Green Path Optimization for E-Commerce Logistics under Carbon Neutrality Goals: A Multi-Objective Grey Wolf Optimizer (MOGWO) Approach

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In e-commerce logistics path planning, it is difficult to balance efficiency and environmental protection due to the lack of carbon emission considerations and multi-objective coordination. To address this problem, this paper constructs a green logistics path optimization method based on the MOGWO (Multi-Objective Grey Wolf Optimizer) algorithm. This method first constructs a graph structure containing distribution centers, customer nodes, and path edges, and sets constraints such as transportation distance, time window, and vehicle capacity; then a linear carbon emission estimation model based on path length, vehicle type, and unit energy consumption parameters is established to provide input for multi-objective optimization. By unifying the dual objectives of minimizing transportation costs and minimizing carbon emissions, and introducing a time window violation penalty term, the path population is dynamically updated using the grey wolf hierarchical search mechanism of MOGWO, and the Pareto frontier is maintained in combination with non-dominated sorting to achieve target equilibrium. The experimental results show that the delivery costs of MOGWO standard orders, expedited orders, large orders, and overseas orders are 3.48, 4.98, 6.82, and 8.47 yuan per order, respectively, and the total transportation costs are 3482.56, 4998.72, 6815.34, and 8483.19 yuan, respectively, which are better than the traditional NSGA-II, PSO, and ACO, and the transportation cost control is efficient; the carbon emissions are reduced by 28.1%, 31.1%, 32.6%, and 32.9%, respectively, achieving effective control of carbon emissions. Based on MOGWO analysis, when the order delivery density is high and the vehicle loading rate increases from 40% to 90%, the unit carbon emission intensity decreases from 0.91kg/km to 0.649kg/km, and the total carbon emissions decrease from 1294.66kg to 899.54kg. The high loading rate can significantly improve carbon efficiency. The average route length in the urban distribution area is 12.84 km, and the average delivery time is 38.7 min, which is better than the 43.37 km and 96.5 min of the cross-regional distribution area, indicating that compact spatial structure and superior traffic conditions are important factors in achieving route optimization.

Povzetek: Za usklajevanja stroškov in emisij v e-trgovinski logistiki je predlagan MOGWO, ki na grafu distribucijskih centrov in kupcev optimira poti glede na stroške, ogljične emisije in časovna okna. Z linearnim modelom emisij ter Pareto iskanjem MOGWO zniža stroške in emisije ter preseže NSGA-II, PSO in ACO.

1 Introduction

Green e-commerce logistics plays a key role in promoting energy transformation and building environmentally friendly supply chains under the "dual carbon" strategy [1], [2]. With rapid urban expansion and rising consumer demand, e-commerce platforms rely more on high-frequency, short-link distribution networks to improve user experience [3], [4]. However, this has led to increased energy waste and greenhouse gas emissions in urban distribution. Traditional logistics route planning often focuses on the shortest route or lowest cost, neglecting factors like traffic congestion, vehicle energy consumption, and delivery time windows, which limits the integration of green, low-carbon principles [5], [6], [7]. E-commerce logistics typically involves multiple points, segments, and overlapping constraints, making it difficult to balance environmental and economic factors in optimization strategies [8], [9], [10]. To achieve carbon neutrality, it is crucial to integrate carbon emission factors into logistics path planning, supporting the development of green supply chains and smart cities.

Existing research has made significant progress in the field of logistics path optimization. Most methods focus on the integration of heuristic search and multi-objective optimization strategies to cope with the challenges of solving multiple constraints in path planning. Representative methods such as NSGA-II (Non-dominated Sorting Genetic Algorithm II) use non-dominated sorting and congestion maintenance strategies to improve the diversity of solution sets, which is suitable for balancing cost and time objectives [11], [12]. Moghadam S S proposed a multi-objective mixed integer nonlinear programming model based on NSGA-II for optimizing e-commerce closed-loop supply chain networks. He took into account both corporate profits and customer satisfaction. Through sensitivity analysis, he further provided management insights on the trade-offs between supply chain costs, pricing strategies, and customer satisfaction [13]. PSO (Particle Swarm Optimization) guides path updates through individual and group extreme values to improve global search capabilities [14], [15]. Tang L proposed an improved particle swarm optimization algorithm combined with a dynamic monkey jumping mechanism, which improves search efficiency through dynamic population grouping and inertia weight adjustment. The algorithm performed better in terms of optimal path fitness value (67.1 km), calculation time (1.26s), and optimal solution success rate (5/10), verifying its high efficiency and practicality [16]. ACO (Ant Colony Optimization) simulates ant colony behavior to adaptively adjust the path selection probability, which is suitable for fast path iteration in dynamic environments [17], [18]. These methods have good performance in solving pure economic goals, such as minimizing distribution costs, but have bottlenecks in carbon emission optimization, distribution time control, and path constraint coupling. The actual adaptability and solution quality control of the current algorithm in green path optimization are still insufficient. It is urgent to design a multi-objective optimization strategy that takes into account both global and fine-grained path modeling to meet the distribution efficiency and emission reduction needs under the guidance of carbon neutrality policies.

Recent studies show that the MOGWO algorithm [19], [20] has strong dynamic adaptability. By simulating the hierarchical predation behavior of gray wolf groups, it adjusts the guidance strategy during the search process, quickly converging to the new Pareto frontier when order density changes or the distribution area expands. MOGWO uses a non-dominated sorting mechanism based on congestion, which preserves solution diversity while improving response speed to order changes, making it effective for e-commerce logistics, such as explosive order growth and frequent customer node changes. In green path planning, MOGWO adapts to complex paths and conflicting goals by maintaining the Pareto frontier and dynamic exchange of information between gray wolf leaders. While MOGWO has been applied in traffic network optimization, power dispatching, and carbon asset allocation with good multi-objective results, it lacks systematic application in e-commerce delivery paths [21], [22]. Some studies did not adequately address constraints like delivery time windows, vehicle capacity, and node topology, resulting in weak model robustness. Others failed to fully exploit MOGWO's dynamic evolution advantages, leading to low solution space coverage in high-dimensional scenarios. Regarding carbon emission estimation, most studies use a unified energy consumption coefficient or average carbon factor, which doesn't accurately reflect emission variations based on vehicle type, distance, and route topology. This paper integrates distribution network topology with carbon emission modeling and utilizes MOGWO's multi-objective optimization to balance route economy and environmental protection in dynamic environments. Relevant work is shown in Table 1.

This study develops a multi-objective green logistics path optimization model that incorporates path constraints, time window constraints, and carbon emission factors to support carbon neutrality goals. The MOGWO algorithm is introduced for efficient solution search and optimization balance. Using real e-commerce distribution network data, a graph structure is created with distribution centers, customer nodes, and connection paths. A linear carbon emission function based on vehicle type, energy consumption, and path length is designed, and accurate carbon emission data is generated from path feasibility judgments. The dual objective function combines transportation cost and carbon emissions, with penalty terms for path conflicts, time window violations, and loading restrictions. A gray wolf population search mechanism improves convergence and solution set diversity, dynamically maintaining a non-dominated solution set. The MOGWO algorithm adjusts the trade-off between carbon emissions and transportation costs, reducing carbon emissions for various orders by 28.1%, 31.1%, 32.6%, and 32.9%, respectively. This paper's contributions include: 1) a path modeling framework balancing distribution efficiency and carbon reduction; 2) a carbon emission estimation mechanism based on vehicle types and path topology; 3) the application of MOGWO to complex constrained path optimization, verified through a multi-index evaluation system, providing theoretical support and algorithmic tools for green e-commerce logistics path planning.

Table 1: Comparison of working methods

Method	Optimization Objectives	Dataset	Performance Metrics	Innovations/Advantages
NSGA-II	Cost, Customer Satisfaction	Simulation Data	Solution Diversity, Convergence Speed	Multi-objective Framework
Hybrid NSGA-II	Profit, Customer Satisfaction	E-commerce Supply Chain Data	Cost, Satisfaction	Closed-loop Supply Chain Design
Improved PSO	Path Length, Time	Urban Logistics Network	Fitness Value, Computation Time	Dynamic Inertia Weight Adjustment
Dynamic ACO	Delivery Time, Cost	IoT Vehicle Trajectories	Path Length, Delay Rate	Adaptive to Dynamic Road Conditions

Traditional MOGWO	Warehouse Efficiency, Cost, Route Reliability	Cross-docking & Regional Networks	Space Utilization, Cost, Reliability	Multi-objective Coordination
Our MOGWO	Transport Cost, Carbon Emissions, Time Windows	Real E-commerce Delivery Network	Cost, Carbon Emissions, SP, GD	1.Precise Carbon Model; 2. Dynamic Pareto Front; 3. Optimal Multi-objective Balance

2 Methods

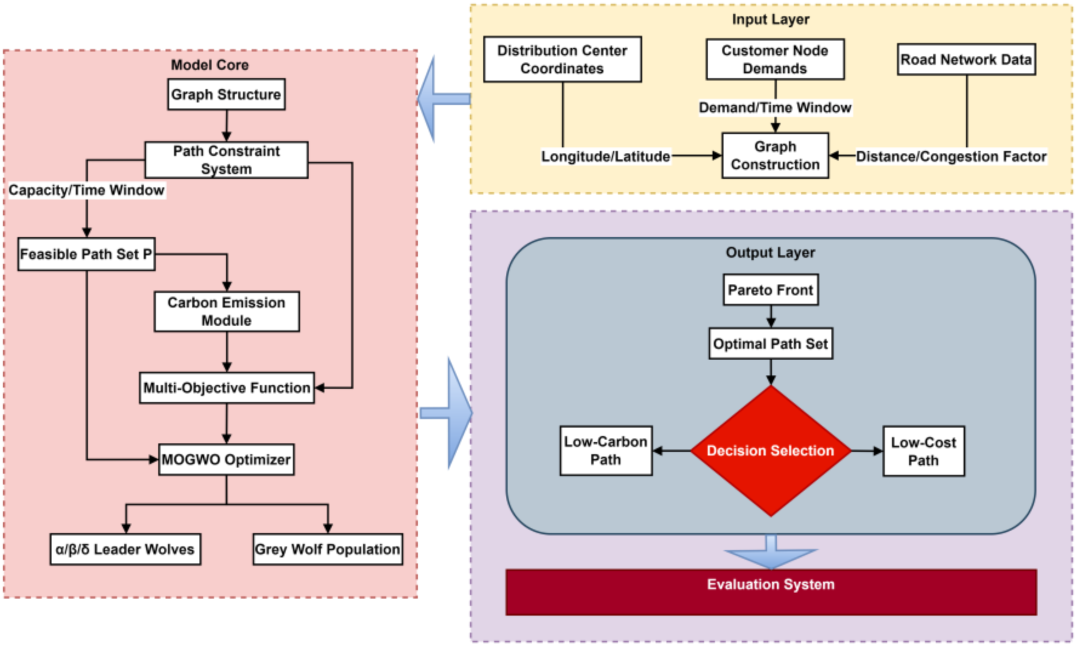

Figure 1: Carbon-neutrality goal-driven green e-commerce logistics path optimization framework

Fig 1 systematically presents the carbon-neutrality goal-driven green e-commerce logistics path optimization framework. The input layer integrates the distribution center coordinates, customer demand (including time windows), and road network data to construct a constrained graph structure. The core layer of the model generates a feasible path set through the path constraint system, calculates the carbon emission matrix by combining vehicle type and energy consumption factor, and constructs a multi-objective function. The MOGWO optimizer uses the leader wolf mechanism to search for the Pareto optimal solution set, dynamically balancing economic and environmental goals. The output layer provides low-carbon/low-cost path solutions and evaluates the system to verify the algorithm's performance. The whole process is tightly coupled with logistics efficiency and carbon neutrality requirements, reflecting the technical path of multi-objective collaborative optimization.

2.1 E-Commerce logistics network modeling

2.1.1 Distribution network data processing and node construction

Based on the distribution data of e-commerce platforms, this study models the coordinates of distribution centers and customer locations as special nodes and ordinary nodes in the graph structure, respectively. Through coordinate transformation, the longitude and latitude are mapped to a point set in a plane rectangular coordinate system to form a node set. Customer nodes are embedded with order requirements and service time window attributes, while distribution center nodes retain capacity constraints and scheduling time attributes, all of which are identified by unique numbers for easy indexing. Subsequently, a set of feasible paths between nodes is constructed, and road traffic conditions, grades, and speed limit information are recorded to form a weighted edge set. Among them, the edge weight includes the congestion-corrected Euclidean distance and estimated travel time. The Euclidean distance calculation formula is:

$$d_{ij} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2} \quad (1)$$

In formula (1), x_i and y_i display the horizontal and vertical coordinates of node i and node j in the plane coordinate system, respectively. If the actual direction of the road deviates from the straight line, it is multiplied by the road polyline coefficient to correct the actual driving distance. The estimated travel time is calculated by dividing the road grade and historical average speed of the reference road by the speed value to obtain the initial travel time. Specifically, the actual driving speed v_{ij} between nodes i and j is determined jointly by the historical benchmark speed v_{base} corresponding to the road grade r and the real-time traffic congestion correction factor α. The calculation formula is: $v_{ij} = \alpha \times v_{\text{base}}$. Subsequent path searches will calculate travel times based on this dynamically updated speed value. After all node and edge attribute information is integrated, the complete graph structure is stored in memory in the form of an adjacency list, which is convenient for rapid indexing and expansion during the optimization process.

2.1.2 Path constraint parameter setting and feasibility screening

For the constructed node and edge sets, each path is given multiple constraints such as transportation distance, time window, and vehicle capacity. The transportation distance directly inherits the corrected distance value obtained in the previous stage; the customer node service time window is defined as t_{arrive}, which means that the delivery service must occur within this time interval, otherwise it is considered infeasible. In actual scheduling, if the cumulative pre-travel and sorting and loading time of a path exceeds the latest service time of the target node, the path can be marked as infeasible. The service time calculation formula is:

$$t_{\text{arrive},j} = t_{\text{depart},i} + \frac{d_{ij}}{v_{ij}} + s_i \tag{2}$$

In formula (2), $t_{\text{depart},i}$ displays the departure time from the node, v_{ij} displays the actual driving speed from node i to j, and s_i displays the service stay time of node i; if t_{arrive} exceeds the latest service time allowed by the node, the path is abandoned. The vehicle capacity constraint adopts a cumulative method, comparing the remaining load of the selected assigned vehicle with the customer demand, and using an inequality expression:

$$\sum_{k \in S} q_k \leq Q \tag{3}$$

In formula (3), $\sum_{k \in S} q_k$ displays the sum of customer demands allocated to the current vehicle route, and Q is the maximum vehicle carrying capacity. Each time the route is expanded, if the inequality does not hold due to the additional customer demand, the route is considered infeasible and pruned.

2.2 Carbon emission calculation module design

2.2.1 Route emission factor determination and vehicle parameter classification

All delivery routes are classified by vehicle type, and energy consumption factors are set for each type of vehicle. Emission levels are estimated based on route length and typical operating efficiency. Vehicle types are divided into three categories: small light trucks, medium-sized vans, and heavy-duty diesel vehicles based on platform operation data. For each type of vehicle, its unit kilometer fuel consumption or electricity consumption data under standard road conditions is collected, and its load range and regular usage intensity are discretized and archived. The path length is derived from the actual distance value recorded in the graph structure, and the energy consumption factor is derived from the energy efficiency accounting standard issued by the Ministry of Transport, and the compromise value is obtained by adjusting the actual operation data of the enterprise.

Taking into account the energy consumption fluctuations caused by different road grades in actual driving, the roads passed by the path are marked in sections, and the road grade parameters are converted into driving condition coefficients to adjust the weight of the energy consumption factor. For example, there are differences in driving resistance between urban roads and suburban roads, and the unit carbon emissions of the same vehicle on the two types of roads can be offset. By applying weighted integration to each road segment length in the route, we develop an interval correction model to enhance the accuracy of carbon emission estimation. When a route matches a specific vehicle type, the system dynamically retrieves the driving condition coefficient-adjusted dynamic unit emission factor from its parameter library based on road classification. This enables efficient batch processing to avoid redundant calculations.

2.2.2 Linear estimation of path emission values and result integration

This paper takes each feasible path as a unit, extracts its distribution distance and vehicle type matching parameters, and uses a linear model to estimate carbon emissions. The formula is expressed as follows:

$$E_{ij} = \alpha_{k,r} \cdot L_{ij} \tag{4}$$

Where E_{ij} displays the transportation carbon emissions from node i to node j, $\alpha_{k,r}$ are the unit emission factors corresponding to vehicle type k a
This formula assumes that under fixed load conditions, unit distance emissions grow linearly, which is suitable for rapid estimation of carbon effects in multi-path, single-task scheduling. After the emission values of all paths are calculated, the results are stored in the form of a sparse matrix. The matrix dimension corresponds to the size of the edge set in the graph. It can be directly introduced as a cost item to participate in the optimization when designing the objective function.

If there are multiple delivery tasks in a path, the path emission is apportioned according to the task ratio, and the calculation method is as follows:

$$E_{ij}^{(n)} = \frac{q_n}{\sum_{m \in P_{ij}} q_m} \cdot E_{ij} \tag{5}$$

Where q_n is the demand for the task, and P_{ij} is the set of all delivery tasks carried by the path. This allocation mechanism allows each order to be quantified in the emission accounting, avoiding redundant emissions between paths. This mechanism can mark the carbon emissions of the paths associated with each task, making it easier to concretize the emission constraints in the subsequent optimization model.

The final output is the carbon emissions corresponding to each path and each task. All results are summarized and written into the data structure for the objective function to call. This module is a static input link before scheduling optimization, and its accuracy directly affects the setting of the path selection weight and the carbon emission constraint boundary.

2.3 Construction of multi-objective function

To address constraints in multi-objective optimization, this paper develops a comprehensive evaluation function that quantifies the overall performance of routing solutions. The function integrates transportation costs, carbon emissions, and time window penalties through weighted aggregation, providing a comparable comprehensive score. Transportation costs are calculated by multiplying each road segment distance with the vehicle's unit operating cost. Before computation, system data including vehicle type, origin/destination nodes, and road classification levels are uniformly retrieved to match corresponding unit costs. Operating costs are stored in the system based on historical data categorized by vehicle type and road conditions. Time window constraints are converted into scheduling cost penalties and incorporated into the evaluation function. The evaluation function is expressed as follows:

$$F = w_1 \cdot C + w_2 \cdot E + P \tag{6}$$

Where C is the transportation cost item, E is the carbon emission value, P is the time window penalty item, and w_1 and w_2 display weight coefficients, which reflect the trade-off between the two in the scheduling priority. This function is mainly used to quickly evaluate a single solution inside the algorithm, and its calculation result is not the final optimization goal. When the cost weight is set to [0.5,0.7] and the emission weight to [0.3,0.5], the objective function demonstrates superior performance in balancing costs and carbon emissions, aligning with the policy orientation of prioritizing emission reduction in e-commerce logistics. Subsequent experiments adopted default values of w_1=0.6 and w_2=0.4 to balance economic considerations with environmental objectives. In the function expression, the penalty item is not an independent target, but is dynamically added depending on whether the path plan violates the time window requirement. If the path does not violate the time constraint, P=0. Otherwise, the path is assigned a value in segments according to the actual delay time and the urgency of the task, ensuring that the time delay is sufficiently punitive in the path evaluation.

The total carbon emission of the path is embedded as an independent target in the objective function, with emission values sourced from static estimations to avoid repeated reading of the path structure. These values are indexed by path number and integrated into the objective function for direct quantification during decoding. Emission limits and penalty intervals are set, with piecewise linear conversion applied to some paths to enhance identification of high emissions.

For time constraints, the delivery time window offset is converted into a cost term, with higher penalties for late arrivals than early ones to prioritize customer service. If a node's arrival time exceeds the allowed interval, a penalty term is calculated accordingly:

$$P_i = \lambda \cdot \max(0, T_i - b_i) + \mu \cdot \max(0, a_i - T_i) \tag{7}$$

Where T_i is the actual arrival time, a_i and b_i are the allowed time windows of the node, and λ and μ are penalty weight parameters. The configuration of penalty weights λ and μ directly determines the rigor of time window constraints in path optimization. Through experimental testing, this study investigates how different parameter combinations affect the objective function. When λ=1.5 and μ=0.3, a balance is achieved between time window violations and cost control. Sensitivity analysis reveals that increasing λ significantly reduces delays but may lead to path redundancy, while excessively high μ values tend to increase vehicle waiting costs. This structure ensures that in the algorithm search, once the path plan deviates from the time specification, the weight is dynamically adjusted at the objective function level to avoid inferior solutions occupying the search forefront.

2.4 Path search mechanism based on MOGWO

2.4.1 Path population initialization and group position update mechanism

In the initial phase, feasible routes meeting capacity and time window requirements are randomly generated based on network node distribution and vehicle constraints to form an initial population. Subsequently, each route individual is assigned a position vector in continuous space, which serves as the meta-parameter guiding local search and updates. The population size matches the number of routes.

Position updates follow the gray wolf hierarchy (α,β,δ), where individuals approach leaders with random perturbations to avoid local optima. Node exchange/insertion/reversal operations preserve path feasibility during optimization.

The position update formulas are expressed as follows:

$$\vec{D} = \left|\vec{C} \cdot \vec{X}_{leader} - \vec{X}_{current}\right| \tag{8}$$

$$\vec{X}_{new} = \vec{X}_{leader} - \vec{A} \cdot \vec{D} \tag{9}$$

Where $\vec{X}_{leader}$ is the leader wolf's position vector, $\vec{X}_{current}$ is the current individual position, $\vec{A}$ and $\vec{C}$ are dynamic adjustment parameters. Parameter $\vec{A}$ gradually decreases with the progress of iteration to achieve exploration-exploitation balance, and $\vec{C}$ introduces random weights to enhance the diversity of solutions.

2.4.2 Pareto frontier maintenance and multi-objective equilibrium mechanism

During iterations, a dynamic Pareto frontier maintains non-dominated solutions through continuous comparison and updating. Solutions are evaluated using objective function vectors, with dominated solutions removed to preserve optimal trade-offs. Crowding distance metrics ensure solution diversity by preferentially retaining sparse and edge-distributed solutions.The multi-objective vector expression of the objective function is as follows:

$$\mathbf{F}(\vec{X}) = \left(C(\vec{X}), E(\vec{X}), T(\vec{X})\right) \tag{10}$$

Where $C(\vec{X})$ is the transportation cost, $E(\vec{X})$ is the carbon emission, and $T(\vec{X})$ is the delivery time penalty. The performance of the individual path $\vec{X}$ is fully described by this three-dimensional vector. Non-dominated sorting ensures that the paths included in the Pareto set do not have absolute disadvantages in each dimension.

3 Method effect evaluation

3.1 Experimental data and settings

This study builds an experimental environment based on the actual operation data of an e-commerce platform. The data covers the coordinates of the distribution center, the geographical location of the customer node, the order demand, the service time window constraints, and the road network information. The coordinates of the distribution center and customer nodes are mapped into a plane rectangular coordinate system through longitude and latitude conversion to form a graph structure of the logistics network. The path transportation distance is calculated using the Euclidean distance and corrected with the actual road polyline coefficient to reflect the actual driving distance. The estimated driving time is obtained through the historical vehicle GPS trajectory and road condition monitoring data statistics to ensure the accuracy of the time estimate. The experiment set the gray wolf population size to 100 with a maximum iteration count of 200. The parameter update rules for $\vec{A}$ and $\vec{C}$ are: $\vec{A} = 2a \cdot r1 - a, \vec{C} = 2r2$, where a decreases linearly from 2 to 0, and r1 and r2 are random vectors within the interval [0,1]. The head wolf selection strategy combines non-dominant sorting with crowding distance. The network consists of 1 distribution center and 50 customer nodes, with an average degree of 3.6, an average demand of 1.8 units per customer node, and a time window span of 90 minutes on average. The data is generated based on real order sampling, and the key parameters are shown in Table 1 and Table 2.

3.2 E-commerce logistics network

To clearly demonstrate the network structure, Figure 2 shows a simplified schematic network with 7 nodes constructed in MATLAB. The e-commerce logistics network log is based on the actual operation of the e-commerce platform, covering the geographical coordinates of distribution centers, multiple customer orders corresponding to orders, demand, and service time windows.

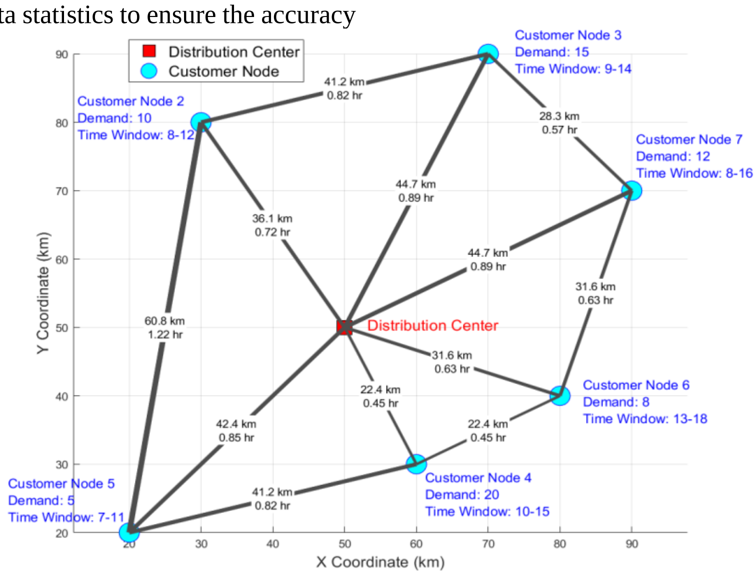

Figure 2: E-commerce logistics network with distance and travel time

Figure 2 shows the spatial layout of distribution centers and multiple customer nodes in an e-commerce logistics network and the characteristics of their interconnected transportation paths. The two-dimensional coordinates of the nodes correspond to the actual geographic locations, ensuring that the path length intuitively reflects the delivery distance. The distribution centers are marked with red squares, and the customer nodes are distinguished by blue dots. The annotation information covers customer needs and time window constraints, revealing the specific requirements of different customers for delivery timeliness and transportation capacity. The thickness of the path line reflects the difference in distance between nodes and also implies the consumption of transportation resources. Thicker and longer paths indicate longer transportation distances, which means that delivery vehicles need to invest more time and cost on this path, increasing operational complexity. Most of the nodes connected by shorter paths are located near the distribution centers, with higher transportation efficiency, but they cannot rely entirely on short-distance delivery due to the diversity of customer demand distribution. Time window constraints also play a key role in this figure. The time windows of some customer nodes are very tight, requiring that the delivery tasks must be completed within a specific time limit. This time limit not only increases the complexity of path scheduling, but also affects the driving order and residence time of vehicles. Due to the significant differences in demand, it is necessary to reasonably allocate the capacity of distribution vehicles - to avoid overloading or empty vehicles, and to improve overall transportation efficiency. The schematic network contains 2D coordinates of 7 nodes to intuitively present the model elements. All subsequent experimental results are simulated and analyzed based on a larger and more representative actual e-commerce logistics data set to fully verify the performance of the algorithm in complex scenarios.

3.3 Carbon emission characteristics

Table 2: Unit carbon emission factors of vehicles and their average load parameters

Vehicle Type	Empty Load Energy Factor (α_1)	Full Load Energy Factor (α_2)	Average Load (tons)
Light Truck	0.18	0.26	1.2
Medium Truck	0.35	0.49	3.8
Heavy Truck	0.68	0.95	8.5

Table 2 lists the unit carbon emission factors and average load parameters of three types of delivery vehicles, providing basic data support for the linear estimation model of transportation carbon emissions. The empty and full load energy consumption factors reflect the difference in fuel consumption of vehicles under different loading conditions, covering the impact of load changes on emissions during actual delivery. The average load value is determined based on typical delivery tasks and vehicle type statistics to ensure the practicality and accuracy of the estimation model. The carbon emission factor data integrates multi-dimensional influencing factors such as road conditions, driving speed, and vehicle technical characteristics, reflecting high adaptability to the real transportation environment. The data provides key input parameters for the calculation of path carbon emissions, which helps to achieve the coordinated optimization of transportation costs and environmental protection goals.

Based on the actual delivery records of an e-commerce company, it covers the operation of different types of delivery vehicles on multiple typical delivery routes. Vehicle types include light trucks, medium trucks, and heavy trucks, route lengths cover a variety of intervals from short to long distances, and road types are subdivided into highways, urban trunk roads, urban local roads, and suburban roads. During the data collection process, the driving distance and road condition information of each route were recorded in detail, and the corresponding carbon emissions were calculated in combination with vehicle technical parameters and unit energy consumption standards. The calculation of carbon emissions uses a linear estimation model, which comprehensively considers the transportation distance, vehicle energy consumption characteristics, and road environmental impact to ensure that the emission data accurately reflects the actual operating conditions. The emission data of each route and vehicle combination is organized in a matrix form to generate a corresponding two-dimensional heat map. This process realizes the visual comparison of carbon emissions of different distribution plans, intuitively presents the specific impact of changes in transportation conditions on emissions, and lays a solid foundation for route optimization and green logistics strategy formulation.

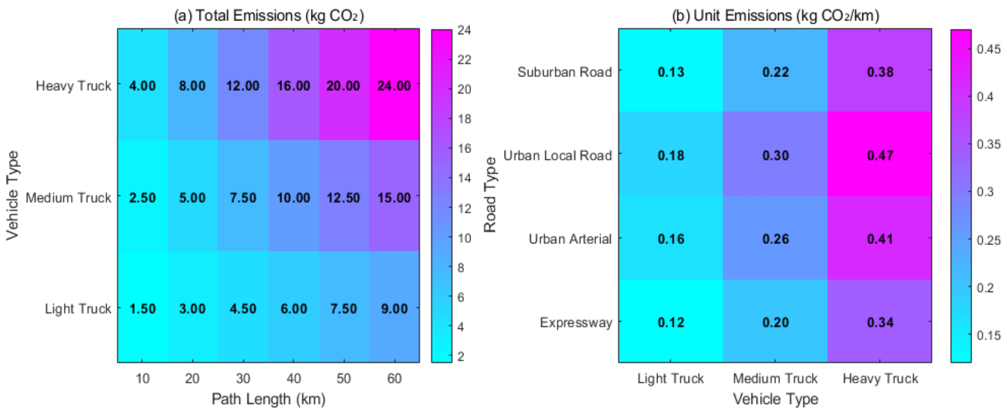

Figure 3: Carbon emission characteristics of different vehicle types

Fig 3 shows the comparison of carbon emission characteristics of different vehicle types under different delivery path lengths and road categories:

Figure a show the trend of total carbon emissions of different vehicle types under different delivery path lengths. As the path length increases, the overall carbon emissions increase, reflecting that the transportation distance directly affects the total carbon emissions. There are significant differences in emissions between different models. Heavy trucks emit much more carbon than light and medium trucks, mainly due to their higher fuel consumption and load capacity, which significantly increases the emission intensity per unit distance traveled. In addition, light trucks show lower emissions in short-distance delivery and are suitable for delivery tasks in cities and suburbs, while heavy trucks are suitable for long-distance bulk cargo transportation, but at a higher environmental cost. Figure b reflects the impact of road type on unit transport carbon emissions. Expressway has relatively low unit emissions due to its smooth traffic conditions and high average vehicle speed. In contrast, Urban Local Road shows the highest unit emission value, reflecting that this type of road has frequent traffic congestion, large speed fluctuations, and frequent starting and braking, which leads to reduced fuel efficiency and increased carbon emissions. The unit emissions of Urban Arterial Road and Suburban Road are between the two, reflecting the regulatory effects of road grade and traffic flow on energy consumption and carbon emissions. The interaction between vehicle type and road conditions highlights the complexity of carbon emissions in the transportation link, emphasizing that multi-dimensional factors must be comprehensively considered in logistics route planning in order to achieve accurate assessment and effective control of carbon emissions.

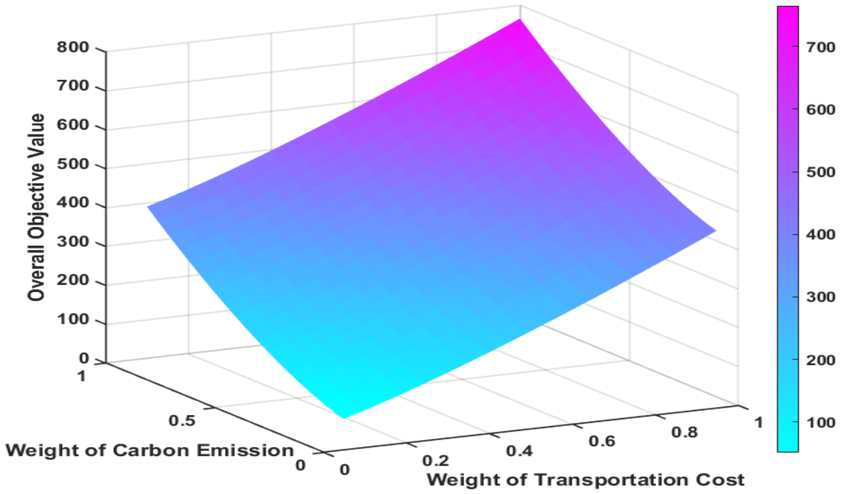

Figure 4: The impact of cost and emission weights on the objective function

Fig 4 reveals the joint impact of transportation cost weight and carbon emission weight on the overall objective function value. The horizontal and vertical axes represent the weight ratios of transportation cost and carbon emission, respectively, with a value range of 0.1 to 1, with high-resolution sampling to ensure rich results. The vertical axis corresponds to the comprehensive evaluation value of the objective function, reflecting the pros and cons of the scheduling scheme under different weight configurations. As the weight of transportation cost increases, the overall target value shows an accelerating upward trend, indicating that the weight of transportation cost has a significant impact on the overall target and has a nonlinear amplification effect. The increase in carbon emission weight also leads to a significant increase in the target value, but the slope of the surface is slightly slower, reflecting that the sensitivity of carbon emission weight is relatively mild, reflecting the complexity of the trade-off between the two indicators in multi-objective scheduling. The color change directly reflects the size distribution of the target value. The data can assist decision makers in identifying sensitive areas for weight parameter settings, and provide a data basis for formulating more scientific and reasonable scheduling optimization strategies. The data clearly reveals the comprehensive impact of weight configuration on the objective function, suggesting that weight selection should avoid extreme single inclination and promote a dynamic balance between transportation costs and carbon emissions. Based on this, the scheduling plan can more effectively balance economic benefits and environmental responsibilities and achieve dual optimization goals.

3.4 Multi-objective evolution in MOGWO path optimization process

The data comes from the iterative records of the simulation of e-commerce logistics path optimization, covering the changes in key indicators of the multi-objective optimization algorithm in 50 iterations. Transportation cost, carbon emissions, and delivery time are used as objective functions, and the model calculates the corresponding value of the optimal path updated in each iteration to form a convergence curve. The position data of the leader wolf comes from the group search mechanism within the algorithm. The position indicators of the three types of leader individuals, α, β, and δ, are extracted in each iteration to reflect their search trajectory in the solution space. During the data collection process, the path is decoded into a position vector, and the position is updated using the search strategy to dynamically adjust the path selection. This process combines mathematical models and heuristic algorithms to achieve optimization iteration of multi-objective functions, record the performance of each step and the dynamic position of individuals, and finally form a complete data set that demonstrates the optimization effect and search behavior.

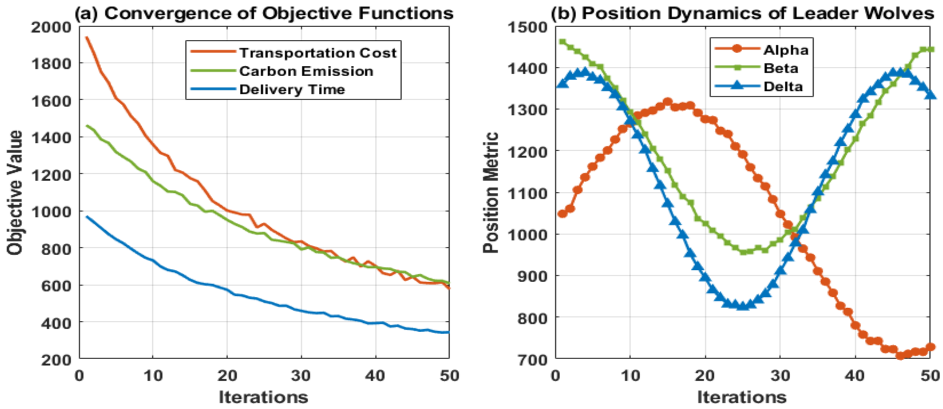

Figure 5: Multi-objective evolution in the MOGWO path optimization process

Fig 5 shows the convergence dynamics of the objective function in the MOGWO path search mechanism and the change behavior of the leader individual position. The combination of the two reveals the evolutionary characteristics of the optimization process.

Fig a reflects the evolutionary convergence characteristics of the path group under multiple objectives. The horizontal axis is the number of iterations, and the vertical axis is three key performance indicators: transportation cost, carbon emissions, and delivery time. The three curves gradually decrease with the increase in the number of iterations, showing a trend of gradually approaching the optimal solution during the search process. Different colors represent three types of targets, and their decline rates are different, indicating that there is asymmetry between the targets and a check-and-balance relationship between multiple targets. The rate of carbon emission decline slows down, suggesting that the optimization process is gradually saturated, and more rounds of search are needed to further compress the emission value. Figure b shows the position changes of the three types of leader wolves α, β, and δ, during the entire search process, simulating the exploration positions they occupy in the path space. This data is used to reflect the dynamic behavior characteristics of each leader in the search phase. The position index is composed of composite variables such as distance and path cost, which are used to abstractly represent the position characteristic value of each individual in the solution space. The fluctuations of the curves indicate that the three types of leading wolves maintain global exploration of the solution space while maintaining local search. The position of wolf α first rises and then falls, indicating that it dominates the solution space update in the early stage, but is replaced by other candidate positions in the later stage. The interlacing of the three curves further reflects the dynamic switching process of dominance of different dimensions in the case of multiple targets. The data changes jointly construct a dynamic cognitive map in the path search mechanism, and explain the behavior mechanism of the MOGWO algorithm in the multi-objective path problem from the two dimensions of performance change and leadership strategy evolution.

3.5 Comparison of E-commerce logistics and traditional logistics path optimization and target conflict analysis

Combined with the MOGWO algorithm for multi-objective optimization, with transportation cost and carbon emissions as dual objective functions, the Pareto solution set is dynamically maintained, and finally, the Pareto frontier comparison results of e-commerce and traditional logistics (NSGA-II) are generated. By simulating the path planning under different order densities and vehicle loading rates, the optimization performance of various logistics modes in terms of cost and carbon emissions is obtained, revealing their target conflict characteristics and path optimization potential.

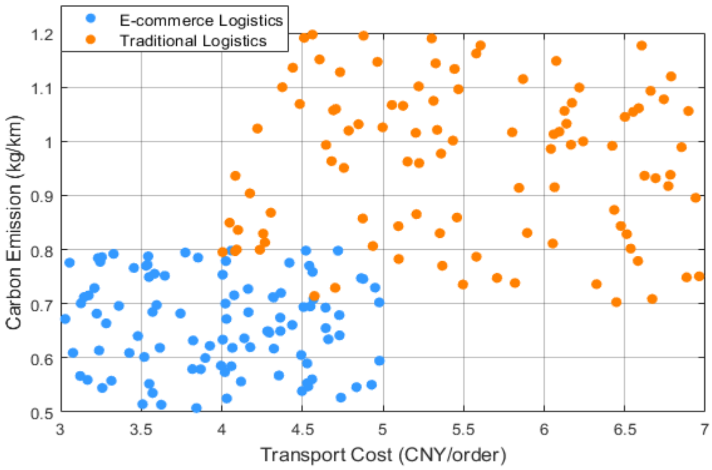

Figure 6: Pareto frontier comparison: MOGWO (e-commerce logistics) and NSGA-II (traditional logistics)

Figure 6 shows the Pareto frontier distribution obtained by using the MOGWO algorithm (labeled as "e-commerce logistics") and the NSGA-II algorithm (labeled as "traditional logistics") for dual-objective optimization under the dual-objective optimization of transportation cost and carbon emission. It can be seen that the solution set of e-commerce logistics is mainly concentrated in areas with low transportation costs, which reflects its stronger cost control ability in scenarios with dense networks and high delivery frequency. Due to the high-frequency and small-batch delivery mode, its carbon emission value is also relatively low - this mode effectively suppresses the growth of unit carbon emissions through route optimization and improves delivery efficiency. In contrast, the solution set distribution of traditional logistics is more dispersed. Although some routes have achieved low carbon emissions, the overall cost is high and the ability to adapt to the development of modern green logistics is limited. This result reveals the core difference between the two logistics systems: e-commerce logistics pays more attention to timeliness and customer experience, and path planning tends to be locally optimized; while traditional logistics focuses on scale effects and has a relatively broad path structure.

3.6 Transportation cost comparison indicators

The unit delivery cost and total transportation cost data are based on the simulation results of transportation paths for various order types in the actual e-commerce logistics distribution network. The MOGWO algorithm is used to iteratively search the delivery path, optimize vehicle scheduling and path selection, and finally generate a delivery plan for the corresponding order type. The MOGWO algorithm in this paper is compared with the three algorithms of NSGA-II, PSO, and ACO; each algorithm is run under the same data set and constraints to ensure the comparability of the results. The unit delivery cost is obtained by accumulating the sum of the transportation costs of each path and dividing it by the corresponding number of orders. The total transportation cost is the sum of the transportation costs of all paths, reflecting the overall distribution of resource consumption levels. The data covers ordinary orders, expedited orders, large orders, and overseas orders, reflecting the impact of different demands on costs.

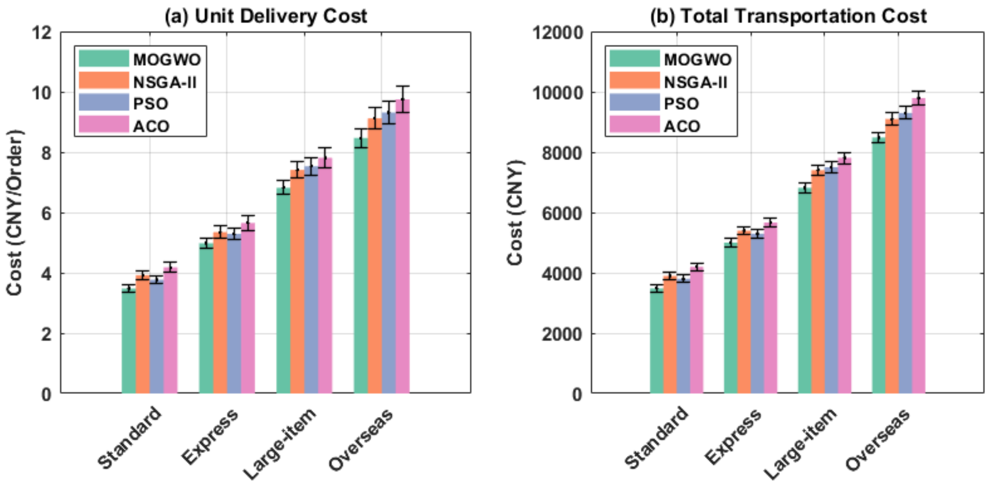

Figure 7: Comparison of unit delivery cost and total transportation cost

Figure 7 compares the transportation cost performance of MOGWO, NSGA-II, PSO and ACO algorithms in standard orders, expedited orders, large orders and overseas orders. Figure 7a shows the unit delivery cost (RMB/order), and Figure 7b shows the total transportation cost (RMB). The error bars represent the standard deviation of 10 independent experiments. The results show that MOGWO maintains the lowest cost in all order types: the unit delivery cost is 3.48, 4.98, 6.82, and 8.47 RMB/order, respectively, and the total transportation cost is 3482.56, 4998.72, 6815.34, and 8483.19 RMB, respectively, with the smallest fluctuation range (standard deviation). The cost reduction is mainly attributed to MOGWO's optimized path planning and vehicle scheduling strategy, which effectively reduces repeated paths and empty load rates. The paired t-test confirms that MOGWO is significantly better than the comparison algorithm ($p<0.01$), verifying its stability and economic advantages in complex logistics scenarios.

Table 3: Performance comparison of metaheuristic algorithms across different problem scales

Problem Scale (Number of Nodes)	Algorithm	Average Runtime (seconds)	Convergence Generations
50	MOGWO	18.3 ± 1.2	85 ± 5
	NSGA-II	22.1 ± 1.8	92 ± 7
	PSO	12.7 ± 0.9	110 ± 8
	ACO	35.6 ± 2.5	135 ± 10
100	MOGWO	67.4 ± 3.1	168 ± 12
	NSGA-II	89.3 ± 4.7	185 ± 15
	PSO	38.2 ± 2.3	210 ± 18
	ACO	142.7 ± 8.9	250 ± 22
200	MOGWO	245.8 ± 15.6	310 ± 25
	NSGA-II	386.5 ± 24.3	410 ± 30
	PSO	142.3 ± 9.8	350 ± 28
	ACO	>600	>500
500	MOGWO	1483.2 ± 98.7	680 ± 55
	NSGA-II	> 2500	>1000
	PSO	728.6 ± 45.2	800 ± 60
	ACO	Not Applicable	-

Table 6 shows the scalability and computational efficiency of each algorithm under different problem scales. This table compares the average running time and convergence number of four algorithms, MOGWO, NSGA-II, PSO and ACO, in logistics networks with 50, 100, 200 and 500 nodes respectively. The results show that PSO has the shortest running time, but the quality of the solution set is poor; ACO takes the longest time to calculate, especially for large-scale problems, it is difficult to converge and has poor scalability; NSGA-II has an intermediate performance, but the computational cost increases significantly with the scale. In contrast, MOGWO has a much lower running time than NSGA-II and ACO while ensuring the quality of the solution set. It shows a better balance between efficiency and performance at 200 nodes, and can effectively converge to ultra-large-scale problems with 500 nodes, verifying its excellent scalability and practicality in complex e-commerce logistics scenarios.

3.7 Carbon emission control levels

Based on e-commerce platform order distribution and vehicle dispatch records, a multi-scenario simulation environment is built, considering various order types and loading statuses. The path optimization algorithm calculates transportation paths and total mileage. Using vehicle energy consumption parameters, carbon emissions are estimated based on path length and energy consumption. The unit carbon emission intensity is calculated by the ratio of total carbon emissions to path distance, reflecting the average carbon emission efficiency of the entire logistics system under specific order density and vehicle loading rate. This index comprehensively integrates the influence of various factors such as vehicle emission factor, path planning quality, vehicle loading rate, and order distribution characteristics.

Table 4: Carbon emission performance under simulated path planning conditions

Order Density	Vehicle Load Rate	Total Carbon Emission (kg)	Route Distance (km)	Carbon emission intensity per unit system (kg CO_2/km)
Sparse	40%	812.64	964.5	0.843
	70%	645.21	953.7	0.677
	90%	577.83	951.2	0.607
Medium	40%	1035.77	1186.3	0.873
	70%	823.94	1162.8	0.709
	90%	738.32	1159.1	0.637
Dense	40%	1294.66	1422.4	0.910
	70%	1019.13	1397.3	0.729
	90%	899.54	1385.6	0.649

Table 4 shows the total carbon emissions and unit carbon emission intensity of logistics paths under different order densities and vehicle loading rates. Order density is classified as sparse, medium, or dense, and vehicle loading rates are 40%, 70%, and 90%. Total carbon emissions are measured in kilograms, and unit carbon emission intensity is calculated as emissions per kilometer. As loading rate increases, total carbon emissions decrease, reflecting improved transportation efficiency. Unit carbon emission intensity, however, better represents the effect of route optimization. In sparse order distribution, higher loading rates lead to a notable decrease in intensity, indicating more efficient route allocation. In medium and dense distributions, the high loading rate still maintains low intensity, showing the regulatory power of route optimization. There is a nonlinear relationship between route length and carbon emission intensity, affected by factors like order distribution, vehicle loading, and route continuity. When order density is high and loading rate rises from 40% to 90%, unit carbon emission intensity drops from 0.91kg/km to 0.649kg/km, and total emissions drop from 1294.66kg to 899.54kg, showing the positive impact of higher loading rates on carbon efficiency.

Table 5: Carbon intensity comparison analysis before and after MOGWO optimization

Order Type	Baseline carbon intensity (kg/order)	Optimized Carbon Intensity (kg/order)	Carbon Intensity Reduction Rate (%)
Standard Order	0.89	0.64	28.1
Expedited Order	1.03	0.71	31.1
Large Order	1.32	0.89	32.6
Overseas Order	1.67	1.12	32.9

Table 5 shows the quantitative results of the carbon neutrality contribution of the MOGWO algorithm under different order types, including the initial carbon intensity, the optimized carbon intensity, and its decline rate. Carbon intensity is defined as the carbon dioxide emissions generated per kilometer of transportation per unit order (kg/km). From the data, it can be seen that in standard orders, expedited orders, large orders, and overseas orders, the carbon intensity decreased by 28.1%, 31.1%, 32.6%, and 32.9%, respectively, indicating that MOGWO can effectively reduce carbon emissions in various delivery scenarios. Among them, the optimization effect of large items and overseas orders is the most significant, indicating that the algorithm has stronger resource scheduling capabilities in complex routes and long-distance distribution. Overall, MOGWO has achieved effective control of carbon emissions while maintaining low transportation costs through a multi-objective collaborative optimization mechanism, verifying its technical feasibility and practical application value in promoting the realization of carbon neutrality goals in green e-commerce logistics systems.

3.8 Path operation efficiency analysis

Table 6: Path transportation efficiency and congestion adjustment coefficient analysis

Road Type	Average Speed (km/h)	Mean Congestion Adjustment Coefficient	Transport Efficiency (km/min)	Standard Deviation (km/min)
Expressway	75.6	1.05	1.25	0.15
Urban Arterial	45.3	1.18	0.68	1.1
Urban Local Road	32.8	1.32	0.43	2.07
Suburban Road	40.1	1.22	0.55	1.12

Table 6 presents the transport efficiency and its influencing factors across four road types: expressways, urban trunk roads, urban local roads, and suburban roads. The average speed reflects traffic conditions, with expressways having the highest speed (75.6 km/h) and urban local roads the lowest (32.8 km/h), indicating severe congestion. The congestion adjustment factor increases as road grade decreases, highlighting a greater impact of congestion on lower-grade roads. Transport efficiency, measured in km/min, reflects vehicle speed on different road sections considering road conditions. The standard deviation indicates stability, with highways showing the least fluctuation (0.15 km/min), while urban and suburban roads are more affected by external factors. These data are crucial for route planning, delivery timeliness, and cost control in e-commerce logistics. The optimization results focus on average delivery path length and time, analyzing the adaptability and stability of the MOGWO optimization strategy in various order densities without comparisons to other algorithms.

Table 7: Evaluation results of path efficiency of different delivery areas under the MOGWO strategy

Distribution Zone Type	Average Path Length (km)	Average Delivery Time (min)	Standard Deviation (Length)	Standard Deviation (Time)
Urban Core Distribution Zone	12.84	38.7	1.15	3.6
Urban-Suburban Transition Zone	18.63	51.4	1.87	4.1
Urban-Rural Integration Zone	27.48	63.2	2.09	5.7
Remote County-Level Delivery Zone	35.92	79.8	3.16	6.2
Cross-Region Hub Aggregation Zone	43.37	96.5	4.02	8.4

Table 7 shows significant differences in average path length and delivery time across distribution area types. Urban areas, with compact structures and dense road networks, have shorter paths and lower time consumption, indicating efficient traffic conditions. In contrast, suburban, urban-rural fringe, and remote areas face longer paths and higher delivery times, with increased variability due to road complexity and sparse distribution points. Cross-regional areas experience even greater challenges, with higher path lengths and delivery times, reflecting transportation infrastructure and geographical difficulties. The urban area, for example, has an average route length of 12.84 km and delivery time of 38.7 minutes, while cross-regional areas show 43.37 km and 96.5 minutes. This demonstrates that optimized regional organization and good traffic conditions are crucial for reducing costs and improving logistics efficiency.

3.9 Evaluation of solution set distribution balance

The experiment analyzes the results of four algorithms (MOGWO, NSGA-II, PSO, ACO) in the same e-commerce logistics path planning scenario. Using a fixed distribution network and order demand, each algorithm is run multiple times with consistent input parameters to ensure stable results. The SP and GD indicators are used to measure the solution set's distribution balance and closeness to the optimal solution. SP reflects solution uniformity, while GD measures the Euclidean distance from each solution to the true Pareto frontier.

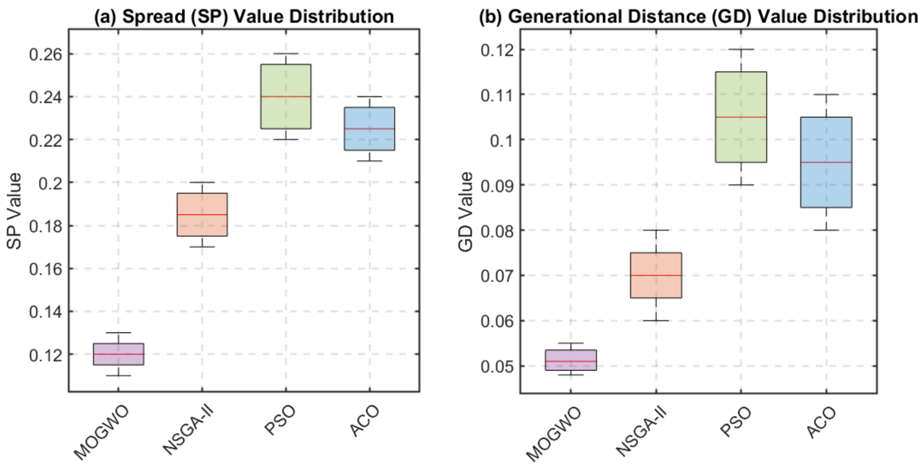

Figure 8: Comparative analysis of solution set distribution metrics

Fig. 8 compares the performance of four algorithms in terms of solution set balance and diversity using Spread (SP) and Generational Distance (GD). The SP indicator reflects solution uniformity, with lower values indicating better balance. The GD indicator measures closeness to the true Pareto frontier, with lower values indicating better quality. The MOGWO algorithm shows the lowest SP median (0.12) and a compact distribution, indicating spatial balance and stability. Other algorithms have higher medians and poorer uniformity. In the GD plot, MOGWO's median (0.051) is significantly lower, indicating its solutions are closer to the optimal Pareto frontier. The GD values for NSGA-II, ACO, and PSO are higher, with PSO showing significant instability. Overall, MOGWO outperforms the others in both balance and solution quality, making it more effective in multi-objective path optimization, path selection, and carbon emission control.

4 Discussion

The green e-commerce logistics path optimization method based on the MOGWO algorithm offers significant advantages in transportation cost control, carbon emission reduction, and solution quality. Compared to classic multi-objective optimization algorithms like NSGA-II, PSO, and ACO, MOGWO demonstrates stronger performance in solving complex constrained problems. This advantage arises from its unique population search mechanism, simulating the hierarchical predation of gray wolves, which enables efficient exploration and avoids local optima. MOGWO's Pareto frontier maintenance, based on non-dominated sorting and congestion calculation, ensures a more uniform and diverse solution set, providing better trade-off options for decision makers.

This performance is partly due to the integration of carbon emission estimation and path constraints in the optimization model, treating carbon emissions as a quantified target rather than an additional cost. The dense nodes and short paths in e-commerce logistics networks also aid MOGWO's rapid convergence. MOGWO can quickly converge to the new frontier when order density changes or distribution area expands by dynamically maintaining Pareto frontier and leading wolf guidance mechanism, effectively responding to order outbreak and node change, showing good scalability in complex dynamic environment, and is suitable for collaborative optimization of large-scale e-commerce logistics network. However, MOGWO's performance weakens in sparse order distributions or wide delivery areas, where its convergence slows, and NSGA-II may show faster initial convergence. Its performance is also sensitive to key parameters like population size and convergence factor, with improper settings leading to stagnation or inefficiency. Although MOGWO excels in typical e-commerce logistics problems, further research is needed to improve its robustness and adaptability to dynamic environments. The current research model exhibits limitations when extended to other regions or logistics networks. Its performance depends on localized parameters such as congestion coefficients for specific road types, vehicle energy consumption factors, and regional traffic control regulations. When applied to new areas with significant variations in road conditions, vehicle composition, or emission standards, the carbon emission calculation module requires recalibration. Additionally, the model currently fails to account for dynamic disturbances like extreme weather or real-time traffic events. Future work will focus on developing parameter adaptive mechanisms to enhance the model's generalization capabilities across diverse urban environments and regulatory frameworks.

5 Conclusions

This paper proposes a green logistics path optimization method using the MOGWO algorithm to address carbon emissions and multi-objective coordination in e-commerce logistics. A refined logistics network model is built by including distribution centers, customer nodes, and path edges, with constraints such as transportation distance, time window, and vehicle capacity. A linear carbon emission model is established, with transportation costs and emissions as dual objectives. A penalty term handles conflicts between path constraints and time windows. The MOGWO algorithm balances economic and environmental goals through the leader wolf mechanism and dynamic Pareto set maintenance. Experimental results show MOGWO’s delivery costs for different order types and total transportation costs, with carbon emissions reduced by 28.1%–32.9%. The algorithm outperforms traditional ones in solution set balance and diversity. The study also highlights the impact of vehicle loading rate, order distribution density, and spatial structure on emissions and efficiency. The contributions include: (1) a multi-objective framework considering delivery efficiency and carbon reduction; (2) an accurate carbon emission estimation mechanism; (3) verification of MOGWO’s superiority in constrained path optimization. Future research can focus on real-time path optimization and multi-vehicle scheduling for green logistics.

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Authorship contribution statement

Zheng WEI: Writing-Original draft preparation, Conceptualization, Supervision, Project administration.

Author statement

The manuscript has been read and approved by all the authors, the requirements for authorship, as stated earlier in this document, have been met, and each author believes that the manuscript represents honest work.

Ethical approval

All authors have been personally and actively involved in substantial work leading to the paper, and will take public responsibility for its content.

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