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Optimizing short food supply chain logistics to lower carbon emissions and enhance operational efficiency for small-scale rural producers☆

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ABSTRACT

Food hubs serve as platforms that aggregate products from small-scale food producers and facilitate their delivery to final consumers, which can enhance their profit margins and foster local economic development. However, the logistics involved in operating food hubs can be particularly costly. The research aims to show the possibilities of improving the environmental and operational efficiency of food hubs by developing a new mathematical model. A Mixed-Integer Linear Programming (MILP) model addresses the ‘producer-to-hub-to-customer’ transport problem, drawing on comprehensive real-world data. Computational experiments demonstrate that enhancing cooperation among producers when delivering goods to the hub can lead to a reduction in logistics costs and carbon emissions. To bolster environmental outcomes, the study presents empirical evidence indicating that transitioning from conventional to electric vehicles can reduce transport costs by nearly one-third and diminish carbon emissions by as much as 70%.

1. Introduction

Food production in Europe remains fragmented. In the European Union (EU) in 2020, there were approximately 9.1 million farms, with over 90 % categorized as family-run operations (Eurostat, 2020). In the food and drink manufacturing sector, some large-scale multinational companies operate amongst a mass of small-scale producers – out of 291,000 companies, an overwhelming 99.2 % are classified as Small and Medium-Sized Enterprises (FoodDrinkEurope, 2020). Small-scale food suppliers frequently find themselves at a disadvantage in terms of bargaining power when compared to larger, more concentrated downstream actors, especially the grocery retailers who dominate the market (Hingley, 2005). Recent trends have shown a concerning decline in the proportion of consumer expenditure on food that farmers receive, indicating an imbalance in the supply chain (Yi et al., 2021). This issue is exacerbated by the long and complex food supply chains in which these producers operate, where food products often traverse a myriad of international actors before finally reaching end consumers (Trienekens et al., 2012). To counteract these challenges, many farmers and small-scale

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food manufacturers are looking to shorten food supply chains by developing direct relationships with consumers. This approach aims to capture a larger share of the value added throughout the supply chain (Evola et al., 2022).

Short Food Supply Chains (SFSCs) are designed to involve "a limited number of economic operators committed to cooperation, local economic development, and close geographical and social relationships between producers, processors, and consumers" (EIP-AGRI, 2015, p.5). Some of the most commonly recognized forms of SFSCs are farmers' markets, community-supported agriculture, box schemes, local farm shops, direct internet sales, and "pick-your-own" farms where consumers engage directly with producers. In certain SFSCs, producers establish direct contact with consumers without any intermediaries, as seen in farmers' markets and pick-your-own schemes, while others may involve a single intermediary, such as a local or regional food hub that facilitates distribution (Kneafsey et al., 2013). Empirical evidence indicates that SFSCs generally offer advantages over conventional long food chains by providing higher price premiums and increased value-added for producers. They improve supplier bargaining power and stimulate more significant local economic multiplier effects, which can enhance community development (Kłoczko-Gajewska et al., 2023; Kneafsey, 2012; Malak-Rawlikowska et al., 2019). However, logistical difficulties, concerning transportation and distribution, often weaken the economic efficiency and environmental performance of SFSCs (Mogale et al., 2018).

Small-scale food producers frequently encounter significant challenges when it comes to transporting their goods. A prominent issue is the underutilization of vehicle space, often resulting in insufficiently filled vehicles. This not only elevates transportation costs because of fixed expenses such as fuel, maintenance, and driver wages, but it also intensifies the financial pressures on producers striving to manage their budgets effectively (Galati et al., 2021). Adding to this dilemma is the fact that many food producers operate independently, which leads to multiple delivery trips to reach their customers. This lack of coordination can drive up transportation expenses and prolong delivery times, causing frustration for both producers and customers who depend on timely deliveries. Moreover, profit margins for food producers are often further constrained by their limited access to centralized food hubs. Such hubs could facilitate the consolidation of orders from various producers, thereby making shipping more efficient and cost-effective (Curry, 2022). In addition, many smaller food producers do not have their own vehicles, compelling them to rely on third-party transport services. This dependency can increase their overall expenses, making it challenging for them to remain competitive in the market. Ultimately, these challenges create a complex range of logistical issues that impact not only food producers but also lead to higher prices for consumers (Paciarotti and Torregiani, 2021). It's a difficult situation that affects all parties involved.

The operational model of SFSCs entails numerous bespoke journeys by geographically dispersed producers and consumers, which leads to high costs associated with the first and last miles of transportation. Consequently, carbon emissions linked to SFSCs can often surpass those of traditional long supply chains, posing a dilemma for sustainability efforts (Majewski et al., 2020). These logistical challenges have triggered a search for innovative strategies to reduce both the financial and environmental burdens associated with SFSC logistics (Morgan et al., 2022). While this discourse centers on SFSCs, it is essential to acknowledge the larger global initiatives aimed at decreasing carbon emissions across all transportation and logistics sectors, which are critical for addressing climate change (Bilican et al., 2024). Considering the motivations and challenges faced by food producers, our research questions is: *how can we optimize the transportation operations of food hubs to reduce the logistics costs and carbon emissions, while enhancing cooperation among producers and mitigating the impact of unused vehicle volume, shipment delays and disruptions*?

To answer the research question, the paper develops and validates a novel mathematical model to optimize the operational efficiency of a food distribution network comprising of producer groups, a hub, and customer zones. The model aims to minimize economic costs, including inventory holding, transportation, and fuel consumption, while simultaneously reducing environmental impacts such as carbon emissions, unused vehicle volume, the number of vehicle trips and addressing disruption. To achieve this, the model incorporates key business constraints, including storage capacity limitations, inventory balancing requirements, and variations in transportation times and shipment delays. Additionally, it considers the impact of vehicle types on fuel consumption. The proposed model is tested and validated using real-world datasets from Food and Drink North East (FADNE), a food distribution hub operating in the North-East of England, providing practical insights into the benefits of producer cooperation and sustainable logistics practices. The study utilizes real-world data from the regional food hub that services over 150 producers. The focus is on the upstream and downstream distribution of food and drink products via various transportation routes and vehicles to the central warehouse and then to the customers. The insights gleaned from this research aim to provide actionable recommendations for food suppliers on improving distribution efficiency, minimizing transportation costs and emissions per route, and adopting optimal inventory policies that align with evolving consumer demands.

The remaining sections of the paper are as follows. We summarize the extant literature in section 2 before highlighting the problem description in section 3. We then present the mathematical model in section 4, followed by environmental analysis and fuel consumption estimations in section 5. Finally, we highlight the computational experiment and results in section 6 and then present a discussion in section 7. Finally, section 8 concludes.

2. Literature review

2.1. Food hubs

Food hubs within Short Food Supply Chains (SFSCs) serve as vital infrastructural platforms that aggregate goods from various local and regional producers, streamlining the fulfilment of delivery orders placed by consumers through an e-commerce website. This operating model presents a promising solution to the logistical challenges associated with SFSCs (Barham et al., 2012). By consolidating products from multiple sources, food hubs can achieve economies of scale in transportation, significantly lowering logistics costs for suppliers as well as reducing their environmental impact. The growing trend of e-commerce further enhances convenience for consumers, allowing them to access a diverse range of local products without the necessity of extensive travel (Janjevic et al., 2019). However, the extent to which a food hub successfully reduces both first and last mile operational and environmental costs hinges on three key factors:

(i) Coordination of Aggregation: The food hub's ability to effectively coordinate the aggregation of products from various producers to the central hub is crucial. This involves organizing the logistics of transportation, managing schedules, and determining any further packaging before final distribution to end consumers. Extant literature highlights the coordination of aggregation – for instance De et al. (2022) developed an optimization model for the Norwegian salmon supply chain logistics network that integrates stakeholders such as producers, distributors, and retailers. The model improves operational efficiency and reduces transportation costs by consolidating shipments, allowing for economies of scale and larger shipments. This approach enhances sustainability and profitability while improving response times and ensuring fresher products reach consumers.

(ii) Vehicle Specifications: The choice of vehicles plays a significant role in the food hub's operational efficiency. Factors such as fuel type, load capacity, and environmental impact must be considered when selecting vehicles for the logistics operations. For example, using electric or hybrid vehicles could greatly reduce greenhouse gas emissions compared to traditional diesel trucks. Previous research by De et al. (2024) introduces an advanced optimization model that focuses on the integration of electric vehicles to improve the efficiency of goods movement. The study illustrates how electric vehicles can promote greater financial sustainability in logistics while minimizing their environmental impact by reducing the carbon footprint.

(iii) Logistics Coordination: An efficient logistics management system is essential to minimize empty vehicle journeys. This involves careful route planning and strategic scheduling to ensure that transport resources are utilized effectively without unnecessary trips. The existing literature, particularly the research conducted by De et al. (2024), emphasizes the vital role of logistics coordination in optimizing supply chain efficiency. A sophisticated mixed-integer nonlinear programming model is introduced by De et al. (2024) to minimize unused vehicle space during transportation. The model considers various factors, including vehicle capacity and load characteristics to enhance decision-making processes within logistics. By addressing these key variables, the study aims to substantially improve resource allocation and reduce operational costs, ultimately contributing to more sustainable transportation practices.

Despite the potential benefits, food hubs currently lack comprehensive optimization models, indicating a gap in empirical research. There is an urgent need for collaboration between practitioners and academics to develop best practices for operating food hubs from financial, operational, and ethical standpoints (Guzman and Reynolds, 2019). The complexity of supply chain logistics in the context of regional food hubs is largely attributed to the geographically dispersed nature of agricultural and producer businesses, alongside the widely scattered consumer base and the fragmented rural–urban transport networks (Doernberg et al., 2022; Rucabado-Palomar and Cuéllar-Padilla, 2020). Coordinated logistics that ensure efficient distribution necessitate meeting various requirements related to order accuracy, timely delivery, product quality, and cost management (Lin et al., 2023; Rajabzadeh and Mousavi, 2023). Inventory planning becomes particularly demanding for food suppliers, where unpredictable changes in consumer preferences and relatively inefficient distribution networks further complicate operations (Liu et al., 2021). Given that logistics is a significant contributor to global carbon emissions, enhancing efficiency in this area is of paramount importance (Rajabzadeh and Mousavi, 2023). Yet, horizontal cooperation between food and beverage producers concerning logistics remains noticeably limited (Ramjaun et al., 2024). This research specifically addresses these challenges by empirically exploring the 'producer-to-hub-to-customer' dynamics within an e-commerce logistics network.

2.2. Optimization models for sustainable supply chain logistics

The existing literature on sustainable supply chains primarily focuses on the development of multi-objective optimization models aimed at achieving two key goals: minimizing operational costs, essential for economic sustainability, and reducing greenhouse gas emissions to address environmental concerns (Benjaafar et al., 2013; Brandenburg et al., 2014). Several studies introduce models and proposed solution methodologies, including optimization frameworks for supply chain network design that balance cost efficiency with the reduction of carbon dioxide emissions (Elhedhli and Merrick, 2012; Wang et al., 2011). However, Rajabzadeh and Mousavi (2023) emphasize a notable oversight in many of these studies — the lack of emphasis on enhancing vehicle utilization within optimization models. Improving vehicle utilization is critical for improving the operational efficiency of supply chain logistics networks, as it can lead to reduced transportation and fuel costs while simultaneously lowering carbon emissions. Additionally, logistics managers frequently face unpredictable disruptions in their transportation networks that result in variable travel times. These disruptions can arise from various factors, including traffic congestion, natural disasters, or mechanical failures, ultimately causing delays in product shipments (Ardekani et al., 2023; Burgos and Ivanov, 2021; Foroozesh et al., 2022). Regrettably, much of the existing literature focussing on optimization models fails to incorporate these variable travel times and potential shipment delays, which can worsen supply chain logistics disruptions. Such disruptions heighten the risk of unmet customer demand, significantly hindering a retailer's capacity to meet consumer needs and potentially resulting in substantial revenue losses (Jabbarzadeh et al., 2016; Jabbarzadeh et al., 2019). In contrast, some earlier research, including work by Jabbarzadeh et al. (2016) and Jabbarzadeh et al. (2019), focused on developing optimization models that consider the implications of unmet customer demand. These studies aim to provide valuable insights into the financial consequences retailers face in real-world scenarios, enhancing the understanding of supply chain challenges. Furthermore, additional studies highlight the importance of incorporating strategic approaches within optimization models to effectively reduce transportation costs and minimize the number of vehicle trips (De et al., 2020; Mogale et al., 2023; Morgan et al., 2022; Prajapati et al., 2022; Rajabzadeh and Mousavi, 2023). This strategic integration involves treating vehicle utilization as an additional objective within the optimization models and adopting direct shipment strategies as a vital constraint, thereby facilitating greater efficiency and sustainability in supply chain operations (Morgan et al., 2022; Rajabzadeh and Mousavi, 2023).

2.3. Research gaps and contribution

Considering the identified research gaps, the contributions of this paper can be outlined as follows. We developed a novel mathematical model aimed at minimizing key costs, including transportation, inventory holding, fuel, penalties for unmet demand, and unused vehicle capacity. Additionally, we introduce useful propositions that focus on storage capacity restrictions while also considering variable shipment times. We address inventory balancing restrictions at both the hub and customer zones, considering variations in travel times. The paper proposes analytical expressions to estimate fuel consumption within the distribution network from producers to hubs to customer zones. It also incorporates carbon emission restrictions to calculate the emissions produced by vehicles. While several studies have touched on sustainability within supply chain logistics (Maiyar and Thakkar, 2019a; Maiyar and Thakkar, 2019b), very few have investigated a phased transition from fuel-based to electric vehicles to assess the impact on carbon emissions (Schiffer et al., 2021). Consequently, to address carbon emissions, our model considers the phased adoption of electric vehicles and integrates electric vehicle charging costs. To enhance managerial relevance, primary data about the input parameters of the mathematical model were provided by an industry stakeholder. The proposed model offers valuable insights for food supply chain policymakers and practitioners, enabling them to better understand logistics costs, carbon emissions, vehicle trips, and unused vehicle capacity. It highlights strategies to reduce cost components and carbon emissions, such as considering direct shipments from producer groups to customer zones. Furthermore, the model provides evidence regarding how demand variations affect economies of scale and how fuel price fluctuations influence fuel costs. It also generates insights for managers on the impact of electric vehicle adoption on the distribution network, particularly in terms of reductions in carbon emissions and fuel consumption. Lastly, the model assists supply chain managers in making informed decisions to respond to shipment delays and disruptions along transportation routes.

3. Problem description

Food and Drink North East (FADNE) is a community interest company dedicated to supporting the food, drink, and hospitality sectors in the North East of England. In Spring 2020, when the Covid-19 pandemic began to impact the UK, farmers' markets, cafés, and restaurants closed, disrupting high-margin market channels and threatening the incomes of producers. In response, FADNE launched "Local Heroes," a regional food hub with an e-commerce website that provided home delivery services and allowed customers to collect orders from the hub. The hub featured products from over 150 different North East producers, including perishable items such as seafood, meat, and dairy, which required refrigerated and temperature-controlled logistics, as well as long-lasting products like jams, confectionery, beer, and spirits. The North East of England is the country's most sparsely populated region, with a population density of 308 people per km2 and a total population of 2.647 million as of 2022 (North East Evidence Hub, 2024). The region's median annual income is £33,000, and the average is £38,300—both significantly lower than the UK averages. The North East also experiences the highest levels of child poverty in England alongside pockets of affluence (North East Evidence Hub, 2024). The area's rural landscape consists of diverse former mining villages, coastal communities with high levels of deprivation, remote farming communities, and prosperous commuter villages (NICRE, 2024a). These economic disparities impact consumption patterns, with supermarkets dominating food purchases in urban areas due to their focus on national and international brands and aggressive pricing. Despite this, there is a segment of consumers in the region actively seeking out local foods (Vittersø et al., 2018; Weatherell et al., 2003). Increasing awareness of sustainability has heightened demand for local, environmentally friendly food options, further supported by initiatives like Local Heroes.

Based in Newcastle upon Tyne, which is home to approximately 300,000 residents, the Local Heroes food hub played a crucial role in addressing the logistical challenges stemming from the region's socio-economic and geographic diversity. The hub's e-commerce platform allowed rural food producers to reach urban markets without the burden of direct transportation. By centralizing deliveries, producers were able to reduce individual transport costs and time. Local Heroes offered free home delivery within a 5-mile radius and facilitated order collection from the hub, making it accessible for consumers in Newcastle. The transport infrastructure in the region reveals stark contrasts; urban centers like Newcastle upon Tyne benefit from efficient networks such as the Tyne and Wear Metro, while rural areas rely heavily on personal vehicles due to limited and infrequent public transport options (NICRE, 2023). Direct sales to consumers—such as through farm shops, farmers' markets, and box schemes—account for approximately 8 % of farm sales within the region (NICRE, 2024b). Farmers are generally keen to increase their involvement in short food supply chains to enhance their margins, gain greater control over product sales, diversify income, and support local initiatives (NICRE, 2024b). However, barriers such as limited demand, lack of time, and inadequate infrastructure, including transportation, persist (NICRE, 2024b). Local Heroes offers a potential solution by providing a streamlined platform for direct sales and deliveries. By addressing logistical challenges and fostering connections between producers and consumers, the initiative contributes to building a more sustainable, low-carbon food distribution system. This underscores the potential of regional hubs to drive innovation within complex socio-economic and spatial contexts.

A core problem facing FADNE's short food supply chain relates to optimizing the producer-hub-customer distribution network for food and drink products. The complexity arises from the varying logistics behaviors of producers and the need to efficiently deliver Stock Keeping Units (SKUs) to customer zones. Specifically, the challenges stem from diverse producer logistics behavior. Producers fall into three categories with different transportation approaches: (i) using the hub's vehicle for shipments (after coordinating with other producers), (ii) using a shared vehicle from one producer for transportation, and (iii) using their own vehicles independently without coordination. Fig. 1 provides a visual illustration of the producer-to-hub-to-customer distribution network pertaining to the three categories and the respective logistics distribution networks.

The FADNE's short food supply chain also aims to address other challenges such as – multiple distribution routes. A product can be moved from producers to the hub, and then to customer zones but could also be shipped from producer groups directly to customer zones. Finally, both producers and customers are grouped based on geographical proximity. Producer groups are formed considering the geographical location of the producers and their willingness to co-operate in logistics. Customers are grouped into customer zones based on their geographical location, which can be accessed from the hub as shown in Fig. 1. However, determining the most cost-effective and time-efficient routes from producers to customers — either through the hub or directly — poses a logistical challenge. The research tries to address the problem related to 'producer-hub-customer' distribution, focussing on the upstream and downstream distribution of food and drink products, via different routes and vehicles.

The mathematical model aims to address these challenges by aiming to minimize the total transportation costs across different routes and vehicle types. The model focusses on optimizing vehicle utilization based on producer cooperation patterns and explores the trade-offs between direct and indirect shipping routes. In summary, the problem involves designing an optimal distribution network considering different logistics patterns, transportation routes, and cost structures. The mathematical formulation in the next section provides a structured approach to solve this problem and identify the most efficient logistics strategy for FADNE's short food supply chain.

4. Mathematical model

This section presents the mathematical formulation for the e-commerce logistics network (producer groups to hub to customer zones). The model is developed to obtain logistics and inventory decisions for a planning horizon comprising of a number of time periods or weeks. The model assumptions include deterministic transportation costs, SKU weight and volume and vehicle capacity. The model considers direct and hub-based routes in the supply chain logistics network. Small-scale producers are responsible for producing and delivering products to the hub, from where they are distributed to customers. FADNE manages customer orders and coordinates product movement to the hub based on demand. If the quantity received exceeds immediate demand, the surplus is stored as inventory at the hub, incurring inventory costs, which are accounted for within the model.

The notations associated with the mathematical model are presented below.

Indices and Sets

t, T Index and set of time period respectively, $t \in T$

s, S Index and set of producer groups respectively,$s \in S$

c, C Index and set of hubs respectively, $c \in C$

r, R Index and set of customer zones respectively, $r \in R$

f, F Index and set of vehicle types respectively,$f \in F$

p, P Index and set of Stock Keeping Units (SKU) types, $p \in P$

Parameters

U^c_{pts}, U^r_{pts} Supply capacity of SKU p available with producer s which can be shipped to hub c and customer zone r respectively at time period t.

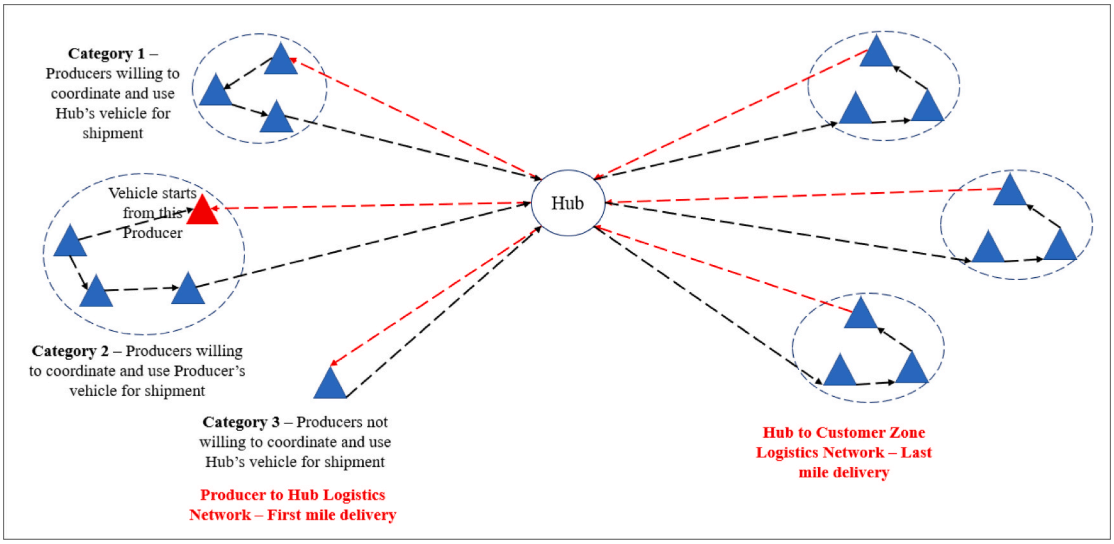


Fig. 1. Visual illustration of the producer-to-hub-to-customer distribution network.

O_{ptc}, O_{ptr} Aggregate order quantity of customers for SKU p to be met by hub c and customer zone r respectively at time period t.

δ_c, δ_r Storage volume available for all SKUs with hub c and customer zone r respectively.

W_p, V_p Weight and volume of SKU p.

W_{tcr}^f, V_{tcr}^f Shipment weight and volume available with vehicle type f operating from hub c to customer zones r at time period t.

W_{tsc}^f, V_{tsc}^f Shipment weight and volume available with vehicle type f operating from producer s to hub c at time period t.

W_{tsr}^f, V_{tsr}^f Shipment weight and volume available with vehicle type f operating from producer s to customer zone r at time period t.

$\underline{I}_{ptc}, \overline{I}_{ptc}$ Minimum and maximum inventory level that can be kept at hub c for SKU p during time period t.

$\underline{I}_{ptr}, \overline{I}_{ptr}$ Minimum and maximum inventory level that can be kept at customer zone r for SKU p during time period t.

$In\overline{T}_{ptc}, In\overline{T}_{ptr}$ In-transit quantity of SKU p which would be arriving in time period t at hub c and customer zone r respectively.

$N_{tsc}^{Max}, N_{tsr}^{Max}, N_{tcr}^{Max}$ Maximum vehicle trips available at time period t on shipment link from producer s to hub c, producer s to customer zone r and hub c to customer zone r respectively.

$C_{tscf}, C_{tsrf}, C_{tcrf}$ Fixed transportation cost per km for shipping SKUs at time period t using a vehicle type f from producer s to hub c, producer s to customer zone r and hub c to customer zone r respectively.

IC_{ptc}, IC_{ptr} Inventory holding cost per unit of SKU p in time period t at hub c and customer zone r respectively.

$B_{pc}^{dem}, B_{pr}^{dem}$ Penalty charges incurred for per unit of unmet demand of SKU p at hub c and customer zone r.

$B_{cr}^{vol}, B_{sr}^{vol}, B_{sc}^{vol}$ Penalty charges incurred for per volume of unused vehicle capacity on the shipment route from hub c to customer zone r, producer s to hub c and producer s to customer zone r respectively.

D_{sc}, D_{sr}, D_{cr} Distance in km between producer s and hub c, producer s and customer zone r and hub c and customer zone r respectively.

$X_{tsc}, X_{tsr}, X_{tcr}$ 1, if shipment can happen during time period t from producer s to hub c, producer s to customer zone r and hub c to customer zone r respectively; 0 otherwise.

$ST_{sc}, ST_{sr}, ST_{cr}$ Shipment time (in terms of number of periods) for transportation of SKUs from producer s to hub c, producer s to customer zone r and hub c to customer zone r respectively.

Decision variables

Inv_{ptc}, Inv_{ptr} Inventory level for SKU p during time period t at hub c and customer zone r respectively.

A_{ptc}, A_{ptr} Total amount available to meet the order of SKU p at hub c and customer zone r respectively during time period t.

$TQ_{ptcrf}, TQ_{ptscf}, TQ_{ptsrf}$ Number of SKU p shipped in time period t using vehicle type f from hub c to customer zone r, producer s to hub c and producer s to customer zone r respectively.

$N_{tcrf}, N_{tscf}, N_{tsrf}$ Number trips made by vehicle type f in time period t on route from hub c to customer zone r, producer s to hub c and producer s to customer zone r respectively.

$UT_{cr}^{vol}, UT_{sr}^{vol}, UT_{sc}^{vol}$ Amount of volume in vehicles that remains unused on shipment route from hub c to customer zone r, producer s to hub c and producer s to customer zone r respectively.

Objective function

$$MinimizeTotalCost = InventoryHoldingCost + TransportationCost + PenaltyCost \tag{1}$$

$$InventoryHoldingCost = \sum_{p\in P}\sum_{c\in C}\sum_{t\in T}\left(IC_{ptc}Inv_{ptc}\right) + \sum_{p\in P}\sum_{r\in R}\sum_{t\in T}\left(IC_{ptr}Inv_{ptr}\right) \tag{2}$$

$$TransportationCost = \left\{\sum_{s\in S}\sum_{c\in C}\sum_{t\in T}\sum_{f\in F} C_{tscf}N_{tscf}D_{sc}X_{tsc} + \sum_{s\in S}\sum_{r\in R}\sum_{t\in T}\sum_{f\in F} C_{tsrf}N_{tsrf}D_{sr}X_{tsr} + \sum_{c\in C}\sum_{r\in R}\sum_{t\in T}\sum_{f\in F} C_{tcrf}N_{tcrf}D_{cr}X_{tcr}\right. \tag{3}$$

$$PenaltyCostforunmetdemand = \left\{\sum_{p\in P}\sum_{c\in C}\sum_{t\in T}\left[Max\left(\left(O_{ptc} - A_{ptc}\right), 0\right)B_{pc}^{dem}\right] + \sum_{p\in P}\sum_{r\in R}\sum_{t\in T}\left[Max\left(\left(O_{ptr} - A_{ptr}\right), 0\right)B_{pr}^{dem}\right]\right. \tag{4}$$

Eq. (1) depicts the objective function of the mathematical model, which aims to minimize total costs, comprising of inventory holding costs, transportation costs, and penalty costs for unmet demand. Eq. (2) highlights the inventory holding costs associated with maintaining inventory of Stock Keeping Units (SKUs) at the hub and customer zones during the planning horizon. Eq. (3) represents the transportation cost incurred during the planning horizon for the shipment of SKUs from producers to the hub, producers to customer zones and the hub to customer zones. Transportation costs are computed by considering the fixed transportation costs, distance from the source to destination and number of vehicles deployed on a shipment route. Eq. (4) illustrates the penalty costs incurred for failing to meet the demand of SKUs during the planning horizon, while considering the aggregate orders of customers and the amount of SKUs available to meet customer demand.

$$\sum_{c\in C}\sum_{f\in F}\left(TQ_{ptscf}X_{tsc}\right) \le U_{pts}^c \forall p \in P, s \in S, t \in T \tag{5}$$

$$\sum_{r\in R}\sum_{f\in F}\left(TQ_{ptsrf}X_{tsr}\right) \leq U^{r}_{pts} \forall p \in P, s \in S, t \in T \tag{6}$$

Equations (5) and (6) depict the supply constraints associated with producers during various time periods. Equations (5) and (6) state the number of SKUs shipped from a supplier to the hub and customer zones respectively should be less than, or equal to, the supply available from a specific producer for a SKU type during the time period.

Proposition 4.1. (.) *Storage capacity restrictions at a hub can be represented using constant shipment time from producers to hub. Although in practice the transportation time from various producers to the hub fluctuates, which should be taken into consideration while depicting the storage capacity constraint.*

Proof: Storage capacity restrictions at hub c during time period t, considers the in-transit inventory of SKUs arriving at time period t, inventory level of SKUs available from the previous time period ($t-1$) and total number of SKUs shipped from various producer and delivered at hub c during time period t. Considering consistent shipment time for two time periods from producers to the hub, the storage capacity constraint can be represented in the following way,

$$\sum_{s\in S}\sum_{p\in P}\sum_{f\in F}\left[\left(TQ_{p(t-2)scf}X_{(t-2)sc}\right)V_p\right] + \sum_{p\in P}\left[\left(In\overline{T}_{ptc} + Inv_{p(t-1)c}\right)V_p\right] \leq \delta_c Fort > 2, \forall t \in T, c \in C \tag{7}$$

Eq. (7) is defined to represent the storage capacity restriction of the hub when the time period, $t > 2$. When the time period $t = 2$ and $t = 1$, the storage capacity restriction of hub can be depicted as:

$$\sum_{p\in P}\left[\left(In\overline{T}_{ptc} + Inv_{p(t-1)c}\right)V_p\right] \leq \delta_c Fort = 2, \forall t \in T, c \in C \tag{8}$$

$$\sum_{p\in P}\left[\left(In\overline{T}_{ptc} + Inv_{p0c}\right)V_p\right] \leq \delta_c Fort = 1, \forall t \in T, c \in C \tag{9}$$

However, when the shipment time from various producers to hubs fluctuate, then a parameter ST_{sc} is considered which aims to predict the transportation time from producers to hub. Integrating the shipment time parameter ST_{sc} within the Eq. (7), helps to realistically depict the storage capacity constraint.

$$\delta_c \geq \begin{cases} \sum_{s\in S}\sum_{p\in P}\sum_{f\in F}\sum_{t>ST_{sc}}\left[\left(TQ_{p(t-ST_{sc})scf}X_{(t-ST_{sc})sc}\right)V_p\right] \\ \quad +\sum_{p\in P}\left[\left(In\overline{T}_{ptc} + Inv_{p(t-1)c}\right)V_p\right],\ t > 1 \\ \sum_{s\in S}\sum_{p\in P}\sum_{f\in F}\sum_{t>ST_{sc}}\left[\left(TQ_{p(t-ST_{sc})scf}X_{(t-ST_{sc})sc}\right)V_p\right] \\ \quad +\sum_{p\in P}\left[\left(In\overline{T}_{ptc} + Inv_{p0c}\right)V_p\right],\ t \leq 1 \end{cases} \forall t \in T, c \in C \tag{10}$$

Eq. (10) depicts the storage capacity constraints for the hub when time period $t > 1$, while including the varying shipment time parameter ST_{sc} in transporting SKUs from producers to the hub. The constraint states that the volume of SKUs delivered to the hub from various producers should be less than or equal to the storage capacity in terms of the volume of the hub for all SKUs combined. Furthermore, the equation considers the inventory level at the hub for the specific SKU types from the previous time period and the in-transit quantity which would be arriving at the hub in the current time period. During time period $t = 1$, the storage capacity constraint for the hub is given in Eq. (9).

Proposition 4.2. (.) *A customer zone's storage capacity restriction should be represented while considering the varying travel time associated with the shipment of SKUs from producers to customer zones and hubs to customer zones.*

Proof: The Storage capacity restriction of a customer zone r during time period t, considers the in-transit inventory of SKUs arriving at customer zone r and inventory levels available at the customer zone r from previous time period ($t-1$). If the travel time for shipping SKUs from producers to customer zones and hubs to customer zones in tow times is considered constant, then the storage capacity constraint can be depicted in the following way:

$$\left.\begin{array}{l} \sum_{s\in S}\sum_{p\in P}\sum_{f\in F}\left[\left(TQ_{p(t-2)srf}X_{(t-2)sr}\right)V_p\right] + \sum_{c\in C}\sum_{p\in P}\sum_{f\in F}\left[\left(TQ_{p(t-2)crf}X_{(t-2)cr}\right)V_p\right] \\ \qquad +\sum_{p\in P}\left[\left(In\overline{T}_{ptr} + Inv_{p(t-1)r}\right)V_p\right] \end{array}\right\} \leq \delta_r Fort > 2, \forall t \in T, r \in R \tag{11}$$

Eq. (11) highlights the storage capacity constraint for customer zones for time period, $t > 2$. Although, when time period $t = 2$ and $t = 1$, the storage capacity restriction for customer zones can be represented as given in equations (12) and (13), respectively.

$$\sum_{p\in P}\left[\left(In\overline{T}_{ptr} + Inv_{p(t-1)r}\right)V_p\right] \leq \delta_r Fort = 2, \forall t \in T, r \in R \tag{12}$$

$$\sum_{p\in P}\left[\left(In\overline{T}_{ptr}+Inv_{p0r}\right)V_p\right]\leq\delta_r Fort=1,\forall t\in T,r\in R \tag{13}$$

When the travelling time varies related to shipment of SKUs from producers to customer zones and hub to customer zones, then the storage capacity constraint given in Eq. (11) needs to integrate the varying shipment time and accordingly, Eq. (14) is presented below.

$$\delta_r\geq\begin{cases}\sum_{p\in P}\left[\left(In\overline{T}_{ptr}+Inv_{p(t-1)r}\right)V_p\right]+\sum_{s\in S}\sum_{p\in P}\sum_{f\in F}\sum_{t>ST_{sr}}\left[\left(TQ_{p(t-ST_{sr})srf}X_{(t-ST_{sr})sc}\right)V_p\right]\\ \quad+\sum_{c\in C}\sum_{p\in P}\sum_{f\in F}\sum_{t>ST_{cr}}\left[\left(TQ_{p(t-ST_{cr})crf}X_{(t-ST_{cr})cr}\right)V_p\right],Fort>1\\ \sum_{p\in P}\left[\left(In\overline{T}_{ptr}+Inv_{p0r}\right)V_p\right]+\sum_{s\in S}\sum_{p\in P}\sum_{f\in F}\sum_{t>ST_{sr}}\left[\left(TQ_{p(t-ST_{sr})srf}X_{(t-ST_{sr})sc}\right)V_p\right]\\ \quad+\sum_{c\in C}\sum_{p\in P}\sum_{f\in F}\sum_{t>ST_{cr}}\left[\left(TQ_{p(t-ST_{cr})crf}X_{(t-ST_{cr})cr}\right)V_p\right],Fort\leq 1\end{cases}\quad\forall t\in T,r\in R \tag{14}$$

Eq. (14) summarises the storage capacity constraint for customer zones while considering the varying shipment time in moving SKUs from producers to customer zones (ST_{sr}) and hubs to customer zones (ST_{cr}). Furthermore, Eq. (14) highlights that the volume of SKUs flowing into the customer zones from various producers and hubs should be less than or equal to the storage capacity (in volume) of the customer zones for all SKUs. Moreover, the equation considers the inventory level (in volume) at the customer zone from the previous time period and the in-transit quantity (in volume) which would be arriving at the customer zone on the current time period.

Proposition 4.3. (.) *The inventory balancing restriction at the hub should consider the varying travel time for the shipment of SKUs from producers to the hub, while incorporating the outward flow from the hub to customer zones, the inventory level available at the hub from the previous time period, and the inward flow of in-transit inventory.*

Proof: The inventory level available at the hub during time period t can be computed considering the inventory level available from the previous time period ($t-1$) and the in-transit inventory arriving at the hub during time period t. Eq. (15) depicts the inventory level available at the hub which considers the number of SKUs arriving at the hub from various producers considering a constant shipment time for 2 time periods and the number of SKUs transported from the hub to various customer zones.

$$Inv_{ptc}=Inv_{p(t-1)c}-\sum_{r\in R}\sum_{f\in F}\left[\left(TQ_{ptcrf}X_{tcr}\right)V_p\right]+\sum_{s\in S}\sum_{f\in F}\left[\left(TQ_{p(t-2)scf}X_{(t-2)sc}\right)V_p\right]+In\overline{T}_{ptc}Fort>2,\forall p\in P,t\in T,c\in C \tag{15}$$

Eq. (15) presents the inventory balancing constraint at the hub during period, $t>2$, while considering the constant shipment time of for two periods. During period $t=2$ and $t=1$, the inventory balancing constraint can be represented in the following way,

$$Inv_{ptc}=Inv_{p(t-1)c}-\sum_{r\in R}\sum_{f\in F}\left[\left(TQ_{ptcrf}X_{tcr}\right)V_p\right]+In\overline{T}_{ptc}Fort=2,\forall p\in P,t\in T,c\in C \tag{16}$$

$$Inv_{ptc}=Inv_{p0c}-\sum_{r\in R}\sum_{f\in F}\left[\left(TQ_{ptcrf}X_{tcr}\right)V_p\right]+In\overline{T}_{ptc}Fort=1,\forall p\in P,t\in T,c\in C \tag{17}$$

When the travel time from producers to hubs varies, the inventory balancing constraint given in Eq. (15) needs to be expanded. The updated inventory balancing constraint given in Eq. (18) incorporates the parameter ST_{sc} which depicts the varying shipment time from producer s to hub c.

$$A_{ptc}=\begin{cases}Inv_{p(t-1)c}+\sum_{s\in S}\sum_{f\in F}\sum_{t>ST_{sc}}\left(TQ_{p(t-ST_{sc})scf}X_{(t-ST_{sc})sc}\right)+In\overline{T}_{ptc},Fort>1\\ Inv_{p0c}+In\overline{T}_{ptc}+\sum_{s\in S}\sum_{f\in F}\sum_{t>ST_{sc}}\left(TQ_{p(t-ST_{sc})scf}X_{(t-ST_{sc})sc}\right),Fort=1\end{cases}\quad\forall p\in P,t\in T,c\in C \tag{18}$$

$$Inv_{ptc}=A_{ptc}-\sum_{r\in R}\sum_{f\in F}\left(TQ_{ptcrf}X_{tcr}\right)\forall p\in P,t\in T,c\in C \tag{19}$$

Eq. (18) depicts that the quantities available at the hub for a specific SKU type for a particular time period should be equal to the inventory level of the hub from the previous time period, plus the quantity shipped from various producers to the hub considering the varying shipment times, plus the in-transit quantity arriving at the hub in the specific time period. Eq. (19) presents that the inventory level at the hub for a SKU type should be equal to the available quantity of SKU type minus the number of products shipped out from the hub to customer zones.

$$Inv_{ptc}=Max\left(O_{ptc},A_{ptc}\right)\forall p\in P,t\in T,c\in C \tag{20}$$

Eq. (20) highlights that the inventory level at a hub should be equal to the maximum value for the ordered amount received at the hub for the SKUs and the quantity available at the hub for a specific SKU type in a time period.

Proposition 4.4. (.) *A customer zone's inventory balancing restriction should be depicted by considering the varying travel time in shipping SKUs from producers to a customer zone and the hub to a customer zone.*

Proof: The inventory available at a customer zone during time period t is computed by considering the in-transit inventory arriving at the customer zone, the inventory available from the previous period ($t-1$) and the aggregated order quantity of customers for SKU p to be met by the customer zone. Furthermore, the inventory balancing restriction given in Eq. (21) below, considers the number of SKUs shipped from the hub to a customer zone and producers to a customer zone with a constant travel time for two time periods. Eq. (21) depicts the inventory balancing constraint for a customer zone during time period $t > 2$, while considering the constant shipment time. Eq. (22) highlights the inventory balancing constraint for the customer zone during time period $t = 2$ and $t = 1$.

$$Inv_{ptr} = Inv_{p(t-1)r} - O_{ptr} + \sum_{c\in C}\sum_{f\in F}\left(TQ_{ptcrf}X_{tcr}\right) + \sum_{s\in S}\sum_{f\in F}\left(TQ_{ptsrf}X_{tsr}\right) + In\overline{T}_{ptr} For t > 2, \forall p \in P, t \in T, r \in R \tag{21}$$

$$Inv_{ptr} = \begin{cases} Inv_{p(t-1)r} - O_{ptr} + In\overline{T}_{ptr}, t = 2 \\ Inv_{p0r} - O_{ptr} + In\overline{T}_{ptr}, t = 1 \end{cases} \forall p \in P, t \in T, r \in R \tag{22}$$

However, in practice the travel time of vehicles from the hub to customer zones and from producers to customer zones varies and, as a result, the inventory balancing restriction given in Eq. (21) needs to be expanded. The revised version of the inventory balancing constraint incorporates the varying shipment time from the hub to customer zones ST_{cr} and from producers to customer zones ST_{sr}.

$$A_{ptr} = \begin{cases} Inv_{p(t-1)r} + \sum_{c\in C}\sum_{f\in F}\sum_{t>ST_{cr}}\left(TQ_{p(t-ST_{cr})crf}X_{(t-ST_{cr})cr}\right) + In\overline{T}_{ptr} \\ \quad + \sum_{s\in S}\sum_{f\in F}\sum_{t>ST_{sr}}\left(TQ_{p(t-ST_{sr})srf}X_{(t-ST_{sr})sr}\right), For t > 1 \\ Inv_{p0r} + \sum_{c\in C}\sum_{f\in F}\sum_{t>ST_{cr}}\left(TQ_{p(t-ST_{cr})crf}X_{(t-ST_{cr})cr}\right) + In\overline{T}_{ptr} \\ \quad + \sum_{s\in S}\sum_{f\in F}\sum_{t>ST_{sr}}\left(TQ_{p(t-ST_{sr})srf}X_{(t-ST_{sr})sr}\right), For t = 1 \end{cases} \forall p \in P, t \in T, r \in R \tag{23}$$

Eq. (23) depicts the inventory balancing constraint for the customer zone during a time period. The equation states that the quantity available at a customer zone for a specific SKU type in a time period should be equal to the inventory level available at the customer zone from the previous time period, plus the amount shipped from various producers and hub to the customer zone considering the varying shipment times, plus the in-transit quantity arriving at the customer zone during the time period.

$$Inv_{ptr} = Max\left[\left(A_{ptr} - O_{ptr}\right), 0\right] \forall p \in P, t \in T, r \in R \tag{24a}$$

$$O_{ptr} \geq \begin{cases} Inv_{p(t-1)r} + \sum_{c\in C}\sum_{f\in F}\sum_{t>ST_{cr}}\left(TQ_{p(t-ST_{cr})crf}X_{(t-ST_{cr})cr}\right) + In\overline{T}_{ptr} \\ \quad + \sum_{s\in S}\sum_{f\in F}\sum_{t>ST_{sr}}\left(TQ_{p(t-ST_{sr})srf}X_{(t-ST_{sr})sr}\right), For t > 1 \\ Inv_{p0r} + \sum_{c\in C}\sum_{f\in F}\sum_{t>ST_{cr}}\left(TQ_{p(t-ST_{cr})crf}X_{(t-ST_{cr})cr}\right) + In\overline{T}_{ptr} \\ \quad + \sum_{s\in S}\sum_{f\in F}\sum_{t>ST_{sr}}\left(TQ_{p(t-ST_{sr})srf}X_{(t-ST_{sr})sr}\right), For t = 1 \end{cases} \forall p \in P, t \in T, r \in R \tag{24b}$$

Equations (24a) and (24b) compute the inventory level at a customer zone for a SKU type by considering the maximum value of a function. The equations consider the relationship between the available quantity of a SKU type at the customer zone and the ordered amount at the customer zone to determine the inventory level. Equations (23), (24a) and (24b) help to compute the inventory level for the customer zone while considering the varying travel time in shipping SKUs from producers to a customer zone and from the hub to a customer zone.

$$\underline{I}_{ptc} \leq Inv_{ptc} \leq \overline{I}_{ptc} \forall p \in P, c \in C, t \in T \tag{25}$$

$$\underline{I}_{ptr} \leq Inv_{ptr} \leq \overline{I}_{ptr} \forall p \in P, r \in R, t \in T \tag{26}$$

Equations (25) and (26) depict the inventory rules adopted by hubs and customer zones. Equations (25) and (26) ensure that the inventory level at the hub and a customer zone respectively for a SKU type at a time period should lie within the specific range associated with the minimum and maximum inventory level that can be kept at the hub and a customer zone during the time period.

$$N_{tsc}^{Max} \geq \sum_{f\in F} N_{tscf} \geq \begin{cases} \sum_{f\in F}\left(\sum_{p\in P}\left(TQ_{ptscf}X_{tsc}W_p\right) \Big/ W_{tsc}^{f}\right) \\ \sum_{f\in F}\left(\sum_{p\in P}\left(TQ_{ptscf}X_{tsc}V_p\right) \Big/ V_{tsc}^{f}\right) \end{cases} \forall s \in S, c \in C, f \in F, t \in T \tag{27}$$

$$N_{tsr}^{Max} \geq \sum_{f\in F} N_{tsrf} \geq \begin{cases} \sum_{f\in F}\left(\sum_{p\in P}(TQ_{ptsrf}X_{tsr}W_p) \Big/ W_{tsr}^f\right) \\ \sum_{f\in F}\left(\sum_{p\in P}(TQ_{ptsrf}X_{tsr}V_p) \Big/ V_{tsr}^f\right) \end{cases} \forall s \in S, r \in R, f \in F, t \in T \tag{28}$$

$$N_{tcr}^{Max} \geq \sum_{f\in F} N_{tcrf} \geq \begin{cases} \sum_{f\in F}\left(\sum_{p\in P}(TQ_{ptcrf}X_{tcr}W_p) \Big/ W_{tcr}^f\right) \\ \sum_{f\in F}\left(\sum_{p\in P}(TQ_{ptcrf}X_{tcr}V_p) \Big/ V_{tcr}^f\right) \end{cases} \forall c \in C, r \in R, f \in F, t \in T \tag{29}$$

Equations (27), (28) and (29) highlight the number of vehicle trips on various transportation routes such as producers to the hub, producers to customer zones, and the hub to customer zones respectively. These equations state that the number of trips made by various vehicle types on the transportation route should be greater than or equal to the total weight and volume of the number of SKUs shipped on the transportation route and divided by the weight and volume available for the vehicle type deployed on the transportation route. Furthermore, equations (27), (28) and (29) highlight the total number vehicle trips made on a shipment link between a producer and the hub, producer and a customer zone, and the hub and customer zone respectively in a time period should be less than or equal to the maximum number of allowable vehicle trips for the shipment link on the specific period.

$$Inv_{ptc}, Inv_{ptr} \geq 0 \forall p \in P, c \in C, r \in R, t \in T \tag{30}$$

$$A_{ptc}, A_{ptr} \geq 0 \forall p \in P, c \in C, r \in R, t \in T \tag{31}$$

$$TQ_{ptcrf}, TQ_{ptscf}, TQ_{ptsrf} \geq 0 \forall p \in P, s \in S, c \in C, r \in R, f \in F, t \in T \tag{32}$$

$$N_{tcrf}, N_{tscf}, N_{tsrf} \geq 0 \forall s \in S, c \in C, r \in R, f \in F, t \in T \tag{33}$$

Equations (30) to (33) depict the non-negative integer variables of the mathematical model. The objective function of the mathematical model can be further extended by considering the unused vehicle volume on shipment routes from a hub to customer zones, producers to a hub, and producers to customer zones as given in Eqs. (34), (35) and (36) respectively.

$$UT_{cr}^{vol} = \sum_{f\in F}\sum_{t\in T}(N_{tcrf}V_{tcr}^f) - \sum_{p\in P}\sum_{f\in F}\sum_{t\in T}(TQ_{ptcrf}V_p) \forall c \in C, r \in R \tag{34}$$

$$UT_{sc}^{vol} = \sum_{f\in F}\sum_{t\in T}(N_{tscf}V_{tsc}^f) - \sum_{p\in P}\sum_{f\in F}\sum_{t\in T}(TQ_{ptscf}V_p) \forall s \in S, c \in C \tag{35}$$

$$UT_{sr}^{vol} = \sum_{f\in F}\sum_{t\in T}(N_{tsrf}V_{tsr}^f) - \sum_{p\in P}\sum_{f\in F}\sum_{t\in T}(TQ_{ptsrf}V_p) \forall s \in S, r \in R \tag{36}$$

Equations (34), (35) and (36) present the unused vehicle volume on shipment routes, which is determined by considering the total volume available for use and total volume used for shipment purposes. The total volume available for use is computed by considering the number of vehicles deployed on the shipment routes from the hub to customer zones, producers to the hub, and producers to customer zones, and the volume of each vehicle types. Furthermore, the volume used is computed using the number of SKUs shipped on different shipment routes and the volume of SKU types. A penalty cost incurred for unused vehicle volume on the shipment routes is computed using the Eq. (37).

$$\begin{aligned} &Penalty cost for unused vehicle volume \\ &= \left\{ \sum_{c\in C}\sum_{r\in R}(B_{cr}^{vol}UT_{cr}^{vol}) + \sum_{s\in S}\sum_{r\in R}(B_{sr}^{vol}UT_{sr}^{vol}) + \sum_{s\in S}\sum_{c\in C}(B_{sc}^{vol}UT_{sc}^{vol}) \right. \end{aligned} \tag{37}$$

Eq. (37) indicates that the penalty cost incurred can be integrated with the objective function (1), which now comprises four terms – inventory holding costs, transportation costs, penalty costs for unmet demand, and penalty costs for unused vehicle volume.

Proposition 4.5. (.) *The relationship between shipment route and the total amount of SKUs transported should be considered while ensuring that the shipment of SKUs will not happen if the remaining time within the planning horizon is less than the shipment time.*

Proof: When the shipment route is closed between producer s and hub c, producer s and customer zone r, and hub c and customer zone r, then $X_{tsc}, X_{tsr}, X_{tcr} = 0$, and in such a scenario, decision variables $TQ_{ptcrf}, TQ_{ptscf}, TQ_{ptsrf}$ takes a value zero or no SKUs are shipped on the transportation links. Furthermore, when the shipment route is open or, $X_{tsc}, X_{tsr}, X_{tcr} = 1$, and if the remaining time $(T - t)$ available within the planning horizon (T) is less than the shipment time required on a specific transportation route or, $ST_{sc}, ST_{sr}, ST_{cr} > (T - t)$, then decision variables $TQ_{ptcrf}, TQ_{ptscf}, TQ_{ptsrf}$ take the value zero, or, $TQ_{ptcrf}, TQ_{ptscf}, TQ_{ptsrf} = 0$. This decision is mathematically illustrated in equations (38), (39) and (40) which help the mathematical model to ensure that the shipment of SKUs does not take place if the vehicle is scheduled to reach the destination after the ending of the planning horizon.

$$TQ_{ptcrf} = \begin{cases} 0, X_{tcr} = 0 \\ 0, X_{tcr} = 1, t > (T - ST_{cr}) \end{cases} \forall p \in P, c \in C, r \in R, f \in F, t \in T \quad (38)$$
$$TQ_{ptcrf} \geq 0, X_{tcr} = 1, t \leq (T - ST_{cr})$$

$$TQ_{ptscf} = \begin{cases} 0, X_{tsc} = 0 \\ 0, X_{tsc} = 1, t > (T - ST_{sc}) \end{cases} \forall p \in P, s \in S, c \in C, f \in F, t \in T \quad (39)$$
$$TQ_{ptscf} \geq 0, X_{tsc} = 1, t \leq (T - ST_{sc})$$

$$TQ_{ptsrf} = \begin{cases} 0, X_{tsr} = 0 \\ 0, X_{tsr} = 1, t > (T - ST_{sr}) \end{cases} \forall p \in P, s \in S, r \in R, f \in F, t \in T \quad (40)$$
$$TQ_{ptsrf} \geq 0, X_{tsr} = 1, t \leq (T - ST_{sr})$$

However, if the shipment route is open or, $X_{tsc}, X_{tsr}, X_{tcr} = 1$, and the remaining time within the planning horizon is more than or equal to the required shipment time or, $ST_{sc}, ST_{sr}, ST_{cr} \leq (T - t)$, then the decision variables $TQ_{ptcrf}, TQ_{ptscf}, TQ_{ptsrf}$ can take a value greater than zero or, $TQ_{ptcrf}, TQ_{ptscf}, TQ_{ptsrf} \geq 0$. This condition is highlighted in equations (38), (39) and (40) which help the mathematical model in ensuring that the shipment of products will occur if the shipment time on a transportation route is less than the remaining time of the planning horizon.

5. Environmental considerations and fuel consumption estimation

The mathematical formulation presented above is further extended by addressing environmental aspects in terms of the fuel consumption of the vehicles used for shipment purposes. The fuel consumption rate ξ for a vehicle type can be computed using Eq. (41), while considering the distance D travelled by the vehicle at a constant speed ρ for a duration τ and carrying a load (or, weight) of W.

$$\xi = \phi_e \tau + \phi_s \rho^3 \tau + \phi_w D(\mu + W) \quad (41)$$

Eq. (41) depicts the analytical expression for fuel consumption, derived from Huang et al. (2017). Here, μ is the vehicle curb-weight and ϕ_e, ϕ_s and ϕ_w are the coefficients of the engine, speed and weight modules respectively. Propositions 5.1, 5.2 and 5.3 help to establish the analytical expression for fuel consumption estimation considering the decision variables of the proposed mathematical model given in section 4.

Proposition 5.1. (.) *Total fuel consumed on the transportation routes from producers to a hub $Fuel^{\xi^f_{tsc}}$, producers to customer zones $Fuel^{\xi^f_{tsr}}$ and hub to customer zones $Fuel^{\xi^f_{tcr}}$ depend on the decision variables of the mathematical model, such as the number of vehicle trips N_{tscf}, N_{tsrf} and N_{tcrf} respectively, and associated vehicle types deployed on the individual shipment links.*

Proof: Using Eq. (41), the fuel consumption rate from producers to a hub, producers to customer zones, and a hub to customer zones are obtained. Equations (42), (43) and (44) depict the fuel consumption rate of vehicle type f deployed on a transportation route in time period t for shipping SKU type p from producer s to hub c, producer s to customer zone r and hub c to customer zone r respectively.

$$\xi^f_{tsc} = X_{tsc}\left\{\phi_e \tau_{sc} + \phi_s \rho^3_{sc} \tau_{sc} + \phi_w D_{sc}\left(\mu + W^f_{tsc}\right)\right\} \forall s \in S, c \in C, f \in F, t \in T \quad (42)$$

$$\xi^f_{tsr} = X_{tsr}\left\{\phi_e \tau_{sr} + \phi_s \rho^3_{sr} \tau_{sr} + \phi_w D_{sr}\left(\mu + W^f_{tsr}\right)\right\} \forall s \in S, r \in R, f \in F, t \in T \quad (43)$$

$$\xi^f_{tcr} = X_{tcr}\left\{\phi_e \tau_{cr} + \phi_s \rho^3_{cr} \tau_{cr} + \phi_w D_{cr}\left(\mu + W^f_{tcr}\right)\right\} \forall c \in C, r \in R, f \in F, t \in T \quad (44)$$

here, ξ^f_{tsc}, ξ^f_{tsr} and ξ^f_{tcr} are the fuel consumption rates on shipping routes from producer s to hub c, producer s to customer zone r, and hub c to customer zone r respectively. Moreover, τ_{sc}, τ_{sr} and τ_{cr} are the travelling times from producer s to hub c, producer s to customer zone r, and hub c to customer zone r respectively, which can be expressed as the shipment time, or respectively, $\tau_{sc} = ST_{sc}$, $\tau_{sr} = ST_{sr}$ and $\tau_{cr} = ST_{cr}$. Furthermore, ρ_{sc}, ρ_{sr} and ρ_{cr} depict the speed of vehicle type f travelling from producer s to hub c, producer s to customer zone r, and hub c to customer zone r, respectively. ρ_{sc}, ρ_{sr} and ρ_{cr} can be further represented in the following way, $\rho_{sc} = \frac{D_{sc}}{ST_{sc}}$, $\rho_{sr} = \frac{D_{sr}}{ST_{sr}}$ and $\rho_{cr} = \frac{D_{cr}}{ST_{cr}}$ where D_{sc}, D_{sr} and D_{cr} are the distances from producer s to hub c, producer s to customer zone r, and hub c to customer zone r, respectively. Therefore, equations (42), (43) and (44) can be further represented as,

$$\xi^f_{tsc} = X_{tsc}\left\{\phi_e ST_{sc} + \phi_s \left(\frac{D_{sc}}{ST_{sc}}\right)^3 ST_{sc} + \phi_w D_{sc}\left(\mu + W^f_{tsc}\right)\right\} \forall s \in S, c \in C, f \in F, t \in T \quad (45)$$

$$\xi^f_{tsr} = X_{tsr}\left\{\phi_e ST_{sr} + \phi_s \left(\frac{D_{sr}}{ST_{sr}}\right)^3 ST_{sr} + \phi_w D_{sr}\left(\mu + W^f_{tsr}\right)\right\} \forall s \in S, r \in R, f \in F, t \in T \quad (46)$$

$$\xi^f_{tcr} = X_{tcr}\left\{\phi_e ST_{cr} + \phi_s\left(\frac{D_{cr}}{ST_{cr}}\right)^3 ST_{cr} + \phi_w D_{cr}\left(\mu + W^f_{tcr}\right)\right\} \forall c \in C, r \in R, f \in F, t \in T \tag{47}$$

Consequently, the number of vehicle types f deployed on the shipment route from producer s to hub c, producer s to customer zone r, and hub c to customer zone r is given as N_{tscf}, N_{tsrf} and N_{tcrf}, respectively. Hence, the fuel consumed by the vehicles $Fuel^{\xi^f_{tsc}}$, $Fuel^{\xi^f_{tsr}}$ and $Fuel^{\xi^f_{tcr}}$ on the shipment links from producers to hub, producers to customer zones, and hub to customer zones, respectively are represented as:

$$\begin{aligned} Fuel^{\xi^f_{tsc}} &= \sum_{s\in S}\sum_{c\in C}\sum_{f\in F}\sum_{t\in T}\left(N_{tscf}\xi^f_{tsc}\right) \\ &= \sum_{s\in S}\sum_{c\in C}\sum_{f\in F}\sum_{t\in T} N_{tscf}\left[X_{tsc}\left\{\phi_e ST_{sc} + \phi_s\left(\frac{D_{sc}}{ST_{sc}}\right)^3 ST_{sc} + \phi_w D_{sc}\left(\mu + W^f_{tsc}\right)\right\}\right] \end{aligned} \tag{48}$$

$$\begin{aligned} Fuel^{\xi^f_{tsr}} &= \sum_{s\in S}\sum_{r\in R}\sum_{f\in F}\sum_{t\in T}\left(N_{tsrf}\xi^f_{tsr}\right) \\ &= \sum_{s\in S}\sum_{r\in R}\sum_{f\in F}\sum_{t\in T} N_{tsrf}\left[X_{tsr}\left\{\phi_e ST_{sr} + \phi_s\left(\frac{D_{sr}}{ST_{sr}}\right)^3 ST_{sr} + \phi_w D_{sr}\left(\mu + W^f_{tsr}\right)\right\}\right] \end{aligned} \tag{49}$$

$$\begin{aligned} Fuel^{\xi^f_{tcr}} &= \sum_{c\in C}\sum_{r\in R}\sum_{f\in F}\sum_{t\in T}\left(N_{tcrf}\xi^f_{tcr}\right) \\ &= \sum_{c\in C}\sum_{r\in R}\sum_{f\in F}\sum_{t\in T} N_{tcrf}\left[X_{tcr}\left\{\phi_e ST_{cr} + \phi_s\left(\frac{D_{cr}}{ST_{cr}}\right)^3 ST_{cr} + \phi_w D_{cr}\left(\mu + W^f_{tcr}\right)\right\}\right] \end{aligned} \tag{50}$$

Therefore, Eq. (48) depicts the dependency of the total fuel consumed on the shipment route from producers to hubs, $Fuel^{\xi^f_{tsc}}$ on the decision variable N_{tscf} of the mathematical model. Eq. (49) highlights the relationship between the fuel consumed on routes from producers to customers zones $Fuel^{\xi^f_{tsr}}$ with the decision variable N_{tsrf}. Furthermore, Eq. (50) depicts the inter-dependency of the decision variables N_{tcrf} of the mathematical model on the total fuel consumed $Fuel^{\xi^f_{tcr}}$ on shipment routes from a hub to customer zones. Hence, the aforementioned rationale completes the proof for proposition 5.1.

The fuel cost incurred from the overall fuel consumed considering all the transportation routes from producers to a hub, producers to customer zones, and hub to customer zones, can be represented as:

$$FuelCost = C^{Fuel}\left(Fuel^{\xi^f_{tsc}} + Fuel^{\xi^f_{tsr}} + Fuel^{\xi^f_{tcr}}\right) = \left\{C^{Fuel}\left[\begin{array}{c}\sum_{s\in S}\sum_{c\in C}\sum_{f\in F}\sum_{t\in T}\left(N_{tscf}\xi^f_{tsc}\right) + \sum_{s\in S}\sum_{r\in R}\sum_{f\in F}\sum_{t\in T}\left(N_{tsrf}\xi^f_{tsr}\right) \\ +\sum_{c\in C}\sum_{r\in R}\sum_{f\in F}\sum_{t\in T}\left(N_{tcrf}\xi^f_{tcr}\right)\end{array}\right]\right. \tag{51}$$

here, C^{Fuel} is the fuel price per litre of fuel used by the vehicle expressed in GBP per litre. Eq. (51) indicates that the fuel costs incurred can be integrated with the objective function (1), which comprises of five terms – inventory holding costs given in Eq. (2), transportation costs given in Eq. (3), penalty costs for unmet demand given in Eq. (4), penalty costs for unused vehicle volume given in Eq. (37), and fuel costs given in Eq. (51). Furthermore, Eq. (52) presented below depicts the carbon emissions constraint for the mathematical model.

$$E^{CO_2}\left[\sum_{s\in S}\sum_{c\in C}\sum_{f\in F}\sum_{t\in T}\left(N_{tscf}\xi^f_{tsc}\right) + \sum_{s\in S}\sum_{r\in R}\sum_{f\in F}\sum_{t\in T}\left(N_{tsrf}\xi^f_{tsr}\right) + \sum_{c\in C}\sum_{r\in R}\sum_{f\in F}\sum_{t\in T}\left(N_{tcrf}\xi^f_{tcr}\right)\right] \leq E^{Max} \tag{52}$$

Eq. (52) ensures that the overall carbon emissions emitted from the vehicle transportation should be less than or equal to the maximum allowable carbon emission restriction. E^{CO_2} depicts the carbon emissions coefficient and E^{Max} represents the maximum allowable carbon emissions limit. Eq. (52) considers fuel consumption on shipment routes from producers to the hub, producers to customer zones, and hub to customer zones and accordingly computes the carbon emissions incurred. The validation of the model is performed by considering a real-world case study of the supply chain logistics network of the 'Local Heroes' food hub, managed by FADNE.

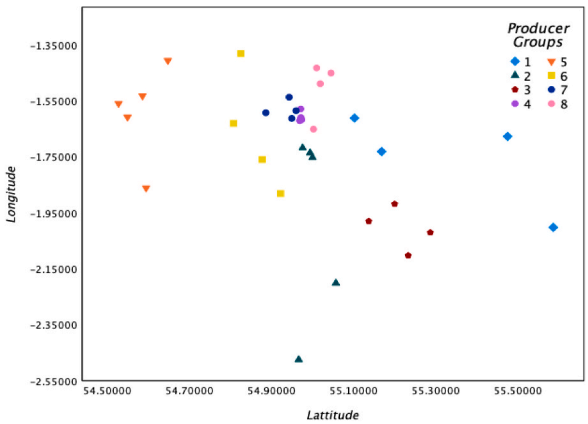
6. Computational experiments and results

This section presents the computational experiments performed for solving the proposed mathematical model. IBM ILOG CPLEX version 22.1.0 optimization studio software was employed having 8 GB RAM with Intel Core i7, 1.8 GHz processor and a 64-bit Windows 11 operating system. The real-world problem considered is that of FADNE's 'Local Heroes' initiative and accordingly, primary data relating to model parameters were collected from the company. To recap, the 'Local Heroes' food hub offered consumers the ability to order food and drink products from up to 150 different North-East producers, with FADNE fulfilling customer orders and arranging deliveries. FADNE's 'Local Heroes' suppliers can be grouped together in geographical clusters depending on their physical location, so that a single vehicle would be responsible to pick up products from producers within the same group and deliver to the hub. Within the current supply chain logistics network, if more nearby producers are willing to coordinate their logistics with each other (due to geographical location) then fewer producer groups are required. However, if fewer producers are willing to co-operate regarding logistics, then more producer groups need to be formed, resulting in more individual/ bespoke journeys. Accordingly, the number of producer groups considered for generating the problem instances for computational experiment purposes ranged from 6 to 24. Fig. 2a provides an example of 8 producer groups which is formed while considering the geographical location of 36 producers and their willingness to coordinate. Furthermore, Fig. 2b presents an example of 17 customer zones while considering the geographical location of the customers.

These producer groups deliver products to the Newcastle-based food hub using cardboard boxes or SKUs. These include SKUs such as meat boxes, wine and cheese boxes, fish boxes, and fruits and vegetable boxes. Furthermore, there can be different types of SKUs with varying weights and volumes and the current study considers four types of SKUs. The weight of SKUs varies from 2 to 5 kg and the volume of SKUs is 0.0425 cubic metres (length – 457 mm, width – 305 mm and height – 305 mm), based on standard industry packing boxes. From the hub, SKUs are shipped to the customer zones for meeting the demand of customers using different types of vehicles. A Ford transit van is used for shipment purposes and the volume of the vehicle is 5.95 cubic metres and weight (payload) of the vehicle is 2000 kg. Furthermore, other vehicle types for performing the experiments includes a DFSK EC35 electric van with a maximum cargo volume of 4.8 cubic metres and weight (payload) of the vehicle 1015 kg. Moreover, transportation cost for the Ford Transit van is GBP 0.3397 per kilometre (or, 54.68 pence per mile) and the transportation cost for the DFSK EC35 electric van is GBP 0.2127 per kilometre (or, 34.84 pence per mile). These data were extracted from https://www.fleetnews.co.uk/tools/van/running-costs/. This research considers 5 – 160 customer zones, where each customer zone aims to meet the demand of 100 – 2000 customers.

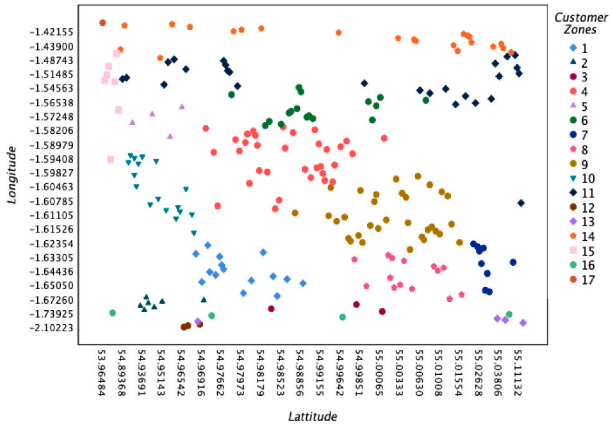
The problem instances were designed considering the logistics network of FADNE, thus considering 6 – 24 producer groups, 5 – 160 customer zones, 5 vehicle types, 4 SKU types, 5 – 10 weeks or time periods and 1 hub. Table A1 provides detailed information about the 12 problem instances ranging from medium to large size problem instances. Table A1 provides useful information pertaining to the number of variables and constraints, total costs, fuel costs, carbon emissions incurred, and total fuel consumed. Table A1 highlights that the problem instances 6, 8, 9, 11, and 12 result in more than 500,000 decision variables and, respectively, 500,000 constraints. Figs. 3a and 3b depict the number of SKUs shipped and fuel costs for the following shipment links: producer groups to hub, producer groups to customer zones, and hub to customer zones. With the increase in the problem size (number of variables and constraints) of the instances, the associated fuel costs and carbon emissions increase, as depicted in Table A1. This is mainly because with the increase in problem size, more SKUs need to be shipped to customer zones (refer to Fig. 3a). Furthermore, problem instances 11 and 12 highlight that although they have the same level of demand (refer to Fig. 3a), the fuel costs and carbon emissions incurred for problem instance 12 exceed those of problem instance 11 (refer to Table A1). This is because problem instance 11 has fewer producer groups when compared with problem instance 12. This result highlights the benefits of producers coordinating their logistics, so that fewer producer groups are required, which reduces fuel costs and carbon emissions.

Table A2 highlights useful information related to transport costs, fuel costs and carbon emissions on three shipment routes – producer groups to the hub, producer groups to customer zones, and the hub to customer zones. Table A3 presents information associated with the aggregate demand of the customer zones and aggregate demand to be passed through the hub. As the number of SKUs shipped to customers increases, the number of vehicle trips also increases, as apparent in Table A3. The number of vehicle trips



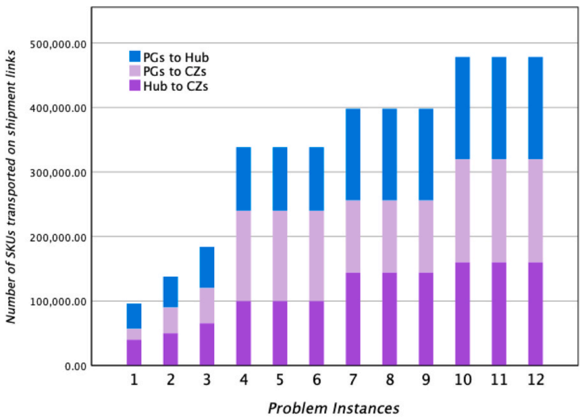
(a)

Fig. 2a. Example of 8 Producer Groups comprising of 36 producers.



(b)

Fig. 2b. Example of 17 Customer Zones having 218 customers.



(a)

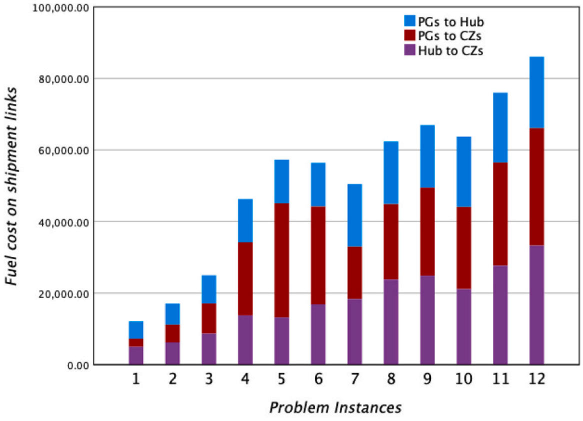
Fig. 3a. Number of SKUs shipped from PGs to Hub, PGs to CZs and Hub to CZs.

from producer groups to customer zones is substantially higher, as the demand to be met increases for a larger number of customer zones, which in the case of problem instances 11 and is around 160 customer zones. Moreover, with the increase in vehicle trips from producer groups to customer zones, and the hub to customer zones, the fuel costs (refer to Fig. 3b) and carbon emissions incurred (refer to Table A2) also increase.

Furthermore, Table A3 depicts the number of SKUs shipped, number of vehicle trips and unused vehicle volume on three transportation routes – producer groups to the hub, producer groups to customer zones, and the hub to customer zones. Within Table A3, if we compare the aggregate demand at customer zones with the total product shipped from the hub to customer zone and producers to customer zone, it can be depicted that 100 % of the demand is met for the problem instances. Results from Tables A1, A2 and A3 establish the robustness of the mathematical model in solving medium to large size problem instances. The next sub-section aims to explore the impact of considering the shipment link from producer groups to customer zones.

6.1. Direct shipment links from producer groups to customer zones

The 'Local Heroes' supply chain logistics network focused on shipping SKUs from producer groups to the hub and subsequently to customer zones. However, within the proposed mathematical model, we considered that the shipment of SKUs could also occur from producer groups to customer zones, so that producers play a greater role in order fulfilment. Hence, the next few experiments investigate the cost components such as total costs, transportation costs and fuel costs incurred when comparing two conditions – (i) no shipment from producer groups to customer zones and (ii) shipment available from producer groups to customer zones. Tables B1 and

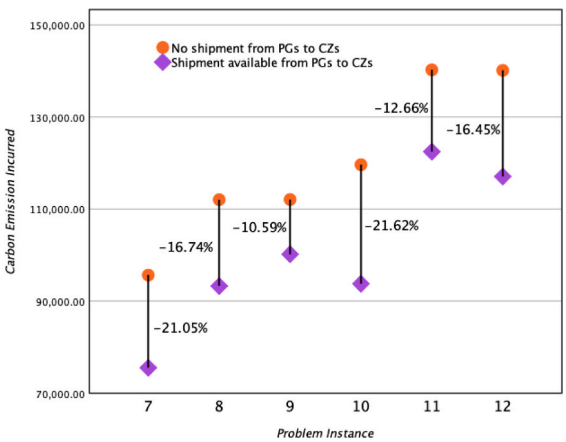


(b)

Fig. 3b. Fuel cost component on shipments links – PGs to Hub, PGs to CZs and Hub to CZs.

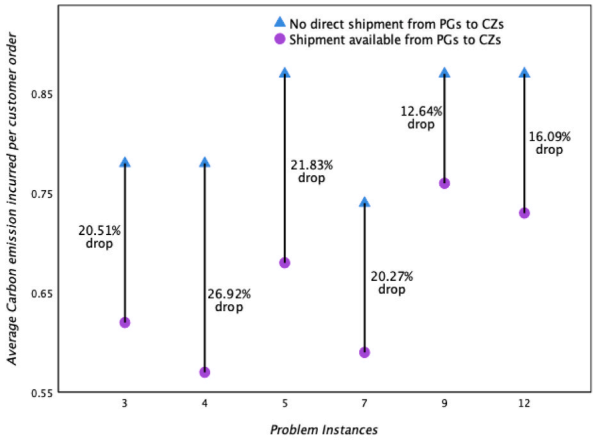
B2 highlight the comparison between two conditions. Due to space limitations, computational experiments are not conducted on all the problem instances and specific instances are chosen for performing the experiments. Within Table B1, results pertaining to instances 7, 8, 9, 10, 11 and 12 are presented and Table B2 highlights the results obtained after conducting experiments on instances 3, 4, 5, 7, 9 and 12. Table B1 indicates that total costs, fuel costs and carbon emissions incurred decrease substantially when shipments occur directly from producer groups to customer zones. This is because fewer vehicle trips are required (refer to Table B2) for meeting customer demand when direct shipment is available from producer groups to customer zones. Fig. 4a provides a visual illustration, highlighting the difference in carbon emissions for the two conditions. For problem instance 11, carbon emissions decrease by 12.66 % when a direct shipment link from producer groups to customer zones is available. Furthermore, for problem instance 12 the number of producer groups increases to 24 and subsequently carbon emissions decrease by 16.45 % when shipment is available from producer groups directly to customer zones. Fig. 4b presents the average carbon emissions incurred per customer in each period respectively, while considering two conditions – no shipment from producer groups to customer zones and shipment available from producer groups to customer zones. The analysis indicates that the average number of vehicle trips to customer zones decreases when transportation is allowed directly from producer groups to customer zones. Moreover, Table B2 highlights that the average total cost and average transportation cost incurred per customer in each period is also less when shipment is allowed from producer groups to customer zones. This indicates that the logistics network with the option of direct transportation from producer groups to customer zones is a more economical option as it helps to reduce average costs and is the more environmentally sustainable option as it mitigates carbon emissions.

Figs. 5a and 5b depict the average number of vehicle trips to customer zones and the average total cost per customer in each period, respectively. Insights from the figures highlight the decrease in average vehicle trips and average total cost per customer when a direct



(a)

Fig. 4a. Carbon emissions for scenarios – no shipment from PGs to CZs and shipment from PGs to CZs.



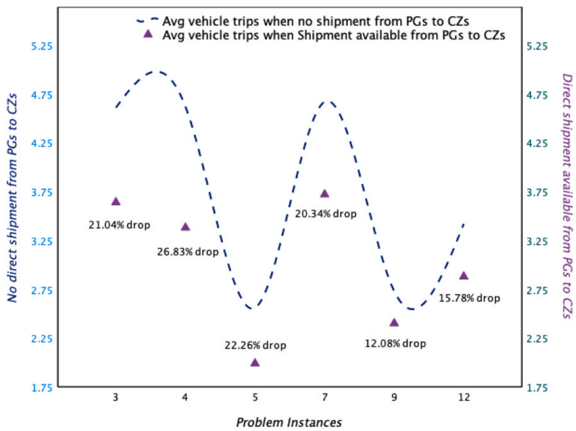
(b)

Fig. 4b. Average carbon emissions incurred per customer order for two conditions.

shipment link from producer groups to customer zones exists. Furthermore, the direct shipment option from producer groups to customer zones lowers average fuel costs, carbon emissions, and fuel consumed per customer in each period (refer to Table B2), thereby standing out as a more environmentally and economically sustainable approach. The next sub-section aims to study the effect of fuel price fluctuations on cost components.

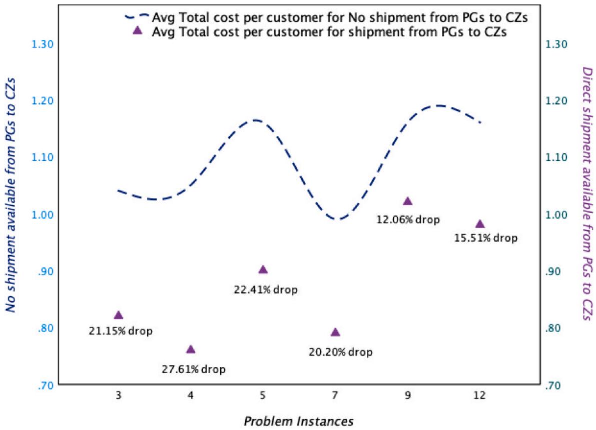
6.2. *Impact of variations in fuel prices*

International energy markets witnessed substantial volatility recently, with marked changes in prices (Tao et al., 2024). Analysing how changes in fuel costs affect logistics systems is thus a research priority (IMF, 2022). Fuel price experiments were conducted on problem instances 11 and 12 while considering four scenarios – the fuel price decreasing by 25 %, fuel price remains at 1.2 GBP per litre (the prevailing price during 2021), fuel price increasing by 25 %, and fuel price increasing by 50 %. Table C1 highlights the results obtained from the fuel price experiments, capturing the impact of changes in the fuel price on total costs and fuel costs. Table C1 depicts the individual fuel cost component for different shipment links – producer groups to hub, producer groups to customer zones, and hub to customer zones. The results indicate that with a drop in fuel price, the total cost and fuel costs decrease and as the fuel price increases, total costs and fuel costs increase. Examining a very substantial increase in fuel prices (up to 2.4 GBP per litre), indicates a substantial and unsurprising increase in fuel costs. Fig. 6a highlights the percentage change in fuel costs and total costs with the change in fuel prices for eight scenarios. Fig. 6b depicts the percentage change in fuel cost components for shipments links from producer groups to hub, producer groups to customer zones and hub to customer zones. Furthermore, the rise in the fuel price leads to an increase in the fuel cost from producer groups to customer zones significantly, given that the majority of the demand of the customer



(a)

Fig. 5a. Average vehicle trips to each customer zone for two conditions.



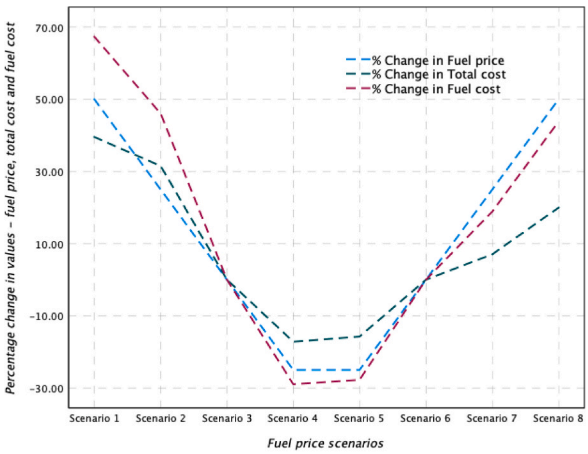
(b)

Fig. 5b. Average total cost per customer order for two conditions.

zones is met directly from producer groups. Insights from Fig. 6b highlights that the percentage change in fuel cost from producer groups to customer zones is more than 80 % for scenario 1 when the fuel price increases by 50 %. The next sub-section investigates the impact of demand variations on cost components and carbon emissions.

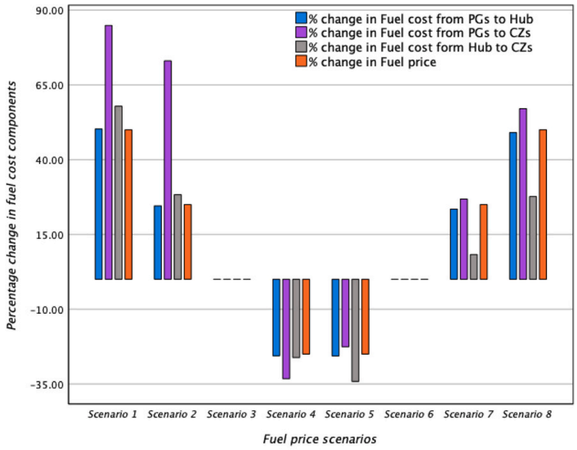
6.3. *The effects of variations in customer demand*

Analysing the resilience of food systems to external shocks has become increasingly important (Hobbs, 2020). Consequently, to validate the robustness of the proposed mathematical model in dealing with demand variations, experiments were conducted on the large problem instances 10 and 11, considering fluctuations in demand from the customer zones. The experiments are designed while considering the insights given in extant literature (Jabbarzadeh et al., 2016). Table D1 highlights the demand experiments on problem instance 11 which considers a possible demand increase from 20 % to 100 % and a decrease in demand from – 20 % to – 60 % when compared with the baseline scenario of instance 11. The results illustrate that with the increase or decrease in aggregate demand, the average values (total costs, fuel costs and carbon emissions) per vehicle trip increases or decreases respectively (Fig. 7a). This is mainly because with the increase in demand there is a gradual increase in average values (total costs, fuel costs, carbon emissions) per order fulfilled as vehicle trips increase. Furthermore, the demand experiments are conducted on problem instance 11 (160 customer zones) while considering that the number of customers increases within the customer zones, and that the number of customers decreases when demand decreases. Table D1 highlights that with an increase in aggregate demand from the customer zones, the average vehicle trips to each customer zone in each time period (or, week) increases as the number of customers within the customer zone increases.



(a)

Fig. 6a. Percentage change in fuel price, total cost and fuel cost for eight scenarios.

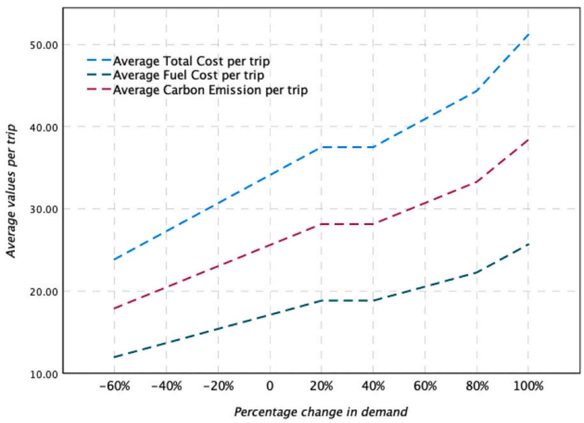


(b)

Fig. 6b. Comparison of the change in fuel price with the change in fuel cost on shipment links from PGs to Hub, PGs to CZs and Hub to CZs.

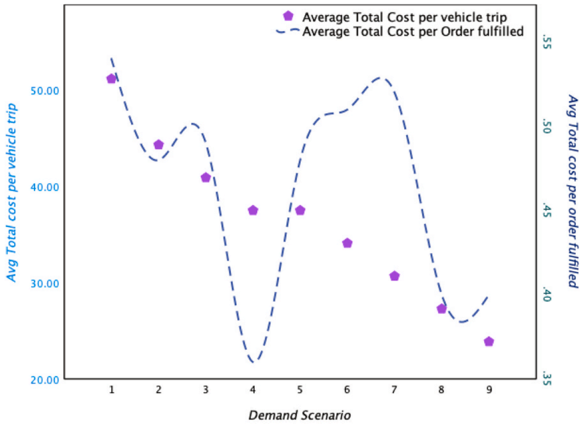
However, in certain cases the average values (total costs, fuel costs and carbon emissions) per order fulfilled decreases when there is an increase in demand, due to economies of scale which highlights that the logistics costs per order might drop under certain scenarios as demand rises. Fig. 7b depicts the comparison of the average total cost per trip with average total cost per order fulfilled. It indicates that as aggregate demand increases from 256,000 to 448,000 SKUs, the average total cost per trip increases from GBP 30.69 to GBP 37.51, although the average total cost per order fulfilled decreases from GBP 0.52 to GBP 0.36. This is due to economies of scale indicating that increases in the number of customers can sometimes help to reduce logistics costs. With the increase in demand from 256,000 to 448,000, the average fuel cost per order fulfilled decreases from GBP 0.26 to GBP 0.18 and the average carbon emissions incurred per order fulfilled decreases from 0.39 KG CO_2 to 0.27 KG CO_2. This highlights the impact of economies of scale in reducing the average fuel cost per order fulfilled and the average carbon emissions incurred per order fulfilled. Table D1 provides detailed information about the average total cost per order fulfilled, average fuel cost per order fulfilled, and average carbon emissions per order fulfilled. Fig. 7b provides evidential support to the insight relating to economics of scale, depicting that that with the increase in demand, the average total cost per vehicle trip increases, although average total costs per order fulfilled decreases in some but not all cases.

Table D2 highlights demand experiments conducted on problem instances 10 and 11, providing information about the average values per customer in each period associated with total costs, fuel costs, transport costs, carbon emissions, fuel consumption and fuel consumed. It is assumed that each customer laces, on average, an order of 2 products. Insights from the Table D2 illustrate that with the decrease in aggregate demand, the average number of vehicle trips per customer zone decreases and furthermore, average transport costs per customer also decreases. Fig. 8a further supports this insight by illustrating the positive correlation between the average number of vehicle trips per customer zone with the average transport cost per customer. Fig. 8b presents various demand scenarios and



(a)

Fig. 7a. Average values per trip with the change in demand for total cost, fuel cost, carbon emission.



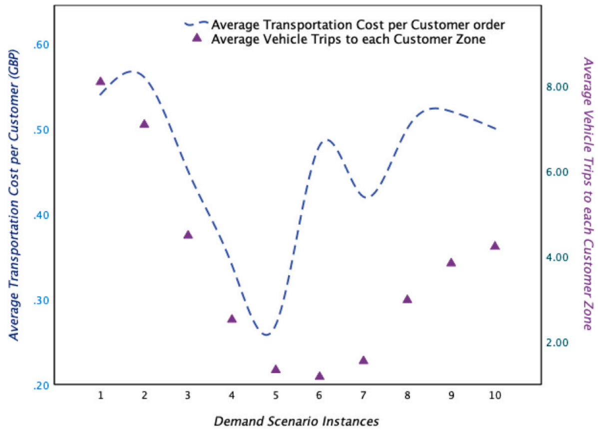
(b)

Fig. 7b. Relationship of average total cost per trip with the average total cost per order fulfilled.

details the average values per customer order for total costs, fuel costs and carbon emissions. As the density of customers in a customer zone increases, demand increases, and as a result the average values per customer for fuel costs, carbon emissions, and fuel consumed also increases. Furthermore, comparing scenarios 1 and 2 within Table D2 and Fig. 8b, indicates that as the aggregate demand increases from 480,000 to 640,000, the average total cost per customer order drops from GBP 1.12 to GBP 1.10 and average carbon emissions incurred per customer order decreases from 0.84 KG CO_2 to 0.82 KG CO_2. This is due to economies of scale, leading to a reduction in logistics cost in terms of the average cost associated with each customer order. Moreover, comparing scenarios 6 and 7 indicates that there is a drop in average total costs per customer order from GBP 0.96 to GBP 0.84 when demand increases from 80,000 to 160,000. Moreover, scenarios 9 and 10 also highlight that with an increase in aggregate demand from 480,000 to 640,000, there is a drop in average total costs per customer order from GBP 1.04 to GBP 1.01. The next sub-section explores the mandatory business restrictions which a company may adopt, in terms of shipping certain customer demands via the hub as there might be a requirement of packaging at the hub (consolidation of orders).

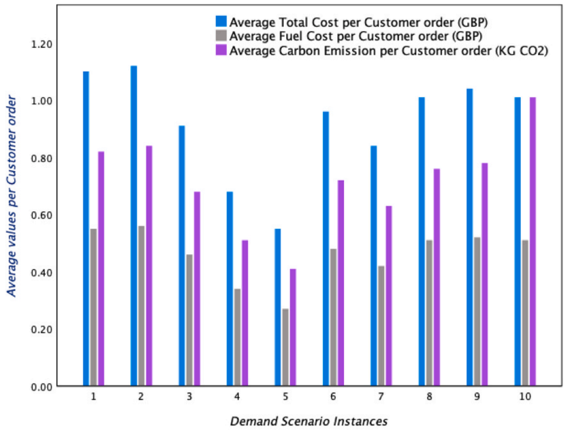
6.4. Impact of business restrictions on customer demand being met via the hub

Computational experiments are performed considering that certain SKUs need to be mandatorily sent to the customer zones via the hub and Table E1 highlights the results obtained from such experiments. Three scenarios are considered – (i) 25 % of SKU demand needs to be shipped to customer zones via the hub, (ii) 50 % of SKU demand needs to be shipped to customer zones via the hub, and (iii) 75 % of SKU demand needs to be shipped to customer zones via the hub. Furthermore, Figs. 9a and 9b highlight the average values per customer order in each period for total costs, fuel costs, carbon emissions incurred, and fuel consumption for the three scenarios. The figures highlight that when 50 % of the aggregate customer demand is sent via the hub then the average values per customer order for



(a)

Fig. 8a. Comparing average transport cost per customer with average vehicle trips for demand scenarios.



(b)

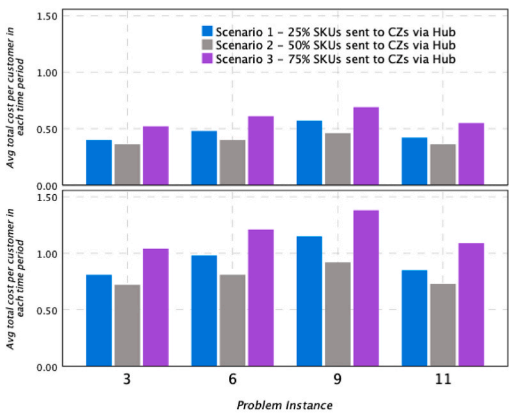
Fig. 8b. Total cost, fuel cost, and carbon emissions per customer order for demand scenarios.

total costs, fuel costs, carbon emissions and fuel consumption are lower compared to the other scenarios (e.g., shipping 25 % and 75 % of customer demand via the hub). This is mainly because the average vehicle trips made to each customer zone in each time period is lowest for scenario (ii) when compared with scenarios (i) and (iii). This also highlights that the total vehicle trips made for scenario (ii) (which is 50 % demand of the customer zones met via the hub), is lower than scenarios (i) and (iii).

Previous experiments related to "no availability of direct shipment from producer groups to customer zones", highlighted that, when all customer demand is shipped via the hub, it is less economically attractive compared against when direct shipment is available from producer groups to customer zones. Furthermore, results from Table E1 emphasize that if 50 % of the customer demand is shipped via the hub, then the total cost reduces substantially compared to when 75 % or 25 % of customer demand is shipped via the hub. So, this result reinforces that the availability of direct shipment from producer groups to customer zones is economically and environmentally beneficial, although keeping restrictions such as a high amount (75 %) or low amount (25 %) of customer demand to be met via the hub, might increase the overall cost components. Furthermore, insights from Table E1 also illustrate that when 50 % of customer demand is met via the hub, then the average unused vehicle volume is the lowest out of the three scenarios. This underlines the greater resource efficiency when 50 % of customer demand is met via the hub. The next sub-section studies the impact of shipment delays on cost components, carbon emissions, and vehicle trips.

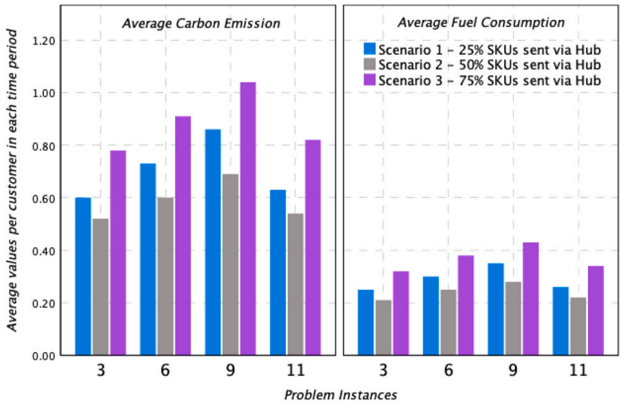
6.5. Impacts of shipment delays

Shipment delays are a major source of customer dissatisfaction and practitioners increasingly evaluate logistics systems in terms of the effects of shipment delays (Akturk et al., 2022). Table F1 presents the results for shipment delay scenarios, which investigate the impact of delays in the shipment of SKUs from the hub to customer zones and from producer groups to the hub. The analysis indicates



(a)

Fig. 9a. Average total costs and average fuel costs per customer when considering the three scenarios.

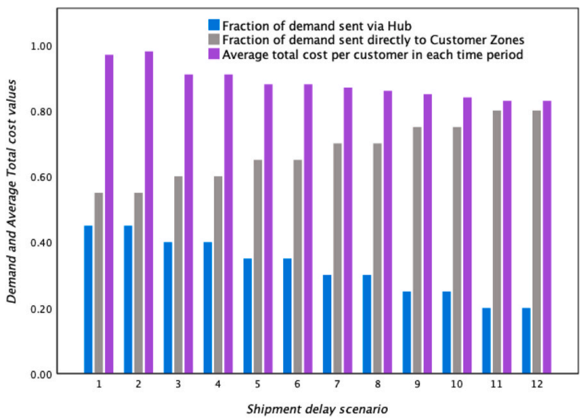


(b)

Fig. 9b. Average carbon emissions incurred and average fuel consumption per customer, considering the three scenarios.

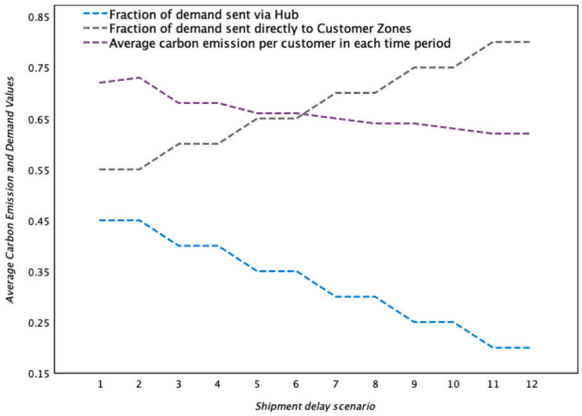
that the percentage of aggregate customer demand sent via the hub gradually decreases from 45 % (scenario 1) to 20 % (scenario 12). This is because of the delay in shipping SKUs either from the hub to customer zones or from producer groups to the hub. In both cases, there is a shipment delay either from the hub or from producer groups. In such a situation, it is imperative to meet the demand of customer zones even when there is a shipment delay and hence, there is a gradual increase in the percentage of SKUs shipped directly from producer groups to customer zones. This also emphasizes the flexibility and resilience of the mathematical model in dealing with shipment delays. Furthermore, Table F1 depicts the percentage of aggregate demand sent directly to customer zones steadily increases from 55 % within scenario 1 to 80 % within scenario 12.

Fig. 10aa and b provides information about the fraction of customer demand sent via the hub and fraction of demand shipped directly to customer zones. Fig. 10a indicates that as the fraction of aggregate demand shipped directly to customer zones increases steadily from scenarios 1 to 12, there is a gradual decrease in the average total cost incurred per customer order from scenarios 1 to 12. Similarly, Fig. 10b highlights that with the increase in the fraction of aggregate demand shipped directly to customer zones, there is a decrease in the average carbon emissions incurred per customer order. Table F1 indicates that as the fraction of aggregate demand sent to customer zones via the hub decreases, the average number of vehicle trips per customer zone also decreases. This is because as the fraction of aggregate customer demand met directly from producer groups increases, most SKUs are directly shipped to the customer zones and as a result the total number of vehicle trips decreases. When there is a shipment delay from the hub to customer zones or from producer groups to the hub, then most of the demand is fulfilled directly from the producer groups to the customer zones, decreasing the total number of vehicle trips. The next sub-section examines the effect of shipment link disruptions on vehicle trips and unused vehicle volume.



(a)

Fig. 10a. Average total cost incurred per customer order and fraction of aggregate demand met via the hub and directly from producer groups during shipment delay scenarios.



(b)

Fig. 10b. Average carbon emission incurred per customer for shipment delay scenarios and its relationship with the fraction of aggregate demand met via the hub and directly from producer groups.

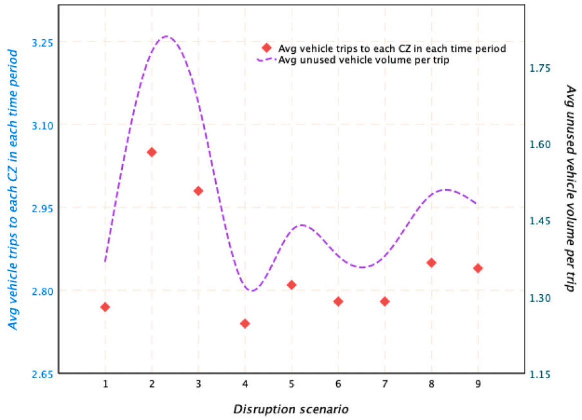
6.6. Impacts of disruption on shipment links

Recent external shocks to food systems (e.g., Covid-19, war in Ukraine) highlight the importance to practitioners and policymakers of considering the effects of disruptions on food logistics (Burgos and Ivanov, 2021; Foroozesh et al., 2022; UK Government, 2022). Consequently, we performed computational experiments to study the impact of disruption on various shipment links from producer groups to the hub, and producer groups to customer zones. Table G1 presents the results obtained after conducting experiments on problem instance 11 while considering nine scenarios with scenario 1 being the baseline scenario of having no disruption on shipment links and the next eight scenarios involve increasing disruption on shipment links. The percentage of shipment links facing disruptions is around 8.3 % for scenario 2 and this increases to two-thirds for scenario 9. As the percentage of shipment links facing disruption increases, the number of links available for product transportation decreases rapidly (Table G1). The analysis indicates that with the decrease in the fraction of shipment links available from producer groups to the hub, the average number of vehicle trips per available shipment link from producer groups to the hub increases. This is because as a substantial number of shipment links are disrupted, the available shipment links need to be used for more vehicle trips to meet the requirements of the hub. Comparing scenarios 6, 7, 8 and 9, it is apparent that as the percentage of shipment links facing disruption increases, the average fuel cost per customer order increases from GBP 0.47 to GBP 0.48. This indicates that while disruption increases average fuel costs per order, the effect is relatively modest. The latter indicates the flexibility of the mathematical model in adjusting to various disruption scenarios while obtaining reasonable fuel cost solutions.

Fig. 11a depicts that for the initial disruption scenarios, the average number of vehicle trips to each customer zone increases and then decreases rapidly for the subsequent scenarios. This is because for the initial disruption scenario, there is an increase in the average number of vehicle trips in each period from producer groups to customer zones, when compared against scenario 1 (baseline scenario). The increase in the average number of vehicle trips to each customer zone leads to a rise in average unused vehicle volume per trip, as depicted in Fig. 11a. Although, as the fraction of shipment links facing disruption increases substantially from scenarios 4 to 9 (Fig. 11b), the average unused vehicle volume per trip and the average number of vehicle trips to each customer zone does not increase steadily (Fig. 11a). The above analysis highlights the robustness of the proposed mathematical model in dealing with various disruption scenarios yet meeting customer demand while not substantially increasing the average number of vehicle trips per customer zone and average unused vehicle volume per trip. Fig. 11b depicts the average carbon emissions incurred per customer order for various disruption scenarios. As the shipment links facing disruption increases, the carbon emissions incurred per customer order increases substantially (Fig. 11b). This is because the average number of vehicle trips to each customer zone increases when there is a lesser number of shipment links available for product transportation. This is important from a policy perspective, indicating the relationship between logistics disruptions and increases in carbon emissions per customer order.

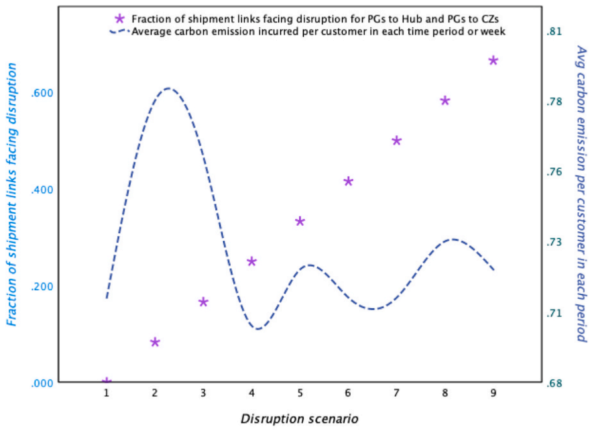
6.7. Deploying electric vehicles

Electric vehicles offer the opportunity to decarbonise logistics, but their adoption depends in part on cost considerations (Osieczko et al., 2021). To assess the impact of deploying electric vehicles on the shipment links, we performed various computational experiments on problem instance 11, while considering different scenarios as given in Tables H1 and H2. Scenario 1 is referred to as the baseline scenario given that the shipment links (from producer groups to hub, producer groups to customer zones, and hub to customer zones) considers only fuel-based vehicles for product transportation. Furthermore, scenarios 2 to 8 consider the deployment of electric vehicles on shipment links, where Table H2 highlights the percentage of shipment links possessing electric vehicles. Table H1 depicts



(a)

Fig. 11a. Comparison of the average number of vehicle trips to each customer zone with the average unused vehicle volume per trip.



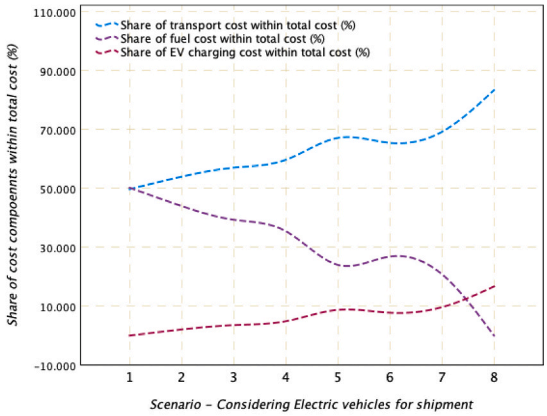
(b)

Fig. 11b. Comparison of average carbon emissions incurred per customer order with the fraction of shipment links facing disruption.

the detailed results pertaining to cost components such as total costs, transport costs, fuel costs, and electric vehicle charging costs obtained after performing the experiments on the eight scenarios.

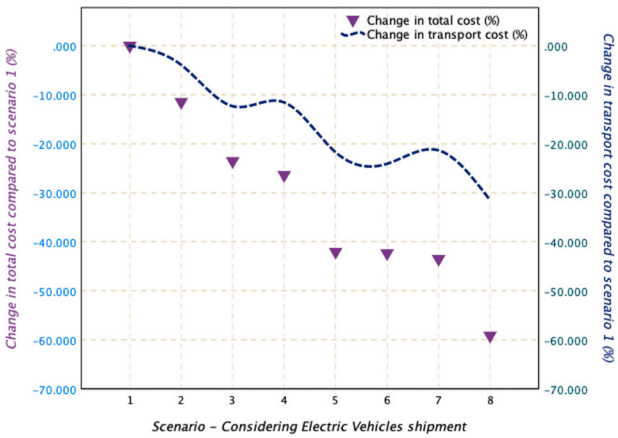
Comparing scenarios 1 to 8, indicates that the share of transport costs within total costs increases gradually, whereas the share of fuel costs within total costs decreases steadily (Fig. 12a). For the baseline scenario (or scenario 1) no electric vehicles are deployed on shipment links, hence the share of fuel costs and transport costs within the total cost component is 50.19 % and 49.70 % respectively. As the share of fuel costs within total costs is quite high, the analysis underlines the desirability of pursuing strategies which lower fuel costs. Hence, scenarios 2 to 7 consider the deployment of electric vehicles alongside fuel-based vehicles and scenario 8 envisages that 100 % of the shipment links use electric vehicles. The fuel cost is zero for scenario 8 and the share of transport costs and electric vehicles charging costs within total cost increases to 83.33 % and 16.66 % respectively. Furthermore, Fig. 12b highlights the percentage change in total costs and transport costs when compared against the baseline scenario. Insights obtained from Fig. 12b imply that when 100 % of the shipment links use electric vehicles, transport costs decrease by 31.50 % and total costs decrease by 59.14 %. In such a scenario, there is a rise in electric vehicle charging costs (Fig. 13a), although the share of electric vehicle charging costs within the total cost is much less, compared with the share of transport costs within total costs (Fig. 12a and Fig. 13a).

Fig. 13b highlights the gradual decrease of carbon emissions through scenarios 1 to 8 and this is due to the deployment of electric vehicles on shipment links. Carbon emissions incurred decrease around 70 % for scenarios 4 to 7 (Fig. 13b). For scenarios 4 to 7, the average number of electric vehicle trips increases substantially leading to a decrease in carbon emissions when compared with the baseline scenario, and this in turn also decreases the average carbon emissions incurred per customer order in each period (Fig. 14b). As there are more electric vehicle trips carried out under scenarios 4 to 8 (Fig. 14a), the average electric vehicle charging costs incurred per customer order in each period also increases (Fig. 14b), although it is modest when compared against the average transport costs



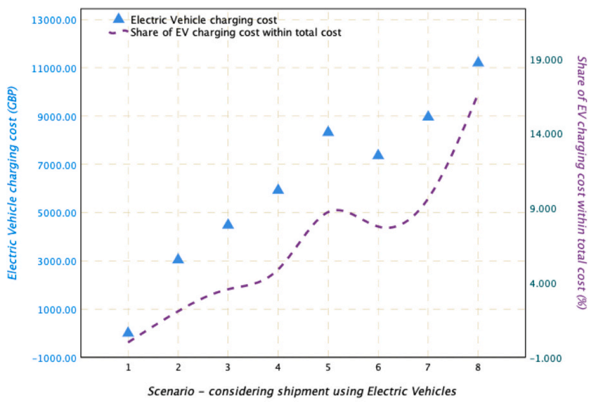
(a)

Fig. 12a. Percentage share of various cost components within total cost.



(b)

Fig. 12b. Percentage change in total costs and transport costs for various scenarios when compared with baseline scenario.



(a)

Fig. 13a. Comparison of EV charging costs with the share of EV charging costs within total costs.

incurred per customer order (Table H1).

7. Discussion

7.1. Comparative analysis

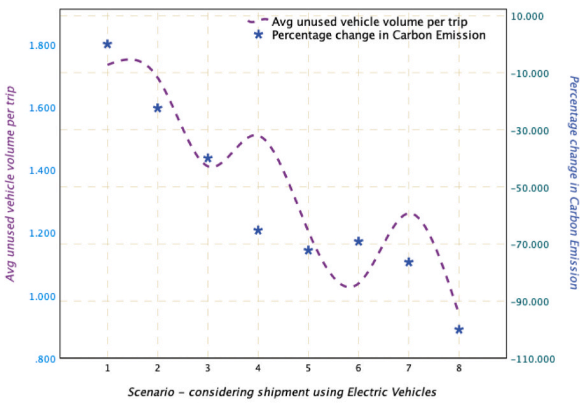
This section reviews the paper's findings against previous studies, identifying novel insights. Many studies address vehicle routing problems, typically focusing on one-to-many (i.e. one supplier distributes to many customers), as well as many-to-one networks (De and Giri, 2020). Some of these studies estimate the benefits that could accrue from suppliers co-operating in distribution, through shared use of vehicles and combining trips (Cheng et al., 2016). For instance, the optimization model of Li et al. (2020) for urban logistics distribution routing problems suggests adopting distribution sharing could reduce costs by 9.4 per cent and carbon emissions by 40.9 per cent. However, as far as we are aware, no previous study considers a producer-to-hub-to-customer transport problem and the benefits that may ensue from direct shipments from producers to customer zones. Importantly, we demonstrate the rationale for a hub (it is never better to have all orders fulfilled through direct shipments from producers to customer zones) but fulfilling some orders through direct shipments can contribute to the twin objectives of cutting financial costs and reducing carbon emissions (Fig. 4b). This is important, as many other solutions presented in the literature to the vehicle routing problem involve a trade-off between financial costs and carbon emissions, or reductions in the quality of customer service (Li et al., 2018).

Several studies investigate the sensitivity of logistics costs to changes in fuel prices (Xiao et al., 2012). Previous research demonstrate that increases in unit fuel costs lead to rises in transport costs but that the effect is rarely proportional, due to constraints relating to vehicle capacities, as well as changes in utilisation rates (Cheng et al., 2016). This study generates a similar conclusion – for example, Table C1 problem instance 11 details how a 25 % increase in fuel prices (assuming no electric vehicles deployed), leads to a 31.51 % increase in total costs. As with changes in total costs, the relationship between changes in fuel prices and carbon emissions is also non-linear.

Variations in customer demand pose a major challenge to the design of distribution systems and solving vehicle routing problems (Sert et al., 2020). In this study, we investigate how fluctuations in demand affect total costs and carbon emissions per vehicle trip. Generally, expansion in demand results in a gradual increase in average costs and emissions per order fulfilled as vehicle trips increase. However, in some cases average costs and carbon emissions per order fulfilled fall due to economies of scale, which stem from an increase in the density of customers in a customer zone (Table D2 and Fig. 8b). The latter finding mirrors work on optimizing on-demand food deliveries, where the density of orders in a driver delivery area is a critical determinant of costs (Ulmer et al., 2022; Yang et al., 2024).

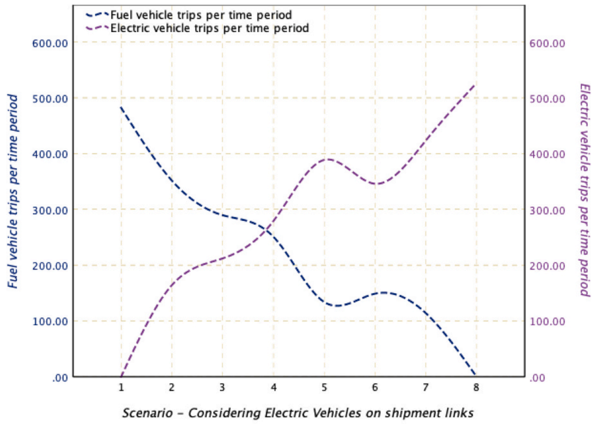
When solving vehicle routing problems it is important to consider the impact of shipment delays and disruption to shipment links (De et al., 2022). Often disruption to shipment links leads to substantial increases in costs. For example, in their analysis for grain transportation, Maiyar and Thakkar (2019a) estimate that the closure of one hub in the network results in supply network costs increasing 4.6 times and greenhouse gas emissions rising by 7 %. In our analysis, disruption to shipment links and shipment delays do not lead to such specular increases in costs and the reasons for this, are informative for the literature. Firstly, the results presented in Table F1 indicate that when shipment delays increase, the percentage of demand fulfilled via the hub gradually decreases, with direct shipment from producers to customer zones acting as a buffer, usefully dampening the effects of disruption on total costs. Similarly, Table G1 generates insights for the literature regarding how disruption to shipment links can lead to substantial increases in the carbon emissions incurred per customer order (Fig. 11b). When considering ways to reduce the carbon emissions of logistics, minimising disruption is often overlooked (Ning et al., 2020).

The literature indicates a substantial interest in the impacts on logistics costs and carbon emissions of the use of electric vehicles.



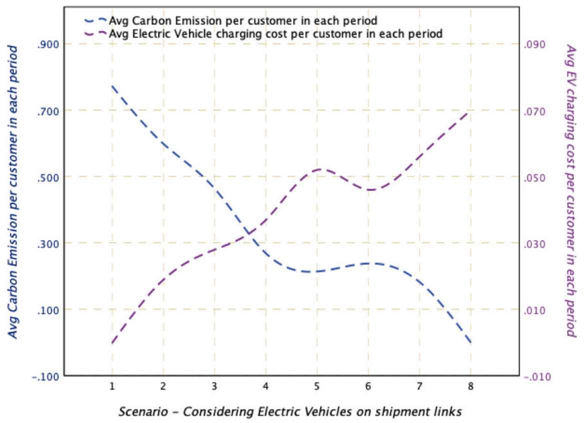
(b)

Fig. 13b. Comparison of avg. unused vehicle volume per trip with percentage change in carbon emissions.



(a)

Fig. 14a. Comparison of average fuel vehicle trips with average electric vehicle trips.



(b)

Fig. 14b. Comparison of average carbon emissions incurred per customer order and average electric vehicle charging costs per customer order.

For instance, Zhu et al. (2020) address the vehicle routing problem for a fleet of electric vehicles. However, as noted by Rajabzadeh and Mousavi (2023), such studies often overlook enhancing vehicle utilisation. Moreover, most logistics providers currently using fuel-based vehicles will not switch entirely to electric vehicles overnight, warranting a consideration of phased increases in electric vehicle deployment. Our analysis indicates that such a phased deployment leads to progressive reductions in total costs, as rises in electric charging costs never exceed savings in fuel costs (see Fig. 12a and Fig. 13a). Considering the magnitude of savings, the estimated reductions in operational costs are consistent with those presented by Melo et al. (2014b) for city logistics operations. Echoing the latter and other studies (Melo et al., 2014a), carbon emissions also decline substantially as electric vehicles replace fuel based ones.

7.2. Managerial insights and contribution to theory

Computational experiments provide insights for managers and policymakers seeking to reduce the financial costs and carbon emissions of food distribution. Specifically, we study the effect of considering direct shipment links between producer groups and customer zones. This highlights that overall carbon emissions and average carbon emissions incurred per customer order decrease by 12 – 16 % for large problem instances when allowing direct shipment links from producer groups to customer zones. Moreover, the study depicts that there is a decrease of 12 – 15 % for the average number of vehicle trips to each customer zone and the average total cost incurred per customer order. For logistics managers, facing cost and environmental pressures, the analysis highlights that the direct shipment option from producer groups to customer zones is cost-efficient given that it reduces the average total cost per customer order. Furthermore, logistics managers can also consider the direct shipment option as advantageous environmentally given that it lowers total carbon emissions and average carbon emissions incurred per customer order. Logistics managers can thus consider direct shipment as a strategy to improve the operational efficiency of the distribution network.

The analysis, however, underlines the rationale for food distribution hubs. It was observed that if 50 % of customer demand is shipped via hub, then it reduces the average total costs per customer order substantially compared to when 75 % or 25 % of customer demand is shipped via hub. For problem instance 11 within Table E1, the average total costs per customer order is 14.1 % less and average carbon emissions incurred per customer order 14.3 % less when comparing the scenario of 50 % customer demand shipped via hub with the scenario of 25 % of customer demand shipped via hub. Moreover, for problem instance 11 (refer to Table E1), it is observed that the average total cost per customer order is 33 % lower and average carbon emissions incurred per customer order is 34.1 % lower when 50 % of the customer demand is shipped via the hub compared to the scenario of 75 % of the customer demand being shipped via the hub. These results indicate that while the direct shipment option from producer groups to customer zones is an economical and environmentally sustainable option, hubs still perform a valuable consolidation function. Moreover, when 50 % of the customer demand is met via the hub, then the average unused vehicle volume per trip and average number of vehicle trips to customer zones are fewer compared with the other scenarios, therefore highlighting better vehicle utilization, and enhanced operational efficiency for the vehicles deployed.

The resilience of food logistics networks to instability in customer demand and rises in fuel costs are important concerns for policymakers and industry managers (UK Government, 2022). A demand variation experiment provides valuable insights for supply chain managers and policy makers in terms of highlighting the benefits of economies of scale as witnessed in certain cases, such as comparing scenarios 7 and 4 in Table D1 (Appendix D). The analysis reveals that a 75 % increase in customer demand helps to reduce the average cost components (total costs and fuel costs) per customer order by 30.8 %. Hence, supply chain managers should be mindful of the fact that an increase in customer demand can lead to a possibility of increasing the average profit per customer order given that there is a chance of reducing the average cost component per customer order. A major difficulty for short food supply chains is reaching a level of sales where economies of scale can be realised (Rucabado-Palomar and Cuéllar-Padilla, 2020).

Useful insights are obtained from the fuel price experiments in terms of understanding the impact of a 50 % rise in fuel prices. This indicates that when direct shipment links between producer groups and customer zones are available, in such cases the fuel cost from producer groups to customer zones increases by 80 %. This indicates that increases in fuel costs can have disproportionate effects. Furthermore, it is also observed that the share of fuel cost components within total costs is much higher (around 50.2 %), when only fuel-based vehicles are adopted for product shipment. Hence, it is important for logistics managers to consider the option of shifting towards electric vehicles to reduce costs (Schiffer et al., 2021). The impact of electric vehicle adoption is studied to understand its effect on carbon emissions, fuel costs, and total costs. We consider a phased approach of deploying electric vehicles on different shipment links. It is observed that when electric vehicles account for 100 % of the shipments within the producer groups – hub – customer zones distribution network, transport costs and total costs decrease by 31.5 % and 59.1 % respectively, compared to the baseline scenario of using only fuel-based vehicles. For the phased approach, when electric vehicles are adopted on shipment links from producer groups to the hub (e.g., upstream logistics network) it can be observed that the average carbon emissions per customer order decreases by 22.4 % and average total costs per customer order decrease by 11.5 % when compared with the baseline scenario. Most customers live in urban areas, where electric vehicles appear particularly suitable (Jones et al., 2020). Specifically, when adopting electric vehicles on the shipment links from producer groups to customer zones and the hub to customer zones, the average total cost per customer order and average carbon emissions incurred per customer order decrease by 43.5 % and 76.4 % respectively. This evidence highlights the importance of considering the replacement of fuel-based with electric vehicles for supply chain and logistics managers to.

The resilience of food logistics networks to delays is also an important concern for policymakers, researchers, and practitioners (Akturk et al., 2022; Burgos and Ivanov, 2021). Consequently, we study the impact of shipment delays on transportation links. This analysis identifies that that the percentage of total customer demand sent directly from producer groups to customer zones increases drastically from 55 % to 80 %, when there are delays on shipment links from producer groups to the hub or from the hub to customer zones. The results highlight the model's resilience and flexibility in providing alternate options for product transportation to handle substantial shipment delays. When we compare the scenario of a 1-week delay in shipping products from producer groups to the hub with the scenario of 6 weeks delay in shipping products from producer groups to the hub, we see the average total cost incurred per customer order decreases by 14.4 %, average fuel cost per customer order decrease by 12.5 %, and average carbon emissions per customer order decrease by 13.9 %. The reductions were possible given that the model provides the options of shipping most of the customer demand directly from producer groups to customer zones, hence there is a decrease in the number of vehicle trips by 14.0 %. This insight highlights the operational efficiency achieved by the model even when dealing with substantial shipment delays.

Finally, we studied the impact of disruption. The model addresses the scenario of disruption to two-thirds of shipment links and yet manages to meet the customer demand by marginally increasing average fuel costs per customer order by 2.1 % and average carbon emissions incurred per customer order by 1.4 %. These results highlight the resilience of the proposed model in dealing with substantial disruptions on shipment links, identifying alternate options for product shipment. Flexibility in allowing direct shipments from producers to customer zones is thus one means to reduce the economic and environmental costs of supply chain disruptions.

We conducted computational experiments on real-world and large-sized problem instances for validating the proposed mathematical model, collecting primary data from Food and Drink North East (FADNE). The results highlight the benefits of adopting direct shipment links from producer groups to customer zones. Analysis of customer demand variability, shipment delays, and disruption on transportation links provide useful insights regarding the proposed model's adaptability and resilience in dealing with highly unpredictable and extreme scenarios. Additionally, it would be valuable to assess the model's applicability in different geographical contexts, such as more densely populated regions or, at the other end of the spectrum, very remote, sparsely populated areas, where transportation challenges and consumer distribution may vary. Adapting the model to regions with different population densities would provide further insights into its flexibility and potential to optimize distribution in diverse environments. Case studies in urban or *peri*-urban settings could offer practical examples of how the model scales or how its assumptions hold up in real-world applications, especially in densely populated areas where traffic congestion is more pronounced.

Lastly, incorporating the possibility of multiple hubs within the model would better reflect the current trends in logistics, where distributed supply chain strategies are becoming more common (De et al., 2022; De et al., 2024). This could be especially relevant in e-commerce and urban logistics, where multiple hubs allow for faster and more efficient last-mile delivery. Additionally, we recognize the importance of addressing the impact of digital technology on food distribution and consumer practices, particularly in the context of food e-commerce (Mwangakala et al., 2024). Digital platforms have indeed transformed consumer behavior and the last-mile delivery process (Basu et al., 2024). By incorporating insights from digital logistics and e-commerce innovations (e.g., the use of Artificial Intelligence in demand forecasting, automation in warehousing, and supply chain transparency), we can better highlight the synergies between traditional food distribution models and digital technologies (Dora et al., 2022).

8. Conclusion

The paper investigates food distribution networks, comprising producer groups, a hub and customer zones, and develops a novel mathematical model with the aim of optimising efficiency in operational logistics while considering economic (costs) and environmental aspects (carbon emissions). The model seeks to lower the cost components related to inventory holding, transportation and fuel consumption and mitigate carbon emissions, unused vehicle volume, number of vehicle trips, while considering variations in transportation time and shipment delays. Propositions address storage capacity restrictions at the hub and customer zones while considering variations in shipment time on the distribution network. Inventory balancing restrictions at the hub and customer zones are presented, while considering variations in vehicle travel times between different actors in the network. Furthermore, fuel consumption is addressed with the assistance of a proposition highlighting the dependency of fuel consumption on vehicle trips and types of vehicles deployed. The mathematical formulation takes into consideration all the propositions in the form of constraints.

The model develops practical insights for food hub operators and their suppliers (e.g. small-scale food producers), as well as third party logistics providers to short food supply chain operators. The analysis is also pertinent to local and regional economic development bodies, which often seek to promote short food supply chains to improve returns to small-scale food producers and benefit rural communities. The model is tested on real-world datasets obtained from Food and Drink North East (FADNE), which operated a food distribution hub in the North-East of England. Furthermore, the proposed model is validated on 12 real-world problem instances while considering FADNE's distribution network. The theoretical model and real-world data provide the basis for important managerial insights. This research demonstrates that cooperation among small-scale producers helps reduce carbon emissions and fuel costs and shows that horizontal collaboration can improve the efficiency of their supply chain network. Experiments show that producer cooperation concerning deliveries reduces logistics costs and carbon emissions by 12–16 %. Switching to electric vehicles can further decrease transport costs for logistics providers by one-third and cut carbon emissions by up to 70 %. The study also evaluates the impact of shipment delays for logistics operators and highlights the mathematical model's resilience in handling such uncertainties. However, the proposed mathematical model can be further extended by considering other real-world instances, for example far more densely and sparsely populated regions. The model could also incorporate the possibility of opening and operating multiple hubs. Finally, the analysis could be extended by considering employment levels and job creation within such a distribution network.

CRediT authorship contribution statement

Arijit De: Writing – original draft, Visualization, Software, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Barbara Tocco:** Writing – review & editing, Writing – original draft, Project administration, Data curation, Conceptualization. **Matthew Gorton:** Writing – review & editing, Writing – original draft, Funding acquisition, Conceptualization.

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.

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Appendix A:. Detailed information about the problem instances solved as part of the computational experiments

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Table A1
Information about problem instances, complexities, cost components and total carbon emission incurred.

	Problem Instance Information						Number of Customers for each CZ	Problem Instance Complexity		Total Cost (GBP)	Total Fuel Cost (GBP)	Total Carbon Emission (KG CO_2)	Total Fuel Consumed (Litre)
	Producer Group (PG)	Hub	Customer Zone (CZ)	Vehicle Type	SKU Type	Time Period/ Weeks		Number of Variables	Number of Constraints				
Problem Instance 1	6	1	5	5	4	5	1200	6594	8066	24,182.44	12,138	18,146	7586.3
Problem Instance 2	12	1	5	5	4	5	2000	11,130	13,922	34,060.79	17,086	25,543	10,679
Problem Instance 3	12	1	40	5	4	5	300	76,509	92,986	49,840.50	25,021	37,393	15,622
Problem Instance 4	12	1	80	5	4	5	300	151,230	183,347	92,219.91	46,292	69,207	28,933
Problem Instance 5	12	1	160	5	4	5	150	300,670	364,067	114,149.43	57,301	85,664	35,813
Problem Instance 6	24	1	160	5	4	5	150	544,102	665,939	112,410.00	56,428	84,359	35,267
Problem Instance 7	12	1	80	5	4	8	200	241,065	292,403	100,643.85	50,521	75,529	31,576
Problem Instance 8	12	1	160	5	4	8	100	479,305	580,643	124,312.72	62,402	93,292	39,001
Problem Instance 9	24	1	160	5	4	8	100	867,637	1,062,479	133,452.86	66,991	100,150	41,869
Problem Instance 10	12	1	80	5	4	10	200	300,955	365,107	127,007.02	63,755	95,314	39,373
Problem Instance 11	12	1	160	5	4	10	100	598,395	725,027	151,434.49	76,013	113,640	47,508
Problem Instance 12	24	1	160	5	4	10	100	1,083,327	1,326,839	171,514.04	86,096	128,710	53,810

Table A2
Information about transport cost, fuel cost and carbon emission on following shipment links – PG to Hub, PG to CZ and Hub to CZ.

Problem Instance	Initial Inventory		Transport cost (GBP)			Fuel Cost (GBP)			Carbon emission (KG CO_2)		
	Hub	Customer Zone (CZ)	PG to Hub	PG to CZ	Hub to CZ	PG to Hub	PG to CZ	Hub to CZ	PG to Hub	PG to CZ	Hub to CZ
Problem Instance 1	800	3000	4806.8	2242	4993.6	4845	2259.8	5033.3	7243.2	3378.5	7524.8
Problem Instance 2	2000	10,000	5825.9	4925.6	6199.5	5872.2	4964.8	6248.8	8778.9	7422.4	9342
Problem Instance 3	1600	0	7813.1	8356.6	8645.4	7875.2	8423	8714.1	11,773	12,592	13,028
Problem Instance 4	1600	0	11,957	20,297	13,673	12,052	20,458	13,782	18,018	30,585	20,603
Problem Instance 5	1600	0	12,076	31,660	13,112	12,172	31,912	13,217	18,198	47,708	19,759
Problem Instance 6	1600	0	12,093	27,159	16,730	12,189	27,375	16,863	18,223	40,925	25,210
Problem Instance 7	1600	0	17,376	14,539	18,208	17,514	14,655	18,353	26,183	21,909	27,437
Problem Instance 8	1600	0	17,342	20,959	23,609	17,480	21,126	23,797	26,132	31,583	35,576
Problem Instance 9	1600	0	17,376	24,424	24,662	17,514	24,619	24,858	26,183	36,805	37,163
Problem Instance 10	1600	0	19,465	22,811	20,976	19,620	22,992	21,143	29,331	34,373	31,609
Problem Instance 11	1600	0	19,312	28,620	27,482	19,465	28,847	27,700	29,101	43,127	41,412
Problem Instance 12	1600	0	19,805	32,577	33,036	19,962	32,836	33,298	29,843	49,090	49,781

PG = Producer Group, CZ = Customer Zone

Table A3
Information about products shipped, vehicles used and unused vehicle volume for following shipment links – PG to Hub, PG to CZ and Hub to CZ.

Problem Instance	Aggregate Demand to be passed through Hub	Aggregate Demand at CZ	Total number of SKUs Shipped			Total number of Vehicle Trips made for transporting products			Total Unused Vehicle Volume while shipping SKUs (cubic metre)		
			PG to Hub	PG to CZ	Hub to CZ	PG to Hub	PG to CZ	Hub to CZ	PG to Hub	PG to CZ	Hub to CZ
Problem Instance 1	40,000	60,000	39,200	17,000	40,000	283	132	294	17.85	62.9	49.3
Problem Instance 2	50,000	100,000	48,000	40,000	50,000	343	290	365	0.85	25.5	46.75
Problem Instance 3	65,600	120,000	64,000	54,400	65,600	460	492	509	17	615.4	240.55
Problem Instance 4	100,000	240,000	98,400	140,000	100,000	704	1195	805	6.8	1160.2	539.75
Problem Instance 5	100,000	240,000	98,400	140,000	100,000	711	1864	772	48.45	5140.8	343.40
Problem Instance 6	100,000	240,000	98,400	140,000	100,000	712	1599	985	54.4	3564	1610.7
Problem Instance 7	144,000	256,000	142,400	112,000	144,000	1023	856	1072	34.85	333.2	258.4
Problem Instance 8	144,000	256,000	142,400	112,000	144,000	1021	1234	1390	22.95	2582.3	2150.5
Problem Instance 9	144,000	256,000	142,400	112,000	144,000	1023	1438	1452	34.85	3796.1	2519.4
Problem Instance 10	160,000	320,000	158,400	160,000	160,000	1146	1343	1235	86.7	1190.8	548.25
Problem Instance 11	160,000	320,000	158,400	160,000	160,000	1137	1685	1618	33.15	3225.8	2827.1
Problem Instance 12	160,000	320,000	158,400	160,000	160,000	1166	1918	1945	205.7	4612.1	4772.8

PG = Producer Group, CZ = Customer Zone

Appendix B:. Experiments addressing the effect of considering direct shipment link from producer groups to customer zones

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Table B1
Comparing the change in cost and carbon emission for two conditions – "no shipment from PGs to CZs" and "shipment available from PGs to CZs".

Problem Instances		Total Cost (GBP)	% Change in Total Cost	Total Fuel Cost (GBP)	% Change in Total Fuel Cost	Total Carbon Emission (KG CO_2)	% Change in Carbon Emission	Producer Groups (PGs) to Hub		Producer Groups (PGs) to Customer Zones (CZs)		Hub to Customer Zones (CZs)	
								Transport Cost (GBP)	% Change	Transport Cost (GBP)	% Change	Transport Cost (GBP)	% Change
	No Shipment from PGs to CZs	127,510	–	63,995	–	95,672	–	30,879	–	–	–	32,611	–
	Shipment available from PGs to CZs	100,643	– 21.07 %	50,521	– 21.05 %	75,529	– 21.05 %	17,376	– 43.72 %	14,539	–	18,208	– 44.16 %
Problem Instance 8	No Shipment from PGs to CZs	149,350	–	74,951	–	112,050	–	30,879	–	–	–	43,482	–
	Shipment available from PGs to CZs	124,312	– 16.76 %	62,402	– 16.74 %	93,292	– 16.74 %	17,342	– 43.83 %	20,959	–	23,609	– 45.70 %
Problem Instance 9	No Shipment from PGs to CZs	149,780	–	74,968	–	112,080	–	30,896	–	–	–	43,482	–
	Shipment available from PGs to CZs	133,520	– 10.85 %	67,025	– 10.59 %	100,200	– 10.59 %	17,664	– 42.82 %	23,168	–	25,664	– 40.97 %
Problem Instance 10	No Shipment from PGs to CZs	159,480	–	80,036	–	119,650	–	38,641	–	–	–	40,764	–
	Shipment available from PGs to CZs	124,960	– 21.64 %	62,728	– 21.62 %	93,778	– 21.62 %	19,329	– 49.97 %	21,826	–	21,078	– 48.29 %

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Table B1 (*continued*)

Problem Instances		Total Cost (GBP)	% Change in Total Cost	Total Fuel Cost (GBP)	% Change in Total Fuel Cost	Total Carbon Emission (KG CO_2)	% Change in Carbon Emission	Producer Groups (PGs) to Hub		Producer Groups (PGs) to Customer Zones (CZs)		Hub to Customer Zones (CZs)	
								Transport Cost (GBP)	% Change	Transport Cost (GBP)	% Change	Transport Cost (GBP)	% Change
Problem Instance 11	No Shipment from PGs to CZs	186,900	–	93,818	–	140,260	–	38,709	–	–	–	54,369	–
	Shipment available from PGs to CZs	163,230	– 12.66 %	81,936	– 12.66 %	122,490	– 12.66 %	19,363	– 49.97 %	33,885	–	28,042	– 48.42 %
Problem Instance 12	No Shipment from PGs to CZs	186,790	–	93,749	–	140,150	–	38,658	–	–	–	54,352	–
	Shipment available from PGs to CZs	156,030	– 16.46 %	78,324	– 16.45 %	117,090	– 16.45 %	19,601	– 49.29 %	30,573	–	27,533	– 49.34 %

Table B2

Comparing average cost components while considering the two conditions "no shipment from PGs to CZs" and "shipment available from PGs to CZs".

		Average Vehicle Trips to each CZ on each period	Number of Vehicle Trips	Average Total Cost (GBP)		Average Transportation Cost (GBP)		Average Fuel Cost (GBP)		Average Carbon Emission (KG CO_2)		Average Fuel consumed (Litre)	
				Per Vehicle Trip	Per Customer in each period	Per Vehicle Trip	Per Customer in each period	Per Vehicle Trip	Per Customer in each period	Per Vehicle Trip	Per Customer in each period	Per Vehicle Trip	Per Customer in each period
Problem Instance 3 (40 CZs, 150 Customers)	No Shipment from PGs to CZs	4.61	1,846	34.11	1.04	16.98	0.52	17.12	0.52	25.59	0.78	10.69	0.32
	Shipment available from PGs to CZs	3.64	1,458	34.12	0.82	16.98	0.41	17.12	0.41	25.59	0.62	10.70	0.26
Problem Instance 4 (80 CZs, 150 Customers)	No Shipment from PGs to CZs	4.62	3,703	34.11	1.05	16.98	0.52	17.11	0.52	25.59	0.78	10.69	0.33
	Shipment available from PGs to CZs	3.38	2,704	34.10	0.76	16.98	0.38	17.11	0.38	25.59	0.57	10.70	0.24
Problem Instance 5 (160 CZs, 75 Customers)	No Shipment from PGs to CZs	2.56	4,103	34.11	1.16	16.98	0.58	17.12	0.58	25.59	0.87	10.69	0.36
	Shipment available from PGs to CZs	1.99	3,191	34.10	0.90	16.98	0.45	17.12	0.45	25.59	0.68	10.70	0.28
Problem Instance 7 (80 CZs, 160 Customers)	No Shipment from PGs to CZs	4.67	3,738	34.11	0.99	16.98	0.49	17.12	0.50	25.59	0.74	10.70	0.31
	Shipment available from PGs to CZs	3.72	2,982	34.10	0.79	16.98	0.39	17.12	0.39	25.59	0.59	10.69	0.24
Problem Instance 9	No Shipment	2.73	4,378	34.11	1.16	16.98	0.58	17.11	0.58	25.59	0.87	10.70	0.36

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Table B2 (*continued*)

		Average Vehicle Trips to each CZ on each period	Number of Vehicle Trips	Average Total Cost (GBP)		Average Transportation Cost (GBP)		Average Fuel Cost (GBP)		Average Carbon Emission (KG CO_2)		Average Fuel consumed (Litre)	
				Per Vehicle Trip	Per Customer in each period	Per Vehicle Trip	Per Customer in each period	Per Vehicle Trip	Per Customer in each period	Per Vehicle Trip	Per Customer in each period	Per Vehicle Trip	Per Customer in each period
(160 CZs, 80 Customers)	from PGs to CZs												
	Shipment available from PGs to CZs	2.40	3,840	34.10	1.02	16.98	0.50	17.12	0.51	25.59	0.76	10.70	0.32
Problem Instance 12 (160 CZs, 100 Customers)	No Shipment from PGs to CZs	3.42	5,472	34.11	1.16	16.98	0.58	17.12	0.58	25.59	0.87	10.69	0.36
	Shipment available from PGs to CZs	2.88	4,608	34.10	0.98	16.98	0.48	17.12	0.49	25.59	0.73	10.70	0.30

Appendix C:. Experiments investigating the impact of variations in fuel prices

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Table C1
Fuel Price experiment on Problem Instances 11 and 12.

	Problem Instance 11 (12 PGs, 1 Hub, 160 CZs, 5 Vehicle Types, 4 SKU Types, 10 Time Periods/Weeks)				Problem Instance 12 (24 PGs, 1 Hub, 160 CZs, 5 Vehicle Types, 4 SKU Types, 10 Time Periods/Weeks)			
	Fuel Price Scenario 1	Fuel Price Scenario 2	Fuel Price (Baseline) Scenario 3	Fuel Price Scenario 4	Fuel Price Scenario 5	Fuel Price (Baseline) Scenario 6	Fuel Price Scenario 7	Fuel Price Scenario 8
Change in Fuel price when compared with Baseline Scenario (%)	50 % Increase (2.4 GBP per litre)	25 % Increase (2.0 GBP per litre)	1.6 GBP per litre	25 % Decrease (1.2 GBP per litre)	25 % Decrease (1.2 GBP per litre)	1.6 GBP per litre	25 % Increase (2.0 GBP per litre)	50 % Increase (2.4 GBP per litre)
Total Cost Incurred (GBP)	228,730	215,570	163,910	135,730	144,500	171,514.04	183,600	205,770
Change in Total Cost incurred (%)	39.54 %	31.51 %	–	– 17.19 %	– 15.75 %	–	7.04 %	19.97 %
Total Fuel cost (GBP)	137,670	120,180	82,279	58,435	62,210	86,096	102,360	123,850
Change in Total Fuel cost (%)	67.32 %	46.06 %	–	– 28.97 %	– 27.74 %	–	18.89 %	43.85 %
Fuel cost from PG to Hub (GBP)	29,506	24,460	19,637	14,612	14,843	19,962	24,653	29,763
Change in Fuel cost from PG to Hub (%)	50.25 %	24.56 %	–	– 25.58 %	– 25.64 %	–	23.49 %	49.09 %
Fuel cost from PG to CZ (GBP)	63,404	59,342	34,291	22,894	25,436	32,836	41,644	51,565
Change in Fuel cost from PG to CZ (%)	84.89 %	73.05 %	–	– 33.23 %	– 22.53 %	–	26.82 %	57.03 %
Fuel cost from Hub to CZ (GBP)	44,760	36,380	28,351	20,929	21,931	33,298	36,059	42,526
Change in Fuel cost from Hub to CZ (%)	57.87 %	28.31 %	–	– 26.17 %	– 34.13 %	–	8.29 %	27.71 %
Total Carbon Emission (KG CO_2)	137,210	143,740	123,010	116,480	124,000	128,710	122,420	123,440

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Table C1 (*continued*)

	Problem Instance 11 (12 PGs, 1 Hub, 160 CZs, 5 Vehicle Types, 4 SKU Types, 10 Time Periods/Weeks)				Problem Instance 12 (24 PGs, 1 Hub, 160 CZs, 5 Vehicle Types, 4 SKU Types, 10 Time Periods/Weeks)			
	Fuel Price Scenario 1	Fuel Price Scenario 2	Fuel Price (Baseline) Scenario 3	Fuel Price Scenario 4	Fuel Price Scenario 5	Fuel Price (Baseline) Scenario 6	Fuel Price Scenario 7	Fuel Price Scenario 8
Change in Total Carbon Emission (%)	11.54 %	16.85 %	–	– 5.30 %	– 3.65 %	–	– 4.88 %	– 4.09 %
Carbon Emission from PG to Hub (KG CO_2)	29,408	29,254	29,357	29,126	29,587	29,843	29,485	29,664
Change in Carbon Emission from PG to Hub (%)	0.17 %	– 0.35 %	–	– 0.78 %	– 0.85 %	–	– 1.19 %	– 0.59 %
Carbon Emission from PG to CZ (KG CO_2)	63,193	70,973	51,266	45,635	50,703	49,090	49,807	51,394
Change in Carbon Emission from PG to CZ (%)	23.26 %	38.44 %	–	– 10.98 %	3.28 %	–	1.46 %	4.69 %
Carbon Emission from Hub to CZ (KG CO_2)	44,611	43,510	42,384	41,719	43,715	49,781	43,127	42,384
Change in Carbon Emission from Hub to CZ (%)	5.25 %	2.65 %	–	– 1.56 %	– 12.18 %	–	– 13.36 %	– 14.85 %

Appendix D:. Studying the effect of customer demand variation

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Table D1
Analysing the impact of demand variation on the average values per trip such as cost component, unused vehicle volume and carbon emission.

Demand Scenario Instances	Aggregate demand for Planning Horizon	Average Demand of each CZ in each Time Period	Number of Customers in a CZ	Average Vehicle Trips to each CZ on each period	Average unused Vehicle volume per Trip (cubic metre)	Average Total Cost per Trip (GBP)	Average Total Cost per Order (GBP)	Average Transport Cost per Trip (GBP)	Average Fuel Cost per Trip (GBP)	Average Fuel Cost per Order (GBP)	Average Carbon Emission per Trip (KG CO_2)	Average Carbon Emission per Order (KG CO_2)	Average Fuel consumed per Trip (Litre)
Problem Instance 11 – Demand scenario 1	640,000	400	200	4.23	0.93	51.18	0.54	25.47	25.67	0.27	38.39	0.40	16.04
Problem Instance 11 – Demand scenario 2	576,000	360	180	3.92	0.98	44.33	0.48	22.08	22.25	0.24	33.27	0.36	13.90
Problem Instance 11 – Demand scenario 3	512,000	320	160	3.89	1.47	40.92	0.49	20.38	20.54	0.24	30.71	0.37	12.84
Problem Instance 11 – Demand scenario 4	448,000	280	140	2.74	0.09	37.51	0.36	18.68	18.83	0.18	28.15	0.27	11.76
Problem Instance 11 – Demand scenario 5	384,000	240	120	3.08	1.28	37.51	0.48	18.68	18.83	0.24	28.15	0.36	11.77
Problem Instance 11 – Demand scenario 6	320,000	200	100	3.01	1.73	34.10	0.51	16.98	17.11	0.25	25.59	0.38	10.69
Problem Instance 11 – Demand scenario 7	256,000	160	80	2.74	1.94	30.69	0.52	15.28	15.40	0.26	23.03	0.39	9.63
Problem Instance 11 – Demand scenario 8	192,000	120	60	1.80	0.78	27.28	0.40	13.58	13.69	0.20	20.47	0.30	8.56
Problem Instance 11 – Demand scenario 9	128,000	80	40	1.36	1.92	23.87	0.40	11.88	11.98	0.20	17.91	0.30	7.49

Table D2
Impact of demand variation on the average values of transportation cost, fuel cost and carbon emission incurred per customer in each period.

Scenario Instances	Aggregate demand for Planning Horizon	Average demand on each Time Period	Average Demand of each CZ in each Time Period	Number of Customer Zones (CZs)	Number of Customers in a CZ	Average Vehicle Trips to each CZ on each period	Average unused Vehicle volume per Trip (cubic metre)	Average Total Cost per Customer in each period (GBP)	Average Transportation Cost per Customer in each period (GBP)	Average Fuel Cost per Customer in each period (GBP)	Average Carbon Emission per Customer in each period (KG CO_2)	Average Fuel consumed per Customer in each period (Litre)
Instance 10 – Scenario 1	640,000	64,000	800	80	400	8.09	0.70	1.10	0.54	0.55	0.82	0.34
Instance 10 – Scenario 2	480,000	48,000	600	80	300	7.09	1.16	1.12	0.56	0.56	0.84	0.35
Instance 10 – Scenario 3	320,000	32,000	400	80	200	4.49	0.29	0.91	0.45	0.46	0.68	0.28
Instance 10 – Scenario 4	160,000	16,000	200	80	100	2.52	1.35	0.68	0.34	0.34	0.51	0.21
Instance 10 – Scenario 5	80,000	8,000	100	80	50	1.34	1.28	0.55	0.27	0.27	0.41	0.17
Instance 11 – Scenario 6	80,000	8,000	50	160	25	1.18	3.28	0.96	0.48	0.48	0.72	0.30
Instance 11 – Scenario 7	160,000	16,000	100	160	50	1.55	1.87	0.84	0.42	0.42	0.63	0.26
Instance 11 – Scenario 8	320,000	32,000	200	160	100	2.98	1.69	1.01	0.50	0.51	0.76	0.31
Instance 11 – Scenario 9	480,000	48,000	300	160	150	3.84	1.54	1.04	0.52	0.52	0.78	0.32
Instance 11 – Scenario 10	640,000	64,000	400	160	200	4.23	0.93	1.01	0.50	0.51	1.01	0.31

Appendix E:. Impact of business restrictions on specific customer demand being met via hub

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Table E1
Experiments considering the mandatory business requirement of certain SKU types shipped via Hub.

Problem Instance	SKU types which must go through the Hub	Aggregate SKUs demand to pass through the Hub	Aggregate SKUs demand for CZs	Average Total Cost (GBP)		Average Transport Cost (GBP)		Average Fuel Cost (GBP)		Average Carbon Emission (KG CO_2)		Average unused Vehicle volume per Trip (cubic metre)	Average Fuel Consumed per Customer per period (Litre)	Average Vehicle Trips to each CZ on each period
				Per Vehicle Trip	Per Customer in each period	Per Vehicle Trip	Per Customer in each period	Per Vehicle Trip	Per Customer in each period	Per Vehicle Trip	Per Customer in each period			
Problem Instance 3	Scenario 1 – SKU type 1	20,000	80,000	34.76	0.81	16.98	0.39	17.12	0.40	25.59	0.60	1.44	0.25	2.35
	Scenario 2 – SKU types 1 and 3	40,000	80,000	34.49	0.72	16.98	0.35	17.12	0.36	25.59	0.52	0.45	0.21	1.40
	Scenario 3 – SKU types 1, 2 and 3	60,000	80,000	34.29	1.04	16.98	0.51	17.11	0.52	25.59	0.78	1.11	0.32	6.10
Problem Instance 6	Scenario 1 – SKU type 3	48,000	192,000	34.32	0.98	16.98	0.48	17.12	0.48	25.59	0.73	2.24	0.30	3.43
	Scenario 2 – SKU types 3 and 4	96,000	192,000	34.28	0.81	16.98	0.40	17.12	0.40	25.59	0.60	0.59	0.25	2.85
	Scenario 3 – SKU types 1, 3 and 4	144,000	192,000	34.16	1.21	16.98	0.60	17.12	0.61	25.59	0.91	1.79	0.38	4.27
Problem Instance 9	Scenario 1 – SKU type 1	64,000	256,000	34.32	1.15	16.98	0.57	17.11	0.57	25.59	0.86	2.79	0.35	2.68
	Scenario 2 – SKU types 1 and 2	128,000	256,000	34.30	0.92	16.98	0.46	17.11	0.46	25.59	0.69	1.25	0.28	2.16
	Scenario 3 – SKU types 1, 2 and 3	192,000	256,000	34.16	1.38	16.98	0.69	17.11	0.69	25.59	1.04	2.30	0.43	3.25

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Table E1 (*continued*)

Problem Instance	SKU types which must go through the Hub	Aggregate SKUs demand to pass through the Hub	Aggregate SKUs demand for CZs	Average Total Cost (GBP)		Average Transport Cost (GBP)		Average Fuel Cost (GBP)		Average Carbon Emission (KG CO_2)		Average unused Vehicle volume per Trip (cubic metre)	Average Fuel Consumed per Customer per period (Litre)	Average Vehicle Trips to each CZ on each period
				Per Vehicle Trip	Per Customer in each period	Per Vehicle Trip	Per Customer in each period	Per Vehicle Trip	Per Customer in each period	Per Vehicle Trip	Per Customer in each period			
Problem Instance 11	Scenario 1 – SKU type 2	112,000	448,000	34.31	0.85	16.98	0.42	17.12	0.42	25.59	0.63	1.70	0.26	3.49
	Scenario 2 – SKU types 3 and 4	224,000	448,000	34.27	0.73	16.98	0.36	17.11	0.36	25.59	0.54	0.00	0.22	2.99
	Scenario 3 – SKU types 2, 3 and 4	336,000	448,000	34.16	1.09	16.98	0.54	17.12	0.55	25.59	0.82	1.32	0.34	4.49

Appendix F:. Examining the effect of shipment delays

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Table F1
Experiments on problem instance 11 to investigate the shipment delay.

Shipment Delay Scenarios	Nature of shipment delay (Problem Instance 11 – 12 PGs, 160 CZs, 100 Customers, 10 Weeks)	Number of Vehicle Trips	Average Vehicle Trips to each CZ on each period	Percentage of Total Demand sent via Hub	Percentage of Total Demand sent directly from PGs to CZs	Average Total Cost per Customer in each period (GBP)	Average Transport Cost per Customer in each period (GBP)	Average Fuel Cost per Customer in each period (GBP)	Average Carbon Emission per Customer in each period (KG CO_2)	Average Fuel Consumed per Customer per period (Litre)
Scenario 1	PGs delay 1 week in delivering SKUs to Hub	4,562	2.85	45 %	55 %	0.97	0.48	0.48	0.72	0.30
Scenario 2	Hubs delay 1 week in delivering SKUs to CZs	4,610	2.88	45 %	55 %	0.98	0.48	0.49	0.73	0.30
Scenario 3	PGs delay 2 weeks in delivering SKUs to Hub	4,301	2.68	40 %	60 %	0.91	0.45	0.46	0.68	0.28
Scenario 4	Hubs delay 2 weeks in delivering SKUs to CZs	4,304	2.69	40 %	60 %	0.91	0.45	0.46	0.68	0.28
Scenario 5	PGs delay 3 weeks in delivering SKUs to Hub	4,143	2.58	35 %	65 %	0.88	0.43	0.44	0.66	0.27
Scenario 6	Hubs delay 3 weeks in delivering SKUs to CZs	4,169	2.60	35 %	65 %	0.88	0.44	0.44	0.66	0.27
Scenario 7	PGs delay 4 weeks in delivering SKUs to Hub	4,083	2.55	30 %	70 %	0.87	0.43	0.43	0.65	0.27
Scenario 8	Hubs delay 4 weeks in delivering SKUs to CZs	4,057	2.53	30 %	70 %	0.86	0.43	0.43	0.64	0.27
Scenario 9	PGs delay 5 weeks in delivering SKUs to Hub	4,028	2.51	25 %	75 %	0.85	0.42	0.43	0.64	0.26
Scenario 10	Hubs delay 5 weeks in delivering SKUs to CZs	3,942	2.46	25 %	75 %	0.84	0.41	0.42	0.63	0.26
Scenario 11	PGs delay 6 weeks in delivering SKUs to Hub	3,920	2.45	20 %	80 %	0.83	0.41	0.41	0.62	0.26
Scenario 12	Hubs delay 6 weeks in delivering SKUs to CZs	3,922	2.45	20 %	80 %	0.83	0.41	0.42	0.62	0.26

Appendix G:. Investigating the impact of disruption on the shipment links

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Table G1
Study the impact of disruption on shipment links by conducting experiment on problem instance 11.

Disruption Scenarios – Problem Instance 11	Percentage of shipment links from PGs to CZs facing disruption	Percentage of shipment links from PGs to Hub facing disruption	Number of shipment links available from PGs to CZs	Number of shipment links available from PGs to Hub	Total Number of Vehicle Trips	Avg. vehicle Trips in each period/week			Avg. Vehicle Trips to each CZ on each period	Avg. unused Vehicle volume per Trip (cubic metre)	Avg. vehicle trips per available links from PGs to CZs	Avg. vehicle trips per available links from PGs to Hub	Avg. Fuel Cost per Customer in each period (GBP)	Avg. Carbon Emission per Customer in each period (KG CO_2)
						PGs to Hub	PGs to CZs	Hub to CZs						
Scenario 1	–	–	19,200	120	4,440	113.7	168.5	161.8	2.77	1.37	0.087	9.47	0.47	0.71
Scenario 2	8.33 %	8.33 %	17,600	110	4,886	114.3	209.9	164.4	3.05	1.78	0.119	10.39	0.52	0.78
Scenario 3	16.66 %	16.66 %	16,000	100	4,772	114.0	201.8	161.4	2.98	1.68	0.126	11.40	0.51	0.76
Scenario 4	25 %	25 %	14,400	90	4,399	113.8	171.1	155.0	2.74	1.32	0.118	12.64	0.47	0.70
Scenario 5	33.33 %	33.33 %	12,800	80	4,503	113.8	173.7	162.8	2.81	1.43	0.135	14.22	0.48	0.72
Scenario 6	41.66 %	41.66 %	11,200	70	4,456	113.8	176.0	155.8	2.78	1.38	0.157	16.25	0.47	0.71
Scenario 7	50 %	50 %	9,600	60	4,451	113.8	173.2	158.1	2.78	1.38	0.180	18.96	0.47	0.71
Scenario 8	58.33 %	58.33 %	8,000	50	4,573	114.3	181.5	161.5	2.85	1.50	0.226	22.86	0.48	0.73
Scenario 9	66.66 %	66.66 %	6,400	40	4,551	115.0	178.2	161.9	2.84	1.48	0.278	40.47	0.48	0.72

Appendix H:. Deploying electric vehicles on the shipment links

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Table H1
Investigating the use of electric vehicles on shipment links – transport cost, EV charging cost and fuel cost.

Scenario – Problem Instance 11	Avg. total cost per customer in each period (GBP)	Avg. transport cost per customer in each period (GBP)	Avg. fuel cost per customer in each period (GBP)	Avg. fuel consumed per customer in each period (litre)	Avg. EV charging cost per customer in each period (GBP)	Transport cost (GBP)			Electric vehicle charging cost (GBP)			Fuel cost (GBP)		
						PGs to Hub	PGs to CZs	Hub to CZs	PGs to Hub	PGs to CZs	Hub to CZs	PGs to Hub	PGs to CZs	Hub to CZs
Scenario 1 (Baseline) – No EVs deployed	1.028	0.511	0.516	0.322	–	19,499	33,070	29,350	–	–	–	19,654	33,333	29,583
Scenario 2 – EVs used from PGs to Hub	0.910	0.491	0.400	0.250	0.019	15,102	35,618	27,906	3053	–	–	–	35,901	28,128
Scenario 3 – EVs used from Hub to CZs	0.786	0.448	0.309	0.193	0.028	19,346	29,843	22,557	–	–	4560.1	19,500	30,080	–
Scenario 4 – EVs used from PGs to CZs	0.757	0.452	0.268	0.167	0.037	19,414	29,725	23,185	–	6009.2	–	19,568	–	23,369
Scenario 5 – EVs on PGs to Hub & PGs to CZs	0.596	0.400	0.143	0.089	0.052	15,123	26,215	22,743	3057.3	5299.7	–	–	–	22,924
Scenario 6 – EVs on PGs to Hub & Hub to CZs	0.593	0.388	0.159	0.099	0.046	15,080	25,291	21,727	3048.7	–	4392.4	–	25,492	–
Scenario 7 – EVs on Hub to CZs & PGs to CZs	0.581	0.402	0.121	0.076	0.056	19,346	24,673	20,387	–	4988	4121.5	19,500	–	–
Scenario 8 – EVs on all shipment links	0.420	0.350	–	–	0.070	15,176	22,450	18,388	3068.1	4538.6	3717.3	–	–	–

EV = Electric Vehicle, PGs = Producer Groups, CZs = Customer Zones

Table H2
Deploying electric vehicles to study the impact on carbon emission, fuel consumption and unused vehicle volume.

Scenario – Problem Instance 11	Percentage of shipment links possessing Electric vehicles	Avg. carbon emission per customer in each period (KG CO_2)	Avg. unused Vehicle volume per Trip (cubic metre)	Fuel consumed (litre)			Carbon emission incurred (KG CO_2)			Total vehicle trips	Avg. Vehicle Trips to each CZ on each period	Avg. vehicle trips in each time period/ week		
				PGs to Hub	PGs to CZs	Hub to CZs	PGs to Hub	PGs to CZs	Hub to CZs			PGs to Hub	PGs to CZs	Hub to CZs
Scenario 1 (Baseline) – No EVs deployed	–	0.771	1.734	12,284	20,833	18,490	29,382	49,832	44,227	4,823	3.014	114.8	194.7	172.8
Scenario 2 – EVs used from PGs to Hub	0.573 %	0.598	1.693	–	22,438	17,580	–	53,671	42,052	5,160	3.225	142.0	209.7	164.3
Scenario 3 – EVs used from Hub to CZs	7.648 %	0.463	1.411	12,187	18,800	–	29,152	44,969	–	5,017	3.135	113.9	175.7	212.1
Scenario 4 – EVs used from PGs to CZs	91.778 %	0.268	1.509	12,230	–	14,606	29,254	–	34,936	5,303	3.314	114.3	279.5	136.5
Scenario 5 – EVs on PGs to Hub & PGs to CZs	92.351 %	0.214	1.204	–	–	14,327	–	–	34,271	5,226	3.266	142.2	246.5	133.9

(*continued on next page*)

Table H2 (*continued*)

Scenario – Problem Instance 11	Percentage of shipment links possessing Electric vehicles	Avg. carbon emission per customer in each period (KG CO_2)	Avg. unused Vehicle volume per Trip (cubic metre)	Fuel consumed (litre)			Carbon emission incurred (KG CO_2)			Total vehicle trips	Avg. Vehicle Trips to each CZ on each period	Avg. vehicle trips in each time period/ week		
				PGs to Hub	PGs to CZs	Hub to CZs	PGs to Hub	PGs to CZs	Hub to CZs			PGs to Hub	PGs to CZs	Hub to CZs
Scenario 6 – EVs on PGs to Hub & Hub to CZs	8.221 %	0.238	1.038	–	15,932	–	–	38,110	–	4,950	3.093	141.8	148.9	204.3
Scenario 7 – EVs on Hub to CZs & PGs to CZs	99.426 %	0.182	1.261	12,187	–	–	29,152	–	–	5,376	3.360	113.9	232.0	191.7
Scenario 8 – EVs on all shipment links	100 %	–	0.939	–	–	–	–	–	–	5,267	3.291	142.7	211.1	172.9

EV = Electric Vehicle, PGs = Producer Groups, CZs = Customer Zones

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