to the original center after servicing all customers, with certain constraints (such as vehicle capacity, customer demand, time window, etc.), in order to achieve certain goals (shortest distance, least cost, etc.). Vehicle Routing Problem with Time Windows (VRPTW) gives the demand for each node and the available service time, and vehicles depart from the distribution center and come back to the original centers with the constraints of non-overloading and least total cost. VRPTW is often encountered in the actual logistics decision-making and it is a typical combination of optimization problem with constraints.

Since Savelsbergh [2] proves the VRPTW Problem is a NP – hard problem, people most committed to the research of heuristic algorithm investigate. We have also considered some efficient heuristics and compared their behavior with the benchmark obtained by using the optimization model, in terms of minimization of the distance traveled and maximization of customer's satisfaction. The rest of the paper is organized as follows. Section 1 is the introduction; Section 2 is the related works; Section 3 is the model of vehicle routing problem; Section 4 is vehicle routing problem with memory of genetic simulated annealing algorithm; Section 5 is example-analysis; and Section 6 is conclusions.

## 2. Related Works

There are many research branches of Vehicle Routing Problem (VRP), such as the multi-objectives or single objective. [3-4] gave a summary description of multi-objective vehicle routing problem. Different to multi-objective vehicle, the most attention focus on single vehicle routing problem are the algorithms. Over the past years quite good results have been achieved

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for the vehicle routing problem with time windows (VRPTW), in both the classes of exact methods and metaheuristics. Surveys can be found in Toth and Vigo [5] and Golden and Assad [6]. BrJaysy and Gendreau [7] give an excellent overview of metaheuristics for the VRPTW.

In [8-13], authors tried to set all kinds of models to solve VRP with single objective by using genetic algorithm. Genetic algorithm simulates the genetic and evolutionary process of organisms in nature and forms in a kind of adaptive global optimization probability search algorithm. Its essence is a community iterative process. First of all, it gets to the solution vector coding and forms the initial population, and then chooses the role of selection, crossover and mutation operator The parallel iteration, produces better performance in next generation group, until the optimal solution meeting specific conditions is generated.

Simulated Annealing (in short SA) algorithm was proposed by Kirkpatrick, and it has been applied to the problem of combination optimization since the year 1983. Acting as extension of local search algorithm, SA chooses the big value state in the field at a certain probability, which is different from local search algorithm. According to the ordering theory of Boltzman, annealing process should follow the laws of thermodynamics in thermal balance of a closed system Raul Ba proposed simulated annealing algorithm to solve VRPTW based on parallel multi-objective [14]. Brian Kallehauge identified and organized a total of 21 references on the VRPTW relative to four seminal papers on formulations of the TSP: arc formulation, arc-node formulation, spanning tree formulation, and path formulation. In his opinion the polyhedral approach of the arc formulation is promising and relatively little research has been conducted along these lines compared to the decomposition approach of the path formulation Originating from simulation of solid annealing process[15]. SA provides a near-optimal solution in the polynomial time, which controls the course of algorithm by a parameter called cooling time schedule, under the acceptance criterion of Metropolis [16].

Many scholars attempt to solve VRPTW by using different mixture algorithms. Mu Q used two tabu search algorithms to solve the VRP problem and a set of test problems has been generated [17] Zhang haigang and Huang Lan [18] suggested to use the two-stage heuristic algorithm and improved Genetic Simulated Annealing Algorithm to solve the VRPTW problem respectively. Yan Qing set up a model of VRP without considering the time-window and the influence of variable fees [19].

For the problem of time window based on different customers demand in logistics distribution, this paper proposed to change the extra time beyond time window to be penalty factor, and regard it as a part of the cost in logistics delivering. A genetic simulated annealing algorithm was conducted aiming to meeting customer time requirements, and optimizing the traveling cost, vehicle depreciation cost and time penalty costs, minimizing the entire operating costs in distribution.

## 3. The Model of Vehicle Routing Problem

### 3.1. Vehicle Routing Problem Description and Assumptions

Vehicle scheduling problem in logistics can be described in general as follows: Starting from a logistics distribution center, different vehicles deliver to different centers. Location and demand for the goods in each distribution the load capacity and volume, the farthest distance of each vehicle, are all steady The vehicle should arrive at the time window between $a_i - b_i$, or else it will be penalized. Therefore, the optimization problem is to determine the route followed by each vehicle to serve its assigned customers, while the distance traveled by the vehicles is minimized and the capacity and time windows constrains are satisfied.

In order to avoid the complexity of the problem, we will solve the problem under the following assumptions: (1) All the goods can be mixed together (2) The limits of volume and weight for each vehicle are only considered (3) The volume and the rated load of vehicles are the same and the number of vehicles is sufficient (4) Every vehicle trip distance cannot exceed its longest journey (5) The coordinates of each logistics distribution are known (6) Each vehicle must return to the distribution center after delivery [20].

### 3.2. Decision Variable

In this section we define the VRPTW as a graph theoretic problem and introduce the notation used throughout the paper, as displayed in the following Table 1.

| Parameters | Meaning |
|---|---|
| M | Is the total number of useable vehicles |
| N | Is the number of customers plus the depot (the depot is noted with number 1, and the customers are noted as $1, 2, \ldots, N$), |
| D | Is the collection of all notes |
| $t_{ij}$ | Is the time from note i to note j |
| $d_{ij}$ | Is the distance from note i to note j |
| V | is the volume capacity of vehicle j |
| $k_{drive}$ | Is the vehicle depreciation expense coefficient |
| W | Is the loading capacity of vehicle j |
| $W_j$ | Is the loading of note j needed |
| $C_0$ | Is the fuel cost of a vehicle in unit distance |
| $C_{ijk}$ | Is the variable charge of vehicle k from note i to note j |
| $C_w$ | Is the transit fee of a vehicle |
| $C_d$ | Is the pay for the driver |
| $C_v$ | Is the depreciation of vehicle |
| $k_0$ | Is the ratio of light fuel consumption with a full load when the fuel consumption |
| $k_{df}$ | Is fuel cost coefficients |
| $k_{oil}$ | Is the ratio of light fuel consumption with a full load when the fuel consumption |
| $k_{way}$ | Is the fixed cost per trip |
| i, j | i, j$\in$D, i$\neq$j |
| $V_j$ | Is the volume of note j needed |
| $W_{ijk}$ | Is the driver additional cost coefficient |
| $k_a$ | Is the loading of vehicle k from note I note j |
| $k_b$ | Is the coefficient of default |
| e | Is the coefficient of default |
| $f$ | Is the penalty of vehicle when it is too early to waiting per unit time |
| $G$ | Is the longest distance between the vehicle |
| $Y_i$ | Is the latency time |
| $X_i$ | Is the lead time |
| $[a_i, b_i]$ | Is the time window of note i |
| $k_{ve}$ | Is the cost coefficient when passing across the bridge |

*Table 1.* The variable definition.

### 3.3. Model Formulation

Next we consider to set up a math mode to solve the VRPTW, with the help of time and capacity constrained shortest paths The VRP with time windows is therefore equivalent to minimizing the function (1).

$$\begin{aligned}\min z = c_0 \sum_{k=1}^{M} \sum_{i=1}^{N} \sum_{j=1}^{N} X_{ijk} \times d_{ij} \\ + \sum_{i=1}^{N} e \times \max\{Y_i, 0\} \\ + \sum_{i=1}^{N} f \times \max\{X_i, 0\} + C_{ijk}\end{aligned} \tag{1}$$

$$C_{ijk} = C_w + C_d + C_v \tag{2}$$

$$C_0 = k_{oil} \times d_{ij} \times \left[k_0 + (1 - k_0) \times \frac{w_{ijk}}{W}\right] \tag{3}$$

$$C_w = k_{way} \times d_{ij} \tag{4}$$

$$C_d = k_{df} + k_{drive} \times d_{ij} \tag{5}$$

$$C_v = k_{ve} \times d_{ij} \tag{6}$$

$$X_i = b_i - t_i \tag{7}$$

$$Y_i = t_i - a_i \tag{8}$$

s.t

$$k_{driver} = \begin{cases} k_a - d_{ij} \times \frac{k_b}{1000} & d_{ij} < G \\ k_a - k_b & d_{ij} \geq G \end{cases} \tag{9}$$

$$\begin{gathered}\sum_{j=1}^{N} X_{ijk} * W_j \leq W \\ i = 1, 2 \ldots, N \quad k = 1, 2, \ldots, M_i\end{gathered} \tag{10}$$

$$\begin{gathered}\sum_{j=1}^{N} X_{ijk} * V_j \leq V \\ i = 1, 2, \ldots, N \quad k = 1, 2, \ldots, M_i\end{gathered} \tag{11}$$

$$\sum_{i=o}^{N} \sum_{j=0}^{N} X_{ijk} * d_{ij} \leq G \quad k = 1, 2, \ldots, M_i \tag{12}$$

Eq. (1) is the objective function of the problem, which consist of fuel cost, the penalty of lead time or latency time and the variable charge of vehicle. Eq. (2) is the total fee of variable cost, including the transit fee of a vehicle, including the pay for the driver and the depreciation of vehicle. Eq. (3) states that the transit cost is proportional to the travel distance. Eq. (4) and Eq. (5) mean that the pay of the driver consists of fixed cost and extra cost which is proportional to the travel distance too. Eq. (6) means that the depreciation charge is proportional to the distance. Eq. (7) and Eq. (8) state the lead time and the latency time. Eq. (9) is the driver additional cost coefficient. Eq. (10) and Eq. (11) state that the load of each vehicle should not exceed the capacity of the specified volume and load capacity. Eq. (12) ensures that the driving distance is in the scale of the farthest distance of each vehicle.

## 4. Vehicle Routing Problem with Memory of Genetic Simulated Annealing Algorithm

The vehicle scheduling problem above has been proved to be the NP – Hard problem [21] by a lot of experts and scholars. Although there are many algorithms in academia, each algorithm has certain shortcomings. In this paper, we put forward a kind of memory of genetic simulated annealing algorithm based on the characteristics of genetic algorithm and simulated annealing algorithm to solve the vehicle scheduling NP-problem, which combines the advantages of both algorithms and will improve the efficiency of algorithm greatly

### 4.1. Simulated Annealing Algorithm with Memory

There are many algorithms in academia to solve vehicle routing problem, but each algorithm has certain shortcomings. In this paper, we put forward a genetic simulated annealing algorithm with memory to solve the vehicle routing NP--problem based on the characteristics of genetic algorithm and simulated annealing algorithm, which combines the advantages of both algorithms and improves the efficiency of algorithm greatly.

In SA, solution $i$ and objective function $f(i)$ are respectively equal to state $i$ and energy $Ei$ in the solid. With the continuous iteration process of "the product of new solution-judge-accept or abandon" towards each value of control parameter $t$, the Metropolis arithmetic [22] is being carried out.

Based on the characteristics of both genetic algorithm and simulated annealing algorithm, this paper proposes a simulated annealing algorithm with memory to solve the vehicle routing problem. The characteristic of the algorithm is described as follows: First, the algorithm temporarily accepts some solutions in a certain probability, which were eliminated in the former steps. Then we make sure that the solution which conducted in the end condition is the best result by using the memory device in the course of search at least.

Step1: setting up the pop-size initial temperature $t_k = t_0$, annealing temperature parameters $\propto$, crossover and mutation parameters respectively $p_c, p_m$, the default termination conditions $N$, $k = 0$.

Step2: Generating an initial population with a number of pop-size randomly, computing the target $f(i)$ of each chromosome, then find the chromosome $i$ which gets to the minimum $f_i(t_k)$ (Is the function of chromosome during temperature $t$ I value) and the corresponding $f$, then $i^* = i, f^* = f$.

Step3: If satisfying terminal condition, then put out the optimal chromosome $i^*$ and solution $f^*$. otherwise choosing a chromosome $j$ from the neighborhood of each chromosome $i$ ($i \in \mathrm{pop}(k)$) according to the probability of acceptance: $A_{ij} = \min\left\{1, \exp\left[-\frac{f_j(t_k)-f_i(t_k)}{t_k}\right]\right\}$ [18]. In order to get a newpop1, this step need to iterate pop-size times, and set $n = 0$.

Step4: Calculating the fitness function in newpop1$(k+1)$,$f_i(t_k) = \exp\left[-\frac{f_j(t_k)-f(\min)}{t_k}\right]$, $f(\min)$ is the minimum in newpop1$(k+1)$, choosing chromosome a number of pop-size to form newpop2 by the method of Roulette recording to the optimal retention strategy at the same time.

Step5: Recalculating the objective function value in newpop2, doing the crossover operation in a GA at rate of $p_c$ to get crosspop and recording the optimal retention strategy at the same time.

Step6: Recalculating the objective function value in newpop2, doing the mutation operation in a GA at rate of $p_m$ to get mutpop recording the optimal retention strategy at the same time.

Step7: Discriminant replication strategy according to the rule of Metropolis to produce the next generation of groups pop$(k+1)$.

Step8: Performing annealing temperature operations $t(k+1) = \propto t(k), k = k+1$.

Step9: Calculating $f_j(t_{k+1})$ in pop$(k+1)$ and finding the chromosome $i$ which gets to the minimum $f_i(t_{k+1})$ and the corresponding $f$.

Step10: Judging the value of $f$. If $f^* < f$, then $i^* = i, f^* = f$, $n = 0$ or else $n = n+1$.

Step11: Judging terminal condition, If $n \geq N$ then algorithm to terminate output $i^*$ and $f^*$ otherwise go back to Step4.

## 4.2. Algorithm Description

(1) Structure of the chromosomes: In order to simplify the calculation and the process, we choose natural number coding to solve the VRP. The solution vector of the above mathematical mode can be arranged into a chromosome with a length of $k+M+1$. In the chromosome $i_j$ represents the $j$-th chromosome. The amount of 0 is $M+1$, which stands for distribution center. The course can be described as follows: the first vehicle conducts the first subpath when it sets off the distribution and goes through the note $i_1, i_2, \ldots, i_s$. $M$ vehicles will construct $M$ subpaths after completing all transportation task in a curtain turn. For example, chromosome 02350147060 means 3 vehicles complete the transportation route of 7 nodes

sub-path 1: distribution 0→node 2→node 3→ node 5→distribution 0, sub-path 2: distribution →node 1→ node 4→node 7→distribution 0, sub-path 3: distribution 0→node 6→distribution 0.

(2) Generation of initial population: Each chromosome in the initial population which is randomly generated with a length of $L$ is a corresponding serial number of a random sequence in distribution. In order to ensure the calculation efficiency, population size can't be too big, generally taking between 10 and 100. In the initial chromosome, $k$ full arrangement will be produced first, and then 0 with a lumber of $M+1$ randomly inserted. It is to make sure that there must be two zeros which are respectively in the first and last of arrangements, and the condition when two consecutive zeros occur in a range isn't promised

(3) Initial temperature and annealing temperature: The determination of the initial temperature chooses the form of $t_0 = k\delta$, $k$ should be large enough, $\delta = f_{\max} - f_{\min}$, $f_{\max}$ and $f_{\min}$ are respectively the maximum and minimum objective function values of the initial population. Annealing temperature function $t(k+1) = \propto t(k), 0 < \alpha < 1$.

(4) Calculating fitness function: the function of total cost is

$$\begin{aligned}\text{minz} = c_0 \sum_{k=1}^{M_j} \sum_{i=1}^{N} \sum_{j=1}^{N} x_{ijk} * d_{ij} + C_{ijk} \\ + M_1\{\sum_{j=1}^{N} x_{ijk} * W_j - W, 0\} \\ + M_2\{\sum_{j=1}^{N} x_{ijk} * V_j - V, 0\}.\end{aligned}$$

$M_1$ and $M_2$ are infinite numbers, representing penalty coefficients, respectively of excess freight and hypervolume of vehicle. $M_1$ and $M_2$ are equal to 1000000, according to the reference in this paper. Fitness function $f_i(t_k) = \exp\left[-\frac{f_j(t_k) - f(\min)}{t_k}\right]$ with acceleration will result in good performance, fast convergence, and less algorithm running time.

(5) Selection, crossover operator: Selection of operator according to the reference in proportion is a random sampling method with return type, based on rotating for pop-size times in roulette, which chooses one to the progeny population. The probability that the parent is being selected is

$$P(x_i) = \text{eval}(x_i) / \sum_{j=1}^{\text{pop-size}} \text{eval}(x_i).$$

The selected chromosome produces offspring according to certain crossover probability. The effect of crossing-over rate between 0.6-0.8 is better [8] in the evolution In order to avoid the feasible solution, crossover operator in this paper is chosen from the reference:

1. Randomly generates a cross: If the parental genes between both sides of the crossover are 0, then make some simple crossovers. Otherwise moving the location of the left crossover left until it is 0. And continue to move rightcross rightly from leftcross as a starting point until the right gene of the rightcross is 0. All above is to ensure the crossover in one chromosome.
2. The condition that one distribution will be visited twice in the offspring still exists after the operation 1, and some adjustments to the offspring are needed. In the descendant, select a repeat of the natural numbers; if the natural number is not within the cross – bit, then delete. If there is a missing visit to a distribution point in the progeny, then supplement natural number for the distribution point on the outside of the chromosomes cross – bit.
3. If there is an empty road, that means there are two continuous zeros in one chromosome after the second step, then go to step 3. One of these zeros – bit and the natural code in the rest of the chromosome at distribution point will be changed. Requirement for the code of nature is that both the first and the last locations of code are not 0.

(6) Mutation operator: The purpose of variation is to improve the search ability of GA and maintain the diversity of population, and prevent "premature" phenomenon. After the variation, a cross in the above 3 step finishing descendant can guarantee a viable offspring.

(7) New individual copy: After all the operation of the initial group is finished, we use the rule of Metropolis to discriminate replication strategy and produce the next generation. First, we will implement optimum reserved strategy. Then both chromosomes $i$ and new chromosome $j$ which comes from the domain of chromosome $i$ will compete to the next generation. Set $f' = f(x_j) - f(x_i)$, if $f' < 0$ then $x_j$ will be copied to the next generation, else $e^{(-f'/t(k) > random[0,1])}$ will be a condition of replication $x_j$ for the next generation of groups.

(8) End condition: When continuous $Q$ generation does not change, we can think of convergence and end at this time, or terminate the algorithm.

(9) Domain structure: the domain of each chromosome consists of all chromosomes generated by random exchange for two genes.

(10) Annealing temperature function: $t(k+1) = \propto t(k)$.

## 5. Example Analysis

This paper writes a program by matlab7.5, comparing the simulation of calculation results. Choosing annealing temperature coefficient $\propto = 0.96$, crossing-over rate and aberration rate are respectively equal to $p_c = 0.7$, $p_m = 0.01$. Algorithm termination conditions $N = 50$, Initial annealing temperature $t_0 = 10$. Vehicle load rating $W = 8$. The data of distributions' locations and nodes' locations are arranged in the following Table 2:

L stands for the distributions' coordinate locations, and D stands for the demanded quantity of each node.

In order to make it easier to understand the nodes' location, we display the distance between each node and the distribution in the following Table 3.

The number of vehicles needed in the reference is $m = [\sum_{i}^{k} g_i/aW] + 1$ [23]. In this paper, $m$

| | DC 0 | node1 | node2 | node3 | node4 | node5 | node6 | node7 | node8 |
|---|---|---|---|---|---|---|---|---|---|
| L | 31,9 | 76,38 | 77,16 | 90,82 | 60,74 | 76,86 | 11,31 | 29,90 | 10,60 |
| D | 0 | 2.46 | 0.41 | 2.16 | 2.27 | 1.83 | 3.76 | 2.54 | 2.39 |

*Table 2.* The initial data of distribution centers (DC) and nodes.

| Distance | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 0 | 53.5 | 46.5 | 93.9 | 71.2 | 89.2 | 29.7 | 81.0 | 55.2 |
| 1 | 53.5 | 0 | 22.0 | 46.2 | 39.4 | 48.0 | 65.4 | 70.1 | 69.6 |
| 2 | 46.5 | 22.0 | 0 | 67.3 | 60.4 | 70.0 | 67.7 | 88.2 | 80.2 |
| 3 | 93.9 | 46.2 | 67.3 | 0 | 31.0 | 14.6 | 94.0 | 61.5 | 83.0 |
| 4 | 71.2 | 39.4 | 60.4 | 31.0 | 0 | 20.0 | 65.2 | 34.9 | 51.9 |
| 5 | 89.2 | 48.0 | 70.0 | 14.6 | 20.0 | 0 | 85.1 | 47.2 | 70.9 |
| 6 | 29.7 | 65.4 | 67.7 | 94.0 | 65.2 | 85.1 | 0 | 61.7 | 29.0 |
| 7 | 81.0 | 70.1 | 88.2 | 61.5 | 34.9 | 47.2 | 61.7 | 0 | 35.5 |
| 8 | 55.2 | 69.6 | 80.2 | 83.0 | 51.9 | 70.9 | 29.0 | 35.5 | 0 |

*Table 3.* The distance between each node and the distribution center.

stands for vehicle number, and [ ] means integer arithmetic. $a$ is a parameter, and $a = 0.85$ [24]. The result of $m$ is 3. Population size is 20 and the number of times of evolvement is up to 50.

According to Figure 1 and relevant data, we can get a result: sub-path 1: $0 \to 8 \to 7 \to 4 \to 0$; sub-path 2: $0 \to 6 \to 0$; sub-path 3: $0 \to 5 \to 3 \to 2 \to 1 \to 0$, The cost of transportation is 502.80, while the cost of transportation is 476.2889312 by using the genetic simulated annealing algorithm with memory. And the time is 1.68 seconds. The result is showed in the following Figure 2.

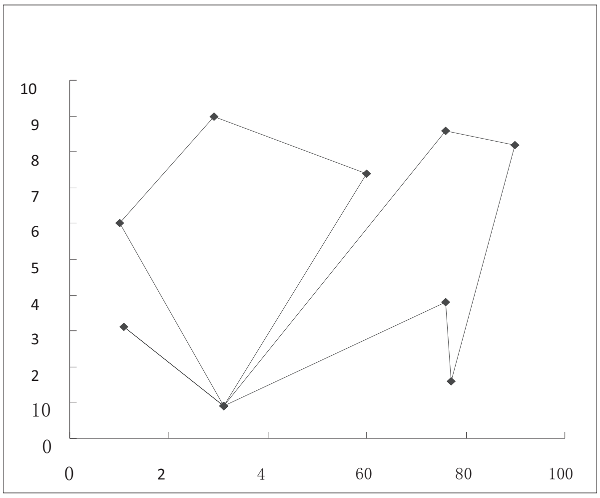


*Figure 1.* The optimal path which is based on 8 nodes calculated by GA.

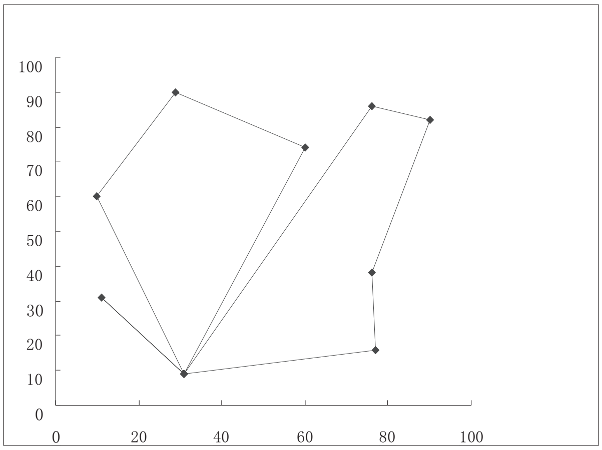


*Figure 2.* The optimal path which is based on 8 nodes calculated by GA-SA.

According to Figure 2 and relevant data, we can get a result: sub-path 1: $0 \to 4 \to 7 \to 8 \to 0$; sub-path 2: $0 \to 6 \to 0$; sub-path 3: $0 \to 5 \to 3 \to 1 \to 2 \to 0$.

We can see that the result calculated by GA-SA has advantages with shorter running time and lower cost under the condition of equal parameters.

| Arithmetic | Solution | Run time | Vehicle amounts | Corresponding path | | |
|---|---|---|---|---|---|---|
| | | | | 1 | 2 | 3 |
| GA | 502.80 | 3s | 3 | 0→8→7→4→0 | 0→6→0 | 0→5→1→2→3→0 |
| GA-SA | 474.40 | 1.68s | 3 | 0→4→7→8→0 | 0→6→0 | 0→5→3→1→2→0 |

*Table 4.* Two kinds of algorithm optimization results.

## 6. Conclusions

In this paper, we have established a complete model of vehicle scheduling problem, by using mathematical method and transforming the time window problem into cost function, in which the completeness and feasibility of the model is considered at the same time. We combined genetic algorithm with simulated annealing algorithm by natural number coding combining, and adding memory function, which fostered strengths and circumvent weaknesses. Time needed for this genetic simulated annealing algorithm is significantly reduced, with good effect. Numerical example results show that the algorithm for solving such as vehicle scheduling problem, which is a kind of NP problem, is really practical, with less running time, more satisfactory solution, and strong practicability.

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