ROBUST OPTIMIZATION OF URBAN COLD-CHAIN LOGISTICS LOCATION-ROUTING BASED ON AN IMPROVED GENETIC ALGORITHM

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This study presents an in-depth exploration of the intricate issue of uncertain demand and time-dependence within urban cold-chain logistics distribution networks. A location-routing model with strict time windows under uncertain demand and time-dependence is proposed to minimize the total costs including transit costs for selected distribution centers, transportation costs, driver salaries, and refrigeration costs. We adopt the budget-of-uncertainty robust approach to deal with the uncertainty of customer requirements, whereas vehicle travel time is calculated using the first in first out principle. To solve the problem, an enhanced genetic algorithm incorporating elite and roulette selection strategy is developed based on model characteristics. This algorithm preserves superior individuals while accelerating convergence speed and enhancing solution efficiency. Finally, randomly generated numerical examples are utilized to verify the feasibility and effectiveness of the model and algorithm.

Keywords: location-routing; service level; time-dependent; uncertain demand; robust optimization

1. Introduction

Urban distribution center location is a crucial decision-making consideration for logistics enterprises [1,2], directly affecting the logistics system's distribution efficiency and control level. The accurate determination of the distribution center's location can significantly improve the operational efficiency and benefit of the entire distribution system [3]. The urban distribution vehicle routing costs account for the highest proportion of the logistics distribution process and has long been a key research area for scholars [4]. Reliable, efficient, and flexible distribution center and distribution route decisions can not only save distribution costs and time but also enhance distribution efficiency and the enterprises' competitiveness [5].

The rationality of facility location and vehicle routing can greatly optimize the system logistics network [6]. The interdependence of these two problems has led to the definition of the location routing problem (LRP), aimed at identifying a optimization solution to the location and vehicle routing problem [7]. The LRP

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concept can be traced back to 1961. Boventer. [8] first discussed the relationship between location selection and transportation costs in the transportation process. Subsequently, scholars analyzed LRP and its variants. Prodhon. [9] analyzed the multi-period location-routing problem and designed a hybrid evolutionary algorithm based on a random expansion of Clarke and Wright's algorithm to solve the model. Koç et al. [10] investigated the location-routing problem in urban distribution and developed an adaptive large-scale neighborhood search algorithm. The algorithm's effectiveness and feasibility were verified through standard instances. Wang et al. [11] analyzed the two-stage location path problem of green, time window pickup, and delivery, and designed a heuristic algorithm based on Lagrangian relaxation to solve the model. Using the Open Location-Routing Problem (OLRP), Mansouri & Eydi. [12] designed a sustainable supply chain model that addresses all sustainability pillars and utilized the NSGA-II, a meta-heuristic method, to solve the proposed model and compare its efficiency with Cplex. Ferreira & Queiroz. [13] proposed a heuristic that combines the simulated annealing method and the artificial algae algorithm to solve a location-routing problem with two-dimensional loading constraints.

Zhang et al. [14] utilized the uncertain information theory to establish a multi-objective model for the emergency facility location-routing problem. The scholars transformed the multi-objective model into a single-objective model predominantly by using the objective function method and by developing a hybrid intelligent algorithm to solve it. Yannis et al. [15] analyzed the location-routing models under stochastic demand, and designed hybrid intelligent algorithms to solve the constructed models. Rahmani& Hosseini., [16] present an extension of the Green Location-Routing Problem (GLRP) that considers traffic congestion and variable speeds and provides a nonlinear mixed-integer programming formulation with preprocessing rules to minimize costs related to depots, servicing penalties, CO_2 emissions, and fuel consumption. A heuristic algorithm based on the PSO algorithm is proposed and shown to yield optimal or near-optimal solutions. Wu et al. [17] investigated the location-routing problem considering the variation of road travel time with vehicle travel time, and a dual-level planning model is constructed. Pekel & Kara. [18] proposed a heuristic search algorithm that combines variable neighborhood search and evolutionary local search to solve the location-routing problem with fuzzy demands. Raeisi & Jafarzadeh. [19] analyzed a multi-objective location-routing problem specifically for hazardous waste, and various algorithms were employed to solve the model. Annarita et al. [20] proposed an indifference zone approach to select the most optimal option from alternative configurations, ensuring correct choice probability while minimizing computational effort. Li & Li. [21] established a multi-objective delivery model for minimizing carbon emission trading costs, and network costs, and maximizing customer satisfaction. They designed an enhanced nondominated sorting genetic algorithm II (NSGA-II), which not only augments the diversity within the initial population but also improves the algorithm's local search capability and elevates its search precision.

Compared with previous studies, the proposed research problem has several contributions in theory and application: (1) In the context of cold-chain logistics, a location-routing model is developed that concurrently takes into account both customer demand uncertainty and vehicle travel time uncertainty. This comprehensive consideration renders the model more realistic and adept at accurately capturing the intricate and dynamic aspects of cold chain logistics. (2) An enhanced genetic algorithm with an elite selection strategy is designed to solve the model. Through this improvement, the algorithm is able to find better solutions while ensuring convergence speed, thus enhancing the practicality and efficiency of the model. and (3) A multidimensional analysis was conducted to examine the impact of the robustness of the delivery system, service level, and road congestion on the total delivery costs. It not only reveals the interaction relationships between various factors but also provides valuable insights and guidance for the actual operation of cold chain logistics.

The remainder of this study is constructed as follows. A problem description and symbol explanation are provided in Section 2. Section 3 and 4 present the model formulation and solution method, respectively. In Section 5, a numerical case study is employed to validate the effectiveness of the proposed model and algorithm. Conclusions are summarized in Section 6.

2. Problem description and notation explanation

2.1 Problem description

Herein, we investigate a city's cold-chain logistics distribution network comprising multiple candidate distribution centers and several customer demand points (Fig. 1).

Owing to the known geographical location of customer points and their requested service time windows, and with uncertain demand at customer points and varying vehicle speeds due to traffic conditions during travel, the problem involves establishing a robust model to minimize total costs and designing an algorithm. thus, the following can be determined:

- Optimal location points for distribution centers, the most efficient delivery routes for vehicles, and the level of distribution services under different robust conditions.
- At the given robustness level, the relationship between total costs, total vehicle travel time, and traffic congestion index is considered when the traffic congestion index is different.

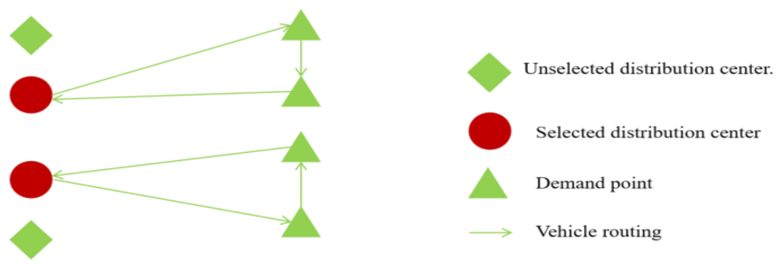


Fig.1 Example of the location-routing problem

2.2 Notation explanation

Before modeling, define the relevant notations as depicted in table 1.

Table 1

Notation description

Notation	Meaning
D	Set of the candidate distribution centres
K_i	Set of refrigerated vehicles owned by the i-th alternative distribution centre. $i \in D$
N	Set of customers
d_{jl}	The distance between the customer point j and the customer point l
q_j	Requirements of the j-th customer
c_1	Transport costs per unit distance
t_{ijl}^k	Travel time of refrigerated vehicle k of distribution centre i from road section j to l
s_j	Service times of refrigerated vehicle for the j-th customer
t_j	Time when the refrigerated vehicle reaches the customer point j
ET_j	Customer j requests the lower limit of service time
LT_j	Customer j requests the upper limit of service time
α_1	Unit time drivers' wages
α_2	Refrigeration costs per unit time during transportation
α_3	Refrigeration costs per unit time during unloading
t_{ij}^{sk}	Time when refrigerated vehicle of distribution center i arrives at customer point j
t_j^d	The time when the refrigerated vehicle leaves the customer point j
λ	Transit costs of goods per unit in distribution centres
Q	Capacity of refrigerated vehicles
Y_k	Y_k is a 0-1 variable: when $Y_k = 1$, refrigerated vehicle k is used; otherwise, $Y_k = 0$
Y_{ij}	Y_{ij} is a 0-1 variable: when $Y_{ij} = 1$, distribution center i serves customer j; otherwise, $Y_{ij} = 0$
X_{ij}^k	X_{ij}^k is a 0-1 variable: when $X_{ij}^k = 1$, the refrigerated vehicle k from distribution center i provides service to the j-th customer; otherwise, $X_{ij}^k = 0$
X_{ijl}^k	X_{ijl}^k is a 0-1 variable: when $X_{ijl}^k = 1$, the refrigerated vehicle k from distribution center i is traveling from road section j to l; otherwise, $X_{ijl}^k = 0$

3. Model development

3.1 Establishment of a location-routing model with uncertain demand and time-dependent

This study presents a location-routing model for urban cold-chain logistics with uncertain demand and time-dependent, which is expressed as follows:

Objective function $\min z = C_1 + C_2 + C_3 + C_4$ (1)

$$C_1 = \lambda \sum_{i \in D} \sum_{j \in N} q_j Y_{ij} \quad (2)$$

$$C_2 = \sum_{k \in K_i} \sum_{i \in D} \sum_{j \in D \cup N} \sum_{l \in D \cup N} c_1 d_{jl} X_{ijl}^k Y_k \quad (3)$$

$$C_3 = \alpha_1 \sum_{k \in K_i} \sum_{i \in D} \sum_{j \in D \cup N} \sum_{l \in D \cup N} X_{ijl}^k Y_k (t_{ijl}^k + s_l + \max\{ET_l - t_l, 0\}) \quad (4)$$

$$C_4 = \alpha_2 \sum_{k \in K_i} \sum_{i \in D} \sum_{j \in D \cup N} \sum_{l \in D \cup N} X_{ijl}^k Y_k (t_{ijl}^k + \max\{ET_l - t_l, 0\}) + \alpha_3 \sum_{k \in K_i} \sum_{i \in D} \sum_{j \in D \cup N} Y_k X_{ij}^k s_j \quad (5)$$

Subject to

$$\sum_{j \in N} X_{ij}^k q_j \le Q \quad \forall k \in K_i, j \in D \quad (6)$$

$$\sum_{i \in D} \sum_{j \in N} X_{ijl}^k = \sum_{i \in D} \sum_{j \in N} X_{ilj}^k \quad \forall l \in N, k \in K_i \quad (7)$$

$$\sum_{i \in D} \sum_{j \in D \cup N} X_{ij}^k = 1 \quad \forall k \in K_i \quad (8)$$

$$\sum_{i \in D} \sum_{j \in D \cup N} X_{ji}^k = 1 \quad \forall k \in K_i \quad (9)$$

$$\sum_{i \in D} \sum_{k \in K_i} \sum_{j \in D \cup N} X_{ijl}^k = 1 \quad \forall l \in N \quad (10)$$

$$\sum_{i \in D} \sum_{k \in K_i} \sum_{\substack{j,l \in S \\ j \ne l}} X_{ijl}^k \le |S| - 1 \quad S \subseteq N \quad (11)$$

$$ET_j X_{ij}^k \le t_{ij}^{sk} \le LT_j X_{ij}^k \quad \forall i \in D, j \in N, k \in K_i \quad (12)$$

$$t_l \le \max(ET_j, t_j) + s_j + t_{ijl}^k + B(1 - X_{ijl}^k) \quad \forall k \in K_i, i \in D \quad (13)$$

$$t_l \ge \max(ET_j, t_j) + s_j + t_{ijl}^k + B(X_{ijl}^k - 1) \quad \forall k \in K_i, i \in D \quad (14)$$

Equation (1) represents minimizes the total costs including transit costs of the distribution center, transportation costs, driver wages, and refrigeration costs. Equation (2) represents the transfer costs of candidate distribution centers. Equation (3) represents the transportation costs of delivery vehicles. Equation (4) represents driver wages. Equation (5) represents the refrigeration costs of delivery vehicles, which is the sum of the refrigeration costs incurred during transportation and unloading processes. Constraint (6) states the load constraint of delivery vehicles.

Constraint (7) is the balance between the inflow and outflow of nodes. Constraints (8) and (9) indicate that vehicles ought to be returned to the initial distribution center after serving customers. Constraint (10) states that each customer can be serviced only once by one vehicle. Constraint (11) prevents sub-loops in the distribution vehicle's distribution routing. Constraint (12) represents the customer's hard time window constraint. Constraints (13) and (14) represent the continuity of delivery time for vehicles.

3.2 Uncertain demand and time-dependent processing

3.2.1 Customer demand uncertainty processing method

There are three methods for addressing customer demand uncertainty: random optimization, fuzzy optimization, and robust optimization. We adopt the method of budget-of-uncertainty robust optimization mentioned in references [22, 23] to deal with the uncertainty of customer requirements (Constraint (6) in the model).

First, define the range of customer demand q_j as $[\bar{q}_j - \hat{q}_j,\ \bar{q}_j + \hat{q}_j]$, where $\bar{q}_j$ denotes the mean value of customer demand and $\hat{q}_j$ denotes the maximum absolute deviation of customer demand.

Second, for $\forall i \in D, k \in K_i$, uncertain budget Γ_{ik} is offered, and a protection function $\beta(X,\Gamma_{ik})$ $(\forall k \in K_i, i \in D)$ is introduced to transform the uncertainty of customer demand.

$$\beta(X,\Gamma_{ik}) = \max_{\{S\cup\{t\}|S\subseteq N,|S|=\lfloor\Gamma_{ik}\rfloor,t\in N\setminus S\}} \{\sum_{j\in S}\hat{q}_j X_{ij}^k + (\Gamma_{ik} - \lfloor\Gamma_{ik}\rfloor)\hat{q}_t X_{it}\}$$

Therefore, the constraint condition (6) can be transformed from the preceding equation:

$$\sum_{j\in N} X_{ij}^k \bar{q}_j + \beta(X,\Gamma_{ik}) \le Q \qquad \forall k \in K_i, i \in D$$

Where, the uncertain budget Notation Γ_{ik} is utilized to adjust the solution's level of robustness, which can take any value from $[0, N]$, and N represents the number of customers being served.

• When Γ_{ik} taking an integer value, it means that there are Γ_{ik} number of demand points where the demand attains its maximum value.

• When Γ_{ik} assumes an integer value, there are $\lfloor\Gamma_{ik}\rfloor$ number of demand points where the demand attains its maximum value.

Third, Z_j is introduced. Meanwhile, the protection function becomes the following programming problem:

Objective function

$$\beta(X,\Gamma_{ik}) = \max \sum_{j\in N} \hat{q}_j X_{ij}^k Z_j \quad \forall i \in D, k \in K_i$$

Subject to $\quad 0 \le Z_j \le 1 \quad \forall j \in N$

$$\sum_{j\in N} Z_j \le \Gamma_{ik}$$

Finally, using the duality theorem, the problem can be transformed into its dual problem as follows:

Objective function $\quad \min \alpha_{ik}\Gamma_{ik} + \sum_{j\in N}\gamma_j$

Subject to $\quad \alpha_{ik} + \gamma_j \ge \hat{q}_j X_{ij}^k \quad \forall j \in N$

$$\alpha_{ik} \ge 0$$

$$\gamma_j \ge 0 \quad \forall j \in N$$

Thus, constraint condition (6) can be transformed into the following constraint problem:

$$\alpha_{ik} + \gamma_j \ge \hat{q}_j X_{ij}^k \quad \forall i \in D, k \in K_i, j \in N \tag{15}$$

$$\alpha_{ik} \ge 0 \quad i \in D, k \in K_i \tag{16}$$

$$\gamma_j \ge 0 \quad \forall j \in N \tag{17}$$

3.2.2 Time-dependent processing method

The travel time of a refrigerated vehicle on a road section is contingent upon the departure time of the refrigerated vehicle and its travel speed during this period. For the entire road section, the researchers merely consider the scenarios of the morning peak and the evening peak. Herein, the method for calculating travel time proposed by Ichoua et al. [24] is adopted. In this approach, the travel speed of the refrigerated vehicle alters when it traverses the boundary of two consecutive periods, guaranteeing that the road network complies with the first-in-first-out (FIFO) criterion. The entire distribution time is divided into n periods $[T_0,T_1]$, $[T_1,T_2],\cdots\cdots$, $[T_{p-1},T_p]$, $[T_p,T_{p+1}],\cdots\cdots$, $[T_{n-1},T_n]$. The travel speeds within each period are $v_1,v_2,\cdots\cdots,v_p$, respectively. Because urban distribution is a regional distribution, the researchers consider only the cases where refrigerated vehicles span at most two periods on the same road section. The calculation formula for the travel time of refrigerated vehicle k from customer point j to customer point l is expressed as follows:

$$t_{ijl}^{k}=\begin{cases}\dfrac{d_{jl}}{v_p} & t_i^d,t_l\in[T_{p-1},T_p]\\ T_p-t_j^d+\dfrac{d_{jl}-(T_p-t_j^d)v_p}{v_{p+1}} & t_i^d\in[T_{p-1},T_p],t_l\in[T_p,T_{p+1}]\end{cases} \tag{18}$$

3.3 Establishing a location-routing robust model

With the treatment of demand uncertainty and time-dependence in 3.2, the following location-routing robust model can be obtained.

Objective function as in Equation (1)

Subject to as in Equation (7-18)

Since the customer demand uncertainty is considered herein, there may be cases where the optimal solution does not meet the constraint conditions. Therefore, the service level is introduced, which can be expressed as follows:

$$Service\ \ Level(SL)=P(\sum_{j\in N}X_{ij}^{k}\tilde{q}_j\leq Q)\quad \forall k\in K_i,i\in D$$

From the literature Ben-Tal & Nemirovski. [22]. Equation (28) can be transformed into the following expression:

$$Service\ Level(SL)=P(\sum_{j\in N}X_{ij}^{k}\tilde{q}_j\leq Q)\geq 1\text{-}[(1-\mu)C(n,\lfloor v\rfloor)+\sum_{l=\lfloor v\rfloor+1}^{n}C(n,l)] \tag{19}$$

Where,

$$C(n,l)=\begin{cases}\dfrac{1}{2^n} & l=0\ or\ l=n\\ \dfrac{1}{\sqrt{2\pi}}\sqrt{\dfrac{n}{(n-l)l}}\exp(n\log(\dfrac{n}{2(n-l)})+l\log(\dfrac{n-l}{l})), & otherwise\end{cases}$$

$$n=|N|,\ v=(\Gamma_i+n)/2,\ \mu=v-\lfloor v\rfloor$$

It can be concluded from Equation (19) that for a given value of Γ_{ik}, we can calculate the lowest service level by Equation (19). By contrast, if the lowest service level is provided, we can also calculate the value of Γ_{ik} backward. There- fore, using the location-routing robust model established herein, the enterprise's decision maker can not only control the robustness of the solution, but also control the refrigerated vehicle service level, and subsequently find out the refrigerated vehicle travelling route that satisfies the service level and the selected distribution centers.

4. Algorithm design

Herein, an enhanced genetic algorithm with elite selection strategy is designed to solve the established model, and the specific solution steps of the algorithm are as follows:

Step 1: Input initial data. Set the initial population value, the maximum number of iterations of the algorithm, the crossover and mutation probability values, the dynamic time Notation, and the algorithm's starting iteration number $gen = 1$.

Step 2: Generating initial populations. The initial population was randomly generated by encoding chromosomes according to the 3-layer coding method. There are d candidate distribution centres and n customer demand points, and the chromosome coding method is specified as follows:

• The first layer code denotes the distribution center selection priority code. The encoding length is d, the value interval is [0,1], and the encoding is sorted in ascending order to obtain a sorting code, namely the selection priority code of the candidate distribution center.

• The second layer code denotes the number of the selected distribution centers. The length of the code is 1, and the value interval is [1,J+0.999], rounded down to the number of selected distribution centers.

• The third level of coding denotes the service priority coding of the demand point: a real number code of length n in the interval [0,1], sorted in ascending order to obtain a ranking code, i.e., the service priority code of the demand.

Step 3: Crossover operation and mutation operation.

• Single point mutation: the gene is mutated by random variation. For example, the parent chromosome is 1, and the offspring's chromosome is 3 after a single point mutation.

• Two-point crossover: the random selection of two chromosomes as parents and two offspring chromosomes are obtained by direct exchange of two parent chromosomes. For example, select two parent chromosomes 3 and 4; the chromosomes of the crossed offspring are 4 and 3.

Step 4: Decoding chromosomes. Based on the code's significance, upon obtaining the candidate distribution centers, the chromosome is decoded as follows as per the load constraints and time window constraints:

(1) Set $u = 1$;

(2) At the outset of the u-th route, $R_u = 0$, where 0 denotes the distribution center;

(3) Attempt to incorporate the j-th point in the chromosome Y into R_u. If the vehicle load and time window are fulfilled after its addition to R_u, proceed to. Otherwise, update u to $u+1$ and return to(2);

(4) Remove the j-th encoding of Y. If Y becomes empty, then proceed to (5). Otherwise, update j to $j+1$, and return to (3);

(5) Output each sub-routing.

Step 5: Selection operation. Calculate the individual's fitness value $F_i = \frac{1}{Z_i}$. Where F_i denotes the fitness value of the i-th chromosome, and Z_i denotes the value of the objective function of the *i*-th first chromosome. We utilize a combination of the elite selection strategy and the roulette strategy to select the individual.

Step 6: Algorithm termination condition. If gen > the algorithm's maximum number of iterations, output the most optimal solution; this marks the end of the algorithm. Otherwise, let gen = gen + 1, and proceed to Step 3.

5. Numerical example

5.1 Data Acquisition and Notation Setting

Illustrating the capabilities of the proposed model and algorithm: we utilize Matlab programming to generate the distribution network of a rectangular area with a side length of $100km*100km$. It is assumed that there are four distri- bution centers available for a candidate in this area and thirty-five customers in need of services. The distribution centers are equipped with refrigerated vehicles of the same type and with a vehicle capacity of eight tons. It is required to select two distribution centers from the given four candidate distribution centers; thus, transfer and distribution services for thirty-five customers can be provided. The spatial layout of the candidate distribution centers and their customers is illustrated in Fig.2. The coordinates of the candidate distribution centers are P1 (45, 75), P2 (65, 70), P3 (15, 28), and P4 (39, 72), respectively. The time windows are all from 5:00 to 19:00. The customer coordinates, average demand, required service time windows, and service times are illustrated in table 2. The notation values in the model are depicted in table 3. The parameter values in the algorithm are depicted in table 4.

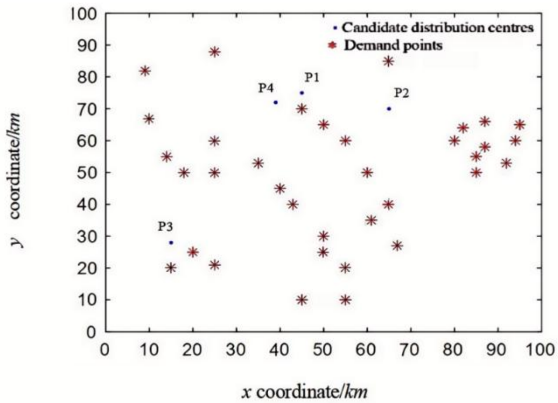


Fig. 2 Spatial layout of candidate distribution centers and demand points

Table 2

Customer requirement points related information

Demand point	1	2	3	4	5	6
Coordinate /km	(35, 53)	(20, 25)	(18,50)	(61,35)	(43,40)	(55,20)
Time window	7:00-10:30	5:30-8:30	6:00-9:00	6:10-10:00	6:30-10:20	7:00-11:30
Average demand	0.5t	1.5t	1.5t	1.1t	2t	1.5t
Service time /min	10	15	15	20	20	20
Demand point	7	8	9	10	11	12
Coordinate /km	(67,27)	(45,10)	(50,25)	(40,45)	(55,60)	(50,65)
Time window	7:00-10:00	6:40-9:30	6:30-11:40	7:00-12:30	7:00-12:00	7:00-10:30
Average demand	2t	1.2t	1t	1.3t	1t	0.5t
Service time /min	25	15	10	15	10	10
Demand point	13	14	15	16	17	18
Coordinate /km	(60,50)	(65,40)	(50,30)	(55,10)	(25,50)	(25,60)
Time window	7:00-11:00	7:00-12:00	6:20-11:30	6:40-11:30	7:00-12:00	6:00-11:30
Average demand	1.5t	2t	2.5t	1.5t	0.5t	2.5t
Service time /min	15	20	25	15	10	25
Demand point	19	20	21	22	23	24
Coordinate /km	(15,20)	(25,21)	(92,53)	(25,88)	(9,82)	(14,55)
Time window	7:00-11:00	5:30-11:00	7:00-11:00	7:00-12:00	6:20-11:30	6:40-11:30
Average demand	1.1t	1.2t	1.3t	1t	0.5t	1.5t
Service time /min	15	15	10	10	15	20
Demand point	25	26	27	28	29	30
Coordinate /km	(82,64)	(10,67)	(85,50)	(45,70)	(94,60)	(85,55)
Time window	7:00-12:00	8:00-11:30	7:00-9:30	5:50-11:00	7:00-11:00	6:30-11:00
Average demand	2t	2.5t	1.5t	0.5t	2.5t	1.1t
Service time /min	25	25	15	10	25	15
Demand point	31	32	33	34	35	
Coordinate /km	(65,85)	(87,58)	(95,65)	(87,66)	(80,60)	
Time window	6:40-12:00	9:00-11:00	8:40-10:30	8:30-10:30	7:00-9:00	
Average demand	1.1t	1.2t	1.3t	1t	0.5t	
Service time /min	15	15	15	15	10	

Table 3

Notation values in the model

Notation	Notation values	Notation	Notation values	Notation	Notation values	Notation	Notation values
c_1	2 RMB/km	α_1	60 RMB/hour	λ	4000 RMB/ton	v (Flat peak period)	25 km/hour
α_2	18 RMB/hour	α_3	20 RMB/hour	Q	8 ton	v (Peak period)	50 km/hour

Table 4

Parameter values in the algorithm

Parameter	Parameter values	Parameter	Parameter values
Population size	100	Crossover probability	0.8
Maximum number of iterations	500	Mutation probability	0.1

5.2 Algorithm performance test

The algorithm designed above is programmed and calculated using the MATLAB R2017a package. The computer operating system is Windows 7-x32, Intel Core i7, CPU @ 3.4GHz, and the memory is 4GB. We present the convergence of the objective function values when the demand disturbance is 20% and the uncertain budget Γ_{ik} takes values of 0, 10, 20, and 30, respectively (Fig. 3). Fig. 3 indicates that the objective function values have a relatively fast converge- nce speed, and relatively satisfactory optimal solutions are obtained in a short time, thereby verifying the feasibility of the model and the effectiveness of the algorithm.

5.3 Comparative analysis of results in different scenarios

5.3.1 Relationship between robustness level and total costs

It is assumed that the deviation value of customer demand is 20% the mean value, i.e., $\hat{q}_j = \bar{q}_j \times 20\%$, It is apparent that the higher the customer demand, the higher the deviation value. Using the algorithm designed herein, we can find the relationship between robustness level and the total costs (table. 5).

• When $\Gamma_{ik} = 0$, all demand points have demand values equal to the mean value, and the total costs of the location-routing is the lowest, with a value of 193,677.18 RMB and a delivery vehicle requirement of six.

• When $\Gamma_{ik} = 35$, all demand points have demand values replaced by the maximum customer demand, the total costs of the location-routing is the highest, with a value of 233,255.11 RMB and a delivery vehicle requirement of eight.

• Regardless of any value of the uncertainty budget, the optimal siting points are P2 and P3.

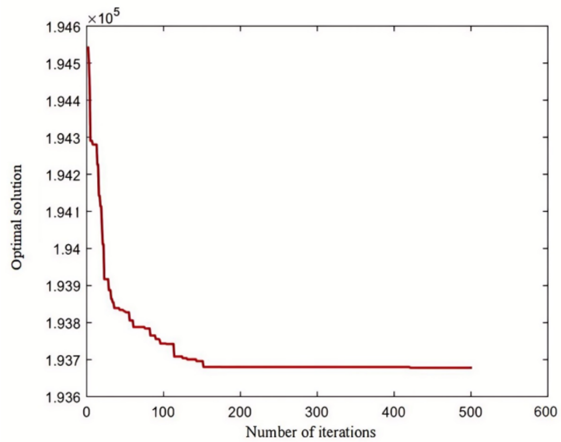
We can conclude that as the robustness of the system increases, the total cost of the system keeps increasing (Fig. 4) and the number of delivery vehicles increases. The opposite is also true. Conversely, the relationship between the system robustness and the total system costs is as follows: the stronger the robustness, the higher the system costs, and the weaker the robustness, the lower the system costs.

Table 5

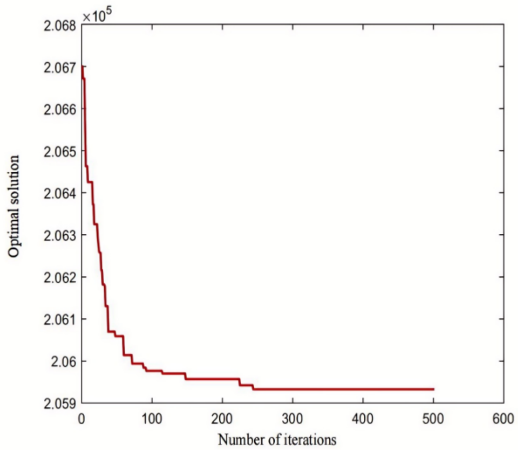
Total costs and minimum service level under uncertain budget

The value of Γ_{ik}	0	2	4	6	8
Total costs /RMB	193677.18	196612.59	198119.35	199740.18	202175.33
Service level/%	42.9761	56.2769	68.8781	79.5901	87.7528
The value of Γ_{ik}	10	12	14	16	18
Total costs /RMB	205932.75	206986.16	209092.16	211060.02	213035.17
Service level/%	93.3195	96.7090	98.5457	98.8885	99.8012
The value of Γ_{ik}	20	22	24	26	28
Total costs /RMB	216078.43	217574.06	220002.13	221774.65	223974.64
Service level/%	99.9396	99.9842	99.9965	99.9993	99.9999

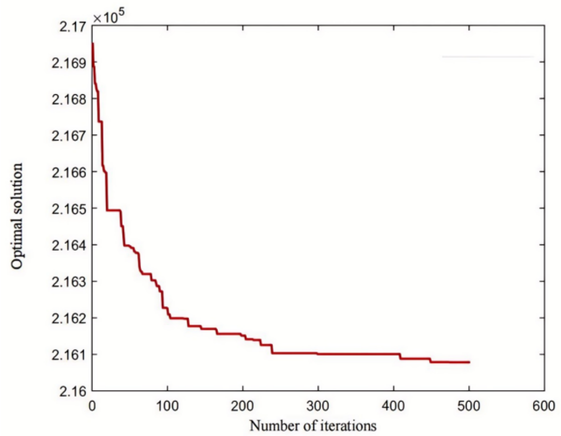
The value of Γ_{ik}	30	32	34	35	
Total costs /RMB	227178.61	229598.46	231787.66	233255.11	
Service level/%	99.9999	99.9999	99.9999	100.0000	



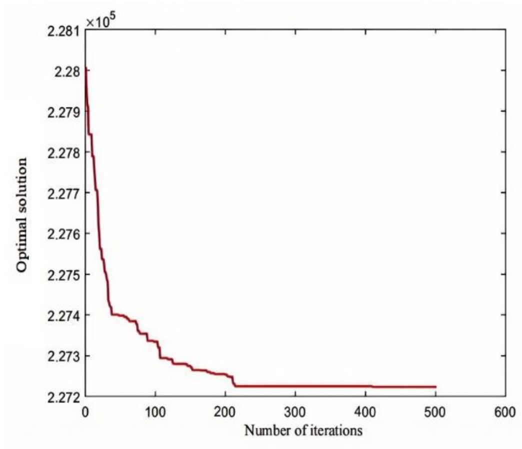
(a) Γ_{ik}=0



(b) Γ_{ik}=10



(c) Γ_{ik}=20



(d) Γ_{ik}=30

Fig. 3 Iteration of the optimal solution at different levels of robustness

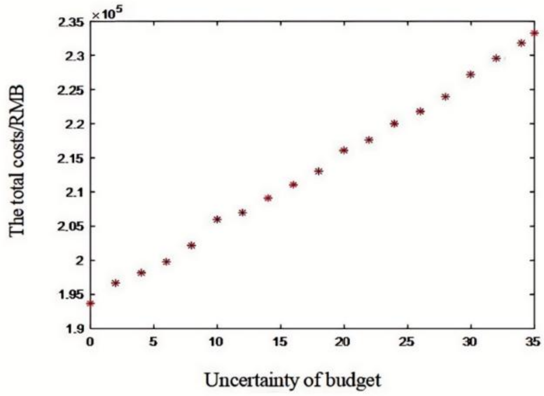


Fig. 4 The relationship between the uncertainty budget and the total costs

5.3.2 Relationship between enterprise's level of distribution services and total costs

Suppose the deviation value of customer demand is 20% the mean. From Equation (19), we can calculate the distribution service level and total costs of the enterprise under different uncertain budget values (table 5). When the uncertainty of customer demand is not considered, the total costs of the firm is 193,677.18 RMB, and the service level is 42.9761%. When the customer demand deviates completely, the enterprise's total delivery cost is 233,255.11 RMB, and the service level is 100%. We can observe that when the service level is enhanced by 57.02389%, the enterprise's total delivery cost increases by 39,577 RMB.

From table 5 and Fig. 5, it can be concluded that when $\Gamma_{ik} = 12$, the enterprise's service level has attained 96.709%; additionally, the total costs has increased by 13308.98 RMB compared to the deterministic demand, and the increase is 6.87% (compared to the deterministic demand). However, the service level has been enhanced by 53.7329%. When the service level is low, the relationship curve between the distribution total cost and service level is relatively flat, and the enterprise can enhance its service level by adjusting the uncertain budget Γ_{ik}. When the service level attains or exceeds 98%, i.e., when $\Gamma_{ik} > 12$, the relationship curve between delivery total costs and service level becomes increasingly steep, and it becomes difficult to improve the enterprise's service level by adjusting the value of the uncertain budget. Therefore, the decision-makers of the enterprise can determine the final delivery scheme based on their own goals.

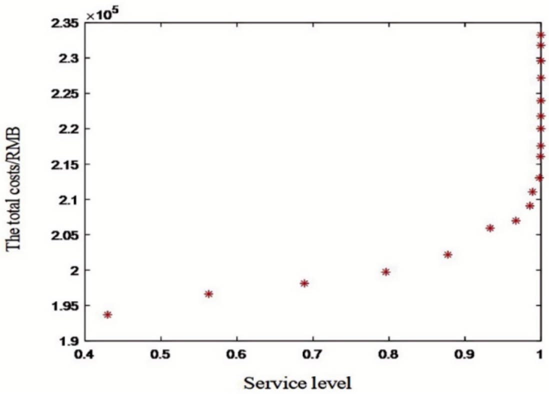


Fig. 5 Relationship between the total costs and service level

5.3.3 Comparatively analyzing results considering the traffic congestion coefficient

This study segments the delivery time and sets the speed of refrigerated vehicles at 25 kilometers per hour during peak hours. However, due to varying congestion levels on the roads, the delivery speed fluctuates accordingly. We introduce a congestion coefficient during peak hours to reflect the varying deli- very speeds, where the delivery speed of the refrigerated vehicle equals peak hour speed divided by the congestion coefficient. Considering the impact of different congestion coefficients on total delivery costs during peak hours with fixed uncertain budgets of 0, 18, and 35 as illustrated in table 6, it can be concluded that regardless of the value of an uncertain budget, total delivery costs and total driving time gradually increase as congestion coefficient increases. When $\Gamma_{ik} = 18$ and $\Gamma_{ik} = 35$, if the refrigerated vehicle is congested, the congestion coefficient's size exerts a limited impact on total delivery costs and driving time, mainly because efforts are made to avoid delivering during congested hours. When $\Gamma_{ik} = 0$, total costs of delivery and incremental increase in refrigerated vehicle travel time gradually increases due to road congestion; however, differences are not quite significant mainly because an enterprise can reasonably arrange deliveries when the customer demand is determined.

6. Conclusion

This study develops a robust model for location-routing with hard time windows under uncertain demand and time-dependent conditions, based on real delivery scenarios. To address uncertain demand, we utilize bounded symmetric intervals to represent its value range and introduce an uncertain budget to control parameter disturbances. By leveraging the strong duality theorem, we transform the nonlinear robust optimization model into a linear programming model. Furthermore, considering the practicalities of the delivery network, we segment the entire delivery time into different periods during which vehicle driving speeds vary. By analyzing the model's characteristics, we design an enhanced genetic algorithm with an elite and roulette selection strategy to solve the established model.

Table 6.

The relationship between vehicle speed, total costs, and total travel time under uncertain budgets

Uncertainty of budget	traffic congestion coefficient	Optimal total costs /RMB	Total vehicle travelling time/min
$\Gamma_{ik}=0$	0.5	193486.16	1474.8
	0.8	193554.25	1524.6
	1.1	193759.10	1681.8
$\Gamma_{ik}=18$	0.5	212925.40	1545.6
	0.8	213135.99	1702.8
	1.1	213180.54	1737.6
$\Gamma_{ik}=35$	0.5	232901.68	1518.6
	0.8	233192.75	1738.8
	1.1	223277.65	1804.8

Finally, through randomly generated case studies, we validate the effectiveness and feasibility of the model and algorithm. The following conclusions are subsequently drawn:

(1) The uncertain budget does not impact optimal distribution center location but significantly affects refrigerated vehicle routing and quantity. An increase from 6 to 8 distribution vehicles is observed as well as a reduction in their service range-indicating a positive correlation between system robustness and total costs.

(2) When the enterprise does not consider the uncertainty of customer demand, its service level is relatively low, only 42.9761%. However, accounting for this uncertainty can lead to higher service levels with even minor adjustments in an uncertain budget contributing positively towards improved service levels to a value not exceeding 96%, beyond which small changes lead to high total costs necessitating careful consideration by decision-makers.

(3) At equivalent uncertain budget levels, increased urban delivery road congestion coefficients prolong vehicle delivery times. However, these increases have only a slight impact on overall costs, which vary slightly around the 300 RMB mark, and on total travel time, which is roughly an hour with some variation. This indicates that road congestion issues have already been factored into company operations.

Despite the novelty of our research, there are still many aspects to be covered. One possible extension could be to consider the comparison of the proposed method with various traditional and advanced optimization algorithms to more accurately reveal its advantages and limitations. Another possible area of work could be addressing the inventory decisions of DCs.

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Ningbo Polytechnic Research Project: Research on Optimization of Agricultural Product Logistics Distribution Network under Uncertain Environment (NZ22RC06); Scientific Research Fund of Zhejiang Provincial Education Department: Demand Forecasting and Dynamic Dispatching Strategy of Emergency Materials under the Background of Sudden Epidemic (Y202250257).

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