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Sustainable supply chain management for perishable products in emerging markets: An integrated location-inventory-routing model

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ABSTRACT

The demand for perishable products in emerging markets has been increasing. However, the perishability of products brings tremendous challenges for firms to build a sustainable supply chain. In this paper, we propose an integrated model of location-inventory-routing for perishable products, considering the factors of carbon emissions and product freshness. First, the economic cost, carbon emission levels, and freshness of the perishable products are analyzed. Second, with the goals of achieving the lowest economic cost and carbon emissions and the highest product freshness, a multi-objective planning model is developed, and constraints are established based on the actual location-inventory-routing situation. Third, the YALMIP toolbox is used to solve the model, and the optimal solution to this complex multi-objective problem is obtained. Finally, the effectiveness and feasibility of the proposed method are verified by the case study, as well as the sensitivity vehicle speed to the results. It is found that the integrated model proposed in this paper is able to significantly improve the efficiency of perishable goods supply chain management from the perspective of global optimization, and vehicle speed is able to significantly affect economic costs and carbon emissions.

1. Introduction

Emerging markets such as China and India are taking measures to expand their market size through the food, agriculture, or rural business sectors of the economy of the country (Choi and Luo, 2019)[1]. Over the past decades, the demand for perishable products has increased dramatically in the emerging markets, and customers in these countries have also become increasingly demanding of the freshness of perishable products. However, perishable products (e.g. vegetables, fruit, milk, etc.) are subject to deterioration shortly after production. Globally, food waste is a severe problem, around 1.3 billion tons of foods are wasted every year, which accounts for one-third of the world's total food production. In the United States, about 15% of perishable products go bad during transportation and sales every year (Ferguson and Ketzenberg, 2005). In Australia, as much as $10,000,000 is wasted every year due to food spoilage (Pitt and Hocking, 2009). Especially for emerging markets, in China, more than 25% of fruits and vegetables deteriorate during

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[1] https://www.gcca.org/building-cold-chain-emerging-markets

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transportation, storage, and sales (Jia and Dong, 2009; Martin, 2015). To alleviate the problems above, it is essential to control inventory, optimize transportation routes, and improve the operation efficiency of the perishable product supply chain. In perishable products supply chain management, location, inventory, and route are the three key decision-making problems. According to the existing literature, the relevant characteristics of the perishable product supply chain in the emerging markets are shown in Table 1.

As shown in Table 1, product freshness is not managed well in the logistics of perishable products in the emerging markets, resulting in a high deterioration rate in the transportation process. This creates an imbalance between supply and demand for fresh products — the demand for fresh products in the emerging markets has been increasing, while a high proportion of fresh products are wasted in the process of transportation. Furthermore, the perishable product supply chain requires a strict temperature and humidity control throughout the entire process including the storage and transportation, etc., causing a significantly higher level of carbon emission. It is well-known that the emerging economies face huge pressure and significant difficulties in controlling carbon emissions, for example, a report by ITIF predicts that 75% of all emissions will come from emerging economies such as China and India by 2040[2]. It is even more challenging for emerging economies to meet the demand for fresh products while controlling for carbon emissions. Even without considering the product freshness and carbon emissions, many companies are having difficulties in achieving the optimal location-inventory-routing and are stuck in a low profitability situation due to the unreasonable location of distribution centers and suboptimal routing plans (Kuo, 2011; Mihajlović et al., 2019). Fresh product producers have to bear additional costs on product preservation, as well as the risks of losing a proportion of the fresh products. These costs and risks may lead to extremely low profits. In recent years, the importance of developing sustainable supply chains has been widely recognized by the academic community and the industry. Our study makes a significant contribution to sustainable supply chain management products by incorporating the factors of carbon emissions and product freshness into the joint model of location, inventory, and routing.

In this paper, we focus on the world's largest producer of fresh products - China. The output of vegetables, fruits, aquatic products, meat, and other fresh products of China ranks the first in the world. The market scale of perishable products in China has been increasing every year and it is expected that the compound annual growth rate will reach 25% by 2020[3]. However, due to the low efficiency of the product purchasing process and even the whole supply chain management, the gross profit margin on perishable products is generally low. Therefore, it is crucially important to study the perishable product supply chain in emerging markets. One main challenge faced by the producers of fresh products in China market is keeping the freshness of perishable products. For example, the fresh deteriorating rates of fruits, vegetables, meat, and aquatic products in inventory and transportation reach 15%, 8%, and 10% in China respectively; whilst the average rate in developed countries is only 5%[4]. Meanwhile, the carbon emission of refrigerated vehicles used in cold chain logistics is nearly almost 20% higher than that of ordinary vehicles, which is against the low-carbon logistics policy advocated by the Chinese government.

As the quality of perishable products in the storage and distribution process will change dynamically, compared with the traditional inventory strategy, the perishable product inventory strategy is more complex. In addition, location selection and route planning are the key to solve the distribution of perishable products and improve the freshness of products. At the same time, controlling the carbon emission in the transportation process is also crucial. Therefore, supplying fresh products to customers while reducing carbon emission at the same time is a common dilemma for the emerging markets. To solve these problems, a systematic and integrated decision-making mechanism involving location, inventory, and route is required. This mechanism integrates solutions for routing inventory problem (RIP), location inventory problem (LIP), and location inventory routing problem (LIRP).

To achieve the minimum economic cost and carbon emission and the maximum product freshness, we develop an integrated location inventory routing model to investigate the optimal scheme under different scenarios. The influence of transportation speed on the objective function is discussed in the paper. The contribution of this study is threefolds. First, our model solves the location, inventory, and routing problems at the same time, realizes the integrated optimization, and provides a very important reference for decision-makers to make plans in the real world. Second, the freshness of products and carbon emissions are also considered in the model. While controlling the freshness and carbon emissions of perishable products, the integrated optimization of manufacturer and distribution center's location inventory routing is carried out to build a sustainable perishable product supply chain. These technical approaches used are more scientific than the previous research results which only consider the economic cost. Third, a new solution methodology is proposed. The YALMIP toolbox is used to solve multi-objective programming problems. The selection of the YALMIP toolbox is mainly based on its two important advantages: (1) almost all optimization software solvers can be easily called; (2) the separation of modeling and algorithm is realized. It provides a new perspective to solve the multi-objective programming problem. It is found that this study can provide a very important reference for enterprises' comprehensive decision-making and guide decision-makers to make production and distribution plans.

The remainder of the research is organized as follows. Section 2 presents the literature review. The research problem is described in section 3. Section 4 constructs the model. Then, the model is solved in section 5. Section 6 presents a case study. Sensitivity analysis is performed in section 7. Section 8 concludes the research.

[2] Our in-depth research: Why we recommend funding the Clean Energy Innovation program at the Information Technology and Innovation Foundation (ITIF) https://lets-fund.org/clean-energy/

[3] http://www.lenglian.org.cn/

[4] Report of solutions and investment strategy planning on China fresh O2O industry 2019–2024 (https://bg.qianzhan.com/)

Table 1
Common characteristics of the perishable product supply chain in the emerging markets*

Features	Perishable product supply chain in the emerging markets	References
Countries	Brazil; China; India etc.	Duarte et al. (2019); Balaji and Arshinder (2016)
Product freshness	Supply-demand imbalance with unmet demand for fresh products; High rate of deterioration	Ning et al. (2013); Jedermann et al. (2014)
Carbon emissions	High-energy consumption due to the lack of advanced refrigeration and preservation technology	Zamudio-Flores et al. (2015)
Distribution center location	Improper location choice; Negligence of regional distribution planning	Wei-Min et al. (2013)
Inventory management	Lack of standardization; Without proper risk control	Chintapalli (2015)
Routing planning	Unreasonable allocation and transportation; Weak transport capacity	Ishii and Nose (1996); Kang and Lee (2007)

* An emerging market is a market with gradually improved market economic system, high economic development speed and great market development potential.

2. Literature review

In this section, due to the lack of direct and closely relevant literature, we provide a brief discussion of relevant literature in four interrelated streams: supply chain management in emerging markets, management strategy for perishable products, carbon emissions limitation mechanism, the inventory management, vehicle routing and facility location in the supply chain.

2.1. Supply chain management in emerging markets

The characteristics of supply chain management in emerging markets cannot be ignored (Wang et al. (2016). For supply chain conceptual model in emerging markets, Wang et al. (2016) address the issue of identification and effective cooperation of supply chain members in emerging markets. How government intervention and relationship importance moderate supplier-buyer collaborative outcomes is investigated. The results indicate government intervention weakens the positive effect of mutual learning on product co-development, while relationship importance strengthens it. Choi and Luo (2019) establish theoretical models to analyze the relationship between the data quality and sustainable fashion supply chain operation in emerging markets. They find that poor data quality lowers supply chain profits and social welfare. Liu et al. (2020a,b) reveal a sequential effect between behavioral (human and soft aspects) and technical (tangible and hard aspects) practices on performance. Results demonstrate that companies in emerging markets should utilize necessary technical green supply chain management practices (e.g., green design, green manufacturing and reverse logistics) to obtain economic, environmental and operational performance. Lorentz et al. (2013) explore the effect of emerging market characteristics on supply network design. Results recommend that a proactive network design approach is needed to maintain performance and competitiveness. For logistics and transportation management strategies in emerging markets, Amaya et al. (2020) study stakeholders' views on sustainable urban freight policies in emerging markets to address logistics issues between cities, the results suggest that stakeholders (Carriers, Receivers, and Citizens) agree on the importance of having space to conduct freight operations in their urban areas. Khan et al. (2019) examine the relationship between logistics operations, social, environmental, and economic indicators, and believes that the application of green technology can mitigate the negative impact of logistics transportation on social and environmental sustainability. Kumar et al. (2019) believe that the lack of cooperation between logistics, warehouses, or cold storage will increase carbon emissions. These literatures demostrate the supply chain conceptual model, logistics and transportation management strategies in emerging markets from different perspectives through empirical research, in addition, the important roles of cooperation relationship, data quality, green technology, integrated network design and infrastructure in the supply chain practices of emerging markets are also clarified. Nevertheless, there is still a substantial gap in the research on how the perishable product manufacturers survive and develop stably in emerging markets. This paper expands the research in this field.

2.2. Management strategy for perishable products

The perishability of products refers to the deterioration of the quality or quantity of products in the process of transportation, storage, and sales (Ghare and Schrader, 1963). Previous research focuses on two key components in the perishable product supply chain: inventory control and technology investment. First, inventory control plays a crucial role in perishable supply chain management. Shin et al. (2019) and Bhaula et al. (2019) study the perishable inventory model under dynamic time and temporary price discounts, respectively. Dye (2020) develops a dynamic joint model of pricing, advertising, and inventory control for perishable products to examine the psychological effect of inventory. Ganesh and Uthayakumar (2019) develop a multi-item inventory model under stochastic demand with dynamic out of stock quantity and price discount. Based on the case study of a dairy enterprise, Yavari and Geraeli (2019) propose a closed-loop supply chain network design model including a perishable product collection center. Li et al. (2017) suggest that product packaging can directly affect the shelf life of products and develop an inventory model to study the optimal packaging decisions and inventory control strategies of enterprises. Second, investment preservation technology is the key to the success of a perishable product supply chain. Dye and Hsieh (2012) study the optimal replenishment strategy and preservation technology investment strategy of retailers while incorporating the impact of preservation technology investment on the deterioration rate. Assuming that the investment of preservation technology can be adjusted dynamically, Chen and Dye (2013) study the decision-making model of ordering and preservation investment of perishable products under the condition of a fixed production cycle. Considering the deterioration rate of perishable products, Hsieh and Dye (2013) propose an optimal production strategy and an optimal technology investment saving technology for enterprises. Bardhan et al. (2019) study the conservation investment and inventory of perishable products. However, these outstanding studies mainly focus on perishable inventory control method and preservation technology in perishable product supply chain,. From a more advanced practical perspective, there is a lack of more comprehensive consideration of carbon emission and distribution optimization issues.

2.3. Carbon emissions limitation mechanism

For the research of carbon emission limitation, the commonly used methods are paying carbon tax and limiting carbon emission. Zhou and Wen (2019) provide a systematic review of carbon-constrained operations management. Carbon constraints, related business strategies, carbon-constrained operation models, and the future research trend are analyzed in their work. Modak and Kelle (2019) propose mathematical models for expected profit maximization considering social work donation and recycling investment under carbon emissions tax. They demonstrate that customers' social work donation has a positive impact on recycling. Li et al. (2018) utilize a stochastic programming approach to capture impacts of different carbon regulatory, carbon cap, carbon tax, carbon cap and trade, and carbon offset, on product configuration decisions with uncertain supplies and demands. Ding et al. (2016) examine permutation flow shop scheduling strategies which can improve carbon efficiency by minimizing the total carbon emissions and making span. Park et al. (2015) investigate the impact of imposing carbon cost on supply chain structure and social welfare. They show that imposing carbon emission charges can significantly influence the supply chain structure when the degree of competition is intense. In addition, when the retailer's profit is low, social welfare can be significantly increased by imposing carbon costs. Daryanto et al. (2019) examine an integrated three-echelon supply chain with carbon emissions. They reveal the effect of carbon emission cost, deterioration, and variable transportation cost on the three-echelon supply chain. The proposed optimal model is illustrated by a numerical example and sensitivity analysis. The results demonstrate that the supply chain integration has obvious benefits in total cost and carbon emission reduction. The relevant literatures on carbon emissions mainly focus on carbon-constrained production and operation management. In addition, the important effects of carbon emissions limitation on production and operation management are clarified. Our paper extends this stream of research by examining the comprehensive model of location-inventory-routing selection considering carbon emission for perishable products.

2.4. Inventory management, vehicle routing and facility location in the supply chain

In this section, we review the main characteristics of the existing models, and the methodologies used, with a particular interest in the papers that take location, inventory, and routing issues into account independently or integrally. The RIP considers the interaction between inventory and transportation. Its objective is to jointly optimize the inventory and distribution of two independent logistics links. Then, the replenishment strategy and transportation strategy are integrated to minimize the total economic cost. Some scholars have already begun to study the RIP under stochastic demand (Chan et al., 2018; Choi et al., 2013; Chow, 2016; Coelho et al., 2014; Gruler et al., 2018; Halman et al., 2016; Markov et al., 2018; Roldán, 2016). Research on the RIP under stochastic demand is generally divided into one-day cycles, rolling cycles, and infinite cycles, depending on the length of the planning period. Kheiri (2020) proposes a new super heuristics algorithm to solve the RIP, which verifies the effectiveness of the hyper-heuristic algorithm, and showed the advantages of data science and technology of the hidden Markov model in heuristic selection. Su et al. (2020) designs an algorithm for RIP, namely a mathematical algorithm, which decomposed the problem into a main problem and two subproblems, and the results are satisfactory. The LIP is an issue that combines location and inventory. That is when a location decision is made, both the inventory cost and inventory parameters are considered. Meissner and Senicheva (2018) predict the level of demand for a month for products with short sales time and very uncertain demand based on the sales data of 15 retailers. The transshipment policy is determined by the dynamic programming method, and the proposed algorithm is proved to be significantly superior to the other algorithms. Considering the uncertainty of demand and carbon price, Wang et al. (2020) studies the green LIP and provided management insights for supply chain emissions in emerging countries. Ozsen et al. (2009) propose the multi-source facility location and inventory model. They utilize the Lagrange relaxation algorithm to solve the model. Berman et al. (2012) discuss the location-inventory model under partial coordination and total coordination and solve the model by Lagrange relaxation algorithm. The results show that the model is economically reasonable and effective. The LIRP refers to the integrated optimization of location, inventory, and transportation. However, due to the complexity of the decision-making process, research on LIRP is very limited. Biuki et al. (2020) introduces three key problems in logistics system optimization: location, routing, and inventory. The three dimensions of sustainable development are brought into the supply chain, and a two-stage comprehensive model is constructed. The genetic algorithm and particle swarm optimization algorithm are combined to solve the model. Forouzanfar et al. (2018) construct a bi-objective nonlinear integer programming model and use the NSGA-II and MOPSO algorithms to solve the model. Considering the probabilistic travel time and stochastic demand of customers, Considering the time windows, Chen et al. (2019) propose a two-stage LIRP that considers the available timeframes. In the first stage, the LIRP is proposed, and in the second stage, some constraints are established. Eventually, a hybrid heuristic algorithm is designed. The results of the numerical example show that the algorithm can improve the convergence speed.

As mentioned above, with the concept of sustainable development gradually gaining popular support in emerging markets, many government intervention policies, enterprise operation management methods, carbon regulatory mechanisms are being implemented, and carbon emission in the operation of cold chain logistics and inventory has become a key issue for logistics companies. To the best of our knowledge, research on the supply chain management for perishable products in emerging markets is fewer in number although it is now growing. In general, on the one hand, the literature on production and logistics problems with carbon emission consideration mainly focuses on the location-routing problem, inventory-routing problem, or location-inventory problem in isolation. However, to achieve systematic optimization, integration decisions should be made according to the relationships among these three factors. In reality, the issue of considering location-routing and inventory simultaneously in the context of emerging markets remains a nearly untapped area. On the other hand, there is limited existing literature considering economic costs and carbon emissions in the operation management of the cold chain. Also, few of them consider the carbon emissions that are generated during the process of building a distribution center. Especially, the existing studies mainly aim to reduce the economic cost. Therefore, the freshness of the products received by the customers has received little attention in firms' production and related logistics issues involving carbon emission constraints. Meanwhile, the existing literature ignores the impact of vehicle speed on economic costs and carbon emissions. Given the gap in the literature, to minimize economic cost and carbon emission, and meanwhile maximize product freshness, and to fill an important research gap, this paper proposes a multi-objective programming model for perishable products. YALMIP toolbox is then designed to solve the model.

Our work differs from these studies in four ways. First, this paper adds the carbon emission of the distribution center into the model because the construction of the distribution center is usually a large project that cannot be ignored. Second, our study also considers the freshness of products. The freshness of the product affects customer satisfaction, which in turn affects the firm reputation. Third, in practice, the economic costs and carbon emissions change with the speed of the vehicles transporting perishable products. Therefore, in this paper, the speed is regarded as a variable for sensitivity analysis to map the change of results. Fourth, location-routing-inventory integration optimization is an NP problem. Ordinary algorithms cannot satisfy the requirements of the solution. In this paper, the YALMIP toolbox has been applied to solve the multi-objective programming problem. The effectiveness of the algorithm is verified through a case study.

3. Problem description

The proposed model takes into account the transportation route, inventory, demand from retailers, and product freshness when determining the locations of distribution centers, meanwhile aims at minimizing the carbon emissions to develop a sustainable supply chain management system. The perishable product supply chain system in our paper is illustrated in Fig. 1.

The supply chain system is composed of manufacturers, distribution centers, and retailers. The problems being addressed are: (1) to optimally determine the quantity and location of distribution centers, (2) to allocate the retailers to the identified distribution centers, and (3) to determine the route of the vehicles. For example, the distribution route of vehicle *u* can be from the manufacturers to the distribution centers or between any of the distribution centers. The distribution route of vehicle *v* is from the distribution centers to the retailers or between any of the retailers. For example, the perishable products for distribution center *2* can be directly transported by the manufacturers, or they can also be delivered to distribution center *1* or distribution center *j* by the manufacturers, and then transported to distribution center *2*. The products for retailer *2* can be directly transported by the distribution centers, they can also be

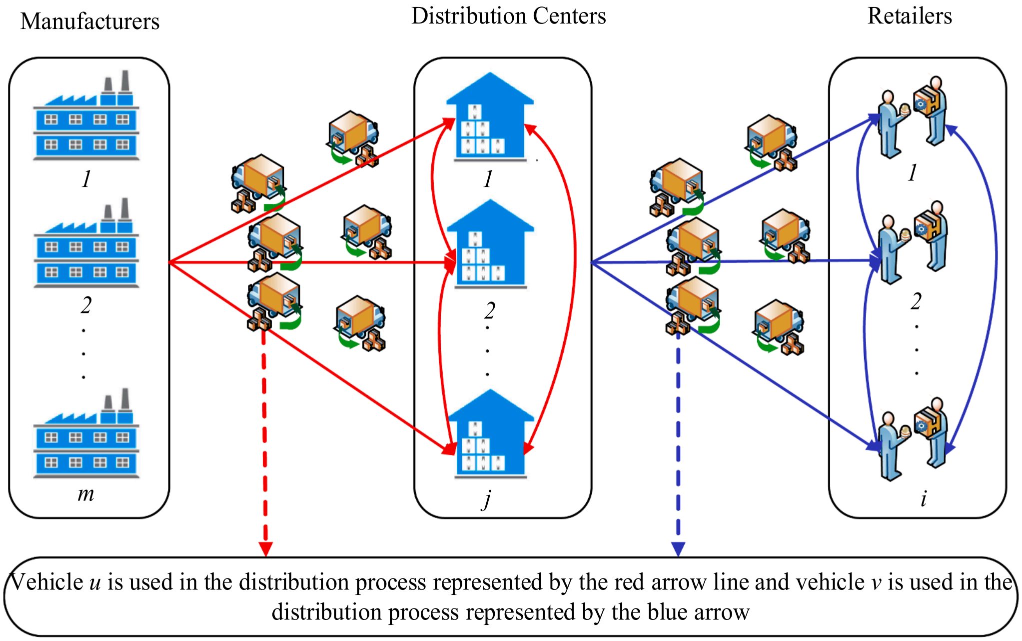

Fig. 1. The perishable product supply chain system.

delivered to retailer *1* or retailer *i* by distribution center *1*, *2,* or *j*, and then transported to retailer *2*. Finally, the location of the distribution centers is determined together with the distribution routes and the lot sizes of the distribution centers. To represent the real-world conditions of the supply chain system as close as possible, we design model assumptions as follows,

(1) A vehicle can only serve one route.
(2) All available vehicles of type u have the same characteristics.
(3) All available vehicles of type v have the same characteristics.
(4) The location of the retailers, the average cost of building the distribution centers, and carbon emissions levels are all known.
(5) The selected locations of the manufacturer and distribution centers according to different optimization objectives are used in the subsequent distribution process.

The list of parameters and variables used in this paper are summarized in Tables 2.

Table 2
Notations and definitions.

Notations	Definition	
Set	I	Retailer with demand set indexed from 1 to I, and $\forall i \in I$.
	J	Distribution center set indexed from 1 to J, and $\forall j \in J$.
	N	The period set of time remarked from 1 to N, and $\forall n \in N$.
	K	Product set from 1 to K, and $\forall k \in K$.
	M	Manufacturer set from 1 to M, $\forall m \in M$.
	U	Set of vehicles between the manufacturers and distribution centers or between distribution centers from 1 to U, $\forall u \in U$.
	V	Set of vehicles between the distribution centers and retailers or among retailers from 1 to V, $\forall v \in V$.
Parameters	α_{jk}^{n}	The safety factor of product k of distribution center j.
	h_{jk}^{n}	The holding cost of per unit product k per unit time at distribution center j in period n.
	g_{k}^{n}	Fixed cost of manufacturing product k.
	γ_{k}^{n}	Variable cost of manufacturing product k.
	f_j	Average cost when distribution center j is built.
	$\widehat{f}_j$	Average carbon emission when distribution center j is built.
	Q_{max}	the maximum vehicle loads.
	$\psi_{\xi wj}^{u}$	Fuel consumption coefficient of vehicle u at speed ξ_{wj}.
	$\psi_{\xi si}^{v}$	Fuel consumption coefficient of vehicle v at a speed ξ_{si}.
	ε_{k}^{n}	Inventory carbon emission of unit product k in period n.
	D_{ik}^{n}	The demand of retailer i for product k in period n.
	e_1	Fuel consumption cost per product per unit distance.
	D_{jik}^{n}	The demand of retailer i for product k supplied by distribution center j in period n.
	W	Infinite positive numbers.
	T_{jk}	The order cycle of product k of distribution center j
	DT_{i}^{max}	The maximum delivery time that retailer i is willing to receive the product, beyond the time, the retailer will reject the product.
	t_{j}^{n}	Replenishment lead time for distribution center j in period n.
Decision variables	S_{jk}^{max}	Maximum storage capacity of product k in distribution center j.
	$\wp_{jk}^{n}$	The number of products k delivered by the manufacturer to distribution center j in period n.
	ξ_{wj}	Delivery speed of vehicle u between w and j.
	ξ_{si}	Delivery speed of vehicle v between s and i.
	Q_{jk}^{n}	The order quantity of product k of distribution center j in period n.
	s_{jk}^{n}	The safety stock of product k of distribution center j in period n.
	$X_j = \begin{cases} 1 & \textit{Distribution center } j \textit{ is established.} \quad \forall j \in J \\ 0 & \textit{otherwise} \end{cases}$	
	$Y_{wj}^{u} = \begin{cases} 1 & \textit{Vehicle } u \textit{ is transported from } w \textit{ to } j. \\ 0 & \textit{otherwise} \end{cases} \quad \forall w \in (M \cup J),$ $i \in I, j \in J$	
	$X_{si}^{v} = \begin{cases} 1 & \textit{Vehicle } v \textit{ is transported from } s \textit{ to node } i. \\ 0 & \textit{otherwise} \end{cases} \quad \forall s \in (I \cup J), i \in I,$ $j \in J$	

4. Model development

4.1. Economic cost analysis

In this section, we discuss the economic cost factors to provide enterprises with information upon which to support their decision-making. In period n, it is assumed that the product demand of distribution center j follows an independent normal distribution $N\left(\mu_{jk}^{n}, \sigma_{jk}^{2n}\right)$. Also, because the market demand for perishable products fluctuates greatly, compared with other inventory strategies, it is better to adopt the (Q, s) strategy, which can monitor the change of inventory when the demand suddenly increases or decreases within a certain range (Ganeshan, 1999). The application of (Q, s) strategy can effectively reduce the inventory level of perishable products, unnecessary inventory backlog, and inventory holding costs. In the age of with information technology, decision-makers can monitor the inventory level in real-time, and the detection cost arising from the real-time monitoring is very low, even insignificant (Cui et al., 2017; Braglia et al., 2019). Because of this, we hence assume that the manufacturer uses the (Q, s) strategy (Saracoglu et al., 2014). After the establishment of distribution center j, the safety stock should be considered. Then, the inventory q_{jk}^{n}, order points r_{jk}^{n} are obtained, which are shown in formulas (1)–(2), respectively (Govindan et al. 2014; Elking et al. 2017; Demey and Wolff, 2016).

$$q_{jk}^{n} = s_{jk}^{n} + \alpha_{jk}^{n}\sqrt{t_{j}^{n}}\sigma_{jk}^{n}, \forall j \in J, k \in K, n \in N. \tag{1}$$

$$r_{jk}^{n} = s_{jk}^{n} + t_{j}^{n}\mu_{jk}^{n} + \alpha_{jk}^{n}\sqrt{t_{j}^{n}}\sigma_{jk}^{n}, \forall j \in J, k \in K, n \in N. \tag{2}$$

where t_{j}^{n} replenishment lead time for distribution center j in period n.

The average inventory of the manufacturer can be obtained by formula (1) and formula (2), as shown in (3):

$$\overline{q}_{jk}^{n} = s_{jk}^{n} + Q_{jk}^{n}/2 + \alpha_{jk}^{n}\sqrt{t_{j}^{n}}\sigma_{jk}^{n}, \forall j \in J, k \in K, n \in N. \tag{3}$$

After establishing the distribution center, the inventory cost of the manufacturer is

$$\sum_{k \in K}\left[\left(h_{jk}^{n}Q_{jk}^{n}/2 + h_{jk}^{n}s_{jk}^{n} + h_{jk}^{n}\alpha_{jk}^{n}\sqrt{t_{j}^{n}}\,\sigma_{jk}^{n}\right)T_{jk} + c(Q_{jk}^{n})\right] \quad \forall j \in J, k \in K, n \in N. \tag{4}$$

where,

$$T_{jk} = Q_{jk}^{n}/\mu_{jk}^{n}, \forall j \in J, k \in K, n \in N. \tag{5}$$

$$c(Q_{jk}^{n}) = g_{k}^{n} + \gamma_{k}^{n}Q_{jk}^{n}, \forall j \in J, k \in K, n \in N. \tag{6}$$

$c(Q_{jk}^{n})$ indicates the production cost of manufacture when the order quantity is Q_{jk}^{n}.

By allowing formula (4) to be divided by T_{jk} and substituting formulas (5)–(6), the cost per unit time of the manufacturer can be obtained as shown in formula (7),

$$\sum_{k \in K}\sum_{n \in N}\sum_{j \in J}\left[h_{jk}^{n}Q_{jk}^{n}/2 + h_{jk}^{n}s_{jk}^{n} + h_{jk}^{n}\alpha_{jk}^{n}\sqrt{t_{j}^{n}}\,\sigma_{jk}^{n} + \mu_{jk}^{n}c(Q_{jk}^{n})/Q_{jk}^{n}\right] \quad \forall j \in J, k \in K, n \in N. \tag{7}$$

Before establishing distribution centers, there is no need to consider the extra safety stock. Therefore, the cost per unit time of the manufacturer is calculated by formula (8):

$$\sum_{k \in K}\sum_{n \in N}\sum_{j \in J}\left[h_{jk}^{n}Q_{jk}^{n}/2 + h_{jk}^{n}\alpha_{jk}^{n}\sqrt{t_{j}^{n}}\,\sigma_{jk}^{n} + \mu_{jk}^{n}c(Q_{jk}^{n})/Q_{jk}^{n}\right] \quad \forall j \in J, k \in K, n \in N. \tag{8}$$

By taking the derivative of formula (8) concerning Q_{jk}^{n}, the optimal order quantity can be as follows,

$$Q_{jk}^{*n} = \sqrt{\frac{2\mu_{jk}^{n}g_{k}^{n}}{h_{jk}^{n}}} \; \forall j \in J, k \in K, n \in N. \tag{9}$$

Then, the cost before establishing distribution centers can be obtained by substituting formula (6) and (9) into formula (8) and is shown as follows,

$$\begin{aligned} &\sum_{k}\sqrt{\frac{h_{jk}^{n}g_{k}^{n}\mu_{jk}^{n}}{2}} + h_{jk}^{n}\alpha_{jk}^{n}\sqrt{t_{j}^{n}}\sigma_{jk}^{n} + \sqrt{\frac{h_{jk}^{n}g_{k}^{n}\mu_{jk}^{n}}{2}} + \mu_{jk}^{n}\gamma_{k}^{n} \\ &= \sum_{k}\sqrt{2h_{jk}^{n}g_{k}^{n}\mu_{jk}^{n}} + h_{jk}^{n}\alpha_{jk}^{n}\sqrt{t_{j}^{n}}\sigma_{jk}^{n} + \mu_{jk}^{n}\gamma_{k}^{n}, \forall j \in J, k \in K, n \in N. \end{aligned} \tag{10}$$

Therefore, the incremental cost due to the establishment of distribution center j is shown as follows,

$$\begin{aligned}&\sum_{k\in K}\sum_{n\in N}\sum_{j\in J}\left\{\left[f_j + h^n_{jk}Q^n_{jk}/2 + h^n_{jk}s^n_{jk} + h^n_{jk}\alpha^n_{jk}\sqrt{t^n_j}\,\sigma^n_{jk} + \mu^n_{jk}c(Q^n_{jk})/Q^n_{jk} - \left(\sqrt{2h^n_{jk}g^n_k\mu^n_{jk}} + h^n_{jk}\alpha^n_{jk}\sqrt{t^n_j}\,\sigma^n_{jk} + \mu^n_{jk}\gamma^n_k\right)\right]X_j\right\}\\ &= \sum_{k\in K}\sum_{n\in N}\sum_{j\in J}\left\{\left[f_j + h^n_{jk}Q^n_{jk}/2 + h^n_{jk}s^n_{jk} + \mu^n_{jk}c(Q^n_{jk})/Q^n_{jk} - \left(\sqrt{2h^n_{jk}g^n_k\mu^n_{jk}} + \mu^n_{jk}\gamma^n_k\right)\right]X_j\right\}\\ &= \sum_{k\in K}\sum_{n\in N}\sum_{j\in J}\left\{\left[f_j + h^n_{jk}Q^n_{jk}/2 + h^n_{jk}s^n_{jk} + \mu^n_{jk}g^n_k/Q^n_{jk} - \sqrt{2h^n_{jk}g^n_k\mu^n_{jk}}\right]X_j\right\}\end{aligned} \quad (11)$$

4.2. Carbon emission analysis

In this section, we mainly consider the carbon emission generated by the process of establishing distribution centers, the vehicle distribution process, and the product inventory (Balamurugan et al., 2018; Cheng et al., 2016; Kuo et al., 2014).

(1) Carbon emissions from distribution centers

Due to the large scale of the distribution center construction and the large number of consumables, the carbon emissions in the construction process cannot be ignored. Therefore, the average carbon emissions in the service life cycle of distribution centers are considered as formulation (12).

$$\sum_{j\in J}\hat{f}_j X_j \quad (12)$$

(2) Transportation-related carbon emissions

Product transportation is the most important link between energy consumption and carbon emissions, and it has practical significance when taken as a combination of vehicle speed, fuel consumption, and carbon emissions (Xiao et al. 2012). In the process of a vehicle being used for distribution, the fuel consumption is related not only to the distance the vehicle travels but also to the vehicles' loading and driving speed.

In general, the fuel consumption p per unit distance approximates to a linear function of the carrying capacity q,

$$p(q) = a(Q_0 + q) + b. \quad (13)$$

where a and b are constants that are greater than zero, Q_0 is the weight of the vehicle itself.

When a vehicle is not loaded, the fuel consumption per unit distance p_0 is obtained by formula (14),

$$p_0 = aQ_0 + b. \quad (14)$$

When the vehicle is fully loaded, the fuel consumption p^* per unit distance is shown in formula (15),

$$p^* = a(Q_0 + Q_{max}) + b. \quad (15)$$

Finally, combining formulas (14) and (15), the relationship between vehicle weight and fuel consumption can be obtained as,

$$p(q) = p_0 + [(p^* - p_0)/Q_{max}]q \quad (16)$$

The carbon emissions of vehicles during the distribution between i and j are

$$e(q_{ij}) = e_0\psi^{\xi}_0 p(q_{ij})d_{ij}, \quad (17)$$

where q_{ij} represents the load capacity between i and j in the routes; e_0 indicates carbon emission coefficient of fuel; ψ^{ξ}_0 is the fuel consumption coefficient when the vehicle is running at the standard speed and d_{ij} represents the distance between i and j.

Therefore, the carbon emissions generated during the distribution process are given as follows,

$$\begin{aligned}&e_0(\psi^u_{\xi_{wj}}\sum_{u\in U}\sum_{w\in(M\cup J)}\sum_{j\in J}(p^u + (p^{*u} - p^u)/Q^u_{max}q^u)d_{wj}Y^u_{wj} +\\ &\psi^v_{\xi_{si}}\sum_{v\in V}\sum_{s\in(I\cup J)}\sum_{i\in I}(p^v + (p^{*v} - p^v)/Q^v_{max}q^v)d_{si}X^v_{si})\end{aligned} \quad (18)$$

(3) Inventory carbon emissions

In this paper, it is assumed that inventory carbon emission is the carbon emissions per unit product in inventory. After multiplying the average inventory and the inventory carbon emissions, the carbon emissions from the product inventory can be obtained,

$$\sum_{j \in J} \sum_{k \in K} \varepsilon_k^n (s_{jk}^n + Q_{jk}^n / 2 + \alpha_{jk}^n \sqrt{t_j^n} \sigma_{jk}^n) \tag{19}$$

Therefore, the carbon emissions generated from the process of location-inventory-routing are shown in formula (20)

$$\begin{aligned} & e_0(\psi_{\xi_{wj}}^u \sum_{u \in U} \sum_{w \in (M \cup J)} \sum_{j \in J} (p^u + (p^{*u} - p^u) / Q_{max}^u q^u) d_{wj} Y_{wj}^u + \\ & \psi_{\xi_{si}}^v \sum_{v \in V} \sum_{s \in (I \cup J)} \sum_{i \in I} (p^v + (p^{*v} - p^v) / Q_{max}^v q^v) d_{si} X_{si}^v) \\ & + \sum_{j \in J} \sum_{k \in K} \varepsilon_k^n (s_{jk}^n + Q_{jk}^n / 2 + \alpha_{jk}^n \sqrt{t_j^n} \sigma_{jk}^n) + \sum_{j \in J} \hat{f}_j X_j \end{aligned} \tag{20}$$

4.3. Freshness analysis

For any perishable product k, the freshness of the product starts deteriorating immediately and decreases rapidly over time once it is produced. In this paper, a monotone continuous decreasing function $\theta_p(DT)$ is used to describe the change in the freshness of product k over time (Sinesio et al. 2018; Van et al. 2010). Assuming the product completion time is 0, the freshness of the product received by retailer i at time t can be expressed as $\theta_p(DT_i)$. Freshness changes with time, as shown in Fig. 2, where $\theta_p(T_i) = 1 - (DT_i / DT_i^{max})^2; 0 \leqslant DT_i \leqslant DT_i^{max}$. When the delivery time exceeds DT_i^{max}, the retailer refuses to accept the product; on this basis, the freshness of the product is 0. Therefore, a model of product freshness is obtained as follows,

$$\begin{aligned} & \sum_{i \in I} \left\{ 1 - \left[\left(\sum_{w \in (M \cup J)} \sum_{j \in J} d_{wj} / \xi_{wj} + \sum_{s \in (I \cup J)} \sum_{i \in I} d_{si} / \xi_{si} \right) / DT_i^{max} \right]^2 \right\} \\ & = \sum_{i \in I} \left\{ 1 - \left[\left(\sum_{w \in (M \cup J)} \sum_{j \in J} DT_{wj} + \sum_{s \in (I \cup J)} \sum_{i \in I} DT_{si} \right) / DT_i^{max} \right]^2 \right\} \end{aligned} \tag{21}$$

Formula (21) demonstrates the formula for calculating the freshness of products, where $w \in (M \cup J)$, $s \in (I \cup J)$, $u \in U$, $v \in V$, $i \in I$, $j \in J$.

4.4. Objective functions

Through the above analysis, the following objective functions and constraints are constructed. The key objectives are to minimize the cost Z_1^C, the carbon emissions Z_2^E, and maximize the freshness Z_3^θ. Regarding minimizing the cost Z_1^C, the total transportation distance is relatively fixed before the establishment of the distribution center because the perishable products are distributed directly from the manufactures to retailers without considering optimization. However, after the establishment of the distribution center, the total transportation distance is constantly changing due to different influencing factors, such as replenishment lead time for the distribution center, the loading capacity of the vehicle, the maximum delivery time allowed by retailer, and so on, therefore, fuel consumption cost should be considered in Z_1^C. The different objective functions are shown as follows,

$$\begin{aligned} minZ_1^C = & \sum_{k \in K} \sum_{n \in N} \sum_{j \in J} \left\{ \left[f_j + h_{jk}^n Q_{jk}^n / 2 + h_{jk}^n s_{jk}^n + \mu_{jk}^n g_k^n / Q_{jk}^n - \sqrt{2 h_{jk}^n g_k^n \mu_{jk}^n} \right] X_j \right\} \\ & + e_1(\psi_{\xi_{wj}}^u \sum_{u \in U} \sum_{w \in (M \cup J)} \sum_{j \in J} (p^u + (p^{*u} - p^u) / Q_{max}^u q^u) d_{wj} Y_{wj}^u \\ & \quad + \psi_{\xi_{si}}^v \sum_{v \in V} \sum_{s \in (I \cup J)} \sum_{i \in I} (p^v + (p^{*v} - p^v) / Q_{max}^v q^v) d_{si} X_{si}^v). \end{aligned} \tag{22}$$

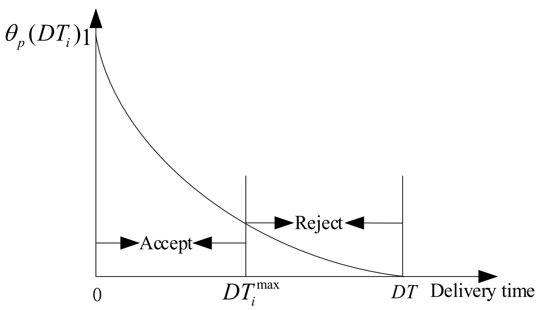

Fig. 2. Product freshness changes and accepted conditions.

$$\begin{aligned}\min Z_2^E = e_0(\psi^u_{\xi_{wj}}\sum_{u\in U}\sum_{w\in(M\cup J)}\sum_{j\in J}(p^u+(p^{*u}-p^u)/Q^u_{max}q^u)d_{wj}Y^u_{wj}\\ +\psi^v_{\xi_{si}}\sum_{v\in V}\sum_{s\in(I\cup J)}\sum_{i\in I}(p^v+(p^{*v}-p^v)/Q^v_{max}q^v)d_{si}X^v_{si})\\ +\sum_{j\in J}\sum_{k\in K}\varepsilon^n_k(s^n_{jk}+Q^n_{jk}/2+\alpha^n_{jk}\sqrt{t^n_j}\sigma^n_{jk})+\sum_{j\in J}\widehat{f}_jX_j.\end{aligned} \tag{23}$$

$$\max Z_3^\theta = \sum_{i\in I}\left\{1-\left[\left(\sum_{w\in(M\cup J)}\sum_{j\in J}DT_{wj}+\sum_{s\in(I\cup J)}\sum_{i\in I}DT_{si}\right)/DT_i^{max}\right]^2\right\} \tag{24}$$

$$\sum_{v\in V}\sum_{s\in(I\cup J)}\sum_{i\in I}q^vX^v_{si}\geqslant D^n_{ik}, \forall i\in I, j\in J, v\in V. \tag{25}$$

$$\sum_{u\in U}\sum_{w\in(M\cup J)}\sum_{j\in J}q^uY^u_{wj}\geqslant\sum_{j\in J}s^n_{jk}, \forall m\in M, i\in I, j\in J, u\in U. \tag{26}$$

$$\sum_{v\in V}X^v_{si}\geqslant 1, s\in(I\cup J), \forall i\in I, j\in J, v\in V. \tag{27}$$

$$\sum_{s\in(I\cup J)}X^v_{si}-\sum_{s\in(I\cup J)}X^v_{is}=0, \forall i\in I, j\in J, v\in V. \tag{28}$$

$$D^n_{ik}+\sum_{j\in J}s^n_{jk}\leqslant\sum_{j\in J}S^{max}_{jk}, \forall n\in N, j\in J, k\in K. \tag{29}$$

$$Q^n_{jk}=Q^{n-1}_{jk}-\sum_{i\in I}D^{n-1}_{jik}+\wp^{n-1}_{jk},\quad \forall j\in J, k\in K, n\geqslant 2. \tag{30}$$

$$Q^n_{jk}\geqslant s^n_{jk}, \forall j\in J, k\in K, n\in N. \tag{31}$$

$$\sum_{j\in J}D^n_{jik}\geqslant D^n_{ik}, \forall i\in I, m\in M, k\in K, n\in N. \tag{32}$$

$$D^n_{jik}\leqslant\frac{max\{DT_i^{max}-DT_{wj}-DT_{si},0\}}{DT_i^{max}-DT_{wj}-DT_{si}}W, \forall w\in(M\cup J), s\in(I\cup J), k\in K, i\in I, j\in J, m\in M. \tag{33}$$

$$Q^n_{jk}\leqslant\sum_{j\in J}\wp^n_{jk}\quad \forall j\in J, k\in K. \tag{34}$$

$$D^n_{jik}\geqslant 0, \forall i\in I, j\in J, k\in K, n\in N. \tag{35}$$

$$\sum_{j\in J}\wp^n_{jk}\geqslant\sum_{i\in I}D^n_{ik}, \forall i\in I, j\in J, k\in K, n\in N. \tag{36}$$

where Eqs. (22), (23) and (24) represent three objective functions, which are to minimize economic costs, carbon emissions, and maximize freshness. Constraint (25) ensures that the sum of the actual distributed perishable products of all of the vehicles passing through retailer i is greater than or equal to the demand of retailer i. Constraint (26) guarantees that the total number of vehicles u that pass through distribution center j is larger than the safety stock of distribution center j. Constraint (27) indicates that at least one vehicle is available for distribution between nodes (from distribution centers to retailers or between retailers). Constraint (28) shows that the sum of the actual distributed perishable products is equal between repetitive nodes. Constraint (29) indicates that the demand of retailer i in period n does not exceed the sum of the safety stock of distribution center j and does not simultaneously exceed the sum of the maximum stock capacity of distribution center j. Constraint (30) is the inventory expression of product k that is available in the early period n of distribution center j. Constraint (31) denotes that at the beginning of period n, the available stock of product k in distribution center j is greater than or equal to the safety stock. Constraint (32) denotes that the demand of retailers i must be met. Constraint (33) is the time constraint of product k. Constraint (34) requires that the order quantity of product k is less than the manufacturer's production when the distribution center is built at j. Constraint (35) is a non-negative variable constraint. Constraint (36) indicates that the production of the manufacturer is greater than the demand of the retailers.

5. Model solving based on YALMIP toolbox

YALMIP is a free MATLAB toolbox developed by Lofberg in 2004, which is featured by its openness, integration, and ease of use

(Lofberg, 2004). YALMIP is a special optimization modeling language, which is widely used to solve optimization problems in traffic engineering, control, and system engineering. At present, there are two common approaches to solve optimization problems: (1) Use solver. Most solvers require the users to describe practical problems in a specific format. This is not only time-consuming in terms of learning but also error-prone in terms of programming. (2) Use the intelligent optimization algorithm. The related theory of an intelligent algorithm mainly comes from the simulation of the social nature of a biological community. As such, the related mathematical analysis and theoretical foundation are relatively weak. There is no exact theoretical basis for setting parameters in intelligent algorithms. The parameters are usually determined by empirical methods, which depend heavily on specific environments and lack standard test sets for performance evaluation. Most importantly, the solution obtained by an intelligent algorithm is far more likely to be a satisfactory solution than an optimal one.

However, using the YALMIP toolbox can solve the problems in the above methods. Especially for the sustainable supply chain management for perishable products, YALMIP has two significant advantages: (1) In addition to its own multi-objective linear programming algorithm, it also provides a programming interface, which can easily involve almost all optimization software solvers. This greatly improves its ability to solve the proposed model. (2) YALMIP toolbox realizes the separation of modeling and algorithm. It provides a unified, simple, and intuitive modeling language for all complex optimization problems. The solver can be specified through parameter settings. Even if no specific solver is specified, the YALMIP toolbox will automatically select the most suitable and installed solver (see Mardani et al. 2018; Wang et al. 2018; Moaveni and Najafi, 2017).

The steps to solve the model using the YALMIP toolbox are given as follows:

Step 1: Defining the decision variables.

A YALMIP toolbox uses a sdpvar () command to define the decision variables. For example, Y = sdpvar (n, m) indicates a matrix of order $n \times m$, for this research issues, Y = sdpvar (M, J) indicates manufacturer M distributes products to distribution center J, Y = sdpvar (J, I) represents distribution center J distributes products to retailer I.

Step 2: Adding the constraints.

Table 3
Parameters used in the case study.

Location number	Location longitude	latitude	Distribution center construction cost yuan/T	Carbon emissions of distribution center construction kg/T	Demand units/T
1	116.53	39.55	1190	241	(3,450,60^2)
2	117.13	38.15	1000	199	(2,599,60^2)
3	121.4	31.2	1110	219	(3,378,60^2)
4	106.53	29.55	950	208	(2,579,60^2)
5	114.47	38.07	900	190	(2,696,60^2)
6	112.48	37.95	900	218	(2,485,60^2)
7	123.48	41.93	890	191	(2,340,60^2)
8	125.37	44.03	900	201	(1,665,60^2)
9	126.68	45.77	925	232	(2,537,60)
10	118.82	32.08	940	235	(2,398,60^2)
11	120.15	30.27	960	230	(2,650,60^2)
12	117.2	32	880	210	(1,695,60^2)
13	119.28	26.07	875	204	(1,841,60^2)
14	115.92	28.77	799	197	(2,970,60^2)
15	117.03	36.65	769	215	(3,173,60^2)
16	113.65	34.77	800	225	(3,244,60^2)
17	114.25	30.58	810	228	(2,509,60^2)
18	113.03	28.2	800	229	(3,473,60^2)
19	113.28	23.13	900	217	(2,909,60^2)
20	110.28	20	900	192	(2,807,60^2)
21	104.05	30.62	890	222	(2,214,60^2)
22	106.75	26.58	700	180	(2,599,60^2)
23	102.65	25.05	720	205	(3,008,60^2)
24	108.93	34.22	860	226	(3,461,60^2)
25	103.82	36.15	700	218	(2,454,60^2)
26	101.78	36.6	705	196	(2,272,60^2)
27	109.35	24.6	740	191	(2,346,60^2)
28	111.7	41.07	690	203	(2,449,60^2)
29	91.08	29.63	685	275	(1,903,60^2)
30	106.25	38.48	785	231	(2,604,60^2)
31	87.57	43.82	750	216	(2,347,60^2)

Note: Considering the depreciation cost of the distribution center, this paper assumes that the distribution center completes a distribution in a cycle T, the carbon emission of distribution center construction is also divided into cycles, and the demand also represents the demand per cycle. Here, T is assumed to be a day, 360 days a year (Mallidis et al. 2012; Wang, 2019).

The YALMIP toolbox defines the constraints in the form of F = [constraints]. For this issues, initialize F = []; then (1) F = [F; sum (j)==J; sum(m)==M]; (2) $F = [F; \sum_{v\in V}\sum_{s\in(I\cup J)}\sum_{i\in I}q^v X^v_{si} \geqslant D^n_{ik}; \ldots; \sum_{j\in J}\wp^n_{jk} \geqslant \sum_{i\in I}D^n_{ik}; \sum_{i\in I}D^n_{ik} \leqslant S^{max}_{jk}]$. In this step, it should be noted that when using a YALMIP toolbox to define inequality constraints, it is not necessary to strictly define them, but ">=" or "<=" must be chosen.

Step 3: Solving the optimization problem.

The YALMIP toolbox uses the optimizer (Constraints, Objective) command to solve the optimization problems. Optimizer (F, f) means solving the objective minimization problem. Here, F denotes the constraints, f represents the objective function, and -f represents solving the objective function maximization problem. In this paper, optimizer (F,Z^C_1) and optimizer (F,Z^E_2) indicates the minimization of the cost and the carbon emissions respectively, also, optimizer (F, -Z^θ_3) represents the maximization of the freshness.

Step 4: Obtaining the value of the decision variable.

After the optimization problem is solved with the optimizer (Constraints, Objective) command. The value of the decision variable can be extracted with the double () command. The double (sdpvar (M, J)) illustrates the distribution relationship between the manufacturer M and distribution center J, the double (sdpvar (J, I)) illustrates the distribution relationship between distribution center J and retailer I.

6. Case study

In this section, we use a case study to present the effectiveness and feasibility of the proposed model. Suppose that a firm plans to build five distribution centers and a manufacturing facility covering 31 major cities in China. It has multiple decision objectives: (1) minimize economic costs; (2) minimize carbon emissions; and (3) maximize product freshness. The related parameters are shown in Table 3 (Ma and Zhou, 2018; Gao et al., 2005). In addition, we assume that the holding cost of unit product k at distribution center j, h_j, is equal to 1. When product k is manufactured, the fixed cost is $g_k = 1$. The variable cost is $a_k = 0.5$. The order lead time is $t_j = 3$. When the delivery time exceeds 10 days, the retailer i refuse to accept the product, that is $T^{max}_i = 10$. The maximum load capacity Q^u_{max} of vehicle u is equal to 10,000. Fuel consumption cost per product per unit distance $e_1 = 5$. Carbon emission coefficient value of fuel $e_0 = 7$. The minimum load capacity Q^v_{max} of vehicle v is equal to 4500. When vehicle u is unloaded, its fuel consumption is 0.3. When vehicle u is fully loaded, its fuel consumption is 0.5. When vehicle v is unloaded, its fuel consumption is 0.1. When vehicle v is fully loaded, its fuel consumption is 0.25. The inventory carbon emission per unit of product is 0.1. When the speed of vehicle u is 90, the speed of vehicle v is 100; then, their fuel coefficient is 1. The safety stock of the distribution centers is 500. For the convenience of description, in the Figures of the case study, we use v to represent the speed of vehicle v, and u to represent the speed of vehicle u.

The example is realized by MATLAB 2015b. With the objective of minimum economic cost, minimum carbon emission, and maximum freshness, different optimization schemes are obtained. Meanwhile, once optimization schemes are determined, the distribution centers will be implemented throughout the subsequent distribution process. The detailed results are shown in Table 4.

In Table 4, it is easy to find the distribution routes and distribution volume of each scheme. Where Q_{ij} represents the capacity of the distribution center. For example, when cost minimization is achieved, location 22 is chosen for the manufacturer, and locations 22, 25, 26, 28, and 29 are chosen as the distribution centers. If location 26 is used as a distribution center, 2,696, 2,398, 254, 2,449 units of perishable products can be distributed to locations 5, 10, 15, and 28, respectively, with a total capacity of 7,797.

Through the analysis of results in Table 4, when the objective is to minimize the economic cost, the optimal plan is to establish location 22 as the manufacturer and locations 22, 25, 26, 28, 29 as the distribution centers. The specific distribution process is shown in

Table 4
Optimal distribution schemes under different objective functions.

Manufacturers	Distribution centers	Distribution route (Distribution volume)	Q_{ij}
22 (f1)	22	1(3,450), 8(1,665), 9(2,537), 12(1,695), 18(3,473), 26(2,272), 29(360), 31(2,347)	17,799
	25	3(3,378), 17(2,509), 20(2,807), 21(2,214), 22 (2,599), 27(2,346), 29(1,543), 30(2,604)	20,000
	26	5(2,696), 10(2,398), 15(254), 28(2,449)	7797
	28	4(2,579), 6(2,485), 7(2,340), 13(1,841), 14(2,970), 16(3,244)	15,459
	29	2(2,599), 11(2,650), 15(2,919), 19(2,909), 23(3,008), 24(3,461), 25(2,454)	20,000
27 (f2)	5	2(2,599), 7(2,340), 14(2,970), 17(2,509), 31(2,347)	12,765
	7	1(3,450), 4(2,579), 6(2,485), 13(1,841), 16(3,244), 22(2,599), 24(3,461), 26(341)	20,000
	20	8(1,665), 9(2,537), 11(2,650), 12(1,695), 18(3,473), 26(1,931)	13,951
	22	3(3,378), 15(2,294), 20(2,807), 21(2,214), 25(2,454), 27(2,346), 29(1,903), 30 (2,604)	20,000
	27	5(2,696), 10(2,398), 15(879),19(2,909), 23(3,008), 28 (2,449)	14,339
30 (f3)	27	8(137), 9(2,537), 10(2,398), 11(2,650), 12(1,695), 13(1,841), 14(2,970), 15(3,173), 16(2,599)	20,000
	28	1(2,395), 2(2,599), 3(3,378), 4(2,579), 5(2,696), 6(2,485), 7(2,340), 8(1,528)	20,000
	29	1 (1,055)	1055
	30	17(2,509), 19(2,909), 20(2,807), 22(2,599), 27(2,346), 28(1,879), 30(2,604), 31 (2347)	20,000
	31	16(645), 18(3,473), 21(2,214), 23(3,008), 24(3,461), 25(2,454), 26(2,272), 28(570), 29(1,903)	20,000

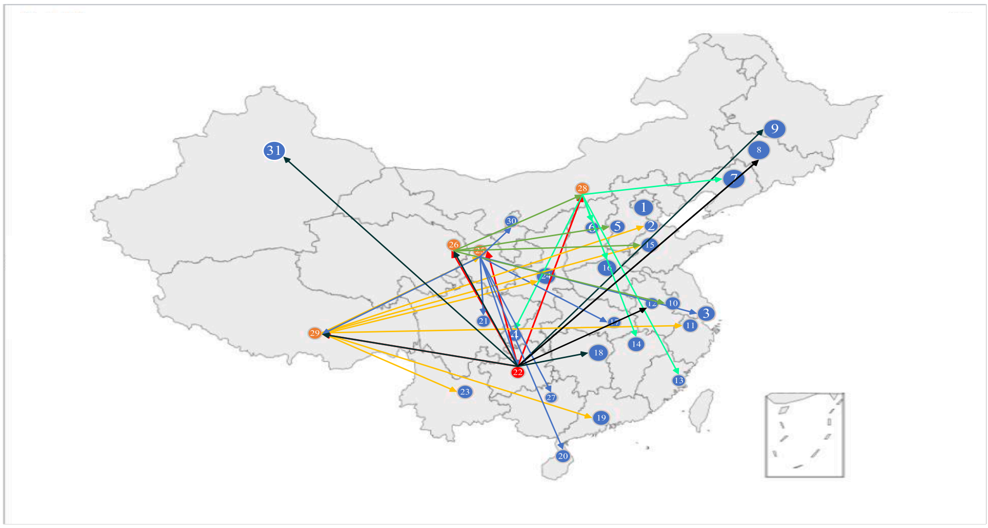

Fig. 3. Product distribution plan with the lowest economic cost.

Fig. 3, where, the red arrow indicates the manufacturer's transportation route to different distribution centers. Other arrows indicate the transportation route from the distribution center to different retailers.

When the objective is to minimize the carbon emissions, the optimal plan here is to establish location 27 as the manufacturer and locations 5, 7, 20, 22, and 27 as the distribution centers. The specific distribution process is shown in Fig. 4.

When product freshness is the primary objective, the optimal plan is to establish location 30 as the manufacturer and locations 27, 28, 29, 30, and 31 as the distribution centers. The specific distribution process is shown in Fig. 5.

In the above figures, the size of the bubble represents the demand in the area. The red dots represent the manufacturer's location, the orange dots represent the distribution centers' locations, and the blue dots represent the retailers. Different lines represent the distribution directions of the manufacturer and distribution centers. The optimal solution of the model is obtained by YALMIP.

7. Sensitivity analysis

In the model, the speed of travel between the manufacturer and distribution centers (or between a distribution center and the retailers) is an important input parameter. In this section, a sensitivity analysis is utilized to reveal the impact of the vehicle speed on

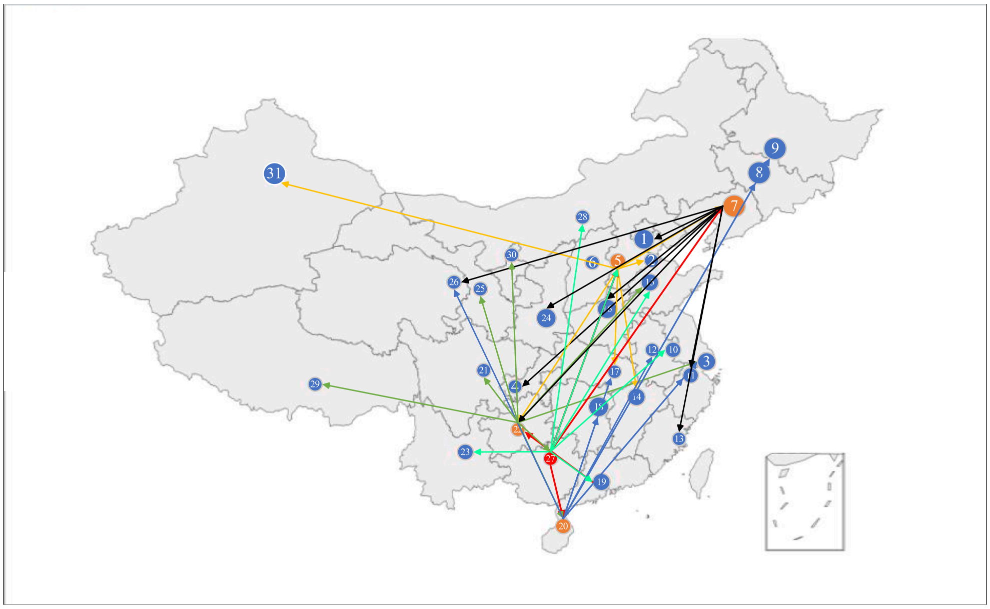

Fig. 4. Product distribution plan to achieve the lowest carbon emissions.

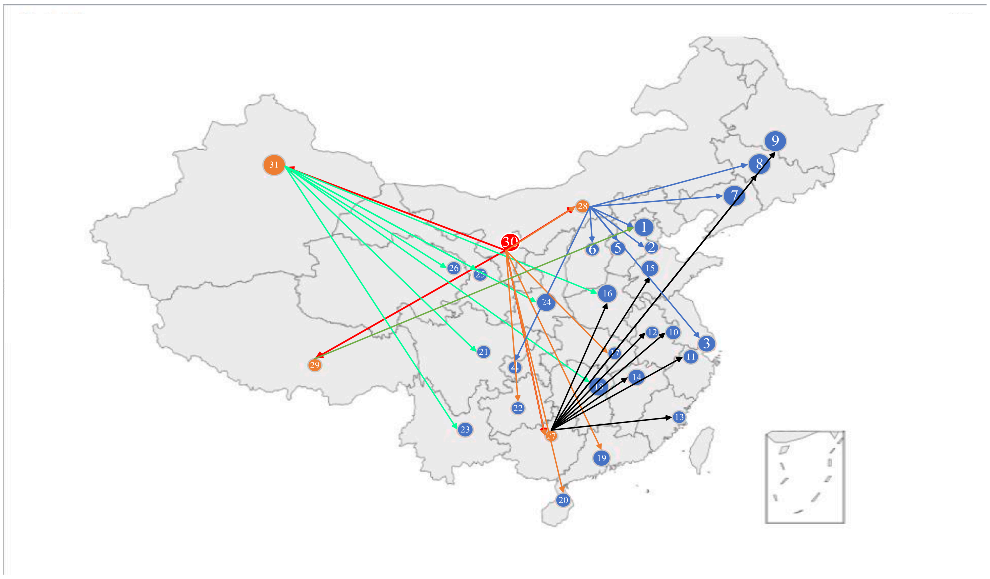

Fig. 5. The product distribution plan aimed to achieve the highest freshness.

the objective function value. First, with the minimum cost, the minimum carbon emissions, and the maximum freshness as the goals, the optimal scheme is obtained. Then, the influence of the speed of vehicles u and v on the objective function is explored. Considering the actual situation, two scenarios are assumed: (1) the speed range of vehicle u is assumed to be between 80 km/h and 110 km/h, and that of vehicle v is between 80 km/h and 120 km/h; (2) the actual speed of vehicle v is assumed to range between 80 km/h and 110 km/h, and that of vehicle u is between 70 km/h and 110 km/h. The fuel consumption at different speeds is shown in Table 5. For example, when the speed of vehicle u is 80 km/h, 90 km/h, 100 km/h and 110 km/h, the fuel consumption coefficients are 0.9, 1.0, 1.1 and 1.2, respectively. When the speed of vehicle v is 80 km/h, 90 km/h, 100 km/h, 110 km/h and 120 km/h, the fuel consumption is 0.8, 0.9, 1.0, 1.1 and 1.25, respectively. Considering that a load of vehicle u is relatively large and the speed of vehicle u should not be too high, the maximum speed of vehicle u allowed in this paper is 110 km/h. The corresponding analysis results are shown in Figs. 6 and 7, respectively.

In the analysis of the above two scenarios, changing the speeds of vehicles u and v leads to a change in the objective function. However, Figs. 6 and 7 only illustrate the speed that affect the objective function. The size and extent of the impact cannot be accurately determined. Therefore, the results of the proposed algorithm are analyzed in detail, and the influence of the speed on objective functions and specific influence trends are obtained.

First, we analyze the impact of the speed on the manufacturers' economic costs. As illustrated by Fig. 8, the economic costs constantly decrease concerning the speeds of vehicles u and v. However, when the speed of vehicle u exceeds 90 km/h and vehicle v exceeds 100 km/h, the manufacturers' costs are constantly on the rise.

Second, we analyze the influence of changing vehicle speeds on a manufacturer's carbon emissions levels. The results of Fig. 9 indicate that with an increase in vehicle speed, the manufacturer's carbon emissions levels continuously decrease. However, when the vehicle speed exceeds 90 km/h and then 100 km/h, the manufacturer's carbon emissions levels show an increasing trend.

Finally, the effect of the speed changing on product freshness is analyzed. The results show that product freshness levels increase concerning the vehicles' speeds. However, the product freshness does not increase infinitely; it tends to maximize at 31. The specific trends are shown in Fig. 10. When the vehicle speed exceeds a certain range, the manufacturer's cost and carbon emissions levels will increase in line with the increasing speed. Therefore, when making decisions, the manufacturer should measure the relationships between all three objectives.

First, assuming the speed of vehicle u is determined, and we study the influence of the change of speed v on the three objective functions. Then, speed of vehicle v is determined, and the influence of the change speed u on the objective function is observed. Through Fig. 6 and Fig. 7, we find that the change trend of the objective function is the same. This means, when the speed of vehicle v is

Table 5
Velocity and corresponding fuel consumption coefficient.

Fuel consumption coefficient	Speed					
	70 km/h	80 km/h	90 km/h	100 km/h	110 km/h	120 km/h
$\psi^{u}_{\xi_{wj}}$	0.8	0.9	1.0	1.1	1.2	–
$\psi^{v}_{\xi_{sj}}$	–	0.8	0.9	1.0	1.1	1.25

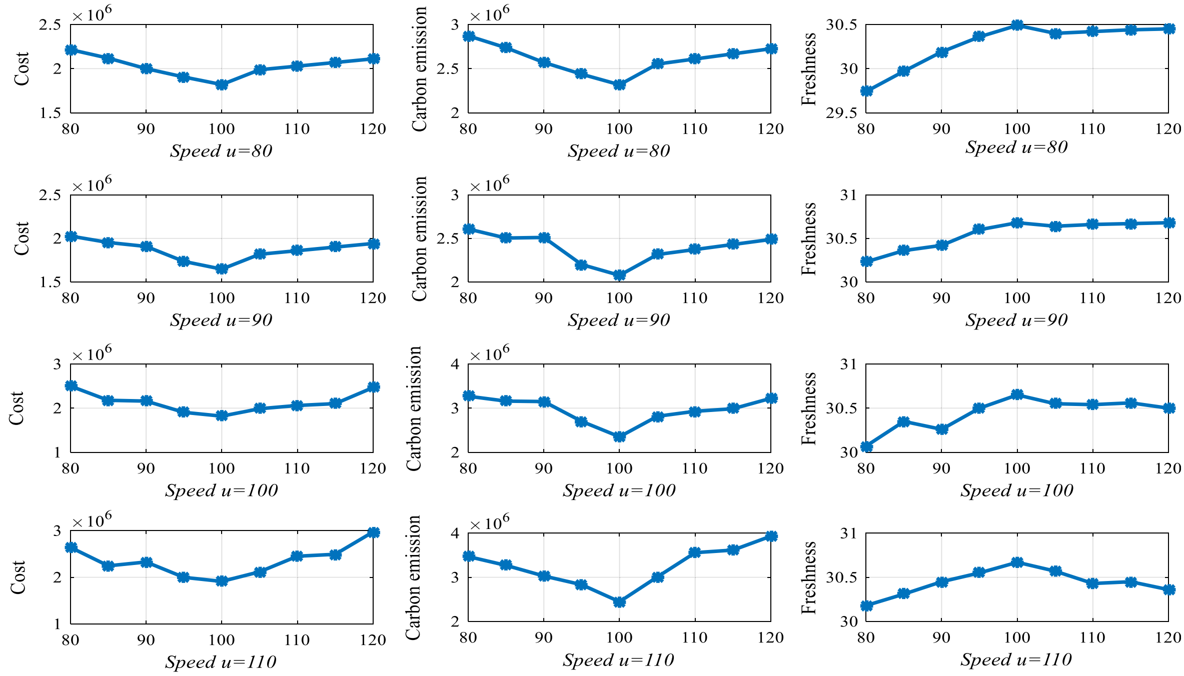

Fig. 6. Trend chart of the objective function of vehicle *u* with the speed of vehicle *v*.

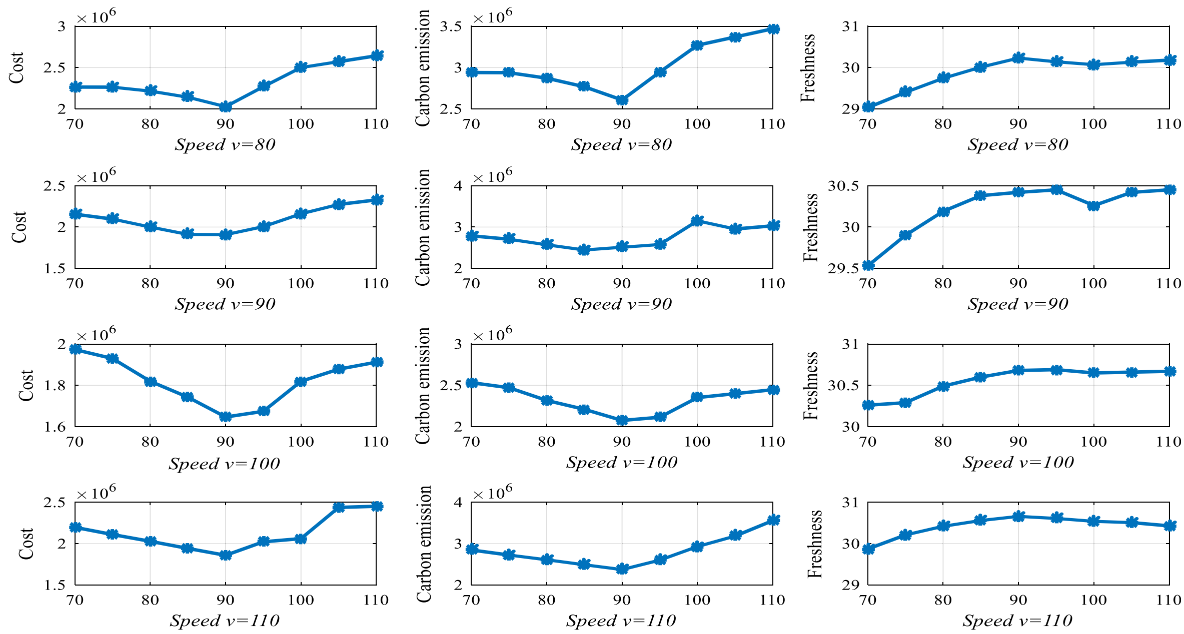

Fig. 7. Trend chart of the objective function of vehicle *v* with the speed of vehicle *u*.

100 km/h and the speed of vehicle *u* is 90 km/h, the economic cost and carbon emission are the lowest. Besides, changing the fuel factor and carbon emission coefficient of the vehicles will not affect the change trend of the results, because, in the model, the fuel factor and carbon emission coefficient are linear with the objective function. Therefore, to a certain extent, it shows that the research results have certain robustness.

Through the analysis, we find that the running speeds of the vehicle *u* and *v* will affect the economic cost, carbon emissions, and product freshness. When the speed of vehicle *u* is 90 km/h and the speed of vehicle *v* is 100 km/h, the total economic cost and carbon emission cost are optimal. As for product freshness, the higher the speed, the higher the freshness product.

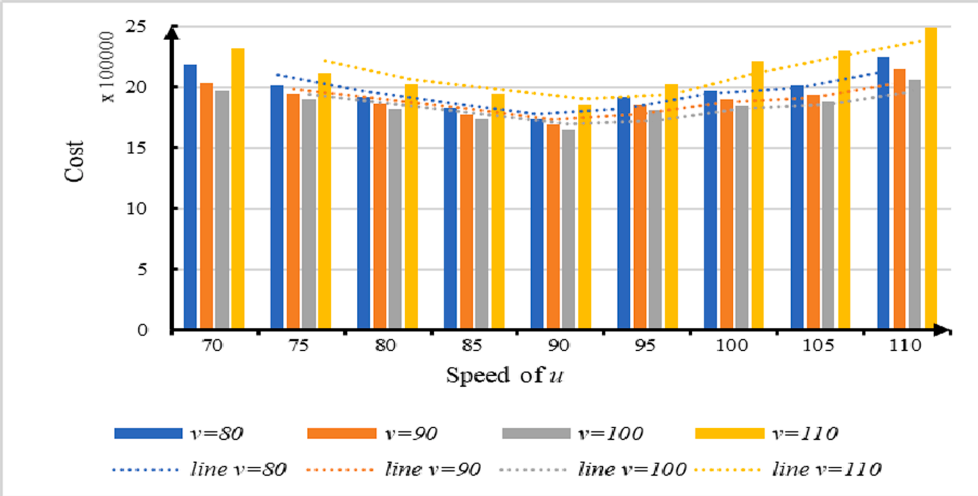

Fig. 8. Trend chart of the impact of vehicle *u* and vehicle *v* on cost.

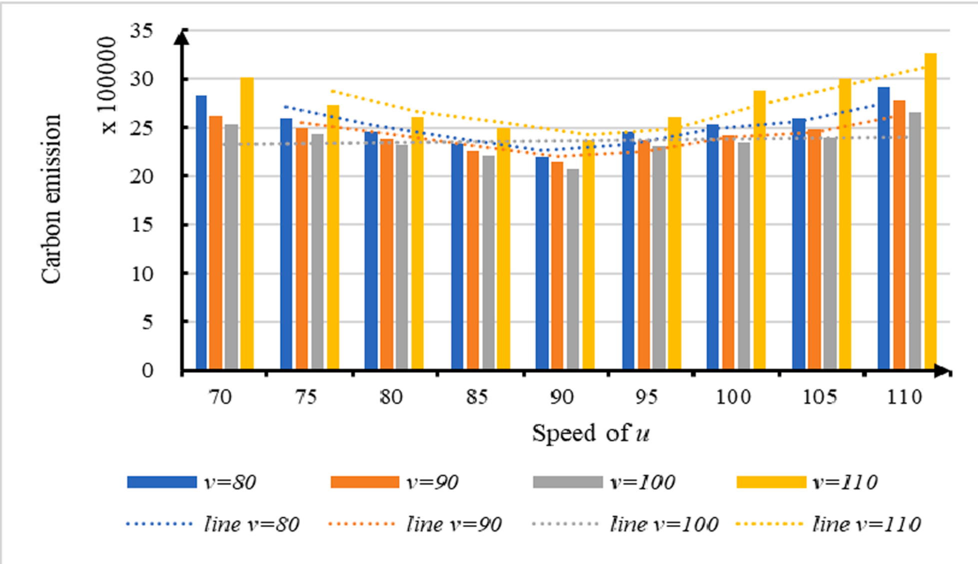

Fig. 9. Trend chart of the impact of vehicle *u* and vehicle *v* on carbon emissions.

However, we cannot blindly pursue the freshness of products without considering the cost of the economy and carbon emissions. Decision-makers should take a holistic approach considering the relationship among product freshness, economic cost, and carbon emission cost. According to the requirements of consumers in different markets, appropriate adjustments should be made.

8. Conclusion

8.1. Summary of findings

The characteristics of perishable products in emerging markets is an important issue that scholars pay attention to. This paper constructs an integrated location, inventory, routing model based on the economic cost, carbon emissions, and product freshness. To solve the model, this paper innovatively uses the YALMIP toolbox algorithm. Finally, an example is given to prove the scientificity and correctness of the proposed method. The research results can improve the efficiency of perishable products supply chain management from a global perspective, and provide a new perspective for sustainable supply chain management research.

From the results, some conclusion can be drawn. To a certain extent, economic costs, carbon emissions, and product freshness are mutually restrictive. The optimization considering single factors (i.e., location, inventory, or routing) cannot help decision-makers to obtain the global optimal operational efficiency. When the decision maker's goal is different, the location and distribution routing of

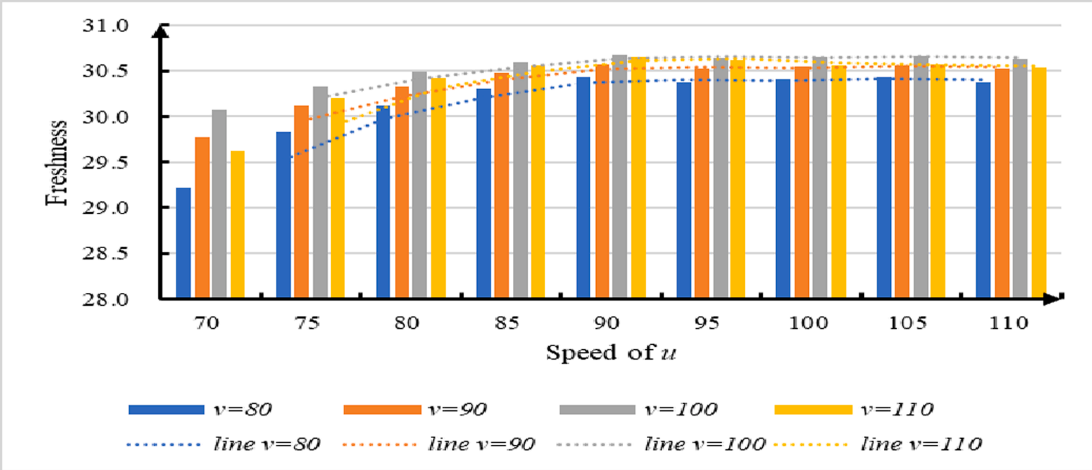

Fig. 10. Trend chart of the impact of vehicle u and vehicle v speeds on freshness.

the manufacturer and distribution center are different. Also, the impact of vehicle speed on economic cost, carbon emissions, and product freshness are analyzed. We find that vehicle delivery speed can affect decision-making. In particular, very high or low vehicle speed will significantly affect economic costs and carbon emissions. Besides, the optimal speed can help the decision-makers to adjust the relationship between objectives better. When the vehicle running speed between the manufacturer and the distribution center is 90 km/h, and that between the distribution center and the retailer is 100 km/h, the economic cost and carbon emissions are optimal. According to the characteristics of perishable products, for consumers, the higher the freshness of products, the higher their satisfaction. However, decision-makers will not blindly pursue the freshness of products. They will balance the relationship between the three objectives according to the development of enterprises.

Zhang et al. (2014) also examined the LIRP, who consider a supply chain network with multiple depots and geographically dispersed customers, each of which faces non-constant demand over a discrete planning horizon. The goal is to determine a set of depots to open, the delivery quantities to customers per period, and the sequence in which they are replenished by a vehicle fleet such that the total system-wide cost is minimized. However, our paper is different from Zhang et al. (2014). In addition to considering the cost, our paper also considers the carbon emissions in the distribution process and the characteristics of the distribution products. These factors play a very important role in the decision-making of operation managers.

8.2. Managerial implications

Our results have important management implications, especially for decision-makers who want to build a sustainable supply chain to meet the fast-growing demand of emerging markets. In terms of methods: This paper innovatively considers multiple objectives to comprehensively study the location routing and inventory of manufacturers and distribution centers, which can more comprehensively analyze the management operation problems. Besides, a heuristic algorithm is usually used to solve multi-objective problems, and YAMIP Toolbox provides a new idea for solving multi-objective problems.

For decision-makers, the location, inventory, and routing planning between manufacturers and distribution centers are very important. Any link will not only affect the economic cost and carbon emissions but also affect the freshness of products. Decision-makers should carefully consider their situation when making plans. Besides, decision-makers can adjust the distribution routing and delivery time according to the different requirements of each retailer for product freshness to improve their profits. At the same time, a sustainable perishable product supply chain requires enterprises to consider the impact of carbon emissions and reduce the deterioration of fresh products during transportation. How to consider these factors simultaneously and establish the decision model of a sustainable supply chain is a great challenge. Our research provides a framework for decision-makers to consider all factors when building a sustainable supply chain.

Our results also have implications for governments in emerging countries that face the challenges of developing economy and controlling carbon emission. With the economic development, consumers in the emerging markets intend to consume more fresh products, which requires a much faster supply chain, and in turn, leads to a higher level of carbon emission. However, low carbon emission is important for a sustainable supply chain and the environment. Our results suggest that it is possible to achieve both objectives at the same time through a joint optimization model. Governments in emerging markets can help the modernization and informatization of sustainable supply chains for perishable products through developing infrastructure, investing in preservation and refrigeration technologies, and building information platforms. Furthermore, governments can motivate firms to adopt the joint optimization model to save energy, reduce emissions, and promote sustainable development through controlling for the carbon trading price.

However, two issues that are not fully considered in our paper deserve further investigation. One issue is about the exploration of period n. Another important issue is the cold chain logistics. Perishable products can be transported through cold-chain logistics, which reduces product deterioration but requires relatively high equipment costs. Therefore, an interesting future research direction is to consider whether to use cold chain logistics.

CRediT authorship contribution statement

Aijun Liu: Conceptualization, Writing - original draft. **Qiuyun Zhu:** Methodology, numerical analysis. **Lei Xu:** Supervision. **Qiang Lu:** Writing - review & editing. **Youqing Fan:** Writing - review & editing.

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