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Integrated Optimization of Order Allocation and Last-Mile Multi-Temperature Joint Distribution for Fresh Agriproduct Community Retail

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Abstract: Community retail is an important research issue in the field of fresh agriproduct e-commerce. This paper focuses on the problem of last-mile multi-temperature joint distribution (MTJD), which combines time coupling, order allocation, and vehicle scheduling. Firstly, according to the temperature of a refrigerated truck in multi-temperature zones, a split-order packing decision is proposed to integrate the different types of fresh agriproduct. Then, the order allocation strategy is incorporated into a comprehensive picking and distribution schedule, while taking into account the time-coupling of picking, distribution, and delivery time limit. To improve consumer satisfaction and reduce order fulfillment costs, an optimization model combining multi-item order allocation and vehicle scheduling is established, to determine the optimal order allocation scheme and distribution route. Finally, taking fresh agriproduct community retail in the Gulou District of Nanjing as an example, the effectiveness and feasibility of the model are illustrated. The numerical results of medium- to large-scale examples show that, compared with the variable neighborhood search algorithm (VNS) and genetic algorithm (GA), the mixed genetic algorithm (MGA) can save 29% of CPU time and 65% of iterations. This study considers the integrated optimization of multiple links, to provide scientific decision support for fresh agriproduct e-commerce enterprises.

Keywords: picking; order splitting; order consolidation; multi-temperature joint distribution

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1. Introduction

The efficient and sustainable transport of basic goods is critical to the livelihoods of the population, as was highlighted in 2020 with the global COVID-19 pandemic. Community retail has become a popular choice for consumers, with its online shopping facility and non-contact distribution. This choice prompted the outbreak of community retail, an emerging industry, and an increase in online orders on fresh product e-commerce platforms, such as Miss Fresh, Fresh Hema, 7fresh, and Dingdong Food. According to reports, fresh product e-commerce transactions reportedly exceeded CNY 230 billion in the first three-quarters of 2021, accounting for 58.4% of the entire e-commerce market [1]. However, with the homogenization of fierce competition, some companies increasingly suffered serious losses. In this context, the critical issue is how to improve customer satisfaction while minimizing costs and making joint decisions regarding multiple logistics links. This study aims to investigate an integrated optimization solution for fresh agriproduct community retailing. Considering the diverse categories and huge demands of fresh agriproducts, a multi-item packaging strategy and picking decision were designed, which were incorporated into distribution scheduling with time windows, aiming to make a joint decision on the three links of picking-order allocation distribution.

Multi-temperature joint distribution (MTJD) allows for the simultaneous delivery of multiple types of products with different temperature requirements to a customer with a multi-compartment vehicle (MCV), where each compartment can be assigned a specific temperature zone. Specifically, the complexity of the last-mile MTJD distribution problem in the front warehouse mode comes from the splitting-order packing strategy, time limit, and distribution route, as shown in Figure 1. Firstly, the key packaging strategy of split orders is to uniformly package the sub-orders belonging to the same vehicle and the same temperature zones, which needs to take into account the weight, compatibility, and demand distribution of the fresh agriproduct. Secondly, the critical time-coupling problem determines the picking time, transit window, and delivery time required for consumer orders. Finally, the scheduling needs to dictate the number of orders to be delivered by the vehicle and the optimal distribution route. In addition, it should be emphasized that this study does not focus on all the logistics activities in Figure 1, but only on MTDJ and distribution.

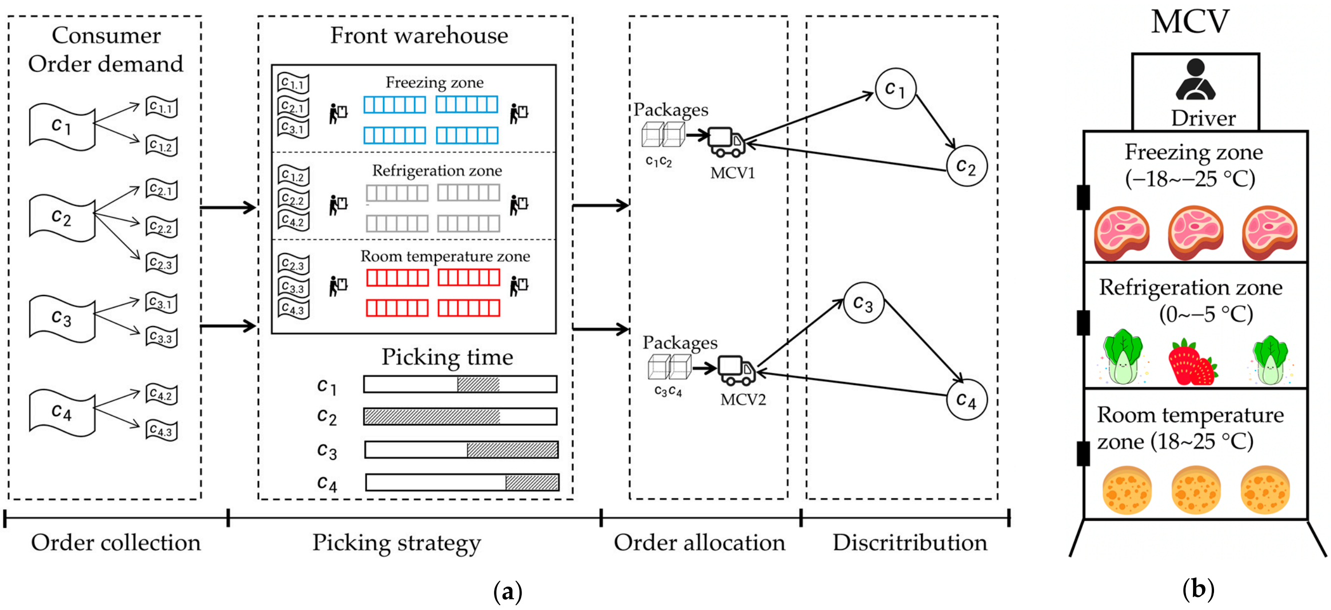


Figure 1. Diagram for integrated multi-item packing and MTJD for fresh agriproduct supply. The layout of MCV in (**a**) is shown in (**b**).

The most relevant literature concerns the cold-chain logistics of fresh agriproduct [2], the path optimization of MTJD [3], the splitting and merging of orders [4], and warehousing and distribution integration [5,6]. In general, prior studies have looked at the actual influencing variables of the distribution process from various angles, to reduce the time requirements and cost of the e-commerce distribution process. However, there is still a research gap concerning the completion of fresh agriproduct order-packaging decisions throughout MTJD last-mile delivery planning. This study focuses on the characteristics of the demand for fresh agriproducts in residents' daily life and designs a multi-item packaging strategy. To meet the time and cost requirements of fresh agriproducts in the context of online retailing, an optimization model combining multi-item order allocation and MTJD is proposed.

The contributions of this paper consist of these three aspects: (1) considering the supply category of agriproduct and the capacity limitations of delivery vehicle temperature zones, a splitting-order packaging strategy is designed. (2) A joint optimization model with order allocation and MTJD is established by integrating the picking-order allocation–distribution schedule. (3) A mixed genetic algorithm (MGA) is proposed to solve the joint optimization model, for which purpose MGA has better performance and efficiency than other solvers.

This paper is organized as follows. In Section 2, the literature related to this study is reviewed. In Section 3, the problem is outlined and the model is built. In Section 4, an MGA based on solving space reduction is designed to solve the proposed model. In Section 5, we report the numerical results of the MTJD of fresh agriproduct community retail in Gulou

District, Nanjing. Finally, Section 6 discusses the conclusions and offers suggestions for future work.

2. Literature Review

Our work is related to three research streams: MTJD, e-commerce order splitting, and the joint optimization of order allocation and distribution.

MTJD is an effective strategy to reduce logistics costs and avoid a decline in the value of fresh agriproducts [7]. It has the advantages of high efficiency and low cost [8] and is suitable for networks where the distribution points are aggregated, and the demand points are scattered [9]. Previous research on MTJD can be grouped into two streams, e.g., a vehicle routing problem with time windows (VRPTW) under MTJD, and a vehicle routing problem (VRP) with MTJD, as shown in Table 1. In the vehicle routing optimization of MTJD, Cho and Li [10] studied a multi-temperature refrigerated container-vehicle routing problem. However, they only addressed the routing problem without considering other constraints, e.g., the time-window constraint when serving customers. Wang et al. [11] looked at routing problems with time windows and an incompatible loading constraint. Zhang and Chen [12] considered the limits of loading per unit volume, related to different frozen foods. Other changes in response to real-life factors are not taken into account, e.g., a time-varying network and dynamic demand. Tsang et al. [13] comprehensively explored real-time changes in perishable products during transport. Martins et al. [14] solved a multi-period setting problem in terms of product complexity. Hou et al. [15] addressed routing problems with real-time traffic information. Golestani et al. [16] solved the hub location problem using MTJD. However, due to the different terminal supply modes of a fresh agriproduct e-commerce company, few studies have conducted joint optimization research on MTJD, order splitting, and merging.

Table 1. Relevant works regarding MTJD.

Stream	Literature	Research Problem
VRP with MTJD	[8]	Developing an advanced MTDJ system for the cold food delivery chain.
	[9]	Suitable operational networks of MTJD technique.
	[10]	The optimal routing distance, as generated by MTDJ.
	[13]	Design a multi-temperature packaging model for perishable foods to optimize routing.
VRPTW under MTJD	[11]	The heterogeneous multi-type fleet vehicle routing problem, with time windows and an incompatible loading constraint.
	[12]	Analyzing the constraints of loading volume.
	[14]	Addressing the time window allocation problem for product complexity.
	[15]	Based on real-time traffic information to solve the dynamic multi-compartment VRP.
	[16]	Jointly optimized hub location and MTJD for the perishable product supply chain.

Order splitting refers to dividing orders into several sub-orders for picking and distribution according to certain factors, such as commodity compatibility and warehouse layout. Order merging is to merge multiple sub-orders of the same customer into the same vehicle. Traditional order splitting is mainly used for multi-supplier selection [17]. With the rapid development of e-commerce, research results regarding online retail order processing are abundant and are mainly divided into order splitting and order merging. Before order splitting, Co et al. [18] clustered the best-selling stock keeping unit (SKU) to minimize the delivery time of a single order. In terms of splitting, Jasin and Sinha [19] proposed an order coupling scheme that was based on demand forecasts. Arezo et al. [20] jointly considered inventory strategy and order segmentation strategy. In terms of the actual process of splitting a single multi-item order at the distribution center, Vahid et al. [21] proved that this is, in fact, a non-deterministic polynomial (NP-hard) problem. After splitting, Zhang et al. [22] integrated splitting orders in a multi-warehouse system. In terms of horizontal reprinting strategy, Naccache et al. [23] proposed a model to integrate orders into vehicles. Zhang et al. [24] proposed an order fulfillment method of package integration.

Gzara et al. [25] resolved the problem of order consolidation in warehouses, to minimize the order fulfillment time. In terms of merge-in-transit methods, Song et al. [26] consolidated the orders into an integration center. Johansson et al. [27] proposed a time-based consolidation strategy for shipments. The existing research results are mostly positioned against a background of multi-warehouse systems; however, there are few studies on fresh agriproduct e-commerce orders. The existing literature related to order splitting can be grouped into two streams, as shown in Table 2.

Table 2. Relevant works discussing order splitting.

Stream	Literature	Research Problem
Order splitting	[18]	Reducing distribution costs by clustering SKUs.
	[19]	Deciding from which facility the items in the order should be fulfilled.
	[20]	Multi-echelon inventory control and order splitting problems.
	[21]	Splitting a single multi-item order in the distribution center.
	[22]	Integrating multi-suborder models via transshipment between warehouses.
Order merging	[23]	Order delivery consolidation-based business-to-consumer (B2C) distribution.
	[24]	Package consolidation approach to the split-order fulfillment problem.
	[25]	Optimizing e-commerce warehouse order processing.
	[26]	Coordinating distribution between suppliers and customers via integration centers.
	[27]	Merging distribution from central warehouses to retailers.

The last-mile costs typically represent a high share of the total logistics costs [28]. The integrated optimization of internal warehouse processes and distribution can improve the efficiency of the system. Order picking and delivery planning are two essential interrelated problems. Shavaki and Jolai [29] examined the optimal scheduling of zone picking and delivery; however, the influence of real-world factors was ignored. On this basis, Chen et al. [30] also considered the conveyance time between picking zones and variable driving speed. In terms of consolidated transportation, Hewitt et al. [31] consolidated orders from a reduced number of shipments. Wei et al. [32] formulated the order integration strategy from the perspective of cost minimization. In connection with split order delivery, Acimovic and Graves [33] considered the impact on future order splitting when allocating current orders, thereby reducing the total cost of order fulfillment. Subramanyam et al. [34] took into account the uncertainty of customer orders. In the context of retail order allocation, this represents the qualitative matching process of orders between warehouses and vehicles. Torabi et al. [35] comprehensively studied an inventory fulfillment–allocation and shipment problem. Liu et al. [36] optimized order allocation by predicting delivery time. Other scholars have also studied the warehouse-distribution integration model. Pulido et al. [37] established a model to combine the location of warehouses with a timely delivery strategy. Wang et al. [38] combined warehouse address and resource distribution to optimize emergency rescue. Previous research on joint optimization could be grouped into five streams as shown in Table 3.

In summary, there is a plethora of literature on the joint optimization of order allocation and distribution. However, few studies have considered a multi-item order packaging strategy. In practice, picking, order allocation, and distribution are three highly related processes for online retailers. Therefore, this study designed an integrated multi-item order packing and MTJD model, taking into account the conditions of spatial and temporal dimensions, to improve consumer satisfaction and reduce distribution costs.

Table 3. Relevant works on the joint optimization of order allocation and distribution.

Stream	Literature	E-Commerce Mode
Order picking + distribution	[29] [30]	Online retailing Front warehouse mode
Order integration + distribution	[31] [32]	Takeaway system E-commerce
Order splitting + distribution	[33] [34]	O2O Online retailing
Order allocation + distribution	[35] [36]	E-tailing Last-mile delivery
Warehouse distribution integration	[37] [38]	On-line purchasing Emergency rescue

3. Problem Description and Model Formulation

3.1. Problem Description

The process of receiving orders from an online e-commerce platform and the front warehouse delivery system to customers include online ordering, order processing, vehicle assignment, and MTJD. In this study, we shed light on picking, order splitting, package consolidation, and distribution to create an integrated optimization model for community retail, as shown in Figure 2. For order collection, the fresh e-commerce platform collects orders from scattered consumers (denoted as $C = \{c_1, c_2, \ldots, c_j\}$). The order information contains demand quantity, expected arrival time, and geographical location. According to the storage temperature of the commodities, the front warehouse is divided into the freezing zone (−18~−25 °C), refrigeration zone (0~−5 °C), and room temperature zone (18~25 °C). When faced with multi-item orders, the order is divided into suborders (denoted as $C_1 = \{c_{1.1}, c_{1.2}, \ldots, c_{1.s}\}$), based on the layout of the front warehouse area. For order picking, retailers consider the weight of the goods and roughly estimate the picking time, to determine the starting picking time and starting distribution time, so that the order can be delivered to the consumer at the expected arrival time. After picking, according to the order allocation decision, the sub-orders of that customer are merged on the same vehicle, and sub-orders in the same temperature zone are packaged. Finally, the optimal order allocation scheme and delivery sequence of each vehicle are designed to minimize the distribution cost and time deviation. In this study, the crucial issue is how to decide upon the start picking time and order allocation strategy, and how to assign the optimal vehicle route.

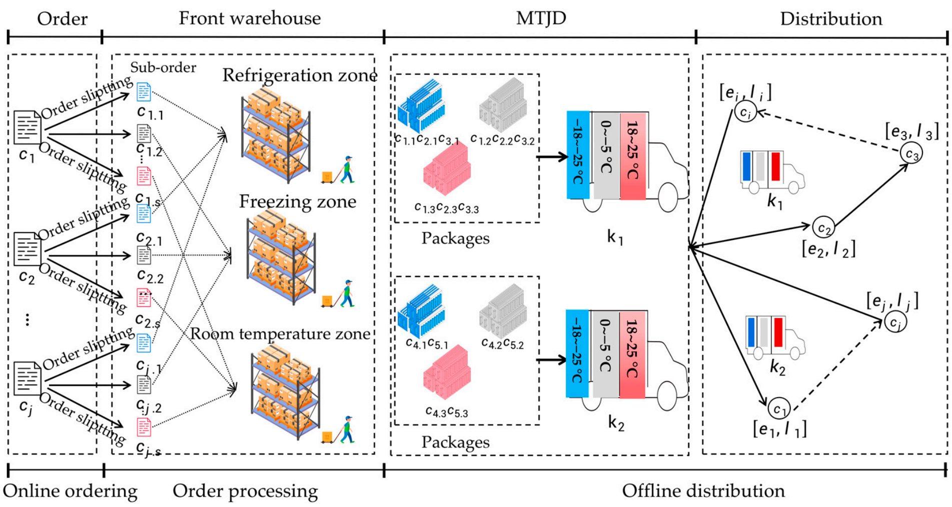


Figure 2. Fresh produce e-commerce online order processing and front warehouse-to-door allocation scheduling diagram.

Generally, order splitting, order consolidation, and distribution involve three decisions, i.e., (1) when to pick, (2) which orders are split and which orders are merged, and (3) how to arrange the optimal distribution routes.

3.2. Objective Function

The proposed model in this study takes into account three objectives for order allocation strategy and distribution scheduling: maturity penalty cost, distribution cost, and refrigeration cost.

3.2.1. Maturity Penalty Cost

In the community retail scenario, time has a significant influence on the penalty cost for retailers because the logistics network promotes timely delivery to consumers and places more emphasis on timeliness. For the customer, the service time window is $[ET_i, LT_i]$, where ET_i denotes the customer's earliest acceptable service time and LT_i refers to the customer's latest acceptable service time. In the case of fresh produce e-commerce, the retailer can determine the picking and distribution time to meet the expected arrival time of the consumers. The model considers two penalty scenarios of arrival time, i.e., an earliness penalty and a tardiness penalty. The per order of maturity penalty cost $U\left(t_i^k\right)$ is pertinent to the bias of the consumer's expected time window $[ET_i, LT_i]$, which can be represented as Equation (1). As a result, the further the vehicle arrival time (t_i^k) deviates from the time window, the higher the penalty cost that would be generated:

$$U\left(t_i^k\right) = \begin{cases} \gamma_1\left(ET_i - t_i^k\right), t_i^k \le ET_i \\ 0, ET_i < t_i^k \le LT_i \\ \gamma_2\left(t_i^k - LT_i\right), LT_i < t_i^k \end{cases} \tag{1}$$

where γ_1 denotes the unit increase rate of the earliness penalty cost, while γ_2 denotes unit tardiness penalty cost, respectively. In terms of the timeliness of customer delivery requirements, customers usually want to receive the product that they have purchased within the shortest time, so advances and delays have different effects on consumer satisfaction. With the different influences of earliness and tardiness on consumer satisfaction, the unit penalty cost parameters are set to $\gamma_1 < \gamma_2$. The maturity penalty cost is equal to the cumulative sum of $U\left(t_i^k\right)$, which can be phrased as in Equation (2):

$$obj_1 = \sum_{k \in K} \sum_{i \in N'} U\left(t_i^k\right). \tag{2}$$

We would wish to minimize obj_1.

3.2.2. Distribution Cost

In this study, the distribution cost is divided into two parts: fixed usage costs and transportation costs. We make $x_{ij}^k \in \{0, 1\}$ a choice variable. If $x_{ij}^k = 1$, the arc (i, j) belongs to the delivery route of vehicle k. That is to say, the vehicle k travels from consumer i to consumer j. Therefore, Equation (3) is used to express the distribution cost:

$$obj_2 = \sum_{k \in K} \sum_{j \in N} \sum_{i \in N} x_{ij}^k \cdot \omega \cdot \tau_{ij} + \sum_{k \in K} \sum_{j \in N'} x_{0j}^k \cdot f. \tag{3}$$

In the model, we would wish to minimize obj_2.

3.2.3. Refrigeration Cost

The refrigeration cost during the vehicle's driving time is related to many factors, e.g., the amount of refrigerant, the temperature difference, the surface area of the compartment, etc. Refrigeration cost per unit time is calculated as $D = p_1 \cdot c_1 \cdot R \cdot A \cdot (\Delta T_1 + \Delta T_2 + \Delta T_3)/3$. Therefore, the refrigeration cost is formulated as in Equation (4):

$$obj_3 = \sum_{k\in K}\sum_{j\in N}\sum_{i\in N} x_{ij}^k \cdot \tau_{ij} \cdot D. \tag{4}$$

3.3. Constraints

In order to simulate the supply of fresh agriproducts in community retail within the MTJD model, a multi-item packaging strategy is adopted, and time-coupling is integrated into the vehicle routing system. The constraints are given as follows:

$$\sum_{p\in P}\sum_{i\in N'} d_{ip} \cdot z_{ip}^k \le q_s, \forall s \in S, k \in K \tag{5}$$

$$z_{ip}^k + z_{ip'}^k \le y_s^k, \forall i \in N', p, p' \in P, s \in S, k \in K, \lambda_{pp'} = 1 \tag{6}$$

$$\sum_{k\in K}\sum_{j\in N'} x_{0j}^k \le K, k \in K \tag{7}$$

$$\sum_{k\in K}\sum_{i\in N} x_{ij}^k = 1, \forall j \in N', i \ne j \tag{8}$$

$$\sum_{k\in K}\sum_{j\in N} x_{ij}^k = 1, \forall i \in N', i \ne j \tag{9}$$

$$\sum_{i\in N} x_{ij}^k = \sum_{i\in N} x_{ji}^k, \forall j \in N', k \in K \tag{10}$$

$$\sum_{j\in N'} x_{0j}^k \le 1, k \in K \tag{11}$$

$$\sum_{i\in N'} x_{i0}^k \le 1, k \in K \tag{12}$$

$$\sum_{i\in N} x_{ij}^k = y_j^k, \forall j \in N', k \in K \tag{13}$$

$$ts_i^k + \alpha \cdot \sum_{p\in P} d_{ip} \cdot y_i^k \le tf_i^k, \forall k \in K \tag{14}$$

$$tf_i^k \le t_0^k, \forall i \in N', k \in K \tag{15}$$

$$t_i^k + \tau_{ij} - \left(1 - x_{ij}^k\right) \cdot M \le t_j^k, \forall i, j \in N, k \in K \tag{16}$$

$$t_0^k \le t_i^k, \forall i \in N', k \in K \tag{17}$$

$$ts_i^k,\ t_i^k \ge 0, \forall i, j \in N, k \in K \tag{18}$$

$$x_{ij}^k,\ y_j^k,\ z_{ip}^k \in \{0, 1\}, \forall i, j \in N, k \in K \tag{19}$$

Constraint (5) represents the loading quantity limit of vehicle s in terms of temperature requirements. Constraint (6) indicates incompatibility between multiple categories. If categories p and p' are inconsistent in terms of temperature requirements, $\lambda_{pp'} = 1$, and the items should be loaded in different temperature zones. Constraint (7) makes sure that the number of vehicles used, k, does not exceed the total number of vehicles, K. Constraints (8) and (9) state that each community can only be served by one vehicle. Constraint (10) represents the network flow balance. Constraints (11) and (12) mean that each vehicle, k, can only leave and return to the front warehouse once at most. Constraint (13) denotes that vehicle k serves community j, if community j is a node in the route taken by this vehicle. Constraint (14) calculates the start picking time and finish picking time. Constraint (15) ensures that the vehicle, k, starts to deliver after picking up all orders of all communities on the route. Constraint (16) eliminates the sub-tours of vehicle k. M is denoted as a large positive constant. If vehicle k delivers from community i to community j, $x_{ij}^k = 1$ and $t_i^k + \tau_{ij} \leq t_j^k$, otherwise Constraint (16) is equal to $t_j^k \geq t_i^k + \tau_{ij} - M$. Constraint (17) depicts the relationship between the vehicle's starting distribution time and its arrival time at the community. Constraint (18) demonstrates the value ranges of ts_i^k and t_i^k. Constraint (19) defines x_{ij}^k, y_j^k, and z_{ip}^k as binary decision variables.

3.4. Model Formulation

According to the discussions in Sections 3.2 and 3.3, the joint decision-making approach for picking and distribution is formulated as a constrained multi-objective optimization model. In order to solve the difference in orders of magnitude between obj_1, obj_2, and obj_3, this study adopts the weighting method, sets the weights of the three objective functions as convex combinations ($\lambda_1, \lambda_2, \lambda_3 \geq 0$ and $\lambda_1 + \lambda_2 + \lambda_3 = 1$), and adopts the min-max normalization method to integrate the multiple objectives into an equivalent objective function [39]. This can be stated as:

$$\min obj = \lambda_1 \left[\frac{obj_1 - \underline{obj_1}}{\overline{obj_1} - \underline{obj_1}} \right] + \lambda_2 \left[\frac{obj_2 - \underline{obj_2}}{\overline{obj_2} - \underline{obj_2}} \right] + \lambda_3 \left[\frac{obj_3 - \underline{obj_3}}{\overline{obj_3} - \underline{obj_3}} \right] \tag{20}$$

$$\text{s.t. } (5) \sim (19) \tag{21}$$

where $\overline{obj_i}$ and $\underline{obj_i}$ indicate the maximum and minimum values of the ith objective, respectively, and their values can be computed as follows. For example, $\underline{obj_1}$, $\underline{obj_2}$, and $\underline{obj_3}$ could be set to 0, according to Constraints (18) and (19) in the model. $\overline{obj_1}$, $\overline{obj_2}$, and $\overline{obj_3}$ could be set according to Constraints (7), (14), (16) and the demand information.

4. Mixed Genetic Algorithm

In this study, the fresh produce retail problem is described as an integrated split order consolidation and vehicle routing problem. When planning vehicle routes, the time attribute of the order takes precedence over the spatial distance attribute. Moreover, the solution space of the package scheme expands rapidly with the splitting of orders, and it is difficult for general solvers to obtain the optimal solution in a short time, while the genetic algorithm is suitable for large-scale solutions. Therefore, we propose to solve the problem in two stages. In the first stage, clustering is carried out according to the latest possible delivery time after the order is packaged, to reduce the solution space. In the second stage, segmented integer encoding is proposed to optimize the vehicle route according to the time attribute of the order. MGA is proposed by combining the k-means clustering algorithm with a genetic algorithm. The algorithm construction concept is shown in Figure 3.

4.1. Reduction of Solution Space

Traditional distribution problems are often clustered according to the geographical location of customer points, but for the joint optimization process of picking–order allocation–distribution, as studied in this paper, time coupling is what we should focus on. This paper creatively proposes to cluster the latest delivery time of the packaged orders. The value of the service customer point is y_i^k, which is preliminarily determined by k-means clustering. The classification of orders can make each order in the chromosome a gene inserted into each class of orders, greatly reducing the number of genes and speeding up the optimization speed of the algorithm.

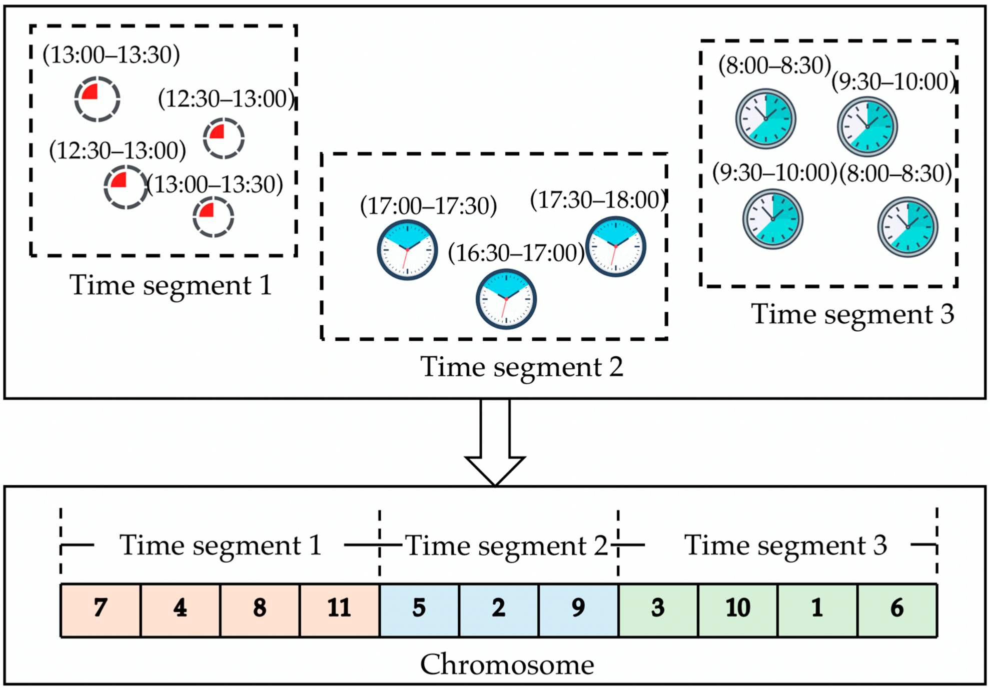


Figure 3. MGA construction concept.

4.2. Efficient Chromosome Coding Method

A traditional genetic algorithm will select the crossover and mutation points at any gene position of the chromosome, which is not suitable when directly solving the order allocation problem with time parameters. Therefore, this paper proposes an efficient chromosome-encoding method, based on the classical genetic algorithm. Based on the *k*-means clustering results determined in Section 4.1, segmented integer chromosome coding based on the order time attribute is adopted.

Crossovers and mutations are performed independently between each segment of the code. In the process of algorithm optimization, the segmental crossover operator and mutation operator are used to act on different segments, to ensure the effectiveness and correctness of the algorithm for solving the problem [40]. The crossover and mutation processes are shown in Figures 4 and 5. A, B, A' and B' represent chromosomes.

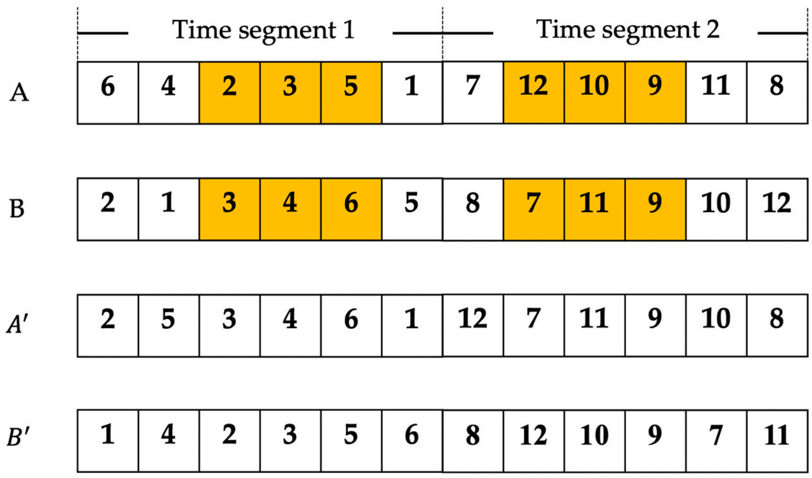


Figure 4. The chromosome segment crossing process.

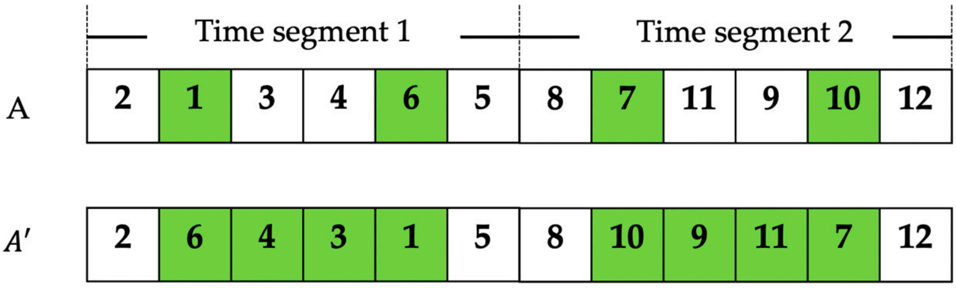


Figure 5. The chromosome segment variation process.

4.3. Implementation of MGA

The pseudo-code of the MGA framework, developed according to Sections 4.1 and 4.2, is shown in Algorithm 1.

Algorithm 1. MGA

Input: (Initialize Solution S, set crossover probability p_c, mutation probability p_m, population size N, the number of evolutionary iterations G.)

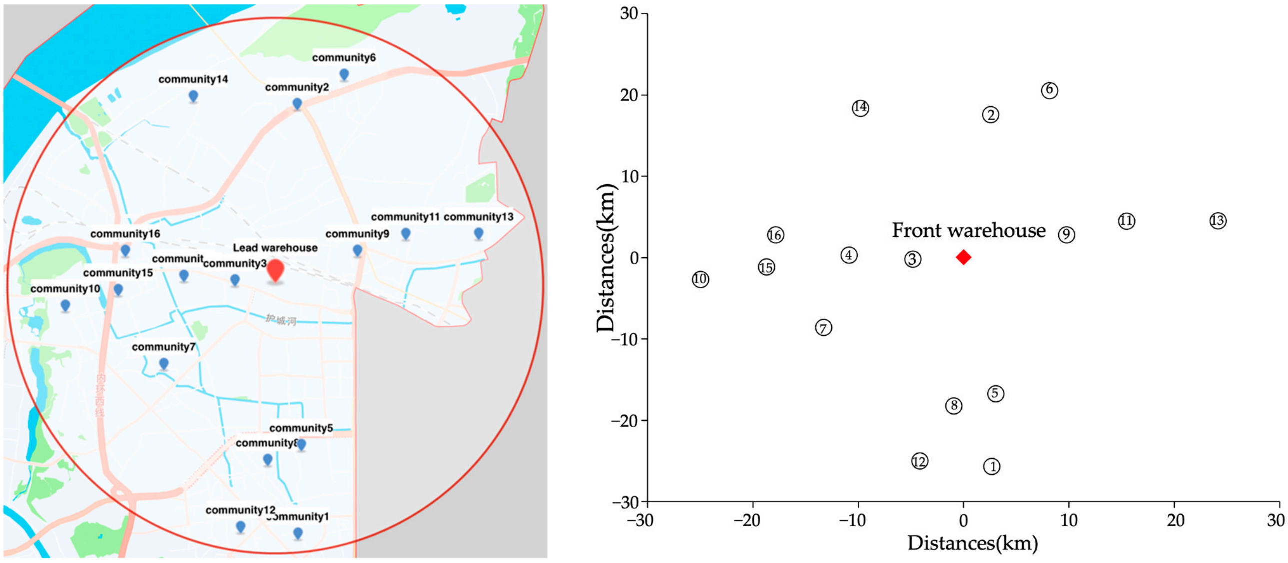
```
generate a solution S using the k-means clustering method        Section 4.1
set S_best := S
While (G ≤ G_max)                                                Section 4.2
    for i to N′
        evaluation of individual populations f_i
    end for
    select parents P_1 from S using roulette selection
    select parents P_2 from S using crossover and mutation
    generate solution S′
    if S′ is better than S_best, then
        S_best = S′
S := S′
end if
end while
return S_best
```

5. Numerical Experiments

The results of the numerical experiments will be reported in this section. Section 5.1 shows the community information of Gulou District, Nanjing, and gives the optimal vehicle scheduling plan. In Section 5.2, we compare the medium- to large-scale numerical results of MGA, the genetic algorithm (GA), and the variable neighborhood search algorithm (VNS) from the points of view of CPU time and iteration. All experiments in this section are performed on an Apple M1 Pro GHz processor with 16 GB RAM designed by Apple in California, while the optimization routines are conducted using MATLAB 2020.

5.1. A Case Study of Fresh E-Commerce in the Gulou District of Nanjing City

In order to verify the practical application of the model, this study takes the distribution of fresh agriproducts to the community by fresh e-commerce in the Gulou District of Nanjing as a numerical example. All the data are derived from government statistics and official news. Gulou District is an important national shipping logistics service center; there are 13 streets and a total of 120 communities. The geographic locations are calculated from the Gao De map in Figure 6a. In this case, the fresh e-commerce company in Gulou District set up only one front warehouse with a distribution range of 3 km. Therefore, we randomly selected 16 communities within the scope of distribution to be representative. In Figure 6b, the red points represent the front warehouse, and the 16 circles represent the community nodes.



(**a**) (**b**)

Figure 6. Schematic diagram of spatial coordinates. (**a**) Geographic location on the Gao De map. (**b**) Position of the coordinates.

Considering the diversity of optional online application (APP) products of fresh e-commerce and the residents' daily diets, this case considers four main product categories, i.e., delicatessen items, vegetables, fruit, and meat. The MCV is mainly divided into three temperature zones, according to the temperature of each food and cold chain logistics, i.e., a room temperature zone (18~25 °C), refrigeration zone (0~−5 °C), and freezing zone (−18~−25 °C). Room temperature products include delicatessen items, refrigeration products include fruit and vegetables, and frozen products include meat items [41]. Therefore, the basis of compatibility of the four products is defined according to the food cold chain temperature, i.e., the compatibility of fruit and vegetables mean that they can be placed in the same temperature zone of the vehicle and stored in the same temperature zone of the lead warehouse. That is to say, according to packing rules, fruit and vegetables cannot be transported in the same zone as delicatessens and meats when suborders are merged, as is shown in Figure 7. The demand quantities of each community node are calculated by multiplying the proportion of the population in Gulou District with the use of the fresh e-commerce APP product and annual fresh agriproduct purchases of households per capita in Nan Jing Province. According to estimates, the purchase demands of delicatessen items, vegetables, fruit, and meat per meal are 196 g, 178 g, 122 g, and 80 g/person/day, respectively [42]. In addition, the customer time window is set based on the optional delivery time for the fresh e-commerce APP. Tables 4 and 5 give each community's detailed coordinates, time window, and four category demands.

According to the news published on the official website of the fresh e-commerce company, the cold chain transportation process uses a Yuejin C300-33 three-temperature refrigerated vehicle made by Saic Motor in China with a rated load of 3.575 tons and a speed of 55 km/h. The refrigeration cost parameters are designed as follows: time R = 2.49 kCal/(h·m^2·°C), p_1 = 3.64 CNY/kCal, S = 29.903 m^2, ΔT_1 = 0 °C, ΔT_2 = 20 °C, ΔT_3 = 40 °C, c_1 = 1.245 CNY/kCal, ω = 1.95 CNY/kCal/h, f = 150 CNY. The maturity penalty parameters are set as follows: γ_1 = 0.833 CNY/unit, γ_2 = 1.667 CNY/unit (citing the data from Hou [15]). The MGA parameters are set as follows: N = 100, M = 1000, p_c = 0.95, and p_m = 0.1. The objective function's parameters are assumed to be $\lambda_1 = \lambda_2 = \lambda_3 = 1/3$.

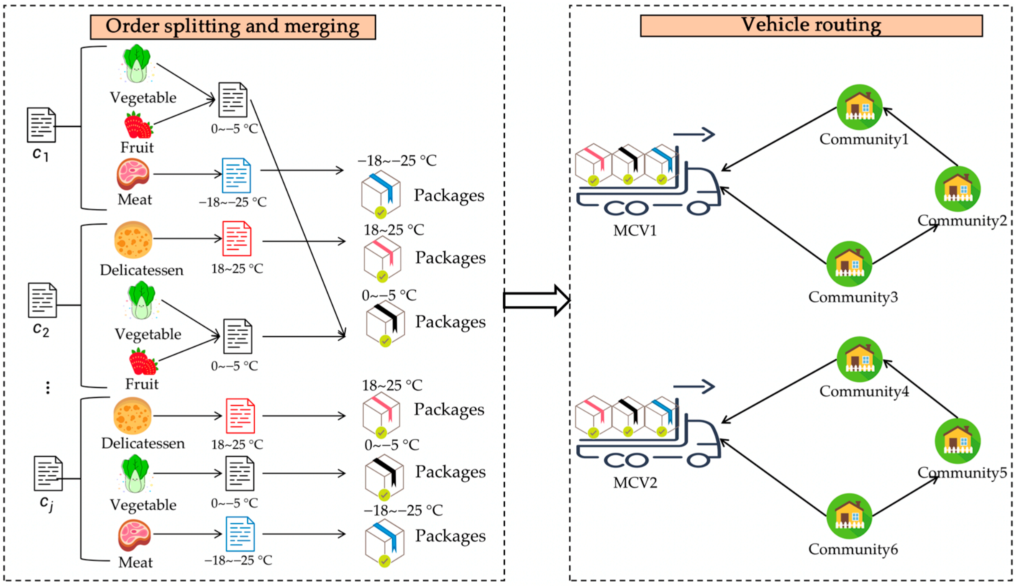


Figure 7. Packing and transportation rules.

Table 4. The consumer information for the case study.

Community Number	Coordinates (km)	Time Window	Community Number	Coordinates (km)	Time Window
1	(2.685, −25.687)	(8:00–8:30)	9	(9.763, 2.793)	(12:00–12:30)
2	(2.6, 17.556)	(10:00–10:30)	10	(−24.949, −2.746)	(17:30–18:00)
3	(−4.799, −0.186)	(17:00–17:30)	11	(15.499, 4.483)	(12:30–13:00)
4	(−10.866, 0.266)	(17:00–17:30)	12	(−4.133, −25.03)	(8:00–8:30)
5	(3.088, −16.762)	(8:00–8:30)	13	(24.157, 4.51)	(13:00–13:30)
6	(8.178, 20.509)	(9:30–10:00)	14	(−9.741, 18.33)	(9:30–10:00)
7	(−13.247, −8.611)	(15:00–15:30)	15	(−18.668, −1.16)	(16:30–17:00)
8	(−0.907, −18.268)	(8:00–8:30)	16	(−17.818, 2.789)	(17:30–18:00)

Table 5. The fresh agriproduct demands of communities in Gulou, Nan Jing.

Community Number	Room Temperature 18~25 °C (s = 1)	Refrigeration 0~5 °C (s = 2)		Refrigeration −18~−25 °C (s = 3)
	Delicatessen (kg)	Vegetables (kg)	Fruit (kg)	Meat (kg)
1	106.2	96.4	66.1	43.3
2	83.4	75.8	51.9	34.0
3	194.1	176.3	120.8	79.2
4	38.8	35.2	24.2	15.8
5	775.8	704.6	482.9	316.7
6	129.9	117.9	80.8	53.0
7	207.8	188.7	129.4	84.8
8	176.4	160.2	109.8	72.0
9	423.4	384.5	263.5	172.8
10	103.8	94.3	64.6	42.4
11	168.2	152.7	104.7	68.6
12	147.8	134.2	92.0	60.3
13	211.6	192.1	131.7	86.4
14	91.8	83.4	57.2	37.5
15	97.1	88.2	60.5	39.6
16	188.7	171.4	117.5	77.0

The Gulou District case is tested 10 times, and the optimal fresh agriproduct distribution routes are shown in Table 6. Seven vehicles are used to deliver fresh agriproducts to 16 communities. For example, points 5 and 9 cannot be combined with other points because the product demand at points 5 and 9 is too high, almost reaching the maximum capacity. There is no point suitable for clustering in the time window of point 7; even though its demand is not great, the order is still delivered by a single vehicle. The points served by vehicles 2, 4, 5, and 7 all have small demand and are suitable for combined transportation in terms of time. The specific routes of these vehicles are shown in Figure 8.

Table 6. Fresh agriproduct demands of communities in Gulou, Nan Jing.

Number	Optimal Vehicle Routing	
Vehicle 1	$0 \rightarrow 9 \rightarrow 0$	
Vehicle 2	$0 \rightarrow 3 \rightarrow 4 \rightarrow 16 \rightarrow 15 \rightarrow 10 \rightarrow 0$	
Vehicle 3	$0 \rightarrow 7 \rightarrow 0$	
Vehicle 4	$0 \rightarrow 8 \rightarrow 12 \rightarrow 1 \rightarrow 0$	
Vehicle 5	$0 \rightarrow 11 \rightarrow 13 \rightarrow 0$	
Vehicle 6	$0 \rightarrow 5 \rightarrow 0$	
Vehicle 7	$0 \rightarrow 14 \rightarrow 12 \rightarrow 6 \rightarrow 0$	
Experimental results	Number of vehicles	Iteration time [s]
	7	59.9

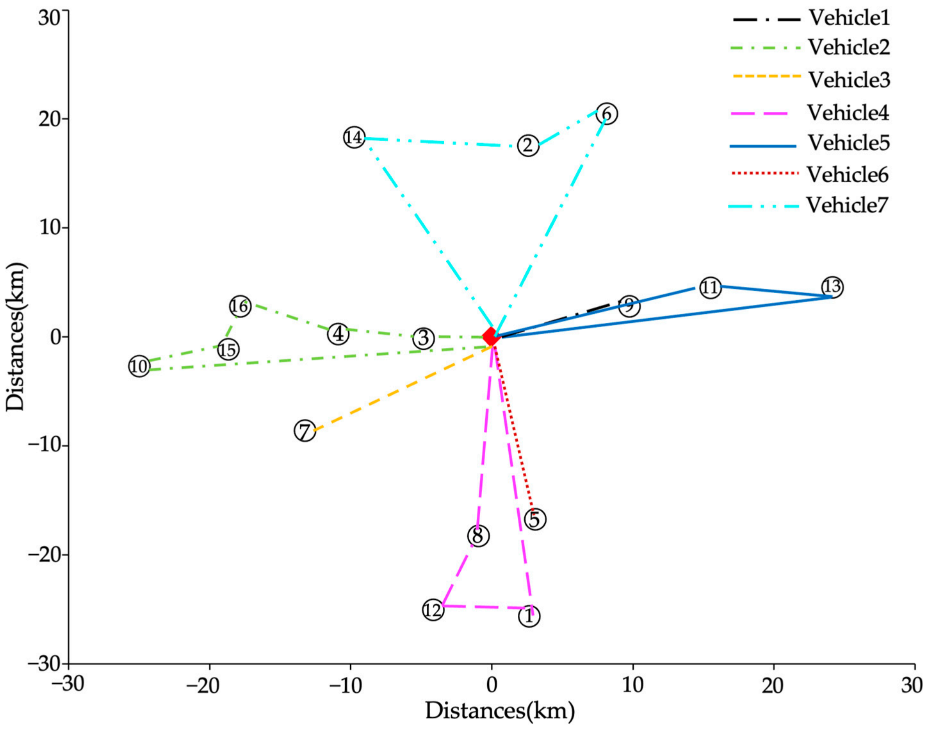


Figure 8. Schematic diagrams of optimal vehicle routes.

5.2. Medium- to Large-Scale Numerical Experiments

In order to further verify the advantages and efficiency of the proposed algorithm, we chose to compare it with the VNS adopted in similar research [43] and GA. Five medium-to large-scale cases were tested in 20, 40, 60, 80, and 100 communities, respectively. In each case, the geographical location of each community node is randomly generated by the integers in (−30, 30), and the demand for agriproduct is randomly generated from (10, 550). We assume that the customer point of each temperature zone commodity demand does not exceed the maximum load of a single interval. The target weight is set as $\lambda_1 = \lambda_2 = \lambda_3 = 1/3$, and the maximum number of iterations is 1000. In order to avoid the influence of accidental deviation, five tests are carried out in each case, and the average value is selected to represent the performance of each algorithm. We report the numerical results of MGA, GA, and VNS, and compare the time intervals and iteration intervals among them in Table 7 and Figure 9.

Table 7. Numerical results of medium- to large-scale cases.

Case	No. Comm.	GA		VNS		MGA	
		CPU Time (s)	Iteration	CPU Time (s)	Iteration	CPU Time (s)	Iteration
1	20	64.98	149	59.46	273	55.33	116
2	40	120.10	243	157.46	144	100.45	57
3	60	131.25	517	231.92	311	124.73	72
4	80	185.36	420	315.07	255	135.48	130
5	100	198.60	309	421.19	155	160.86	44

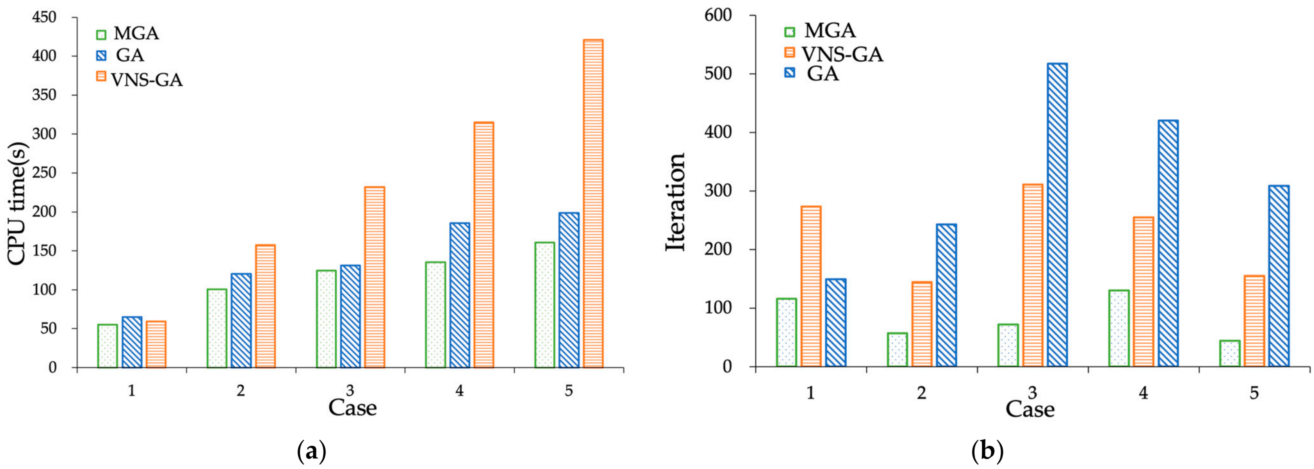


Figure 9. Comparison of the computational performance of MGA, GA, and VNS. (**a**) Comparison of CPU time between MGA, GA, and VNS. (**b**) Comparison of the iteration number between MGA, GA, and VNS.

In five experiments, the maximum iteration number of MGA is 130, while the minimum iteration number of GA and VNS are 149 and 144, respectively. The numerical results show that with an increase in the number of communities, the number of iterations of MGA presents obvious advantages over GA and VNS. At the same time, compared with GA and VNS, MGA reduces the CPU running time by 29% and the number of iterations by 65%, on average. Especially in the large-scale case of 100 communities, VNS needs the longest CPU running time and GA requires a large iteration number, while MGA reduces the iteration number and can converge upon the optimal solution in a shorter time. Generally, the performance and efficiency of the MGA algorithm that is proposed in this research are constantly better than those of GA and VNS in solving the comprehensive optimization problem of order allocation and MTJD.

6. Discussion and Conclusions

6.1. Academic Implications

This study proposes a new paradigm of last-mile MTJD for fresh agriproduct distribution to address the research gap in community retail. The distribution model of community retail has small-batch, multi-frequency, and multi-project characteristics. The traditional cold chain distribution mode cannot meet all order requests. Consequently, the use of MCV for distribution calculation was proposed in this manuscript, which can be further extended to e-commerce businesses with product incompatibility. Through this study, the research gap in multi-item order packaging strategy in the field of fresh agriproduct has been filled by constraining product compatibility and integrating sub-orders. This research on the joint optimization of picking strategy, order allocation strategy, and distribution strategy fills a gap in the field of fresh agriproduct e-commerce research concerning overall multi-link optimization. Moreover, medium- to large-scale numerical experiments have proved the superiority of MGA in terms of computational performance. Compared with GA and VNS, MGA can, on average, save 29% of CPU time and 65% of iterations. Last, but not least, this study provides a case study of community retail based on MTJD, which provides a valuable reference for making decisions using the new model.

6.2. Managerial Implications

This study proposes an integrated optimization model that simultaneously considers picking, order allocation, and MTJD path optimization. In order to solve the problem of a large and diversified demand for agriproducts, a multi-item packaging strategy was designed according to the multi-temperature zone. The optimization model integrates order packaging strategy and distribution route planning according to consumer demand, geographical location, and time window, providing a feasible method to solve the problem of last-mile MTJD of the front warehouse in e-commerce enterprises. Generally, the joint optimization model proposed in this study could balance the conflict between the time dimension and space dimension and provide more decision-making possibilities for retailers by making full use of order information, which has broad application prospects in the fresh agriproduct e-commerce industry.

6.3. Limitations and Future Research

This study provides new directions for further research on last-mile MTJD for community retail. Firstly, this study only considers a front warehouse and a particular vehicle type. With the expansion of the research scale, the research directions of multiple front warehouses and multiple vehicle types can be considered. Secondly, weather temperature changes, vehicle speed changes, uncertainties in customer orders, and community service time changes have not been taken into account. Further research should consider the changes of these factors in an actual situation, thus bringing the model closer to reality. Thirdly, the sizes of the different temperature zones of delivery vehicles can be adjusted in the future to improve the vehicle loading rate. Finally, enabling different levels of service in terms of delivery to customers can be considered, e.g., prioritizing customers whose business is critical for the distribution company.

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Abbreviations

i	If $i = 0$, front warehouse, else $i = 1, \ldots, N'$, community nodes
j	If $j = 0$, front warehouse, else $j = 1, \ldots, N'$, community nodes
k	Vehicle, $k = 1, \ldots, K$
s	Temperature zone type $s = 1, \ldots, S$
p	Commodity type, $p = 1, \ldots, P$
p'	Commodity type, $p' = 1, \ldots, P$
Index Sets	
N	Set of nodes including one front warehouse and multiple consumers
N'	Set of consumer nodes, $N' = N/\{0\}$
K	Set of vehicles
S	Set of temperature zone types
P	Set of commodity types purchased by customers
Parameters	
d_{ip}	The demand quantity of category p of customers i (kg)
γ_1	Unit increase rate of earliness penalty cost (CNY/min)
γ_2	Unit increase rate of tardiness penalty cost (CNY/min)
f	Fixed usage cost of vehicle (CNY)
ω	Unit distribution cost of vehicle (CNY/kCal/h)
n	Number of vehicles
q_s	Loading capacity of vehicle s temperature layer (ton)
a	Order unit weight picking time (min/kg)
τ_{ij}	Distribution time between consumer i and j (min)
p_1	Unit refrigerant price (CNY/kCal)
c_1	Heat load coefficient during loading and unloading process (CNY/kCal)
R	Heat transfer coefficient (kCal/$\left(\mathrm{h{\cdot}m^2{\cdot}{}^\circ C}\right)$)
A	Average surface area of refrigerator (m^2)
ΔT_1	The temperature difference between inside and outside of the room temperature compartment (°C)
ΔT_2	The temperature difference between inside and outside of the refrigerated compartment (°C)
ΔT_3	The temperature difference between inside and outside of the frozen compartment (°C)
$[E_i, L_i]$	Customer i Satisfaction Time Window (h)
M	A large positive constant
Decision Variables	
x_{ij}^k	Binary decision variable. If $x_{ij}^k = 1$, vehicle k serves from consumer i to consumer j
y_i^k	Binary decision variable. If $y_i^k = 1$, consumer i is served by vehicle k
y_s^k	Binary decision variable. If $y_s^k = 1$, the vehicle k is used to deliver s temperature zone product
z_{ip}^k	Binary decision variable. If $z_{ip}^k = 1$, the category p of consumer i is loaded in vehicle k
$\lambda_{pp'}$	Binary decision variable. If $\lambda_{pp'} = 1$, categories p and p' of fresh food are incompatible in temperature layer and they should be loaded in different temperature zones of fresh food are incompatible in temperature layer and they should be loaded in different temperature zones
t_i^k	Arrival time of vehicle k at consumer i
ts_i^k	Start picking time of vehicle k for consumer i order
tf_i^k	Finish picking time of vehicle k for consumer i order

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