## RESEARCH

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# Edge intelligence empowered delivery route planning for handling changes in uncertain supply chain environment

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## Abstract

Traditional delivery route planning faces challenges in reducing logistics costs and improving customer satisfaction with growing customer demand and complex road traffic, especially in uncertain supply chain environment. To address these challenges, we introduce an innovative two-phase delivery route planning method integrating edge intelligence technology. The novelty of our approach lies in utilizing edge computing devices to monitor real-time changes in road conditions and dynamically adjust delivery routes, thereby providing an effective solution for efficient and flexible logistics. Initially, we construct a mixed-integer programming model that minimizes the total cost under constraints such as customer destinations and time windows. Subsequently, in the cloud-edge collaborative mode, edge computing devices are utilized to collect real-time road conditions and transmit it to the cloud server. The cloud server comprehensively considers customer demand and road condition changes and employs adaptive genetic algorithms and A-star algorithms to adjust the delivery routes dynamically. Finally, comprehensive experiments are conducted to validate the effectiveness of our method. The results demonstrate that our approach can promptly respond to changes in customer demands and road conditions and flexibly plan the optimal delivery routes, thereby significantly reducing overall costs and enhancing customer satisfaction.

**Keywords** Uncertain supply chain, Cloud-edge collaboration, Changes in demand and road condition, Route planning, Hybrid meta-heuristic algorithm

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## Introduction

In uncertain supply chain environment, the logistics industry is evolving rapidly and facing numerous challenges, in which the most critical is the precise and efficient planning of delivery routes [1]. As customer demands become more diverse and urban traffic environments increasingly complex, this challenge has become more pronounced. Logistics route planning has to flexibly respond to changes in delivery locations and times caused by factors such as plan alterations or temporary demands [2], while also considering unpredictable factors like traffic congestion and route disruptions [3]. These dynamic factors add extra uncertainty to the selection and optimization of delivery routes, significantly impacting the improvement of logistics efficiency and customer satisfaction. In recent years, edge intelligence technology,



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combined with cloud computing and the Internet of Things (IoT), has been applied by scholars to new intelligent logistics models to optimize the logistics delivery process [4–6]. This not only enhances the precision and efficiency of logistics route planning and reduces costs, but also significantly improves customer satisfaction. Furthermore, this technology plays a crucial role in reducing energy consumption and carbon emissions during transportation, contributing to the development of an environmentally friendly logistics system and effectively alleviating urban traffic congestion.

Edge intelligence refers to the rapid processing and analysis of data at the network edge, aimed at reducing latency and enhancing efficiency [7]. This technology demonstrates immense potential in delivery route planning. It is capable of real-time processing of complex traffic and delivery data to optimize decision-making and significantly improve delivery efficiency [8]. Compared to traditional logistics route planning [9, 10], edge intelligence offers a flexible and efficient route planning solution that can quickly respond to environmental changes, such as traffic fluctuations. The rise of this technology is attributed to its ability to reduce central processor delays when handling large volumes of data and effectively utilize the growing amount of data generated by the Internet of Things (IoT) devices. Figure 1 provides a simple example of an edge intelligence empowered delivery route planning that considers two types of changes in uncertainty, i.e., customer demand changes and road condition changes. Delivery vehicles start their routes at 8 AM and sequentially complete delivery tasks along the planned route. After the vehicle completes the first delivery task for customer 1 at destination A, the edge computing device detects a change in the road conditions leading to the next delivery destination. To avoid delays for subsequent customers, the cloud server is required to adjust the route temporarily. As the vehicle approaches customer 2 at destination B, the route needs to be adjusted again due to the delivery destination being changed from C to D by customer 3 through the terminal device.

Edge intelligence empowers delivery route planning, utilizing IoT devices at the edge for data collection and analysis, facilitating intelligent interaction between vehicles, cloud servers, and edge computing devices. In this study, we propose a novel approach that employs edge computing devices to monitor real-time changes in road conditions, allowing for timely adjustments in delivery routes. Unlike previous studies that focused on static road conditions or probabilistic planning in uncertain environments [11, 12], our method concentrates on using real-time changes in road conditions to dynamically plan delivery routes, thus more effectively handling the constantly changing road conditions. In addition, we focus on changing customer demands, including changes in customer time windows and destinations. Customers set their demands through terminal devices, including delivery destinations and time windows. Subsequently, the cloud server

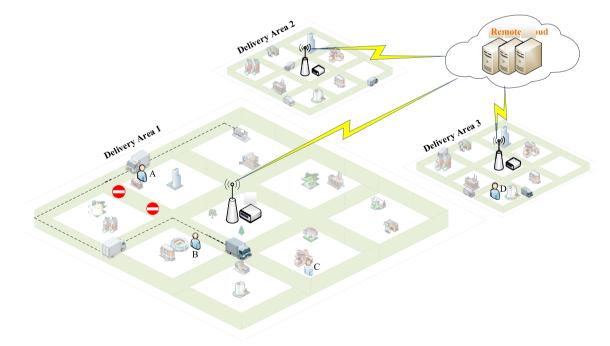


Fig. 1 Illustration of edge intelligence empowered delivery route planning for handling changes in uncertain supply chain environment

and edge computing devices coordinate to develop the optimal delivery routes. Edge computing devices are responsible for monitoring real-time road conditions, calculating whether changes have affected the original route, and sending this information back to the cloud server for route adjustments [13, 14]. This study aims to develop an efficient and flexible delivery route planning method adapted to uncertain environments by integrating edge intelligence techniques so as to reduce delivery costs and improve customer satisfaction. Compared to previous probabilistic planning methods in uncertain environments, our method increases the timeliness and accuracy of delivery routes while significantly reducing uncertainty and efficiency losses in the delivery process by instantly capturing and analyzing road condition changes.

We explore the delivery route planning empowered by edge intelligence in uncertain supply chain environment. This study aims to develop an innovative delivery route planning method to address the changes in road conditions and customer demands within an uncertain supply chain environment, thereby enhancing the efficiency of logistics delivery and customer satisfaction. The contributions of this paper are summarized as follows:

- We develop a mixed-integer programming model that minimizes the total delivery cost while meeting customer demands, including soft constraints of destination and time windows, as well as limitations on vehicle capacity and endurance.
- 2) We propose a two-stage route planning method to address these changes. In the first stage, an initial solution is generated based on the initial customer demands, aiming to minimize the total journey while satisfying customer demands. In the second stage, we dynamically adjust the route through the cloud-edge collaboration mode, which utilizes edge computing devices to collect real-time road conditions, calculate to determine whether the changes have affected the original route, and send the results back to the cloud server. The cloud server receives demand changes from customers and road condition changes from edge computing devices, runs the adaptive genetic algorithm and adaptive A-star algorithm to guide vehicle route adjustment.
- 3) We validate the effectiveness of our proposed method through experiments and demonstrate their efficiency and practicality in addressing route planning problems involving changes in customer demands and road conditions through planning and analysis of actual cases.

Overall, our work effectively addresses the challenges of changing road conditions and customer demands in an uncertain supply chain environment. The proposed optimization model and route planning method provide practical solutions for enhancing logistics delivery efficiency and customer satisfaction.

The remainder of this paper is organized as follows: Related works section reviews previous related research. Problem description section provides a detailed description of the research problem and the corresponding mathematical model. Proposed method section introduces our method for solving the problem. Simulation experiment section presents a case study and experimental results. Finally, in Conclusion section, we discuss the conclusions and future research directions.

#### **Related works**

In recent years, route planning in the field of supply chains has received significant attention, and we have reviewed a series of related literature and conducted an in-depth study of this topic.

#### Route planning in traditional supply chain environment

The traditional supply chain is a linear process for moving products from suppliers to consumers aiming to minimize costs [15]. To achieve this, various solutions have been proposed for different scenarios. For instance, Liu et al. [16] used a hybrid heuristic algorithm to develop cost and time-optimized route planning solutions for the e-commerce industry with time and vehicle capacity constraints, demonstrating attention to practical business demands. Archetti et al. [17] and Shelbourne et al. [18] focused on vehicle route problems with release dates and deadline constraints. The former minimized completion time using MILP model with an iterative local search method, while the latter optimized total costs using a path-relinking algorithm.

Additionally, some scholars have focused on considering customer service time in route planning research. For example, Bae et al. [19] examined multi-location vehicle routing problems with time windows, distinguishing between vehicles for product delivery and those for installation services, and solved this problem using heuristic and genetic algorithms. Han et al. [20] studied optimization strategies for door-to-door delivery systems under soft time window conditions, aiming to reduce total distance and delivery personnel work time using a MILP model and heuristic algorithms. While these studies provide solutions for logistics route planning, their practical application may be limited when facing dynamic changes in customer demands and road conditions.

#### Route planning in uncertain supply chain environment

Demand-side uncertainty factors are commonly related to customer demand and are modeled using probabilistic distribution parameters. For example, Zhang et al. [21] addressed the uncertainty of customer demand in the fresh supply chain distribution problem using probability distributions. They developed a probabilistic programming model and an improved genetic algorithm to minimize delivery costs while ensuring freshness. Liu et al. [12] introduced uncertainty in demand in the context of electric vehicle delivery and developed a twostage adaptive robust model to accommodate changes in demand. Furthermore, Özarık et al. [2] considered the uncertainty of customer demand from a temporal perspective, optimizing delivery routes using a probabilistic planning model and the ALNS algorithm to address the uncertainty of customer appearance times. These studies highlight the importance of managing demand-side uncertainty in supply chain delivery routes.

In research on supply-side uncertainty, transportation and service times are the primary focus. Goli et al. [22] addressed the uncertainty of transportation times in the organ transplant supply chain by constructing a possibility programming model and optimizing total costs through simulation. Liu et al. [11] described the uncertainty of customer service times using probability distributions and minimized assembly times in urban delivery problems using a stochastic programming model and a hybrid heuristic algorithm. Despite these contributions to addressing transportation and service time uncertainties, there has been less research on the impact of changing road conditions on transportation times. In this context, Liu et al. [23] introduced real-time traffic conditions and developed a mixed-integer programming model to minimize the total travel time in the supply chain, using a hybrid algorithm that combines ant colony systems and virtual traffic modeling (ACS-VTM) to explore optimal vehicle routes.

Additionally, several studies have focused on addressing uncertainties from both supply and demand sides simultaneously. For instance, Yan et al. [24] used budget uncertainty theory to handle fuzzy random demands and travel times, proposing a vehicle route planning method based on particle swarm optimization to minimize total costs and maximize customer satisfaction. Goel et al. [1] focused on random demand and service times, solving the time-window-constrained vehicle route planning problem with an improved ant colony system, aiming to balance total transportation costs and customer satisfaction. Further, Samani et al. [25] developed a fuzzy programming model for blood supply chain network planning, considering supply chain disruption risks and uncertainties in input data such as blood supply and demand, facility costs, and transportation costs. While these studies have made progress in handling uncertainties, they still lack a comprehensive consideration of the overall impact of changes in customer demand and road conditions on the supply chain. Zhang et al. [26] paid more attention to the uncertainties in travel and service times caused by traffic congestion and customer delays, providing new methods to handle these uncertain parameters, yet they did not fully explore response mechanisms to customer demand changes.

## Application of cloud computing and edge computing in route planning

In the field of route planning, the application of cloud computing technology is flourishing, with numerous scholars successively proposing a series of innovative methods and systems. The application of cloud computing has been widely discussed and researched, particularly in intelligent city logistics. For instance, Nowicka et al. [4] conducted an in-depth analysis of the role of cloud computing in intelligent city logistics, especially emphasizing its potential in adapting to the dynamically changing transportation environment and effectively managing urban traffic. Meanwhile, Chen et al. [27] utilized cloud computing technology to acquire real-time traffic conditions and optimized the routes of cold chain logistics vehicles using parallel genetic algorithms, analyzing delivery times and costs. Yu et al. [28] also explored an online planning algorithm for cold chain logistics shipping routes in a cloud computing environment to enhance delivery efficiency.

Additionally, the role of edge computing in optimizing logistics delivery routes is becoming increasingly prominent. Li et al. [29] proposed a dynamic vehicle delivery route optimization method that combines cloud computing, edge computing, and terminal device collaboration, effectively resolving issues of irrational routes and neglecting real-time road conditions in logistics delivery. Yao et al. [8] developed a real-time cache-assisted route planning system based on mobile edge computing (CARPS-MEC) that significantly reduces communication and computation time by caching frequently used routes, thereby significantly shortening response times. Xue et al. [30] introduced a cooperative route planning system for multi-connected vehicles supported by edge computing, which effectively reduces traffic congestion through cross-domain load balancing. Furthermore, Wang et al. [14] investigated the optimization design of intelligent logistics systems and supply chain management,

enhancing the accuracy of logistics system positioning and the efficiency of supply chain management using edge computing and IoT technology.

Overall, cloud computing and edge computing not only significantly improves computational efficiency and response speed in route planning but also enhances the capability to handle large-scale data and complex realtime road conditions. It demonstrates great potential and practical value in managing uncertainties in road condition changes.

#### **Problem description**

#### **Description and assumptions**

We study the problem of optimizing the routes of delivery vehicles based on customer demands and real-time road conditions, in order to mitigate the impact of customer demand and traffic condition changes on delivery, and to reduce total cost. Therefore, the research quescapacity and arrival time not exceeding the customers' time window.

#### Mathematical model

We introduce a mathematical model for dynamic delivery route planning in the problem. The main notations are shown in Table 1.

## 1) Transportation cost

The transportation cost, denoted as TC, is represented as the sum of the initial route cost and the incremental or decremental route cost due to customer demand changes and the incremental or decremental route cost due to road condition changes. The energy consumption required for transportation is the primary source of this cost, and its formula is shown in Eq. (1).

$$TC = c_1 \left( \sum_{k=1}^{K} \sum_{i=0}^{M} \sum_{j=0}^{M} d_{ij} x_{ijk} + \sum_{k=1}^{K} \sum_{i=0}^{M} \sum_{j=0}^{M} d_{ij} (x_{ijk}^+ - x_{ijk}^-) + \sum_{k=1}^{K} \sum_{i=0}^{M} \sum_{j=0}^{M} d_{ij} (x_{ijk}^{++} - x_{ijk}^{--}) \right)$$
(1)

tion of this paper can be described as follows: During the delivery process, how to handle the uncertainties caused by changes in customer demands (such as destinations and time windows) and changes in road conditions (such as sudden accidents, traffic congestion) along the route, to ensure that customer demands are met to the greatest extent while minimizing the total cost.

The dynamic delivery route planning problem studied in this paper focuses on changes in customer demands and road conditions during the delivery process, for which the assumptions are as follows.

Assumption 1: The delivery center must complete all the customers' delivery tasks. Multiple vehicles are deployed for preliminary optimization to formulate a delivery plan, ensuring that the vehicles complete the delivery tasks on time.

Assumption 2: Road condition changes are collected and sent to the cloud server by edge computing devices, while demand changes are sent to the cloud server by the customers through terminal devices. The cloud server receives these changes and runs the algorithms to adjust the route until all tasks are completed.

Assumption 3: Each vehicle is responsible for delivering to multiple customer demand points, with the total load not exceeding the vehicle's maximum  $c_1$  represents the transportation cost per unit distance.  $x_{ijk}$  is a binary variable representing the delivery routes, where all  $x_{ijk}$  with the same k constitute a contiguous route, i.e., the driving route of vehicle k.  $x_{ijk}^+$  and  $x_{ijk}^-$  represent route adjustments due to customer demand changes, while  $x_{ijk}^{++}$  and  $x_{ijk}^{--}$  represent adjustments due to road condition changes.

### 2) Time window penalty cost

Each customer has specific requirements for delivery time, and delivering goods within the stipulated time window  $[e_i, l_i]$  can significantly save costs. The high demand for vehicles and other resources in logistics may lead to goods arriving early or late, thereby incurring costs for early waiting and late penalties. Considering practical situations, this paper adopts a soft time window constraint approach. Deliveries outside the time window incur additional penalty costs, denoted as PC, as shown in Eq. (2).

$$PC = c_2 \sum_{k=1}^{K} \sum_{i=0}^{M} \left( w_{ik} + max[0, (t_{ik} - l_i)] \right)$$
(2)

 $c_2$  represents the penalty cost per unit of time,  $w_{ik}$  is the waiting time of vehicle k at demand point of customer *i*, and  $t_{ik}$  is the time of arrival of vehicle k at demand point of customer *i*.

Notations	Descriptions
i,j,n	<i>i</i> , <i>j</i> is customer id, <i>i</i> , <i>j</i> = 0,1,2,, <i>M</i> , <i>M</i> is the number of customers, 0 is the delivery center; <i>n</i> is the traffic node.
k	Delivery vehicle number ( $k = 1, 2,, K$ ), K is the number of vehicles.
e <sub>i</sub> , l <sub>i</sub>	Earliest and latest time for customer <i>i</i> .
X <sub>ijk</sub>	Binary variable on whether vehicle k moves from i to j. $X_{ijk}$ is the set of $x_{ijk}$
$x_{iik}^+, x_{iik}^-$	$x_{ijk}^+$ is the route added to $x_{ijk}$ after a demand change; $x_{ijk}^-$ is the route reduced from $x_{ijk}$ after a demand change.
$x_{ijk}^+, x_{ijk}^-$ $x_{ijk}^{++}, x_{ijk}^{}$	$x_{ijk}^{++}$ is the route added to $x_{ijk}^+$ after a change in road conditions; $x_{ijk}^{}$ is the route reduced from $x_{ijk}^-$
ijn ijn	after a change in road conditions.
d <sub>ij</sub>	Distance between <i>i</i> and <i>j</i> .
$D_k$	Endurance of vehicle k.
t <sub>ik</sub> , t <sub>jk</sub>	Arrival time of vehicle <i>k</i> at <i>i</i> and <i>j</i> .
t <sub>ijk</sub>	Time required for vehicle k to travel from i to j.
b <sub>ik</sub>	Departure time of vehicle k from i, $b_{ik} \ge 0$ .
W <sub>i</sub>	Weight of goods for customer <i>i</i> .
$W_k$	Capacity of vehicle k.
v <sup>m</sup> <sub>ijk</sub>	Speed of vehicle <i>k</i> at time <i>m</i> of the travel from <i>i</i> to <i>j</i> .
d <sup>m</sup> <sub>ijk</sub>	Distance travelled by vehicle <i>k</i> from <i>i</i> to <i>j</i> at time slot <i>m</i> .
r	Road conditions of the section from <i>i</i> to <i>j</i> at time slot <i>m</i> .
0	Time slot, $o = 1, 2, \dots, O$ , $O$ is the number of time slot.
$\pi^{\circ}$	Time interval $\pi^{\circ} = [\zeta_{\circ}, \xi_{\circ}], \zeta_{\circ}$ and $\xi_{\circ}$ are the left and right time boundary of $\pi^{\circ}$ .
V	Number of vehicles on the current road segment.
Q	Number of edge computing devices (ECD).
$\lambda_{V2V}$	Data transmission rate based on V2V technology.
$\lambda_{V2I}$	Data transmission rate based on V2I technology.
$\omega_{\scriptscriptstyle V}$	Data amount of vehicle v computing task transferred to the edge server.

## 3) Vehicle cost

The cost of completing all customers' delivery task is positively correlated with the number of vehicles scheduled for delivery. Therefore, it is crucial to reduce the number of vehicles needed for delivery tasks. *VC* represents the total cost of the vehicles required to complete the tasks, as detailed in Eq. (3), where  $c_3$  denotes the cost per vehicle. these tasks according to customer demands and road conditions to determine the optimal route. In the edge computing context, adapting to changes in customer demands and road conditions involves a process akin to computation task offloading as described in [31]. This process encompasses the computation task's transmission, offloading to the edge server, route replanning by the server, and sending the new route to the vehicle. The total time for this is modeled as follows.

$$f_{\nu}(t) = \sum_{q=1}^{Q} \sum_{\nu'=1}^{V} F_{q}^{\nu}(t) \cdot G_{\nu}^{\nu'}(t) \cdot (1 - F_{\nu}^{q}(t)) \cdot \frac{\omega_{\nu}}{\lambda_{V2V}} \cdot (\theta_{\nu,\nu'} + 1) + \sum_{q=1}^{Q} F_{\nu}^{q}(t) \cdot \frac{\omega_{\nu}}{\lambda_{V2I}} + \sum_{q=1}^{Q} F_{\nu}^{q}(t) \cdot \frac{l_{\nu}}{u_{\nu} \cdot p} + \frac{\omega_{\nu'}}{\lambda_{V2I}}$$
(4)

$$VC = c_3 \sum_{k=1}^{K} \sum_{j=0}^{M} x_{0jk}$$
(3)

## 4) Edge service time cost

Once delivery starts, vehicles periodically request tasks from the server, which processes and evaluates  $F_q^{\nu}(t)$  and  $G_{\nu}^{\nu'}$  are binary variables, where  $F_q^{\nu}(t)$  is 0 if vehicle v is in range of edge device q, and 1 if not;  $G_{\nu}^{\nu'}$  is 0 if a task transmits from  $\nu$  to  $\nu'$ , and 1 otherwise.  $\theta_{\nu,\nu'}$  counts vehicles rerouted from  $\nu$  to  $\nu'$ .  $\lambda_{V2V}$  and  $\lambda_{V2I}$  are the Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) data transmission rates, respectively.  $\omega_{\nu}$  and  $\omega'$  represent the data sizes of vehicle  $\nu$ 's task and the results post-execution, respectively. p is each resource unit's processing capacity;  $u_{\nu}$ , the edge server's unit count;  $l_{\nu}$ , the task length.

The entire delivery process is divided into *O* time periods, each represented as  $[\zeta_o, \xi_o]$ . At the start of each time period  $\zeta_o$ , vehicles initiate task requests to the server. Considering the cost of using edge computing services, we set the cost per unit of time as  $c_4$ . Therefore, the total cost of using edge services during the entire vehicle delivery process is calculated as *EC*, with the calculation formula provided in Eq. (5).

$$EC = c_4 \sum_{o=1}^{O} f_{\nu}(\zeta_o) \tag{5}$$

The total cost to complete all delivery tasks, by dynamically adjusting delivery routes in response to changes in customer demands and road conditions, can be expressed as:

$$Cost = TC + PC + VC + EC \tag{6}$$

The constraints related to customer demands (destination, time window), the capacity and endurance of the vehicles are as follows.

$$\sum_{k=1}^{K} \sum_{i=0, i \neq j}^{N} x_{ijk} = 1 \qquad \forall j \in N$$
(7)

$$\sum_{k=1}^{K} \sum_{i=0, i \neq j}^{N} x_{ijk} + x_{ijk}^{+} - x_{ijk}^{-} = 1 \qquad \forall j \in N$$
(8)

$$\sum_{k=1}^{K} \sum_{i=0, i\neq j}^{N} x_{ijk} + x_{ijk}^{+} - x_{ijk}^{-} + x_{ijk}^{++} - x_{ijk}^{--} = 1 \qquad \forall j \in N$$
(9)

$$\sum_{i=0}^{N} \sum_{j=0}^{N} w_i x_{ijk} \leqslant W_k \qquad \forall k \in K$$
(10)

$$\sum_{i=0}^{N} \sum_{j=0}^{N} d_{ij} x_{ijk} \leqslant D_k \qquad \forall k \in K$$
(11)

Equations (7)-(9) collectively emphasize the importance of customer coverage in the routing process. Specifically, Eq. (7) ensures that the planned route, based on the original demand, encompasses all customers without omissions. Equation (8) states that the adjusted route must meet the demands of all customers, even if demand changes before the delivering state. Equation (9) further asserts that any modifications to the route, prompted by changes in road conditions, should not result in any customer being left out. Equation (10) requires the cumulative load of a vehicle not to exceed the vehicle's load capacity. Equation (11) requires the total distance of the vehicle routes not to exceed its endurance, a constraint that ensures the vehicle can complete its deliveries without running out of power.

### **Proposed method**

We propose a two-stage delivery route planning method for handling changes in uncertain supply chain environment, as shown in Fig. 2. In the first stage, the supply chain system plans the initial delivery route after receiving the initial customer demands, as detailed in Algorithm 1. This route has a minimum total vehicle travel distance while satisfying the constraints of customer destination and time window demand, as well as vehicle endurance and load constraints. In the second stage, if the customer demand changes in the undelivered state, the remaining routes are optimized based on the changed customer demand to minimize the impact of the change on the subsequent delivery tasks, as detailed in Algorithm 2. If the road conditions on the remaining routes change (e.g., traffic congestion), a new and faster route is selected based on the changed road conditions to avoid delivery delays, as detailed in Algorithm 3.

## Route planning for the initial customer demands in the first stage

As the initial route planning does not necessitate an exact optimal solution, our approach employs a genetic algorithm based on [32]. This algorithm is enhanced by an adaptive encoding scheme to generate the initial population so that the genetic algorithm can adaptively solve our optimization model, which is detailed in Algorithm 1.

Algorithm 1 Route planning for initial customer demands

Algori	Algorithm 1 Route planning for initial customer demands.									
Input	customer demands: $n_i, e_i, l_i$ ; vehicle capacity: $W_k$ ; vehicle									
	endurance: D <sub>k</sub>									
Outp	optimal route: X <sub>ijk</sub>									
ut										
1	Encode a chromosome									
2	Population initialization									
3	while not reach maximum iterations									
4	<b>if</b> chromosome satisfy constraints of $n_i e_i J_i$ , $W_k$ and $D_k$									
5	fitness←travel distance of chromosome									
6	Selection, Crossover and mutation operation									
7	end									
8	end									
9	Decode optimal chromosome to X <sub>iik</sub>									

The input parameters include customer demands, such as destination and time window, and vehicle restrictions, such as capacity and endurance. The output parameters are the optimal routes  $X_{ijk}$ . First, a chromosome is encoded

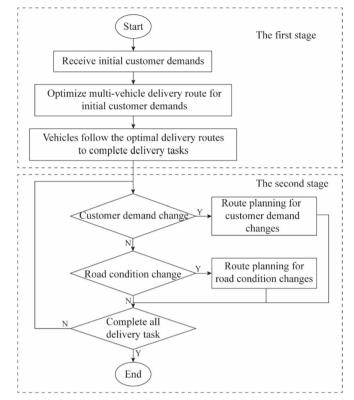


Fig. 2 Two-stage route planning method for handling customer demand changes and road condition changes

and then the population is initialized by that chromosome (lines 1–2). The encoding scheme is as follows: the initial chromosome is encoded as {1, 2, ..., U, U+1, U+2, ..., U+K-1}, where U is the number of customers and K is the number of available vehicles. {1,2, ..., U} represents the customer ID, {U+1, U+2, ..., U+K-1} represents separation flags to distinguish the customer IDs responsible for different vehicles. Second, the normalized genetic operators are executed until reaching the maximum iterations (lines 3–8). Population initialization, selection crossover and mutation operations are detailed in the work of Zhang et al. [21]. Finally, the optimal chromosome is decoded into an optimal route  $X_{iik}$  (line 9).

### Route planning for handling changes in the second stage

In order to mitigate the impact of uncertainties in both customer demand and delivery delays on costs and customer satisfaction, the second stage handles two types of changes in uncertain supply chain environments, i.e., customer demand changes and road condition changes.

#### Handling customer demand changes

The supply chain system only accepts changes in demand from customers who have not yet been delivered. If the customer demand changes, the algorithm adjusts the remaining route based on the current route to meet the changed demand. The adjustment method is detailed in Algorithm 2.

Algorithm 2 Route planning for handling customer demand changes

Algori	thm 2 Route planning for handling customer demand changes.
Input	changed customer demand list: $iList$ ; vehicle routes: $X_{ijk}$
Outp	adjusted route: X <sub>ijk</sub>
ut	
1	while iList is not empty
2	changedDemand $\leftarrow$ iList(1)
3	$r \leftarrow find(any(X_{ijk} == changedDemand, 2));$
4	update the changed customer demands in route ۲
5	if changedDemand then
6	X <sup>+</sup> <sub>iik</sub> , X <sup>-</sup> <sub>iik</sub> ← Algorithm1(n <sub>i</sub> ,e <sub>i</sub> ,I <sub>i</sub> ,W <sub>k</sub> ,D <sub>k</sub> )
7	end
8	$X_{ijk} \leftarrow X_{ijk} + X_{iik}^+ - X_{iik}^-$
9	end

The input parameters include the changed customer demand list and vehicle routes. The demand change list stores the customer ID, changed destination, and time window demand. The delivery route stores the current vehicle routes in  $X_{ijk}$ . The output parameters are the new routes adjusted to the changed demands, also stored in  $X_{ijk}$ . First, the changed customer demands are stored in a

list and the algorithm loops through the list until it is empty (line 1). Second, the route *r*, where the demands have changed, is identified and the demands on it are subsequently updated (lines 2-4). Third, if a demand changes, Algorithm 1 is used to adjust the route for all undelivered customer demands, obtaining added roads  $X_{iik}^+$  and deleted road  $X_{iik}^-$  from the route (lines 5–7). Finally, the new route  $X_{ijk}$  is updated through  $X_{iik}^+$  and  $X_{iik}^-$  (line 8).

#### Handling road condition changes

Most studies that consider the state of the road network assume that the traffic state is known and lacks a response mechanism to road condition changes due to unexpected conditions (e.g., traffic accidents) in practical situations [33, 34]. In order to minimize delivery delays caused by road condition changes (e.g., road congestion), we need to avoid congested roads and choose a road that can reach the next customer in the shortest possible time. The A-star algorithm has numerous applications in finding the shortest reachable route between two points [35] and can adapt well to unexpected situations. Therefore, we implement a delivery route planning algorithm that adaptively handles road condition changes based on the A-star, as detailed in Algorithm 3.

Algorithm 3 Route planning for handling road condition changes

Algorithm 3 Route planning for handling road condition changes. Input start and target node: n<sub>i</sub>,n<sub>i</sub>; changed road condition list: pList; route: X<sub>ijk</sub> Outp adjusted route: Xiik ut 1 n<sub>c</sub>←n<sub>i</sub> 2 while  $n_c \neq n_i$  do 3  $n_n \leftarrow X_{ijk}(find (X_{ijk} = = n_c) + 1)$ if ismember(pList, [n<sub>c</sub>, n<sub>n</sub>]) then 4 5 t<sub>nnk</sub>←b<sub>nck</sub>+t<sub>ncnnk</sub> 6 if  $t_{n_nk} > I_{n_n}$  then nSet the set of next feasible nodes of n7 8 n<sup>new</sup>← the node of minf<sub>iik</sub>(nSet) Add path of  $[n_c, n_n^{new}]$  to  $X_{ijk}^{++}$  and path of  $[n_c, n_n]$ 9 ] to  $\chi_{ijk}^{--}$ 10 end 11 end 12 n<sub>c</sub>←n<sup>ne</sup> 13 **end** 

14 - X-- $X_{ijk} = X_{ijk}$ +  $X_{iik}^{++}$ 

The input parameters include the start node  $n_i$ , target node  $n_i$ , and route  $X_{ijk}$ . The output parameter is the adjusted route for the road condition changes. The start node  $n_i$  is assigned to the current node  $n_c$ ; if  $n_c$  is not the target node  $n_i$ , it enters the loop (lines 1–2).  $n_n$  is the next node of the  $n_c$  in the route  $X_{ijk}$ , if the road condition changes in the road from  $n_c$  to  $n_n$ , calculate the time  $t_{n_nk}$ to reach the next customer through this road (lines 3-5). When road travel time leads to delivery delays for the next customer, the A-star algorithm picks the least timeconsuming roads from available alternatives. This process involves identifying a new next node  $n_n^{new}$ , added road  $X_{iik}^{++}$ , and removed road  $X_{iik}^{--}$  (lines 6–10). The loop then updates the current node  $n_c$ , and finally, the route  $X_{ijk}$  is updated with  $X_{ijk}^{++}$  and  $X_{ijk}^{--}$ . The formulas for estimating road travel time are detailed in Eqs. (12) and (13).

$$f_{ijk}(n_n) = g_{ijk}(n_n) + h_{ijk}(n_n)$$
(12)

$$g_{ijk}(n_n) = g_{ijk}(n_c) + t_{n_c n_n k}$$
<sup>(13)</sup>

In these equations,  $f_{ijk}(n_n)$  is a heuristic function of travel time for vehicle  $\vec{k}$  on node  $n_n$  from customer i to  $j.g_{ijk}(n_n)$  is the actual travel time of vehicle k from customer *i* to node  $n_n$ .  $h_{iik}(n_n)$  is an estimate of the travel time of vehicle k from node  $n_n$  to customer j.n<sub>c</sub> is the previous node of  $n_n$ .  $t_{n_c n_n k}$  is the travel time of vehicle k from node  $n_c$  to  $n_n$ .

In time-varying road networks, the travel speed of a vehicle departing from node  $n_c$  to  $n_n$  at a specific time t will be affected by the prevailing road conditions  $r_{n_c n_n}$ . The road conditions may change from node  $n_c$  to  $n_n$ , which complicates the calculation of the vehicle travel time. We refer to the speed step function of Ichoua et al. [36] and divide the whole delivery process into O time intervals, denoted as  $\pi_o = [\zeta_o, \xi_o](o = 1, 2, \dots, O)$ . The travel speed is assumed to be constant for each interval to make it easy to calculate without loss of generality, and the travel time from  $n_c$  to  $n_n$  is calculated as follows.

Step 1:  $o \leftarrow 1$ ,  $d \leftarrow d_{n_c n_n}$ ,  $t \leftarrow b_{n_c k}$ ,  $t_{n_c n_n k}(b_{n_c k}) \leftarrow 0$ . Step 2: If  $\zeta_0 \leq t \leq \xi_0$ , go to step 3; otherwise, repeat o = o + 1 until  $\zeta_o \le t \le \xi_o$ , then go to step 3. Step 3: If  $\left(t + \frac{d}{v_{n_c n_n}^0}\right) > \xi_o$ , then go to step 4; otherwise,  $t_{n_c n_n k}(b_{n_c k}) \leftarrow t_{n_c n_n k}(b_{n_c k}) + \frac{d}{v_{n_c n_n}^o}, t_{n_n k} \leftarrow t_{n_c k}$ +  $T_{n_c n_n k}(t_{n_c k})$ . Then,  $t_{n_c n_n k}(b_{n_c k})$  and  $t_{n_n k}$  are output as the travel time from node  $n_c$  to  $n_n$  and the arrival time at node  $n_{\mu}$ . Step 4:  $t_{n_c n_n k}(b_{n_c k}) \leftarrow t_{n_c n_n k}(b_{n_c k}) + (\zeta_{o+1} - t),$   $d \leftarrow d - v_{n_c n_n}^o \times (\zeta_{o+1} - t), \quad t \leftarrow \zeta_{o+1}, \quad o \leftarrow o + 1,$ 

and go back to step 3.

#### Simulation experiment

#### Parameter setting

We consider a 400 square kilometer urban area covered by the supply chain system, as shown in Fig. 3. Blue circles represent traffic nodes, and the numbers on the right

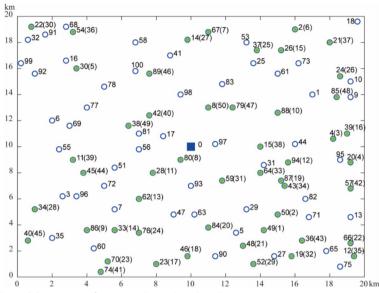


Fig. 3 Location of traffic nodes and destinations of customer demands in the urban area

side represent node IDs. The green stars represent the destinations of customer demands, and the customer IDs are in the right parentheses. The blue square in the center represents the delivery center. There are 100 traffic nodes in the case, and each node can be connected to other nodes. Road condition changes in specific subregions can impact traffic efficiency. Each subregion has a Road-side Unit (RSU) for monitoring local road conditions and real-time communication with nearby delivery vehicles. Consequently, data transmission rates for Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) technologies are set at  $\lambda_{V2V} = 1$  Gb/s and  $\lambda_{V2I} = 600$  Mb/s, respectively, ensuring efficient and accurate information transfer.

Based on practical situation, the supply chain system operates vehicles from 8:00 to 18:00, receiving customer demand change requests during these hours. The system comprises 10 vehicles, each with a 200 kg load capacity  $(W_k)$  and a 100 km range  $(D_k)$ . The start-up cost for each vehicle is 100 yuan per trip. The supply chain system has received 50 initial customer demands before the vehicles start their tasks, and the demands is shown in Table 2.

In an uncertain supply chain environment, customers may change their demands for their own reasons. To simulate such changes, we set up details for customer's changed demand regarding the modified time, new destination, new time window, and new service time, as detailed in Table 3.

In practice, the road conditions change unpredictably on each road section. In order to simulate such changes, we set some critical parameters involving the occurrence time, duration, road and congestion level, as detailed in Table 4.

## Experimental results and efficiency analysis Route planning results for handling customer demand and road condition changes

According to the proposed model and algorithm, a total of four vehicles are required to complete all the delivery tasks and satisfy customer demands. The metrics affecting the cost include distance travelled, waiting time, and start-up cost (constant values, not in the table). Metrics affecting customer satisfaction include violation of customer's destination and time window demand, which we uniformly denote by violated customers. Additionally, the travel distance and load are constrained by the endurance and load capacity, respectively.

Changes in customer demands and road conditions may lead to inefficiencies and delivery delays in the delivery routes, thus violating customer demand and reducing customer satisfaction. In order to handle such changes, the proposed method replans the delivery routes to cover the new demands and reselects a new delivery road according to the road network conditions to minimize delivery delays. The adjusted routes and their evaluation metrics for handling changes in customer demand and road conditions are detailed in Table 5, where the bold numbers in the routes represent detoured traffic nodes.

#### Comparison results with baseline method

To verify the superiority of the method proposed in this paper, we established two baseline methods for comparison: the Adaptive Large Neighborhood Search (ALNS) [2] joint algorithm and the Modified Ant Colony System (MACS) [1].

Customer id	Location	Weights /kg	Time windows	Service time /min	Customer id	Location	Weights /kg	Time windows	Service time / min
1	49	3	15:30~18:00	20	26	24	10	15:20~17:20	20
2	50	23	16:30~18:00	20	27	14	12	14:20~16:20	20
3	4	6	12:00~14:00	20	28	34	26	11:40~13:40	20
4	20	16	12:30~14:30	20	29	52	12	13:00~15:00	20
5	30	10	10:10~12:10	20	30	22	22	09:30~11:30	20
6	2	18	15:50~18:00	20	31	59	3	15:50~17:50	20
7	67	9	10:40~12:40	20	32	19	11	08:10~10:10	20
8	80	20	08:00~09:00	20	33	64	7	14:40~16:40	20
9	86	22	16:00~18:00	20	34	43	3	08:00~09:50	20
10	88	32	10:50~12:50	20	35	12	20	10:20~12:20	20
11	28	13	08:50~10:50	20	36	54	18	13:00~15:00	20
12	94	3	10:00~12:00	20	37	21	15	16:00~18:00	20
13	62	7	08:00~09:00	20	38	15	3	08:00~08:40	20
14	33	29	08:00~09:10	20	39	11	26	16:00~18:00	20
15	26	4	16:20~18:00	20	40	42	19	16:00~18:00	20
16	39	25	16:30~18:00	20	41	74	12	12:20~14:20	20
17	23	16	13:10~15:10	20	42	57	15	11:20~13:20	20
18	46	29	09:40~11:40	20	43	36	12	11:40~13:40	20
19	87	3	08:40~10:40	20	44	45	3	09:50~11:50	20
20	84	13	10:30~12:30	20	45	40	12	12:30~14:30	20
21	48	3	16:40~18:00	20	46	89	7	12:30~14:30	20
22	66	44	10:30~12:30	20	47	79	5	16:30~18:00	20
23	70	23	11:20~13:20	20	48	85	3	16:20~18:00	20
24	76	29	08:00~10:00	20	49	38	10	14:30~16:30	20
25	37	4	14:20~16:20	20	50	8	3	10:40~12:40	20

## Table 2 Information of the customer initial demands

 Table 3
 Information of customers' changed demands

Customer id	Modified time	New location	New time windows	New service time/min
39	8:00	78	15:00~17:00	20
3	8:10	31	8:30~10:00	20
15	8:30	55	10:00 ~ 12:00	20
48	9:30	9	12:00~14:00	20
16	10:00	63	14:00~16:00	20
2	11:30	16	15:00~17:00	20
22	12:00	29	15:30~17:30	20

Figure 4 illustrates a comparative analysis of ALNS, MACS, and our method for a rate of customer demand changes from 5 to 25% under a fixed 10% rate of road condition changes. Two performance measures are the total delivery cost and the number of customers with demand violations (an important indicator of customer satisfaction).

Figure 4a plots cost (RMB) as a function of the rate of customer demand changes. ALNS (black squares) maintains a relatively consistent higher curve, suggesting that it is a stable method but more costly. MACS (red circles) shows a significantly fluctuating cost curve that reaches its lowest cost at a 10% rate of customer demand changes, with a lower overall cost than ALNS. This suggests that

Table 4 Information of unpredictable road condition in the delivery routes

Occurrence time	Duration/ min	Start junction	End junction	Congestion level
9:20	20	43	19	3
11:00	30	45	67	3
15:30	30	37	24	3
12:20	20	88	8	1.5
13:30	60	57	89	3

MACS can handle customer demand changes against their impact on costs but is less stable. Our method (blue triangles) has an overall cost almost equal to MACS, but the curve is less volatile and has a downward trend. This shows that our method can handle demand changes well to reduce their impact on total costs and be more stable.

Figure 4b plots the number of customers with demand violations as a function of the rate of customer demand changes. ALNS shows a higher curve, with the number of violating demand customers exceeding 9, indicating that the method is weakly coping with customer demand changes. MACS has an average number of customers with demand violations of 4 and fluctuates, indicating that the method can handle some customer demand changes but is less stable. Our method shows the lowest curves, the number of customers with demand violations is below 2, and the curves fluctuate less, indicating that our method is strong enough to handle customer demand changes and is superior to the other two methods.

In summary, Fig. 4 shows the cost efficiency and customer satisfaction of the three methods in handling customer demand changes. ALNS has higher costs and lower customer satisfaction and performs the worst in handling customer demand changes. MACS is more cost-effective in handling customer demand changes than ALNS but is less stable, and customer satisfaction is better than ALNS but still not good enough. Our method is more cost-effective and stable than the other two, has significantly higher customer satisfaction, and handles demand changes well.

Figure 5 illustrates the performance of the three methods for a fixed customer demand change rate of 15% and a road condition change rate from 5 to 25%. The evaluation metrics are the total delivery cost and the number of customers with demand violations.

Table 5 Results of delivery route planning for handling changes in customer demand and road condition

Vehicle	Delivery route	Travel distance/ km	Travel load/kg	Wait time/min	Violated customers
1	[0,15(38),87(19),43(34), <b>50</b> ,19(32),46(18),84(20),94(12),36(43),12(35),63(16),23(17),6 4(33),29(22),59(31),49(1),48(21),0]	80.66	198	54	0
2	[0,80(8),33(14),28(11),31(3),45(44), <b>38</b> ,67(7),30(5),54(36),14(27),37(25), <b>73</b> ,24(26),21 (37),9(48),2(6),0]	93.29	170	42	1
3	[0,62(13),76(24),70(23),88(10), <b>79</b> ,8(50),57(42), <b>8</b> ,89(46),38(49),16(2),42(40),79(47),0]	79.74	173	139	0
4	[0,22(30),55(15),34(28),74(41),40(45),52(29),20(4),78(39),86(9),0]	96.20	152	145	1

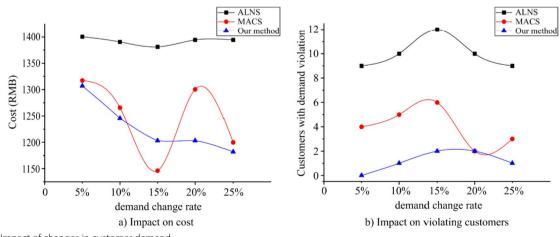


Fig. 4 Impact of changes in customer demand

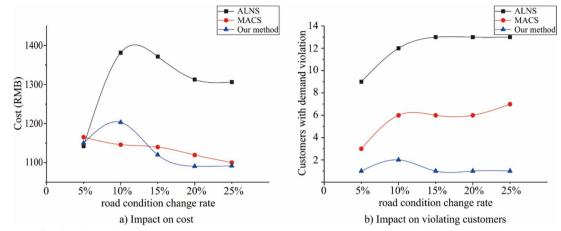


Fig. 5 Impact of road condition changes in the delivery routes

Figure 5a plots the cost (RMB) as a function of the rate of road condition changes. ALNS (black squares) shows that the cost curve rises as the rate of road condition changes increase and then stays high, suggesting that the method can only withstand a small amount of the changes. MACS (red circle) shows a gently declining cost curve, which indicates that it is resistant to disruptions in costs caused by road condition changes. In contrast, our method (blue triangles) shows that costs start to decline significantly when the rate of road condition changes increases to 10%, and after 15% the costs are lower than the other two methods, demonstrating the potential costeffectiveness for handling road condition changes.

Figure 5b plots the number of customers with demand violations as a function of the rate of road condition changes. ALNS shows a rising trend in the curve of the number of customers with demand violations, all of which are above 9, reflecting that ALNS faces a serious challenge in maintaining customer service quality as road conditions deteriorate. MACS shows a gradual increase in the number of customers with demand violations whose average is about 5, suggesting that customer service quality continues to decline as road conditions deteriorate. In contrast, our method shows consistently excellent performance across all the road condition change rates with the lowest number of customers with demand violations, highlighting its robustness in ensuring customer satisfaction.

Together, Fig. 5 shows that while all three methods are sensitive to road condition changes, our method is the most stable, providing low costs and excellent customer service in the face of the changes. ALNS is costly and has more customers with demand violations when road conditions change. MACS is cost-effective but results in more customers with demand violations when road conditions change more. However, our method is the most balanced, offering both cost-effectiveness and a low number of customers with demand violations, suggesting that it has the potential to be a superior method in dynamic road condition scenarios.

## Impact of traveling speed and vehicle capacity on delivery efficiency

This study assumes that vehicles travel at three different speeds, and several sets of repeated experiments are conducted to analyze the impact of speed on the results. Data analysis reveals that the average travel speed for urban delivery vehicles is approximately 30 km/h. Based on this finding, the vehicle travel speed was adjusted by  $\pm 20\%$  to evaluate the effects of speed variations on the delivery performance. Results are averages of multiple replicate experiments, as detailed in Table 6.

Table 6 indicates that variations in travel speed result in different total delivery costs and affect the number of customers with demand violations. When the travel speed is increased by 20%, there is 13.4% rise in total delivery costs, while the number of customers with demand violations decreases by 6.7%. Conversely, 20% decrease in travel speed leads to 5.6% reduction in total costs but an 18.6% increase in customers with demand violations. These outcomes align with expectations: higher speeds are more likely to meet customer demands, but the total cost increases. On the other hand, lower speeds can reduce total costs but potentially lead to an increase in customers with demand violations.

The vehicle capacity is set at a baseline of 200 kg per vehicle. In order to analyze the impact of vehicle capacity on delivery efficiency, several sets of repetitive

Vehicle speed	Total violated customers	Vehicle number	Total travel distance	Wait time/min	Total cost
36 km/h	3	4	376	595.2	1371.2
30 km/h	3.2	4	365.8	443.4	1209.2
24 km/h	3.8	4	396.8	344.2	1141.0

Table 6 Impact of different vehicle speeds on delivery efficiency

 Table 7
 Impact of different vehicle capacities on delivery efficiency

Vehicle capacity	Total violated customers	Vehicle number	Total travel distance	Wait time/min	Total cost
250 kg	4.6	4	396.6	397.2	1193.8
200 kg	3.2	4	365.8	443.4	1209.2
150 kg	2.6	5	388.2	602.8	1491.0

experiments were conducted with a variation of  $\pm 25\%$ in vehicle capacity while other conditions remained constant. The results are averages of data from multiple replicated experiments, as detailed in Table 7.

Table 7 shows the impact of vehicle capacity on the total delivery cost and the number of customers with demand violations. Increasing vehicle capacity by 25% reduces total costs by 1.3% and increases the demand violations by 43.8%. In contrast, 25% reduction in capacity increases total costs by 23.3% and reduces demand violations by 18.8%. Notably, lower capacity necessitates more vehicles, significantly elevating costs. These results suggest that higher vehicle capacity reduces total costs but increases the number of demand violations, while lower vehicle capacity has the opposite effect.

#### Conclusion

We explore the delivery route planning problem in uncertain supply chain environment, considering changes in customer demand and road conditions. We propose a two-stage delivery route planning method and design an adaptive genetic algorithm for handling the customer demand changes and an adaptive A-star algorithm for handling the road condition changes. The efficiency and effectiveness of the proposed methods are verified through comparative experiments. Specifically, our method is more cost-effective, more stable, and more responsive to customer demands than traditional route planning methods and can handle customer demand changes well. Moreover, our method is the most stable to keep a lower total cost and lower number of customers with demand violations in complex road conditions, showing great potential for application in dynamic road condition scenarios. In addition, we investigate the impact of the speed and capacity of vehicles on the total cost and the demand violations. The results show that increasing vehicle speed can reduce the number of customers with demand violations but increase the total cost. In conclusion, our method enables flexible delivery route planning to handle customer demand and road conditions changes, effectively reducing total cost and improving customer satisfaction. Future research will integrate predictive modeling for these changes in uncertain supply chain environment to improve the efficiency of solving such route planning problems.

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#### Authors' contributions

Yiping Wen and Gaoxian Peng conceived the method and designed the experiments. Gaoxian Peng performed the experiments, analyzed the data, and wrote the manuscript. Tiancai Li provided crucial data for the research. All authors approved the final manuscript.

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#### Availability of data and materials

The datasets generated and analyzed during the current study are not publicly available due to concerns regarding participant privacy. Data will not be shared to ensure the protection of participants' confidentiality.

#### Declarations

#### Competing interests

The authors declare no competing interests.

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