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RESEARCH ON OPTIMISATION OF COUNTY-LEVEL URBAN EXPRESS DELIVERY USING A MULTI-STRATEGY IMPROVED GENETIC ALGORITHM

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Abstract

In this paper, a multi-objective vehicle path optimisation model with capacity constraints and time windows is proposed for the logistics and distribution problem of a single distribution center in a county city. The model comprehensively considers the objectives of enterprise cost, distribution efficiency, employee job satisfaction and customer satisfaction, and designs an improved genetic algorithm (IGA) incorporating multi-strategy to solve the problem. The IGA incorporating multi-strategy generates the initial population through an ant colony algorithm and combines the Bernoulli chaotic mapping operator, Gaussian operator and Sigmoid operator to improve the selection, crossover and mutation operations. The method of this paper is validated on the Solomon dataset and the real data of An'yue County, respectively. When compared with the comparison algorithms, the total distance travelled by all vehicles is reduced by a maximum of 63.10% and 34.37%. At the same time, the remaining loading margins of the vehicles were reduced by a maximum of 65.29% and 36.34%, respectively, and the maximum and minimum time difference between the work of the employees (T), was reduced by a maximum of 78.88% and 37.55%, respectively. The research work in this paper provides an efficient and intelligent solution for county urban express delivery and enriches the related field research.

Key Words

County-level express delivery, improved genetic algorithm (IGA), multi-objective optimisation, multi-strategy integration

1. Introduction

With the rapid development of the internet economy and e-commerce business models, express delivery, as an essential component of logistics and distribution, has increasingly garnered attention from enterprises [1]–[3]. In 2024, the volume of China's postal industry's sending business and the postal industry's business revenue were completed at 193 billion pieces and 1.7 trillion yuan, of which, the volume of express delivery business and business revenue were completed at 174.5 billion pieces and 1.4 trillion yuan, respectively. The ongoing expansion of e-commerce continues to drive express delivery demand, posing heightened demands and challenges for urban logistics management [4].

The key to solving urban express delivery problems [5]–[7] lies in reasonably planning the number of vehicles and their routing paths, known as the vehicle routing problem (VRP). However, through extensive on-site investigations and literature reviews, we found that traditional delivery modes have increasingly exposed problems, such as inefficiency, high costs, excessive labour intensity, and unstable service quality, especially when confronted with substantial market demand and complex delivery environments. Therefore, exploring a people-oriented, efficient, and intelligent urban express delivery mode has significant practical value.

Against this background, this paper conducts a comprehensive and in-depth study on the VRP in urban express delivery services. Unlike existing studies focusing on large cities with multiple distribution centers, we focus specifically on county-level cities featuring a single distribution center, highlighting constraints such as vehicle loading capacity and delivery time windows, defined herein as the VRP with capacity constraints and time windows (VRP-CC-TW).

The VRP-CC-TW primarily involves a set of customer points with their respective demands, service durations, time windows, vehicle loading capacities, and designated start and end points. By considering various constraints and optimisation objectives, the goal is to identify an optimal solution that fulfills all customer demands.

Specifically, by considering customer satisfaction, employee well-being, and enterprise distribution costs, we transform the VRP in the express delivery service domain into a multi-objective combinatorial optimisation model with capacity constraints and time windows. The primary

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objectives of this study are to minimise the number of vehicles used in express delivery, maximise vehicle loading rate, and reduce total travel distance, while improving customer satisfaction and employee satisfaction. Higher employee satisfaction correlates positively with enhanced employee well-being. To address this, delivery routes and loading rates for each vehicle must be rationally planned according to individual customer demand and specific time-window requirements, while simultaneously balancing working hours per employee and limiting maximum working durations.

Essentially, the VRP-CC-TW is an operations research optimisation problem characterised by multiple constraints and multiple objectives. Therefore, to effectively solve this problem, it is necessary to coordinate the relationships among various objective functions and identify an optimal solution that satisfies all constraints. Given that the genetic algorithm (GA) [8]–[10] possesses strong global search capability, high robustness, and strong adaptability, it has been widely applied with significant advantages in solving multi-objective VRP in express delivery. However, GA also suffers from weak local search ability and a risk of converging to local optima. Based on these considerations, this study adopts an improved genetic algorithm (IGA) incorporating multiple strategies to solve the multi-objective combinatorial optimisation model with capacity constraints and time windows.

Through on-site investigations and literature review, we found that express delivery in county-level cities still faces the following issues.

1. Due to the unreasonable allocation of customer points, problems such as low delivery efficiency, high operational costs, heavy employee workload, and unstable service quality frequently occur.
2. In actual delivery processes within counties, couriers primarily rely on personal experience for route planning, which makes it difficult to ensure consistency and stability in service. Therefore, this study comprehensively considers enterprise cost, delivery efficiency, employee job satisfaction, and customer satisfaction, and constructs a multi-objective VRP-CC-TW (MO-VRP-CC-TW) model with the goal of minimising the total cost across these objectives. Subsequently, we design a multi-strategy IGA to solve the MO-VRP-CC-TW model. Finally, the proposed method is validated using both Solomon benchmark datasets and real-world data.

The main contributions of this work are as follows.

1. We define an MO-VRP-CC-TW model that comprehensively considers factors such as enterprise cost, delivery efficiency, employee working hours, and customer satisfaction in county-level express delivery. Specifically, enterprise cost is mainly related to the vehicle loading rate and the number of vehicles used; delivery efficiency is associated with the total travel distance of all vehicles; employee job satisfaction depends on the balance of working time among vehicles and the maximum working time; and customer satisfaction is determined by whether the deliveries are completed within the specified time windows.
2. This paper proposes a multi-strategy IGA. First, the initial population of the GA is generated using the ant colony optimisation (ACO) algorithm. Then, the selection, crossover, and mutation operations are respectively enhanced by incorporating the Bernoulli chaotic mapping operator, Gaussian operator, and Sigmoid operator. The IGA significantly enhances both the efficiency and solution quality in solving the MO-VRP-CC-TW problem.
3. This paper validates the proposed method using both the Solomon dataset and express delivery data from An'yue County.

2. Related Work

This paper primarily extends and supplements research on the VRP and provides a comprehensive review of the existing literature. In 1959, Dantzig and Ramser [11] first introduced the basic concept of VRP and applied it to truck dispatching in highway transportation management. In 1962, Clarke and Wright [12] expanded the VRP concept from truck scheduling to more general linear optimisation problems in logistics and transportation. Over the decades, significant progress has been made in the study of multi-objective VRP. Desrochers *et al.* [13] investigated VRPs with time windows and capacity constraints, dividing the problem into a restricted master problem and subproblems, and used column generation to iteratively solve them, achieving reliable solutions even for large-scale instances with up to 100 customers. Wang *et al.* [14] developed a five-objective model for multi-objective VRP in logistics, but did not consider minimising the differences in working hours among employees, which may lead to workload imbalance. Garcia-Najera and Lopez-Jaimes [15] addressed this issue and proposed a six-objective model to consider employee work time equity. VRP with time windows is a widely studied combinatorial optimisation problem in logistics [16]. To better reflect real-world scenarios, researchers such as Amiri *et al.* [17], Iqbals *et al.* [18], and Srivastava *et al.* [19] have explored the problem from the perspective of soft time windows. As research has progressed, studies on VRP have become more diverse and in-depth: Jiang *et al.* [20], Goeke and Schneider [21], Amiri *et al.* [17], and Ren *et al.* [22] explored VRPs from the perspective of different vehicle types; Erdogan and Miller-Hooks [23], Sadati and Çatay [24], and Schneider *et al.* [25] investigated VRPs involving new energy vehicles; Avci and Topaloglu [26] and Li *et al.* [27] focused on VRPs with simultaneous pickup and delivery; while Silva *et al.* [28] and Wu and Jian [29], [30] examined dynamic VRPs. In addition, Pillac *et al.* [31] introduced the concept of dynamic level and proposed improving VRPs by enhancing service quality. Li *et al.* [32], Eydi and Ghasemi-Nezhad [33], and Kovacs *et al.* [34] studied VRPs from the perspective of customer satisfaction. A special form of VRP, the Open VRP, was first proposed by Sariklis and Powell [35], and has since been further investigated by several researchers [36]–[38]. However, most existing studies focus primarily on enterprise cost, or only consider customer satisfaction, or a combination of both,

Table 1
Symbols Explanation

Symbol	Explanation
i, j	Delivery depot.
n	The total number of express delivery stations.
K	The total number of vehicles.
v	The driving speed.
D	Maximum vehicle load capacity
T	The maximum working hours.
T_0	The initial working hours of the vehicle.
d_{ij}	The Euclidean distance from delivery station i to delivery station j.
m_i	The demand at delivery station i.
T_i	The service time at the i-th delivery station.
T_{ki}	The arrival time of the k-th vehicle at delivery station i.
E_i	The earliest expected service start time at delivery station i.
L_i	The latest expected service start time at delivery station i.
C_{ki}	The penalty value for the k-th vehicle serving delivery station i outside the expected service time window.
c_1, c_2	The penalty coefficient.
a_1, a_2, a_3, a_4, a_5	The coefficient of the objective function.
x_{ik}	The service result of the k-th vehicle at delivery station i.
x_{ij}^k	The result of the k-th vehicle traveling from delivery station i to delivery station j.

while largely ignoring employee satisfaction. In practice, excessive working hours or workloads can reduce employee motivation, negatively affecting service quality and, in turn, lowering customer satisfaction with the enterprise. Therefore, in addition to enterprise cost and customer satisfaction, it is essential to incorporate employee satisfaction into the VRP framework to address the real challenges currently facing express delivery systems.

Over the past decades, researchers have proposed a wide variety of algorithms to address different variants of the VRP problem. These algorithms can generally be categorised into two main types: exact algorithms and heuristic algorithms. Exact algorithms are typically represented by methods such as Branch-and-Cut [39] and dynamic programming [40]. For instance, Dellaert *et al.* [41] proposed an improved Branch-and-Cut algorithm to solve VRPs with time windows and capacity constraints. Marco [42] further enhanced the work based on Casazza's model [43]. Similarly, Dumez *et al.* [44] and Senna *et al.* [45] have also made notable contributions to the development of exact algorithms in the VRP domain. Compared with exact algorithms, heuristic algorithms have been widely applied due to their fast solution speed. Common heuristic methods include tabu search [46], GA [47], simulated annealing [48], and neighbourhood search algorithms [49]. Jie *et al.* [50] and Wang and Zhou [51] investigated VRPs with capacity and range limitations for electric vehicles using neighbourhood search strategies. Sadati and Çatay [24], when solving the green VRP, proposed a hybrid method combining neighbourhood search with tabu search. For VRPs with time windows in multi-depot scenarios, researchers such as Cai *et al.* [52], Wu and Gao [53], and Mu *et al.* [54] applied tabu search, ant colony optimisation, and GA, respectively. In recent years, discrete orthogonal moments (DOMs) and their fast computation methods have been widely applied in fields such as intelligent computing, image analysis, and signal modelling [55]–[57]. These developments provide important references for mathematical modelling, environmental feature extraction, and real-time performance optimisation in path planning algorithms. For Krawtchouk, Meixner, and Charlier discrete moments, researchers have proposed fast computation methods based on Clenshaw recurrence formulas, digital filter structures, and image block decomposition, enabling low-latency and high-precision moment feature calculations. These methods significantly reduce computational complexity and accumulated numerical errors, allowing rapid modelling and real-time updates of environmental features or map information in dynamic environments. Consequently, they offer valuable insights for local environment perception and real-time path optimisation in path planning algorithms. Nie [58] proposed a new value iteration-based path planning method called capability iteration network (CIN). CIN utilizes sparse reward maps and encodes the capability of the agent with state-action transition probability, rather than a convolution kernel in previous models. As a representative heuristic algorithm, GA is known for its strong global search capabilities in multi-objective optimisation and is thus widely used to solve VRPs. Researchers such as Liu *et al.* [10], Amiri *et al.* [17], Srivastava *et al.* [19], Pillac *et al.* [31], and Eydi and Ghasemi-Nezhad [32] have made improvements and optimisations to traditional GA approaches, achieving notable results in solving VRP-related problems. Therefore, this paper also adopts GA for solving the VRP, while addressing its inherent weakness in local search capability through targeted improvements and optimisation.

In this study, we employ an IGA that integrates multiple strategies to solve the MO-VRP-CC-TW model. Initially, we construct a multi-objective model that comprehensively considers key factors, such as enterprise costs, delivery efficiency, customer satisfaction, and employee job satisfaction. Subsequently, we enhance the traditional GA from four critical aspects: initial population generation, selection mechanisms, crossover operations, and mutation processes. The IGA is then applied to solve the multi-objective model, enabling the simultaneous optimisation of multiple objectives in a single execution to derive a combined optimal solution. Finally, we conduct experimental validations using both the Solomon dataset and real-world data from An'yue County to evaluate the effectiveness and practicality of the proposed method. The results demonstrate the robustness and applicability of our approach in addressing complex vehicle routing problems under various constraints and objectives.

3. MO-VRP-CC-TW Model

3.1 Problem Description and Assumptions

In a given region, there exists a certain number of express delivery stations, each with specified demand for goods, service time, expected delivery time windows (including the earliest and latest allowable delivery times), and geographical coordinates. The express delivery center supplies the required goods to these stations, and vehicles are responsible for delivering the goods to the customer points. Each vehicle departs from the distribution center, visits the assigned customer points to complete delivery tasks, and finally returns to the center. Under a set of constraints, the objective is to minimise the total delivery cost, maximise efficiency, balance employee working hours, and achieve the highest level of customer satisfaction.

Therefore, the following eight assumptions are established at the beginning of the study.

1. The coordinates of one distribution center and multiple express delivery stations are known in advance.
2. All vehicles must depart from the distribution center and return to it after completing their deliveries, thereby forming a closed loop.
3. Each express delivery station can only be served by one vehicle, and the demand at each station does not exceed the maximum loading capacity of a single vehicle.
4. All vehicle types are the same, have the same load capacity, and travel at a uniform speed.
5. The service time and time window for each delivery station are known and remain unchanged.
6. This study adopts soft time windows, meaning that arriving earlier or later than the expected time window at a delivery station will incur a time penalty.
7. All vehicles have a fixed and identical departure time from the distribution center each day.
8. Unexpected events such as vehicle breakdowns, traffic congestion, road closures, and construction are not considered during the delivery process.

3.2 Symbols and Model Formulation

Based on the problem description and assumptions, the MO-VRP-CC-TW model in this paper can be described as: k vehicles depart from a central depot to serve n delivery points. In the entire model, the distribution center warehouse is represented by 0, the set of nodes representing the delivery stations is denoted as $N = \{1, 2, 3, \cdots, n\}$,and the set of all vehicles is denoted as $K = \{1, 2, 3, \cdots, k\}$. The list of symbols used in this paper is shown in Table 1.

The MO-VRP-CC-TW model in this paper can be specifically represented by the following mathematical formulas:

Decision variables:

$$x_{\mathrm{ik}} = \begin{cases} 1, & \text{node } i \text{ is served by vehicle } k \\ 0, & \text{else} \end{cases} \tag{1}$$

$$x_{\mathrm{ij}}^{k} = \begin{cases} 1, & \text{The } k-th \text{ vehicle travels from node } i \text{ to node } j \\ 0, & \text{else} \end{cases} \tag{2}$$

$$m_i, C_{\mathrm{ki}}, T_i \geq 0. \, (i \in N, k \in K) \tag{3}$$

Objective function:

$$\min F = a_1 z_1 + a_2 z_2 + a_3 z_3 + a_4 z_4 + a_5 z_5 \tag{4}$$

Constraints:

$$z_1 = \sum_{k=1}^{K} \sum_{i=0}^{n} \sum_{j=0}^{n} d_{\mathrm{ij}} x_{\mathrm{ij}}^{k} \tag{5}$$

$$z_2 = \sum_{k}^{K} Z_{\mathrm{kD}} \tag{6}$$

$$z_{\mathrm{kD}} = 1 - \frac{\sum_{i=1}^{n} m_i \sum_{j=0}^{n} x_{\mathrm{ij}}^{k}}{D} * 100\% \tag{7}$$

$$z_3 = \sum_{k=1}^{K} \sum_{j=1}^{n} x_{0j}^{k} \tag{8}$$

$$z_4 = \max\{z_{\mathrm{kt}}\} - \min\{z_{\mathrm{kt}}\} \tag{9}$$

$$z_{\mathrm{kt}} = \frac{z_{\mathrm{kl}}}{v} + \sum_{i=0}^{n} \sum_{j=0}^{n} T_i x_{\mathrm{ij}}^{k} \tag{10}$$

$$z_{\mathrm{kt}} \leq T \tag{11}$$

$$z_{\mathrm{kl}} = \sum_{i=0}^{n}\sum_{j=0}^{n} d_{\mathrm{ij}} x_{\mathrm{ij}}^{k} \tag{12}$$

$$z_5 = \sum_{k=1}^{K}\sum_{i=1}^{n} C_{\mathrm{ki}} \tag{13}$$

$$C_{\mathrm{ki}} = \begin{cases} 0 & E_i \le T_{\mathrm{ki}} \le L_i \\ x_{\mathrm{ik}}\left(E_i - T_{\mathrm{ki}}\right) * c_1 & T_{\mathrm{ki}} \le E_i \\ x_{\mathrm{ik}}\left(T_{\mathrm{ki}} - L_i\right) * c_2 & L_i \le T_{\mathrm{ki}} \end{cases} \quad (i \in N, k \in K) \tag{14}$$

$$\sum_{i=1}^{n} m_i \sum_{j=0}^{n} x_{\mathrm{ij}}^{k} \le D; (k \in K) \tag{15}$$

$$\sum_{j=0}^{n} x_{\mathrm{ij}}^{k} = \sum_{j=0}^{n} x_{\mathrm{ji}}^{k} \le 1; (i \in N, k \in K) \tag{16}$$

$$\sum_{k=1}^{K}\sum_{j=0}^{n} x_{\mathrm{ij}}^{k} = 1; (i \in N) \tag{17}$$

$$\sum_{k=1}^{K}\sum_{i,j\in S} x_{\mathrm{ij}}^{k} \le |S| - 1; (S \subseteq N, 2 \le |S| \le n-1, k \in K) \tag{18}$$

Equations (2)–(3) define the range and value constraints of decision variables. In (4), F represents the fitness function, which is formulated as a weighted sum of five sub-objectives. The coefficients a_1 to a_5 are the objective weights used to balance the relative importance of each optimisation goal. In (6), Z_1 denotes the total travel distance of all vehicles. (7), (8) define Z_2, the total remaining loading capacity of all vehicles, where Z_{kD} represents the remaining capacity ratio of vehicle k. Equation (9) defines Z_3, the total number of vehicles used. Equations (10) and (13) describe Z_4, which reflects employee job satisfaction. Here, Z$_{kt}$ denotes the total working time of vehicle k, including both travel time and customer service time. Each vehicle's working time must not exceed the maximum allowed working time T, ensuring a reasonable employee workload. Z_{kl} denotes the travel distance of vehicle k. Equations (13) and (14) define the time window penalty function C_{ki}, which penalises vehicles that arrive outside the customer's specified time window, including both early and late arrivals. Z_5 represents customer satisfaction and is calculated as the total time window deviation penalties across all service points–the smaller the value, the better the adherence to customer expectations. Equation (16) includes the vehicle capacity constraint D, ensuring that the load delivered by each vehicle does not exceed its maximum capacity. Equations (17)–(18) specify that each delivery station can only be served by one vehicle, and that each vehicle must start and end at the distribution center.

4. Multi-strategy Integrated Genetic Algorithm

The urban express delivery routing optimisation problem is a non-deterministic polynomial (NP) problem. Therefore, considering the characteristics of the model and practical applications, this paper will use a GA with strong robustness and fast solution speed to solve the problem. In the 1970s, John Holland first proposed the GA, whose core concept is to find the optimal solution to a problem by simulating the process of natural selection. In this process, the population represents all possible solutions, and each individual corresponds to a specific solution. In a GA, the initial population, selection, crossover, and mutation operations are critical to the performance of the algorithm. In the urban express delivery routing optimisation process, to avoid the traditional genetic algorithm getting stuck in local optimal solutions during the search process, this paper proposes a multi-strategy IGA. Specifically, this paper first uses the ACO algorithm to generate the initial population for the GA. Then, the Bernoulli chaotic mapping operator, Gaussian operator, and Sigmoid operator are used to optimise the selection, crossover, and mutation operations, respectively.

4.1 Initial Population

The initial population of a GA is usually generated randomly, but this method has difficulty in simultaneously ensuring both the quality and diversity of the population. Therefore, this paper uses the ACO algorithm to create the initial population. ACO simulates the foraging behaviour of ants to perform path optimisation. In this process, ants release pheromones along the paths they traverse, and the concentration of pheromones changes depending on the path length and the number of ants. Shorter or better paths accumulate more pheromones, thereby attracting other ants to select these paths. This selection mechanism further reinforces the pheromone concentration. As a result, ACO can maintain a balance between the diversity and quality of the initial population during the selection process, while also obtaining better and more efficient structures and outcomes.

The probability that the k-th ant moves from its current position i to the next position j at time t in ACO is given by the following (19):

$$p(t) = \begin{cases} \frac{[\tau_{\mathrm{ij}}(t)]^{\alpha}[\eta_{\mathrm{ij}}(t)]^{\beta}}{\sum[\tau_{\mathrm{ij}}(t)]^{\alpha}[\eta_{\mathrm{ij}}(t)]^{\beta}} & j \in A_k \\ 0 & j \notin A_k \end{cases} \tag{19}$$

In (19), $\tau_{ij}(t)$, represents the pheromone level on the feasible path between nodes i and j at time t; $\eta_{ij}(t)$, represents the distance factor at time t; A_k, represents the set of feasible next points for the k-th ant; and α and β represent the weights of the pheromone and distance factors, respectively.

The pheromone concentration at time *t+1* is calculated using the following (20):

$$\tau_{\mathrm{ij}}(t+1) = (1-\rho)\,\tau_{\mathrm{ij}}(t) + \sum\ {}_{k=1}^{m}\Delta\tau_{\mathrm{ij}}^{k}(t, t+1) \tag{20}$$

$$\Delta\tau_{\mathrm{ij}}^{k}(t, t+1) = \begin{cases} \frac{Q}{L_k} & \text{The } k-th \text{ ant} \\ 0 & \text{Others} \end{cases} \tag{21}$$

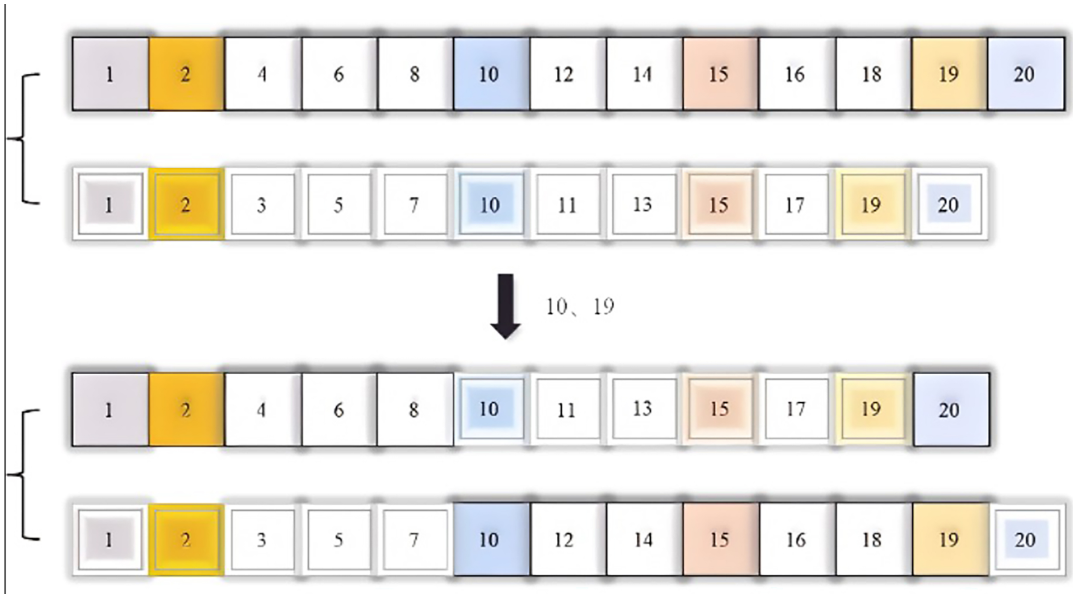

Figure 1. Adaptive crossover operation.

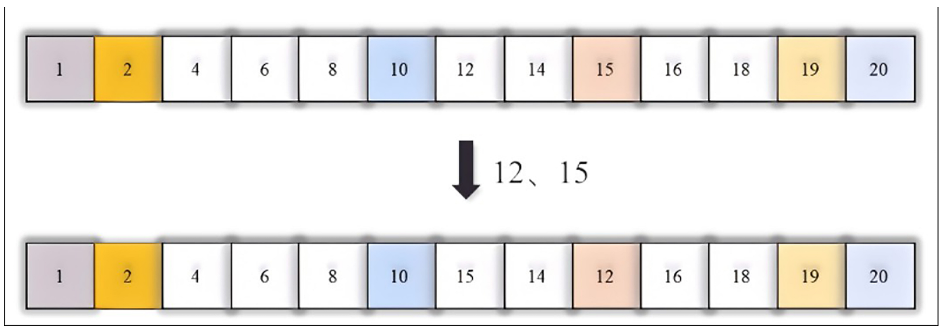

Figure 2. Adaptive mutation operation.

In (20) and (21), $\rho, Q,$ and L_k represent the pheromone evaporation factor, a constant, and the path length of the k-th ant, respectively.

4.2 Encoding and Decoding Scheme of the Initial Solution

In the proposed algorithm, the processes of encoding and decoding play a crucial role. To effectively represent the delivery routes, a natural number encoding method is adopted, where each individual's gene sequence is represented by the nodes along the route. Specifically, the length of the encoded path is n+k-1, where n is the number of customer nodes and k-1 denotes the route separators used to distinguish different vehicle segments. Each encoding instance is mapped to a specific vehicle routing path through permutations of natural numbers.

For example, given the encoded sequence: 0, 3, 1, 5, 0, 2, 4, this encoding represents the routes of two vehicles. The route for vehicle 1 is 0→3→1→5→0, and the route for vehicle 2 is 0→2→4. This encoding effectively represents the transportation paths of multiple vehicles and provides a foundation for subsequent optimisation algorithms.

The decoding process is carried out in the following steps.

1. *Path Division:* The encoded sequence is divided into different path segments based on path separators, identifying the specific routes for each vehicle.
2. *Constraint Check:* Each path segment undergoes verification of constraint conditions. First, the capacity constraint is checked to ensure that the transportation capacity for each vehicle satisfies $\sum m_i \leq$D. Next, the time window constraint is verified to ensure $E_i \leq T_{ki} \leq L_i$.
3. *Path Adjustment:* If a path does not meet the above constraints, the order of the path segments is adjusted, or idle vehicles may be inserted to rearrange the route, thus fulfilling the optimisation requirements of the overall schedule.

Through the above encoding and decoding process, the algorithm in this paper can effectively generate transportation solutions that comply with practical constraints and perform further optimisation to solve the multi-vehicle routing problem.

4.3 Selection Operation

To improve the path optimisation effect of urban express delivery, this paper introduces Bernoulli chaotic mapping into the genetic algorithm, utilising its randomness, ergodicity, and nonlinearity to enhance the selection operator. In the selection process, the effectiveness of the selection operation is strengthened by introducing the Bernoulli chaotic mapping formula, as shown in (22) and (23):

$$B^{(t)} = \begin{cases} \frac{B^{(t-1)}}{1-\eta}, B^{(t)} \in (0, 1-\eta] \\ \frac{B^{(t-1)}-1+\eta}{\eta}, B^{(t)} \in (1-\eta, 1) \end{cases} \tag{22}$$

$$C^{(t)} = \text{int}\left(N \times B^{(t)}\right) + 1 \tag{23}$$

In (22) and (23), η is the control parameter, N represents the number of individuals in the population, $B^{(t)}$ denotes the Bernoulli chaotic mapping random number generated after the t-th iteration, and $C^{(t)}$ refers to the index of the individual in the selection operation, where the int() function is used to round the value. The initial value of the Bernoulli chaotic mapping is a random number uniformly distributed within the range (0,1).

The GA performs the selection operation using a binary random tournament. The specific steps are as follows.

Step 1: Use the Bernoulli chaotic mapping formula to generate two random numbers, select the two individuals corresponding to these indices from the population, and compare their fitness values. The individuals with the higher fitness will be inherited into the next generation population.

Step 2: Repeat Step 1 until N individuals are obtained for the next generation population.

4.4 Adaptive Crossover Operation

In GA, the crossover operation generates new individuals by exchanging parts of the genes between two parent individuals. The selection of crossover probability is crucial for the speed of population evolution. In the early stages, a higher crossover probability can effectively promote the rapid evolution of the population, while in the later stages, a lower crossover probability helps preserve the genes of the best individuals. Therefore, during the evolution process, the crossover probability needs to be dynamically adjusted to achieve adaptive optimisation. In this paper, the fitness of individuals is calculated using (24), and then the Gaussian operator in (25) is used to adaptively adjust the crossover probability in a dynamic manner.

$$\text{pc\_}int = \begin{cases} \text{pc\_}l, f\_m = f\_a \\ \frac{\text{pc\_}h*(f\_m-f)}{f\_m-f\_a}, f \geq f\_a, \text{and}, f\_m \neq f\_a \\ \text{pc\_}h, f < f\_a, \text{and}, f\_m \neq f\_a \end{cases} \tag{24}$$

$$pc = pc\_\text{int} * e^{-\left(\frac{t}{T}\right)^2} \tag{25}$$

In (24) and (25), the minimum and maximum values of crossover probability are denoted as pc_l and pc_h , respectively. The maximum and average fitness values correspond to f_m and f_a, while t and T represent the current generation and the total number of generations, respectively.

The specific crossover operation is shown in Fig. 1. Two parent individuals (*e.g.,* gene sequences in an array) will exchange parts of their sequences according to a certain crossover probability. The process depicted in the figure involves partial gene sequences of two parent individuals (such as 1, 2, 4, 6, 8, 10... and 1, 2, 3, 5, 7, 10...) being swapped to generate new individuals, thus driving the evolution of the population. This process continuously adjusts the crossover probability, updating the population at the right moments to achieve a better search performance.

4.5 Adaptive Mutation Operation

In GA, the mutation operation involves modifying part of an individual's genes, such as deletion, exchange, or mutation, to generate new gene segments and form entirely new individuals. The magnitude of the mutation probability directly influences the diversity of the population. In the early stages of the algorithm, since there is a large individual variation in the population, using a lower mutation probability can accelerate the evolution process. In later stages, as the population's variation gradually decreases, individuals are more likely to fall into local optima. At this point, increasing the mutation probability can enhance the population's diversity and help the algorithm escape from local optima. Therefore, the mutation probability needs to be dynamically and adaptively adjusted according to the evolution process. In this paper, the individual fitness values are calculated using (26), and then the mutation probability is adaptively adjusted using the Sigmoid operator in (27) to meet the demands of different stages.

$$\text{pm\_}int = \begin{cases} \text{pm\_}l, f\_m = f\_a \\ \frac{\text{pm\_}h*(f\_m-f)}{f\_m-f\_a}, f \geq f\_a, \text{and}, f\_m \neq f\_a \\ \text{pm\_}h, f < f\_a, \text{and}, f\_m \neq f\_a \end{cases} \tag{26}$$

$$pm = pm\_\text{int} * \frac{1}{1+e^{-\frac{t}{T}}} \tag{27}$$

In (26) and (27), pm_l and pm_h, represent the minimum and maximum values of the mutation probability, respectively.

The mutation operation randomly selects certain positions in the gene sequences of some individuals to make changes (such as flipping the values of certain genes or swapping positions), which helps to increase the diversity of the population. The process shown in Fig. 2 illustrates the gene exchange between two individuals. For example, the values 12 and 15 in the array are swapped to generate new individuals.

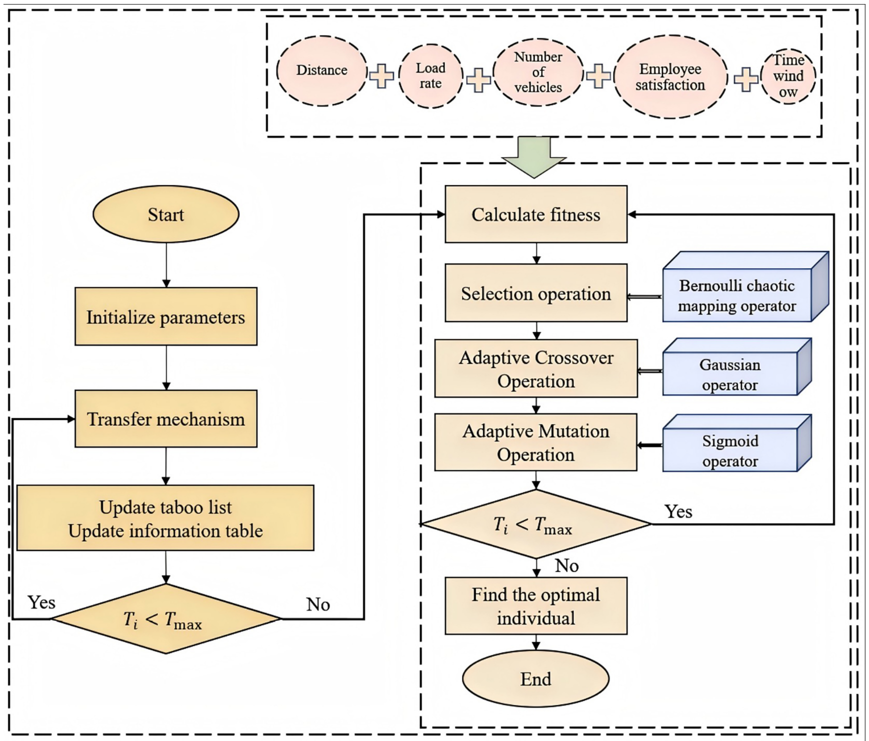

Figure 3. The algorithm flowchart of this paper.

4.6 The Algorithm in This Paper.

In this paper, for the GA, we first use the ACO algorithm to generate the initial population. Then, we incorporate the Bernoulli chaotic mapping operator, Gaussian operator, and Sigmoid operator into the selection, adaptive crossover, and adaptive mutation operations, respectively. Additionally, the fitness of the GA is determined by considering distance, remaining load rate, number of vehicles, employee satisfaction, and time windows (customer satisfaction). The final result is the IGA based on multiple strategies. The algorithm's principle is illustrated in Fig. 3.

5. Experimental Analysis

To verify the effectiveness and practicality of the multi-strategy integrated IGA proposed in this paper in solving MO-VRP-CC-TW, we conducted tests from two aspects: one using the Solomon dataset and the other employing real delivery data from An'yue County's express delivery company.

5.1 Experimental Environment and Parameter Settings

The experiments were conducted using MATLAB R2022a on a Windows 11 system with an i7-12700H processor. The parameter settings in this study were primarily based on references [9], [10], [17]–[19], [31], [32], with optimisation objectives including total travel distance of all vehicles, remaining vehicle load rate, number of vehicles, employee work satisfaction, and customer satisfaction. These parameters were further fine-tuned through multiple optimisation runs based on actual results. The final parameter settings used in this study are shown in Table 2.

Table 2
Parameter Settings

Parameter	Setting
α	1
β	2
ρ	0.5
T	1,000
pc_l	0.7
pc_h	0.9
pm_l	0.1
pm_h	0.3
a_1	0.2
a_2	0.2
a_3	0.1
a_4	0.3
a_5	0.2

5.2 Solomon Dataset Test

In order to verify the superiority of the proposed algorithm in the delivery process, we compared it with

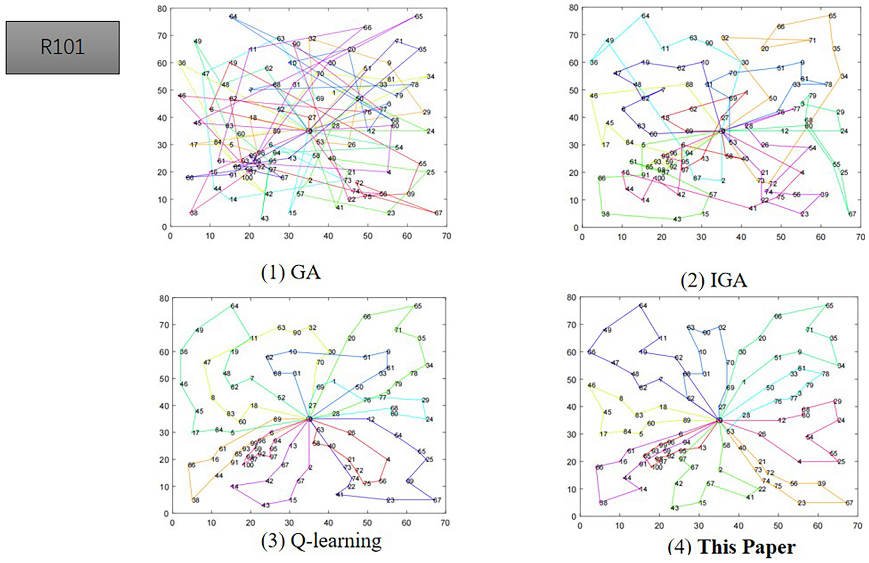

Figure 4. Scheduling diagram of dataset R101; (a) GA; (b) IGA; (c) Q-learning; and (d) This paper.

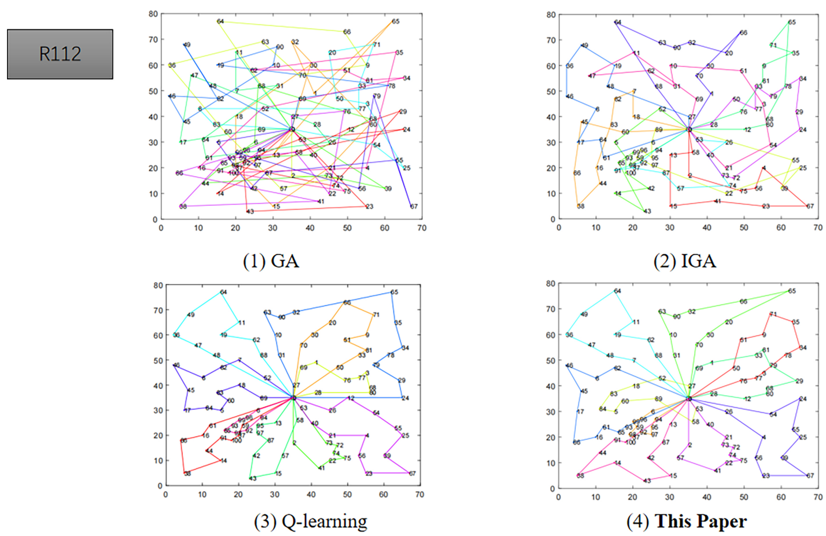

Figure 5. Scheduling diagram of dataset R112; (a) GA; (b) IGA; (c) Q-learning; and (d) This paper.

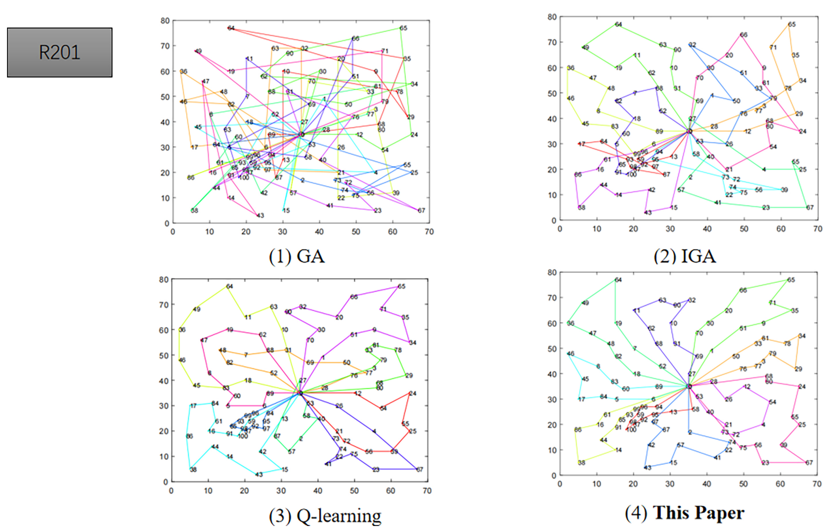

Figure 6. Scheduling diagram of dataset R201; (a) GA; (b) IGA; (c) Q-learning; and (d) This paper.

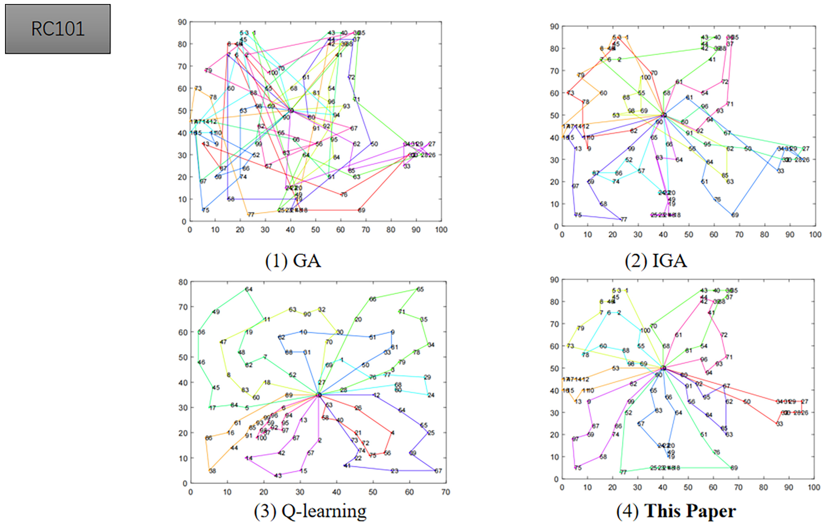

Figure 7. Scheduling diagram of dataset RC101; (a) GA; (b) IGA; (c) Q-learning; and (d) This paper.

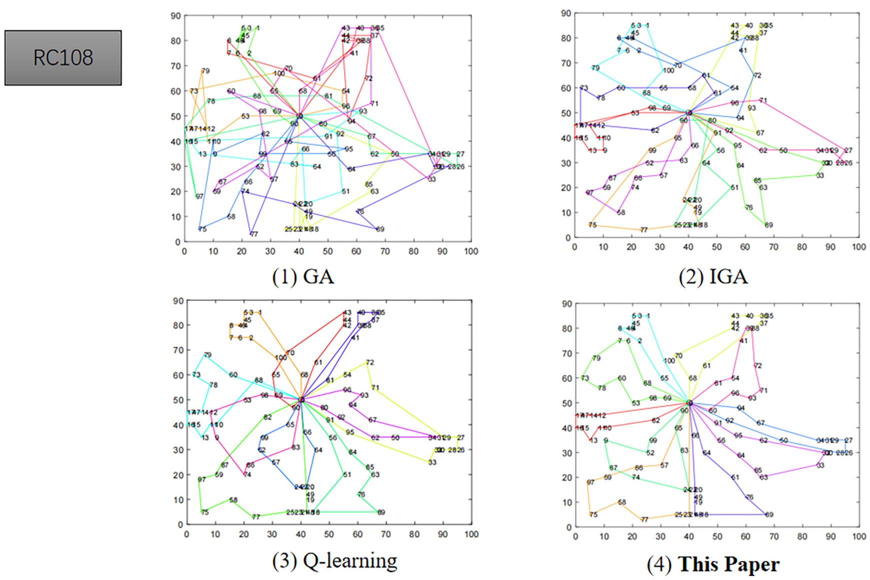

Figure 8. Scheduling diagram of dataset RC108; (a) GA; (b) IGA; (c) Q-learning; and (d) This paper.

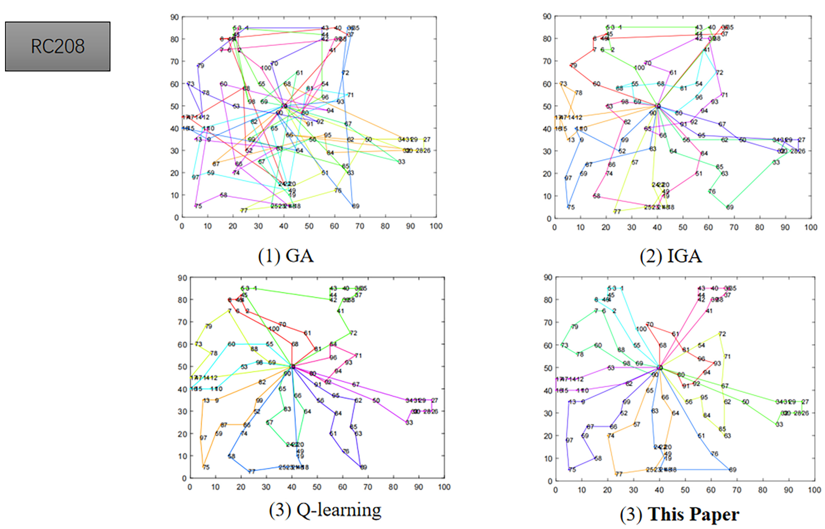

Figure 9. Scheduling diagram of dataset RC208; (a) GA; (b) IGA; (c) Q-learning; and (d) This paper.

Table 3
Comparison and Analysis of Different Algorithms

Different Algorithms Different Datasets	GA	IGA	Q-learning	**This Paper**	
R101	Total distance	2549.695	1374.4271	897.26	**940.7253**
	Total remaining capacity	0.413	0.326	0.271	**0.272**
	Total F value	343.74	323.26	310.63	**307.17**
	Total T difference	30.12	16.2	19.28	**12.63**
	runtime	2.01	3.26	63.79	**2.58**
R112	Total distance	2557.2574	1299.9467	947.9831	**957.5929**
	Total remaining capacity	0.503	0.317	0.22	**0.218**
	Total F value	302.65	286.67	280.66	**283.53**
	Total T difference	30.27	15.54	22.23	**12.83**
	runtime	2.27	3.58	65.57	**2.69**
R201	Total distance	2541.5237	1148.8653	1011.853	**943.0911**
	Total remaining capacity	0.465	0.332	0.253	**0.281**
	Total F value	379.04	367.18	368.23	**365.45**
	Total T difference	17.88	16.22	19.26	**12.12**
	runtime	1.98	3.16	63.52	**2.42**
RC101	Total distance	2696.3694	1430.3173	1154.1785	**1104.5579**
	Total remaining capacity	0.397	0.272	0.21	**0.182**
	Total F value	215.46	176.82	170.41	**166.21**
	Total T difference	40.57	11.42	15.64	**8.57**
	runtime	2.22	3.03	65.53	**2.37**
RC108	Total distance	2054.0456	1339.5683	1149.5261	**1129.6999**
	Total remaining capacity	0.478	0.363	0.248	**0.256**
	Total F value	177.32	155.69	155.16	**152.75**
	Total T difference	37.48	14.62	16.85	**11.55**
	runtime	2.34	2.98	65.57	**2.44**
RC208	Total distance	2597.6872	1398.9098	1112.0232	**1091.8635**
	Total remaining capacity	0.412	0.299	0.23	**0.143**
	Total F value	203.11	208.43	196.84	**189.36**
	Total T difference	24.72	35.12	20.54	**9.95**
	runtime	2.21	3.15	64.96	**2.63**

the GA, IGA [10] and Q-learning Algorithm, and tested them on the Solomon dataset. The Solomon dataset provides information on customer points, demand, time windows, and vehicle capacities of different scales. To avoid randomness and errors in the calculations, we randomly selected 6 datasets for testing, including R101, R112, R201, RC101, RC108, and RC208. The scheduling results are shown in Figs. 4–9.

From the scheduling results shown in Figs. 4–9, we can observe that the paths planned by the proposed method are clearly superior to the results obtained by GA, IGA, and Q-learning, and the assigned tasks are more balanced. By analysing the results in Figs. 4–9, we can obtain the data results shown in Table 3.

Based on the data presented in Table 3, the method proposed in this paper exhibits significant advantages over the GA, IGA, and Q-learning algorithms across multiple key metrics in the R101, R112, R201, RC101, RC108, and RC208 datasets. Specifically, the proposed approach achieves remarkable performance in reducing total vehicle travel distance, minimising residual loading capacity, optimising the objective function value (F), and narrowing the difference in employee working hours (T).

In terms of total vehicle travel distance, the proposed method reduces it by up to 63.10%, thereby substantially enhancing. For residual loading capacity, it achieves a maximum reduction of 65.29%, optimising it to 0.143 and consequently lowering enterprise costs in a significant manner. In the aspect of differences in employee working hour (T), the method achieves a maximum reduction of 78.88%, with the shortest time disparity reduced to 8.57, significantly improving employee satisfaction and happiness. Furthermore, the objective function value (F) is improved by up to 22.85%, validating the superiority and stability of the proposed solution in addressing courier delivery problems.

Although the GA algorithm has certain advantages in runtime, its solution quality is relatively/comparatively inferior. In contrast, the proposed method delivers higher-quality solutions with only a marginal increase in computational time, maintaining high efficiency alongside significantly improved solution quality and stability. This fully demonstrates its practicality and feasibility in real-world applications.

5.3 An'yue County Dataset Testing

In order to further verify the applicability of the algorithm in real scenarios and the reliability of solving practical problems, this study is based on field research, and 50 representative stations of express delivery enterprises in An'yue County are selected to test the actual delivery data. An'yue County is one of the world's five major lemon producing areas and China's only lemon commodity production base county, An'yue County's e-commerce market has a high degree of activity and growth potential, which provides rich application scenarios and data support for courier delivery business. In 2023, the e-commerce transaction volume in Anyue County reached 14.7 billion yuan, Online retail sales amounted to 3 billion yuan.Among these, the online retail sales of agricultural products reached 1.9 billion yuan. In An'yue County, the daily average volume of completed express deliveries reaches 100,000 shipment, while approximately 30,000 shipments are collected daily.

The delivery area selected for this case study (fig. 5) covers multiple regions with high courier demand, including main roads in urban areas, surrounding residential areas, schools, and supermarkets. The road network structure in this region is relatively well-developed, featuring clear distribution of primary and secondary roads, providing a certain level of traffic capacity. However, peak hours during the morning and evening often experienced local road congestion, potentially leading to delivery delays and path uncertainties. Delivery tasks are mainly concentrated between 7:30 a.m. and 12:30 p.m., imposing higher

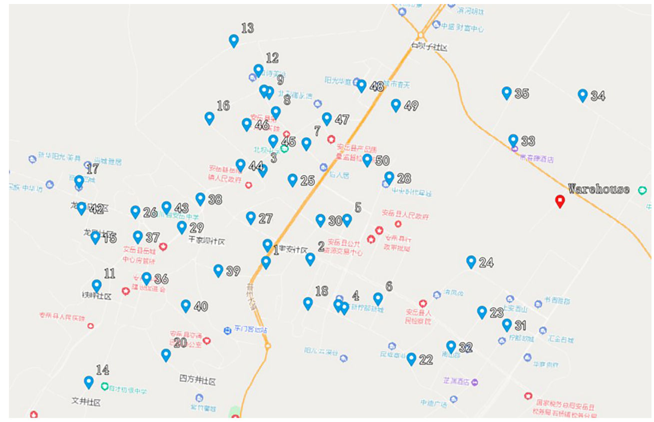

Figure 10. An'yue county express delivery stations.

requirements on the timeliness and accessibility of path planning. The fleet consists of standard light-duty trucks with uniform loading capacity. To improve operational efficiency and rout accuracy, some vehicles are equipped with electronic navigation and mobile terminals, enabling route tracking and on-site information feedback.

Guided by a people-oriented approach, this case study pays particular attention to the workload and time equity of delivery personnel. Given the characteristics of county-level express delivery–namely, "many points, small volumes, and strong time sensitivity"–unreasonable task allocation can easily lead to excessive workload for certain employees, negatively affecting service quality and employee satisfaction. Therefore, in optimising route planning, it is necessary not only to meet basic constraints such as delivery time windows and vehicle capacity but also to balance the number of delivery tasks and working hours assigned to each employee through the model. This ensures a more equitable and reasonable workload distribution, thereby achieving a multi-dimensional optimisation of enterprise efficiency, customer experience, and employee well-being. The distribution of delivery stations is shown in Fig. 8, and the corresponding data are provided in Table 4. Deliveries begin at 7:30 a.m. each day and must be completed by 12:30 p.m.

We compared the proposed algorithm, GA, IGA, and Q-learning using the An'yue County dataset, and the scheduling results are shown in Fig. 11.

From the scheduling results in Fig. 11, we can observe that the scheduling outcomes of the proposed method are significantly better than those of the comparison algorithms. By analysing the results in Fig. 11, we can obtain the comparison of the remaining load capacity for each vehicle, as shown in Fig. 12. Additionally, we can derive the data results in Table 5.

From the vehicle load capacity comparison chart in Fig. 12, it can be seen that the proposed method significantly reduces the remaining load capacity of each vehicle, effectively improving the vehicle load rate and thus reducing enterprise costs. Through the data results in Table 5, we can observe that the total travel distance of all vehicles decreased by up to 34.37%, thereby effectively improving the efficiency of courier delivery. The remaining load

Table 4
An'yue County Dataset

NO.	Longitude	Latitude	Service time	Demand	Time Window
0	105.3632055	30.1081326	\	\	\
1	105.3424406	30.10239359	10	85	7:30-10:30
2	105.345631	30.10291643	10	75	9:30-12:30
3	105.3415682	30.10818276	13	85	8:00-12:00
4	105.3484825	30.09997457	11	80	9:30-11:30
5	105.348011	30.10558785	10	85	8:30-11:00
6	105.3508747	30.10077742	15	75	9:30-12:00
7	105.3445163	30.11011808	10	75	9:30-12:30
8	105.3421152	30.11186178	12	80	8:00-11:30
9	105.3415054	30.11305006	10	35	7:00-12:30
10	105.348025	30.10010295	10	40	7:30-10:30
11	105.3302693	30.09982532	13	40	10:30-12:30
12	105.3406154	30.11433603	10	45	8:30-10:30
13	105.3386914	30.11597967	10	35	8:30-10:00
14	105.3301903	30.09344032	10	45	9:30-11:30
15	105.3374156	30.11110263	12	40	7:30-11:30
16	105.3284536	30.10635842	10	40	8:30-10:30
17	105.3457998	30.10002763	14	45	8:30-11:30
18	105.3632055	30.1081326	10	5	8:30-11:30
19	105.3357411	30.09575439	15	10	9:30-12:30
20	105.3411335	30.11311544	10	15	10:00-11:30
21	105.353819	30.09709074	15	5	9:30-11:30
22	105.3586008	30.10056318	10	15	8:30-12:00
23	105.3573547	30.10373284	10	5	10:30-12:30
24	105.3437851	30.10777451	12	15	10:00-12:30
25	105.3326587	30.10479079	10	5	8:30-11:30
26	105.3410403	30.10515438	14	30	9:30-10:30
27	105.3507059	30.10853976	10	35	8:30-12:30
28	105.3361022	30.10409996	10	30	8:00-11:30
29	105.3460905	30.10542266	10	35	7:30-11:30
30	105.360539	30.09990127	10	30	7:30-12:30
31	105.3566229	30.09814943	13	35	10:30-12:30
32	105.3593097	30.11161178	10	30	7:30-12:30
33	105.3638637	30.11481663	10	25	10:30-12:30
34	105.3584131	30.11449417	10	35	8:30-11:00
35	105.3338471	30.10060224	14	85	7:30-12:30
36	105.332985	30.10321708	14	85	8:30-11:30
37	105.3372583	30.10599673	10	82	10:30-12:00
38	105.3390336	30.1015712	10	80	7:30-10:30
39	105.3368875	30.09909541	15	80	8:30-12:30
40	105.3424301	30.10349438	10	85	10:30-12:30
41	105.3299153	30.10291894	13	75	8:00-12:00
42	105.3287796	30.10469926	10	80	9:30-10:30

continued

NO.	Longitude	Latitude	Service time	Demand	Time Window
43	105.334876	30.10525252	11	85	10:00-11:30
44	105.3399426	30.1083745	11	82	7:30-12:30
45	105.3421202	30.11008055	10	82	10:30-11:30
46	105.3401185	30.11095486	11	80	10:00-11:30
47	105.3458041	30.11179572	10	45	8:30-10:30
48	105.3480201	30.11403558	13	5	8:30-10:30
49	105.3506362	30.11305457	10	12	9:30-12:30
50	105.34901	30.10948087	11	35	8:30-10:30

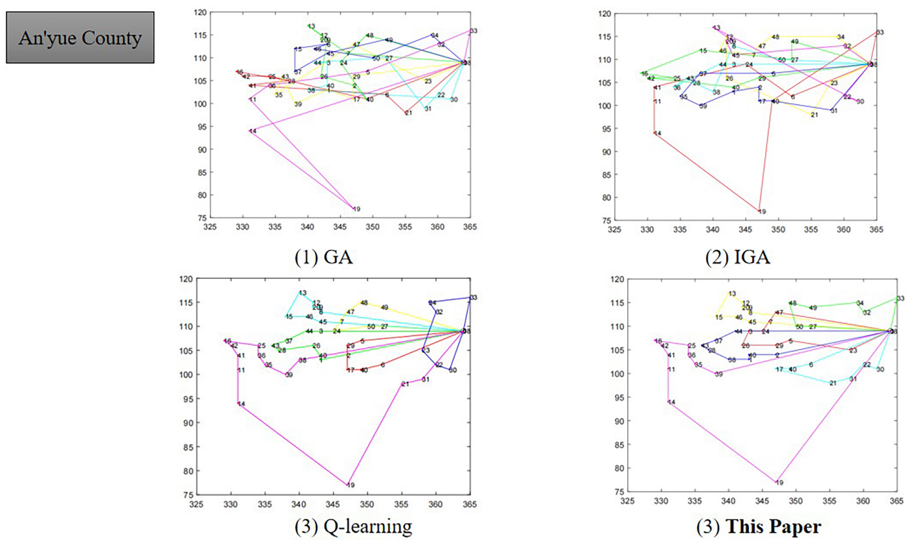

Figure 11. An'yue county scheduling map; (a) GA; (b) IGA; (c) Q-learning; and (d) This paper.

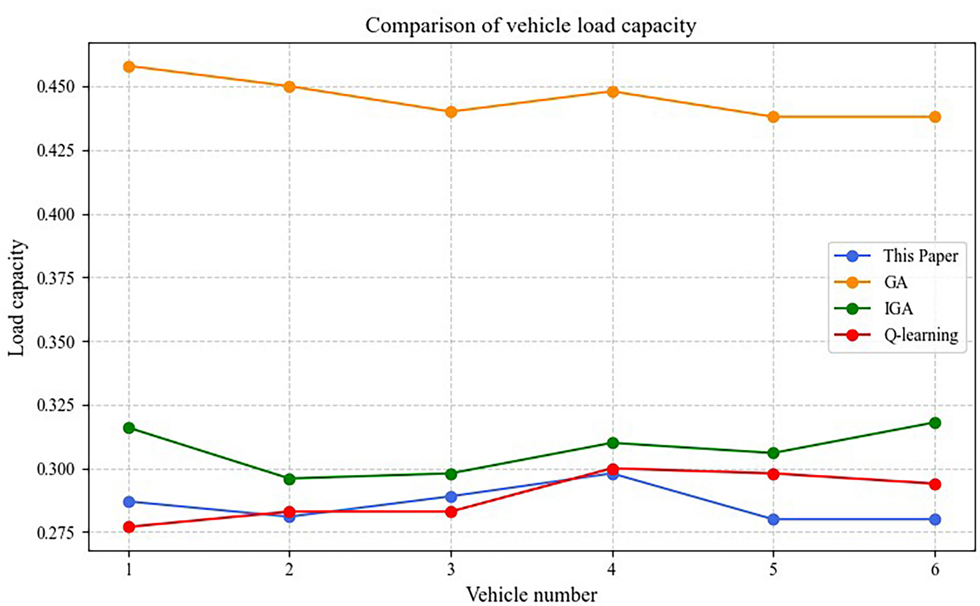

Figure 12. Comparison of vehicle load residuals.

capacity of all vehicles decreased by up to 36.34%, reducing delivery costs and enhancing the company's competitiveness. The maximum and minimum time differences (T) in employees' work hours decreased by up to 37.55%, better balancing their working hours and improving employee satisfaction and well-being. The overall objective function F value increased by 7.63%, which effectively proves that the proposed method has high reliability and versatility

Table 5
Algorithm Data Analysis

An'yue County	GA	IGA	Q-learning	This Paper
Total distance	521.947	492.3683	368.7822	**342.5259**
Total remaining capacity	0.443	0.316	0.277	**0.282**
Total F value	146.67	135.67	136.51	**135.48**
Total T difference	30.04	20.38	20.63	**18.76**

in solving courier delivery problems in county-level cities.

6. Summary

This study focuses on the VRP in county-level urban express delivery. To address existing issues in traditional delivery practices–such as low efficiency, high costs, heavy employee workloads, and unstable service quality–a MO-VRP-CC-TW model is proposed. The model comprehensively considers multiple objectives, including enterprise cost, delivery efficiency, employee job satisfaction, and customer satisfaction. A multi-strategy IGA is designed to solve this model. Through experiments on both the Solomon benchmark dataset and real-world data from An'yue County, the proposed method demonstrates significant advantages in multi-objective optimisation, path planning, and practical applicability. The results show that the proposed multi-strategy IGA effectively reduces total travel distance, improves vehicle loading rates, mitigates imbalances in employee working hours, and significantly enhances customer and employee satisfaction. Moreover, the IGA outperforms traditional genetic algorithms and other comparative methods in terms of optimisation speed and global search capability, demonstrating strong robustness and adaptability. In particular, tests in real-world scenarios reveal the high practical value of the proposed method in reducing enterprise operational costs, improving delivery efficiency, and enhancing employee well-being. The proposed model assumes a static distribution environment, without considering the influence of dynamic factors such as real-time traffic conditions, road congestion, or unexpected events. Meanwhile, in modelling employee satisfaction, the focus is primarily placed on the balance of working hours, while other multidimensional factors – such as workload intensity, task complexity, and mental fatigue – have not yet been fully incorporated. Future research could further extend the model to adapt to dynamic environments and integrate human-centered value criteria. Finally, although the experimental validation covers both standard benchmark datasets and real-world case studies, the testing scale remains relatively limited. For large-scale node networks, multiple distribution centers, or multi-objective and multi-constraint scenarios, the scalability and real-time computational efficiency of the algorithm still require further enhancement. In future work, we will incorporate employee fatigue considerations by setting reminders for maximum continuous working hours, thereby further improving job satisfaction and happiness. Additionally, we will introduce advanced multi-objective metaheuristic algorithms such as NSGA-II and MOEA/D for comparative analysis to comprehensively verify the superiority of our method in multi-objective optimisation. We also plan to integrate big data, dynamic traffic information, and unexpected events to enhance the algorithm's real-time performance and adaptability.

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