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ORIGINAL RESEARCH

# A joint sustainable order-packing vehicle routing optimisation for the cold chain e-fulfilment

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## Abstract

Due to the new normal caused by the pandemic, consumer behaviour has now shifted to online shopping not only for general commodities but also for food and other perishable products. Therefore, e-commerce fulfilment is now integrated with cold chain capabilities to satisfy stringent requirements on time-criticality and product quality, leading to the concept of cold chain e-fulfilment. In the cold chain e-fulfilment process, perishable orders are packed in thermal packaging solutions and delivered to consumers before the quality preservation time window. To secure a sufficient time buffer during last mile delivery, excessive use of thermal packaging materials is applied, which creates an adverse environmental impact on our eco-system. Aligning with low-carbon business practices, this study proposes a novel joint optimization model, namely the Joint Optimization of Sustainable Order Packing and Multi-Temperature Delivery Problem (JOSOPMDP), for order packing and vehicle routing decisions, where the sustainable use of thermal packaging materials is promoted without negatively influencing product quality and customer satisfaction. To evaluate its viability and performance, three sets of computational experiments are subsequently conducted. It is found that the proposed model is feasible to strike a balance between order packing and vehicle routing decisions. Compared with the traditional strategy, the average total cost and satisfaction level are improved by 3.26% and 47.88%, respectively. Consequently, this research fosters sustainable thinking in the cold chain e-fulfilment process, minimizing environmental impact.

**Keywords** Sustainability · Order packing · Last mile delivery · Cold chain · E-fulfilment

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## 1 Introduction

Cold chain research has received continuous practical interest in recent years, with particular emphasis on pre-cooling, storage, packaging, and distribution stages in handling temperature-sensitive products, such as food and pharmaceuticals (Andoh et al., 2022; Yan et al., 2022). The cold supply chain is distinguished from the conventional one, due to their requisite for consistent thermal control throughout the supply chain journey. In particular, maintaining low temperatures enhances the longevity of perishables and mitigates microbial alterations, thus providing consumers with safe and quality cold chain products (James & James, 2010).

Over the past decade, the proliferation of refrigeration usage in both developed and developing nations has led to a substantial increase for the cold supply chain and e-fulfilment (Loisel et al., 2021). Due to the new normal caused by the pandemic, consumer behaviour is now shifted to online shopping for not only general commodities but also food and other perishable products. Taking the Chinese market as an example, based on iiMedia Research's report, the total demand for cold chain logistics in China witnessed a 5.35% increase to reach 240 million tons from January to August 2023. Additionally, the total revenue of cold chain logistics experienced a growth of 3.41%, amounting to $43.3 billion. It is projected that by 2025, the size of the cold chain logistics market will expand significantly and reach $121.9 billion. Moreover, fresh e-commerce transactions are expected to soar to $90.8 billion by 2027 (iiMedia Research, 2023). In addition, the Statista's analysis revealed that the cold chain market in North America is poised to witness a twofold expansion over a six-year period from 2018 to 2024, ultimately reaching a staggering value of $142.6 billion (Statista, 2020).

Therefore, e-commerce fulfilment is now integrated with cold chain capabilities to satisfy stringent requirements on time-criticality and product quality, leading to the concept of cold chain e-fulfilment. Different from traditional e-commerce, it has more stringent requirements in terms of temperature and time, as shown in Table 1. The customers in this process place orders through various platforms, enabling the delivery of perishable food to its destination using thermal packaging for long-distance or intra-city transportation, as depicted in Fig. 1. Focusing on the last-mile delivery in the cold chain e-fulfilment, the present modalities are facilitated by considering (i) cold chain packaging and (ii) multi-temperature characteristics. The former approach employs the packaging materials, for example foam boxes and eutectic plates, to form a microenvironment conducive to the short-term temperature preservation. However, the cold chain packaging materials are not conveniently recycled, which is counterproductive to the goal of green logistics operations (Yingfei et al., 2022). In addition, this method would carry a certain level of risk of quality deterioration due to the limited cooling capacity, if the packaging materials were not properly applied. The latter is aimed to incorporate multi-temperature characteristics for the last mile delivery in the e-fulfilment process. The theory of multi-temperature joint distribution (MTJD) was proposed for distributing goods with varying temperature requirements in trucks, thus catering to market demands for fragmented orders (Kuo & Chen, 2010). But unfortunately, this way necessitates high operational standards and equipment for handling e-commerce orders, which incurs substantial operating costs (Ndraha et al., 2018). Especially for the last-meter delivery between truck parking locations and consumer destinations, merely using multi-temperature refrigerated trucks cannot effectively preserve the product safety and quality.

However, the extant literature is limited to achieve a balance between the cost, sustainability and quality assurance in applying cold chain packaging for cold chain e-fulfilment (Behdani et al., 2019; Fan et al., 2020; Song et al., 2022). An evident paradox emerges between

**Table 1** The difference between cold chain and conventional supply chain in E-Fulfillment

| Aspect | | Cold chain e-fulfillment | Conventional e-fulfillment |
|---|---|---|---|
| Facilities | Storage | Specialized cold storage facilities with temperature-controlled environments to preserve product freshness and integrity | Typical pallet racking systems and storage equipment |
| | Packaging | Specialized insulated packaging to maintain temperature integrity and protect cold chain items from temperature fluctuations | Standard packaging materials for ease of handling and better protection |
| | Transportation | Refrigerated trucks, reefers, or temperature-controlled containers used to maintain the required temperature during transportation | Non-temperature-controlled vehicles and delivery methods |
| Management | Inventory management | Advanced inventory systems with real-time temperature tracking to ensure product quality and monitor expiration dates | Standard inventory management systems, e.g. first-in-first-out and last-in-first-out |
| | Regulatory compliance | Compliance with strict regulations and guidelines (e.g., GDP, HACCP) to ensure safety and quality standards for temperature-sensitive products | Compliance with standard operating procedures, focusing on productivity and customer satisfaction |
| | Reverse logistics | Specialized processes for handling product returns, recalls, and disposal of temperature-sensitive items | Typical logistics process to return goods back to upstream entities |

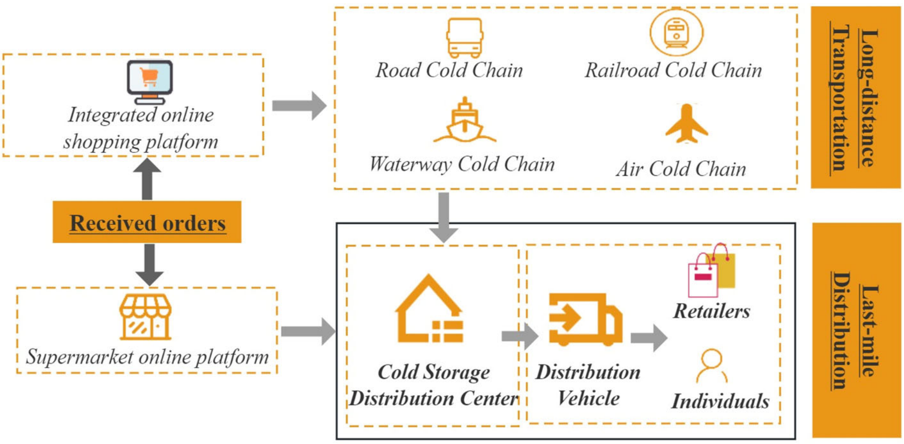


**Fig. 1** Generic process of the cold chain e-fulfilment

the costs associated with cold chain packaging and the freshness of food; it becomes arduous to achieve maximum satisfaction in terms of quality while keeping packaging expenditures to a minimum (Mercier et al., 2017). Undoubtedly, when assuring the product quality along the entire e-fulfilment process, it is inevitable to apply cold storage facilities, refrigerated transportation and cold chain packaging for minimising the fluctuations of environmental condition (Xu et al., 2018). However, achieving effective quality assurance by using the aforementioned technologies contradicts to the goals of low-carbon/carbon-neural initiatives, for example, hydrofluorocarbon emission from refrigeration systems and non-biodegradable styrofoam, as well as the extra electricity for refrigeration. Since the extant literature and industrial practices merely hint some green operations management and strategies for order fulfilment operations (Defraeye et al., 2014; Wang et al., 2020), the research on incorporating the low-carbon concept into cold chain e-fulfilment is emerging for in-depth investigation. Thus, an optimal balance between cost, product quality and sustainability should be urgently struck, without which carbon emissions from the cold chain e-fulfilment operations could be out of control, not to mention the goal of carbon neutrality.

In consideration of the aforementioned motivation, this study presents a joint optimization model for sustainable order packing and multi-temperature delivery in the context of cold chain e-fulfilment. The proposed model recommends the use of cold chain packaging constructed from a variety of refrigeration materials, selected in accordance with the distribution distance and necessary handling temperature. This approach fosters multi-temperature distribution and allows for adaptable amendments to the relationship between refrigeration time and distribution time. It maintains the quality of the transported items, mitigates unnecessary refrigeration wastage, and enhances the efficiency of the entire terminal distribution link. By doing so, the model thus realises substantial economic value together with sustainable use of cold chain packaging materials.

This paper is organised as follows. Section 2 reviews the existing order packing and vehicle routing methods for logistics optimisation. Section 3 describes the proposed model of sustainable order packing and multi-temperature delivery, as well as its solution algorithm. The computational experiments appear in Sect. 4, where different case scenarios are conducted to examine the model performance. Finally, Sects. 5 and 6 indicates managerial implications and draws conclusions, respectively.

## 2 Literature review

This study primarily concentrates on the last mile delivery for the cold chain e-fulfilment. In the quest to address challenges associated with cost, quality and sustainability, extant models related to order packing and vehicle routing problems for cold chain operations are reviewed in the following.

### 2.1 Order packing in cold chain

In the context of cold chain management, the vital significance of fresh packaging cannot be overstated, given its substantial implications for product quality and shelf life. Packaging typically employs insulative or low thermal conductivity materials, often supplemented with phase change materials, leading to a degree of flexibility in their shape and size. This inherent variability consequently results in dynamic packaging costs and a variable potential for perishability containment. As a result, the refinement of packaging methodologies becomes a topic of considerable importance, necessitating scrutiny from both cost-efficiency and product quality maintenance perspectives (Defraeye et al., 2015). A significant body of academic research has delved into the impact of packaging environments on the containment potential of the package. Factors such as humidity, ventilation, and light have contributed to the evolution of enhanced packaging methodologies (Defraeye et al., 2014; Han et al., 2015). Nonetheless, in practical implementations, obstacles emerge due to the complexity of these boxes' recycling processes and the high cost of packaging materials, thereby imposing a substantial financial burden on businesses. Furthermore, maintaining an acceptable level of environmental impact poses a formidable challenge, and the insulation capability of the boxes is inherently time-constrained. This complexity renders it challenging to assess the consistency of preservation ability across varying distribution locations (Zhao et al., 2020). To surmount these constraints and to enhance practical implementation, some scholars have advocated for the use of multiplicative heuristic algorithms to optimise order packaging strategies. This approach signifies a shift in focus from merely reducing material consumption to enhancing material use efficiency for cost containment (Xia et al., 2018). However, in the practical realm, the effectiveness of an optimised packaging method for cold chain logistics depends on the delivery route as well. Therefore, the integration of order-packing vehicle routing problem can effectively balance the cost, quality assurance and sustainability in the cold chain e-fulfilment.

### 2.2 Vehicle routing in cold chain

The Vehicle Routing Problem (VRP) has maintained a sustained prominence in academic discussion for several decades. Scholars have primarily concentrated on enhancing economic feasibility through the refinement of routing schemes and vehicle scheduling strategies (Gendreau et al., 2014). In relation to distribution challenges bound by stringent time windows, a non-deterministic polynomial-time (NP)-hard optimisation problem is established to calibrate issues pertaining to cost, capacity, and time limitations. Further exploration has illuminated the relative effectiveness of this algorithm in addressing such constraint-bound issues (Gutierrez et al., 2018). Academics have also proposed economically viable and efficient solutions in scenarios where customer demand is uncertain and round-trip replenishment is allowable (Kyriakidis & Dimitrakos, 2019). Notably, the occurrence of demand, in reality, exhibits both randomness and significant correlation, necessitating the integration of comparable heuristics and adaptive demand predictors (Latorre-Biel et al., 2021). Upon examination of numerous typical VRP instances, it becomes apparent that recent research has leaned towards exploring methodologies that can be generalised to path planning problems with minimal practical constraints, rather than solutions uniquely crafted for highly customised problems (Braekers et al., 2016). Approaches that embody such generalisability are invariably more harmonious with real-world applications.

Within the sphere of transportation activities, cold chain logistics commands significant attention due to its inherent characteristics. Unlike conventional transportation planning, it is intrinsically time- and temperature-sensitive, mandating the prompt delivery of perishable goods to the end consumer under optimal conditions (Theophilus et al., 2021). However, the observed variability and volatility in the practical execution of this logistics sector are substantial (Theophilus et al., 2021). As a result, researchers increasingly emphasise the practicality, efficiency, and adaptability of constructing optimal cold chain transportation paths. Consequently, optimisation algorithms and strategies specifically designed for cold chain logistics have emerged. For instance, within the specific context of ice cream transportation, the chaotic search algorithm proved to be a feasible solution for urban distribution facing strict time windows and randomised demand, compared to the forbidden search algorithm (Dávila et al., 2021). In an effort to transition from the cold chain logistics model with the fixed-temperature characteristics and achieve a socio-economically balanced interplay of cost and carbon emission, a multi-temperature combined distribution model has been proposed. This strategy notably enhances the flexibility of cold chain logistics, whilst simultaneously strengthening operational efficiency across various logistics activities, such as storage, loading and unloading, sorting, and distribution (Wang & Zhao, 2013). Unquestionably, within the context of cold chain logistics, particularly in light of recent low-carbon initiatives, the paramount objectives extend beyond mere delivery efficiency. They also encapsulate the optimisation of customer value, product quality, and process sustainability. The heterogeneity in the nature of goods necessitating transportation, coupled with their disparate temperature requirements, posits significant hurdles towards the attainment of a sustainable last-mile delivery mechanism for cold chain e-fulfilment.

## 2.3 Summary and research gap

Through summarising the emergence of this research topic, it is implied that sustainable use of cold chain packaging materials in the cold chain e-fulfilment is regarded as important as the above three factors, apart from considering cost, productivity and quality. In other words, cost, productivity, product quality and sustainability become four major pillars in the cold chain e-fulfilment operations. It is emerging to explore a low-carbon and sustainable way to optimize the order packing and vehicle routing problems in an integrated perspective so as to align to the global trend and benefit to our next generation (Pan et al., 2020; Tseng et al., 2016). In practical terms, the intersection of these two aspects, namely order packing and vehicle routing for cold chain e-fulfilment, constitutes the primary focus of this study, as shown in Fig. 2. This study distinguishes itself from other cold chain transportation research by providing a more holistic approach to process optimisation, spanning from packaging to transportation. It is vital to underscore that within this multi-objective optimisation model, a balance point can be ascertained between packaging and transportation costs. This facilitates the formation of an effective interrelationship between these two elements in practical scenarios.


**Fig. 2** Research gap of the last mile delivery in the cold chain e-fulfilment

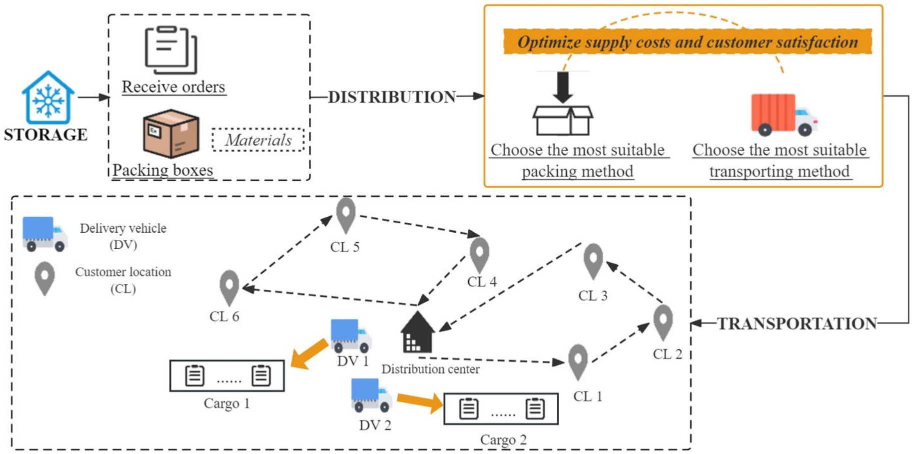


**Fig. 3** Order packing and vehicle routing in the JOSOPMDP

## 3 Research methodology

Based on the aforementioned research gap, the research methodology, comprising the problem description, mathematical model and solution algorithm, is depicted in this section.

### 3.1 Problem description

Throughout the comprehensive continuum of cold chain e-fulfilment from the initial phase of order picking, packing until delivery to the final destination, there persists an inherent risk of thermal fluctuations, resulting in the quality deterioration. As shown in Fig. 3, this study focuses on the e-order fulfilment process for cold chain products, in which shipments are optimally packed and delivered with the minimal use of cold chain packaging materials and maximal food safety to achieve sustainability. This problem disrupts the conventional decision-making logic of first selecting packaging and then optimising the logistics path. Instead, the proposed combinatorial optimisation process involves simultaneously choosing the most material-saving packaging method based on the handling requirements of the goods to be distributed, and identifying the optimal distribution path to reach the final destination within the packaging's preservation capacity. In a nutshell, the joint optimization of sustainable order packing and multi-temperature delivery problem (JOSOPMDP) is formulated to provide practical insights in packing and delivery e-orders of cold chain shipments.

### 3.2 Model description

This study delineates the assumption of various factors pertinent to the multi-temperature last mile delivery, encompassing packaging configuration, vehicular allocation, and route planning parameters. In accordance with these premises, an optimization model based on the JOSOPMDP is meticulously constructed. Subsequently, a comprehensive explication of the algorithm for resolving the above problem is presented.

In this problem, it is assumed that there are $n$ types of perishable goods, namely $S = \{s_1, s_2, \ldots, s_n\}$, and $m$ types of refrigerated packaging boxes, namely $B = \{b_1, b_2, \ldots, b_m\}$. The scenario accommodates requests for $N$ distinctive customer locations, where each request from customers comprises at least one type of perishable goods. Theses perishable commodities need to be individually encased and subsequently consolidated into a truck for delivery to the customer locations. The customer orders in this model is defined as $O_i = [\alpha_{si} \cdot s | \forall s \in S]$ for the customer location $i \in N$ where the parameter $\alpha_{si}$ is modelled as in Eq. (1).

$$\alpha_{si} = \begin{cases} 1, & \text{Goods } s \text{ sent to the customer } i \\ 0, & \text{Otherwise} \end{cases} \tag{1}$$

Initially, when dealing with a series of orders, it is crucial to consider the maximum insulation time required for the goods to be dispatched to each respective destination. This time is reliant on the properties of each individual item, as well as the insulation capabilities of the packaging container. As such, it is defined that $O_{i \in N}$ present the order per customers, $q_{s \in S}$ represent the weight of each item, and $w_{b \in B}$ represent the capacity of each packaging container. For the use of cold chain packaging, a time–temperature relationship is assumed for each package, as in Eq. (2), where coefficients $\theta_{b \in B}$ and $\theta'_{b \in B}$ denote the slope and constant in the linear relationship, $T_s$ presents the range of upper and lower handling temperature per perishable goods. According to the selected cold chain packaging type, the material cost $C_{b \in B}$ is defined for the evaluation of the total packaging cost.

$$A_{sib} = \theta_{b \in B} \cdot \max(\underline{T_s}, \overline{T_s}) + \theta'_{b \in B} \tag{2}$$

For each order, characterized by the inclusion of multiple items, each item can be packaged separately in distinct boxes. The decision variable of packing the goods $s$ by using the packaging box $b$ for the customer location $i$ is defined as in Eq. (3).

$$\beta_{sib} = \begin{cases} 1, & \text{Goods } s \text{ sent to customer } i \text{ and packed with } b \\ 0, & \text{Otherwise} \end{cases} \tag{3}$$

This leads to a total number of potential packaging arrangements that can be mathematically represented as $|B_n|^{O_i}$. The packaging option for each order can be described as $pk_i^n$ and the quality preservation time corresponding to each commodity is $A_{sib}$. Also, the above packaging option is constrained by the total capacity of the packaging boxes, namely $\beta_{sib} q_s \leq w_b$, where $q_s$ and $w_b$ denotes the weight of goods and capacity of the packaging boxes. With considering the corresponding packaging costs, the total packaging cost required $C_{pk_i^n}$ is presented as in Eq. (4).

$$C_{pk_i^n} = \sum_{b \in B} \sum_{s \in S} \beta_{sib} C_b \tag{4}$$

When the goods within an order are encapsulated utilizing the cold chain packaging boxes, the packages can be consolidated into a single shipment denoted as $f_i$ to transport to the customer $i$, where $f_i = [\beta_{sib} \cdot s \cdot b | \forall s \in S, \forall i \in N, \forall b \in B]$. Subsequently, the weight $q_{f_i}$ and shelf life $A_{f_i}$ of the shipment $f_i$ are expressed as in Eqs. (5) and (6).

$$q_{f_i} = \sum_{b \in B} \sum_{s \in S} \beta_{sib} \cdot w_b \tag{5}$$

$$A_{f_i} = \min_{b \in B} (\beta_{sib} \cdot A_{sib}), \text{ where } \beta_{sib} \neq 0 \tag{6}$$

During the delivery stage, there are $N$ shipments to deliver the goods to customers, in which each shipment encompasses with $b^{|O_i|}$ distinct types of packaging. Thus, there are $\prod_{i=1}^{N} b^{|O_i|}$ possible combinations in consolidating the shipments, namely $pl_n = (f_1, f_2, \ldots f_N)$, and the total cold chain packaging cost is modelled as in Eq. (7).

$$Z_1 = \sum_{i=1}^{N} C_{pk_i^n} \tag{7}$$

After completing the cold chain packaging process, the shipments are consolidated and loaded in trucks for last mile delivery. The formulation of an effective delivery strategy necessitates a balance between cost minimization and customer satisfaction maximization. Essential factors, including the geographical distance between delivery locations, the volumetric and weight specifications of the cargo, and the customer time windows, are considered for the optimisation.

Regarding the last mile delivery, the fleet of $k \in K$ delivery trucks is considered, where $Q_k$ is the maximum load of each vehicle. To ensure the sufficient number of trucks for optimisation, the minimal number of trucks for completing all shipments $pl_n$ is defined as in Eq. (8).

$$\min|k| = \left\lceil \frac{\sum_{i=1}^{N} q_{f_i}}{Q_k} \right\rceil \tag{8}$$

To oversee the complicated optimisation process, the penalty factor for exceeding vehicle capacity $\gamma$ and the total number of load violation $D_k$ are introduced. Moreover, the parameter $v$ is the average driving speed of each vehicle; $d_{ij}$ is the distance between the points $i$ and $j$ in the distribution; $p_c$ is the fixed cost of each vehicle, $p_r$ is the fuel cost per kilometer of the vehicle. Overall, decision variables of the route optimisation are expressed as in Eqs. (9) to (11).

$$x_{ijk} = \begin{cases} 1, \text{ where vehicle } k \text{ passess from the location } i \text{ to } j \\ 0, \text{ Otherwise} \end{cases} \tag{9}$$

$$y_{ik} = \begin{cases} 1, \text{ Location } i \text{ is reached by vehicle } k \\ 0, \text{ Otherwise} \end{cases} \tag{10}$$

$$\sigma_{f_i k} = \begin{cases} 1, \text{ Shipment } f_i \text{ is distributed by vehicle } k \\ 0, \text{ Otherwise} \end{cases} \tag{11}$$

When considering the customer satisfaction in the last mile delivery, this model proposes two pivotal dimensions, namely (i) product quality window, and (ii) customer time window, as shown in Fig. 4. By combining the above two dimensions, the overall satisfaction $CT_f$ is defined for shipment $f_i$ at time $t_{f_i}$ when the vehicle arrives at the customer $i$. Given that the optimal route $J$ is obtained for visiting all customer locations, the time to visit a specific customer location is expressed as in Eq. (12).

$$t_{f_j} = \sum_{j \in J \cup \{0\}} \sigma_{f_j k} \frac{d_{j,j+1}}{v} \tag{12}$$

On one hand, for transporting cold chain products with cold chain packaging, the quality preservation time per package is defined above. When the transportation time exceeds the quality preservation time, the corresponding quality deterioration is modelled in the product quality window as shown in Fig. 4a. When the vehicle arrives at the time $t_{f_i} \in \left[0, A_{f_i}\right]$,

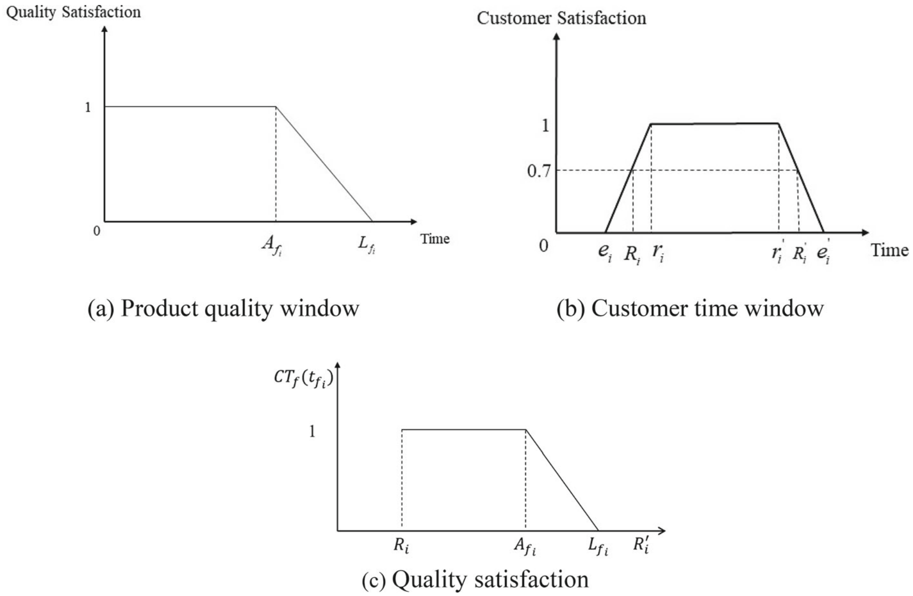


**Fig. 4** Illustration of product quality and customer time windows

the quality satisfaction is equal to 1; when vehicle arrives in $t_{f_i} \in (A_{f_i}, L_{f_i}]$, quality satisfaction linearly decreases over time; Otherwise, the quality satisfaction is equal to 0 for customers, when $t_{f_i} \in (L_{f_i}, \infty)$. On the other hand, the customer time window to receive the delivery is modelled as shown in Fig. 4b. The customer satisfaction is rated at 1 when the delivery time is within the scheduled time periods, namely $t_{f_i} \in \left[r_i, r_i'\right]$. When the delivery is reached at $t_{f_i} \in [e_i, r_i)$ and $t_{f_i} \in \left(r_i', e_i'\right]$ which are the tolerance period of customers, the customer satisfaction linearly decreases over time. If the delivery is made beyond $\left[e_i, e_i'\right]$, the customer satisfaction is rated at 0. In this study, the customer satisfaction is set at 0.7 or above, which is expressed as $\left[R_i, R_i'\right]$. Consequently, the overall satisfaction based on the above considerations is shown as Fig. 4c and modelled in Eqs. (13) and (14).

$$\text{For } t_{f_i} \in \left[R_i, R_i'\right] : CT_f\left(t_{f_i}\right) = \begin{cases} 1, \text{ when } t_{f_i} \in \left[0, A_{f_i}\right] \\ 1 - \tau * \left(t_{f_i} - A_{f_i}\right), \text{ when } t_{f_i} \in \left(A_{f_i}, L_{f_i}\right] \\ 0, \text{ when } t_{f_i} \in \left(L_{f_i}, \infty\right) \end{cases} \tag{13}$$

$$\text{For } t_{f_i}\left[R_i, R_i'\right] : CT_f\left(t_{f_i}\right) = 0 \tag{14}$$

During the transportation process, fixed and variable costs are incurred. Fixed costs refer to costs that do not vary with the last mile delivery process, such as the purchase and lease of vehicles and equipment, insurance cost, and salaries of administrative staff. Transportation costs, on the other hand, are variable costs that increase according to the distance transported including fuel, maintenance, and labor costs. Both types of costs must be considered in the fleet management to ensure that transportation operations are efficient and cost-effective.

The vehicle type and load in this model are assumed to be the same. Therefore, the change in fixed cost is related to the number of vehicles actually involved in dispatching the goods.

Its function is defined as $Z_2$ in Eq. (15).

$$Z_2 = \sum_{k \in K} \sum_{j \in I} x_{0jk} \cdot p_c \tag{15}$$

Transportation cost is mainly reflected in fuel consumption, and there is a proportional relationship with the mileage of dispatching vehicles. Its function is defined as $Z_3$ in Eq. (16).

$$Z_3 = \sum_{k=k_{min}}^{k_{max}} \sum_{i=0}^{N} \sum_{j=0}^{N} x_{ijk} \cdot \left[ d_{ij} p_r + \gamma (D_k - Q) \right] \tag{16}$$

The utilization of diverse vehicles for cargo transportation can yield varying degrees of transportation costs and satisfaction levels in terms of quality and delivery time. Moreover, the weight of the shipped goods and the time constraints for delivery can also fluctuate based on the type of goods packaging. Consequently, it is imperative to devise a multi-objective model that incorporates these variables. This model is integral to deriving a relatively optimal solution, as elucidated in Eqs. (17) and (18). Constraint (19) limits the maximum load of dispatching vehicles; Constraint (20) limits the delivery time for the customer satisfaction evaluation; Constraint (21) ensures that each customer is only served by one truck; Constraint (22) ensures that the starting point and end point of dispatching vehicles are in the depot; Constraints (23) and (24) ensure that each point to be distributed is only served once.

$$\text{Min.} G_1 = Z_1 + Z_2 + Z_3 \tag{17}$$

$$\text{Max.} G_2 = \frac{1}{N} \sum_{i=1}^{N} CT_f \left( t_{f_i} \right) \tag{18}$$

Subject to:

$$\sum_{i=1}^{N} \sigma_{f_i k} q_f \leq Q, \ \forall k \in K \tag{19}$$

$$R_i \leq a + t_{f_i} \leq R_i', \ \forall i \in N \tag{20}$$

$$\sum_{k \in K} y_{ik} = 1 \tag{21}$$

$$\sum_{j=1}^{N} x_{0jk} - \sum_{i=1}^{N} x_{i0k} = 0, \ \forall k \in K \tag{22}$$

$$\sum_{i=0}^{N} x_{ijk} = y_{jk}, \ \forall k \in K \tag{23}$$

$$\sum_{j=0}^{N} x_{ijk} = y_{jk}, \ \forall k \in K \tag{24}$$

### 3.3 Solution algorithm

To address the complex and NP-hard problem presented in the above investigation, traditional approaches typically dissect the problem into two distinct but interrelated components: order packing optimization and route optimization. These components are subsequently optimized independently, with significant emphasis on the application of heuristic algorithms. Such algorithms, fundamentally a stochastic search technique, emulates the random selection processes inherent in biological evolution (Kim et al., 2017). Such an approach often yields near-to-optimal solutions for optimization problems when evaluated against a diverse set of objectives. These objectives may include, but are not limited to, minimization of travel distance, reduction in transit time, and decrease in carbon emissions. However, this paper proposes an alternative approach: a joint optimization of both order packing and delivery route aspects, potentially enhancing the model's practical applicability.

The innovative optimization algorithm presented in this research ingeniously integrates a cyclical principle based on the genetic algorithm (Li & Li, 2022). It incorporates the packaging selection phase within the evolutionary progress of the delivery route optimization, facilitating a more holistic and multidimensional evolutionary process. As shown in Fig. 5, the process flow of the solution algorithm is graphically illustrated. At the beginning, the stock keeping units (SKUs) from e-commerce platforms are defined, while customers can place the orders which are the combination of different SKUs. Since the cold chain packaging materials, namely the packages, have the capacity constraint, all feasible packaging plans can be generated for the order fulfilment. In order to deliver customer orders in an optimal manner, the permutation of cargo plans is thus considered, namely $\prod_{i\in N} |B_n|^{O_i}$. For instance, when considering Order 1 with four packaging plans, Order 2 with two packaging plans and Order

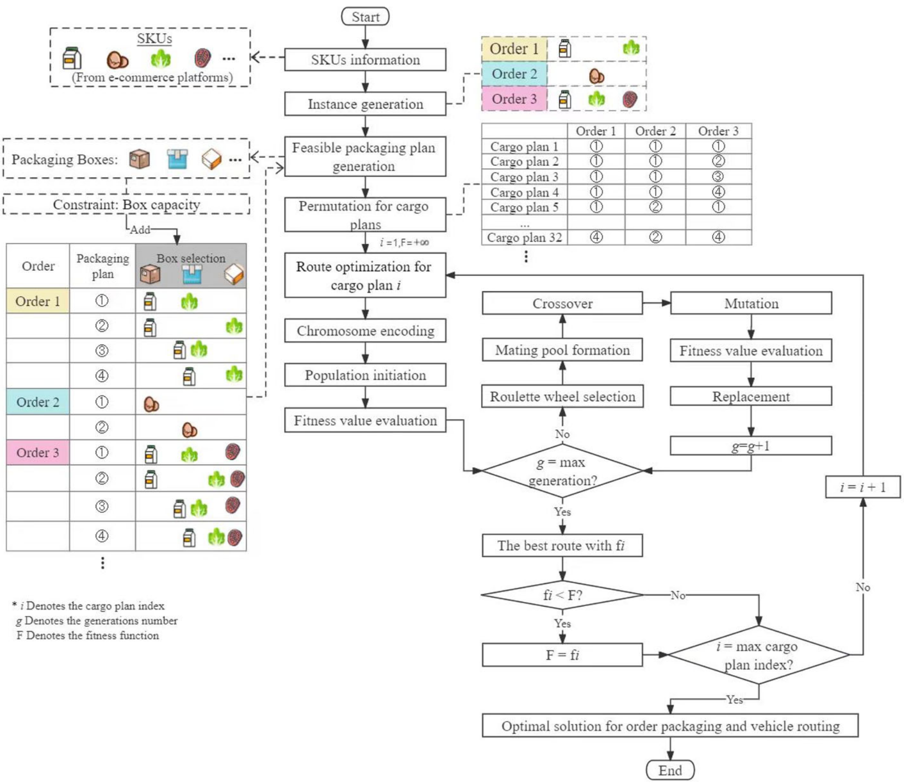


**Fig. 5** Process flow of the solution algorithm for JOSOPMDP

3 with four packaging plans, the number of cargo plans for optimisation is 32 in total. For each cargo plan, the route optimisation is initialized with the fitness $F_0 = -M$, where $M$ is an arbitrary and large positive integer. In addition, the fitness function for the evolutionary process is defined as $F = \omega_1 G_1 - \omega_2 G_2$. Through applying the genetic algorithm (GA), the optimal route per each cargo plan can be obtained by deploying the genetic operators, including roulette wheel selection, crossover, mutation and replacement. Consequently, the optimal solution for optimizing both order packing and vehicle routing can be derived to minimize the costs and maximize the customer satisfaction.

## 4 Computational experiments

In order to examine the key concepts posited in this study, this section delineates four case scenarios. These scenarios present an exhaustive exploration of solutions to the JOSOPMDP from diverse perspectives, highlighting the potential for real-life deployment.

### 4.1 Instance generation

For examining the feasibility and performance of the proposed model, the testing instances are generated by considering the perishable goods and cold chain packaging materials, so as to achieve the joint optimisation of order packing and vehicle routing problems for the cold chain e-fulfilment.

According to industrial practices, nine stock keeping units (SKUs) of perishable commodities are considered, in which they have their own specific handling temperature ranges (in °C) and volumetric weight (in kg) as shown in Table 2. The list of above SKUs is applied to generate customer orders for the computational experiments, while the specific cold chain packaging as shown in Table 3 is considered to perform the optimal order packing operations. In Table 3, there are nine types of cold chain packaging with different volumetric weights (in kg), temperature preservation capabilities (in terms of $\theta_{b\in B}$ and $\theta_{b\in B'}$) and corresponding order packing cost (Tsang et al., 2018). Regarding the transportation process, all the trucks are assumed to be the same with the specifications: (i) volumetric weight of 300 kg, (ii) fixed cost of $2,000, (iii) speed of 45km/h, and (v) fuel consumption of $19/km.

**Table 2** Commodity data for the instance generation

| # | Name | Temperature range (in °C) | Volumetric weight (in kg) |
|---|---|---|---|
| SKU 1 | Cabbage | 0 to 4 | 4 |
| SKU 2 | Carrot | 5–15 | 3 |
| SKU 3 | Banana | 13–14 | 5 |
| SKU 4 | Agaric | 10–22 | 1.5 |
| SKU 5 | Watermelon | 4 to 10 | 6 |
| SKU 6 | Fresh shrimp | $\leq -15$ | 2.5 |
| SKU 7 | Egg | 4–7 | 3 |
| SKU 8 | Almond | 0–8 | 0.8 |
| SKU 9 | Fresh milk | $-2$ to 0 | 1 |

**Table 3** Cold chain packaging types for order packing

| Type | Volumetric weight (in kg) | $\theta_{b \in B}$ | $\theta_{b \in B'}$ | Material cost (in $) |
|---|---|---|---|---|
| 1 | 1.5 | 0.2049 | 14.058 | 65 |
| 2 | 1.5 | 0.3148 | 6.3269 | 90 |
| 3 | 1.5 | 0.5357 | − 0.3346 | 125 |
| 4 | 3 | 0.2220 | 14.223 | 90 |
| 5 | 3 | 0.3000 | 7.5462 | 120 |
| 6 | 3 | 0.2819 | 8.3115 | 85 |
| 7 | 6 | 0.1995 | 11.412 | 125 |
| 8 | 6 | 0.1934 | 12.192 | 100 |
| 9 | 6 | 0.3308 | 7.7923 | 130 |

Although only nine SKUs and another nine cold chain packaging methods are considered in this study, the number of combinations of the cargo plans is already too large, leading to the computationally-expensive optimisation process. For instance, when considering the order fulfilment process with five customer orders and each order contains all nine SKUs, the ways to package the SKUs is $9^9 = 387,420,489$, assuming that all cold chain packaging methods are suitable for all nine SKUs. Thus, the number of possible cargo plans is $387,420,489^5 = 8.73 \times 10^{42}$. In order to examine the model viability and performance, the SKUs and package types are grouped in advance to generate the instances for computational experiments. As shown in Table 4, the SKUs were divided into three groups according to the weight of the foodstuffs, and the packages were also divided into three groups according to the capacity of the packages for the instance generation. Therefore, the customer orders are randomly generated through the uniform pseudorandom number generator for experiments.

In addition to the instance generations, the route optimisation per cargo plan is made by using the GA to optimize the fitness value in accordance with the proposed solution algorithm, while all the defined constraints, like quality and customer time window, truckload capacity and flow constraints, can be satisfied. To initialize the GA for the time-efficient route optimisation, the algorithmic parameters are set as follows: (i) population size of 50; (ii) number of generations of 30; (iii) crossover rate of 0.75; (iv) mutation rate of 0.03; (v) generation gap of 0.7. Also, the weights $\omega_1$ and $\omega_2$ between two objective functions to evaluate the fitness value are set at 1 and 100, respectively.

**Table 4** Experimental Grouping

| Groups | SKUs/packaging types |
|---|---|
| Items (I) | SKU 2 (Carrot), SKU 3 (Banana), SKU 4 (Agaric) |
| Items (II) | SKU 1 (Cabbage), SKU 7 (Egg), SKU 9 (Fresh milk) |
| Items (III) | SKU 5 (Watermelon), SKU 6 (Fresh shrimp), SKU 8 (Almond) |
| Boxes (I) | Packaging boxes 2, 5 and 9 |
| Boxes (II) | Packaging boxes 1, 4 and 7 |
| Boxes (III) | Packaging boxes 3, 6 and 8 |

**Table 5** Information of the customer orders with locations and time windows

| Order | Items (I) | Items (II) | Items (III) | Location | Time window |
|---|---|---|---|---|---|
| 1 | Agaric<br>Carrot<br>Banana | Fresh milk<br>Egg<br>Cabbage | Almond<br>Watermelon<br>Fresh shrimp | (29, 40) | 29 to 139 |
| 2 | Banana<br>Agaric | Egg<br>Fresh milk | Fresh shrimp<br>Almond | (23, 35) | 23 to 134 |
| 3 | Agaric<br>Carrot | Fresh milk<br>Cabbage | Almond<br>Watermelon | (56, 73) | 56 to 173 |
| 4 | Banana | Egg | Fresh shrimp | (72, 44) | 72 to 144 |
| 5 | Carrot | Cabbage | Watermelon | (43, 6) | 43 to 106 |
| 6 | Carrot<br>Agaric | Cabbage<br>Fresh milk | Watermelon<br>Almond | (99, 40) | 99 to 140 |
| 7 | Banana<br>Agaric<br>Carrot | Egg<br>Fresh milk<br>Cabbage | Fresh shrimp<br>Almond<br>Watermelon | (69, 74) | 69 to 174 |

### 4.2 Case 1: feasibility study in different item-box combinations

For Case 1, it is aimed to investigate the feasibility of the proposed model, where the Boxes (I), (II) and (III) are applied to package the generated customer orders from Items (I), (II) and (III). Table 5 shows information of seven randomly generated orders with specific locations and time windows. For the route optimisation based on the customer orders, the simulated environment in a 100*100 coordinate plane with the range of time window [0, 200] is established. According to the proposed solution algorithm, the constraint of the packaging capacity is applied to filter out those infeasible packaging options for products. In return, the total number of cargo plans for Items (I), Items (II) and Items (III) are 7776, 3888 and 3888 for the route optimisation. Through the GA-based optimisation process, it is found that the proposed model is promising to obtain the optimal routes among different item groups in using Boxes (I) with the satisfaction level of 1. In other words, all the orders are fulfilled and delivered within the quality and customer time windows, while the optimal routes with the optimal cold chain packaging plan are illustrated in Fig. 6. The balance between two objective functions of the JOSOPMDP for the fitness evaluation is appropriately struck. Furthermore, the costs associated to the optimal solution for order packing and vehicle routing for all the item-box combinations are summarized in Table 6. Overall, the average total cost and satisfactory level of the proposed model among different settings are 6453.53 and 0.89, respectively.

### 4.3 Case 2: comparison with the traditional order fulfilment process

To highlight the value of the proposed model, the conventional approach in the order fulfilment process is considered, where it is assumed that the perishable products are packed with best fit packaging option in term of its volumetric weight, referred to the 3-dimensional knapsack problem. Its primary objective is to maximise the space utilisation of the package boxes, while phase change materials, like eutectic plates, are put in the available spaces. Therefore, it is worth investigating the differences between the proposed and the conventional approaches, and thus the reasonability to adopt the proposed model can be justified. Table 7 shows the

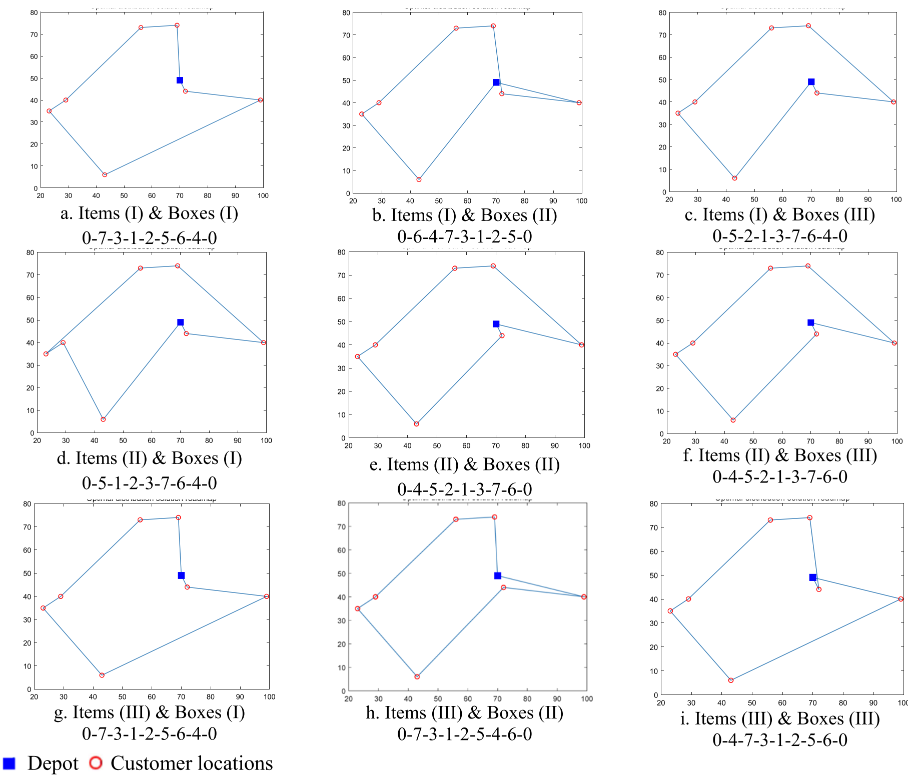


**Fig. 6** Optimal routes with the optimal packaging plan in three item groups

costs and satisfaction levels of using the traditional packaging strategy. In average, the total cost and satisfaction level to fulfil all customer orders are \$6621.88 and 0.68. Compared with Case 1, the average improvements in terms of packaging cost, transportation cost, total cost and satisfaction level are 4.50%, 2.84%, 3.26% and 47.88%.

### 4.4 Case 3: robustness study to the random order generations

In addition to the feasibility and benchmarking with the traditional method, the model robustness for the random order generation process is investigated in this case. From the above computational experiments, the random seed of '123' is applied to control the uniform pseudorandom number generator, and thus it is worth modifying the random seed to examine the optimality stability. In this case, another ten arbitrary sets of the random seed, namely '125', '222', '333', '345', '397', '451', '588', '693', '789' and '891' are considered, where Items (I) and Boxes (I) are applied to inspect the total cost and satisfaction level. Figure 7 demonstrates the corresponding experimental results when using different random seeds. When changing the randomness seed, the total quantities of the generated seven orders are slightly different such that the total costs among the settings can be different. However, the satisfaction levels among different settings are relatively stable, such that all the product quality and service

**Table 6** Optimal solutions for different item-box combination

| Item-box combination | | Total no. of cargo plans | Packaging cost ($) | Delivery cost ($) | Total cost ($) | Satisfaction level |
|---|---|---|---|---|---|---|
| Items (I) | Boxes (I) | 7776 | 1590.00 | 4723.45 | 6313.45 | 1.00 |
| Items (I) | Boxes (II) | 7776 | 1300.00 | 5285.07 | 6585.07 | 1.00 |
| Items (I) | Boxes (III) | 7776 | 1415.00 | 5013.80 | 6428.80 | 0.84 |
| Items (II) | Boxes (I) | 3888 | 1670.00 | 4920.25 | 6590.25 | 1.00 |
| Items (II) | Boxes (II) | 3888 | 1335.00 | 5116.88 | 6451.88 | 0.69 |
| Items (II) | Boxes (III) | 3888 | 1375.00 | 5076.02 | 6451.02 | 0.70 |
| Items (III) | Boxes (I) | 3888 | 1630.00 | 4683.78 | 6313.78 | 1.00 |
| Items (III) | Boxes (II) | 3888 | 1335.00 | 5119.63 | 6454.63 | 1.00 |
| Items (III) | Boxes (III) | 3888 | 1430.00 | 5062.86 | 6492.86 | 0.76 |

**Table 7** Optimal results with using the traditional packaging strategy

| Item-box combination | | Total no. of cargo plans | Packaging cost ($) | Delivery cost ($) | Total cost ($) | Satisfaction level |
|---|---|---|---|---|---|---|
| Items (I) | Boxes (I) | 1 | 1700.00 | 4919.75 | 6619.75 | 0.70 |
| Items (II) | Boxes (I) | 1 | 1710.00 | 4914.13 | 6624.13 | 0.66 |
| Items (III) | Boxes (I) | 1 | 1710.00 | 4911.75 | 6621.75 | 0.67 |

time windows can be satisfied. It shows that the proposed model is robust to strike an optimal balance between order packing and vehicle routing.

## 5 Results and discussion

Based on the computational experiments as above, the results are further discussed in this section so as to elaborate the phenomenon of different experimental cases. Moreover, the insights to the cold chain e-fulfilment are explicitly elaborated to guide the sustainable development.

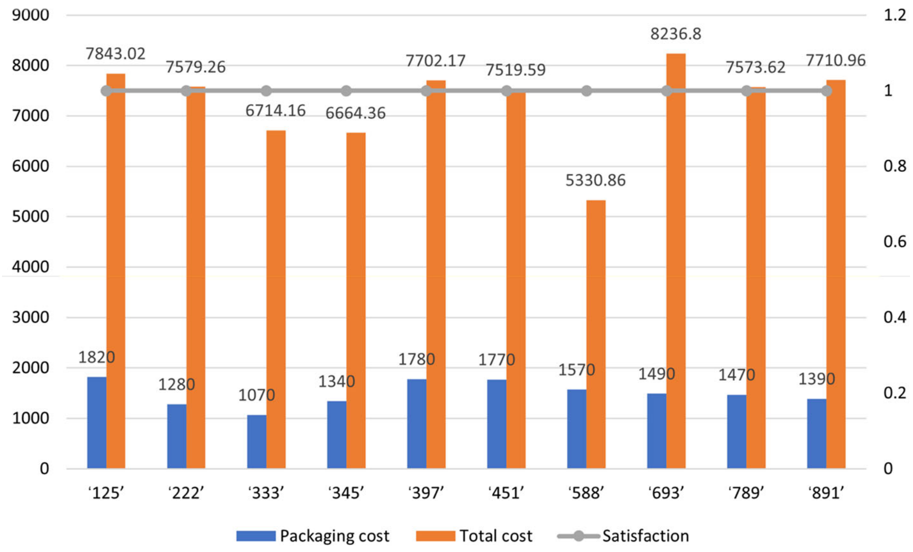


**Fig. 7** Experimental results of different random seeds

### 5.1 Discussion on the experimental cases

The aforementioned three experiments progressively showcase the potential of JOSOPMDP in the industry. The effectiveness of the proposed model in connecting packaging and transportation schemes is convincingly demonstrated by Case 1 through the manipulation of goods to be delivered and subsequent order generation. Furthermore, it effectively showcases that the model can successfully accommodate crucial factors such as location, time, and order randomness within real-world scenarios. In our observations, the utilization of Boxes (I) has emerged as a standout solution for meeting consumer demands while effectively controlling costs within a limited area across three categories of items. The primary rationale behind this success lies in the superior and average insulation capacity of these boxes, which enable them to maintain optimal environmental temperature for any weight or temperature-sensitive items during transportation. This key feature ensures that the quality and integrity of the goods are preserved throughout the journey, aligning perfectly with industry requirements. In contrast, Boxes (II) only exhibited an average slope coefficient of 0.2088 for insulation capacity, which raises concerns about their ability to safeguard temperature-sensitive Items (II) during transit. Moreover, the slope coefficient falls within the range of 0.1995 to 0.2220 (variance = 0.00009198) indicating that there is minimal variation in the insulation performance among the three box types. Especially for products kept at low temperatures, this category of packaging faces challenges in ensuring an adequate preservation time during distribution. Indeed, the minor differences observed among goods with varying temperature requirements within the same order impose challenges on transportation tasks with diverse destinations. This limitation poses a notable risk of violating customer expectation time windows and product deterioration, ultimately compromising customer satisfaction. Furthermore, Boxes (III) displayed significant variations in insulation capacity across different volumes, making it challenging to achieve relative equilibrium in preserving goods' shelf life within the same order and thereby increasing distribution complexity. Notably, when employing this particular packaging boxes, the overall customer satisfaction score among all three groups averaged merely 0.77.

In addition, Fig. 6a, d, g reveal significant disparities in the formulation of transportation plans for different orders among the same types of packing boxes. Notably, for Items (II), the most cost-effective and efficient route differs from the other two commodities due to their lower temperature requirements compared to room temperature, which primarily necessitates a higher demand for refrigeration capacity in the packaging material. Therefore, In the context of fixed packaging boxes, it is essential to mitigate the adverse effects on vehicle scheduling and routing in the distribution process. This diverges from conventional logistics practices where a single optimal path is applicable across all order situations. This divergence from the norm highlights the importance of tailored approaches in cold chain transportation. Such targeted strategies can optimize order efficiency while flexibly adapting to the changing and intricate demands of modern logistics. The implications of this understanding emphasize the reliability and credibility of the fundamental principles outlined in this paper, facilitating the swift provision of effective guidance for personalized cold chain logistics planning. Furthermore, compared to the current packaging and distribution methods employed in the market, the JOSOPMDP model demonstrates a significant optimization effect. Case 2 reveals that under identical packaging types and goods for delivery, the traditional strategy only satisfies an average of 68% of customer requirements what means it increases the likelihood of product deterioration during delivery, leading to food waste, damage to enterprise reputation, and a range of adverse consequences. Additionally, this necessitates an additional investment of 3–7% in packaging costs, which further strains capital turnover for enterprises over an extended period and reduces their operating profit. Furthermore, the utilization and disposal of excessive refrigeration materials have resulted in a certain degree of environmental pollution. For example, the employment of refrigeration packaging materials such as dry ice leads to the emission of greenhouse gases, while foam boxes and other low-temperature phase change materials pose challenges for recycling, contradicting the objective of establishing an eco-friendly supply chain system. By adopting JOSOPMDP instead of conventional selection strategies, there is a significant enhancement in customer satisfaction, thereby minimizing food wastage caused by spoilage. Simultaneously, it achieves an optimal balance between packaging and shipping costs while no longer relying on the depletion of non-renewable environmental resources for distribution purposes. This has significant implications for the sustainability of the cold chain E-fulfilment. The general applicability of this model is further demonstrated in Case 3, wherein various distribution layouts and uncertain order scenarios can be simulated by altering the random seed. As illustrated in Fig. 7, this model consistently formulates effective packaging and transportation strategies to meet customers' demands for food quality. Consequently, it holds significant potential for broad application in cold chain logistics by offering more efficient and sustainable solutions for the industry.

### 5.2 Managerial implications

Cold chain logistics imposes stringent requirements on packaging containers and the distribution environment. The temperature during the process, from the distribution centre to the customer's hands, is prone to fluctuations. Although refrigerated trucks can provide effective cooling, they cannot completely eliminate the risk of food personnel. Moreover, operating refrigerated trucks incurs significant costs and requires specific equipment, placing considerable economic pressure on enterprises. Therefore, utilizing passive packaging for delivering fresh food presents a superior alternative. This approach ensures that products with varying temperature requirements do not interfere with each other while reducing the impact of manual handling on temperature stability. On this basis, the JOSOPMDP model is employed to standardize the order packaging and vehicle route planning processes, effectively mitigating the adverse effects of localized optimization on overall operations in logistics. The packaging scheme obtained through this model saves the use of excessive cooling materials, and also maximizes the utilization of resources in the distribution scheme. In other words, this model achieves a harmonious balance between packaging and transportation costs while ensuring customer satisfaction with product quality. This innovation significantly contributes to insulation material conservation and the reduction of fixed transportation costs, thereby enhancing resource utilization within the enterprise and optimizing the cost management strategy. In fact, the logistics industry is consistently confronted with the challenge of mitigating environmental pollution. Undoubtedly, this model aligns with the "reduce" principle of sustainable development. In the long term, economizing on packaging and transportation resources not only safeguards non-renewable energy sources by alleviating strain on coal and soil resources but also diminishes carbon dioxide emissions, thereby mitigating the adverse impact of greenhouse gases on global temperatures. Consequently, within the social development requirements, this represents one of the effective approaches for traditional logistics enterprises to transition towards "Green Logistics". Moreover, the timely delivery of fresh food provides a competitive edge for enterprises to establish their reputation. Customer trust reinforces the business image of the enterprise, and the potential business value should not be underestimated. In brief, JOSOPMDP generates dual business value at both economic and social levels. Consequently, it serves as a practical guideline for designing management solutions and making resource allocation decisions that promote mutually beneficial outcomes for buyers and sellers. Further integration with Warehouse Management System (WMS) and Transportation Management System (TMS) facilitates the seamless exchange of information, establishing a visually dynamic and adaptable supply system for cold chain distribution centres. This integration facilitates real-time temperature monitoring and control across the entire supply chain, from warehouse to last mile delivery. While WMS tracks the status of temperature-sensitive inventory, TMS considers vehicle scheduling; when combined with the JOSOPMDP model, companies can ensure that cold chain goods reach their destination in optimal condition while maintaining product quality and regulatory compliance. This not only provides comprehensive visibility for all stakeholders but also enables proactive response by triggering timely alerts and notifications in case of temperature deviations or emergencies. Moreover, in comparison to existing planning strategies, the model proposed in this paper can effectively minimize the inefficient utilization of cold chain packaging materials including eutectic plates, ice packs, dry ice and so on, while also reducing fuel consumption waste during the distribution process. In addition, the distribution efficiency of the system effectively mitigates food waste caused by spoilage. Consequently, it contributes to mitigating the environmental impact caused by human commercial activities and promotes sustainable development of the cold chain supply system. Another noteworthy salient consideration pertains to quality assurance. During food transportation, evaluating management efficiency primarily relies on food quality. JOSOPMDP quantifies customer satisfaction and employs it as a crucial criterion for formulating enterprise strategies. This approach ensures the effectiveness of deliveries to a substantial degree, aligning the interests of businesses with customer expectations and enhancing overall operational performance in the cold chain logistics sector.

## 6 Conclusion

This study demonstrates the potential of the JOSOPMDP to optimize cold chain e-fulfilment by connecting packaging and transportation decisions. Across varied delivery items, locations, and order volumes, the proposed model formulated the sustainable decisions on order packing and vehicle routing plans tailored to the perishable goods, outperforming conventional strategies. It enabled the selection of optimal thermal packaging to balance insulation needs and environmental impact, improving customer satisfaction by 47.88% on average. Unlike fixed logistics plans, the proposed model optimises the delivery routes with the balance of costs and customer satisfaction in terms of product quality and service time. By optimizing packaging sustainability and delivery efficiency simultaneously, JOSOPMDP unlocks more agile, economical, and eco-friendly cold chain e-fulfilment. This pioneering approach paves the way for further supply chain advancements through cross-functional integration and customization. In future, the research foundation in this work can be further extended with more real-life case studies to better quantify the sustainability value from the proposed model. Moreover, the distributionally robust optimisation process can also be considered to enhance the solution practicality in the industry.

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### Declarations

**Conflict of interest** The authors declare that there is no conflict of interest.



## Appendix A: List of notations

| Symbol | Description (Value range) |
|---|---|
| $S, s_n$ | Types of perishable foods ($S = \{s_1, s_2, \ldots, s_n\}$) |
| $B, b_m$ | Types of packaging boxes ($B = \{b_1, b_2, \ldots, b_m\}$) |
| $i, j, N$ | Delivery location ($i, j \in N$) |
| $O_{i \in N}$ | Orders for each customer |

| Symbol | Description (Value range) |
|---|---|
| $q_{s\in S}$ | Weight of each item |
| $w_{b\in B}$ | Capacity of each packaging boxes |
| $\theta_{b\in B}, \theta'_{b\in B}$ | Fresh-keeping capacity coefficient of packing box |
| $T_s$ | Preservation temperature range ($s \in S$) |
| $C_{b\in B}$ | Total cost of packaging boxes |
| $A_{sib}$ | Time–temperature relationship of cold chain packaging($\forall i \in N; \forall s \in S; b \in B$) |
| $\alpha_{si}, \beta_{sib}$ | Decision variables ($\forall i \in N; \forall s \in S; b \in B$) |
| $\|O_i\|^{B_n}$ | Total number of potential packaging arrangements |
| $pk_i^n$ | The packaging option for each Oder ($\forall i \in N; \forall n \in \left(1, 2, \ldots, \|O_i\|^{B_n}\right)$) |
| $C_{pk_i^n}$ | Total packaging costs ($\forall i \in N; \forall n \in \left(1, 2, \ldots, \|O_i\|^{B_n}\right)$) |
| $f_i$ | Delivery single cargo ($\forall i \in N$) |
| $q_{f_i}$ | Weight of cargos ($\forall i \in N$) |
| $A_{f_i}$ | Shelf life of cargos ($\forall i \in N$) |
| $pl_n$ | Specific permutations of the packaging method for the merchandise ($\forall n \in \left(1, 2, \cdots \prod_{i=1}^{N} B_n{}^{\|O_i\|}\right)$) |
| $k$ | Number of truckers |
| $Q_k$ | Maximum load of each vehicle |
| $\gamma$ | Penalty factor |
| $D_k$ | Total number of load violation |
| $v$ | Average driving speed |
| $d_{ij}$ | Distance between two points ($i, j \in N$) |
| $p_c$ | fixed cost of each vehicle |
| $p_r$ | Variable cost of each vehicle |
| $x_{ijk}, y_{ik}, \sigma_{f_ik}$ | Decision variables ($\forall i \in N; \forall j \in N; \forall k \in \left(k_{min,\ldots,}k_{max}\right)$) |
| $CT_f$ | Quality satisfaction |
| $t_{f_i}$ | Actual arrival time ($\forall i \in N$) |
| $J$ | Optimal route for visiting all customer locations |
| $\tau$ | Freshness penalty factor |
| $r_i, r'_i$ | Customer expectation time window |
| $e_i, e'_i$ | Soft time window |
| $R_i, R'_i$ | Request time window |
| $Z_1$ | Total packaging cost |
| $Z_2$ | Total fixed transportation cost |

| Symbol | Description (Value range) |
|---|---|
| $Z_3$ | Total variable transportation cost |
| $a$ | Start time |
| $G_1$ | Total cost |
| $G_2$ | Overall satisfaction |

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