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Multi-objective Cold Chain Logistics Path Optimization Using Heuristically-Initialized and Catastrophe-Enhanced NSGA-II for E-commerce Distribution

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The swift advancement of e-commerce poses challenges to the cost, efficiency, and quality assurance of fresh food and pharmaceutical Cold Chain Logistics (CCL). To reduce transportation costs, decrease refrigeration energy consumption, improve customer satisfaction with time and freshness of goods, the research proposes an e-commerce CCL distribution path optimization model based on improved non-dominated sorting genetic algorithm II. This model takes the total transportation cost, customer time satisfaction, average freshness of goods, and total refrigeration energy consumption as multiple objectives. It generates high-quality initial solutions through heuristic population initialization and combines dynamic disaster mechanisms to avoid local optima, enhancing the algorithm's global search ability and convergence speed. In the experimental verification of Solomon Benchmark Problem and Berlin52 standard dataset, a population size of 100 and a maximum iteration of 300 are set up in the experimental environment. The proposed optimization method is compared with the original algorithm, multi-objective evolutionary algorithm based on adaptive reference points, and non-dominated sorting genetic algorithm II based on simulated annealing improvement. Experiments show that the optimization model is better than the traditional algorithm in indicators such as total transportation cost, refrigeration energy consumption, customer time satisfaction, and product freshness. Among them, the total transportation cost is the lowest at 5923.47 yuan, and customer time satisfaction and average product freshness reach 0.954 and 0.962 respectively. The total refrigeration energy consumption drops to 87.93 kWh, the optimal route mileage is 436.59 km, the delivery time is 945.38 minutes, and the cargo damage rate is 2.35%. The results show that this optimization method can efficiently coordinate multi-objective conflicts, achieve path optimization, cost reduction, and service quality improvement, and provide stable and efficient decision support for e-commerce CCL distribution.

Povzetek: Predlagan je izboljšan model NSGA-II za optimizacijo poti hladne verige v e-trgovini, ki hkrati znižuje stroške in energijo ter izboljša časovno zadovoljstvo in svežino.

1 Introduction

The rapid development of e-commerce has profoundly changed consumption patterns, especially with the continuous growth of online transaction volume for fresh food and pharmaceutical products, which has raised higher demands for cold chain logistics. Cold Chain Logistics (CCL), as a key link in ensuring the quality and safety of temperature sensitive goods, not only concerns consumer experience and health and safety, but also affects enterprise cost control and operational efficiency. However, the short shelf life of fresh products and strict temperature and timeliness requirements for drug transportation have made CCL face problems such as high transportation costs, low distribution efficiency, and easy loss of goods [1-2]. These challenges limit the improvement of e-commerce service quality. At present, there has been some progress in the optimization of CCL paths in academia and enterprises. However, traditional methods generally suffer from slow convergence speed, susceptibility to local optima, lack of effective multi-objective balancing ability, and poor initial solution quality. Especially in the face of high-dimensional and complex constrained distribution scenarios, the optimization effect is significantly limited [3-4]. Based on this, a multi-objective (MO) optimization model for e-commerce CCL distribution paths was designed. In terms of solving strategies, a typical MO Genetic Algorithm (GA), Non-dominated Sorting Genetic Algorithm II (NSGA-II), is introduced for improvement. By using heuristic population initialization to generate high-quality initial solutions, and combining dynamic disaster mechanisms to enhance global search capabilities and avoid local optima, MO collaborative optimization can be achieved. The research aims to construct an MO optimization model that takes into account transportation costs, refrigeration energy consumption, time satisfaction, and product freshness, and solve it through efficient algorithms to provide a more scientific path planning solution for e-commerce CCL. The innovation of the research lies in the integration of time window sorting and load verification mechanism into population initialization, ensuring that the initial solution is reasonable in both spatial and temporal dimensions. At the same time, a dynamic disaster strategy based on the Hypervolume index is introduced to adaptively increase population diversity when algorithm evolution stagnates, significantly improving search accuracy and stability. It is expected to provide an optimized solution that balances efficiency and cost for e-commerce CCL, promoting the upgrading of intelligent scheduling technology in the industry.

2 Literature review

The optimization methods for CCL distribution paths are increasingly becoming a research hotspot for enhancing efficiency, cutting costs, and maintaining service quality. In order to meet people's demand for fresh food and optimize the efficiency of CCL distribution, X. Pang proposed a dynamic path planning model for CCL vehicles grounded in an improved Ant Colony (AC) algorithm. By improving the algorithm to enhance convergence and solution accuracy, and optimizing the delivery path under static and dynamic demands, significant reductions in time and travel distance were achieved [5]. To cut transportation costs and enhance delivery efficiency, X. Wang et al. proposed a traffic task simulation and path optimization method based on real-time A* search algorithm. By combining real-time traffic data, congestion information, vehicle capacity, and time window constraints, the goal of significantly reducing delivery costs and improving transportation efficiency was achieved [6]. To balance costs, low-carbon efficiency, and consumer satisfaction in cold chain distribution, X. Li et al. proposed an MO cold chain vehicle routing model that combines a decomposition-based MO algorithm with a fruit fly optimization algorithm. The advantages of the algorithm in convergence and solution set performance were verified through numerical experiments, achieving the goal of reducing carbon emissions (CE) and fuel consumption [7]. C. Fang et al. proposed an MO optimization model considering delivery time windows to optimize costs, reduce product degradation, and CE in long-distance cold chain transportation. By improving the AC algorithm to solve the Pareto optimal solution, it was achieved to improve customer satisfaction and model effectiveness while reducing transportation costs and CE [8]. To balance cost, quality, timeliness, and environmental goals in CCL, M. Yu proposed a comprehensive model based on the dual-mode position route problem. By analyzing factors such as environmental temperature, path flexibility, and mixed fleet, it achieved the improvement of distribution quality and solution efficiency while reducing costs and emissions [9].

Meanwhile, the NSGA-II algorithm has demonstrated extensive application value and significant effects in MO optimization problems across multiple fields. This algorithm was proposed by Deb et al. in 2002. It effectively balanced convergence and solution set distribution through fast non-dominated sorting, crowding distance calculation and elite retention strategy, and has become one of the benchmarks of multi-objective evolutionary algorithms [10]. For example, S. Nazari et al. proposed an MO optimization method based on NSGA-II to optimize window and shading design to lower energy usage in buildings and enhance occupant comfort, achieving the goal of significantly improving energy use and thermal comfort by selecting appropriate window to wall ratios and shading configurations [11]. To improve the scheduling efficiency of the intelligent trackless auxiliary transportation system in coal mines, C. Jia proposed an enhanced NSGA-II that integrates Levy flight, random walk, and adaptive weight strategy, achieving optimization effects of reducing transportation costs by about 19%, shortening waiting time by about 56%, and reducing transportation deviation by about 40.5% [12]. To improve the performance of natural gas engines in high-altitude environments, Z. Yu et al. proposed an MO optimization approach grounded in the NSGA-II. By constructing a response surface model and optimizing compression ratio, ignition timing, and bypass valve diameter, the goal of reducing NOx emissions while maintaining fuel economy was achieved [13]. To achieve energy consumption optimization and surface quality control in orthogonal turning and milling processes, K. Tang et al. proposed a green decision-making method based on NSGA-II. By constructing high-precision energy consumption and surface roughness models and introducing MO optimization, the dual goals of reducing energy consumption and improving machining accuracy were achieved [14].

In summary, although significant achievements have been made in the optimization of CCL distribution and the application of NSGA-II MO optimization, there are still problems such as slow convergence speed, insufficient response to dynamic demand, limited balance between cost and service quality, and incomplete consideration of environmental factors. Therefore, research proposes an optimization model for e-commerce CCL distribution path based on improved multi-objective genetic algorithm. By optimizing the initialization population, introducing dynamic disaster mechanisms, and multi-objective collaborative scheduling, we can improve service levels while reducing transportation costs and CEs, providing more efficient and reliable solutions for complex CCL distribution problems. Table 1 presents the comparative results of different CCL and multi-objective optimization algorithms.

Table 1: Comparative summary of previous studies on CCL and multi-objective optimization algorithms

Study	Optimization method	Application scenario	Research objective	Key results
X. Pang [5]	Improved Ant Colony Optimization (ACO)	CCL distribution (static/dynamic demand)	Enhance routing accuracy and efficiency	Significant reduction in delivery time and travel distance
X. Wang et al. [6]	Real-time A* Search Algorithm	Traffic task simulation	Reduce transportation cost and improve efficiency	Noticeable decrease in delivery cost and improvement in transport efficiency
X. Li et al. [7]	Decomposition-based multi-objective + Fruit Fly Optimization	Cold chain vehicle routing	Balance cost, carbon efficiency, and customer satisfaction	Lower CEs and fuel consumption, optimized logistics expenditure
C. Fang et al. [8]	Improved ACO	Long-distance cold chain transportation	Optimize cost, CE, and customer satisfaction	Reduced transport cost and emissions, enhanced customer satisfaction
M. Yu [9]	Bi-modal Location–Routing Model	CCL	Optimize cost, quality, timeliness, and environmental performance	Reduced cost and emissions, improved delivery quality
S. Nazari et al. [11]	NSGA-II	Building energy optimization	Minimize energy consumption and improve thermal comfort	Improved energy efficiency and occupant comfort
C. Jia [12]	Improved NSGA-II (Levy flight + adaptive weights)	Intelligent mine transport scheduling	Reduce transport cost and deviation	Cost reduced by 19%, waiting time by 56%, deviation by 40.5%
Z. Yu et al. [13]	NSGA-II + Response Surface Model	Plateau natural gas engine optimization	Reduce NOx emissions while maintaining fuel economy	NOx emissions decreased, fuel economy maintained
K. Tang et al. [14]	NSGA-II	Green orthogonal turning–milling process	Optimize energy consumption and surface quality	Reduced energy usage and improved surface accuracy

3 Design of optimization model for CCL distribution path in e-commerce

3.1 Design of optimization model for e-commerce CCL distribution path

In recent years, e-commerce has rapidly penetrated into every aspect of people's daily life, changing traditional consumption patterns and supply chain systems. Consumers have increasingly high demands for shopping convenience, product quality, and delivery time, especially in categories such as fresh food and pharmaceuticals that require strict quality standards. Logistics service quality has become an important factor affecting purchasing decisions and customer loyalty. With the rapid growth of transaction volume on e-commerce platforms, CCL is facing challenges such as large delivery order scales, complex routes, and tight delivery times. This not only puts higher demands on enterprise logistics management, but also brings about resource allocation and environmental energy consumption issues at the social level [15]. To acquire a more profound comprehension of this complex process and its potential optimization space, the study first analyzed the implementation process of e-commerce CCL, as shown in Figure 1 [16].

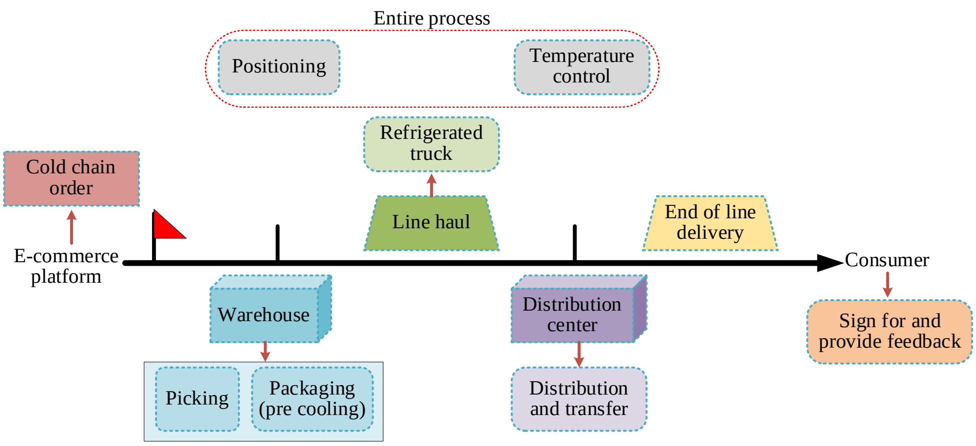


Figure 1: Schematic diagram of e-commerce CCL implementation process

As shown in Figure 1, after placing an order on the e-commerce platform, the system recognizes it as a cold chain order and triggers the subsequent logistics process. Next, picking and packaging are carried out in the warehouse, and the goods are pre cooled in the cold storage and cold media such as ice packs or dry ice are added to ensure temperature control. Refrigerated trucks carry out long-distance transportation and monitor temperature and location throughout the entire process. After arriving at the distribution center, the goods quickly circulate in a low-temperature environment. Insulated boxes or refrigerated trucks for final delivery are used to ensure quick handover. Finally, the consumer inspects the product and confirms that the temperature control is correct before completing the signing process. To ensure the efficient and stable operation of CCL distribution, multiple influencing factors need to be comprehensively considered in the optimization process, as shown in Figure 2.

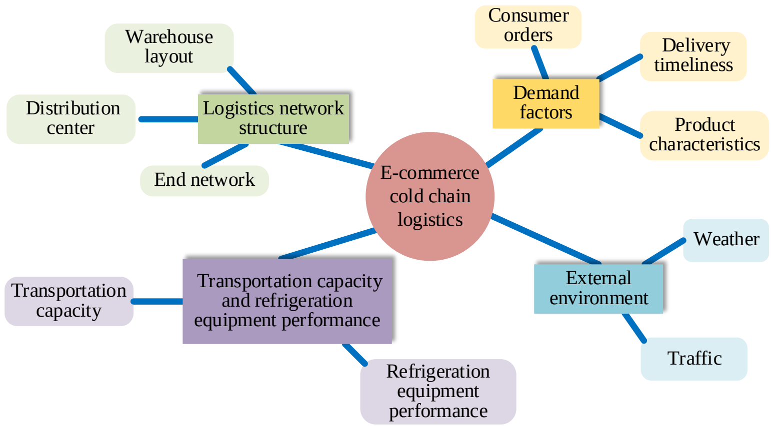


Figure 2: Schematic diagram of special factors affecting e-commerce CCL

As shown in Figure 2, the influencing factors of e-commerce CCL include multiple dimensions. Demand factors involve consumer orders, delivery time, and product characteristics, which affect the selection of delivery routes. The logistics network structure includes warehouse layout, distribution centers, and end networks, which determine the feasibility and efficiency of routes. The external environment such as weather, traffic, etc. affects the transportation time and temperature control. Transportation capacity and refrigeration equipment performance affect distribution efficiency and energy consumption [17-18]. Taking into account these influencing factors, a multi-objective optimization model for CCL distribution is designed. The overall architecture of the model is shown in Figure 3.

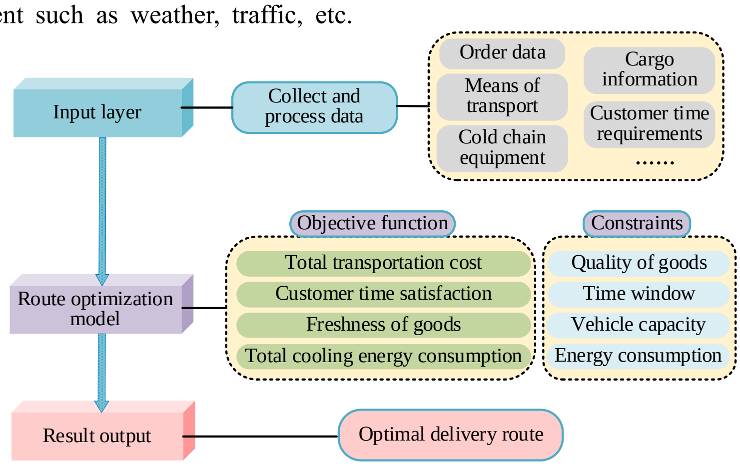


Figure 3: The overall structure of the e-commerce CCL distribution path optimization model

As shown in Figure 3, firstly, the data input module collects and processes multidimensional information related to delivery, such as order data, freshness requirements of goods, and customer time requirements. Then, the path optimization model forms an MO optimization problem by setting multiple objective functions and combining them with constraints. The optimization objectives include minimizing total transportation costs, maximizing customer time satisfaction, maximizing average freshness of goods, and minimizing total refrigeration energy consumption, while meeting constraints such as goods quality, time window, vehicle capacity, and energy consumption. On this basis, the Improved NSGA-II (I-NSGA-II) algorithm is used as the solving algorithm to handle the trade-off relationships between multiple objectives through its powerful global search capability. Finally, the result output module generates a delivery route plan based on the optimization results, providing specific information such as transportation costs, time, freshness of goods, and energy consumption to assist dispatchers or system users in making final decisions. Among them, reducing the total transportation cost includes fixed costs, transportation costs, refrigeration costs, and time window penalty costs, as expressed in equation (1).

$$f_1(x)=\sum_{N}^{i=1}(C_{\text{fixed}}+C_{\text{transport}}(i)+C_{\text{cooling}}(i)+C_{\text{time penalty}}(i)) \quad (1)$$

In equation (1), $f_1(x)$ represents minimizing the total transportation cost function; N is the number of paths; i represents path index; C_{fixed} is the fixed costs; $C_{\text{transport}}(i)$ represents the transportation cost of the i th path; $C_{\text{cooling}}(i)$ indicates the cooling cost of the i th path; $C_{\text{time penalty}}(i)$ represents the time window penalty cost of the i th path. At the same time, the study used a linear fuzzy membership function to calculate the time satisfaction of each customer, with the goal of taking the average of all customer satisfaction levels, as shown in equation (2) [19-20].

$$f_2(x)=-\frac{1}{M}\sum_{M}^{j=1}\mu_{\text{time}}(j) \quad (2)$$

In equation (2), $f_2(x)$ represents the function of maximizing customer time satisfaction; M indicates the number of customers; j represents customer index; $\mu_{\text{time}}(j)$ is the fuzzy membership function, and its expression is presented in equation (3) [21-22].

$$\mu_{\text{time}}(j)=\begin{cases} 0, T_{\text{de}}(j)<T_{\text{st}}(j) \\ \dfrac{T_{\text{de}}(j)-T_{\text{st}}(j)}{T_{\text{end}}(j)-T_{\text{st}}(j)}, T_{\text{st}}(j)\le T_{\text{de}}(j)\le T_{\text{end}}(j) \\ 1, T_{\text{de}}(j)>T_{\text{end}}(j) \end{cases} \quad (3)$$

In equation (3), $T_{\text{st}}(j)$ represents the earliest expected time for the customer to receive the goods; $T_{\text{end}}(j)$ indicates the latest expected time for the customer to receive the goods; $T_{\text{de}}(j)$ indicates the actual delivery time of the customer. The freshness of goods is related to temperature changes and transportation time during transportation, as shown in equation (4) [23].

$$f_3(x)=\sum_{N}^{i=1}\left(\frac{1}{1+\alpha T_{\text{transit}}(i)}\right) \quad (4)$$

In equation (4), $f_3(x)$ represents the function of maximizing the average freshness of goods; α indicates the temperature influencing factor; $T_{\text{transit}}(i)$ indicates the transportation time of the i th path. The energy consumption of refrigeration is related to the usage time and equipment power of cold chain equipment, as presented in equation (5) [24].

$$f_4(x)=\sum_{N}^{i=1}P_{\text{cooling}}(i)\cdot T_{\text{cooling}}(i) \quad (5)$$

In equation (5), $f_4(x)$ represents minimizing the total refrigeration energy consumption function; $P_{\text{cooling}}(i)$ refers to the power of cold chain equipment in path; $T_{\text{cooling}}(i)$ indicates the usage time of the cold chain equipment for the first path. To ensure the feasibility of the distribution plan, the model needs to satisfy key constraints. The first is the vehicle capacity constraint, as shown in equation (6).

$$\sum_{j\in R_k} q_j \le Q, \quad \forall k\in\{1,2,\dots,K\} \quad (6)$$

In equation (6), R_k represents the customer set served by the route k ; q_j represents the customer demand; Q represents the maximum load of the vehicle. To ensure the quality and freshness of the goods, temperature control is the core constraint that must be met, as shown in equation (7).

$$T_{min}\le T_k(t)\le T_{max}, \quad \forall k\in\{1,2,\dots,K\}, \forall t\in[0,T_{max}] \quad (7)$$

In equation (7), $T_k(t)$ represents the cargo compartment temperature of the vehicle at that time t ; T_{min} and T_{max} respectively represent the minimum temperature and maximum limit temperature required by the goods. These constraints jointly ensure the feasibility of the distribution plan in terms of operations, technology and resources, and provide a complete mathematical framework for multi-objective optimization.

3.2 I-NSGA-II algorithm design

To effectively solve the optimization model of e-commerce CCL distribution path, the NSGA-II algorithm is studied to handle multi-objective optimization problems. The basic process of the original NSGA-II algorithm is shown in Figure 4 [25].

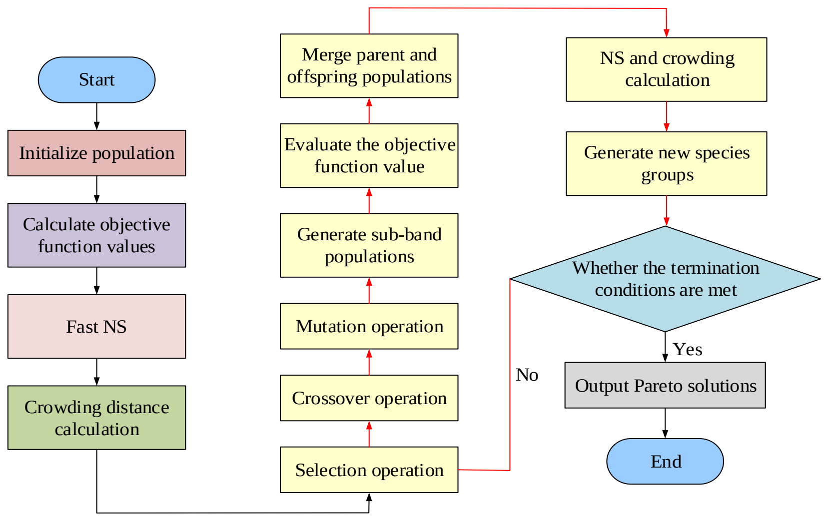


Figure 4: NSGA-II algorithm flow chart

As shown in Figure 4, the NSGA-II algorithm maintains diversity and convergence by randomly generating the initial population, non dominated sorting, and crowding selection. The crossover and mutation operations simulate the evolutionary process, and after multiple iterations, a set of Pareto optimal solutions is finally obtained [26-27]. However, traditional NSGA-II has problems such as slow convergence speed and weak local search ability when dealing with complex problems. Especially when facing high-dimensional and MO optimization problems, it may fall into local optima, resulting in a decline in the solution's quality [28]. Therefore, improvements were made to NSGA-II, and the specific improvement strategy is shown in Figure 5.

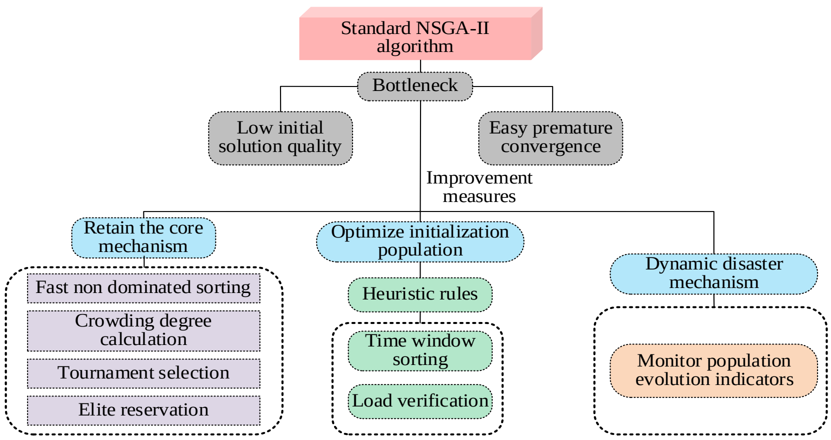


Figure 5: NSGA-II algorithm improvement strategy

As shown in Figure 5, the research mainly improves the quality of the population and avoids falling into local optima by optimizing the initialization population and introducing dynamic disaster mechanisms. Firstly, to accelerate algorithm convergence and improve the quality of initial solutions, a population initialization method that integrates heuristic rules was designed. By introducing time window sorting and load verification mechanisms, the overall quality of the initial population was effectively improved, laying the foundation for subsequent genetic evolution [29]. Secondly, to overcome the problem of declining population diversity and falling into local optima in the later stages of evolution, a dynamic catastrophe mechanism is introduced. Assuming that during the optimization process of a certain delivery route, the algorithm cannot find a better route in consecutive iterations, the dynamic disaster mechanism will randomly adjust the delivery order or node selection of some vehicles, generate new candidate routes, and re-explore the search space, effectively avoiding falling into local optima. This mechanism intelligently judges the convergence stagnation state by monitoring the changes in population evolution indicators. To achieve this, the relative improvement rate of the solution set quality between the current generation and the previous generation needs to be calculated, and the calculation formula is presented in equation (8) [30-31].

$$\eta_g = \frac{|HV_g - HV_{g-G}|}{HV_{g-G}} \quad (8)$$

In equation (8), g represents the algebra of the current algorithm iteration; G indicates the inspection interval; η_g is the relative improvement rate; HV_g is the hypervolume value of the Pareto front corresponding to the g th generation; HV_{g-G} is the hypervolume value of the Pareto front corresponding to the $g-G$ th generation. The formula quantifies the speed of population evolution by calculating the relative change range of hypervolume index after G generations, and carries out large-scale disturbance and mutation on non elite individuals after triggering, so as to effectively help the algorithm jump out of the local optimal region and re explore the global situation [32-33]. The population initialization process of the optimized NSGA-II is presented in Figure 6.

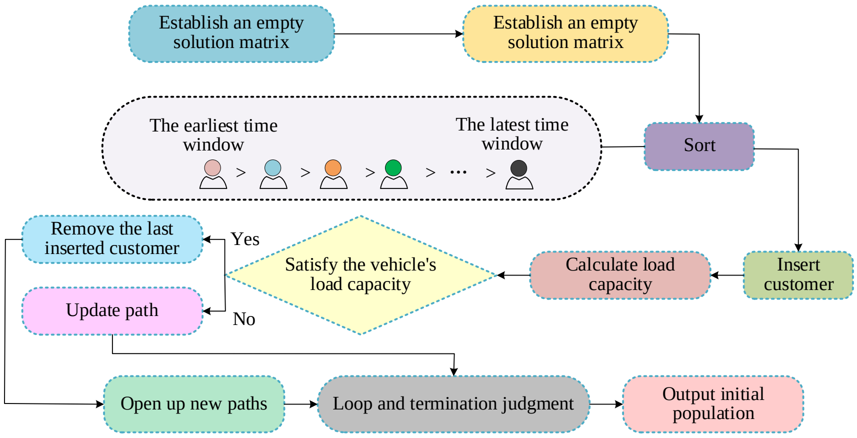


Figure 6: Schematic diagram of population initialization of I-NSGA-II algorithm

As presented in Figure 6, the population initialization process of the I-NSGA-II starts from establishing an empty solution matrix. Subsequently, the algorithm does not randomly insert the remaining customers, but sorts them based on their earliest available service time, prioritizing customers with earlier time windows to generate a more reasonable sequence in the time dimension. After inserting each new customer, the total load of the current path will be calculated in real-time, and it will be determined whether it exceeds the vehicle capacity constraint. If exceeded, the algorithm removes the last inserted customer and temporarily store the current path. Then it activates the new vehicle and starts the construction of the next path. This process iterates until all customers have been assigned, and finally outputs a high-quality initial chromosome population that meets the constraints of load and time window, laying a solid foundation for subsequent genetic iteration optimization. The pseudocode for heuristic population initialization is shown in Table 2.

Table 2: Heuristic population initialization pseudocode

Algorithm 1. Heuristic Population Initialization
Input: Customer set C = {c1, c2, ..., cn}, depot d0, vehicle capacity Q
Output: Initial feasible population P
1. Initialize population P ← ∅
2. Sort customers C by distance from depot d0
3. For each vehicle v in fleet V do
4. Initialize remaining load q ← Q, route Rv ← [d0]
5. While q > 0 and unserved customers exist do
6. Select next customer c with minimal incremental distance satisfying demand(c) ≤ q
7. Append c to Rv, update q ← q - demand(c)
8. End While
9. Append depot d0 to Rv, add Rv to solution set S
10. End For
11. Add solution S to population P
12. Repeat until |P| = PopSize
13. Return P

The overall process of the I-NSGA-II improved by the above strategy is shown in Figure 7.

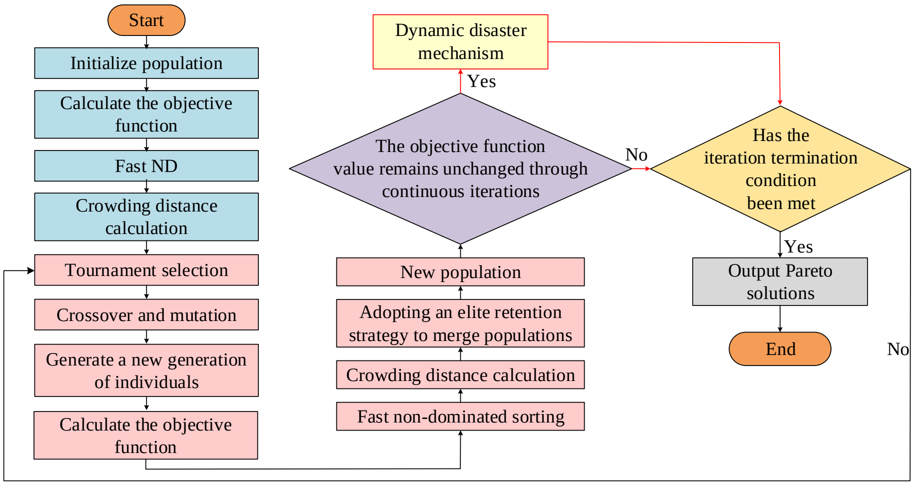


Figure 7: I-NSGA-II algorithm flow chart

The improved I-NSGA-II starts with population initialization, first calculates the objective function value for each individual, and then performs fast NS and crowding calculation to evaluate the fitness of individuals, the calculation of crowding degree is shown in equation (9) [34].

$$I_d^{[m]} = \frac{I_m(d+1) - I_m(d-1)}{f_m^{\max} - f_m^{\min}} \quad (9)$$

In equation (9), $I_d^{[m]}$ represents the degree of crowding; $f_m^{\max}$ and $f_m^{\min}$ respectively represent the max and min values of the m th objective function in the current non dominated hierarchy; $I_m(d+1)$ and $I_m(d-1)$ respectively represent the value of the current individual d on the m th target of the previous and subsequent individuals in the sorting sequence. Through tournament selection, the algorithm selects outstanding individuals for crossover and mutation operations to generate a new generation of individuals. After merging the parent and child populations, NS and crowding calculation are performed again, and the elite retention strategy is used to screen out the new generation population. When the objective function value continues to iterate without significant changes, triggering a disaster increases population diversity. This process persists until the predetermined max iteration count has been attained, and ultimately outputs a set of evenly distributed Pareto optimal solutions, providing decision-makers with multiple path optimization solutions that balance conflicting objectives such as transportation costs, energy consumption, customer satisfaction, and product freshness. The pseudocode of the I-NSGA-II algorithm is shown in Table 3.

Table 3: Pseudo-code of I-NSGA-II algorithm

I-NSGA-II for CCL Path Optimization
Algorithm: I-NSGA-II (Improved NSGA-II) Input: - Initial population (P) - Problem-specific parameters (time window, vehicle capacity, etc.) - Max iterations (MaxIter) - Disaster threshold (DisasterThreshold) Output: - Optimal solution set (Pareto Front) 1. Initialize population P with size N - Randomly generate individuals or use heuristic initialization 2. Evaluate fitness for each individual in P - For each individual, evaluate its objective functions (e.g., cost, time, etc.) 3. Set iteration counter k = 0 4. While k < MaxIter: a. Perform selection, crossover, and mutation to generate offspring Q b. Evaluate fitness for individuals in Q c. Combine P and Q into the mating pool R (P + Q) d. Sort R based on dominance (NSGA-II non-dominated sorting) e. Apply crowding distance sorting to R for diversity preservation f. Select new population P' from R using crowding distance and elitism g. Apply disaster condition check:

- If any individual violates disaster condition (e.g., temperature, load), initiate recovery
h. Check constraint satisfaction:
- Ensure vehicles do not exceed capacity and time window constraints are respected
i. If a new disaster is detected:
- Apply dynamic disaster mitigation (e.g., reroute or adjust vehicle schedules)
j. Increment iteration counter k
5. Output: Pareto optimal solutions (P')

4 Validation of optimization model for CCL delivery path in e-commerce

4.1 Performance verification of I-NSGA-II

The experimental environment for the research was based on Python 3.8 for algorithm implementation, mainly using the Distributed Evolutionary Algorithms in Python (DEAP) library to implement the I-NSGA-II, and using MATLAB for result visualization and performance analysis. The key experimental parameters were set as follows: population size of 100, maximum evolutionary generation of 300, crossover and mutation probabilities of 0.9 and 0.1, respectively, and a dynamic disaster mechanism based on the improvement rate of the Hypervolume index was introduced. To ensure the certainty and reproducibility of the results, the seed of the random number generator was fixed at 42 in all comparative experiments reported. The specific experimental equipment configuration is presented in Table.4.

Table 4: Experimental equipment configuration table

Type	Name	Configuration/Model
Hardware	Processor	Intel Core i7-10700K (8 cores, 16 threads)
Hardware	Memory	32GB DDR4 (Corsair Vengeance LPX)
Hardware	Storage	1TB SSD (Samsung 970 EVO Plus)
Hardware	GPU	NVIDIA GeForce GTX 1660 Ti
Hardware	Operating system	Windows 10 Pro 64-bit
Software	Programming language	Python 3.8
Software	Algorithm library	DEAP 1.0 (for GA implementation)
Software	Visualization tool	MATLAB 2021a (for analysis & visualization)
Software	Development environment	Visual Studio Code 1.62

Based on the experimental environment in Table.4, two open-source datasets were used as data sources to guarantee the feasibility of the algorithm under various scales and constraints. The first dataset was Solomon Benchmark Problem, which is widely used to evaluate algorithms for vehicle routing problems and delivery path optimization, covering various customer needs, locations, time windows, and other information. The second dataset was the Berlin52 dataset, which was a classic dataset for traveling salesman problems. Although the traveling salesman problem was relatively simplified compared to CCL, Berlin52 provided standard city coordinates and a path benchmark with known optimal solutions, which was very suitable for testing the core capabilities of algorithms in path structure optimization and global spatial search. To make it applicable to the multi-objective optimization scenario of CCL in this study, the model parameters were mapped as shown in Table 5.

Table 5: Dataset characteristics and constraint mapping

Feature	Solomon benchmark problem	Berlin52 (After mapping)
Problem type	Vehicle Routing Problem with Time Windows (VRPTW)	Traveling Salesman Problem transformed to Multi-objective VRPTW
Number of nodes	100	51 (1 depot + 50 customer points)
Capacity constraint	200	800
Time windows	Predefined time windows	Randomly generated time windows
Cold chain mapping	Directly Applicable: Route length determines transportation time and energy consumption; Time window constraints affect service quality.	Parameterized Mapping: Distance determines transportation cost and energy consumption; Total transportation time affects product freshness; Added time window constraints.
Validation focus	Algorithm performance in complex VRPTW scenarios	Fundamental route optimization capability and multi-objective generalization

The study first conducted parameter sensitivity analysis, and the results are shown in Table 6.

Table 6: Compare algorithm performance under different disaster-triggering thresholds and inspection intervals

Trigger threshold	Check interval	Total transportation cost (yuan)	Hypervolume	Optimal path mileage (km)	Total cooling energy consumption (kW · h)	Convergence algebra
0.05%	10	6021.54	0.849	445.72	90.15	285
0.05%	20	5987.83	0.861	441.08	89.23	265
0.05%	50	6054.16	0.838	449.91	91.04	241
0.10%	10	5950.29	0.868	438.95	88.41	270
0.10%	20	5923.47	0.87	436.59	87.93	248
0.10%	50	5941.88	0.865	439.14	88.52	230
0.50%	10	6125.77	0.821	455.33	93.87	195
0.50%	20	6089.42	0.829	451.67	92.95	182
0.50%	50	6158.69	0.815	458.24	94.61	175

The parameter sensitivity analysis results in Table 6 indicated that the triggering threshold and check interval of the dynamic disaster mechanism had a significant impact on the algorithm performance. The optimal parameter combination was a threshold of 0.1% and an interval of 20, at which point the algorithm achieved the best balance in terms of total transportation cost and energy efficiency indicators. When the threshold was too low, such as 0.05%, the disaster mechanism was too sensitive. Although population diversity was maintained, frequent disturbances disrupted the inheritance of excellent genes, resulting in delayed convergence and increased costs. When the threshold was too high, such as 0.5%, the disaster was difficult to activate, the algorithm fell into local optima, and various performance indicators significantly deteriorated. The impact of inspection intervals was equally crucial: excessive inspection at intervals of 10 resulted in redundant calculations, while at intervals of 50, there was insufficient response to convergence stagnation. It is worth noting that within the parameter range of 0.05% to 0.10% threshold, the algorithm performance fluctuated by less than 3%, proving that I-NSGA-II had good robustness within a reasonable parameter range, providing effective guidance for parameter settings in practical applications. Secondly, the proposed I-NSGA-II algorithm was compared with the original NSGA-II algorithm to verify the effectiveness of the improved strategy, as shown in Figure 8.

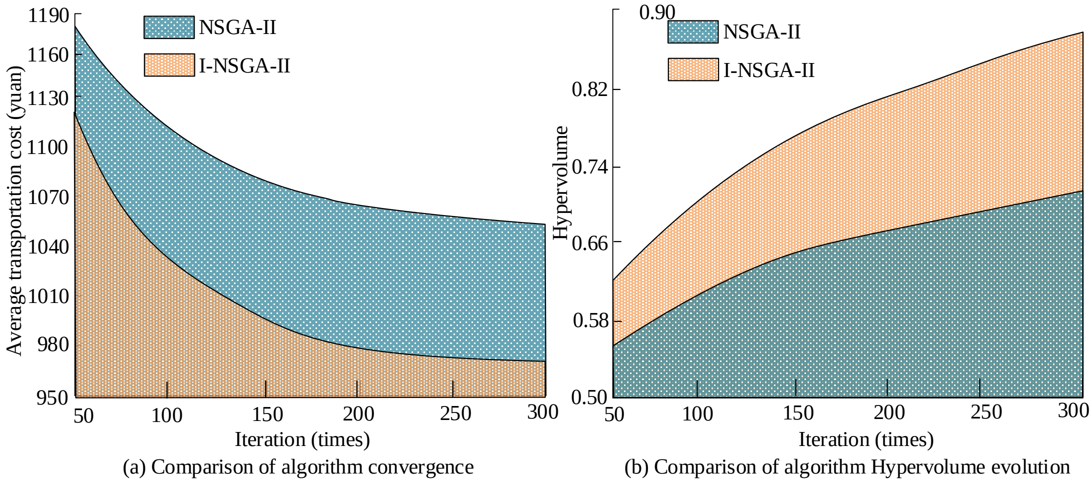


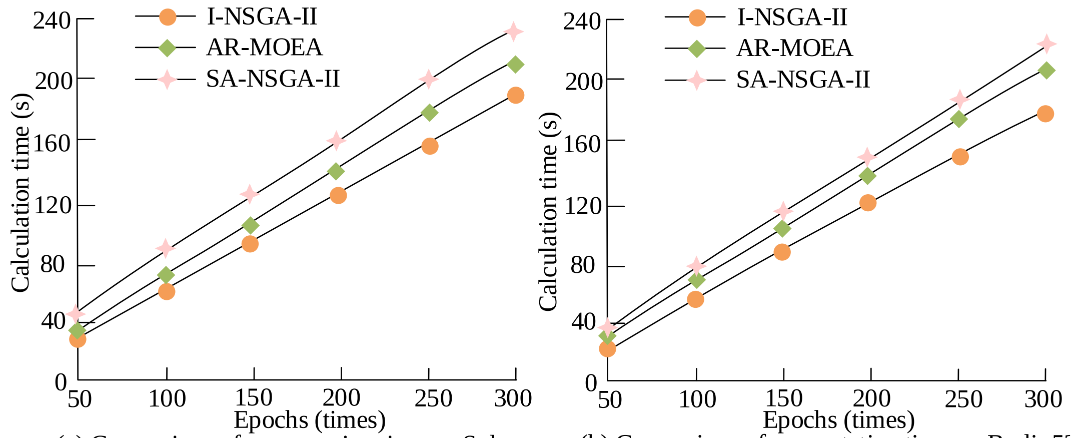
Figure 8: Comparison of convergence performance and Hypervolume evolution

According to Figure 8 (a), at 50 iterations, the average transportation cost of I-NSGA-II was 1120 yuan, which was 60 yuan lower than NSGA-II's 1180 yuan By the time of 300 iterations, the transportation cost of I-NSGA-II further decreased to 968 yuan, while the cost of NSGA-II remained at around 1055 yuan. This indicated that I-NSGA-II could more effectively optimize path selection and reduce transportation costs. The main reason was that I-NSGA-II introduced a dynamic catastrophe mechanism, which enabled the algorithm to avoid falling into local optima in the later stage and quickly approach the optimal solution. Based on Figure 8 (b), I-NSGA-II consistently outperformed NSGA-II in the Hypervolume metric, indicating that I-NSGA-II could provide a more uniform and Pareto front solution set. At 300 iterations, the Hypervolume value of I-NSGA-II reached 0.87, while NSGA-II was 0.72. This was mainly attributed to the dynamic catastrophe mechanism of the I-NSGA-II algorithm, which could effectively avoid early convergence and conflicts between multiple objectives, ensuring a more balanced distribution of the solution set. To accurately evaluate the independent contributions and synergistic effects of the proposed improvement strategies, four control experiments were designed: Config A (original NSGA-II algorithm as a benchmark), Config B (only adding heuristic initialization), Config C (only adding dynamic disaster mechanism), and Config D (complete I-NSGA-II algorithm, including all improvements). The experimental results are shown in Table 7.

Table 7: Contribution analysis of different improvement components

Config	Components	Total cost (yuan)	Hypervolume	Best route (km)	Energy (kW·h)	Generations	Cost reduction
A	Baseline (NSGA-II)	6328.91	0.721	472.15	101.58	278	-
B	+ Heuristic Init.	6085.34	0.826	452.88	93.47	192	3.85%
C	+ Dynamic Catastrophe	6146.72	0.843	457.21	95.12	265	2.88%
D	Full Model (I-NSGA-II)	5923.47	0.87	436.59	87.93	175	6.41%
Config	Components	Total Cost (yuan)	Hypervolume	Best Route (km)	Energy (kW·h)	Generations	Cost Reduction

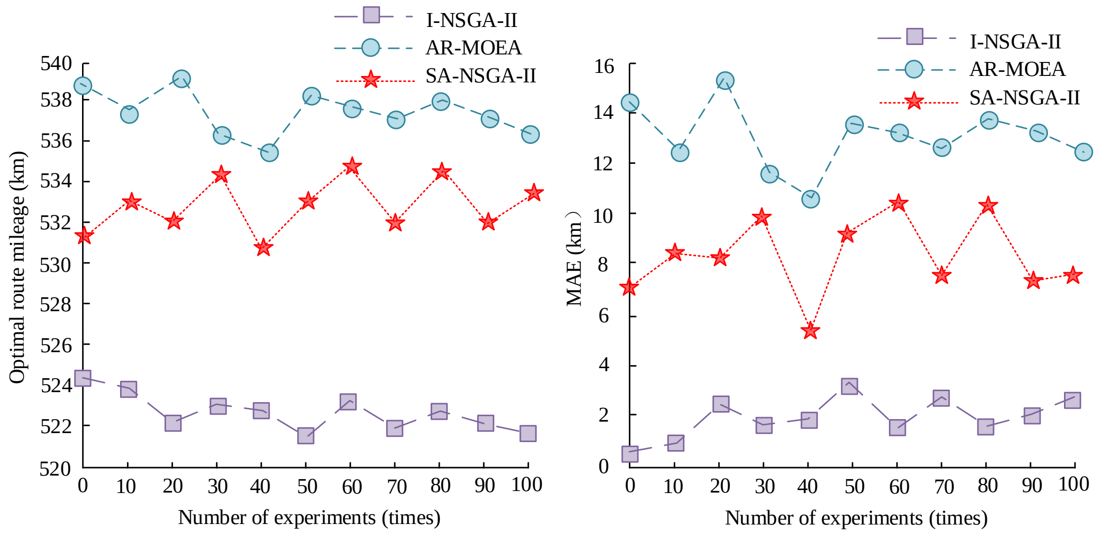
According to Table 7, the ablation experiment results clearly revealed the independent contributions and synergistic effects of the two improvement strategies. Using only heuristic initialization, Config B reduced transportation costs by 3.85% and significantly reduced convergence generations from 278 to 192, proving that it greatly accelerated early search efficiency by providing high-quality initial solutions. Config C, which only introduced dynamic disaster mechanism, exhibited the best diversity preservation ability, with a Hypervolume of 0.843, indicating that it could effectively avoid premature convergence, but the improvement in convergence speed was limited. The complete I-NSGA-II achieved a cost reduction of 6.41% and the fastest convergence speed of the 175th generation, with an improvement greater than the sum of the independent contributions of each component. This fully demonstrated the strong synergistic effect between heuristic initialization and dynamic catastrophe mechanism: high-quality initial solutions lay the foundation for global search, while dynamic catastrophe ensured that the algorithm was not limited to local regions, jointly achieving a dual breakthrough in convergence speed and solution set quality. To further validate the effectiveness of the I-NSGA-II algorithm, a multi-objective evolutionary algorithm based on adaptive reference points (AR-MEA) and an improved NSGA-II algorithm based on SA (SA-NSGA-II) were introduced for comparison. Firstly, the computation time of three algorithms on two datasets was compared, and the outcomes are presented in Figure 9.



(a) Comparison of computation time on Solomon Benchmark Problem dataset (b) Comparison of computation time on Berlin52 Dataset

Figure 9: Comparison of computing time between different algorithms on two data sets

From Figure 9 (a), at 300 iterations, the computation time of I-NSGA-II on the Solomon Benchmark Problem dataset was 181.74 seconds, which was an average improvement of 18.03% compared to AR-MOEA and SA-NSGA-II, demonstrating higher efficiency. Explanation: I-NSGA-II reduced unnecessary computational burden by introducing dynamic disaster mechanisms and efficient population initialization strategies. Based on Figure 9 (b), compared to the Solomon Benchmark Problem dataset, the computation time of the Berlin52 dataset was generally shorter. This was mainly related to the complex Solomon Benchmark Problem dataset, which contained more constraints and delivery path problems. However, I-NSGA-II still exhibited superior computational performance, with a computation time of 174.92s after 300 iterations, which was still lower than the average improvement of 19.47% for the other two algorithms. This once again confirmed that I-NSGA-II could efficiently explore the solution space and quickly converge in complex multi-objective optimization problems. Meanwhile, the study compared the mileage and Mean Absolute Error (MAE) of three algorithms for solving the optimal path on the Solomon Benchmark Problem dataset. The known reference optimal path was 524.61 km, and the results are shown in Figure 10.



(a) Comparison of optimum total mileage (b) Comparison of MAE

Figure 10: Comparison of MAE between optimal path mileage and sum of three algorithms under different experimental times

As presented in Figure 10 (a), the I-NSGA-II obtained the lowest average optimal path mileage in all 100 experiments, which was 522.96 km, and the data fluctuation was minimal, significantly better than AR-MOEA's 537.48 km and SA-NSGA-II's 532.98 km. This indicated that its heuristic initialization strategy provided high-quality initial solutions, and combined with dynamic disaster mechanisms, effectively avoided local optima, thereby achieving stable and globally optimal path search capabilities. Figure 10 (b) shows that the MAE of the I-NSGA-IIwas only 1.65 km, much lower than the comparison algorithms AR-MOEA's 12.97 km and SA-NSGA-II's 8.37 km. This indicated that the I-NSGA-II, through elite preservation and adaptive search mechanism, always kept the solution set close to the true Pareto front, significantly improving the accuracy and stability of the solution.

4.2 Validation of the optimization model for CCL distribution paths

To verify the effectiveness of the I-NSGA-II algorithm in solving the optimization problem of e-commerce CCL distribution paths, a comparative test was conducted on the Solomon standard dataset using the controlled variable method on three algorithms: I-NSGA-II, SA-NSGA-II, and AR-MOEA. Moreover, inferential statistical tests were used for comparative analysis. Considering that most performance indicators data approximately follow a normal distribution, paired sample t-test was chosen for hypothesis testing in the study. The comprehensive optimization results of the three algorithms are shown in Table 8.

Table 8: Comparison of comprehensive optimization results of CCL distribution of three algorithms

Evaluation metrics	I-NSGA-II	SA-NSGA-II	*p*-value (vs SA-NSGA-II)	AR-MOEA	*p*-value (vs AR-MOEA)
Total transportation cost (yuan)	5923.47	6328.91	< 0.001**	6637.24	< 0.001**
Fixed cost (yuan)	1200	1200	-	1200	-
Transportation cost (yuan)	3304.62	3618.37	< 0.001**	3792.86	< 0.001**
Refrigeration cost (yuan)	927.18	983.42	0.002**	1062.59	< 0.001**

Time window penalty cost (yuan)	491.67	527.12	0.019*	581.79	< 0.001**
Customer time satisfaction	0.954	0.918	0.007**	0.886	< 0.001**
Average freshness of goods	0.962	0.927	0.001**	0.903	< 0.001**
Total cooling energy consumption (kW·h)	87.93	96.24	0.004**	104.71	< 0.001**

According to Table 8, the I-NSGA-II algorithm had the lowest total transportation cost of 5923.47 yuan, which was an average reduction of 8.63% compared to SA-NSGA-II and AR-MOEA, and this difference was highly statistically significant (p<0.001). And its transportation cost is the lowest, at 3304.62 yuan, indicating shorter path mileage and higher fuel efficiency. The refrigeration cost was significantly reduced to 927.18 yuan, thanks to shorter transportation time and reduced energy consumption of refrigeration equipment. The time window penalty cost was only 491.67 yuan, which proved that it could better meet the customer's timeliness requirements. These optimizations directly improved the quality of terminal services, resulting in customer time satisfaction and average product freshness reaching 0.954 and 0.962, respectively. In terms of total refrigeration energy consumption, I-NSGA-II had the lowest 87.93 kWh, further demonstrating its energy-saving advantages. The fundamental reason was that the heuristic initialization of I-NSGA-II provided a high-quality search starting point, while the dynamic disaster mechanism effectively avoided local optima, enabling it to globally coordinate the complex relationship between path, time, and energy consumption, thereby systematically achieving cost reduction and efficiency improvement. To further analyze the performance of the three algorithms in CCL distribution, this study compared the optimal distribution paths obtained by the three algorithms using 25 customer nodes, 1 distribution center, and 5 distribution vehicles selected from a certain location as examples. The results are shown in Figure 11.

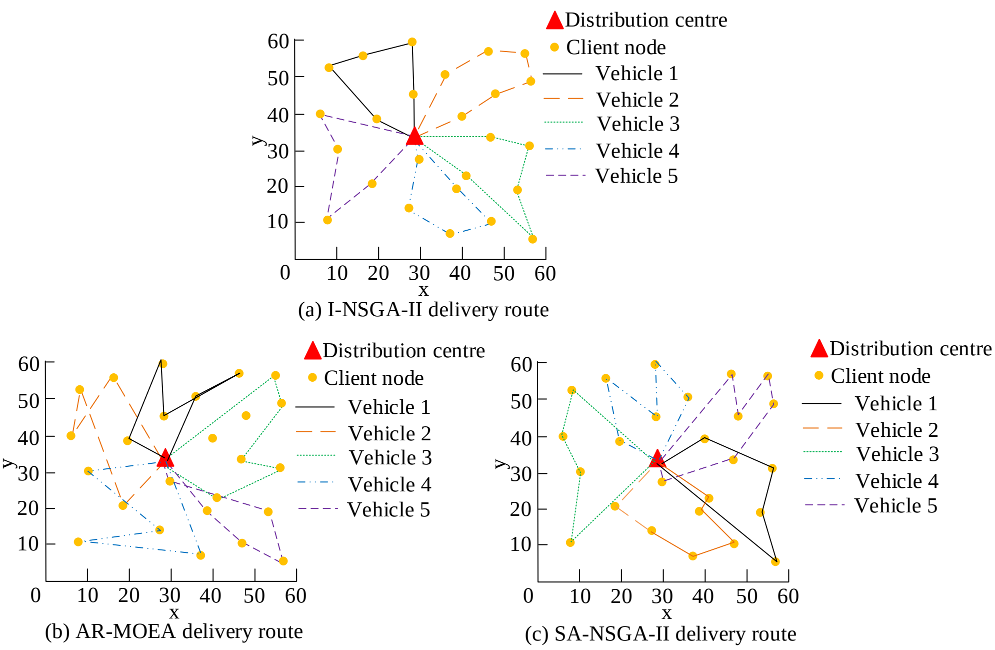
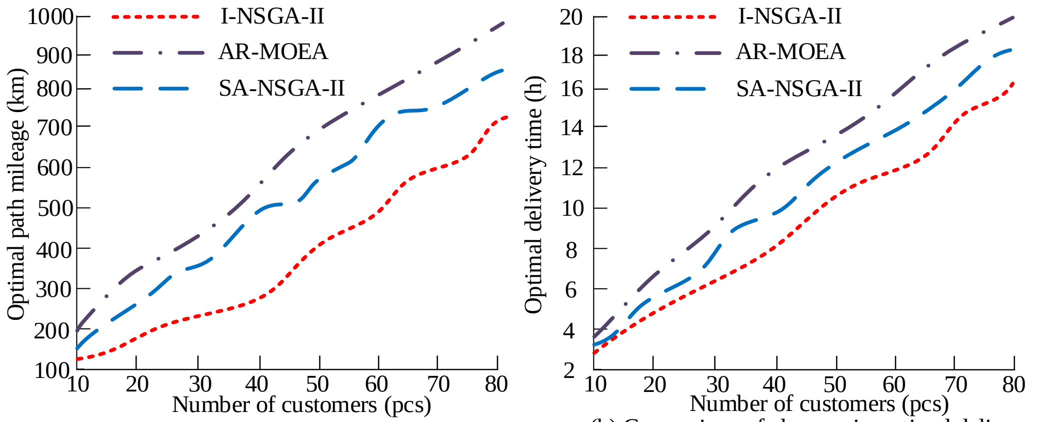


Figure 11: A comparison of the optimal route map of three algorithms in CCL distribution

Figure 11 visually illustrates the path optimization effects of three algorithms: the delivery path of I-NSGA-II exhibited clear spatial partitioning characteristics, with compact and non intersecting vehicle paths, balanced loads, and continuous coverage, indicating its successful achievement of MO collaborative optimization. The path of AR-MOEA had obvious intersections and overlaps, some vehicle paths were lengthy, and the service order of edge customer points was chaotic, reflecting that its reference point-based search mechanism was prone to generating redundant paths under complex spatial constraints. Although the path of SA-NSGA-II was more regular than AR-MOEA, there were still local loops and a small number of intersections, and the task allocation between vehicles was uneven. For example, the path of vehicle 5 was significantly too short, indicating that although the local search characteristics of simulated annealing mechanism could improve convergence, it was difficult to globally coordinate spatial conflicts between paths. Overall, I-NSGA-II generated high-quality initial solutions through heuristic initialization and combines dynamic disaster mechanisms to escape local optima, thereby efficiently approaching the Pareto optimal solution set with good spatial distribution and cost energy consumption while maintaining population diversity. At the same time, the optimal route mileage and delivery time of the algorithm were compared under different customer numbers, and the results are shown in Figure 12.



(a) Comparison of changes in optimal path mileage with increasing number of customers

(b) Comparison of changes in optimal delivery times with increasing number of customers

Figure 12: Comparison of optimal path mileage and delivery time of algorithm with different number of users

According to Figure 12 (a), when the number of customers was 80, the mileage of I-NSGA-II was about 713.24 km, which was an average reduction of 21.22% compared to the other two algorithms. This indicated that the heuristic initialization strategy of I-NSGA-II provided a better path starting point, while the dynamic disaster mechanism effectively avoided local optima, enabling efficient coordination of multi vehicle path planning. Based on Figure 12 (b), I-NSGA-II achieved the fastest delivery efficiency across all customer scales with its shortest path. In the 80-customer scenario, the delivery time was 16.35 hours, which was an average reduction of 14.04% compared to other algorithms. This was because shorter paths directly translated into less travel time, and the algorithm effectively reduced waiting and detours by optimizing the order of customer point services and task allocation between vehicles, which was crucial for ensuring the quality of fresh products. Finally, the study compared the CCL distribution path optimization models proposed by three other scholars, and the outcomes are presented in Table.9.

Table 9: Comprehensive performance comparison of different CCL distribution path optimization models

Evaluation metrics	I-NSGA-II	Reference [5]	Reference [9]	Reference [35]
Total transportation cost (yuan)	5923.47	6358.92	6189.24	6412.65
Customer time satisfaction	0.95	0.89	0.92	0.87
Average freshness of goods	0.96	0.91	0.93	0.9
Total cooling energy consumption (kW·h)	87.93	102.45	96.81	105.27
Optimal path mileage (km)	436.59	482.17	458.32	491.04
Total delivery time (min)	945.38	1028.64	987.25	1053.91
Vehicle utilization rate (%)	96.32	88.75	92.16	86.43
Damage rate (%)	2.35	4.18	3.27	4.65

According to Table 9, the optimization model based on I-NSGA-II proposed by the research performed the best in all key performance indicators. The most significant feature was that it reduced the cargo damage rate to 2.35%, which was an average decrease of 41.74% compared to the comparative model. This was directly due to the algorithm's precise optimization of delivery routes and times: the optimal route mileage and total delivery time were reduced to 436.59 km and 945.38 min, respectively, thereby reducing quality degradation caused by the cumulative effect of temperature fluctuations. The optimization of the path brought significant reductions in both cost and energy consumption, with a total transportation cost of 5923.47 yuan and a total refrigeration energy consumption of 87.93 kW·h, reaching the lowest levels respectively. In the end, these technological advantages were transformed into excellent terminal service indicators, with customer time satisfaction and average product freshness reaching 0.95 and 0.96, respectively, proving that the model could not only achieve economic goals, but also effectively ensure the quality of CCL goods and customer experience. Its 96.32% vehicle utilization rate further indicated that the algorithm achieved near optimal configuration efficiency in resource scheduling. These results fully proved the effectiveness and progressiveness of the optimization model proposed in the study in solving the problem of CCL path optimization.

5 Discussion and interpretation

The research findings demonstrated that the CCL distribution path optimization method based on I-NSGA-IIwas notably better than traditional NSGA-II, SA-NSGA-II, and AR-MOEA algorithms in MO aspects such as transportation cost, refrigeration energy consumption, customer time satisfaction, and product freshness. This advantage not only verified the effectiveness of the improvement strategy, but also confirmed the superiority of the idea of deeply integrating problem domain knowledge into the core of the algorithm. Compared with other recent NSGA-II improvement work, the innovation of the research is that its improvement strategy is not a general performance improvement, but a customized design that closely revolves around the unique constraints and goals of the CCL path optimization problem. First of all, the heuristic population initialization strategy studied deeply integrates the domain knowledge of logistics and distribution, and directly embeds logistics scheduling rules through the "time window sorting" and "load verification" mechanisms. The generated initial solution inherently satisfies complex spatio-temporal constraints and is more direct and efficient. Secondly, the core of the dynamic catastrophe mechanism introduced in the study lies in the adaptive triggering based on the Hypervolume indicator. This is essentially different from SA-NSGA-II which simply introduces local search operators such as simulated annealing. The SA mechanism focuses on local fine-grained search to improve convergence, while the dynamic catastrophic mechanism is a macroscopic, intelligent control strategy oriented to population diversity. When the algorithm evolution is stagnant, it can effectively help the algorithm jump out of the local Pareto frontier by perturbing non-elite individuals and re-explore the global environment, thereby better handling the trade-off relationships between multiple conflicting objectives such as "transportation cost", "refrigeration energy consumption" and "goods freshness", and ensuring the uniformity and extensiveness of the final solution set distribution.

From the perspective of path optimization effect, the delivery routes generated by I-NSGA-II had obvious spatial partitioning characteristics, with compact vehicle paths, balanced loads, and continuous coverage, significantly reducing crossings and detours compared to other algorithms. This spatial structure optimization not only reduced transportation mileage and costs, but also reduced the operating time and energy consumption of refrigeration equipment, further improving the freshness of goods and customer satisfaction. For comparison purposes, Table 10 presents the main performance indicators of the proposed I-NSGA-II compared to references [5] and [7].

Table 10: Comparative analysis of cross model comprehensive performance

Evaluation metrics	I-NSGA-II	Reference [5]	Reference [7]	Reference [9]
Total transportation cost (yuan)	5923.47	6358.92	6412.65	6189.24
Customer time satisfaction	0.954	0.891	0.872	0.925
Average freshness of goods	0.962	0.914	0.907	0.931
Total cooling energy consumption (kW · h)	87.93	102.45	105.27	96.81
Optimal path mileage (km)	436.59	482.17	491.04	458.32
Total delivery time (min)	945.38	1028.64	987.25	1053.91
Damage rate (%)	2.35	4.18	3.27	4.65

From Table 10, the I-NSGA-II algorithm proposed in the study achieved optimal performance in multiple key indicators such as total transportation cost, customer satisfaction, freshness of goods, and refrigeration energy consumption. This systemic advantage was rooted in the core methodological differences between it and the comparative model. Compared with the random or simply constructed population initialization methods commonly used in references [5] and [7], the heuristic initialization strategy studied deeply integrated domain knowledge (time window sorting and load verification), generated high-quality initial solutions in both spatiotemporal dimensions, and laid a superior starting point for subsequent progress, directly promoting lower transportation costs and shorter path mileage. At the same time, facing the common problems of slow convergence of the model in large-scale scenarios in reference [7] and the tendency of the models in references [5] and [9] to fall into local optima, the dynamic catastrophe mechanism introduced by I-NSGA-II adaptively increased population diversity by monitoring the Hypervolume index, effectively ensuring the global exploration ability of the algorithm, enabling it to jump out of the local Pareto front and discover more outstanding equilibrium solutions between conflicting objectives. Therefore, the research method achieved a more efficient and thorough exploration of complex trade-offs between multiple objectives through the collaboration of high-quality initialization and intelligent global search, ultimately achieving multiple optimization goals of cost reduction, efficiency improvement, and quality enhancement.

Meanwhile, the results revealed the adaptability of the algorithm in the face of different customer sizes and delivery constraints. Although it performed stably on standard datasets, there is still room for improvement in the real-time response capability of path optimization in large-scale dynamic orders and unexpected event scenarios. In addition, the model assumed that external conditions such as traffic conditions, weather changes, and equipment reliability were relatively stable, which ensured the comparability of algorithm performance in benchmark testing. However, in practical application scenarios, these external conditions often exhibit dynamic changes and inevitable uncertainties exist. To achieve generalization from static optimization to dynamic scheduling, subsequent research can introduce a real-time data input mechanism to enable the model to dynamically adjust scheduling strategies based on real-time changes in traffic flow, weather conditions, or equipment status. Moreover, by using probability models, robust optimization, or reinforcement learning methods, the uncertainty of the external environment is incorporated into the algorithm decision framework, thereby improving stability and reliability in practical scenarios.

In summary, the optimization model proposed in the study showed high efficiency and optimization effects in CCL distribution, and could provide a reference for related logistics scheduling. Meanwhile, the model had cross-domain promotion potential and could be applied to scenarios such as vehicle route planning, emergency logistics dispatch, and intelligent manufacturing scheduling. In the future, by further introducing dynamic scheduling algorithms and uncertainty modeling methods, the generalization ability and practical value of the model in actual complex environments will be significantly improved.

6 Summary

E-commerce CCL faces problems such as high transportation costs, low efficiency, and susceptibility of product quality to temperature control during the distribution process. To reduce costs, decrease refrigeration energy consumption, and improve customer satisfaction and product freshness, an MO distribution path optimization model based on the I-NSGA-II was proposed. This model improved the initial solution quality through heuristic population initialization and introduced a dynamic disaster mechanism to enhance global search capability, avoiding falling into local optima. The experimental outcomes based on Solomon Benchmark Problem and Berlin52 dataset showed that the improved algorithm outperformed traditional NSGA-II, SA-NSGA-II, and AR-MOEA algorithms in key indicators such as total transportation cost, refrigeration energy consumption, customer time satisfaction, and average freshness of goods. The total transportation cost was 5923.47-yuan, customer time satisfaction and average freshness of goods reached 0.954 and 0.962, respectively. The total refrigeration energy consumption was reduced to 87.93 kWh, the optimal route mileage was 436.59 km, the delivery time was 945.38 minutes, and the cargo damage rate was 2.35%. When the number of customers was 80, the optimal mileage of I-NSGA-II was 713.24 km and 16.35 h, which was 21.22% and 14.04% lower than other algorithms, respectively. The findings indicated that the model could effectively optimize the CCL path, achieve MO collaborative optimization, provide reliable basis for distribution decision-making, and balance economy and service quality.

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