A multi-objective lot sizing procurement model for multi-period cold chain management including supplier and carrier selection

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Abstract

The rapid expansion of the cold chain market is a key supply chain trend, but its high energy consumption conflicts with low-carbon goals. To address this, the paper proposes a multi-objective lot sizing procurement (LSP) model for managing the procurement of perishable products in the cold chain. This model, constrained by limited inventory and transportation capacity, aims to optimize multi-period procurement plans, order allocation, and minimize total costs and carbon emissions. The proposed multi-objective LSP model adopts a posteriori mode, which contributes to enhancing the model's applicability, especially in countries where carbon tax and trading systems are not fully developed. To enhance decision makers' decision efficiency and preserve the diversity of the original Pareto solutions as much as possible, the K-means++ algorithm is employed to prune the original Pareto solution set, providing decision makers with three representative solutions (cost priority, balanced, and carbon priority solutions). In addition, the paper conducts sensitivity analysis, stability experiments, and compares the multi-objective LSP model with the benchmark model (relaxed carbon emission constraints). Experiments show that the multi-objective LSP model can quickly and stably provide decision makers with lot sizing purchasing plan for numerical examples of different scales, and effectively control the total carbon footprint of the entire cold chain at low cost.

Keywords Low carbon, Lot sizing, Cold chain, Procurement, Dynamic demand

1 Introduction

Since the 1990s, people have gradually come to realize that controlling carbon emissions to combat climate change is an imminent event that can affect future generations. The United Nations Framework Convention on Climate Change first adopted in 1992 stated that reducing carbon dioxide emissions is a common international responsibility and obligation [1]. The Kyoto Protocol, adopted in 1997, is a legally binding international treaty that limits "greenhouse gas" emissions from industrialized countries [2]. After several rounds of international climate convention negotiations, countries have proposed own carbon emission reduction plans. Over 120 countries and regions have set carbon neutrality goals. In 2020, China pledged to peak carbon emissions by 2030 and achieve neutrality by 2060 [3]. The European Union and the United States aim for carbon neutrality by 2050, with the U.S. also targeting carbon-free electricity by 2035 [4,5]. To promote the development of low carbon economy, emission trading scheme are constructed and the carbon tax are proposed [6]. With the enhancement of consumers' low carbon awareness, companies have increased low carbon investment to develop low-carbon economy [7,8]. Several essential links of the supply chain generate greenhouse gases, such as procurement, production, storage and transportation [9]. Therefore, more and more scholars take low-carbon supply chain management as their research interests. The cold chain market grows by over 10% annually due to its ability to provide the necessary low-temperature environment for various products [10]. As an essential part of the supply chain, it has significant development potential. However, maintaining low temperatures throughout production, transportation, processing, storage, and sales requires special refrigeration equipment and high electricity consumption [11], making cold chain costs 40%-60% higher than ordinary supply chains and resulting in a larger carbon footprint [10]. These high carbon emissions and energy consumption conflict with the concept of a low-carbon economy [12]. Thus, developing a low-carbon cold chain is essential for fostering an environmentally friendly society and advancing the low-carbon revolution.

Lot sizing procurement plays a pivotal role in supply chain management. By devising sound procurement plans, enterprises can effectively reduce procurement costs, transportation expenses, and optimize inventory management [13]. Against the backdrop of green economic development, especially in perishable products' cold chain management, lot sizing procurement becomes particularly crucial [14]. A scientifically sound lot sizing procurement plan can minimize product spoilage, lower energy consumption in cold storage and transportation, thus significantly influencing the overall cost and carbon emissions level of the entire cold chain system. Many studies have focused on exploring lot sizing procurement models to achieve optimal purchasing plans for cost reduction, yielding significant results [15–25]. In recent years, an increasing number of low-carbon lot sizing procurement models have been developed with the goal of minimizing costs and carbon emissions by determining the optimal purchase plan [26–33]. In existing research, few studies have simultaneously incorporated supplier selection and carrier selection into lot sizing procurement models. To our knowledge, there is currently a lack of research on low-carbon lot sizing procurement models for perishable products with limited inventory capacity and carrier capability constraints that simultaneously consider supplier and carrier order allocation to achieve minimum costs and carbon emissions. Moreover, the majority of relevant studies employ a priori mode to address multi-objective problems. This mode either requires precise specification of the weights for cost objectives and carbon emission objectives or relies on well-established carbon tax and trading systems. The former necessitates determining convincing weights, as this directly impacts the optimal solution. The latter sets extremely high demands on a country's level of development in low-carbon regulatory frameworks.

Based on the above limitations of existing studies, this paper proposes a multi-objective lot sizing procurement (LSP) model for the procurement management of perishable products within the cold chain. Considering limited inventory and transportation capacity, the model can offer an optimal multi-period procurement plan for multiple products, along with order allocation between suppliers and carriers, aiming to achieve the minimum total cost and minimum carbon emissions across the entire cold chain. To improve the applicability of the low carbon lot sizing procurement model in developing countries with imperfect emission trading scheme and carbon tax policy, the multi-objective LSP model adopts the posterior mode based on a wellperforming multi-objective slime mold algorithm. Meanwhile, the multi-objective LSP model adopts the diversity-based pruning method to facilitate the decision maker's decision-making.

The multi-objective LSP model presented in this paper successfully addresses key challenges in low-carbon lot-sizing procurement across multi-period, multi-product, multi-supplier, and multi-carrier scenarios. The model's effectiveness is validated through two numerical cases, demonstrating its ability to control the carbon footprint while maintaining cost efficiency. By utilizing the K-means++ algorithm, the model distills a broad set of non-dominated solutions into three representative options—cost priority solution (CTPS), balanced solution (BDS), and carbon priority solution (CNPS)—offering decision-makers reliable and diverse choices. Moreover, the critical role of transportation planning is highlighted, as it significantly influences both costs and carbon emissions within the cold chain procurement process. The study also underscores the impact of inventory loss rates on overall costs and emissions, noting that while increasing transportation frequency and reducing inventory levels can mitigate costs, it may also escalate carbon emissions. Overall, this research confirms that the proposed multi-objective LSP model is a robust tool for developing efficient and sustainable procurement strategies, providing valuable insights and practical solutions for decision-makers in the cold chain logistics sector.

The contributions of this paper are highlighted in the following aspects.

(1) This study introduces a multi-objective lot sizing procurement (LSP) model for the procurement management of perishable products within the cold chain. Under constraints of limited inventory and transportation capacity, this model can offer optimal multi-period procurement plans for multiple products, along with order allocation of suppliers and carriers, to achieve the lowest total cost and carbon emissions for the entire cold chain.

(2) Most of the current research adopts the a priori mode, which uses carbon tax and carbon trading mechanisms to transform multiple objectives into a single objective, which has excessive requirements on the national carbon emission reduction system, limiting the applicability of this method [12,34–36]. The multi-objective LSP model proposed in this paper adopts a posteriori mode, which contributes to enhancing the model's applicability, especially in countries where carbon tax and trading systems are not fully developed.

(3) This study utilizes the K-means++ algorithm to prune the original Pareto solution set, aiming to enhance decision makers' decision efficiency. The proposed multi-objective LSP model employs a posterior mode, resulting in a Pareto solution set that contains a large number of high-dimensional solutions. Hence, this paper employs the K-means++ algorithm to prune the original Pareto solution set, providing decision makers with three representative solutions (CTPS, BDS, and CNPS). This approach not only aims to further improve decision-making efficiency but also strives to preserve the diversity of the original Pareto solutions as much as possible, providing decision makers with an expanded selection space.

The remainder of this paper is organized as follows. In Section 2, the paper reviews the literature related to lot sizing procurement problem. Section 3 describes the problem addressed in this paper and the mathematical modeling process. The proposed multi-objective LSP model is introduced in Section 4. Section 5 presents the numerical cases. Section 6 presents the experimental results. In Section 7, this paper includes sensitivity analysis, stability experiments, and comparisons with the benchmark model. Sections 8 and 9 present the conclusions, contributions, limitations, and future research of this paper, respectively.

2 Literature review

Lot sizing is a problem of determining purchasing quantities and their timing, and every inventory and production inventory system faces this problem [37]. **Table 1** lists the key details of relevant literature, highlighting the distinctions and connections between existing studies and this paper. The widely recognized economic order quantity (EOQ) model has been employed to determine lot sizing, and its application extends extensively to supply chain management and inventory control [38]. After many years, a dynamic version of the economic lot size model was proposed to determine the optimal lot sizing under dynamic demand, aiming to minimize total costs [19]. Liao and Rittscher [21] considered the selection of multiple suppliers in lot sizing problems to achieve cost minimization. Stefan Minner [18] and Zamani Dadaneh et al. [25] further improved the lot sizing procurement model, allowing for the optimization of the optimal purchase lot sizes for multiple products. Gan et al. [22] explored lot sizing problem by incorporating the limitation of inventory capacity into their study. In later studies, carrier selection was incorporated into lot sizing problems, while also introducing constraints related to limited transportation capacity [20,28]. By simultaneously incorporating supplier and carrier selection into lot sizing problems, it is possible to determine the optimal lot sizes across the entire supply chain, leading to further cost reduction along the chain. Kaur et al. [31] have developed a low-carbon procurement and logistics model that encompasses multiple periods, products, suppliers, and carriers. This comprehensive model takes into account the entire supply chain to determine the optimal procurement lot sizes, as well as the allocation of orders among suppliers and carriers. The model not only focuses on minimizing the overall cost of the supply chain but also takes into consideration the carbon emissions associated with the supply chain. As global climate change issues come to the forefront, governments and international organizations are increasingly putting forth goals and policies aimed at reducing carbon emissions. Implementing low-carbon measures can help to enhance a company's reputation and reduce its operational costs. Therefore, many studies have considered the carbon emissions of the supply chain, with reducing supply chain carbon emissions being one of their optimization objectives [26,27]. Due to the significant energy consumption required for refrigeration in both storage and transportation processes of the cold chain, it results in substantial carbon emissions. Therefore, reducing carbon emissions should be a key focus in studying lot sizing problem within the cold chain. Hariga et al. [28] introduced a hybrid economic and environmental minimization model for the cold chain, aiming to optimize lot sizes to achieve minimal costs and carbon emissions. Chen et al. [32] further explored the loss of perishable goods in the cold chain. Some studies [23,29,30] have also taken into account the carbon emissions during transportation processes in the lot sizing procurement problem of the cold chain. Based on existing research, this paper introduces a multi-period, multi-product lot sizing procurement model for perishable goods with constraints on inventory capacity and transportation capacity. This model integrates the allocation of orders between carriers and suppliers.

The low-carbon lot sizing procurement problem is a multi-objective challenge that seeks to simultaneously minimize carbon emissions and total costs. Methods to solve multi-objective problems are divided into priori mode and posteriori mode. The prior mode is that the decision maker assigns weights to different goals according to their preferences, aggregates multiple objectives into one objective, and can obtain an optimal solution. Different from the prior mode, the posterior mode generates a non-dominated solution set, and the decision maker selects an appropriate solution from this solution set. At present, research on addressing the low-carbon lot sizing procurement issue primarily adopts a priori mode, combining multiple objectives into a single objective through two main methods. The first approach involves integrating cost and carbon emissions as a single objective by assigning them different weights [26,27], while the other approach involves transforming carbon emissions into enterprise costs through carbon taxes and carbon trading policies [12,34–36]. Although using a priori mode to address multi-objective problems is relatively straightforward and simple, these two methods also have their drawbacks. In the first approach, the determination of weights imposes a high requirement on model users. Only reasonable weights can produce logical results, and even slight variations in weights could result in significant outcome changes. For the second approach, it requires the country where the enterprise operates to have established a sound carbon tax and trading system. Currently, only a handful of developed countries have implemented relatively comprehensive carbon tax and trading systems. Therefore, for the majority of countries that have not established a complete carbon tax and trading system, adopting this approach is difficult or impractical. The adoption of a posterior mode can help circumvent the aforementioned challenges and enhance the applicability of the low-carbon lot sizing procurement model in countries with incomplete carbon tax and trading systems. Therefore, this paper adopts a posterior mode and uses a metaheuristic optimization algorithm to solve multi-objective problems. While the posterior mode can provide decision makers with rich and diverse options [39], efficiently selecting the appropriate solution from a large and high-dimensional set of solutions is also a significant challenge for decision makers. To enhance decision makers' efficiency, the multi-objective LSP model proposed in this paper prunes the original Pareto solution set using the k-means++ algorithm. This process aims to derive three representative solutions (cost priority, balanced, and carbon priority solutions) for decision makers to select from. This approach aims to improve decision efficiency while preserving the diversity of available solutions as much as possible.

Table 1 Contribution of this paper and literature review

Reference	MD	CD	MP	LTC	LI	SS	MO	CRP	Solution method	Final solution
This paper	**Dynamic**	✓	✓	✓	✓	✓	✓	**Carbon minimization**	**Heuristic algorithm**	**Representative solutions**
Boonmee and Sethanan (2016)	Dynamic				✓			None	Heuristic algorithm	Unique solution
Mazdeh et al. (2015)	Dynamic					✓		None	Heuristic algorithm	Unique solution
Stefan Minner (2009)	Dynamic		✓		✓			None	Heuristic algorithm	Unique solution
Najafi and Zolfagharinia (2024)	Dynamic	✓				✓	✓	None	LP	Pareto solution
Sargut and Işık (2017)	Dynamic	✓			✓			None	LP	Unique solution
Wagner and Whitin (1958)	Dynamic							None	LP	Unique solution
Azadnia et al. (2015)	Dynamic		✓		✓	✓	✓	SCS	WSM, AUGMECON	Unique solution
Choudhary and Shankar (2014)	Dynamic			✓	✓	✓	✓	None	WSM, LP	Unique solution
Shalke et al. (2018)	Dynamic		✓		✓	✓	✓	SCS	LP	Unique solution
Liao and Rittscher, (2007)	Dynamic					✓	✓	None	WSM, Heuristic	Unique solution
Hariga et al. (2017)	Constant	✓		✓			✓	Carbon tax	LP	Unique solution
Jing and Mu (2020)	Dynamic	✓			✓		✓	Carbon minimization	LP	Unique solution
As'ad et al. (2020)	Dynamic	✓		✓	✓		✓	Carbon cap	LP	Unique solution
Alireza et al. (2024)	Dynamic	✓	✓			✓	✓	None	Heuristic algorithm	Unique solution
Kaur et al. (2017)	Dynamic		✓	✓		✓	✓	Carbon trade	LP	Unique solution
Gan et al. (2019)	Uncertainty				✓			None	LP	Unique solution
Wang (2024)	Dynamic	✓						None	Heuristic algorithm	Unique solution
Liu et al. (2018)	Dynamic	✓			✓			None	LP	Unique solution
Chen et al. (2022)	Constant	✓					✓	Carbon trade	LP	Unique solution
Zamani Dadaneh et al. (2023)	Uncertainty		✓		✓	✓		None	LP	Unique solution

MD = Market demand, CD = Cold products, MP = Multi-product, LTC = Limited transportation capacity, LI = Limited inventory, SS = Supplier selection, MO = Multi-objective, CRP = Carbon regulatory policy, SCS = Sustainability criteria score, LP = Linear programming, AUGMECON = Augmented ε-constraint method, WSM = Weighted sum method.

3 Problem definition and mathematical modeling

3.1 Problem description

This paper proposes a multi-objective lot sizing procurement (LSP) model for perishable products with limited inventory capacity in cold chain management, aiming to minimize both the total procurement cost and carbon emissions throughout the entire cold chain. This multi-objective LSP model can provide lot sizing procurement plans for scenarios with multiple periods, multiple products, multiple carriers, and multiple suppliers. It includes the product purchase quantities, supplier order allocations, and carrier order allocations for each period. This paper assumes that purchasers conduct their purchasing activities in a carbon-sensitive market. Specifically, purchasers need to determine the appropriate purchase lot size X_{tijm} (Purchase lot size of product i supplied by supplier j and carried by carrier m in period t) for each period. This determination must take into account multiple product demands, the dynamic prices of these products, the supply capacities of various suppliers, as well as the transport capacities and quotes from multiple carriers. Therefore, the purchasers aim to achieve cost and carbon emissions minimization. **Fig. 1** depicts the research scope and composition of the objective functions for the multi-objective LSP model. The purchasers' costs include raw material purchase costs, holding costs (electricity consumption for storing products in the cold storage and personnel management expenses), transportation costs, ordering costs (the costs of order confirmation and quotation between the purchaser and supplier, excluding product purchase and transportation expenses), and holding loss costs (the cost of perishable products lost during storage). Carbon emissions are the total carbon emissions of the entire cold chain, including carbon emissions from the storage (the carbon emissions resulting from the electricity consumption and refrigerant leakage in the cold storage) and transportation process (the carbon emissions generated from the combustion of fossil fuels and refrigerant leakage in refrigerated vehicles).

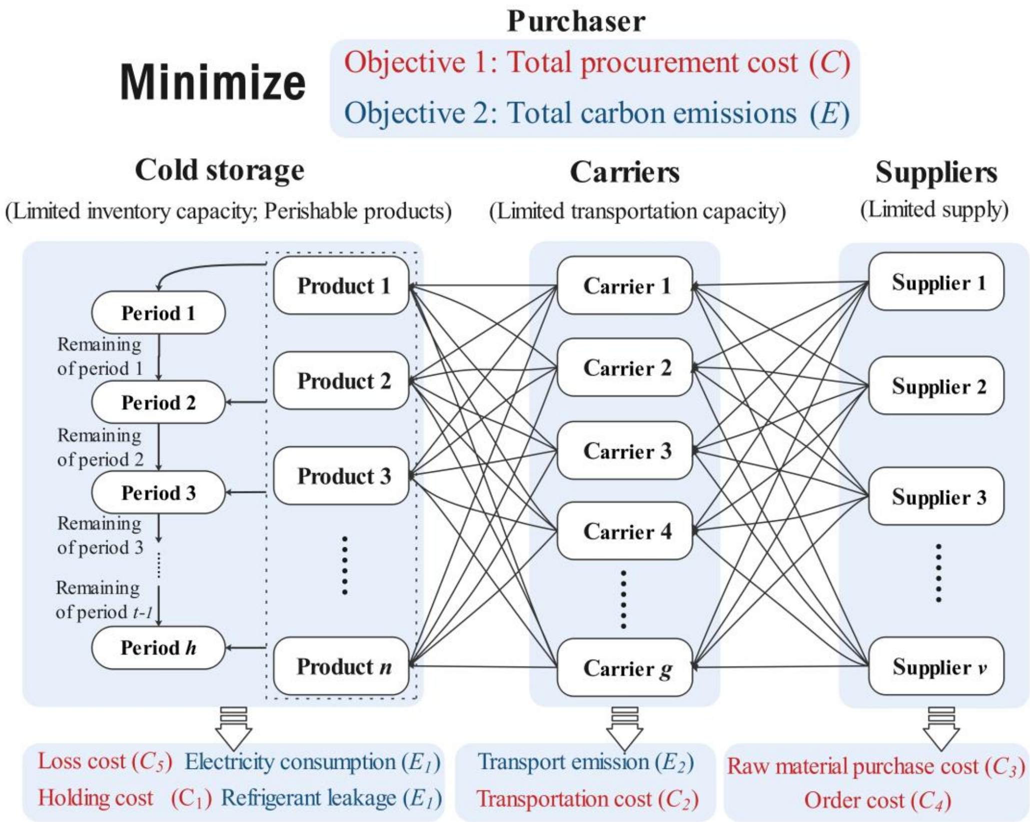


Fig.1 The graphical depiction of the problem proposed in this paper

3.2 Mathematical modeling

3.2.1 Hypothesis

We propose a multi-objective LSP model to achieve the optimal allocation of purchase orders for cold chain in a multi-period, multi-product, multi-carrier, and multi-supplier scenario. The hypotheses of the model are proposed based on existing studies [40–42] and research needs. In this paper, we add hypotheses for maximum storage capacity and inventory loss rate, which bring the model closer to the reality. The hypothesizes of this model are as follows:

- Products:

(a) The product is perishable, and the longer the storage time, the greater the product loss.
(b) The types of products to be purchased are known.
(c) The products are homogeneous and purchasers will not select suppliers based on the quality of the products.
(d) Each product can be produced by multiple suppliers.

- Facilities:

(a) The maximum storage capacity and inventory loss rate are known.
(b) The distance between the purchaser and multiple suppliers is known.
(c) Carbon emission factor for storage electricity consumption, carbon emission factor for storage refrigerants, and carbon emission factor for multiple refrigeration vehicles are known.

- Action:

(a) Suppliers have completed the product pre-cooling process.
(b) Each purchase will be completed within the period and no backorders will be

allowed.

(c) Demand, product prices, supplier capacities, carrier capacities and transportation prices are certain and dynamic.

(d) Stockouts are not permitted.

3.2.2 Notations

The proposed multi-objective LSP model contains two objectives: (1) Minimize the total cost of the purchaser. (2) Minimize the carbon emissions of the entire procurement process. The decision variables, indices, and parameters in the multi-objective LSP model are presented in **Table 2**.

Table 2 Notations in the proposed multi-objective LSP model

Indices	Meaning
M	Set of carriers $M=\{1,2,\ldots,g\}$
J	Set of suppliers $J=\{1,2,\ldots,v\}$
T	Set of periods $T=\{1,2,\ldots,h\}$
Θ	Set of products $\Theta=\{1,2,\ldots,n\}$
j	Index for suppliers
i	Index for products
t	Index for periods
m	Index for carriers
Parameters	**Meaning**
d_j	Distance between purchaser and supplier j (km)
A_{ti}	Inventory loss rate of product i in period t (%)
e	Carbon emission factors for storage electricity consumption $(kg/(kg\cdot t))$
r	Carbon emission factors for storage refrigerants $(kg/(kg\cdot t))$
β_m	Carbon emission factor for refrigeration vehicle of carrier m $(kg/(kg\cdot t))$
L_m	Maximum loading capacity of the refrigerated vehicle of the carrier m (kg)
MC	Maximum storage capacity (kg)
D_{ti}	Demand of the product i in period t (kg)
P_{tij}	Price of product i supplied by supplier j in period t $(\$)$
TC_m	Unit transportation cost of carrier m $(\$/km)$
O_{tij}	Ordering cost of product i in period t at supplier j $(\$/time)$
H_{ti}	Unit holding cost of product i in period t $(\$/kg)$
SC_{tij}	Supply capacity of supplier j for product i in period t (kg)
Φ_{jm}	Carrier capacity provided by carrier m for supplier j (kg)
Decision variables	**Meaning**
X_{tijm}	Purchase lot size of product i supplied by supplier j and carried by carrier m in period t (kg)
U_{tijm}	Binary variable, which is 1 if $X_{tijm}>0$ and 0 otherwise
I_{ti}	Inventory quantity of product i in period t (kg)

3.2.3 Objective functions and constraints

Objective 1:

$$Minimize \quad C = C_1 + C_2 + C_3 + C_4 + C_5 \tag{1}$$

where

$$C_1 = \sum_t \sum_i I_{ti} H_{ti} \tag{2}$$

$$C_2 = \sum_m \sum_t \sum_j \left[TC_m d_j \cdot ceil\left(\sum_i X_{tijm} \Big/ L_m \right) \right] \tag{3}$$

$$C_3 = \sum_t \sum_i \sum_j \left(P_{tij} \sum_m X_{tijm} \right) \tag{4}$$

$$C_4 = \sum_t \sum_i \sum_j \left(O_{tij} \sum_m U_{tijm} \right) \tag{5}$$

$$C_5 = \sum_t \sum_i \left(I_{ti} A_{ti} \sum_j P_{tij} \Big/ v \right) \tag{6}$$

Objective 2:

$$Minimize \quad E = E_1 + E_2 \tag{7}$$

where

$$E_1 = \sum_t \sum_i \left[(e + r) I_{ti} \right] \tag{8}$$

$$E_2 = \sum_t \sum_j \sum_m \left[ceil\left(\sum_i X_{tijm} \Big/ L_m \right) \beta_m d_j L_m + mod\left(\sum_i X_{tijm} \Big/ L_m \right) \beta_m d_j \right] \tag{9}$$

Subject to:

$$\begin{cases} (1 - A_{it}) I_{(t-1)i} + \sum_j \sum_m X_{tijm} = D_{ti} + I_{ti}, & \forall i, t > 1 \\ \sum_j \sum_m X_{tijm} = D_{ti} + I_{ti}, & \forall i, t = 1 \end{cases} \tag{10}$$

$$\sum_m X_{tijm} \le SC_{tij}, \quad \forall t, i, j \tag{11}$$

$$\sum_i X_{tijm} \le \Phi_{jm}, \quad \forall t, j, m \tag{12}$$

$$\sum_i I_{(t-1)i} + \sum_i \sum_j \sum_m X_{tijm} \le MC, \quad \forall t \tag{13}$$

$$\begin{cases} \sum_j \sum_m X_{tijm} \ge D_{ti}, & \forall i, t = 1 \\ I_{(t-1)i} + \sum_j \sum_m X_{tijm} \ge D_{ti}, & \forall i, t > 1 \end{cases} \tag{14}$$

$$U_{tijm} \in \{0, 1\}, \quad \forall t, i, j, m \tag{15}$$

$$I_{ti} \text{ and } X_{tijm} \text{ are integer}, \quad \forall t, i, j, m \tag{16}$$

Eq. (1) is the cost minimization objective, which means that the minimization of the purchaser's total procurement cost. **Eq. (2)** calculates the total holding cost of the purchaser. **Eq. (3)** calculates the total transportation cost paid by the purchaser, where different types of products can be transported in the same vehicle and $ceil(a)$ returns the smallest integer greater than or equal to a. **Eq. (4)** calculates the total raw material purchase cost of the purchaser. **Eq. (5)** calculates the order processing cost paid by the purchaser. ***C4*** does not include transportation costs. **Eq. (6)** calculates the total loss cost of the purchaser's holding process. Because the prices of products from different suppliers vary and we cannot distinguish the supplier of the damaged products, we use the average price to calculate the loss cost. **Eq. (7)** represents the carbon emission minimization objective, which shows that the minimization of carbon emissions throughout the procurement process. **Eq. (8)** calculates the carbon footprint from the holding process, which is mainly generated by electricity consumption and refrigerant leakage. **Eq. (9)** calculates the carbon emissions from the transportation process, where $mod\left(a\right)$ returns the remainder of a and the carbon emissions of refrigerated vehicles are closely related to the load weight.

Constraint (10) is the inventory balance formula. The inventory quantity is equal to the current period purchase minus the current period demand in the first period. In other periods, the inventory quantity in period t is equal to the sum of the inventory in period $t-1$ and the purchase quantity in period t minus the demand quantity in period t. **Constraint (11)** ensures that the purchase volume of each product is not greater than the supplier's supply capacity per period. **Constraint (12)** ensures that the orders allocated to suppliers do not exceed the transportation capacity provided by the carrier for the current period. **Constraint (13)** indicates that purchasers do not hold more product than the maximum storage capacity of the refrigerated warehouse. **Constraint (14)** means that the products purchased by purchasers are available to meet demand in each period. **Constraint (15)** is an indicator variable for the existence of an order for product i supplied by supplier j and carried by carrier m in time period t. **Constraint (16)** is an integer constraint; the inventory quantity and purchase lot size must be integers.

4 Solution approach

The multi-objective LSP problem is a multi-objective mixed-integer linear programming problem (MILP). Finding an optimal solution for this multi-objective problem is undeniably a challenging task. Therefore, this paper employs the multi-objective slime mold algorithm (MOSMA) to address this issue, as MOSMA is an exceptionally effective multi-objective optimization algorithm that has demonstrated outstanding performance in solving various optimization problems. MOSMA is designed using non-dominated sorting and crowding distance mechanisms to maintain Pareto dominance and solution diversity, respectively, making it superior in generating high-quality solutions across different types of problems [38]. The posterior-based multi-objective optimization algorithm generates a set of Pareto solutions, often containing hundreds or thousands of non-dominated solutions. This presents a new challenge for model users - determining which non-dominated solution to select as the final solution, and the vast number of non-dominated solutions further increases the difficulty of this selection. To address this issue, the paper adopts the K-means++ algorithm as a pruning method. The motivation for using K-means++ lies in its ability to enhance solution diversity by grouping similar solutions and selecting representative ones, adapt to the data distribution, reduce randomness and improve stability, and provide easily interpretable results. Ultimately, the model will provide three representative solutions for users: cost priority, balanced, and carbon priority solutions. The structural diagram of the solution approach is shown in **Fig. 2**.

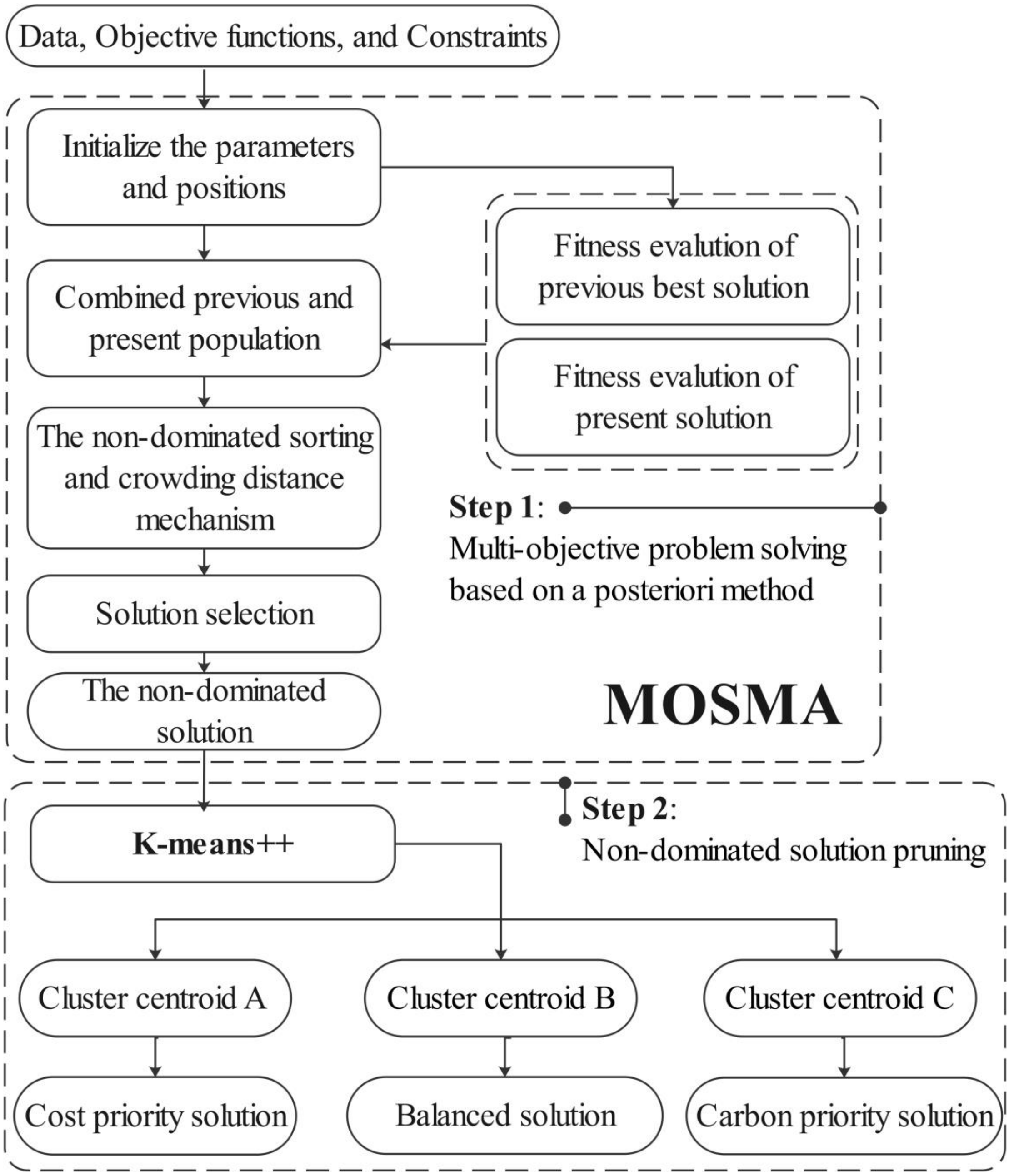


Fig.2 The structural diagram of the solution approach

4.1 Obtaining the Pareto optimal solution set

MOSMA is a metaheuristic algorithm that simulates the foraging behavior of slime molds. In this paper, a brief introduction to MOSMA will be provided, for more details refer to Premkumar et al. [38]. The superior planning ability of the slime mold has gained the attention of biologists as well as scientists in other fields. For example, the famous Tokyo subway line experiment, in which scientists used light spots to simulate the coastline and terrain and put food in important subway stations around Tokyo. Amazingly, after 26 hours the slime mold formed a foraging path very similar to the Tokyo subway network [44]. MOSMA demonstrates outstanding performance in optimization problems, excelling in both benchmark optimization tasks and real-world engineering applications. In benchmark optimization scenarios, MOSMA significantly enhances the estimation precision of Pareto fronts, particularly in linear, nonlinear, continuous, and discrete optimization problems, and efficiently identifies optimal solution sets that meet constraints in both constrained and unconstrained benchmark functions. For instance, it successfully optimizes complex multi-objective problems like TNK (Tanikawa), KITA, CONSTR (Constrained Test Problem), OSY (Osyczka and Kundu), and SRN (Srinivas and Deb), surpassing other algorithms in performance metrics such as Generational Distance (GD), Inverted Generational Distance (IGD), Maximum Spread (MS), and Spacing. In practical engineering applications, MOSMA's versatility shines through, optimizing material usage and geometric design in 2-bar truss designs, enhancing precision and efficiency in CNC (Computer Numerical Control) machine tool design, and optimizing vehicle structures for enhanced safety and reduced manufacturing costs in side-impact collision designs. These instances underscore MOSMA’s prowess in diverse, multi-objective optimization challenges, serving as a robust tool for engineering optimization design [38]. The pseudocode for MOSMA can be found in the **Appendix B: Table B6**.

MOSMA simulates foraging behavior and negative feedback mechanism of slime mold. To solve the multi-objective LSP problem using MOSMA, we set the minimum cost and minimum carbon emissions for the entire supply chain as the food for the slime mold, with the final position of the slime mold being the solution X_{tijm} that we aim to obtain.

Set the population size *n* and the maximum number of iterations *max_iter*. Initialize the population positions $\vec{X}(i)$, where i=1, 2, ..., *n*. Calculate the initial fitness value *E(j)* for each individual. Set *BE* as the maximum fitness value across all iterations. The following equation simulates the process of slime mold approaching food.

(1) Calculate the Step Size:

$$c = \tanh\left|E(j) - BE\right| \tag{17}$$

(2) Calculate the direction vector:

$$\vec{vb} = [-a, a] \tag{18}$$

$$a = \operatorname{arctanh}\left[-\left(\frac{i}{max\_i}\right) + 1\right] \tag{19}$$

(3) Calculate the Weight Vector:

$$W\left(Index\right)=\begin{cases}1+rand1\cdot\log\left(\dfrac{be-E\left(j\right)}{be-we}+1\right), & condition\\ 1-rand1\cdot\log\left(\dfrac{be-E\left(j\right)}{be-we}+1\right), & others\end{cases} \tag{20}$$

$$Index=sort\left(E\left(j\right)\right) \tag{21}$$

(4) Update Individual Positions:

$$\overrightarrow{X\left(i+1\right)}=\begin{cases}\overrightarrow{vc}\cdot\overrightarrow{X\left(i\right)}, & rand1\geq c\\ L\left(i\right)+\overrightarrow{vb}\cdot\left(W\cdot\overrightarrow{X_a}-\overrightarrow{X_b}\right), & rand1<c\end{cases} \tag{22}$$

$i\in 1,2,\ldots,n$

Where $\vec{X}$ is the current position of an individual; $L\left(i\right)$ is the location where the smell of the food is the strongest at the current moment, i is the number of iterations. $\overrightarrow{X_a\left(i\right)}$ and $\overrightarrow{X_b}$ represent the locations of two random individuals, respectively. $\overrightarrow{vc}$ takes value between 0 and 1 and decreases linearly. BE indicates the maximum fitness in all iterations. $E\left(j\right)$ denotes the fitness of $\vec{X}$. $rand1$ represents a random number taken from [0, 1]. max_i is the maximum number of iterations. be and we represent the maximum and minimum fitness in the current iteration, respectively. W indicates the weight of individual. $condition$ refers to the search patterns of slime molds depending on the food quality.

(5) Simulate positive and negative feedback mechanism:

The positive and negative feedback mechanism between the slime mold's vein width and food exists in the wrap food process. The higher the concentration of food, the stronger the waves generated by the bio-oscillator, which leads to faster cytoplasmic flow and thicker venous walls. This mechanism can be modeled by the following formula.

$$\overrightarrow{X\left(i+1\right)^*}=\begin{cases}rand2\cdot\left(UB-LB\right)+LB, & rand2<z\\ L\left(i\right)+\overrightarrow{vb}\left(W\cdot\overrightarrow{X_a\left(i\right)}-\overrightarrow{X_b\left(i\right)}\right), & rand1<c\\ \overrightarrow{vc}\cdot\overrightarrow{X\left(i\right)}, & rand1\geq c\end{cases} \tag{23}$$

Where $rand2$ is a random number that takes value in [0,1]; z is a preset value; UB and LB are the upper and lower bounds of the search range, respectively.

MOSMA can solve multi-objective optimization problems by adding the non-dominated sorting mechanism which allows a series of non-dominated Pareto solutions to be derived. Simultaneously, MOSMA introduces the crowding distance mechanism to achieve diversity of non-dominated solutions [45].

(6) Perform non-dominated sorting:

Select a slime mold individual $\vec{X}_k$ and compare the dominance and non-dominance relationship between $\vec{X}_k$ and other slime mold individuals $\vec{X}_l, k\neq l$. If no individual $\vec{X}_l$ dominates $\vec{X}_k$, mark $\vec{X}_k$ as a non-dominated individual.

Repeat the above steps for all slime molds, all marked individuals are classified into the first-level non-dominated layer. Next, repeat the above steps for the remaining unlabeled individuals to obtain other non-dominated layers.

(7) Calculate the crowding distance to ensure diversity of non-dominated solutions: The crowding distance is obtained by the following formula.

$$C\_Dis_k^j = \frac{E_{k+1}^j - E_{k-1}^j}{E_{max}^j - E_{min}^j} \tag{24}$$

Where, E_{k+1}^j and E_{k-1}^j represent the j^{th} objective function values of the $\left(k+1\right)^{th}$ and $\left(k-1\right)^{th}$ slime molds, respectively. E_{max}^j and E_{min}^j are the maximum and minimum values of the j^{th} objective function.

(8) Select the next generation:

a. Merge current population P_0 with new solutions P_j to create P_i.

b. Evaluate P_i and sort based on non-dominated sorting and crowding distance.

c. Select the top n individuals to form the new population P_0.

(9) When the maximum number of iterations is reached, output the optimal solutions and the Pareto front.

4.2 Pruning the original Pareto solution set

When utilizing MOSMA to solve the multi-objective LSP problem, we obtain a set of Pareto solutions, typically comprising several hundred to thousands of non-dominated solutions. To simplify the decision-making process for decision makers in selecting solutions, we employ the k-means++ algorithm as a pruning method to select three representative solutions—cost priority, balanced, and carbon priority solutions—from the original non-dominated solution set. We set the number of clusters to 3, with each cluster center representing one of the representative solutions. The cluster center with the lowest cost is designated as CTPS, the cluster center with the lowest carbon emissions as CNPS, and the remaining cluster center as BDS. Consequently, these representative solutions effectively represent other non-dominated solutions while preserving the diversity of the non-dominated solutions.

Arthur and Vassilvitskii [41] proposed the k-means++ algorithm based on the k-means algorithm. To avoid the artificial interference of initial cluster center selection, K-means++ algorithm adopts a heuristic approach to find the initial centers of k-means clustering. Because the values of different objective functions have different magnitudes, we need to normalize the original Pareto front before using the k-means++ algorithm. The formula is shown below.

$$x_m^j = \frac{E_m^j - \min\left\{E_1^j, E_2^j, ..., E_m^j\right\}}{\max\left\{E_1^j, E_2^j, ..., E_m^j\right\} - \min\left\{E_1^j, E_2^j, ..., E_m^j\right\}} \tag{25}$$

Where x_m^j represents the normalized value of the j^{th} objective function. The following are the calculation steps of the k-means++ algorithm.

Step 1: Selection of k initial cluster centers.

① An observation is selected uniformly at random from the non-dominated solution set $\mathbf{X}$. The selected solution is taken as the first cluster centers, denoted as c_1.

② The distance from each observation to c_1 is calculated. Denote the distance between c_j and the observation $x_m = \left(x_m^1, x_m^2, \ldots, x_m^n\right)$ as $dis\left(x_m, c_j\right)$.

③ The next center of cluster c_2 is chosen at random from $\mathbf{X}$, the probability is

$$P\left(c_2 = x_m\right) = \frac{dis^2\left(x_m, c_1\right)}{\sum_{j=1}^{n} dis^2\left(x_j, c_1\right)} \tag{26}$$

④ Select the j^{th} center of cluster c_j:

a. Calculate distances from non-dominated solutions to all cluster centers and assign solutions to the closest cluster center.

b. The probability that the c_j is chosen randomly from $\mathbf{X}$ is

$$P\left(c_j = x_m\right) = \frac{dis^2\left(x_m, c_p\right)}{\sum_{\left\{h; x_h \in C_p\right\}} dis^2\left(x_h, c_p\right)} \tag{27}$$

Where, C_p represents the solution set assigned to cluster centers c_p.

⑤ Repeat step ④ until centers of cluster c_k have been selected.

Step 2: The distance from each observation to the center of all clusters was calculated separately.

Step 3: K-means++ uses a two-stage iterative algorithm to minimize the sum of the distances from the solutions to the cluster centers.

① The first stage adopts batch update, where each iteration needs to reassign all solutions to the nearest cluster centers, and then reselect new cluster centers.

② The second stage adopts online updates, which means that whenever the sum of distances can be reduced by individually reassigning points, reassignment is performed and the cluster center is recalculated after each reassignment.

Step 4: Repeat **Steps 2 - 3** until the cluster assignment remains the same.

Step 5: The three cluster centers correspond to the CTPS, BDS, and CNPS, respectively.

4.3 Evaluation metrics

Adequate representativeness of the pruned results is necessary because a fully representative solution reflects the complexity and diversity of the problem. In this way, decision makers can better understand the conflicts and synergies between different objectives and thus make a more comprehensive assessment. If the pruned solutions are not sufficiently representative, it may lead to decision-making bias by overlooking some important solutions and their corresponding trade-off relationships. This will limit the vision of the decision maker and lead to incomplete or one-sided decisions. Therefore, this paper introduces two metrics, relative Euclidean index (REI) and relative cosine index (RCI) [39], to evaluate the representativeness of representative solutions to the original Pareto solution set.

4.3.1 Relative Euclidean index

$$REI_k = \frac{\lambda_k}{\lambda_1} \tag{28}$$

$$\lambda_k = \frac{1}{N} \sum_{i=1}^{N} \min_j \left\| x_i - r_j^k \right\| \tag{29}$$

Where REI_k is the relative Euclidean index of the solution set containing k solutions. λ_k is the average of the sum of the Euclidean squared distances between all original non-dominated solutions and their nearest representative solutions. r_j^k is a member of the representative solution set containing k non-dominated solutions. N is the number of original non-dominated solutions. The interval of REI is $\left(0,+\infty\right)$. The value of REI approaching 0 indicates that the representative solution set is an excellent representation of the original non-dominated solution. In other words, the selected representative solution set has a relatively high diversity. Conversely, a value of REI exceeds 1 means that the representativeness of a single solution is also better than the selected representative solution set. That is to say, the selected representative solution set does not reflect the characteristics of the original non-dominated solution set well.

4.3.2 Relative cosine index

$$RCI_k = \frac{\xi_k - \xi_1}{1-\xi_1} \tag{30}$$

$$\xi_k = \frac{1}{N}\sum_{i=1}^{N}\max_j \frac{x_i \cdot r_k^j}{\left\|x_i\right\| \cdot \left\|r_k^j\right\|} \tag{31}$$

where RCI_k is a relative indicator used to measure the representativeness of a representative solution set containing k non-dominated solutions. ξ_k is the average of the cosine similarity of all original non-dominated solutions and their nearest representative solutions. RCI_k applies cosine similarity to measure the representativeness of the representative solution set. The interval of RCI_k is $\left(-\infty,1\right]$. A larger value of cosine similarity means that the two non-dominated solutions are more similar. Therefore, a value of RCI_k approaching 1 indicates that the representative solution set is distributed along the original Pareto front and can perfectly represent the original non-dominated solution set. Conversely, if the value of RCI_k is negative, it indicates that the representative solution set is less representative than that of a single non-dominated solution. In other words, the representative solution set is invalid.

5 Numerical illustrations

This paper uses two numerical cases to test the robustness and effectiveness of the multi-objective LSP model proposed in this paper. The two cases simulate lot sizing procurement problems for cold chain at different scales: small-scale problem (7 periods, 3 suppliers, 2 products and 2 carriers) and large-scale problem (7 periods, 7 suppliers, 6 products and 2 carriers). Assuming that the maximum storage capacity (*MC*) is 1000 kg. The carbon emission coefficients in the multi-objective LSP model adopted the calculated results of Bin et al. [42]. The price of each product is determined by the supplier and varies by period and supplier. Each supplier can offer multiple products, but their supply capacity for each product is limited and dynamically changes over time. Similarly, the carrier's transportation capacity is limited and varies by period. Product demand, order processing costs, and unit holding costs also fluctuate dynamically. Therefore, we used multiple random functions to generate these data, and the datasets and random functions are shown in **Appendix A: Tables A1-A9**. The key parameters of the multi-objective LSP model are showed in **Table 3**. All models in this paper were coded in Matlab 2020a, running on a laptop with 1.8GHz AMD Ryzen 7 4800U processor, 16GB of RAM, and operating system Win10.

Table 3 The key parameters of the multi-objective LSP model

Parameter	Symbol	Value	Reason
Carbon emission coefficients			
Carbon emission coefficient for electricity consumption	e	$0.0002355\left(kg/(kg\cdot t)\right)$	Bin et al. [42]
Carbon emission factors for storage refrigerants	r	$0.00005644\left(kg/(kg\cdot t)\right)$	
Carbon emission factor for 1.5t refrigeration vehicle	β_1	$0.000292\left(kg/(kg\cdot t)\right)$	
Carbon emission factor for 10t refrigeration vehicle	β_2	$0.0000751\left(kg/(kg\cdot t)\right)$	
MOSMA			
Population size	S_p	500	Trial-error manner
Iteration number	N_i	2000	Trial-error manner
K-means++			
The number of clusters	N_k	3	Research needs
Maximum iteration	N_{max_i}	10000	Common value
Distance measure method	M_d	Euclidean distance	Preset

6 Computational Results

This paper uses the multi-objective LSP model to solve two cases mentioned above. For each case, the multi-objective LSP model provides three feasible solutions, namely cost priority solution, balanced solution, and carbon priority solution. And this paper further calculates the cost, carbon emissions and lot sizing of each feasible solution. In addition, the relative cosine index (RCI) and relative Euclidean index (REI) of representative solution are also calculated to evaluate the representativeness of feasible solutions.

For case1: small-scale problem (7 periods, 3 suppliers, 2 products and 2 carriers), the solution output from the model is three 4-dimensional arrays containing 84 values $X_{tijm}^{c1\_type}$, $t \in \{1,2,\ldots,7\}$, $i \in \{1,2\}$, $j \in \{1,2,3\}$, $m \in \{1,2\}$, $type \in \{\text{'}CTPS\text{'}, \text{'}BDS\text{'}, \text{'}CNPS\text{'}\}$. For case2: large-scale problem (7 periods, 7 suppliers, 6 products and 2 carriers), the solution output from the model is three 4-dimensional arrays containing 588 values $X_{tijm}^{c2\_type}$, $t \in \{1,2,\ldots,7\}$, $i \in \{1,2,\ldots,6\}$, $j \in \{1,2,\ldots,7\}$, $m \in \{1,2\}$, $type \in \{\text{'}CTPS\text{'}, \text{'}BDS\text{'}, \text{'}CNPS\text{'}\}$. For example, $X_{4231}^{c2\_CTLS} = 4835$ denotes purchase lot size of product 2 supplied by supplier 3 and carried by carrier 1 in period 4 is 4835 kilograms and this purchase quantity assigned is from the cost priority solution of Case 2. Since a four-dimensional array is difficult to display, we aggregate the purchase quantities provided by different suppliers and carriers to show the purchase quantities of each product for different periods provided by different representative solutions. The lot sizing corresponding to three representative solutions are shown in **Tables 4** and **5**.

Table 4 Three representative lot sizing procurement plans provided for case 1 using the multi-objective LSP model

Product	Type	Period1	Period2	Period3	Period4	Period5	Period6	Period7
P1	Demand	31000	58000	33000	40000	34000	33000	45000
	CTPS	56030	33008	33026	46367	27619	38680	39325
	BDPS	57655	41285	26973	39027	39565	42051	29729
	CNPS	41897	70496	38923	39895	31111	51697	6000
P2	Demand	57000	54000	38000	51000	52000	50000	54000
	CTPS	102446	8812	74565	14438	53775	50373	51990
	BDPS	99762	17646	70587	14665	52917	76478	27587
	CNPS	91681	46029	35696	60449	56670	56079	17038

Notes: "CTPS" represents the lot sizing of cost priority solution; "BDPS" represents the lot sizing of balanced solution; "CNPS" represents the lot sizing of carbon priority solution.

Table 5 Three representative lot sizing procurement plans provided for case 2 using the multi-objective LSP model

Product	Type	Period1	Period2	Period3	Period4	Period5	Period6	Period7
P1	Demand	95000	93000	65000	52000	96000	75000	88000
	CTPS	126520	69026	128950	25560	56476	90911	72342
	BDPS	131928	70620	120795	24056	59495	95920	67971
	CNPS	98161	105909	83871	118071	32204	56353	78522
P2	Demand	71000	83000	56000	56000	85000	83000	69000
	CTPS	126016	106573	33214	105084	53592	83188	12241
	BDPS	129479	110430	35722	97101	56066	80415	12152
	CNPS	93093	86910	68863	108862	75422	15709	66445
P3	Demand	62000	73000	56000	98000	76000	65000	96000
	CTPS	114595	54720	84277	92832	73824	34761	83139
	BDPS	117568	57385	82758	94233	68406	36103	82442
	CNPS	94361	43036	77031	124765	63001	37985	92657
P4	Demand	64000	82000	97000	53000	74000	99000	73000
	CTPS	86006	67196	135585	100580	24139	81498	57350
	BDPS	90283	66695	132651	101248	19922	82530	58916
	CNPS	72437	90848	102118	75040	50766	90314	65969
P5	Demand	70000	60000	81000	58000	55000	84000	63000
	CTPS	78723	74387	64589	99537	36340	92484	30512
	BDPS	81220	69023	61754	100203	37631	95772	29943
	CNPS	95858	92681	83815	46243	68726	60659	36123
P6	Demand	75000	76000	90000	56000	69000	86000	74000
	CTPS	82411	118937	59827	45140	63873	118227	41789
	BDPS	80138	123801	57818	49476	58560	120830	39592
	CNPS	110545	80221	86241	53562	93614	72517	39725

The multi-objective LSP model proposed in this paper allows purchasers to store products, so products that are not sold out in the current period can be used for the next period. From observing **Tables 4** and **5**, it is evident that in both Case 1 and Case 2, the three representative plans provided by the multi-objective LSP model meet the demand for all products in each period, with zero inventory at the end of the final period. Specifically, in some periods, the procurement volume exceeds the demand, while in others, the demand exceeds the procurement volume. This indicates that the proposed multi-objective LSP model can intelligently calculate the optimal procurement plan based on product demand in each period, supplier prices and supply capacity in each period, and carrier capacity and pricing, thereby minimizing procurement costs and the carbon emissions of the entire cold chain while meeting current demand. Additionally, significant differences can be observed in the procurement plans of different representative solutions. For instance, in Case 2, CTPS and BDS procure significantly more of Product 1 in the first period compared to CNPS, which opts to increase procurement of Product 1 in the second period. In this period, the procurement by CTPS and BDS for Product 1 is even lower than the demand. These differences arise from the need to balance low cost and low carbon emissions, with each solution having a different focus: CTPS prioritizes cost reduction, whereas CNPS emphasizes carbon emission reduction. The multi-objective LSP model must comprehensively consider demand, dynamic pricing, supply capacity, transportation capacity, and product deterioration to procure the appropriate quantities at different times. It is not feasible to buy as much as possible when prices are low because excessive one-time procurement leads to increased holding, loss, transportation costs, and carbon emissions, along with limitations in storage and transportation capacities. Considering such a multitude of factors and quickly formulating an appropriate procurement plan is an almost impossible task for purchasers. We further calculated the costs, carbon emissions, *REI*, and *RCI* for the different solutions of the two cases, as detailed in **Table 6**.

For both cases, the three representative solutions provided by the multi-objective LSP model show significant differences in total cost and total carbon emissions. In Cases 1 and 2, CTPS reduces total costs by 7.18% and 0.51% respectively compared to CNPS, while increasing total carbon emissions by 15.02% and 13.40%. The total cost and total carbon emissions for BDS fall between those of CTPS and CNPS. Among the sub-costs, the total raw material purchase cost (C3) is the highest, accounting for 90.91%-93.14% of the total cost. The cost priority solution achieves the smallest C3 by purchasing when the product price is lowest. The carbon priority solution has the largest C3 because it focuses on the reduction of carbon emissions. Excluding C3, the largest of the sub-costs is the total transportation cost (C2), accounting for 4.46%-4.98% of the total cost. In other words, planning the transportation of products properly is crucial for purchasers to reduce costs. Meanwhile, a large amount of carbon emissions will be generated during the transportation process. The carbon emissions from the transportation process (E2) are the main source of carbon emissions for the whole model, which accounts for 99.27%-99.76% of the total carbon emissions. Therefore, through the design of the procurement plan and the selection of suppliers and carriers, the purchaser can get a combination of different total costs (C) and total carbon emissions (E). *REI* and *RCI* of the representative solutions for cases1 and 2 are (0.18, 0.97) and (0.16, 0.98), which indicates that the representative solution provided by the multi-objective LSP model can adequately represent the original non-dominated solution set.

Table 6 The costs, carbon emissions, *REI*, and *RCI* for the different solutions of the two cases

Datasets	REI	RCI	Type	C1	C2	C3	C4	C5	C	E1	E2	E
Case1	0.18	0.97	CTPS	21163.14	150215	2964005.63	19994	27064	3182442	35.90	15169.70	15205.60
			BDS	30070.43	154360	3015987.63	21166	39145	3260729	50.30	14157.61	14207.91
			CNPS	59304.56	152770	3117121.37	20171	79381	3428748	96.42	13123.02	13219.44
Case2	0.16	0.98	CTPS	253362.42	832185	15326653.13	47886	287545	16747631	372.08	89989.63	90361.71
			BDS	262578.56	827730	15339825.15	47886	300516	16778536	387.87	89185.41	89573.27
			CNPS	232258.49	838015	15432435.42	47886	283611	16834206	342.91	79340.67	79683.58

Notes: **C1** is the total holding cost of the purchaser; **C2** is the total transportation cost paid by the purchaser; **C3** is the total raw material purchase cost of the purchaser; **C4** is the total order processing cost paid by the purchaser; **C5** calculates the total loss cost of the purchaser's holding process; **C** is the purchaser's total procurement cost. **E** is the total carbon emissions throughout the procurement process; **E1** is the carbon footprint from the holding process; **E2** is the carbon emissions from the transportation process.

7 Discussion

In this section, the paper conducts a comparative analysis between the multi-objective LSP model and a benchmark model with relaxed carbon emission constraints. Additionally, it performs a sensitivity analysis of the inventory loss rate and examines the stability of the multi-objective LSP model.

7.1 Comparison of proposed and benchmark model

In this section, we relax the carbon emission constraints in the multi-objective LSP model, forming a benchmark model to validate the superiority of the proposed multi-objective LSP model in addressing low-carbon procurement issues. The benchmark model is a single-objective model, with assumptions and symbols identical to those of the multi-objective LSP model. The mathematical model of the benchmark model, compared to the multi-objective LSP model, only excludes **Eqs. (7) - (9)**. Both models are applied to two case studies, with the results shown in **Figs 3 and 4**. Procurement plans for cases 1 and 2 using the benchmark model are shown in **Appendix B: Tables B1** and **B2**. The comparative data between the benchmark model and the proposed multi-objective LSP model can be found in **Appendix B: Tables B3**.

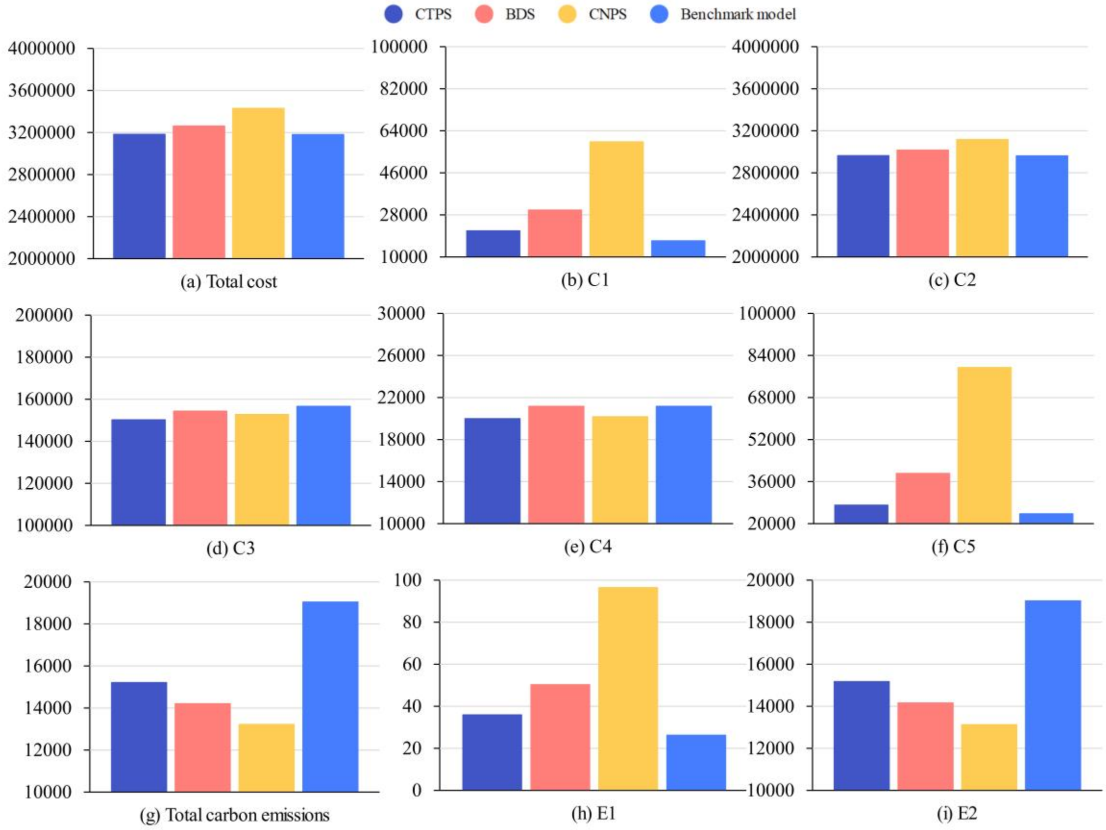


Fig. 3 Results of the benchmark model and the multi-objective LSP model for case 1

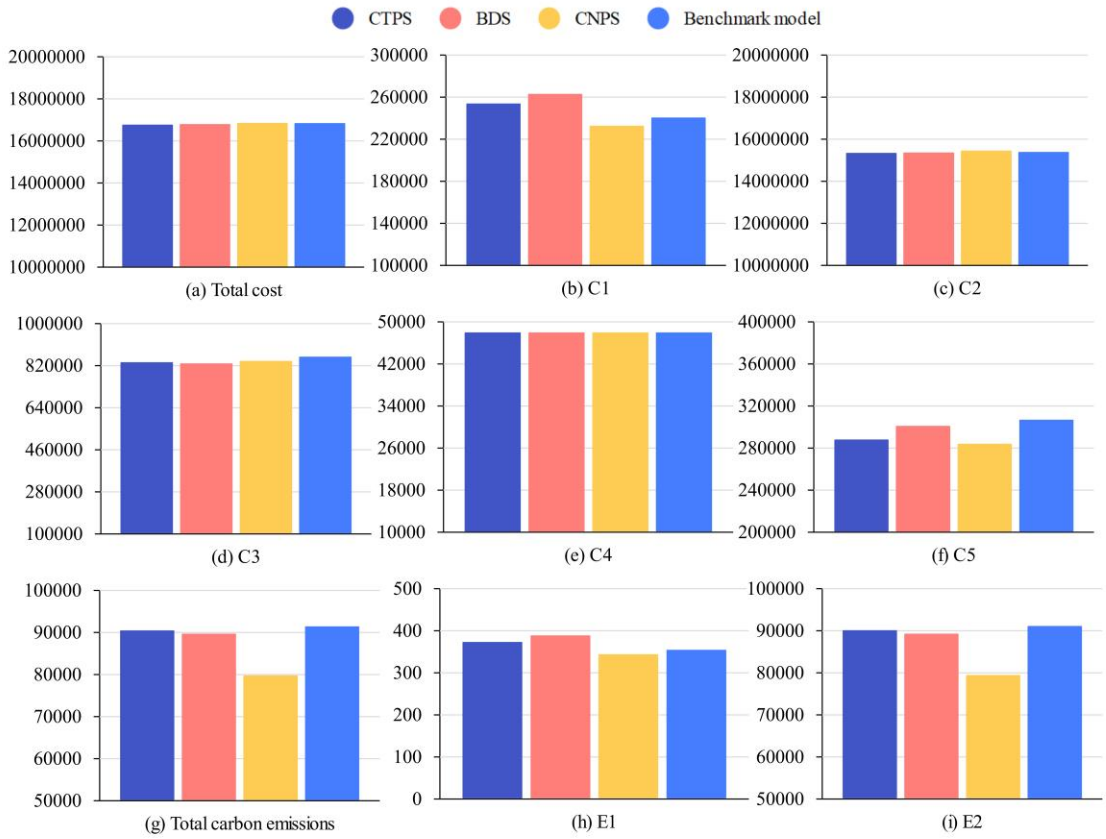
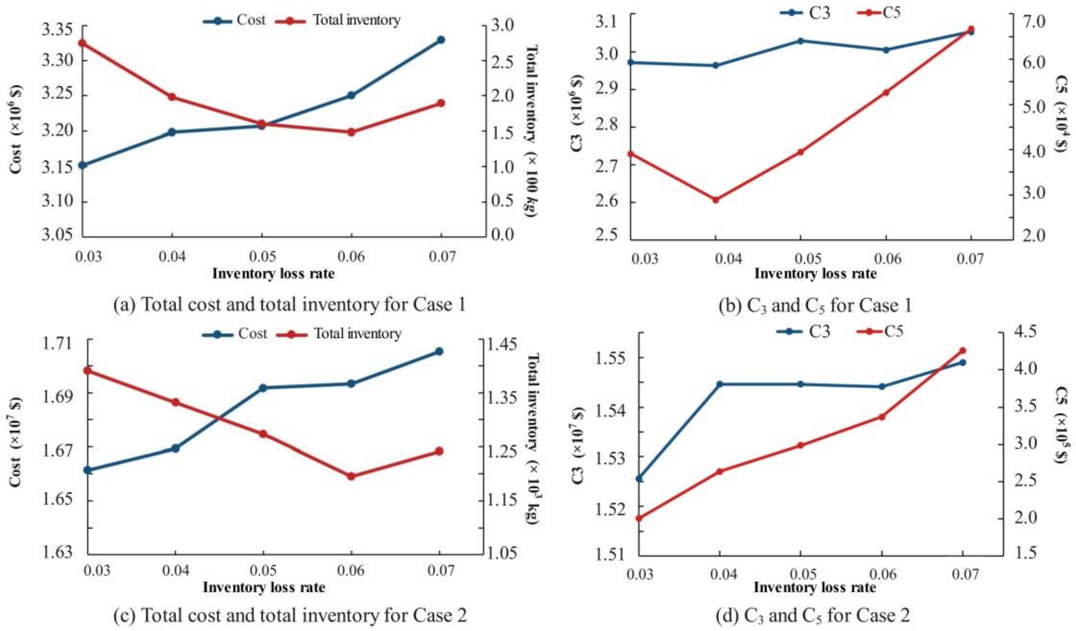


Fig. 4 Results of the benchmark model and the multi-objective LSP model for case 2

From **Figs. 3** and **4**, it can be observed that the cost characteristics of the procurement plan provided by the benchmark model are very similar to those of CTPS (both in terms of total cost and sub-costs). Specifically, for Case 1, compared to the benchmark model, CTPS showed a slight increase of 0.07% in total cost and a significant decrease of 20.13% in total carbon emissions. In Case 2, compared to the baseline model, CTPS demonstrated a decrease of 0.42% in total cost and a reduction of 1.07% in total carbon emissions. It is evident that the CTPS provided by the multi-objective LSP model optimizes procurement plans to achieve minimal purchasing costs while also minimizing carbon emissions as much as possible. Even when comparing CNPS with the benchmark model, for Case 1, CNPS incurs a cost increase of only 7.81%, resulting in a 30.56% reduction in total carbon emissions. For Case 2, CNPS incurs a cost increase of only 0.09%, leading to a 12.76% reduction in total carbon emissions. It is evident that the proposed multi-objective LSP model's CNPS can achieve a significant reduction in carbon emissions at a minimal cost increase. These results demonstrate the remarkable capability of the multi-objective LSP model proposed in this paper in solving low-carbon cold chain procurement problems. The model can provide decision-makers with a range of reliable, effective, cost-effective, and low-carbon procurement options.

7.2 Sensitivity analysis

This paper conducts a sensitivity analysis of inventory loss rate to study the impact of inventory loss rate on procurement planning, cost, and carbon emissions. The variation range of the inventory loss rate is 0.03 to 0.07 with a step size of 0.01. The results of the sensitivity analysis are presented in **Fig. 5**, where the numerical labels refer to the total costs and total carbon emissions.



(a) Total cost and total inventory for Case 1

(b) C_3 and C_5 for Case 1

(c) Total cost and total inventory for Case 2

(d) C_3 and C_5 for Case 2

Fig. 5 Sensitivity analysis on inventory loss rate

According to **Fig. 5**, as the inventory loss rate increases, the total cost of procurement increases. This is because as the inventory loss rate increases, holding loss costs (C5) will also rise. Additionally, with escalating product losses, buyers are compelled to procure more goods to meet demand, thereby increasing raw material purchase costs (C3). As illustrated in **Fig. 5**, the solution proposed by the multi-objective LSP model for cost reduction involves reducing inventory levels by increasing the frequency of procurement and decreasing the quantity of products purchased per batch. However, this strategy involves a trade-off, as increasing frequency of procurement to reduce inventory leads to higher transportation costs and carbon emissions. It is notable that when the inventory loss rate reaches 0.07, the inventory level actually increases. This anomaly occurs because the multi-objective LSP model determines that, at this point, the benefits of reducing inventory are outweighed by the associated losses. Therefore, it suggests a modest increase in inventory to achieve optimal cost savings and minimize carbon emissions.

7.3 Stability experiments

To verify the high stability of the multi-objective LSP model, this paper conducts ten replicate experiments (assuming conditions, parameters, and data are unchanged) for cases1 and 2, respectively. **Table 7** presents the descriptive statistics of the stability experiment results for Cases 1 and 2. Detailed information can be found in the **Appendix B: Tables B4** and **B5**.

Based on the results of 10 replicate experiments, the average, standard deviation, and coefficient of variation for cost and carbon emissions were calculated in this paper. For case1, coefficients of variation for the costs of cost priority, balanced, and carbon priority solutions are 0.01, 0.01, 0.01, respectively; Coefficients of variation for the carbon emissions of cost priority, balanced, and carbon priority solutions are 0.08, 0.05, 0.08, respectively. For case2, coefficients of variation for the costs of cost priority, balanced, and carbon priority solutions are 0.01, 0.01, 0.01, respectively; Coefficients of variation for the carbon emissions of cost priority, balanced, and carbon priority solutions are 0.04, 0.04, 0.05, respectively. The coefficients of variation for costs and carbon emissions are very small for cases 1 and 2, indicating that the differences in results across 10 replicate experiments are small. That is to say, the results of the multi-objective LSP model are stable over 10 replicate experiments. The above results illustrate that the multi-objective LSP model can stably solve lot sizing procurement problem in complex scenarios. In addition, the REI and RCI of 10 replicate experiments were also calculated. For case1, coefficients of variation for REI and RCI are 0.30 and 0.05. For case2, coefficients of variation for REI and RCI are 0.58 and 0.03. The coefficients of variation for RCI in two cases are very small. The coefficients of variation for REI in two cases are slightly larger, but the averages (0.21 and 0.11) and standard deviation (0.06 and 0.07) of the REI are very small in cases 1 and 2. This shows that the multi-objective LSP model can stably provide decision makers with representative solutions that can effectively represent the original non-dominated solution set.

Table 7 The results of stability experiments

Datasets	Metrics	Cost priority solution		Balanced solution		Carbon priority solution			
		Cost	Carbon	Cost	Carbon	Cost	Carbon	REI	RCI
Case1	AVG	3227189.90	15605.22	3273650.68	13989.60	3343146.31	12870.90	0.21	0.94
	SD	37301.18	1227.77	37134.96	657.21	46593.89	1028.80	0.06	0.04
	CV	0.01	0.08	0.01	0.05	0.01	0.08	0.30	0.05
Case2	AVG	16836301.66	91240.13	16847849.27	91004.33	16884228.40	89740.72	0.11	0.98
	SD	131984.21	3445.63	127443.83	3473.52	147595.58	4725.03	0.07	0.03
	CV	0.01	0.04	0.01	0.04	0.01	0.05	0.58	0.03

8 Managerial insights

Low carbon economy has become a social consensus, cold chain logistics with high energy consumption characteristics must pay attention to carbon emission reduction technology. The development of low carbon cold chain management not only can effectively reduce the cost of carbon emissions of enterprises, but also help to improve the public reputation of enterprises. Therefore, it is urgent for the cold chain associated enterprises to vigorously develop low-carbon cold chain management. Low carbon lot sizing procurement for perishable products is an extremely complex system, which usually involves multiple periods and multiple processes, such as lot size issues, supplier selection and carrier selection. Experiments show that the multi-objective LSP model proposed in this paper can achieve considerable carbon emission reduction at a low cost and has high stability. By using the multi-objective LSP model, purchasers can obtain three feasible solutions and then choose the most suitable low-carbon cold chain procurement and logistics plan according to their business development needs. This will greatly improve the efficiency of enterprises and reduce the total cost and carbon emission of the whole process of cold chain procurement and logistics. In addition, sensitivity analysis experiments have shown that an increase in inventory loss rate will significantly increase total costs and total carbon emissions. The inventory loss rate increased from 0.03 to 0.07, and the total cost increased by 3% and 5.62%, respectively, while carbon emissions remained relatively stable. Reducing the inventory loss rate by improving and investing in cold storage will help to reduce the total cost and carbon emissions of the cold chain system. Further analysis of the sensitivity analysis results reveals that as the inventory loss rate increases, the procurement plans provided by the multi-objective LSP model show a decrease in inventory levels and an increase in transportation frequency to control the rise in total costs and carbon emissions. However, when the inventory loss rate reaches 0.07, the inventory levels instead begin to rise. This indicates that when the technological level of cold storage facilities remains unchanged, reducing a certain amount of product inventory can lower overall costs and carbon emissions. However, once the inventory loss rate surpasses a certain threshold, continuing to reduce inventory levels becomes unwise. It’s important to note that decision makers must consider hundreds of factors and strike a balance between reducing inventory, increasing transportation costs, and raising carbon emissions. This is an extremely complex and difficult task to accomplish. The application of multi-objective LSP models will effectively solve this challenge and find the optimal solution to the problem for decision makers. The multi-objective LSP model proposed in this paper will effectively promote the development of low carbon cold chain procurement system.

9 Conclusions and further research directions

This paper proposes a multi-objective LSP model to solve low carbon lot sizing procurement problems in a multi-period, multi-product, multi-supplier, multi-carrier scenario. In the multi-objective LSP model, MOSMA is used in the first step to obtain the non-dominated solution set. The solution set contains too many solutions and these solutions have high dimensional characteristics. Therefore, it is challenging for decision makers to quickly select a solution that meet their needs from the non-dominated solution set. To solve this problem, the multi-objective LSP model adopts K-means++

to prune the non-dominated solution set to obtain three representative solutions (cost priority, balanced, and carbon priority solutions). Decision makers can greatly ease the burden of decision-making by selecting suitable representative solutions that align with their specific needs. This paper uses two numerical cases (large-scale and small-scale problems) to test the effectiveness of the multi-objective LSP model. Additionally, through comparisons with a benchmark model, sensitivity analysis, and stability experiments, this study further validates that the proposed multi-objective LSP model can effectively address low-carbon cold chain procurement issues and provide decision-makers with reliable and efficient procurement plans. The specific research findings are as follows.

(1) The proposed multi-objective LSP model effectively addresses the low-carbon cold chain transportation problem, enabling cost-effective control of the total carbon footprint of the entire cold chain.

(2) This paper uses the K-means++ algorithm to prune the non-dominated solution set, yielding three representative solutions: CTPS, BDS, and CNPS. These solutions maintain high representativeness and preserve the diversity of the original solution set as much as possible. In other words, the proposed multi-objective LSP model can provide decision-makers with reliable and effective cold chain procurement plan options.

(3) Product transportation planning is the core task of the entire cold chain procurement process, as it accounts for a significant portion of both cost and carbon emissions. Effective planning of product transportation is crucial for reducing costs and carbon emissions in the procurement process.

(4) An increase in inventory loss rates leads to higher costs and carbon emissions in the entire cold chain procurement process. To mitigate the rising costs associated with higher inventory loss rates, increasing transportation frequency and reducing inventory levels can be effective, although this approach further escalates carbon emissions.

Although the proposed multi-objective LSP model can effectively solve low-carbon lot sizing procurement problems in complex scenarios, there are still two limitations in this paper. One is that the model assumes that demand is known; the other is that the selection of suppliers only considers product output and price. Therefore, we can relax the known demand assumption and try to use artificial intelligence technology to forecast demand in future research. In addition, more factors should be considered in the selection of suppliers, such as product quality, corporate reputation, and supply reliability, which will further improve the risk resistance and sustainability of the supply chain.

Acknowledgments This paper is supported by National Natural Science Foundation of China (72104046), Major project of the National Social Science Fund (22&ZD159), and Statistical Science Key Research Program of China(2023LZ032).

Declaration of Competing Interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

See **Tables A1-A9**.

Table A1 The product price of case 1 ($)

Product	Supplier	Period1	Period2	Period3	Period4	Period5	Period6	Period7
P1	S1	6853	6513	6240	6240	6903	6489	6369
	S2	6622	6402	6123	6417	6945	6338	6111
	S3	6351	6076	6184	6049	6491	6900	6781
P2	S1	3443	3004	3869	3260	3911	3145	3580
	S2	3106	3775	3084	3800	3182	3136	3550
	S3	3962	3818	3400	3431	3264	3870	3145

Random function: Price = randi([6000 7000],3,7)

Table A2 Supplier availability of case1 (t)

Product	Supplier	Period1	Period2	Period3	Period4	Period5	Period6	Period7
P1	S1	93	96	145	144	87	122	130
	S2	96	110	110	149	98	98	95
	S3	92	102	93	111	109	122	88
P2	S1	93	96	145	144	87	122	130
	S2	96	110	110	149	98	98	95
	S3	92	102	93	111	109	122	88

Random function: Supplier availability = randi([80 150],3,7)

Table A3 The carrying capacity of the carrier (t) and distance from supplier to the purchaser (km) of case1

	Supplier 1	Supplier 2	Supplier 3	TC
Carrier 1	194	178	181	5
Carrier 2	12	11	15	30
Distance	65	66	71	—

Random function: carrying_capacity_C1 = randi([150 200],1,3)*1.5;
carrying_capacity_C2 = randi([100 150],1,3)*10; Distance = randi([50 100],3,1);
TC is unit transportation cost of carrier

Table A4 Order processing cost of case 1 ($)

	Period1	Period2	Period3	Period4	Period5	Period6	Period7
Supplier 1	1003	1121	1092	895	1019	996	958
Supplier 2	834	811	995	983	1008	1050	947
Supplier 3	905	1172	1031	1186	892	1072	1196

Random function: Order processing cost = randi([800 1200],3,7)

Table A5 The product price of case 2 ($)

Product	Supplier	Period1	Period2	Period3	Period4	Period5	Period6	Period7
P1	S1	5568	5569	5529	5450	5997	5818	5911
	S2	5075	5469	5165	5083	5078	5869	5182
	S3	5054	5011	5602	5229	5443	5084	5264
	S4	5531	5337	5263	5914	5106	5400	5145
	S5	5779	5162	5654	5152	5962	5260	5136
	S6	5934	5795	5689	5826	5004	5800	5870
	S7	5130	5311	5748	5538	5775	5431	5580

P2	S1	3550	3076	3903	3111	3942	3015	3547
	S2	3145	3240	3945	3781	3957	3043	3296
	S3	3853	3123	3491	3390	3575	3169	3745
	S4	3622	3184	3489	3241	3059	3649	3189
	S5	3351	3240	3338	3404	3235	3732	3687
	S6	3513	3417	3900	3096	3353	3648	3183
	S7	3402	3049	3369	3132	3822	3451	3368
P3	S1	5626	5447	5378	5623	5194	5430	5409
	S2	5781	5306	5812	5587	5226	5185	5595
	S3	5081	5509	5533	5207	5170	5905	5262
	S4	5930	5511	5351	5301	5227	5980	5603
	S5	5776	5818	5939	5471	5436	5439	5711
	S6	5487	5795	5876	5230	5311	5111	5221
	S7	5436	5644	5550	5845	5924	5258	5117
P4	S1	3296	3029	3964	3395	3098	3654	3699
	S2	3319	3929	3547	3367	3262	3494	3198
	S3	3424	3731	3521	3988	3335	3779	3030
	S4	3508	3489	3231	3037	3680	3715	3744
	S5	3085	3579	3489	3886	3136	3904	3500
	S6	3262	3237	3624	3914	3721	3891	3480
	S7	3801	3459	3679	3796	3106	3334	3905
P5	S1	4610	4887	4471	4818	4649	4173	4417
	S2	4618	4028	4059	4818	4801	4391	4657
	S3	4860	4490	4682	4723	4454	4832	4628
	S4	4806	4168	4042	4150	4432	4804	4292
	S5	4577	4979	4071	4660	4826	4060	4432
	S6	4183	4713	4522	4519	4083	4399	4015
	S7	4240	4500	4096	4973	4133	4527	4985
P6	S1	6167	6921	6418	6667	6882	6856	6590
	S2	6106	6052	6984	6178	6669	6645	6226
	S3	6372	6738	6301	6128	6190	6376	6385
	S4	6198	6269	6701	7000	6369	6191	6583
	S5	6490	6423	6667	6171	6461	6428	6252
	S6	6339	6548	6539	6032	6982	6482	6290
	S7	6952	6943	6698	6561	6156	6120	6617

Random function: P1 = randi([5000 6000],7,7); P2 = randi([3000 4000],7,7);
P3 = randi([5000 6000],7,7); P4 = randi([3000 4000],7,7);
P5 = randi([4000 5000],7,7); P6 = randi([6000 7000],7,7)

Table A6 Supplier availability of case2 (t)

Product	Supplier	Period1	Period2	Period3	Period4	Period5	Period6	Period7
P1	S1	108	99	108	103	150	133	89
	S2	128	93	137	127	116	138	128
	S3	129	138	133	111	142	136	115
	S4	111	110	106	139	121	102	93
	S5	81	143	95	134	90	117	115
	S6	103	107	136	91	94	86	90
	S7	110	134	147	141	108	87	83
P2	S1	129	142	147	83	149	82	81
	S2	115	99	85	146	140	146	139

	S3	118	94	87	131	135	101	119
	S4	111	120	90	132	116	100	140
	S5	88	125	91	84	92	103	104
	S6	114	109	124	141	108	113	111
	S7	140	94	120	146	89	126	83
P3	S1	86	104	117	108	89	85	87
	S2	85	100	131	84	119	86	88
	S3	135	132	130	135	114	136	125
	S4	144	80	135	103	143	146	103
	S5	117	83	100	123	136	128	126
	S6	87	127	129	132	132	89	133
	S7	138	122	119	87	83	131	121
P4	S1	134	126	87	97	144	92	108
	S2	129	131	90	143	130	98	124
	S3	88	117	91	129	119	108	90
	S4	89	87	93	119	102	85	107
	S5	86	124	102	93	91	128	91
	S6	80	88	102	95	124	108	133
	S7	110	89	95	85	150	149	141
P5	S1	145	111	130	136	141	107	139
	S2	126	98	125	140	124	90	132
	S3	146	133	109	115	105	81	120
	S4	91	96	107	125	150	109	92
	S5	145	84	137	147	95	93	147
	S6	136	134	102	111	126	131	98
	S7	120	127	137	84	122	106	145
P6	S1	97	121	105	88	145	99	134
	S2	100	119	148	101	134	127	146
	S3	128	121	104	131	83	113	87
	S4	117	116	142	135	106	124	92
	S5	109	85	112	129	130	96	87
	S6	122	131	109	80	131	92	114
	S7	133	150	95	139	95	138	93

Random function: Supplier availability = randi([80 150],7,7)

Table A7 The carrying capacity of the carrier (t) and distance from supplier to purchaser (km) of case2

	S1	S2	S3	S4	S5	S6	S7	TC
Carrier 1	123	147	93	126	96	126	127.5	5
Carrier 2	70	60	60	80	90	50	80	30
Distance	97	70	52	67	87	90	77	—

Random function: carrying_capacity_C1 = randi([80 100],1,7)*1.5;
carrying_capacity_C2 = randi([3 10],1,7)*10;
Distance = randi([50 100],7,1)
TC is unit transportation cost of carrier

Table A8 Order processing cost of case 2 ($)

Product	Period1	Period2	Period3	Period4	Period5	Period6	Period7
P1	1092	1164	1106	1142	892	1185	1032
P2	999	877	1024	1185	958	1014	1012

P3	1124	973	873	1072	1082	1186	1161
P4	942	1100	999	961	1023	846	1016
P5	829	815	1007	1174	1103	820	973
P6	1036	1179	1198	992	1199	922	1017

Random function: Order processing cost = randi([800 1200],6,7)

Table A9 Unit holding cost of product ($)

Case	Product1	Product 2	Product 3	Product 4	Product 5	Product 6
Case1	275	157	—	—	—	—
Case2	159	178	205	246	247	165

Random function：
Case1: Unit holding cost = randi([150 300],2,1)
Case2: Unit holding cost = randi([150 300],6,1)

Appendix B

See **Tables B1 – 6**.

Table B1 Procurement and logistics plans provided for case 1 using the relaxed LSP model

Product	Type	Period1	Period2	Period3	Period4	Period5	Period6	Period7
P1	Demand	31000	58000	33000	40000	34000	33000	45000
	Lot sizing	31001	58010	35879	58411	12845	64268	13732
P2	Demand	57000	54000	38000	51000	52000	50000	54000
	Lot sizing	57724	54759	36554	57402	62986	42757	45032

Table B2 Procurement and logistics plans provided for case 2 using the relaxed LSP model

Product	Type	Period1	Period2	Period3	Period4	Period5	Period6	Period7
P1	Demand	95000	93000	65000	52000	96000	75000	88000
	Lot sizing	111489	105648	84104	66159	54399	64117	86181
P2	Demand	71000	83000	56000	56000	85000	83000	69000
	Lot sizing	74108	113927	45174	80301	79757	66636	50550
P3	Demand	62000	73000	56000	98000	76000	65000	96000
	Lot sizing	79631	126063	101512	71595	35423	56393	71127
P4	Demand	64000	82000	97000	53000	74000	99000	73000
	Lot sizing	68910	95661	82956	54528	132726	62030	49989
P5	Demand	70000	60000	81000	58000	55000	84000	63000
	Lot sizing	80196	94951	80726	50182	73340	54714	45806
P6	Demand	75000	76000	90000	56000	69000	86000	74000
	Lot sizing	96883	77397	128657	76212	35160	64766	57930

Table B3 Comparison of proposed and benchmark model

Data set	Model	Cost	Rate	Carbon	Rate
Case1	CTPS	3182442.22	0.07%	15205.60	-20.13%
	BDS	3260730.68	2.53%	14207.91	-25.37%
	CNPS	3428748.04	7.81%	13219.44	-30.56%
	Benchmark model	3180301.70	—	19036.89	—
Case2	CTPS	16747631.76	-0.42%	90361.71	-1.07%
	BDS	16778536.16	-0.24%	89573.27	-1.93%
	CNPS	16834206.29	0.09%	79683.58	-12.76%
	Benchmark model	16818711.22	—	91335.35	—

Notes: "CTPS" represents the cost priority solution; "BDS" represents the balanced solution; "CNPS" represents the carbon priority solution; "Carbon" refers to the total carbon emissions; "Cost" is the cost that purchaser need to pay; "Rate" refers to the ratio by which "CTPS", "BDS", and "CNPS" are improved over "Benchmark model".

Table B4 The results of replicate experiments for case1

No.	Cost priority solution		Balanced solution		Carbon priority solution			
	Cost	Carbon	Cost	Carbon	Cost	Carbon	REI	RCI
1	3222598.55	17412.08	3314500.90	14976.63	3344927.64	13880.12	0.12	0.98
2	3182591.58	17700.77	3204193.57	14692.29	3290091.97	14224.19	0.15	0.90
3	3182442.22	15205.60	3260730.68	14207.91	3428748.04	13219.44	0.18	0.97
4	3227396.40	16104.55	3286082.78	14257.25	3383357.21	12804.14	0.30	0.86
5	3237927.70	15660.41	3259233.37	13790.37	3365751.43	11983.99	0.19	0.97
6	3294713.44	14301.21	3308407.87	13183.68	3358047.81	11871.04	0.28	0.89
7	3191168.43	14294.95	3234745.31	13749.87	3275477.27	11288.02	0.29	0.97
8	3213114.55	14705.56	3271200.25	12915.22	3336412.21	12207.41	0.16	0.96
9	3250225.03	16083.32	3272192.25	14502.28	3295082.04	14211.21	0.19	0.95
10	3269721.15	14583.79	3325215.87	13620.52	3353570.50	13019.49	0.20	0.95
AVG	3227189.90	15605.22	3273650.68	13989.60	3343146.31	12870.90	0.21	0.94
SD	37301.18	1227.77	37134.96	657.21	46593.89	1028.80	0.06	0.04
CV	0.01	0.08	0.01	0.05	0.01	0.08	0.30	0.05

Note: "Cost" refers to the cost that the purchaser needs to pay in the cold chain; "Carbon" refers to the total carbon emissions in the cold chain; "SD" represents standard deviation; "CV" represents coefficient of variation; "AVG" represents average.

Table B5 The results of replicate experiments for case2

No.	Cost priority solution		Balanced solution		Carbon priority solution			
	Cost	Carbon	Cost	Carbon	Cost	Carbon	REI	RCI
1	16747631.76	90361.71	16778536.16	89573.27	16834206.29	79683.58	0.17	0.98
2	16938489.25	87989.31	16939022.18	87984.74	16939636.78	87662.77	0.13	0.98
3	16610965.61	97213.21	16611043.52	97212.51	16611706.87	97212.42	0.05	0.99
4	16788997.95	90131.71	16796482.39	90010.28	16801416.98	89852.33	0.21	0.97
5	16798493.78	92168.86	16811362.89	91941.13	16814065.23	91575.97	0.16	0.97
6	16761852.77	88928.13	16776087.37	88239.77	16832172.06	87941.64	0.15	0.91
7	16734212.18	94969.04	16771541.01	94901.65	16791666.65	94788.78	0.10	0.99
8	16917312.42	95588.09	16920108.77	95220.40	17141634.66	93736.83	0.13	0.99
9	17001618.20	88915.75	17010802.32	88826.56	17010825.97	88826.54	0.01	0.99
10	17063442.69	86135.47	17063506.06	86132.96	17064952.47	86126.31	0.01	0.99
AVG	16836301.66	91240.13	16847849.27	91004.33	16884228.40	89740.72	0.11	0.98
SD	131984.21	3445.63	127443.83	3473.52	147595.58	4725.03	0.07	0.03
CV	0.01	0.04	0.01	0.04	0.01	0.05	0.58	0.03

Note: “Cost” refers to the cost that the purchaser needs to pay in the cold chain; “Carbon” refers to the total carbon emissions in the cold chain; “SD” represents standard deviation; “CV” represents coefficient of variation; “AVG” represents average.

Table B6 The pseudocode for MOSMA

```
Pseudo: MOSMA
Input:
- Population size n
- Maximum number of iterations max_iter
- Search space bounds UB and LB
Output:
- Non-dominated solutions and Pareto front
Begin
1. Initialize the population positions X(i), i = 1, 2, ..., n within the bounds UB and LB
2. Evaluate the initial fitness E(i) for each individual in the population
3. Set BE to be the best fitness value among the initial population
4. while (iteration < max_iter) do
    a. for each individual i in the population do
        i. Calculate the step size c:
            c = tanh(|E(i) - BE|)
        ii. Calculate the direction vector vb:
            vb = [-a, a]
            a = arctanh (-(iteration / max_iter) + 1)
        iii. Calculate the weight vector W for each fitness value:
            W = [0] * n
            sorted_indices = sort(E) # Sort E in ascending order
            for j = 1 to n/2 do
                if condition:
                    W(sorted_indices(j)) = 1 + rand1 * log((BE - E(sorted_indices(j))) / (BE - worst_E) +1)
                else:
                    W(sorted_indices(j)) = 1 - rand1 * log((BE - E(sorted_indices(j))) / (BE - worst_E) + 1)
                end if
            end for
        iv. Update the position of each individual:
            if rand1 >= c then
                X(i) = vc * X(i)
            else
                X(i) = L(i) + vb * (W * X_a - X_b)
            end if
        v. Simulate positive and negative feedback mechanism:
            if rand2 < z then
                X(i) = rand2 * (UB - LB) + LB
            else if rand1 < c then
                X(i) = L(i) + vb * (W * X_a - X_b)
            else
                X(i) = vc * X(i)
            end if
        end for
    b. Calculate the crowding distance to ensure the diversity of non-dominated solutions:
        for each individual i in the population do
            C_Dis_i^j = (E(sorted_indices(i+1)) - E(sorted_indices(i-1))) / (E_max^j - E_min^j)
        end for
    c. Perform non-dominated sorting:
        for each individual k in the population do
            Compare dominance and non-dominance relationships between X_k and other individuals X_l
            if no individual X_l dominates X_k then
                Mark X_k as a non-dominated individual
            end if
        end for
        Repeat for remaining unlabeled individuals to obtain other non-dominated layers
    d. Select the next generation:
        i. Merge current population Po with new solutions Pj to create Pi
        ii. Evaluate Pi and sort based on non-dominated sorting and crowding distance
        iii. Select the top n individuals to form the new population Po
5. end while
6. Output the optimal solutions and the Pareto front
End
```

References

[1] Bodansky D. The United Nations Framework Convention on Climate Change: A Commentary . Yale J Int Law 1993;18:451–558.

[2] Breidenich C, Magraw D, Rowley A, Rubin J. The Kyoto Protocol to the United Nations Framework Convention on Climate Change. Am J Int Law 1998;92:315–31. https://doi.org/10.2307/2998044.

[3] Mallapaty S. How China could be carbon neutral by mid-century. Nature 2020;586:482–4. https://doi.org/10.1038/d41586-020-02927-9.

[4] Du S, Qian J, Liu T, Hu L. Emission allowance allocation mechanism design: a low-carbon operations perspective. Ann Oper Res 2020. https://doi.org/10.1007/s10479-018-2922-z.

[5] Chen X, Yang H, Wang X, Choi TM. Optimal carbon tax design for achieving low carbon supply chains. Ann Oper Res 2020. https://doi.org/10.1007/s10479-020-03621-9.

[6] Jia Z, Lin B. Rethinking the choice of carbon tax and carbon trading in China. Technol Forecast Soc Change 2020;159:120187. https://doi.org/10.1016/j.techfore.2020.120187.

[7] Fu H, Lei Y, Zhang S, Zhao K, Zhao Y. Unravelling the carbon emissions compliance in sustainable supply chains: The impacts of carbon audit cooperation. Omega 2024;129:103143. https://doi.org/10.1016/j.omega.2024.103143.

[8] Xia L, Bai Y, Ghose S, Qin J. Differential game analysis of carbon emissions reduction and promotion in a sustainable supply chain considering social preferences. Ann Oper Res 2022. https://doi.org/10.1007/s10479-020-03838-8.

[9] Jauhari WA, Pujawan IN, Suef M. Sustainable inventory management with hybrid production system and investment to reduce defects. Ann Oper Res 2022. https://doi.org/10.1007/s10479-022-04666-8.

[10] Zhao B, Gui H, Li H, Xue J. Cold Chain Logistics Path Optimization via Improved Multi-Objective Ant Colony Algorithm. IEEE Access 2020;8:142977–95. https://doi.org/10.1109/ACCESS.2020.3013951.

[11] Yang L, Braun JE, Groll EA. The impact of fouling on the performance of filter-evaporator combinations. Int J Refrig 2007;30:489–98. https://doi.org/10.1016/j.ijrefrig.2006.08.006.

[12] Zhang LY, Tseng ML, Wang CH, Xiao C, Fei T. Low-carbon cold chain logistics using ribonucleic acid-ant colony optimization algorithm. J Clean Prod 2019;233:169–80. https://doi.org/10.1016/j.jclepro.2019.05.306.

[13] Claassen GDH, Kirst P, Van ATT, Snels JCMA, Guo X, van Beek P. Integrating time-temperature dependent deterioration in the economic order quantity model for perishable products in multi-echelon supply chains. Omega 2024;125:103041. https://doi.org/10.1016/j.omega.2024.103041.

[14] Khalili-Fard A, Hashemi M, Bakhshi A, Yazdani M, Jolai F, Aghsami A. Integrated relief pre-positioning and procurement planning considering non-governmental organizations support and perishable relief items in a humanitarian supply chain network. Omega 2024;127:103111. https://doi.org/10.1016/j.omega.2024.103111.

[15] Boonmee A, Sethanan K. A GLNPSO for multi-level capacitated lot-sizing and scheduling problem in the poultry industry. Eur J Oper Res 2016.

https://doi.org/10.1016/j.ejor.2015.09.020.
[16] Mazdeh MM, Emadikhiav M, Parsa I. A heuristic to solve the dynamic lot sizing problem with supplier selection and quantity discounts. Comput Ind Eng 2015. https://doi.org/10.1016/j.cie.2015.02.027.
[17] Wang G. Order assignment and two-stage integrated scheduling in fruit and vegetable supply chains. Omega 2024;124:103013. https://doi.org/10.1016/j.omega.2023.103013.
[18] Minner S. A comparison of simple heuristics for multi-product dynamic demand lot-sizing with limited warehouse capacity. Int J Prod Econ 2009. https://doi.org/10.1016/j.ijpe.2008.08.034.
[19] Wagner HM, Whitin TM. Dynamic Version of the Economic Lot Size Model. Manage Sci 1958. https://doi.org/10.1287/mnsc.5.1.89.
[20] Choudhary D, Shankar R. A goal programming model for joint decision making of inventory lot-size, supplier selection and carrier selection. Comput Ind Eng 2014. https://doi.org/10.1016/j.cie.2014.02.003.
[21] Liao Z, Rittscher J. Integration of supplier selection, procurement lot sizing and carrier selection under dynamic demand conditions. Int J Prod Econ 2007. https://doi.org/10.1016/j.ijpe.2006.10.003.
[22] Gan X, Sethi SP, Xu L. Simultaneous Optimization of Contingent and Advance Purchase Orders with Fixed Ordering Costs. Omega (United Kingdom) 2019. https://doi.org/10.1016/j.omega.2018.10.010.
[23] Liu H, Zhang J, Zhou C, Ru Y. Optimal purchase and inventory retrieval policies for perishable seasonal agricultural products. Omega (United Kingdom) 2018. https://doi.org/10.1016/j.omega.2017.08.006.
[24] Siemon M, Schiffer M, Walther G. Integrated purchasing and production planning for a non-Ferrous metal production network. Omega (United Kingdom) 2021. https://doi.org/10.1016/j.omega.2019.102136.
[25] Zamani Dadaneh D, Moradi S, Alizadeh B. Simultaneous planning of purchase orders, production, and inventory management under demand uncertainty. Int J Prod Econ 2023. https://doi.org/10.1016/j.ijpe.2023.109012.
[26] Azadnia AH, Saman MZM, Wong KY. Sustainable supplier selection and order lot-sizing: An integrated multi-objective decision-making process. Int J Prod Res 2015. https://doi.org/10.1080/00207543.2014.935827.
[27] Nourmohamadi Shalke P, Paydar MM, Hajiaghaei-Keshteli M. Sustainable supplier selection and order allocation through quantity discounts. Int J Manag Sci Eng Manag 2018. https://doi.org/10.1080/17509653.2016.1269246.
[28] Hariga M, As’ad R, Shamayleh A. Integrated economic and environmental models for a multi stage cold supply chain under carbon tax regulation. J Clean Prod 2017. https://doi.org/10.1016/j.jclepro.2017.08.105.
[29] Jing F, Mu Y. Dynamic lot-sizing model under perishability, substitution, and limited storage capacity. Comput Oper Res 2020. https://doi.org/10.1016/j.cor.2020.104978.
[30] As’ad R, Hariga M, Shamayleh A. Sustainable dynamic lot sizing models for cold products under carbon cap policy. Comput Ind Eng 2020. https://doi.org/10.1016/j.cie.2020.106800.
[31] Kaur H, Singh SP. Modeling low carbon procurement and logistics in supply chain: A key towards sustainable production. Sustain Prod Consum 2017. https://doi.org/10.1016/j.spc.2017.03.001.
[32] Chen G, Wahab MIM, Fang L. Optimal replenishment strategy for a

single-manufacturer multi-retailer cold chain considering multi-stage quality degradation. Appl Math Model 2022. https://doi.org/10.1016/j.apm.2021.11.019.

[33] Najafi M, Zolfagharinia H. A Multi-objective integrated approach to address sustainability in a meat supply chain. Omega 2024;124:103011. https://doi.org/10.1016/j.omega.2023.103011.

[34] Kaur H, Singh SP. Sustainable procurement and logistics for disaster resilient supply chain. Ann Oper Res 2019;283:309–54. https://doi.org/10.1007/s10479-016-2374-2.

[35] Kaur H, Singh SP. Modeling low carbon procurement and logistics in supply chain: A key towards sustainable production. Sustain Prod Consum 2017;11:5–17. https://doi.org/10.1016/j.spc.2017.03.001.

[36] Khezeli M, Najafi E, Molana MH, Seidi M. A sustainable and resilient supply chain (RS-SCM) by using synchronisation and load-sharing approach: application in the oil and gas refinery. Int J Syst Sci Oper Logist 2023;10:2198055. https://doi.org/10.1080/23302674.2023.2198055.

[37] Yano CA, Lee HL. Lot Sizing with Random Yields: A Review. Oper Res 1995;43:311–34. https://doi.org/10.1287/opre.43.2.311.

[38] Harris FW. How Many Parts to Make at Once. Oper Res 1990. https://doi.org/10.1287/opre.38.6.947.

[39] Petchrompo S, Wannakrairot A, Parlikad AK. Pruning Pareto optimal solutions for multi-objective portfolio asset management. Eur J Oper Res 2022;297:203–20. https://doi.org/10.1016/j.ejor.2021.04.053.

[40] Tian T, Sun S. Low-carbon transition pathways in the context of carbon-neutral: A quadrilateral evolutionary game analysis. J Environ Manage 2022;322:116105. https://doi.org/10.1016/j.jenvman.2022.116105.

[41] Shekarabi Hoseini AS, Gharaei A, Karimi M. Modelling and optimal lot-sizing of integrated multi-level multi-wholesaler supply chains under the shortage and limited warehouse space: generalised outer approximation. Int J Syst Sci Oper Logist 2019;6:237–57. https://doi.org/10.1080/23302674.2018.1435835.

[42] Amin-Tahmasbi H, Sadafi S, Ekren BY, Kumar V. A multi-objective integrated optimisation model for facility location and order allocation problem in a two-level supply chain network. Ann Oper Res 2022. https://doi.org/10.1007/s10479-022-04635-1.

[43] Premkumar M, Jangir P, Sowmya R, Alhelou HH, Heidari AA, Chen H. MOSMA: Multi-Objective Slime Mould Algorithm Based on Elitist Non-Dominated Sorting. IEEE Access 2021. https://doi.org/10.1109/ACCESS.2020.3047936.

[44] Atsushi T, Seiji T, Tetsu S, Kentaro I, P. BD, D. FM, et al. Rules for Biologically Inspired Adaptive Network Design. Science (80-) 2010;327:439–42. https://doi.org/10.1126/science.1177894.

[45] Sun W, Chen H, Liu F, Wang Y. Point and interval prediction of crude oil futures prices based on chaos theory and multiobjective slime mold algorithm. Ann Oper Res 2022. https://doi.org/10.1007/s10479-022-04781-6.

[46] Arthur D, Vassilvitskii S. K-means++: The advantages of careful seeding. Proc Annu ACM-SIAM Symp Discret Algorithms 2007;07-09-Janu:1027–35.

[47] Bin L, Jiawei L, Aiqiang C, Theodorakis PE, Zongsheng Z, Jinzhe Y. Selection of the cold logistics model based on the carbon footprint of fruits

and vegetables in China. J Clean Prod 2022;334:130251.
https://doi.org/10.1016/j.jclepro.2021.130251.