Optimization of Multi-temperature Joint Distribution Paths for Convenience Store Chains

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Abstract: Purpose - Convenience stores are the main driving force of the small retail format in China. In order to meet customer demands, maintain product quality, reduce waste, and stay competitive in the fast-paced retail environment, convenience stores conduct daily food deliveries, with transportation costs accounting for the largest share of logistics expenses. Consequently, the daily operation costs of chain convenience stores increase. Therefore, the aim of this paper is to optimize the distribution paths of chain convenience stores with multiple distribution centers in order to reduce operational costs, reduce carbon dioxide emissions, etc. Design/methodology/approach - A mathematical model of the multi-temperature joint distribution problem with multiple distribution centers was constructed to minimize the total cost. In the model, six kinds of costs were considered. In addition, a two-stage algorithm was designed. The K-means algorithm was used to cluster match the demand points with the distribution centers, and the genetic algorithm was used to solve the routing problem of each distribution rate of total cost was 26.35%, the optimization rate of other costs was greater than 45%. Note that through case solving, the K-means algorithm was used to convert the single problem of multiple distribution centers into multiple problems of one distribution center. The multi-temperature joint distribution pattern was applied to the food distribution of chain convenience stores so that they could improve the delivery time and reduce the number of vehicles, carbon dioxide emissions, and total cost. Originality/value - Previous research on multi-temperature joint deliveries has predominantly focused on distribution form a single distribution centers.

Keywords: multiple distribution centers; multi-temperature joint distribution; path optimization of chain convenience stores

1 INTRODUCTION 1.1 Background

As an important commercial facility, convenience store chains bear the important responsibility of serving and safeguarding people's livelihood and promoting convenient consumption, and are an important retail format for the convenience and benefit of the people. On 31 December 2019, the Ministry of Commerce and 13 other departments jointly issued the "Guidance on Promoting the Accelerated Development of Branded Chain Convenience Stores" (later referred to as the "Guidance"), and in April 2020, the General Office of the Ministry of Commerce issued a notice, requiring the comprehensive promotion of convenience stores to resume business, especially under the situation of epidemic prevention and control [1]. After the pandemic, people's needs and psychology have shifted. They now prioritize convenience, proximity, and food safety. Chain convenience stores stand out for their high standards, centralized procurement, and uniform logistics distribution, which ensure the safety of products, especially food safety. This aligns with the current focus of people. In contrast, mom-and-pop stores, while geographically close to communities, offer limited product variety and have lower standards. Large supermarkets, although spacious and well-stocked, are often located far from residential areas, making it inconvenient for residents to shop. In 2021 - 2022, the State Council and the Ministry of Transport and other five departments have successively put forward new requirements for the development of multico-distribution. temperature Multi-temperature co-partitioning offers several key advantages over traditional distribution methods. It optimizes resource utilization, reduces carbon emissions, and enhances the safety and quality of temperature-sensitive products, particularly food. By consolidating various temperature zones within a single operation, it simplifies the distribution network, lowers operating costs, improves delivery times, and provides greater flexibility in responding to market dynamics and consumer preferences. This approach not only enhances customer satisfaction but also streamlines inventory management and is well-suited for businesses with diverse product offerings. However, food distribution in convenience store chains is characterised by multiple batches, varieties and small batches, and currently mainly uses multi-vehicle transport, which will lead to a series of problems such as urban road congestion and increased distribution costs. At the same time, the number of convenience store chains continues to grow rapidly, but although the number of refrigerated trucks has increased, the distribution capacity lags far behind the number of shops, and there are problems such as the quality of food which in the distribution process cannot be guaranteed. The emergence of these problems has hindered further development of convenience store chains. To further promote the development of chain convenience stores, this article summarizes several issues that need to be addressed in food distribution: 1. How to resolve the problem of mismatch between the delivery methods and the characteristics of food distribution. 2. How to address the issue of food quality decline and the inability to guarantee food safety. 3. How to tackle the problem of an increasing number of stores that do not match the distribution capacity. In order to guarantee that the chain of convenience stores can maintain healthy and gradual growth, this article is dedicated to achieving costeffective food distribution, reducing the number of vehicles, maintaining food quality, enhancing on-time delivery, and addressing the changing needs and preferences of consumers post-pandemic.

1.2 Review 1.2.1 The Literature Review

 (1) Chain convenience store vehicle routing problem: Most previous studies on convenience store chain distribution path optimization have considered path optimization with time windows. For example, Xu [2] considered the warehouse cost and transportation cost, and established a model of vehicle path problem based on time windows to optimize the logistics transportation and distribution of convenience store chains by simulation software eM-Plan. However, when constructing the total cost minimization model in this article, the cost analysis in the food distribution process is not comprehensive enough, and the selected time window is fixed. Chen [3] constructed a mathematical model for distribution route optimization of convenience stores in chain enterprises with the objective of reducing distribution costs and improving distribution efficiency, divided distribution areas with an improved K-mean algorithm, and optimized distribution routes in each area with an ant colony algorithm. However, the algorithm employed in this paper still has certain limitations. Liu and Liu [4] used the mileage saving method to plan distribution routes for a convenience store chain as an example in order to reduce distribution costs and meet the requirements of cold chain transportation on distribution time, but this article ignores the shortcomings of the mileage saving method. Liu [5] constructed a route optimisation model for Y's distribution large supermarkets, small and medium-sized to convenience stores and hotels with the shortest distribution distance as the optimisation objective, and solved Y's distribution optimisation model based on an ant colony algorithm; this article does not consider road obstruction and the ant colony algorithm used has capacity limitations. Zheng [6] optimised the delivery paths of petrol station chain convenience stores with the objectives of reducing enterprise logistics costs and improving delivery levels, solving the problems of unreasonable delivery and wasteful delivery vehicles commonly found in petrol station convenience stores; but the constraints considered in this paper are not comprehensive enough. Gong et al. [7] proposed a convenience store delivery with optimised delivery and pick-up scheme by extending the general delivery and pick-up path problem with time windows mathematical model, in which the cost of pallets is considered in addition to the basic cost-influencing factors. Similarly, the algorithm used in this paper still has certain shortcomings. Li et al. [8] proposed a multi-chromosome genetic algorithm with time windows for the convenience store chain delivery path planning problem under soft time windows to solve the delivery path optimisation problem of single yard, multi-model, convenience store chain with dense semi-soft time windows. This article only considers a single distribution center. Suwatcharachaitiwong et al. [9] proposed a drug delivery via convenience store, locker and home delivery distribution system in which the convenience store can serve as a pick-up location where customers can conveniently pick up their medicines at the convenience store, which can reduce the operational costs of the logistics company providing the drug delivery service. Some scholars have also applied the multitemperature co-dispensing service approach to the logistics and distribution of convenience store chains, but only for the case of single distribution centres. For example, Xue [10] analysed and summarised the problems of convenience store chain enterprises in logistics distribution in China, and constructed a cold storage type multitemperature co-allocation optimisation model, which was solved using standard genetic algorithms. Secondly, to

address the shortage phenomenon of some shops, a solution of replenishment during daytime was proposed, and a multi-temperature co-distribution replenishment optimization model with time windows was built and solved by a genetic algorithm combined with variable domain search. Furthermore, this paper solely relied on the classical genetic algorithm, which has certain limitations. Some other literature combines actual data to optimise specific convenience store distribution paths. For example, literature [11, 12] both analysed the current situation of logistics distribution of a realistic convenience store, constructed a distribution path optimisation model with the objective of minimising total cost and considering time windows, and solved it using genetic algorithms or improved genetic algorithms. Zhu et al. [13] took a convenience store chain in Taiyuan City as an example in order to reduce the distribution distance of the chain, limiting the capacity of vehicles and solving the distribution route using a mileage saving algorithm to obtain a solution with shorter distance, less time and lower transportation cost than the existing solution. However, the article only takes into account transportation distance costs, which is not comprehensive enough.

(2) Multi-depot vehicle routing problem:

Dantzig and Ramser [14] first introduced the Vehicle Routing Problem in 1959, focusing on finding the optimal route for gasoline delivery between bulk oil depots and numerous refueling stations. Over time, the Vehicle Routing Problem has evolved from single distribution centers to multiple distribution centers. Kaabachi et al. [15] studied a new variant of the Multiple Depot Vehicle Routing Problem with Time Windows, aiming to minimize fuel consumption and associated emission costs. They established an integer programming model that includes constraints such as time windows and vehicle capacity. They solved the problem using Ant Colony Optimization and local search techniques, although this study did not consider carbon emissions. Ren et al. [16] addressed the challenge of timely delivery of small batches of fresh produce to specific areas in the context of traditional regional distribution. They developed a closed-loop fresh produce minimal delivery cost mathematical model, incorporating multiple distribution center resources, information sharing, and soft time window constraints. They used an Artificial Fish Swarm Hybrid Algorithm to solve the problem. Compared to traditional methods, their algorithm effectively reduced total costs and carbon emission costs, but the article did not provide a comprehensive analysis of costs. Dauer and Prata [17] dealt with the Multiple Depot Vehicle Scheduling Problem by modeling it using space-time networks. They introduced two methods to reduce the problem's scale and proposed a variable-fixed mixed-integer programming heuristic algorithm. Paul et al. [18] introduced a Multiple Depot, Multiple Period, Closed-Loop Vehicle Routing Problem where different groups of customers are served by different vehicles within a limited time, aiming to minimize total travel distance or cost. They proposed a hybrid algorithm combining Tabu Search and variable neighborhood search. Lalla-Ruiz and Mes [19] presented a mathematical formula based on dual objectives and an improved Multiple Depot Open Vehicle Routing Problem. By considering constraints like vehicle remaining capacity,

their formula enhanced convergence speed, as verified through numerical experiments. Fan et al. [20] introduced a semi-open Multiple Distribution Center Joint Delivery Model to address fresh product distribution. They constructed an optimization model with the objective of minimizing the sum of vehicle transportation costs, dispatching costs, time penalty costs, and fresh product loss costs. They used Ant Colony Algorithms for solving. Ma et al. [21] applied electric vehicles in a multi-distribution center delivery model, creating a Multiple Distribution Center Semi-Open Electric Vehicle Routing Optimization Model with time windows. They designed an Ant Colony Algorithm to solve it. The semi-open multi-distribution center joint delivery optimizes logistics resources, vehicle routes, and reduces overall delivery costs. These solutions are useful in improving the efficiency of enterprises and the quality of service to customers, but they cannot solve the problems of low vehicle loading rate and high transportation costs brought about by the traditional cold chain distribution method of "ambient + refrigerated + frozen" multi-vehicle distribution.

(3) Multi-temperature shared delivery vehicle routing problem:

In response to this problem, multi-temperature co-distribution has emerged to break the traditional "dedicated vehicle" phenomenon in cold chain distribution. In 2010, Kuo and Chen [22] were the first to propose a food cold chain logistics service model based on the multitemperature joint distribution system. The proposed service model promoted the innovation of logistics services and enabled logistics departments to have competitive advantages in the protection of perishable goods and temperature-sensitive products. Tsang et al. [23, 24] considered multi-temperature characteristics of goods, service level, transportation cost, and the number of trucks and proposed a multi-temperature distribution planning system based on the Internet of things. Research on the application of multi-temperature joint distribution to vehicle routing problems can be divided into two categories: the first category pertains to the delivery of temperature-requirement different goods with heterogeneous vehicles. Wang et al. [25] divided the goods into cold goods and non-cold goods and used refrigerated vehicles and non-refrigerated vehicles to distribute the corresponding goods. In addition, they established relevant models and used the tabu search algorithm and C-W algorithm to solve and analyze the models. Lu and Wang [26] proposed a multi-temperature joint distribution mathematical model with fuzzy travel time. The model aimed to maximize customer satisfaction value and considered the travel time as a triangular fuzzy number; the heterogeneous vehicle sets were under different capacity constraints. The second category pertains to the delivery of goods with different temperature requirements using a single car. Cold storage multi-temperature joint distribution refers to the combination of a normal temperature vehicle and cooler boxes to achieve the purpose of delivering a variety of products with different temperatures. In previous studies, the general distribution technology has been compared with the cold-storage multitemperature joint distribution technology [27-29]. Furthermore, a binary integer programming model has been developed in previous studies to minimize the total

cost. Based on the developed model, the optimal distribution cycle of multi-temperature food was analyzed by using a traditional multi-vehicle distribution system and multi-temperature joint distribution system. The vehicle load and departure time for each multi-temperature food order were optimized by considering the demand for multitemperature food over time. Huang and Lu [30] set the driving time of vehicles under different road conditions as a random variable subject to the independent normal distribution, studied the rejection of goods due to the damage rate of goods, and constructed a multi-temperature joint distribution dynamic path optimization model to minimize the distribution cost. In mechanical multitemperature joint distribution, a vehicle is divided into compartments, and each part is maintained at different temperatures to hold products. Chen and Hsu [31] established a distribution scheduling mathematical model that considered the time-varying demand of multitemperature food. The model was used to estimate the greenhouse gas emissions of the traditional multi-vehicle distribution system and mechanical multi-temperature joint distribution system. Martins et al. [32] studied the vehicle routing problem with mechanical multi-capacity constraints and time window constraints to minimize transportation costs and penalty costs for failure to arrive in the specified time window. These studies mostly consider the optimisation of the vehicle path problem from a single distribution centre, whereas convenience store chains have a wide range of products, and a single distribution centre may not stock all types of products due to the constraints of warehouse conditions, thus the optimisation of the vehicle path problem from multiple distribution centres has a positive effect in responding quickly to customer demand and improving customer satisfaction. Compared with previous studies, the cost of model construction in this paper is more comprehensive: fixed costs, variable costs, refrigeration costs, cargo loss costs, time penalty costs, and carbon emission costs. Additionally, it considers three different temperature zones. Soft time windows with earliest and latest arrival times are implemented to enhance the punctuality of food deliveries to demand points. The research aims to provide a more precise study of the multi-temperature shared distribution path optimization problem for chain convenience stores under the context of multiple distribution centers.

1.2.2 The Literature Location

In this paper, the literature analysis tool named CiteSpace was used to conduct keyword clustering analysis on the literature after 2000. In the Web of Science (WOS) core database, the literature was retrieved with 'Chain Convenience Store' as the main topic. Subsequently, duplicate removal was performed using CiteSpace, and 227 pieces of literature were obtained. From Fig. 1, it can be inferred that there are not many studies on the distribution path optimization of the chain convenience stores at present. Moreover, research in China and other countries primarily pertains to marketing strategy, operation mechanism, and operation mode. Existing studies often fail to consider the characteristics of the food distribution of multiple batches, varieties, and small quantities of chain convenience stores and focus more on reducing the delivery time and distance. Literature was retrieved using 'Multi-temperature' and 'Joint Delivery (Joint Distribution)' as the main topic, and 14 pieces of literature were obtained after duplicate removal. Some literature provided analyses on the application of coldstorage multi-temperature joint distribution to the goods distribution of chain convenience stores. From the literature, it can be inferred that compared with coldstorage multi-temperature joint distribution, the operation mode of mechanical multi-temperature joint distribution is simple and easy to manage. From Fig. 2, it can be inferred that the two patterns of multi-temperature distribution are for one distribution center. However, when the enterprise scale expands and demand points increase, one distribution center cannot satisfy the demand. Therefore, it is necessary to study the situation of multiple distribution centers. Literature was retrieved with 'Multi-depot (Multiple Distribution Centers)' and 'Joint Delivery (Joint Distribution)' as the main topic, and 518 pieces of literature were obtained after duplicate removal. From Fig. 3, it can be inferred that research on multiple distribution centers does not consider chain convenience stores or multitemperature joint distribution. In summary, the path optimization of food distribution of chain convenience stores with multiple distribution centers requires further investigation. Because the multi-temperature joint distribution pattern is able to distribute small quantities of different varieties of goods, it can satisfy the characteristic demand of multiple batches, varieties, and small quantities of food distribution in chain convenience stores. Therefore, it is crucial to study the multi-temperature joint distribution path optimization of chain convenience stores with multiple distribution centers. After sorting out and analyzing relevant literature, it is found that the analysis of cost factors is not comprehensive enough when establishing the total cost minimization model, and there are several problems. First, the relevant literature almost selects only three to five models from the six types of costs, namely fixed cost, variable cost, cooling cost, food damage cost, time punishment cost, and carbon dioxide emission cost. These six types of costs will greatly affect the final total delivery cost. Second, many studies did not divide the cost of cooling or food damage into the cost of transportation and opening the door, or did not consider the three temperature zones. The food in the cold storage area and the frozen area needs to be delivered in the whole cold chain. Opening the door when the vehicle reaches the demand point will cause air convection inside and outside the compartment, which will affect the storage temperature of the food, leading to an increase of the cooling cost and the cost of goods damage. Food in the normal temperature zone may also be subject to a small amount of damage due to some factors during distribution. Therefore, the cost of food damage needs to consider three temperature zones. Third, many studies only use soft time windows when analyzing the cost of time punishment. Although the soft time window can limit the arrival time of vehicles to a certain extent, it is not mandatory to limit the earliest and latest arrival time of vehicles. The arrival time of vehicles may be far from the expected time window. The mixed time window can not only limit the earliest and latest arrival time of vehicles, but also give the vehicle time

flexibility. These three points should be considered at the same time when building the model to make the model more perfect.

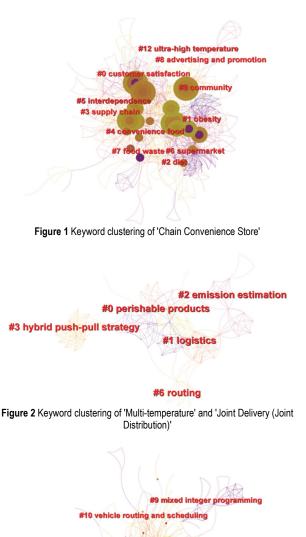




Figure 3 Keyword clustering of 'Multi-depot (Multiple Distribution Centers)' and 'Joint Delivery (Joint Distribution)'

1.3 Paper's Contributions

This paper constructs a convenience store chain path optimisation model that considers total cost minimisation in a multi-distribution centre scenario, and includes the cost of goods damage (in the 3 temperature zones during travel and when the doors are opened) and the cost of carbon emissions in the total cost, in order to make the costing more comprehensive and to demonstrate that the multi-temperature co-distribution service approach is more advantageous in the distribution of convenience store chains. This paper takes the food distribution of chain convenience stores as the research object and establishes a distribution path optimization model with multi-temperature joint distribution as the service pattern

and multiple distribution centers. Given the problem that the cost analysis is not comprehensive enough, this paper considers six types of costs, includes fixed cost, variable cost, cooling cost, food damage cost, time punishment cost, and carbon dioxide emission cost. In addition, in the analysis of cooling and food damage cost, the cost of vehicle transportation and the cost of opening the door are taken into account, and the food damage cost also takes into account the situation of three temperature zones respectively. This paper also uses a mixed time window to limit the arrival time of vehicles.

1.4 Outline

The rest of the paper is structured as follows. Section 2 gives the analysis process of various costs and the solution method of the model. In section 3, the construction case is solved, and the results of multi-vehicle distribution and multi-temperature joint distribution are compared and analyzed. Section 4 summarizes the results of the section 3, and gives the problems that need to be further discussed in the future.

2 METHODS AND MATERIALS 2.1 Methods

In this study, the mechanical multi-temperature joint distribution service was adopted to carry out food distribution in urban chain convenience stores. First, a detailed cost analysis was carried out, which not only considered the general cost factor but also considered the carbon dioxide emission cost of distribution. A path optimization model with minimum total distribution cost was constructed to optimize the chain convenience store distribution path for multiple distribution centers.

2.1.1 Distribution Cost Analysis

1. Fixed cost:

The fixed cost of the vehicle includes costs such as the salary of the driver and depreciation of the vehicle. Fixed costs are constant, i.e., independent of vehicle mileage and the number of customers. Fixed cost is proportional to the number of vehicles carrying out distribution operations.

$$C_1 = g \sum_{k=1}^{n} Y_k \tag{1}$$

In the equation above, n is the number of vehicles, and g is the fixed cost of invoking each vehicle. Because only vehicles of the same model are considered, g is a fixed value. Y_k is the 0 - 1 variable; if the value is 1, it means that the distribution center transfers the vehicle, otherwise the vehicle will not be called.

2. Variable cost:

Variable cost is generated in the process of vehicle distribution, and it includes fuel consumption, maintenance, and storage costs of distribution vehicles. Variable cost is generally related to the distance of distribution vehicles and is generally positively correlated.

$$C_{2} = b \sum_{i=1}^{m} \sum_{j=1}^{m} \sum_{k=1}^{n} Y_{ijk} d_{ij}$$
⁽²⁾

In the equation above, *b* is the cost per unit distance traveled by each car, which is set as a constant, and *m* is the number of nodes. Y_{ijk} is the 0 - 1 variable; when the value is 1, it means that the kth vehicle runs from node *i* to node *j*, otherwise the value is 0; d_{ij} is the distance between node *i* and *j*, which is represented in this study by the straight-line distance between two nodes.

3. Cooling cost:

(1) Cooling cost during driving:

Multi-temperature cold-chain vehicles rely on refrigerants for cooling. The consumption of refrigerants depends on the heat load of the vehicle during driving, the heat transfer coefficient of the vehicle, the temperature difference between the inside and outside of the vehicle, and the surface area inside and outside the vehicle.

$$C_{3-1} = P_z \sum_{i=1}^{m} \sum_{j=1}^{m} \sum_{k=1}^{n} \sum_{h=2}^{3} H_{3-1h} t_{ijk} Y_{ijk}$$
(3)

$$H_{3-1h} = (1+\alpha) R_h \sqrt{S_n S_w} \Delta T_h \tag{4}$$

In the equation above, P_z is the unit cooling cost, h represents the temperature area or the variety of foods (1. normal temperature; 2. cold storage; 3. frozen), and H_{3-1h} is the heat load generated in the cold storage area and frozen area during driving; α is the deterioration degree of the vehicle, R_h is thermal Conductivity, $\sqrt{S_n S_w}$ is the average surface area of the vehicle, ΔT_h is the temperature difference value between the inside and outside of each compartment, and t_{ijk} is the driving time of the kth vehicle from node *i* to node *j*. The cooling cost of the normal temperature area is zero.

(2) Cooling costs when opening doors:

When the unloading service is carried out, the door opening causes convection of air inside and outside the carriage, and the thermal load changes.

$$C_{3-2} = P_z \sum_{i=1}^{m} \sum_{k=1}^{n} \sum_{h=2}^{3} H_{3-2h} T_i Y_{ihk}$$
(5)

$$H_{3-2h} = \beta (0.54V_h + 3.22) \Delta T_h \tag{6}$$

In the equation above, H_{3-2h} is the thermal load when the door is opened, β is the door open frequency coefficient (0 times: 0.25, 1 - 5 times: 0.5, 6 - 10 times: 0.75, more than 10 times: 1), and V_h is the volume of each temperature compartment, Y_{ihk} is the 0 - 1 variable; when the value is 1, it means that the kth vehicle delivers the h food to node *i*, otherwise the value is 0.

4. Damage cost:

(1) Damage cost during driving:

Assuming that the temperature of each temperature compartment remains constant during the distribution process, the damage to goods in the vehicle is only proportional to time. It is assumed that the damage rate in the respective temperature compartment is constant.

$$C_{4-1} = \sum_{i=1}^{m} \sum_{j=1}^{m} \sum_{k=1}^{n} \sum_{h=1}^{3} Y_{ihk} P_h q_{ih} \left(1 - e^{-\delta 1 h t i j k} \right) Y_{ijk}$$
(7)

 P_h is the unit value of each product, δ_{1h} is the food damage rate of each temperature compartment during driving.

(2) Damage cost when opening doors:

When unloading is conducted after arriving at the demand point, the convection of air inside and outside the carriage leads to intensified food damage. Consequently, the damage rate in the cold storage area and the frozen area increases. However, the damage rate in the normal temperature area remains unchanged.

$$C_{4-2} = \sum_{i=1}^{m} \sum_{k=1}^{n} \sum_{h=1}^{3} Y_{ihk} P_h q_{ihk} \left(1 - e^{-\delta 2hT_i} \right)$$
(8)

In the equation above, δ_{2h} is the food damage rate of each temperature compartment for an open vehicle door $(\delta_{22} > \delta_{12} \delta_{23} > \delta_{13} \delta_{11} = \delta_{21})$, q_{ih} is the demand for each kind of food at node *i*, q_{ihk} is the remaining load of each kind of food for the kth vehicle after serving node *i*, and T_i is the service time at node *i*.

5. Time punishment cost:

In logistics distribution, customers usually have requirements pertaining to the arrival time of vehicles. In this study, the mixed time window was used to constrain the arrival time. $[ET_2, LT_1]$ represents the expected time window, and $[ET_1, LT_2]$ represents the acceptable time window.

$$C_{5} = \begin{cases} \sum_{i=1}^{m} \sum_{j=1}^{m} \sum_{k=1}^{n} \theta_{1} (ET_{2} - t_{ik}) & ET_{1} < t_{ik} < ET_{2} \\ 0 & ET_{2} < t_{ik} < LT_{1} \\ \sum_{i=1}^{m} \sum_{j=1}^{m} \sum_{k=1}^{n} \theta_{2} (t_{ik} - LT_{1}) & LT_{1} < t_{ik} < LT_{2} \\ M & \text{others} \end{cases}$$
(9)

In the equation above, θ_1 is the coefficient of time punishment cost for early arrival, θ_2 is the coefficient of time punishment cost for late arrival, t_{ik} is the time when the kth vehicle arrives at node *i*, *M* is an infinite positive number.

6. Carbon emission cost:

During the vehicle distribution, fuel consumption produces carbon emissions, which are related to vehicle load.

$$C_{6} = P_{c} E \gamma \sum_{i=1}^{m} \sum_{j=1}^{m} \sum_{k=1}^{n} \left\{ \left[\sum_{h=1}^{3} \left(Q_{0} + q_{ijh} \right) \right] - 2Q_{0} \right\} d_{ij} Y_{ijk}$$
(10)

 P_c is the unit carbon emission cost, E is the fuel consumption per unit vehicle, γ is the carbon dioxide emission coefficient, Q_0 is the vehicle weight when it is empty, q_{ijh} represents the h food with a carrying weight of q from node i to node j.

2.1.2 Mathematical Model

The following constraints were considered for building the mathematical model:

• Each vehicle departs from its distribution center and returns to the starting point after completing the operation.

The same type of vehicle is used in the process.

• Regardless of traffic congestion and other conditions, vehicles maintain a uniform speed.

• Each demand point is serviced by one vehicle, and the demand can be satisfied in one service.

• The sum of the demands of all the demand points on one path does not exceed the rated load of the vehicle, and the sum of the demands of all the demand points for each kind of product does not exceed the rated load of each temperature compartment of the vehicle

• Location information of each demand point, demand information, service time, and time window required by customers are known.

• The distance between each demand point is replaced by the straight-line distance.

• During distribution, the temperature of each temperature compartment remains constant, and the food damage rate in the same compartment is certain.

Based on cost analysis, the model for path optimization of chain-convenient multi-temperature joint distribution with multi-distribution centers was established to minimize the total cost.

$$MinC = C_1 + C_2 + C_3 + C_4 + C_5 + C_6$$
(11)

s.t.

$$\sum_{i=1}^{m} \sum_{k=1}^{n} Y_{ijk} = 1 \quad j = u+1, u+2, ..., m$$
(12)

$$\sum_{i=u+1}^{m} \sum_{k=1}^{n} Y_{ik} = m - u \tag{13}$$

$$\sum_{i=1}^{u} \sum_{j=1}^{u} Y_{ijk} = 0 \quad k = 1, 2, ..., n$$
(14)

$$\sum_{i=1}^{u} \sum_{j=u+1}^{m} Y_{ijk} = \sum_{i=1}^{u} \sum_{j=u+1}^{m} Y_{jik} \quad k = 1, 2, ..., n \quad (15)$$

$$t_{jk} = t_{ik} + t_{ijk} + T_i \tag{16}$$

$$\sum_{i=u+1}^{m} \sum_{h=1}^{3} Y_{ihk} q_{ih} \le Q_h \quad k = 1, 2, ..., n$$
(17)

In this model, Eq. (11) minimizes the total cost, including fixed cost, variable cost, refrigeration cost, food damage cost, time punishment cost, and carbon emission cost. Eq. (12) ensures that each demand point can only be provided by one vehicle, and *u* is the number of distribution centers. Eq. (13) ensures that all demand points are delivered goods, and Eq. (14) guarantees that the vehicles are not directly connected between the distribution centers. Eq. (15) ensures that the distribution vehicles start from their respective distribution centers and return to the starting point after completing the task, and Eq. (16) ensures that the delivery operation is continuous and continues to node j after the delivery of node i. Eq. (17) makes sure that the sum of demands of each point on one path for a certain type of food does not exceed the rated load of each temperature compartment of the products.

2.1.3 Two-stage Algorithm Design

The solution to the multi-temperature joint distribution path optimization problem of chain convenience stores under multi-distribution centers can be divided into two stages. In the first stage, the K-means algorithm is used to cluster match the demand points and distribution centers. Consequently, the multi-distribution center problem is transformed into multiple single-distribution center problems. In the second stage, an ordinary genetic algorithm is used to solve the path problem of each distribution center after cluster matching.

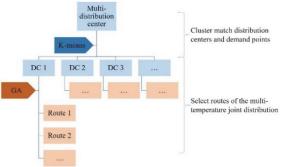


Figure 4 Flow chart of the two-stage algorithm

K-means clustering helps in reducing the complexity of the problem. Using K-means in the first stage allows you to break down the complex multi-distribution center problem into smaller, more manageable single-distribution center problems. K-means provides an efficient and relatively quick way to initially group demand points into clusters. This initial clustering can serve as a starting point for the genetic algorithm. It helps reduce the search space for the genetic algorithm, making it easier to find good solutions. Genetic algorithms are good at local optimization and can be used to further refine the solutions for each distribution center after the clustering stage. This allows for fine-tuning the delivery routes, considering factors like vehicle capacity, time windows, and other constraints specific to each distribution center. K-means focuses on data exploration and initial grouping, while the genetic algorithm emphasizes exploitation by optimizing routes within each cluster. This trade-off between exploration and exploitation often leads to high-quality solutions. It takes advantage of the data reduction and initial grouping capabilities of K-means and the local optimization and fine-tuning abilities of genetic algorithms to efficiently tackle the multi-distribution center problem, producing better solutions than using either algorithm in isolation.

1. Keans algorithm cluster matching:

In this study, the K-means algorithm, which is a typical clustering algorithm based on partitions, is used to cluster match the demand points and distribution centers. Moreover, it has a simple execution process and fast calculation speed. It uses the similarity measurement method to measure the relationship between the given data and then categorizes the closely related data as the same set. In this paper, the similarity measure was based on distance. Assuming that there are K distribution centers, the k-means algorithm should divide all demand points into K classes. K-means clustering algorithm flow is shown in

Fig. 5. The specific steps of the k-means clustering algorithm used in this study are as follows.

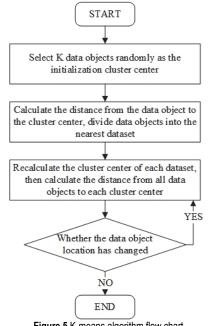


Figure 5 K-means algorithm flow chart

Step 1: The number of clusters, K value, was determined. The K initial clustering centers were randomly selected.

Step 2: The distance between each data object and the cluster center was determined, and then the data were divided into sets based on their distance from the cluster center. When all data objects were divided, K data sets were obtained.

Step 3: The mean value of each data set was recalculated, and the mean value was taken as the new cluster center.

Step 4: The distance of each data object from the new K initialization cluster centers was calculated and divided again.

Step 5: Steps 2, 3, and 4 were repeated until there was no data to be updated to other data sets; this ensured that the location of the cluster center did not change.

After completing the clustering of demand points, the divided service area was matched with the distribution centers, and the service scope of each distribution center was determined. The specific steps are as follows:

Step 1: The distance between each distribution center and the cluster center was calculated. Subsequently, an $N \times N$ 2-dimensional matrix was obtained. Each element in the matrix represented the distance between the distribution center and the cluster center, as presented in Eq. (18).

$$S = \begin{bmatrix} d_{(1,1)} & \cdots & d_{(1,K)} \\ \vdots & \ddots & \vdots \\ d_{(K,1)} & \cdots & d_{(K,K)} \end{bmatrix}$$
(18)

Step 2: There were K elements in S with different rows and columns, and N! combinations were obtained. The elements in each combination were added to obtain N! sum of distances D_i . The combination with the smallest value was the best solution. If there are 3 distribution centers, then a $S_{(3\times3)}$ distance matrix is obtained with a total of 3! = 6 combinations, as presented in Eq. (19).

$$D_{1} = d_{(1, 1)} + d_{(2, 2)} + d_{(3, 3)}$$

$$D_{2} = d_{(1, 2)} + d_{(2, 1)} + d_{(3, 3)}$$
...
$$D_{6} = d_{(1, 3)} + d_{(2, 2)} + d_{(3, 1)}$$
(19)

To select the combination with the smallest value, the following equation was adopted:

$$D_{\min} = \min(D_1, D_2, ..., D_6)$$
(20)

In the equation above, if the smallest value combination is $D_{\min} = D_6$, then DC.1 provides service to the third area, DC.2 provides service to the second area, and DC.3 provides service to the first area.

2. Genetic algorithm to solve routing problem:

Genetic algorithm (GA) is a classical intelligent optimization algorithm that is widely used in vehicle routing problems and has strong stability and global searchability. Therefore, GA was used in this study to develop the model and design the genetic algorithm.

(1) Encode:

The vehicle routing of each distribution center was encoded using natural numbers; 0 represented the distribution center, and the other numbers represented the demand points. Moreover, each chromosome represented the different vehicle delivery routing information.

(2) Population initialization:

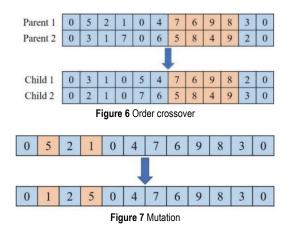
The generation of the initial population was the basic step for the subsequent steps. Optimal population size can improve the solving efficiency of the genetic algorithm. In this study, the population size was set to 200.

(3) Fitness function:

The fitness function was used to evaluate the merits and demerits of the chromosomes, and the inferior chromosomes were rejected. The fitness value was non-negative, and a larger fitness value was considered better. The distribution routing optimization model in this study aimed at minimizing the total cost. Note that the fitness value was inversely proportional to the objective function. Therefore, the reciprocal of the objective function was set as the fitness function.

(4) Selection, Crossover, and Mutation:

Selection is defined as the passing of good individual genes from one generation to the next. The higher the fitness value, the better the quality of the preserved chromosomes; otherwise, the chromosomes are eliminated. In this study, the roulette method was adopted for Selection. Crossover is defined as the exchange of genes between two chromosomes to form two new offspring chromosomes. The offspring chromosomes have different characteristics from the parent chromosome. Thus, Crossover can ensure that the fitness value of the offspring chromosomes is superior. In this study, Order Crossover (OX) was used. Mutation is defined as an auxiliary operation that facilitates the local search ability of the algorithm and improves the solving efficiency. In this study, two non-zero points were randomly selected for the exchange to achieve chromosome mutation. The Crossover probability of P_c was 0.9, and the Mutation probability of P_m was 0.005.



(5) Termination:

In the context of a random search algorithm, GA is different from the precise algorithm. In GA, the algorithm termination condition must be set manually, otherwise, it will continue to circulate wirelessly. In this study, GA stopped calculations after 1000 iterations.

Certainly, the method employed in this article also has certain limitations. K-means requires the pre-specification of the number of clusters (K), while real-world data often exhibit variability. Additionally, two-stage methods are generally less suitable for scenarios where demand and distribution center locations undergo dynamic changes, as they do not readily accommodate real-time updates.

2.2 Case Study

Real demand data is difficult to obtain. Therefore, the location information of the demand points and information on the demands were randomly generated using MATLAB, and a random case was obtained for comparative analysis. Moreover, the other related parameters were set according to existing literature. Subsequently, 60 coordinate points were randomly generated in the square coordinate axis area of 50×50 . From the coordinate points, three points were selected as distribution centers, while others were set as chain convenience stores. The information on the locations and demands is shown in the appendix. Assuming enough mechanical multi-temperature vehicles are operational, and the vehicles run at a constant speed of 40 km/h, the following data were obtained: the start-up cost of the vehicle was 600 yuan, the driving cost per unit distance was 3 yuan/km. The ordinary temperature was 20 °C, the temperature in the cold storage area was 2 °C, and the temperature of the frozen area was –18 °C. The volume and load rating of the three temperature compartments were the same, the vehicle weight was 8 T, and the load rating of each temperature compartment was 1.4 T. The acceptable time window of each convenience store was set as 6:00 - 10:00, and the operation time of vehicles in each convenience store w 10 minutes. In order to compare the multi-temperature joint distribution, multi-vehicle distribution, and multi-vehicle distribution pattern, the

start-up cost of the normal temperature vehicles and refrigerated vehicles were set at 200 yuan and 400 yuan, respectively. However, the other parameters remain unchanged. The values of the other parameters are presented in Tab. 1.

l able 1 Parameter Settings									
Name	Value	Name	Value	Name	Value				
P_z	1.5 / yuan/W	α	0.1	R_h	1, 1.3 / W·/ (m ² ·°C)				
$\sqrt{S_n S_w}$	1.2	V_h	7.3 / m ³	P_h	4000, 5000, 3000 / yuan				
$\theta_{1,2}$	20,25 / yuan/h	P_c	500 / yuan/t	δ_{1h}	0.005, 0.012, 0.01				
Ε	0.14 / L/ (t·km)	γ	2.6 / kg/L	δ_{2h}	0.005, 0.014, 0.015				

RESULTS 3

In this study, the K-means algorithm was adopted to match the distribution centers and demand points, and the results are shown in Tab. 2. The vehicle routing problem with multiple distribution centers was converted to three single distribution center vehicle routing problems. Subsequently, GA was used to solve the vehicle routing problems, and the best solution was selected from the 10 solutions for analysis. The vehicle roadmap and cost optimization table of each distribution center are presented in Fig. 8, Fig. 9, Tab. 3, Tab. 4, Tab. 5, and Tab. 6, and the total cost is presented in Tab. 7. As can be seen from Tab. 3, Tab. 4 and Tab. 5, in terms of cost optimization, each distribution center has been optimized to varying degrees except for fixed costs, among which the optimization degree of variable cost is the most significant. The reason for the decrease of variable cost is the following: when the multi-temperature co-distribution mode is adopted, the three types of food demand of each demand point can be satisfied by one vehicle, and when the multi-vehicle distribution mode is adopted, the three types of food are distributed to each demand point by different vehicles, which leads to the unnecessary round-trip mileage of the distribution distance compared with the single-vehicle distribution, therefore, the optimization degree of variable cost is more significant.

I able 2	Distribution centers and demand points cluster matching
Distribution	Demand Point
Center	
0	7, 9, 11, 15, 16, 20, 25, 26, 27, 30, 37, 38, 39, 40, 41, 43,
	45, 49, 50, 52, 55, 56
1	5, 8, 10, 12, 14, 22, 24, 28, 29, 32, 33, 36, 42, 47, 48, 51,
	54
2	3, 4, 6, 13, 17, 18, 19, 21, 23, 31, 34, 35, 44, 46, 53, 57,
	58, 59

Table 2 Distribution contains and demond a siste electron motivity

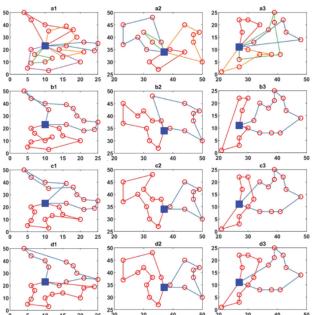


Figure 8 Vehicle route map of multi-temperature joint distribution and multi-vehicle distribution (a: Multi-temperature, b: Ordinary temperature, c: Cold storage, d: Frozen)

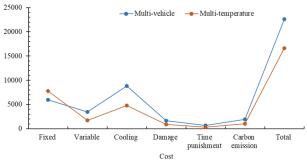


Figure 9 The cost comparison between Multi-vehicle and Multi-temperature

		Table 3 Vehicle routes			
DC	Route				
1	а	Route 1: 1-17-31-56-42-1, Route 2: 1-40-41-50-16-1, Route 3: 1-51-10-46-39-1			
		Route 4: 1-21-12-26-44-27-38-1, Route 5: 1-28-53-8-57-1			
	b	Route 1: 1-17-12-31-56-42-44-16-27-50-40-41-38-1, Route 2: 1-26-21-57-8-53-39-10-46-51-28-1			
	с	Route 1: 1-17-12-31-56-42-44-16-38-40-41-50-27-1, Route 2: 1-28-51-39-53-8-46-10-57-21-26-1			
	d	Route 1: 1-26-17-42-56-44-16-27-41-40-50-38-1, Route 2: 1-28-51-39-53-8-46-10-21-57-12-31-1			
2	a Route 1: 2-11-33-13-43-34-2, Route 2: 2-15-55-52-6-2				
		Route 3: 2-30-23-9-2, Route 4: 2-25-49-29-48-37-2			
	b	Route 1: 2-34-25-49-29-48-37-55-15-2, Route 2: 2-52-6-11-13-43-33-23-30-9-2			
	с	Route 1: 2-15-25-49-29-48-37-55-2, Route 2: 2-52-6-11-33-13-43-34-23-30-9-2			
	d	Route 1: 2-15-25-49-29-48-37-55-2, Route 2: 2-52-6-11-30-23-33-13-43-34-9-2			
3	а	Route 1: 3-32-20-19-7-3, Route 2: 3-35-36-24-14-3			
		Route 3: 3-54-45-47-58-4-3, Route 4: 3-18-60-5-59-22-3			
	b	Route 1: 3-5-59-45-7-19-20-58-47-4-14-32-3, Route 2: 3-35-24-36-18-60-54-22-3			
	c	Route 1: 3-14-4-7-58-20-19-7-45-59-5-3, Route 2: 3-35-36-24-32-22-54-60-18-3			
	d	Route 1: 3-5-59-45-7-19-20-58-47-4-3, Route 2: 3-35-36-24-14-32-22-54-60-18-3			

Table 4 Results of DC Number. 1								
Cost Pattern	Fixed	Variable	Cooling	Damage	Time punishment	Carbon emission	Total	
Ordinary temperature	400.00	459.72	0.00	111.99	142.95	258.70	1373.37	
Cold storage	800.00	476.60	1123.30	431.09	142.35	271.11	3244.45	
Frozen	800.00	462.38	2449.47	233.51	157.35	258.39	4361.11	
Multi-vehicle	2000.00	1398.71	3572.78	776.59	442.65	788.20	8978.93	
Multi-temperature	3000.00	761.76	1975.17	369.56	149.08	447.90	6703.46	
The optimization of value	-1000.00	636.95	1597.61	407.03	293.57	340.30	2275.46	
The optimization rate / %	-50.00%	45.54%	44.72%	52.41%	66.32%	43.17%	25.34%	

Table 5 Results of DC Number. 2									
Cost Pattern	Fixed	Variable	Cooling	Damage	Time punishment	Carbon emission	Total		
Ordinary temperature	400.00	345.03	0.00	74.39	4.52	197.10	1021.03		
Cold storage	800.00	338.38	794.50	249.57	27.95	188.95	2399.35		
Frozen	800.00	342.39	1744.18	141.98	33.82	187.02	3249.40		
Multi-vehicle	2000.00	1025.80	2538.68	465.94	66.30	573.07	6669.78		
Multi-temperature	2400.00	445.11	1347.28	236.87	119.48	255.75	4804.50		
The optimization of value	-400.00	580.69	1191.40	229.07	-53.18	317.31	1865.28		
The optimization rate / %	-20.00%	56.61%	46.93%	49.16%	-80.22%	55.37%	27.97%		

Table 6 Results of DC Number. 3									
Cost Pattern	Fixed	Variable	Cooling	Damage	Time punishment	Carbon emission	Total		
Ordinary temperature	400.00	350.04	0.00	72.13	47.04	193.88	1063.08		
Cold storage	800.00	343.84	846.90	226.82	84.58	188.28	2490.42		
Frozen	800.00	343.04	1851.92	154.07	49.89	188.45	3387.37		
Multi-vehicle	2000.00	1036.92	2698.82	453.02	181.52	570.61	6940.88		
Multi-temperature	2400.00	536.45	1499.00	276.94	101.45	315.36	5129.20		
The optimization of value	-400.00	500.47	1199.82	176.09	80.07	255.24	1811.68		
The optimization rate / %	-20.00%	48.26%	44.46%	38.87%	44.11%	44.73%	26.10%		

.

Table 7 Results of all distribution centers									
Cost Pattern	Fixed	Variable	Cooling	Damage	Time punishment	Carbon emission	Total		
Ordinary temperature	1200.00	1154.79	0.00	258.50	194.51	649.68	3457.49		
Cold storage	2400.00	1158.82	2764.70	907.48	254.89	648.33	8134.22		
Frozen	2400.00	1147.81	6045.58	529.56	241.07	633.86	10997.87		
Multi-vehicle	6000.00	3461.42	8810.27	1695.55	690.47	1931.87	22589.58		
Multi-temperature	7800.00	1743.32	4821.45	883.37	370.01	1019.01	16637.16		
The optimization of value	-1800.00	1718.11	3988.82	812.18	320.45	912.86	5952.42		
The optimization rate / %	-30.00%	49.64%	45.27%	47.90%	46.41%	47.25%	26.35%		

Each distribution center was analyzed separately. In the multi-temperature joint distribution pattern, DC 1 required five vehicles, and DC 2 and DC 3 required four vehicles. In the multi-vehicle distribution pattern, each distribution center required two ordinary temperature vehicles, two cold storage vehicles, and two frozen vehicles. In terms of cost, the optimization rates of variable cost, cooling cost, damage cost, time punishment cost, carbon emission cost, and total cost of DC 1 were 45.54%, 44.72%, 52.41%, 66.32%, 43.17%, and 25.34%, respectively. The optimization rates of variable cost, cooling cost, damage cost, carbon emission cost, and total cost of DC 2 were 56.61%, 46.93%, 49.16%, 55.37%, and 27.97%, respectively. Note that the time punishment cost remained unchanged. The optimization rates of the variable cost, cooling cost, damage cost, time punishment cost, carbon emission cost, and total cost of DC 3 were 48.26%, 44.46%, 38.87%, 44.11%, 44.73%, and 26.10%, respectively. On the whole, 13 vehicles were required in the multi-temperature joint distribution pattern, while in the multi-vehicle distribution pattern, six ordinary temperature, cold storage, and frozen vehicles were required. Thus, the total number of vehicles was 18. In terms of cost, the optimization rates of variable cost, cooling cost, damage cost, time punishment cost, carbon emission cost, and total cost were 49.64%, 45.27%, 47.90%, 46.41%, 47.25%, and 26.35%, respectively. It can be seen from the above results that the chain convenience stores adopted the multi-temperature joint distribution to

deliver foods that require different temperatures. Compared with multi-vehicle distribution, multi-temperature joint distribution reduced the costs and food damage significantly, increased the punctuality of the distribution, and reduced the cooling cost and carbon dioxide emission in the distribution process. Note that the number of vehicles in the multi-temperature joint distribution pattern was smaller, and the variable cost, cooling cost, and carbon dioxide emission cost were also low. Furthermore, in the multi-temperature joint distribution pattern, one vehicle delivered the three types of food. Consequently, all the chain convenience stores received the three types of food; this reduced the time punishment cost significantly. Simultaneous delivery of different types of food to chain convenience stores also reduced the food damage compared with separate deliveries. Because the technical requirements of the multitemperature vehicles were high, the fixed cost increased compared with ordinary vehicles. However, the other costs optimization degree was larger, and the total cost was lower.

4 CONCLUSIONS AND FUTURE WORK

Chain convenience stores deliver a wide variety of foods, including ordinary-temperature foods, cold-storage foods, and frozen foods. Because foods are delivered daily from distribution centers to chain convenience stores, the demands for different food items vary. This study adopted the multi-temperature joint distribution pattern to solve the problem of food distribution in chain convenience stores with multiple distribution centers. In this study, the total cost was taken as the measurement index. A mathematical model was established to minimize total cost, which included six types of costs: fixed cost, variable cost, cooling cost, damage cost, time punishment cost, and carbon dioxide emission cost. To make the model more accurate, the cooling cost and damage cost were subdivided into the cost during driving and the cost during the opening of the door. The K-means algorithm was used to transform the path optimization problem of multi-distribution centers into multiple single-distribution center path optimization problems, which reduced the complexity and scale of the problem. Subsequently, the multi-distribution center problem was transformed into three single-distribution center problems, and the genetic algorithm was used to solve the vehicle routing problem. According to the results of the case analysis, the multi-temperature joint distribution pattern could meet the requirements of food distribution in convenience stores, which include multiple batches, varieties, and small quantities. In addition, compared with multi-vehicle distribution, a multi-temperature joint distribution could reduce the number of vehicles and the total cost and improve the punctuality of food delivery. By conducting solution analysis of random cases, the number of vehicles was reduced from 18 to 13, and the total cost was reduced by 26.35%. Aside from the fixed cost, the optimization rate of other costs was greater than 45%. Based on the situation of each distribution center separately, it can be concluded that the cost was reduced significantly. Note that the optimization rate of the total cost was more than 25%. This article validates the feasibility of a multi-temperature shared service approach for food distribution in a multidistribution center setting for chain convenience stores. It demonstrates that the implementation of this method can not only effectively reduce the operational costs of businesses but also decrease carbon emissions. Thus, the multi-temperature joint distribution method has a good effect on the food distribution of chain convenience stores. This article primarily investigates the multi-temperature shared delivery route optimization problem for chain convenience stores with multiple distribution centers, thereby contributing to the enrichment of the field of route optimization for chain convenience stores and multitemperature shared delivery route optimization. However, due to the limited research capabilities and a somewhat narrow perspective of the author, this article has certain limitations. This article only considers a single vehicle type and source. In real-life logistics, businesses may use various vehicle types for delivery, including a combination single-temperature, dual-temperature, of and triple-temperature vehicles, or a mix of company-owned and leased vehicles. Therefore, in future research, it is important to consider different vehicle types and sources. This article utilizes the K-means algorithm and genetic algorithm to solve the proposed problem. It only qualitatively compares the advantages and disadvantages of these algorithms. In future research, there is a need for a quantitative comparison of the results obtained from various clustering and heuristic search algorithms to identify the most suitable algorithm for solving the

multi-temperature shared delivery route optimization problem in a multi-distribution center setting for chain convenience stores. The vehicle routing problem of multiple distribution centers studied in this paper is a closed problem, i.e., the vehicles need to return to the starting distribution center after completing the operation. However, the multiple distribution centers problem includes an open problem. The vehicles do not have to return to the starting point and can return to any distribution center after completing the operation. Therefore, the open problem will be explored further in future research.

Acknowledgements

The research is supported by Fujian Province Science and Technology Innovation Think Tank Research Project (Grant No.: FJKX-2022XKB008) and Interdisciplinary Practice in Green Civil and Hydraulic Engineering of Fujian Agriculture and Forestry University (Grant No.: 71202103d).

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Appendix

Number	X Y		Demand points and distribution of Demand for ordinary temperature / t	Demand for cold storage / t	Demand for frozen / t	Acceptable time window (ET1,LT2)
1	10 2					
2		1				
3		4				
4		8	0.17	0.38	0.14	(8.0, 9.2)
5	34 8	3	0.24	0.32	0.41	(6.3, 9.1)
6	32 3	0	0.12	0.26	0.22	(6.5, 8.2)
7	48 1	4	0.31	0.12	0.34	(6.8, 8.8)
8	11 3	;	0.23	0.41	0.49	(6.1, 8.5)
9	36 3	8	0.17	0.24	0.27	(7.4, 8.8)
10	12 1	3	0.18	0.34	0.38	(6.8, 8.6)
11	31 3	5	0.37	0.14	0.27	(6.8, 8.3)
12	21 1	8	0.29	0.15	0.36	(7.2, 8.4)
13	23 3		0.46	0.32	0.14	(6.3, 8.0)
14		20	0.14	0.29	0.47	(6.8, 9.4)
15	39 3	5	0.40	0.46	0.18	(6.3, 9.0)
16	18 3	6	0.39	0.42	0.21	(7.5, 9.4)
17		23	0.32	0.39	0.42	(7.7, 8.2)
18	21 1		0.17	0.12	0.30	(6.7, 9.4)
19		7	0.34	0.13	0.41	(7.4, 9.2)
20	42 2		0.22	0.14	0.26	(6.6, 8.9)
21		4	0.15	0.42	0.21	(7.1, 8.7)
22		0	0.19	0.48	0.11	(7.7, 8.4)
23		2	0.46	0.37	0.37	(7.2, 9.1)
24		22	0.13	0.15	0.27	(6.7, 8.3)
25	44 4		0.20	0.39	0.28	(6.6, 8.1)
26		20	0.12	0.14	0.34	(6.9, 9.2)
27	16 3		0.28	0.15	0.12	(6.8, 9.0)
28		20	0.11	0.36	0.23	(6.7, 9.1)
29	47 4		0.46	0.23	0.41	(7.1, 9.0)
30	33 3		0.18	0.36	0.38	(7.5, 8.6)
31		.9	0.14	0.40	0.15	(6.8, 8.6)
32		3	0.22	0.33	0.15	(6.9, 9.2)
33		0	0.28	0.40	0.14	(6.2, 8.5)
34	33 4		0.14	0.19	0.10	(6.0, 9.2)
35	28 1		0.50	0.39	0.27	(6.6, 9.2)
36		22	0.22	0.45	0.39	(7.3, 8.0)
37		0	0.12	0.13	0.31	(7.9, 9.0)
38	11 3		0.22	0.25	0.14	(7.9, 9.4)
39	6 9		0.12	0.25	0.35	(6.9, 8.7)
40		4	0.30	0.37	0.15	(6.5, 8.1)
41		50	0.40	0.34	0.15	(7.5, 9.3)
42		26	0.35	0.42	0.14	(7.5, 8.9)
43		15	0.14	0.25	0.16	(7.5, 8.5)
44		60	0.13	0.18	0.17	(7.5, 9.5)
45	41 8		0.41	0.13	0.18	(6.2, 8.3)
46		0	0.46	0.41	0.23	(7.4, 9.0)
47		21	0.31	0.18	0.23	(6.9, 8.9)
48 49		8	0.14	0.26	0.19 0.20	(6.4, 8.6)
49 50		2 0	0.43 0.24	0.32	0.20	(6.2, 8.2)
50		.6	0.22	0.19	0.46	(7.6, 8.0)
51	35 2		0.40	0.36	0.38	(6.4, 8.6)
52	5 5 5		0.40	0.16	0.32	(6.3, 8.3)
55	5 5 27 6		0.10	0.16	0.17	(7.3, 9.1)
54 55) 64	0.12	0.22	0.18	(7.8, 8.6)
55 56		.4 25	0.34	0.22	0.47	(7.4, 9.1)
57		.0	0.39	0.19	0.38	(6.3, 8.9)
58		25	0.39	0.14	0.32	(7.9, 8.3) (7.1, 9.4)
59	39 2 38 8		0.41	0.14	0.23	(7.1, 9.4) (7.4, 8.4)
<u> </u>	27 3		0.22	0.14	0.35	(7.4, 8.4) (6.1, 9.4)
00	21 3		0.22	V.1 I	0.00	(0.1, 7.4)