Modelling and analysing supply chain disruption: a case of online grocery retailer

D. G. Mogale[1] · Xun Wang[1] · Emrah Demir[1] · Vasco Sanchez Rodrigues[1]

Abstract

Supply Chains (SCs) are becoming more vulnerable to disruption risks because of globalisation, competitiveness, and uncertainties. This study is motivated by an online grocery retailer in the UK that experienced multiple disruption risks, such as demand and supply shocks, facility closures, and disruption propagation simultaneously in 2020. The main purpose of this study is to model and perform quantitative analyses of a range of SC disruption risks affecting the UK online retailer. We have attempted to study how UK retailers responded to the first and second waves of the pandemic and the effect on multiple products. Six scenarios are developed based on SC disruption risks and their impacts on SC performance are analysed. The quantitative analysis of two strategies used by grocery retailers during the pandemic, namely vulnerable priority delivery slots and rationing of products, illustrates that rationing of products had a greater SC impact than the use of priority delivery slots. The effects of two resilience strategies, backup supplier and ramping up distribution centre capacity, are also quantified and discussed. Novel managerial insights and theoretical implications are discussed to make online grocery SC more resilient and robust during future disruptions.

Keywords Supply chain risk management · Risk modelling · Ripple effect · Grocery supply chain resilience · Simulation

1 Introduction

Recent global events such as the COVID-19 pandemic, Suez Canal blockage, Russia-Ukraine war and Brexit severely affected the global SCs, resulting in shortages of raw materials, components, and goods, as well as fuel, containers, and workers (Roh et al. 2022; Zhou et al. 2023). SCs are becoming more susceptible to disruption risks that influence the overall SC operations (Waters 2011). Internal, SC and external risk events impact the SC facilities and generate shortages and delays in the SC network. The effects of such disruption propagate to the upstream or downstream members of the SC, resulting in a decline in its operational and financial performance (Dolgui et al. 2020; Ivanov 2020). Most companies optimise the SC for efficiency, not for resilience (Golan et al. 2020; Sharma et al. 2021). In the traditional structure, SC resilience mainly protects from a single-point failure, but recent risk events caused multiple disruptions simultaneously, in the form of supply shortages (supply risk), facility closures and demand surges (demand risk) in the network (Ali et al. 2022). It is quite difficult to deal with different types of disruptions at the same time and maintain efficiency and reilence in the supply chain. Hence, researchers and practitioners are exploring more robust and resilient SCs that can sustain multiple disruptions simultaneously and quickly recover from these disruptions and return to an original or new desirable state (Queiroz et al. 2022; Yu et al. 2021). The modelling and quantitative analysis of SC disruption risks is an unexplored area in Supply Chain Risk Management (SCRM) despite established literature (Ghadge et al. 2021; Hosseini and Ivanov 2021; Ivanov 2021).

The retail sector plays a vital role in the UK's economy and accounts for 5.2% of the UK's Gross Domestic Product (GDP) in 2020. This sector employed 9.3% of all UK employees in 2019 and provided essential goods and services to customers (The Office for National Statistics (ONS) 2021). This sector has gone through significant transformations in the last decade with new digital technologies such as Internet of Things, Artificial Intelligence, Robotics etc., rising competition, large use of the Internet and sophisticated

✉ D. G. Mogale
MogaleD@Cardiff.ac.uk

1   Logistics and Operations Management Section, Cardiff Business School, Cardiff University, Colum Dr, Cardiff CF10 3EU, UK

customers. In the last 25 years, food stores have constantly been the dominant retail sector in this industry. The online retail sales share in total retail sales had 27.9% in 2020 against 3.4% in 2007 (ONS 2021). Millions of people turned to online shopping in recent times, and currently, more than half of UK consumers are shopping online (Statista.com). According to the Global Supply Chain Risk Report (2019), supplier criticality and global sourcing are the key risks in the retail sector (http://wef.ch/risks2019). Supplier criticality denotes the significant dependency on suppliers and global sourcing illustrates the growing inclination towards sourcing from low-cost high-risk countries. The UK's economy recently plunged into an SC crisis because of the lowest stocks at major retailers since 1983 (Partington and Partridge 2021). This happened because of workers shortage and transportation disruption caused by the pandemic and Brexit. Thus, we need to study how UK retail sector can effectively and efficiently manage SC risks.

The UK retail sector is facing several major challenges, including a lack of warehouse staff, a shortage of Heavy Goods Vehicles (HGV) drivers and food-grade CO_2, high freight costs, rising fuel prices, and increased Brexit-related red tape (theguardian.com). This research study is motivated by these challenges. SCs in the UK and global SCs experienced widespread disruptions in 2021 and these disruptions hit the news headlines. Ports closures, rising waiting time of goods at ports, the US-China trade war, fire at one of the largest semiconductor makers for the automotive industry, Suez Canal blockage and increased border controls due to Brexit are some of the reasons behind the global SC crisis. The pandemic occurred during these times which made the situation worst. SC problems caused the late deliveries, higher prices, empty petrol stations and supermarket shelves. Many UK retailers struggled to get goods and materials from the EU and within the UK in recent times. Several major retailers across the UK reported these problems and emphasised the need for an SCRM approach (Garnett et al. 2020). The first-tier suppliers also faced some challenges while supplying products to these retailers. One of the most important elements during any crisis is food. During crises, governments try to ensure sufficient availability of food/grocery items and control food prices. Similar to other sectors in the UK, the grocery retail sector has been affected by the recent crises. The effect was generally positive (beneficial) because numerous customers over-purchased and overstocked the grocery items during crises which helped to leap the annual sales and core profitability. Major retailers' earnings were more than their estimates. However, they need to tackle some of the major challenges mentioned above to prepare the SCs for future crises and ensure everyone gets enough food at reasonable prices. To deal with the above-discussed SC challenges and make SC more robust and resilient, this

research aims to model and quantify the impact of SC disruptions on the online grocery retailer and to evaluate their response policies as well as resilience strategies that can make the grocery supply chain more responsive in future crises. The following four research questions are addressed in this study.

RQ1. What is the effect of disruption on online grocery SC?
RQ2. What is the impact of response strategies followed by online grocery retailers on their SC performance?
RQ3. Which resilience strategy is more suitable for online grocery retailers?
RQ4. How can online grocery SC resilience be improved?

There are various ways to address these above RQs such as a qualitative approach by doing interviews with experts from the industry and then trying to discuss the answers of these RQs in the subjective form. Many scholars discussed the generic answers to these RQs without considering the real-time data from the industry during the early stages of the pandemic (Carissimi et al. 2023). The second approach is the quantitative modelling and analysis of the pandemic as a unique disruption risk. There are limited studies available on quantitative modelling of disruption risks with real-time data hence we decided to address the RQs through a quantitative approach.

This research study makes the following four important contributions to the body of literature. First, we consider the pandemic as an SC disruption risk and model it through the mathematical modelling approach. Second, we analyse the effect of the pandemic on the grocery retail sector by considering a real-world case study from the UK. Scenarios of positive and negative SC performance dynamics are examined. The third vital contribution is related to response strategies followed by grocery retailers to fight this pandemic. Two practical policies (priority delivery slots and limiting the maximum number of products sold to each customer) are investigated in this research. Finally, a quantitative analysis of two resilience strategies is discussed to manage the disruption and make SC more resilient.

The article is structured as follows. Section 2 reviews the relevant literature on supply chain risk management and simulation-based supply chain risk modelling, with a focus on pandemics. In Section 3, the underline problem along with details on data collection, and mathematical and simulation models are presented. The experimental setup and results are discussed in Sections 4 and 5, respectively. Section 6 is devoted to the discussion and implications of the study, while Section 7 concludes the article and suggests avenues for future research.

2 Literature review

SCRM is a broad topic hence only relevant and recent literature on it is discussed here. The first subsection looked at the studies related to uncertainty and risk in supply chains, vulnerability, and resilience. The simulation-based supply chain risk modelling approaches are discussed in the second subsection.

2.1 Supply chain risk management (SCRM)

The SCRM literature has developed significantly in the last two decades and become a growing research area (Pournader et al. 2020; Fahimnia et al. 2015). Risk occurs due to the uncertain future and this uncertainty may bring unexpected and risky events (Waters 2011). When these unexpected risky events occur, they may cause damage. Supply chain vulnerability is the exposure to disturbances due to risks that affect the ability of the supply chain to meet the end customers' demand (Jüttner 2005). Supply chain resilience is a supply chain's ability to return to its original or move to a new, more desirable state after being disturbed (Christopher and Peck 2004; Glickman and White 2006). The impact of the pandemic on the dairy SC was assessed by Karwasra et al. (2021). Recently, Shi et al. (2021) and Montoya-Torres et al. (2023) discussed the present and future research topics in logistics and SCM area considering Covid-19. The SCRM is the identification, assessment, mitigation and monitoring of supply chain risks. Interested readers can refer to the review articles by Baryannis et al. (2019), Colicchia and Strozzi (2012), Fan and Stevenson (2018), Heckmann et al. (2015), Ho et al. (2015), Pournader et al. (2020), Fahimnia et al. (2015), Ribeiro and Barbosa-Povoa (2018), Rajagopal et al. (2017), Li et al. (2022), Rinaldi et al. (2022), Suryawanshi and Dutta (2022) and Ghadge et al. (2012) for other related SCRM studies.

2.2 Simulation-based supply chain risk modelling

Supply chain risk modelling is getting more attention because companies are looking for quantitative risk measures which will be helpful to assess and prioritize the risks and prepare mitigation plans (Aqlan and Lam 2016; Ghadge et al. 2021). Mathematical and optimisation modelling is the dominating research methodology in SCRM. Simulation modelling is an under-explored area and needs attention to deal with uncertainty and limited historical risk data (Ivanov 2017; Hosseini and Ivanov 2021). These are mainly used when stochastic parameters exist in a SC network. Only a few studies adopted modelling and simulation techniques to study the complexities of SCRM (Maliki et al. 2022;

Tordecilla et al. 2021). Scholars used different simulation techniques, such as Discrete-event simulation (DES), Agent-Based Simulation (ABS) or Multi-agent-based Simulation, System Dynamics (SD), Monte Carlo Simulation and Petri Nets based on the nature of the problems. A summary of the key existing studies focusing on simulation-based risk modelling is given in Table 1.

We can see from Table 1, the DES technique was extensively used by various scholars for supply chain risk analysis (Schmitt and Singh 2012, Schmitt et al. 2017, Ivanov 2019 and Tan et al. 2020). Most of the authors addressed the manufacturing SC problems and focused on disruptions risk in their articles. Limited studies considered multiple products. Redundant suppliers and inventory buffers were the most used SC resilience strategies. Only Ivanov (2017) considered real-life data while addressing the four-stage supply chain problem. The mathematical models were also proposed by a few authors. The simulation-optimisation methods are being used by the academic community for the analysis of supply chain risks (Ojha et al. 2018).

2.3 Research gaps

We can easily observe from Table 1 that most of the scholars analysed the 2 and 3 stages of the SC network and considered various types of disruptions. The impact of disruptions is mainly analysed on the manufacturing, automotive and electronics industries using DES (Aqlan and Lam 2016; Ivanov 2018). Among the considered papers, a lack of scholars focused on grocery supply chains and tried to analyse the influence of SC disruptions. The authors who used the simulation method did not use realistic data (Dolgui et al. 2020; Ivanov 2019). Mathematical models were seen in limited studies (Burgos and Ivanov 2021; Ghadge et al. 2021). In the current work, we have analysed the impact of disruptions on an online grocery retailer with the help of realistic data. To the best of our knowledge, the quantitative analysis of the impact of response strategies followed by online retailers on SC performance is not discussed in the previous studies (Singh et al. 2021). Regarding the impact of resilience strategies on SC, almost all previous authors theoretically discussed existing resilience strategies but their impacts on SC performance have not been quantified (Sodhi et al. 2021; Sharma et al. 2020).

3 Problem overview, data and model development

3.1 Problem overview

The grocery retailer considered in this study manages its SC operations with a limited number of large and centralised

Table 1 Summary of existing studies related to simulation-based risk modelling

Reference	Risk addressed		SCN	Multi-product	Methodology	SC type/Application industry	Real-life data	Alternative strategies used by retailers	Scenario	Resilience strategy	Quantification of Resilience strategies	Mathematical model
	Operations	Disruption										
Aqlan and Lam (2016)	✓	✓	1 stage	✓	DES (Software type) + GP	High-end sever Manufacturing				Redundant suppliers and inventory sharing		✓
Ivanov (2017)		✓	4 stages		DES	Non-perishable products Manufacturing	✓			Capacity flexibility		
Ivanov (2018)		✓	4 stages		DES	Electronics products manufacturing				Backup sourcing and Facility Fortification		
Ivanov (2019)		✓	3 stages		DES	Non-perishable Manufacturing				Backup contractors and capacity flexibility		✓
Tan et al. (2020)		✓	2 stages		DES + ABS	Computer equipment Manufacturing				Backup plant and capacity		
Schmitt et al. (2017)		✓	4 stages		ABS + GA	Electronics products manufacturing				Expedite orders and Inventory buffer		
Dolgui et al. (2020)		✓	2 stages		DES + ABS	FMCG				Coordinated production-ordering		
Carvalho et al. (2012)		✓	2 stages		DES	Automotive supply chain				Transhipment and Inventory buffer		
Li et al. (2017)		✓	4 stages		Monte Carlo	Mobile phone supply chain network				Flexible sourcing		
Schmitt and Singh (2012)		✓	3 stages	✓	DES	Consumer packaged goods				Backup plant and Inventory buffer		
Present study	✓	✓	**4 stages**	✓	**DES**	**Grocery supply chain**	✓	✓	✓	**Backup supplier and capacity flexibility**	✓	✓

warehouses located across the UK. Its network includes suppliers, Customer Fulfilment Centres (CFCs), spokes and customers. Numerous suppliers located across the UK and Europe supply the products to various CFCs which store products and assort the customer orders. The CFCs supply the different products to several spokes as per the customer's orders received online. Spoke plays the role of cross-dock in this supply chain and does not store the products. At spoke, the outbound vehicles coming from CFCs are unloaded and then products are re-loaded onto small delivery vans which fulfil customers' orders. The customers who are nearby to CFCs are directly served by CFCs. Different types of capacitated vehicles including single and double-deck trailers, delivery vans and trucks are used to transfer products from one point to another point. The overview of this supply chain network is shown in Fig. 1 below.

Currently, the company has limited storage and logistics capacity which became the major hurdle to satisfy the growing demand of customers. In addition to the regular customers, millions of new customers moved to this retailer during the first wave of the pandemic in 2020. The retailer struggled to accommodate all new customers because of supply shortages, the spike in demand from regular customers, limited storage, and logistics capacity. The surge in demand and limited logistics capacity resulted in the delivery slots shortage problem and many customers did not get slots for their delivery. To help the elderly and vulnerable people, this retailer introduced priority delivery slots which helped to tackle the societal challenge also. Some other policies such as limiting the maximum number of products sold to each customer had helped to provide access to products to all sections of society. Overall, the company's profit significantly increased during the first and second waves of

the pandemic. The company was interested to study the effect of the pandemic on their performance, the impact of response and resilience strategies followed by them and some ways to make their SC more robust and resilient to deal with future pandemics.

3.2 Data and model specification

This online retailer sells numerous grocery products to millions of customers. We have considered five products (i.e., Eggs, Pasta, Plain Bagels, Self-rising flour and Chicken Breast Fillets) whose demand is significantly affected in the first and second waves of the pandemic. The SC network comprising one supplier, one CFC, two spokes and ten customers is considered here for simplicity purposes. The data for aggregate weekly demand and prices of products, capacity of warehouses, lead time, order received, and order picked is obtained from the online retailer for the whole year 2020 (Jan to Dec 2020). We have considered the following assumptions. The transportation cost from CFC to spoke and spoke to customers is product and distance based, i.e., one unit per ton per unit distance. The fixed delivery cost between suppliers and CFC is 500 units per trip. The inventory carrying cost at CFCs is 0.001 unit per kg per day. Suppliers supply these products in trailers (capacity 28 tons) to CFC. The CFC keeps the stock of these products and transfers them to spokes. The CFC also fulfils the orders of nearby customers. Trucks with a capacity of 20 tons are used to transfer products to spokes and delivery vans having a capacity of 3.5 tons to meet the demand of nearby customers from CFC and spokes. In order to consider a large geographical area, we use the demand of one single customer to represent the total demand of 100 real customers. The summary
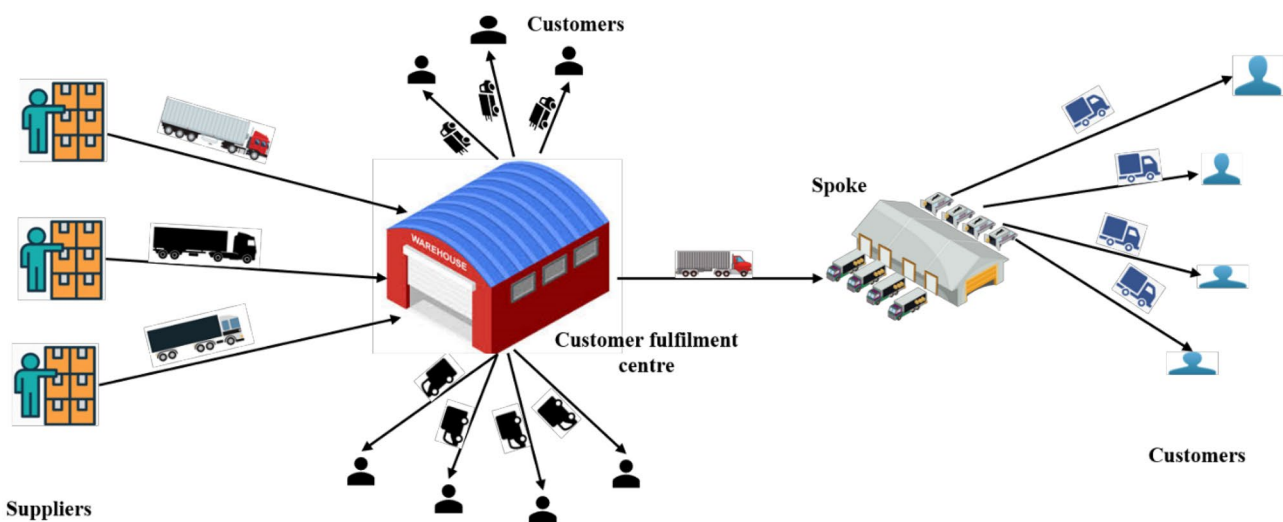

Fig. 1 Multi-stage supply chain network of e-grocery distribution company

of the real data related to different products is given in Table 7 (Appendix). CFC follows the Min–Max inventory policy whereas spokes follow the cross-dock policy. These policies closely resemble the actual ordering policies used in the company. The summary of inventory control parameters for CFC and spokes is given in Tables 8 and 9 (Appendix). The values in this table are produced following the customers' demand and other real data.

3.3 Mathematical formulation

The mathematical model is developed to study the company's existing network. The objective function of the model is to maximise the profit that is obtained by subtracting the total cost from the revenue.

Assumptions:

- Each customer point represents the aggregate demand of many customers.
- Demand and capacity of CFCs are deterministic and well-known in advance.
- Each spoke works as a cross-dock.
- Multiple products and time periods are considered.
- Transportation costs are considered with travelled distances.

Set/Indices

I Set of suppliers indexed by $i \in I$
J Set of customer fulfilment centres (CFCs) indexed by $j \in J$
K Set of spokes indexed by $k \in K$
L Set of customers who are supplied from CFCs indexed by $l \in L$
M Set of customers who are supplied from spokes indexed by $m \in M$
P Set of products indexed by $p \in P$
V Set of vehicle types indexed by v_1, v_2, v_3
T Set of time periods $t \in T$

Parameters

d_{ij} Distance between supplier i and CFC j in km
d_{jk} Distance between CFC j and spoke k in km
d_{jl} Distance between CFC j and customer l in km
d_{km} Distance between spoke k and customer m in km
tc_{ij} Fixed delivery cost from supplier i to CFC j in $
tc_{jk} Unit transportation cost per unit distance from CFC j to Spoke k in $
tc_{jl} Unit transportation cost per unit distance from CFC j to customer l in $

tc_{km} Unit transportation cost per unit distance from spoke k to customer M in $
h_j Unit inventory carrying cost per day in $
pc_p Unit purchasing cost of product p in $
sp_p Unit selling price of product p in $
D_{lp} Weekly demand of product p from customers l in Kgs
D_{mp} Weekly demand of product p from customers m in Kgs
G_j Storage capacity of CFC j in Kgs
U_v Capacity of vehicle type v in Kgs

Decision variables

Q_{ij}^p Shipment quantity of product type p between supplier i and CFC j in Kgs
Q_{jk}^p Shipment quantity of product type p between CFC j and spoke k in Kgs
Q_{jl}^p Shipment quantity of product type p between CFC j and customer l in Kgs
Q_{km}^p Shipment quantity of product type p between spoke k and customer m in Kgs
$N_{ij}^{v_1}$ Number of vehicle type v_1 used between supplier i and CFC j
$N_{jk}^{v_2}$ Number of vehicle type v_2 used between CFC j and spoke k
$N_{jl}^{v_3}$ Number of vehicle type v_3 used between CFC j and customer l
$N_{km}^{v_3}$ Number of vehicle type v_3 used between spoke k and customer m
I_j^p Inventory of product type p available at CFC j in Kgs
S_i^p Purchased quantity of product type p from supplier i

Objective function

Maximise Profit = Revenue − Total cost (1)

The objective function (1) maximises profit by subtracting the sum of total costs from revenue.

Revenue = Selling price of the product *demand of the product

$$\text{Revenue} = \sum_{l=1}^{L} \sum_{m=1}^{M} \sum_{p=1}^{P} sp_p D_{lmp} \qquad (1.1)$$

The revenue is calculated using Eq. (1.1).

Total cost = Total purchasing cost + Total transportation cost + Total inventory carrying cost

Total purchasing cost = Purchasing cost of product type p * purchased quantity of product type p

$$\text{Total purchasing cost} = \sum_{i=1}^{I} \sum_{p=1}^{P} pc_p S_{ip}$$

Total transportation cost = Transportation cost between supplier and CFCs + Transportation cost between CFCs and spokes + Transportation cost between CFCs and customers + Transportation cost between spokes and customers

$$\text{Maximise profit } = \sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{p=1}^{P} sp_p D_{lmp} - \left[\begin{array}{l} \sum_{i=1}^{I}\sum_{p=1}^{P} pc_p S_{ip} + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{p=1}^{P} tc_{ij}d_{ij}Q_{ij}^p + \sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{p=1}^{P} tc_{jk}d_{jk}Q_{jk}^p \\ + \sum_{j=1}^{J}\sum_{l=1}^{L}\sum_{p=1}^{P} tc_{jl}d_{jl}Q_{jl}^p + \sum_{k=1}^{K}\sum_{m=1}^{M}\sum_{p=1}^{P} tc_{km}d_{km}Q_{km}^p + \sum_{j=1}^{J}\sum_{p=1}^{P} h_j I_j^p \end{array} \right] \tag{1.3}$$

Transportation cost between supplier and CFCs $= \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{p=1}^{P} tc_{ij}d_{ij}Q_{ij}^p$

Transportation cost between CFCs and spokes $= \sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{p=1}^{P} tc_{jk}d_{jk}Q_{jk}^p$

Transportation cost between CFCs and customers $= \sum_{j=1}^{J}\sum_{l=1}^{L}\sum_{p=1}^{P} tc_{jl}d_{jl}Q_{jl}^p$

Transportation cost between spokes and customers $= \sum_{k=1}^{K}\sum_{m=1}^{M}\sum_{p=1}^{P} tc_{km}d_{km}Q_{km}^p$

Total transportation cost $= \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{p=1}^{P} tc_{ij}d_{ij}Q_{ij}^p + \sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{p=1}^{P} tc_{jk}d_{jk}Q_{jk}^p$
$+ \sum_{j=1}^{J}\sum_{l=1}^{L}\sum_{p=1}^{P} tc_{jl}d_{jl}Q_{jl}^p + \sum_{k=1}^{K}\sum_{m=1}^{M}\sum_{p=1}^{P} tc_{km}d_{km}Q_{km}^p$

Total inventory carrying cost = Inventory carrying cost at CFCs

Total inventory carrying cost $= \sum_{j=1}^{J}\sum_{p=1}^{P} h_j I_j^p$

Total cost = Total purchasing cost + Total transportation cost + Total inventory carrying cost

$$\text{Total cost} = \begin{array}{l} \sum_{i=1}^{I}\sum_{p=1}^{P} pc_p S_{ip} + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{p=1}^{P} tc_{ij}d_{ij}Q_{ij}^p + \sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{p=1}^{P} tc_{jk}d_{jk}Q_{jk}^p + \sum_{j=1}^{J}\sum_{l=1}^{L}\sum_{p=1}^{P} tc_{jl}d_{jl}Q_{jl}^p \\ + \sum_{k=1}^{K}\sum_{m=1}^{M}\sum_{p=1}^{P} tc_{km}d_{km}Q_{km}^p + \sum_{j=1}^{J}\sum_{p=1}^{P} h_j I_j^p \end{array} \tag{1.2}$$

The second term of objective function consists of three types of cost i.e., purchasing, transportation and inventory carrying cost (Eq. 1.2). The first and last term in Eq. (1.2) illustrates the purchasing and inventory carrying cost,

respectively. The remaining terms (second to fifth) shows transportation cost in between the suppliers, CFCs, spokes and customers.

Maximise Profit = Revenue – Total cost

The mathematical form of objective function is represented using Eq. (1.3).

Subject to

$$Q_{jl}^p = D_{lp} \quad \forall j, \ \forall l, \ \forall p \tag{2}$$

$$Q_{km}^p = D_{mp} \quad \forall k, \ \forall m, \ \forall p \tag{3}$$

The constraint (2) and (3) are demand satisfaction constraints.

$$\sum_{p=1}^{P} I_j^p \leq G_j \quad \forall j \tag{4}$$

Constraint (4) makes sure that the inventory available at each CFC should be less that its capacity.

$$\sum_{p=1}^{P} Q_{ij}^{p} \leq N_{ij}^{v_1} U_{v_1} \quad \forall i, \forall j \tag{5}$$

The vehicle capacity constraint between supplier and CFC is shown by Eq. (5).

$$\sum_{p=1}^{P} Q_{jk}^{p} \leq N_{jk}^{v_2} U_{v_2} \quad \forall j, \forall k \tag{6}$$

$$\sum_{p=1}^{P} Q_{jl}^{p} \leq N_{jl}^{v_3} U_{v_3} \quad \forall j, \forall l \tag{7}$$

$$\sum_{p=1}^{P} Q_{km}^{p} \leq N_{km}^{v_3} U_{v_3} \quad \forall k, \forall m \tag{8}$$

Similarly, the vehicle capacity constraint between CFCs and spoke, CFCs and customers, and spokes and customers are defined by constraint set (6)–(8).

$$Q_{ij}^{p}, Q_{jk}^{p}, Q_{jl}^{p}, Q_{km}^{p}, I_{j}^{p}, S_{i}^{p} \geq 0 \quad \forall i, \forall j, \forall k, \forall l, \forall m, \forall p \tag{9}$$

$$N_{ij}^{v_1}, N_{jk}^{v_2}, N_{jl}^{v_3}, N_{km}^{v_3} \in \mathbb{Z}^{+} \quad \forall i, \forall j, \forall k, \forall l, \forall m \tag{10}$$

Finally, constraint (9) and (10) depicts the non-negativity and integer constraints, respectively.

3.4 Digital twin and simulation model

Simulation and digital twins are important components of Industry 4.0 (Machado et al. 2020). Digital SC twins are computerised models for physical networks at any given time (Ivanov and Dolgui 2021). The digital twins involve more flows, networks and operational parameters hence they are more complicated than simulation models. The real-time data is updated in digital twins through external systems and databases. The digital twins help to improve the SC visibility and resilience with this real-time transparency. We can analyse the impact of disruption, develop alternative SC networks and conduct KPI analysis using real-time data. A multi-stage supply chain network of the online grocery retailer in the UK is modelled using anyLogistix SC simulation and optimisation software. The application of this software for SC resilience analysis has been growing recently because of its integrated features of optimisation and simulation (Ivanov 2020; Singh et al. 2021; Burgos and Ivanov 2021). Figure 2 depicts the simulation model developed in Personal Learning Edition of anyLogistix software and this model was run on the 8 GB RAM with Intel Core i7 1.8 GHz processor and 64-bit Operating System of Windows 8. The customer places an online order on the retailer's platform and then receives products either from nearby CFCs or spokes. Suppliers dispatch products to CFCs as per their orders received from them.
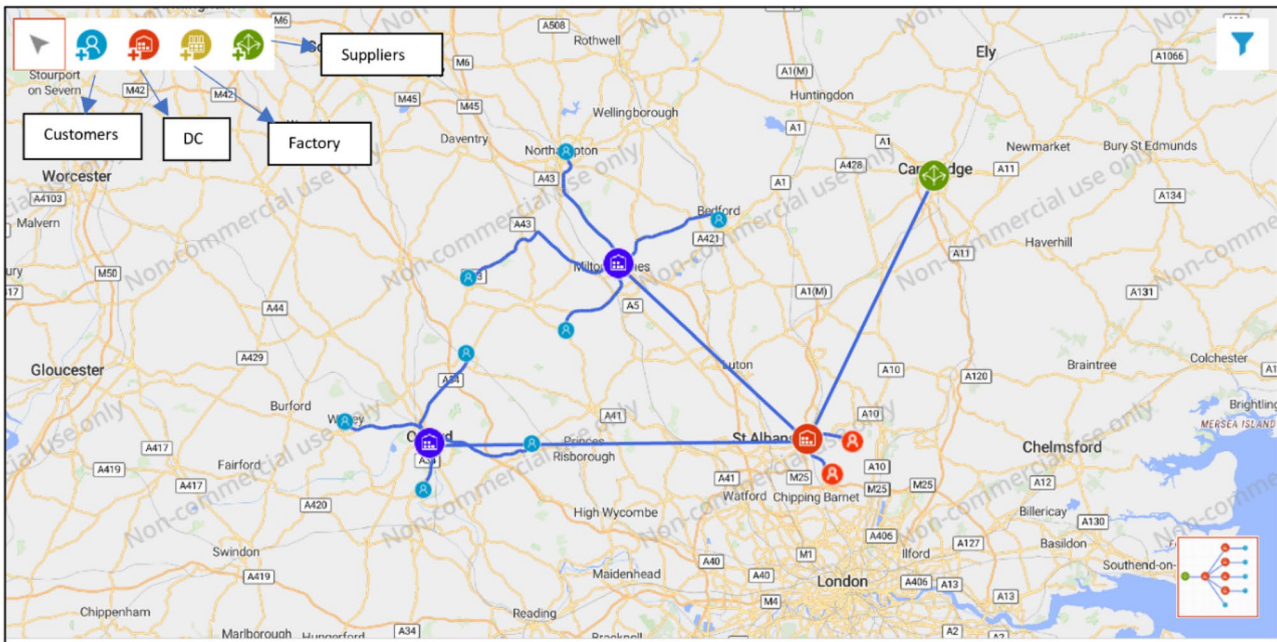

Fig. 2 Supply chain network in "anyLogistix" software

4 Experimental set-up

Initially, the mathematical model is solved without considering any disruptions and obtained the optimal results of the model. Next, the disruption is modelled in anyLogistix using various risk events like demand variations, supplier closures, CFCs and spokes closures. The impact of the disruption is analysed based on the following Key Performance Indicators (KPIs). The disruption mainly affects the financial and operational performance of the organisation hence we considered the financial indicators, product-related indicators, expected lead time and fulfilment-related indicators.

4.1 COVID-19 pandemic scenarios

The first national lockdown was imposed on 23rd March 2020 due to the continuous spread of the virus and the UK government ordered people to stay at home and leave home only for limited reasons. The lockdown was further extended for 'at least' three weeks on 16th April 2020 and eased on 10th May 2020 when the UK passed the peak of the first wave of the pandemic. The second wave of COVID-19 hit the country in early September which led to the imposition of new restrictions on 22nd September 2020. The second national lockdown was imposed on 31st October 2020 following the soaring cases and death toll across the country. The new tougher restrictions were enforced on 19th December after finding a new variant of the virus and continued till the end of the year. This overall timeline of the pandemic in 2020 in the UK is shown in Fig. 3. The simulation scenarios are developed based on this timeline and are outlined in Table 2.

4.1.1 Scenario 0: baseline scenario

This scenario analyses the performance of the online grocery retailer without disruptions and will be used to compare the performance with disruptive events.

4.1.2 Scenario 1: demand variations

The whole year 2020 is categorised into five distinct periods mentioned in Table 3 following the timeline described in Fig. 4. The baseline is considered a business-as-usual scenario and base demand (100%) corresponds to this scenario. Among the considered five products, the demand for Self-rising flour (SRF) and pasta increased by almost 407% and 168% respectively during the first national lockdown. Eggs, Plain Bagels (PB) and Chicken Breast Fillets (CBF) also experienced growth in demand, but their magnitude was lower compared with SRF and pasta. The next period is the time after the lifting of the first lockdown (10th May) till the start of the second lockdown (30th Oct). The demand for products varied (dropped compared to the first lockdown) because of no strict lockdown and social distancing measures. The fourth period corresponds to the second national lockdown in the UK (31st October to 2nd December 2020). The variations in demand for different products are given in the below table. The last and fifth period from 3rd to 31st Dec 2020 was the period after the second national lockdown. The online retailer received many orders from new customers who joined this retailer during the first lockdown. To replicate this case of additional customers, three new customers are included in addition to the existing 10 customers. Among these three new customers, one will be supplied by
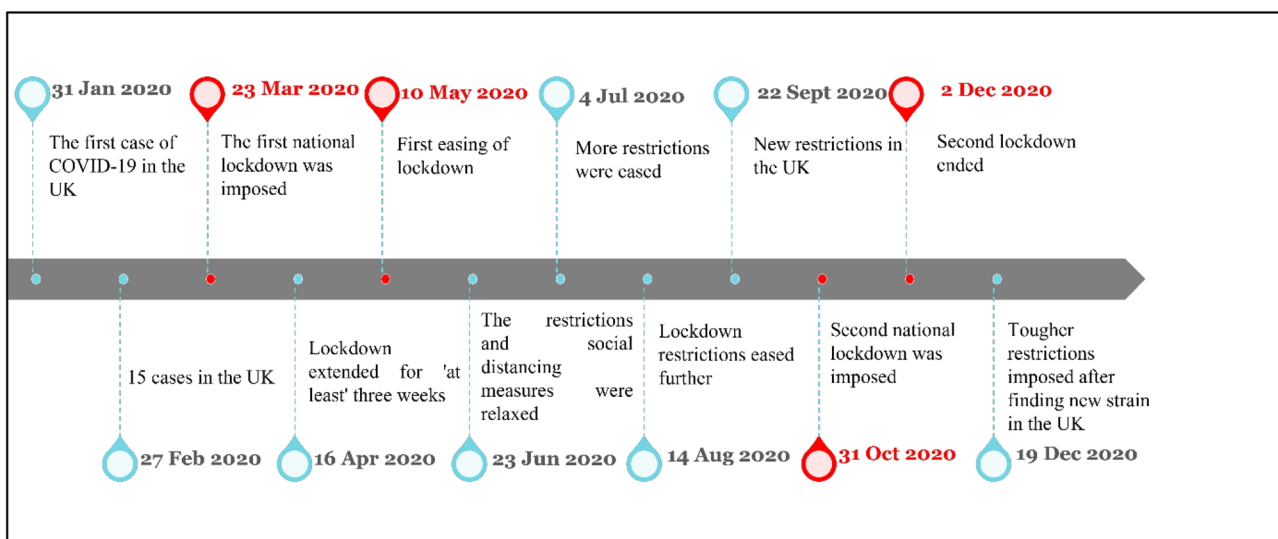

Fig. 3 The COVID-19 timeline in the UK (Source: Institute for Government analysis)

D. G. Mogale et al.

Table 2 Simulation scenarios

Scenario no	Scenario name	Supplier	CFC	Spokes	Customers	Disruption Starting date	Disruption Ending date	No. of days disruption occurred	Disruption Starting Day	Disruption Ending day
0	Baseline	Active	Active	Active	Normal demand	-	-	-	-	-
1	Demand variations	Active	Active	Active	Demand spike and collapse	-	-	-	-	-
2	Supplier disruption	Disrupted	Active	Active	Normal demand	25/03/20 1/11/20	13/04/20 15/11/20	20 15	84 305	103 319
3	CFC disruption	Active	Disrupted	Active	Normal demand	10/04/20 10/11/20	29/04/20 24/11/20	20 15	100 314	119 328
4	Spokes disruption	Active	Active	Disrupted	Normal Demand	20/04/20 16/11/20	09/05/20 30/11/20	20 15	110 320	129 334
5	Ripple effect	Disrupted	Disrupted (after 10 days of supplier disruption)	Disrupted (after 15 days of supplier disruption)	Normal Demand	Sup:25/03/20 CFC: 04/04/20 Spoke: 09/04/20	13/04/20 23/04/20 28/04/20	20 20 20	84 94 99	103 113 118
6	COVID-19	Disrupted	Disrupted	Disrupted	Demand spike and collapse	25/03/20 1/11/20	13/04/20 15/11/20	20 15	84 305	103 319

CFC, the second will be by spoke 1 and the last by spoke 2. It means that this scenario consists of additional demands from existing customers and orders from new customers.

The details about supplier (scenario 2), CFC (scenario 3) and spokes (scenario 4) disruptions are given in Table 2.

4.1.3 Scenario 5: ripple effect

The "ripple effect" is a phenomenon of disruption propagation and its impact on SC performance (Ivanov 2017). If the supplier stops supplying the products to the CFC, then after some time CFC and spokes would struggle to meet the customers' demand because of lack of inventory. CFC and Spokes remain closed for some days until they receive enough stock. This overall scenario of ripple effect is replicated in simulation software by creating some delays after the occurrence of disruption.

4.1.4 Scenario 6: COVID-19 scenario

This scenario simulates the effect of disruption on the online grocery retailer by combining scenarios 1, 2, 3, and 4 together. The overall performance of the online grocery retailer considering two pandemic lockdowns in 2020 is analysed in this scenario.

5 Results and analysis

The results of all six scenarios are discussed in this section by focusing on RQ1 what the impact of disruption on online grocery retailer is. Furthermore, cross-comparison analysis of scenarios provides additional insights into the effect of disruption on the retailer.

5.1 Scenario 0: baseline scenario

The ELT service level indicates the ratio of on-time orders to the total ongoing deliveries and late orders negatively influence this service level. Service level 1 (Fig. 4) portrays all customers receiving their orders within the ELT and without any delays. The lead time of each product ordered is shown by the histogram in Fig. 4. The X-axis depicts the lead time in days and the Y-axis indicates the occurrence of orders with a specific lead time. The lead time for most orders is between 0 and 0.34 days. The maximum lead time (1.247 days) (within the ELT) is obtained for a few orders. Regarding shipped vehicles, the delivery vans made maximum trips to transfer products to customers from CFC and spokes. The capacity of trailers and trucks are higher compared to van hence their number of trips are smaller. The simulation results show the on-hand inventory levels at the CFC for each product category. The Min–Max inventory

Table 3 Different demand levels

Event	Period	Products	Coefficient
Baseline	01/01/2020 – 22/03/2020	Eggs	1
		Self-rising flour	1
		Plain bagels	1
		Chicken breast fillets	1
		Pasta	1
Base demand variations during first national lockdown	23/03/2020 – 09/05/2020	Eggs	1.75
		Self-rising flour	5.07
		Plain Bagels	1.35
		Chicken breast fillets	1.28
		Pasta	2.68
Base demand variations after the first national lockdown	10/05/2020 – 30/10/2020	Eggs	1.38
		Self-rising flour	2.29
		Plain Bagels	1.17
		Chicken breast fillets	0.94
		Pasta	1.35
Base demand variations during the second national lockdown	31/10/2020 – 02/12/2020	Eggs	0.91
		Self-rising flour	3.06
		Plain Bagels	1.21
		Chicken breast fillets	0.73
		Pasta	1.30
Base demand variations after the second national lockdown	03/12/2020 – 31/12/2020	Eggs	1.21
		Self-rising flour	1.02
		Plain Bagels	1.04
		Chicken breast fillets	0.69
		Pasta	0.67

policy (s, S) is used in this study that allows ordering products up to maximum level (S) when the inventory level reaches minimum point (s). No abrupt trends or patterns in inventory levels are observed during the whole year.

5.2 Scenario 1: demand variations

The simulation outcome of demand variations in terms of KPIs is presented in Fig. 5. The impact of the pandemic on all products is not the same. The simulation outcome reveals that the demand variations positively affect the revenues because of the drastic increase in demand for maximum products due to the customers' panic buying and stockpiling behaviour. The new customers' entry is also one of the major reasons behind the sale of a higher number of products during the first lockdown. The inventory levels were reduced when demand increased which led to an increase of lead time and late orders. The ELT service level fell below 1 because of late orders during the first lockdown and never came back to normal till the end of the year. Most of the orders are delivered between 0 and 0.37 days, but a few orders reached 2.26 days. The number of vehicle trips is higher compared to the baseline scenario because of

increased orders. After the first lockdown, the demand for all products except CBF was still higher than the base demand but lower than the first lockdown. Hence, the on-inventory level for CBF was slightly increased whereas other product levels were decreased. Overall, we observed that the inventory level reduced when demand increased and vice versa.

5.3 Scenario 2: supplier disruption

Figure 6 depicts the simulation results after the supplier shut down for 20 days in the first lockdown and 15 days in the second lockdown. According to these results, the profit of SC was slightly reduced because of the rise in transportation costs during the lockdowns. The on-hand inventory levels of all products were reduced when the supplier stopped supplying to CFC. Thus, the inventory carrying cost is not substantially reduced. The late orders started escalating when the supplier disrupted and continued till the end of the year. These late orders negatively affected the service level which falls below one when suppliers disrupted for the first time in March 2020. Regarding lead time, maximum orders are delivered within 2.8 days however few customers received their orders in 21.247 days because of a lack of stock at CFC.

Fig. 4 Simulation results for baseline (disruption free) scenario

The number of trailers trips between the supplier and CFC was reduced due to the supplier's disruptions in the first and second lockdowns. More trips of trucks and vans compared to the baseline scenario happened to transfer products due to less than truckload and lower inventory levels.

5.4 Scenario 3: CFC disruption

The profit is significantly reduced when CFC is closed for a few days during two lockdowns. The CFC was unable to fulfil customers' demand in closure time hence revenue generated by selling the products is decreased. The late orders started increasing around 100 days when CFC closed on the 10th of April 2020 due to the spread of COVID-19 in it (Fig. 7). These late orders continue to rise a few days after the opening of CFC because of the huge backlog generated during closure time. The number of late orders remain constant till the second lockdown but again started rising when CFC closed on the 10th of Nov for 15 days in the second lockdown. The second lockdown affected the progress of the service level when it was improving after the impact of the first lockdown. Although maximum orders need an average of 4.6 days to reach customers, few

orders are delivered in 25.256 days. The number of trips of the trailer from supplier to CFC is reduced compared with the baseline because of 35 days of closure during the entire year. The on-hand inventory at CFC remained constant during lockdowns because CFC was not able to transfer products to spokes and meet the demands of nearby customers.

5.5 Scenario 4: spokes disruption

Figure 8 presents the results of the simulation model when spokes were closed for several days. The profit of the online grocery retailer decreased significantly due to a drop in the number of products sold when the spokes became inactive. The on-hand inventory at the CFC had little impact on the closure because the CFC uses a min–max policy for inventory management. During the first lockdown, many customers did not receive their products on time after the spoke closure, leading to a significant increase in late orders. A similar pattern of late orders was observed during the second lockdown. The service level dropped below one due to these late orders and never returned to normal afterwards.

Fig. 5 Simulation results: Demand variations scenario
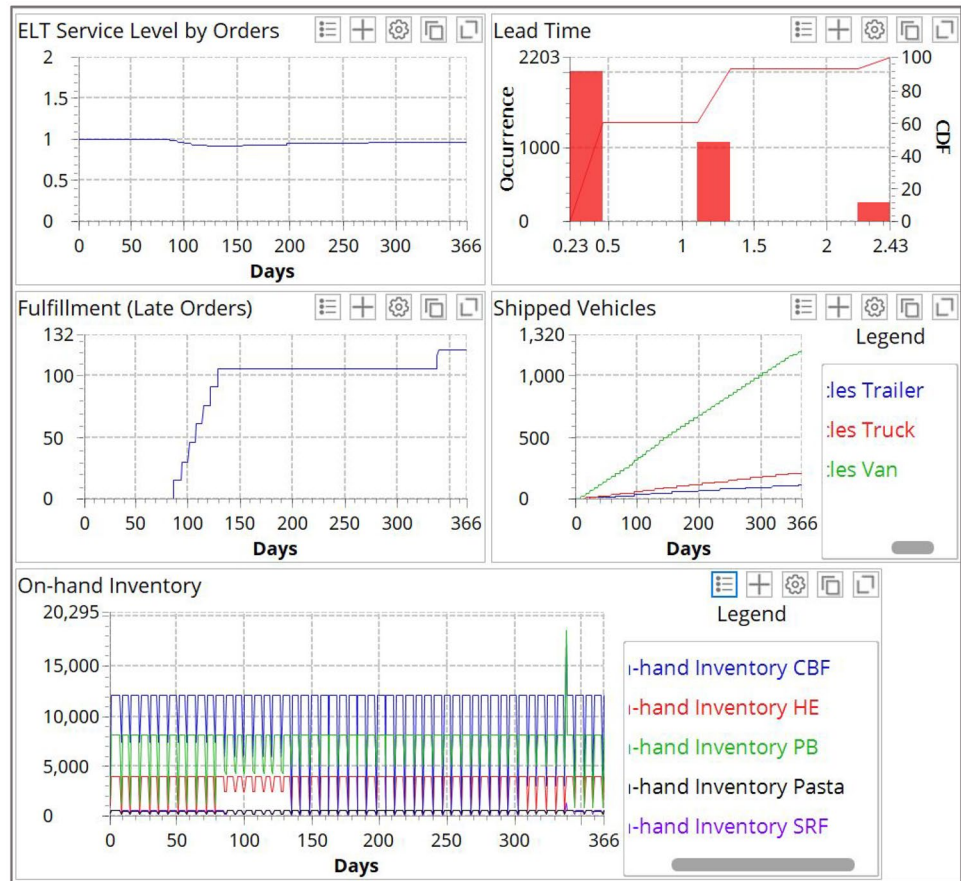
5.6 Scenario 5: ripple effect

Scenario 5 demonstrates the impact of disruption propagation on the performance of the online grocery food retailer using Fig. 9. According to the results, the ripple effect significantly impacted the profit performance as the number of products sold decreased when the impact of supplier disruption propagates to CFC and spokes. The inventory levels for all products considerably reduced during lockdowns which led to an increase in late orders. The magnitude of the rise of late orders and drop-in service level in this scenario is higher because of the simultaneous closure of facilities for a limited period compared with scenarios 2, 3 and 4.

5.7 Scenario 6: simultaneous disruptions

Figure 10 shows the impact of demand variations and facility disruptions on the SC performance of the online grocery retailer. Despite the closure of facilities during two lockdowns, the retailer's profit significantly improved due to higher demand from existing and new customers. The inventory levels for all products remained consistent until the reopening of all facilities, after which the inventory level for CBF increased drastically due to a collapse in customer demand. The graph of late orders clearly shows an increasing trend after the facilities were disrupted, remaining constant from the first lockdown to the second lockdown. The ELT service level decreased significantly to 86.7% by the end of the year due to a growing number of late orders and the simultaneous occurrence of different disruptive events. The CFC was able to deliver most orders within 5.8 days, with some exceptions taking up to 32.25 days to reach customers. This scenario, which includes demand variations and facility closures, resulted in lower profit than the demand variation scenario.

5.8 Cross-comparison analysis

The cross-comparison analysis of all scenarios was conducted here to generate more insights and see the overall impacts. Table 4 depicts the results in terms of various KPIs for this cross-comparison analysis and helps to address some of the major issues encountered by the retailer. This table clearly shows the revenues, total costs and profits for each scenario as a financial performance. The profit is calculated by subtracting the total costs from revenues. The baseline scenario shows good profitability. The total cost ($6.8Mn) is almost 77% of the revenue ($8.8Mn). The purchasing cost

Fig. 6 Simulation results: Supplier disruptions scenario
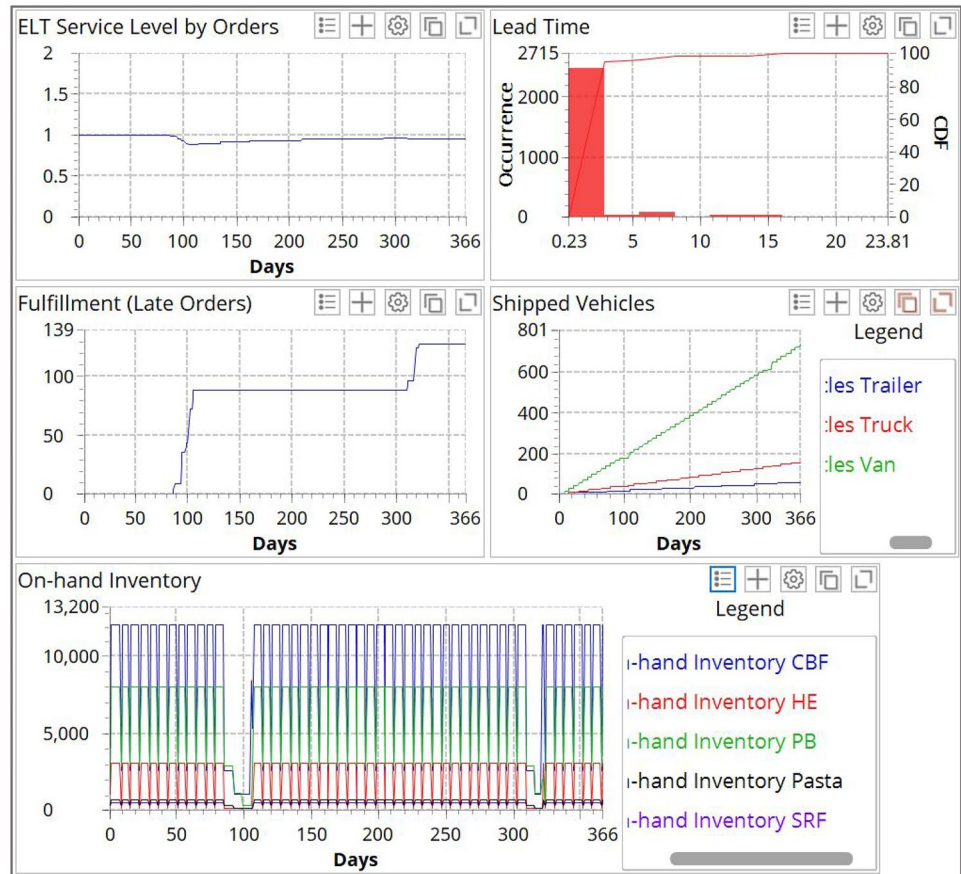
contributes significantly to the total cost because the retailer does not produce anything but purchases all products. The inventory carrying cost has a very limited contribution to total costs because maximum grocery products are perishable in nature that need to be replenished regularly.

Scenario 1, which involved a demand spike from existing customers and the entry of new customers, had the most positive impact on the supply chain performance. The revenue increased by $2.92 million compared to the baseline scenario, thanks to the growth in sales. However, the transportation costs increased by almost 65% compared to the baseline, as many additional trips were required to meet the increased demand from customers.

Similarly, the online retailer purchased more products which led to a rise in purchasing costs by 32% compared with the baseline scenario. Mean lead time and late orders are also increased due to demand variations and the entry of new customers. The 11 dropped orders depict the number of orders that CFC could not fulfil due to insufficient stock.

Scenario 2 illustrates that supply shortages for certain periods do not have a strong effect on financial performance. CFC can manage the customers' demand with additional lead time despite the supplier's two times closure. Hence, the mean lead time is increased by nearly 127% compared with

the baseline. The slight reduction (less than 1%) in profit is obtained because of the Min–Max policy that helped to manage small supply variations and avoid inventory shortages. ELT service level reached 95.1% because CFC was not able to meet demands on time when supply stopped.

The effect of the pandemic on online grocery SC performance is worst in scenario 3 when CFC stopped working for certain periods in two lockdowns. The worst effect shows that the CFC is a vital member of the company's supply chain. The revenue generated shrunk by approximately 2% as compared to the baseline scenario due to lower sales. The total number of trips made by all vehicles is reduced a little because no products moved from CFC to spokes and customers. The spokes cannot keep stock of inventory and work as a crossdock. Hence, they cannot meet the demands of customers on their own when CFC became inactive. Due to this inability, the late orders are higher than in the previous two scenarios. These late orders influenced the service level which experienced a significant drop compared with the previous two scenarios. The 50 dropped orders show the number of orders that customers could not place because CFC was closed for certain periods. Like the last scenario, scenario 4 shows the negative impact on SC performance when the spokes stopped working two times. The number of products sold to customers reduced

Fig. 7 Simulation results: CFC disruption scenario

hence revenues (decreased by almost 3.79%) and profit (reduced by 4%) compared to the baseline scenario. Product movement between CFC and spokes stopped completely during spokes closures hence transportation costs were reduced. Spoke directly delivers orders to customers hence dropped orders increased compared with the CFC disruption scenario.

The revenue generated and total costs of scenario 5 are lower than baseline as well as the previous three scenarios because two facilities remained closed simultaneously for a certain period due to the ripple effect. The simultaneous closures of facilities increased the mean lead time and dropped orders against all previous scenarios. The additional lead time is the primary reason behind the late orders that escalated considerably as compared with previous scenarios. The negative effect of late orders appeared on the service level that reached to lowest (86.2%).

The SC of the online grocery retailer experienced a very positive effect of COVID-19 in scenario 6. Due to the demand growth of major products and the entry of new customers, revenue generated by selling products drastically increased by approximately 25% compared with the baseline scenario but lower than scenario 1. Scenario 1 does not have the combination of all scenarios hence their revenue and profit are higher than the COVID-19 scenario. The profit is nearly 17% higher than the baseline scenario and higher than all scenarios except

scenario 1. Many orders, new customers, and limited storage and logistics capacity contributed to the rise in mean lead time and dropped orders. All vehicles made a total number of 1448 trips lower than scenario 1 to dispatch products to customers. The late and dropped orders are highest in this scenario because of the simultaneous consideration of disruptive events. The service level is somewhat better than scenario 5 and worse than all other scenarios.

Among all scenarios, scenario 1 (demand variations) has a very significant positive impact on the SC performance of the online grocery retailer followed by scenario 6. In case of negative effect, scenario 3 (CFC disruption) made the worst effect on profit followed by scenario 5 (ripple effect). The mean lead time of scenario 5 is the highest hence its ELT service level is the worst among all scenarios. All vehicles made the highest trips in scenario 1 and late and dropped orders reached the maximum level in scenario 6.

6 Mitigation strategies used by grocery retail sector

Many food retailers and giant supermarkets across the UK implemented various strategies to deal with the panic buying and stockpiling behaviour of customers throughout the

Fig. 8 Simulation results: Spokes disruption scenario

pandemic (Sky News 2020). People with pre-existing conditions are most vulnerable to catching the virus if they visit supermarkets for grocery shopping. Buying more than needed means that these vulnerable may face shortages of items like pasta, toilet rolls, and self-rising flour. Product prices may increase strongly hitting the vulnerable and poor people of the society. All major retailers worked with the UK government to develop various measures and strategies to deal with panic buying and avoid artificial shortages. Online retailers and supermarkets introduced many measures such as rationing the number of each item customers can buy, prioritizing home delivery slots for vulnerable people, and prioritising passes for in-store shopping and e-gift cards. In this study, we have analysed the effect of some of these measures followed by the online retailer.

6.1 Vulnerable priority delivery slots

The online grocery retailer had kept some priority delivery slots for vulnerable people. This subsection presents the results of the simulation model after embedding priority delivery slots in scenario 6. The online retailer normally supplies orders to customers from 5.30 am to 11.30 pm. Customers select the slots

and then get orders from the retailer during that slot. The online retailer kept three hours (5.30 am to 8.30 am) every day in two lockdowns as priority delivery slots during which it delivers orders to vulnerable customers only. Normal customers can get orders after 8.30 am. This scenario has been replicated in the simulation software while defining the start and end times of shipping orders. As per the results, the online retailer experienced a negligible impact on financial performance compared with the Covid-19 scenario because of the similar number of customer orders received and CFC was able to deliver those orders with some additional lead time. The mean lead is slightly increased (by more than 1%) because of priority delivery slots. The rest of the KPIs like service level, shipped vehicles, and dropped and late orders are identical to scenario 6. These results (Table 5) demonstrate that the online retailer can deliver priority orders to vulnerable people without affecting its financial performance with slightly more lead time.

6.2 Limit on maximum products sold to customers

This scenario put the limit on the maximum number of products sold to each customer per order. The impact of the first lockdown was more severe than the second lockdown. The

Fig. 9 Simulation results: Ripple effect scenario
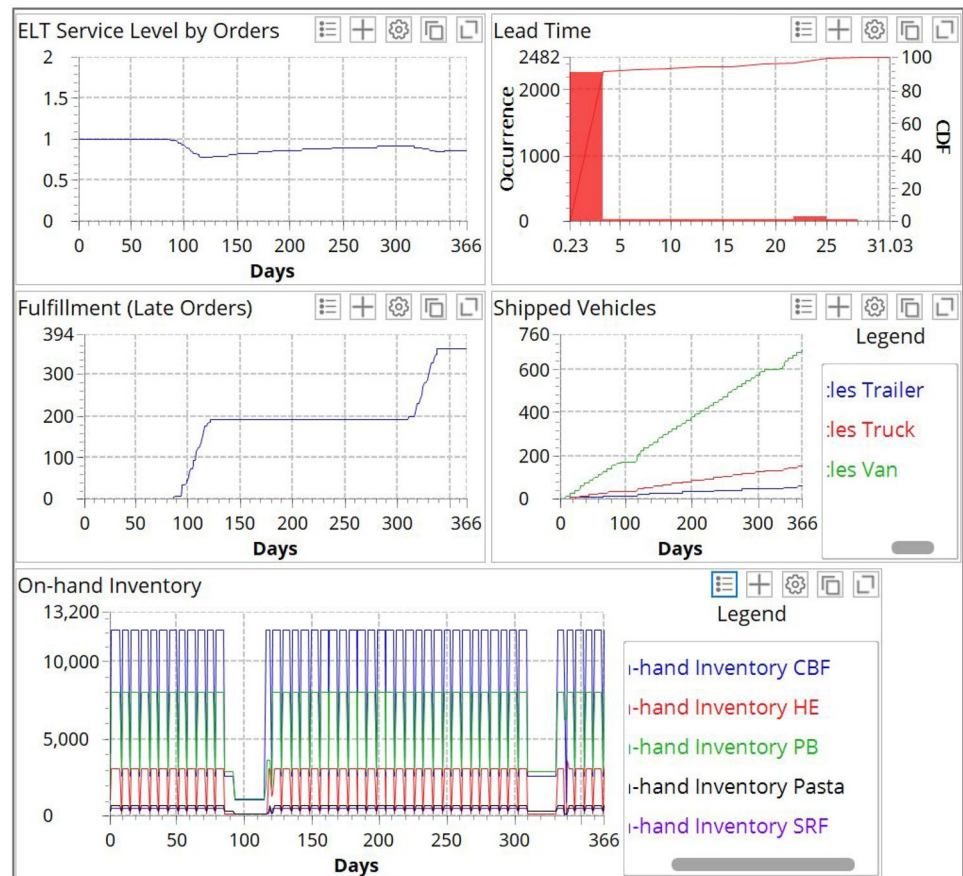
first lockdown was completely new, and people were worried about catching the virus and shop closures. Thus, panic buying, and stockpiling started by them. Following this new pattern of shopping and supplier shortages, supermarkets and online retailers put restrictions on maximum products, especially dried pasta, self-rising flour, toilet rolls, hand sanitiser and many others sold to each customer. To mimic this situation, we have considered that each customer can buy up to 30% more products compared with their normal demands (base demand) in the first lockdown and up to 50% more products in the second lockdown. The second lockdown was not very hard hence customers have flexibility of buying products up to 50% compared with base demands. The results (Table 5) show a slight reduction (-0.66%) in revenue generated and profit (-0.91%) compared with the scenario of Covid-19 because of restrictions put on customers' orders for each product. Suppliers struggled to supply all requested products on time to CFC. The lower number of product movements from supplier to CFC, CFC to spokes and customers decreases the transportation cost as well. The mean lead time is 1.537 days which is slightly lower than scenario 6 hence the late orders are also a little lower compared with scenario 6. The ELT service level is somewhat better than it. The cap on the maximum number of products

bought does not have any effect on dropped orders but late orders decreased by almost 3% compared to the vulnerability slot scenario. The shipped vehicles also increased by approximately 3% compared with scenario 6 because vehicles travelled with less than truckload capacity.

By comparing the vulnerable delivery slots and rationing goods scenario, we find that minor negative effect of the latter on the SC performance of the retailer than the former. The rationing avoided the panic buying and stockpiling behaviour of customers that's why profit is slightly reduced compared with the Covid-19 scenario. The mean lead time of the rationing scenario is lower than the vulnerable delivery slot which led to a reduction of late orders.

7 Supply chain resilience strategies

The supply, demand, production, transportation and logistics stages collapsed due to the lockdowns and border closures. Many resilience strategies could have been used in different stages like preparedness for risky events, response and recovery to deal with these problems. The supply disruptions, supply shocks and shortages could be managed effectively using multiple and varied suppliers

Fig. 10 Simulation results: COVID-19 scenario

along with keeping backup suppliers at different locations (Chowdhury et al. 2021; Moosavi and Hosseini 2021). Building temporary capacity, increasing production in early stages, balancing between local and domestic production, and distributing manufacturing systems are some of the strategies that may solve the production-related problems that occurred during the pandemic. In this study, we use the backup supplier and ramp-up CFC

Table 4 Cross-comparison analysis

Performance impact	Scenario 0: Disruption free (Baseline)	Scenario 1: Demand variations	Scenario 2: Supplier disruptions	Scenario 3: CFC disruption	Scenario 4: Spokes disruption	Scenario 5: Ripple effect	Scenario 6: Covid-19
Revenue (USD)	8,829,293	11,748,952	8,829,293	8,659,499	8,489,705	8,353,870	11,031,896
Total cost (USD)	6,820,788	9,010,177	6,822,211	6,903,666	6,562,169	6,497,487	8,679,507
Profit (USD)	2,008,505	2,738,775 ⬆	2,007,082 ⬇	1,755,833 ⬇	1,927,536 ⬇	1,856,382 ⬇	2,352,389 ⬆
Mean lead time (days)	0.404	0.771	0.917	1.626	0.406	1.915	1.618
Dropped orders	0	11	0	50	100	140	200
Total demand by customers (kg)	1,447,186	2,014,289	1,447,186	1,447,186	1,447,186	1,447,186	2,018,023
Total shipped vehicles	937	1573	943	915	903	915	1448
Demand placed (orders) by customers	2600	3298	2600	2600	2600	2600	3380
Late orders	0	125	127	290	100	359	451
ELT service level by orders (%)	100	96.2	95.1	88.8	96.2	86.2	86.7

Table 5 Simulation results: Vulnerable delivery slots and Limit on maximum products sold to customers

Performance impact	Scenario 6: Covid-19	Vulnerable priority delivery slots	Limit on maximum products sold to customers
Revenue (USD)	11,031,896	11,031,457	10,958,583
Total cost (USD)	8,679,507	8,679,200	8,627,805
Profit (USD)	2,352,389	2,352,256	2,330,778
Mean lead time (days)	1.618	1.635	1.537
Dropped orders	200	200	200
Total demand by customers (kg)	2,018,023	2,017,922	1,985,699
Total shipped vehicles	1448	1448	1462
Demand placed (orders) by customers	3380	3380	3380
Late orders	451	451	440
ELT service level by orders (%)	86.7	86.7	87

capacity strategies to curb the impact of the pandemic on the retailer because of their popularity and relevance in the retail sector.

7.1 Backup supplier

The online grocery retailer considered in this study buys different products from multiple suppliers located in the UK and Europe. Scenario 2 shows the impact of supplier disruptions on the SC performance of the retailer. It is observed from Table 4 that the profit slightly decreased after supplier disruptions. We want to depict how the multi-supplier or backup supplier strategy helps to maintain similar profit performance during disruption as well. The backup supplier provides supply to distribution centres when the main supplier stopped working due to some unexpected risky events. Scenario 2 represents that the main supplier stops working for 20 days in the first lockdown and 15 days in the second lockdown. One backup supplier is added into scenario 2 that supplies products to CFC when the main supplier stops supplying products to CFC. Figure 11a depicts that the main

supplier is active and supplying products to CFC. When the main supplier stopped working the backup supplier started supplying products to CFC which helped it to reduce the late orders completely and improve the profit to the level of the baseline scenario. This backup supplier supplied almost 10% of the total products supplied to CFC throughout the year.

7.2 Ramping up CFC capacity

The retailer has very limited large warehouses located across the UK to keep products and supply mainly to several spokes and nearby customers. The limited storage capacity of CFC is one of its major constraints to accept new customers during the first lockdown and satisfy the growing demand of existing customers. Furthermore, this limited capacity of CFC was the primary reason behind the spike in late orders during two lockdowns. Hence, the impact of the storage capacity of CFC on the SC performance especially on late orders and dropped orders indicators is analysed in this section. The storage capacity of CFC was 45,000 kg in all scenarios considered in Table 4. Scenario 6 (COVID-19) is
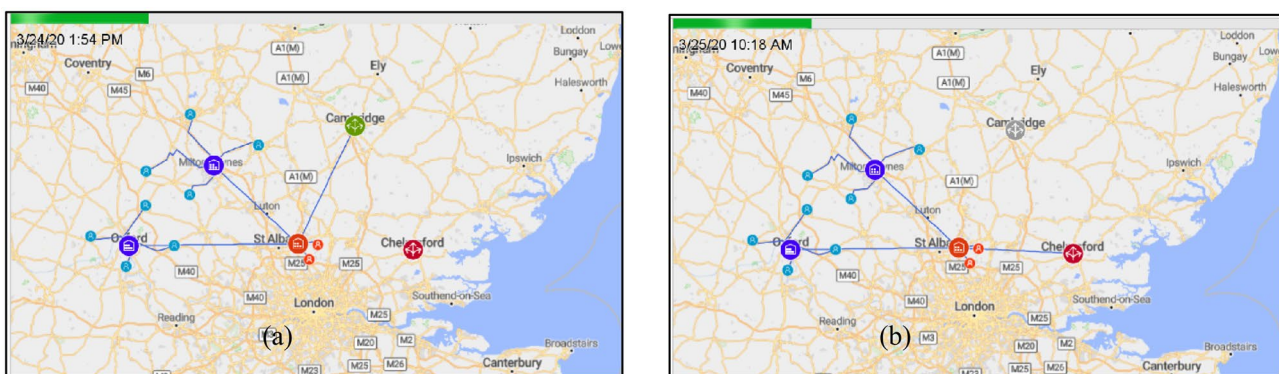

Fig. 11 a Main supplier supplying products to CFC and **b** Back up supplier supplying products to CFC

considered for comparison of the results of this strategy. The storage capacity is increased by 25%, 50%0.75% and 100% of its current capacity to see the effect on SC performance. The rest of the parameters and events of scenario 6 remained the same. The results of this resilience strategy are given in below Table 6. There is no effect on revenue generated because the number of products sold to customers remained the same after the increments of CFC capacity.

Similarly, the purchasing cost also has not changed because the number of products purchased from suppliers is similar. As the capacity of CFC increases the inventory cost also increases by minimum value (less than 1%) because CFC can store additional products to meet customers' orders on time and avoid any lost orders. In scenario 6, sometimes vehicles between suppliers and CFCs move with less than truckload capacity because of limited storage capacity at CFC. Also, the limited inventory available at CFC made less than truckload trips between spokes and customers. The sufficient CFC capacity allows the vehicles to move with full truckload capacity. Hence, the number of shipped vehicles is reduced when CFC capacity increases which led to the reduction of transportation costs by almost 10% compared with scenario 6. The reduction in total expenses helped to enhance the profit marginally after a gradual increment of CFC capacity. The mean lead time started decreasing when CFC capacity increased and reached 1.237 (days) when capacity increased by 100%. The sufficient availability of products at CFC prevented the LTL deliveries which resulted in the fall in mean lead time and late orders as well. Reducing late orders improved the ELT service level, reaching 89.3% when capacity increased by 75% and 100%. It is observed from Table 6 that many of the performance indicators are not significantly changed after the increment of CFC capacity by 100% as compared with the 75% increment. Therefore, the 75% rise in CFC capacity is optimal to reduce the number of late orders and improve the mean lead time and ELT service level.

8 Discussion and implications

This section focuses on how the SC resilience of retailers can be improved and what measures companies should consider for future disruptions. The decision-makers, online grocery retailers and other stakeholders involved in the grocery SC can find several managerial insights from the current study. The developed simulation model helps to analyse the impact of future disruptions on SC performance. The food retailers can visualise the effect of facilities disruptions like supplier, facility, distribution centres and cross docks on the supply chain and take necessary measures to manage this effect. The impact of the demand variation scenario can give evidence about how to deal with the sudden demand spike and collapse. The decision-makers can explore the ripple effect scenario to understand how the disruption propagates downstream from upstream and affects the entire supply chain. The last scenario explains what happens when all risky events occur simultaneously and affect all supply chain operations. The simulation analysis of the strategies used by supermarkets and retailers to manage panic buying and stockpiling behaviour can be used to see which strategy is beneficial for both customers and food retailers. The food retailer and policymakers can use this model to see the benefits of resilience strategies like backup suppliers and ramping up the DC capacity during disruptions.

We found that when disruption comes from the demand side (scenario 1), then it is a good thing for the company and when it comes from the supply side (scenarios 2, 3, 4 and 5), then it is a bad thing. The inventory is mostly kept in the warehouse in the retail sector hence warehouse plays a crucial role in the retail sector and its disruption severely affects SC performance. The CFC disruption has the worst impact on the SC performance of grocery retailers among all disruptions. Thus, retailers need to use effective and efficient mitigation strategies to avoid the disruption of warehouses (CFCs) and if disrupted, it needs to be quickly restored using resilience

Table 6 Impact of CFC capacity increment on SC performance

Performance impact	Scenario 6: Covid-19	25% increase of CFC capacity	50% increase of CFC capacity	75% increase of CFC capacity	100% increase of CFC capacity
Revenue (USD)	11,031,896	11,031,896	11,031,896	11,031,896	11,031,896
Total cost (USD)	8,679,507	8,661,620	8,660,129	8,659,646	8,659,657
Profit (USD)	2,352,389	2,370,276	2,371,767	2,372,250	2,372,239
Mean lead time (days)	1.618	1.325	1.251	1.237	1.237
Dropped orders	200	200	200	200	200
Total shipped vehicles	1448	1402	1397	1378	1378
Late orders	451	405	365	360	360
ELT service level by orders (%)	86.7	88	89.2	89.3	89.3

strategies. Grocery retailers can fulfil the priority orders of vulnerable people without affecting their financial performance. The mean lead time will slightly increase while delivering these priority orders. The priority orders help to protect and support vulnerable people during crises. Rationing of goods was dominantly used by grocery retailers to tackle the panic buying and stockpiling behaviour of customers and maintain the proper flow of goods across the supply chain. This strategy can be used for future disruptions also because in this strategy profit reduces by less than 1% compared with the pandemic scenario. Grocery retailers can reduce the mean lead time and late orders with the help of this strategy. Regarding resilience strategies, grocery retailers can use a backup supplier strategy during crises to come back to their original performance (baseline scenario). The CFC plays an important role in the grocery supply chain thus its capacity augmentation helps to enhance the SC performance. Results reveal that grocery retailers can increase CFC capacity by 75% to improve profit and reduce mean lead time and late orders.

9 Conclusions

This study has been motivated by the disruptions faced by the grocery retail sector in the UK. This sector experienced various disruptive events like supply shortages, demand spike and collapse, and distribution centres closures when the national lockdown was imposed in the UK. The case company considered here was interested to analyse the effect of these events and their strategies on the SC performance and explore some resilience strategies to manage future disruptions. We have made the following four academic contributions to the previous literature. The disruption risks have been modelled mathematically as well through simulation modelling (Singh et al. 2021). The effect of these disruptions on the grocery retail sector is investigated by taking the case study from the UK. The grocery retail sector followed two important mitigation strategies including vulnerable delivery slots and rationing of goods to manage the disruption (Hobbs 2021). The impact of these two strategies on the grocery retail sector's performance is quantified and explored (Burgos and Ivanov 2021). The quantification of two resilience

strategies is another major contribution of this study (Chowdhury et al. 2021; Ghadge et al. 2021).

The exciting findings of this study are mentioned below.

- The demand variation (spike) has the strongest positive impact on SC profit followed by the Covid-19 scenario.
- With regards to negative effects, the profit of the online grocery retailer reached to lowest when CFC was disrupted (scenario 3) followed by scenario 5 when disruption propagated.
- There was negligible impact on the financial performance of the grocery retailer compared with the Covid-19 scenario when priority delivery slots were used. The mean lead time was slightly (more than 1%) increased because of priority slots.
- The restrictions put on the customers buying slightly affected the profit and reduced the mean time and late orders compared with the Covid-19 scenario.
- Backup supplier strategy helped to bring the profit of the grocery retailer to its original level.
- The capacity of CFC should be enhanced by 75% to improve profit and decrease mean time and late orders.

The effect of vulnerable priority delivery slots and rationing products followed by the online grocery retailer on SC performance is also discussed in detail. Finally, two important resilience strategies (backup supplier and capacity augmentation) and their impacts on the grocery supply chain are quantified. Multiple managerial insights and academic implications based on the results are also suggested.

Similar to other research studies, this study has some limitations which could open the doors for future research. The simulation model can be extended further by including environmental impact into it. The logistics capacity limitation can make the mathematical formulation more realistic. The other type of costs like warehousing cost, facility closure and reopening costs could add further value to the mathematical formulation. The formulation of a multi-objective model is another future research avenue. This study considers only two measures followed by grocery retailers and two resilience strategies to see the impact of them on the supply chain. In future, scholars could explore more measures and resilience strategies for deeper analysis.

Appendix: input parameters

Table 7 Summary of the real data of different products

Products	Avg. Demand (kg)	Avg. Lead time (day)	Selling Price (USD) per kg	Purchasing cost (USD) per kg
Eggs	293.67	1.75	3.1	1.8
Self-rising flour	26.74	5.6	1.42	1
Plain Bagels	860.6	1.8	4.56	3
Chicken Breast Fillets	1,571.68	2.2	7.58	6
Pasta	30.36	6.5	6.37	5

Table 8 Inventory control policy parameters of CFC

Facility	Product	Inventory policy	s	S	Initial stock
CFC	Eggs	MIN–MAX	1000	3000	1000
CFC	Self-rising flour	MIN–MAX	250	500	250
CFC	Plain Bagels	MIN–MAX	1800	8000	1800
CFC	Chicken Breast Fillets	MIN–MAX	4000	12000	4000
CFC	Pasta	MIN–MAX	300	600	300

Table 9 Inventory control policy parameters of spokes

Facility	Product	Inventory policy	Initial stock
Spoke 1	Eggs	Cross-dock policy	0
Spoke 1	Self-rising flour	Cross-dock policy	0
Spoke 1	Plain Bagels	Cross-dock policy	0
Spoke 1	Chicken Breast Fillets	Cross-dock policy	0
Spoke 1	Pasta	Cross-dock policy	0
Spoke 2	Eggs	Cross-dock policy	0
Spoke 2	Self-rising flour	Cross-dock policy	0
Spoke 2	Plain Bagels	Cross-dock policy	0
Spoke 2	Chicken Breast Fillets	Cross-dock policy	0
Spoke 2	Pasta	Cross-dock policy	0

Declarations

References

Ali I, Sadiddin A, Cattaneo A (2022) Risk and resilience in agri-food supply chain SMEs in the pandemic era: a cross-country study. Int J Logist Res Appl 1–19. https://doi.org/10.1080/13675567.2022.2102159

Aqlan F, Lam SS (2016) Supply chain optimization under risk and uncertainty: A case study for high-end server manufacturing. Comput Ind Eng 93:78–87. https://doi.org/10.1016/j.cie.2015.12.025

Baryannis G, Validi S, Dani S, Antoniou G (2019) Supply chain risk management and artificial intelligence: State of the art and future research directions. Int J Prod Res 57:2179–2202. https://doi.org/10.1080/00207543.2018.1530476

Burgos D, Ivanov D (2021) Food retail supply chain resilience and the COVID-19 pandemic: A digital twin-based impact analysis and improvement directions. Transp Res Part E Logist Transp Rev 152. https://doi.org/10.1016/j.tre.2021.102412

Carissimi MC, Prataviera LB, Creazza A et al (2023) Blurred lines: the timeline of supply chain resilience strategies in the grocery industry in the time of Covid-19. Oper Manag Res 80–98. https://doi.org/10.1007/s12063-022-00278-4

Carvalho H, Barroso AP, Machado VH, Azevedo S, Cruz-Machado V (2012) Supply chain redesign for resilience using simulation. Comput Ind Eng 62(1):329–341

Chowdhury P, Paul SK, Kaisar S, Moktadir MA (2021) COVID-19 pandemic related supply chain studies: A systematic review. Transp Res Part E Logist Transp Rev 148:102271. https://doi.org/10.1016/j.tre.2021.102271

Christopher M, Peck H (2004) Building the resilient supply chain. Int J Logist Manag 15(2):1–14

Colicchia C, Strozzi F (2012) Supply chain risk management: A new methodology for a systematic literature review. Supply Chain Manag 17:403–418. https://doi.org/10.1108/13598541211246558

Dolgui A, Ivanov D, Rozhkov M (2020) Does the ripple effect influence the bullwhip effect? An integrated analysis of structural and operational dynamics in the supply chain†. Int J Prod Res 58:1285–1301. https://doi.org/10.1080/00207543.2019.1627438

Fahimnia B, Tang CS, Davarzani H, Sarkis J (2015) Quantitative models for managing supply chain risks: A review. Eur J Oper Res 247:1–15. https://doi.org/10.1016/j.ejor.2015.04.034

Fan Y, Stevenson M (2018) A review of supply chain risk management: Definition, theory, and research agenda. Int J Phys Distrib Logist Manag 48:205–230. https://doi.org/10.1108/IJPDLM-01-2017-0043

Garnett P, Doherty B, Heron T (2020) Vulnerability of the United Kingdom's food supply chains exposed by COVID-19. Nat Food 1:315–318. https://doi.org/10.1038/s43016-020-0097-7

Ghadge A, Dani S, Kalawsky R (2012) Supply chain risk management: Present and future scope. Int J Logist Manag 23:313–339. https://doi.org/10.1108/09574091211289200

Ghadge A, Er M, Ivanov D, Chaudhuri A (2021) Visualisation of ripple effect in supply chains under long-term, simultaneous disruptions: A system dynamics approach. Int J Prod Res. https://doi.org/10.1080/00207543.2021.1987547

Glickman TS, White SC (2006) Security, visibility and resilience: The keys to mitigating supply chain vulnerabilities. Int J Logist Syst and Manag 2(2):107–119

Golan MS, Jernegan LH, Linkov I (2020) Trends and applications of resilience analytics in supply chain modeling: Systematic literature review in the context of the COVID-19 pandemic. Environ Syst Decis 40:222–243. https://doi.org/10.1007/s10669-020-09777-w

Heckmann I, Comes T, Nickel S (2015) A critical review on supply risk - definition, measure and modeling. Omega (United Kingdom) 52:119–132. https://doi.org/10.1016/j.omega.2014.10.004

Ho W, Zheng T, Yildiz H, Talluri S (2015) Supply chain risk management: A literature review. Int J Prod Res 53:5031–5069. https://doi.org/10.1080/00207543.2015.1030467

Hobbs JE (2021) Food supply chain resilience and the COVID-19 pandemic: What have we learned? Can J Agric Econ 69:189–196. https://doi.org/10.1111/cjag.12279

Hosseini S, Ivanov D (2021) A multi-layer Bayesian network method for supply chain disruption modelling in the wake of the COVID-19 pandemic. Int J Prod Res 0:1–19. https://doi.org/10.1080/00207543.2021.1953180

Ivanov D (2017) Simulation-based ripple effect modelling in the supply chain. Int J Prod Res 55:2083–2101. https://doi.org/10.1080/00207543.2016.1275873

Ivanov D (2018) Revealing interfaces of supply chain resilience and sustainability: a simulation study. Int J Prod Res 56(10):3507–3523

Ivanov D (2019) Disruption tails and revival policies: A simulation analysis of supply chain design and production-ordering systems in the recovery and post-disruption periods. Comput Ind Eng 127:558–570. https://doi.org/10.1016/j.cie.2018.10.043

Ivanov D (2020) Predicting the impacts of epidemic outbreaks on global supply chains: A simulation-based analysis on the coronavirus outbreak (COVID-19/SARS-CoV-2) case. Transp Res Part E Logist Transp Rev 136. https://doi.org/10.1016/j.tre.2020.101922

Ivanov D (2021) Supply Chain Viability and the COVID-19 pandemic: a conceptual and formal generalisation of four major adaptation strategies. Int J Prod Res 59:3535–3552. https://doi.org/10.1080/00207543.2021.1890852

Ivanov D, Dolgui A (2021) A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0. Prod Plan Control 32:775–788. https://doi.org/10.1080/09537287.2020.1768450

Jüttner U (2005) Supply chain risk management: Understanding the business requirements from a practitioner perspective. Int J Logist Manag 16:120–141. https://doi.org/10.1108/09574090510617385

Karwasra K, Soni G, Mangla SK, Kazancoglu Y (2021) Assessing dairy supply chain vulnerability during the Covid-19 pandemic. Int J Logist Res Appl 0:1–19. https://doi.org/10.1080/13675567.2021.1910221

Li R, Dong Q, Jin C, Kang R (2017) A new resilience measure for supply chain networks. Sustainability 9(1):144

Li Z, Sheng Y, Meng Q, Hu X (2022) Sustainable supply chain operation under COVID-19: Influences and response strategies. Int J Logist Res Appl 0:1–27. https://doi.org/10.1080/13675567.2022.2110220

Machado CG, Winroth MP, Ribeiro da Silva EHD (2020) Sustainable manufacturing in Industry 4.0: An emerging research agenda. Int J Prod Res 58:1462–1484. https://doi.org/10.1080/00207543.2019.1652777

Maliki F, Souier M, Dahane M, Ben Abdelaziz F (2022) A multi-objective optimization model for a multi-period mobile facility location problem with environmental and disruption considerations. Ann Oper Res. https://doi.org/10.1007/s10479-022-04945-4

Montoya-Torres JR, Muñoz-Villamizar A, Mejia-Argueta C (2023) Mapping research in logistics and supply chain management during COVID-19 pandemic. Int J Logist Res Appl 26:421–441. https://doi.org/10.1080/13675567.2021.1958768

Moosavi J, Hosseini S (2021) Simulation-based assessment of supply chain resilience with consideration of recovery strategies in the COVID-19 pandemic context. Comput Ind Eng 160:107593

Office for National Statistics (ONS) (2021) Economic trends in the retail sector, Great Britain: 1989 to 2021. https://www.ons.gov.uk/economy/nationalaccounts/balanceofpayments/articles/economictrendsintheretailsectorgreatbritain/1989to2021

Ojha R, Ghadge A, Tiwari MK, Bititci US (2018) Bayesian network modelling for supply chain risk propagation. Int J Prod Res 56:5795–5819. https://doi.org/10.1080/00207543.2018.1467059

Partington R, Partridge J (2021) UK plunges towards supply chain crisis due to staff and transport disruption. The Guardian. https://www.theguardian.com/business/2021/aug/24/uk-retailers-stock-supply-shortages-covid-pingdemic. Accessed 5 Feb 2022

Pournader M, Kach A, Talluri S (2020) A review of the existing and emerging topics in the supply chain risk management literature. Decis Sci 51:867–919. https://doi.org/10.1111/deci.12470

Queiroz MM, Ivanov D, Dolgui A, Fosso Wamba S (2022) Impacts of epidemic outbreaks on supply chains: mapping a research agenda amid the COVID-19 pandemic through a structured literature review. Springer, US

Rajagopal V, Prasanna Venkatesan S, Goh M (2017) Decision-making models for supply chain risk mitigation: A review. Comput Ind Eng 113:646–682. https://doi.org/10.1016/j.cie.2017.09.043

Ribeiro JP, Barbosa-Povoa A (2018) Supply chain resilience: Definitions and quantitative modelling approaches – A literature review. Comput Ind Eng 115:109–122. https://doi.org/10.1016/j.cie.2017.11.006

Rinaldi M, Murino T, Gebennini E et al (2022) A literature review on quantitative models for supply chain risk management: Can they be applied to pandemic disruptions? Comput Ind Eng 170:108329. https://doi.org/10.1016/j.cie.2022.108329

Roh J, Tokar T, Swink M, Williams B (2022) Supply chain resilience to low-/high-impact disruptions: The influence of absorptive capacity. Int J Logist Manag 33:214–238. https://doi.org/10.1108/IJLM-12-2020-0497

Schmitt AJ, Singh M (2012) A quantitative analysis of disruption risk in a multi-echelon supply chain. Int J Prod Econ 139:22–32. https://doi.org/10.1016/j.ijpe.2012.01.004

Schmitt TG, Kumar S, Stecke KE et al (2017) Mitigating disruptions in a multi-echelon supply chain using adaptive ordering. Omega (united Kingdom) 68:185–198. https://doi.org/10.1016/j.omega.2016.07.004

Sharma M, Joshi S, Luthra S, Kumar A (2021) Managing disruptions and risks amidst COVID-19 outbreaks role.pdf. Oper Manag Res 1–14

Sharma R, Shishodia A, Kamble S et al (2020) Agriculture supply chain risks and COVID-19: mitigation strategies and implications for the practitioners. Int J Logist Res Appl 0:1–27. https://doi.org/10.1080/13675567.2020.1830049

Shi X, Liu W, Zhang J (2021) Present and future trends of supply chain management in the presence of COVID-19: A structured literature review. Int J Logist Res Appl 0:1–30. https://doi.org/10.1080/13675567.2021.1988909

Singh S, Kumar R, Panchal R, Tiwari MK (2021) Impact of COVID-19 on logistics systems and disruptions in food supply chain. Int J Prod Res 59:1993–2008. https://doi.org/10.1080/00207543.2020.1792000

Sky News (2020, March 22) Coronavirus: Major supermarkets enforce new rules to stop panic buys. https://news.sky.com/story/coronavirus-no-more-bulk-buying-as-sainsburys-puts-limits-across-all-groceries-11959451

Sodhi MMS, Tang CS, Willenson ET (2021) Research opportunities in preparing supply chains of essential goods for future pandemics. Int J Prod Res. https://doi.org/10.1080/00207543.2021.1884310

Suryawanshi P, Dutta P (2022) Optimization models for supply chains under risk, uncertainty, and resilience: A state-of-the-art review and future research directions. Transp Res Part E Logist Transp Rev 157:102553. https://doi.org/10.1016/j.tre.2021.102553

Tan WJ, Cai W, Zhang AN (2020) Structural-aware simulation analysis of supply chain resilience. Int J Prod Res 58:5175–5195. https://doi.org/10.1080/00207543.2019.1705421

The Global Risks Report (2019) https://www3.weforum.org/docs/WEF_Global_Risks_Report_2019.pdf

Tordecilla RD, Juan AA, Montoya-Torres JR et al (2021) Simulation-optimization methods for designing and assessing resilient supply chain networks under uncertainty scenarios: A review. Simul Model Pract Theory 106:102166. https://doi.org/10.1016/j.simpat.2020.102166

Waters D (2011) Supply chain risk management: vulnerability and resilience in logistics. Kogan Page Publishers

Yu Z, Razzaq A, Rehman A et al (2021) Disruption in global supply chain and socio-economic shocks: A lesson from COVID-19 for sustainable production and consumption. Oper Manag Res 15:233–248. https://doi.org/10.1007/s12063-021-00179-y

Zhou XY, Lu G, Xu Z et al (2023) Influence of Russia-Ukraine war on the global energy and food security. Resour Conserv Recycl 188:106657. https://doi.org/10.1016/j.resconrec.2022.106657