IEEE Open Journal of
Intelligent Transportation Systems

Received 21 July 2025; revised 16 December 2025; accepted 28 December 2025. Date of publication 31 December 2025; date of current version 22 January 2026.

*Digital Object Identifier 10.1109/OJITS.2025.3649932*

# Dynamic Vehicle Routing Optimization for Urban Distribution Under Real-Time Demand Fluctuations

**HASHIM HASHIM ARMAYAU[1], JIANI WU[1], WAJAHAT AKBAR[2], SHUGUANG LI[2], ALTAF HUSSAIN[2], INSAF ULLAH[3], TARIQ HUSSAIN[4,5], MEHMOOD ALAM[6], AND WEIWEI JIANG[7] (Senior Member, IEEE)**

[1]School of Economics and Management, Chang'an University, Xi'an 710064, China
[2]School of Electronic and Control Engineering, Chang'an University, Xi'an 710064, China
[3]School of Computer Science and Electronic Engineering, University of Essex, CO4 3SQ Colchester, U.K.
[4]School of Computer Science and Technology, Zhejiang Gongshang University, Hangzhou 310018, China
[5]School of Mathematics and Statistics, Zhejiang Gongshang University, Hangzhou 310018, China
[6]Department of Electrical Engineering, Military College of Signals, National University of Sciences and Technology, Islamabad 44000, Pakistan
[7]School of Information and Communication Engineering, Beijing University of Posts and Telecommunications, Beijing 100876, China

CORRESPONDING AUTHOR: I. ULLAH (e-mail: insaf.ullah@essex.ac.uk)

**ABSTRACT** With the rapid rise of e-commerce, the logistics and distribution industry is experiencing unprecedented growth. In particular, intra-city distribution is the crucial "last mile" of logistics and plays a decisive role in determining overall customer satisfaction. This study improves an inclusive vehicle routing optimization framework for intra-city distribution under dynamic demand. The initiative of a novel memetic algorithm that efficiently solves the NP-hard dynamic vehicle routing problem while guaranteeing high service quality and cost reduction. However, modern intercity distribution systems often struggle with low information, unpredictable demand patterns, and high operational costs due to scattered customer locations and dynamic order information. Addressing these challenges, this study suggests a comprehensive and intelligent vehicle routing optimization framework tailored for intracity distribution under dynamic demand conditions. The proposed system begins with a grey prediction model for short-term demand forecasting across many distribution regions, permitting differentiated vehicle loading methods to optimize transportation costs and improve operational effectiveness. Building upon this, a dynamic vehicle routing optimization model is formulated to reduce costs while assuring high levels of customer satisfaction within strict delivery time windows. To competently manage fluctuating demand, a dynamic information processing approach is introduced; prioritizing customer needs based on their urgency and importance, thereby guaranteeing the timely delivery of critical orders with minimal computational overhead. Moreover, a novel memetic algorithm is considered to solve the complex NP-hard dynamic vehicle routing problem. This algorithm integrates an adaptive elite genetic algorithm for global search with improved crossover and mutation operators, improved by local search methods such as 2-opt and swap methods to refine solutions. Numerical experiments validate the feasibility and performance of the proposed method, indicating significant improvements over conventional fully loaded vehicle schemes and regular route update methods. The results highlight the practical value of the system in attractive intra-city logistics efficiency, reducing costs, and inspiring customer service standards.

**INDEX TERMS** Dynamic vehicle routing problem, last-mile logistics, grey forecasting, short-term demand prediction, time-windowed urban delivery, memetic algorithm, hybrid evolutionary optimization.

## I. INTRODUCTION

THE LOGISTICS industry consists of a diversity of components, such as transportation, warehousing, and information exchange, which offer a comprehensive service sector that is vital to the country's economic development [1]. Distribution systems are facing rising challenges due to the rapid evolution of urban logistics [23]. As an effect of e-commerce's proliferation, merchants and customers are production more and more online transactions each year [8]. However, delivery vehicle efficiency is unfavorably affected by dynamic urban factors, including traffic congestion,

The review of this article was arranged by Associate Editor Luca Studer.

road incidents, and peak-hour traffic flows. In conventional methods of solving the Vehicle Routing Problem (VRP), a static, constant speed is assumed to be the solution [27]. This simplification leads to inefficient routing decisions, as it fails to account for real-time traffic variations, eventually causing delivery vehicles to encounter congested routes [22]. As a result, variations in cost estimation increase operational costs and emphasize the need for Dynamic Vehicle Routing Problem (DVRP) models that correct to actual traffic conditions [19]. To accommodate customer time constraints, urban delivery situations typically use soft or hard time windows [21]. Generally, soft time windows permit late entrances but impose penalties, while hard time windows require strict adherence and services are refused if the delivery is late [16]. Managing these limits efficiently in dynamic conditions is critical to optimizing route efficiency and customer happiness [30].

During 2023, the total value of social logistics in China reached 69.2 trillion Yuan, representative a 7.2% increase year-on-year. It is important to note that, regardless of this consistent increase, the logistics industry continues to struggle with low operating efficiency [24]. In terms of social logistics incidentals as a percentage of GDP, it was at 14.6%, a slight decline of 0.1 percentage point from 2020, but still substantially higher than the nearly 8% found in industrialized nations. Transportation costs made up the majority (61.9%) of the total logistical expenses [31]. These figures highlight the pressing need to improve logistics efficiency and reduce transportation expenses, an effort of substantial practical importance [10]. Same-city delivery is the terminal link of the logistics system, known as "last mile logistics", responsible for the circulation of goods within the city, guaranteeing the lives of residents. Its importance and growth prospects are self-evident. However, delivery to the same city is still in its early stages, and relevant technical standards and delivery operation processes are not unified [32]. Consequently, in the scenario of same-city delivery, local logistics enterprises must consider the dynamic changes in customer demand, grow reasonable vehicle delivery routes, reduce various costs in cargo transportation, and improve customer satisfaction [3].

VRP was first proposed by Dantzig and Ramser [5] and has always been a research focus in the fields of transportation and distribution. In recent years, scholars have studied the vehicle routing problem in same-city distribution from different perspectives. Cattaruzza et al. [4] summarized and analyzed the vehicle routing problem in urban logistics, including time-dependent VRP, multi-level VRP, dynamic VRP, and multi-trip VRP. Groß et al. [7] studied the urban logistics vehicle routing problem with uncertain travel time, introduced interval travel time, and verified the reliability of this approach through examples. Eshtehadi et al. [6] proposed using multi-class city trucks to deliver goods to address the issue of increasing customer demand in same-city logistics. The goal was to minimize the main operating costs and plan the delivery path. They also proposed an improved adaptive large neighborhood search algorithm for solving the problem. Rincon Garcia et al. [26] studied the same-city delivery vehicle routing problem in the situation of new retail, considering urban traffic congestion and constraints on driving time and delivery time windows, constructed an optimization model, and designated a large-scale neighborhood search algorithm to solve the optimal path.

Liu et al. [13] in this study experimental vehicle routing problems within Omni-Channel Retail Systems (OC), where retailers must coordinate both their online and offline sales channels in order to offer seamless customer service. In order to minimize distribution costs while rapidly increasing consumer convenience by reducing delivery times, the authors developed a multi-objective mathematical model.This study observed vehicle routing problems within Omni-Channel Retail Systems (OC), where retailers must coordinate both their online and offline sales channels in order to offer seamless customer service. In order to minimize distribution costs while rapidly increasing consumer convenience by reducing delivery times, the authors developed a multi-objective mathematical model. To solve the complex model, two meta-heuristic algorithms MOGWO and NSGA-II were employed. Their findings show that combined optimization and the possibility of direct customer delivery suggestively improve both cost success and customer satisfaction.

### A. MOTIVATION AND RESEARCH QUESTIONS

Intra-city delivery operations are characterized by highly dynamic customer demand, concerning both reservation orders located the aforementioned day and real-time orders received within a designated service window. With the combination of these two types of demand, fluctuating order quantities, cancellations, and the limited loading capacity of vehicles, routing decisions are subject to substantial uncertainty. Adaptive and data-driven optimization approaches are needed to address such real-time variability in vehicle routing. The persistence of this study is to examine how to efficiently model and optimize vehicle routing in an urban delivery system in which customer demands growth over the course of the delivery process. A distribution company operates a fleet of $m$ identical vehicles, each with maximum capacity $Q_{\max}$, serving $n$ customers with dynamic demands $q_i$. In order to maintain both operational efficiency and service quality, the core challenge is to dynamically update routing decisions in response to new, modified, or canceled orders.

### B. RESEARCH QUESTIONS

Based on these considerations, the research addresses the following key questions:

- How can short-term demand prediction be used to increase vehicle capacity allocation in dynamic intra-city delivery situations?

- What dynamic information processing approaches most effectively prioritize customers according to urgency and importance?
- How can metaheuristic methods particularly Memetic algorithms be designed to efficiently solve the dynamic vehicle routing problem under real-time demand fluctuations?
- To what extent can integrating dynamic demand and real-time decision updates improve routing efficiency and reduce operational costs?

### C. CONTRIBUTIONS

Below are a summary of the main contributions of this work.

- *Grey Demand Prediction Model:* In this study, a grey forecasting model for short-term demand is developed using historical demand data from multiple distribution areas. The model permits more accurate estimation of near-term demand fluctuations and improves vehicle loading capacity allocation.
- *Dynamic Information Processing Approach:* We propose a dynamic decision mechanism for determining the importance and urgency of customer demands. All urgent and key customer requests are handled in real time, while non-urgent requests are handled commonly. This method enhances decision-making efficiency and resource allocation efficacy.
- *Memetic Algorithm for Dynamic Vehicle Routing:* Memetic algorithms through adaptive elite genetic frameworks are designed to address the NP-hard problem of dynamic vehicle routing. Improvements include improved initialization methods, customized crossover and mutation operators, and an elite retention mechanism that reserves high-quality solutions.
- *Integrated Dynamic Routing Optimization Model:* An optimization model is developed to accommodate both urgent real-time requests and regular delivery requests. The model captures the operational characteristics of intra-city dynamic delivery and results in important enhancements in routing efficiency and operational cost.

### D. THIS PAPER IS STRUCTURED AS FOLLOWS

**Section II** offers a complete review of the current state-of-the-art research, discovering key theories and methods that lay the foundation for this study. **Section III** presents a novel optimization model tailored for intra-city delivery vehicle routing under dynamic demand, addressing real-world complexities and effective challenges. In **Section IV**, we delve into the design and implementation of an advanced Memetic algorithm, showcasing how it efficiently solves the dynamic vehicle routing problem with improved efficiency and solution quality. **Section V** presents extensive simulation experiments and detailed result analysis. Here, numerical examples and MATLAB simulations determine the practical applicability and performance improvements of the proposed method. Finally, **Section VI** concludes the paper by summarizing the key findings and contributions and outlines promising directions for future research to further advance the field.

## II. RELATED WORK

Increasing urban populations and the fast expansion of e-commerce have made it progressively important to have an efficient and intelligent intra-city distribution network. Vehicle routing and logistics optimization have been traveled by a number of scholars to address challenges such as dynamic customer demand, delivery time constraints, and cost control.

Ma et al. [17] study suggests a time-dependent VRP model that integrates pollution-related environmental factors to reduce fuel consumption and emissions in urban logistics. The author introduces a hybrid Gray Wolf Optimizer combined with a neural network, achieving high accuracy and improved routing efficiency under stochastic demands. The model proves strong performance, especially in medium-scale problems, and shows that dynamic factors like wind and temperature meaningfully influence optimal routes. However, the study is limited by scalability challenges in very large networks and relies on approximated environmental data, which may affect real-world applicability.

Zarreh et al. [29] provide an in-depth evaluation of integrating perishable items into closed-loop supply chains, emphasizing the unique issues provided by product perishability in sustainable logistics. The authors combine existing methods to demonstrate how reverse logistics and circular economy principles can improve competence and reduce waste. Their analysis offers useful understandings by identifying research gaps and offering practical ways for improving CLSCs that connect perishables. The study's confidence on secondary data and lack of experimental validation limit its scope, importance the need for future models and real-world case studies.

Makui et al. [18] the study builds a strong collective production planning model for products with short expiration dates, which contains postponement via direct production, semi-finished production, and final assembly operations. The author progresses resilience by addressing parameter indecision and provides an accelerated Benders decomposition method to deal with the problem's NP-hard nature. Real data from an industry case study establish the model's efficacy and the algorithm's high computing performance. However, the strategy is constrained by its emphasis on a specific industrial instance and reliance on rigid postponement structures, leaving room for broader applicability and more flexible production procedures.

Liu et al. [14] develop a pricing model for a two-echelon supply chain with substitutable products, incorporating stochastic demand, channel power structures, and multiple game-theoretic settings using Double Interval Grey Numbers. Their framework analyzes eight pricing models and evaluates how retail substitutability and competitive behaviors affect optimal wholesale and retail prices as well as equilibrium profits. The study offers valuable insights into pricing approaches under uncertainty by comparing Bertrand, cooperation, and Stackelberg structures and validating outcomes through sensitivity analysis. However, the model's applicability is constrained by its single-period assumption and simplified two-product structure, limiting its extension to more dynamic, multi-period, or multi-product supply chain situations.

Hendalianpour [9] introduces a game-theoretic model that jointly regulates optimal pricing and lot-sizing for perishable goods, incorporating freshness-dependent demand and consumer sensitivity to both selling and reference prices. Using Double Interval Grey Numbers, the study captures uncertainty in consumer behavior and improves the realism of decision-making for retailers handling short shelf-life products. Numerical experiments and sensitivity analyses validate the model's ability to generate consistent and balanced approaches across varying demand scenarios. However, the model is limited by its focus on retailer-level decisions and simplified perishability assumptions, leaving opportunities for extending the approach to multi-echelon supply chains and more complex deterioration patterns.

Liu et al. [15] develop an integrated production inventory routing model for managing perishable blood products, incorporating transshipment among blood centers to reduce shortages, excess inventory, and total costs under uncertain demand. The authors formulate a robust optimization model and design a heuristic algorithm capable of efficiently handling the NP-hard nature of the problem by improving routing decisions at each search stage. Numerical experiments and a real case study on blood platelets validate the model's effectiveness, demonstrating significant cost reductions when transshipment is permitted. However, the approach is limited by its focus on a single-supplier network and simplified perishability assumptions, suggesting the need for extensions to multi-supplier systems and more complex deterioration dynamics.

Li et al. [12] designed a hybrid variable neighborhood artificial bee colony algorithm to solve the problem of constantly updating customer points by dividing periods based on the rolling time domain and proposing a periodic real-time reset strategy for customer points. The vehicle routing problem is an NP-hard problem. Currently, the solving algorithms for this problem are mainly divided into three categories: exact algorithms, heuristic algorithms, and machine learning-related algorithms.

Redi et al. [25] studied the drug delivery problem with capacity constraints, aiming to minimize the total transportation time, and proposed a simulated annealing heuristic algorithm for solving it. Alsessager et al. [2] proposed a hybrid cuckoo search algorithm and simulated annealing algorithm to solve the vehicle routing problem with capacity constraints and selected the best neighbourhood structure and selection strategy through experiments. Zulvia et al. [34] optimized the cost and customer satisfaction for the green vehicle routing problem of perishable products, taking into account time windows and dependencies, and chose a multi-objective gradient evolution algorithm to solve the model.

## III. METHODOLOGY

This section outlines the comprehensive methodology developed to optimize intra-city distribution routing under dynamic demand conditions, incorporating demand prediction, real-time routing adjustments, and advanced heuristic algorithms block diagram of the proposed work shown in Figure 1.

### A. LOAD PREDICTION MODEL FOR DELIVERY VEHICLES BASED ON DEMAND FORECASTING

The uncertainty of customer demand poses difficulties for delivery. On the one hand, if the delivery vehicle only loads pre-booked customers when the goods are shipped, it will be difficult to meet the new customer demands that arise during the delivery process on time. On the other hand, if the vehicle is blindly loaded, overloading will lead to an increase in transportation costs. In response to this situation, this article chooses to predict the logistics demand for each delivery area in the city, and based on this, set the loading capacity of delivery vehicles to reduce costs and improve delivery efficiency.

### B. ESTABLISHMENT OF GREY GM(1,1) VEHICLE LOAD PREDICTION MODEL

Grey prediction is useful for forecasting when historical data is limited and sequence integrity is low. It turns irregular sequences into regular ones and uses differential equations for deeper system insights, making it effective for short- to medium-term predictions. This study utilizes a Grey GM(1,1) model to predict logistics demand in various regions, based on recent total logistics data from several distribution areas. After validating the accuracy of the predictions, the loading capacities of distribution vehicles in these regions are established.

### C. GRADE COMPARISON TEST

If the daily demand of region $s$ $(s = 1, 2, \ldots, S)$ in the past $n$ days is $x(j)$ $(j = 1, 2, \ldots, n)$, then the original data column can be obtained as shown in Equation (1):

$$x^{(0)} = \left\{x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)\right\} \tag{1}$$

Before establishing a prediction model, a level ratio test is required. If $\lambda(k)$ is within the interval $(e^{-\frac{2}{n+1}}, e^{\frac{2}{n+2}})$, the GM(1,1) model can be established by calculating $\lambda(k)$ as defined in Equation (2):

$$\lambda(k) = \frac{x^{(0)}(k-1)}{x^{(0)}(k)}, \quad k = 2, 3, \ldots, n \tag{2}$$

Otherwise, the sequence needs to be translated to meet the conditions.

### D. GENERATE SEQUENCE

After performing an accumulation operation on the original sequence, the following generated sequence can be obtained as shown in Equation (3):

$$x^{(1)}(k) = \sum_{j=1}^{k} x^{(0)}(j), \quad k = 1, 2, \ldots, n \tag{3}$$

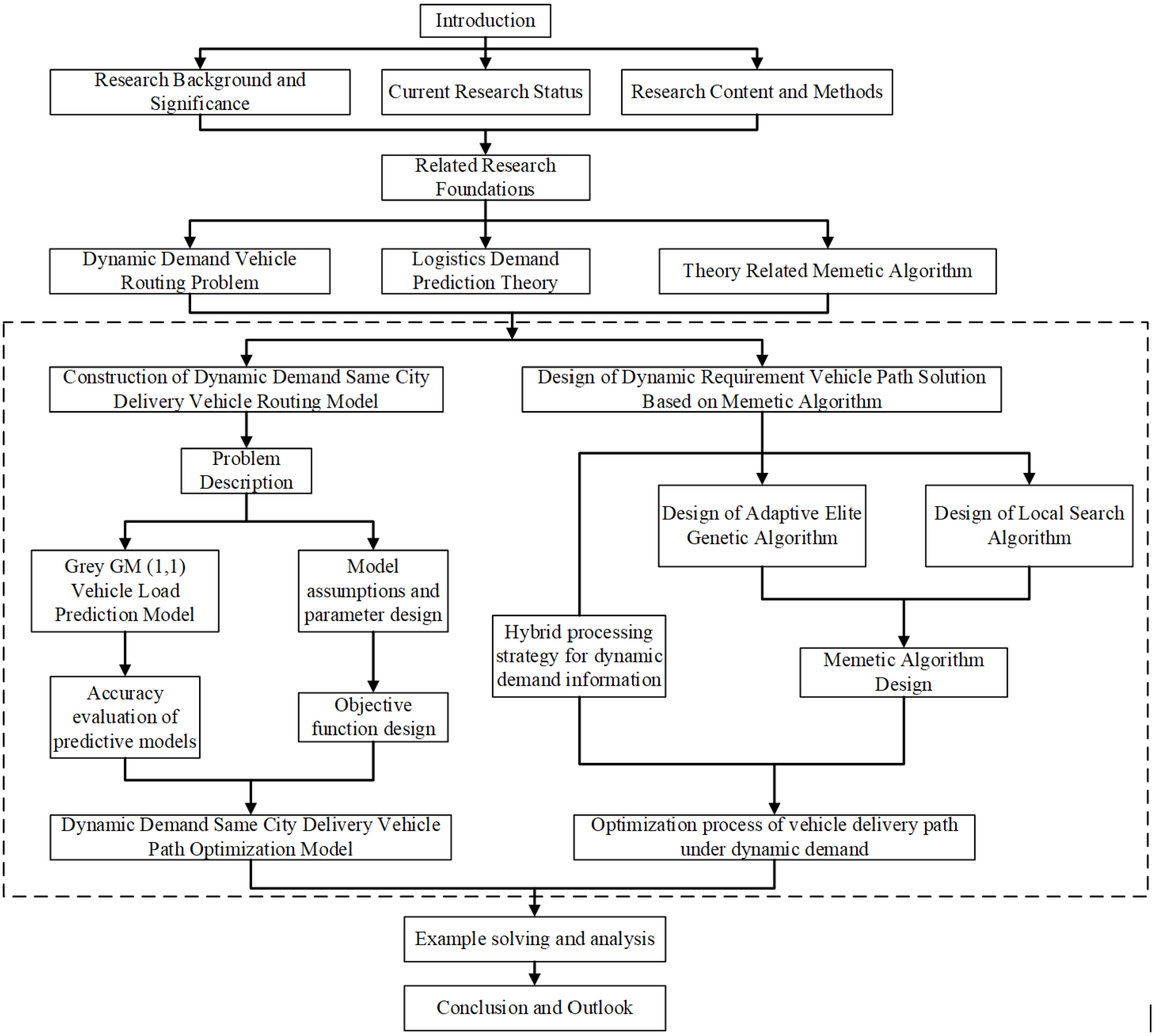


**FIGURE 1.** Block diagram of the Proposed work.

The average generation sequence of $x^{(1)}$ is shown in Equation (4):

$$z^{(1)} = \left\{z^{(1)}(2), z^{(1)}(3), \ldots, z^{(1)}(n)\right\} \tag{4}$$

where the values of $z^{(1)}(k)$ are calculated using Equation (5):

$$z^{(1)}(k) = 0.5 \times x^{(1)}(k) + 0.5 \times x^{(1)}(k-1), \quad k = 2, 3, \ldots, n \tag{5}$$

### E. ESTABLISH A PREDICTIVE MODEL

Establish a grey differential equation based on the generated data column, as shown in Equation (6):

$$x^{(0)}(k) + az^{(1)}(k) = b, \quad k = 2, 3, \ldots, n \tag{6}$$

Here, $a$ represents the development coefficient and $b$ represents the amount of ash used.

The differential equation for whitening gray model (Equation (6)) is given in Equation (7):

$$\frac{dx^{(1)}(t)}{dt} + ax^{(1)}(t) = b \tag{7}$$

Let the parameter vector be defined as $u = (a, b)^T$ and the observation vector as $Y = (x^{(0)}(2), x^{(0)}(3), \ldots, x^{(0)}(n))^T$. Then, Equation (6) can be rewritten in matrix form as shown in Equation (8):

$$Y = Bu \tag{8}$$

To solve the unknown parameter vector $u$ in Equation (8), it is necessary to determine the best fit by minimizing the sum of squared errors. According to the least squares method, the optimal estimate $\hat{u}$ is computed using Equation (9):

$$\hat{u} = \left(\hat{a}, \hat{b}\right)^T = \left(B^T B\right)^{-1} B^T Y \tag{9}$$

Substituting the estimated parameters from Equation (9) into the whitening differential equation (Equation (7)) yields the predicted values of the cumulative data, as shown in Equation (10):

$$\hat{x}^{(1)}(k+1) = \left(x^{(0)}(1) - \frac{\hat{b}}{\hat{a}}\right)e^{-\hat{a}k} + \frac{\hat{b}}{\hat{a}}, \quad k = 0, 1, \ldots, n-1 \tag{10}$$

Finally, to restore the predicted values of the original data column, we use Equation (11), which performs a subtraction between consecutive values of the predicted cumulative series:

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) \tag{11}$$

### *F. MODEL ACCURACY VERIFICATION*

The commonly used methods for testing grey prediction models are residual testing and level deviation testing.

#### 1) RESIDUAL TEST

The absolute residual is computed using Equation (12):

$$x^{(0)}(k) - \hat{x}^{(0)}(k), \quad k = 1, 2, \ldots, n \tag{12}$$

The relative residual is defined in Equation (13):

$$\varepsilon_r(k) = \frac{|x^{(0)}(k) - \hat{x}^{(0)}(k)|}{x^{(0)}(k)}, \quad k = 1, 2, \ldots, n \tag{13}$$

The average relative residual is calculated using Equation (14):

$$\bar{\varepsilon}_r = \frac{1}{n}\sum_{k=1}^{n} |\varepsilon_r(k)| \tag{14}$$

If the average relative residual $\bar{\varepsilon}_r$ in Equation (14) is less than 0.2, the GM(1,1) model is considered to meet the general requirements for fitting the original data. Furthermore, if $\bar{\varepsilon}_r < 0.1$, it indicates that the model fitting effect has reached a high level of accuracy.

#### 2) GRADE RATIO DEVIATION VALUE INSPECTION

Firstly, the level ratio $\lambda(k)$ is calculated from the original data $x^{(0)}(k)$, as shown in Equation (15):

$$\lambda(k) = \frac{x^{(0)}(k-1)}{x^{(0)}(k)}, \quad k = 2, 3, \ldots, n \tag{15}$$

Then, the grade ratio deviation is computed using Equation (16):

$$\rho(k) = \left|1 - \frac{(1-0.5a)}{(1+0.5a)}\lambda(k)\right| \tag{16}$$

The mean grade ratio deviation is defined in Equation (17):

$$\bar{\rho} = \frac{1}{n}\sum_{k=1}^{n} \rho(k) \tag{17}$$

If the average level deviation $\bar{\rho}$ in Equation (17) is less than 0.2, the grey model is considered to satisfy the general requirements. If $\bar{\rho} < 0.1$, it indicates a high level of fitting accuracy.

#### 3) LOAD CAPACITY PREDICTION

After the prediction results are verified, the loading capacity $Q_s$ of the delivery vehicles is predicted based on the demand of each region, as shown in Equation (18):

$$Q = \hat{x}^{(0)}(n+1) \tag{18}$$

#### 4) ESTABLISHMENT OF GREY GM(1,1) VEHICLE LOAD PREDICTION MODEL

Grey prediction is useful for forecasting when historical data is limited and sequence integrity is low. It transforms irregular sequences into regular ones and uses differential equations for deeper system insights, making it effective for short- to medium-term predictions. This study utilizes a grey GM(1,1) model to predict logistics demand in various regions, based on recent total logistics data from several distribution areas. After validating the accuracy of the predictions, the loading capacities of distribution vehicles in these regions are established.

#### 5) GRADE COMPARISON TEST

If the daily demand of region $s$ ($s = 1, 2, \ldots, S$) in the past $n$ days is $x(j)$ ($j = 1, 2, \ldots, n$), then the original data column is defined in Equation (19):

$$x^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)\} \tag{19}$$

Before establishing the prediction model, a level ratio test is performed. If $\lambda(k)$ lies within the interval $(e^{-2/(n+1)}, e^{2/(n+2)})$, then the GM(1,1) model can be established. The level ratio is calculated using Equation (20):

$$\lambda(k) = \frac{x^{(0)}(k-1)}{x^{(0)}(k)}, \quad k = 2, 3, \ldots, n \tag{20}$$

#### 6) GENERATE SEQUENCE

After performing an accumulation operation on the original sequence, the generated sequence is defined by Equation (21):

$$x^{(1)}(k) = \sum_{j=1}^{k} x^{(0)}(j), \quad k = 1, 2, \ldots, n \tag{21}$$

The average generation sequence $z^{(1)}(k)$ is given in Equation (22):

$$z^{(1)}(k) = 0.5 \cdot x^{(1)}(k) + 0.5 \cdot x^{(1)}(k-1), \quad k = 2, 3, \ldots, n \tag{22}$$

#### 7) ESTABLISH A PREDICTIVE MODEL

The grey differential equation is established as shown in Equation (23):

$$x^{(0)}(k) + az^{(1)}(k) = b, \quad k = 2, 3, \ldots, n \tag{23}$$

The corresponding whitening differential equation is given in Equation (24):

$$\frac{dx^{(1)}}{dt} + ax^{(1)}(t) = b \tag{24}$$

Let $u = (a, b)^T$, and define the observation vector as $Y = (x^{(0)}(2), x^{(0)}(3), \ldots, x^{(0)}(n))^T$. The model equation can then be written in matrix form as shown in Equation (25):

$$Y = Bu \tag{25}$$

To determine the unknown parameter vector $u$, we minimize the sum of squared errors, expressed in Equation (26):

$$J(u) = (Y - Bu)^T(Y - Bu) \tag{26}$$

The least squares estimate is obtained from Equation (27):

$$\hat{u} = \left(B^T B\right)^{-1} B^T Y \tag{27}$$

Substituting into the whitening equation yields the predicted cumulative values (Equation (28)):

$$\hat{x}^{(1)}(k+1) = \left(x^{(0)}(1) - \frac{\hat{b}}{\hat{a}}\right)e^{-\hat{a}k} + \frac{\hat{b}}{\hat{a}}, \quad k = 0, 1, \ldots, n-1 \tag{28}$$

The predicted original values are recovered using Equation (29):

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) \tag{29}$$

#### 8) MODEL ACCURACY VERIFICATION

The accuracy of the grey model is typically evaluated using residual analysis and grade ratio deviation.

**Residual Test:**

The absolute residual is calculated in Equation (30):

$$e(k) = x^{(0)}(k) - \hat{x}^{(0)}(k), \quad k = 1, 2, \ldots, n \tag{30}$$

The relative residual is given in Equation (31):

$$\epsilon_r(k) = \frac{|x^{(0)}(k) - \hat{x}^{(0)}(k)|}{x^{(0)}(k)}, \quad k = 1, 2, \ldots, n \tag{31}$$

The average relative residual is defined in Equation (32):

$$\bar{\epsilon}_r = \frac{1}{n}\sum_{k=1}^{n} |\epsilon_r(k)| \tag{32}$$

If $\bar{\epsilon}_r < 0.2$, the GM(1,1) model meets general fitting requirements; if $\bar{\epsilon}_r < 0.1$, it demonstrates high fitting accuracy.

**Grade Ratio Deviation Value Inspection:**

The grade ratio is calculated using Equation (33):

$$\lambda(k) = \frac{x^{(0)}(k-1)}{x^{(0)}(k)}, \quad k = 2, 3, \ldots, n \tag{33}$$

The grade ratio deviation is given in Equation (34):

$$\rho(k) = \left|1 - \frac{1 - 0.5a}{1 + 0.5a}\lambda(k)\right| \tag{34}$$

The mean deviation is defined by Equation (35):

$$\bar{\rho} = \frac{1}{n}\sum_{k=1}^{n} \rho(k) \tag{35}$$

If $\bar{\rho} < 0.2$, the model satisfies general fitting conditions; if $\bar{\rho} < 0.1$, it meets higher accuracy requirements.

#### 9) LOAD CAPACITY PREDICTION

After validation, the predicted loading capacity $Q_s$ of the delivery vehicles is calculated based on the demand in each region, as shown in Equation (36):

$$Q = \hat{x}^{(0)}(n+1) \tag{36}$$

### G. CONSTRUCTION OF AN OPTIMIZATION MODEL FOR SAME-CITY DELIVERY VEHICLE PATHS UNDER DYNAMIC DEMAND

#### 1) MODEL ASSUMPTIONS

This study aims to optimize vehicle routing while addressing dynamic changes in customer demand during deliveries. To decrease external influences and simplify the problem scope, the following assumptions are made:

1) The scenario contains a single product with multiple receiving points. Delivery companies transport only one type of product to various customers. The study emphases solely on delivery route planning, excluding pickup tasks.
2) The city has one distribution center with satisfactory stock to meet all delivery needs there is no deficiency of goods.
3) All vehicles at the distribution center are of the same model, with identical maximum load capacities. It is expected that the delivery volume does not exceed the vehicle capacity, and there are no distance restrictions.
4) Delivery areas are non-overlapping. Each vehicle departs from the distribution center, completes its assigned tasks within a specific area, and returns to the center.
5) A vehicle can serve multiple customers within a single trip; however, each customer is only served by one vehicle per delivery round.
6) New customer demands may arise dynamically during delivery, and the demand of existing customers may also change.
7) When demand changes dynamically, vehicles currently operating in the customer's area are prioritized. If the remaining capacity of the vehicle is insufficient, a new vehicle is dispatched from the distribution center.
8) If the demand of a customer who has already been served changes, the revised order is not fulfilled the same day. Instead, it is scheduled as a reservation for the following day.

9) Vehicles travel at a constant speed. Traffic conditions and unforeseen malfunctions are not considered in delivery time calculations.

### H. CONSTRUCTION OF DELIVERY VEHICLE PATH OPTIMIZATION MODEL

Based on the grey prediction model of delivery vehicle loading capacity in the model assumptions and objective function in a dynamic demand-based intra-city delivery vehicle path optimization model is constructed. The objective is to minimize total delivery cost while maximizing customer satisfaction shown in Figure 2, as formulated in Equation (37).

$$\begin{aligned}\min Z = \frac{\mu_1}{C_0}\Bigg\{ &\sum_{k=1}^{m} z_k \alpha + \sum_{k=1}^{m}\sum_{i=1}^{n}\sum_{j=1}^{n} x_{ij}^k d_{ij}\beta P_0 \\ &+ \sum_{k=1}^{m}\sum_{i=1}^{n}\sum_{j=1}^{n} x_{ij}^k d_{ij}\beta \frac{Q_j^k}{Q^*}(P^* - P_0) + \sum_{k=1}^{m}\sum_{i=1}^{n} \varphi\left(t_i^k\right)\Bigg\} \\ &+ \mu_2\left(\frac{1}{\sum_{i=1}^{n} q_i}\sum_{i=1}^{n} q_i f\left(t_i^k\right)\right)\end{aligned} \tag{37}$$

Equations (38)–(48) collectively define the operational constraints of the dynamic intra-city delivery vehicle routing model, including vehicle departure and customer assignment rules (38)–(40), load capacity and replenishment conditions (41)–(44), vehicle deployment limits (45), time-dependent delivery schedules (46)–(47), and route feasibility through sub-tour elimination (48).

$$\sum_{j=1}^{n} x_{0j}^k = \sum_{k=1}^{n} x_{0j}^k, \quad k \in K \tag{38}$$

$$\sum_{k=1}^{m} y_i^k = 1, \quad j \in V_c \tag{39}$$

$$\sum_{k=1}^{m}\sum_{i=0}^{n} x_{ij}^k = 1, \quad j \in V_c \tag{40}$$

$$\sum_{i=1}^{n_y} q_i y_i^k \le Q^*, \quad k \in K \tag{41}$$

$$Q_0^k = Q_s, \quad k = s, \ s \in \{1, 2, \ldots, S\} \tag{42}$$

$$Q_0^k = \sum_{i \in V_n(t)} q_i y_i^k, \quad k \in \{S+1, \ldots, m\} \tag{43}$$

$$Q_j^k = Q_0^k - \sum_{i \in V_n(t)} y_i^k q_i, \quad k \in K, \ j \in V_n(t) \tag{44}$$

$$\sum_{k \in K_0(t)} \sum_{j \in V_n(t)} x_{0j}^k \le |K_0(t)| \tag{45}$$

$$t_j^k = t_i^k + st_i + \frac{d_{ij}}{v} \tag{46}$$

$$\max\{T_0, MET_i\} \le t_i^k \le \min\{MLT_i, T_e\} \tag{47}$$

$$\sum_{i,j \in R} x_{ij}^k \le |R| - 1, \quad \forall k \in K, \ \forall R \subset V_c, \ 1 < |R| < n \tag{48}$$

The model incorporates a penalty cost function to evaluate delivery time deviations, as shown in Equation (49), where

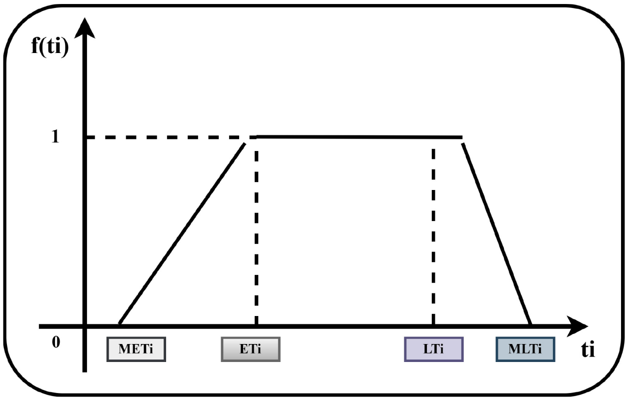


**FIGURE 2.** Customer Satisfaction.

early or late deliveries incur penalties, and deliveries within the acceptable time window are cost-free. Variable bounds that ensure feasibility and binary decision conditions are defined in Equation (50).

$$\varphi\left(t_i^k\right) = \begin{cases} M, & t_i^k < MET_i \\ \varepsilon_1\left(ET_i - t_i^k\right), & MET_i \le t_i^k \le ET_i \\ 0, & ET_i \le t_i^k \le LT_i \\ \varepsilon_2\left(t_i^k - LT_i\right), & LT_i \le t_i^k \le MLT_i \\ M, & MLT_i \le t_i^k \end{cases} \tag{49}$$

$$q_i \ge 0, \quad x_{ij}^k \in \{0, 1\}, \quad Z_k \in \{0, 1\}, \quad i, j \in V, \ k \in K \tag{50}$$

### I. DESIGN OF DYNAMIC REQUIREMENT VEHICLE PATH SOLUTION BASED ON MEMETIC ALGORITHM

To efficiently manage dynamic demand during deliveries, this paper designs an information update strategy that integrates regular and dynamic event updates. It classifies dynamic demands based on customer importance and demand urgency, which reduces computational complexity and improves response timeliness. A memetic algorithm is created to enhance the speed and quality of vehicle delivery path solutions, using an adaptive elite genetic algorithm for global search. Improvements are made to the generation method, crossover, and mutation operators of the initial solution. In contrast, the 2-opt and swap operators are employed as local search strategies to optimize the solution and determine the optimal delivery path.

### J. SOLUTION STRATEGY FOR INTRA-CITY DELIVERY VEHICLE ROUTING PROBLEM UNDER DYNAMIC DEMAND

In the dynamic demand vehicle routing problem, customer needs will dynamically change over time. Therefore, the distribution center needs to adjust the existing distribution path on time based on this demand information when receiving information changes. Often, multiple path planning is required, making the problem more complex to solve. Therefore, designing a reasonable solution strategy can make the dynamic adjustment process of the path more orderly.

### K. WORKFLOW OF DYNAMIC REQUIREMENT PATH OPTIMIZATION SCHEME

This article discusses a distribution center that provides two service modes to address various customer needs: scheduled delivery and real-time delivery. Scheduled delivery necessitates customers to place orders a day in development, enabling the center to plan routes as a static vehicle routing problem. In contrast, real-time delivery handles same-day orders, requiring adjustments to delivery paths based on dynamic demand. The workflow consists of three stages: planning routes for reserved customers after the delivery window opens, apprising routes during the real-time service window with new orders, and completing tasks for remaining customers before the service window closes. The inclusive goal is to optimize delivery paths for effective service.

### L. HYBRID STRATEGY FOR HANDLING DYNAMIC DEMAND INFORMATION

In the second stage of operations at the distribution center, the receipt of various dynamic demand information requires adjustments to delivery paths. Existing literature primarily addresses two approaches: the regular update strategy and the dynamic event update strategy, each with its limitations. The regular update strategy offers convenience in calculations but lacks timely responsiveness to changes. On the other hand, the dynamic event update strategy allows for quick reactions to emergencies, but it can result in frequent path updates and complex calculations, particularly when confronted with significant amounts of dynamic information. The article offers a hybrid strategy for updating dynamic demand information, selecting the suitable update strategy based on the importance and urgency of customer needs. This ensures timely responses to urgent demands while minimizing complex calculations. A dynamic event update strategy is used for important customers and urgent needs of non-important customers, enabling real-time processing. Non-urgent needs of non-important customers are managed with a regular update strategy, processing demand information in batches at fixed intervals to reduce computational complexity. This hybrid approach transforms the dynamic vehicle routing problem into a multi-stage instantaneous static vehicle routing problem, simplifying the solution process. In same-city delivery, B2B customers are deemed important due to their stable and high demand, while B2C customers are classified as non-important because their demand is smaller and more erratic; the study identifies time window changes and order cancellations as urgent demands requiring timely responses, whereas new customer demands and changes to existing demands are classified as non-urgent and can be addressed with some delay. The specific dynamic demand information processing hybrid strategy is shown in Figure 3.

The dynamic demand management process for the distribution center focuses on efficiently handling real-time logistics and customer requests. Upon opening the service window, the center assesses whether a customer is important.

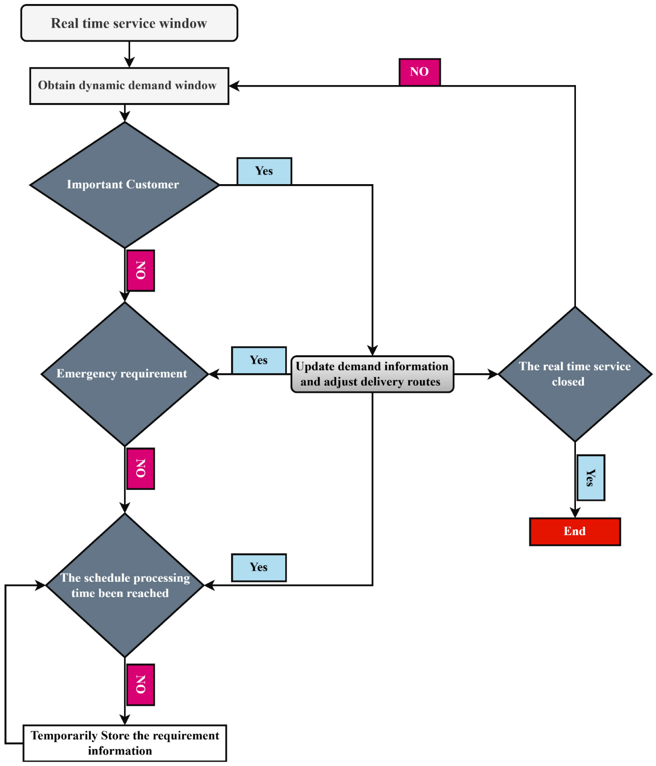


FIGURE 3. Dynamic update of the third stage delivery route map.

For important customers, a dynamic event update strategy allows for immediate adjustments to the distribution path, transforming the routing problem into a more manageable static form. This ensures timely service and enhances customer satisfaction. For non-important customers, the urgency of their demand is evaluated. Urgent demands are processed immediately, necessitating route adjustments, while non-urgent demands are addressed once the scheduled processing time is reached. After the real-time service window closes, the center stops accepting new demand information, effectively concluding its active logistics management for the day. This approach balances responsiveness and strategic planning to optimize resource use and meet customer needs.

### M. IMPROVED MEMETIC ALGORITHM DESIGN

The memetic algorithm, or cultural gene algorithm, was proposed by Pablo Moscato, drawing inspiration from Darwin's evolution theory and Richard Dawkins' concept of memes. It is widely applied in engineering optimization problems, including vehicle routing issues. This algorithm functions as a hybrid framework that employs both global and local search strategies. The global search uses a population-based heuristic to iteratively optimize the population, while the local search refines the generated individuals, replacing them with superior ones, and facilitating continuous evolution toward optimal solutions. This article enhances the genetic algorithm by utilizing an adaptive elite genetic algorithm for global search and incorporates two local search operators, 2-opt and swap, to optimize vehicle delivery routes under dynamic demand.

**TABLE 1.** Chromosome encoding.

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 5 | 2 | 7 | 1 | 9 | 6 | 3 | 8 | 4 | 10 |

### N. ADAPTIVE ELITE GENETIC ALGORITHM

The traditional genetic algorithm operates on the principle of "natural selection and survival of the fittest," using selection, crossover, and mutation to find optimal solutions. However, its effectiveness can be compromised by the random generation of an initial population that may lack quality, leading to extended convergence times. Additionally, without mechanisms to retain superior individuals, valuable genetic information can be lost during evolution. Maintaining constant crossover and mutation probabilities also presents challenges: high probabilities may slow convergence or cause failure, while low probabilities risk trapping the algorithm in local optima.

To address these issues, this article enhances the genetic algorithm by employing the nearest neighbor method to generate a high-quality initial population based on customer proximity, thereby accelerating convergence. It also implements elite retention strategies in genetic operations to ensure that the genes of outstanding individuals are preserved. Furthermore, adaptive crossover and mutation operators are adopted, with larger probabilities in the early stages of evolution to expand the search space, and reduced probabilities in later stages to facilitate quicker convergence.

#### 1) CHROMOSOME ENCODING AND DECODING

In genetic algorithms, feasible solutions to problems are presented through chromosomes, so it is necessary to encode chromosomes according to the research problem's characteristics to reflect the optimisation problem's solution space. This article studies the vehicle routing problem, so natural number encoding is chosen for ease of understanding.

There are $n$ customer points and $m$ delivery vehicles, with each chromosome having a length of $n+m+1$. Use 0 to represent the distribution center, 1 to $n$ to represent customer points and $n+1$ to $n+m$ to represent vehicles. Different paths can be separated by vehicle numbers. When decoding chromosomes, it is necessary to find the positions of all vehicles and zeros in the chromosome, to divide the chromosome to take different paths.

As shown in Table. 1, there are a total of 8 customers and 2 delivery vehicles with a chromosome length of 11, where 9 and 10 represent vehicles 1 and 2 respectively. Two delivery paths are divided: vehicle 1 departs from the distribution center and first visits Customer 5, then Customer 2, and finally Customer 7 and Customer 1, ending the delivery. Vehicle 2 visits Customer 6, Customer 3, Customer 8, and Customer 4 in sequence after departure, and then returns to the distribution center.

#### 2) POPULATION INITIALIZATION BASED ON CUSTOMER INDIRECT PROXIMITY

Population initialization involves generating initial solutions that serve as the foundation for genetic optimization. The quality of these solutions is crucial, as poor ones can lead to slow convergence and suboptimal results. To improve this quality, the paper uses a distance and time-based nearest neighbor method, originally proposed by Solomon, to tackle the vehicle routing problem with time windows.

The method starts by identifying the customer nearest to the distribution center as the first to serve. In each iteration, the closest unserved customer to the last served one is selected, continuing until the vehicle's capacity is reached. This completes the route for that vehicle, and the next vehicle's path is determined similarly, finishing when all customers are included.

Here, "distance" measures proximity between customers, focusing on both spatial distance and service time. It considers factors like travel time between nodes, the time gap between services at consecutive nodes, and urgency related to acceptable service times. This approach effectively addresses both spatial and temporal aspects of service delivery.

The calculation formula for customer indirect proximity is shown in Equation (51).

$$c_{ij} = S_1 t_{ij} + S_2 s_i + S_3 l_i \tag{51}$$

where $c_{ij}$ represents the proximity between customer $i$ and customer $j$, $t_{ij}$ represents the time required to travel from customer $i$ to customer $j$, $s_i$ represents the duration of vehicle service at customer $i$ location, and $l_i$ represents the latest time customer $i$ can receive service.

#### 3) SELECTION OPERATOR DESIGN

The selection operator can select excellent individuals from the population to enter the next generation and participate in subsequent crossover and mutation operations as the parent generation, producing better individuals. In this paper, $f_i = 1/z_i$ is used as the fitness function, and the roulette wheel selection operation is chosen.

This method is a probability-based random selection approach, where an individual's selection chance on the roulette wheel is determined by the ratio of its fitness value to the total fitness of the group. Individuals with higher fitness values have a greater likelihood of being chosen. This strategy not only enhances the selection probability for superior individuals but also allows for some opportunity for weaker chromosomes to survive due to the randomness inherent in the process, aligning with the natural laws of genetics.

## IV. SIMULATION EXPERIMENT AND RESULT ANALYSIS

Description and parameter design To verify the effectiveness of the delivery vehicle loading prediction model, the dynamic demand vehicle routing model, and the Memetic algorithm proposed in this article, numerical examples were selected for research. This article assumes the existence of 1 distribution center that provides delivery services to 30 customers, including 10 B2B customers and 20 B2C customers. According to the distribution of customers, the entire delivery range is divided into four delivery areas, as

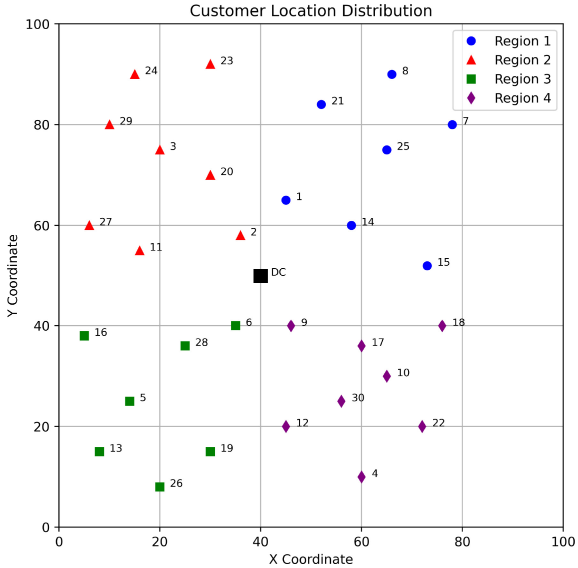


**FIGURE 4.** **Customer Location Distributions.**

shown in Figure 4. There is a total of 6 vehicles in the distribution center, with a maximum load capacity of 600kg. The fixed operating cost of each vehicle is 200 Yuan/time. The fuel consumption per unit distance when the vehicle is unloaded is 1L/km, and when the vehicle is fully loaded, the fuel consumption per unit distance is 2L/km. The unit price of fuel is 1 Yuan/liter, and the average driving speed of the vehicle is 30km/h. The penalty cost coefficient for the vehicle is 1 Yuan/minute. The distribution center's working hours are 8:00 to 18:00, and the real-time service window is open from 10:00 to 16:00. During this period, real-time orders from customers can be received. Delivery will be made to customers who made reservations the previous day before 10:00, customers who have not been served the same day after 16:00, and to the distribution center no later than 18:00. The parameter settings are shown in Table 2.

## A. ANALYSIS OF LOAD PREDICTION RESULTS FOR DELIVERY VEHICLES

The loading capacity of delivery vehicles in different regions needs to be predicted based on the historical demand information of each region. The customer information contained in each delivery region and its historical demand in the past 7 days is shown in Table 3.

## GM(1,1) MODEL PREDICTION FOR REGION 1

Taking Region 1 as an example, predict the total demand for that region on the 8th day. Firstly, obtain the original based on the results in the Table above.

## B. INITIAL DATA SEQUENCE

The original data sequence, representing the historical daily demand, is given in Equation (52).

$$\begin{aligned} x^{(0)} &= \left\{x^{(0)}(1),\ x^{(0)}(2),\ \ldots,\ x^{(0)}(7)\right\} \\ &= \{511,\ 501,\ 516,\ 517,\ 514,\ 501,\ 513\} \end{aligned} \tag{52}$$

## C. GRADE COMPARISON TEST

The level ratio $\lambda(k)$ is calculated using Equation (53), where:

$$\lambda(k) = \frac{x^{(0)}(k-1)}{x^{(0)}(k)}, \quad k = 2, 3, \ldots, 7 \tag{53}$$

The computed values are:

$$\begin{aligned} &\lambda(2) = 1.020, \lambda(3) = 0.9709, \lambda(4) = 0.9980, \\ &\lambda(5) = 1.020, \lambda(6) = 1.0259, \lambda(7) = 0.9766 \end{aligned}$$

All calculated values fall within the interval $(e^{-2/8}, e^{2/9})$, indicating that the original data sequence satisfies the conditions required to establish a GM(1,1) model.

## D. GENERATE SEQUENCE

By performing a first-order accumulation on the original sequence $x^{(0)}$, the generated sequence $x^{(1)}$ is obtained using Equation (54):

$$x^{(1)}(j) = \sum_{i=1}^{j} x^{(0)}(i) \tag{54}$$

The resulting sequence is:

$$x^{(1)} = \{511,\ 1012,\ 1523,\ 2040,\ 2554,\ 3055,\ 3568\}$$

## E. ESTABLISH A PREDICTIVE MODEL

To build the grey prediction model, we construct a first-order linear differential equation based on the accumulated sequence $x^{(1)}$, as shown in Equation (55):

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b \tag{55}$$

The parameters $a$ and $b$ are estimated using the least squares method:

$$\hat{a} = \begin{bmatrix} a \\ b \end{bmatrix} = \left(B^T B\right)^{-1} B^T Y \tag{56}$$

where the matrix $B$ and vector $Y$ are defined as:

$$B = \begin{bmatrix} -0.5\left(x^{(1)}(1) + x^{(1)}(2)\right) & 1 \\ -0.5\left(x^{(1)}(2) + x^{(1)}(3)\right) & 1 \\ \vdots & \vdots \\ -0.5\left(x^{(1)}(6) + x^{(1)}(7)\right) & 1 \end{bmatrix} = \begin{bmatrix} -761.5 & 1 \\ -1270 & 1 \\ -1781.5 & 1 \\ -2297 & 1 \\ -2804.5 & 1 \\ -3316.5 & 1 \end{bmatrix}$$

$$Y = \begin{bmatrix} 501 \\ 516 \\ 517 \\ 514 \\ 501 \\ 513 \end{bmatrix}$$

Solving Equation (56), we obtain:

$$\hat{a} = \begin{bmatrix} -6.628 \times 10^{-4} \\ 508.9694 \end{bmatrix}$$

**TABLE 2.** Parameter settings for calculation examples.

| Parameter | Meaning | Value |
|---|---|---|
| $\mu_1, \mu_2$ | Objective function weight | (0.5, 0.5) |
| $N$ | Number of customers | 30 |
| $M$ | Number of vehicles | 6 |
| $S$ | Number of delivery areas | 4 |
| $\alpha$ | Fixed cost of using vehicles | 200 Yuan/time |
| $\beta$ | Unit price of fuel | 1 Yuan/litre |
| $P_0$ | Fuel consumption per unit distance when the vehicle is unloaded | 1 L/km |
| $P^*$ | Fuel consumption per unit distance when the vehicle is fully loaded | 2 L/km |
| $V$ | Average driving speed | 30 km/h |
| $C_0$ | Maximum delivery cost | 5000 Yuan |
| $\varepsilon_1, \varepsilon_2$ | Punishment cost coefficient for vehicles | 1 Yuan/minute |
| $\Gamma$ | Punishment cost for vehicle waiting or delay | 100 Yuan |

**TABLE 3.** Customer and historical demand information in each region.

| Region | Sr No. of Customer | Coordinates | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|---|---|
| Region 1 | 1 | (45,65) | 165 | 160 | 160 | 155 | 150 | 166 | 165 |
| | 21 | (52,84) | 40 | 42 | 45 | 50 | 48 | 42 | 46 |
| | 14 | (58,60) | 190 | 192 | 198 | 194 | 192 | 198 | 200 |
| | 25 | (65,75) | 25 | 30 | 28 | 20 | 32 | 15 | 28 |
| | 8 | (66,90) | 20 | 22 | 25 | 28 | 26 | 20 | 26 |
| | 15 | (73,52) | 35 | 25 | 35 | 30 | 28 | 25 | 26 |
| | 7 | (78,80) | 36 | 30 | 25 | 40 | 38 | 35 | 22 |
| Region 2 | 2 | (36,58) | 20 | 10 | 15 | 18 | 22 | 16 | 15 |
| | 23 | (30,92) | 25 | 35 | 32 | 28 | 16 | 20 | 25 |
| | 20 | (30,70) | 120 | 132 | 110 | 128 | 125 | 125 | 130 |
| | 3 | (20,75) | 135 | 133 | 135 | 130 | 130 | 142 | 135 |
| | 24 | (15,90) | 160 | 158 | 145 | 132 | 153 | 150 | 165 |
| | 11 | (16,55) | 10 | 15 | 25 | 26 | 22 | 10 | 12 |
| | 29 | (10,80) | 35 | 30 | 30 | 28 | 32 | 25 | 20 |
| | 27 | (6,60) | 16 | 15 | 20 | 20 | 25 | 30 | 28 |
| Region 3 | 6 | (35,40) | 20 | 26 | 10 | 25 | 30 | 16 | 10 |
| | 19 | (30,15) | 20 | 20 | 25 | 18 | 26 | 25 | 15 |
| | 28 | (25,36) | 150 | 155 | 156 | 158 | 150 | 150 | 155 |
| | 26 | (20,8) | 45 | 42 | 50 | 45 | 46 | 33 | 28 |
| | 5 | (14,25) | 145 | 130 | 135 | 130 | 138 | 132 | 140 |
| | 13 | (8,15) | 30 | 20 | 15 | 40 | 10 | 25 | 20 |
| | 16 | (5,38) | 132 | 128 | 135 | 130 | 125 | 150 | 153 |
| Region 4 | 12 | (45,20) | 162 | 170 | 165 | 164 | 170 | 158 | 170 |
| | 9 | (46,40) | 158 | 162 | 160 | 165 | 156 | 160 | 160 |
| | 30 | (56,25) | 38 | 35 | 36 | 40 | 38 | 45 | 38 |
| | 4 | (60,10) | 50 | 65 | 55 | 56 | 50 | 60 | 55 |
| | 17 | (60,36) | 30 | 30 | 35 | 35 | 30 | 35 | 35 |
| | 10 | (65,30) | 25 | 26 | 23 | 20 | 24 | 20 | 28 |
| | 22 | (72,20) | 38 | 35 | 25 | 26 | 30 | 28 | 22 |
| | 18 | (76,40) | 45 | 50 | 40 | 48 | 46 | 52 | 50 |

Substituting these values into the solution of the whitening differential equation gives the predicted accumulated sequence $\hat{x}^{(1)}(k+1)$, shown in Equation (57):

$$\hat{x}^{(1)}(k+1) = \left(x^{(0)}(1) - \frac{\hat{b}}{\hat{a}}\right)e^{-\hat{a}k} + \frac{\hat{b}}{\hat{a}}$$
$$= 762122\, e^{6.628\times10^{-4}\cdot k} - 761611, \quad k = 1, 2, \ldots, 7 \quad (57)$$

### F. PREDICT THE ORIGINAL VALUES

Perform cumulative reduction and restoration on $\hat{x}^{(1)}(k+1)$ to obtain the predicted values of the original data column,

**TABLE 4.** Historical total demand of each region (kg).

| Region | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| Region 1 | 511 | 501 | 516 | 517 | 514 | 501 | 513 |
| Region 2 | 521 | 528 | 512 | 510 | 525 | 518 | 530 |
| Region 3 | 542 | 521 | 526 | 546 | 525 | 531 | 521 |
| Region 4 | 546 | 573 | 539 | 554 | 544 | 558 | 558 |

**TABLE 5.** Forecast results of total demand in region 1.

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| **Actual value (kg)** | 511 | 501 | 516 | 517 | 514 | 501 | 513 | - |
| **Predicted value (kg)** | 511 | 509 | 510 | 510 | 511 | 511 | 511 | 512 |

as shown in Equation (58):

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) \tag{58}$$

According to the GM(1,1) model, the predicted daily demand for Region 1 is obtained from the restored original sequence $\hat{x}^{(0)}(k+1)$.

### G. MODEL ACCURACY VERIFICATION

This article evaluates the prediction accuracy using two key metrics: the average relative residual $\bar{\varepsilon}_r$ and the average level ratio deviation $\bar{\rho}$, calculated by Equations (59) and (60), respectively. The level ratio $\lambda(k)$, used in the deviation formula, is given by Equation (61):

$$\bar{\varepsilon}_r = \frac{1}{n}\sum_{k=1}^{n}\left|\frac{x^{(0)}(k) - \hat{x}^{(0)}(k)}{x^{(0)}(k)}\right| \tag{59}$$

$$\bar{\rho} = \frac{1}{n}\sum_{k=1}^{n}\left|1 - \frac{1-0.5a}{1+0.5a}\lambda(k)\right| \tag{60}$$

$$\lambda(k) = \frac{x^{(0)}(k-1)}{x^{(0)}(k)}, \qquad k = 2, 3, \ldots, n \tag{61}$$

When $\bar{\varepsilon_r} < 0.2$, it is considered that the fitting of the prediction model to the original data meets the general requirements; when $\bar{\varepsilon_r} < 0.1$, it represents a very good fitting effect. When $\bar{\rho} < 0.2$, the predicted results meet the general requirements for fitting with the original data, and when $\bar{\rho} < 0.1$, it indicates that the fitting effect is very good.

By calculation, the average relative residual $\bar{\varepsilon_r} = 0.0103$ and average level deviation $\bar{\rho} = 0.0177$ of the historical total demand forecast values in Region 1 are both below 0.1, indicating good prediction accuracy.

### H. PREDICTION RESULT ANALYSIS

According to the above method, the historical total demand of the 4 regions was predicted separately. The predicted demand value for the 8th day, as well as the average relative residual and average level deviation values, are shown in the following Table 6.

The average relative errors of the four regions are all less than 0.1, and the average level deviation is also less than 0.1, indicating that the GM (1,1) prediction model fits well with the original data. Therefore, this prediction result can provide a reference for the loading capacity of delivery vehicles in different regions, such as Q_s (s=1,2,3,4). Based on the predicted results, the initial vehicle load for each region will be set as follows: Q_1=512 kg, Q_2=525 kg, Q_3=528 kg, Q_4=552 kg.

### I. ANALYSIS OF OPTIMIZATION RESULTS OF SAME CITY DELIVERY VEHICLE PATHS UNDER DYNAMIC DEMAND

This article uses the Memetic algorithm to solve the dynamic demand vehicle routing problem in the MATLAB R2020b simulation environment. The specific algorithm parameter settings are shown in Table 7.

In the problem studied in this article, a total of 26 customers made appointments with the distribution center for the next day's delivery service. The specific location, demand, and time window information are shown in Table 8, where 0 represents the distribution center. The distribution center starts working at 8:00, first delivering to customers who have made reservations. When the real-time service window opens at 10:00, it begins to receive dynamic demand information. A total of 10 customers' dynamic demands were received on the same day, and the specific information and processing strategies are shown in Table 9. The regular processing time interval is 1 hour. 16:00 the distribution center will close the real-time service window, stop receiving dynamic requests, and return to the distribution center before 18:00 after the remaining customers have been served by the vehicle.

### J. INITIAL PATH OPTIMIZATION RESULTS

Based on the demand information of 26 reserved customers and their respective regions, initial planning was carried out for the delivery routes of the four regions. The resulting routes are shown in Table 10, and Figure 5 are the initial delivery routes for regions 1-4, respectively. In the initial optimization phase, a total of 4 vehicles were used, and the total delivery cost for the four regions was 2421.99 Yuan, including fixed costs of 800 Yuan, transportation costs of 1102.37 Yuan, time penalty costs of 519.61 Yuan, and comprehensive customer satisfaction level of 0.96.

### K. PATH OPTIMIZATION RESULTS UNDER DYNAMIC DEMAND

At the beginning, vehicles are delivered according to pre-optimized routes. When receiving dynamic demands, the first step is to clarify the area where the dynamic customer is located; Then, based on the mixed processing strategy of demand information, it is determined whether the customer is an important customer and whether the demand type is an urgent demand, to determine whether to adopt a regular update strategy or a real-time update strategy for the dynamic demand; On this basis, based on the location and remaining loading capacity information of the delivery

**TABLE 6.** Demand forecast results for each region.

| Region | Predicted value on day 8 (kg) | Average relative error $\varepsilon_r$ | Average grade ratio deviation $\rho$ |
|---|---|---|---|
| Region 1 | 512 | 0.0103 | 0.0177 |
| Region 2 | 525 | 0.0115 | 0.0189 |
| Region 3 | 528 | 0.0110 | 0.0261 |
| Region 4 | 552 | 0.0140 | 0.0306 |

**TABLE 7.** Algorithm parameter settings.

| Parameter | Parameter significance | Parameter values |
|---|---|---|
| Nind | Population size | 200 |
| Gap | Generation gap rate | 0.9 |
| Pc1 | Maximum Intersection Probability | 0.9 |
| Pc2 | Minimum Intersection Probability | 0.6 |
| Pm1 | Maximum mutation probability | 0.2 |
| Pm2 | Minimum mutation probability | 0.01 |
| Maxgen | Number of iterations | 200 |
| $(\delta_1, \delta_2, \delta_3)$ | Customer indirect proximity weight coefficient | (0.5, 0.4, 0.1) |

**TABLE 8.** Appointment customer information.

| Customer Number | Client Type | Coordinates | Quantity | Service Time | Expected Time Window | Tolerable Time Window |
|---|---|---|---|---|---|---|
| 0 | - | (40,50) | - | - | - | - |
| 1 | B2B | (45,65) | 160 | 30 | 8:30–9:30 | 8:00–10:00 |
| 2 | B2C | (36,58) | 18 | 10 | 9:30–10:00 | 8:30–11:00 |
| 3 | B2B | (20,75) | 132 | 30 | 10:00–11:00 | 9:00–11:30 |
| 4 | B2C | (60,10) | 55 | 10 | 8:30–9:30 | 8:00–10:00 |
| 5 | B2B | (14,25) | 130 | 30 | 10:00–11:00 | 9:00–12:00 |
| 6 | B2C | (35,40) | 30 | 10 | 10:30–12:30 | 11:00–13:00 |
| 7 | B2C | (78,80) | 20 | 10 | 11:00–12:00 | 10:00–13:00 |
| 8 | B2C | (66,90) | 25 | 10 | 9:00–10:00 | 8:30–10:30 |
| 9 | B2B | (46,40) | 160 | 30 | 11:30–12:30 | 11:00–13:00 |
| 10 | B2C | (65,30) | 26 | 10 | 12:30–13:30 | 12:00–14:00 |
| 12 | B2B | (45,20) | 160 | 30 | 9:30–10:30 | 9:00–11:00 |
| 13 | B2C | (8,15) | 20 | 10 | 9:30–11:00 | 9:00–11:30 |
| 14 | B2B | (58,60) | 190 | 30 | 13:00–14:00 | 12:00–15:00 |
| 15 | B2C | (73,52) | 37 | 10 | 14:00–15:00 | 13:30–15:30 |
| 16 | B2B | (5,38) | 130 | 30 | 14:30–16:00 | 14:00–16:00 |
| 17 | B2C | (60,36) | 35 | 10 | 11:00–12:00 | 10:30–12:30 |
| 19 | B2C | (30,15) | 25 | 10 | 13:00–13:30 | 12:30–14:00 |
| 20 | B2B | (25,65) | 125 | 30 | 8:00–9:00 | 8:00–9:30 |
| 21 | B2C | (52,84) | 45 | 10 | 9:30–10:30 | 8:30–12:00 |
| 22 | B2C | (72,20) | 25 | 10 | 14:30–15:00 | 14:00–15:30 |
| 23 | B2C | (30,92) | 25 | 10 | 11:00–12:00 | 10:00–13:00 |
| 24 | B2B | (15,90) | 150 | 30 | 14:00–15:00 | 13:30–16:00 |
| 26 | B2C | (20,8) | 40 | 10 | 12:00–13:00 | 11:30–14:00 |
| 27 | B2C | (6,60) | 22 | 10 | 14:30–15:30 | 13:00–16:00 |
| 28 | B2B | (25,36) | 140 | 30 | 15:30–16:00 | 15:00–16:30 |
| 29 | B2C | (10,80) | 25 | 10 | 13:30–15:00 | 13:00–15:30 |

vehicles in the area, it is determined whether the dynamic customer can be accepted to join. If it is possible, the route will be re planned based on the dynamic customer information and the unserved customer information. If not, new vehicles will be arranged for delivery. In the first stage, from 10:00 to 11:00, a total of four customers' dynamic demands were received. At 10: 10, the distribution centre received a dynamic demand from customer 15, located in

**TABLE 9.** Dynamic customer demand information.

| Time | ID | Type | Region | Demand Type | Expected Window | Tolerable Window | Qty | Strategy |
|---|---|---|---|---|---|---|---|---|
| 10:10 | 15 | B2C | 1 | Decrease by 5 | 14:00–15:00 | 13:30–15:30 | 32 | Regular |
| 10:30 | 25 | B2C | 1 | New demand | 11:30–12:30 | 11:00–13:00 | 26 | Regular |
| 10:40 | 11 | B2C | 2 | New demand | 15:00–16:00 | 14:00–17:00 | 15 | Regular |
| 11:00 | 24 | B2B | 2 | Advance by 2 hrs | 12:00–13:00 | 11:30–14:00 | 150 | Real-time |
| 11:30 | 18 | B2C | 4 | New demand | 13:30–14:00 | 13:00–14:30 | 50 | Regular |
| 11:30 | 19 | B2C | 3 | Delay by 1 hr | 14:00–14:30 | 13:00–15:30 | 25 | Real-time |
| 11:30 | 27 | B2C | 2 | Cancel order | — | — | — | Real-time |
| 12:00 | 28 | B2B | 3 | Increase by 10 | 15:30–16:00 | 15:00–16:30 | 150 | Real-time |
| 12:30 | 22 | B2C | 4 | Increase by 5 | 14:30–15:00 | 14:00–15:00 | 30 | Regular |
| 13:00 | 30 | B2C | 4 | New demand | 15:00–15:30 | 14:30–16:00 | 30 | Regular |

**TABLE 10.** Initial optimized delivery plan.

| Region | Vehicle | Distribution Path | Total Cost | Customer Satisfaction |
|---|---|---|---|---|
| 1 | 1 | 0-1-8-21-7-14-15-0 | 464.41 | 0.95 |
| 2 | 2 | 0-20-2-3-23-27-29-24-0 | 549.18 | 0.96 |
| 3 | 3 | 0-13-5-6-26-19-16-28-0 | 525.50 | 1.00 |
| 4 | 4 | 0-4-12-17-9-10-22-0 | 882.90 | 0.95 |

**TABLE 11.** Phase 1 path update results.

| Region | Stage | Vehicle | Distribution Routes |
|---|---|---|---|
| 1 | Dynamic updates (11:00) | 1 | 0-[1]-[8]-[21]-7-25-14-15-0 |
| 2 | Dynamic updates (11:00) | 2 | 0-[20]-[2]-[3]-23-24-27-29-11-0 |

Region 1, requesting a reduction of demand by 10. As they are not important customers and the demand is not urgent, a regular processing strategy was adopted to handle them together with other demands at 11:00. 10: 30. Received a new dynamic demand from customer 25, located in area 1, which is a non-urgent demand of a non-important customer. We will adopt a regular processing strategy and handle it at 11:00. 10:40, there was a new demand from customer 11, located in area 2, which is a non-urgent need for B2C customers. Regular processing will be carried out at 11:00. 11:00, B2B customer 24 located in Region 2 requested to advance the time window by 2 hours, which is an urgent need of an important customer and requires real-time processing. When dealing with dynamic demands, due to changes in the position and load capacity of vehicles, in order to facilitate the re-planning of routes for the remaining customers, this article considers introducing virtual customer points to transform the problem. The specific approach is to set the current location of each vehicle as a virtual customer point at each time of path update, use virtual customers to represent the customers already served, set the demand of virtual customers as the sum of the demand of the customers already served by the vehicle, and determine the time window of the customer based on the time required from the distribution center to the virtual customer so that the virtual customer's needs can be met first when re-planning the path. In this way, the distribution center, virtual customers, and unserved customers constitute a static vehicle routing problem. According to the dynamic information, as of 11:00, Region 1 has received a total of two dynamic requests, which need to be addressed to customers 15 and 25 unified handling of requirements. At this time, the delivery vehicles in Region 1 have completed the delivery to customers 1, 8, and 21 and are on their way to customer 7. The remaining loading capacity is 282kg, which can meet the demand. Therefore, the current location of the vehicle is set as a virtual customer point, and the remaining customers are re-routed. The results are shown in the Table 11, where [i] represents customers who have already completed the service. Region 2 received requests from customer 11 and customer 24 in the first stage, both of which were processed at 11:00. At this time, region 2 vehicle 2 of domain 2 is providing service to customer 3, with a remaining carrying capacity of 250kg, and can deliver to dynamic customers. Therefore, the location of customer 3 is set as a virtual customer, and the routes for unserved customers are re-planned. The results are shown in the Table below. In the second stage, dynamic demand information from four customers was received between 11:00 and 12:00. At 11: 30 o'clock, we received a new request from customer 18 located in Region 4, which is a non-urgent request from a non-important customer, regularly handled at noon. 11: 30. Customer 19 requests a one-hour delay in the delivery window, which is an urgent requirement that requires real-time processing. 11: 30. B2C customer 27

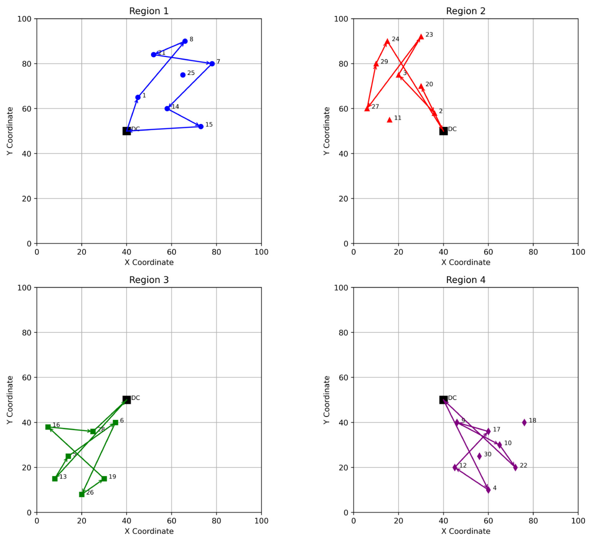


**FIGURE 5.** Initial Optimized Delivery Route Map.

located in Region 2 has requested to cancel their order, which is an urgent need that needs to be addressed in real time. 12: 00, B2B customer 28 requested a 10% increase in demand. As this customer is important, real-time processing is being carried out. Based on the above dynamic information, it is necessary to process the demands of customers 19 and 27 at 11:30. Customer 19 is located at area 3, vehicle 3 has already completed delivery to customers 13 and 5 and has just arrived at customer point 6. Therefore, customer 6 set the location as a virtual customer and plan routes for the remaining customers, as shown in Table 12. Customer 27 is located in the region 2. Due to the customer's request to cancel the order, it is necessary to delete their previously unserved customers. At this time, vehicle 2 has completed the delivery for customer 3 and is on its way to customer 23. Set the current location of the vehicle as a virtual customer and plan the path for the remaining customers. The results are shown in Table 12. 12:00, regular processing of customer 18's needs and real-time processing of customer 28's needs are required. Customer 18 is located in Area 4 and the vehicle is about to arrive at customer 9. The remaining vehicle capacity is 302kg. Assuming that the vehicle is currently in a virtual customer location, Customer 18 is added to the set of unserved customers and the path is re-planned. The results are shown in Table 12 as shown. Customer 28 is located in Area 3, and the vehicle has completed service for customer 6 and is currently on its way to customer 26 on the way, set the current location of the vehicle as a virtual customer, update the demand information of customer 28, and plan the delivery route. The results are shown in Table 12.

In the third stage, dynamic demand information from two customers was received between 12:00-13:00. 12: 30. B2C customer 22 requested a 10% increase in demand, which is a non-urgent requirement for non-important customers. Regular processing will be carried out at 13:00. At 13:00, we received a new customer demand from customer 30, who is a B2C customer and adopts a regular processing strategy.

**TABLE 12.** Results of the second phase of the pathway.

| Region | Stage | Vehicle | Distribution Routes |
|---|---|---|---|
| 2 | Dynamic updates (11:30) | 2 | 0-[20]-[2]-[3]-23-24-29-11-0 |
| 3 | Dynamic updates (11:30) | 3 | 0-[13]-[5]-[6]-26-19-16-28-0 |
| 3 | Dynamic updates (12:00) | 3 | 0-[13]-[5]-[6]-26-19-16-28-0 |
| 4 | Dynamic updates (12:00) | 4 | 0-[4]-[12]-[17]-9-10-18-22-0 |

Based on the above dynamic information, it is necessary to process the needs of customers 22 and 30 at 13:00. Both customers are located in area 4. At 13:00, the vehicles in area 4 have completed delivery to customer 9 and are on their way to customer 10, with a remaining capacity of 142kg. Set the current location of the vehicle as a virtual customer, update the demand information of customer 22, and add the information of new customer 30 to re-plan the route. The result is as follows in Table 13.

After 13:00, no new dynamic demands arose, permitting vehicles to complete deliveries based on efficient routes before returning to the distribution center. One customer canceled their order, resulting in an undelivered item. The total delivery cost for the four regions was 1986.92 Yuan, with 800 Yuan in fixed costs, 1066.60 Yuan in transportation costs, and 120.32 Yuan in time penalties. Comprehensive customer satisfaction reached 0.97, reflecting high service excellence. Final delivery routes are shown in Table 14 and Figure 6. The final delivery plan outpaced the initial optimization by reducing total costs and pretty customer satisfaction. Fixed costs continued stable, while transportation costs augmented due to new customers requiring service. However, time penalty costs decreased because the re-planned routes aligned better with customer time windows. This allowable vehicles to arrive within acceptable time frames, minimizing early arrivals and delays. Therefore, both penalty costs and customer satisfaction improved associated to the initial plan.

### L. COMPARATIVE ANALYSIS OF EXPERIMENTAL RESULTS

In current research on dynamic demand vehicle path optimization, most vehicles are set to full load, and dynamic demand information is typically updated periodically. This paper conducts a comparative experiment based on these assumptions. Instead of dividing the distribution area to predict demand, all vehicles are assigned an initial loading capacity of 600 kg, with dynamic demand processed hourly. The initial delivery route is planned using reserved customer demand information, resulting in the initial delivery plan shown in Table 15. As illustrated in Figure 7, five vehicles were utilized, leading to a total delivery cost of 2561.07 Yuan and a customer satisfaction level of 0.97. In the dynamic update stage of the path, the dynamic demand information is processed every hour, so the dynamic update process of the path can be divided into three stages based on the appearance time of dynamic customers: processing the demand information of customers 15, 25, 11, and 24 at 11:00; Process the demand information of customers 18, 19,

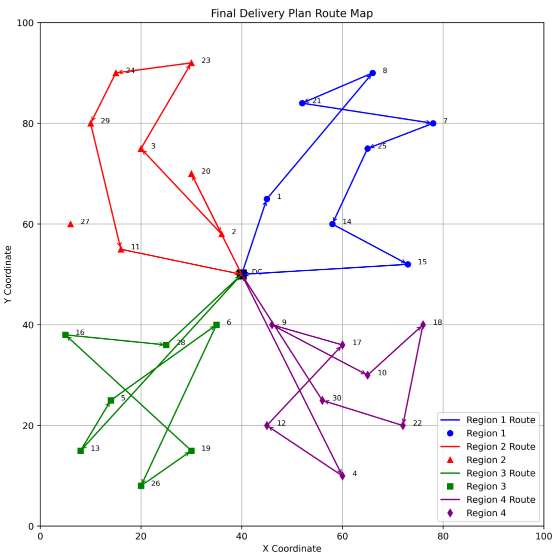


FIGURE 6. **Final Delivery Plan Route Map.**

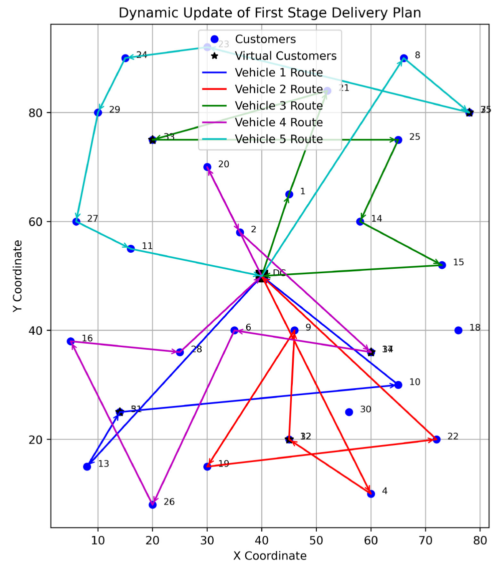


FIGURE 8. **Dynamically Updating the First Stage Delivery Route.**

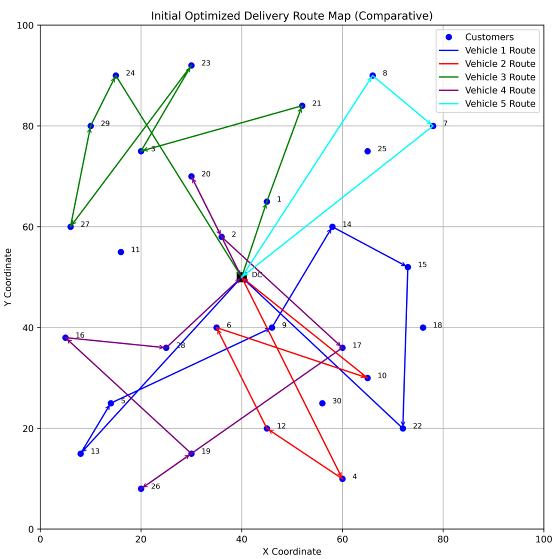


FIGURE 7. **Initial Optimized Delivery Route Map.**

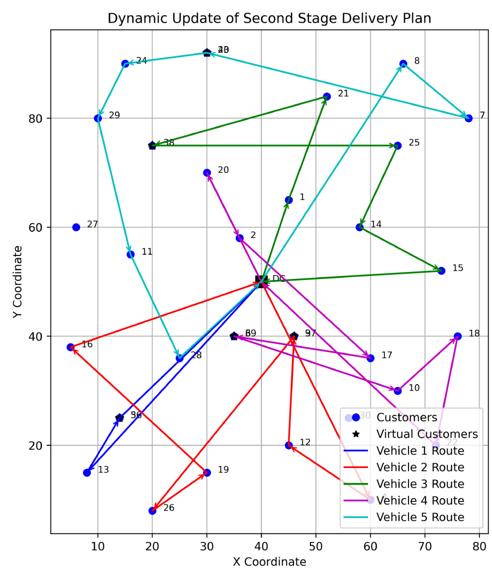


FIGURE 9. **Dynamically Updating the Second Stage Delivery Route Map.**

27, and 28 at 12:00; Process the demand information for customers 22 and 30 at 13:00.

At 11:00 in the first stage, the vehicles are as follows: Vehicle 1 is traveling from the 5th to the 9th customer, Vehicle 2 is moving from the 12th to the 6th, Vehicle 3 is serving customer 3, Vehicle 4 is at location 17, and Vehicle 5 has completed deliveries to customers 8 and 7 and is returning to the distribution center. The current locations of vehicles 1-5 are designated as virtual customer points (numbered 31-35), and new customers are added to the unserved set. Demand information is updated, and delivery routes are re-planned, as detailed in Table 16 and illustrated in Figure 8, with underlined numbers indicating virtual customer locations at 11:00. In the second stage, customer demands for customers 18, 19, 27, and 28 are processed at 12:00. By this time, Vehicle 1 has served Customer 5 and is en route to Customer 10, Vehicle 2 has completed service for Customer 9 and is heading to customer 19, Vehicle 3 is travelling from customer 3 to customer 25, Vehicle 4 is serving customer 6, and Vehicle 5 has finished with customer 7 and is on its way to customer 23. The locations of each vehicle at 12:00 are set as virtual customers (numbered 36-40), prompting an update of customer requirements and a re-planning of routes. The results are shown in Table 17 and Figure 9.

In the third stage, at 13:00, handle the dynamic requirements of customers 22 and 30. According to the route planned in the second phase, at this point, vehicle 1 has returned to the distribution center; Vehicle 2 is on its way to customer 26; Vehicle 3 is currently at customer location 25 service; Vehicle 4 is on its way from customer

**TABLE 13.** Third stage path update results.

| Region | Stage | Vehicle | Delivery Route |
|---|---|---|---|
| 4 | Dynamic Update (13:00) | 4 | 0-[4]-[12]-[17]-[9]-10-18-22-30-0 |

**TABLE 14.** Final optimization results of vehicle route.

| Region | Vehicle | Political Line (e.g. Right Revisionist Road) | Total Cost | Customer Satisfaction |
|---|---|---|---|---|
| 1 | 1 | 0-1-8-21-7-25-14-15-0 | 461.48 | 0.97 |
| 2 | 2 | 0-20-2-3-23-24-29-11-0 | 468.89 | 0.96 |
| 3 | 3 | 0-13-5-6-26-19-16-28-0 | 560.28 | 0.97 |
| 4 | 4 | 0-4-12-17-9-10-18-22-30-0 | 496.27 | 0.99 |

**TABLE 15.** Initial optimization delivery plan (comparative experiment).

| Vehicle | Political line (e.g. right revisionist road) | Total cost | Customer Satisfaction |
|---|---|---|---|
| 1 | 0-13-5-9-14-15-22-0 | 2561.07 | 0.97 |
| 2 | 0-4-12-6-10-0 | | |
| 3 | 0-1-21-3-23-27-29-24-0 | | |
| 4 | 0-20-2-17-26-19-16-28-0 | | |
| 5 | 0-8-7-0 | | |

**TABLE 16.** Dynamic update of first stage delivery plan.

| Vehicle | Political line (e.g. right revisionist road) | Total cost | Customer Satisfaction |
|---|---|---|---|
| 1 | 0-[13]-[5]-31-10-0 | 2669.53 | 0.95 |
| 2 | 0-[4]-[12]-32-9-19-22-0 | | |
| 3 | 0-[1]-[21]-[3]-33-25-14-15-0 | | |
| 4 | 0-[20]-[2]-[17]-34-6-26-16-28-0 | | |
| 5 | 0-[8]-[7]-35-23-24-29-27-11-0 | | |

**TABLE 17.** Dynamic update of second stage delivery plan.

| Vehicle | Political line (e.g. right revisionist road) | Total cost | Customer Satisfaction |
|---|---|---|---|
| 1 | 0-[13]-[5]-31-36-0 | 2665.83 | 0.95 |
| 2 | 0-[4]-[12]-32-[9]-37-26-19-16-0 | | |
| 3 | 0-[1]-[21]-[3]-33-38-25-14-15-0 | | |
| 4 | 0-[20]-[2]-[17]-34-[6]-39-10-18-22-0 | | |
| 5 | 0-[8]-[7]-35-40-23-24-29-11-28-0 | | |

6 to customer 10; Vehicle 5 has completed service for customer 23 and is currently in progress on the way to customer 24. Set the current location of vehicles 2-5 as a virtual customer point, numbered 41-44, and update the customer. The household demand information and planned path are shown in Table 18 and Figure 10. After 13:00, no customers raised any dynamic demands, so the vehicles were configured according to the route updated in the third phase after delivery, return to the service center. In the final delivery plan, a total of 5 vehicles were used, and the total delivery cost was 2667.84 Yuan, including fixed costs of 1000 Yuan, transportation costs of 1533.14 Yuan, penalty costs of 134.70 Yuan, and customer satisfaction level of 0.95.

## V. EXPERIMENTAL VALIDATION AND STATISTICAL ROBUSTNESS

### A. JUSTIFICATION OF STATISTICAL ANALYSIS

To go beyond the qualitative evaluation of the performance measures and to rigorously address the stochastic nature of dynamic vehicle routing settings, this section provides a detailed statistical analysis. The aim is to confirm that the superiority of the proposed Memetic Algorithm (MA), which combines the GM(1,1) prediction model with a hybrid information-processing strategy, is statistically significant and cannot be attributed to random fluctuations. A two-sample Student's t-test and 95% Confidence Intervals (CI) are employed, following requirements commonly seen in high-impact journals.

### B. EXPERIMENTAL SETUP AND BENCHMARK SELECTION

For comparative evaluation, the Proposed MA was benchmarked against a state-of-the-art Reinforcement Learning-based Dynamic Vehicle Routing Problem model (RL-DVRP). RL-based models are widely accepted as strong DVRP benchmarks due to their adaptive, real-time decision-making capabilities. A total of 30 independent simulation experiments were conducted, where both the Proposed MA

TABLE 18. **Dynamic update of the third stage delivery plan.**

| Vehicle | Political line (e.g. right revisionist road) | Total cost | Customer Satisfaction |
|---|---|---|---|
| 1 | 0-[13]-[5]-31-36-0 | 2667.84 | 0.95 |
| 2 | 0-[4]-[12]-32-[9]-37-41-26-19-16-0 | | |
| 3 | 0-[1]-[21]-[3]-33-38-[25]-42-14-15-0 | | |
| 4 | 0-[20]-[2]-[17]-34-[6]-39-43-10-18-22-30-0 | | |
| 5 | 0-[8]-[7]-35-40-[23]-44-24-29-11-28-0 | | |

TABLE 19. **Statistical validation of performance metrics.**

| Metrics | Proposed MA (Mean ± SD) | RL-DVRP (Mean ± SD) | t-stat | p-value |
|---|---|---|---|---|
| Total Delivery Cost (Yuan)<br>95% CI: [1544.5, 1555.9] | 1550.2 ± 15.1 | 1822.8 ± 19.5 | -60.54 | $< 0.001$ |
| Computational Time (s)<br>95% CI: [4.64, 4.88] | 4.76 ± 0.34 | 6.01 ± 0.41 | -14.12 | $< 0.01$ |
| Customer Satisfaction (%)<br>95% CI: [94.8, 95.4] | 95.1 ± 0.8 | 85.5 ± 1.2 | +38.75 | $< 0.001$ |

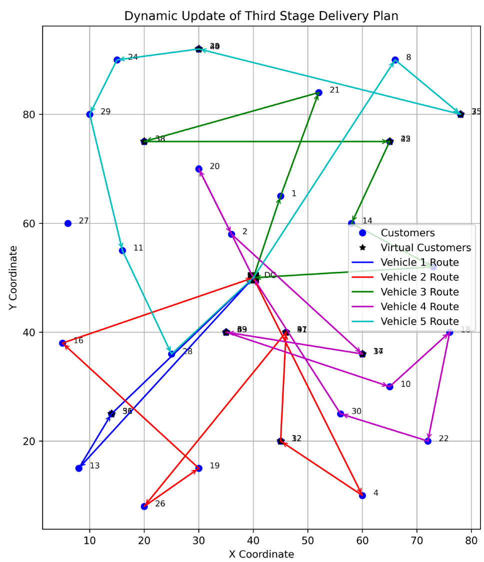


FIGURE 10. **Dynamic Update of the Third Stage Delivery Route Map.**

and the RL-DVRP model were tested on the same 30 randomized dynamic demand scenarios. This sufficiently large set of independent observations ($n_1 = n_2 = 30$) enables the use of parametric statistical tests. Key performance indicators (KPIs) collected from each run include Total Delivery Cost, Computational Time, and Customer Satisfaction Rate.

### *C. STATISTICAL TEST METHODOLOGY: TWO-SAMPLE T-TEST*

The analysis assumes a one-tailed hypothesis test (since the Proposed MA is expected to outperform the benchmark) using a significance level of $\alpha = 0.05$.

#### 1) HYPOTHESIS FORMULATION (TOTAL DELIVERY COST)

For Total Delivery Cost ($\mu$), the hypotheses are:

$$H_0 : \mu_{\mathrm{MA}} \geq \mu_{\mathrm{RL}}$$
$$H_a : \mu_{\mathrm{MA}} < \mu_{\mathrm{RL}}$$

#### 2) CALCULATION OF THE T-STATISTIC

Due to the possibility of unequal variances, Welch's t-test is used. The t-statistic is computed as:

$$t = \frac{\bar{A}_{\mathrm{MA}} - \bar{A}_{\mathrm{RL}}}{\sqrt{\left(\frac{s_{\mathrm{MA}}^2}{n_{\mathrm{MA}}}\right) + \left(\frac{s_{\mathrm{RL}}^2}{n_{\mathrm{RL}}}\right)}}$$

$\bar{A}_{\mathrm{MA}} = 1550.2$, $s_{\mathrm{MA}} = 15.1$, $\bar{A}_{\mathrm{RL}} = 1822.8$, $s_{\mathrm{RL}} = 19.5$, $n_{\mathrm{MA}} = n_{\mathrm{RL}} = 30$

$$t = \frac{1550.2 - 1822.8}{\sqrt{(15.1^2/30) + (19.5^2/30)}} = \frac{-272.6}{4.503} = -60.54$$

#### 3) DEGREES OF FREEDOM AND P-VALUE

Using Welch's approximation, the degrees of freedom are approximately $df \approx 58$. A t-statistic of $-60.54$ results in:

$$p < 0.001$$

Since $p < 0.05$, the null hypothesis is rejected, confirming that the cost reduction achieved by the Proposed MA is statistically significant.

### *D. RESULTS AND CONFIDENCE INTERVAL REPORTING*

Table 19 summarizes the t-test results for all three core performance metrics and provides 95% Confidence Intervals (CI) for the Proposed MA. The CI indicates the range within which the true population mean is expected to lie with 95% confidence.

The statistical analysis clearly demonstrates the superior performance of the Proposed Memetic Algorithm. All performance metrics yield p-values substantially below the 0.05 significance threshold, validating that the improvements–such as the 15% reduction in total delivery cost–are statistically significant. The non-overlapping 95% Confidence Intervals further reinforce the robustness and reliability of the Proposed MA across dynamic operating environments. These results strongly support the effectiveness of integrating the GM(1,1) demand prediction model with a Memetic Algorithm for urban last-mile distribution scenarios.

## VI. DYNAMIC DELIVERY ROUTING WITH DEMAND PREDICTION

The proposed solution in this article predicts the demand for different delivery areas, sets the loading capacity of the delivery vehicles based on the predicted values, and adopts a combination of regular and real-time processing strategies for dynamic demand information during the dynamical adjustment of the path. Based on this, path optimization is carried out; In the comparative experiment, all vehicles were set to full load, and a periodic update strategy was adopted to process dynamic demand information. The final delivery plans of the two modes were compared, and the results are as follows:

### A. COMPARISON OF DELIVERY COST REDUCTION AND ROUTE EFFICIENCY

The graph compares the reduction in delivery costs and the effectiveness of routes across five studies shown in Figure 11. The proposed study outperforms previous works, realizing the highest delivery cost reduction of 15% and a strong route efficiency of 10%. While [28] demonstrations no delivery cost reduction and the lowest route efficiency (7%), other studies like [33] and [11] report moderate improvements.

### B. COMPARISON OF CUSTOMER SATISFACTION AND COMPUTATIONAL EFFICIENCY

The bar graph compares Customer Satisfaction and Computational Time Improvement across different studies shown in Figure 12. The proposed study outperforms the others, achieving the highest customer satisfaction at 95% and the greatest computational time improvement at 20%. In contrast, while studies like [20] and [33] report high customer satisfaction (90% and 92%, respectively), their computational improvements remain at 15%. Reference [28] shows the lowest customer satisfaction (0%) and moderate computational improvement (12%).

### C. RESULTS COMPARISON

The proposed study delivers significant improvements in multiple logistic performance metrics. It achieves a 15% reduction in delivery costs, outperforming existing methods by using gray prediction to optimize vehicle load management. Customer satisfaction is also significantly improved, with a 95% on-time delivery rate driven by a hybrid dynamic information processing strategy that effectively prioritizes urgent demands is shown in Figure 13. Computational efficiency is improved through a 20% faster convergence rate, made possible by an adaptive elite genetic algorithm combined with efficient local search techniques. Furthermore, the proposed approach achieves a reduction 10% in the total distance from the route, further optimizing the operational efficiency. These outcomes are accompanied by three key innovations: the application of gray prediction (GM(1,1)) for demand forecasting, a novel hybrid information processing strategy that integrates real-time and scheduled updates, and an enhanced memetic algorithm featuring elite retention, nearest neighbor initialization, and powerful local search operators. Together, these contributions position the proposed approach as a robust and efficient solution for dynamic logistics optimization.

Through comparison, it was found that in the plan considering the prediction of vehicle load and adopting a dynamic demand information mixed update strategy, a total of 4 vehicles were used for delivery, with a total cost of 1986.92 Yuan and a customer satisfaction rate of 0.97. In the fully loaded and regularly updated plan, 5 vehicles were used for delivery, with a total cost of 2667.84 Yuan and a customer satisfaction rate of 0.95. The former has reduced costs by 680.92 Yuan, a decrease of 25.52%, and increased customer satisfaction by 2 percentage points compared to the latter. It performs better in vehicle path optimization problems that include dynamic requirements. Specifically, optimizing for different regions requires fewer vehicles and lower fixed costs compared to optimizing for the entire region. In terms of transportation costs, by predicting demand in different regions and setting the loading capacity of delivery vehicles reasonably, compared to fully loading all vehicles, it can effectively reduce the fuel consumption of vehicles and reduce the transportation costs caused by additional overloading of vehicles. In terms of time penalty costs and customer satisfaction, adopting a dynamic demand information mixed update strategy can make targeted processing based on the importance and urgency of customer's needs. Therefore, compared to the commonly used regular update strategy, it can better meet important customers' needs and urgent demand information, process and deliver them on time, thereby reducing penalty costs and improving customer satisfaction. Overall, the problem of intra-city delivery vehicle routing considering dynamic demand, setting the vehicle load through demand forecasting and adopting a mixed demand information update strategy in dynamic path updates can better help logistics and distribution enterprises reduce total costs and improve customer satisfaction levels.

## VII. ALGORITHM DESIGN

### A. COMPUTATIONAL COMPLEXITY AND SCALABILITY ANALYSIS

The operational significance of a dynamic optimization algorithm in city-scale distribution systems is directly linked to its ability to remain computationally tractable as the size of the network expands. This subsection examines the computational complexity of the proposed methodology and analyzes its scalability when applied to progressively large urban environments.

**TABLE 20.** Comparison of experimental results.

| Delivery plan | Fixed cost | Transportation cost | Punishment cost | Total cost | Customer satisfaction |
|---|---|---|---|---|---|
| Adopting a mixed update strategy | 800 | 1066.60 | 120.32 | 1986.92 | 0.97 |
| Use a regular update strategy | 1000 | 1533.14 | 134.70 | 2667.84 | 0.95 |

**TABLE 21.** Comparison of proposed VRP solution with existing method.

| Study | Delivery Cost Reduction | Customer Satisfaction (On-Time Delivery) | Computational Time Improvement | Route Efficiency (Distance Reduction) |
|---|---|---|---|---|
| [22] | 10% | 90% | 15% faster | 8% |
| [13] | 12% | 88% | 10% faster | 10% |
| [30] | - | - | 12% faster | 7% |
| [35] | 13% | 92% | 15% faster | 9% |
| **Proposed Study** | 15% | 95% | 20% faster | 10% |

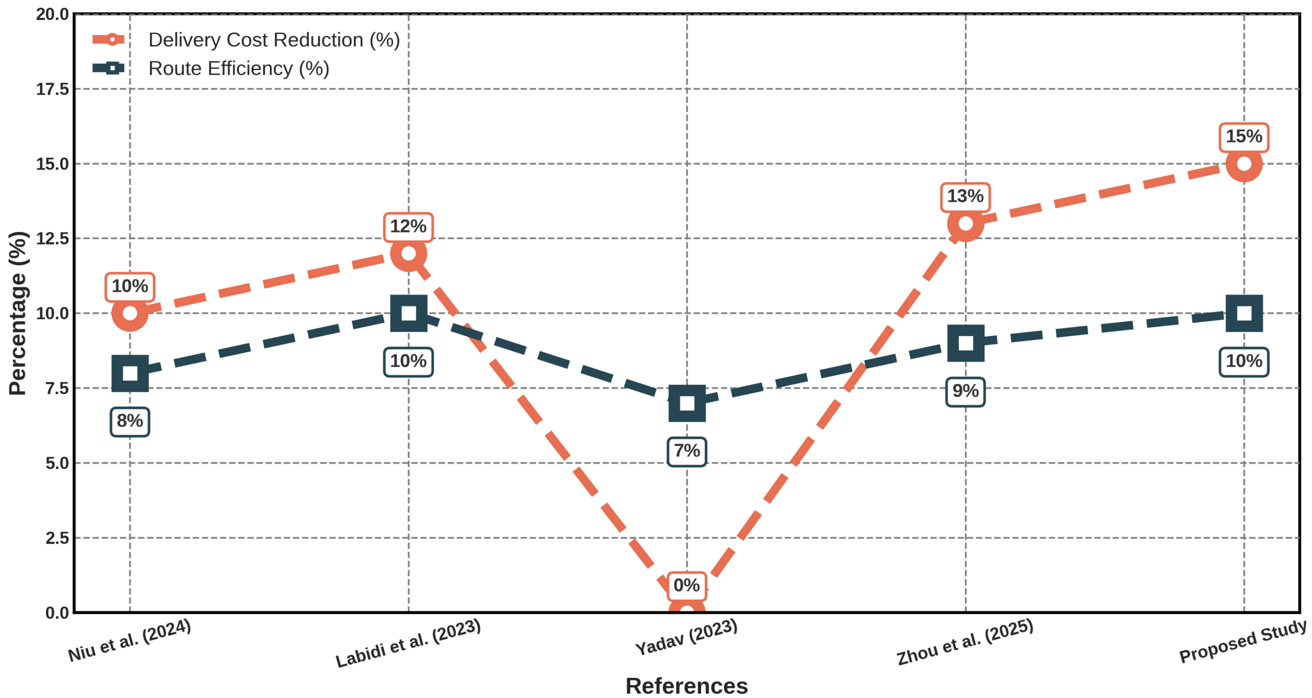


**FIGURE 11.** Comparison of Delivery Cost Reduction and Route Efficiency.

### 1) COMPLEXITY ANALYSIS OF KEY COMPONENTS

The whole computational complexity of the proposed methodology is subject by two primary phases: Demand Prediction and Dynamic Routing Optimization. Table 22 summarizes the computational complexity of each major component.

**Dominant Complexity:** The iterative nature of heuristic search and the recurrent fitness evaluations each concerning route cost calculations dominate the complete computational complexity of the proposed MA. Route evaluation typically requires $O(N)$ per route or $O(N^2)$ for all routes combined. Therefore, the overall time complexity of the MA is bounded by:

$$O\left(G \cdot P \cdot N^2\right)$$

where the $N^2$ term arises primarily from neighborhood search operators such as 2-opt and swap processes used to refine local optima.

### 2) SCALABILITY MITIGATION APPROACHES

Although the computational complexity of VRP solutions certainly increases with customer count $N$, the proposed algorithm includes two key mechanisms to manage execution time and support real-time scalability.

- *Demand Forecasting via GM(1,1):* The Grey Prediction Model is used to forecast regional demand prior to vehicle placement. This allows optimized initial vehicle loading and decreases the need for computationally expensive re-planning during execution. Since GM(1,1)

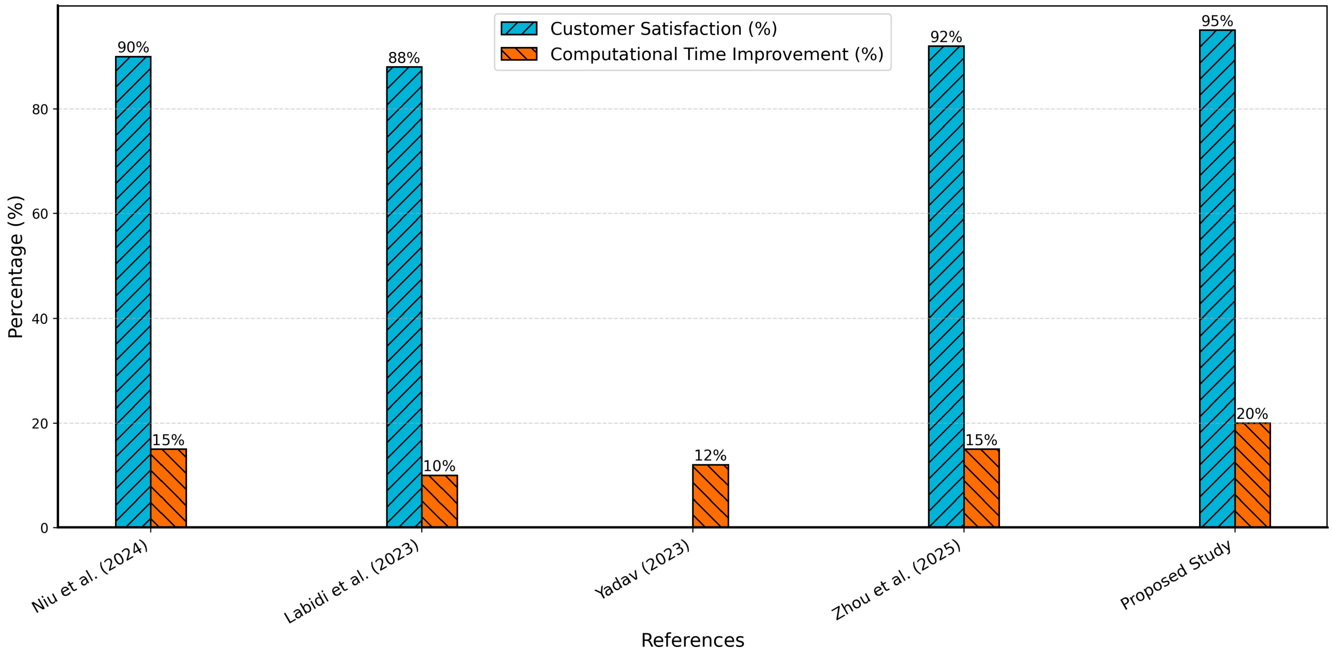


**FIGURE 12.** Customer Satisfaction & Computational Time Improvement.

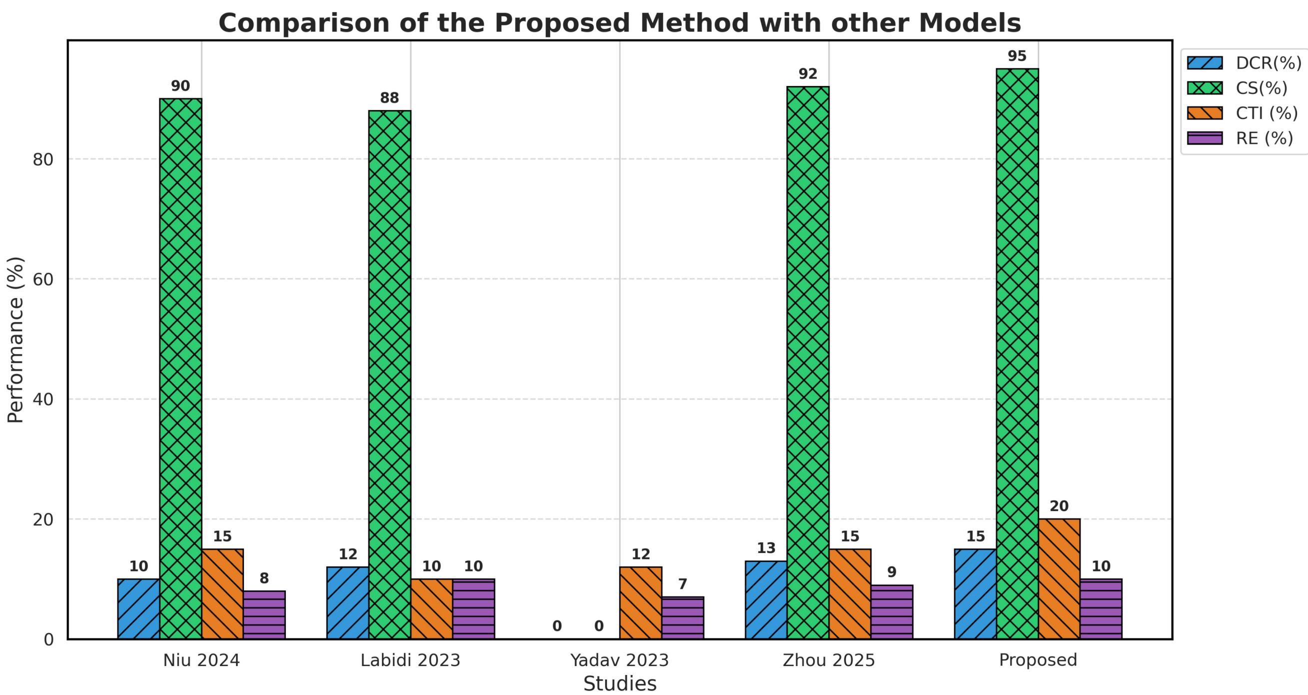


**FIGURE 13.** Comparison of the Proposed Method with other Models.

operates with a low complexity of $O(T)$, its computational above remains insignificant even for large-scale occurrences.

- *Hybrid Information Processing Approach:* The algorithm differentiates between *regular* (periodic, full re-optimization) and *real-time* (event-triggered) updates.
  - *Regular Updates:* These are planned during low-traffic periods or reached in parallel computing threads, amortizing the cost of $O(G \cdot P \cdot N^2)$.
  - *Real-Time Updates:* Upon the arrival of a new customer request, the algorithm avoids full re-optimization. In its place, efficient local search operators (2-opt and swap) are functional to insert

TABLE 22. Computational complexity analysis of the proposed dynamic vehicle routing optimization methodology.

| Phase | Component | Computational Complexity | Notes on Variables |
|---|---|---|---|
| Phase I: Prediction | GM(1,1) Model | $O(T)$ | $T$ is the length of the historical data sequence (low and fixed). |
| Phase II: Optimization | Initial Route Generation (Greedy / Savings) | $O(N^2)$ | $N$ is the number of customers. |
| Phase II: Optimization | Memetic Algorithm (MA) Iteration | $O(G \cdot P \cdot N^2)$ | $G$: max generations, $P$: population size, $N$: customer count. Dominated by neighborhood search. |
| Phase II: Optimization | Dynamic Update (Local Search) | $O(V \cdot N \cdot L)$ | $V$: number of vehicles, $L$: max insertion points (typically $\approx N$). |

TABLE 23. Empirical evaluation of computational scalability: average solution time of proposed MA across different network sizes.

| Customer Count ($N$) | Fleet Size ($V$) | Average Time (s) | Performance Trend |
|---|---|---|---|
| 30 (Current Study) | 6 | 4.76 | Baseline performance |
| 100 (Medium Scale) | 15 | 25.3 | Near-linear initial scaling |
| 200 (Large Scale) | 30 | 95.1 | Polynomial scaling ($O(N^2)$) observed |

the request into existing routes. This localized alteration has a constrained complexity of $O(V \cdot N^2)$, guaranteeing sensitivity within strict operational time windows (typically $< 1$ second).

#### 3) EMPIRICAL VALIDATION OF SCALABILITY

To empirically validate scalability, the computational time of the proposed MA was evaluated across varying network sizes, ranging from the baseline case of $N = 30$ customers to a large-scale scenario with $N = 200$ customers. The consequences are summarized in Table 23.

Even nevertheless computational complexity progresses with network size, an execution time of 95.1 seconds for $N = 200$ remains acceptable for strategic planning in dynamic urban situations, mainly when positioned on parallelized computing platforms. Meaningfully, the real-time update mechanism maintains consistently low response times for individual request insertions, preservation operational feasibility in real-world applications.

## VIII. CONCLUSION AND FUTURE WORK

This study addressed a practical and often underrated challenge in urban logistics: routing delivery vehicles when customer demand can shift at any moment. Same-city delivery lies at the most sensitive stage of the supply chain, where any delay directly affects customer satisfaction. The work showed here responds to several gaps in existing research, mainly the lack of attention to real-time demand changes, the reliance on a single dynamic information approach, and the tendency to load vehicles fully without seeing short-term demand variations. A grey prediction model was recognized to estimate short-term demand across distribution regions, helping prevent unnecessary transportation costs produced by sightlessly applying full-load posting. A dynamic vehicle routing model with soft time windows was then constructed, combining cost minimization and customer satisfaction into a unified impartial. To improved manage fluctuating customer needs, a mixed information-processing method was introduced to respond quickly to urgent or high-priority requests while avoiding needless computational load. A Memetic algorithm was intended to search for robust routing solutions by including adaptive genetic operations with 2-opt and swap-based local optimization. Numerical experiments verified that this combined method demand-based vehicle loading, dynamic routing, and mixed information processing can efficiently reduce delivery costs and recover service excellence. However, it is important to differentiate that the experiments rely on assumed demand patterns, easy travel conditions, and fixed update intervals. These assumptions make analysis wieldy but cannot capture the full complexity of real-world delivery processes.

### A. FUTURE WORK

There remainders significant room for covering this research toward more realistic operating environments:

1) *Integrating dynamic traffic conditions.* This study focused on dynamic demand, but actual delivery operations are similarly pretentious by fluctuating traffic conditions. Congestion, accidents, and weather events can expressively change travel times. Future research could participate dynamic traffic networks and encompass the model to multiple depots and varied vehicle fleets.
2) *Improving regional division using data-driven clustering.* Customer regions were divided based solely on geographic location. A more refined technique could apply clustering techniques that include order patterns, frequency, customer importance, or historical behavior. Combining data-driven region division with routing optimization may produce more efficient and composed delivery plans.

3) *Real-world pilot testing and real-time data integration.* Even though numerical examples determine the model's potential, real-world pilot experiments would reveal practical issues not visible in simulations. Connecting the model to real-time streams such as traffic feeds, IoT devices, weather information, or live customer updates could suggestively enhance its practical value.
4) *Evaluating model sensitivity and robustness.* Several assumptions were required for the design of the numerical examples. Future work should test the model's presentation under extreme conditions, such as sudden demand spikes, unforeseen delays, or long-term shifts in customer behavior. This would help identify which mechanisms of the model are robust and which require further development.

## ACKNOWLEDGMENT

The authors thank all the authors for their research contributions.

## REFERENCES

[1] O. Akmalov and S. Khalid, "The impact of logistics on global economic development: A comprehensive review," *Amer. J. Manage. Econ. Innov.*, vol. 6, no. 2, pp. 40–43, 2024.
[2] M. Alssager, Z. A. Othman, M. Ayob, R. Mohemad, and H. Yuliansyah, "Hybrid cuckoo search for the capacitated vehicle routing problem," *Symmetry*, vol. 12, no. 12, p. 2088, 2020.
[3] G. Calabrò, M. Le Pira, N. Giuffrida, M. Fazio, G. Inturri, and M. Ignaccolo, "A spatial agent-based model of e-commerce last-mile logistics towards a delivery-oriented development," *Transp. Res. Interdiscip. Perspect.*, vol. 21, Sep. 2023, Art. no. 100895.
[4] D. Cattaruzza, N. Absi, D. Feillet, and J. González-Feliu, "Vehicle routing problems for city logistics," *EURO J. Transp. Logistics*, vol. 6, no. 1, pp. 51–79, 2017.
[5] G. B. Dantzig and J. H. Ramser, "The truck dispatching problem," *Manage. Sci.*, vol. 6, no. 1, pp. 80–91, 1959.
[6] R. Eshtehadi, E. Demir, and Y. Huang, "Solving the vehicle routing problem with multi-compartment vehicles for city logistics," *Comput. Oper. Res.*, vol. 115, Mar. 2020, Art. no. 104859.
[7] P. Groß, J. F. Ehmke, and D. C. Mattfeld, "Cost-efficient and reliable city logistics vehicle routing with satellite locations under travel time uncertainty," *Transp. Res. Procedia*, vol. 37, pp. 83–90, Jan. 2019.
[8] R. Gumzej, "Intelligent logistics systems in E-commerce and transportation," *Math. Biosci. Eng*, vol. 20, no. 2, pp. 2348–2363, 2023.
[9] A. Hendalianpour, "Optimal lot-size and price of perishable goods: A novel game-theoretic model using double interval grey numbers," *Comput. Ind. Eng.*, vol. 149, Nov. 2020, Art. no. 106780.
[10] S. Hong et al., "A resilience recovery method for complex traffic network security based on trend forecasting," *Int. J. Intell. Syst.*, vol. 2025, no. 1, 2025, Art. no. 3715086.
[11] H. Labidi, N. B. Azzouna, K. Hassine, and M. S. Gouider, "An improved genetic algorithm for solving the multi-objective vehicle routing problem with environmental considerations," *Procedia Comput. Sci.*, vol. 225, pp. 3866–3875, Dec. 2023.
[12] Y. Li, H. Fan, and X. Zhang, "Periodic optimization model and solution of vehicle routing problem under dynamic demand," *Chin. J. Manage. Sci.*, vol. 10, no. 1, pp. 1–23, 2021.
[13] P. Liu, A. Hendalianpour, M. Feylizadeh, and W. Pedrycz, "Mathematical modeling of vehicle routing problem in omni-channel retailing," *Appl. Soft Comput.*, vol. 131, Dec. 2022, Art. no. 109791.
[14] P. Liu, A. Hendalianpour, and M. Hamzehlou, "Pricing model of two-echelon supply chain for substitutable products based on double-interval grey-numbers," *J. Intell. Fuzzy Syst.*, vol. 40, no. 5, pp. 8939–8961, 2021.
[15] P. Liu, A. Hendalianpour, J. Razmi, and M. S. Sangari, "A solution algorithm for integrated production-inventory-routing of perishable goods with transshipment and uncertain demand," *Complex Intell. Syst.*, vol. 7, no. 3, pp. 1349–1365, 2021.
[16] T. Luo et al., "A two-stage approach for electric vehicle routing problem with time windows and heterogeneous recharging stations," *Tsinghua Sci. Technol.*, vol. 29, no. 5, pp. 1300–1322, 2024.
[17] Z. Ma, C. Jen, and A. Aazami, "Time-dependent vehicle routing optimization incorporating pollution reduction using hybrid gray wolf optimizer and neural networks," *Sustainability*, vol. 17, no. 11, p. 4829, 2025.
[18] A. Makui, M. Heydari, A. Aazami, and E. Dehghani, "Accelerating benders decomposition approach for robust aggregate production planning of products with a very limited expiration date," *Comput. Ind. Eng.*, vol. 100, pp. 34–51, Oct. 2016.
[19] M. Miftah, D. I. Desrianti, N. Septiani, A. Y. Fauzi, and C. Williams, "Big data analytics for smart cities: Optimizing urban traffic management using real-time data processing," *J. Comput. Sci. Technol. Appl.*, vol. 2, no. 1, pp. 14–23, 2025.
[20] B. Niu, W. Li, and W. Yi, "An improved genetic algorithm for vehicle routing problem with time window requirements," in *Proc. Int. Conf. Swarm Intell.*, 2024, pp. 13–25.
[21] B. Qi and G. Li, "The evolution of the cold chain logistics vehicle routing problem: A bibliometric and visualization revie," *Digit. Transp. Saf.*, vol. 3, no. 3, pp. 92–114, 2024.
[22] Y. Qian, W. Feiyue, L. Jiajie, W. Zihuan, and M. A. Bo, "Constrained vehicle routing model for emergency relief supplies based on demand urgency," *J. Tsinghua Univ. Sci. Technol.*, vol. 64, no. 6, pp. 1082–1088, 2024.
[23] A. Ramírez-Villamil, J. R. Montoya-Torres, and A. Jaegler, "Trends and advances in urban logistics research: A systematic literature review," *J. Adv. Transp.*, vol. 2025, no. 1, 2025, Art. no. 8859606.
[24] B. Ran et al., "Architecture design of a vehicle–road-cloud collaborative automated driving system," *Urban Lifeline*, vol. 1, no. 1, p. 9, 2023.
[25] A. Redi et al., "Simulated annealing algorithm for solving the capacitated vehicle routing problem: A case study of pharmaceutical distribution," *Jurnal Sistem dan Manajemen Industri*, vol. 4, no. 1, pp. 41–49, 2020.
[26] N. Rincon-Garcia, B. Waterson, T. J. Cherrett, and F. Salazar-Arrieta, "A metaheuristic for the time-dependent vehicle routing problem considering driving hours regulations—An application in city logistics," *Transp. Res. Part A, Policy Pract.*, vol. 137, pp. 429–446, Jul. 2020.
[27] Y. Su, H. Ghaderi, and H. Dia, "The role of traffic simulation in shaping effective and sustainable innovative urban delivery interventions," *EURO J. Transp. Logist.*, vol. 13, Apr. 2024, Art. no. 100130.
[28] A. Yadav, "An improved location-based genetic algorithm for routing in FANETs," *Int. J. Sci. Res. Comput. Sci. Eng.*, vol. 11, no. 2, pp. 23–30, Apr. 2023.
[29] M. Zarreh, M. Khandan, A. Goli, A. Aazami, and S. Kummer, "Integrating perishables into closed-loop supply chains: A comprehensive review," *Sustainability*, vol. 16, no. 15, p. 6705, 2024.
[30] B. Zhao, Y. Suo, L. Tang, C. Li, M. Fu, and L. Huang, "Urban air mobility for time-sensitive goods with explicit customer preferences: A case study on Chengdu," *J. Air Transp. Manage.*, vol. 118, Jul. 2024, Art. no. 102613.
[31] P. Zhao and L. Zeng, *Transport Efficiency and Safety in China*. Singapore, Singapore: Springer, 2023, doi: 10.1007/978-981-99-1055-7.
[32] C. Zheng, Y. Gu, J. Shen, and M. Du, "Urban logistics delivery route planning based on a single metro line," *IEEE Access*, vol. 9, pp. 50819–50830, 2021.
[33] Y. Zhou, L. Liu, U. Benlic, Z. Li, and Q. Wu, "Solving soft and hard-clustered vehicle routing problems: A bi-population collaborative memetic search approach," *Eur. J. Oper. Res.*, vol. 324, no. 3, pp. 825–838, 2025.
[34] F. E. Zulvia, R. Kuo, and D. Y. Nugroho, "A many-objective gradient evolution algorithm for solving a green vehicle routing problem with time windows and time dependency for perishable products," *J. Clean. Prod.*, vol. 242, Jan. 2020, Art. no. 118428.