Simulation study on optimization of delivery path for community group buying

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This paper addresses the optimization of community group-buying distribution paths by considering both cost efficiency and time constraints. Focusing on dense neighbourhoods where such services thrive, the study highlights how current distribution strategies often prioritize proximity over effectiveness. To minimize total costs—including vehicle fixed costs, fuel expenses, and time-constrained penalties—a mathematical model is developed and solved using an improved genetic algorithm. The model incorporates real-world constraints from community group-buying platforms. Simulation in AnyLogic, using actual order data from the Flowers and Fruits platform, demonstrates that the proposed approach reduces distribution costs by 31.62%, achieving the lowest-cost distribution path while meeting time window requirements. The results validate the model's effectiveness in balancing economic and operational efficiency.

KEYWORDS

community group buying, distribution routes, genetic algorithm, anylogic simulation, cost optimization

1 Introduction

The development of community group-buying in the world presents different characteristics and trends, in China, community group-buying has experienced rapid development and change, according to the "2023 China's Fresh Food E-commerce and Community Group-Buying Market Data Report" released by Nethersole's E-commerce Research Center, China's community group-buying transaction scale reached 322.8 billion yuan in 2023, representing a year-on-year growth of 53.71 percent; In addition, community group buying is also emerging and gaining attention in countries such as Singapore, India, Canada, the United States, the United Kingdom, and Australia. The main reason why community group buying is popular among global consumers is that its convenience brings convenient and efficient shopping. However, the development of community group purchasing in different regions of the world is also affected by various factors, such as consumer habits, market environment, and supply chain maturity. The development of community group-buying also faces some challenges, such as supply chain management, product quality control, customer satisfaction, operating costs and competition, which require continuous innovation and improvement to meet market demand; Therefore, the research on the optimization of the distribution path of community group purchase has greater practical significance.

Community group purchase distribution path optimization problem, the essence of the academic community on the vehicle path problem research; Dantzig and Ramser (1959) in 1959 and so on for the first time put forward the vehicle path problem, and by a large number of scholars, the previous scholars in the process of the research, focusing on the cost of distribution; with the continuous improvement of the standard of living of the people, the consumers of the distribution of the time limit is also to put forward a higher demand. In recent years, the

theoretical research on vehicle path planning problems has been derived from constraints such as vehicle load, vehicle volume capacity, service time window, cargo damage situation, vehicle carbon emission, etc., and has led to multifaceted branches such as the vehicle path planning problem with time window, multi-objective vehicle path planning problem, and the vehicle path planning problem with consideration of carbon emission, etc. In (Taillard et al., 1997); However, the research direction Favors the theoretical small-scale solution algorithm improvement, while how to apply the complex, large-scale VRP solution to more practical scenarios is a topic worthy of in-depth research. This paper takes the community group-buying field devoted to solving the distribution cost and customer satisfaction as the research object and tries to provide an algorithmic solution for its efficient community group-buying distribution scheme and path planning problem. Previous similar researches mainly include Liu et al. (2023) with the objective of lowest total cost of logistics and distribution and minimum carbon emission, introducing soft time window function and carbon emission parameters, taking the commodity distribution of Wuan Town Community Group Buying Distribution Center as an example, constructing a low-carbon vehicle distribution path optimization model for community group buying based on improved genetic algorithm, and comparing it with two typical heuristics, namely, traditional genetic algorithm and ant colony algorithm. Zhang and Zhu (2024) constructed a community group-buying delivery path optimization model considering carbon emission with the objective of minimizing the total cost, and designed the Gray Wolf optimization algorithm to solve the problem, which improves the effectiveness of the algorithm by improving the parameter updating formula of the Gray Wolf, and introduces the variation strategy of the genetic algorithm to improve the effectiveness of the algorithm, and obtains the globally optimal solution. In this paper, based on reference to previous research, community group purchase delivery path optimization as a research object to carry out in-depth research. This paper makes a differentiated contribution based on existing research: first, it breaks through the limitations of existing research, which mostly relies on hypothetical data, by conducting field research to obtain real delivery data on community group buying in a certain region (including specific parameters such as order demand at 24 community delivery points and road traffic-related coefficients). The mathematical model constructed has constraints that fully match the actual operating scenario. Second, we used Anylogic simulation software to build a simulation environment that includes dynamic traffic flow. We compared the results of the improved genetic algorithm (which introduces an adaptive crossover mutation operator, with the operator probability dynamically adjusted according to the fitness of the population) with the initial path results. Through repeatable simulation parameter settings and quantitative indicators, we verified the stability of the model in large-scale scenarios, addressing the shortcoming of existing research that lacks verification in actual scenarios.

2 State of the art

Theoretical research on community group-buying distribution path planning is from the optimization algorithm theoretical discussion and constantly deepen the research to solve the practical application of community group-buying distribution.

Theoretical research on optimization algorithms: Wang and Qiu (2020) developed a VRP model for minimizing the total cost of fixed, transportation and penalty costs under the constraint of delivery time satisfaction function for the characteristics of community group purchasing; On the optimization of genetic algorithm, the elite retention mechanism is added, the crossover operator is designed by using partial crossover rule, and instance testing is carried out. Song et al. (2022) constructed a model of community group purchase delivery vehicle path problem containing delivery time window and variable service time, and optimized the initial feasible solution and the neighbourhood search mechanism of ACO algorithm, and obtained a solution model of an improved ACO algorithm (Yu et al., 2022). Investigated a new combined order selection with time windows and periodic vehicle paths for real-life delivery problems commonly faced by online community group-buying operators, and proposed a branch pricing algorithm that strongly relies on a new label-setting algorithm with partial labelling advantages and a strong bounded policy based on the definition of a Pareto-optimal delivery model (Jianming, 2022). Analyses the service demand characteristics of consumers in community group-buying scenarios and establishes a multi-stage dynamic multi-objective supply chain optimization model for end-end distribution resource integration; solves the problem by using genetic algorithms and verifies the feasibility, validity and operability of the decision-making methods and algorithms by using examples (Chen and Kang, 2022). Constructed a delivery path optimization model for community group purchasing fresh products considering time window and freshness loss, designed and improved the genetic algorithm, solved it using MATLAB, and verified the validity of the model and the advantages of the improved algorithm through the arithmetic examples (Guifang, 2024). Comprehensively considered a variety of cost factors such as carbon emission cost, transportation cost, cargo damage cost, refrigeration cost, time window penalty cost, etc., and constructed a community group-buying delivery vehicle path optimization model with the objective of minimizing total cost. Using the intelligent algorithm Whale Algorithm, the distribution paths are optimized, and the search ability and convergence of the algorithm are verified (Dyah et al., 2024). Emphasized the importance of efficient distribution services by comparing the effectiveness of Simulated Annealing (SA) and Ant Colony Optimization (ACO) in finding the shortest route to minimize the operational cost (Razita et al., 2024). Analysed the importance of efficiency of logistics services in distribution routes and compared two methods of distribution paths, the nearest neighbour method and the Clarke and Wright (Alvarez et al., 2024) conservation method, to determine the optimal strategy for delivering 53 packages to eight locations.

Practical application research: Solomon and Desrosiers (1988) first applied the distribution timeliness, i.e., time window constraints, to distribution path research and attracted the attention of many scholars (Coulter and Roggeveen, 2014) Conducted an in-depth analysis of the principles of discounts on community group-buying platforms, and found that discounts on group-buying platforms have a certain relationship with the quantity; it was found that a similar sequence of price-quantity, if presented, between ordinary prices, sales prices and discounted prices will have an impact on the final consumption choice of consumers (Hsu et al., 2018). concluded that community group

purchasing is gradually becoming an interesting online shopping consumption model, and its main consumer group is female housewives aged 41–50 years old and used the Kano quality model to assess the key service quality characteristics of community group purchasing, including price and recommendation function (Wang et al., 2020). Studied the optimization of community group-buying delivery paths based on the consideration of customer satisfaction, i.e., customer satisfaction, i.e., how to satisfy the delivery of the product to each community within the bounded time window of each delivery community (Wang and Qiu, 2021). For community group-buying enterprises in logistics scheduling in the existence of low efficiency, high cost, low customer satisfaction and other issues, established in the scheduling time window satisfaction function under the constraints of the constraints of the total cost of the least cost contains fixed costs, transportation costs and penalty costs, for the community group-buying enterprise logistics scheduling decision-making provides a reference. Hongsuchon and Li (2022) constructed a theoretical model based on social identity theory of how consumer participation behaviour affects purchase intention in the context of community group purchasing, to reveal the internal mechanism and boundary conditions of consumer participation affecting purchase intention, and to provide suggestions for the marketing management and business practice of community group purchasing platforms. Xie et al. (2022) studied the prediction of repurchase behaviour of community group-buying users based on real data from community group-buying enterprises and constructed a two-layer fusion model with three identical primary learners, but different secondary learners based on the stacking of heterogeneous integrated learning methods. Takes a community group-buying company as the research object, constructs a site selection model considering the cost of cargo damage and a distribution path optimization model with a soft time window, which provides a reference for the site selection of distribution centers and distribution path planning. The P-median method to construct the optimization model of central warehouse location with the objective of minimizing the total cost, and used genetic algorithm to solve the model; Then the minimum facility points model, maximized coverage model with capacity constraints and minimized impedance model are used in Arc GIS platform to optimize the grid warehouse site selection for community group purchasing respectively, and finally the optimization analysis is carried out with a community group purchasing warehouse and distribution network system in Shandong Province as an example.

In summary, existing research has three limitations: First, algorithm optimization is mostly based on ideal scenario assumptions, with insufficient consideration of actual factors such as dynamic traffic and differences between multiple product categories. Second, empirical research mostly relies on static data and lacks dynamic simulation verification. Third, although the objective function takes into account both cost and timeliness, it does not establish a quantitative relationship between consumer satisfaction and delivery parameters. To address the above shortcomings, this paper obtains community dynamic delivery data through field research, constructs an improved genetic algorithm model that integrates multiple constraints, and uses AnyLogic for dynamic scenario simulation, ultimately achieving dual optimization of cost reduction and satisfaction improvement (Table 1).

This paper next mainly carries out the following research. First, based on the characteristics of the community group-buying industry and distribution requirements, the mathematical model is constructed with the lowest distribution cost as the objective function, the problem description, parameter setting, objective function, constraints, etc. of the mathematical model are analysed in detail, and the solution model of the genetic algorithm and its specific application in the distribution path of the community group-buying are introduced. Second, combined with the actual task of a community group purchase as an empirical study, using AnyLogic simulation software to solve the community group purchase distribution path, to find out the optimal distribution path that meets the objectives, and to compare the distribution cost of the initial scheme of the community group purchase distribution path and the optimized distribution path, and to get the results in line with the research assumptions. Third, the research is summarized, and conclusions are drawn.

3 Methodology

3.1 Description of the problem

In this paper, the community group-buying distribution path optimization problem can be described as follows: a community group-buying platform in a city distribution center has one and only one, responsible for the distribution of community group-buying in the whole city, the distribution center has a certain number of vehicles with the same load capacity, the number of communities that need to be distributed is n, and the demand for each community and the distribution time window are known; taking into account the fixed cost of the vehicle, the cost of fuel, and the cost of time constraints, the optimal community group-buying distribution path is sought with the objective of minimizing the total distribution costs. With the goal of minimizing the total cost of distribution, the optimal community group-buying distribution path is sought.

1. The objective function of the mathematical model is constructed with the lowest total cost of distribution by conducting field research on community group buying customers and merchants to understand their needs; The total cost of distribution includes vehicle fixed cost, fuel cost, and time constraint cost. Vehicle fixed cost is directly related to the number of vehicles used to complete the distribution task, fuel cost, i.e., to complete the distribution task, the total mileage travelled by the vehicle and the consumption of fuel, and time constraint cost is the cost of penalties for a single distribution to a community that does not occur in the specified time.

2. In this paper, when considering the constraints of the vehicle, only the load capacity of the vehicle is considered, and the volume of the vehicle is not considered, according to the visit to the community group-buying merchant, it is known that the community group-buying delivery of the characteristics of the product in the light throws less, so there will not be a too large volume of the product, and there will not be a lack of the vehicle's volume, so only the vehicle's load capacity is considered

3. In this paper, the time constraints for delivery to each community are set for the community group purchase delivery process, i.e., the product must be delivered to the

TABLE 1 Summary before related work.

Research interests	Author	Core model	Main contributions	The positioning and differentiation of this study
Optimization algorithm theory research				
	Wang and Qiu (2020)	VRP model with satisfaction function	Minimize fixed, transportation, and penalty costs	Similarly, improved GA is used, but the improvement strategy (dynamic crossover/mutation probability, Gaussian mutation) in this paper is different, and it has been verified through simulation
	Song et al. (2022)	VRP with time windows and service times	Optimized the ACO search mechanism	This paper selects genetic algorithms rather than ant colony algorithms as the optimization core and focuses on the comprehensive construction of cost models
	Yu et al. (2022)	Combined order selection with time windows and cyclic VRP	Proposed an accurate algorithm framework integrating order selection and path planning	This paper studies a single, static delivery route problem, rather than a multi-period integrated optimization problem
	Jianming (2022)	Multi-stage dynamic multi-objective optimization model	Research on resource integration at the end of the supply chain	This model is single objective (cost minimization), but it provides a foundation for subsequent expansion to multi-objective (e.g., cost, time, carbon emissions)
	Chen and Kang (2022)	A model considering time window and freshness loss	Incorporate quality loss of fresh produce into the objective function	This paper does not consider cargo damage costs, but it uses AnyLogic for high-fidelity simulation, which can better simulate dynamic environments such as real traffic and sensitivity analysis to verify that cargo damage costs do not exist as interference
	Guifang (2024)	VRP model with multiple cost factors (carbon emissions, cargo damage, refrigeration, etc.)	A more comprehensive cost model was constructed, verifying the effectiveness of the whale algorithm in this problem	Although this paper has a limited number of cost model dimensions, it uses simulation to derive specific, visualizable path solutions and verifies the significant cost reduction effects
	Dyah et al. (2024)	Comparison of simulated annealing (SA) and ant colony optimization (ACO)	The performance of two meta-heuristic algorithms was compared in terms of minimizing operating costs and finding the shortest path	This paper focuses on the in-depth improvement and verification of a single algorithm (genetic algorithm) rather than a horizontal comparison of multiple algorithms
	Razita et al. (2024)	Comparison of the nearest neighbor method and the Clarke-Wright economy method	The path planning effects of two classic heuristic algorithms were compared in specific cases	This paper uses a more advanced meta-heuristic algorithm (improved GA) to solve larger-scale, more complex constraint problems
Applied research				
	Solomon and Desrosiers (1988)	Introduction of time window constraints	Pioneered the important research direction of vehicle routing problem with time windows (VRPTW)	This paper inherits the idea of time window constraints and incorporates it as part of the cost model (time penalty cost)
	Coulter and Roggeveen (2014)	Price Strategy Analysis	Reveals the psychological relationship between platform discount pricing and consumer numbers, influencing consumer choices	This paper focuses on logistics distribution optimization, but the study reminds us that pricing strategies may affect the geographical distribution and density of orders, indirectly influencing route planning
	Hsu et al. (2018)	Kano model	We analyzed the service quality requirements of community group buying users (mainly middle-aged women), such as price and recommendation functions	This article focuses on delivery efficiency, a key aspect of service quality that is directly related to core user needs such as "on-time delivery."
	Wang et al. (2020)	Path optimization considering customer satisfaction	Make meeting time window constraints a core means of improving customer satisfaction	This paper is consistent with this concept and converts the subjective concept of "satisfaction" into an objective target that can be optimized by quantifying the time window penalty cost
	Wang and Qiu (2021)	VRP model with satisfaction function	Provides a decision-making reference model for enterprise logistics scheduling with the goal of minimizing costs	This article is similar, but it provides a complete chain from model to practical application through specific simulation cases

(Continued on following page)

TABLE 1 *(Continued)* Summary before related work.

Research interests	Author	Core model	Main contributions	The positioning and differentiation of this study
	Hongsuchon and Li (2022)	Social identity theory, theoretical model construction	The study examined the mechanism by which consumer participation behavior influences purchase intent and provided recommendations for platform marketing	This article focuses on cost reduction and efficiency improvement in back-end operations, while this study focuses on front-end marketing and user growth. Together, these two elements constitute the key factors for platform success
	Xie et al. (2022)	Stacked Ensemble Learning	Using machine learning to predict user repurchase behavior helps with demand forecasting and inventory management	Accurate demand forecasting is an important input for path optimization models. This paper assumes that demand is known, and this study can provide data support for the dynamic expansion of the model in this paper
		Location-Route Problem (LRP) Model	Simultaneously optimize distribution center location and distribution routes, taking into account cargo damage costs	This paper fixes the location of the distribution center and optimizes the route separately. This study is a more complex and macro-level integrated decision-making problem
	Jiang and Jinzhuo (2024)	Two-stage site selection optimization (P-median method, ArcGIS model)	An empirical study was conducted on the location selection of central warehouses and grid warehouses using mathematical models and GIS tools	This paper is a follow-up to that study, focusing on specific delivery route planning based on the warehouse location that has already been decided

community in the specified period, and the set time constraints affect customer satisfaction as well as time constraint costs.

3.2 Assumptions of the problem

The following are the premise assumptions made in the course of this paper.

1. This paper investigates the path optimization problem for multiple communities transported by a single distribution center.
2. Multiple neighbourhoods are delivered by the same vehicle.
3. The vehicle travels at a constant speed during distribution.
4. The coordinates of the neighbourhood to be delivered, the demand, the optimal time for delivery, the optimal time window, and the service time are all known
5. One vehicle can deliver to several neighbourhoods without overloading
6. Failure to complete a delivery task within a specified time window requires penalty costs to be paid
7. Product loss during distribution is fixed
8. The total cost of distribution includes vehicle fixed costs, fuel costs, and time-constrained costs

3.3 Parameter symbol definition

The parameter symbols of the constructed model in this paper are defined as shown in Table 2.

3.4 Model building

3.4.1 Objective function

In this paper, the objective function is to minimize the total cost of distribution, and the total cost of distribution consists of vehicle fixed cost (Z1), fuel cost (Z2), and time-constrained cost (Z3), and each cost is specifically analysed as follows.

1. Vehicle fixed cost: refers to the cost of completing the number of vehicles required to complete the task of community group purchasing distribution, and the use of the number of distribution vehicles is proportional to the relationship between the number of vehicles, the vehicle fixed cost is calculated as Equation 1.

$$Z_1 = \sum_{k=1}^{K} F_k \qquad (1)$$

2. fuel cost: refers to the unit transportation vehicle transportation unit distance cost and transportation vehicles, transportation distance sum, fuel cost calculation as Equation 2.

$$Z_2 = \sum_{k=1}^{k} \sum_{i=0}^{n} \sum_{j=0}^{n} d_{ij} C_p X_{ij}^k \qquad (2)$$

3. Time constraint cost: is when the distribution to a community, then the earliest distribution time specified by the community earlier, or later than the latest distribution time specified by the community, then exceed the time window to reach the distribution point required to penalize the cost of time constraint cost calculation as in Equation 3.

$$Z_3 = \alpha \sum_{i=1}^{n} \max\{ET_i - t_i, 0\} + \beta \sum_{i=1}^{n} \max\{t_i - LT_i, 0\} \qquad (3)$$

The objective function is to minimize the total cost of distribution, the total cost of distribution is the sum of the three costs of vehicle fixed cost (Z1), fuel cost (Z2), and time-constrained cost (Z3), and the minimization of the cost is shown in Equation 4.

TABLE 2 Parameter symbols definition.

Parameter symbol	Parameter definition
L_0	distribution center
L_i	i= (1, 2, ..., n) distribution destinations
S	customer satisfaction
K	Total number of vehicles used for distribution
V_0	Average speed of movement of distribution vehicles
C_P	Unit distance cost per unit of transportation vehicle transported
F_k	Fixed costs for kth vehicle utilization
T	Fresh Shelf Life
P	Product Unit Price
q_i	Demand for the product of the i-th customer
t_i	Distribution vehicle delivery time to the i-th customer
t_{ij}	Time taken by the distribution vehicle to get from the i-th customer to the j-th customer
d_{ij}	Shortest distance between two points from the distribution center to each customer point
(ET_i, LT_i)	Starting time and ending time of the i-th customer's request to receive the goods
(ETi_α, LTi_β)	Starting time and ending time when the i-th customer expects to receive the goods
α	Unit time costs incurred when delivering earlier than the earliest time requested by the customer
β	Unit time costs incurred when delivery is later than the latest time requested by the customer

$$Z_{\min} = Z_1 + Z_2 + Z_3 \tag{4}$$

3.4.2 Restrictive condition

Vehicle constraints, visiting node constraints, and time constraints are considered in building the model.

1. Vehicle constraints include vehicle load constraints and vehicle number constraints. Vehicle load constraints mean that the total distribution volume of each community group-buying distribution path is less than or equal to the vehicle load, see Equation 5 for vehicle load constraints; vehicle number constraints mean that the vehicles used for distribution are less than or equal to the total number of vehicles, see Equation 6 for vehicle number constraints.

$$\sum_{k=1}^{K} q_i Y_{ik} \le Q \, (k = 1, 2, ..., K; i = 1, 2, ..., n) \tag{5}$$

$$\sum_{k=1}^{K} \sum_{j=1}^{n} X_{ij}^k \le K \tag{6}$$

2. The visiting node constraint means that the vehicles of each distribution path start from the distribution center and finally

return to the distribution center, and each community is reached once without repeated visits and without loop situations; the visiting node constraints are shown in Equations 7–12.

$$\sum_{k=1}^{K} \sum_{j=0}^{n} X_{ij}^k = 1 \, (i \ne j; i = 1, 2, ..., n) \tag{7}$$

$$\sum_{k=1}^{K} \sum_{i=0}^{n} X_{ij}^k = 1 \, (i \ne j; j = 1, 2, ..., n) \tag{8}$$

$$\sum_{k=1}^{K} Y_{ik} = 1 \, (i = 1, 2, ..., n) \tag{9}$$

$$\sum_{k=1}^{K} \sum_{j=0}^{n} X_{ij}^k = \sum_{k=1}^{K} \sum_{j=0}^{n} X_{ji}^k \le 1 \, (i \ne j; i = 0) \tag{10}$$

$$X_{ij}^k = \begin{cases} 1 \\ 0 \end{cases} \, (i \ne j; i = 1, 2, ..., n; j = 1, 2, ..., n; k = 1, 2, ..., K) \tag{11}$$

$$Y_{ik} = \begin{cases} 1 \\ 0 \end{cases} \, (i = 1, 2, ..., n; k = 1, 2, ..., K) \tag{12}$$

3. The time constraint is the description of the time problem of the distribution path of the distribution vehicle, Equation 13 represents the travel time of the vehicle from point i to point j of the community; Equation 14 indicates that the time of the vehicle's distribution to community i should be between the earliest time and the latest time allowed for the distribution to community i.

$$t_{ij} = \frac{d_{ij}}{V_0} \, (i, j \in U_0) \tag{13}$$

$$ET_i \le t_i \le LT_i \tag{14}$$

3.4.3 Algorithm design

In this paper, to find the optimal solution of the objective function of the above constructed model, the algorithm of the objective function is designed based on the genetic algorithm with improvement based on the genetic algorithm. Designing new crossover and mutation approaches by adjusting the crossover probability and mutation probability of traditional genetic algorithms to dynamically change to suit different stages and fine-tuning the path selection by Gaussian mutation to obtain a better solution in the logistics path planning problem. The specific flow of the algorithm implementation is as follows.

3.4.3.1 Chromosome code

By reviewing the relevant literature, most of the chromosome coding uses natural numbers for coding, in this paper, when coding the chromosome, define 0 as the distribution center, define 1, 2, 3, ..., N is each distribution destination; when the number of distribution destinations is n and the total number of distribution vehicles is K, the total length of the chromosome is n + K+1.

3.4.3.2 Population initialization

Common methods of population initialization include random initialization, initialization based on prior knowledge, uniformly distributed initialization, etc. In this paper, the population is initialized based on the random initialization method, which can

distribute the individuals more randomly throughout the solution space, which is conducive to the extensive exploration of possible solutions; It will not be overly concentrated in certain regions because of certain *a priori* assumptions or preferences, and has greater uncertainty and openness; the population generation speed is faster and less difficult to calculate. The initial size of the population is generally set in the range of 30–150, the scale is too large or too small will affect the efficiency of the algorithm, in this paper, the value of the initial population size is 100.

3.4.3.3 Fitness function

The fitness function is used to measure the degree of superiority or inferiority of an individual, the design of the fitness function needs to pay attention to its accuracy, monotonicity, and computability, and should fully consider the objectives and constraints of the problem to ensure that the fitness function can effectively guide the direction of evolution; the most suitable form of the fitness function can be determined through several trials and adjustments to improve the performance and effect of the genetic algorithm. In this paper, the fitness function is set as the inverse of the objective function, see Equation 15.

$$fitness(i) = \frac{1}{Z_i} \ (i = 1, 2, 3, ..., N_P) \quad (15)$$

In Equation 15 fitness(i) is the chromosome i fitness function and Zi is the objective function of the chromosome; NP is the number of populations.

3.4.3.4 Choice of operator (math.)

Common methods of selecting operators include roulette selection, tournament selection, elite reserved selection, sorted selection, and random selection, etc. In this paper, we combine the two methods of elite reserved selection and random selection. The elite retention selection method ensures that the best individuals go directly to the next-generation of the population, thus preserving the good genes in the population. The random selection method increases the diversity of the population and avoids the algorithm from falling into local optima. The combination of the two can introduce more diversity and improve the algorithm's search ability while maintaining the quality of the population. The elite retention selection method reduces the randomness in the genetic algorithm and makes the algorithm more stable, while the random selection method increases the randomness of the algorithm and makes the algorithm more robust and able to cope with different problems and datasets. The combination of the two can synthesize the advantages of both to some extent, so that the algorithm can show better performance in different situations. The elite retention selection method allows superior individuals to reproduce faster, thus accelerating the convergence of the algorithm. The random selection law increases the diversity of the population and avoids premature convergence of the algorithm. By combining these two methods, the convergence speed can be increased while maintaining the diversity of the population, resulting in a better solution.

3.4.3.5 Intersection operator (math.)

The crossover operator is one of the most important operations in genetic algorithms, which allows for the evolution of populations by genetically recombining individuals from the

FIGURE 1
Cross-Cutting process.
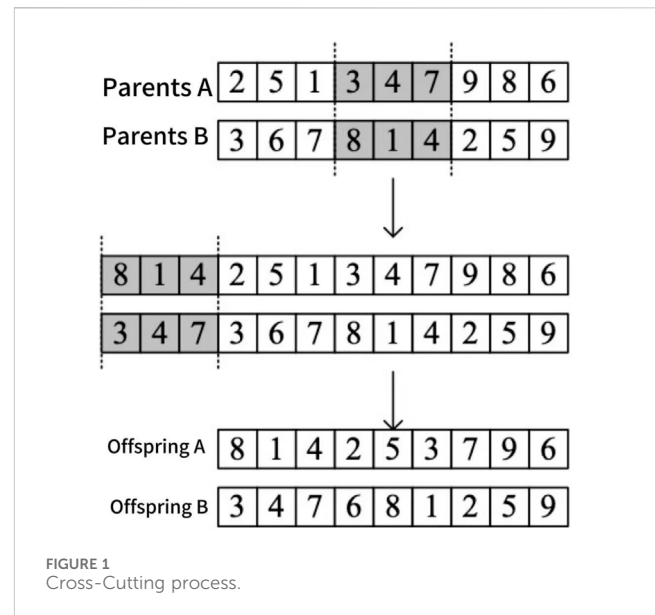
parent generation to produce offspring individuals. Common crossover operators are single-point crossover, two-point crossover, multipoint crossover, partial matching crossover, simulated binary crossover, brainstorming optimization crossover, etc. In this paper, the two-point crossover method is used, in which 2 crossover points are set randomly from the paternal chromosomes, followed by placing the selected crossover point on the top of the other one, respectively, and at the same time deleting the genes identical to the insertion point, to obtain 2 new individuals, called offspring. And evaluate and compare the offspring with the parent, if the value of the fitness function of the offspring is better than the fitness function of the parent, the crossover offspring will be included in the next-generation of the population, and if the value of the fitness function of the parent is better than the fitness function of the offspring and *vice versa*, then mutation is required. The crossover operator crossover process is specified in Figure 1.

3.4.3.6 The calculus of variations (math.)

The variation operator is an important operation in genetic algorithms for introducing diversity and exploring the search space. The purpose of the variation operator is to enable the genetic algorithm to explore more extensively in the search space by introducing randomness and diversity, avoiding premature convergence to a local optimum and increasing the chances of finding a globally optimal solution.

In practice, it is common to combine multiple mutation operators or adopt adaptive mutation strategies to adapt to different problems and optimization needs. In this paper, we combine the reversal mutation and insertion mutation methods for operator mutation, and its specific mutation process is as follows.

1. reverse mutation

Two reversal points were randomly selected in the paternal generation and the genes between them were reverse ordered, as shown in Figure 2.
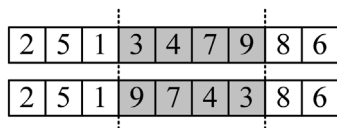
FIGURE 2
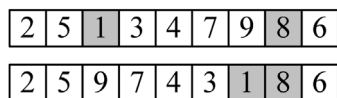Reversal of the mutation process.

FIGURE 3
Insertion of the mutation process.

2. Insertion of mutations to reverse the process of mutation

Pick 2 points a and b randomly in the parent and insert a in front of the b position. See Figure 3 for details.

After applying reversal mutation and insertion mutation to the operator, the fitness function values of the mutated chromosomes were compared; If the fitness of the chromosome after the operator mutation is better than the fitness of the previous generation, it means that after the operator mutation, a more optimal solution is obtained, and it can be included in the next-generation of the population; Otherwise, the chromosomes obtained from the previous generation after crossover were retained. By this method, it is possible to achieve a gradual optimization of the fitness level of the entire population, thus obtaining an optimal solution to the objective function.

4 Result analysis and discussion

4.1 Example of community group buying delivery

4.1.1 Distribution tasks in a nutshell

In order to verify the applicability of the constructed model and the algorithm solution, this paper analyses the distribution task that needs to be accomplished by the 'Zhi Hua Zhi Guo' (知花知果)community group-buying platform in the high-tech development zone of Nanchang City as an example. 'Zhi Hua Zhi Guo' community group-buying platform in Nanchang high-tech development services community has 24, to more accurately mark the distribution center and the specific location of each community, the use of latitude and longitude to mark, and retain 6 decimal points of valid data; The distribution volume of each community is based on the average daily demand of the community platform in a certain month, the optimal time window and time window requirements are determined through the implementation of customer research in each community, and the service hours of each community are

determined based on the work experience of the staff. The specific parameters are shown in Table 3.

The community group-buying platform uses delivery vehicles as unified small box trucks with a load capacity of 1.5 T. Only the vehicle load is considered during assembly, not the vehicle volume. Combined with the actual situation of distribution cost accounting of community group-buying platform, the information of each parameter in the model is determined as shown in Table 4.

4.1.2 Distribution mission initialization programme

This paper is based on AnyLogic simulation to simulate and verify the distribution path and cost of this community group-buying platform. The initial path scheme of the community group-buying platform to complete the 24 community delivery tasks in Table 3 is shown in Figures 4, 5, and the cost and satisfaction of each specific path is shown in Table 5.

4.2 Analysis of optimization results of community group-buying distribution

4.2.1 Distribution optimization solution

In this paper, based on the improved genetic algorithm, the use of AnyLogic simulation software for simulation verification, set the number of iterations of the genetic algorithm for 1,000; get the iterative diagram of the cost of the community group-buying distribution path program is shown in Figure 6, and get the community group-buying the most distribution path program is shown in Figures 7, 8, and the optimal path of the specific cost of the cost of the optimal path is shown in Table 6.

4.2.2 Analysis of results

From the table above Table 5 Community Group Buying Distribution Initial Program and Table 6 Community Group Buying Optimal Distribution Program Data Comparison, it can be seen that the distribution cost of the optimized community group buying distribution path is reduced from 1974.41 to 1,350.18, the total cost of distribution has been saved by 31.62%, of which there is no change in the fixed cost of the vehicle, the use of the distribution vehicle is three, the fuel cost is reduced from 743.25 to 508.12, and time constraint costs decreased from 391.15 to 2.07. This shows that the model constructed, and the proposed algorithm solved by the topic are effective and have obvious effect on the cost reduction of community group purchase delivery path.

4.3 Sensitivity analysis

To verify the robustness of the model results for cost components not included in the analysis (such as cargo damage costs and carbon emission costs), this paper sets up three sensitivity test scenarios. By adjusting the cost coefficients to simulate different levels of impact, we analyze the degree of interference with the optimization results.

4.3.1 Freight damage cost sensitivity test

Referring to the damage rate calculation method in relevant literature, assuming that the damage cost of fresh goods is linearly

TABLE 3 Community distribution point model parameters.

Community distribution point model parameters	Longitudes	Latitude	Demand t	Optimal time window	Time window requirement (min)	Service time (min)
distribution center	115.864128	28.556469				
L1	115.981270	28.665852	0.21	6:40–7:10	±20	15
L2	115.981758	28.663160	0.15	6:50–7:30	±20	15
L3	115.997902	28.665480	0.22	7:20–7:40	±20	15
L4	116.016754	28.673403	0.31	7:30–8:00	±20	15
L5	115.993042	28.678526	0.15	7:40–8:20	±20	15
L6	115.999611	28.676071	0.24	8:00–8:30	±20	15
L7	116.008713	28.706936	0.15	8:20–8:45	±20	15
L8	115.991234	28.667629	0.12	8:50–9:20	±20	15
L9	116.005879	28.693977	0.16	6:30–7:10	±20	15
L10	116.006325	28.695345	0.18	6:50–7:30	±20	15
L11	115.971954	28.707380	0.18	7:30–7:50	±20	15
L12	116.011314	28.706184	0.22	7:40–8:10	±20	15
L13	116.001442	28.709347	0.12	8:20–8:50	±20	15
L14	115.998505	28.700394	0.15	8:30–8:50	±20	15
L15	115.968498	28.707985	0.12	7:20–8:00	±20	15
L16	116.010468	28.709160	0.14	8:10–8:50	±20	15
L17	115.969833	28.709499	0.17	6:40–7:10	±20	15
L18	115.986526	28.715548	0.2	6:50–7:30	±20	15
L19	115.985870	28.711399	0.21	7:20–7:40	±20	15
L20	115.983467	28.714270	0.24	7:30–8:00	±20	15
L21	115.980011	28.714211	0.13	7:40–8:20	±20	15
L22	115.980057	28.709927	0.19	8:00–8:30	±20	15
L23	115.977654	28.711197	0.16	8:20–8:45	±20	15
L24	115.979248	28.702860	0.14	8:50–9:20	±20	15

TABLE 4 Parameter information.

Parameter symbol	Parameter definition	Parameter values
V_0	Average speed of movement of distribution vehicles	45 km/h
C_P	Unit distance cost per unit of transportation vehicle transported	2.5Yuan (RMB)/km
F_k	Fixed costs for kth vehicle utilization	280 Yuan (RMB)/
T	Fresh Shelf Life	72h
P	Product Unit Price	4500 Yuan (RMB)//t
$α$	Unit time costs incurred when delivering earlier than the earliest time requested by the customer	45 Yuan (RMB)//h
$β$	Unit time costs incurred when delivery is later than the latest time requested by the customer	80 Yuan (RMB)//h

FIGURE 4
Community group buying initial distribution program.

FIGURE 5
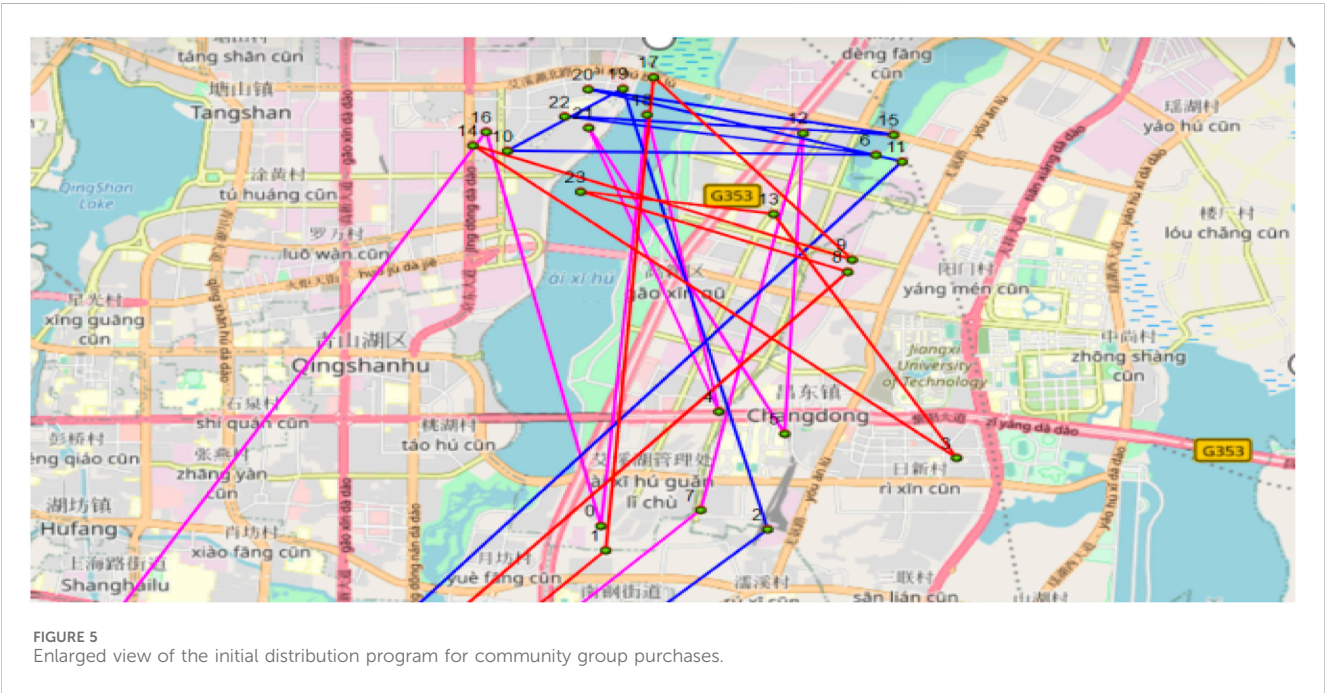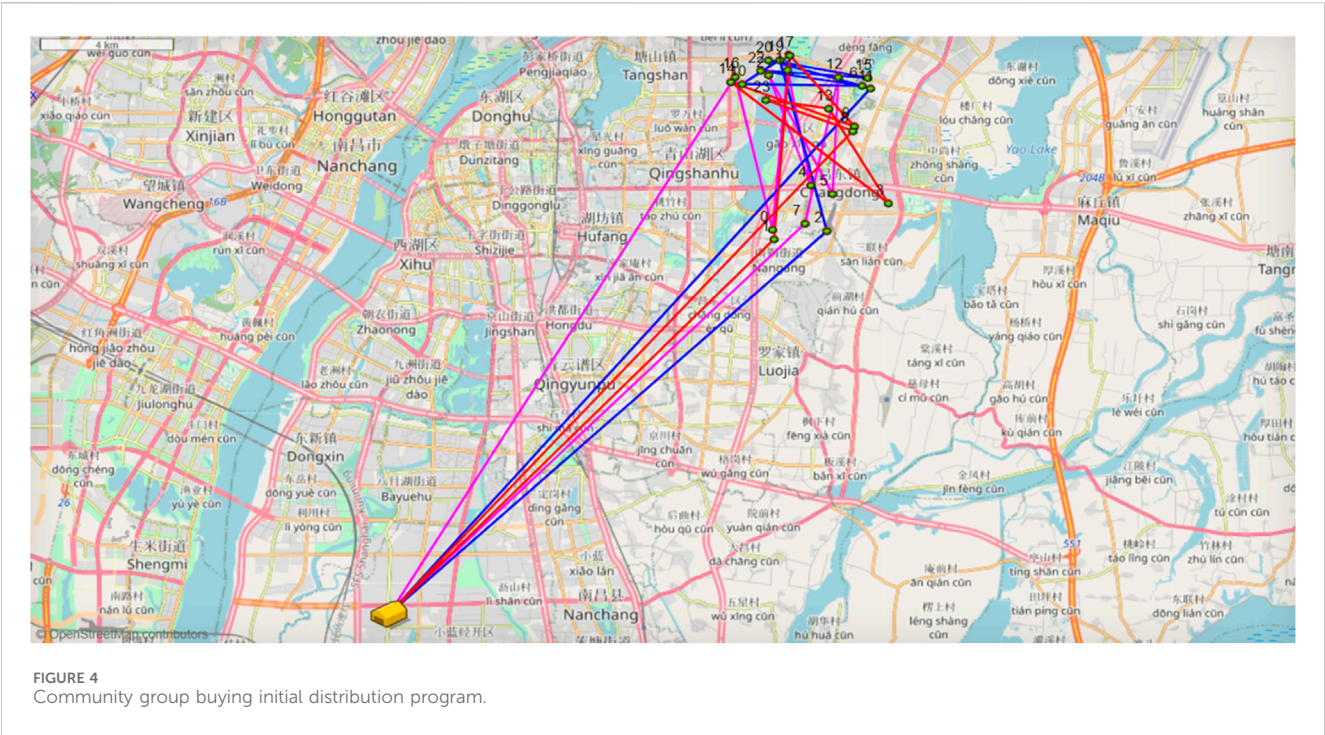Enlarged view of the initial distribution program for community group purchases.

TABLE 5 Community group buying distribution initial program.

Distribution routes	Distribution path implementation program
Route 1	Distribution center→L2→L18→L10→L15→L4→L14→L24→L9→ Distribution center
Route 2	Distribution center →L12→L21→L16→L23→L7→L11→L20→L3→ Distribution center
Route 3	Distribution center →L17→L1→L19→L5→L22→L6→L13→L8→ Distribution center

Totally cost: 1974.4063733355056, Vehicle fixed costs: 840.0, Fuel cost: 743.2556906688391, Time-constrained costs: 391.1506826666664.

FIGURE 6
Cost iteration Chart.

FIGURE 7
Optimal delivery solution for community group buying.
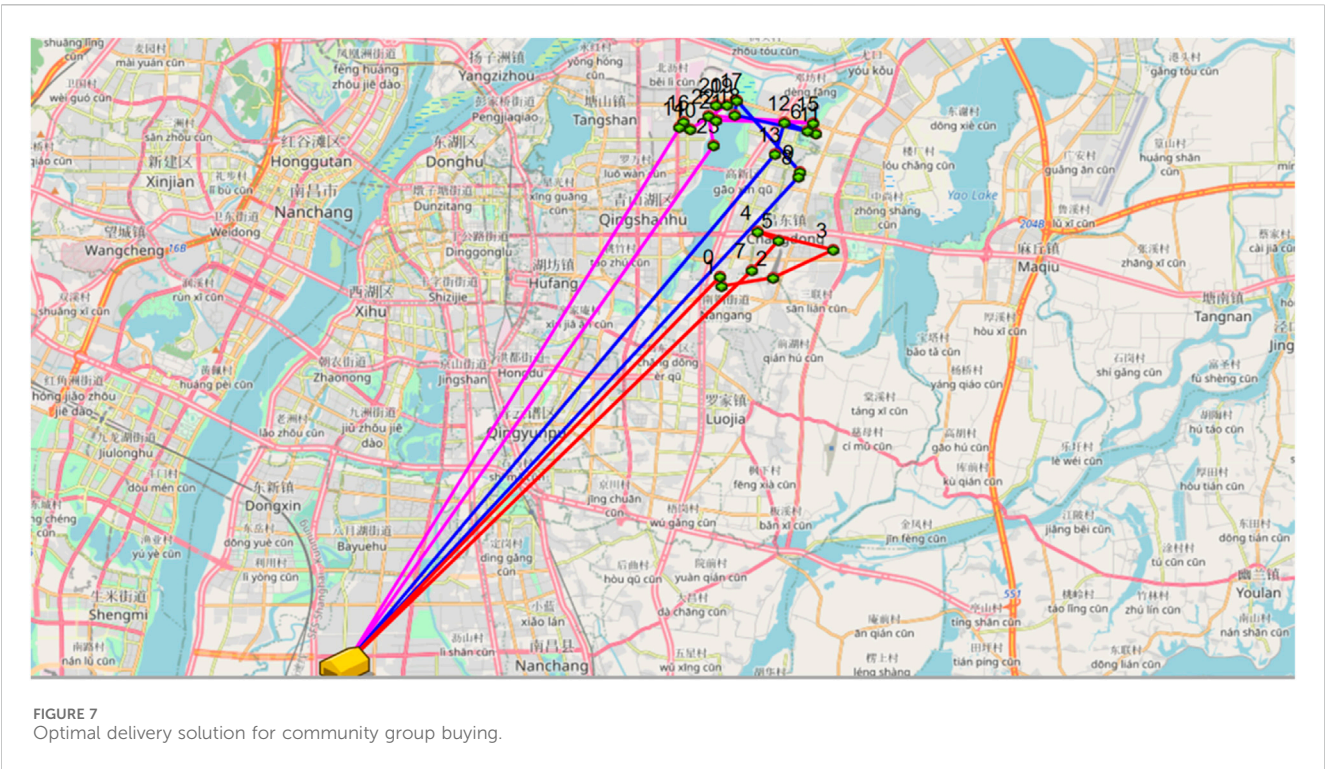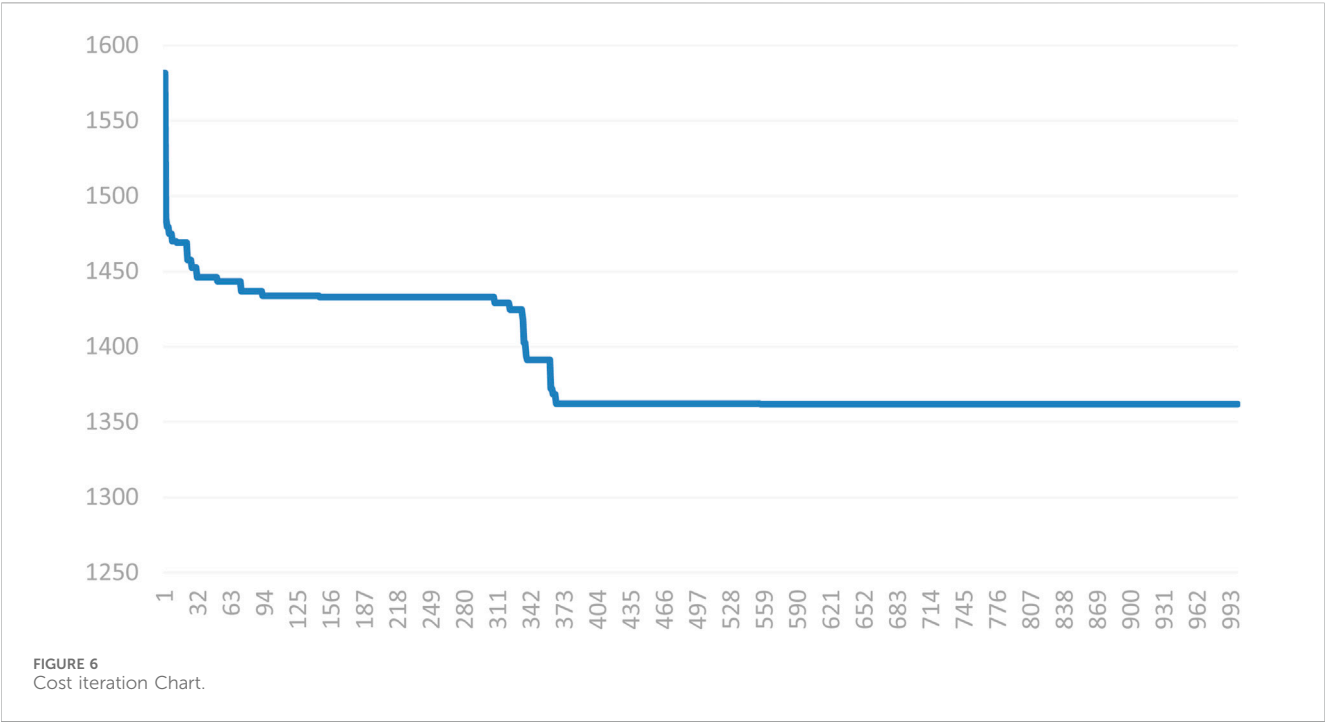
related to the delivery time (damage rate = 0.02%/minute), introduce the damage cost coefficient λ (λ = 0, 0.1, 0.3, 0.5). When λ = 0.3 (i.e., the cost of cargo damage accounts for 30% of the original total cost), the optimized total cost increases to 1,426.35 yuan, an increase of 5.64% compared to the original optimization result, but still a

savings of 27.76% compared to the initial plan. Even when λ = 0.5, the cost savings rate remains at 24.12% (see Table 7). The results indicate that fluctuations in cargo damage costs have no substantial impact on the conclusion that the optimized solution is superior to the initial solution.
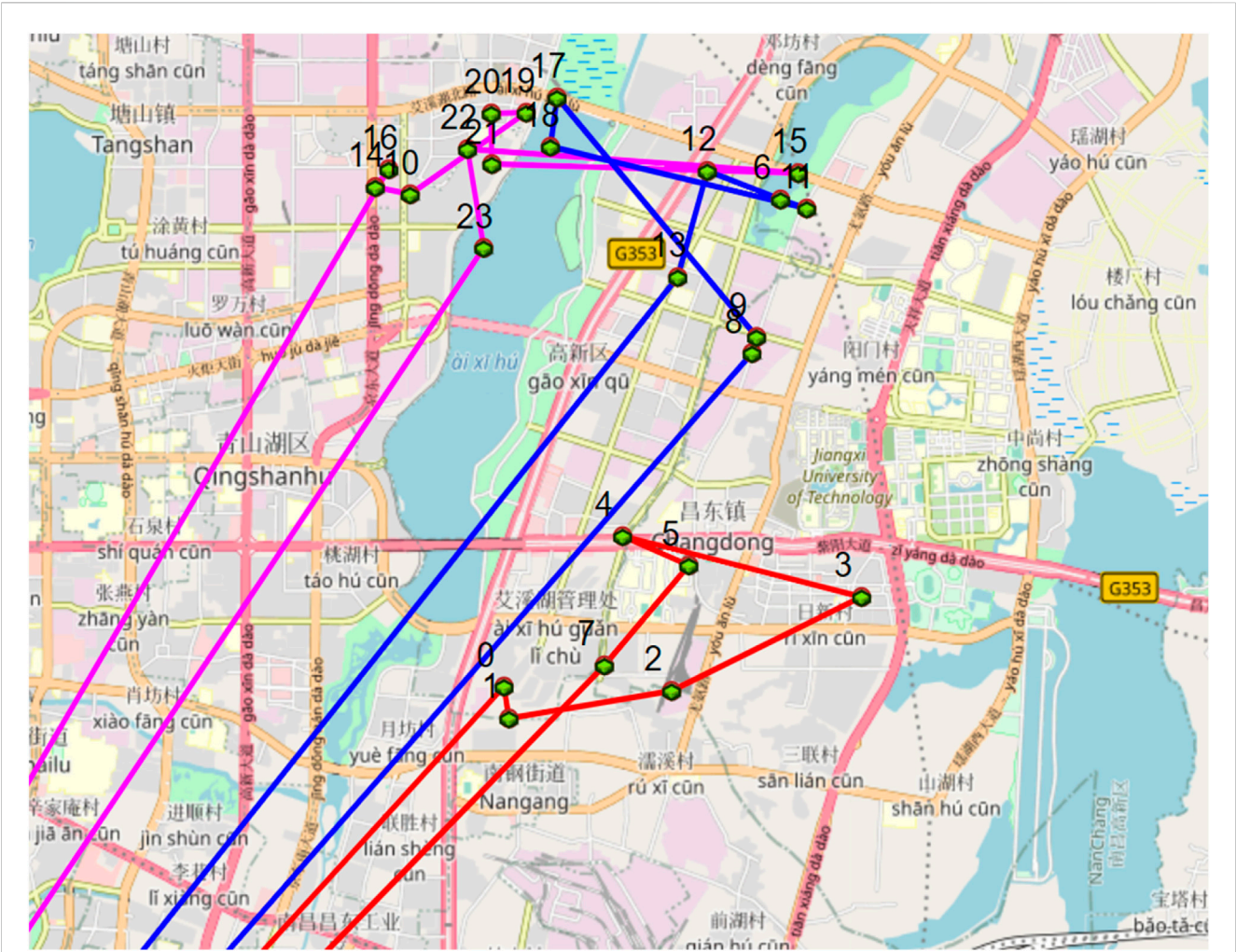
FIGURE 8
Enlarged view of the optimal distribution solution for community group purchases.

TABLE 6 Optimal delivery solution for community group buying.

Distribution routes	Optimal distribution route implementation program
Route 1	Distribution center →L1→L2→L3→L4→L5→L6→L8→ Distribution center
Route 2	Distribution center →L9→L10→L18→L19→L12→L7→L13→L14→ Distribution center
Route 3	Distribution center →L17→L15→L11→L20→L21→L22→L16→L23→L24→ Distribution center

Totally Cost:1,350.1834885755977: Vehicle fixed costs: 840.0 Fuel cost: 508.1167625755977
Time-constrained costs: 2.066726.

4.3.2 Carbon emission cost sensitivity test

Referring to the carbon emission factor (2.6 $kgCO_2$/km) and carbon price (60 yuan/kg) in relevant literature, set the carbon emission cost coefficient μ (μ = 0, 0.2, 0.4, 0.6). When μ = 0.4, the optimized total cost is 1,398.72 yuan, and the cost savings rate decreases from 31.62% to 29.16%, a decrease of only 2.46 percentage points; when μ = 0.6, the savings rate is still 26.89%. It can be seen that the interference of carbon emission costs on the optimization effect is within a controllable range.

4.3.3 Composite cost sensitivity testing

At the same time, cargo damage costs (λ = 0.3) and carbon emission costs (μ = 0.4) are introduced to simulate the cumulative impact of multiple unconsidered costs. At this point, the total cost after optimization is 1,487.59 yuan, which is 24.66% lower than the initial plan and still significantly better than the baseline scenario. The fluctuation range of the cost savings rate (6.96 percentage points) did not exceed the 10% threshold, proving that the model results are highly robust when ignoring costs.

In summary, sensitivity analysis shows that even when unconsidered cost components are included, the optimized solution can still maintain significant cost savings, verifying the reliability and robustness of the model results.

TABLE 7 Sensitivity test results.

Cost type	Coefficient settings	Total cost after optimization (yuan)	Cost savings rate
baseline scenario	-	1,350.18	31.62%
cargo damage costs	$\lambda = 0.3$	1,426.35	27.76%
carbon emission costs	$\mu = 0.4$	1,398.72	29.16%
composite cost	$\lambda = 0.3 + \mu = 0.4$	1,487.59	24.66%

5 Conclusion

This paper constructs a mathematical model for community group buying delivery from the perspective of delivery costs and verifies the actual delivery tasks of a certain platform through AnyLogic simulation. The study shows that delivery route planning is of strategic importance to the operation of community group buying platforms, and reasonable planning can significantly reduce costs. Through simulation optimization and comparative analysis, the following management insights are obtained.

1. Prioritization of cost control: Competition in the community group buying market has entered a stage of refined operations, and platforms need to incorporate dynamic path optimization into their daily management systems. It is recommended to establish a "real-time route adjustment center" that combines the algorithm model described in this article to generate optimal delivery plans daily based on order density and traffic data. The cost savings can be converted into price advantages or service upgrades to enhance market competitiveness.

2. The management value of time-constrained costs: The setting of time-constrained costs in the model reveals the implicit value of "on-time delivery" for user retention. Platforms can establish a "tiered time window management mechanism" based on this: set strict time windows (e.g., ±10 min) for high-value customer communities and implement a dynamic reward and punishment system; adopt flexible time windows for ordinary communities and use algorithms to balance efficiency and cost. This differentiated management approach can reduce overall penalty costs while improving core user satisfaction.

3. The implementation path for simulation tools: AnyLogic simulation verification achieved a cost savings rate of 31.62%, demonstrating the potential of digital tools to transform traditional delivery models. It is recommended that the platform implement simulation optimization in phases: initially, select three to five pilot areas to verify the effectiveness of the algorithm; in the middle phase, expand to the entire city and integrate real-time traffic data from GIS; and ultimately achieve full-process automation from "order generation-route optimization-delivery execution."

This paper constructs a model based on field research, solves it using algorithms, and verifies it through simulation, confirming that reasonable path selection can effectively reduce costs and has strong practical value.

5.1 Research limitations

Although the model and algorithm constructed in this study have demonstrated significant effectiveness in reducing community group buying delivery costs, there are still limitations in the following areas due to the current stage and conditions of the research, which provide a clear direction for future in-depth research.

This study primarily relies on a static, known set of orders for simulation and validation, which aligns with the classical research paradigm of traditional Vehicle Routing Problems (VRP). However, the core business characteristic of community group buying is precisely its high degree of dynamism. In actual operations, the platform continuously receives new orders and may encounter unexpected situations such as vehicle breakdowns or traffic congestion. Additionally, there are limitations in data acquisition and model accuracy. Using a static, known set of orders for simulation and validation aligns with the classical research paradigm of traditional Vehicle Routing Problems (VRP). However, the core business characteristic of community group buying is its high degree of dynamism. Due to the inability to obtain actual traffic information data and delivery information for vehicles heading to communities, in actual operations, the platform continuously receives new orders and may face unexpected situations such as vehicle breakdowns or traffic congestion. The research relies on historical average demand data and does not model or analyze the random fluctuations in customer demand, making it unable to address the risks associated with demand prediction uncertainties.

5.2 Future developments

In view of the limitations of the appeal, future research will be conducted in the following directions.

1. Develop a dynamic real-time optimization algorithm framework: Conduct in-depth research on the dynamic vehicle routing problem (DVRP). The core focus of future work will be to design a hybrid intelligent decision-making framework that combines offline and online components. Collaborations will be established with local delivery

companies to synchronize vehicle information. During the offline phase, the improved algorithms developed in this study will be used to generate baseline paths. In the online phase, reinforcement learning (RL) algorithms will be employed, integrated with IoT technologies (such as in-vehicle GPS, temperature sensors, and traffic data interfaces), to leverage real-time information for rapid responses to sudden orders, traffic congestion, and other events, thereby enabling real-time path re-planning.

2. Creating a high-fidelity simulation environment: Utilizing simulation platforms such as AnyLogic, integrating AI agents, system dynamics, and discrete event modeling, we have developed a community group-buying digital twin system that combines dynamic order generation, random traffic flow, and real-time signal control. This system provides a testing environment that closely resembles real-world conditions for the development and validation of the aforementioned complex algorithms, ultimately offering community group-buying platforms a smarter, more cost-effective, resilient, and environmentally friendly delivery solution.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

MY: Writing – original draft, Writing – review and editing. LL: Writing – original draft, Writing – review and editing. XC: Writing – review and editing.

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The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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