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Two-stage optimization of instant distribution of fresh products based on improved NSGA-III algorithm

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A B S T R A C T

As an important part of the fresh produce business format, fresh food instant delivery encounters numerous challenges. Issues like high losses, complex cold chains and time sensitivity lead to increased costs. Additionally, the living space of end-delivery personnel is under pressure and the talent market is saturated. The platform algorithms focus on the interests of themselves and customers while relatively overlooking those of delivery personnel, which affects the overall operation quality, resulting in a significant reduction in delivery efficiency and a remarkable decline in service quality, and further leading to the loss of user stickiness. Therefore, optimizing the fresh food delivery route and considering the interests of multiple parties to improve efficiency and service quality is a crucial research issue in the field of fresh food instant delivery. This paper designs a three-objective static model for fresh food instant delivery aiming at minimizing the total cost, maximizing customer satisfaction and maximizing riders satisfaction. Considering the dynamic changes of orders during the actual operation process and in combination with the dynamics of newly added orders, a multi-objective dynamic model with the goals of minimizing the total cost, minimizing the average customer dissatisfaction and maximizing the income fairness of riders is further established. Based on the constructed models and by incorporating the SPBO strategy, the NSGA-III algorithm is improved and designed to make it more adaptable to the multi-objective optimization requirements in the fresh food instant delivery scenario. This study selects five operational points within a specific region of a fresh food self-operated platform and the order data from a particular day as research cases to obtain the relevant parameters required for the model and conduct case analysis. Based on the platform's business priorities and development needs, appropriate Pareto solutions are selected. Additionally, the feasibility and effectiveness of the improved algorithm are verified through algorithmic comparison. The research aims to provide valuable references and insightful implications for the management decisions of relevant fresh food self-operated platforms, as well as to continuously optimize the management and service of the instant delivery process.

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1. Introduction

With the rapid development of fresh produce e-commerce, the position of fresh products in the consumer market has become increasingly prominent (Yang et al., 2022). Fresh produce e-commerce platforms represented by Dingdong Maicai and Missfresh have changed the pattern of traditional fresh produce consumption through the new retail model of "placing orders online-fast home delivery". This model not only meets consumers' strict requirements for the fresh quality of fresh products and delivery efficiency, but also promotes the vigorous development of the instant delivery industry (Fan et al., 2022). Data show that the scale of the fresh e-commerce market has continued to grow in recent years, with a compound annual growth rate of about 7%. The instant delivery industry has also entered a new era of hour-level fulfillment for all product categories and scenarios, becoming a key link connecting online and offline consumption (Cui et al., 2022). However, the industry still faces many challenges. Firstly, the problem of high loss rates of fresh products is particularly prominent. Due to the perishable and vulnerable characteristics of fresh products (Bi et al., 2021), in the process of distribution, it is easy to cause quality degradation due to temperature fluctuations, improper packaging or transportation delays, and the loss rate of distribution increases significantly, which directly affects user experience and platform reputation (Yu & Xiao, 2021) (Jiang et al., 2023). Secondly, compared with general industrial products, the supply chain management of fresh agricultural products is more

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complex (Ming et al., 2021). Fresh product delivery requires temperature control throughout the process and involves the coordination of multiple links such as warehousing, transportation, and last-mile delivery. Any mistake in any link may lead to a decline in product quality. In addition, fresh delivery requires high timeliness, and consumers usually expect to receive goods within 1-2 hours or even less, which poses a severe challenge to the response speed and scheduling ability of the distribution network (Wang et al., 2022). These problems are superimposed layer by layer and ultimately transmitted to the end of the delivery process, manifested as a severe squeeze on the living space of riders. With the expansion of the industry scale, the number of delivery workers has become saturated, leading to increased competition in the industry. While platform algorithms pursue the maximization of their own interests and the improvement of customer satisfaction, they often overlook the protection of delivery workers' rights and interests (Ling et al., 2022). For example, the algorithm system tends to shorten delivery times and increase the number of orders, but does not fully consider the work intensity and income fairness of delivery workers. This imbalance has led to a decline in delivery workers' job satisfaction, which in turn has caused a decline in delivery efficiency and service quality (Li 2024) (Xu et al., 2024). In the long run, this vicious cycle may lead to a decrease in user stickiness and a loss of market share, ultimately affecting the sustainable development of the industry.

For the problem of instant delivery of fresh food, a fresh food vehicle routing problem with customer classification and split demand was proposed, introducing a knapsack-based demand splitting method and constructing a multi-objective model incorporating customer importance, soft time windows, and freshness loss costs (Xia et al., 2021). To improve the quality of takeaway delivery services, a multi-objective routing model with customer priority, time windows, and dynamic constraints was developed (Zhang et al., 2021). A multi-objective optimization framework considering soft time windows, payment mechanisms, and deliverymen's order mix was established, focusing on total cost and customer time satisfaction (Zhang et al., 2020). To address the dynamics and timeliness of online-to-offline (O2O) fresh takeaway orders, an immediate distribution route optimization model was established with the goal of minimizing distribution distance, and a rolling time delay distribution algorithm was designed to solve it (Yu et al., 2022). To solve the large-scale instant delivery vehicle routing problem during peak hours, a knowledge-driven ant colony optimization algorithm was proposed (Hou et al., 2023). A multi-objective collaborative routing optimization strategy was proposed, integrating deliverymen's fatigue, path costs, and customer satisfaction into a framework with soft time window constraints (Ling et al., 2024). From the perspective of customer satisfaction, customer psychological behavior related to delivery time and fresh quality was studied, and a mixed-integer nonlinear programming model with time and quality satisfaction functions was proposed, solved by an improved adaptive large neighborhood search algorithm (Huang et al., 2024). The closed-loop inventory routing problem for perishable food packaged by multiple types of recyclable transport items (RTIs) was explored, and a customized kernel search (KS) mathematical heuristic algorithm was designed as an efficient solution (Zhang et al., 2024). A bi-objective mixed-integer linear programming model with customer priorities and delivery time windows was constructed, and an adaptive large neighborhood search algorithm was proposed to obtain Pareto frontiers (Liang et al., 2024). To address the problems of high cost and large loss in the terminal distribution of fresh e-commerce retail parcels, a loss function for fresh products was constructed, and a multi-party collaborative distribution vehicle routing optimization model was proposed, with an algorithm framework combining k-means clustering and ALNS designed to solve it (Rao et al., 2025).

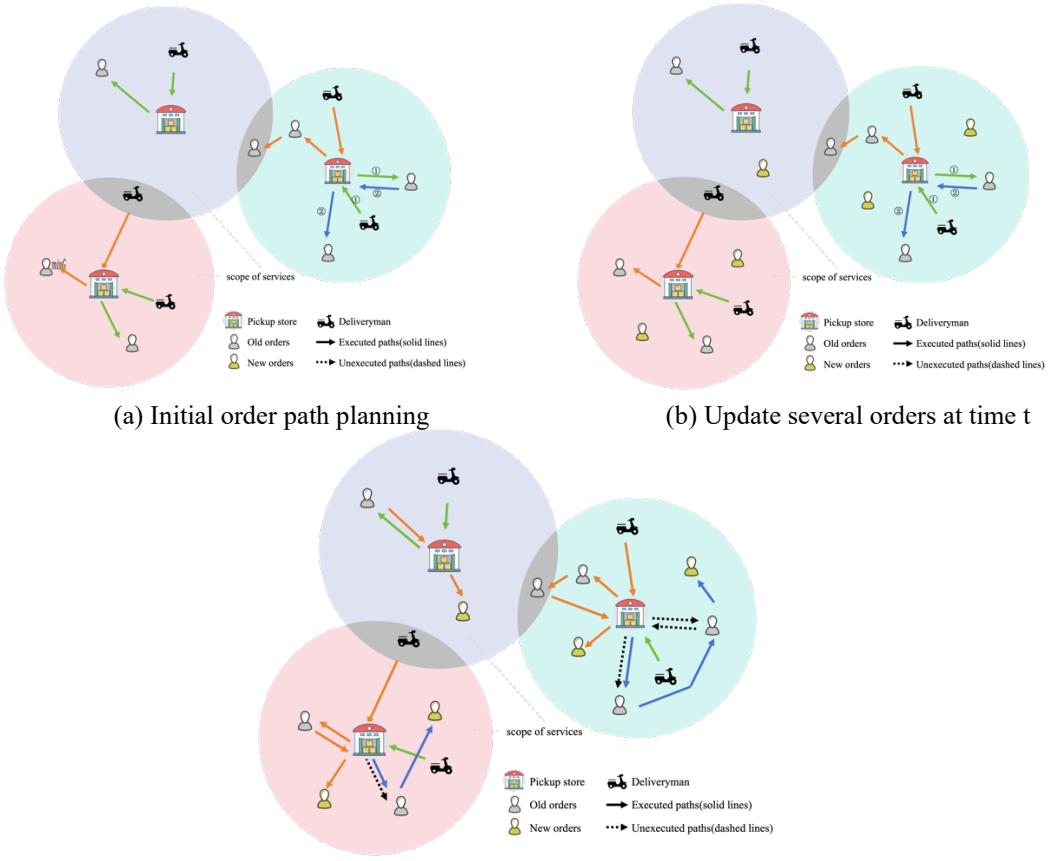
For solving multi-objective path optimization problems, a non-dominated sorting Genetic Algorithm (NSGA) was proposed, in which individuals are distributed in Pareto optimal space to achieve solution diversity (Srinivas & Deb, 1994). Based on the NSGA algorithm, an improved version, NSGA-II, was developed (Deb et al., 2002). To address high-dimensional optimization problems, the NSGA-III algorithm was proposed, combining Pareto dominance and decomposition strategies (Deb et al., 2014). A new bi-objective mixed integer linear programming model was introduced, along with a multi-objective metaheuristic evolutionary algorithm, whose effectiveness was verified by comparing it with NSGA-II and Pareto Archived Evolution Strategy (PAES) (Goodarzi et al., 2020). An immediate distribution routing optimization model was constructed to balance distribution costs, customer satisfaction, and deliverymen's income, and a hybrid ant colony algorithm was proposed to solve the problem effectively (Jiang et al., 2022). To address the last-mile problem in instant delivery, a strategy was designed to estimate time, distance, and paths accurately, improving real-time distribution path quality and time-distance estimation accuracy (Wang et al., 2023). A mixed integer programming model was proposed to optimize the allocation of heterogeneous orders and the scheduling of couriers, along with a column generation model and heuristic solution process (Zhen et al., 2023). A bi-objective time-varying vehicle routing problem with delivery failure probability (TDVRPDFP) was proposed, and a mixed integer linear programming model and NSGA-II algorithm were implemented to solve it (Menares et al., 2023). A UAV-driven smart distribution network design framework was proposed, and an improved NSGA-III algorithm was developed to solve the bi-objective nonlinear programming model (Sun et al., 2024). An adaptive multi-objective genetic algorithm with a greedy initialization strategy (AMAG-GIS) was proposed to handle the HGCVRPTW problem, improving population diversity through adaptive multi-mutation operators (Zhao et al., 2024). A three-stage multimodal multi-objective differential evolution algorithm (3S-MMDEA) was proposed to solve the Vehicle Routing Problem with Time Windows (VRPTW), improving logistics distribution efficiency (Zhang et al., 2024). An integrated planning drone and robot-assisted truck (DART) delivery model was developed, minimizing total distribution cost while maximizing customer satisfaction (Zhao et al., 2025). A model combining operational efficiency, environmental protection, and social responsibility was proposed, utilizing NSGA-II and multi-objective particle swarm optimization (MOPSO) for optimization (Gouraji et al., 2025). In summary, many studies have proposed optimization models that consider minimizing transportation costs, time, or energy consumption. With the rise of fresh e-commerce, researchers have begun to pay attention to multi-dimensional problems such

as real-time adjustment of distribution routes, freshness maintenance, transportation cost control and customer satisfaction. With the popularity of just-in-time delivery service, researchers have further explored new problems such as fairness of deliverers, just-in-time routing optimization, and multi-objective scheduling. With the progress of technology, combined with algorithms such as ant colony algorithm, genetic algorithm and simulated annealing, researchers have optimized the efficiency and fairness of distribution routes, and proposed new calculation methods, such as adaptive algorithm based on real-time logistics status and multi-party fairness algorithm based on deep reinforcement learning. Although the research on multi-objective routing optimization has made significant progress, there are still shortcomings, and this study will focus on the following points: (1) Consider multiple just-in-time distribution centers. Most of the existing research focuses on the routing optimization problem of a single instant distribution center. In this paper, we will consider multiple even distribution centers, and optimize the distribution routing by coordinating the orders of multiple distribution centers. (2) Consider the long-term development goal of balanced interests among subjects. This paper considers the tripartite equilibrium of platform, consumer and deliverer, and does not adopt the conventional multi-objective research method of linear weighting, but considers the Pareto optimum to achieve the interests of the three parties. (3) Research on algorithm improvement. In this paper, the strategy is improved based on the non-dominated sorting algorithm to obtain better model solution results.

2. Mathematical model design

2.1 Problem description

Assume a fresh food self-operated platform, such as Dingdong Maicai or Hema Fresh, operates within a certain area with M supply centers (pickup points) and R delivery staff. Customers place orders for fresh agricultural products from merchants on the platform, and each order requires home delivery within a specified time frame. Each order has different time requirements, but considering the characteristics of instant delivery, such as rapid response and strong timeliness, customer demand orders appear in real time. Upon order arrival, the platform assigns orders to delivery staff based on certain rules. Initially, delivery staff are randomly distributed within the area. After accepting an order, a delivery staff member must pick up the order from the nearest store. As demand orders emerge, pickup points dynamically change, and a delivery staff member may serve multiple customers in a single round of delivery. The delivery vehicle has a maximum load capacity of Q. After completing all assigned deliveries, the delivery staff updates their location, which becomes the starting position for the next pickup point. During the delivery process, if a new order is inserted, the system must consider whether to adjust the route to prioritize the new pickup. A conceptual diagram illustrating the problem is shown in Fig. 1.



(a) Initial order path planning

(b) Update several orders at time t

(c) Path Planning after Order Insertion at time t

Fig. 1. Diagram of dynamic routing optimization problem of instant distribution of fresh products considering multi-objectives

2.2 Problem assumptions

To obtain suitable solutions, the model is based on the following assumptions:

(1) Riders do not mark orders as delivered in advance.
(2) Each customer is served by exactly one delivery staff member.
(3) Delivery vehicles are homogeneous.
(4) After picking up goods, the current load must not exceed the maximum load capacity of the vehicle.
(5) Delivery staff must first pick up goods from the supply center before delivering them to customers.
(6) Due to the difficulty in quantifying the impact of factors such as terrain, road conditions, and traffic on the optimization of delivery routes, traffic conditions are not considered. The delivery vehicle speed is assumed to be a constant average value throughout the delivery.

2.3 Initialization model construction

2.3.1 Basic parameter

According to the needs of initializing the model, our study set the following basic parameters and decision variables, as shown below.

Table 1
Symbol description of initialization model

Symbol	Description
N	$N = \{1,2,3,\ldots,n,n+1,\ldots,2n\}$, The set of all nodes, including pickup points and delivery points,
P	The set of all pickup points, $P = \{1,2,3,\ldots,p,\ldots,n\}$.
D	The set of all delivery points, $D = \{n+1, n+2,\ldots,2n\}$.
R	The set of all delivery staff/vehicles, $R = \{1,\ldots,r\}$.
r	The number of delivery vehicles.
$\|D\|$	The number of orders served.
Q	Maximum capacity of a delivery vehicle.
q_i	Transport volume of customer point i, where $q_i > 0$ for $i \in P$,and $q_i < 0$ for $i \in D$.
a_i	Order placement time for order *i*.
Δt_i	Service time at node i.
t_{ij}	Travel time from node *i* to node j.
b_i	Expected delivery time for order i.
v	Average vehicle speed.
c	Operating cost per unit distance.
u	Preservation cost per unit time.
c_{ir}	Comprehensive income per order for delivery staff r.
w_r	Total income of delivery staff r, $\sum_{i \in D} c_{ir} = w_r$.
d_{ij}	Distance between node i and node j.
x_{ijr}	A binary variable, $x_{ijr} = 1$ if vehicle r travels from node i to node j, and $x_{ijr} = 0$ otherwise.
y_{ipr}	A binary variable, $y_{ipr} = 1$ if order i is assigned to pickup point p and delivered by delivery staff r,and $y_{ipr} = 0$ otherwise.

2.3.2 Model setting

Based on the aforementioned parameters, an initial model is constructed, including objective functions and constraints. The objective functions are formulated to represent total operational cost, customer satisfaction, and delivery staff satisfaction. The model is as follows:

$$\text{minimize} f_1 = \sum_{r \in R} \sum_{i \in N} \sum_{j \in N} c d_{ij} x_{ijr} + \sum_{r \in R} \sum_{i \in P} \sum_{j \in D} u t_{ij} y_{ipr} \quad (1)$$

$$\text{minimize} f_2 = \frac{1}{|D|} \sum_{i=1}^{n} (b_i - a_i) \quad (2)$$

$$\text{minimize} f_3 = \min \{\max \{|w_r - \overline{w_r}|\}\}, r \in R \quad (3)$$

subject to

$$\sum x_{ijr} \leq 1, \forall r \in R \quad (4)$$

$$\sum y_{ipr} = 1, \forall i \in D \quad (5)$$

$$\sum x_{ijr} = \sum x_{jir}, \forall i, j \in N \quad (6)$$

$$\sum q_i \leq Q \quad (7)$$

$$b_j \geq a_i + t_{ij} + \Delta t_i + \Delta t_j, \forall i \in N, j \in D \quad (8)$$

$$x_{ijr} = \{0,1\}, i, j \in N, r \in R \quad (9)$$

$$y_{ipr} = \{0,1\}, i, p \in N, r \in R \quad (10)$$

Eqs. (1-3) represent the objective functions. Specifically, Eq. (1) represents the objective of minimizing total cost, Eq. (2) represents the objective of maximizing average customer satisfaction by minimizing the average total service time, and Eq. (3) represents the objective of delivery staff fairness, measured by income disparity. Eqs. (4-5) represent the constraints ensuring that each delivery and pickup point is visited exactly once. Eq. (6) represents the flow balance constraint. Eq. (7) represents the vehicle capacity constraint. Eq. (8) represents the time constraints, while Eqs. (9-10) represent the 0-1 decision variables.

2.4 Dynamic adjustment model construction

2.4.1 Basic paramaters

Based on the initial model, the relevant parameters and decision variables of the dynamic model are as follows.

Table 2
Symbol description of dynamic adjustment model

Symbol	Description
P	The set of all pickup points, $P = \{P_1, \ldots, P_p\}$.
D	The set of all delivery points, D= $\{D_1, \ldots, D_d\}$
R	The set of all delivery staff/vehicles, $R = \{1, \ldots, r\}$.
N	The set of all nodes, $N = \{P \cup D\} = \{P_1, \ldots, P_p, D_1, \ldots, D_d\}$.
O	The set of orders, O= $\{O_1, \ldots, O_{o-1}, O_o\}$.
L_r	The set of rides of vehicle *r*, $L_r = \{(P_i, C_j) \mid i \in P, j \in C\} \cup \{(r, P_j) \mid r \in R, j \in C\}$
T'	The set of discrete time points, $t \in T'$.
$M(t)$	The set of new orders.
$O^U(t)$	The set of orders that have not been picked up or delivered in the previous stage.
$O^D(t)$	The set of orders that have been picked up and not shipped in the previous stage.
$O^Y(t)$	The set of orders that have been picked up and shipped in the previous stage.
$O^A(t)$	The set of all orders pending service after a new order is inserted at time *t*, $A^U(t)$=$M(t) + O^U(t) + O^D(t)$.
$D^A(t)$	The set of all delivery points pending service after a new order is inserted at time *t*.
$R(t)$	The set of all vehicle/riders locations after a new order is inserted at time *t*.
$O^R(t)$	The set of pending orders assigned to riders *r* at time *t*.
$L_r(t)$	The re-planned route after a new order is inserted at time *t*.
Q	Maximum load capacity of the delivery vehicle (constant).
q_i	The demand of order O_i.
$q_0^r(t)$	The load carried by riders *r* at time *t*, $q_0^r(t) \leq Q$.
i_r	The random starting position of riders *r*.
a_i	Order time of O_i.
Δt_i	Service time at node *i*.
b_i	Actual delivery time of order O_i.
LT_i	Expected delivery time of order O_i.
LT_i^+	The maximum allowable delivery time for order O_i, beyond which penalty costs begin to maximize.
v	Average vehicle travel speed.
c	Unit transportation/operating cost of the vehicle.
u	Unit freshness maintenance cost.
c_{ir}	Income per order for riders *r*.
w_r	Total income of delivery staff r, $\sum_{i \in D} c_{ir} = w_r$.
d_{ij}	Travel distance from node *i* to node *j*.
t_{ij}	Delivery time from node *i* to node *j*.
$S(t_i)$	Penalty cost function for late delivery of order O_i.
$c^{'}$	Penalty cost for exceeding the delivery time by *t* minutes.
γ	Penalty coefficient for each *t*-minute delay.
c_{max}	Maximum penalty cost for late delivery.
$M(i)$	Customer satisfaction function.
θ	Promised delivery time threshold.
δ	Customer satisfaction degradation rate per minute.
F_r	Whether riders have completed the delivery task; if yes, then 1, otherwise 0.
x_{ijr}	Whether riders *r* travel from node *i* to node *j*; if yes, then 1, otherwise 0.
y_{ipr}	Whether order *i* is assigned to pickup point p and delivered by riders *r*; if yes, then 1, otherwise 0.

2.4.2 Model analysis

(1) Penalty cost

The high demand for fresh products ensures that even if deliveries are late, orders are generally still accepted. However, such delays incur penalty costs. Many studies describe these penalty costs using a piecewise step function, which reflects the time sensitivity of customers to real-time delivery of fresh products. This sensitivity directly impacts the platform's service evaluation. Drawing on previous research, different penalty functions are designed for different time intervals: If the order is delivered within the expected delivery time, the customer is satisfied with the delivery service, and no penalty cost is incurred; If the order is delivered late, beyond the expected delivery time, the customer's sensitivity to time increases, characterized by a sensitivity coefficient $\gamma, \gamma = c_1/(LT_i^+ - LT_i)$. The penalty cost increases as the delay grows; When the delay exceeds LT_i^+, the penalty cost reaches and remains at its maximum value c_{max}, regardless of further delay.

The corresponding diagram and function expression are as follows:

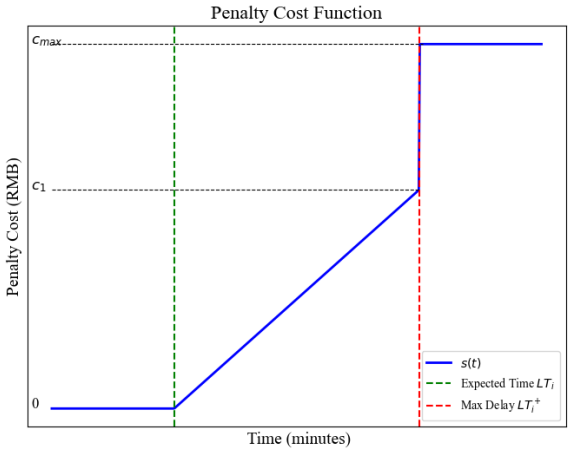


Fig. 2. The timeout penalty cost function

$$s(t) = \begin{cases} 0, & \text{if } t \le LT_i, \\ \gamma \cdot (t - LT_i), & \text{if } LT_i < t \le LT_i^+, \\ c_{max}, & \text{if } t > LT_i^+. \end{cases} \tag{11}$$

(2) Customer satisfaction function

For customer satisfaction, due to the direct sensitivity of customers to delivery time, deliveries made within the promised threshold before the expected time do not affect customer satisfaction. However, if the delivery time exceeds the promised threshold, customer satisfaction begins to decrease at a rate of δ per minute of delay. Satisfaction declines further with increasing delay, and in cases of severe delay, customer satisfaction drops to zero. The ideal scenario is for the overall average customer satisfaction to be as close to 1 as possible. The specific graph and function expression are as follows:

Fig. 3. Customer satisfaction function

$$M(i)=\begin{cases}1, & \text{if } t \le LT_i+\theta,\\ 1-\delta\cdot\left(t-(LT_i+\theta)\right), & \text{if } LT_i+\theta < t \le LT_i^+,\\ 0, & \text{if } t > LT_i^+.\end{cases} \tag{12}$$

2.4.3 Model setting

$$minimize\ F_1=\sum_{r\in R}\sum_{i\in N}\sum_{j\in N} cd_{ij}x_{ijr}+\sum_{r\in R}\sum_{i,j\in N}\sum_{p\in P} ut_{ij}y_{ipr}+\sum_{i=1}^{n} S(t_i) \tag{13}$$

$$minimize\ F_2=1-\frac{1}{|O|}\sum_{i\epsilon O} M(i) \tag{14}$$

$$minimize F_3=min\{max\{|w_r-\overline{w_r}|\}\},\ r\in R \tag{15}$$

subject to

$$\sum_{\mathrm{j}\in N} x_{i_r jr}=\sum_{\mathrm{i}\in N} x_{jir}\ ,\forall i,j\in N \tag{16}$$

$$\sum_{\mathrm{j}\in N} x_{i_r jr}\ \le 1,\forall r\in R \tag{17}$$

$$\sum_{\mathrm{i}\in N} x_{jir}=0(F_r=1) \tag{18}$$

$$q_0^r(t)=q_0^r(t-1)+\sum_{O_i\in O^R(t)} q_i\cdot y_{ipr}-\sum_{O_i\in O^Y(t)} q_i\cdot y_{ipr} \tag{19}$$

$$q_0^r(t)\le Q,\forall r\in R \tag{20}$$

$$\sum_{i=1}^{N} y_{ipr}=1,\ \ \forall r\in R \tag{21}$$

$$\mathrm{a}_i\le b_i\le LT_i,\forall O_i\in O^A(t) \tag{22}$$

$$\sum_{j\in D} y_{\mathrm{ipr}}\cdot x_{ijr}\le y_{\mathrm{ipr}},\forall r\in R,i\in N \tag{23}$$

$$b_j\ge a_i+t_{ij}+\Delta t_i+\Delta t_{\mathrm{j}},\forall(i,j)\in L_r \tag{24}$$

$$b_i(t)\ge a_i+\sum_{j\in N} t_{ij}\cdot x_{ijr},\forall O_i\in O^A(t),r\in R \tag{25}$$

$$t_{ij}=\frac{d_{ij}}{v} \tag{26}$$

$$F_r=\{0,1\},r\in R \tag{27}$$

$$x_{ijr}=\{0.1\},i\in N,j\in N,r\in R \tag{28}$$

$$y_{ipr}=\{0.1\},i\in N,r\in R \tag{29}$$

The formulas (13), (14), and (15) represent the objective functions. Formula (16) represents the flow balance constraint; formulas (17) and (18) represent that the delivery person, starting from their random initial position, can only choose one path to the next node, and that after completing the task, no further incoming paths are available. Formulas (19) and (20) represent the weight capacity constraints; formula (21) represents that all customer points are served. Formula (22) represents that the order delivery time is greater than the order time and less than or equal to the expected delivery time. Formula (23) represents the service order constraint; formula (24) represents that the actual delivery time from node i to j should consider the service time at the node. Formula (25) represents that the updated time still satisfies the time window constraint. Formula (26) represents the relationship between delivery time and distance between two nodes. Formulas (27), (28), and (29) represent the constraints for decision variables.

3. Algorithm design

3.1 Algorithm design concept

The design concept of the dynamic algorithm in this paper is mainly based on obtaining the initialization by solving the static model and then conducting dynamic solving in combination with dynamic information. Specifically, when solving the dynamic model, the initialization part of the static model is first called to obtain the basic model parameters and data structures. Then, according to the time T when a new order is inserted based on the dynamic characteristics, part of the data is updated. As shown in Fig. 4, the basic configuration of the static model is combined with the real-time changes of the dynamic model.

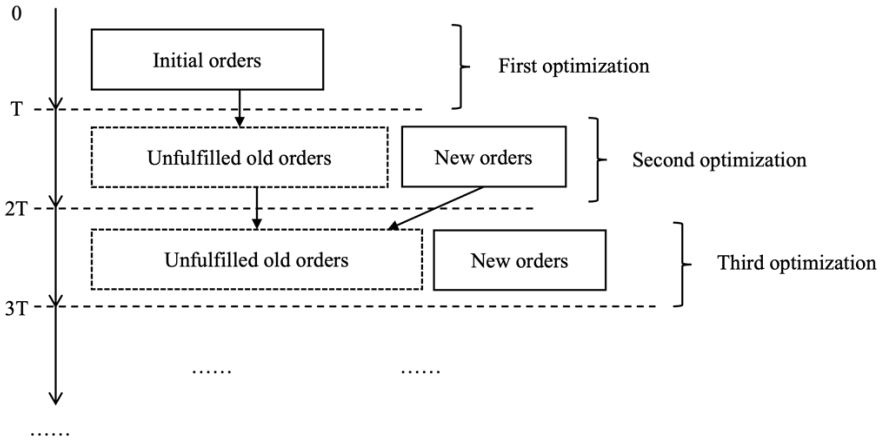


Fig. 4. The design of dynamic solution algorithm

3.2 Algorithm improvement and solution process

In this paper, the optimization algorithm combining NSGA-III and SPBO improvement strategy will be used to obtain the improved NSGA-III algorithm, abbreviated as S-NSGA-III. The specific algorithm flow is shown in Fig. 5.

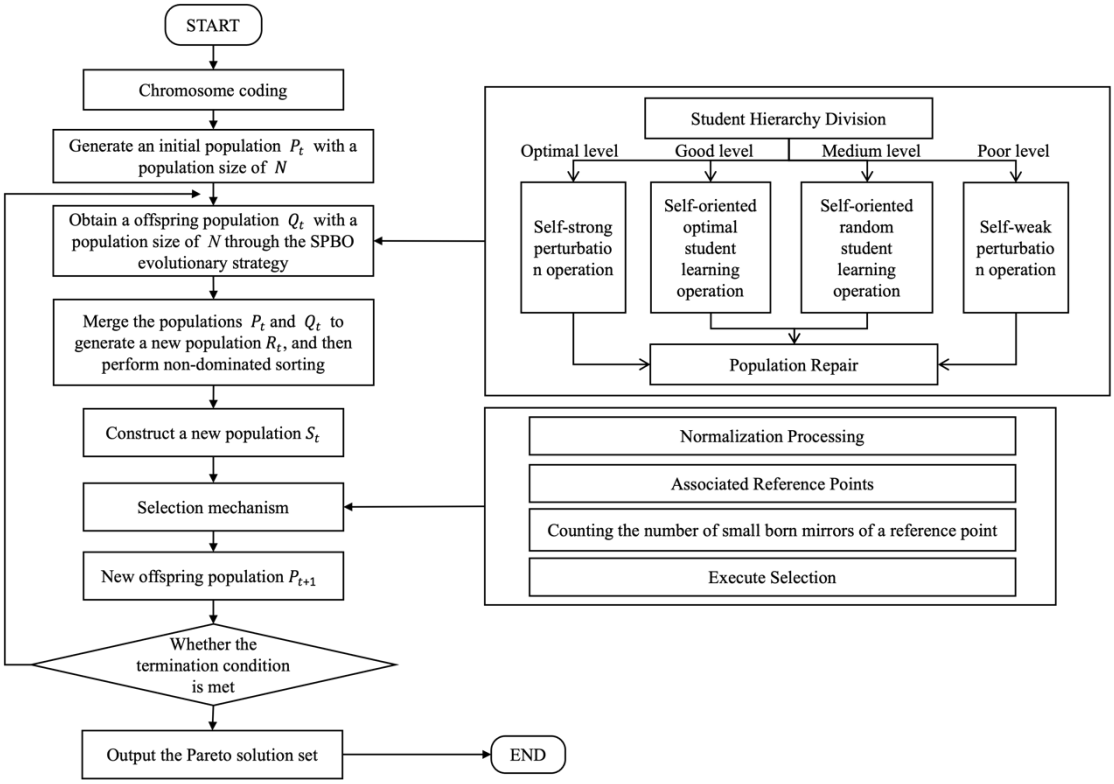


Fig. 5. Algorithm flow chart

(1) Encoding and decoding

The standard NSGA-III encoding rules are not fully applicable to solving the multi-objective instant delivery model for fresh products in this paper. The algorithm in this paper adopts ordinal encoding. Suppose there are m orders, b pickup

points/delivery centers, the total number of deliverymen capable of serving b pickup points is *a*, and the maximum number of deliverymen that each delivery center can dispatch is *c*.

During decoding, the gene loci in the encoding are divided into three categories: deliveryman number, delivery center number, and order point number. The delivery route of each deliveryman consists of one or more delivery centers and demand points until the next deliveryman number is encountered. A dictionary is used to store the delivery route of each deliveryman, that is, the route of each deliveryman is initialized, and the route of each deliveryman is empty at the beginning.

(2) Initial population Generation

This paper adopts the standard initial population generation method of NSGA-III. When generating the initial population, in this problem, each individual corresponds to a delivery route sequence, including all pickup points and delivery points. To ensure the diversity and exploration ability of the population, the generation process of the initial population is completed by randomly shuffling the given input sequence (including all delivery points and order information). This process ensures that each individual's delivery route has different starting points and permutation orders, thus avoiding premature convergence and increasing the opportunity to explore the potential solution space. First, a reasonable delivery order is randomly selected from the input set of pickup points and delivery points. Each delivery route sequence will be regarded as an individual, and each element in the route sequence represents a delivery node.

(3) Population repair

The deliveryman must be the starting point of each route. Therefore, the repair operation will check the generated individual routes and place the deliveryman at the starting point of the route. If the starting point of the route is not a deliveryman, the repair process will move the deliveryman to the beginning of the route through a swap operation. Since the maximum delivery capacity of each vehicle is limited, the individuals generated by random permutation may cause the total demand of some routes to exceed the maximum load capacity of the vehicle after decoding. To ensure that the solutions obtained during the evolution process satisfy the capacity constraint, a penalty factor p is introduced to calculate the overload amount. Specifically, the overload amount of each vehicle will incur additional costs, and for each additional overload unit, the vehicle dispatch cost will increase by p. To ensure the strictness of the capacity constraint, the penalty factor p must be set large enough, far exceeding the actual cost of vehicle dispatch. In this paper, the value is set as10^7.

(4) Evolutionary improvement operations

To enhance the optimization effect of the algorithm, this paper introduces the improved idea of SPBO (Student Position-Based Optimization). Different evolutionary operations are applied to different types of individuals to achieve a balance between global and local searches, promote the diversity and quality of solutions. Meanwhile, a learning operation is introduced. Excellent students extract coding information from the top-performing student to adjust their own code positions, ensuring the convergence of the population and accelerating the convergence speed. The main operations are as follows:

If an individual is the top-performing student, a strong perturbation operation is used to adjust itself and generate a new individual. As shown in Figure 6, the code position of the population to be adjusted is denoted as J, and a random integer I between 1 and D is generated. The positions of individual J and individual I are swapped, and the new individual is denoted as newIndividual. The fitness value is determined by the weighted sum of the objective functions. This swap operation changes the relative positions at four places: the left and right sides of J and the left and right sides of I. That is, it changes the distance at four points, resulting in a relatively large perturbation compared to the original individual.

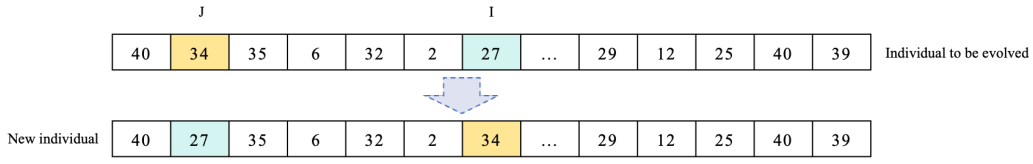


Fig. 6. Diagram of the strong perturbation operation

For any individual, a weak perturbation operation is used for mutation. The individual undergoes local reverse ordering to generate a new individual. As shown in Fig. 7, the code position of the population to be adjusted is denoted as J, and a random integer I between 1 and D is generated. The sequence between individual J and individual I is reversed, and the new individual is denoted as new Individual. This swap operation changes the relative positions at two places: one side of J and one side of I. That is, it changes the distance at two points, resulting in a relatively small perturbation compared to the original individual.

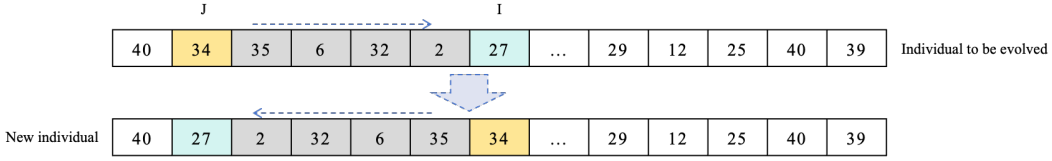


Fig. 7. Diagram of the interval reverse operation

If an individual is an excellent student, a learning operation is carried out with the top-performing student individual to adjust itself and generate a new individual. As shown in Fig. 8, the J-th element in the individual to be adjusted is denoted as G1. Here, J = 2 and G1 = 34. Secondly, the elements on the left and right sides of G1 = 34 in the optimal individual (32, 38) are found, and the left-hand side element is preferentially selected and denoted as G2 = 32. Then, the position of element G2 in the individual to be adjusted is found and denoted as I, where I = 5. Finally, the sequence of positions between individual [J + 1] and individual [I] is reversed, that is, the sequence of positions from the 3rd to the 5th is reversed, and the new individual is denoted as new Individual. In the optimal individual, G1 and G2 are adjacent. After adjustment, G1 and G2 are also adjacent in the new individual, and the relative positions of other elements change minimally.

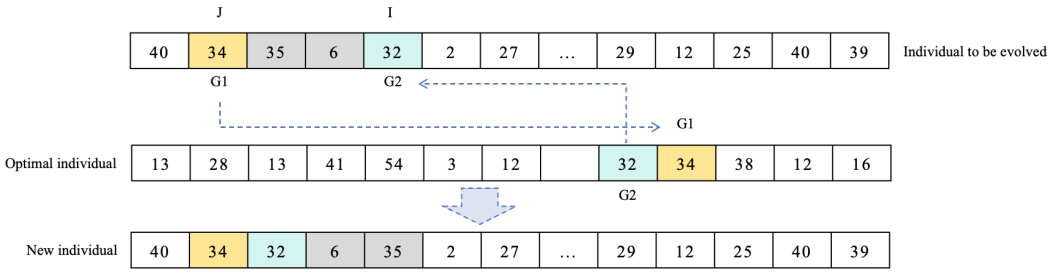


Fig. 8. Diagram of the learned mutate on operation

(5) Steps related to the selection operation

The specific selection operation steps of NSGA-III based on associated reference points are as follows (where steps 3 to 4 are the main contents of the selection mechanism):

Step 1: Merge the parent population P_t and the offspring population Q_t, to form a combined population R, $R = P_t \cup Q_t$, $|R| = 2N$.

Step 2: Non-dominated sorting. Perform non-dominated sorting on the combined population R, and divide it into multiple non-dominated layers $F_1, F_2, F_3 \ldots, F_k$, where F_1 represents all non-dominated solutions, F_2 represents the individuals dominated by but superior to other solutions, and so on, expressed as $F_1 \succ F_2 \succ F_3 \succ \ldots \succ F_k$; find the critical layer F_k among a series of non-dominated layers to make it satisfy formula (30), and then delete n solutions in the critical layer,

$$\sum_{i=1}^{k-1} |F_i| < N, \sum_{i=1}^{k} |F_i| \geq N \tag{30}$$

Step 3: Associated reference points. (a) Normalization processing. Normalize the objective function values $f(r)$ of all individuals r in the population R, and define the extreme points $e_1, e_2, e_3 \ldots, e_m$ as the optimal solutions in each objective dimension. Calculate the hyperplane intercept a_i using the extreme points. Finally, normalize each solution r according to formula (31). (b) Calculate the association with reference points. Calculate the cosine distance $\mathrm{Cosine}(r, z_j)$ between the normalized objective $f'(r)$ of each solution r and the reference point z_j. Then, calculate the Euclidean distance $d(r, z_j)$ corresponding to the cosine distance according to formula (32). Finally, find the nearest reference point for each individual r to obtain the reference point set Z.

$$f'(r) = \left(\frac{f_1(r)}{a_1}, \frac{f_2(r)}{a_2}, \ldots, \frac{f_m(r)}{a_m}\right) \tag{31}$$

$$d(r, z_j) = \| f'(r) \| \cdot \sqrt{1 - \mathrm{Cosine}^2(r, z_j)} \tag{32}$$

Step 4: Calculate the crowding degree of each reference point. Calculate the number of its associated solutions $\rho(z_j) = |\{r \in F_1 \cup F_2 \cup \cdots \cup F_{k-1} : \pi(r) = j\}|$, and $\rho(z_j)$ is the crowding degree of the reference point z_j, representing the number of solutions associated with z_j in the non-critical layers.

Step 5: Delete the redundant solutions in the critical layer F_k. (a) Find the sparsest reference point z_{min}, $z_{min} = \arg \min_{z_j \in Z} \rho(z_j)$. If there are multiple reference points with the same crowding degree, randomly select one. (b) Delete solutions from the critical layer. If $\rho(z_{min}) = 0$, delete the solution with the smallest nearest distance; otherwise, randomly delete an associated solution. (c) Update the crowding degree of the reference point. That is, update the crowding degree of the reference point according to $\rho(z_{min}) = \rho(z_{min}) + 1$. (d) Delete repetitions. Repeat the above process until n individuals are deleted, and at this time, the size of the new population remains N.

Step 6: Update the population. After deleting n individuals, the remaining population Q, $Q = F_1 \cup F_2 \cup \cdots \cup F_{k-1} \cup F_k'$, where F_k' is the set of individuals in the critical layer after deletion, satisfying $|Q| = N$.

3.3 Result verification method:ε-constraint method and its comparison strategy

In this study, to verify the validity of the results, the ε-constraint method will be adopted. This method transforms some objectives into constraints, simplifying the multi-objective optimization problem into a single-objective problem. We will use this method to generate Pareto solutions and compare them with the results of the S-NSGA-III algorithm. The relevant experimental settings for the comparison are shown in Appendix A.2.

4. Empirical study

4.1 Data source

The self-owned fresh food distribution platform has 5 main supply stores in an area of Wuxi, Jiangsu Province, China, serving the surrounding areas. It mainly uses its own distribution personnel for distribution, and there is no difference between the functions of the pick-up point and the distribution center. Four stores of a self-operated fresh food distribution platform, namely distribution centers, are mainly selected, which are denoted as pick-up warehouses. The latitude and longitude coordinates are shown in Table 3.

Table 3
Supply store longitude and latitude coordinate information

No.	x	y
1	120.284179	31.502367
2	120.290175	31.493425
3	120.318740	31.506233
4	120.339136	31.492918
5	120.295717	31.461647

The actual data of a fresh self-operated distribution platform is desensitized. Based on the desensitization data, the following example is designed: the distribution platform receives fresh orders in the responsible area, the order is delivered in real time, the starting position of the delivery clerk is random, the order is assigned after updating the position of the delivery clerk each time, and the delivery is carried out after picking up the goods at the supply store. Combined with the business scenario, 5 supply stores start to enter the peak at 10:00, so 10:00 is taken as the research sample node, and it is assumed that 50 initial orders of users have been received before this time. In the process of order execution, new orders are inserted at time T to replan the unexecuted orders in the current order pool. Table 4 shows the detailed information of 10 order points, including order line number, customer longitude, customer latitude, demand, estimated service time, expected delivery time and whether it is a reservation order. The position relationship is shown in Fig. 9.

Table 4
Partial order information

NO.	Longitude	Latitude	Demand /Kg	Estimated time of service /min	Expected time of delivery /min	Whether it is a reservation order (1= yes, 0= no)
1	120.28249	31.528697	8	5	32	0
2	120.319001	31.475057	4	5	41	1
3	120.33458	31.508339	6	5	23	1
4	120.269422	31.464832	15	9	152	1
5	120.304174	31.479279	5	4	154	0
6	120.318606	31.515667	6	5	239	0
7	120.274695	31.469778	10	6	78	0
8	120.300921	31.518019	10	7	28	0
9	120.28337	31.530101	2	3	170	0
10	120.306363	31.446683	8	5	225	0

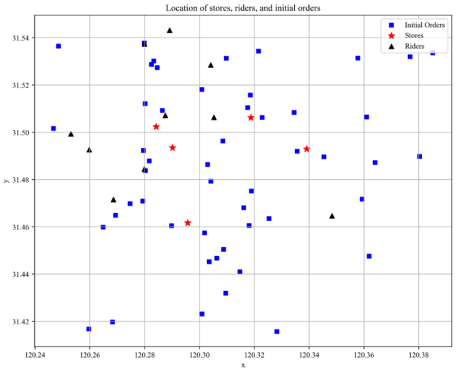


Fig. 9. Diagram of the relationship between user order, rider location, and store location

4.2 Parameter setting

The parameters of the multi-objective route optimization model of instant fresh distribution and the parameters of S-NSGA-III algorithm are assigned and explained, and the specific settings are shown in Table 5.

Table 5
Model parameter setting

Parameter Category	Set Parameter	Assignment Situation
Vehicle-related Parameters	All delivery vehicles r	10 units
	Average driving speed of vehicles v	15 km/h
	Maximum load-carrying capacity of vehicles Q	80 kg
Time-related Parameters	Threshold of delivery time promised by the platform θ	30 min
	Average service time for picking up goods at the warehouse Δt_i	5 min
	Latest acceptable delivery time for reservation order i, LT_i^+	30 min
	Latest acceptable delivery time for real-time order i, LT_i^+	60 min
	Satisfaction decline rate per minute δ	0.2
Cost-related Parameters	Unit operation cost c	0.8 RMB/m
	Unit fresh-keeping cost u	0.01 RMB/min
	Overtime penalty cost c_1	3 RMB
	Maximum overtime penalty cost c_{max}	10 RMB
Algorithm-related Parameters	Population size (N)	[30,50]
	Maximum number of iterations (E)	[100,200,300]
	Saving interval (generations)	20
	Insertion interval T	20 min

Algorithm parameters were determined through grid search over ranges set based on the characteristics of the current research problem(see appendix). (1) In the static optimization (Phase I), the (N=50, E=200) configuration optimally balances computational efficiency and solution quality. Its moderate population size enables rapid static solution generation while preserving computational capacity for dynamic order adjustments, ensuring both timely responsiveness and optimization flexibility in delivery operations. (2) In the dynamic adjustment (Phase II), the parameter selection can not only adapt to the environmental requirements, but also adhere to the consistent evaluation criteria (convergence rate, resource efficiency and population diversity). After comparison, the population size N is selected as 30 and the maximum number of iterations is 200. See the appendix 1.3 for the detailed parameter adjustment process.

4.3 Model solving

In this paper, the improved NSGA-III algorithm and its comparison algorithm are implemented on MATLAB R2021B software, and the operation test is carried out on a notebook computer with macOS Ventura 13.5 system, Apple M1 processing chip and 16GB running memory. A case study with an insertion interval T=15min will be conducted in this paper. The solution of the improved NSGA-III algorithm (S-NSGA-III) is divided into static initial solution and dynamic solution.

4.3.1 Initial model solving

After solving the model, 28 groups of results were obtained. After eliminating overlapping schemes, 8 groups of initial path schemes remained. Meanwhile, 2 groups of schemes were obtained through the ε-constraint solution (see Table 6). By comparison, it was found that the objective quality of the schemes obtained by ε-constraint was significantly lower than that of the schemes solved by S-NSGA-III, thus verifying that the 8 groups of initial schemes had a good optimization effect. Since there is no absolute superiority or inferiority in the results of the multi-objective functions, in this study, after Z-score standardization, considering the research background and the imbalance of interests among the platform, users, and riders in the actual scenario, the weights of the three objective functions were set as (0.3, 0.3, 0.4), and evaluation was carried out through linear weighted summation (the specific results are shown in Table 7). Comprehensive comparison shows that Scheme 3 has the smallest value of the comprehensive objective function and best meets the research needs. Therefore, **Scheme 3** was selected as the basis for subsequent dynamic adjustment.

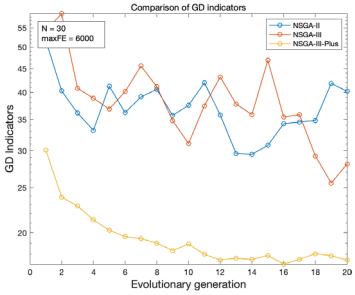
Table 6
Comparison of objective function results of the three paths

Path number	Total Cost /RMB	Average Customer Delivery Time/min	Degree of Difference in riders Income / RMB
1	81.38	38.23	17.95
2	86.36	41.88	8.45
3	81.07	38.34	9.55
4	77.91	39.3	15.05
8	91.97	44.1	6.05
20	91.74	44.3	6.05
24	96.99	46.21	5.95
26	80.47	39.07	15.05
Epsilon-1	119.98	59.40	10.45
Epsilon-2	126.41	58.97	19.45

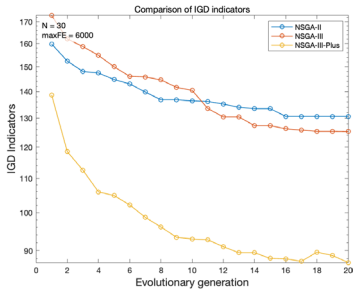
Table 7
Comparison of objective function summation results of three paths after Z-score standardization

Path number	1	2	**3**	4	8	20	24	26
Weighted sum value after standardization	0.021	-0.216	**-0.723**	-0.28	0.058	0.067	0.49	-0.19

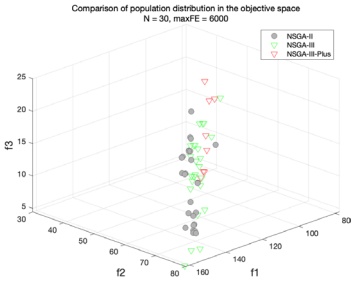
To verify the effectiveness and result usability of using the S-NSGA-III algorithm for solving static and dynamic models, the performance of the improved S-NSGA-III algorithm is compared with that of NSGA-II and NSGA-III. The comparison of static solution indicators is shown in Figure 10. It is found that compared with the NSGA-II and NSGA-III algorithms, in the comparison of IGD and GD indicators, S-NSGA-III shows a better convergence speed and convergence accuracy in the middle and later stages of evolution, and can converge to the true Pareto front more quickly and accurately. In terms of the population distribution in the objective space, it combines the exploration ability of NSGA-II and the convergence of NSGA-III. In conclusion, S-NSGA-III performs better in convergence performance, comprehensive performance, and the speed of finding the region of high-quality solutions. Therefore, for the model in this paper, using the improved S-NSGA-III algorithm for solving has certain effectiveness and feasibility.



(a) Comparison of GD indicators



(b) Comparison of IGD indicators



(c) Comparison of population distribution in the objective space

Fig. 10. Comparison of initial solution algorithm indicators

4.3.2 Dynamic adjustment model solving

Based on the aforementioned results and analysis, a dynamic multi-objective optimization approach is adopted for the delivery of instant fresh products. During order execution, 20 new orders are inserted every T=20 minutes, and the routes for pending and new orders are replanned. Twenty-eight candidate solutions are generated, yielding 9 Pareto optimal solutions after removing duplicates. Simultaneously, the ε-constraint method is used to obtain 8 sets of solutions, with their objective function values listed in Table 8. The comparison reveals that the ε-constraint solutions are of inferior quality and struggle to balance the three objectives, demonstrating the effectiveness of the proposed algorithm in collaboratively optimizing the three objectives. Next, the trade-offs and applicability of the 9 solutions obtained by the proposed algorithm under different operational conditions are analyzed, examining these solutions from the perspective of the extreme values of the three optimization objectives.

Table 8
Summary of objective functions of S-NSGA-III (vs ε-constraints）

Path number	Total cost /RMB	Average customer dissatisfaction	Degree of income disparity among riders /RMB
4	106.5152	0.0000	37.75
23	107.4470	0.1582	28.75
5	109.212	0.0033	16.75
27	110.4020	0.0000	16.75
2	112.5113	0.0000	12.25
20	114.2638	0.0033	11.75
7	116.8254	0.0000	9.25
1	118.3459	0.0000	7.75
9	123.7391	0.0000	7.25
Epsilon-1	214.2208	0.0362	27.2500
Epsilon-2	135.4544	0.0430	39.2500
Epsilon-3	195.7063	0.0660	11.2500
Epsilon-4	130.3314	0.0423	27.7500
Epsilon-5	221.4321	0.0444	7.7500
Epsilon-6	151.5089	0.0455	18.7500
Epsilon-7	264.0419	0.0722	43.7500
Epsilon-8	166.2429	0.0488	15.7500

The analysis is as follows. If the fresh food platform is currently facing significant cost pressures and operational financial constraints, prioritizing cost control would favor the selection of Path 4. This path yields the lowest total cost of 106.5152 yuan, albeit with a substantial rider income disparity of 37.75 yuan. However, it ensures a zero average customer

dissatisfaction level. In contrast, Path 5 incurs a slightly higher total cost of 109.212 yuan but reduces the rider income gap significantly to 16.75 yuan while maintaining a negligible customer dissatisfaction level of 0.0033. This option may better align with the platform's current need to ensure basic operations while balancing a certain level of service quality, even if it temporarily sacrifices income equity among riders.

As the platform overcomes its challenging phase and matures, achieving long-term stable development will require balancing the interests of all stakeholders. Under the premise of maintaining a reasonable operational economy, Paths 1 and 9 exhibit smaller rider income disparities (7.75 yuan and 7.25 yuan, respectively) while maintaining zero average customer dissatisfaction. The total costs for Path 1 and Path 9 are 118.3459 yuan and 123.7391 yuan, respectively. If the platform is willing to moderately concede profits to pursue higher rider income equity, Path 9 would be preferable. Conversely, if the platform still needs to preserve a stronger cost advantage to ensure operational economy, Path 1 represents a relatively equitable and economically viable alternative. The specific path details are shown in Table 9 and Fig. 11.

Table 9
The first set of initial path schemes with new orders

Path	Distribution Path	Mileage Traveled /km	Income/RMB
1	1-[13]-46-*[13]-48-50-49	32.5	14.71
2	2-[13]-40-*[13]-21-32-77-79-39-41-51-62-61-64	44	37.34
3	3-[11]-45-*[11]-37-72-66-70-35-23-26	34	20.5
4	4-[15]-38-65-*[15]-31-83-[15]-82-84-74	43	25.58
5	5-[12]-57-[15]-36-76	29.5	8.78
6	6-[11]-24-*[11]-71-73-68-16-42-67	31	24.4
7	7-[15]-60-*[13]-17-33-25-[11]-69-19-28	30	24.14
8	8-[13]-*58-59-56-47-34	37	18.85
9	9-*[13]-30-[13]-27-78-29-75-81-55-53-80-54	43.5	38.16
10	10-[14]-44-52-*[14]-63-22-18-85-43-[11]-20	38	23.5

Results of the objective function for the third set of solutions:
Total cost: 118.35; Average customer dissatisfaction: 0.0000; Degree of income disparity among delivery workers: 7.75

Note: Numbers with "[]" represent the pickup warehouses, 1-10 represent the vehicle numbers, and the rest are user numbers; "*" represents the current task execution status of the vehicle.

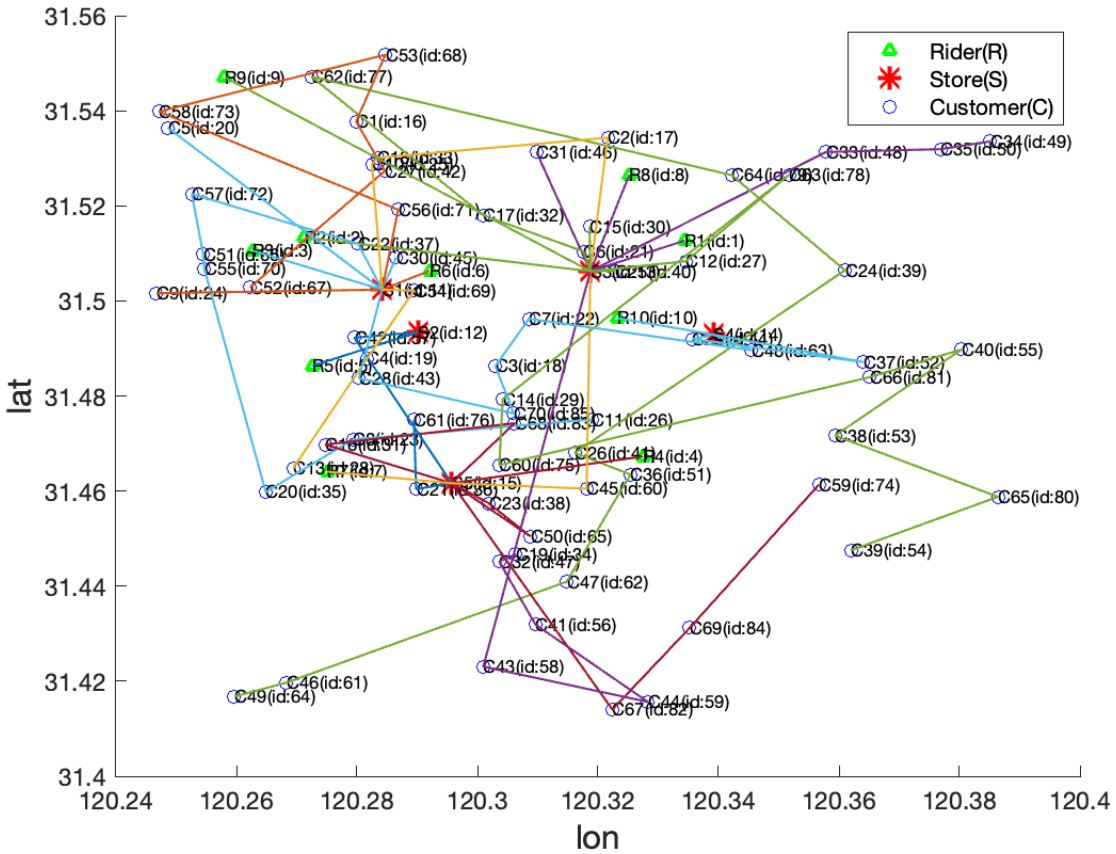
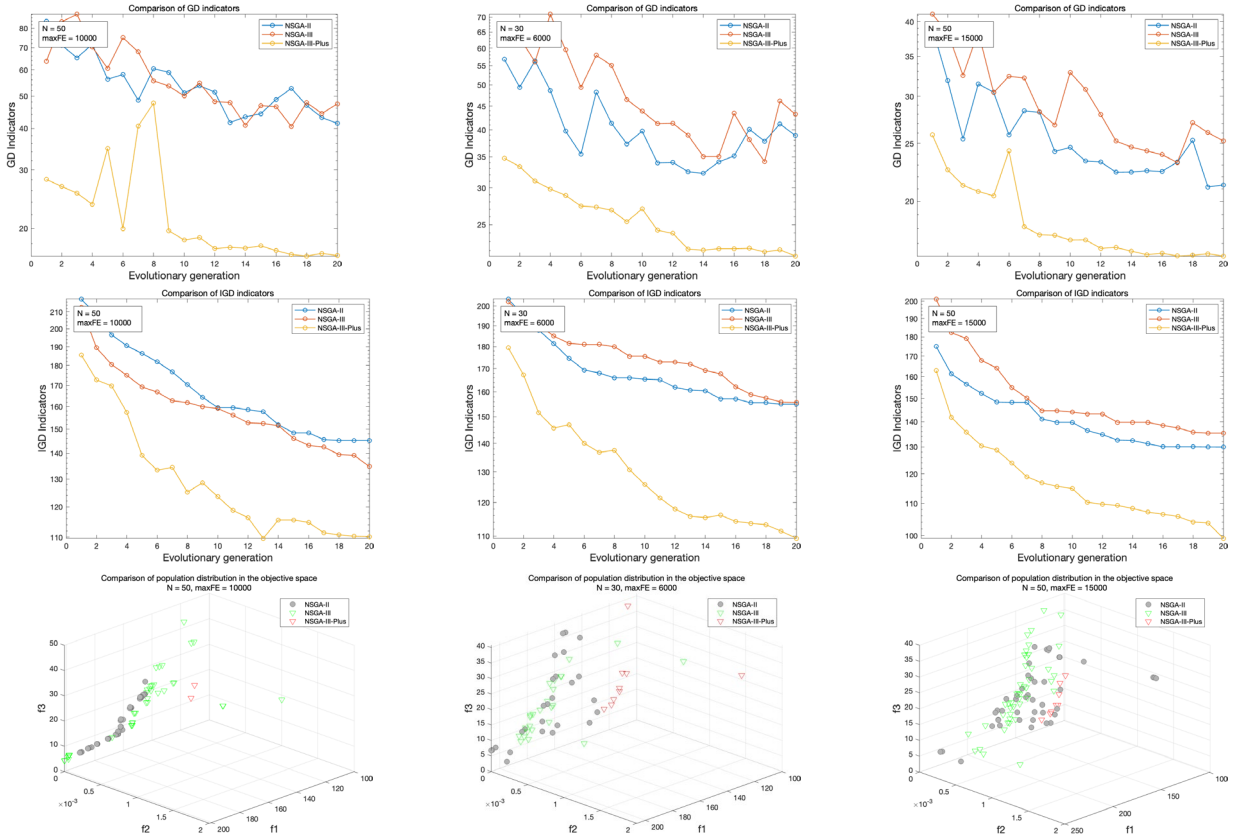


Fig. 11. The first set of solutions

4.3.3 Parameter sensitivity analysis

In order to better understand the impact of calculating the insertion interval T in the dynamic algorithm of S-NSGA-III on the solution results, a sensitivity analysis of the calculation of T is carried out. In S-NSGA-III algorithm, the value of T is 15 minutes, 20 minutes and 25 minutes respectively, and the optimal parameter combination is confirmed for its population size

and maximum number of evaluations respectively. Other parameters are set as in Section 4.2. NSGA-II and NSGA-III were used for comparison, respectively. The comparison results of algorithm indexes are shown in Figure 13, which verifies the effectiveness and feasibility of S-NSGA-III for solving the dynamic model. Then, the solution results under the three parameters are analyzed respectively.



T=15min (N=50, maxFE=10000) | T=20min (N=30, maxFE=6000) | T=25min (N=50, maxFE=15000)

Fig. 12. Comparison plots of GD index, IGD index and population distribution in target space at T=15min, T=20min and T=25min

To select relatively optimal solutions from the Pareto solution sets (after removing duplicates) obtained under the three T values, we performed Z-score standardization on the objective functions of each Pareto set, followed by weighted summation. Referring to Section 4.2, the weights were set to 0.3, 0.3, and 0.4, respectively. Although the detailed calculations are not presented here, the results are summarized in Tables 10-12.The analysis reveals that: (1) When T=15 minutes, the relatively superior solution corresponds to the 8th Pareto individual. (2) When T=20 minutes, the 2nd Pareto individual emerges as the preferred solution. (3) When T=25 minutes, the 4th Pareto individual proves to be the most favorable.

Table 10
Pareto solution corresponding objective function and weighted sum ranking in dynamic adjustment stage (T=15min)

Path number	Total cost /RMB	Average customer dissatisfaction	Degree of income disparity among riders /RMB	Value of the standardized weighted sum objective function	Rank
1	110.1532	0.0000	15.75	0.1	2
8	**112.6101**	**0.0000**	**11.25**	**-0.1**	**1**

Table 11
Pareto solution corresponding objective function and weighted sum ranking in dynamic adjustment stage (T=20min)

Path number	Total cost /RMB	Average customer dissatisfaction	Degree of income disparity among riders /RMB	Value of the standardized weighted sum objective function	Rank
1	118.3460	0.0000	7.75	-0.1808	6
2	**112.5113**	**0.0000**	**12.25**	**-0.3259**	**1**
4	106.5153	0.0000	37.75	0.3806	8
5	109.2122	0.0033	16.75	-0.3077	2
7	116.8254	0.0000	9.25	-0.2052	5
9	123.7392	0.0000	7.25	0.1034	7
20	114.2639	0.0033	11.75	-0.2272	4
23	107.4471	0.1583	28.75	1.0236	9
27	110.4021	0.0000	16.75	-0.2607	3

Table 12
Pareto solution corresponding objective function and weighted sum ranking in dynamic adjustment stage (T=25min)

Path number	Total cost /RMB	Average customer dissatisfaction	Degree of income disparity among riders /RMB	Value of the standardized weighted sum objective function	Rank
1	123.1356	0.0000	2.7500	-0.0172	5
3	105.1880	0.0000	8.7500	-0.1866	4
4	**108.0940**	**0.0000**	**5.7500**	**-0.3668**	**1**
5	99.2809	0.0010	14.2500	0.6584	8
7	113.9880	0.0000	3.7500	-0.3142	2
41	104.0715	0.0000	12.2500	0.1228	6
44	107.2575	0.0015	5.7500	0.4067	7
45	113.0720	0.0000	4.2500	-0.3030	3

Based on the comparative results above, the selection of specific algorithm parameters must also account for the platform's actual computational resources. Therefore, we further compare the time complexity and solution time under different parameter configurations, as summarized in Table 13.

Table 13
Computational Complexity Comparison

T	Dominant Term	Operation Count	Speedup Ratio
T=15min	$O(\mathrm{MN}^3 + \mathrm{KL})$	3.8×10^9	1.00×(baseline)
T=20min	$O(\mathrm{MN}^3)$	5×10^8	7.6×
T=25min	$O(\mathrm{MN}^3 + \mathrm{KL}\log \mathrm{N})$	5.6×10^9	0.68×

Table 14
Comparison of objective function and running time under different parameters

Comparison of algorithm parameters	T=15min	T=20min	T=25min	Relative Improvement (vs T=20min)
Pareto solution	2	9	8	+350% (15min) -11.1% (25min)
Total cost /RMB	112.6101	112.5113	108.0940	+0.09% (15min) -3.9% (25min)
Degree of income disparity among riders /RMB	11.25	12.25	5.75	+8.9% (15min) -53.1% (25min)
Algorithm Runtime	959.33±36.17ms	749.82±69.27ms	858.67±66.67ms	-21.8% (15min) +14.5% (25min)

The comparative analysis demonstrates that T=20min delivers optimal performance (see Table 14), achieving an 86.8% reduction in computational complexity and 21.8% faster runtime (749.82ms vs 959.33ms), while generating 350% more Pareto solutions (9vs2) with only a 0.09% cost increase (112.51RMB vs 112.61RMB). Although T=25min shows advantages in cost (108.09 RMB, -3.9%) and income equality (5.75RMB, -53.1%), its 11.2×higher complexity and 11.1% fewer solutions (8vs9) make T=20min the superior choice for dynamic delivery optimization.

5. Conclusion

This paper addresses the multi-objective just-in-time distribution problem for fresh products. It develops static and dynamic models to solve this problem. The static model focuses on initial optimization with the objective of minimizing total costs (operation and maintenance costs), maximizing customer satisfaction (measured by average service time), and improving riders satisfaction (measured by revenue balance). The dynamic model adds time dynamic factors on the basis of the static model. It incorporates time-window overtime penalties into total costs, redefines customer satisfaction as a time-sensitive function based on average dissatisfaction, and continues to measure employee satisfaction by revenue balance. These models combine constraints such as time window and vehicle capacity to form a comprehensive multi-objective distribution system. Then, combined with the idea of SPBO evolution, an improved algorithm S-NSGA-III was proposed. Compared with NSGA-II and NSGA-III, the proposed algorithm has obvious advantages in solving static and dynamic models, and has better convergence, distribution and search ability. Using data from a self-owned fresh food platform, the study analyzes the Pareto solutions of two models. Considering the operational needs of the platform, development goals and the balance between various stakeholders, a set of Pareto path schemes with stability and sustainability are selected. These solutions provide practical options for decision making and support steady growth in a competitive market. Although this study is based on a self-operated fresh food platform, other distribution models, such as crowdsourcing and community group-buying, provide valuable directions for future research.

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Appendix

A.1 Selection of algorithm parameters

A.1.1Results of different parameter combinations for the static solution (Phrase I)

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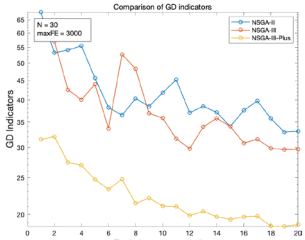
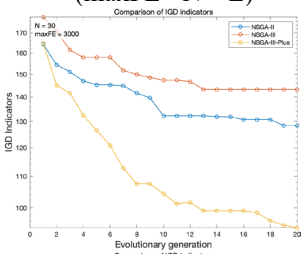
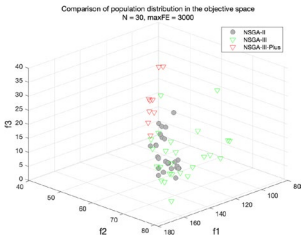
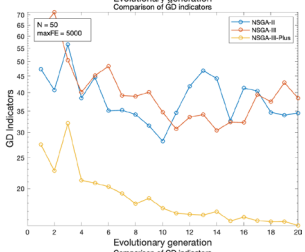
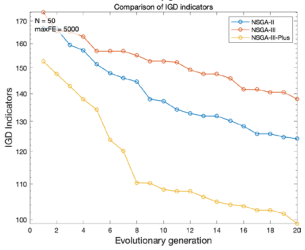
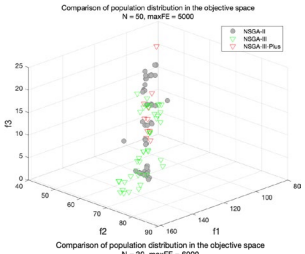
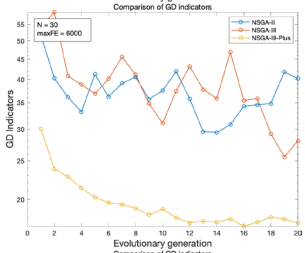
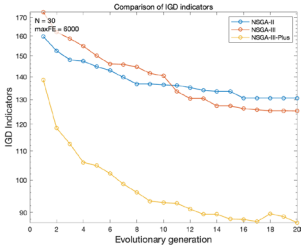
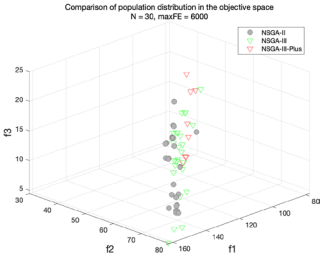
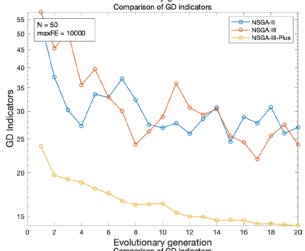
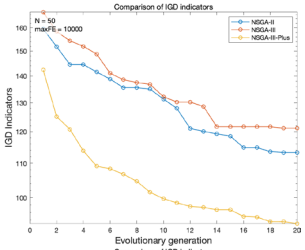
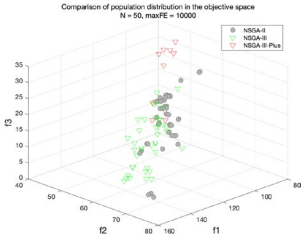
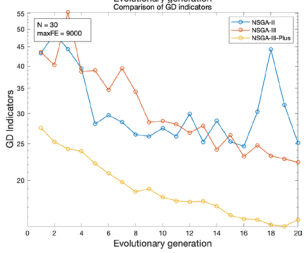
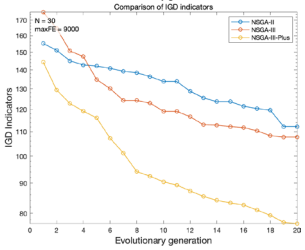
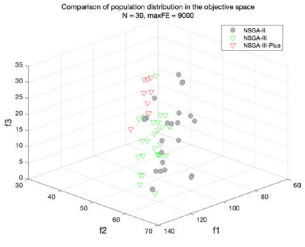
(30,100)			
(50,100)			
(30,200)			
(50,200)			
(30,300)			

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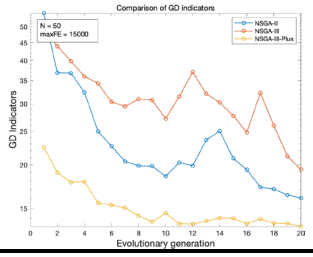

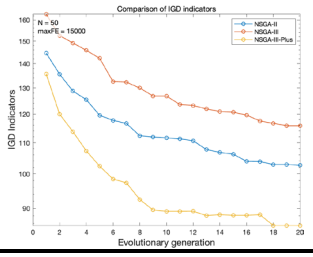

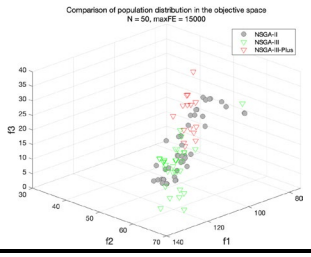

A.1.2 Results of different parameter combinations at phrase II (T=15min)

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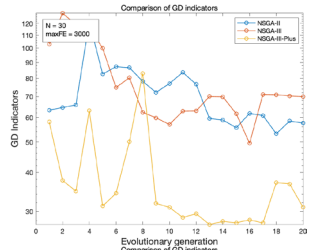
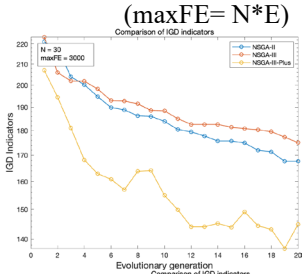
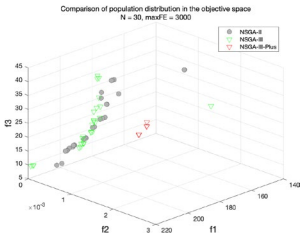
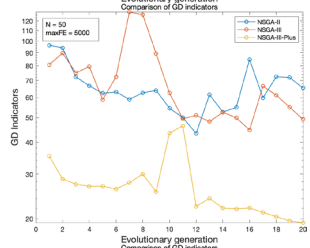
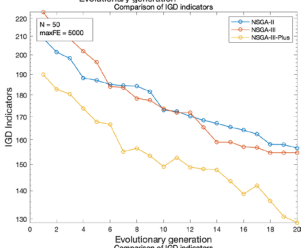
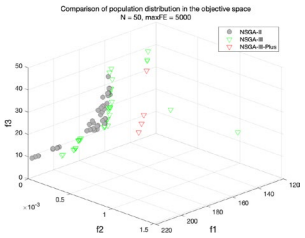
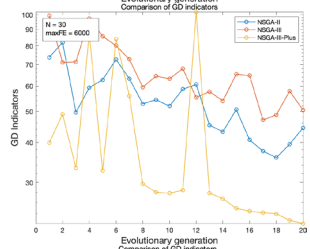
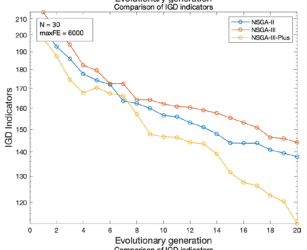
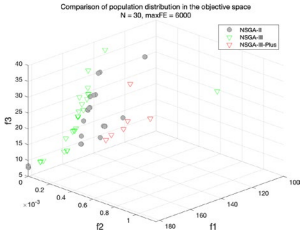
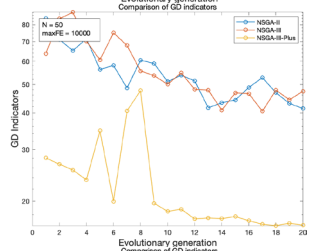
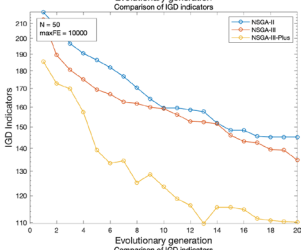
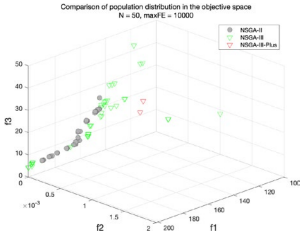
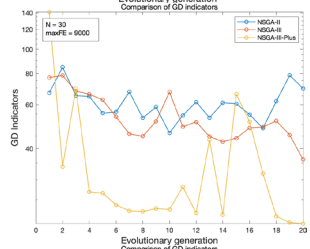
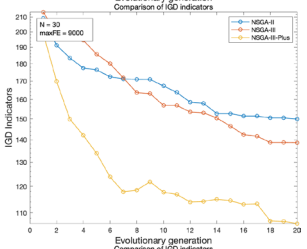
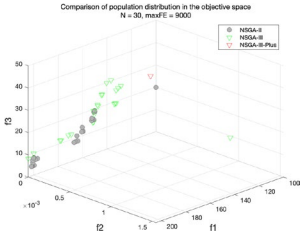
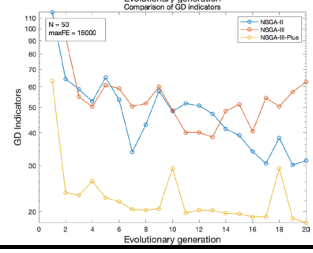
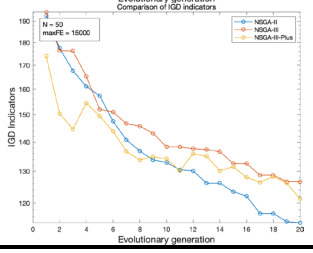
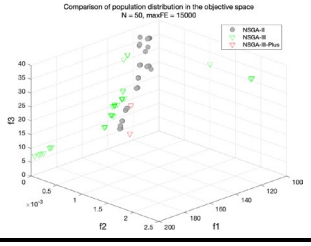
(30,100)			
(50,100)			
(30,200)			
(50,200)			
(30,300)			
(50,300)			

A.1.3 Results of different parameter combinations at phrase II (T=20min)

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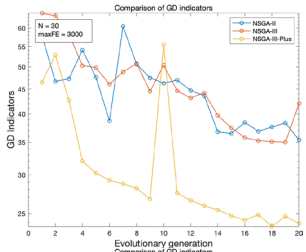
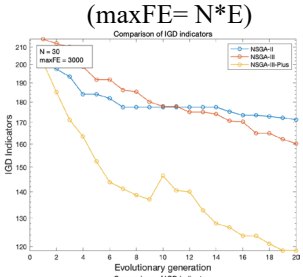
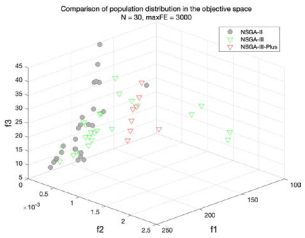
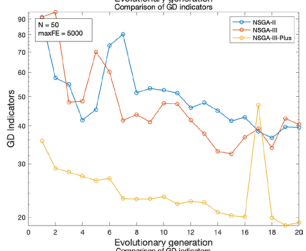
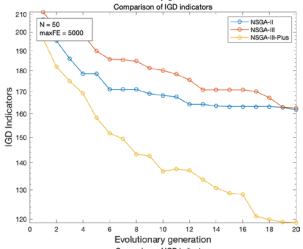
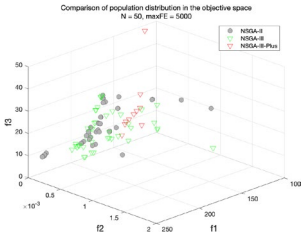
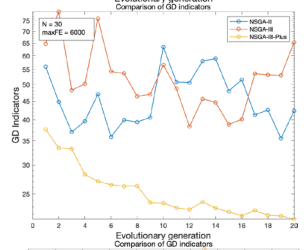
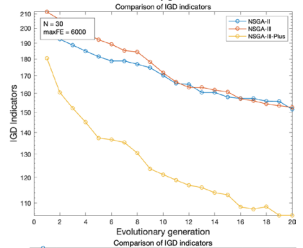
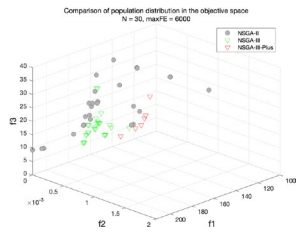
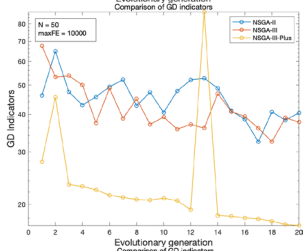
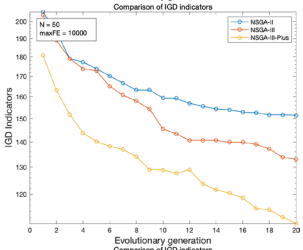
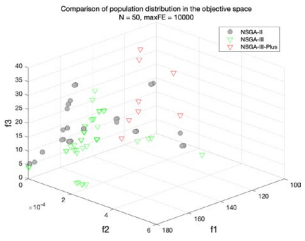
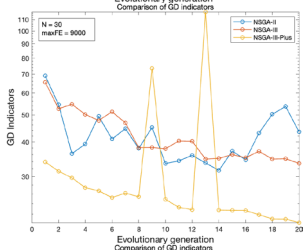
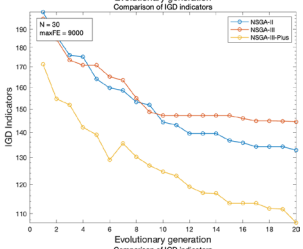
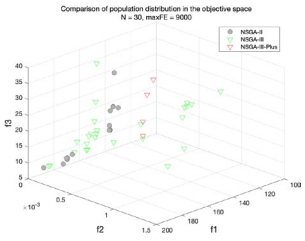
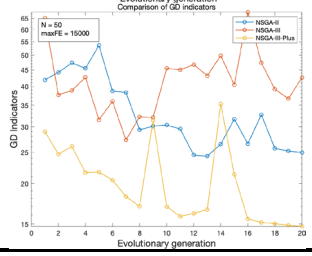
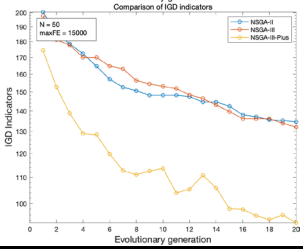
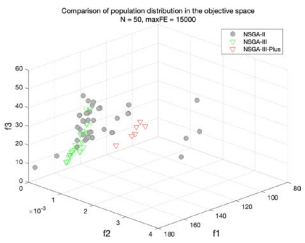
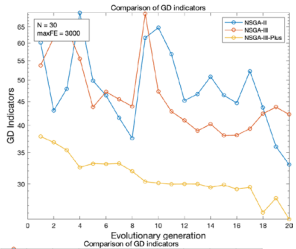
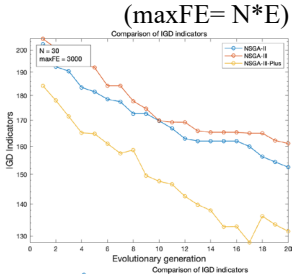
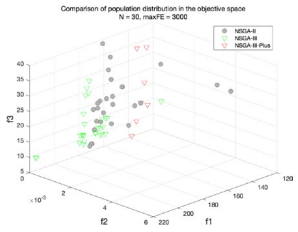
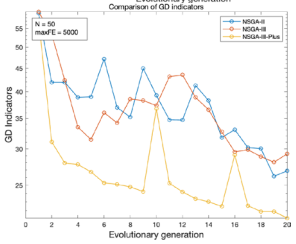
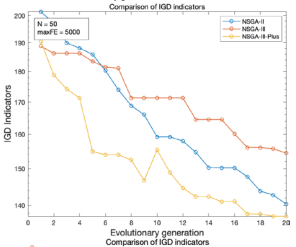
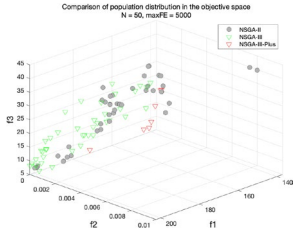
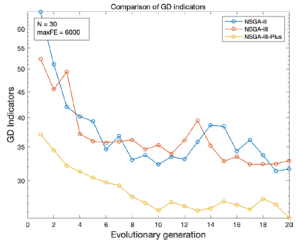
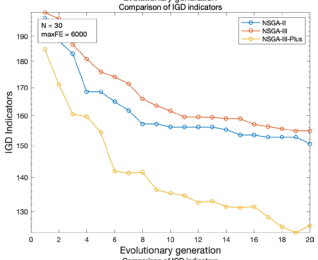
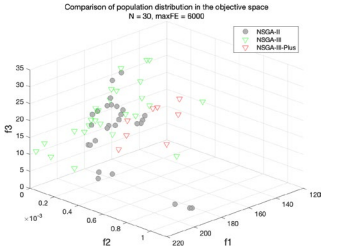
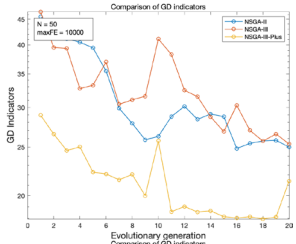
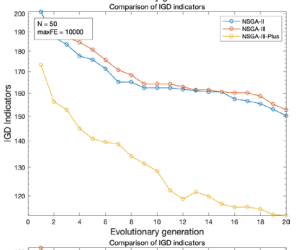
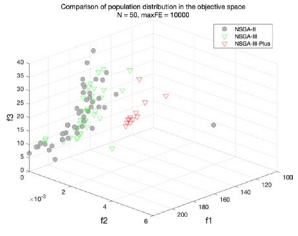
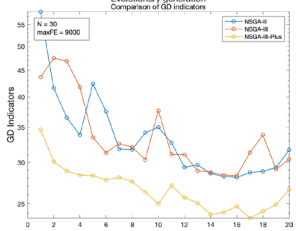
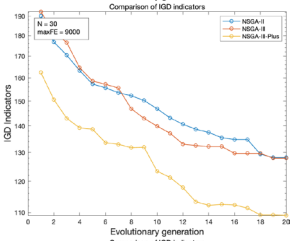
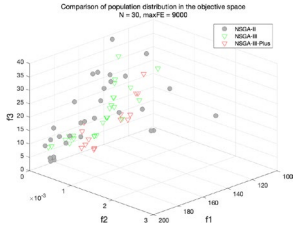
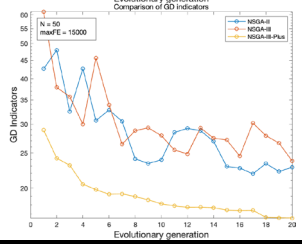
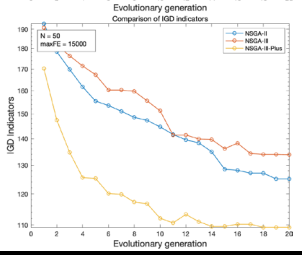
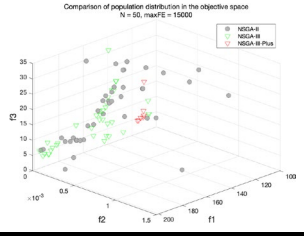
(30,100)			
(50,100)			
(30,200)			
(50,200)			
(30,300)			
(50,300)			

A.1.4 Results of different parameter combinations at phrase II (T=25min)

(N,E)	GD	IGD	Population distribution in the objective space
		(maxFE= N*E)	
(30,100)			
(50,100)			
(30,200)			
(50,200)			
(30,300)			
(50,300)			

A.2 The setting of ε-constraint

A.2.1 Algorithm Hyperparameters

Parameter	Population size	Maximum generations	Crossover rate	Mutation rate	Step size factor
Value	5	1000	0.6	0.05	0.1

A.2.2 ε-Constraint Configurations

A.2.2.1 Static Model Setting

Static Model	Combinations of ε-constraint [Cost,Delivery time, Income disparity]			Description
1	Inf	Inf	Inf	Unconstrained baseline
2	Inf	30	Inf	Time-constrained only
3	100	Inf	Inf	Cost-constrained only
4	Inf	Inf	10	Income disparity-constrained only
5	100	30	Inf	Cost & time constrained
6	Inf	30	10	Time & income disparity constrained
7	100	Inf	10	Cost & income disparity constrained
8	100	30	10	Fully constrained

A.2.2.2 Dynamic Model Setting

Dynamic Model	Combinations of ε-constraint [Cost,Dissatisfaction, Income disparity]			Description
1	Inf	0.01	Inf	Dissatisfaction-constrained only
2	120	Inf	Inf	Cost-constrained only
3	Inf	Inf	12	Income disparity-constrained only
4	120	0.01	Inf	Cost & dissatisfaction constrained
5	Inf	0.01	12	Dissatisfaction & income disparity constrained
6	120	Inf	12	Cost & income disparity constrained
7	120	0.01	12	Fully constrained
8	Inf	Inf	Inf	Unconstrained

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