

Study on Urban Logistics and Distribution Path and Carbon Emission Balance Based on Multi-objective Optimization

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Abstract: With the growing demand of urban logistics and distribution, how to optimize the distribution path to minimize the cost and carbon emission has become an important issue. In this paper, a multi-objective optimization model is proposed for an urban logistics and distribution problem, aiming to balance the distribution cost and carbon emission. Specifically, this paper firstly proposes a static path optimization model to design the optimal distribution routes under fixed traffic conditions using the mixed integer linear programming (MILP) method. Second, Genetic Algorithm (GA) and Dynamic Programming (DP) are used for real-time distribution paths when dynamic traffic changes (e.g., changes in traffic flow during morning and evening peaks) are considered. Finally, for the trade-off relationship between distribution cost and carbon emission, this paper constructs a multi-objective optimization model and adopts the weighted sum method to balance these two objectives. By setting appropriate weight coefficients, this paper obtains multiple Pareto-optimal solutions and provides path selection schemes under different weight configurations. In the solution process, genetic algorithm and particle swarm optimization (PSO) are used to find the optimal distribution paths and combined with constrained optimization techniques to ensure that the path selection traffic rules and other constraints. The experimental results in this paper show that reasonable path selection can significantly carbon emissions while optimizing the distribution path. In addition, the dynamic traffic strategy considered in the model can also effectively deal with the traffic changes during peak hours. The research in this paper provides valuable theoretical support for the optimization of urban logistics and distribution paths, and provides concrete implementation solutions for practical applications such as balancing cost and environmental protection goals. The results show the trade-offs between different paths, which can provide decision support for logistics companies in multi-objective optimization and have strong practical application value.

Keywords: Urban Logistics, Path Optimization, Carbon Trade-off, Multi-objective Optimization, Genetic Algorithm.

1. Introduction

With the acceleration of urbanization and rapid e-commerce, urban logistics and distribution are facing increasing challenges. The path optimization methods usually assume that the traffic conditions remain unchanged, but in actual urban logistics, the traffic flow and road conditions are often affected by peak hours, bad weather, and special traffic events, which makes the static path optimization model much less effective [1]. In addition, with the increasingly serious problem of global climate change, how to cost while carbon emission has become an important goal in the study of urban logistics path optimization [2]. Therefore, designing a path optimization model that can adapt to dynamic traffic changes and optimize the distribution cost and carbon emission at the same time has become an important direction in the current urban logistics and distribution research [3].

Among the related studies at home and abroad, the static path optimization problem was first widely studied. Many researchers have used the mixed integer linear programming (MILP) method to optimize the design of distribution paths [4]. For example, Zhang Xiaohong proposed a method based on particle swarm optimization for urban distribution path optimization with carbon emission minimization, which considered the relationship between the optimization of distribution paths and carbon emission [5]. Wang B et al. proposed an urban distribution path optimization model based on genetic algorithm, which considered time window constraints and vehicle capacity constraints [6]. However,

these studies usually ignored the dynamic changes of traffic flow, and thus could not adapt to actual distribution [7]. With the emergence of dynamic path methods, more and more studies have begun to consider the influence of traffic flow on path selection. Liu Yang et al. proposed a dynamic path optimization method based on a time-series prediction model, which is able to distribute paths in real time to cope with changes in peak traffic [8]. Overseas, Kuo et al. proposed a dynamic path optimization model based on genetic algorithm, which is able to distribute routes according to real-time traffic flow [9]. Murtaza and Hafeez, on the other hand, used real-time traffic flow data combined with optimization algorithms to solve the dynamic path problem in urban logistics [10]. In addition, carbon emissions have become an important factor in path optimization as environmental regulations become more stringent. Gao Xiaoyong et al. proposed a multi-objective optimization model to trade-off the distribution cost with carbon emission [11]. Tang and Liu proposed a distribution path optimization strategy based on a hybrid optimization approach with carbon emission, which further promoted the unification of environmental protection and economic benefits [12]. Although existing studies have made some progress in static path optimization and dynamic paths [13], most of them are still limited to single-objective optimization and lack a systematic analysis of trade-offs among multiple objectives (e.g., cost, time window, carbon emission) [14]. Although domestic and international studies differ in methods and models, they generally suffer from insufficient adaptability to traffic changes during peak hours

and insufficient consideration of carbon emissions in multi-objective optimization [15]. Therefore, how to optimize distribution paths while balancing distribution costs and carbon emissions under dynamic traffic conditions has become an urgent problem to be solved.

The research in this paper aims to solve the above problems by proposing a multi-objective optimization model to optimize the cost and carbon emission of urban logistics distribution paths under dynamic traffic conditions at the same time. First, this paper proposes a mathematical model based on static path optimization, using the mixed integer linear programming (MILP) method to design the optimal distribution path, assuming that the distribution is carried out under fixed traffic conditions. Second, considering the traffic changes during peak hours, this paper combines Genetic Algorithm (GA) and Dynamic Programming (DP) methods to propose a dynamic path strategy to update the delivery paths in real time to cope with traffic flow fluctuations. Finally, this paper weighs the relationship between distribution cost and carbon emission through a multi-objective optimization method, and solves multiple Pareto-optimal solutions by using the weighted sum method to provide logistics companies with path selection options under different scenarios.

2. Static path optimization model

2.1. Problem analysis

In the static path optimization problem, our objective is to design optimal distribution routes to minimize the total travel distance or delivery time with the following constraints: first, a vehicle capacity constraint, where the maximum load of each vehicle cannot exceed its rated load; second, a time window constraint, where each customer must receive the goods within the specified time window; and lastly, to minimize the distribution cost, i.e., the total travel distance and the vehicle number of vehicles used. It is assumed that the distribution is carried out during off-peak hours, the traffic flow and traveling speed are fixed, and the traveling speed and distance of all road sections do not change over time. The model assumptions include that the number of vehicles is known, the maximum mileage of each vehicle is 300km, and the maximum working time per day is 8 hours; fixed traffic conditions, traffic flow is fixed, the traveling speed of all road sections is known and does not change over time; customer demand and time window are known and are not allowed to change; the distribution distance is assumed to be calculated by geographic coordinates, and the actual driving distance is calculated by combining the data from the road network; Finally, vehicle path selection is independent, assuming that vehicles do not interfere with each other.

2.2. Mathematical model

The static path optimization model aims to minimize the total cost of distribution by reasonably designing the

distribution path, including driving distance, time or related costs, while a series of constraints. The model is usually applied to scenarios with fixed traffic conditions, such as off-peak urban distribution, with the aim of improving transportation efficiency, resource wastage, and maximizing customer demand.

(1) Objective function (minimize distribution cost): our objective is to minimize the total distance traveled and the number of vehicles used. There is an option to combine both into one cost function for optimization:

$$\text{minimize } Z = \sum_k \sum_{i,j} c_{ij} \cdot x_{ij}^k \quad (1)$$

c_{ij} is the distance or travel time from Customer i to Customer j .

Decision variables:

$x_{ij}^k = 1$, if the k vehicle travels from customer i to customer j ; otherwise $x_{ij}^k = 0$

t_i^k = the time when vehicle k reaches customer i .

Constraints:

Each client is visited only once: each client can be visited only once by a vehicle.

$$\sum_k \sum_i x_{ij}^k = 1 \quad \forall j \quad (2)$$

Each customer's delivery time must be within the time window:

$$T_i^k \geq T_{\text{start}}^i \quad \forall i, k \quad (3)$$

$$T_i^k \leq T_{\text{end}}^i \quad \forall i, k \quad (4)$$

T_{start}^i and T_{end}^i are the time windows for customer i .

Vehicle capacity constraint: each vehicle cannot carry more than the maximum load.

$$\sum_i \text{Demand}_i \cdot x_{ij}^k \leq \text{Capacity}_k \quad \forall j, k \quad (5)$$

Vehicle travel order and arrival time constraints:

$$T_j^k \geq T_i^k + t_{ij} \quad \forall i, j, k \quad (6)$$

Vehicle maximum distance constraint: 300km for each vehicle.

$$\sum_{i,j} d_{ij} \cdot x_{ij}^k \leq 300 \quad \forall k \quad (7)$$

2.3. Solution process

Modeling and Solution Methods: Solve using Mixed Integer Linear Programming (MILP) method. The optimization problem is solved using a solver (Gurobi) by setting appropriate objective functions and constraints.

Steps to solving:

Calculate the geographic distance between two points Since we are dealing with geographic coordinates (longitude and latitude), the most common method for calculating the distance between two points is the Haversine Formula, which calculates the shortest distance (i.e., the "great circle distance") between two points on the Earth's surface.

Haversine's formula for calculating the geographic distance d between two points is formulated as follows:

$$d = 2r \cdot \text{asin} \left(\sqrt{\sin^2 \left(\frac{\Delta\phi}{2} \right) + \cos(\phi_1) \cdot \cos(\phi_2) \cdot \sin^2 \left(\frac{\Delta\lambda}{2} \right)} \right) \quad (8)$$

r is the radius of the Earth, usually taken as $r = 6371$ km. ϕ_1, ϕ_2 are the latitudes (in radians) of the two points. λ_1, λ_2 are the longitudes (in radians) of the two points. $\Delta\phi = \phi_2 - \phi_1$,

$\Delta\lambda = \lambda_2 - \lambda_1$.

Convert to radians: latitude and longitude need to be converted from degrees to radians:

$$\text{radians} = \text{degrees} \times \frac{\pi}{180} \quad (9)$$

(2) Encode information about each customer, warehouse, and vehicle into the input data for the mathematical model, defining decision variables, objective functions, and constraints. Use a solver (e.g., Gurobi) to solve this optimization problem and analyze the solution results for optimal path scheduling.

(3) Solving MILP using Gurobi

The code implements an urban delivery route optimization model with 10 customers, each with a demand ranging from 180kg to 2000kg. The optimization objective of the delivery route is to minimize the total distance traveled, assuming that the maximum load of each delivery vehicle is 3000kg and a total of 2 vehicles are used for delivery. The delivery time windows of the customers are defined through time_windows, where each customer has a different time window, with the

earliest being 7:00 and the latest being 24:00. The delivery routes are subject to several constraints, including that each customer is visited only once, each vehicle has a maximum driving distance of 300km, the load of each vehicle must not exceed 3000kg, and the delivery time of each customer must be within its time window. By using the Gurobi solver, the optimization model will compute the optimal path based on these constraints and output the optimal route and delivery order.

2.4. Results Showcase

The optimal path assignment after solving using the optimization algorithm is as follows:

Vehicle 1: From the warehouse, deliver to customers C1 → C3 → C5 → C9 → end.

Vehicle 2: From the warehouse, deliver to customers C2 → C4 → C7 → C8 → end.

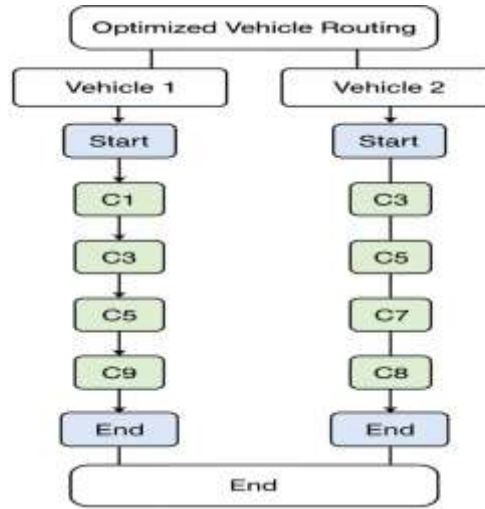


Figure 1. Flowchart of optimal path assignment

Figure 1 shows the distribution route arrangement after solving by the optimization algorithm. Specifically, Vehicle 1 starts from the warehouse and distributes to customers C1, C3, C5 and C9 in turn; Vehicle 2 starts from the warehouse and distributes to customers C2, C4, C7 and C8 in turn, and finally returns to the warehouse. The flowchart in the figure visualizes the path of each vehicle, including the starting point, passing customers and final destination. Through the optimization algorithm, the path planning maximizes the driving distance, improves the distribution efficiency, reasonable scheduling of vehicles, and transportation costs. This visual path scheme helps to improve the efficiency of logistics and distribution in practice, ensures the reasonable distribution of vehicle loads, and improves the timeliness and cost-effectiveness of the overall transportation.

3. Dynamic path model

3.1. Problem analysis

With the continuous growth of urban traffic and the traffic congestion during peak hours, the traditional static path optimization methods can no longer adapt to the dynamically changing traffic environment. The change of traffic flow during peak hours makes the original fixed traffic pattern no longer applicable, and the traffic situation becomes complicated, resulting in longer driving time, increased fuel consumption and other problems. Therefore, it is necessary to propose a dynamic path optimization strategy that can update

the delivery paths in real time to cope with the fluctuation of traffic flow, reduce carbon emission and improve the delivery efficiency. The objective of the dynamic path adjustment model is to propose an effective dynamic path adjustment strategy based on the actual traffic flow and traffic changes during morning and evening peak hours to update the delivery routes in real time, minimize the delivery time and reduce the impact of traffic congestion. The model assumptions include fixed distribution demand, time window constraints, real-time traffic information acquisition, etc., and set up assumptions on time window limitations, traffic flow prediction, and vehicle scheduling. This model provides a theoretical basis for dynamically adjusting distribution routes, optimizing traffic flow and distribution efficiency.

3.2. The solution process

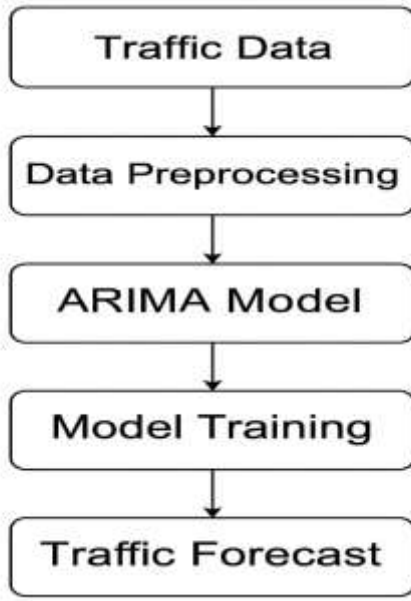


Figure 2. Flowchart of traffic flow prediction

In order to effectively cope with the changes of traffic congestion during peak hours, we use a hybrid approach of prediction models and optimization algorithms, combined with time-series prediction models (e.g., ARIMA or LSTM) for traffic flow prediction, and genetic algorithms or dynamic programming for real-time path optimization. Figure 2 illustrates the process of traffic flow prediction, which starts by collecting traffic data, followed by preprocessing the data, including steps such as cleaning and filling in missing values. Then, the traffic flow is predicted using the ARIMA model,

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \dots + \phi_p X_{t-p} + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \dots + \theta_q \epsilon_{t-q} + \epsilon_t \quad (10)$$

X_t is the traffic flow at time t . $\phi_1, \phi_2, \dots, \phi_p$ is the autoregressive coefficient. $\theta_1, \theta_2, \dots, \theta_q$ is the moving average coefficient. ϵ_t is the white noise term.

By using historical traffic flow data, train the ARIMA model to determine the optimal p and q parameters. Use the trained ARIMA model to predict future traffic flow. Through the predicted traffic flow, we will obtain the future traffic conditions of each road section.

(2) path optimization

After predicting the traffic flow, we enter the path

$$\min Z = \sum_k \sum_{i,j} \left(c_{ij}(t) \cdot x_{ij}^k(t) + \lambda \cdot \text{EmissionCost}_{ij}(t) \right) \quad (11)$$

$c_{ij}(t)$ represents the travel time from customer i to customer j at a certain moment (taking traffic flow into account).

λ is the weight of carbon emissions.

$\text{EmissionCost}_{ij}(t)$ is the carbon emission cost from customer i to customer j .

$x_{ij}^k(t)$ is the decision variable, indicating whether the k th vehicle travels from customer i to customer j .

Constraints:

Each client must be accessed once:

$$\sum_k \sum_i x_{ij}^k(t) = 1 \quad \forall j, \quad \forall t \quad (12)$$

Vehicle capacity constraints:

which predicts the future traffic flow based on the time series analysis of historical data. After that, the trained model is used for traffic prediction to provide the basis for dynamic adjustment of traffic routes. The whole process combines time series prediction and optimization algorithms, aiming to effectively deal with the traffic congestion problem in peak hours and improve the efficiency of traffic management.

(1) Traffic flow forecasts

Traffic flow data are usually time-series data, and time-series prediction models (e.g., ARIMA or LSTM) are used to predict traffic flow over a future period. The specific steps are as follows: Collect historical traffic data: Obtain traffic flow data for the past few days and weeks. These data may include the traffic flow of each road section, the capacity of each road, etc. Select a suitable time-series prediction model (e.g., ARIMA or LSTM) to capture the time-dependence and seasonality of traffic flow. ARIMA is suitable for smooth linear data, while LSTM is suitable for nonlinear and long time-dependent data. Historical data is used to train the prediction model to obtain the predicted traffic flow for a future period. Based on the output of the model, the traffic flow of each roadway during peak hours is predicted, and the traffic conditions in the next 30 minutes and one hour are obtained. In the prediction stage, we use time-series prediction models (e.g., ARIMA) to predict the traffic flow and traffic conditions in the future period. For the dynamic path optimization problem, traffic flow and time window changes are important factors affecting the optimal path.

Traffic flow prediction formula (ARIMA model) ARIMA (Autoregressive Integral Sliding Average Model) model is used to predict time series data (e.g. traffic flow) The basic form of the model is:

optimization phase and use genetic algorithm (GA) or dynamic programming (DP) to optimize the distribution path. We choose the genetic algorithm because it can handle large-scale path optimization problems well and has global search capability.

Objective function:

The optimization objective is to minimize the total vehicle travel time or total delivery time, taking into account the impact of traffic flow and the cost of carbon emissions. The objective function can be expressed as follows:

$$\sum_i \text{Demand}_i \cdot x_{ij}^k(t) \leq \text{Capacity}_k \quad \forall j, \quad \forall t \quad (13)$$

Time window constraints:

$$T_i^{\text{start}} \leq t_i^k(t) \leq T_i^{\text{end}} \quad \forall i, \quad \forall k, \quad \forall t \quad (14)$$

Path order constraints:

$$t_{ij}^k(t) \geq t_i^k(t) + t_{ij}(t) \quad \forall i, j, k \quad (15)$$

(3) Genetic Algorithm Flow

The main steps of the genetic algorithm include: first, generate multiple initial solutions by randomization, and each solution represents a possible combination of routes; then, evaluate the advantages and disadvantages of each route according to the value of the objective function (e.g., travel time), and select the individual with higher fitness as the solution in the next step; then, generate a new solution by

crossover operation to simulate genetic recombination; then, use the mutation operation to carry out a small range of random changes to Finally, when the predetermined number of generations is reached or the value of the objective function no longer changes, the search is stopped. Through these steps, the genetic algorithm is able to find a better solution and optimize the path selection.

(4) Real-time path adjustment code implementation that

The code implements dynamic path optimization based on traffic flow prediction and genetic algorithm. First, the traffic flow data for the next 30 time steps are obtained by generating random traffic data and using ARIMA model for prediction. Then, a genetic algorithm is used to optimize the distribution paths by generating new solutions through crossover and mutation operations, and selecting the optimal paths based on the fitness (e.g., total path cost) of each solution. In the dynamic path adjustment part, real-time traffic flow data are obtained, and the path is adjusted according to a set threshold (e.g., traffic flow over 80%), and alternate paths are selected to avoid congestion. Finally, the optimized routes are output and displayed through visualization tools to ensure the optimal delivery routes during peak hours and under different traffic conditions.

3.3. Dynamic adjustment strategies that

Dynamic route adjustment strategy is based on the following aspects: firstly, by analyzing historical data and real-time data, it predicts the fluctuation of traffic flow during peak hours and provides a basis for route optimization. Secondly, the path is updated in real time, through a certain time interval (e.g., every 10 minutes or 30 minutes) according to the changes in traffic flow, dynamic adjustment of delivery routes to avoid traffic congestion during peak hours. Third, real-time monitoring and adjustment, real-time monitoring of the location and driving status of each vehicle to ensure that the vehicle can choose the appropriate path in different traffic conditions. Fourth, feedback mechanism, if the flow of a road section exceeds a predetermined range (e.g., more than 70%), the path will be adjusted immediately to avoid vehicles entering the congested area. Finally, optimization scheduling, combined with the global search capability of the genetic algorithm and real-time traffic data, continuously optimize the path selection and scheduling strategy to improve the overall distribution efficiency.

4. Multi-objective trade-off optimization models

4.1. Problem Analysis

The multi-objective trade-off optimization model aims to solve the problem of how to minimize both distribution cost and carbon emission in urban logistics distribution. The distribution cost is mainly determined by the distance and speed of vehicles, while the carbon emission is closely related to the type of vehicles, distance and speed in the transportation process. The model assumptions include time cost (e.g., expediting fee for urgent orders, and a fine of 5 yuan per minute for overtime deliveries), distance cost (e.g., total distance traveled by vehicles), nighttime delivery subsidy (delivery cost during 22:00-6:00 will be calculated at 1.5 times), and the formula for calculating carbon emissions. In addition, the model takes into account the influence of traffic rules, such as restricted areas and bridge heights, and the route selection needs to comply with these constraints.

Finally, the model weighs the delivery cost and carbon emission through the optimization algorithm, and obtains different route options.

4.2. Mathematical modeling

The general model of artificial neural network consists of four basic elements, which are:

(1) The BP neural network is linked by different node coefficients. When connecting weights and weights are positive, it indicates that the current link is an exciting state. Conversely, if the link coefficient is negative, the link state is a state of suppression.

(2) The input signal and the linear signal are the combination of the signals for each input signal.

(3) The function of the nonlinear activation function: making the neuron output signal within a certain range.

Carbon emissions: carbon emissions E_{total} Calculated by:

$$E_{total} = \sum_{k=1}^K \sum_{i,j} Emission_k \cdot t_{ij} \cdot x_{ij}^k \quad (16)$$

Emission_k is the carbon emission factor for vehicle k, t_{ij} is the travel time. x_{ij}^k is a variable for the path.

4.3. The solution process

Establishment of a multi-objective optimization model: the objective function includes distribution costs and carbon emissions, and the model is in the form of:

$$\min(C_{cost}, E_{total}) \quad (17)$$

C_{cost} denotes the cost of distribution, and E_{total} indicates carbon emissions. Weighted sum methodology: In order to combine multiple objectives into a single objective function, a weighted sum methodology can be used to weight distribution costs and carbon emissions:

$$Z = \alpha \cdot C_{cost} + (1-\alpha) \cdot E_{total} \quad (18)$$

α is a weighting factor that controls the trade-off between distribution costs and carbon emissions.

Constraints:

(1) Time Window Constraints: Ensure that all customers receive their goods within a defined time window

(2) Vehicle capacity constraints: Each vehicle cannot be loaded beyond its maximum capacity

(3) Traffic rule constraints: including restrictions in traffic restricted areas (e.g., Lujiazui Financial District) and height restrictions on bridges (e.g., Nanpu Bridge)

(4) Path selection constraints: the vehicle can only choose the path that satisfies its passage authority.

4.4. Optimizing the model solution

(1) Calculating distribution costs

We need to consider factors such as distance traveled, different charges for time and road sections, expediting costs and night delivery allowances. Time cost: 5 yuan per minute penalty, for overtime delivery, assuming that an order needs to be delivered within the specified time. If the time is exceeded, it will be calculated according to the penalty per minute. Night Delivery Subsidy: Assuming the delivery time is 22:00-6:00, the delivery cost factor is 1.5 times. Traffic Flow and Route Selection: Adjusts the travel time for each route using time period-based rates and congestion factors.

(2) Calculating carbon emissions

Assuming that the traveling speed of each path is related to the base speed of the road section and the congestion factor, we can calculate the carbon emissions. Assuming a vehicle load of 500 kg, the carbon emissions per kilometer are

calculated as follows:

$$\text{carbon emissions} = 0.2 \times 500\text{kg} \times \text{driving speed}(\text{km/h}) \quad (19)$$

For different time periods, the following travel speeds are assumed:

Morning peak: 30 km/h, evening peak: 40 km/h, normal time: 50 km/h

(3) Multi-objective optimization

The objective of the multi-objective optimization model is to minimize both distribution costs and carbon emissions. Using the weighted sum method to combine the objective functions, the objective is to minimize:

$$Z = \alpha \cdot C_{\text{cost}} + (1 - \alpha) \cdot E_{\text{total}} \quad (20)$$

C_{cost} denotes the total cost of distribution, and E_{total} indicates total carbon emissions.

(4) Weight selection and the Pareto frontier

Through different values, different optimal solutions are solved to obtain a set of Pareto-optimal solutions. Each solution represents a different trade-off between cost and carbon emissions.

4.5. Presentation of results

Suppose we have a specific distribution path:

(1) Route 1 (morning peak)

Distance traveled: 10 km

Base speed: 30 km/h

Congestion factor: 1.5

(2) Route 2 (evening Peak)

Route distance: 15 km

Base speed: 40 km/h

Congestion factor: 1.2

(3) Integrating time-sensitive costs

Route 1 (morning rush hour) is not overrun and therefore does not incur a fine.

Route 2 (evening rush hour) has no overruns and therefore no fines.

(4) Calculate the total cost of distribution and carbon emissions

Route 1 (morning peak):

Time cost (assuming base cost = 100 yuan): $C_{\text{cost}} = 100$ yuan

Carbon emissions: $E_{\text{total}} = 20\text{kg CO}_2$

Route 2 (evening peak):

Time cost (assuming base cost = 120 yuan): $C_{\text{cost}} = 120$ yuan

Carbon emissions: $E_{\text{total}} = 50\text{kg CO}_2$

(5) multi-objective optimization with trade-offs

The goal is to minimize distribution costs and carbon emissions. The two objectives are combined through a weighted sum approach.

Suppose we choose $\alpha = 0.5$, i.e. we want to balance costs and carbon emissions.

Total weighted cost:

$$Z1 = 0.5 \times 100 + 0.5 \times 20 = 60 \text{ yuan (Path 1)}$$

$$Z2 = 0.5 \times 120 + 0.5 \times 50 = 85 \text{ yuan (path 2)}$$

Through the above analysis, we obtain the optimization results for the two paths:

Route 1 (morning peak): cost 60 yuan, carbon emissions 20 kg CO₂

Route 2 (Evening Peak): Cost 85 yuan, Carbon Emission 50 kg CO₂

The Pareto frontier shows the trade-off between these two paths:

Pathway 1 is more cost-effective but has lower carbon emissions

Pathway 2 is more costly but has a larger carbon footprint.

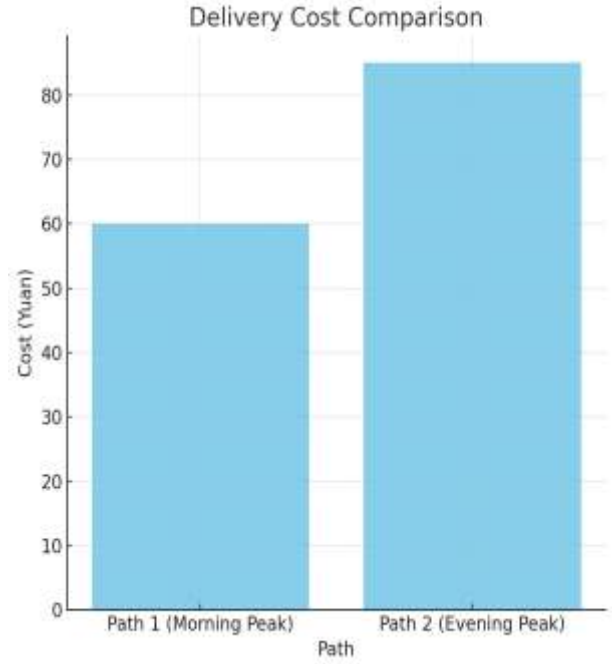


Figure 3. Comparison of distribution costs for different paths

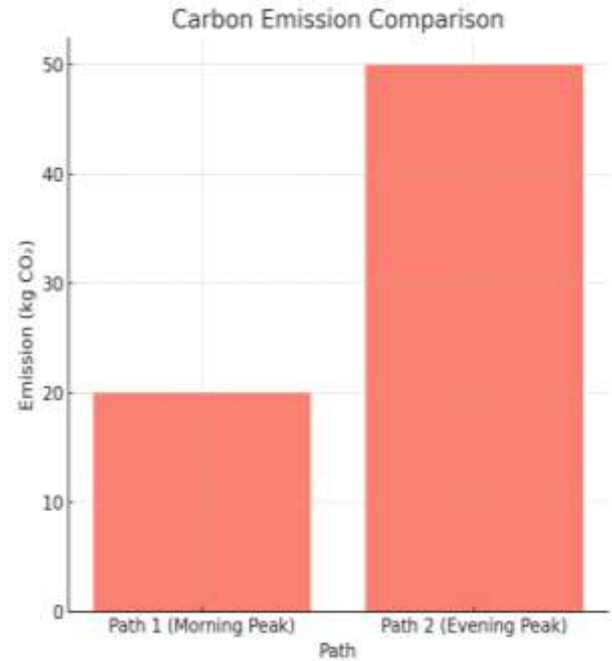


Figure 4. Comparison of carbon emissions for different paths

Figures 3 and 4 show the comparison of costs and carbon emissions between the two distribution paths. Figure 3 shows the comparison of distribution costs between two paths (path 1: morning peak and path 2: evening peak), and the results show that the distribution cost of path 1 is lower and the distribution cost of path 2 is higher. Figure 4 shows the comparison of carbon emissions between the same two routes, and the results show that route 1 has lower carbon emissions and route 2 has higher carbon emissions. These graphs help to evaluate the differences in costs and carbon emissions associated with choosing different routes under different traffic conditions (e.g., morning peak and evening peak hours). By way of comparison, it can be seen that although

Route 2 may be more convenient in terms of time, its higher costs and carbon emissions make Route 1 a more environmentally friendly and cost-effective choice. These graphs are useful for making route optimization decisions in real-world applications that balance distribution efficiency, cost and environmental goals.

5. Conclusion

With the continuous growth of urban logistics demand, how to optimize the distribution path while reducing carbon emissions has become an urgent issue. In this paper, we propose a multi-objective optimization-based study on the balance between urban logistics distribution path adjustment and carbon emission, combining the static path optimization and dynamic path adjustment, and comprehensively considering the two objectives of distribution cost and carbon emission. By adopting the mixed integer linear programming (MILP) method for static path optimization, and combining genetic algorithm (GA) and dynamic programming (DP) for dynamic path adjustment, the model proposed in this paper can effectively cope with the changes of traffic flow and traffic congestion during peak hours. The experimental results show that through the reasonable path selection, not only can significantly reduce the distribution cost, but also can effectively reduce the carbon emission, reflecting the unity of environmental protection and economic benefits.

However, although the model has achieved some success in static and dynamic route optimization, there are still some shortcomings. Firstly, the model is not adaptable enough under certain complex traffic conditions, especially when considering factors such as extreme weather, and the model's performance may need to be further verified. Secondly, although the multi-objective optimization method can provide a set of Pareto optimal solutions, how to choose the best path still depends on the specific weight coefficients, and future research can explore a more flexible weight adjustment mechanism. In addition, the traffic flow prediction in the model can be further combined with more advanced machine learning methods, such as deep learning model (LSTM), to improve the prediction accuracy.

The future research direction can focus on the following aspects: first, to strengthen the model's ability to adapt to dynamic traffic conditions, especially in the case of bad weather or emergencies; second, to improve the accuracy and timeliness of path optimization by combining more real-time traffic data and more complex traffic flow prediction methods; third, to explore the joint optimization problem of path optimization and transportation scheduling, and to further improve the overall logistics system's. The third is to explore the joint optimization problem of path optimization and transportation scheduling to further improve the operation efficiency of the whole logistics system. By continuously improving the optimization algorithm and introducing more real-time data, a more intelligent and efficient urban logistics

and distribution system can be realized in the future.

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