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Fuzzy Demand Vehicle Routing Problem With Soft Time Window Based on Genetic Algorithm

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Abstract

In the distribution process of primary processed agricultural products, because the merchants can not accurately obtain the number of orders, the demand for goods is vague regularly, and the distribution time is needed to meet expectations, otherwise it will affect the subsequent sales and product quality. So time will also have an impact on the fuzzy distribution path and the overall distribution cost. According to the reality, this paper establishes a fuzzy demand vehicle routing model with soft time window constraints. The objective function is minimizes the total cost in the process of distribution. In the process of solving the model, firstly, the theory of credibility measure is used to deal with the fuzzy demand, then the adjusted genetic algorithm is used to solve the optimal path. Finally, the results of solving the optimal path planning on the simulated data are given.

Key words: FVRP; Fuzzy credibility; Fuzzy simulation; Soft time window; Genetic algorithm

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INTRODUCTION

Collection and delivery of primary processed agricultural products is a very traditional distribution Pattern. The main distribution time of primary processed products is in the early morning, the manufacturer produces the products in the evening, and the distribution center needs to ensure that every merchant can get fresh primary processed products in time for sale in the market. This kind of processed agricultural products mainly include primary processed soybean products, fresh yogurt, primary processed aquatic plants, primary processed aquatic products and so on. For manufacturers, the merchant's needs are often vague, and they need to deliver it on time within the time period they need. Otherwise, it will not only affect the quality of products, but also affect the business of the merchants, which may invisibly increase the cost of distribution. So this paper adds the distribution time window to the original problem of fuzzy vehicle routing model, and changes the objective equation into the total cost. Finally, a fuzzy demand vehicle routing problem with soft time window (FDVRPWSTW) is proposed.

The tranditional vehicle routing problem (VRP) was first proposed by Dantzig and Ramser (Dantzing & Ramser, 1959, pp.80-91) in 1959. It refers to a certain number of merchants, merchants have different needs, and the distribution center provides goods to merchants, a team is responsible for distributing goods and organizing appropriate driving routes. The goal is to meet the needs of merchants and to achieve the shortest distance, the lowest cost and the least time spent under certain constraints. The vehicle routing problem is a classic complex combinatorial optimization problem. It has always been a research hotspot in the field of operations research and portfolio optimization. In the past, and the model was proposed under strict assumptions. For example， most VRP models assumed that merchant demand information, vehicle information, and road condition information were determined. However, in the actual environment, many information such as road conditions, user needs, vehicle conditions, etc, are vague and uncertain. And now scholars turn from the traditional deterministic problem to the Fuzzy Vehicle Routing Problem (FVRP).

Jiaoman Du et al. (Du, Li, Yu, Ralescu, & Zhou, 2017), defines the risk and accident probability involved in the transportation of dangerous goods as fuzzy numbers, and considers the multi-depot vehicle routing problem (MDVRP) under the condition of fuzzy risk measurement. Gulcin Dinc Yalcin et al. (Gulcin & Nihal, 2015) put forward two objective functions of multi-objective programming model on the basis of vehicle routing problem with return journey, and proposed FMOP-VRPB algorithm based on fuzzy multi-objective programming to solve this problem. Brito J, et al. (Brito, Martinez, Moreno, & Verdegay, 2015) improved the open vehicle routing problem model based on the actual situation, and pointed out that merchant demand and travel time are usually uncertain, so proposed a fuzzy path planning problem with capacity and time window constraints and COVRPTW, and proposed a hybrid heuristic process based on GRASP and VNS combined with ACO design to solve the model. Cao Erbao, et al. (Cao, Lai, & Li, 2009) studied the vehicle routing problem with fuzzy demand, and established a fuzzy chance-constrained programming model based on the theory of fuzzy credibility, and used differential evolution algorithm to solve the problem. Zhang Xiaonan and Fan Houmin (2016) aim at the vehicle routing problem with fuzzy demand, establish and optimize the model based on the theory of credibility measure, determine the actual demand after reaching the target point, then adjust it in real time, and simulate the practice demand with stochastic simulation algorithm and design a new hybrid decentralized search and variable domain decentralized search algorithm. Li Yang, Fan Hooming, Zhang Xiaonan and Yang Xiang (2018) build a fuzzy chance-constrained optimization model based on credibility theory to deal with the fuzzy needs of merchants, and design a two-stage variable neighborhood search algorithm to solve and optimize the scheme. in the rescheduling stage, they design a stochastic simulation algorithm to simulate the actual needs of merchants, then they propose a rescheduling strategy to adjust and optimize the scheme. Wang Lianfeng and Song Jianjian (2012) also analyzed the possibility of failure of existing vehicle service, and established a fuzzy expectation model based on the theory of fuzzy credibility. Finally, a parallel particle swarm optimization algorithm with double taboos was designed to solve the model. Sun Guohua (2012) proposed an open multi-depot vehicle routing problem with time windows, established a model, and designed a genetic algorithm to solve it. Finally, the optimal solution was given.

The innovation of this paper is to add time constraints to the trandition fuzzy vehicle routing problem, because the existing merchants not only have uncertain demand for goods, but also have requirements on service time,the goods need to be delivered in the best time window, exceeding the time window will bring some penalty costs to the distribution center, so the paper puts forward the idea of taking time to meet the demand. Fuzzy demand path planning model with soft time window constraints is established. Finally, the optimal path is solved by stochastic simulation algorithm, adjusted genetic algorithm and different time loss cost coefficients and subjective preferences of distributors.

1. FUZZY CREDIBILITY THEORY

Fuzzy theory was put forward by Zadeh (1965) in 1965. As the theory expands the theoretical category of random numbers, scholars have studied it and put forward the concepts of fuzzy variable (Kaufman, 1975), fuzzy possibility theory (Zadeh, 1978) and credibility theory (Liu, 2004). The model in this paper is based on the theory of fuzzy credibility proposed by Liu.

Concept:

Θ: Nonempty set

P(Θ): Power set, Each element in P(Θ) is called a fuzzy event.

Cr{A}: credibility measure of fuzzy event{A}, A is an arbitrary event of P(Θ).

Credibility measure is a map function from P to [0,1]. The set function has several important mathematical properties. Li and Liu (2006) propose the following 4 properties:

property 1 Normalization: Cr{Θ}=1;

property 2 Monotonicity:for each event $A \subset B$,have $Cr\{A\} \leqslant Cr\{B\}$;

property 3 Self duality: for each event $A \in P(\Theta)$,have $Cr\{A\}+Cr\{A^c\}=1$;

property 4: for each event A if $Cr\{A\} \leq\leq 0.5$, have $Cr\{A\} \wedge 0.5 = \sup_i Cr\{A\}$.

we call(Θ,P(Θ),Cr)is a creditability space,Fuzzy variable ξ is defined as a function from the credibility space (Θ,P(Θ),Cr)to the real number set R. The expected value of fuzzy variable ξ is $E[\xi]=\int_0^{+\infty} Cr\{\xi \geq r\}dr-\int_{-\infty}^0 Cr\{\xi \leq r\}dr$, For any number a,b,have $E[a\xi+b]=aE[\xi]+b$; The variance of fuzzy variable ξ is $V[\xi]=\int_0^{\infty} Cr\{(\xi-E[\xi])^2 \geq r\}dr$; For any number a,b,have $V[a\xi+b]=a^2V[\xi]$;

In the process of measuring the fuzzy number, if the possibility of a fuzzy event is 1, the event may not happen. On the other hand, even if the necessity of a fuzzy event is 0, the event may happen. However, if the credibility of a fuzzy event is 1, then the event will be established; conversely, if the credibility of a fuzzy event is 0, then the event will not be established. So credibility measure is equivalent to probability measure in random theory, and it has better properties than probability measure. Consider the triangular fuzzy number used in the model, and its credibility is measured as follows:

$d=(d_1,d_2,d_3)$

$$Cr\{d \geq r\} = \begin{cases} 1, & \text{if } r \leq d_1 \\ \frac{2d_2-d_1-r}{2(d_2-d_1)}, & \text{if } d_1 \leq r \leq d_2 \\ \frac{d_3-r}{2(d_3-d_2)}, & \text{if } d_2 \leq r \leq d_3 \\ 0, & \text{if } r \geq d_3 \end{cases} \tag{1}$$

2. PROBLEM DESCRIPTION AND MODEL BUILDING

2.1 Problem Description

The fuzzy demand vehicle routing problem with soft time window (FDVRPWSTW) have many basic assumption. Suppose there is only one transportation center, multiple merchants to be served, each merchant has a soft time window, and the penalty function is a linear function; after the vehicle departs from the transportation center, it serves a certain number of merchants and returns to the transportation center. Each vehicle has the same Capacity; information on distribution centers, merchant points, and distribution vehicles is known, and all vertices (including distribution centers and merchant points) are fully interconnected, each merchant point is fuzzy and independent of each other, all delivery vehicles are of the same model, maximum load The weight and vehicle performance are the same; the merchant points can only be serviced by one car in the pre-optimization stage. Each vehicle has only one service line. The starting point is the distribution center. The sum of the fuzzy demand of each merchant on each service line cannot exceed the vehicle. Load capacity; distribution center capacity, available vehicles, and distribution capacity to meet merchant service requirements, can send multiple vehicles at the same time (not exceeding the total number of available vehicles) for distribution services, merchant demand is sufficient, and single merchant demand does not exceed the maximum vehicle Load capacity; the vehicle is fully loaded when it departs from the distribution center. Each merchant can only be serviced by one car at a time, and each car can only be used once. Merchant needs are uncertain.

Model related symbols are expressed as follows:

Suppose there is only one transportation center, and there are n merchants to be serviced, which are represented by{0,1,2, …, n}, 0 is represented the transportation center。The distance between point i and point j is c_{ij}, and the soft time window of each node is$[e_i,l_i]$,where $(i\in 0...n)$,e_i and l_i respectively represent the earliest and the latest service time,$[e_0,l_0]$ represent the service time of the distribution center. K={1,2,...,k} expressed as a collection of delivery vehicles. The capacity of each car is C, Unit time travel distance is t, Unit path cost is G. The demand for each merchant i is a triangular fuzzy number $d=(d_{1i},d_{2i},d_{3i})$, and $d_{1i}\leq d_{2i}\leq d_{3i}\leq C$. when the vehicle arrives at the merchant time exceeds the merchant time window $[e_i,l_i]$ The penalty function is:

$$F(T_i^k)=via*\max(e_i-T_i^k,0)+vib*\max(T_i^k-l_i,0)$$

T_i^k Indicates the time when vehicle k arrives at user i, and $T_0^k=0$;a is the unit cost of early service;b is the unit cost of the delayed service. s_i Indicates the service time after the vehicle reaches point i. X_{ijk} Indicates whether the vehicle k is directly from point i to point j, If it is directly arrived $X_{ijk}=1$, else $X_{ijk}=0$.

2.2 Model Building

Since the merchant's demand is vague, this paper use fuzzy credibility theory to solve the needs .When a vehicle transports m merchants, the total carrying capacity is $d'_m=\sum_{i=1}^{m} d_i$, The remaining carrying capacity of the vehicle is $Qm=C-\sum_{i=1}^{m} d_i$, Q_m is also a triangular fuzzy number:

$$Qm=(C-\sum_{i=1}^{m} d_{3i},C-\sum_{i=1}^{m} d_{2i},C-\sum_{i=1}^{m} d_{1i})=(q_{1m},q_{2m},q_{3m}) \tag{2}$$

And,$q_{1m}\leq q_{2m}\leq q_{3m}$, When a vehicle needs to serve the next merchant point, it needs to set a pre-set preference value α . Only the creditability of the next merchant demand less than the vehicle's remaining transport capacity is greater than α , the next merchant point will be served, and expressed as:

$$Cr=Cr\{Q_k\geq d_{k+1}\}=Cr\{d_{1,k+1}-q_{3,k},d_{2,k+1}-q_{2,k},d_{3,k+1}-q_{1,k}\leq 0\}\geq \alpha \tag{3}$$

$$Cr = \begin{cases} 0, & \text{if } d_{1,k+1} \geq q_{3,k} \\ \frac{q_{3,k}-d_{1,k+1}}{2(d_{2,k+1}-q_{2,k}-d_{1,k+1}+q_{3,k})}, & \text{if } d_{1,k+1} \leq q_{3,k}, d_{2,k+1} \geq q_{2,k} \\ \frac{d_{3,k+1}-q_{1,k}-2(d_{2,k+1}-q_{2,k})}{2(q_{2,k}-d_{2,k+1}+d_{3,k+1}-q_{1,k})}, & \text{if } d_{2,k+1} \leq q_{2,k}, d_{3,k+1} \geq q_{1,k} \\ 1, & \text{if } d_{3,k+1} \geq q_{1,k} \end{cases} \tag{4}$$

When the value of Cr is greater than the given preference value α, the vehicle will continue to complete the next merchant's transportation task. If the value of Cr is less than α, the vehicle will return to the centre to complete the distribution business after loading. In the actual vehicle transportation process, when the vehicle arrives at the merchant according to the agreed path, the merchant's demand is a definite value. Therefore, the task may fail because the residual transport capacity of the vehicle can not meet the merchant's demand. The vehicle should return to the distribution center to load product and drive to the failure point to continue to complete the remaining transport task. These situations will create extra travel distance and extra time cost. Therefore, when evaluating the vehicle routing, it is necessary to consider not only the predicted distance traveled along the predicted route, but also the additional cost caused by the possible path failure. It is assumed that the additional cost caused by distribution failure is linearly correlated with the additional path cost generated in the process of fuzzy simulation with a coefficient of β. Therefore, the distribution path total cost = fuzzy cost +β * actual cost.

So, the model of FDVRPWSTW is fallowing:

$$\min \sum_{k=1}^{k}\sum_{i=1}^{n}\sum_{j=0}^{n}c_{ij}*X_{ijk}*t*G+\sum_{k=1}^{k}\sum_{j=0}^{n}F(T_i^k) \tag{5}$$

$$s.t.Cr(\sum_{j=0}^{n}\sum_{i=0}^{n} d_i x_{ijk} \leq C) \geq a \tag{6}$$

$$\sum_{i=0}^{n}\sum_{k=1}^{k} x_{ijk}=\sum_{j=0}^{n}\sum_{k=1}^{k} x_{ijk}=1, \tag{7}$$

$$\sum_{i=0}^{n} x_{ijk}-\sum_{i=0}^{n} x_{jik}=0, \quad (8)$$

$$\sum_{j=0}^{n} x_{ojk}=\sum_{i=1}^{n} x_{iok}\leq 1, \quad (9)$$

$$T_i^k+s_i+\frac{c_{ij}}{t}\leq T_j^k \qquad i<j, \quad (10)$$

$$T_i^k+s_i+\frac{c_{io}}{t}\leq l_o, \quad (11)$$

$$X_{ijk}\in\{0,1\} \quad \text{and} \quad i,j=0,1,...,n;k=1,...,K \quad (12)$$

The (5) representative the objective, The objective is to minimize the total cost of distribution, which includes the cost of transportation route and the Penalty costs over time windows. The constraint (6) To ensure that vehicles are serving merchants when selecting merchants, The crediility of loading is not greater than Q, which is higher than pre-set confidence level $\alpha\alpha$. The constraint (7) to ensure that each merchant completes the service only by one vehicle at a time. The constraint (8) to ensure The number of vehicles coming from each merchant point is the same as the number of vehicles entering. The constraint (9) to ensure the vehicle starts from the distribution center and returns to the distribution center. The constraint (10) represents the relationship between vehicle start time and arrival time at two adjacent merchant points on a path. The constraint (11) to ensure the time that vehicle return does not exceed the latest return time required by the distribution center. Constraints (12) are attributes of decision variables.

3. FDVRPWSTW SOLVED BASED GENETIC ALGORITHM

In order to solve the modified model, the classical genetic algorithm is redesigned. For a given subjective preference value $\alpha\alpha$ and additional cost coefficient β, Random generation of n triangular fuzzy numbers, these fuzzy numbers serve as demand of the merchant. Using genetic algorithm to get the expected travel path of merchants under fuzzy demand. When the vehicle arrives at the merchant, Merchant needs are determined. In this paper, we use stochastic simulation algorithm to simulate the actual demand of merchants. When the actual demand exceeds the remaining capacity of the vehicle, the vehicle will return to the transport center and then to the merchant, thus generating additional driving distance and calculating the corresponding time cost.

3.1 Stochastic Simulation Algorithm

For each merchant, the actual demand of each merchant is needed to generate the estimated additional driving distance. The actual demand can be generated by simulation method. The specific steps are as follows:

Step1:

(1) A number x is generated randomly within each merchant's fuzzy demand number and calculate it's membership degree u.

(2) Generate a random number a with a range of [0, 1].

(3) Compare a and u. If a is less than u, x is the actual demand of the merchant.

(4) Otherwise, repeat the above steps until all the simulated "actual" requirements of all merchants are generated.

Step2: Calculate the additional travel distance due to failure based on the actual demand.

Step3: Repeat step1 and Step2 M times.

Step4: The average value of M-times simulation is calculated as an estimate of the additional driving distance due to the possible failure of the route arrangement.

3.2 Adjusted Genetic Algorithm

Genetic algorithm is a computational model simulating the natural selection and genetic mechanism of Darwin's biological evolution theory. It is a method of searching the optimal solution by simulating the natural evolution process. The main components of genetic algorithm are initialization of population, calculation of fitness, selection, crossover, mutation, adjustment and reset. Steps are as follows:

(1) Initialization population

1. Generate random merchant permutations.

2.Remove the leftmost merchant in the merchant ranking, calculate the credibility according to the merchant's demand and the remaining transport capacity of the current vehicle, and assign the merchant to the current vehicle if the conditions are met; otherwise, assign a new car.

3. Choose the next merchant in the arrangement.

4. Repeat the 2 and 3 steps until all the merchants are arranged to produce a viable chromosome.

5. Repeat 1-4 steps until the number of chromosomes is given.

(2) Computational fitness

The fuzzy path length of each individual is calculated and stochastic simulation is carried out to obtain the actual additional travel distance of each individual corresponding to each path, and the fitness value of each individual is calculated.

(3) Choice

The roulette selection operator is used, that is, according to the fitness ratio and cumulative probability of each individual in the whole population, and through the interval range of the random number to select the individual. Such individuals can make the most suitable individuals have the greater probability of being selected.

(4) Crossing

Individuals that need to be crossed are selected by crossover probability pc, and new individuals are generated by crossover rules. Partial crossover is used here. Firstly, the crossover positions r_1 and r_2 are randomly generated, where r_1 and r_2 are less than the length of chromosome, and then the length r_3 is randomly generated, exchanging the individuals whose length is r_3 at the positions of r_1 and r_2, respectively.

(5) Variation

Random mutation probability pm, the corresponding location of the mutation operation, that is, randomly generated merchant points.

(6) Adjustment and replacement

Check whether the number of merchants in each new chromosome is normal, if not, it needs to be adjusted and filled. Then check whether the number of merchants in the chromosome meets the time requirements and constraints. If the constraints are not satisfied, the chromosome will be re-initialized.

4. NUMERICAL EXPERIMENTS AND RESULTS ANALYSIS

At present, there is no standard test data in the model. The test data set in this paper is as follows. The random experiment consists of 25 merchants. The location of the parking lot is 1 (35, 35). The coordinates, ambiguities and time windows of each merchant are listed as follows:

Table 1
Simulated Data

Point	i	j	a	b	c	e	l
1	35	35	0	0	0	0	230
2	41	49	10	23	58	66	171
3	35	17	8	36	41	40	80
4	55	45	9	26	48	45	126
5	55	20	14	31	45	83	159
6	15	30	12	23	56	76	94
7	25	30	10	32	49	41	109
8	20	50	18	25	59	51	91
9	10	43	14	33	43	62	92
10	55	60	13	34	45	101	157
11	30	60	19	35	43	72	128
12	20	65	9	29	42	67	143
13	50	35	17	21	58	20	86
14	30	25	17	24	52	33	59
15	15	10	11	39	51	20	169
16	30	5	14	23	43	60	130
17	10	20	6	37	57	57	103
18	5	30	5	31	53	87	97
19	20	40	13	40	47	46	86
20	15	60	17	21	50	42	96
21	45	65	19	29	48	47	89
22	45	20	7	22	41	46	100
23	45	10	14	40	45	53	97
24	55	5	12	20	42	104	159
25	65	35	5	36	43	35	200
26	65	20	10	37	45	95	190

In the process of solving the problem, the subjective preferences of decision makers are 0.1, 0.5, 1, and the additional cost coefficients are 1.5 and 5, respectively. The maximum capacity of vehicles is 150, the number of vehicles is 10, via is 0.3, vib is 1.3. The parameters of genetic algorithm are as follows: the number of fuzzy simulations is 50, the number of population is 30, and the number of iterations is 1000. The adjust genetic algorithm program is compiled with MATLAB R2014, and the results are as follows:

Table 2
Result 1

β		1.5	
a	a=0.1	a=0.5	a=1
Total cost	956.8	968.3	979.6
Fuzz cost	758	787	805
Actual cost	0	0	0
Time cost	198.8	181.3	174.6

To be continued

Continued

β	1.5		
a	a=0.1	a=0.5	a=1
route	7-5-26-25 15-18-17 20-6-8 14-3-16 23-22-4-10-2 19-11 24-13 9-21-12	22-26-25 14-17-16-15 3-23-24 18-6-7 8-9-20-12 2-4-5-19 13-21-11-10	26-25-5 18-9 14-3 20-12-8 10-21-11 16-15-7 22-23-24-29-6 4-17-2 13

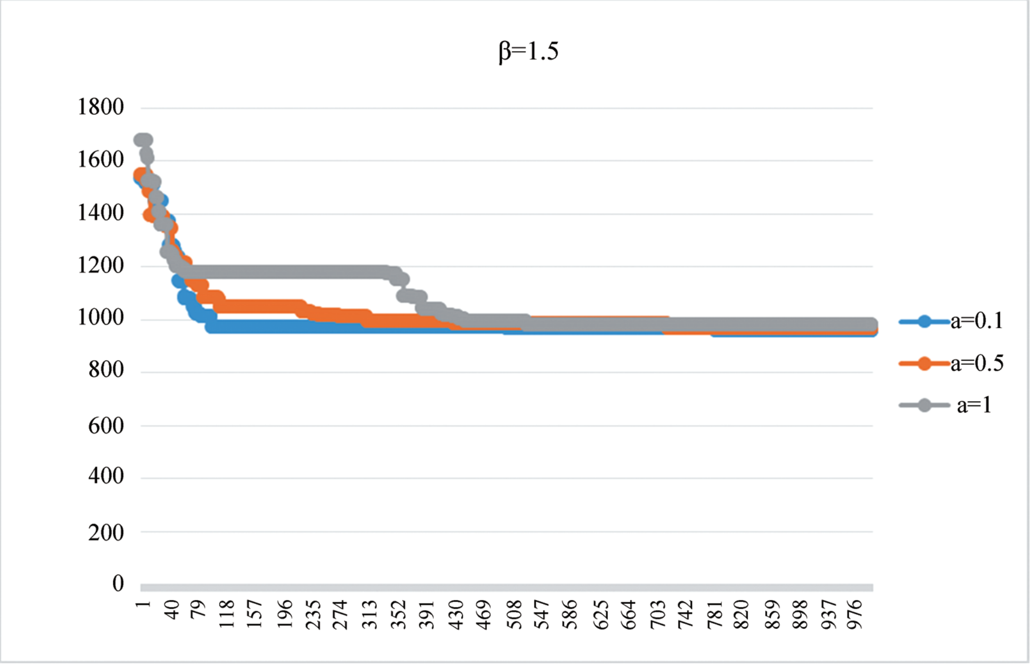

Figure 1
β=1.5

Table 3
Result 2

β	5		
a	a=0.1	a=0.5	a=1
Total cost	927.2	1004.2	1047.9
Fuzz cost	753	784	796
Actual cost	0	0.6	1.36
Time cost	174.2	217.2	245.1
route	9-19-8 16-23-24-26 12-10-25 17-6-15 14-22-3-7 5-13-4-11 18-20-2 21	23-22-25 15-9-11 21-20-12-10 16-19-18 4-13-2 3-6-24-26 8-14-19-5 7	7-19 22-26-24-5 14-9-20-11 21-2-10 15-16-6 8-18-25 23-3-17-13 12-4

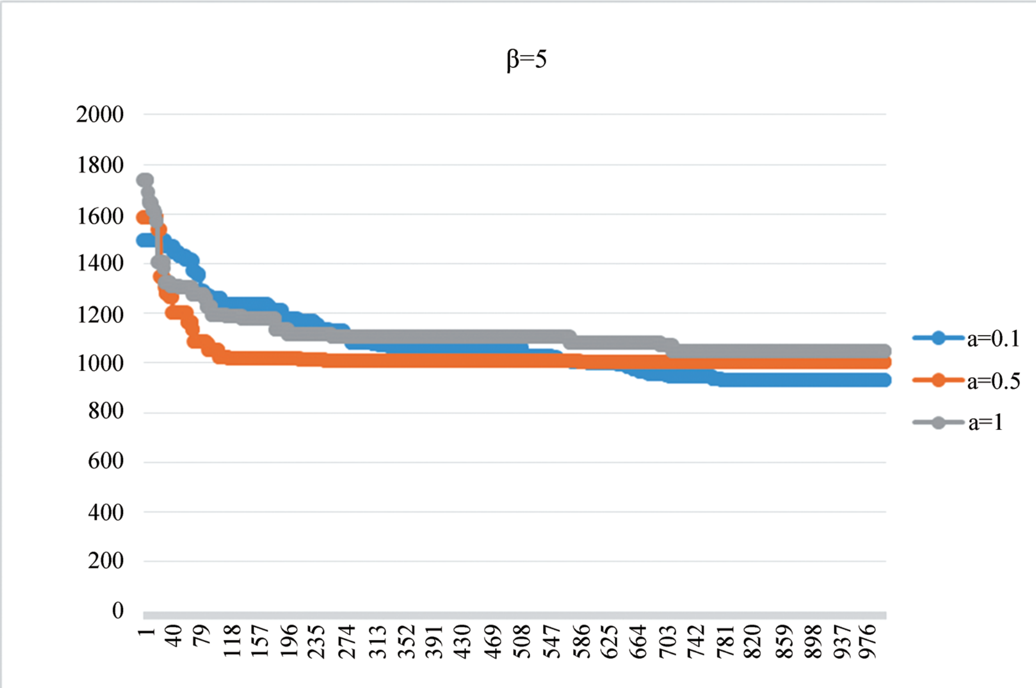

Figure 2
β=5

The results show that when the β is small, the main cost comes from the transportation cost of the route. When the β is high, the time cost increases rapidly. In order to offset the increase of time cost, the path with strong uncertainty and possible failure will be adopted, which will lead to the increase of the actual path cost.

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CONCLUSION

Based on the problems in reality, the traditional fuzzy vehicle routing problem is extended by adding soft time window and fuzzy demand, and the vehicle routing problem with soft time window model is established. A genetic algorithm based on stochastic simulation is proposed to solve the problem. Finally, the results of path planning are given through experimental data. This paper studies the vehicle routing problem with soft time window and fuzzy demand. More complex fuzzy vehicle scheduling problems may include open vehicle routing planning, multiple vehicle scheduling problems in transportation, and vehicle rescheduling strategies. Further research should start from these aspects to find heuristic or sub-heuristic algorithms to solve these problems.

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