ISSN: 2688-9323

Vehicle Path Optimization Study Considering the Potential Value of Customers

Yuyuan Yi[1], Weibin Deng[1,*], and Yiming Zhang[2]

[1] Chongqing Smart Posts Engineering Technology Research Center, Chongqing University of Posts and Telecommunications, Chongqing, China

[2] 78111 troops, People's Liberation Army of China, Chengdu, China

*Corresponding Author Email: dengwb@cqupt.edu.cn

Abstract

With the continuous expansion of China's pharmaceutical market, the distribution model led by third-party logistics enterprises has emerged, and its distribution cost occupies an important position in the cost of pharmaceutical supply chain. Due to the diversified needs of different customers for the timeliness and service quality of logistics and distribution, it is difficult to realize the efficient utilization of resources by simply relying on the current value of customers, and it is also necessary to take into account the potential value of customers. On the basis of previous research on customer value in the vehicle path optimization problem, it is found that if enterprises prioritize the needs of high-value customers and deliver medicines within their optimal time window, they can improve the repurchasing power of customers and the spreading power to potential customers. Accordingly, a pharmaceutical logistics path optimization Model 1s constructed with the objectives of minimizing transportation costs and maximizing service impact, taking into account the potential value of customers.P Experiments on actual operational data of pharmaceutical logistics enterprises show that service impact is increased by about 5% under this model, vehicle delivery time is reduced by about 13%, the number of customers delivered within the optimal service time is increased by 14%, and the number of customers delivered within the acceptable service time The number of customers delivered within the window increased by 4%.

Keywords

Customer Potential Value; Vehicle Path Optimization; Genetic Algorithm; Pharmaceutical Logistics.

1. Introduction

With the aggravation of social aging trend and people's increasing health awareness, China's pharmaceutical market has shown continuous growth, and is firmly ranked as the world's second largest drug consumption market. According to the data of China Business Industry Research Institute (CBIRI), from 2012 to 2023, the sales scale of China's top 100 pharmacy chains increased from 43.9 billion yuan to 297.6 billion yuan, and the number of pharmacies climbed from 424,000 to 655,000, which has realized a relatively fast growth. This trend is further supported by statistics from Zhongkang CMH, which shows that the pharmaceutical sales scale of China's pharmaceutical retail market has reached 501.5 billion yuan in 2023, a year-on-year growth of 3.3%.

Pharmaceutical logistics companies are logistics companies focusing on the pharmaceutical industry, and their core business is to integrate multiple aspects of pharmaceutical sales, storage and transportation to achieve efficient, safe and reliable circulation of pharmaceutical products to downstream pharmaceutical retail customers, and to provide strong logistics

ISSN: 2688-9323

protection for the entire pharmaceutical industry. Among them, downstream pharmaceutical retail customers (referred to as pharmaceutical customers) include pharmacies, large public hospitals, community hospitals, rural health offices and individual clinics. For pharmaceutical logistics enterprises, scientific and reasonable selection of distribution center location and optimization of vehicle distribution path is the key to improve the efficiency of the entire pharmaceutical distribution network. According to the "two-eight principle" of customer value, the profits of enterprises are often generated by 20% of high-value customers, so when optimizing the vehicle path, we should also give priority to the needs of high-value customers, and deliver medicines within the optimal window of time, thus improving the impact of the service.

In pharmaceutical logistics, Campelo et al [1] used a decomposition strategy based on mathematical planning to solve a complex consistent vehicle path problem.Singh et al [2] constructed an optimization model combining the FAHP and FTOPSIS methods to achieve efficient delivery of perishable products.Wen et al [3] proposed an optimization Model 1n a probabilistic linguistic setting integrating the SWARA and the CoCoSo method in a probabilistic language environment to comprehensively evaluate and effectively select pharmaceutical logistics providers from multiple dimensions.Lin et al [4] constructed a distributor vaccine transportation decision-making model, and deeply explored the influence mechanism of retailer inspection policy on distributor's decision-making.Yuan and Gao [5] constructed a multicenter location and routing optimization for pharmaceutical distribution companies in a dynamic uncertain environment. Model.

In vehicle path optimization, Goel et al [6] constructed a vehicle path optimization model that simultaneously satisfies minimizing transportation cost and maximizing customer satisfaction.Marinelli et al [7] proposed a two-stage capacity-constrained vehicle path problem incorporating environmental factors.Vakil et al [8] investigated the inventory - - path problem for a dispersed pharmaceutical retailer to minimize transportation costs and maximize customer satisfaction. -path problem with the objective of minimizing the sum of transportation and inventory costs and constructs a mixed integer linear programming model.Kramer et al [9] constructs a pharmaceutical distribution model that minimizes the distribution cost and solves the path optimization problem under multiple distribution centers and dynamic time window conditions.Janga et al [10] consider road transportation to construct a pharmaceutical distribution optimization model for temperature specific storage. distribution optimization model.Gutiérrez-Sánchez and Rocha-Medina [11] provided a systematic classification and review of vehicle routing problems with time-window constraints, routing planning problems with both pickup and delivery functions, and periodic vehicle routing problems with periodic execution.Mahmood [12] provided an in-depth exploration of the accommodated vehicle routing problem (CVRP), focusing on the performance of the Sweep clustering algorithm and the Meerkat family algorithm.

In terms of customer value, Verhoef and Donkers [13] argued that customer value consists of the benefits that a customer currently creates for the firm and the benefits that the customer may bring to the firm in the future.Kotler [14] argued that the essence of CRM lies in the establishment of a strong and lasting relationship with the firm's most valuable customers.Hunt and Arnett [15] explicitly pointed out that customer value management has become the core of customer relationship management.Lamrhari et al. [16] constructed a comprehensive social customer relationship management (CRM) analytical framework that integrates multiple advanced analytical methods, aiming to effectively improve customer retention, promote new customer acquisition, and accelerate the conversion of potential customers.Liu and Chen [17] optimized and upgraded the traditional RFM model, integrating redundancy, frequency, and conversion of potential customers. considering redundancy, frequency and maintenance value.

ISSN: 2688-9323

When exploring the issue of pharmaceutical customer value, the current academic focus is mainly on the perspective of third-party pharmaceutical logistics enterprises, which are committed to constructing and optimizing their own distribution centers. On this basis, scholars have further constructed the evaluation index system of third-party pharmaceutical logistics service providers, with a view to improving service quality and efficiency. However, this research orientation often ignores the real needs and expectations of downstream retailer customers, which to some extent limits the improvement of pharmaceutical logistics service level. In addition, although some scholars have constructed prediction models to estimate the future economic value of customers based on their past purchasing behaviors, these studies have mainly focused on the manufacturing industry, banking industry and other fields, and the research on the potential value of customers in the pharmaceutical logistics industry is still insufficient and needs to be explored further.

2. Path Optimization Model Construction

2.1. Description of the Problem

In a particular clustered area, there exists a pharmaceutical logistics distribution center with a number of transport vehicles available for dispatch, whose main task is to provide pharmaceutical delivery services to multiple pharmaceutical customers, each of which has a well-defined location and pharmaceutical demand. It is important to note that each customer has a specific service time window constraint covering acceptable and optimal service time ranges. During the delivery process, the principle is to ensure that each customer is only served by a single vehicle for a single visit and that the transport vehicle is returned to the distribution center after all deliveries have been completed. The goal is to minimize the transportation cost and maximize the service impact by optimizing the travel path of the transportation vehicles and the service sequence of the customers, while observing the above constraints.

The article focuses on the following two core objectives:

(1) Minimization of transportation costs. Transportation costs mainly include fixed costs due to vehicle activation and variable costs that increase with distance traveled. This objective aims to reduce distribution costs by optimizing routes and improving transportation efficiency.

(2) Maximization of service impact. Service impact emphasizes the deepening of customer repurchase power and positive spread. Priority is given to meeting the distribution needs of large-value customers and ensuring that goods are delivered within their optimal time window in order to maximize service impact.

2.2. Model Building

2.2.1. Model Assumption

In order to reduce the computational complexity and highlight the research focus on the potential value of customers and service impact, the following assumptions are made for the study of the pharmaceutical logistics path optimization model aiming at minimizing transportation cost and maximizing service impact:

(1) The geographic locations of distribution centers and customer points have been determined by the coordinate system;

(2) Customer demand has been confirmed before the start of the distribution cycle and there are no temporary changes;

(3) All distribution vehicles travel at a uniform standard speed and the unit cost of travel remains consistent;

(4) The earliest departure time for distribution vehicles is set at 7:00 a.m;

ISSN: 2688-9323

(5) The total amount of inventory in the distribution center is sufficient to meet the sum of demand at all customer locations;

(6) During transportation, the impact of uncontrollable factors such as vehicle breakdowns, road congestion, or weather changes on distribution timelines and costs is not considered;

(7) If the delivery vehicle completes the service within the optimal time window specified by the customer will result in 100% customer satisfaction;

(8) Only if customers achieve 100 percent satisfaction will they publicize the business with a certain probability; otherwise, customers will not publicize.

2.2.2. Description of Symbols

Based on the mathematical description of the pharmaceutical customer logistics path distribution optimization problem, the relevant variables in the study are defined as shown in Table 1.

Table 1. Variable definition

Variant	Define	Variant	Define
N	Total number of pharmaceutical logistics customers	b_i	Unit profit
i, j	Customer Number	θ_1	Penalty factor
k	Vehicle number	θ_2	Penalty factor
Q_s	Distribution Center Maximum Capacity	η_i	Satisfaction
Q_k	Maximum vehicle weight	$p'(i)$	Relative factor for number of purchases
v	Vehicle speed	Z_1	Fixed dispatch costs
C_0	Unit fixed dispatch costs	Z_2	Traveling costs
C_1	Unit traveling Costs	Z_3	Penalty costs
C_{ij}	Distance from client i to client j	R_i	Number of clients
x_{0j}^k	Decision variables	r_i	Potential value
x_{ij}^k	Decision variables	ρ_i	Customer acceptance rate
$[E_i, L_i]$	Optimal time window	2	Effective advocacy efforts
$[EE_i, LL_i]$	Acceptable time window	CV_i	Customer repurchase power
t_{ij}	travel time	BV_i	Customer evangelism
s_i	Arrival time	PV_i	Service Impact
w_i	Service time	H	Larger positive numbers
q_i	Quantity demanded	ε	Sensitivity factor

2.3. Related Function

2.3.1. Transportation Cost Function

In evaluating vehicle transportation costs, two key factors were considered. The first is the fixed cost of dispatching a vehicle, which includes the driver's salary, routine maintenance of the vehicle and some other related costs.

$$Z_1 = \sum_{k=1}^{K} \sum_{j=1}^{N} c_0 x_{0j}^k \tag{1}$$

where c0 denotes the fixed departure cost per unit of vehicle; x_{0j}^{k} means that it is 1 if vehicle k drives from the distribution center to customer j and 0 otherwise.

The second is the driving cost during the distribution process; this cost is based on the product of the number of miles driven by the transportation vehicle and the unit cost per kilometer.

$$Z_2 = \sum_{i=0}^{N}\sum_{j=0}^{N}\sum_{k=1}^{K} c_1 c_{ij} x_{ij}^{k} \tag{2}$$

where c1 denotes the cost per unit distance traveled by the delivery vehicle; cij denotes the distance from customer i to customer j; and x_{ij}^{k} indicates that it is 1 if vehicle k is traveling from customer i to customer j, and 0 otherwise.

2.3.2. Penalty Cost Function

The penalty cost function is determined by the potential value of customers and customer satisfaction. In order to ensure long-term relationships with high-value customers and reduce the potential risk of loss, pharmaceutical logistics companies need to prioritize the needs of this group of customers when delivering, i.e., delivering within their optimal service time window.

[Ei, Li] is the optimal time window in which customers expect to be served; while [EEi, LLi] is the acceptable time window for customers. If the transportation vehicle arrives at the customer at a time other than [EEi, LLi], the penalty cost is set to a larger number; if the transportation vehicle arrives within the customer's optimal time window [Ei, Li], no penalty cost will be incurred; and if the vehicle arrives within the acceptable time window [EEi, LLi] in addition to the optimal time window, a penalty cost will be incurred, and the specific penalty value is computed with the The calculation of the penalty value is related to the time difference between the actual arrival time and the optimal time window, and also related to the potential value of the customer, for the higher potential value of the customer, the greater the penalty cost for overtime or late arrival.

Based on the above, the penalty cost function Pi(si) is defined to describe the penalty cost at different arrival times.

$$P_i(s_i) = \begin{cases} H & s_i < EE_i, s_i > LL_i \\ r_i\theta_1(E_i - s_i) & EE_i < s_i < E_i \\ 0 & E_i \le s_i \le L_i \\ r_i\theta_2(s_i - L_i) & L_i < s_i < LL_i \end{cases} \tag{3}$$

where H is a more positive number that constrains the vehicle to deliver the medicine as close as possible to the customer's acceptable service time window. ri is the potential value of the customer, and the cost of the vehicle to deliver early or overtime is positively related to the potential value of the customer, since a customer with a high potential value suffers more from the firm's inability to deliver on time. θ_1 and θ_2 are the penalty cost coefficients for early and overtime delivery, respectively. Therefore, the penalty cost is:

$$Z_3 = \sum_{i=1}^{N} P_i(s_i) \tag{4}$$

ISSN: 2688-9323

2.3.3. Service Impact Function

Service influence includes repurchase power and diffusion power. Among them, repurchase power is the customer's prediction of it's subsequent purchasing behavior based on this service satisfaction, i.e., only delivery within the customer's optimal service time window [Ei, Li] can ensure the customer's satisfaction and consideration of repurchase. The customer repurchase force CVi is calculated as:

$$CV_i = \eta_i p^{'}(i) q_i b \tag{5}$$

where η_i is customer i 's satisfaction with this purchase service, and this indicator is mainly related to the delivery time of the medicine. If the medicine is delivered within the optimal service time window expected by the customer, then η_i =1, otherwise η_i =0. In addition, the relative coefficient of the number of purchases is introduced $p^{'}(i)$, which is obtained by calculating the ratio of the number of times that customer i has requested the delivery service in the last two months to the total number of times that it has requested the delivery service in the last year. qi is the quantity of the demanded quantity by customer i; and b is the profit per unit of the medicine. To simplify the calculation, it is assumed that the customer's base quantity for the next purchase is the same as the current purchase, i.e., it has the same profit value qib.

Propagation power can be interpreted as the ability to attract and achieve effective conversion of a potential customer group. When a transportation vehicle provides service within the optimal time window [Ei, Li] specified by customer i, customer i will be satisfied with the service performance of vehicle k and engage in word-of-mouth propagation. ri denotes the potential value of a customer, which reflects the breadth and depth of propagation of existing customers to potential customers. Meanwhile, given the uncertainty of potential customers in the process of information reception ρ_i, the customer acceptance rate is introduced to measure the probability that potential customers will be converted into actual purchasing customers after successfully receiving the relevant information. Therefore, the formula for the effectiveness of publicizing the delivery service after customer i receives the goods is:

$$I_i = \eta_i \times r_i \times \rho_i \tag{6}$$

Assuming that there are Ri potential customers around customer i who have the same purchase needs as him, and the demand of the potential customers is the same as the demand of customer i, the effective communication power that customer i can inspire is:

$$PV_i = I_i R_i q_i b \tag{7}$$

To summarize, the service impact obtained by the vehicle after completing the delivery task to customer i is:

$$BV_i = CV_i + PV_i = \eta_i p^{'}(i) q_i b + \eta_i r_i \rho_i R_i q_i b \tag{8}$$

2.4. Model Building

The objective function of logistics cost minimization is expressed as:

$$\min C = \min(Z_1 + Z_2 + Z_3) = \min(\sum_{i=0}^{N}\sum_{j=0}^{N}\sum_{k=1}^{K} c_1 c_{ij} x_{ij}^{k} + \sum_{k=1}^{K}\sum_{j=1}^{N} c_0 x_{0j}^{k} + \sum_{i=1}^{N} P_i(s_i)) \tag{9}$$

The objective function for maximizing service impact is expressed as:

$$\max BV_i = \max(\eta_i p^{'}(i) q_i b + \eta_i r_i \rho_i R_i q_i b_i) \tag{10}$$

Minimizing logistics cost and maximizing service impact are two optimization objectives with opposite directions. In order to unify these two objectives and study the overall optimal solution, it is first necessary to make their optimization directions consistent. To this end, the optimization objective of service influence is transformed into its negative form, see equation 11, i.e., minimizing the sum of the loss of service influence of the enterprise.

$$\min BV_i = -\max BV_i = -\max(CV_i + PV_i) = -\max(\eta_i p^{'}(i) q_i b + \eta_i r_i \rho_i R_i q_i b_i) \tag{11}$$

The two objective functions are jointly solved to find the optimal solution that minimizes the loss of service impact while satisfying the minimization of logistics cost. Given the order of magnitude difference between service impact and total distribution cost, a sensitivity coefficient ε is introduced to dynamically adjust the weight of service impact in the comprehensive optimization objective. As a result, the objective function is:

$$\begin{aligned}\min = &\sum_{i=0}^{N}\sum_{j=0}^{N}\sum_{k=1}^{K} c_1 c_{ij} x_{ij}^{k} + \sum_{k=1}^{K}\sum_{j=1}^{N} c_0 x_{0j}^{k} + r_i \theta_1 \sum_{i=1}^{N} \max((E_i - s_i), 0) + \\ &r_i \theta_2 \sum_{i=1}^{N} \max((s_i - L_i), 0) - (\eta_i p^{'}(i) q_i b + \eta_i r_i \rho_i R_i q_i b)\end{aligned} \tag{12}$$

The constraints are as follows:

(1) Each customer can only be serviced once by a vehicle.

(2) The number of vehicles used in the distribution process is less than the number of vehicles already in the distribution center.

(3) The quantity demanded by all customers on a distribution route at one time must not exceed the vehicle's carrying capacity.

(4) Each vehicle departs from the distribution center and returns to the distribution center.

(5) Flow conservation constraints, i.e., a vehicle arriving at a customer point must leave that customer point and drive to the next customer point.

(6) The formula for the moment sj at which a vehicle arrives at a customer point.

(7) Decision variables η_i, y_i^k, x_{ij}^k are 0-1 variables.

3. Calculus Analysis

3.1. Introduction to the Algorithm

In order to verify the accuracy of the pharmaceutical logistics path optimization model considering the potential value of customers and the effectiveness of the solved algorithms, real customer data provided by P pharmaceutical logistics enterprises were used for analysis. The

ISSN: 2688-9323

distribution center (latitude and longitude: 107.339, 30.05) delivers medicines to 20 customers on a certain day as an example for the path optimization study.

The customer information table contains key data such as: latitude and longitude coordinates of each customer point, delivery time window requirements (including the optimal time window and acceptable time window), the amount of drugs required, and the potential value of the customer, as shown in Table 2.

Table 2. Customer information

i	Lon, Lat	$[E_i, L_i]$	$[EE_i, LL_i]$	q_i	r_i
1	107.289, 30.075	7:30-8:30	7:00-9:30	1.5	0.35
2	107.301, 29.906	7:10-8:20	6:50-8:50	0.6	0.92
3	107.346, 30.208	7:40-8:30	7:10-9:40	0.48	0.48
4	107.363, 30.213	8:00-8:30	7:50-8:50	0.36	0.59
5	107.324, 30.139	8:00-9:10	7:20-10:00	0.66	0.48
6	107.289, 29.897	7:10-8:20	6:50-8:50	0.72	0.16
7	107.309, 30.128	7:40-8:30	7:10-9:10	1.08	0.64
8	107.337, 29.988	7:40-8:40	7:20-8:50	0.84	0.59
9	107.299, 29.814	7:00-7:50	6:40-8:20	1.2	0.74
10	107.359, 30.157	8:10-9:20	8:00-10:30	0.78	0.32
11	107.317, 29.731	7:10-8:20	7:00-9:30	0.42	0.57
12	107.298, 30.221	7:50-8:30	7:00-9:30	0.96	0.96
13	107.330, 30.015	7:40-8:40	7:30-9:50	1.08	0.79
14	107.320, 30.089	7:30-8:30	7:00-10:10	0.72	0.05
15	107.344, 29.737	6:50-8:00	6:30-8:30	0.54	0.74
16	107.338, 30.107	7:30-8:30	6:50-9:40	0.78	0.33
17	107.354, 30.082	7:50-8:40	7:00-9:30	0.24	0.28
18	107.312, 30.158	7:40-8:40	7:10-9:20	0.54	0.6
19	107.347, 29.915	7:40-8:30	7:20-8:50	0.6	0.21
20	107.361, 29.926	6:30-7:30	6:20-7:50	1.38	0.61

The results of the following three models are calculated to further illustrate the effectiveness of the pharmaceutical logistics path optimization model with minimum transportation cost and maximum service impact considering the potential value of customers through analysis and comparison.

Model 1: Bi-objective model of pharmaceutical logistics route optimization with minimum transportation cost and maximum service impact considering the potential value of customers.

Model 2: The dual-objective model of pharmaceutical logistics path optimization with minimum transportation cost and maximum service impact without considering the potential value of customers.

Model 3: A single-objective model of pharmaceutical logistics path optimization with minimum transportation cost considering the potential value of customers.

According to the management practice and historical data of P pharmaceutical logistics enterprises, the model parameters are assigned values. The maximum capacity of the distribution center Qs is 18t, the fixed cost of vehicle dispatch C0 is 300 yuan/vehicle, the cost of driving per unit distance C1 is 0.9 yuan/km, the maximum vehicle load Qk is 8t, the profit of the unit of medicine b is 20 yuan/kg, the penalty cost of delivering the medicine outside the acceptable service time is 300 yuan/hour, the penalty cost coefficient θ_1 is 100, and θ_2 is 150. To simplify the arithmetic, it is assumed that the vehicle can be unloaded directly after delivering to the customer and go to the next customer point, i.e., the customer service time is 0. The sensitivity coefficient of the service influence is set to 0.9, the number of customers with the same purchasing needs around customer i, Ri, is set to 10, and the acceptance rate of the customer ρ_i is set uniformly to 50% for the number of times of purchasing relative coefficients $p^{'}(i)$ are set uniformly to 0.6. It is assumed that the delivery vehicle starts from the distribution center at 7:00 a.m. Assuming that the distribution vehicle starts at 7:00 a.m., starts from the distribution center and performs the distribution task, travels at a constant speed of 50km/h, distributes to each customer in turn, and returns to the distribution center after completing the delivery of the medicine.

3.2. Calculus Solution

3.2.1. Model 1 Solving

According to the genetic algorithm process, with the help of Matlab2022 platform, the distribution center data, customer information and vehicles and other parameters are substituted into model one, run 20 times and record the calculation results, calculate the transportation cost and service impact, select the smallest comprehensive objective of a group of calculation results, its transportation cost is 1179, BVi is 474, and the min comprehensive objective is 1629. The optimal service time delivery percentage is denoted by t1. Acceptable time delivery percentage is denoted by t2. Through the genetic algorithm to solve to the The path optimization scheme of Model 1 is shown in Table 3.

Table 3. Path optimization scheme of model 1

Distribution routes	Transportation costs	BV_i	min	t_1	t_2
0-11-15-5-7-18-3-0	1179	474	1629	0.35	0.95
0-19-8-9-2-17-4-14-10-16-0					
0-1-20-6-13-0					

As shown in Table 3, pharmaceutical logistics companies need to send a total of 3 vehicles for delivery. The number of customers who received their shipments within the customer's optimal service time window was 35%, i.e., the optimal time window requirement was met for 7 customer points, including customer 7, customer 18, customer 9, customer 2, customer 17, customer 6, and customer 13. The number of customers who received their medicines within the customer's accepted time window was 95%, i.e., only 1 customer did not have a delivery within its acceptable service time, i.e., customer 16.

3.2.2. Model 2 Solving

Because the potential value of the customer affects the penalty cost and potential value function, the role of the potential value of the customer is removed beforehand in this model, and then the bi-objective model of pharmaceutical logistics path optimization with the minimum transportation cost and the maximum service impact is solved. The set of transportation cost with the smallest comprehensive objective is 1249 yuan, BVi is 412, and the min comprehensive objective is 1967. the path optimization scheme of model two is obtained through genetic algorithm solving as shown in Table 4.

Table 4. Path optimization scheme of model 2

Distribution routes	Transportation costs	BV_i	min	t_1	t_2
0-5-18-9-13-17-19-8-3-0	1249	412	1967	0.3	0.9
0-20-10-12-1-7-6-4-0					
0-11-15-2-14-16-0					

ISSN: 2688-9323

As shown in Table 4, pharmaceutical logistics companies need to send a total of 3 vehicles for delivery. The percentage of customers receiving medicines within the customer's optimal service time window is 0.3, i.e., the optimal time window requirement is met for 6 customer locations, including customer 9, customer 13, customer 1, customer 2, customer 14, and customer 16. the percentage of customers receiving medicines within the acceptable time window is 0.9, i.e., there are 2 customer locations that are not delivered within the service time window, i.e., customer 3 and customer 4.

3.2.3. Model 3 Solving

The single-objective model solution for pharmaceutical logistics path optimization with transportation cost minimization under consideration of potential customer value (the model's comprehensive objective is transportation cost). Transportation cost minimization is 961 and BVi is 148. model three path optimization scheme is obtained by genetic algorithm solution as shown in Table 5.

Table 5. Path optimization scheme of model 3

Distribution routes	Transportation costs	BV_i	min	t_1	t_2
0-1-10-3-7-15-4-12-16-8-14-9-13-6-5-19-11-2-0	961	148	0.15	0.35	961
0-20-18-17-0					

As shown in Table 5, pharmaceutical logistics companies need to send a total of 2 vehicles for delivery. The percentage of customers who received medicines within the customer's optimal service time window was 0.15, i.e., the optimal time window requirement was met for 3 customer points, including customer 18, customer 17, and customer 7. The percentage of customers who received medicines within the customer's accepted time window was lower, at 0.35, i.e., there were 13 customer points that were not delivered within the service time window, including customer 10, customer 4, customer 12, and customer 16, Client 8, Client 14, Client 9, Client 13, Client 6, Client 5, Client 19, Client 11 and Client 2.

3.3. Analysis of Results

3.3.1. Service Impact Analysis

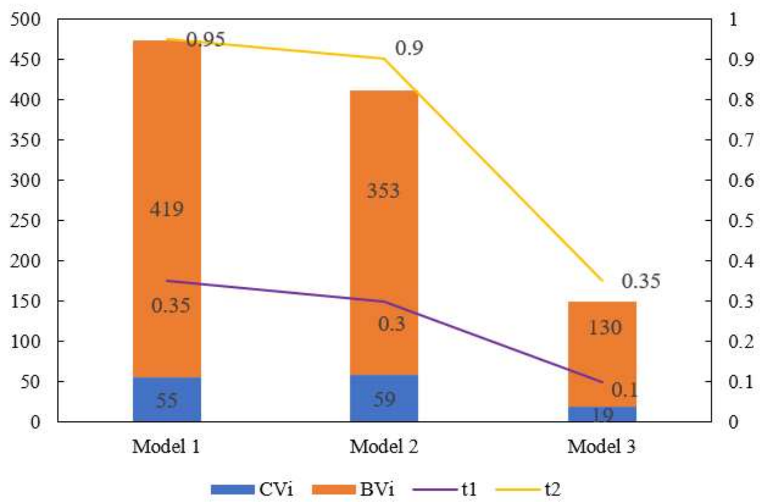

Figure 1. Comparison of service influence and service time delivery proportion among the three models

Service influence mainly includes two aspects of repurchase power and dissemination power, to ensure that the maximum service influence, but also to ensure that the priority to meet the

ISSN: 2688-9323

distribution needs of high-value customers, here through the service influence, the optimal service time delivery percentage and the acceptable service time delivery percentage of the analysis of models 1, 2and 3, the specific situation is shown in Figure 1.

As can be seen from Figure 1, Model 3 is lower than Models 1 and 2 in terms of service impact, optimal service time delivery ratio and acceptable service time delivery ratio, with a service impact of only 149, an optimal service time delivery ratio of only 0.1 and an acceptable service time delivery ratio of 0.35. This proves that Model 3, when incorporating the customer value considerations, is optimized only for the logistics cost, but ignores the improvement of service impact, resulting in 13 customers failing to complete the delivery within their acceptable service times. This proves that Model 3 only optimizes the logistics cost, but neglects the improvement of service impact, resulting in 13 customers failing to complete delivery within their acceptable service time.

In summary, compared with Model 3, Models 1 and 2 show superior performance in service impact optimization, which further confirms the advantage of the dual-objective optimization model over the single-objective model. Meanwhile, the service impact of model one is 474, the percentage of optimal service time delivery is 0.3, and the percentage of acceptable service time delivery is as high as 0.95, which is overall better than model two.

3.3.2. Customer Potential Value Analysis

Based on the results of the above arithmetic example, a comparative analysis of the distribution that fails to satisfy the customer's acceptable time window under the three models is shown in Table 6.

Table 6. Number of customers not delivered within acceptable time under each model

Model	Failure to deliver to customers within the acceptable time window	r_i
Model 1	Client 16	0.33
Model 2	Client 3,4	0.48, 0.59
Model 3	Client 10, 4, 12, 16, 8, 14, 9, 13, 6, 5, 5, 19, 11 and 2	0.32, 0.59, 0.96, 0.33, 0.59, 0.05, 0.74, 0.79, 0.16, 0.59, 0.21, 0.57 and 0.92

As can be seen in Table 6, Model 1 performs well in terms of delivery punctuality, with only 1 customer not delivered within the acceptable time window. In contrast, the performance of Model 2 and Model 3 is unsatisfactory, with the number of customers not delivered within the acceptable time window being 2 and 13, respectively, and there are many customers with high potential value. According to the theory of large customer value, the influence of high-value customers on the enterprise is particularly significant, so it is crucial for the development of the enterprise to ensure the service satisfaction of high-value customers. Taken together, Model 1 shows better performance than Models 2 and 3 in terms of delivery punctuality and customer potential value.

3.3.3. Time and Cost Analysis

Through the above calculations, Model 1 is now compared and analyzed with Model 2 and Model 3 respectively in terms of total distribution time and transportation cost, and the results are shown in Table 7.

According to the comparative analysis in Table 7, in terms of delivery time, Model 1 demonstrates a clear advantage, with a total of 541 minutes consumed during delivery, which is a 13% decrease compared to Model 2's 623 minutes and a 14% increase compared to Model 3's 631 minutes.

Table 7. Comparison of time and cost between model 1 and model 2 and model 3

Model	Total delivery time (minutes)	Transportation costs
Model 2	623	1249
Model 1	541	1179
difference	82, 13% reduction	70, 5% reduction
Model 3	631	961
Model 1	541	1179
difference	90, 14% reduction	-1179, an increase of 18%

In terms of transportation costs, Model 3 demonstrates lower costs compared to Models I and 2. This is mainly attributed to the fact that Model 3, as a single-objective model, has a core optimization objective of minimizing transportation costs only, without having to consider factors such as service impact. However, this strategy also results in a higher number of customers who are not delivered within an acceptable time window for the customer, and many of these are potentially higher-value customers. Therefore, even though Model 3 is optimal in terms of transportation cost, the risk of customer churn it may bring cannot be ignored, which is not conducive to the long-term development of the enterprise. In contrast, although Model 1 is slightly higher than Model 3 in terms of transportation cost, it achieves 5% optimization compared with Model 2, which shows that the dual-objective model that considers the potential value of customers is better than the dual-objective model that does not consider the potential value of customers.

In summary, through in-depth analysis of the service impact, customer potential value and time and cost of the three models, the following conclusion is drawn: in the bi-objective model of pharmaceutical logistics path optimization with minimum transportation cost and maximum service impact under consideration of the potential value of the customer, this strategy significantly improves the service impact even though the enterprise may face a higher transportation cost. In addition, the Model 1mproves the timeliness of pharmaceutical logistics and distribution, and provides more accurate logistics and distribution services for customers, especially for customers with higher potential value, whose distribution needs are prioritized. Although from a short-term perspective, the enterprise may need to bear more cost expenditures, in the long run, this strategy helps the enterprise to establish a good image and expand its brand influence, which in turn is conducive to the development of the enterprise and the acquisition of more high-quality customers.

4. Conclusion

Pharmaceutical logistics distribution center location and its vehicle path planning have been attracting much attention as a core issue in modern logistics. In this paper, we focus on the optimization of pharmaceutical logistics vehicle paths considering the potential value of customers, aiming to further incorporate the key factor of potential value of customers on the basis of the traditional transportation cost as the optimization objective. To this end, a dual-objective optimization Model 1s constructed to minimize the transportation cost while also pursuing the maximization of customer service impact, and a genetic algorithm is designed with the help of MATLAB software to realize the efficient solution of the model.

When studying the pharmaceutical logistics distribution network, it is assumed that all transportation vehicles have the same specifications and maintain a uniform speed throughout the distribution process. However, in actual operation, logistics companies will choose transportation vehicles with appropriate specifications according to different distribution needs to ensure efficient and flexible services. In addition, the traveling speed of distribution vehicles is often affected by a variety of factors of real-time road conditions, such as traffic

ISSN: 2688-9323

congestion and road conditions. Therefore, future research on optimization of pharmaceutical logistics distribution can be extended to the model of multi-vehicle co-matching, and comprehensively consider the impact of real road conditions on the distribution process.

Acknowledgments

This work is supported by the Chongqing Technology Innovation and Application Development Project (CSTB2022TIAD-GPX0015) and the Chongqing Social Science Planning Project (2021ZDZK14).

References

[1] CAMPELO P, NEVES-MOREIRA F, AMORIM P, et al. Consistent vehicle routing problem with service level agreements: a case study in the pharmaceutical distribution sector[J]. European Journal of Operational Research, 2018, 273(1): 131-145.

[2] SINGH K R, CHAUDHARY N, SAXENA N. Selection of warehouse location for a global supply chain: a case study[J]. 2MB Management Review, 2018, 30(4): 343-356.

[3] WEN Z, LIAO H, REN R, et al. Cold Chain Logistics Management of Medicine with an Integrated Multi-Criteria Decision-Making Method[J]. International Journal of Environmental Research and Public Health, 2019, 16(23): 4843.

[4] LIN Q, ZHAO Q, LEV B. Cold chain transportation decision in the vaccine supply chain[J]. European Journal of Operational Research, 2020, 283(1): 182-195.

[5] YUAN Z, GAO J. Dynamic uncertainty study of multi-center location and route optimization for medicine logistics company[J]. Mathematics, 2022, 10(6): 953.

[6] GOEL R, MAINI R, BANSAL S. Vehicle routing problem with time windows having stochastic customers demands and stochastic service times: modelling and solution[J]. Journal of Computational Science, 2019, 34: 1-10.

[7] MARINELLI M, COLOVIC A, DELL'ORCO M. A novel dynamic programming approach for two-echelon capacitated vehicle routing problem in city logistics with environmental considerations[J]. Transportation Research Procedia, 2018, 30: 147-156.

[8] VAKIL P, HOSSEINI-MOTLAGH S M, GHOLAMIAN M R, et al. A developed model and heuristic algorithm for inventory routing problem in a cold chain with pharmaceutical products[J]. Industrial Management Journal, 2017, 9(2): 383-407.

[9] KRAMER R, CORDEAU J F, IORI M. Rich vehicle routing with auxiliary depots and anticipated deliveries: an application to pharmaceutical distribution[J]. Transportation Research Part E: Logistics and Transportation Review, 2019, 129: 162-174.

[10] JANGA V, AWOKE D, GENALE A S, et al. Cold chain logistics method using to identify optimal path in secured network model with machine learning[C]. International Conference on Image Processing and Capsule Networks. Cham: Springer International Publishing, 2022: 725-735.

[11] GUTIÉRREZ-SÁNCHEZ A, ROCHA-MEDINA L B. VRP variants applicable to collecting donations and similar problems: a taxonomic review[J]. Computers & Industrial Engineering, 2022, 164: 107887.

[12] MAHMOOD N. Solving capacitated vehicle routing problem using meerkat clan algorithm[J]. International Arab Journal of Information Technology, 2022, 19(4): 689-694.

[13] VERHOEF P C, DONKERS B. Predicting customer potential value an application in the insurance industry[J]. Decision Support Systems, 2001, 32(2): 189-199.

[14] KOTLER P. Kotler on marketing: how to create, win and dominate markets[J]. Journal of the Academy of Marketing Science, 2007, 29(4): 421-422.

[15] HUNT S D, ARNETT D B. Market segmentation strategy, competitive advantage, and public policy: grounding segmentation strategy in resource-advantage theory[J]. Australasian Marketing Journal (AMJ), 2004, 12(1): 7-25.

ISSN: 2688-9323

[16] LAMRHARI S, EL G H, OUBRICH M, et al. A social CRM analytic framework for improving customer retention, acquisition, and conversion[J]. Technological Forecasting and Social Change, 2022, 174: 121275.

[17] LIU Y, CHEN C. Improved RFM model for customer segmentation using hybrid meta-heuristic algorithm in medical IoT applications[J]. International Journal on Artificial Intelligence Tools, 2022, 31(1): 2250009.