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An IRP model to improve the sustainability of cold food supply chains under stochastic demand

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ABSTRACT

There has been limited progress in addressing the demand uncertainty inherent over time and the sustainability impact on food logistics. This paper aims to fill this gap, addresses the sustainability of cold food supply chains, and proposes a mixed-integer programming model to solve a multi-period inventory routing problem (IRP) under non-stationary stochastic demand, route-dependent costs, and environmental concerns. The study investigates the replenishment and routing plans to minimise the total expected cost while producing a minimum amount of CO_2 emission. Due to the uncertainty of demand, we apply the static-dynamic strategy and propose a mathematical model under the (R,S) replenishment policy to maintain flexibility in ordering decisions under a pre-determined replenishment schedule. Our numerical experiments suggest that the (R,S) policy reduces inventory costs significantly, since it solves the excess inventory issue caused by the higher buffer stock levels due to the pre-determined order quantities in the (R,Q) policy. However, the resulting CO_2 emission levels and routing costs remain similar in both models. Due to the reduced inventory costs, the (R,S) policy makes a significant improvement on the total cost. Moreover, our numerical experiments show that the difference between the cumulative ending inventory levels for the (R,Q) and (R,S) policies increasingly grows as the time horizon gets longer, and it results in increasingly larger differences in the total cost values for both policies.

1. Introduction

The global food system faces pressing environmental sustainability challenges, and in addressing these challenges, the food supply chain (FSC) is an area that has received increasing attention. Improved routing of food logistics can reduce time, costs, and related emissions. Over the last years, considerable literature has emerged addressing vehicle routing in food logistics. In traditional food logistics, reducing costs and increasing responsiveness were the primary objectives of a supply chain network. However, sustainability studies are becoming increasingly crucial to protect the environment and also to improve food supply chains' social and economic aspects (see Bottani et al. (2019)). Amorim and Almada-Lobo (2014) focuses on environmental measures of CO_2 emissions within supply chain models, and Shashi et al. (2018) states that one of the primary sources of CO_2 emissions in a food supply chain is the transportation and inventory activities.

According to the Secretary-General, UN (2019), freight storage and transportation activities will generate 36% of all permissible emissions by 2050. Moreover, transporting and storing temperature-sensitive products requires additional energy consumption to keep them at an ideal temperature, resulting in higher CO_2 emissions (see Babagolzadeh et al. (2020)). A well-designed cold food supply chain (CFSC) model is required to manage these costs and CO_2 emissions. The need for a practical CFSC model that explores the impact of non-stationary stochastic demand on operational decisions of storage and transportation in CFSCs leads to our motivation here. The proposed model aims to assist decision-makers in reducing various costs associated with CFSCs—such as holding, transportation, unit ordering, fixed replenishment, and refrigeration—while also focusing on CO_2 emission reduction.

The well-known Inventory Routing Problem (IRP) offers a framework to address both inventory management and routing challenges. The NP-hard inventory routing problem handles inventory management and vehicle routing simultaneously (Jemai et al., 2013). However, a practical model could be achieved using the IRP. Limited studies have been conducted on inventory routing problems with non-stationary stochastic demand consideration. In most existing studies, the probability distribution function for uncertain demand is considered static.

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However, this does not reflect reality, creating a gap in the literature when it comes to investigating IRP in a non-stationary stochastic environment. Soysal et al. (2015) presented a model to handle inventory and routing decisions using the (R, Q) policy. This policy pre-determines replenishment timing and order quantities before the start of the planning horizon, and it does not allow enough flexibility in making replenishment decisions. Moreover, the IRP models considering CFSCs and environmental concerns have not been widely studied in the literature. We aim to address this gap and make a significant contribution to the field. Briefly, in this study, we develop a novel model to determine the replenishment and vehicle routing plans of a CFSC with non-stationary stochastic demand by taking routing and refrigeration costs and total CO_2 emissions into account.

In this study we employ the (R, S) policy presented by Tarim and Kingsman (2004, 2006). Using the (R, S) policy, replenishment periods are determined at the start of the planning horizon, while order quantities are determined after observing the demand realisations, in a similar manner to the static-dynamic strategy of Bookbinder and Tan (1988).

We argue that the presented model under the (R, S) policy provides a more effective way to deal with non-stationary demand uncertainty. The aim is to determine the replenishment times, quantities, vehicle routing plans, and CO_2 emissions. In the context of non-stationary uncertain demand, this primary question addressed in this study is how to optimise inventory management decision while also addressing environmental concerns in CFSCs. The CFSC setting is a Distribution Centre (DC) transporting items to a number of retailers, under the requirement that the inventory levels must satisfy a fixed minimum service level.

The structure of the rest of this paper is organised in the following way: In Section 2, we provide a literature review about the IRP and CFSCs. Then we describe the problem that we consider in Section 3, introduce the methods that we use to calculate CO_2 emissions produced due to transportation and refrigeration activities in Sections 3.1 and 3.2, respectively, formulate our mathematical model in Section 3.3 and introduce the deterministic-equivalent constraints in Section 3.4. In Section 4, we present our numerical experiments and discuss the results we obtained. Finally, we conclude our study in Section 5 and outline several possible directions for future research.

2. Related literature

In this section we review the relevant contributions to identify the existing research gap and position our study within the existing body of knowledge. The literature reviewed primarily covers three areas, as the problem overlaps with these literature streams. Table 1 summarises the CFSC literature we conduct.

2.1. Sustainable cold food supply chain models

Most existing literature on CFSC pays particular attention to sustainability. This is since preserving the temperature of cold products within the recommended limits comes at the cost of higher energy consumption and further emission. James and James (2010) studied the impact of CFSCs on global climate change and discovered that cold storage facilities account for approximately 50% of carbon emissions in these chains. According to Waltho et al. (2019), transportation and storage activities account for more than one-third of the total emission generated by a CFSC. This prompts an increasing research interest in the sustainability aspects of CFSCs. Numerous researchers introduced mathematical models for CFSC to incorporate environmental considerations into the traditional supply chain management models. These models broaden the focus from merely the business aspects of supply chains to include sustainability issues (Al Theeb et al., 2020, Allaoui et al., 2018).

A review of the relevant literature identifies the parameters to be measured and lays the groundwork for our work. Studies have been conducted to determine the CO_2 emission of an empty vehicle. A variety of metrics have been used to evaluate carbon emissions, including the energy used by vehicles, distance travelled, and load transferred. Validi et al. (2014), Hsiao et al. (2017), Bottani et al. (2019), and Babagolzadeh et al. (2020) evaluated carbon emission only in terms of the quantity of energy that was used by vehicles. Mallidis et al. (2012), Pan et al. (2013), Soysal et al. (2014), Danloup et al. (2015), Moheb-Alizadeh and Handfield (2018), Musavi and Bozorgi-Amiri (2017), Hariga et al. (2017), Zhen et al. (2019) and Li et al. (2019) calculated an empty vehicle's emission per unit of distance travelled. Mallidis et al. (2012), Elhedhli and Merrick (2012), Galal and El-Kilany (2016), Ghahremani Nahr et al. (2020), Saif and Elhedhli (2016), Boronoos et al. (2021), and Zarbakhshnia et al. (2019) calculated carbon emission according to the quantity of load transfer. As a result, distance and load unit are considered essential factors in the computation of CO_2 emission. Authors such as Pan et al. (2013), Bortolini et al. (2016), Danloup et al. (2015), Chen and Hsu (2015), Soysal et al. (2014), Musavi and Bozorgi-Amiri (2017), Tordecilla-Madera et al. (2018), Shamayleh et al. (2019), Jiang et al. (2020) and Mohebalizadehgashti et al. (2020) computed the carbon emission by concurrently calculating the distance and the amount of load transmitted. Bozorgi et al. (2014), Bozorgi (2016) analysed transportation emissions based on the number of fully loaded refrigerated trucks that travelled during each period, the average load, and the distance travelled for transferring various cold products. Similarly, Moheb-Alizadeh and Handfield (2018) considered time, distance, and load quantity to be the critical components of CO_2 emission. This implies that distance and load unit are essential factors in CO2 emission computations. Stellingwerf et al. (2018) adopted a broader perspective. They determined the fuel consumption in a CFSC based on the load weight, road slope, distance travelled, and vehicle speed. The carbon emission generated by the chill transport is also addressed in their study by considering the amount of fuel used to refrigerate the load. They discovered that including chill transport emission in their calculations resulted in considerable route adjustments. Galal and El-Kilany (2016) also addressed the emission of chill transport in their studies, and Fichtinger et al. (2015) studied the emission of chill inventory management. Chen and Hsu (2015) and Stellingwerf et al. (2018) were unique in considering the CO_2 emissions resulting from opening vehicle doors and unloading products. However, recent studies such as Zhang and Chen (2014) suggest that offloading in high-temperature environments significantly impacts CO_2 emission. Recently, in order to enhance resilience and sustainability of food supply chains, Singh et al. (2023) employ the digital twin technology. Aazami and Saidi-Mehrabad (2021) considers a multi-level supply chain for perishable products and develop a heuristic. Turan and Ozturkoglu (2022) develop a conceptual framework for CFSCs. Shi et al. (2022) propose an intelligent green scheduling system, proposes a multi-objective optimisation model, and an optimisation algorithm for a cold supply chain with deterministic demand, by taking CO_2 emission concerns into account. Moreover, Chen et al. (2022) study a CFSC model with deterministic demand and proposes an optimal replenishment schedule by considering CO_2 emissions.

2.2. Cold food supply chain models and demand uncertainty

Uncertainty is an inherent aspect of decision-making in real-world scenarios. Most supply chain and inventory management research assumes that the demand parameter is known or the probability distribution is known and static if the parameter is unknown. In other words, the parameter is stationary stochastic (Zhang and Chen, 2014) and the safety stock was conveniently determined. Yavari and Geraeli (2019), Soysal et al. (2015), Zhen et al. (2019), Mohebalizadehgashti et al. (2020), Galal and El-Kilany (2016), Ghahremani Nahr et al. (2020), Tamjidzad and Mirmohammadi (2017), Solyalı et al. (2012), Torabi et al. (2015), and Amin and Zhang (2013) are among the papers considering stationary stochastic demand.

Table 1
Summary of the CFSC literature review. D, S, and NS represent deterministic, stationary stochastic, and non-stationary stochastic, respectively.

#	Author	Year	Demand type	Fixed dispatching cost	Fixed ordering cost	Linear travel costs	Penalty cost/ Service level	Holding cost	Empty vehicle travelling emission	Load transferring emission	Primary refrigeration emission	Chill transfer emission	Unloading emission
1	Al Theeb et al. (2020)	2020	D			*	P	*					
2	Allaoui et al. (2018)	2018	D			*							
3	Amorim and Almada-Lobo (2014)	2014	D			*							
4	Bortolini et al. (2016)	2016	D			*		*		*			
5	Bottani et al. (2019)	2019	D			*	P		*	*			
6	Bozorgi et al. (2014)	2014	D	*		*			*	*			
7	Bozorgi (2016)	2016	D			*		*		*			
8	Chen and Hsu (2015)	2015	D							*			*
9	Danloup et al. (2015)	2015	D			*			*	*			
10	Elhedhli and Merrick (2012)	2012	D			*				*			
11	Fichtinger et al. (2015)	2015	D		*	*							
12	Hariga et al. (2017)	2017	D	*				*	*	*			
13	Hsiao et al. (2017)	2017	D	*		*			*				
14	Li et al. (2019)	2019	D			*			*	*			
15	Mallidis et al. (2012)	2012	D			*		*	*	*			
16	Meneghetti and Monti (2015)	2015	D										
17	Musavi and Bozorgi-Amiri (2017)	2017	D			*			*	*			
18	Torabi et al. (2015)	2015	D			*	P			*			
19	Pan et al. (2013)	2013	D			*			*	*			
20	Tordecilla-Madera et al. (2018)	2018	D	*	*	*		*		*			
21	Saif and Elhedhli (2016)	2016	D		*	*		*		*			
22	Shamayleh et al. (2019)	2019	D		*	*		*		*			
23	Soysal et al. (2014)	2014	D	*		*	P	*	*	*			
24	Stellingwerf et al. (2018)	2018	D			*		*		*		*	
25	Validi et al. (2014)	2014	D		*	*				*			
26	Zarbakhshnia et al. (2019)	2019	D			*		*		*			
27	Babagolzadeh et al. (2020)	2020	S	*			P	*	*	*			
28	Jiang et al. (2020)	2020	S			*	P			*			
29	Solyalı et al. (2012)	2012	S	*		*		*					
30	Galal and El-Kilany (2016)	2016	S			*	S	*		*		*	
31	Ghahremani Nahr et al. (2020)	2020	S		*	*	P	*		*			
32	Amin and Zhang (2013)	2013	S			*							
33	Moheb-Alizadeh and Handfield (2018)	2018	S		*	*		*	*	*			
34	Mohebalizadehgashti et al. (2020)	2020	S			*				*			
35	Yavari and Geraeli (2019)	2019	S		*	*		*					
36	Zhen et al. (2019)	2019	S			*		*		*			
37	Soysal et al. (2015)	2015	S			*	S	*		*			
38	Tarim and Kingsman (2006)	2006	NS		*		P	*					
39	Tarim and Smith (2008)	2008	NS		*		S	*					
40	Seth and Pandey (2009)	2009	NS				P	*					
41	Tunc et al. (2011)	2011	NS	*	*		P	*					
42	Zhang and Chen (2014)	2014	NS				S						
43	Pauls-Worm et al. (2014)	2014	NS		*		S	*					
44	Purohit et al. (2016)	2016	NS	*	*		S	*					
45	Gutierrez-Alcoba et al. (2017)	2017	NS			*	P	*					
46	Sinaga et al. (2016)	2016	NS			*	S	*					
47	Chen et al. (2022)	2022	D	*	*	*		*	*	*	*	*	*
48	Shi et al. (2022)	2022	D	*		*	P	*	*	*	*	*	*
49	Jahdi et al.	2024	NS		*	*	S	*	*	*	*	*	*

Babagolzadeh et al. (2020) recently proposed a two-stage stochastic programming model for minimising the economic and environmental impacts of a temperature-sensitive food supply chain with stationary stochastic input data. Similarly, Mohebalizadehgashti et al. (2020) developed a multi-objective mixed-integer linear programming model and applied several decision trees to analyse stationary uncertainty. Soysal et al. (2015) presented an optimisation model for minimising total cost while meeting CO_2 emission and service level requirements and uncertain stationary demand. They employed the fuel consumption parameters for transportation and refrigeration derived in Barth et al. (2005), Franceschetti et al. (2013), Demir et al. (2012), Stellingwerf et al. (2018), Bektaş and Laporte (2011), and Tassou et al. (2009) (Soysal et al., 2015) might be the most relevant research regarding the extent and objectives; thus, uncertain demand is considered stationary, and emissions generated by cold facilities are neglected. Recently, Köseli et al. (2023) combined refrigeration activities with the IRP model and took CO_2 emissions generated by refrigeration into account. Both Soysal et al. (2015) and Köseli et al. (2023) calculated the CO_2 emissions using the amount of fuel consumption.

Demand often has a varying probability distribution in practice (Graves and Willems, 2008). Stationary demand has a static distribution, though this is not the case with non-stationary demand (Silver, 1973). Zhang and Chen (2014) explain that if the probability distribution is not steady, demand is non-stationary stochastic. However, research on non-stationary demand in CFSCs is limited, with most studies focusing on stationary demand. Considering a stationary demand rather than a non-stationary parameter significantly increases the costs of a supply chain (Tunc et al., 2011). Therefore, conducting research on CFSCs with non-stationary stochastic demand is critical.

2.3. Lot-sizing problem with non-stationary stochastic demand

Lot-sizing problem with non-stationary stochastic demand has been studied by Silver (1973), Bollapragada and Morton (1999), Beyer and Ward (2002), Zhang and Chen (2014), Iida (2002), Seth and Pandey (2009), Tunc et al. (2011), Pauls-Worm et al. (2014), Purohit et al. (2016), Gutierrez-Alcoba et al. (2017), Sinaga et al. (2016), Tarim and Smith (2008) and Tarim and Kingsman (2006). These studies exclude supply chain routing, although inventory management and vehicle routing significantly impact overall supply chain costs (Beyer and Ward, 2002). As one of the primary contributions of this study, we investigate the effect of non-stationary uncertainty on the inventory management and routing of a CFSC using the (R, S) policy.

2.4. Our contribution and the literature gap addressed

The main contributions of our study could be summarised as follows: We propose a mixed-integer programming (MIP) IRP model that enables significant cost savings for CFSCs, allows flexibility in ordering decisions and solves the excess buffer stock and higher holding cost issue caused by the pre-determined order quantities found by the (R, Q) policy. Moreover, we incorporate CO_2 emissions caused by various refrigeration activities to the non-perishable version of the inventory routing problem in Soysal et al. (2015) by employing the findings of Köseli et al. (2023) related to refrigeration. Hence, we simultaneously cover environmental concerns regarding CO_2 emissions, refrigeration and transportation activities, and inventory control under non-stationary stochastic demand and a service level constraint. Our aim is to fill this gap in the literature.

3. Problem description

In this paper, we study a single-item cold food supply chain (CFSC) problem comprised of a single distribution centre and $V \geq 1$ retailers. The supply chain structure in this study is depicted in Fig. 1. Demand is stochastic and non-stationary, demand distributions may vary over time and across retailers, and demand realisations for each retailer i in each period t, d_{it}, are independent random variables with known probability density functions $g_{it}(d_{it})$ and cumulative distribution functions $G_{it}(d_{it})$. We re-formulate the (R, Q) model developed by Soysal et al. (2015) according to the static-dynamic (R, S) policy proposed by Tarim and Kingsman (2004), and extend the model into the cold supply chain case by taking the total CO_2 emission concerns into account.

Our motivation to re-model the problem can be explained as follows: The (R, Q) policy has been one of the most well-known policies used for handling inventory systems. According to this policy, Q units are ordered as the inventory level is at the reorder point R. Therefore, the exact timing and quantities of future orders are known to the suppliers in advance. Soysal et al. (2015) have developed a multi-period IRP model to compute all inventory and routing decisions under the (R, Q) policy. Their study aims to find the optimised routes and replenishment size for retailers in such a way that total expected costs (including routing and inventory) are minimised. Given that the (R, Q) policy provides rigid plans at the beginning of the planning horizon, there would not be any flexibility to develop recourse actions later to respond to future realisations of demand. To meet these uncertain demands and to avoid stock-outs under the (R, Q) policy, it is essential to keep more safety stocks which results in higher inventory holding costs for the system. Therefore, to deal with these types of uncertainties dynamically, we employ the (R, S) policy which allows us to develop recourse actions to be able to deal with such uncertainties as they arise. The (R, S) policy works in the same manner as Bookbinder and Tan (1988)'s static-dynamic strategy. According to the (R, S) policy, the replenishment timings are fixed at the beginning of the horizon. Order-up-to-levels are also decided at the beginning of the planning horizon. However, the order quantities are determined later as demand become known. Thus, the distribution centre knows the timing of future orders and prepares to fulfil them, although the order quantities are unknown.

Note that some other methods, i.e., the dynamic uncertainty strategy of Bookbinder and Tan (1988) and the rolling horizon approach, can provide optimal results. not necessarily recommended in practice, since decisions need to be reviewed each period as the realised demand value becomes known and the outcome of each decision may need a set-up in the next period. This approach could require a decision set-up almost every period (Bookbinder and Tan, 1988). Since we aim to develop a model which is computationally efficient and easy to implement in practice, and provides near-optimal results while allowing flexibility in ordering decisions, we apply the static-dynamic strategy and the (R, S) policy.

We define the problem on a complete graph $\mathcal{G} = \{\mathcal{V}, \mathcal{A}\}$, where $\mathcal{V} = \{0, \dots, V\}$ is the set of nodes in which the node 0 represents the distribution centre and the remaining nodes represent the retailers, and $\mathcal{A} = \{(i, j) : i, j, \in V, i \neq j\}$ is the set of arcs representing the path between nodes i and j. We also denote $\mathcal{V}' = \{1, \dots, V\}$ by the set of retailers. Items are shipped from the distribution centre to each retailer over a finite planning horizon of T periods, and using at most $K \geq 1$ available identical vehicles with a known finite capacity C per vehicle. We define the set of vehicles by $\mathcal{K} = \{1, \dots, K\}$ and the set of periods bt $t \in \mathcal{T}' = \{1, \dots, T\}$. We assume that the capacities of the distribution centre and each retailer are unlimited. The load carried by vehicle k from retailer i to retailer j, F_{ijkt}, cannot exceed the vehicle capacity at any time. The binary variable δ_{it} indicates that if a replenishment order for retailer i is scheduled at the beginning of period t or not. S_{it} denotes the order-up-to level for retailer i in period t, and the ending inventory level for retailer i in period t is denoted by I_{it}. Orders for the same retailer can be shipped by multiple vehicles. The part of the order for retailer i which is carried by vehicle k is denoted by Q_{ikt}. The binary decision variable X_{ijkt} indicates if vehicle k traverses the arc (i, j) in period t or not. In each period t, vehicle k can only travel a single route starting and ending at the distribution centre, visits retailer i, and carries order for retailer i, i.e., $Q_{ikt} > 0$, if and only if a replenishment order is scheduled for that retailer, i.e., $\delta_{it} = 1$. Thus, it is not required to visit all the retailers in each period, and it is not required to operate all the K vehicles in a single period. The inventory level for all retailers at the beginning of the planning horizon, I_{i0}, is set to be zero. Replenishment lead times are not addressed in this study. However, lead times could be incorporated without loss of any generality. There is a service level requirement, therefore the customer demand in each period and for each retailer must be satisfied with a probability of at least α. Unsatisfied demand is backordered in the next period. Items have an indefinite shelf life and no waste occurs due to perishability. In our problem, we classify the costs as the inventory, transportation, and refrigeration costs. For any retailer i, there are three different types of inventory costs: A fixed setup cost per order which is represented by A_i and a variable ordering cost c_i which is linear in the order quantity $\sum_{k=1}^{K} Q_{ikt}$ are incurred at the beginning of each replenishment period. In addition, a holding cost h_i which is linear in the inventory on hand is incurred at the end of period t. Transportation costs consist of fuel consumption costs and driver wages. The driver wage per second is denoted by r. Moreover, the amount of fuel used for cooling the vehicles while transportation and due to the heat entering while opening the vehicle doors to load or unload the items result in refrigeration costs. Our aim is to determine the replenishment periods, order-up-to levels, and shipment routes that minimise the total inventory, transportation, and refrigeration costs while producing minimal CO_2 emissions.

In the following, we explain the procedure that we apply to calculate the total fuel consumption and emissions due to transportation and refrigeration activities.

3.1. Emissions due to the transportation activities

Since the CO_2 emissions produced during transportation activities are caused by fuel consumption, we estimate how much fuel is used. In order to estimate the fuel consumption, we employ the same approach as in Soysal et al. (2015) and Köseli et al. (2023). Hence, we estimate the total fuel consumption as follows:

$$f_t = \lambda\bigg(y(a/f) + \gamma\beta a f^2 + \gamma s(\mu + F)a\bigg), \tag{1}$$

where a is the distance (m), f is the constant speed (m/s), F is the load (kg), $\lambda = \xi/(\kappa\psi)$, $y = k_e N_e V_e$, $\gamma = 1/(1000\epsilon\omega)$, $\beta = 0.5 C_d A_e \rho$, $s = g\sin\phi + gC_r\cos\phi$, k_e is the engine friction factor (kJ/rev/l), N_e is the engine speed (rev/s), V_e is the engine displacement (l), μ is the curb weight (kg), g is the constant of gravitation (9.81 $\mathrm{m/s^2}$), ϕ is the road angle, C_d is the coefficient of aerodynamic drag, C_r is the coefficient of rolling resistance, A_e is the frontal surface area ($\mathrm{m^2}$), ρ is the air density ($\mathrm{kg/m^3}$), ϵ is the vehicle drive train efficiency, ω is the diesel engine efficiency parameter, ξ is the fuel to air mass ratio, κ is the heating value of a typical diesel fuel (kJ/g), and ψ is the conversion factor from (g/s) to (l/s). After we estimate the fuel consumption, we use a conversion factor u in terms of (kg/l) in order to calculate the amount of the CO_2 emission produced.

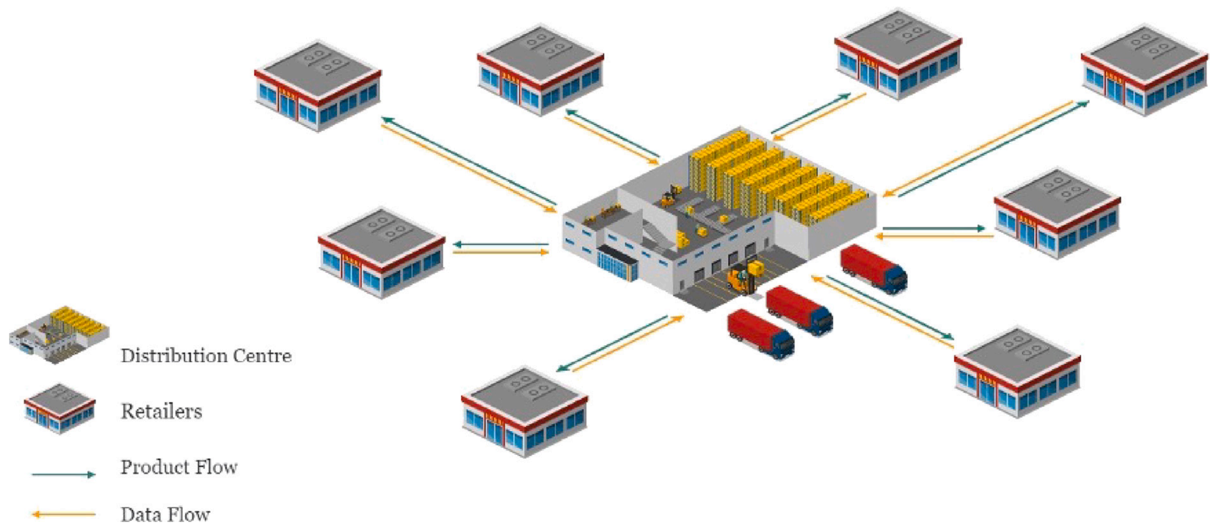

Fig. 1. Schematic representation of the supply chain network in this study.

3.2. Emissions due to the refrigeration activities

We apply the formulation described in Köseli et al. (2023) to estimate the CO_2 emission produced during refrigeration activities. The energy used to maintain and control the temperature is dependent on the heat entering through vehicle surface and the heat entered inside the vehicle when the doors are opened for loading or unloading. Eq. (2) calculates the total amount of heat (kWh) entering inside a vehicle in period t through vehicle surfaces:

$$H_w = \frac{\sum_{(i,j)\in\mathcal{A}} a_{i,j} X_{ijkt} U S_k \Delta T}{3.6 * 10^6 f}. \tag{2}$$

Note that we divide the power by $3.6 * 10^6$ to convert Joules (J) to kilowatt-hours (kWh),t a_{ij} is the distance between retailers i and j (m), U is the heat transfer coefficient (W/m^2/K), S_k is the surface area of vehicle k (m^2), and ΔT is the temperature difference (K) between the inside and the outside of the vehicle. Eq. (3) calculates the total amount of heat enters inside the vehicle through the opened doors during loading or unloading activities:

$$H_s = \sum_{(i,j)\in\mathcal{A}} H_i X_{ijkt}, \tag{3}$$

where H_i denotes the heat (kWh) entering inside the vehicle through the opened doors at the location of retailer i. Then we calculate the amount of fuel consumed for refrigeration, denoted by f_r, as follows:

$$f_r = \frac{H_w + H_s}{\mu_e \mu_p P_f},$$

where μ_e denotes the efficiency for converting the chemical energy from the fuel to electricity to supply power to the refrigeration system, μ_p is the coefficient of performance, and P_f is the energy content of the fuel (kWh/l). Finally, by using the conversion factor u, we calculate the total CO_2 emission produced while refrigerating the vehicles.

3.3. Mathematical model

We hereby present the chance-constrained model that formulates our problem:

$$\min\ TC = \sum_{i\in\mathcal{V}'}\sum_{t\in\mathcal{T}}\left(h_i I_{it}^{+} + A_i\delta_{it} + c_i\delta_{it}(S_{it} - I_{it-1})^{+}\right) \tag{4a}$$

$$+ \sum_{(i,j)\in\mathcal{A}}\sum_{k\in\mathcal{K}}\sum_{t\in\mathcal{T}} \lambda \Big(y(a_{ij}/f)X_{ijkt} + \gamma\beta a f^2 X_{ijkt}$$

$$+ \gamma s(\mu X_{ijkt} + F_{ijkt})a_{ij} \Big)\, l \tag{4b}$$

$$+ \sum_{(i,j)\in\mathcal{A}}\sum_{k\in\mathcal{K}}\sum_{t\in\mathcal{T}} (a_{ij}/f)X_{ijkt} r \tag{4c}$$

$$+ \sum_{(i,j)\in\mathcal{A}}\sum_{k\in\mathcal{K}}\sum_{t\in\mathcal{T}} f_r X_{ijkt} \tag{4d}$$

subject to

$$I_{i0} = 0, \quad i\in\mathcal{V}'. \tag{5}$$

$$I_{it} = S_{it} - d_{it}, \quad i\in\mathcal{V}', t\in\mathcal{T}. \tag{6}$$

$$\sum_{k\in\mathcal{K}'} Q_{ikt} = S_{it} - I_{it-1}, \quad i\in\mathcal{V}', t\in\mathcal{T}. \tag{7}$$

$$S_{it} \geq I_{it-1}, \quad i\in\mathcal{V}', t\in\mathcal{T}. \tag{8}$$

$$S_{it} - I_{it-1} \leq \mathcal{M}\delta_{it}, \quad i\in\mathcal{V}', t\in\mathcal{T}. \tag{9}$$

$$I_{it} \geq \sum_{s=1}^{t}\left(G^{-1}_{d_{i,t-s+1}+d_{i,t-s+2}+\cdots+d_{i,t}}(\alpha) - \sum_{m=t-s+1}^{t} d_{im}\right)P_{its}, \quad i\in\mathcal{V}', t\in\mathcal{T}. \tag{10}$$

$$\sum_{s=1}^{t} P_{its} = 1, \quad i\in\mathcal{V}', t\in\mathcal{T}. \tag{11}$$

$$P_{its} \geq \delta_{i,t-s+1} - \sum_{m=t-s+2}^{t}\delta_{im}, \quad i\in\mathcal{V}', t\in\mathcal{T}, s = 1,\dots,t. \tag{12}$$

$$\sum_{i\in\mathcal{V}, i\neq j} X_{ijkt} = \sum_{i\in\mathcal{V}, i\neq j} X_{jikt}, \quad j\in\mathcal{V}', k\in\mathcal{K}, t\in\mathcal{T}. \tag{13}$$

$$\sum_{j\in\mathcal{V}, i\neq j} X_{ijkt} \leq 1, \quad i\in\mathcal{V}, k\in\mathcal{K}, t\in\mathcal{T}. \tag{14}$$

$$\sum_{j\in\mathcal{V}, i\neq j} F_{ijkt} = \sum_{j\in\mathcal{V}, i\neq j} F_{jikt} - Q_{ikt}, \quad i\in\mathcal{V}', k\in\mathcal{K}, t\in\mathcal{T}. \tag{15}$$

$$F_{ijkt} \leq C X_{ijkt} - Q_{ikt}, \quad (i,j)\in\mathcal{A}, k\in\mathcal{K}, t\in\mathcal{T}. \tag{16}$$

$$\sum_{j\in\mathcal{V}'} F_{j0kt} \leq 0, \quad k\in\mathcal{K}, t\in\mathcal{T}. \tag{17}$$

$$\sum_{(i,j)\in\mathcal{A}}\sum_{k\in\mathcal{K}}\sum_{t\in\mathcal{T}} \lambda\Big(y(a_{ij}/f)X_{ijkt} + \gamma\beta a f^2 X_{ijkt} + \gamma s(\mu X_{ijkt} + F_{ijkt})a_{ij}\Big) \geq 0. \tag{18}$$

$$\sum_{(i,j)\in\mathcal{A}}\sum_{k\in\mathcal{K}}\sum_{t\in\mathcal{T}} f_r X_{ijkt} \geq 0. \tag{19}$$

Note that $(x)^{+} = \max(x, 0)$ and $(x)^{-} = \min(x, 0)$.

The objective function given in Eqs. (4a)–(4d) is composed of four parts: Eqs. (4a), (4b), (4c), and (4d) minimises the total inventory, transportation, routing, and refrigeration costs throughout the planning horizon, respectively. Constraints (5)–(12) are related to inventory decisions. Constraint (5) initialises the inventory levels at the beginning of the planning horizon to zero. Constraint (6) is the inventory balance equation and reflects that the expected inventory level for each customer at the end of each period is equivalent to the expected inventory level at the beginning of the period subtracting the expected demands in that period. The expected inventory level at the beginning of periods could be interpreted as order-up-to-levels or the level that the inventory could be raised to at the beginning of periods. If there is no replenishment in that period, S_{it} is considered as the opening stock level. Constraint (7) states that in each period t, the sum of all the amount of order for each retailer i carried by the operating vehicles must be equal to the order-up-to level for that retailer. Constraints (8) and (9) ensures if there is no replenishment in period t for retailer i, the order-up-to level is equal to the opening inventory level. Constraint (10) is the service level constraint. Note that $G^{-1}_{d_{i,t-s+1}+d_{i,t-s+2+\cdots+d_{i,t}}}$ denotes the inverse cumulative distribution function of the total demand for retailer i as of period t since the last replenishment in period $t-s+1$. Constraints (11) and (12) track the last replenishment. Constraints (13)–(17) are related to routing and flow control. In particular, constraint (13) ensures the flow conservation between nodes. According to constraint (14), each vehicle can be assigned to at most one route in each period. Constraint (15) states that the total load decreases after each retailer is visited. According to constraint (16), the load on each vehicle cannot exceed the vehicle capacity, and constraint (17) ensures the total load on each vehicle cannot be non-negative when returning to the distribution centre. Constraint (15) also performs as a subtour elimination constraint since the load is monotonically decreasing after each visit (see Bard and Nananukul (2009), Treitl et al. (2014) and Soysal et al. (2015)). Finally, constraints (18) and (19) enforce the total fuel consumption to be non-negative. Recall that f_r in Eq. (19) represents the fuel usage for refrigeration and the notation is the same as in Köseli et al. (2023).

3.4. Deterministic-equivalent approximation

Since we determine the replenishment schedule before any demand realisation occurs, we consider a deterministic-equivalent approximation to the model. Therefore, we replace the stochastic variables S_{it}, I_{it}, Q_{ikt}, and d_t with their expectations $\mathbb{E}S_{it}$, $\mathbb{E}I_{it}$, $\mathbb{E}Q_{ikt}$, and $\mathbb{E}d_t$, respectively. Then, we re-write the objective function in terms of the expected total cost as follows:

$$\begin{aligned}\min\ \mathbb{E}TC = &\sum_{i\in\mathcal{V}'}\sum_{t\in\mathcal{T}}\Big(h_i\mathbb{E}I^+_{it} + A_i\delta_{it} + c_i\delta_{it}(\mathbb{E}S_{it}-\mathbb{E}I_{it-1})^+\Big)\\ &+\sum_{(i,j)\in\mathcal{A}}\sum_{k\in\mathcal{K}}\sum_{t\in\mathcal{T}}\lambda\Big(y(a_{ij}/f)X_{ijkt} + \gamma\beta a f^2 X_{ijkt}\\ &+\gamma s(\mu X_{ijkt}+F_{ijkt})a_{ij}\Big)l\\ &+\sum_{(i,j)\in\mathcal{A}}\sum_{k\in\mathcal{K}}\sum_{t\in\mathcal{T}}(a_{ij}/f)X_{ijkt}r\\ &+\sum_{(i,j)\in\mathcal{A}}\sum_{k\in\mathcal{K}}\sum_{t\in\mathcal{T}} f_r X_{ijkt}\end{aligned}$$

We finally re-write constraints (5)–(10) and (15)–(16) by replacing the stochastic variables with their expectations, respectively:

$$\mathbb{E}I_{i0}=0,\quad i\in\mathcal{V}'.$$

$$\mathbb{E}I_{it}=\mathbb{E}S_{it}-\mathbb{E}d_{it},\quad i\in\mathcal{V}',t\in\mathcal{T}.$$

$$\sum_{k\in\mathcal{K}'}\mathbb{E}Q_{ikt}=\mathbb{E}S_{it}-\mathbb{E}I_{it-1},\quad i\in\mathcal{V}',t\in\mathcal{T}.$$

Table 2
Input parameters for the experiments.

Input parameters	Values
Fixed setup cost (A)	{10, 25, 100}
Unit ordering cost (c)	{0.05, 0.1}
Unit holding cost (h)	0.06
Service level (α)	{0.95, 0.975}
Coef. of variation	{0.05, 0.1, 0.2}
Vehicle speed (f)	80 km/h
Number of vehicles (K)	2
Vehicle capacity (C)	4 tonnes
Planning horizon (T)	8

$$\mathbb{E}S_{it}\geq\mathbb{E}I_{it-1},\quad i\in\mathcal{V}',t\in\mathcal{T}.$$

$$\mathbb{E}S_{it}-\mathbb{E}I_{it-1}\leq\mathcal{M}\delta_{it},\quad i\in\mathcal{V}',t\in\mathcal{T}.$$

$$\mathbb{E}I_{it}\geq\sum_{s=1}^{t}\left(G^{-1}_{d_{i,t-s+1}+d_{i,t-s+2+\cdots+d_{i,t}}}(\alpha)-\sum_{m=t-s+1}^{t}\mathbb{E}d_{im}\right)P_{its},\quad i\in\mathcal{V}',t\in\mathcal{T}.$$

$$\sum_{j\in\mathcal{V},i\neq j}F_{ijkt}=\sum_{j\in\mathcal{V},i\neq j}F_{jikt}-\mathbb{E}Q_{ikt},\quad i\in\mathcal{V}',k\in\mathcal{K},t\in\mathcal{T}.$$

$$F_{ijkt}\leq CX_{ijkt}-\mathbb{E}Q_{ikt},\quad (i,j)\in\mathcal{A},k\in\mathcal{K},t\in\mathcal{T}.$$

4. Numerical study

In this section we discuss the numerical experiments that we conducted to test and evaluate our model, and compare the (R,S) model we propose with the (R,Q) model presented by Soysal et al. (2015). In order to find the order-up-to levels, the replenishment periods, and the vehicle routes, we implemented both models using IBM ILOG CPLEX 22.1.0 software. We then performed simulation runs of 10,000 replications using MATLAB to find the order quantities and to measure the service levels that we achieved. We conducted our numerical experiments on a Macbook Pro with an Apple M1 Max 10 core CPU and a 64 GB RAM.

4.1. Experimental design

In our experimental study, we consider various combinations of demand patterns, fixed setup and unit ordering costs, service levels, coefficient of variations, fuel prices, and vehicle speeds. In total, we observe the performance of our model for 146 instances. We then use a refrigeration cost added version of the (R,Q) model of Soysal et al. (2015) without perishability, referred to as M_F in that paper and we will refer to as RQ in our paper, as a benchmark to our (R,S) model which we will refer to as RS, and make comparisons between these two models in terms of CO_2 emissions, costs, cumulative order quantities and safety stocks, service levels, vehicle routes, and the number of vehicles used. We generate instances in which the fixed setup cost takes values from the set $A\in\{10,25,100\}$ and the unit ordering cost takes values from the set $c\in\{0.05,0.1\}$. In our instances, we consider the service levels to be taken from the set $\alpha\in\{0.95,0.975\}$. We assume that there are $K=2$ identical vehicles with a capacity of $C=4000$ kg which operate between $V=4$ retailers and a distribution centre in a finite planning horizon of $T=8$ periods. The fuel price is $l=1.7$ Euros per litre and all the vehicles has an average speed of $f=80$ km/h. We also test the base case for $l=1.2$ and $f=40$ We then test our model on a larger instance in which $V=11$, $K=2$, and $C=15000$. All these parameter values are summarised in Table 2. Moreover, we run the numerical experiments for 4 normally distributed different demand sets with the coefficients of variations taking values from the set $cv\in\{0.05,0.1,0.2\}$. We consider random, seasonal, cyclic, and stationary demand distribution patterns for each

Table 3
Demand patterns and parameters.

Demand patterns	Retailers	Period							
		1	2	3	4	5	6	7	8
Random	1	900	400	1000	600	500	1400	1300	300
	2	1400	1200	1700	1200	800	1100	1500	1800
	3	500	500	1250	600	1300	600	1000	1900
	4	1050	900	1500	1100	800	700	900	900
Seasonal	1	400	600	900	1000	1400	1300	500	300
	2	1200	1200	1400	1700	1800	1500	1100	800
	3	500	500	600	1250	1900	1300	1000	600
	4	400	500	1100	2500	2200	1600	800	600
Cyclic	1	400	900	1000	600	500	1400	1300	300
	2	1200	1400	1700	1200	800	1500	1800	1100
	3	500	600	1250	500	600	1300	1900	1000
	4	500	2500	1100	400	800	2200	1600	600
Stationary	1	800	800	800	800	800	800	800	800
	2	1350	1350	1350	1350	1350	1350	1350	1350
	3	950	950	950	950	950	950	950	950
	4	1200	1200	1200	1200	1200	1200	1200	1200

retailer. We refer to these demand patterns as the demand set 1, 2, 3, and 4, respectively. In order to construct our demand set 1, we take the base case demand set of Soysal et al. (2015) for the first 4 periods and the demand set 1 of Soysal et al. (2015) for the last 4 periods of our planning horizon. Since our aim is to observe the differences between the performances of RQ and RS in a long enough planning horizon and a large enough retailer set rather than in a larger retailer set, and in order to speed up the computation, we take $V = 4$. Since the computational requirements increasingly grows as V gets larger, we consider a subset of their retailer set and only take the first 4 retailers for our base case study and sensitivity analysis. We then sort the same demand means to obtain our demand sets 2, 3, and 4. Table 3 summarises the demand distribution means for each demand pattern, retailer, and period. Finally, we perform another numerical experiment by running our model for different planning horizon lengths to analyse the relationship between the planning horizon length and the cumulative safety stock differences between RS and RQ. In this study we consider the same vehicle and emission parameter settings as of Soysal et al. (2015) and the same refrigeration parameter settings as of Köseli et al. (2023). Table 4 illustrates the values for the vehicle and emission parameters, and Table 5 illustrates the refrigeration parameter values, respectively. Table 6 shows the distances between the distribution centre and each retailer. We use the same distance set as in Soysal et al. (2015) in our study. Note that we consider the retailers 5–11 only in the extended case.

Table 4
Vehicle and emission parameters.

Notation	Description	Value
u	Emission conversion factor (kg/l)	2.63
ξ	Fuel-to-air mass ratio	1
κ	Heating value of a typical diesel fuel (kJ/g)	44
ψ	Conversion factor (g/l)	737
k_e	Engine friction factor (kJ/rev/l)	0.2
N_e	Engine speed (rev/s)	33
V_e	Engine displacement (l)	5
ρ	Air density (kg/m^3)	1.2041
A_e	Frontal surface area (m^2)	3.912
μ	Curb-weight (kg)	6350
g	Gravitational constant (m/s^2)	9.81
Φ	Road angle	0
C_d	Coefficient of aero dynamic drag	0.7
C_r	Coefficient of rolling resistance	0.01
ϵ	Vehicle drive train efficiency	0.4
ω	Efficiency parameter for diesel engines	0.9
l	Fuel price per litre (€)	1.7
r	Driver wage (€/s)	0.003

Table 5
Refrigeration parameters.

Notation	Description	Value
S_k	Surface area for the vehicle k (m^2)	165
ΔT	Temperature difference (K)	18
U	Heat transfer coefficient (W/m^2/K)	0.7
μ_e	The chemical to refrigeration energy conversion efficiency	0.3
μ_p	Coefficient of performance	0.67
P_f	Energy content of the fuel (kWh/l)	8.8
H_i	Heat entering during service time at stop i (kWh)	4

4.2. Base case results

This section provides a numerical example in order to measure the performance of our (R, S) model RS. As the base case of our study, we consider the scenario in which the demand pattern is random, the fixed setup cost is $A = 25$, the unit ordering cost is $c = 0.1$, the service level is $\alpha = 0.95$, and the coefficient of variation is $cv = 0.1$. We hereby present the results of the base case scenario and compare the performance of RS with RQ, in terms of total cost, CO_2 emissions, vehicle routes, service levels, and cumulative safety stock levels.

Recall that using the deterministic-equivalent model, we determine the replenishment cycle plan, the routes, and the assigned vehicles. We then determine the order quantities by observing the realised demand and the actual inventory state. For the base case, Table 7 summarises the optimisation results. As seen from Table 7, the routing plan proposed by RS has a 32.27 h of total driving time which is slightly less than that of RQ, 34.58 h. Since we assume the vehicle speed is constant, the routing policy of RS leads to a lesser amount of total distance travelled. Hence, RS results in a lower total fuel cost due to the transportation activities, 808.20, in comparison to 861.37 found by RQ. Similarly, the total wage paid to the drivers is less in RS than in RQ, 348.48 vs 373.42. The lesser amount of the total travelling distance reduces the total fuel consumption to refrigerate the vehicles, and the refrigeration cost calculated by RS is 165.38 which is less than the refrigeration cost of 172.73 incurred by RQ. Since the

Table 6
Distances between the nodes (km). Retailers 5–11 are used in the extended case.

	DC	1	2	3	4	5	6	7	8	9	10	11
DC	0	67	89.2	126	78.1	70.6	106	66.3	64.4	156	151	35.5
1	73.2	0	154	191	143	144	141	101	74.3	166	176	61.5
2	70.8	136	0	65.9	62.9	113	158	118	126	218	212	97.2
3	126	192	69.5	0	98.9	171	233	193	182	274	268	153
4	78.4	144	63.2	99.7	0	123	185	145	134	226	220	105
5	70.9	144	105	163	115	0	50.2	58.4	120	155	220	105
6	106	131	161	222	175	50.9	0	41.6	75.3	105	199	84.4
7	66.5	91.2	121	182	135	58.2	40.1	0	35.3	117	159	44.4
8	67.4	149	185	137	92.7	0	74.4	34.5	0	92.1	120	34.8
9	158	166	239	276	228	155	106	116	92.4	0	69.6	126
10	150	176	232	268	220	221	192	152	119	70	0	119
11	35	60.3	116	153	105	106	83.6	43.7	30.6	123	118	0

Table 7
Summary of the base case optimisation results.

Model	Emission (kg)	Driving time	Transportation fuel cost	Refrigeration cost	Total wage	Total routing cost	Inventory cost	Total cost
(R,S)	1506.19	32.27	808.20	165.38	348.48	1322.06	4923.38	6245.44
(R,Q)	1599.81	34.58	861.37	172.73	373.42	1407.52	5341.30	6748.82

Table 8
Summary of the base case simulation results, 10,000 reps.

Model	Total routing cost	Avg inventory cost	Avg total cost	95% CI for avg total cost
(R,S)	1321.95	4939.32	6261.27	[6260.61, 6261.94]
(R,Q)	1407.52	5339.88	6747.40	[6743.45, 6751.35]

Table 9
The replenishment plan and the order-up-to levels for the base case.

Retailer	Period							
	1	2	3	4	5	6	7	8
Replenishment periods								
1	1	0	1	0	0	1	0	1
2	1	1	1	1	0	1	1	1
3	1	1	1	0	1	0	1	1
4	1	1	1	1	1	1	1	0
Order-up-to levels								
1	1462	562	2309	1309	709	3049	1649	349
2	1630	1397	1980	2237	1037	1281	1747	2096
3	1082	582	2078	828	2136	836	1165	2213
4	1281	2911	582	466	1863	2562	1565	765

total routing cost consists of the transportation, refrigeration and wage costs, RS leads to a lower amount of total routing cost compared to RQ which are 1322.06 and 1407.52, respectively. Moreover, since CO_2 emissions occur as a result of fuel consumption, it is directly related to the total fuel cost. Therefore, our RS model generates a lesser amount of CO_2 emission of 1506.19 kg in comparison to 1599.81 kg of RQ. The deterministic-equivalent solution results in a total inventory cost of 4923.38 and 5341.30 according to RS and RQ, respectively. Thus, the total deterministic-equivalent cost is 6245.44 for RS and 6748.82 for RQ.

Table 8 presents a summary of the simulation results. According to Table 8, the average inventory cost over 10,000 replications is 4939.32 for RS and 5339.88 for RQ, which are very close to the deterministic-equivalent inventory cost values. Notice that even though all the routing decisions are pre-determined and is not affected by random demand realisations, there is a slight difference of 0.11 in total routing costs between the optimisation and simulation results. This is due to the amount of vehicle load depends on order sizes and the fuel consumption is affected by the amount of vehicle load. In Table 11, the achieved service levels for each retailer and in each period are given, and both RS and RQ are sufficient to meet the 95% service level requirement.

The resulting ordering policy found by RS is given in Table 9. In the Replenishment Periods section, 1 indicates there is a replenishment order and 0 states that there is no ordering. For instance, for retailer 1 the replenishment periods are 1, 3, 6, and 8. At the beginning of each replenishment period t for each retailer i, the actual inventory starting inventory level I_{it-1} is observed and an amount of order that is sufficient to meet the order-up-to level S_{it} is placed. If t is not a replenishment period, even if I_{it-1} is less than S_{it} no order is placed. Similarly, if there is sufficient inventory to meet S_{it} at the beginning of replenishment period t no order placement occurs. Unlike RQ and as a result of the static-dynamic strategy, there is a flexibility in ordering decisions such that order quantities depend on the actual inventory level and are determined after the demand realisations. Table 10 visualises the order quantities and the ending inventory levels for the base case and with respect to both RS and RQ. The order quantities in RS are determined according to the ordering policy while in RQ they are pre-determined and cannot be changed as demand is realised.

In Table 12, the assigned routes for each vehicle and the number of assigned vehicles in each period with respect to RS and RQ are given. Except in periods 1, 3, and 7, both RS and RQ propose the same routes even though the assigned vehicles might differ. While RS suggests employing only Vehicle 2 in period 7, RQ suggests employing

Table 10
The order quantities and the ending inventory levels for the base case.

Policy	Retailer	Order quantities Period								Ending inventory levels Period								
		1	2	3	4	5	6	7	8	0	1	2	3	4	5	6	7	8
(R,S)	1	1462	0	2147	0	0	1487	1663	0	0	562	162	1309	709	209	1649	349	49
	2	1630	1167	1783	1957	0	1044	1566	1849	0	230	197	280	1037	237	181	247	296
	3	1082	0	1996	0	1908	0	929	2048	0	582	82	828	228	836	236	165	313
	4	1281	2730	171	384	1797	2299	1203	0	0	181	411	82	66	263	362	765	165
(R,Q)	1	1462	0	2202	0	0	1487	1663	0	0	562	162	1364	764	264	351	714	414
	2	2179	724	1810	2063	0	1148	1542	1873	0	779	303	413	1276	476	524	566	639
	3	1116	0	1990	0	1992	0	1037	2011	0	616	116	856	256	948	348	385	496
	4	1281	3276	0	404	1670	2312	1421	0	0	181	957	457	461	531	643	1264	664

Table 11
Achieved service levels (%), $\alpha = 0.95$, 10,000 reps.

α-Service levels									
Policy	Retailer	Period							
		1	2	3	4	5	6	7	8
(R,S)	1	1.0000	0.9493	1.0000	1.0000	0.9489	1.0000	0.9655	0.9740
	2	0.9512	0.9469	0.9486	1.0000	0.9496	0.9495	0.9526	0.9513
	3	1.0000	0.9662	1.0000	0.9507	1.0000	0.9501	0.9491	0.9521
	4	0.9532	0.9494	0.9597	0.9527	0.9492	0.9531	1.0000	0.9529
(R,Q)	1	1.0000	0.9493	1.0000	1.0000	0.9460	0.9479	0.9973	0.9468
	2	1.0000	0.9469	0.9476	1.0000	0.9462	0.9514	0.9480	0.9478
	3	1.0000	0.9462	1.0000	0.9486	1.0000	0.9510	0.9494	0.9497
	4	0.9532	1.0000	0.9482	0.9470	0.9469	0.9479	0.9994	0.9505

Table 12
Assigned routes for each vehicle and the number of assigned vehicles.

Routes									
		Period							
Policy	Vehicle	1	2	3	4	5	6	7	8
(R,S)	V1	0–1–0	–	0–1–0	–	0–4–3–0	0–4–2–0	–	–
	V2	0–4–3–2-0	0–4–2–0	0–4–3–2-0	0–4–2–0	–	0–1–0	0–4–3–2-0	0–3–2–0
(R,Q)	V1	0–1-4-0	–	0–1–0	–	0–4–3–0	0–4–2–0	0–4–3–2-0	0–3–2–0
	V2	0–2–3–0	0–4–2–0	0–3–2–0	0–4–2–0	–	0–1–0	0–1–0	–
No of vehicles vs policy	(R,S)	2	1	2	1	1	2	1	1
	(R,Q)	2	1	2	1	1	2	2	1

both vehicles. In both RS and RQ, the same number of vehicles are employed for all the other periods.

Table 13 shows that RQ yields a greater number of cumulative order quantities and ending inventory levels compared to RS due to its static nature. Thus the unit ordering and inventory holding costs are higher in RQ. Moreover, since the amount of vehicle load affects the fuel consumption it is possible that the larger amount of order size might increase the fuel consumption and the total CO_2 emission. On the contrary, the flexibility in order size decisions in RS allows lower number of cumulative order quantities and ending inventory levels, hence lower inventory costs. We will provide a detailed analysis on the relationship between the planning horizon length and the cumulative ending inventory levels and order quantities in Section 4.5.

4.3. Performance of the (R,S) model

We hereby conduct an extensive sensitivity analysis and compare the performance of RS with RQ under various parameter settings and scenarios. Table 14 summarises the average percentage increases of RQ above RS, i.e., $100(RQ/RS - 1)$ in terms of costs, cumulative order sizes and ending inventory levels, and CO_2 emissions. We observe from Table 14 that in all the instances, RS has a significant advantage over RQ in terms of total cost. The average total cost by RQ was calculated to be 9.35% worse than RS with a 95% confidence interval of [8.43, 10.26]. Although the average total routing costs for both models are similar, the average inventory cost is 12.55% higher for RQ than that of RS, as a result of higher inventory holding and variable ordering costs caused by the accumulated ending inventory and larger order sizes. This observation explains why RS performs better than RQ in terms of total cost. On average, the cumulative ending inventory levels in RQ are 52.76% greater than in RS and the cumulative order quantities are found to be 4.82% greater in RQ compared to in RS. In other words, the inventory holding costs and the total variable ordering costs are 52.76% and 4.82% greater in RQ than in RS. The amount of CO_2 emission is in line with fuel consumption, therefore both models generate similar levels of emission and have similar environmental impact. Even though RQ generates 0.54% more CO_2 than RS, we cannot conclude that RS has less environmental impact or vice versa since the 95% confidence interval is [−0.19, 1.27]. The performance of RS over RQ is similar for all the 4 demand sets in terms of routing costs. However, RS performs better than RQ in terms of total cost and inventory costs with similar levels of percentage differences for all the demand patterns. In case of the cyclic demand pattern, RS tends to have less environmental impact. For all the other demand patterns, the environmental impact is similar. The effect of α on the general performance of RS over RQ is similar between each α values, and also similar to the overall performance results. RS performs better than RQ in terms of total cost and inventory

Table 13
Comparison of the cumulative order quantities and ending inventory levels.

Policy	Period							
	1	2	3	4	5	6	7	8
	Cumulative order quantity							
(R, S)	5455	9352	15 449	17 790	21 495	27 678	31 376	35 273
(R, Q)	6038	10 038	16 040	18 507	22 169	27 116	32 779	36 663
	Cumulative Ending Inventory							
(R, S)	1555	2407	4906	6946	8491	10 919	12 445	13 268
(R, Q)	2138	3676	6766	9523	11 742	13 608	16 537	18 750

Table 14
Average percentage increases of RQ above RS (*i.e.* $100 * (RQ/RS - 1)$). All the other parameter values of the instances marked with (*) are the same as of the base case.

Parameter	Avg emission	Avg emission 95% CI	Avg cum order quantity	Avg cum ending inventory	Avg cum end inv + ord Q	Avg inv cost	Avg transport fuel cost	Avg refrg fuel cost	Avg total wage	Avg total routing cost	Avg total cost	Avg total cost 95% CI
Overall	0.54	[−0.19 1.27]	4.82	52.76	18.84	12.55	0.63	0.12	0.49	0.52	9.35	[8.43, 10.26]
Random	1.45	[−0.22, 3.12]	4.46	51.96	19.27	11.88	1.55	1.00	1.66	1.51	9.41	[7.49, 11.34]
Cyclic	1.67	[0.21, 3.13]	5.66	52.16	19.12	13.04	1.92	0.42	1.79	1.70	9.99	[8.06, 11.93]
Seasonal	−0.79	[−2.48, 0.90]	4.87	52.29	18.53	13.12	−1.00	0.33	−1.12	−0.88	9.31	[7.49, 11.26]
Stationary	−0.19	[−0.81, 0.43]	4.29	54.63	18.42	12.16	0.03	−1.27	−0.36	−0.23	8.68	[7.08, 10.28]
$\alpha = 0.95$	0.19	[−0.75, 1.13]	4.40	51.13	17.61	11.66	0.28	−0.21	0.17	0.18	8.58	[7.40, 9.76]
$\alpha = 0.975$	0.88	[−0.24, 2.00]	5.25	54.39	20.07	13.43	0.97	0.45	0.82	0.86	10.11	[8.74, 11.49]
$cv = 0.05$	−1.24	[−2.50, 0.02]	2.05	38.91	9.64	6.46	−1.24	−1.18	−1.35	−1.27	4.18	[3.81, 4.55]
$cv = 0.1$	0.79	[−0.21, 1.79]	4.17	50.30	16.87	11.12	0.89	0.35	0.92	0.82	8.33	[7.59, 9.07]
$cv = 0.2$	2.06	[0.72, 3.40]	8.25	69.10	29.91	20.06	2.23	1.19	1.91	2.02	15.54	[14.28, 16.79]
$A = 10$	1.71	[0.61, 2,81]	5.31	65.02	20.41	16.35	1.79	1.38	1.64	1.69	11.83	[10.10, 13.56]
$A = 25$	1.16	[−0.33, 2.66]	5.14	58.91	19.74	13.75	1.17	1.16	1.09	1.14	10.24	[8.73, 11.74]
$A = 100$	−1.27	[−2.27, 0.27]	4.02	34.35	16.36	7.54	−1.08	−2.18	−1.25	−1.26	5.98	[5.07, 6.89]
$c = 0.05$	0.47	[−0.53, 1.48]	4.79	52.29	18.69	14.23	0.56	0.08	0.42	0.46	10.07	[8.68, 11.46]
$c = 0.1$	0.60	[−0.47, 1.67]	4.85	53.23	18.98	10.86	0.69	0.16	0.57	0.59	8.62	[7.45, 9.80]
Base Case	6.22	–	3.71	39.71	13.61	8.11	6.58	4.44	7.16	6.46	7.76	–
$l = 1.2$*	−4.77	–	3.78	102.41	23.72	11.18	−4.08	−8.17	−3.75	−4.43	8.07	–
$f = 40$*	−2.03	–	3.71	63.55	20.16	10.47	−1.08	−5.66	−0.86	−1.54	7.42	–

cost for all the coefficient of variation values. As the coefficient of variation increases, RS has a tendency to generate less CO_2 emission and to incur less routing cost compared to RQ. For $cv = 0.2$, RS leads to produce less emission than RQ, and incurs less number of total routing cost. Moreover, as the coefficient of variation increases, the percentage cumulative ending inventory and order size increases of RQ above RS gets larger, so RS proposes a much better solution in terms of order quantities and ending inventory levels, and inventory costs. The average percentage difference in total cost increases from 4.18 and to 15.54, yielding a much better total cost improvement since the confidence intervals for each coefficient of variation do not overlap each other. In contrast to the coefficient of variation, as the fixed setup A increases the percentage differences of RQ over RS tend to decrease. Despite the total cost incurred by RS still being lower than by RQ, reducing A results in much better cost improvement and lower number of accumulated ending inventory levels and ordered items. While RS generates less CO_2 emission for $A = 10$, both models tend to generate similar levels of emission for the larger fixed setup cost values. As the unit ordering cost c increases, the percentage total cost increase of RQ above RS tend to decrease, but we cannot conclude that it decreases since the confidence intervals overlap. For both the unit ordering cost parameters $c = 0.05$ and $c = 0.1$, the total cost and the order quantities are lower in RS than in RQ. As c increases, the changes in the percentage increases will not be significant. Finally, decreasing the fuel price to $l = 1.2$ and the vehicle speed to $f = 40$ leads to poorer RS performance over RQ in terms of the average routing costs and the emissions, compared to the base case.

Note that due to the higher holding costs incurring in RQ, RS outperforms all instances in terms of total cost. However, since RQ is based on the static uncertainty strategy of Bookbinder and Tan (1988), it might be more suitable for such cases in which a considerable preparation is required before the time horizon begins (see Bookbinder and Tan (1988)). In addition, since RS outperforms RQ in all instances since it reduces the excess ending inventory and the inventory costs, there is no threshold or certain critical values that would change the superiority of RS over RQ.

Table 15
Demand parameters for the extended case.

Retailers	Periods			
	1	2	3	4
1	900	400	100	600
2	1400	1200	1700	1200
3	500	500	1250	600
4	1100	2500	500	400
5	1050	900	1500	1100
6	1200	500	400	1400
7	800	700	500	500
8	1900	400	300	1300
9	800	400	700	1300
10	1100	1600	400	300
11	2600	3200	2500	3200

4.4. Modified larger case study

In order to test the performance of our model for larger network setting, we have increased the number of retailers to $V = 11$. For this case, we use the demand pattern given in Table 15 and we extend the distance matrix provided in Table 6 so as to include the retailers 5–11. Since the total load on all vehicles might increase as V or T grows, we need to increase K or C. For convenience, we employ $K = 2$ vehicles with a capacity of $C = 15000$ and set the time horizon as $T = 4$ periods. The demand pattern and the retailers given in Table 15 are the same as the base case demand set of Soysal et al. (2015).

Increasing the number of retailers or increasing V while keeping the total capacity the same greatly increase the size (number of constraints, decision variables, etc.) and the complexity of the model. Therefore, it would take too much time to perform the numerical experiment for all the instances in the previous numerical study. Increasing K without changing C has no effect on the routes, costs, etc, and many vehicles would stay intact. Moreover, the in the larger case we obtained similar results to the base case.

Table 16
Summary of the extended case optimisation results.

Model	Emission (kg)	Driving time (h)	Transport fuel cost	Refr cost	Total wage	Total routing cost	Total inv cost	Total cost
(R, S)	1363.10	26.99	748.24	132.84	291.49	1172.57	5286.72	6459.29
(R, Q)	1370.80	26.99	753.02	132.84	291.49	1177.35	5558.83	6736.18

Table 17
Assigned routes for each vehicle and the number of assigned vehicles for the extended case.

Routes					
Policy	Vehicle	Periods			
		1	2	3	4
(R, S)	V1	0–1–8–9–10–0	0–11–4–2–0	0-1-11–7–5–2–3–0	–
	V2	0–11–7–6–5–2–3–4–0	–	–	0–11–8–9–6–5–0
(R, Q)	V1	0–11–7–6–5-2-3-4–0	–	–	–
	V2	0–1–8–9–10–0	0–11–4–2–0	0–1-11–7–5–2–3–0	0–11–8–9–6–5-0
No of vehicles vs policy	(R, S)	2	1	1	1
	(R, Q)	2	1	1	1

Table 18
Comparison of the cumulative order quantities and ending inventory levels for the extended case.

Policy	Period			
	1	2	3	4
	Cumulative order quantity			
(R, S)	23 152	30 902	42 385	50 658
(R, Q)	23 433	31 836	43 828	52 591
	Cumulative ending inventory			
(R, S)	23 152	65 712	71 697	74 055
(R, Q)	23 433	68 860	76 288	80 579

Tables 16 and 17 give the deterministic-equivalent optimisation results and the routing decisions for the larger case, respectively. In general, the performance of RS over RQ is similar to the base case. As seen from Table 17, both models propose the same routes and employs the same number of vehicles, although the assigned vehicles for a particular route might be different. Hence, both models offer the same total driving time, refrigeration cost, and total wage. There is a minor difference between the transportation fuel costs caused by the amount of vehicle load since RQ has larger order quantities compared to RS, as provided in Table 18. In addition, the number of cumulative ending inventory levels is about 8.81% greater in RQ than in RS, and it is less than the base case in which the percentage difference is 41.31% (see Fig. 2).

4.5. Planning horizon length vs cumulative ending inventory and order size

We hereby analyse the relationship between the length of the planning horizon and the difference in the cumulative ending inventory levels found via RS and RQ. In order to analyse that relationship, we extend the planning horizon to $T = 40$ periods. We consider the demand set 1 and modify it such that after every 8 periods the 8-period demand mean sequence is recurring. As seen from Fig. 1, the increase rate of cumulative ending inventory levels for RQ is greater than that of RS. Therefore, as t increases the difference between the cumulative inventory levels for both models increases. Hence, the percentage differences increase. For instance, when $t = 8$, the cumulative ending inventory levels for RS and RQ are found to be 15684 and 20408, respectively, with a percentage difference of 30.12%. These values become 40014, 69381, and 73.39% for $t = 20$. At the end of the planning horizon when $t = 40$, we obtain the cumulative ending inventory levels of 172595 for RQ and 76543 for RS, and a percentage difference of 125.49%. This phenomenon is the main factor that makes the model of Soysal et al. (2015) find high inventory holding and total inventory costs compared to our (R, S) model. Therefore, we can conclude that the static-dynamic structure of RS helps avoiding placing unnecessary orders and holding unnecessary items in the inventory. On the contrary, even though RQ calculates larger order quantities than RS in most periods, the percentage differences in the order quantities between RQ and RS do not differ significantly, as seen in Fig. 1. The percentage difference is 4.31% when $t = 8$, while it is 2.91% for $t = 20$ and 2.36% for $t = 40$.

In this study, a planning horizon with $T = 40$ periods has been taken to represent a long enough planning horizon in which the differences between the ending inventory levels in RQ and RS are significantly large. Although a 40-period planning horizon being taken as more of a theoretical exercise, it also applies in medium-term tactical planning or long-term strategic planning, etc., (see Okongwu et al. (2016)), depending on the cold supply chain structure.

5. Concluding remarks and managerial insights

We have studied a cold supply chain model with refrigerated vehicles, multiple retailer, and a single distribution centre. We formulated the problem as an IRP model with the refrigeration cost component and which employs the (R, S) policy proposed by Tarim and Kingsman (2004). Then we compared the performance of our model with the refrigeration component added and no perishability version of Soysal et al. (2015)'s IRP model which employs the (R, Q) policy. Our numerical experiments show that by applying the (R, S) policy instead of the (R, Q) policy, although we did not make a significant improvement to reduce CO_2 emissions and total routing costs, we reduced inventory costs significantly. Since the majority of the incurred costs consists of inventory costs, we made a significant improvement on the total cost. This work is premised on a recognition that impact on sustainability needs to be considered when seeking to reduce other costs in CFSCs. Hence the inclusion of sustainability in the optimisation model developed in this study. The results are encouraging, as the model reduces inventory costs together with a positive impact on harmful emissions.

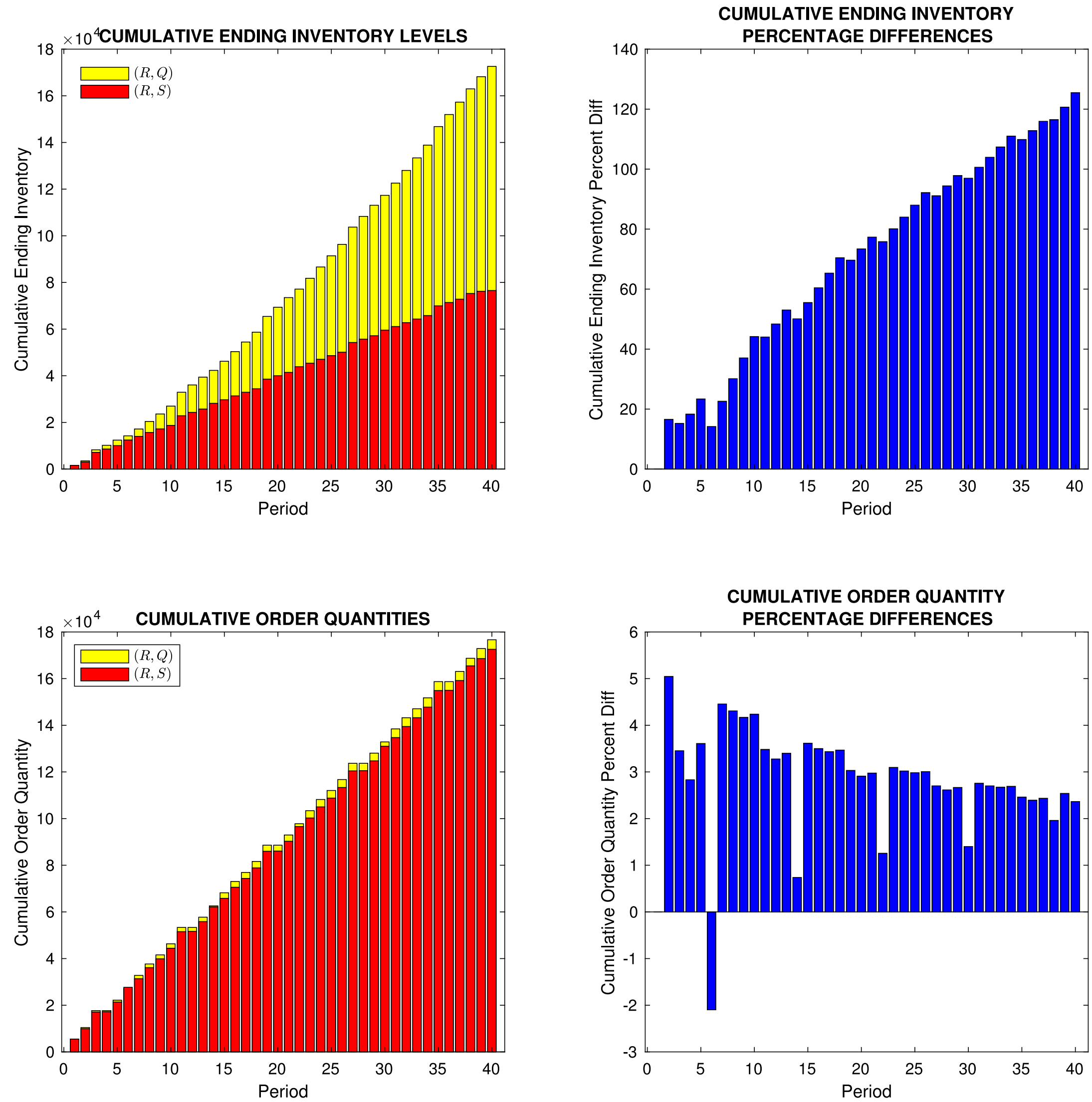

Fig. 2. Comparison of the cumulative ending inventory levels and percentage differences found via the (R, Q) and (R, S) models.

Our model also solves the excess cumulative ending inventory level issue resulted in Soysal et al. (2015)'s model and caused by the predetermined order quantities. Since our (R, S) formulation calculates order-up-to levels rather than order quantities it handles demand uncertainties well, allows flexible order size decisions that consider the actual inventory level and the realised demand, and prevents excess ending inventory and excess inventory holding costs.

This study contributes to the body of knowledge via the (R, S) policy and by developing a mixed-integer programming model responsive to non-stationary demand uncertainties inventory, transport, and refrigeration costs, and CO_2 emissions in terms of cost. The extensive computational results indicate that the proposed model can significantly reduce the total inventory costs compared to the more conventional RQ model while dealing with stochastic demand. However, RS performs similarly to RQ in terms of CO_2 emissions. Given the growing global concern for environmental sustainability, this finding could be seen as a missed opportunity. Another possible way to reduce the carbon footprint could be developing a multi-objective model in order to allow trade-offs between the total cost and the total CO_2 emissions. Adding carbon capacity constraints, i.e., limiting CO_2 emissions per vehicle, etc., could be considered some other improvements in this model.

Since RS provides highly accurate solutions, allows flexibility on ordering decisions, and avoids replenishment timing decision set-ups and reviews which might be required for every period in the dynamic strategy, it could be easily applied to most real-world food logistics networks and utilised by executives and decision-makers concerned with the CFSC logistics.

Several possible future directions related to this study might be modifying this formulation for the multi-supplier and multi-retailer problem setting, adding a positive lead time, or considering a fleet consisting of non-identical vehicles with various properties in terms of fuel consumption, refrigeration activities, capacity, etc. The model could also be extended to consider additional environmental and social sustainability measures, such as perishability, food quality and safety, waste, shelf life, food expiration date, etc., as well as monitoring the perishability of products by adding new variables to the current model and keeping track of the age of products.

CRediT authorship contribution statement

Soodeh Jahdi: Conceptualization, Data curation, Formal analysis, Writing – original draft, Writing – review & editing. **Suheyl Gulecyuz:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Seamus O'Reilly:** Conceptualization, Methodology, Project administration. **Barry O'Sullivan:**

Funding acquisition, Supervision. **S. Armagan Tarim:** Conceptualization, Funding acquisition, Investigation, Methodology, Supervision.

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.

Data availability

Data will be made available on request.

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References

Aazami, Adel, Saidi-Mehrabad, Mohammad, 2021. A production and distribution planning of perishable products with a fixed lifetime under vertical competition in the seller-buyer systems: A real-world application. J. Manuf. Syst. 58, 223–247.

Al Theeb, Nader, Smadi, Hazem J., Al-Hawari, Tarek H., Aljarrah, Manar H., 2020. Optimization of vehicle routing with inventory allocation problems in cold supply chain logistics. Comput. Ind. Eng. 142, 106341.

Allaoui, Hamid, Guo, Yuhan, Choudhary, Alok, Bloemhof, Jacqueline, 2018. Sustainable agro-food supply chain design using two-stage hybrid multi-objective decision-making approach. Comput. Oper. Res. 89, 369–384.

Amin, Saman Hassanzadeh, Zhang, Guoqing, 2013. A multi-objective facility location model for closed-loop supply chain network under uncertain demand and return. Appl. Math. Model. 37 (6), 4165–4176.

Amorim, Pedro, Almada-Lobo, Bernardo, 2014. The impact of food perishability issues in the vehicle routing problem. Comput. Ind. Eng. 67, 223–233.

Babagolzadeh, Mahla, Shrestha, Anup, Abbasi, Babak, Zhang, Yahua, Woodhead, Alice, Zhang, Anming, 2020. Sustainable cold supply chain management under demand uncertainty and carbon tax regulation. Transp. Res. D. 80, 102245.

Bard, Jonathan F., Nananukul, Narameth, 2009. Heuristics for a multiperiod inventory routing problem with production decisions. Comput. Ind. Eng. 57 (3), 713–723.

Barth, Matthew, Younglove, Theodore, Scora, George, 2005. Development of a heavy-duty diesel modal emissions and fuel consumption model.

Bektaş, Tolga, Laporte, Gilbert, 2011. The pollution-routing problem. Transp. Res. B 45 (8), 1232–1250.

Beyer, Dirk, Ward, Julie, 2002. Network Server Supply Chain at HP: A Case Study. Springer.

Bollapragada, Srinivas, Morton, Thomas E., 1999. A simple heuristic for computing nonstationary (s, S) policies. Oper. Res. 47 (4), 576–584.

Bookbinder, James H., Tan, Jin-Yan, 1988. Strategies for the probabilistic lot-sizing problem with service-level constraints. Manage. Sci. 34 (9), 1096–1108.

Boronoos, M., Mousazadeh, M., Torabi, S. Ali, 2021. A robust mixed flexible-possibilistic programming approach for multi-objective closed-loop green supply chain network design. Environ. Develop. Sustain. 23, 3368–3395.

Bortolini, Marco, Faccio, Maurizio, Ferrari, Emilio, Gamberi, Mauro, Pilati, Francesco, 2016. Fresh food sustainable distribution: Cost, delivery time and carbon footprint three-objective optimization. J. Food Eng. 174, 56–67.

Bottani, Eleonora, Casella, Giorgia, Nobili, Majcol, Tebaldi, Letizia, 2019. Assessment of the economic and environmental sustainability of a food cold supply chain. IFAC-PapersOnLine 52 (13), 367–372.

Bozorgi, Ali, 2016. Multi-product inventory model for cold items with cost and emission consideration. Int. J. Prod. Econ. 176, 123–142.

Bozorgi, Ali, Pazour, Jennifer, Nazzal, Dima, 2014. A new inventory model for cold items that considers costs and emissions. Int. J. Prod. Econ. 155, 114–125.

Chen, Wei-Ting, Hsu, Chaug-Ing, 2015. Greenhouse gas emission estimation for temperature-controlled food distribution systems. J. Clean. Prod. 104, 139–147.

Chen, G., Wahab, M.I.M., Fang, L., 2022. Optimal replenishment strategy for a single-manufacturer multi-retailer cold chain considering multi-stage quality degradation. Appl. Math. Model. 104, 96–113.

Danloup, Nicolas, Mirzabeiki, Vahid, Allaoui, Hamid, Goncalves, Gilles, Julien, Denyse, Mena, Carlos, 2015. Reducing transportation greenhouse gas emissions with collaborative distribution: A case study. Manag. Res. Rev. 38 (10), 1049–1067.

Demir, Emrah, Bektaş, Tolga, Laporte, Gilbert, 2012. An adaptive large neighborhood search heuristic for the pollution-routing problem. European J. Oper. Res. 223 (2), 346–359.

Elhedhli, Samir, Merrick, Ryan, 2012. Green supply chain network design to reduce carbon emissions. Transp. Res. D: Transp. Environ. 17 (5), 370–379.

Fichtinger, Johannes, Ries, Jörg M., Grosse, Eric H., Baker, Peter, 2015. Assessing the environmental impact of integrated inventory and warehouse management. Int. J. Prod. Econ. 170, 717–729.

Franceschetti, Anna, Honhon, Dorothée, Van Woensel, Tom, Bektaş, Tolga, Laporte, Gilbert, 2013. The time-dependent pollution-routing problem. Transp. Res. B 56, 265–293.

Galal, N.M., El-Kilany, K.S., 2016. Sustainable agri-food supply chain with uncertain demand and lead time. Int. J. Simul. Model. 15 (3), 485–496.

Ghahremani Nahr, Javid, Pasandideh, Seyed Hamid Reza, Niaki, Seyed Taghi Akhavan, 2020. A robust optimization approach for multi-objective, multi-product, multi-period, closed-loop green supply chain network designs under uncertainty and discount. J. Ind. Prod. Eng. 37 (1), 1–22.

Graves, Stephen C., Willems, Sean P., 2008. Strategic inventory placement in supply chains: Nonstationary demand. Manuf. Serv. Oper. Manag. 10 (2), 278–287.

Gutierrez-Alcoba, Alejandro, Rossi, Roberto, Martin-Barragan, Belen, Hendrix, Eligius M.T., 2017. A simple heuristic for perishable item inventory control under non-stationary stochastic demand. Int. J. Prod. Res. 55 (7), 1885–1897.

Hariga, Moncer, As' ad, Rami, Shamayleh, Abdulrahim, 2017. Integrated economic and environmental models for a multi stage cold supply chain under carbon tax regulation. J. Clean. Prod. 166, 1357–1371.

Hsiao, Yu-Hsiang, Chen, Mu-Chen, Chin, Cheng-Lin, 2017. Distribution planning for perishable foods in cold chains with quality concerns: Formulation and solution procedure. Trends Food Sci. Technol. 61, 80–93.

Iida, Tetsuo, 2002. A non-stationary periodic review production–inventory model with uncertain production capacity and uncertain demand. European J. Oper. Res. 140 (3), 670–683.

James, S.J., James, C.J.F.R.I., 2010. The food cold-chain and climate change. Food Res. Int. 43 (7), 1944–1956.

Jemai, Zied, Rekik, Yacine, Kalaï, Rim, 2013. Inventory routing problems in a context of vendor-managed inventory system with consignment stock and transshipment. Prod. Plan. Control 24 (8–9), 671–683.

Jiang, Jiehui, Zhang, Dezhi, Meng, Qiang, Liu, Yajie, 2020. Regional multimodal logistics network design considering demand uncertainty and CO2 emission reduction target: A system-optimization approach. J. Clean. Prod. 248, 119304.

Köseli, İlker, Soysal, Mehmet, Çimen, Mustafa, Sel, Çağrı, 2023. Optimizing food logistics through a stochastic inventory routing problem under energy, waste and workforce concerns. J. Clean. Prod. 136094.

Li, Yongbo, Soleimani, Hamed, Zohal, Mostafa, 2019. An improved ant colony optimization algorithm for the multi-depot green vehicle routing problem with multiple objectives. J. Clean. Prod. 227, 1161–1172.

Mallidis, Ioannis, Dekker, Rommert, Vlachos, Dimitrios, 2012. The impact of greening on supply chain design and cost: A case for a developing region. J. Transp. Geogr. 22, 118–128.

Meneghetti, Antonella, Monti, Luca, 2015. Greening the food supply chain: An optimisation model for sustainable design of refrigerated automated warehouses. Int. J. Prod. Res. 53 (21), 6567–6587.

Moheb-Alizadeh, Hadi, Handfield, Robert, 2018. An integrated chance-constrained stochastic model for efficient and sustainable supplier selection and order allocation. Int. J. Prod. Res. 56 (21), 6890–6916.

Mohebalizadehgashti, Fatemeh, Zolfagharinia, Hossein, Amin, Saman Hassanzadeh, 2020. Designing a green meat supply chain network: A multi-objective approach. Int. J. Prod. Econ. 219, 312–327.

Musavi, MirMohammad, Bozorgi-Amiri, Ali, 2017. A multi-objective sustainable hub location-scheduling problem for perishable food supply chain. Comput. Ind. Eng. 113, 766–778.

Okongwu, Uche, Lauras, Matthieu, François, Julien, Deschamps, Jean-Christophe, 2016. Impact of the integration of tactical supply chain planning determinants on performance. J. Manuf. Syst. 38, 181–194.

Pan, Shenle, Ballot, Eric, Fontane, Frédéric, 2013. The reduction of greenhouse gas emissions from freight transport by pooling supply chains. Int. J. Prod. Econ. 143 (1), 86–94.

Pauls-Worm, Karin G.J., Hendrix, Eligius M.T., Haijema, René, van der Vorst, Jack G.A.J., 2014. An MILP approximation for ordering perishable products with non-stationary demand and service level constraints. Int. J. Prod. Econ. 157, 133–146.

Purohit, Arun Kr, Choudhary, Devendra, Shankar, Ravi, 2016. Inventory lot-sizing with supplier selection under non-stationary stochastic demand. Int. J. Prod. Res. 54 (8), 2459–2469.

Saif, Ahmed, Elhedhli, Samir, 2016. Cold supply chain design with environmental considerations: A simulation-optimization approach. European J. Oper. Res. 251 (1), 274–287.

Secretary-General, UN, 2019. Agriculture Development, Food Security and Nutrition : Report of the Secretary-General. UN, [New York] :. 2019-08-02, p. 17, URL http://digitallibrary.un.org/record/1639820, Submitted pursuant to General Assembly resolution 72/238.

Seth, Dinesh, Pandey, Manjit Kumar, 2009. A multiple-item inventory model for a non-stationary demand. Prod. Plan. Control 20 (3), 242–253.

Shamayleh, Abdulrahim, Hariga, Moncer, As' ad, Rami, Diabat, Ali, 2019. Economic and environmental models for cold products with time varying demand. J. Clean. Prod. 212, 847–863.

Shashi, Shashi, Cerchione, Roberto, Singh, Rajwinder, Centobelli, Piera, Shabani, Amir, 2018. Food cold chain management: From a structured literature review to a conceptual framework and research agenda. Int. J. Logist. Manag. 29 (3), 792–821.
Shi, Yuhe, Lin, Yun, Lim, Ming K., Tseng, Ming-Lang, Tan, Changlu, Li, Yan, 2022. An intelligent green scheduling system for sustainable cold chain logistics. Expert Syst. Appl. 209, 118378.
Silver, Edward A., 1973. A heuristic for selecting lot size quantities for the case of a deterministic time-varying demand rate and discrete opportunities for replenishment. Prod. Invent. Manage. 2, 64–74.
Sinaga, Syamsuriadi, Pertiwi, Liza Setyaning, Ardian, Toni, 2016. Inventory simulation optimization under non stationary demand. Int. J. Appl. Eng. Res. 11 (1), 524–529.
Singh, Gaurvendra, Rajesh, R., Daultani, Yash, Misra, Subhas Chandra, 2023. Resilience and sustainability enhancements in food supply chains using digital twin technology: A grey causal modelling (GCM) approach. Comput. Ind. Eng. 179, 109172.
Solyalı, Oğuz, Cordeau, Jean-François, Laporte, Gilbert, 2012. Robust inventory routing under demand uncertainty. Transp. Sci. 46 (3), 327–340.
Soysal, Mehmet, Bloemhof-Ruwaard, Jacqueline M., Haijema, Rene, Van Der Vorst, Jack G.A.J., 2015. Modeling an inventory routing problem for perishable products with environmental considerations and demand uncertainty. Int. J. Prod. Econ. 164, 118–133.
Soysal, Mehmet, Bloemhof-Ruwaard, Jacqueline M., Van Der Vorst, Jack G.A.J., 2014. Modelling food logistics networks with emission considerations: The case of an international beef supply chain. Int. J. Prod. Econ. 152, 57–70.
Stellingwerf, Helena M., Laporte, Gilbert, Cruijssen, Frans C.A.M., Kanellopoulos, Argyris, Bloemhof, Jacqueline M., 2018. Quantifying the environmental and economic benefits of cooperation: A case study in temperature-controlled food logistics. Transp. Res. D 65, 178–193.
Tamjidzad, Shahrzad, Mirmohammadi, S. Hamid, 2017. Optimal (r, Q) policy in a stochastic inventory system with limited resource under incremental quantity discount. Comput. Ind. Eng. 103, 59–69.
Tarim, S. Armagan, Kingsman, Brian G., 2004. The stochastic dynamic production/inventory lot-sizing problem with service-level constraints. Int. J. Prod. Econ. 88 (1), 105–119.
Tarim, S. Armagan, Kingsman, Brian G., 2006. Modelling and computing (Rn, Sn) policies for inventory systems with non-stationary stochastic demand. European J. Oper. Res. 174 (1), 581–599.
Tarim, S. Armagan, Smith, Barbara M., 2008. Constraint programming for computing non-stationary (R, S) inventory policies. European J. Oper. Res. 189 (3), 1004–1021.
Tassou, S.A., De-Lille, Gauthier, Ge, Y.T., 2009. Food transport refrigeration–approaches to reduce energy consumption and environmental impacts of road transport. Appl. Therm. Eng. 29 (8–9), 1467–1477.
Torabi, S.A., Baghersad, Mansouri, Mansouri, S.A., 2015. Resilient supplier selection and order allocation under operational and disruption risks. Transp. Res. E 79, 22–48.
Tordecilla-Madera, Rafael, Polo, Andrés, Cañón, Adrián, 2018. Vehicles allocation for fruit distribution considering CO2 emissions and decisions on subcontracting. Sustainability 10 (7), 2449.
Treitl, Stefan, Nolz, Pamela C., Jammernegg, Werner, 2014. Incorporating environmental aspects in an inventory routing problem. A case study from the petrochemical industry. Flex. Serv. Manuf. J. 26, 143–169.
Tunc, Huseyin, Kilic, Onur A., Tarim, S. Armagan, Eksioglu, Burak, 2011. The cost of using stationary inventory policies when demand is non-stationary. Omega 39 (4), 410–415.
Turan, Cansu, Ozturkoglu, Yucel, 2022. A conceptual framework model for an effective cold food chain management in sustainability environment. J. Model. Manag. 17 (4), 1262–1279.
Validi, Sahar, Bhattacharya, Arijit, Byrne, P.J., 2014. A case analysis of a sustainable food supply chain distribution system—A multi-objective approach. Int. J. Prod. Econ. 152, 71–87.
Waltho, Cynthia, Elhedhli, Samir, Gzara, Fatma, 2019. Green supply chain network design: A review focused on policy adoption and emission quantification. Int. J. Prod. Econ. 208, 305–318.
Yavari, Mohammad, Geraeli, Mohaddese, 2019. Heuristic method for robust optimization model for green closed-loop supply chain network design of perishable goods. J. Clean. Prod. 226, 282–305.
Zarbakhshnia, Navid, Soleimani, Hamed, Goh, Mark, Razavi, Seyyedeh Sara, 2019. A novel multi-objective model for green forward and reverse logistics network design. J. Clean. Prod. 208, 1304–1316.
Zhang, Y., Chen, X.D., 2014. An optimization model for the vehicle routing problem in multi-product frozen food delivery. J. Appl. Res. Technol. 12 (2), 239–250.
Zhen, Lu, Huang, Lufei, Wang, Wencheng, 2019. Green and sustainable closed-loop supply chain network design under uncertainty. J. Clean. Prod. 227, 1195–1209.