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Multi-Objective Path Planning Strategy for Fresh E-Commerce Warehouse Based on Improved NSGA-II

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Abstract: Traditional single-objective route planning struggles to meet modern demands in fresh food e-commerce due to advancements in AI and rising economic expectations. To address this, this study proposes a multi-objective path planning model that balances delivery time and product freshness, aiming to reduce costs and improve punctuality. A solution model integrating chaotic sequences and an enhanced Fast Non-Dominated Sorting Genetic Algorithm II (NSGA-II) is developed to minimize operational expenses and enhance customer satisfaction. Results showed the improved algorithm achieved fitness values of 0.16 (training set) and 0.14 (test set), confirming its effectiveness for multi-objective path planning. In cost optimization, it converged to a lower level within 150 iterations, outperforming the standard NSGA-II. For customer satisfaction, it stabilized at 0.71 after ~200 iterations. The multi-objective model yielded a total cost of 11,592.25 and an average satisfaction of 0.84, improving cost efficiency by 0.60% and satisfaction by 6.33% over single-objective models (cost-only or satisfaction-only). In a practical application, adopting Scheme D met cost targets while exceeding industry satisfaction benchmarks. Compared to traditional methods, maximum delivery distance decreased by 22%, and overtime orders dropped by 10%. These findings demonstrate that the proposed approach effectively optimizes fresh food e-commerce logistics, supporting business growth while reducing operational costs.

Keywords: NSGA-II; fresh food e-commerce; multi-objective; path planning; average customer satisfaction; chaotic sequences.

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1. Introduction

In the current era of rapid development in Electronic Commerce (EC), Fresh Food Electronic Commerce (FFEC) is an important branch with enormous market potential (Wang et al., 2024; Li et al., 2023; Zhu and Zhou, 2023). Consumers' demand for delivery time and the freshness of fresh products is increasing day by day, and enterprises need to achieve maximum operational efficiency while meeting this demand. This contradiction motivates the transition from Single-Objective (SO) to Multi-Objective (MO) path planning in e-commerce warehouses (Feng et al., 2023; Prajapati et al., 2023; Zhang et al., 2023).

Guan et al. (2022) proposed a hybrid machine learning model to analyze online evaluations and identify factors that affect Customer Satisfaction (CS) in fresh-produce EC. Platform, product, logistics, and pandemic variables significantly impact CS, with logistics being the most influential. Hai et al. (2023) explored the coordination of a second-tier fresh produce EC Supply Chain (SC) (FFEC firms and suppliers) via a new framework to enhance performance and competitiveness. Under specific parameters, the contract achieves Pareto optimization. Xiong et al. (2021) presented path processing and tracking methods to address the A algorithm's limitations (ignoring vehicle contours, unsmooth paths, lack of speed planning), improving its suitability for vehicle planning. Oubbati et al. (2020) proposed a novel three-tier SDN-based vehicle path-planning architecture (addressing the neglect of traffic dynamics), enabling optimal navigation, real-time traffic collection, and enhanced situational awareness in urban roads. Li et al. (2022) developed a pseudo-random sampling strategy (based on major spatial axes) to solve inefficient path planning and low roadmap reuse. The improved PRM algorithm outperformed conventional PRM algorithms in both speed and path length. Monoarfa et al. (2024) examined the role of e-logistics service quality in FFEC's sustained purchase intentions, identifying it as a key determinant of consumer acceptance. Kong et al. (2023) analyzed FFEC's SC (upstream shipping, midstream cold chain, downstream retail) to enhance the competitiveness of the fresh food SC, providing a basis for SC improvement and innovative retail formats. Li (2023) proposed an IoT-based dynamic path optimization model for EC logistics. Its optimal solution had a minimum cost of $41,224 and a total distribution distance of 9035 km, ensuring market stability and industry development.

In summary, even though the present study on logistics path planning and FFEC distribution has yielded some results, there are still flaws. Some algorithms have limitations. For example, Algorithm A does not consider the vehicle contour, resulting in an uneven path and poor speed planning. Some algorithms have low efficiency, low roadmap reuse rates, and lack guidance on sampling point selection. On the other hand, in certain scenarios, environmental factors must be fully considered. However, existing methods are inadequate for dealing with these complex situations. In addition, effective MO path planning solutions are lacking for problems such as simultaneous arrival at a fixed time. Based on this, to reduce delivery costs and improve on-time delivery, the study proposes an MOPPM that considers delivery time and product freshness. The solution model for FFEC warehouse planning includes an enhanced Fast Non-Dominated Sorting Genetic Algorithm II (NSGA-II) and chaotic sequences. This model considers two goals: increasing average CS and lowering Total Cost (TC). The goal of this study is to develop an MO routing model for fresh-food e-commerce warehouses that accounts for delivery time and product freshness. The study proposes an improved NSGA-II algorithm that incorporates chaotic sequences to optimize the balance between minimizing total enterprise costs and maximizing CS. Key contributions include: ① An innovative routing model addressing dual objectives and fresh product characteristics, overcoming the limitations of SO models. ② An enhanced NSGA-Ⅱ algorithm featuring chaotic sequence initialization and stochastic segment quadratic exchange crossover to improve optimization efficiency and stability. ③ Practical routing optimization solutions for fresh food e-commerce enterprises, validated through multi-scenario experiments and case studies.

2. Methods and Materials

2.1. MOPPM Construction for FFEC Warehouse

In the traditional central warehouse model, fresh commodities are stored remotely and distributed via the cold chain after orders are placed, which fails to respond to customer demand in a timely manner. The front warehouse model locates warehouses near consumers and uses intelligent technology to predict demand and stock products in advance. This model shortens distribution distance, ensures product quality, and improves customer satisfaction. However, immature operations lead to high costs and poor timeliness (Liu et al., 2024; Wang et al., 2023; Zhu et al., 2023). To address this, the study proposes an MOPPM considering delivery time and commodity freshness. Its Objective Function (OF) is comprehensive and forward-looking. It is not limited to a single dimension; rather, it seeks to maximize the average CS score while minimizing the enterprise’s Total Cost (TC). The mathematical expression for costs in fresh front warehouse operations is given by Eq. (1).

$$\begin{cases} C_1 = \sum_{i=1}^{m} \left(C_{i1} + C_{i2} \right) y_i \\ C_2 = \mathrm{C_T} \sum_{i=1}^{m} \sum_{j=1}^{n} \sum_{k=1}^{K} x_{ijk} d_{ij} \\ C_3 = \mathrm{C_V} \sum_{i=1}^{m} \sum_{j=1}^{n} \sum_{k=1}^{K} x_{ijk} \\ F_1 = C_1 + C_2 + C_3 \end{cases} \tag{1}$$

In Eq. (1), F_1 denotes the TC. i denotes FFEC front warehouse. C_{i1} and C_{i2} denote its site selection cost and operation cost, respectively. y_i denotes its decision variable. C_2 denotes the vehicle transportation cost. $\mathrm{C_T}$ denotes vehicle unit transportation cost. k denotes the transportation vehicle. j denotes the customer. x_{ijk} denotes the decision variable of vehicle transportation cost and vehicle usage cost. C_3 denotes vehicle usage cost. $\mathrm{C_V}$ denotes vehicle fixed cost. Among them, C_{i1} denotes fixed expenditures for the front-loading warehouse of fresh produce. These expenditures include site leasing and renovation costs, which are calculated as the product of the region's average commercial real estate rent and the warehouse's area. C_{i2} covers depreciation of storage equipment, personnel salaries, and cold chain energy consumption, with the calculation Eq. (2) based on industry experience.

$$C_{2i} = k_d \times C_{1i} + s \times M \tag{2}$$

In Eq. (2), k_d denotes the depreciation coefficient of industry warehousing equipment. s represents employee salaries. M indicates the number of warehouse staff. C_2 consists of transportation and operational costs. C_3 represents the annual cost allocation for vehicle acquisition and insurance, set at 30,000 yuan per vehicle per year. When converted based on average daily usage frequency and combined with transportation costs, this yields the total distribution cost. The trapezoidal segmented satisfaction function is chosen to represent time satisfaction in this study. In the context of fresh food delivery, the trapezoidal segmented function is a sound theoretical and practical model for representing time satisfaction. From a practical standpoint, customers have clear expectations about how long it will take to receive fresh products. Within the optimal delivery window, CS peaks align with their psychological expectation of timely receipt of fresh items. Satisfaction gradually declines when deliveries occur too early or too late. The trapezoidal function accurately depicts this fluctuating trend (Gao et al., 2023). Fig. 1 illustrates the connection between vehicle arrival time and client satisfaction.

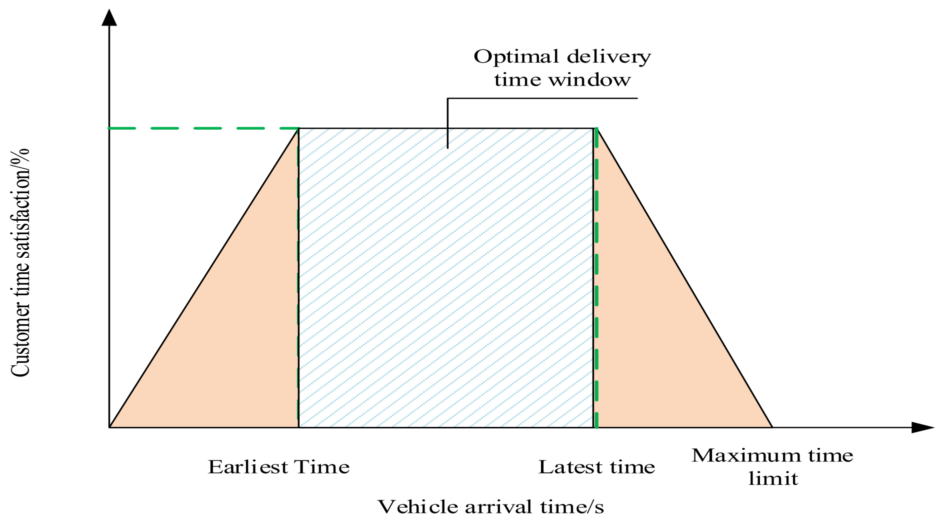


Fig. 1. Schematic of the relationship between CS and vehicle arrival time

In Fig. 1, there exists an optimal delivery time window. CS is highest within this window. CS declines if the car comes too early (before the earliest time) or too late (beyond the latest time). It varies in a trapezoidal pattern. When the arrival time exceeds the maximum time limit, CS drops to zero. This relationship reflects customers' expectations for fresh delivery times. Timely delivery ensures product freshness and enhances customer experience. From this, an expression for the time satisfaction function f_1 can be obtained, as shown in Eq. (3).

$$f_1\left(t_j\right) = \begin{cases} t_j / E_j, & 0 < t_j < E_j \\ 1, & E_j \le t_j \le L_j \\ \left(R_j - t_j\right) / \left(R_j - L_j\right), & L_j < t_j \le R_j \\ 0, & t_j > R_j \end{cases} \tag{3}$$

In Eq. (3), E_j and L_j display the earliest and latest times in the optimal delivery time window, respectively. R_j denotes the maximum time the customer will tolerate. In fresh-product delivery, the quality of goods decreases as time increases. The study expresses its change in terms of the freshness function f_2. The freshness function uses an exponential decay model, as shown in Eq. (4).

$$f_2(t) = e^{-kt} \tag{3}$$

In Eq. (4), t denotes delivery time (minutes), while k represents the spoilage coefficient determined by product category of 0.002 for vegetables, 0.005 for meat, and 0.008 for aquatic products. These values are derived from experimental data that meet the shelf-life specifications for different categories in the Technical Specifications for Fresh Agricultural Products Cold Chain Logistics (GB/T 31080-2014). The freshness satisfaction threshold is set at 0.3, established through post-sale data analysis from enterprises. During the study, by combining the factors covered by the f_1 function and the f_2 function, it is possible to successfully derive the average satisfaction function F_2 about the customers, as shown in Eq. (5).

$$F_2 = \frac{1}{n}\sum_{j=1}^{n} \lambda f_1\left(t_j\right) + (1-\lambda) f_2\left(t_j\right) \tag{5}$$

In Eq. (5), λ denotes the time satisfaction weight, which takes the value of 0.5 in this study. n denotes the number of customers. Through the above content study, to get the FFEC warehouse MOPPM mathematical expression, as shown in Eq. (6).

$$\begin{cases} \min F_1 = C_1 + C_2 + C_3 \\ \max F_2 = \frac{1}{n}\sum_{j=1}^{n} \lambda f_1\left(t_j\right) + (1-\lambda) f_2\left(t_j\right) \end{cases} \tag{6}$$

The model requires a combination of constraints to be considered. First, the vehicle capacity constraint must be taken into account, see Eq. (7).

$$\sum_{j-1}^{n} q_j X_{ijk} \le Q_k, \quad \forall i, k \tag{7}$$

In Eq. (7), q_j denotes the order quantity of customer j (kg), and Q_k represents the maximum load capacity of vehicle k (kg). The uniqueness constraint for customer service is specified in Eq. (8).

$$\sum_{i-1}^{m}\sum_{k-1}^{K} X_{ijk} = 1, \quad \forall j \tag{8}$$

This means Customer j is served by only one pre-warehouse-vehicle combination. The pre-warehouse service scope constraints are shown in Eq. (9).

$$d_{ij} \le 1.5, \quad \forall i, j \tag{9}$$

In Eq. (9), d_{ij} denotes the distance (in kilometers) between the forward warehouse i and customer j. The time window constraint is specified in Eq. (10).

$$a_j \le t_{ij} \le b_j, \quad \forall i, j \tag{10}$$

In Eq. (10), t_{ij} denotes the vehicle's arrival time at customer j, while $\left[a_j, b_j\right]$ represents customer j expected time window (based on historical order statistics).

2.2. MOPPM Solving Based on Improved NSGA-II

After constructing the FFEC warehouse MOPPM, an intelligent algorithm is required for the solution. MO optimization considers two or more OFs and requires comprehensive consideration of objective relationships, with algorithms divided into normalized and non-normalized types. Normalized methods convert MO to SO optimization but have subjective weight determination and may fail to obtain Pareto optimal solutions (POS). Non-normalized methods use the Pareto mechanism to avoid these issues (Williams, 2023). Since the model must balance enterprise and customer needs (not reducible to SO), this study adopts the improved NSGA-II for solving the MO model. The simple genetic algorithm (SGA) is a biocomputational model for individual selection that searches for fitness, updates populations via crossover-mutation, and converges on optimal solutions. It also serves as a basic framework for developing algorithms. The mathematical definition is expressed in Eq. (11).

$$SGA = \left(C, E, P_0, M, \Phi, \Gamma, \Psi, T\right) \tag{11}$$

In Eq. (11), C, E, P_0, M, Φ, Γ, Ψ, and T denote the individual coding method, fitness evaluation function, initial population, population size, selection operator, crossover operator, variation operator, and termination condition, respectively. Fig. 2 depicts the flow of its algorithm.

In Fig. 2, the process begins with encoding problem space parameters into a binary format and initializing the population. First, a fitness function calculates each individual's fitness score. Then, selection operations identify high-performing individuals for the next generation. Cross-over and mutation operations are performed to update the population. The algorithm terminates when either the termination condition is met or the optimal solution is found. In this case, the optimal solution is output. However, SGA struggles to balance sub-objectives in MO problems, so NSGA is selected. NSGA-II with an elite strategy outperforms NSGA in reducing computational complexity, optimizing low-dimensional problems, and improving solution distribution, making it more suitable for two-objective problems. The flow diagram of NSGA-II is shown in Fig. 3.

NSGA-II (Fig. 3) assigns fitness values via quick non-dominant sorting: grouping individuals by non-dominance level, then computing adjacent OF values for crowding-measure-based classification, with both steps completing fitness assignment. For population comparison, the same non-dominated layer prioritizes higher crowding. Otherwise, the individual with lower dominance is marked as dominant. Fig. 4 maintains population diversity in search.

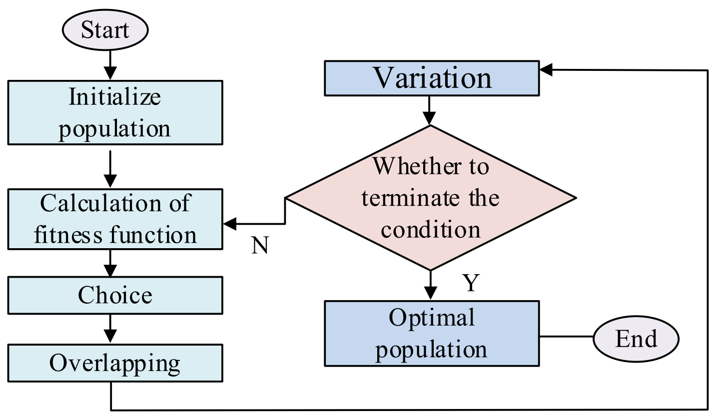


Fig. 2. Schematic diagram of SGA flow

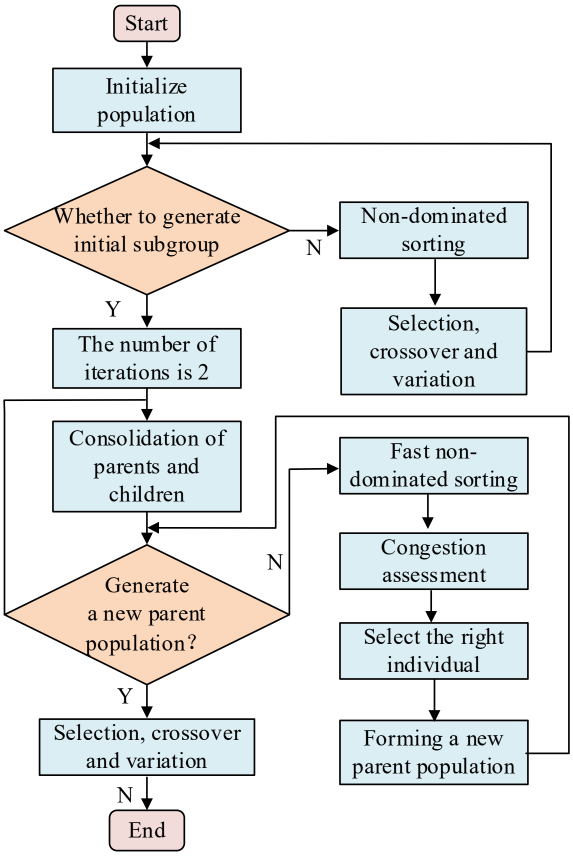


Fig. 3. Flow diagram of NSGA-II

Fig. 4 first sorts the solutions on the same frontier by their OF values in ascending order. The crowding distance of the extreme points is set to infinity. Then, the distance between each individual and its neighbors is calculated, normalized to eliminate scale effects, and summed. NSGA-II's elite strategy prevents the loss of excellent individuals from the parent generation. Moreover, the elite selection strategy is schematically shown in Fig. 5.

In Fig. 5, the t-th generation offspring merge with the parent population to form a new population of size 2N. After fast non-dominated sorting and crowding-degree calculation, N individuals are selected as the new parent population Pt+1. Traditional NSGA-II's random initial population hinders rapid optimization to high-quality solution areas, causing slow convergence. This study innovatively introduces logistic-mapping-generated chaotic sequences (ergodicity, randomness and regularity) to optimize the initial population distribution, as shown in Eq. (12).

$$z_{i(j+1)} = \mu z_{ij}\left(1 - z_{ij}\right), i = 1, 2, \cdots, m, \mu \in [0, 4] \tag{12}$$

In Eq. (12), μ denotes the control parameter, whose value is adjusted to ensure the mapping remains in a fully chaotic state. The initial chaotic variable z_{i1} is sampled from the range $[0,1]$, and an iterated chaotic sequence $\{z_{i1}, z_{i2}, \ldots, z_{im}\}$ of length m is generated.

The introduction of chaotic sequences is well-supported by theoretical and empirical evidence. The research demonstrates that the ergodic nature of chaotic motion allows initial populations to uniformly cover the solution space. This effectively solves the issue of population clustering caused by traditional random initialization. Furthermore, chaotic sequences generated by logistic maps exhibit both randomness and regularity. This makes them a popular choice for initializing intelligent algorithms, as they help achieve an optimal balance between population diversity and convergence speed (Wu et al., 2023). This sequence is then mapped to the decision variable space for path planning, as shown in Eq. (13).

$$X_{ij} = z_{ij}\left(UB_j - LB_j\right) + LB_i, i = 1, 2, \cdots, m \tag{13}$$

In Eq. (13), X_{ij} denotes the mapped integer decision variable, UB_j represents the upper bound of the j decision variable, and LB_j indicates its corresponding lower bound. The mapped decision variables are encoded using natural-number coding for the delivery-node sequence. Their feasibility is verified by multiple constraints, ultimately yielding an initial population with chaotic characteristics.

Chaotic sequences improve the algorithm's performance in two ways: they ensure uniform coverage of the solution space (by avoiding local optima through ergodicity) and accelerate convergence (by exploring high-quality solutions early through a combination of randomness and regularity). The NSGA-II selection operator uses tournament selection for the initial population and an elite strategy plus crowding comparison to retain excellent genes. The crossover operator generates random segments for gene exchange (leftmost region of crossover segments, Fig. 6) to enhance gene diversity.

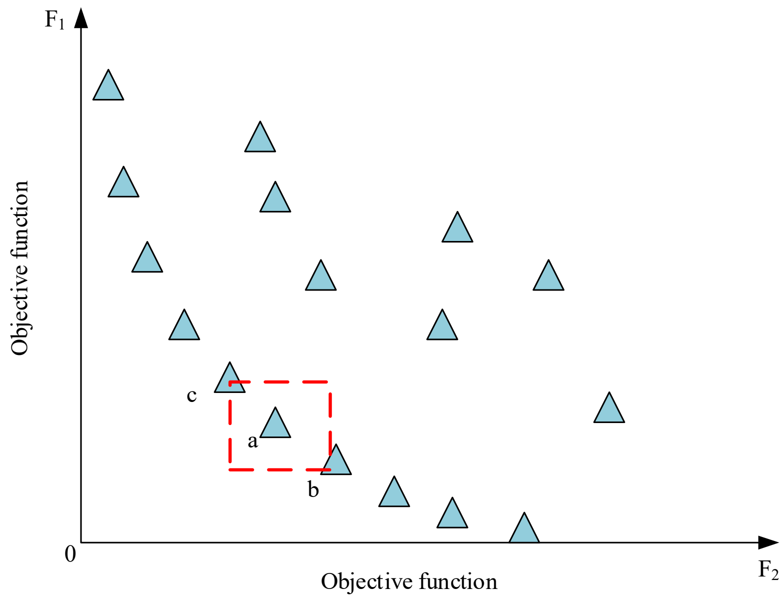


Fig. 4. Schematic diagram of congestion

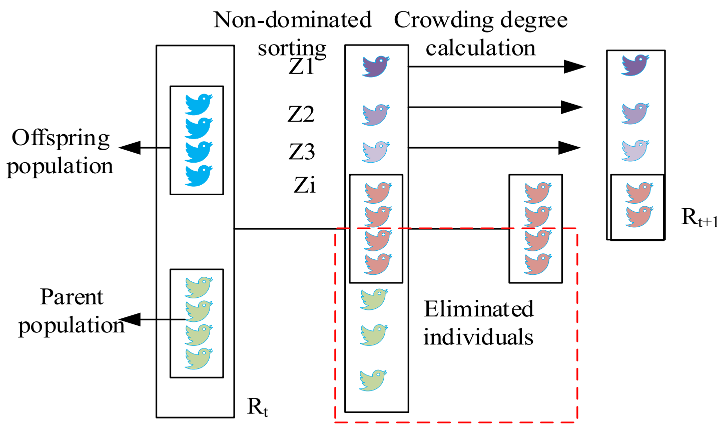


Fig. 5. Schematic diagram of elite selection strategy

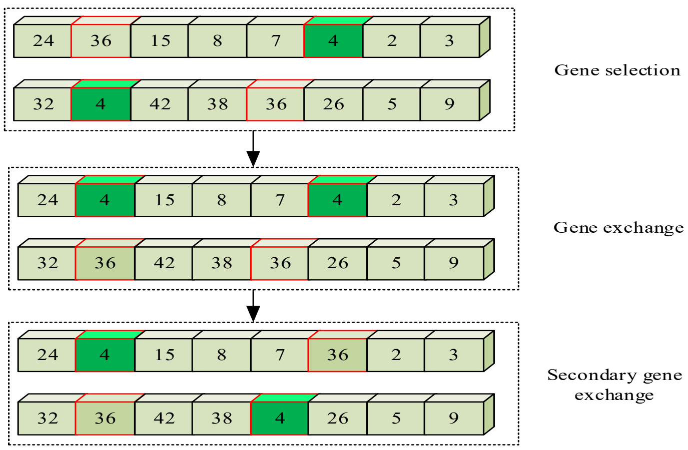


Fig. 6. Schematic diagram of cross operation

In Fig. 6, when processing parental chromosomes, a random algorithm generates specific crossover segments with randomly determined positions and lengths. Then, the gene swap operation is performed by exchanging the leftmost gene between the parental chromosomes and the randomly selected crossover segment. Due to the altered gene sequence order, the resulting chromosomes will contain two identical genes, necessitating a secondary swap repair. These operations result in the acquisition of modified chromosomes, thereby enhancing genetic diversity through gene exchange. Standard NSGA-II's single/multi-point crossover easily generates invalid chromosomes. This study proposes a "random segment+secondary exchange" crossover operator (repairing duplicates to reduce invalid chromosomes and enhance diversity). A single-point mutation can disrupt high-quality genes. Therefore, an adjacent exchange mutation is designed to swap adjacent genes, fine-tune routes, preserve excellent structures, and reduce the risk of local optima. The improved NSGA-II's pseudocode is shown in Table 1.

In this study, the adaptation index $Fitness$ is calculated by integrating two OFs: TC (F_1) and average CS (F_2). To ensure consistent measurement despite their differing dimensions and value ranges, a weighted summation method is employed for the adaptation index calculation, as shown in Eq. (14).

$$Fitness = \alpha \cdot \frac{F_1 - F_{1min}}{F_{1max} - F_{1min}} + (1-\alpha) \cdot \frac{F_{2max} - F_2}{F_{2max} - F_{2min}} \tag{14}$$

In Eq. (14), α is used to balance cost and satisfaction, with a value of 0.5. The satisfaction index is quantified by weighing the sum of the time and freshness functions, with the threshold determined through enterprise research.

3. Results

3.1. Model and Algorithm Performance Testing

Authoritative and representative datasets are chosen to conduct experimental testing in order to confirm the efficacy of the models and algorithms. Vehicle routing problem (VRP), as a classic problem in the field of logistics and distribution, has attracted much attention. The RC105 dataset in the Solomon dataset is a widely used classic dataset in this field. The test using this data can strongly demonstrate the reliability and practicality of the model and algorithm. The Solomon RC105 dataset includes 100 customer nodes with order demands of 5-20 kg and an 8-hour time window (0-480 minutes, with ±30 minutes of flexibility) to accommodate the timeliness sensitivity of customers of fresh foods. The vehicles have a load capacity of 1,000 kg, with fixed costs of 30 yuan/trip and unit transportation costs of 5 yuan/km, which is consistent with real cold chain configurations (e.g., Foton Aoling one-ton refrigerated trucks). Distance units are converted from Solomon standard units to kilometers to ensure alignment with actual operations. Table 2 displays the experimental setup and particular parameter configurations.

Table 1. Pseudocode for Improving the NSGA-II Algorithm

Algorithm: Improved NSGA-II with Chaotic Sequence

Input: Customer demand Q, Vehicle capacity C, Time window [a_i,b_i], Freshness threshold [F_min, F_max]
Output: Pareto optimal solution set of distribution paths
1. Parameter initialization:
    Population size N=200, Crossover probability p_c=0.9, Mutation probability p_m=0.05,
    Maximum iterations T=500, Chaotic initial value x0=0.37, Control parameter μ=4
2. Generate initial population via chaotic sequence:
    a. For i from 1 to N:
        i. x_i = μ*x_{i-1}*(1-x_{i-1}) // Logistic mapping
        ii. y_i = low + (high - low)*x_i // Linear transformation to decision space
    b. Encode y_i into chromosome (node sequence + vehicle number)
    c. Check feasibility (satisfy vehicle capacity & 1.5km service range)
    d. Form initial population P0
3. For t from 1 to T:
    a. Non-dominated sorting of Pt to get non-dominated layers F1, F2,...
    b. Calculate crowding distance for each individual in Fk
    c. Selection: Tournament selection (k=2) + elite retention
    d. Crossover: Randomly select crossover segment, swap leftmost genes, eliminate duplicates via secondary swap
    e. Mutation: Randomly select mutation point, swap adjacent genes on the right
    f. Generate offspring population Qt
    g. Combine Pt and Qt to form Rt (size=2N)
    h. Non-dominated sorting of Rt, calculate crowding distance
    i. Select top N individuals to form Pt+1
4. After T iterations, output the final Pareto optimal solution set

Table 2. Experimental running environment and parameter settings

/	Category	Set items
JRE	Operating system	Win 7 operating system
	Developer components	JDK 7、Eclipse
	CPU	Intel (R) Core (TM) i9-10900X
	GPU	Nvidia RTX 3090 GPU
	Platform software environment	Python3.8、PyTorch1.10.0
Parameter setting	Programming language	Java
	Batch size	8
	Learning rate initial value	0.001
	Learning rate initial value	Adam
	Freshness ceiling	0.8
	Freshness lower limit	0.6
	Minimum fresh satisfaction	0.3
	Total planned cost	1200000
	Unit transportation cost	5
	Vehicle fixed costs	30
	Time satisfaction weight	0.5
	Cross probability	0.9
	Probability of variation	0.05
	Population size	200
	Maximum number of iterations	500

Sensitivity tests are conducted on key parameters (cross probability, variation probability, and time satisfaction weight), with 30 repetitions for each group of experiments. The results are shown in Table 3.

Table 3. Key parameter sensitivity analysis results

Parameter type	Parameter	Total cost (RMB)	Average	Convergence iterations
Crossing probability	0.7	11896.32±98.45	0.81±0.028	215
	0.8	11724.58±89.63	0.83±0.023	192
	0.9	11592.25±86.32	0.84±0.021	168
	0.95	11638.74±92.17	0.83±0.025	175
Mutability probability	0.03	11701.26±95.34	0.82±0.027	189
	0.05	11592.25±86.32	0.84±0.021	168
	0.08	11654.89±91.78	0.83±0.024	172
Time satisfaction weight	0.3	11486.72±88.54	0.79±0.029	170
	0.4	11521.37±87.16	0.82±0.025	169
	0.5	11592.25±86.32	0.84±0.021	168
	0.6	11735.64±93.28	0.85±0.022	171

As shown in Table 3, the optimal parameters are: crossover probability 0.9 (minimizes TC, maximizes satisfaction, fastest convergence, improper values have drawbacks), mutation probability 0.05 (insufficient diversity or unstable convergence otherwise), and time satisfaction weight 0.5 (balances cost and satisfaction, adjustments affect either factor). The selected parameters are rational and stable, with the weight's sensitivity analysis shown in Table 4.

Table 4. Multi-objective weight sensitivity test results

Weight	Total cost (RMB)	Average satisfaction	Fitness value (test set)
0.3	11472.58±89.43	0.78±0.032	0.18±0.019
0.4	11536.81±87.25	0.82±0.026	0.16±0.017
0.5	11592.25±86.32	0.84±0.021	0.14±0.015
0.6	11689.43±92.67	0.85±0.023	0.15±0.016
0.7	11825.76±98.34	0.86±0.024	0.17±0.018

As shown in Table 4, the fitness value reaches its lowest point when the weight is set to 0.5, indicating optimal cost-satisfaction balance. When the weight is below 0.5, there is insufficient optimization of satisfaction due to low cost weighting. Conversely, when the weight exceeds 0.5, excessive satisfaction weighting causes significant cost increases. These findings validate the rationality of setting the weight to 0.5, which balances the optimization of corporate efficiency and customer experience.

The study firstly selects SGA, traditional NSGA-II as the comparison algorithm for improving NSGA-II. The obtained comparison of iterative performance of each algorithm is shown in Fig. 7.

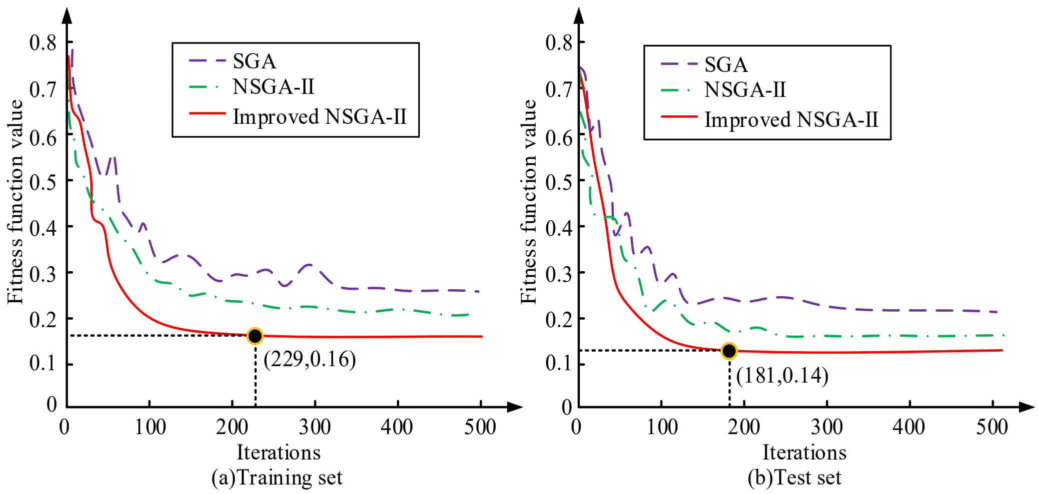


Fig. 7. Iterative performance of different algorithms in training and test sets

Fig. 7(a) and Fig. 7(b) show the iterative curves of the fitness values of different algorithms in the training set and test set, respectively. The improved NSGA-II has the best iteration performance in both the training set and the test set. In the training set, the improved NSGA-II needs only 229 iterations to reach a steady state. The fitness value at this point is 0.16. In the test set, the algorithm reaches a steady state in 181 iterations and the fitness value at the steady state is 0.14. The training results demonstrate that the enhanced NSGA-II is useful and capable of resolving the FFEC warehouse MOPPM. Fig. 8 displays the outcomes of various strategies for resolving MOPPM.

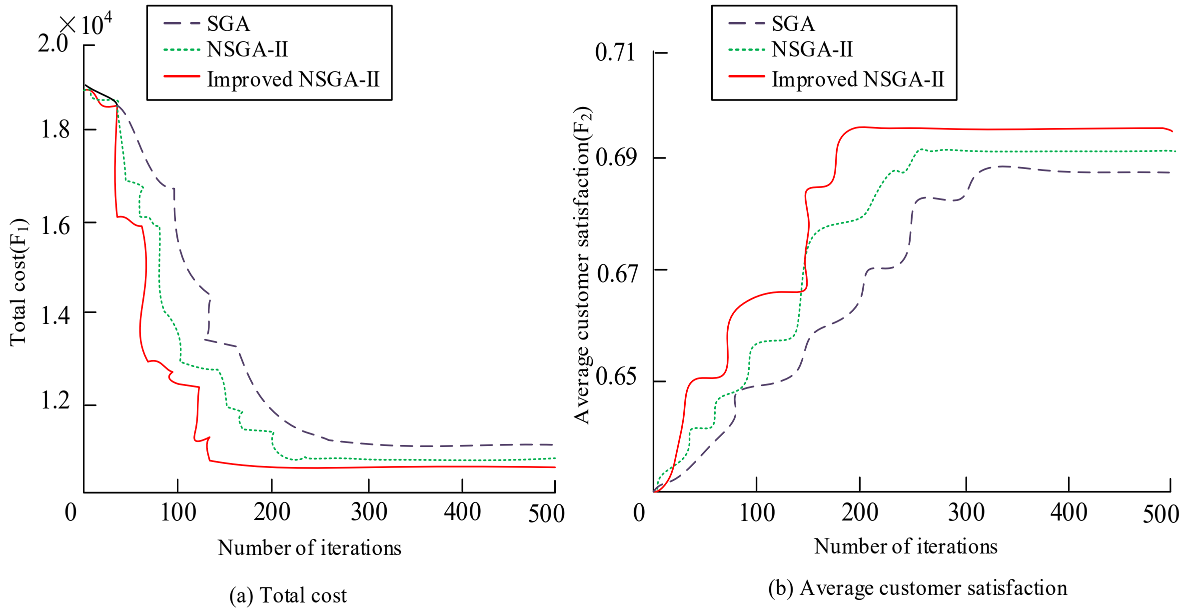


Fig. 8. Comparison of different algorithms for solving MOPPMs

Fig. 8 shows that both the original and improved NSGA-II algorithms have a decreasing and then stable TC during iteration. The improved version reaches a lower TC at approximately 150 iterations (fewer than the original version), achieves an average CS of 0.71 at approximately 200 iterations (higher than the original version's slow convergence), and exhibits less fluctuation. The results confirm that the proposed MOPPM converges well to optimal solutions. The improved NSGA-II outperforms the traditional method in terms of objective values and computational efficiency. Figure 9 presents the statistical analysis of commodity quality versus transportation time before and after the improvement of the MO optimization. The comparison results of the visualized Pareto front between the improved NSGA-Ⅱ and the benchmark method are shown in Fig. 9.

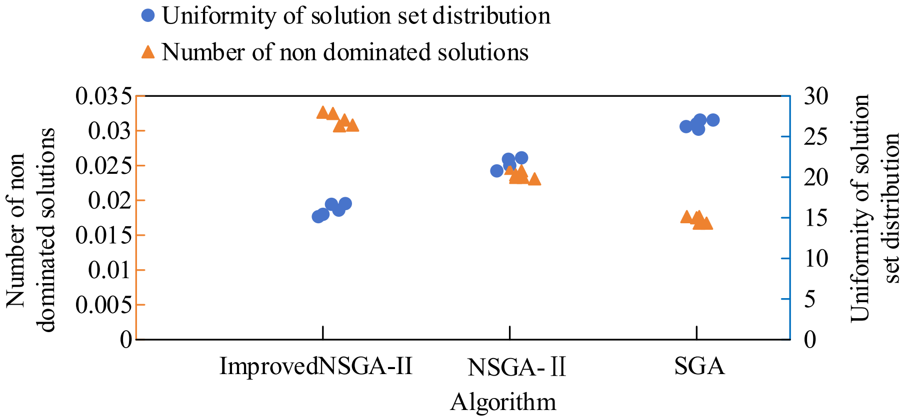


Fig. 9 Visualized comparison of the improved NSGA-Ⅱ and benchmark methods on the Pareto frontier

Fig. 9 reveals that the Pareto front of the improved NSGA-Ⅱ algorithm is positioned in the upper-left quadrant compared to traditional NSGA-Ⅱ and SGA. This indicates that the improved algorithm achieves higher satisfaction at the same cost and reduces costs at the same satisfaction level. Furthermore, the improved NSGA-II shows more uniform dispersion (standard deviation of 0.018) and a greater number of optimal solutions (28). This reflects its superior diversity and comprehensive optimization.

Fig. 10 shows that before MO optimization, commodity quality fluctuates widely and increases as transit time increases. After optimization, quality concentrated in the high-value sector, transit time is significantly reduced, and CS rises by 13.25%. To further verify the effectiveness of MOPPM for FFEC warehouses in optimizing CS and reducing corporate costs, a comprehensive comparative analysis of two SO models and the proposed MO model is conducted, focusing on cost management and customer experience. The results are shown in Table 5.

In Table 5, the TC of the research model is 11,592.25, and the average satisfaction is 0.84. The TC of the model that only considers CS is 12,692.25, and the average satisfaction is 0.79. The TC of the model that only considers business cost is 11,662.75, and the average satisfaction is 0.56. In terms of optimization rate, the research model compares favorably with the one that only considers business cost or the CS model. The TC and satisfaction are improved by 0.60% and 6.33%, respectively. This indicates that the research model performs better in balancing business cost and CS. The study conducts 30 independent repeated experiments to further improve the NSGA-II and standard NSGA-II algorithms, with t-test analysis of significant differences, as shown in Table 6.

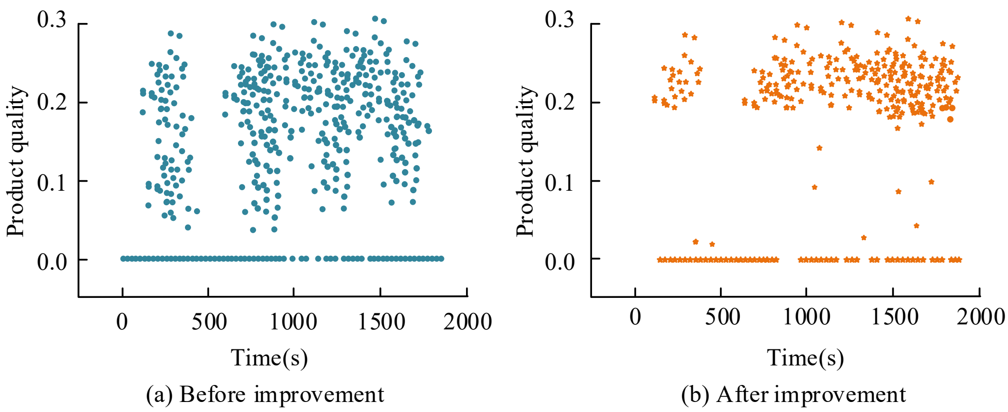


Fig. 10. Commodity quality changes with transportation time before and after MO optimization

Table 5. Comparison results of different models

Object function	Total cost (F)	Average satisfaction ((F2)
Research model	11592.25	0.84
A model that only considers CS	12692.25	0.79
A model that only considers the	11662.75	0.56
Optimization rate	0.60% (Compared to a model that only	6.33% (Compared to the model that

Table 6. Statistical comparison of NSGA-II and standard NSGA-II algorithm performance

Experiment Parameters	Improve NSGA-II	Standard NSGA-II	Significance of difference (p-
Total cost (RMB)	11592.25±86.32	11876.53±124.75	0.023
Average satisfaction	0.84±0.021	0.78±0.035	0.017
Fitness value (training set)	0.16±0.018	0.23±0.027	0.009
Fitness value (test set)	0.14±0.015	0.21±0.023	0.006

Table 6 shows the improved NSGA-II outperforms standard NSGA-II across core metrics (p<0.05, smaller standard deviations), with fitness p<0.01 (chaotic sequence enhances stability and avoids random deviations). To verify generalizability, MOEA/D and SPEA2 are used as benchmarks, with three scenarios: small (3 forward warehouses/50-day orders), medium (8/120), large (15/300). Key metrics (TC, average CS, convergence iterations) are analyzed, with 30 independent repetitions per experiment. The results are displayed in Table 7.

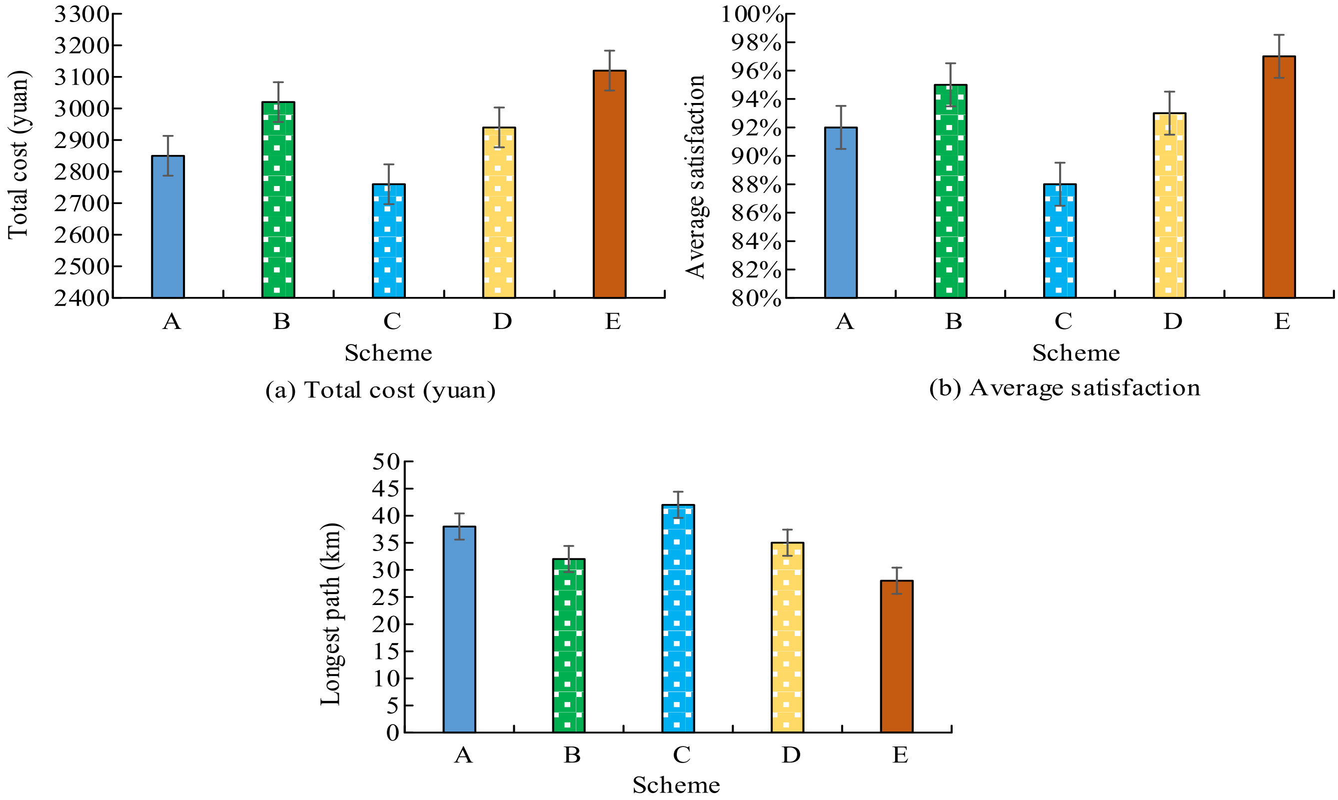
Table 7. NSGA-II universality test across warehouse scales and order volumes

Warehouse	Algorithm	Total cost (RMB)	Average	Convergence iterations
Small	Improve NSGA-II	4826.37±52.14	0.85±0.018	125
	MOEA/D	5132.68±78.42	0.79±0.025	187
	SPEA2	5219.45±86.73	0.77±0.031	203
Medium	Improve NSGA-II	11592.25±86.32	0.84±0.021	168
	MOEA/D	11984.17±156.28	0.76±0.042	217
	SPEA2	12103.89±189.43	0.75±0.038	265
Large	Improve NSGA-II	28643.79±124.56	0.82±0.025	243
	MOEA/D	30215.87±213.45	0.74±0.039	325
	SPEA2	31568.22±247.89	0.72±0.045	382

Table 7 shows that the improved NSGA-II outperforms MOEA/D and SPEA2 across small, medium, and large-scale scenarios. Key advantages include small-scale TC reduced by up to 7.53% (vs. SPEA2), improved convergence speed by 38.42%, medium-scale satisfaction increased by 12.0% (vs. SPEA2), large-scale TC reduced by 9.26% (vs. SPEA2), and satisfaction increased by 13.89%. The algorithm balances cost and CS and exhibits strong convergence stability, with more pronounced advantages in complex scenarios, thereby validating its universality and efficiency in fresh EC MO path planning.

3.2. Example Application Analysis

After validating the MOPPM study for FFEC warehouses and improving the NSGA-II model, it is applied to an FFEC enterprise in a first-tier city (eight front warehouses and 120 daily community deliveries) to verify its practicality. This enterprise faces high cold chain costs (a fixed cost of 500 yuan/vehicle and a variable cost of 3 yuan/km), customer sensitivity to delivery time (a 10% drop in satisfaction for delays of 10 minutes or more), and a cost-satisfaction imbalance from traditional SO planning. Five feasible solutions are generated using the improved NSGA-II to compute the POS set. The results are shown in Fig. 11.



(a) Total cost (yuan)

(b) Average satisfaction

(c) Longest path (km)

Fig. 11. Results for each indicator under different programs

Fig. 11(a) represents the TC results under different scenarios. Fig. 11(b) represents the average CS results under different scenarios. Fig. 11(c) shows the longest-path planning results for different schemes. Schemes B/D increase satisfaction by 3-5 percentage points at a 4-6% increase in cost, reflecting an inverse relationship. The company finally adopts Scheme D because it meets the cost control line (<3000 yuan) and its satisfaction exceeds the industry benchmark (90%). Finally, the longest delivery distance is reduced by 22% compared to the traditional scheme, and the number of overtime orders is reduced by 10% through dynamic time-window allocation. The findings demonstrate that using the research approach may successfully lower FFEC businesses operational expenses, raise CS, and encourage sound growth. The actual cost analysis results of the enterprise after adopting scheme D are shown in Table 8.

Table 8. Cost-effectiveness analysis of Option D

Index	Original plan	Scheme D	Change rate
Average daily cost in yuan	3215	2980	-7.3%
Degree of satisfaction	0.78	0.84	+7.7%
Timeout order rate	15%	5%	-66.7%

As shown in Table 8, the company reduced its average daily cost from 3,215 yuan under the original plan to 2,980 yuan after adopting Solution D (a 7.3% decrease), while CS improved from 0.78 to 0.84. With an annual operation of 300 days, the total cost savings amount to 70,500 yuan.

4. Conclusion

The objective of the study was to address the problems of irrational distribution paths, high operating costs, and low CS in FFEC warehouses by proposing an MOPPM that accounted for distribution time and product freshness. Additionally, the study considered the dual objectives of minimizing enterprise TC and maximizing average CS. It established an FFEC warehouse planning solution model that incorporates chaotic sequences and an improved NSGA-II. This was done to reduce distribution costs and improve on-time performance. The results indicated that the improved algorithm performed well on the training and test sets, with high fitness values and could be used for model solving. The improved algorithm required fewer iterations and exhibited greater stability in TC and average CS OFs. The TC of the MO model was 11592.25, and the average satisfaction amounted to 0.84. Compared with the model that considered only the cost of the enterprise or CS, the TC and satisfaction improved by 0.60% and 6.33%, respectively. In the application case, the enterprise adopted Scheme D with significant results, reducing the longest delivery distance and the number of overtime orders. This demonstrated how the research approach can successfully reduce business operating expenses, advance computer science, and promote the sound growth of businesses. However, the research also has certain limitations. First, the model has limitations in adapting to scenarios. It does not fully account for scenarios such as multi-warehouse coordination in cross-regional distribution or dynamic route adjustments during adverse weather conditions. Currently, it is only applicable to single-city, short-distance forward warehouse distribution models. Second, the algorithm is inefficient: in large-scale scenarios, its computational complexity increases with the dimensionality of the decision variables, resulting in slightly insufficient real-time responsiveness. Targeted research can be conducted from three aspects: ① IoT data integration: It integrates real-time traffic congestion data, temperature sensor data from cold chain vehicles, and real-time customer order data to build a dynamic MO route-planning model, enabling real-time adaptive route adjustments. ② Algorithm efficiency optimization: It integrates reinforcement learning algorithms (such as DQN) with improved NSGA-Ⅱ to reduce computational complexity in large-scale scenarios and enhance real-time response speed. ③ Full SC extension: It expands the model from warehouse route planning to the entire 'warehouse replenishment-vehicle scheduling-customer segmentation-reverse logistics' SC, achieving global optimization of fresh e-commerce SCs.

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Institutional Review Board Statement

Not applicable.

Declaration of Artificial Intelligence (AI) Tools

The author used AI tools solely for language editing and readability improvement. The author reviewed and verified all content and takes full responsibility for the accuracy and integrity of the manuscript.

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