



# Low-Carbon Oriented Routing Optimisation in Logistics Distribution Systems with Road Congestion Considerations

Xiao GUO<sup>1</sup>, Fuya YUAN<sup>2</sup>, Yuhan FU<sup>3</sup>

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<sup>1</sup> guoxiao@bwu.edu.cn, School of Logistics, Beijing Wuzi University, Beijing, China

<sup>2</sup> Corresponding author, yuanfy@cqupt.edu.cn, School of Modern Posts, Chongqing University of Posts and Telecommunications, Chongqing, China

<sup>3</sup> fyh0717@163.com, School of Logistics, Beijing Wuzi University, Beijing, China



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## ABSTRACT

In the context of global decarbonisation initiatives, the logistics sector faces dual challenges: its substantial energy consumption and carbon footprint conflict with societal goals for a low-carbon economy, while escalating pressures from urban traffic congestion also inflate distribution costs. The environmental externalities and economic losses induced by the combination of inefficient routing and congestion have jointly motivated the emerging research field of low-carbon vehicle routing optimisation. To reconcile these issues, this study develops a bi-level programming framework for low-carbon-oriented vehicle routing optimisation that explicitly accounts for road congestion. The upper-level model aims to minimise the total cost (including vehicle fixed cost, transportation cost, carbon emission cost and time-window penalty) by internalising a carbon tax constraint. The lower-level model employs a user equilibrium (UE) model, focusing on minimising travel time from the perspective of road users. A hybrid solution methodology (GA-Tent & Frank-Wolfe) is proposed, integrating an enhanced genetic algorithm with Tent chaos mapping for global optimisation and a modified Frank-Wolfe algorithm for traffic assignment. Finally, a case study using the Sioux Falls network demonstrates that traffic congestion increases carbon emissions, but a moderate carbon tax increase can effectively reduce vehicle carbon emissions. These insights suggest policymakers should implement progressive carbon pricing mechanisms coupled with dynamic congestion pricing, while logistics operators should prioritise route optimisation systems with real-time traffic adaptation capabilities.

## KEYWORDS

vehicle routing optimisation; low-carbon; road congestion; logistics distribution.

## 1. INTRODUCTION

With the deepening of the global carbon emission reduction framework under the Paris Agreement, the logistics and transportation industry, as the third largest source of global carbon emissions [1], is facing increasingly stringent emission control pressures. The latest data from the International Energy Agency (IEA) reveal that the transportation sector accounts for 24% of global energy-related carbon emissions, with road freight contributing 8% of this sector's total [2]. Alarming, without robust intervention measures, logistics-related emissions are projected to surge by 22% by 2050 [3]. Against this backdrop, unlocking the deep decarbonisation potential within the logistics sector, especially urban freight, has become a critical lever for achieving global climate goals.

An in-depth analysis of emission sources identifies inefficient route planning as a major cause of high carbon emissions from freight vehicles: a substantial 21% to 25% of emissions originate from unnecessary vehicle miles travelled [4–5]. Compounding this challenge is the reality of urban logistics: traffic congestion. It can be argued that the impact of traffic congestion on logistics carbon emissions is disastrous. Firstly, congestion forces vehicles into frequent states of idling, low-speed crawling and rapid

acceleration/deceleration, significantly increasing emissions per unit distance. Secondly, congestion directly prolongs vehicle operating time and total energy consumption by drastically increasing the time vehicles spend on roads. Research confirms that emissions per unit time during idling and low-speed driving induced by congestion can be 3.5–4.1 times higher than under normal driving conditions [6–7]. The resulting losses in environmental sustainability and economic efficiency (e.g. fuel waste, time delays, reduced fleet utilisation) stemming from inefficient routes and exacerbated congestion have collectively spurred the rapid development of the emerging research field known as the low-carbon vehicle routing problem (LC-VRP). LC-VRP aims to integrate carbon emission minimisation as a core optimisation objective, alongside or in trade-off with traditional goals such as cost (e.g. distance, time, number of vehicles) and service level (e.g. time windows).

Although the LC-VRP provides a theoretical framework for green logistics by incorporating carbon emission objectives alongside traditional operational metrics, it suffers from significant limitations, including the failure to account for real-time road congestion states and inherent model staticity. To overcome the aforementioned limitations, this paper proposes a bi-level LC-VRP model that integrates a carbon-tax mechanism and congestion feedback. The proposed model aims to minimise the total cost throughout the delivery process, using a user equilibrium model to characterise road users' travel behaviour and derive the shortest travel times across the network under congested conditions. Furthermore, a GA-Tent & Frank-Wolfe hybrid algorithm is designed for an efficient solution. The case study shows that the proposed framework significantly reduces vehicle carbon emissions with only a modest increase in cost, thereby providing a viable tool for policymakers and logistics operators to balance economic and environmental goals. This approach helps lower vehicle emissions and identifies the delivery route with the minimum total cost, including vehicle fixed cost, transportation cost, carbon emission cost and time-window penalty.

The remainder of this paper is organised as follows. Section 2 reviews the relevant literature and summarises the principal contributions. Section 3 formulates the low-carbon freight-delivery problem under road congestion as a bi-level programming model, in which the lower-level problem is represented by a user-equilibrium (UE) assignment to obtain time-dependent travel times. Section 4 presents a hybrid solution method combining an improved genetic algorithm, Tent chaotic mapping and Frank-Wolfe algorithm. Section 5 conducts a numerical experiment using the Sioux Falls network. Section 6 concludes and suggests future research directions.

## 2. LITERATURE REVIEW

Significant advances have been achieved in the LC-VRP field, with research centring on two primary aspects: route modelling with multi-factor integration and enhancement of solution algorithms.

### 2.1 Route modelling

Scholars have included a wide range of factors in route modelling, such as fleet characteristics [8], vehicle capacity [9], multi-product specifications [10], transport weight [11] and travel time [12], among others. Traffic congestion, a key dynamic variable affecting transport efficiency, has long been underestimated. Cui et al. (2025) address high-risk hazardous-material transportation by introducing the concept of time-dependent arc capacity and formulate a vehicle routing model that simultaneously minimises total transportation cost and system-wide risk [13]. Building on this theoretical foundation, scholars have gradually deepened dynamic traffic modelling. For example, Liu et al. (2020) presented a method to compute period-specific speeds, proving that avoiding peak hours and congestion cuts vehicle travel time and distribution costs [14]. Yao et al. (2019) used a traffic condition index to represent real-time urban traffic, showing that considering traffic conditions can reduce carbon emissions by 13–14% [15]. Xiao et al. (2025) focused on environmental costs and developed a vehicle-routing optimisation model that captures how dynamic speed changes on steep road segments affect carbon emissions [16]. Ferreira et al. (2025) developed a vehicle-routing optimisation model for green commodity distribution that allows split deliveries of different products [17].

In low-carbon oriented route optimisation modelling, research has evolved through three major paradigm shifts:

- 1) **Emission quantification.** This paradigm converts carbon emissions into quantifiable objective functions or constraints like carbon caps and carbon taxes. By analysing the drivers of carbon reduction in small-portion meals, Xue & Zou (2025) quantify emissions across the full chain of meal preparation, packaging, delivery and waste management, and formulate optimisation models [18]. Islam et al. (2021) studied hybrid fleet green cluster logistics by combining hydrogen fuel cell and conventional vehicles, using

mathematical modelling and a hybrid particle swarm algorithm [19]. Liu et al. (2025) address a green distribution setting with stochastic demand and a heterogeneous fleet by constructing a dynamic heterogeneous vehicle routing model that internalises carbon emission costs [20]. Kuppusamy et al. (2023) integrated carbon cap-and-trade policies into electric vehicle adoption decisions for fleets [21].

- 2) **Parameter optimisation.** This paradigm dynamically adjusts routing decisions by incorporating vehicle load, speed and road gradient parameters to cut empty mileage and fuel use. Cai et al. (2021) explored low-carbon autonomous vehicle routing via a nonlinear mixed-integer programming model with dynamic speed optimisation, showing notable emission reductions [22]. Chen et al. (2020) established a model for fresh e-commerce VRP with time windows and carbon constraints [23]. Liao et al. (2024) integrate life-cycle assessment with the vehicle routing problem to derive a greenhouse-gas emission estimator, optimising parameter combinations across the entire waste-handling chain [24].
- 3) **Equilibrium decision-making.** Seeking Pareto-optimal solutions between cost and emission reduction for low-carbon supply chain strategies. Kuo et al. (2023) created a bi-objective drone-assisted VRP model solved by NSGA-II, reducing delivery time by 9% and emissions by 23% [25]. Peng et al. (2025) further studied urban time-dependent VRP with drone assistance, proposing a mixed-integer programming model, solved via a variable neighbourhood search-based metaheuristic [26].

## 2.2 Solution algorithm

As a classic NP-hard problem, the vehicle routing problem (VRP) demands advanced algorithms to tackle its computational complexity. With the growing complexity of logistics and information technology, traditional heuristic algorithms like genetic algorithms and ant colony optimisation are becoming inadequate. Recent advances focus on improving algorithmic efficiency and accuracy through innovative hybrid and adaptive methods. Patel (2001) was a pioneer in integrating quantum-inspired population update mechanisms into genetic algorithms to prevent premature convergence and maintain population diversity [27]. Guo et al. (2022) developed a three-dimensional ant colony optimisation algorithm for the multi-compartment VRP, incorporating a three-dimensional pheromone matrix and heuristic rules to manage carbon emission costs [28]. Zhang et al. (2026) construct a multi-objective vehicle routing model with time windows for a heterogeneous fleet operating under seasonal demand fluctuations in the steel-parts distribution sector, and use it to derive fleet-configuration plans tailored to different demand scales [29]. Liu et al. (2025) proposed a branch-price-and-cut algorithm for time-dependent green VRPs, integrating bidirectional labelling and temporal adjustment techniques [30]. Zhu et al. (2024) proposed a joint optimisation method for bus scheduling and seat allocation based on scheduled travel, considering the randomness of travel time, and designed the SAT-MCS-G algorithm for solving it [31].

Hybrid methodologies have proven effective in complex scenarios. Su et al. (2024) introduced a lightweight genetic algorithm combined with variable neighbourhood search for multi-depot VRPs with customer satisfaction constraints [32]. Pham et al. (2025) leveraged the whale optimisation algorithm and Grey Wolf optimiser, incorporating opposition-based learning and mutation techniques to solve the capacitated vehicle routing problem [33]. Wang et al. (2025) designed a two-stage algorithm for time-dependent green VRPs, considering real-time traffic congestion and variable speeds [34]. Hou et al. (2025) formulated a crowdsourcing delivery model using an adaptive constrained multi-objective differential evolution algorithm to minimise travel distance and driver compensation costs [35].

However, existing LC-VRP approaches face limitations in real-world applications. Firstly, most classical LC-VRP models assume static or averaged traffic conditions, underestimating congestion's spatiotemporal dynamics and its impact on emissions. Secondly, traditional frameworks rely on simplified emission calculations, lacking detailed modelling of vehicle emissions under congestion. Furthermore, existing research inadequately integrates dynamic demand changes for low-carbon path optimisation, hindering timely and reliable green logistics decisions. To address these issues, this paper integrates low-carbon economics and traffic congestion effects to optimise logistics routes, balancing enterprise economic and environmental benefits. The paper's contributions are:

- 1) A bi-level programming model incorporating carbon tax constraints and traffic congestion was constructed. The upper-level model minimises total logistics costs by integrating the carbon tax mechanism. The lower-level model uses a user equilibrium (UE) model to simulate route choices of logistics and regular vehicles, capturing travel times under network congestion.
- 2) A hybrid solving strategy combining an improved genetic algorithm (with Tent chaotic mapping) and the Frank-Wolfe algorithm was proposed. Tent chaotic mapping enhances the upper-level genetic algorithm's

global search capability, avoiding local optima. The lower-level traffic assignment is efficiently solved using the Frank-Wolfe algorithm, providing accurate congestion-induced time cost feedback to the upper model.

### 3. MATHEMATICAL MODEL

#### 3.1 Problem description and assumptions

This study focuses on optimising logistics vehicle routing in urban road networks affected by congestion. A fleet of identical-capacity vehicles operates from a distribution centre to serve multiple customers with known demands, locations and time windows. Congestion impacts vehicle speed and travel time. The road network includes both logistics and social vehicles. Logistics vehicles operate with organisation, periodicity and high frequency to complete deliveries efficiently at low cost, while social vehicles have diverse goals. The study uses a bi-level programming model: the upper-level optimises logistics routes, and the lower-level models social vehicle equilibrium. The model assumptions are:

- 1) One distribution centre serves multiple customers, with vehicles departing from and returning to it [29].
- 2) All delivery vehicles are of the same model and have the same carrying capacity [16].
- 3) The distribution centre’s capacity meets total customer demand [20].
- 4) Each customer is served by one vehicle, which can handle multiple points [24, 29].
- 5) Vehicles maintain constant speed [24].

#### 3.2 Mathematical formulations

In order to facilitate the establishment of an optimisation model, *Table 1* first lists some basic symbols used in the model.

##### *Multi-cost factors*

The cost per delivery mission for a vehicle is a fixed cost, determined by the number of deliveries it completes. If a distribution centre has a fleet of  $m$  vehicles, the total fixed cost for the logistics delivery vehicles is denoted as *Equation (1)*.

$$C_1 = \sum_{k=1}^m v_k z_k \tag{1}$$

The delivery vehicles consume fuel continuously during their trips. So, the fuel cost for logistics delivery vehicles can be represented by *Equation (2)*.

$$C_2 = \sum_{i=1}^n \sum_{j=1}^n \sum_{k=1}^m \sigma \delta t_{ij} x_{ij}^k \tag{2}$$

With carbon taxes rising, logistics firms face higher delivery costs and must optimise routes for low-carbon transport to cut emission costs. The carbon emission cost for delivery vehicles during transport is shown in *Equation (3)*.

$$C_3 = \sum_{i=1}^n \sum_{j=1}^n \sum_{k=1}^m c_0 \omega \delta t_{ij} x_{ij}^k \tag{3}$$

During deliveries, vehicles may arrive early or late due to various factors, incurring penalty costs. This is analysed using hybrid time window constraints. The three scenarios are as follows: (i) if the delivery vehicle arrives before time  $t_i^A$ , an early-arrival penalty cost is incurred. (ii) If the delivery vehicle arrives between times  $t_i^A$  and  $t_i^L$ , no penalty cost is incurred. (iii) If the delivery vehicle arrives after  $t_i^L$ , a late-arrival penalty cost is incurred. Moreover, customers’ tolerance levels for early and late arrivals differ. To address this,  $\mu_1$  and  $\mu_2$  are introduced as positive penalty coefficients to adjust the penalties for early and late arrivals of the vehicle, respectively. The mathematical relationships for these penalty costs are detailed in constraint (4).

$$C_4 = \mu_1 \sum_{i=1}^n \max(t_i^A - t_{ik}^e, 0) + \mu_2 \sum_{i=1}^n \max(t_{ik}^e - t_i^L, 0) \tag{4}$$

Table 1 – Subscripts and parameters used in this paper

Notations	Definition
$K$	Set of vehicles, $K = \{1,2,3, \dots, m\}$ , where $m$ represents the number of vehicles owned by the distribution centre.
$N$	Set of road network nodes, $i, j \in N, N = \{0,1,2,3, \dots, n\}$ , where 0 represents the distribution centre, the remaining nodes $\{1,2,3, \dots, n\}$ represent the customers' locations. Here $n$ represents the number of customers.
$R$	Set of all possible paths in the road network, $r \in R$ .
<b>Parameters</b>	
$v_k$	The operating cost of vehicle $k$ .
$t_i^A$	The start service time of customer $i$ .
$t_i^L$	The end service time of customer $i$ .
$t_{ik}^e$	The time at which vehicle $k$ arrives at customer $i$ .
$\sigma$	Price per litre of fuel.
$\delta$	Fuel consumption per unit of time, unit: L/hour.
$t_{ij}$	The actual travel time on the road segment $(i, j)$ considering traffic congestion.
$c_0$	Carbon tax price.
$\omega$	Carbon emissions per litre of fuel consumed.
$\mu_1$	Penalty factor for early arrival of vehicles.
$\mu_2$	Penalty factor for the late arrival of vehicles.
$C_1$	Fixed cost.
$C_2$	Fuel cost.
$C_3$	Cost of carbon emissions.
$C_4$	Time-window penalty cost.
$d_i$	The demand of customers $i$ , unit: ton.
$c_{ij}$	Traffic capacity on road segment $(i, j)$ .
$Q$	The total number of traffic vehicles in the road network.
$q_{ij}^1$	Traffic volume of social vehicles.
$q_{ij}^2$	Traffic volume of logistics delivery vehicles.
$t_0$	Free flow time on the road section.
<b>Variables</b>	
$x_{ij}^k$	$\in \{0,1\}$ , 1 for vehicle $k$ passes through $(i, j)$ , 0 otherwise.
$y_i^k$	$\in \{0,1\}$ , 1 for vehicle $k$ serves customer $i$ , 0 otherwise.
$z_k$	$\in \{0,1\}$ , 1 for use of vehicle $k$ , 0 otherwise.
$\varphi_r$	$\in \{0,1\}$ , 1 for use of path $r$ , 0 otherwise.
$\eta_{ij}^r$	$\in \{0,1\}$ , 1 for path $r$ contains road segment $(i, j)$ , 0 otherwise.

### Bi-level programming model

This study designs a bi-level programming model for low-carbon logistics route optimisation.

#### 1) Upper-level model

The upper-level model of the bi-level programming model is mainly used to solve the optimisation problem of logistics distribution paths, and its research object is logistics distribution vehicles.

$$\min Z = C_1 + C_2 + C_3 + C_4 \tag{5}$$

$$\sum_{i=0}^n \sum_{j=1}^n \sum_{k=1}^m x_{ij}^k \leq m \tag{6}$$

$$\sum_{k=1}^m \sum_{j=1}^n x_{ij}^k = d_i, i \in N \setminus \{0\} \tag{7}$$

$$\sum_{k=1}^m y_i^k = 1, i \in N \setminus \{0\} \tag{8}$$

$$\sum_{i=0}^n \sum_{k=1}^m x_{ij}^k = 1, j \in N \tag{9}$$

$$\sum_{j=0}^n \sum_{k=1}^m x_{ij}^k = 1, i \in N \tag{10}$$

$$\sum_{i=1}^n \sum_{k=1}^m y_i^k = n \tag{11}$$

$$\sum_{j=1}^n \sum_{k=1}^m x_{0j}^k = \sum_{i=1}^n \sum_{k=1}^m x_{i0}^k \tag{12}$$

$$\sum_{i,j \in S} x_{ij}^k \leq |S| - 1, \forall S \subseteq N, 1 < |S| < m, \forall k \tag{13}$$

$$\sum_{k=1}^m y_i^k \geq d_i, i \in N \setminus \{0\} \tag{14}$$

Equation (5) represents the objective function of the upper-level optimisation model, aiming to minimise the total cost, which includes fixed costs ( $C_1$ ), fuel consumption costs ( $C_2$ ), carbon emission costs ( $C_3$ ) and time-window penalty costs ( $C_4$ ). In which  $C_2$  and  $C_3$  include  $t_{ij}$ , as the travel time function for road segment  $(i, j)$ , derived from the lower-level model. Constraint (6) limits the number of delivery vehicles available on the road network to ensure that the total number of vehicles assigned to delivery routes does not exceed the total number of vehicles owned, i.e.  $m$ . Constraint (7) ensures that the total amount of goods delivered to each customer by all vehicles equals the customer’s demand. Constraint (8) ensures that each customer in the network is served by exactly one vehicle to prevent duplicate services and enhance delivery efficiency. Equation (9) guarantees that each customer  $i$  is served by at least one vehicle, while Equation (10) indicates that each vehicle  $k$  must serve at least one customer. Equation (11) ensures that all customers are visited. Constraint (12) is a vehicle flow balance equation for the distribution centre, signifying that all vehicles depart from and return to the distribution centre after completing their tasks. Equation (13) ensures that the routes obtained are continuous without forming subtours; that is, each vehicle’s route is free of closed loops. Here,  $S$  is a true subset of the node set  $N$ , and  $|S|$  denotes the number of nodes in the subset.  $|S|-1$  indicates that a true subset containing  $|S|$  nodes can have at most  $|S|-1$  edges without forming a closed loop. Constraint (14) defines the range of the decision variable  $x_{ij}^k$ , which is a binary variable, taking values of 0 or 1.

2) Lower-level model

The lower-level planning problem adopts the UE equilibrium model, which minimises the total travel time on the road network when road users choose their travel paths. The impedance function adopts the BRP function.

$$\min T = \sum_{r \in R} \int_0^{x_{ij}^k} t_{ij}(\tau) d(\tau) \tag{15}$$

$$\sum_{i=0}^n \sum_{j=0}^n (q_{ij}^1 + q_{ij}^2) = Q \tag{16}$$

$$q_{ij}^1 + q_{ij}^2 \geq 0, i, j \in N \tag{17}$$

$$q_{ij}^1 + q_{ij}^2 = \sum_{r \in R} \varphi_r \eta_{ij}^r, i, j \in N \tag{18}$$

$$t_{ij}(\tau) = t_0 \left[ 1 + \alpha \left( \frac{q_{ij}^1 + q_{ij}^2}{c_{ij}} \right)^\beta \right], i, j \in N \tag{19}$$

Equation (15) in the lower-level model aims to minimise the total travel time across all paths, where  $t_{ij}(\tau)$  represents the travel time on the road segment from node  $i$  to node  $j$  under traffic flow  $\tau$ . Equation (16) is a total traffic constraint ensuring that the sum of social traffic flow  $q_{ij}^1$  and logistics traffic flow  $q_{ij}^2$  across all road segments equals the overall traffic demand  $Q$ . Equation (17) imposes a non-negative flow constraint to ensure that traffic flow on each road segment cannot be negative. Equation (18) represents the traffic allocation constraint, indicating that the traffic flow on each road segment is the sum of the flows of all paths including that segment. Equation (19) is the Bureau of Public Roads (BPR) function, with parameters  $\alpha$  and  $\beta$  used to adjust the shape of the function to better fit actual traffic flow data.

4. SOLUTION ALGORITHM

The bi-level programming model developed in this study is a typical NP-hard problem. For large-scale instances, exact solvers such as CPLEX or GAMS usually fail to deliver optimal solutions within acceptable time limits. Consequently, heuristics and meta-heuristics are preferred. Genetic algorithms (GA), in particular, have been shown to possess several desirable features [36–37]: (i) strong global exploration that mitigates premature convergence; (ii) low dependence on initial solutions; (iii) inherent parallelism that accelerates simultaneous evaluation of multiple individuals; and (iv) high flexibility across complex, non-convex problem domains. Exploiting these strengths, we propose a genetic algorithm enhanced by Tent chaotic mapping and hybridised with the Frank-Wolfe algorithm (GA-Tent & Frank-Wolfe hybrid algorithm) to efficiently solve the bilevel model.

4.1 Improved genetic algorithm

1) Chaos initialisation

To overcome genetic algorithms’ limitations, such as premature convergence and local optima, this study combines chaotic variables with genetic algorithms, enhancing solution quality for the vehicle routing model. Among chaotic sequences, Tent mapping is chosen for its consistency and search efficiency. The study uses Tent mapping to generate chaotic sequences with an initial population size of 100, as expressed in Equation (20).

$$x_{n+1} = \begin{cases} 2x_n, & 0 \leq x_n \leq 0.5, n = 1, 2, \dots \\ 2(1 - x_n), & 0.5 < x_n \leq 1, n = 1, 2, \dots \end{cases} \tag{20}$$

2) Fitness function

To assess gene chromosome adaptability in genetic algorithms, a fitness function proportional to the total delivery cost is designed, favouring lower-cost paths:

$$fit(i) = \frac{1}{C(i)} = \frac{1}{C_1(i) + C_2(i) + C_3(i) + C_4(i)} \tag{21}$$

where  $fit(i)$  represents the fitness function value of the corresponding chromosome  $i$ , and  $C(i)$  represents the objective function value from a low-carbon perspective.

### 3) Selection probability

Solutions with higher fitness values have a greater chance of entering the next iteration, and their probabilities are computed using Equation (22).

$$P_i = \frac{fit(i)}{\sum_{i=1}^n fit(i)} \quad (22)$$

### 4) Genetic operator

The utilisation rate of individuals with crossed chromosomes is determined by the crossover probability  $P_c$ . This article selects adaptive crossover probability to overcome the situation of high or low utilisation rate as much as possible. Its specific expression is:

$$P_c = \begin{cases} \frac{2}{\pi} \times \arccos\left(\frac{d}{D}\right) \times P_c^{max}, & P_c > P_c^{min} \\ P_c^{min}, & P_c \leq P_c^{min} \end{cases} \quad (23)$$

where  $P_c^{min}=0.2$  and  $P_c^{max}=1.0$ , and  $d$  is the current iteration number during the genetic operation, and  $D$  is the total number of iterations in the genetic operation. This study uses a cyclic crossover method to perform crossover operations, and the specific steps are as follows:

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#### Genetic algorithm: cyclic crossover method

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**Step 1:** Select two chromosomes from the parents for crossover.

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**Step 2:** According to Equation (22), selecting and determining chromosomes for paternal hybridisation, and then marking cycling nodes.

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**Step 3:** Based on the cyclic nodes obtained in Step 1, select the corresponding paternal genes and copy them to the corresponding positions in the offspring genes.

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**Step 4:** According to the cyclic nodes of the other paternal hybrid chromosomes identified in Step 1, copy the remaining nodes to the empty spaces in the offspring.

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**Step 5:** Apply the same method to other offspring.

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Based on the crossover operation, adaptive probability is used to solve mutation probability  $P_b$ , as shown in Equation (24), where  $d$  is the current iteration algebra, and  $D$  is the total number of iterations. The general range of  $P_b$  values is usually between [0.001, 0.01].

$$P_b = 0.005 + 0.005 \times \frac{d}{D} \quad (24)$$

This paper selects a type of mutation before and after flipping as the mutation control operation in the genetic algorithm. The specific operation steps are as follows:

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#### Genetic algorithm: mutation operation

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**Step 1:** Combine the mutation probability formula  $P_b$  to determine the parent individual corresponding to the mutation.

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**Step 2:** Randomly select two nodes with different inversion positions on the chromosomes of the paternal individual determined in Step 1, and perform corresponding inversion control operations on them.

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**Step 3:** Use the flipping control mutation operation in Step 2 to obtain mutated offspring and complete the genetic algorithm mutation operation.

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The termination condition designed in this article is that the number of repeated calculations reaches the set maximum number of iterations.

## 4.2 Frank-Wolfe algorithm

For the lower-level UE equilibrium model, the Frank-Wolfe algorithm is used to solve the road traffic volume and actual travel time in the equilibrium state. According to the Frank-Wolfe algorithm, finding feasible descent directions during iterations can be transformed into finding the shortest path problem. The specific solution process is as follows:

### Frank-Wolfe algorithm:

**Step 1: Initialisation.** Perform an all-or-nothing assignment based on  $t_{ij}^0 = t_{ij}(0), \forall i, j$ , obtain a set of link flows  $x_{ij}^1$ . Set iteration counter  $n=1$ .

**Step 2:** Update the impedance of each circuit segment  $t_{ij}^n = t_{ij}(x_{ij}^n), \forall i, j$ .

**Step 3:** Finding direction for the next iteration. Find the shortest path between road sections based on the updated impedance  $t_{ij}^n, \forall i, j$  of each road section, and again apply the all-or-nothing allocation method to the traffic flow to get the additional flow  $y_{ij}^n$ .

**Step 4:** Determine the optimal iteration step  $\mu$ , that is, find the value  $\mu$  that matches the equation:  $\sum_i \sum_j (y_{ij}^n - x_{ij}^n) t_{ij} [x_{ij}^n - \mu(y_{ij}^n - x_{ij}^n)] = 0, 0 < \mu < 1$ .

**Step 5:** Update the roadway traffic volumes and determine a new iteration starting point:  $x_{ij}^{n+1} = x_{ij}^n + \mu(y_{ij}^n - x_{ij}^n)$ .

**Step 6: Convergence test.** If there exists  $\sqrt{\sum_i \sum_j (x_{ij}^{n+1} - x_{ij}^n)^2} / \sum_i \sum_j x_{ij}^n \leq \varepsilon; \varepsilon$  is a pre-set precision parameter, then  $x_{ij}^{n+1}$  is the required equilibrium solution, stop the algorithm; otherwise make  $n=n+1$ , go to Step 2. The time impedance function on the road section is the BPR function.

## 5. CASE STUDY

### 5.1 Sioux Falls

This study adopts a representative Sioux Falls transportation network (Figure 1) for numerical analysis [38]. The road network consists of 24 nodes, 76 links and 576 OD pairs, with vehicular demand between each OD pair on individual links detailed in Appendix 1. Within this transportation system, Node 10 serves as the freight distribution centre, while 10 demand nodes (Nodes 1, 5, 7, 11, 13, 14, 18, 19, 20 and 22) require service provisions. The model parameters are systematically listed in Table 2. Table 3 summarises the demand quantities, service durations and service time windows for these demand nodes. The distribution centre dispatches transport vehicles with a 10-ton load capacity to serve these demand nodes. Key network characteristics include: distance of the road section, practical link capacity ( $c_{ij}$ ), and zero-flow travel time for each link (provided in Table 4). The BPR (Bureau of Public Roads) function is employed to model traffic flow dynamics, incorporating parameters that account for both fixed and variable travel time components.

Table 2 – Values for each parameter of the model

Parameters	Values	Parameters	Values	Parameters	Values
$v_k$	400 yuan/vehicle	$\delta$	120 L/hour	$\alpha$	0.15
$c_0$	0.5 yuan/kg	$\mu_1$	0.2 yuan/minute	$\beta$	4
$\omega$	2.63 kg/L	$\mu_2$	1 yuan/minute		

Table 3 – Transportation task information

Customer	Demand/ton	Service time/hour	Service time window/hour	Customer	Demand/ton	Service time/hour	Service time window/hour
1	3	0.5	[6:00,8:00]	14	4.5	0.5	[8:00,9:00]
5	4.5	0.5	[9:00,12:00]	18	2.5	1	[9:00,11:00]
7	3	0.5	[8:00,11:00]	19	4	0.75	[9:00,12:00]
11	5.5	1	[6:00,7:00]	20	5	0.5	[9:00,11:00]
13	3	0.75	[6:00,7:00]	22	3	1	[8:00,9:00]

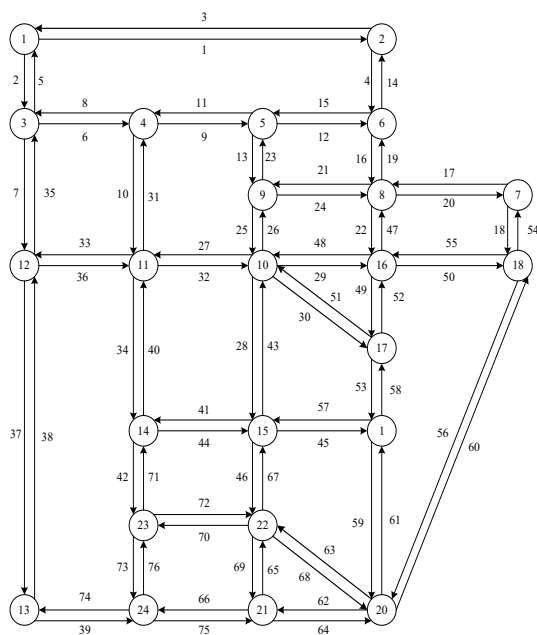


Figure 1 – Sioux Falls network diagram

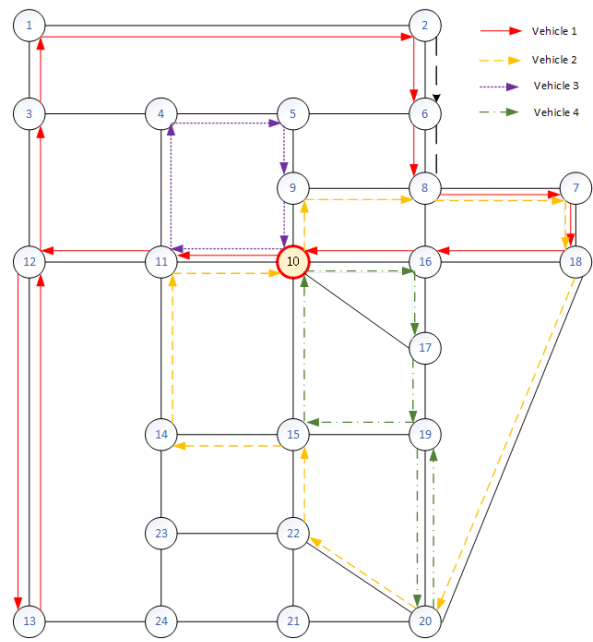


Figure 2 – The path diagram in Case 1

Table 4 – Segment parameters

Section number	Distance (km)	Time (h)	Road capacity	Section number	Distance (km)	Time (h)	Road capacity
1-3	18	0.3	2400	33-36	18	0.3	450
2-5	12	0.2	2400	34-40	12	0.2	450
4-14	15	0.25	450	37-38	9	0.15	2400
6-8	12	0.2	1800	39-74	9	0.15	450
7-35	12	0.2	2400	41-44	12	0.2	450
9-11	6	0.1	1800	45-57	12	0.2	1800
10-31	18	0.3	450	46-67	12	0.2	900
12-15	12	0.2	450	49-52	6	0.1	450
13-23	15	0.25	900	50-55	9	0.15	1800
16-19	6	0.1	450	53-58	6	0.1	450
17-20	9	0.15	450	56-60	18	0.3	2400
18-54	6	0.1	2400	59-61	12	0.2	450
21-24	30	0.5	450	62-64	18	0.3	450
22-47	15	0.25	450	63-68	15	0.25	450
25-26	9	0.15	450	65-69	6	0.1	450
27-32	15	0.25	900	66-75	9	0.15	450
28-43	18	0.3	1200	70-72	12	0.2	450
29-48	15	0.25	450	73-76	6	0.1	450
30-51	24	0.4	450				

### 5.2 Result analysis

#### Traffic condition analysis

This section evaluates three operational scenarios. **Case 1:** Traffic congestion effects are neglected. **Case 2:** Traffic congestion impacts are incorporated based on *Case 1*, while carbon emission costs remain unaccounted for. **Case 3:** Extends *Case 2* by integrating carbon emission costs and traffic congestion dynamics through the developed bi-level optimisation model. For all scenarios, comparative experiments were conducted with the total delivery cost as the optimisation objective.

#### 1) Result of Case 1

Table 5 – Vehicle routing for Case 1

Vehicle number	Distribution nodes passed through	Passing through
1	10→13→1→7→10	27→33→37→38→35→5→1→4→16→20→18→55→48
2	10→18→22→14→10	26→24→20→18→56→63→67→44→40→32
3	10→11→5→10	27→31→9→13→25
4	10→20→19→10	29→49→53→59→61→57→43

The optimal routing configuration for *Case 1* (ignoring traffic congestion) is shown in *Figure 2* and summarised in *Table 5*. In this ideal scenario, the distribution centre deployed 4 vehicles to serve all customers. Delivery vehicles mainly used high-capacity trunk links (e.g. links 27 and 48) connecting hub nodes, reflecting the genetic algorithm’s priority of geometric proximity in non-congested conditions. All paths formed a closed-loop structure returning to node 10, with an average detour ratio of 1.18 (±0.05), indicating path symmetry and the need for minimal detours.

#### 2) Result of Case 2

The optimised routing scheme from the enhanced genetic algorithm is shown in *Figure 3* and detailed in *Table 6*. The distribution centre uses four vehicles to serve all customers. Vehicle 1 takes route 10→1→13→22→10, Vehicle 2 follows 10→11→14→10, Vehicle 3 navigates 10→20→19→10 and Vehicle 4 goes via 10→18→7→5→10. This solution effectively coordinates network utilisation, leveraging key links like 27, 28 and 29. All vehicles return to the depot (Node 10), demonstrating efficient resource allocation within network constraints.

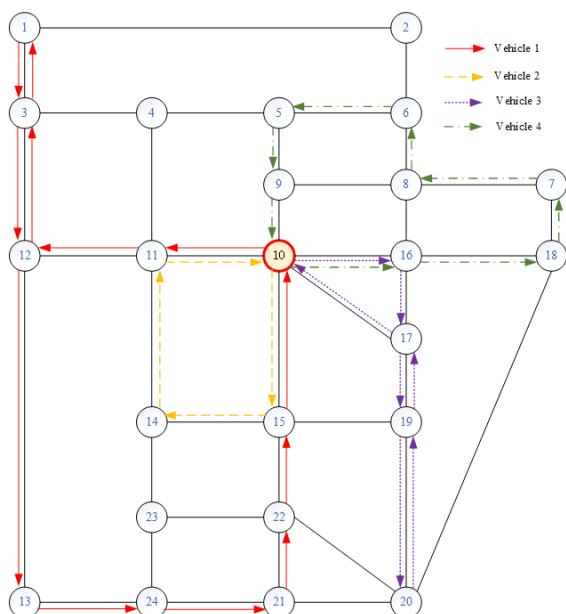


Figure 3 – The path diagram in Case 2

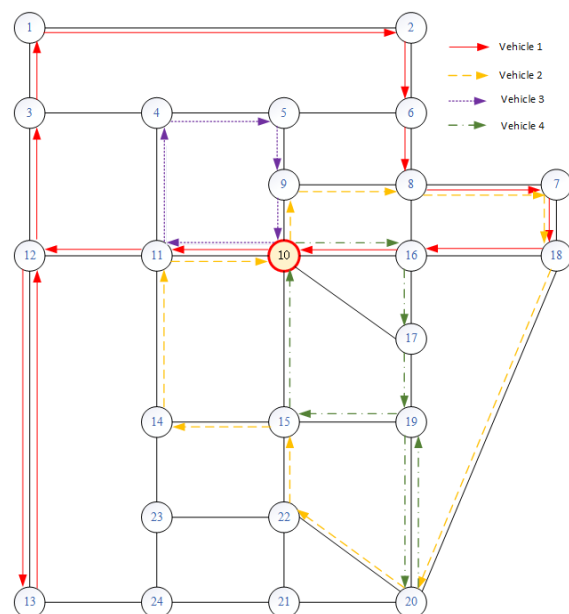


Figure 4 – The path diagram in Case 3

Table 6 – Vehicle routing for Case 2

Vehicle number	Distribution nodes passed through	Passing through
1	10→1→13→22→10	27→33→35→5→2→7→37→39→75→65→67→43
2	10→11→14→10	28→41→40→32
3	10→20→19→10	29→49→53→59→61→58→51
4	10→18→7→5→10	29→50→54→17→19→15→13→25

## 3) Result of Case 3

The congestion-responsive routing scheme, as illustrated in *Figure 4* and detailed in *Table 7*, demonstrates adaptive path selection through an improved genetic algorithm. The distribution centre deploys four vehicles with differentiated routing strategies: Vehicle 1 navigates 10→1→13→22→10 via links 26-23-11-8-5-2-7-39-76-72-67-43, while Vehicle 2 services 10→20→19→10 through critical sections 29-50-56-61-58-52-48. Vehicle 3 operates route 10→14→11→10 utilising links 28-44-40-32, complemented by Vehicle 4's trajectory 10→18→7→5→10 traversing 26-24-20-18-54-17-19-15-13-25. This configuration reveals systematic congestion avoidance patterns, particularly through alternative link utilisation (e.g. links 26/23 replacing 27/33 in *Case 2*) and adjusted node sequencing. The algorithm maintains depot-centric route closure (Node 10) while optimising spatial-temporal resource allocation under dynamic traffic constraints, achieving feasible solutions through prioritised connectivity of secondary arterial links during congestion scenarios.

Table 7 – Vehicle routing for Case 3

Vehicle number	Distribution nodes passed through	Passing through
1	10→13→1→7→10	27→33→37→38→35→5→1→4→16→20→18→55→48
2	10→18→22→14→10	26→24→20→18→56→63→67→44→40→32
3	10→11→5→10	27→31→9→13→25
4	10→20→19→10	48→49→53→59→61→57→43

## 4) Comparative analysis

Table 8 – Total cost composition table

Serial number	Number of vehicles	Total cost	Fuel consumption costs	Cost of carbon emissions
Case 1	4	1793.64	138.15	8.89
Case 2	4	1860.28	154.67	-
Case 3	4	1874.31	163.06	12.23

Table 9 – Distribution costs under different traffic conditions

Travel demand multiplier	Number of vehicles	Total cost	Fuel consumption costs	Cost of carbon emissions
1.1	4	2007.76	220.67	16.57
1.3	4	2149.43	363.55	28.04
1.5	4	2377.85	545.60	47.24

*Table 8* presents the total cost composition for *Cases 1, 2* and *3*. In *Case 1* (no traffic congestion considered), the total cost is 1793.64 yuan, including 138.15 yuan fuel cost and 8.89 yuan carbon emission cost. In *Case 2* (traffic congestion considered but not carbon emission costs), the total cost rises to 1,860.28 yuan, with fuel cost at 154.67 yuan. In *Case 3* (both traffic congestion and carbon emission costs considered), the total cost is 1,874.31 yuan, the fuel cost is 163.06 yuan, and the carbon emission cost is 12.23 yuan. These results show that traffic congestion increases delivery costs and carbon emissions, influencing route choices. Based on *Case*

3, this study investigates the impact of different levels of traffic congestion on delivery costs by setting travel demand multipliers of 1.1, 1.3 and 1.5 times the baseline. The corresponding delivery costs under these varying traffic conditions are detailed in *Table 9*.

Based on the above results, the following inference can be drawn. Without considering any traffic congestion conditions, the total cost is the lowest. With the increase in travel demand and the worsening of urban road congestion, the total cost of logistics distribution is gradually increasing. The worse the road conditions, the greater the carbon emissions. Therefore, good transportation conditions are conducive to energy conservation and emission reduction.

*Carbon emission analysis*

This section analyses how different carbon tax prices affect carbon emissions and costs. Since carbon emission costs are a key part of total costs, changes in carbon tax prices significantly impact the total cost. Within a certain range, higher carbon tax prices lead to lower carbon emissions, achieving a more environmentally friendly effect. The analysis focuses on *Case 3*, which considers both carbon emission costs and traffic congestion. The study sets the carbon tax price from 0.05 yuan/kg to 28 yuan/kg. *Figures 5 and 6* show that as carbon tax prices rise, total and carbon emission costs increase, with higher tax prices leading to faster cost growth. *Figure 6* indicates that increasing the carbon tax from 0.05 to 6 yuan/kg reduces carbon emissions by 30.53%, but further increases to 16 yuan/kg only reduce emissions by an additional 13.09%. Thus, to balance emission reduction and cost efficiency, the carbon tax should be kept below 6 yuan/kg, aiding enterprise cost control and sustainable development.

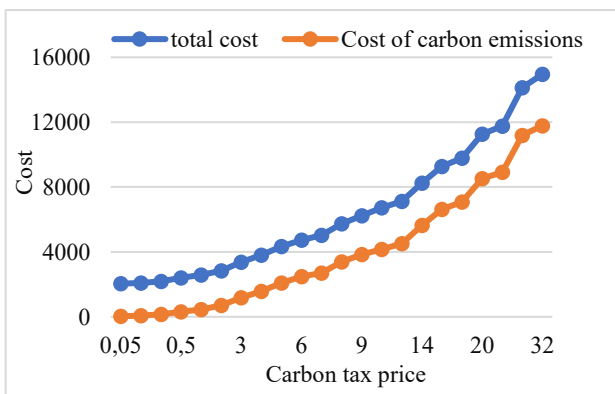


Figure 5 – Trend of total cost and carbon emission cost changes

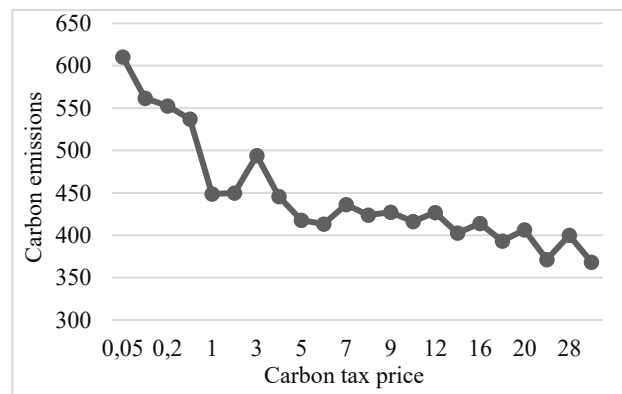


Figure 6 – Carbon emissions

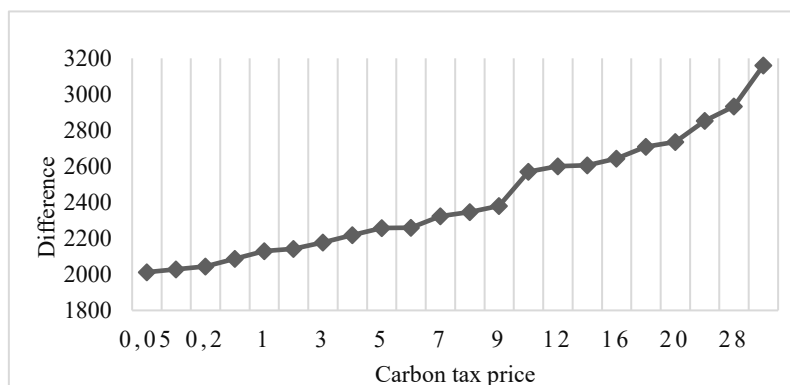


Figure 7 – Difference between total cost and carbon emissions cost

*Figures 5 and 6* show that increasing the carbon tax price leads to higher total and carbon emission costs, but lower carbon emissions. Combined with *Figure 4*, it can be seen that for the OD pair from node 10 to customer point 20, the route 29-50-56 (27 km) is chosen over 29-49-53-59 (24 km) due to lighter traffic, lower fuel and carbon emission costs, and no time penalty costs. This route balances cost-effectiveness and customer satisfaction. However, as the carbon tax rises further, avoiding higher carbon emission costs might cause delivery time violations, reducing customer satisfaction since time penalty costs are lower than increased

carbon emission costs. This highlights the importance of setting a reasonable carbon tax quota to reduce emissions effectively. *Figure 7* shows that as the carbon tax price rises, the difference between total cost and carbon emission cost increases. This indicates that a higher carbon tax price not only directly raises carbon emission costs but also negatively impacts other costs, reducing corporate profits. This underscores the necessity of setting a reasonable carbon tax quota to prevent excessive cost pressures on enterprises.

## 6. CONCLUSIONS

In urban logistics, traffic congestion cuts delivery efficiency and raises carbon emissions. This paper tackles vehicle delivery route optimisation from a low-carbon angle, factoring in road congestion. A bi-level planning model is built. The upper level, based on the traditional vehicle routing model and with a carbon tax mechanism, aims to minimise total costs, such as fixed, fuel, carbon emission and time window penalty costs. The lower level uses a user equilibrium model to depict route choices of logistics and social vehicles, addressing extended travel time from congestion. In algorithm design, an improved genetic algorithm and Frank-Wolfe algorithm integrating Tent chaos perturbation are proposed for the bi-level model. The Sioux Falls network example verifies the model and algorithms. Analysis of Cases 1–3 shows traffic congestion hikes delivery costs and emissions, yet a reasonable carbon tax rise can drive route optimisation, cutting emissions and achieving economic and environmental benefits. This offers key guidance for urban logistics' low-carbon development.

The bi-level planning framework constructed in this study has the potential for further expansion. For instance, it can be extended to more complex scenarios involving multiple distribution centres and heterogeneous customers. Future research directions mainly include: (1) Expanding the model to more complex and realistic scenarios, such as considering multiple distribution centres serving multiple customers simultaneously. (2) Unlike the fixed demand scenario studied in this paper, future research can extend the demand to uncertain or dynamically changing situations to further explore their impact on delivery route optimisation. (3) Considering the diversification of delivery vehicles, including differences in vehicle load capacities, to better accommodate the complex demands in real-world logistics distribution. (4) Although the proposed GA-Tent & Frank-Wolfe hybrid algorithm has achieved satisfactory results, there is still room for improvement in both solution quality and computational efficiency. Moreover, recent studies have shown that self-adaptive genetic algorithms [39], polyploid schemes [40] and hyper-heuristics [41] significantly outperform conventional GAs in areas such as production scheduling and multi-objective optimisation. In this regard, future work will systematically benchmark the current algorithm against these state-of-the-art paradigms and develop problem-specific adaptive operators.

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Appendix 1 – OD's travel demand

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1		9	9	42	17	25	42	68	42	110	42	17	42	25	42	42	34	9	25	25	9	34	25	9
2	9		9	17	9	34	17	34	17	5	17	9	25	9	9	34	17	0	9	9	0	9	0	0
3	9	9		17	9	25	9	17	9	25	25	17	9	9	9	17	9	0	0	0	0	9	9	0
4	42	17	17		42	34	34	59	59	102	127	51	51	42	42	68	42	9	17	25	17	34	42	17
5	17	9	9	42		17	17	42	68	85	42	17	17	9	17	42	17	0	9	9	9	17	9	0
6	25	34	25	34	17		34	68	34	68	34	17	17	9	17	76	42	9	17	25	9	17	9	9
7	42	17	8	34	17	34		85	51	161	42	59	34	17	42	119	85	17	34	42	17	42	17	9
8	68	34	17	59	42	68	85		68	136	68	51	51	34	51	187	119	25	59	76	34	42	25	17
9	42	17	9	59	68	34	51	68		237	119	51	51	51	85	119	76	17	34	51	25	59	42	17
10	110	5	25	102	85	68	161	136	237		0	170	161	178	339	373	331	59	153	212	102	220	153	68
11	42	17	25	119	42	34	42	68	119	339		119	85	136	119	119	85	17	34	51	34	93	110	51
12	17	9	17	51	17	17	59	51	51	170	119		110	59	59	59	51	17	25	42	25	59	59	42
13	42	25	9	52	17	17	34	51	51	161	85	110		51	59	51	42	9	25	51	51	110	68	59
14	25	9	9	42	9	9	17	34	51	178	136	59	51		110	59	59	9	25	42	34	102	93	34
15	42	9	9	42	17	17	42	51	76	339	119	59	59	110		102	127	17	69	93	68	220	85	34
16	42	34	17	68	42	76	119	187	119	373	119	59	51	59	102		237	42	110	136	51	102	42	25
17	34	17	9	42	17	42	25	119	76	331	85	51	42	59	127	237		51	144	144	51	144	51	25
18	9	0	0	9	0	9	59	25	17	59	9	17	9	9	17	42	51		25	34	9	25	9	0
19	25	9	0	17	9	17	76	59	34	153	34	25	25	25	68	110	144	25		102	34	102	25	9
20	25	9	0	25	9	25	34	76	51	212	51	24	51	42	93	136	144	34	102		102	203	59	34
21	9	0	0	17	9	9	42	34	25	102	35	25	51	34	68	51	51	9	34	102		153	59	42
22	34	9	9	34	17	17	34	42	59	220	93	59	110	102	220	102	144	25	102	203	153		178	93
23	25	0	0	42	9	9	17	25	42	153	110	59	68	93	85	42	51	9	25	59	59	178		59
24	9	0	0	17	0	9	9	17	17	65	51	42	68	34	34	25	25	0	9	34	42	93	59	