Research Article

Optimizing Terminal Delivery of Perishable Products considering Customer Satisfaction

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Freshness of products and timeliness of delivery are two critical factors which have impact on customer satisfaction in terminal delivery of perishable products. This paper investigates how to make a cost-saving vehicle scheduling for perishable products by maximizing customer satisfaction. Customer satisfaction is defined from the two aspects of freshness and time window. Then we develop a priority function based on customer satisfaction and use the hierarchical clustering method to identify customer service priority. Based on the priority, a multiobjective vehicle scheduling optimization model for perishable products is formulated to maximize customer satisfaction and minimize total delivery costs. To solve the proposed model, a priority-based genetic algorithm (PB-GA) is designed. Numerical experiments and sensitivity analysis are performed to show the validity and advantage of our approach. Results indicate that PB-GA can achieve better solutions than traditional genetic algorithm. The improvement of customer satisfaction is higher than the decrease rate of total costs within a certain shelf life range, which reveals that the proposed method is applicable to the terminal delivery of perishable products.

1. Introduction

With the popularization of online shopping and the improvement of delivery service, more and more customers buy perishable products on Business-to-Customer (B2C) platforms. However, freshness of products and timeliness of delivery are two critical factors affecting customer satisfaction in B2C experience [1]. Thus, it is an important issue to make reasonable delivery plans for perishable products with the consideration of customer satisfaction in terminal delivery.

Perishable products, such as fruits, vegetables, and meat, have short delivery timespans. These products may start deteriorating from the moment they are produced and the freshness appears to be decreasing as transportation time elapses until spoilt [2, 3]. Freshness is one of the primary concerns when customers buy perishable products. However, in China, the damage rate of perishable products reaches up to 30%, much higher than the 5% in developed countries.

Especially for terminal delivery, it makes great influences on customer's overall satisfaction. Therefore, distributors require to take into account the freshness factor in terminal delivery planning. Moreover, timeliness is another important factor of customer satisfaction. If distributors are not able to deliver products on time, the customer satisfaction probably decreases.

Taking these two factors into consideration, it is a difficulty for logistics service providers to ensure freshness and timeliness during terminal delivery because perishable products need to be handled in a special way not the traditional cost-saving way. From the customer satisfaction view, we study a multiobjective vehicle scheduling problem for perishable products in terminal delivery.

To sum up, our contribution includes three aspects. (1) We define a customer priority function considering the freshness and time window to qualify customer satisfaction and use the hierarchical clustering method to classify customers

into different service priorities. (2) Taking customer service priority as one of constraints, we establish a multiobjective vehicle scheduling optimization model for perishable products. The objective functions consist of maximizing customer satisfaction and minimizing total costs. (3) Then we design a priority-based genetic algorithm for the proposed model, which could produce satisfactory terminal delivery plans.

The remainder of this paper is organized as follows. Section 2 presents a brief review on related studies. In Section 3, a mathematical model of multiobjective vehicle scheduling optimization for perishable products is formulated. To solve the model, a priority-based genetic algorithm is designed in Section 4. In Section 5, numerical experiments and sensitivity analysis are presented to show the validity and advantage of our work. The paper is concluded in Section 6.

2. Literature Review

Considering customer satisfaction in perishable products delivery has been continuously a concern in both academic research and industry application. In this review, we focus on two parts directly related to delivery problems for perishable products. Firstly, we look into what has been done in perishable products distribution with time windows and the definition of customer satisfaction. Secondly, some related studies on the multiobjective modelling for VRP are briefly reviewed.

2.1. VRPTW for Perishable Products and Definition of Customer Satisfaction. The well-known vehicle routing problem with time windows (VRPTW) has been discussed deeply in the literature. In recent years, many scholars have studied VRPTW for perishable products in various aspects. Osvald and Stirn [4] extended a heuristic algorithm for distributing fresh vegetables where perishability was set as a critical factor. The problem was formulated as a VRPTW with time-dependent travel time (VRPTWTD). Considering the randomness of perishable products in delivery process, Hsu et al. [5] extended the VRPTWTD model that the perishability cost was served as a stochastic manner. Chen et al. [6] focused on production scheduling and vehicle routing with time windows to maximize the expected total profit of supplier. Ahumada and Villalobos [7] and Yan et al. [8] followed a produce through all stages of production and distribution to build an integrated model for perishable products. Wang and Yu [9] took different delivery modes into consideration and established a perishable product delivery network to minimize the total costs. Coelho and Laporte [10] compared two suboptimal policies and computed optimal joint replenishment and delivery decisions for perishable products effectively. Firoozi et al. [11] developed an efficient network for storage and perishable products distribution. Ruan and Shi [12] formulated an Internet of Things-based framework for monitoring and assessing the freshness of in-transit fruits. These studies mainly belonged to traditional VRPTW, and most researches took the minimization of total costs as the optimization objective. They converted the damage rate of perishable products into corresponding damage cost and entrusted with different weights for each

cost. However, the weighting method has a certain degree of subjectivity. Moreover, perishable products have the characteristic of perishability and the spoilt products can decrease customer satisfaction tremendously. In this sense, the above studies only simply considered the economic perspective and ignored customer satisfaction for distributing perishable products.

Some researchers took customer satisfaction into consideration. Rong et al. [13] determined product deterioration by time and temperature. If the customer requirement was not satisfied, a penalty cost would be incurred for the spoilt food. Considering quality time window, Jia et al. [14] formulated a production-distribution-inventory model to control product quality and satisfy customer requirement. Amorim and Almada-Lobo [15] examined relationship between distribution scenarios and the cost-freshness trade-off. Cao et al. [16] introduced fuzzy appointment time to reflect customer preference time window and defined service start time of fuzzy membership functions as customer satisfaction. The above studies play an important role for the following research works, but the studies mainly describe customer satisfaction from the view of delivery timeliness. For perishable products, freshness is a key factor affecting customer satisfaction while these studies do not take into account the perishability.

2.2. Multiobjective Modelling for VRP. Multiobjective modelling for VRP is commonly used in fields of microcalamities management and emergency logistics, which take humanitarian factors into consideration [17–22]. With perishability concerned in this paper, we mainly concentrate on multiobjective VRP for perishable products. Amorim et al. [23] developed a novel model that decoupled the minimization of delivery costs from the maximization of the freshness state of delivered products. Atashbar and Baboli [24] designed a multiobjective routing problem for perishable items in a disaster relief. In this situation, the first objective was to maximize satisfaction and demands coverage, and the second objective was to minimize the total time needed to transfer perishable products. Bortolini et al. [25] constructed a multiobjective perishable distribution model considering distribution costs, delivery time, and carbon emissions. Rahimi et al. [26] applied social issue to perishable products delivery, aiming at minimizing distribution costs and maximizing social issue which was calculated by vehicle accident rate and number of expired products. Wang et al. [27] proposed an effective distribution route that minimized the total costs and maximized freshness state of delivered products. We noted that the above studies enhanced the traditional multiobjective models for VRP to make them more adaptable for perishable products delivery. However, these studies formulated multiobjective models from different perspectives which made objective functions different from each other. In this paper, our focus is mainly on maximizing customer satisfaction and minimizing total logistics costs.

According to the above analysis, we try to define customer satisfaction from the aspects of freshness and time window. Moreover, we combine customer satisfaction with terminal delivery which can make a reasonable vehicle scheduling for

perishable products. A multiobjective mathematical model and hybrid algorithm are proposed to solve the problem.

3. Problem Description and Formulation

3.1. Problem Description. The delivery processes of perishable products are as follows: customers buy perishable products on B2C platform and submit orders to suppliers. When vehicles start their travel from suppliers, the freshness is assumed to be perfect. During long-distance transportation to local distribution centers (LDCs), the freshness decreases based on freshness reduction rate of each product. In this paper, we deal with a vehicle routing problem from a LDC (depot) to customers for delivering perishable products.

A terminal delivery network is described by a graph $G(V, E)$, where V is the set of nodes and E is the set of arcs. In the network, the node set V consists of the set of customers N and the depot is denoted as 0, and the arc set E represents shortest distance routes among nodes in the network. The assumptions are as follows:

(1) Demand of each customer is less than the maximum capacity of vehicles.

(2) A type of perishable products is with the same shelf life.

(3) A type of vehicles is with the same capacity.

3.2. Definitions of Customer Satisfaction and Service Priority. As discussed in the Introduction, customer satisfaction mainly comes from the freshness and timeliness of delivered products. In this section, we define customer satisfaction from these two factors, respectively, and then convert it into customer service priority.

(1) Satisfaction on Freshness. In general, freshness of perishable products often decreases with the duration time of transportation. According to the existing studies, freshness of unit product purchased by customer i can be defined as $\theta_i = 2 - e^{(\ln 2/T)t_{0i}}$, where t_{0i} is the transportation time from depot to customer i and T is the shelf life of products [28]. Additionally, the more the customer demands are, the greater the loss will be for the same duration time. Therefore, we take the proportion of total demands into consideration, so the freshness satisfaction for customer i is defined as

$$\frac{\theta_i \cdot q_i}{\sum_{i \in N} q_i}, \tag{1}$$

where q_i is the demand of customer i and N is the number of customers.

(2) Satisfaction on Time Window. Delivery plans often route vehicles based on customer specific time window. But in many real-life cases, the deviation of time window does not directly incur any penalty cost, and it only has negative effect on satisfaction level [29]. Hence, we apply the fuzzy theory
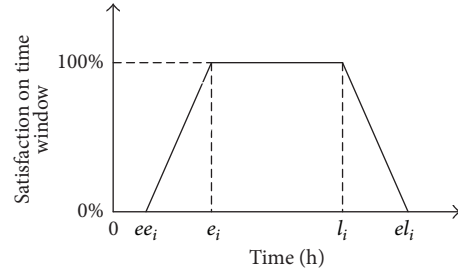

FIGURE 1: Satisfaction on time window.

to describe this reality. The satisfaction on time window for customer i is defined as

$$U(t_i) = \begin{cases} \dfrac{(t_i - ee_i)}{(e_i - ee_i)}, & t_i \in [ee_i, e_i) \\ 100\%, & t_i \in [e_i, l_i] \\ \dfrac{(el_i - t_i)}{(el_i - l_i)}, & t_i \in (l_i, el_i] \\ 0, & t_i \notin [ee_i, el_i], \end{cases} \tag{2}$$

where $[e_i, l_i]$ represents the expected arrival time interval for customer i during which the satisfaction level will be 100%. The lower bound ee_i represents the earliest arrival time that a customer can endure when a service starts earlier than e_i. Similarly, the upper bound el_i represents the latest arrival time that customer can endure when service starts later than l_i. When customer is served within $[ee_i, e_i]$ or $[l_i, el_i]$, the satisfaction level is with an ascending or a descending linear relationship with actual arrival time t_i, respectively. Otherwise, the satisfaction level will be 0. Figure 1 denotes the satisfaction on time window at different arrival times.

(3) Customer Satisfaction. Both freshness and time window have great influence on customer satisfaction. Based on the definitions in Formulas (1) and (2), the customer satisfaction can be expressed as

$$\frac{\alpha \sum_{i \in N} (\theta_i \cdot q_i)}{\sum_{i \in N} q_i} + \frac{\beta \sum_{i \in N} U(t_i)}{N}, \tag{3}$$

where α is freshness sensitivity coefficient, β is time window sensitivity coefficient, and $\alpha + \beta = 1$.

(4) Service Priority Based on Customer Satisfaction. The priority refers to the service order for each customer. Higher priority often needs earlier service. In this paper, we identify service priority based on the customer satisfaction on both freshness and time window. Under constraints of the number of vehicles and capacity limits, it is reasonable to prioritize the customers in order to maximize the freshness satisfaction and meet expected time window. Based on the above analysis

on customer satisfaction, we construct a priority evaluation function for customer i as follows:

$$P(i) = \alpha (1 - \theta_i) \frac{q_{\max} - q_i}{q_{\max}}$$
$$+ \beta \left(\frac{|t_{0i} - e_i|}{|l_i - e_i|} + \frac{|l_i - t_{0i}|}{|l_i - e_i|} \right), \quad (4)$$

where the freshness of perishable products for customer i is $\theta_i = 2 - e^{\ln 2((d_{oi}/v)/T)}$, $q_{\max}$ is the maximal demand of all customers, and t_{0i} is the travel time from depot to customer i.

The first item in Formula (4) reflects the freshness factor. Obviously, the smaller the distance d_{0i} and the bigger the demand q_i, the smaller the first item, that is, to provide high service priorities for the customers with closer distances to depot and larger demands. Similarly, the second item reflects the time window factor. When $t_{0i} \in [a_i, b_i]$, then $|t_{0i} - e_i|/|l_i - e_i| + |l_i - t_{0i}|/|l_i - e_i| = 1$; when $t_{0i} \notin [a_i, b_i]$, then $|t_{0i} - e_i|/|l_i - e_i| + |l_i - t_{0i}|/|l_i - e_i| > 1$, that is, to provide high service priorities for the customers who are more consistent with the expected time window. Thus, the smaller value of $P(i)$, the higher service priority for customer i.

Meanwhile, we deal with Formula (4) to eliminate dimension. Let $U_1(i)$ be the first item in Formula (4), and $U_1 \max$ is the maximum of $U_1(i)$. Similarly, let $U_2(i)$ be the second item, and $U_2 \max$ is the maximum of $U_2(i)$. Thus, standardized priority evaluation function for customer i is defined:

$$P'(i) = \alpha \frac{U_1(i) - U_1 \min}{U_1 \max - U_1 \min} + \beta \frac{U_2(i) - U_2 \min}{U_2 \max - U_2 \min}. \quad (5)$$

Formula (5) means that when $\alpha = 0$, $\beta \neq 0$, the evaluation function only considers the time window factor and does not take freshness into consideration. On the contrary, when $\alpha \neq 0$, $\beta = 0$, it only considers the freshness factor and ignores the time window. Similar to $P(i)$, the smaller the value of $P'(i)$, the higher the service priority for customer i. At the same time, all customers will be served from high priority to low.

(5) Hierarchical Clustering for Service Priority. According to the above analysis, we can calculate $P'(i)$ for each customer, but different values of $P'(i)$ refer to different priority levels. Moreover, too many levels may greatly limit the selection of delivery routes. Thus, it is better to assign customers with similar values of $P'(i)$ into the same priority level, which can also mean the same cluster. Hierarchical clustering [30] is a useful pattern recognition method for organizing items into groups or clusters. The degree of similarity is high between items in the same cluster and low in different clusters. Given a set of N items to be clustered, the basic procedures of the hierarchical clustering are as follows.

Step 1. Assign N items to N clusters. Each cluster contains just one item. Calculate the $N * N$ distance (or similarity) matrix.

Step 2. Merge the two clusters with the largest similarity into one single cluster. In this step, two clusters are reduced and one new cluster is created.

Step 3. Compute distances (or similarities) between the new cluster and each of the old clusters. Update distance matrix.

Step 4. Repeat Steps 2 and 3 until all items are clustered into a single cluster of size N.

Based on the hierarchical clustering, we can group customer service priorities into clusters. According to results of clustering, we redefine customer service priority as P_i for customer i (each value of P_i represents a cluster). More details are stated in Section 5.2.

3.3. Optimization Model. In this study, we deal with terminal delivery of perishable products considering customer satisfaction using a vehicle scheduling model. The parameters and variables are defined as follows.

Parameters

N: a set of customers, $N = \{n \mid n = 1, 2, \ldots, |N|\}$.

N^+: a set of depot and customers where $n = 0$ denotes the depot, $N^+ = \{n \mid n = 0, 1, \ldots, |N|\}$.

K: a set of vehicles, $K = \{k \mid k = 1, 2, \ldots, |K|\}$.

c_0: transportation cost per unit distance.

d_{ij}: distance between customers i and j, $i, j \in N^+$.

F_c: fixed vehicle cost per trip.

ST_i: service time for customer i (min).

Δt: long-distance travel time before arriving LDC (h).

Q: maximum capacity per vehicle (kg).

q_i: demand of customer i (kg).

v_0: average travel speed (km/h).

T: shelf life of perishable product (h).

Variables

θ_i: freshness of products for customer i, $i \in N$.

t_{ij}: travel time from customer i to j, $i, j \in N^+$.

t_i: arrival time of customer i, $t_0 = 0$ is the initial time.

$[a_i, b_i]$: delivery time window of customer i.

P_i: priority of customer i.

x_{ijk}: binary variable, $x_{ijk} = 1$ if vehicle k travels from customer i to j; otherwise $x_{ijk} = 0$.

On the basis of Section 3.2, we can determine the priority of each customer. Then a mathematical model of multi-objective vehicle scheduling optimization for perishable

products considering customer satisfaction can be given as follows:

Maximize $\quad$ LP1 $= \dfrac{\alpha \sum_{i \in N} (\theta_i \cdot q_i)}{\sum_{i \in N} q_i} + \dfrac{\beta \sum_{i \in N} U(t_i)}{N}$ $\quad$ (6)

Minimize $\quad$ LP2

$$= c_0 \sum_{i \in N^+} \sum_{j \in N^+} \sum_{k \in K} d_{ij} x_{ijk} + F_c \sum_{j \in N} \sum_{k \in K} x_{0jk} \quad (7)$$

Subject to: $\quad \displaystyle\sum_{j \in N} \sum_{k \in K} x_{0jk} \leq K$ $\quad$ (8)

$$\sum_{j \in N} x_{0jk} = \sum_{j \in N} x_{j0k} \leq 1, \quad \forall k \in K \quad (9)$$

$$\sum_{i \in N^+} \sum_{j \in N^+} x_{ijk} q_i \leq Q, \quad \forall k \in K \quad (10)$$

$$\sum_{i \in N^+} \sum_{k \in K} x_{ijk} = 1, \quad \forall j \in N \quad (11)$$

$$\sum_{i \in N^+} \sum_{k \in K} x_{jik} = 1, \quad \forall j \in N \quad (12)$$

$$\left(P_j - P_i\right) x_{ijk} \geq 0,$$
$$\forall i, j \in N^+, \ i \neq j, \ k \in K \quad (13)$$

$$\theta_i = 2 - e^{\ln 2((t_i + \Delta t)/T)}, \quad \forall i \in N^+ \quad (14)$$

$$t_j = \left(t_i + \frac{d_{ij}}{v_0} + \mathrm{ST}_i\right) x_{ijk},$$
$$\forall i, j \in N^+, \ k \in K \quad (15)$$

$$x_{ijk} \in \{0, 1\}, \quad i, j \in N^+, \ k \in K. \quad (16)$$

In this model we formulate two objective functions: objective (6) maximizes the average customer satisfaction from the freshness and time window. We note that the definition of $U(t_i)$ is the same as that in Formula (2). Objective (7) minimizes the total logistics cost which includes transportation cost and fixed cost. Constraint (8) ensures that number of used vehicles should not exceed the number of available vehicles. Constraint (9) guarantees that a vehicle leaves from the depot center and must return back after completing its delivery task. Constraint (10) limits each vehicle from being overweight on one route. Constraints (11) and (12) ensure each customer is served only once by one vehicle. Constraint (13) ensures each vehicle serves the customers on one route from high priority to low. Constraint (14) is freshness function of products for customer i. Constraint (15) expresses the arrival time for customer j. Constraint (16) indicates x_{ijk} is a binary decision variable, which equals 1 if vehicle k travels from customer i to j.

4. Priority-Based Genetic Algorithms

The customer data and service priority based on Section 3.2 are given as initial parameters. Then we propose a priority-based genetic algorithm (PB-GA), comparing to the traditional genetic algorithm (T-GA). There are somewhat differences between two algorithms. Feasible solutions for initial population are created by two strategies: "Priority Rule + Nearest Neighbor Rule" and "random generation." Then we transform constraints into fitness function and evaluate it based on sorting matrix; in addition, improved genetic operators are used to ensure customer service priority in crossover and mutation operations. The procedure of PB-GA is shown in Figure 2. The details will be stated below.

4.1. Encoding and Initial Population. We use sequence encoding with natural numbers $0 \sim n$ to express delivery routes, where $n = 0$ means the depot. Feasible solutions for initial population are created by two strategies: the first strategy is "Priority Rule + Nearest Neighbor Rule" with probability ρ, and the second one is random generation with probability $(1 - \rho)$. At first we define two rules.

Rule 1 (priority rule). In each subroute, delivery order of each vehicle is carried out by customer service priority from high to low.

Rule 2 (nearest neighbor rule). Select the nearest Euclidean distance from current node as the next delivery node.

On the basis of these two rules, the "Priority Rule + Nearest Neighbor Rule" strategy is explained in detail as in the following steps.

Step 1. Sort customer service priority P_i from high to low. If there is more than one customer with the same value of P_i, then sort them according to the ascending order in Euclidean distance from the LDC.

Step 2. Select the first customer point from sort order in Step 1; if this customer is not served by any vehicle, then set it as *Seed* which is the first service point for a vehicle and then move to Step 3. If all customers have been served, then move to Step 6.

Step 3. Select other customer points to generate the route. Pick the next unserved customer point based on Rules 1 and 2 and calculate total demands $\sum q_i$ in the subroute. If $\sum q_i \leq Q$, then combine it to form the subroute and move to Step 5; otherwise move to Step 4.

Step 4. Iterate Step 3, until the total amount of current subroute exceeds the maximum capacity of vehicle. Then move to Step 5.

Step 5. Stop the current subroute, and move back to Step 2.
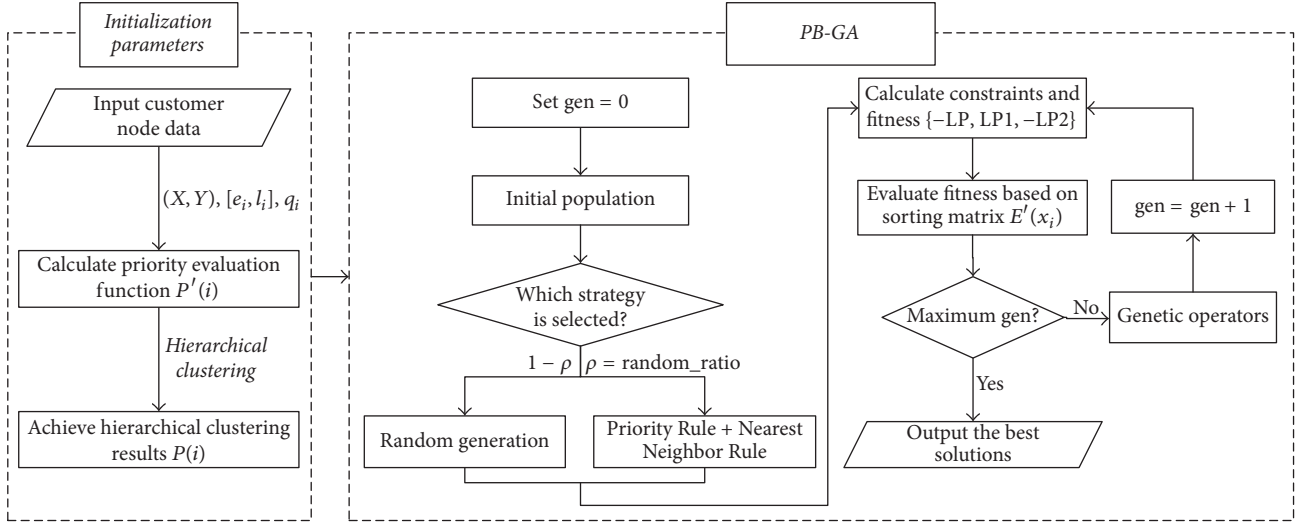
Step 6. Output vehicle routing results.

FIGURE 2: The procedure of PB-GA.

4.2. Genetic Operators

4.2.1. Selection Operator.
A roulette wheel selection mechanism will be used to select the prospective parents based on their fitness computed by the evaluation function. The probability of an individual being selected is positive proportional to fitness. That is, the probability of selected individual i is $p_i = F_i / \sum_{i \in N} F_i$, $i = 1, 2, \ldots, N$, where N is the population size and F_i is the fitness of individual i.

4.2.2. Crossover and Mutation Operators.
Classical Order Crossover (OX) can better retain neighbor relationship in chromosome. But it may also produce infeasible route sequence because of priority violation. Therefore, this paper employs a priority-based crossover. When the initial solution is generated by "Priority Rule + Nearest Neighbor Rule," crossover operator should not be applied to the *Seed* (the first delivery point of a subroute). Hence, it can reduce the change of order priority in a route. The mutation operator first selects randomly two break points in a chromosome and then makes an exchange of these two points. Also the mutation operator should not be applied to the *Seed*.

4.3. Constraints Handling and Fitness Function.
To meet the constraints of the number of vehicles, capacity of vehicle, and service priority, this paper converts these three constraints into a penalty term LP and adds it as a new objective function. The expression of LP is given by

$$\text{LP} = M_1 \max \left(\sum_{j \in N} \sum_{k \in K} x_{0jk} - K, 0 \right)$$

$$+ M_2 \max \left(\sum_{i,j \in N^+} \sum_{k \in K} x_{ijk} q_i - Q, 0 \right)$$

$$+ M_3 \max \left(\sum_{i,j \in N^+} \sum_{k \in K} \left(P_i - P_j \right) x_{ijk}, 0 \right), \tag{17}$$

where M_1, M_2, and M_3 (large positive numbers) represent penalty coefficients of the number of vehicles, capacity of vehicle, and service priority, respectively. Constraints handling and evaluation of fitness function are as follows.

Step 1. LP represents constraints of this model, so we set LP as the first goal. Subsequently, the other objectives are downgraded in turn. Thus, three objectives are reformed for each individual: max $-$LP, max LP1, and max $-$LP2. And we express the multiple objectives as $\text{Obj}_1 = -\text{LP}$, $\text{Obj}_2 = \text{LP1}$, and $\text{Obj}_3 = -\text{LP2}$.

Step 2. Calculate the Obj_1, Obj_2, and Obj_3 of all population chromosomes, and then rank them from small to large.

Step 3. After sorting chromosomes, the individual fitness of the three objectives is calculated and the overall fitness of each chromosome is calculated by sorting matrix [31].

$$E_j(i) = \begin{cases} \left(N - R_j(i) \right)^2 & R_j(i) > 1 \\ kN^2 & R_j(i) = 1 \end{cases} \tag{18}$$

$$E(i) = E_1(i) + E_2(i) + E_3(i),$$

where $R_j(i)$ is the ranking number of the jth objective function for chromosome i, and $j = 1, 2, 3$, $E_j(i)$ is the fitness value of chromosome i in objective j, $E(i)$ is the overall fitness of chromosome i, N is the population size, and $k \in (1, 2)$ is a constant to increase the fitness value for the optimal individual.
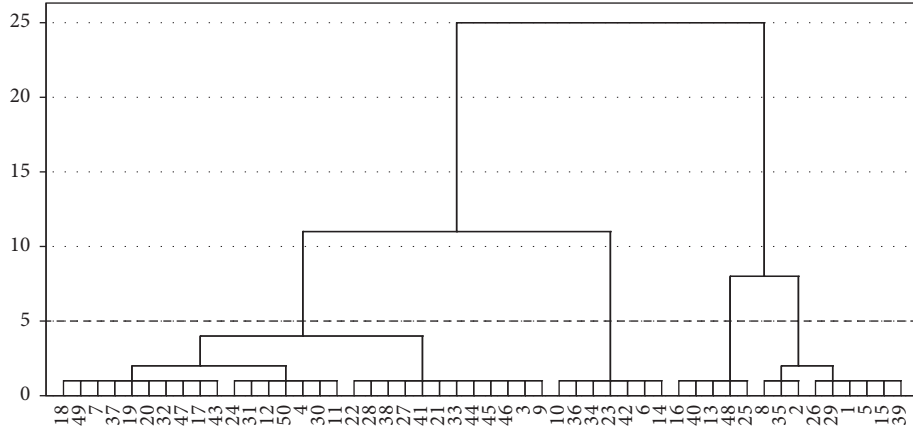
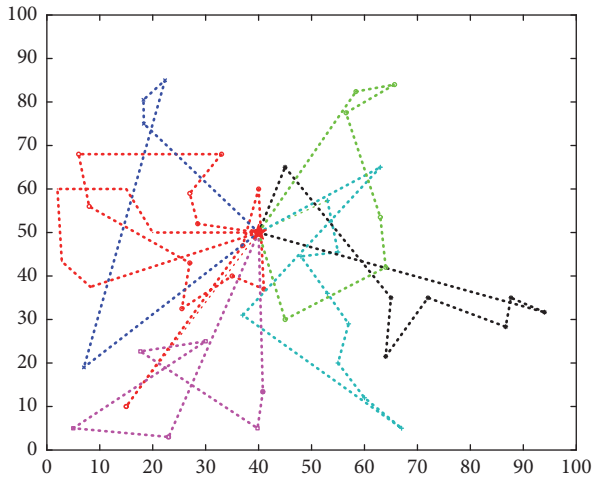FIGURE 3: Results of the hierarchical clustering.

FIGURE 4: Optimal vehicle routes results by PB-GA.

5. Numerical Experiments

In order to validate the mathematical model and heuristic algorithm, numerical experiments are designed with a randomly generated 50-point example. Afterwards, the computational results are shown and the proposed method is compared. Furthermore, sensitivity analysis of the shelf life of perishable products is presented to explore the applicability of this paper.

5.1. Data Description. Fifty customer nodes are randomly generated on the two-dimensional plane with a range between (0 km, 0 km) and (100 km, 100 km). The depot is located at (40 km, 50 km). For simplicity, we set the lower and upper bound of fuzzy time window $ee_i = 0$, $el_i = 10$, and service time $ST_i = 5$ min. More detailed customer data are shown in Table 1, such as (X, Y), expected arrival time window $[e_i, l_i]$, and customer demand q_i. Another parameter setting is shown in Table 2.

5.2. Results of Hierarchical Clustering for Customer Service Priority. In this section, we use the hierarchical clustering method to divide 50 customer priorities into several groups. Figure 3 shows the clustering results. Noticeably, when the reference value equals 5, all 50 customers are divided into four clusters.

In terms of clustering results, we can calculate average priority value for each cluster (AVG $P'(i)$) in Table 3. As we illustrate in Section 3.2, a small value of $P'(i)$ corresponds to a high service priority for customer i. Therefore if a cluster has a small value of average priority, it comes to a high service priority for this cluster. As average priority value of cluster 1 is smallest among the other clusters, which present the highest priority, we set it as $P_i = 1$. By that analogy, four other clusters are assigned to four different service priority levels. The service priority level for customer i can be expressed as $P_i = \{1, 2, 3, 4\}$, where $P_i = 1$ represents the highest priority and $P_i = 4$ represents the lowest one. In this way, customers will be served from high to low priority.

5.3. Experimental Results of Vehicle Scheduling. Numerical experiments are implemented with MATLAB R2011b. We set GA parameters as follows: population size $N = 200$, crossover rate $P_c = 0.8$, mutation rate $P_m = 0.01$, and maximum iterations gen = 500. Ten times of experiments by PB-GA and T-GA are carried out, respectively. The optimal vehicle routes for each algorithm are as follows.

(1) Optimal Vehicle Routes by PB-GA. Table 4 and Figure 4 show the optimal vehicle schedule by PB-GA. The result indicates that the delivery plans by PB-GA are directly affected by the priority constraint; namely, the service sequence order established in each subroute is from high priority to low. In this situation, the number of vehicles is 7, customer satisfaction LP1 is 80.12%, and the total cost LP2 is 1294.26.

(2) Optimal Vehicle Routes by T-GA. Table 5 and Figure 5 describe the optimal vehicle schedule by T-GA where the number of vehicles is the same with that by PB-GA, but customers are not served as priority order. In this case, due

TABLE 1: Details of customer node data with 50 customers.

Customer	(X, Y)	$[e_i, l_i]$/h	q_i/kg
0	(40, 50)	[0, 10]	0
1	(22, 85)	[0, 1.2]	50
2	(18, 75)	[0, 1.3]	70
3	(26, 33)	[0, 1.4]	18
4	(45, 65)	[1.1, 1.6]	9
5	(18, 23)	[0, 2]	49
6	(41, 37)	[2.2, 2.7]	16
7	(5, 5)	[1.2, 1.7]	16
8	(18, 81)	[0, 1.1]	70
9	(60, 12)	[1.3, 1.8]	31
10	(20, 50)	[1.5, 2]	5
11	(67, 5)	[2.4, 2.9]	25
12	(64, 42)	[1.2, 1.7]	9
13	(8, 38)	[0, 1.5]	100
14	(23, 3)	[2.5, 3]	7
15	(53, 57)	[0, 1.93]	52
16	(3, 43)	[0, 1.1]	100
17	(8, 56)	[1.5, 2]	8
18	(64, 22)	[0, 1.2]	8
19	(37, 31)	[0.6, 1.1]	14
20	(6, 68)	[1.5, 2]	30
21	(53, 36)	[0, 1.1]	25
22	(55, 46)	[0, 0.7]	37
23	(40, 60)	[2.4, 2.9]	21
24	(2, 60)	[1.3, 1.8]	5
25	(40, 5)	[0, 1.6]	90
26	(94, 32)	[0, 1.5]	60
27	(48, 45)	[0, 3.3]	26
28	(29, 52)	[0, 1.2]	36
29	(88, 35)	[0, 1.5]	60
30	(57, 29)	[1.6, 2.1]	18
31	(30, 25)	[1.6, 2.1]	23
32	(55, 20)	[1.4, 19]	19
33	(87, 28)	[0, 1.4]	30
34	(37, 47)	[1.4, 1.9]	6
35	(66, 84)	[0, 1.2]	70
36	(15, 10)	[2.5, 3]	20
37	(63, 65)	[0.5, 1]	8
38	(27, 59)	[0, 1.6]	35
39	(7, 19)	[0, 1.2]	54
40	(58, 82)	[0, 1.1]	100
41	(57, 78)	[0, 1.1]	30
42	(15, 60)	[2.6, 3.1]	17
43	(27, 43)	[0.7, 1.2]	9
44	(33, 68)	[0, 3.5]	26
45	(63, 54)	[0, 1.6]	17
46	(35, 40)	[0.2, 0.7]	16
47	(65, 35)	[0.9, 1.4]	3
48	(41, 13)	[0, 1.7]	110

TABLE 1: Continued.

Customer	(X, Y)	$[e_i, l_i]$/h	q_i/kg
49	(45, 30)	[0.9, 1.4]	17
50	(72, 35)	[1.9, 2.4]	30

TABLE 2: Parameter setting of experiments.

Parameter	Value
Transport cost per unit distance (¥/km)	$c_0 = 0.5$
Fixed vehicle cost per trip (¥)	$F_c = 100$
Service time for customer i (min)	$ST_i = 5$
Long-distance travel time before arriving LDC (h)	$\Delta t = 12$
Maximum capacity per vehicle (kg)	$Q = 300$
Average travel speed (km/h)	$v_0 = 40$
Shelf life for perishable product (h)	$T = 40$

to the loose of priority constraint, the customer satisfaction LP1 is 74.96% which is lower than that by PG-GA and the total cost LP2 drops to 1272.57.

5.4. Experimental Results Analysis

5.4.1. Results Analysis 1: Comparison of Optimal Results. This paper conducts a further comparison of optimal gaps in subgoal LP1 (customer satisfaction) and subgoal LP2 (the total costs) between two algorithms. Components of each subgoal are shown in Table 6.

(1) Compared with T-GA, the optimal gap of PB-GA in subgoal LP1 is 6.89%. In particular, the degrees of satisfaction with freshness and time window are effective, with the improvement of 3.29% and 12.27%, respectively. Thus, it reveals that PB-GA can promote the freshness of perishable products as well as achieve better solutions to satisfy the expected arrival time for customers.

(2) In terms of subgoal LP2, PB-GA has higher total costs than T-GA. However, with an overall perspective of two subobjectives, PB-GA only costs 1.7% more and gets 6.89% improvement rate in customer satisfaction with the same number of vehicles. Obviously, this increased cost is acceptable for logistics service providers, whereas the customer satisfaction can be enhanced significantly in comparison with T-GA. Thus, PB-GA tends to achieve better solutions for terminal delivery of perishable products.

5.4.2. Results Analysis 2: Sensitivity Analysis of Shelf Life for Perishable Products. It is worth noting that perishable products are characterized as time-sensitive items. Their shelf life has a great influence on perishable products' quality and freshness. In this section, we make a sensitivity analysis of shelf life to explore two algorithms' effects on customer satisfaction and the total costs.

It is observed from Figure 6 that as shelf life of products becomes longer, both of the algorithms have stronger effect. That is because a longer shelf life will keep perishable products with higher quality of freshness; moreover, it can increase customer satisfaction. Additionally, it is evident from this figure that PB-GA gets better solutions in customer

TABLE 3: Service priority for customer nodes.

Cluster	Customer nodes	Average priority value for each cluster (AVG $P'(i)$)
1	{13, 16, 25, 40, 48}	0.060
2	{1, 2, 5, 8, 15, 26, 29, 35, 39}	0.288
3	{3, 7, 9, 11, 12, 17, 18, 19, 20, 21, 22, 24, 27, 28, 30, 31, 32, 33, 37, 38, 41, 43, 44, 45, 46, 47, 49, 50}	0.550
4	{6, 10, 14, 23, 34, 36, 42}	0.827

TABLE 4: Optimal vehicle schedule by PB-GA.

Vehicle schedule	Priority	Customer satisfaction LP1/%		Total costs LP2/¥	
		Freshness	Time window	Transport cost	Fixed cost
0-28-38-44-20-17-43-3-46-6-23-34-36-0	2-2-2-2-2-2-2-2-1-1-1-1	71.88	79.79	123.92	100.00
0-15-22-27-21-30-32-9-11-19-37-0	3-2-2-2-2-2-2-2-2-2	73.48	95.75	95.21	100.00
0-2-8-1-39-0	3-3-3-3	73.68	98.09	78.85	100.00
0-26-29-33-50-18-47-4-0	3-3-2-2-2-2-2	72.65	89.57	84.07	100.00
0-48-25-5-31-7-14-0	4-4-3-2-2-1	73.64	86.46	93.02	100.00
0-40-35-41-45-12-49-0	4-3-2-2-2-2	73.83	95.75	67.72	100.00
0-13-16-24-42-10-0	4-4-2-1-1	74.47	88.95	51.48	100.00
Number of vehicles = 7		LP1 = 80.12%		LP2 = 1294.26	

TABLE 5: Optimal vehicle schedule by T-GA.

Vehicle schedule	Priority	Customer satisfaction LP1/%		Total costs LP2/¥	
		Freshness	Time window	Transport cost	Fixed cost
0-43-31-39-24-20-12-47-50-26-33-18-9-37-0	1-2-3-1-2-1-1-2-3-2-1-2-1	67.14	64.45	164.75	100.00
0-3-36-7-14-11-32-6-46-38-2-44-41-0	2-2-2-1-2-2-2-2-2-4-2-2	66.58	67.55	140.66	1050.00
0-27-22-21-49-30-29-45-35-4-23-0	2-2-2-2-2-3-2-3-1-2	71.50	85.76	93.19	100.00
0-19-48-25-5-34-0	2-4-4-3-1	74.02	88.78	54.67	100.00
0-13-16-17-42-10-0	4-4-2-2-1	74.43	91.86	47.50	100.00
0-8-1-40-15-0	3-4-4-3	72.97	93.84	60.13	100.00
0-28-0	2	76.26	60.21	11.67	100.00
Number of vehicles = 7		LP1 = 74.96%		LP2 = 1272.57	

TABLE 6: Comparison of the optimal results.

	Number of vehicles	LP1/% Customer satisfaction	Satisfaction		LP2/¥ Total costs	Transport cost
			Freshness	Time window		
PB-GA	7	80.12%	73.38%	90.24%	1294.26	594.26
T-GA	7	74.96%	71.04%	80.38%	1272.57	572.57
Gap	0%	6.89%	3.29%	12.27%	−1.70%	−3.79%

satisfaction than T-GA within the shelf life interval of 20–55 h. That is because customer service priority is set based on subgoal LP1, and PB-GA will make every effort to improve customer satisfaction. We can figure out that it is effective to solve the delivery problem of perishable products by PB-GA.

Figure 7 illustrates that the total cost by PB-GA is higher than that by T-GA. That is because PB-GA will have a concern about the priority of customer to guarantee the satisfaction, so it will make the cost a little more than T-GA. However, the two total costs are close.

Compared with T-GA, Table 7 shows the optimal gaps of subgoals LP1 and LP2 by PB-GA under different shelf lives. It shows that, between 20 and 40 h, the optimal gap of satisfaction increases remarkably which is higher than the dropped cost gap. However, between 45 and 55 h, the increased cost gap is higher than the improvement of customer satisfaction. That is because when shelf life turns to be quite long, it no longer has the feature of perishability. Under these circumstances, PB-GA does not fit the normal products with long shelf life and T-GA is better. But in this paper,
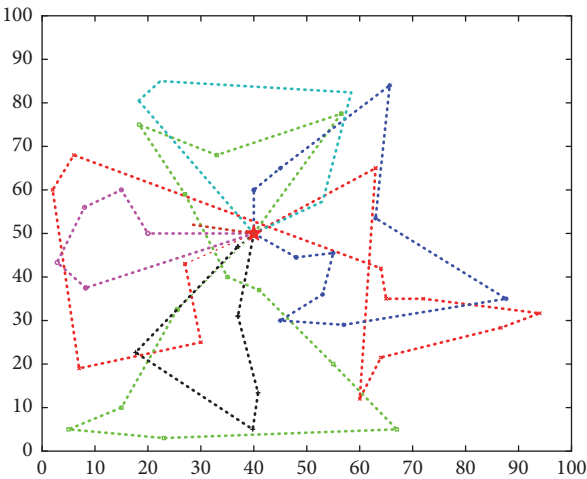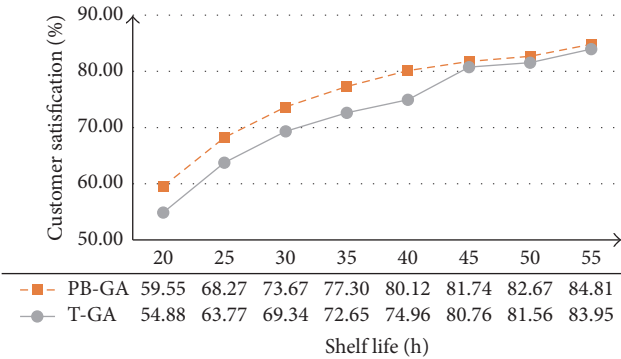
Figure 5: Optimal vehicle routes results by T-GA.

	20	25	30	35	40	45	50	55
PB-GA	59.55	68.27	73.67	77.30	80.12	81.74	82.67	84.81
T-GA	54.88	63.77	69.34	72.65	74.96	80.76	81.56	83.95

Shelf life (h)

Figure 6: Results comparison of subgoal LP1.

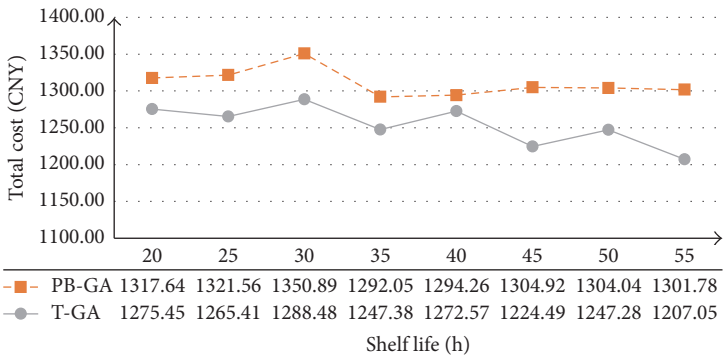|	20	25	30	35	40	45	50	55
PB-GA	1317.64	1321.56	1350.89	1292.05	1294.26	1304.92	1304.04	1301.78
T-GA	1275.45	1265.41	1288.48	1247.38	1272.57	1224.49	1247.28	1207.05

Shelf life (h)

Figure 7: Results comparison of subgoal LP2.

Table 7: Optimal gaps of LP1 and LP2 by PB-GA.

Shelf life/h	20	25	30	35	40	45	50	55
Optimal gap/%								
LP1	8.51	7.06	6.24	6.40	6.88	1.23	1.36	1.02
LP2	−3.31	−4.41	−4.84	−3.58	−1.70	−6.57	−4.55	−7.85

what we focus on are perishable products and the proposed algorithm still has a better effect on products within 45 h shelf life. So the applicability of PB-GA mainly focuses on perishable products with short shelf life.

6. Conclusions

This paper considers customer satisfaction in terminal delivery in order to deal with vehicle scheduling problem for perishable products. The main contributions of this paper include the following. (1) We qualify customer satisfaction from aspects of product freshness and time window. Based on priority evaluation function, we identify service priority for each customer as the service order in vehicle scheduling. (2) We construct a multiobjective vehicle scheduling optimization model for perishable products considering customer satisfaction. A priority-based genetic algorithm is designed to solve the problem. (3) Numerical experiments illustrate effectiveness of the proposed method which has improvements for customer satisfaction within a certain shelf life range. The sensitivity analysis reveals the adaptability in solving perishable products terminal delivery problem.

It is worth noting that some places need to be improved; for example, we did not consider multiple depots, multiple vehicle types, or multiple types of perishable products; however, these cases commonly exist in fresh products B2C e-commerce environment. We will conduct further studies considering the above problems.

Competing Interests

The authors declare that they have no competing interests.

Acknowledgments

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