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Logistics transportation path optimization based on priority theory and improved NSGA-II algorithm

Jin Zhang[1,*] and Yue Wang[2]

[1] School of Business Administration, Shanghai Urban Construction Vocational College, Shanghai, 201415, PR China
[2] School of Foreign Languages, East China Normal University, Shanghai, 200000, PR China

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Abstract. With the rapid increase in transportation vehicles, traffic congestion has become a major factor affecting logistics efficiency. To address this issue, this study introduces priority theory into logistics transportation scheduling. By considering factors such as urgency, importance, and customer satisfaction, transportation tasks are ranked and prioritized to identify optimal multi-objective path solutions in complex logistics environments. The Non-Dominated Sorting Genetic Algorithm II (NSGA-II) is enhanced through the integration of Simulated Binary Crossover and Gaussian Mutation to construct a logistics transportation path optimization model. Comparative experiments demonstrate that the proposed model achieves the lowest anti-generation distance (0.07) and distribution index (0.005) with stable convergence. In terms of on-time performance, the model maintains 100% punctuality within 30 days, outperforming comparison algorithms. Furthermore, its generation gap (0.010), distribution breadth (0.008), inverse generation gap (0.084), and hypervolume (0.978) closely match those obtained using Lingo software, indicating high accuracy and robustness. Experimental results confirm that the proposed optimization model effectively enhances logistics transportation efficiency by accurately determining optimal routes and demonstrates strong adaptability to complex and dynamic logistics conditions.

Keywords: NSGA-II algorithm / path optimization / priority / logistics transportation / elitism strategy

1 Introduction

Logistics transportation is an important support for the operation of modern social economy, and also an important link between production and consumption [1]. The path directly influences the cost and efficiency of logistics transportation. Reasonable path selection can greatly cut down transportation costs, improve transportation efficiency, enhance service quality, reduce environmental impact, and lower transportation risks [2,3]. However, existing path optimization methods suffer from high computational complexity and limited data processing capabilities. With the growth in demand for instant retail and emergency medical deliveries, daily order volumes can fluctuate by 30%–50%. Meanwhile, traditional dispatch models face increased order delays due to morning rush hour congestion in urban centers and time-to-delivery volatility on long-distance routes in rural areas. Logistics companies must meet multiple requirements—lowest cost, fastest delivery, and highest customer satisfaction—yet existing methods often focus on single objectives, limiting their applicability. Priority dispatch lacks scientific quantification, with most firms relying on manual experience to classify order urgency. This frequently delays high-priority orders (e.g., perishable food spoilage alerts, medical emergency supplies), resulting in elevated customer complaint rates. Therefore, the goal of reducing costs and increasing efficiency can be achieved by applying scientifically reasonable algorithms to optimize logistics transportation routes.

The Non-dominated Sorting Genetic Algorithm II (NSGA-II) has been broadly utilized for its efficient and accurate performance. For example, Wang X's team proposed a scheduling method based on an improved NSGA-II algorithm to address material delivery delays in workshops. By employing dynamic search to identify optimal solutions, the approach minimizes task duration. Experimental comparisons validated that this method effectively resolves scheduling deficiencies in timeliness, significantly enhancing task processing efficiency [4]. Manizadeh et al. investigated and modeled dual fuels in engines, establishing models with key variables such as engine speed and improved them through NSGA-II and

* Corresponding author: zhangj850810@163.coms

genetic algorithms. The results emphasized the crucial role of optimal parameters in balancing environment and economy [5]. To avoid the problem of local thermal discomfort, experts such as Bai Y used NSGA-II to optimize the human body local model and combined it with fuzzy comprehensive evaluation to enhance the method. The findings denoted that the optimized overall prediction average vote and local prediction average vote were cut down by an average of 54.8% and 58.8%, respectively, with a small difference in energy consumption [6].

In addition, setting and using priorities reasonably can significantly improve the response speed, resource utilization efficiency, and overall performance of the system. These characteristics have attracted many scholars to conduct research. For example, Geng Q et al. explored the choice of transportation for low-income groups and studied the construction of a transportation selection system based on priority theory. By analyzing the decision-making behavior of low-income groups in different travel scenarios, the priority of commuting plans can be obtained. The findings showed that low-income groups were influenced by personal risk preferences and had bounded rationality when making commuting decisions under uncertain conditions [7]. Bosse A et al. proposed a dynamic prioritization scheme addressing time-based differences and mechanisms in transportation services. This approach allocates shipments based on order urgency. Research indicates that the proposed scheme effectively integrates time constraints, increases revenue, and yields significant service improvements [8].

In summary, the NSGA-II algorithm is sensitive to parameter settings and has limited global search capabilities. It predominantly employs single-point crossover, which tends to disrupt the continuity of logistics path nodes and generate invalid solutions. The proposed approach, combining simulated binary crossover with Gaussian mutation, not only avoids path structure disruption and preserves high-quality path features but also enhances population diversity. This addresses the traditional algorithm's susceptibility to local optima and weak adaptability to dynamic scenarios. Therefore, by improving NSGA-II and integrating it with priority theory, a logistics transportation path optimization model (LTPOM) is constructed. The research aims to determine the optimal transportation route and distribution plan through scientific methods and algorithms, to achieve the goals of minimizing transportation costs, maximizing transportation efficiency, and optimizing service quality. The novelty of the research lies in improving the mutation and crossover operations of NSGA-II, accelerating the convergence speed of the population towards the Pareto front, and enhancing local search capabilities. The LTPOM is not only of great significance to logistics companies, but also has a positive impact on society and the environment.

2 Methods and materials

2.1 Path optimization model based on improved NSGA-II

Optimizing routes in logistics transportation can accelerate the flow of goods, reduce delays and unexpected situations during transportation, and improve the reliability and

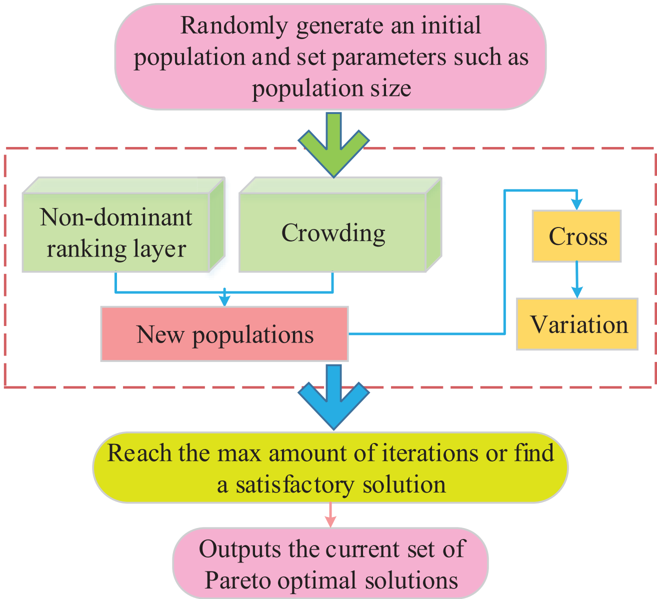


Fig. 1. Improved NSGA-II operating diagram.

stability of distribution. Although NSGA-II is widely used in logistics transportation path optimization, there is also a problem of easily falling into local optima [9,10]. Therefore, to further optimize the logistics transportation path, a path optimization model is obtained by improving its mutation and crossover operations, as shown in Figure 1.

As shown in Figure 1, firstly, a path is randomly generated, and the diversity of solutions is maintained through non-dominated sorting and congestion calculation. Then, partial crossover and Gaussian mutation operations are performed, and the optimal solution is selected according to the elitism strategy. When the termination condition is met, the optimized path is output [11,12]. When selecting individuals with the same non-dominated level during the operation, when two or more individuals have the same non dominated level, individuals with higher crowding values will be prioritized for selection, encouraging the population to evolve towards less crowded areas in the target space, thereby increasing the diversity of the population, as shown in equation (1).

$$\begin{cases} f_k^N(a) = \dfrac{f_k(a) - f_{k,min}}{f_{k,\max} - f_{k,min}} \\ E(a) = \displaystyle\sum_{k=1}^{K} w_k \cdot \dfrac{f_k(a+1) - f_k(a-1)}{f_{k,\max} - f_{k,min}} \end{cases}. \quad (1)$$

In equation (1), $f_k^N(a)$ denotes the normalized objective function value of the ath individual under the kth objective function, k represents the objective functions for cost, timeliness, and customer satisfaction, $E(a)$ indicates the weighted congestion level of the ath individual, and w_k signifies the weight of the kth objective function, $f_k(a+1)$ and $f_k(a-1)$ denote the OF values of the adjacent individuals of the ath individual under the kth OF, and $f_{k,\max}$ and $f_{k,\min}$ denote the max and mini OF values of all individuals under the kth OF, respectively. To increase the

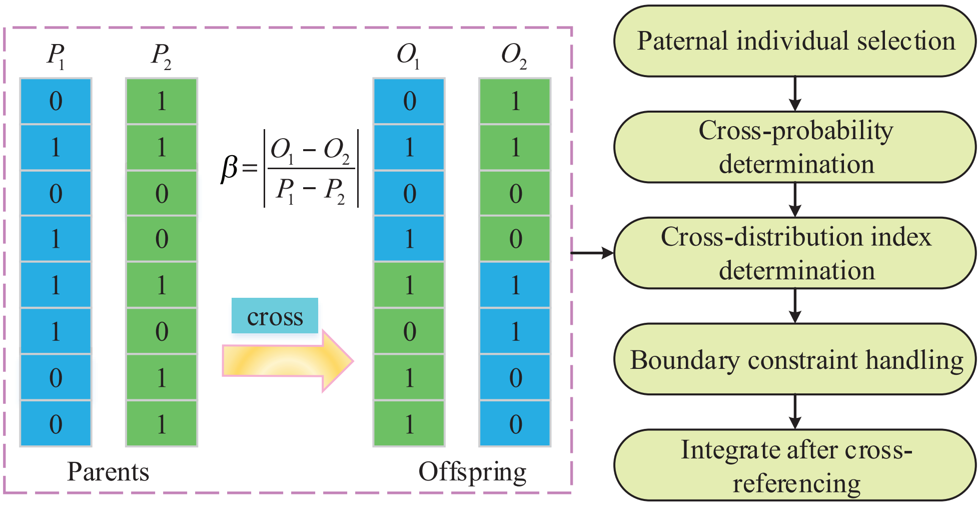


Fig. 2. Schematic diagram for simulated binary crossover.

diversity of the population and explore new solution space regions, simulated binary crossover operation is chosen, as shown in Figure 2.

As shown in Figure 2, simulated binary crossover controls the degree of gene exchange by generating a crossover distribution index β, thereby simulating the crossover behavior of binary bits between parental individuals. Then, the Gaussian operator is used for mutation operation to avoid falling into local optima, thereby improving the global search ability and convergence speed of the algorithm, as shown in equation (2).

$$L'_{aj} = L_{aj}\left(1 + \frac{1}{W} Gauss(1, W)\right). \tag{2}$$

In equation (2), L'_{aj} represents the position of the new gene in the chromosome after Gaussian mutation, L_{aj} represents the position of the jth gene in the population's ath individual in the chromosome, W refers to the amount of genes in the chromosome, $Gauss(1, W)$ means a Gaussian distribution. To ensure that the mutated gene values have both randomness and meet the requirements for selecting logistics transportation routes, further operations are carried out by rounding and rounding, as shown in equation (3).

$$L'_{aj} = \left(Round\left(L_{aj}\left(1 + \frac{1}{W} Gauss(1, W)\right)\right)\right)\%W. \tag{3}$$

In equation (3), $Round()$ is the rounding operation, rounding the calculation result to the nearest integer, and $\%W$ is the remainder operation, ensuring that the mutated gene value is within the valid range of the chromosome (i.e. between 1 and W). If the proportion of elite individuals is too low, high-quality path information from the parent generation (such as low-congestion, short-distance, and high-priority order-matched routes) will be lost. The model must then re-search the previously discovered optimal solution region, prolonging convergence time and failing to meet the time-sensitive requirements of dynamic logistics order adjustments. If the elite ratio is too high, the proportion of high-quality individuals in the population becomes excessive, suppressing the generation of new solutions. This causes the algorithm to become trapped in local optima (e.g., confined to a fixed route pattern, unable to adapt to dynamic scenarios like sudden traffic restrictions or last-minute order additions). Therefore, the study employs an elite retention strategy, as shown in Figure 3.

As shown in Figure 3, this strategy ensures that the optimal solution is not lost during the evolution process by retaining excellent individuals from both the parent and offspring [13,14]. In addition, the degree of dispersion or diversity of solutions in the multi-objective space is measured as denoted in equation (4).

$$d_m = min_n\left(\sum_{k=1}^{Y} |f_k^m - f_k^n|\right). \tag{4}$$

In equation (4), d_m denotes the minimum distance between the mth solution and the nearest solution to the true Pareto front, f_k^m is the function value of the mth solution on the kth OF, n is the nearest solution to the true Pareto front for comparison with other solutions, and Y denotes the total amount of OFs. The search performance and solution quality of the algorithm in the solution space are measured and compared, as shown in equation (5).

$$f_{GD} = \frac{\sqrt{\sum_{m=1}^{y} (d_m)^2}}{y}. \tag{5}$$

In equation (5), f_{GD} is a function of generation distance, and y is the number of Pareto optimal solutions. The search effectiveness of the algorithm in the solution space is evaluated, as shown in equation (6).

$$f_{SP} = \sqrt{\frac{\sum_{m=1}^{y} (\bar{d} - d_m)^2}{y - 1}}. \tag{6}$$

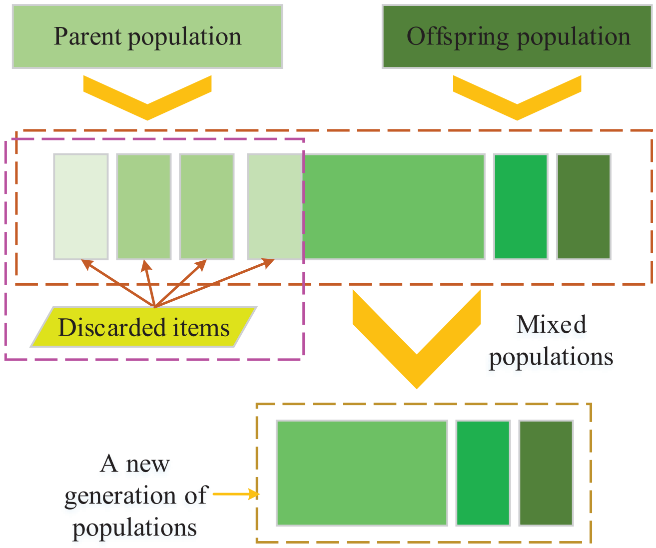


Fig. 3. Principle diagram of elite retention strategy.

In equation (6), d is the average value of all d_m, f_{SP} is the function expression of the distribution index, and the smaller the value of f_{SP}, the more uniform and extensive the distribution of the solution set in the target space, covering more of the target space. The distance between two solutions is calculated, as denoted in equation (7).

$$d\left(z^*, z\right) = \sqrt{\sum_{m=1}^{y} \left(z_m^* - z_m\right)^2}. \tag{7}$$

In equation (7), $d\left(z^*, z\right)$ denotes the minimum distance from the generated solution $d\left(z^*, z\right)$ to the real solution z, and z_m^* and z_m are the mth target values in the solution set, respectively. In addition, the search performance of the algorithm in the solution space is further evaluated, as shown in equation (8).

$$f_{IGD} = \frac{\sum_{m=1}^{|Z|} min_{m=1}^{|Z^*|} d\left(z^*, z\right)}{|Z|}. \tag{8}$$

In equation (8), f_{IGD} is a function expression of the inverse generation distance, and $|Z|$ denotes the amount of solutions in the true Pareto frontier solution set. Additionally, the model's time complexity O is as shown in equation (9).

$$O = O\left(T \cdot N^2 K + T \cdot NW\right). \tag{9}$$

In equation (9), T represents the iteration count. The "≤1 min emergency update" requirement specifies that the iteration count should fall between 150 and 250 to avoid exceeding the time limit due to excessive iterations or insufficient convergence accuracy due to too few iterations. N denotes the population size. By evaluating the search performance in the solution space, it ensures that the algorithm can not only find high-quality solutions, but also evenly distribute these solutions in the solution space, thereby better exploring and utilizing the entire solution space. The improved NSGA-II significantly improves convergence speed and resolution quality, thereby achieving path optimization.

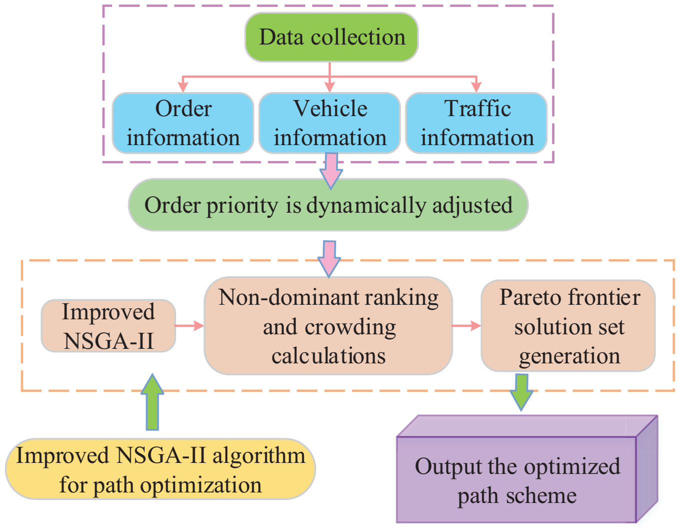


Fig. 4. Flow chart of logistics and transportation path optimization model.

2.2 A logistics transportation route optimization model integrating priority theory and improved NSGA-II

The path optimization model based on the improved NSGA-II algorithm can generate low-cost, high-efficiency logistics route solutions in static scenarios. However, in real-world logistics transportation, orders are not fixed but dynamically change due to factors such as urgent customer demands, unexpected traffic conditions, and last-minute order additions. A static model that relies solely on algorithmic path optimization cannot swiftly respond to dynamic order adjustments, often leading to order delays and imbalanced resource allocation. Therefore, by applying priority theory to classify and rank dynamically changing orders, the algorithm prioritizes fulfilling high-value, high-urgency order demands during path optimization. This enables more rational allocation of logistics resources and enhances resource utilization efficiency, thereby constructing a dynamic optimization model that better aligns with real-world logistics transportation, as shown in Figure 4.

As shown in Figure 4, the process begins by collecting order, vehicle, and traffic information. Based on the collected information, the priority of orders is dynamically adjusted. Then, the improved NSGA-II is used for path optimization, including non-domination sorting, congestion calculation, and Pareto front solution set generation. Finally, the optimized path plan is output [15,16]. Based on real-time urban traffic data and the typical order response update frequency in the logistics industry, the study sets the order priority update cycle to 15 min. Critical events such as sudden traffic status changes, new high-urgency orders, or vehicle anomalies trigger instant updates within ≤1 min, bypassing the base cycle. Additionally, load constraints require the total weight of orders per vehicle to be $\leq$0.95 times the vehicle's rated load capacity. Overloaded orders are split, with high-priority orders retained while remaining cargo's priority is downgraded. Flow constraints limit logistics vehicles per unit time on road segments to $\leq$70% of segment saturation flow (120 vehicles/hour for single-lane one-way roads, 220 for dual-lane, 300 for triple-lane) and concurrent vehicle counts within zones (80 in urban cores, 50 in urban-rural fringes, 30 in rural areas). From the Pareto frontier solution set generated by the improved NSGA-II algorithm, exclude path schemes that violate load capacity and flow rate constraints, retaining only feasible solutions. If the number of feasible solutions is zero, trigger one additional iteration to generate a new solution set. The commonly used analytic hierarchy process primarily relies on subjective judgment, making it difficult to update in real time and prone to misjudging urgent orders. In contrast, the entropy weight method relies on objective metric data, allowing for rapid recalculation after data updates, making it highly practical. Therefore, the study quantifies the relevant metrics of orders, the priority of orders is displayed, and the corresponding paths are selected for transportation, as shown in equation (10).

$$H = \{h_1, h_2, \cdots, h_i, \cdots, h_p\}. \tag{10}$$

In equation (10), H means the set of evaluation indicators, h_i means the ith evaluation indicator, and p means the total amount of evaluation indicators. By quantifying the degree of evaluation of orders and evaluating the different evaluation levels that orders may achieve under various evaluation indicators, the abstract is transformed into specific indicators, as shown in equation (11).

$$U = \{u_1, u_2, \cdots, u_l, \cdots, u_t\}. \tag{11}$$

In equation (11), U is the set of evaluation levels, u_l is the lth evaluation level, and t is the total amount of evaluation results. In addition, to display the degree of evaluation indicators under the corresponding evaluation results, the qualitative evaluation results are transformed into quantitative evaluation results through a fuzzy judgment matrix, as shown in equation (12).

$$Q = \begin{bmatrix} q_{11} & q_{12} & \cdots & q_{1t} \\ q_{21} & q_{21} & \cdots & q_{2t} \\ \cdots & \cdots & \cdots & \cdots \\ q_{p1} & q_{p2} & \cdots & q_{pt} \end{bmatrix}. \tag{12}$$

In equation (12), Q is the fuzzy judgment matrix, and q_{pt} is the membership degree of the pth evaluation index to the tth evaluation level, with a value between 0 and 1. The priority of logistics transportation orders is influenced by various factors, as shown in Figure 5.

As shown in Figure 5, the priority of logistics transportation orders is influenced by multiple factors, which are divided into two categories: social value and economic value. Social value encompasses the delivery of urgent medical supplies and the transportation of emergency disaster relief materials (both factors relate to public safety and social stability, carrying higher priority weighting). Economic value includes the transport of high-value goods, orders from

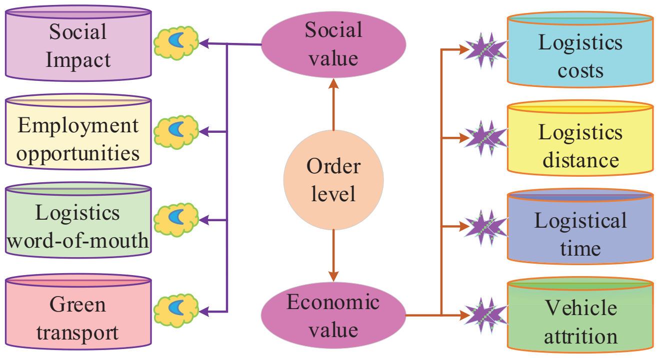


Fig. 5. Classification chart of influencing factors of order level.

long-term cooperative clients, and time-sensitive fresh produce orders (these three factors directly impact corporate revenue and customer retention). These factors collectively determine the priority of orders, that is, when logistics companies handle multiple orders, they will determine which order should be prioritized based on these factors. Due to the varying degrees of importance of various factors affecting logistics transportation orders, weights are assigned to each factor as shown in equation (13).

$$\omega = \{\omega_1, \omega_2, \cdots, \omega_r\}. \tag{13}$$

In equation (13), ω is the weight vector, and ω_r denotes the weight corresponding to the rth evaluation indicator. The weights assigned to each indicator reflect its relative importance in the overall evaluation. These weights are determined based on the principle of information entropy (IE), where the entropy values of each indicator are calculated to determine its weight, as shown in equation (14) [17].

$$P_{il} = \frac{x_{il}}{\sum_{i=1}^{p} x_{il}}. \tag{14}$$

In equation (14), P_{il} represents the proportion of indicators, and x_{il} represents the score of the ith evaluation indicator on the lth evaluation level. Then, calculate the information entropy e_l for each order evaluation metric. A smaller entropy value indicates greater variation in that metric across different order samples, signifying a higher effective contribution to distinguishing order priorities. Conversely, a larger entropy value indicates a lower contribution. Therefore, by constructing a metric that directly reflects contribution based on information entropy, we calculate the entropy value for each metric to objectively determine their respective weights, thereby avoiding subjective bias, as shown in equation (15).

$$\begin{cases} e_l = -g\sum_{l=1}^{p}(P_{il}(\ln P_{il})) \\ g = \dfrac{1}{\ln(t)} \end{cases}. \tag{15}$$

In equation (15), e_l is the IE of the lth indicator, and g is the corresponding adjustment coefficient. The smaller the

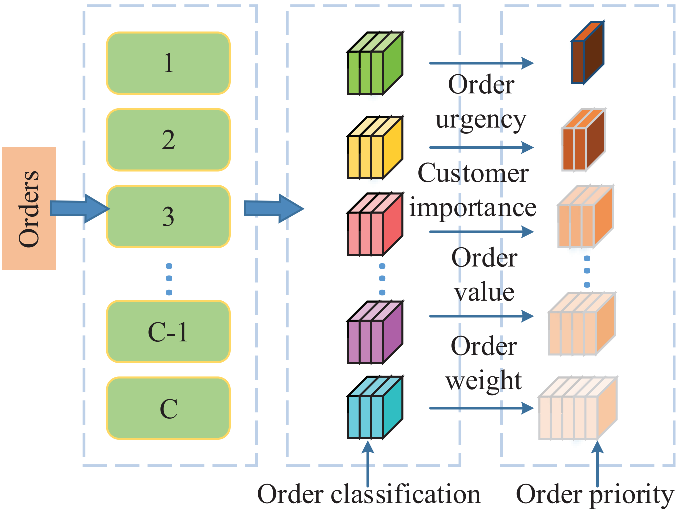


Fig. 6. Schematic diagram of order priority.

e_l, the greater the difference in the lth indicator and the more information it provides. The weights of the evaluation indicators sre further determined, as shown in equation (16).

$$d_l = 1 - e_l. \tag{16}$$

In equation (16), d_l represents the IE redundancy of the lth indicator, which is the proportion of the effective information content of that indicator to the total information content. The larger the d_l, the more important the indicator is in the evaluation. Therefore, the calculation formula for the weight of evaluation indicators is denoted in equation (17).

$$\omega_l = \frac{d_l}{\sum_{l=1}^{p} d_l}. \tag{17}$$

In equation (17), ω_l denotes the weight corresponding to the lth evaluation indicator. The greater the weight, the higher the importance of the indicator in the evaluation. In summary, the fuzzy membership degree is transformed into specific scores, and each order is quantitatively evaluated as shown in equation (18).

$$\begin{cases} \lambda = \omega * Q * Z^T \\ Z = \{10, 7, 5, 3, 1\} \end{cases}. \tag{18}$$

In equation (18), λ is the total score for each order, and Z^T is the score corresponding to each evaluation level. Therefore, by scoring logistics orders, their priority can be determined, as shown in Figure 6.

From Figure 6, by scoring logistics transportation orders (The evaluation scale is set at 100 points, with 90–100 points indicating extremely high priority, 80–90 points indicating high priority, 60–80 points indicating medium priority, and 0–60 points indicating low priority), determining their priority, and selecting routes for logistics transportation based on the preferred level, a reasonable arrangement of transportation routes can be achieved, further realizing path optimization. Therefore, by combining priority theory with an improved NSGA-II optimization model, logistics transportation routes can obtain more efficient and comprehensive solutions.

3 Results

3.1 Performance testing of LTPOM

To verify the performance of the LTPOM based on the fusion priority theory and the improved NSGA-II, a comparative experiment was conducted between the LTPOM based on Multi-Objective Evolutionary Algorithms (MOEAs), NSGA-II, Non-dominated Sorting Genetic Algorithm III (NSGA-III), and Strength Pareto Evolutionary Algorithm 2 (SPEA2) and the optimization model proposed in the study. Sample selection covers three typical logistics scenarios: urban core areas (e.g., office clusters, large shopping mall concentrations), urban-rural fringe zones (industrial parks, small logistics hubs), and rural regions (township/village clusters, agricultural production and distribution bases). Samples are balanced across scenarios (1:1:1) and include orders with varying priority levels. The urban core area comprises 280 nodes (35% office clusters, 25% commercial complexes, 40% residential communities), with congestion coefficients ranging from 0.8 to 2.5, road speed limits between 30–60 km/h, and segment lengths of 0.3–2.8 km. The urban-rural fringe area contains 150 nodes (40% industrial parks, 20% logistics hubs, 40% township communities), with congestion coefficients ranging from 0.6 to 1.8, road speed limits of 40–80 km/h, and segment lengths of 1.2–5.5 km; Rural areas include 90 nodes (60% village clusters, 30% agricultural production and distribution bases, 10% township service centers), congestion factor 0.5–1.2, road speed limit 30–60 km/h, segment length 2.5–12.8 km. The experimental server features an Intel Core i7-12700H CPU, 16 GB of DDR5 memory (4800 MHz frequency), and an NVMe SSD (1 TB capacity, with read/write speeds of 3500 MB/s and 3000 MB/s respectively). Additionally, three logistics dispatch experts were invited to evaluate the route proposals generated by each model on an intuitive scale (1–5 points, where 5 indicates the most intuitive). The average scores were calculated. Furthermore, the average values of Generation Distance (GD), Spread Performance evaluation (SP), Inverted Generational Distance (IGD), and Hypervolume (HV) of the model were tested in 30 samples, as denoted in Table 1.

According to Table 1, among the five models, the GD, SP, and IGD of the proposed LTPOM were the smallest, with values of 0.010, 0.008, and 0.084, respectively; Its HV was the highest, at 0.978, and its performance metrics are comparable to those obtained using Lingo software. The GD, SP, and IGD of the LTPOM based on NSGA-II were all smaller than those based on NSGA-II, and the HV was also larger. The LTPOM based on SPEA2 had moderate indicators, high HV, but high GD and IGD. The LTPOM based on NSGA-II had larger GD, SP, and IGD, and smaller HV. The HV of the LTPOM based on MOEAs was extremely low, and the GD, SP, and IGD were also high,

Table 1. Comparison of performance indicators of models.

Model	GD	SP	IGD	HV	Rating
Research proposes	0.010	0.008	0.084	0.978	4.2
NSGA-II	0.032	0.015	0.173	0.659	2.8
NSGA-III	0.016	0.010	0.097	0.826	3.5
MOEAs	0.019	0.020	0.190	0.019	2.5
SPEA2	0.017	0.019	0.187	0.709	3.0
Lingo	0.007	0.004	0.056	0.996	/

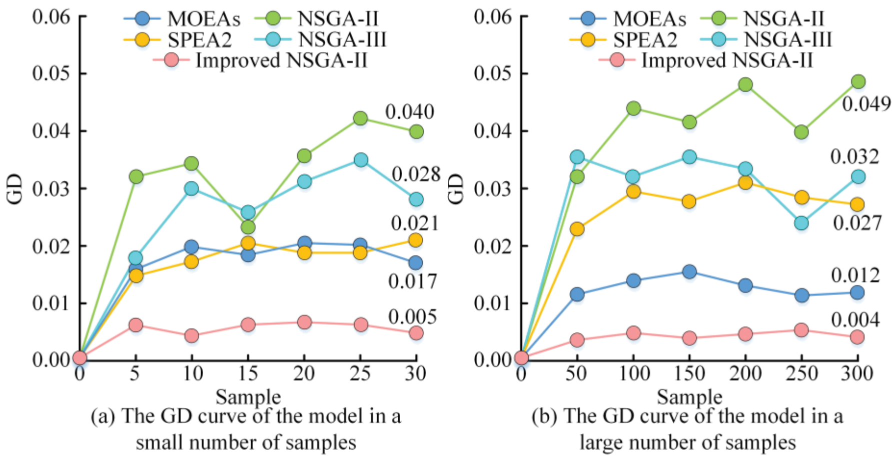


Fig. 7. GD curves of the model.

resulting in the weakest overall performance. The comparative findings denoted that the LTPOM performed better than other models in all indicators, exhibiting stronger convergence, distribution, and comprehensive optimization capabilities. To investigate the convergence of the fusion priority theory and the improved NSGA-II LTPOM, experiments were conducted on 30 (non-peak hours) and 300 (morning and evening rush hours) samples respectively to test the GD of different LTPOMs in samples of different sizes, as shown in Figure 7.

In Figure 7a, the GD values of various LTPOMs were generally high, among which the GD curve of the proposed optimization model fluctuated less, and the GD value was always the lowest, fluctuating at GD=0.005 overall; The GD curves based on MOEAs and SPEA2 LTPOMs were close and have small fluctuations; The GD curve of the LTPOM based on NSGA-III fluctuated greatly, with a maximum GD of 0.035; The GD curve of the LTPOM based on NSGA-II fluctuated sharply and showed an overall upward trend, with a maximum GD of 0.042. In Figure 7b, the GD values of each LTPOM decreased, and the GD curve of the proposed optimization model fluctuated less. The GD value was always the lowest, fluctuating at GD=0.003 overall. The GD curve of the LTPOM based on MOEAs fluctuated slightly, with an overall fluctuation at GD=0.011. The GD curves of the LTPOM based on NSGA-III and the optimization model based on SPEA2 intersected and fluctuated greatly, with maximum GDs of 0.036 and 0.030, respectively. The GD curve of the LTPOM based on NSGA-II fluctuated sharply and showed an overall upward trend, with a maximum GD of 0.048. The experiment showed that the proposed optimization model exhibited the best convergence under different sample sizes. In addition, to verify the coverage of the fusion priority theory and the improved NSGA-II LTPOM, comparative experiments were conducted on different sample sizes (Off-peak and Rush Hour) to further explore the HV of different models, as shown in Figure 8.

In Figure 8a, the HV values of various LTPOMs were generally low, and the HV value of the proposed optimization model was always the highest, approaching or reaching 1.00. The HV value of the optimization model based on MOEAs was always the lowest, and the overall HV curve fluctuated at HV=0.10. In Figure 8b, the HV values of each LTPOM were improved, and the HV value of the proposed optimization model remained the highest with minimal fluctuations. The HV value of the optimization model based on MOEAs was always the lowest, and the overall HV curve fluctuated at HV=0.05. The data showed that the proposed optimization model had the highest solution set quality and wide coverage area under different sample sizes.

3.2 Application effect analysis of LTPOM

To verify the performance of the fusion priority theory and the improved NSGA-II LTPOM in practical applications, the study uses a logistics company as an example. This

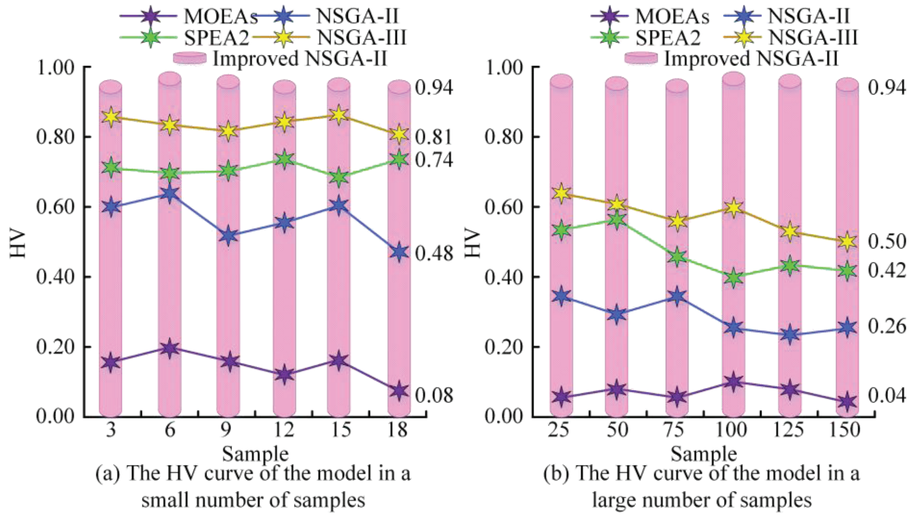


Fig. 8. HV curves of the model.

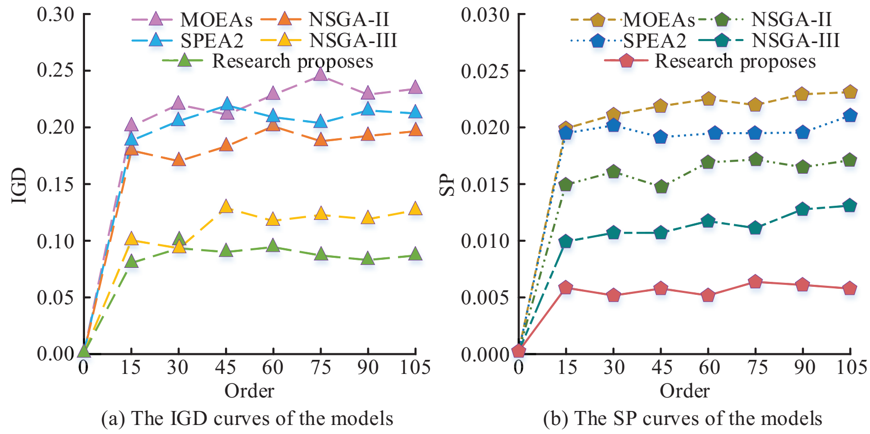
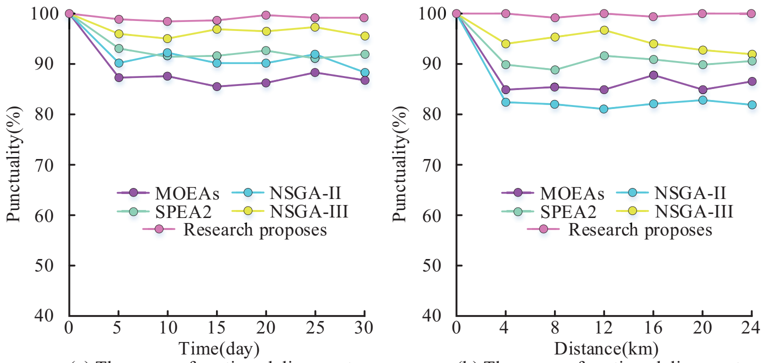


Fig. 9. Performance comparison of models under different orders.

company operates six delivery vehicles, handles an average of 18 to 22 orders per day, and processes approximately 550 orders per month. Its service radius spans 50 kilometers, covering 280 nodes, and it employs 12 staff members. The company tested the performance metrics of 105 orders in LTPOMs based on MOEA, NSGA-II, NSGA-III, and SPEA2, as denoted in Figure 9.

In Figure 9a, the IGD value of the proposed LTPOM was always the lowest, and the IGD curve was relatively flat, fluctuating overall at IGD=0.07. The IGD value of the optimization model based on NSGA-III and SPEA2 was slightly higher than the optimization model proposed in the study, but still better than the optimization model based on NSGA-II and MOEAs. In Figure 9b, the SP value of the proposed LTPOM was always the lowest, and the overall SP curve fluctuated at SP=0.005. The SP value of the optimization model based on NSGA-II and MOEAs was relatively high. The experiment showed that the IGD and SP curves of all models showed an overall upward trend, but the optimized model proposed by the study had the slowest upward trend, indicating that it exhibited the best convergence and distribution under different order quantities. To verify the effectiveness of the fusion priority theory and the improved NSGA-II LTPOM in practical applications, LTPOMs based on MOEA, NSGA-II, NSGA-III, and SPEA2 were used to explore the on-time performance of the logistics company within 30 days and at different distances, as shown in Figure 10.

In Figure 10a, the on-time rate curve of the proposed optimization model was always at the top, with the highest order on-time rate within 30 days, and the curve fluctuated at 100%. The on-time curves of these two optimization models based on NSGA-II and MOEAs were generally lower than other models, especially performing poorly between days 10–20. In Figure 10b, as the delivery distance increased, the on-time performance of all models decreased,



(a) The curve of on-time delivery rate for orders

(b) The curve of on-time delivery rate for orders

Fig. 10. Timeliness curves of the model at different times and distances.

Table 2. Profit comparison of models.

Model	Labor cost		Vehicle cost		Time		Hourly profit	
	100	150	100	150	100	150	100	150
Research proposes	1698.12	2100.20	1183.56	1650.80	3.20	4.80	974.48	1093.54
NSGA-II	2977.02	3500.50	1489.26	1800.30	5.61	7.36	273.39	502.61
NSGA-III	2419.82	2800.60	1291.33	1550.20	4.56	6.45	501.94	720.81
MOEAs	2913.34	3300.40	1359.81	1700.50	5.49	7.28	314.54	549.33
SPEA2	2520.65	2900.30	1297.59	1600.40	4.75	6.71	459.31	670.54

but the optimized model proposed by the study had the smallest decrease and always maintained the highest on-time performance. The on-time performance of the optimization models based on NSGA-III and SPEA2 was slightly lower than that of the proposed optimization model, but still outperformed the optimization models based on NSGA-II and MOEAs in most days and distances. Comparison showed that the proposed optimization model exhibited the highest order punctuality rate under different time and distance conditions, indicating that it has stronger robustness, adaptability, and practicality in actual logistics scheduling. To further explore the practical value of LTPOMs, comparisons were carried out on LTPOMs in the same order, the testing model calculated the fixed costs (RMB) (including delivery personnel and driver fixed wages, insurance fees, etc.), variable costs (yuan) (including vehicle fuel expenses, temporary repair costs, etc.), time (h), and profit (yuan/h) for completing 100 orders and 150 orders (a sudden 50% increase in orders), as shown in Table 2.

According to Table 2, for the same order, the optimization model proposed by the research institute achieved the shortest completion times of 3.20 h and 4.80 h, respectively; other models took between 4.56 and 7.36 h. Additionally, the optimization model proposed by the research institute achieved the lowest total costs of 2,881.68 yuan and 3,751.00 yuan, respectively, while generating the highest profits of 974.48 yuan/h and 1,093.54 yuan/h. The data showed that the proposed optimization model could complete order tasks more efficiently and quickly in path planning and scheduling, and was also more economical in path selection.

4 Discussion

The research aimed to improve and optimize the NSGA-II, further integrated priority theory, and ultimately constructed an LTPOM. By conducting comparative experiments on the proposed LTPOM, more accurate experimental results were obtained, and a deeper exploration was conducted on it. The GD, SP, IGD, and HV of the proposed optimization model were 0.010, 0.008, 0.084, and 0.978, respectively. All performance indicators were superior to other comparative models and met the optimization conditions for logistics transportation paths. At the same time, the IGD and SP values of the proposed LTPOM were always the lowest, and the curves were relatively flat, fluctuating at IGD=0.07 and SP=0.005 respectively. Compared with other models, the curve of the proposed optimization model had the slowest upward trend. The findings denoted that the LTPOM had significant performance. However, there is still a problem of high computational complexity in optimizing the model. Zhao et al. connected features from two-dimensional and three-dimensional domains and further integrated these features through a shared Multi-Layer Perceptron (MLP) to solve the problem of ineffective improvement in segmentation accuracy. This provided a new approach for optimizing LTPOMs, by utilizing MLP for integration, thereby improving the learning ability and segmentation accuracy of complex scene analysis [18]. Expert Pacal I developed a new hybrid shift Windows multi-head self attention module and rescaled model using residual-based MLP. By applying transfer learning and data augmentation techniques, efficient and robust training could be achieved, which can improve model performance. Therefore, it is considered to introduce MLP to optimize the model, thereby improving accuracy, training speed, and parameter efficiency [19]. In addition, Lin F et al. proposed a grafted eXtreme gradient boosting model framework that can integrate a large amount of aerodynamic data obtained from computational fluid dynamics with a small amount of aerodynamic data obtained from flight tests to obtain more accurate aerodynamic data at low cost. Research showed that the eXtreme gradient boosting method performed well in processing large-scale datasets, which can be used to optimize the model and minimize computational complexity [20]. In summary, the integration of priority theory and the improved NSGA-II LTPOM has broad application prospects and research value.

5 Conclusion

In response to the sensitivity of existing logistics transportation path models to parameters and the tendency to fall into local optima, this study combines priority theory with the improved NSGA-II to construct an LTPOM. Comparative experiments showed that the GD, SP, and IGD of the proposed LTPOM were the smallest, with values of 0.010, 0.008, and 0.084, respectively. Its HV was the highest, at 0.978. Experimental tests were conducted on LTPOMs based on MOEA, NSGA-II, NSGA-III, and SPEA2 to achieve performance indicators for 105 orders. The findings showed that the IGD value of the proposed optimization model was consistently the lowest, and the IGD curve was relatively flat, fluctuating at IGD=0.07 overall. The SP value of the proposed optimization model was always the lowest, and the SP curve was relatively flat, fluctuating overall at SP=0.005. At the same time, experimental tests were conducted on the on-time performance of the model for orders at different times and distances. The findings showed that the on-time performance curve of the research-proposed optimized model always remained at the top, with slight fluctuations at 100% as time increased. As the delivery distance increased, the on-time curve of the proposed optimization model showed a minimal decrease, and the curve still fluctuated at 100%. In addition, comparisons were conducted on LTPOMs in the same order. The results denoted that the proposed optimization model had the shortest completion time of 3.20 h, the lowest total cost of 2881.68 yuan, and the highest profit of 974.48 yuan/h in the same order. The findings demonstrated that the proposed optimization model had significant performance, strong applicability, and high practical value. However, the calculation of the optimization model is relatively complex, and the testing experiments of the optimization model are not comprehensive enough. The experiments did not consider the influence of various environmental factors. Future research can improve the practicality and efficiency of the optimization model by addressing the shortcomings.

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Conflicts of interest

All authors declare that they have no conflicts of interest.

Data availability statement

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Author contribution statement

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Jin Zhang and Yue Wang. The first draft of the manuscript was written by Jin Zhang, manuscript review and revison were performed by Yue Wang and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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