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# Applying digital twins for inventory and cash management in supply chains under physical and financial disruptions

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**ABSTRACT**

Supply chains (SCs) operate in a highly disruptive environment, where they face a variety of disruptions in product and cash flows. In such an environment, determining suitable inventory and cash replenishment policies ensures that cash and inventory are at the right place at the right time and provides a productive SC with high customer service levels. In this study, we first examine the impact of the disruptions in physical and financial flows on SC performance. We then, investigate the potential of a SC digital twin framework to help decision-makers in managing inventory and cash throughout the SC during disruption, currently absent from the literature. The proposed SC digital twin framework integrates machine learning (ML) and simulation to identify the inventory and cash replenishment policies that minimise the impact of the disruptions on SC performance. This approach proves effective in a SC disrupted by demand increase, capacity reduction, and credit purchase increase. Results show that employing the SC digital twin leads to a noticeable reduction in the cash conversion cycle for upstream members of the SCs. We observe that the cash conversion cycle for the upstream SC members is greatly impacted by the inventory policy employed by their immediate downstream members.

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**KEYWORDS**
Supply chain disruptions; digital twins; cash management; machine learning; ripple effect

## 1. Introduction

Supply chain (SC) disruptions are low-frequency-high-impact events that range from internal SC problems such as supplier failure to external events such as societal disasters (e.g. the financial crisis in 2008) that lead to disruptions in physical and financial flows of the SCs. The physical flow disruptions result in product shortages and delivery delays that propagate downstream of the SCs. The financial flow disruptions lead to payment delays that propagate upstream of the SCs. This phenomenon is known as the ripple effect and adversely impacts the financial and operational performance of the SCs (Dolgui and Ivanov 2021). The ripple effect occurs when a SC disruption spreads throughout a SC rather than remaining localised or being contained at one part of the SC (Dolgui, Ivanov, and Sokolov 2018). In some cases, the disruption is amplified in either upstream or downstream of the SC. Epidemic outbreaks are a special case of SC disruptions featuring long-term disruption existence and its unpredictable scaling that trigger disruptions in SC physical and financial flows and lead to the ripple effect in the SCs (Ivanov 2020b).

The coronavirus (COVID-19) outbreak is the most recent example of an epidemic outbreak. The world economy has been hit hard by the outbreak of COVID-19. The global GDP in 2021 dropped by 3.2% from 2019 and firms all over the world observed significant supply, demand, financial, and logistics disruptions that led to profitability reduction for many. In times of crisis such as this, increasing financing from SC partners is a promising solution that helps the firms to improve their financial position (Borg 2021; Deloitte 2020). This increased financing might be achieved by increasing credit purchase which increases the days payable outstanding and consequently decreases the cash conversion cycle (CCC) for a SC member (Errico, De Noni, and Teodori 2022; Caniato, Moretto, and Rice 2020). The shortened CCC for the SC member is achieved at the expense of lengthening the CCC for its upstream SC member. To counteract the impact, the upstream member may in turn increase credit purchase from its supplier. From the SC perspective, this might adversely impact the financial performance of the furthest upstream members of the SC as they do not have upstream members to increase

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credit purchases from them. This may cause liquidity constraints for the furthest upstream members of the SC that in turn decreases the resilience of the SC to physical flow disruptions as the furthest upstream members would lack sufficient financial resources required for implementing strategies that mitigate the impact of physical flow disruptions on SC performance. Consequently, these endanger the existence of the SC.

Under these circumstances, determining suitable inventory and cash replenishment policies for SC members is key to minimising the impact of disruptions on SC performance. To identify these policies, SC planners need to consider the complex interactions between a wide range of variables in the presence of disruptions in physical and financial flows (e.g. demand growth, capacity reduction, credit purchase increase), which may result in an intractable problem (Bischak et al. 2014). To address this, modelling techniques that efficiently capture the complexities and dynamic behaviour of SCs need to be employed.

Simulation models have been widely applied to investigate the impact of disruptions on SC performance and also evaluate the suitable inventory policies for SC members, owing to their capability in capturing complexities and incorporating the dynamic behaviour of SCs. These models focus on studying the impact of physical flow disruptions such as supply, demand, and logistics disruptions on SC performance and ignore the impact of disruptions in financial flow, i.e. payment disruptions, on SC performance (e.g. Llaguno, Mula, and Campuzano-Bolarin 2021; Giannoccaro and Iftikhar 2022). Moreover, the simulation models are only able to compare the effects of varied inventory and cash replenishment policies on SC performance under disruptions through performing what-if analysis and are not able to guide inventory and cash replenishment policies. Machine learning can be more efficient than simulation in identifying the suitable inventory and cash replenishment policies as it is able to assist decision-makers in setting out inventory and cash replenishment policies by generating decision rules. Machine learning has been mostly applied to demand forecasting in SCs (e.g. Lau, Zhang, and Xu 2018; Kantasa-Ard et al. 2021; Guo et al. 2021; Zhu et al. 2021) while its application for predicting and managing disruptions has been more sparse (e.g. Baryannis, Dani, and Antoniou 2019; Brintrup et al. 2020).

From this point of view, this work develops a SC digital twin framework for managing inventory and cash in SCs under disruptions in physical and financial flows. The developed framework aims to answer two research questions: (1) What are the impacts of disruptions in physical and financial flows on SC performance? and (2) How can a SC digital twin help in identifying the inventory and cash replenishment policies that minimise the impact of the disruptions on SC performance? By addressing these research questions it is possible to both understand and minimise the impact of disruptions in physical and financial flows giving the potential for fair distribution of financial resources among SC members which in turn improves the resilience of a SC to physical flow disruptions. To answer the first question, the framework uses discrete-event simulation (DES) which is a widely-used tool for modelling SC disruptions to examine the impact of disruptions on SC performance. To answer the second question, the framework applies the decision tree algorithm which is a machine learning technique to explain the complex relationships between the controllable factors that impact SC performance. To illustrate the effectiveness of our approach, we compare its performance against the case that does not employ the decision tree algorithm. This study aims to show that machine learning can assist managers in making decisions that are hard to deal with by using other approaches and therefore would result in increased performance.

The remainder of the paper is organised as follows: the literature review is presented in Section 2. Section 3 describes the impact of inventory and cash replenishment policies on SC financial performance. Section 4 introduces the decision tree algorithm and the developed simulation model for the case study. Section 5 presents the impacts of three disruption scenarios on SC performance and shows the performance of the decision tree algorithm in managing the disruptions. In Section 6, we offer solutions for resilience enhancement. Finally, Section 7 summarises the study's outcomes and presents further research directions.

## 2. Literature review

The literature review is organised in line with three major SC research domains that are relevant to this study. These are disruption management, finance, and digital twins.

### 2.1. SC disruption management

Literature on SC disruption management have applied different modelling methodologies to strategies for mitigating the impact of the disruptions on SC performance. As in this study, we use simulation modelling to study the impact of disruptions on SC performance hence we provide an exhaustive review of the studies that employed simulation. We then also present a complementary review of other methodologies.

#### 2.1.1. SC simulation with disruption risks

Simulation is a powerful tool for modelling SC disruptions as it is able to handle time-dependent and gradual disruption duration, capacity degradation and recovery, and duration of recovery measures (Ivanov 2017a; Dolgui, Ivanov, and Sokolov 2018). Simulation models efficiently deal with randomness constraints such as variation in shipping times (Ivanov and Dolgui 2020). Moreover, the impact of disruption mitigation strategies on SC financial, customer, and operational performance indicators could be analysed using simulation modelling (Li et al. 2019; Pavlov et al. 2019). Dolgui, Ivanov, and Sokolov (2018) classified the disruption mitigation strategies into proactive and reactive. The proactive strategies focus on the creation of SC protections without considering recovery measures in SC design. While, reactive strategies refer to designing SC structures and processes which can be adjusted when disruption occurs. Three simulation methods including discrete-event simulation, system dynamics simulation, and agent-based simulation have been employed to model SC disruptions.

Discrete-event simulation (DES) has been used to model severe SC disruptions and analyse the SC resilience. Theme 1, as shown in Table 1, corresponds to the studies in which DES was applied as simulation technique. For instance, Carvalho et al. (2012) investigated the impact of redundant inventory and back-up transport on SC performance under transportation disruption. Schmitt and Singh (2012) studied the impacts of supply and demand disruptions on fulfilment rate in a multi-echelon fast moving consumer goods (FMCG) supply chain. They analysed the effects of redundant inventory, back-up capacity, and eliminating of backorders on mitigating the effects of the disruptions. Ivanov (2017) studied the ripple effect in a four-stage SC in presence of supply disruptions. The ripple effect refers to the disruption propagation from the initial disruption point throughout the SC (Ivanov et al. 2019b). The results showed that the ripple effect intensifies the performance impacts of the disruptions. Ivanov (2020) investigated the impact of COVID-19 on global SCs. The results of the study indicated that the timing of the closing and opening of the facilities at different echelons in a global SC is the major determinant of the epidemic outbreak impact on the SC performance rather than disruption duration or the speed of epidemic propagation.

The second group of papers used System Dynamics (SD) as the simulation technique. For instance, Wilson (2007) studied the impact of transportation disruptions on SC inventory levels and fulfilment rate. Bueno-Solano and Cedillo-Campos (2014) investigated the impacts of border disruptions on inventory levels and total cost in a global automotive SC. The results showed that an increase in disruption duration leads to an exponential increase in SC total cost. Spiegler, Naim, and Wikner (2012) investigated the impacts of a generic disruption which included changes in system parameters on inventory levels and shipment rates in a general SC. They found that any unexpected increase in lead time will have a significant reverse impact on SC performance. Olivares-Aguila and ElMaraghy (2020) studied the impacts of production capacity and supply disruptions on profit, service level, and inventory levels in SCs. The results showed that the disruptions happening downstream of the SC have more destructive effects on SC performance compared to the disruption occurring upstream of the SC. Llaguno, Mula, and Campuzano-Bolarin (2021) reviewed the state of the art literature on ripple effect in SCs and presented a conceptual framework that was validated by SD simulation for mitigating its effects.

The third category contains studies that applied agent-based simulation (ABS) as the simulation technique. Tranvouez, Ferrarini, and Espinasse (2006) investigated the impact of production disruptions on forecasted production schedule in workshops and recommended using a cooperative repair method to mitigate the impact of the disruptions. Wu et al. (2012) examine the impact of the stock-out disruptions on the market shares in a two-echelon SC. They found that reducing the duration of the stockout by keeping higher levels of inventory improves the market shares of the SC members. Giannakis and Louis (2011) studied the impact of production disruptions on SC profitability in manufacturing SCs. Xu, Wang, and Zhao (2014) studied the impact of capacity disruptions at suppliers on the SC service level in a three-stage SC. The results showed that the adverse effects of the disruptions on SC performance should be mitigated through recovery measures such as back-up suppliers and proactive resilience planning.

Continuing with ABS, Giannoccaro and Iftikhar (2022) investigated the impact of trust and topology on SC resilience under environmental disruptions. Ledwoch, Yasarcan, and Brintrup (2018) studied the impact of inventory mitigation and contingent rerouting strategies on SC total cost and service level under supply disruptions in two SC topologies: randomly organised supply networks and scale-free supply networks. Nair and Vidal (2011) examined the relationship between supply network topology and its robustness under supply disruptions. They found that in the presence of disruptions the robustness of a supply network is negatively associated with its average path length and clustering coefficient while it is positively associated with its largest connected component and the maximum distance in its

**Table 1.** Review of SC simulation with disruption risks.

| Authors(years) | Simulation technique | Disruption type | Performance indicator/s | Mitigation strategy/s | Mitigation plans | Case study |
|---|---|---|---|---|---|---|
| Carvalho et al. (2012) | DES | Transportation disruptions | Lead time ratio<br>Total cost | Proactive<br>Reactive | Redundant inventory<br>Back-up transport | Automotive SC |
| Schmitt and Singh (2012) | DES | Supply disruptions<br>Demand spikes | Demand fill rate | Proactive<br>Reactive | Redundant inventory<br>Back-up capacity<br>Eliminating backorders | FMCG SC |
| Ivanov (2017) | DES | Supply disruptions | Total cost Revenue<br>Profit<br>Service level<br>Inventory | Reactive | Capacity recovery | General SC |
| Ivanov (2018) | DES | Supply disruptions | Service level<br>Inventory | Proactive<br>Reactive | Risk mitigation inventory<br>Back-up supplier<br>Facility fortification | Smartphone SC |
| Ivanov (2017b) | DES | Capacity disruption | Total cost<br>Revenue<br>Profit<br>Service level<br>Inventory | Proactive<br>Reactive | Redundant inventory<br>Back-up capacity<br>Dual sourcing | General SC |
| Ivanov (2020b) | DES | Supply disruptions<br>Transportation disruptions<br>Demand disruptions | Revenue<br>Profit<br>Service level | Proactive<br>Reactive | Risk mitigation inventory<br>Capacity recovery | Lightning equipment SC |
| Wilson (2007) | SD | Transportation disruptions | Demand fill rate<br>on-hand inventory<br>in-transit inventory | Proactive | Vendor managed inventory | General SC |
| Bueno-Solano and Cedillo-Campos (2014) | SD | Supply disruptions<br>Border disruptions | Total cost<br>Inventory | – | – | Automotive SC |
| Olivares-Aguila and ElMaraghy (2020) | SD | Production capacity reductions<br>Supply disruptions | Profit<br>Inventory<br>Backlog<br>Service level | Proactive<br>Reactive | Production Expediting<br>Back-up capacity | Assembly products SC |
| Spiegler, Naim, and Wikner (2012) | SD | Generic disruption<br>Lead time uncertainty | Inventory<br>Order rate<br>Shipment rate | Proactive | Optimising control parameters including lead time, inventory adjustment time, WIP adjustment time, and demand smoothing time | Single-echelon general SC |
| Huang et al. (2012) | SD | Supply disruptions | Inventory<br>Backlog<br>Profit | Reactive | Back-up supplier | General SC |
| Llaguno, Mula, and Campuzano-Bolarin (2021) | SD | Supply disruptions<br>Production capacity reductions | Service level<br>Profit | Proactive | Redundant inventory<br>Back-up supplier | General SC |
| Tranvouez, Ferrarini, and Espinasse (2006) | ABS | Production disruptions | Forecasted schedule | Reactive | Cooperative repair method | Industrial SC |
| Wu et al. (2012) | ABS | Stock-out disruption | Market share | Proactive | Redundant inventory | Retail SC |
| Giannakis and Louis (2011) | ABS | Production disruptions | Profit | Proactive<br>Reactive | Back-up supplier<br>Back-up contractors<br>Awarding discount and delaying the order | Manufacturing SC |
| Xu, Wang, and Zhao (2014) | ABS | Capacity disruption | Service level | Proactive | Back-up supplier<br>Back-up retailer | General SC |
| Nair and Vidal (2011) | ABS | Node disruptions | Inventory<br>Backlog<br>Total cost | – | – | General SC |

(*continued*)

**Table 1.** Continued.

| Authors(years) | Simulation technique | Disruption type | Performance indicator/s | Mitigation strategy/s | Mitigation plans | Case study |
|---|---|---|---|---|---|---|
| Li and Zobel (2020) | ABS | Node disruptions | Resilience | – | – | Automotive SC |
| Giannoccaro and Iftikhar (2022) | NK ABS | Environmental disruptions | Resilience | Proactive<br>Reactive | Trust<br>Network topology | General SC |
| Ledwoch, Yasarcan, and Brintrup (2018) | ABS | Supply disruptions | Total cost<br>Service level | Proactive<br>Reactive | Inventory mitigation<br>Contingent rerouting | General SC |
| Chauhan, Perera, and Brintrup (2021) | ABS | Supply disruptions | Service level | – | – | Automotive SC |
| Dolgui, Ivanov, and Rozhkov (2020) | DES<br>ABS | Production capacity reductions | Inventory<br>Service level<br>Total cost | Reactive<br>Proactive | Redundant inventory<br>Back-up capacity<br>Eliminating backorders<br>Capacity recovery | Perishable products SC |
| Ivanov (2019) | DES<br>Linear programming | Storage capacity reduction | Profit<br>Service level<br>Lead time<br>Inventory | Proactive<br>Reactive<br>Revival | Redundant Inventory<br>Back-up contractors<br>Capacity flexibility | Beverage SC |
| Ivanov and Rozhkov (2020) | DES<br>ABS<br>Parametrical optimisation | Production capacity reductions | Inventory<br>Lost orders | Proactive<br>Reactive | Redundant inventory<br>Supply chain coordination | Beverage SC |

largest connected component. Li and Zobel (2020) presented a framework to measure the resilience of a SC in presence of the ripple effect. Chauhan, Perera, and Brintrup (2021) developed a failure propagation model to investigate the impact of a nested pattern topology on the robustness of SCs under supply disruption. They found that the nested SCs are more robust than non-nested SCs against random disruptions, whereas they are more vulnerable to hub disruptions due to the unavailability of alternative suppliers.

Finally, theme 4 includes studies that integrated DES with other simulation and/or optimisation approaches. Dolgui, Ivanov, and Rozhkov (2020) combined DES and ABS to investigate the impact of the production capacity disruptions on inventory levels, service level, and total cost in a perishable product SC. It was shown that the disruption propagation downstream of the SC known as the ripple effect can be a driver of the bullwhip effect which refers to the demand amplification upstream of the SC. Ivanov (2019) integrated DES and linear programming to address an integrated network design and production-ordering management problem under capacity disruption in a beverage supply chain. Ivanov and Rozhkov (2020) integrated DES, ABS, and parametrical optimisation to determine the optimal values to the inventory and production decisions parameters under production capacity disruption, again in a beverage SC.

Previous research on SC simulation with disruption risks focuses on studying the impact of physical flow disruptions including supply, demand, and logistics disruptions on SC performance. However, the impact of financial flow disruptions, i.e. credit purchase increase, on SC performance has not been investigated. To fill the gap, in this study, in addition to the supply and demand disruptions the impact of increasing credit purchase on SC performance is studied. Moreover, the literature lacks studies that integrate machine learning (ML) and simulation to minimise the impact of demand, available production capacity, and financial flow disruptions on SC performance.

### *2.1.2. Non-simulation techniques for SC disruption management*

In addition to simulation, researchers have applied other methodologies to model disruptions and improve the resilience of SCs. For instance, Mohammed, de Sousa Jabbour, and Diabat (2021) developed an integrated framework including a multi-attribute decision making algorithm and a multi-objective programming model to measure the resilience of a dairy manufacturing enterprise in terms of its internal dynamic capabilities and the resilience of its suppliers. The results showed the necessity of internal resilience in addition to resilient sourcing. Cheng, Elsayed, and Huang (2021) reviewed resilience metrics and developed three metrics: instantaneous resilience at specific time instants, overall resilience and average resilience over a time period to measure the resilience of a SC. Sokolov et al. (2016) employed graph theory and analytic hierarchy process to study the ripple effect in SCs and identified the SC topologies that are resilient to the ripple effect.

Some studies pointed out the need for designing frameworks that can help in SC performance analysis in presence of pandemics such as COVID-19. Ivanov (2021a) proposed the Active Usage of Resilience Assets (AURA) framework and stated its two major advantages as (1) reduction of efforts for disruption prediction and (2) value creation from resilience assets. Ivanov (2020a) theorised the notion of viable SC which integrated agility, resilience, and sustainability and demonstrated its value for designing SCs which are adaptable to changes. Ivanov and Dolgui (2021b) conceptualised a human-centred ecosystem viability perspective on SC resilience. Ivanov (2021c) analysed the impact of four adaptation strategies including intertwining, scalability, substitution, and repurposing to maintain SC viability in the wake of a pandemic. Ivanov and Dolgui (2020) highlighted the need for incorporating survivability as a new angle into SC resilience frameworks when facing pandemics and presented a game-theoretic model to illustrate the viability formation in an intertwined supply network. Whilst these non-simulation techniques add to the richness of SC disruption management research, they, like simulation research, lack the consideration of financial flows.

### 2.2. SC finance

Supply chain finance consists of a range of buyer-led or seller-led initiatives such as financial loans and trade credits that create liquidity in the SC. SC finance decreases the cost of capital for SC members and accelerates cash flow within SC networks through applying financing solutions on the assets and liabilities of SC members (Gomm 2010; Wuttke et al. 2013). There are three main financing solutions: (1) third-party financing that includes financing of the SC members by the third-party creditors such as banks, (2) internal SC financing that comprises financing of the SC members by their suppliers or customers, and (3) mixed financing that contains third-party and internal SC financing.

For the third-party SC financing, Huang, Fan, and Wang (2019) developed an analytical model to identify the optimal operational strategies in a SC consisting of a supplier, a capital-constrained retailer, and a third-party logistic (3PL) provider that offered financing to the retailer. They found that the retailer's order quantity and the profit of the SC under the 3PL financing were higher compared to when the financing was not available. Yu, Huang, and Guo (2020) developed an analytical model to analyse the efficiency of a SC financing strategy called self-guarantee that was built on blockchain technology. The developed model contained a multi-sided platform, a customer, a bank, and multiple transportation service providers. In the developed model, the customer was guaranteed by himself rather than being guaranteed by the platform. The results showed that the self-guarantee strategy improves the financing efficiency compared to platform-guarantee. Although it may not be beneficial when the customer's opportunity cost is higher than the platform opportunity cost. Chen, Zhou, and Zhong (2017) investigated the impact of buyback guarantee financing on profitability in a two-echelon SC including a supplier and a capital-constrained retailer that required supplier's buyback guarantee to secure bank financing. It was shown that the buyback guarantee financing results in higher profitability of the SC compared to when the financing is not available. Huang, Yang, and Tu (2019) presented a game theoretic model to address a financing problem in a two-echelon supply chain including a supplier and a financially constrained retailer that received financing from a bank by supplier credit guarantee loan. It was shown that increasing the wholesale price by the supplier weakens the retailer's bargaining position in finance securing from the bank.

For the internal SC financing, Tang, Li, and Cai (2020) developed a game theoretic model to optimise the trade credit and pricing decisions in a two-echelon SC including a retailer and a manufacturer. The results showed that the financing of the retailer by the manufacturer increases the profitability of the SC. Qin et al. (2020) developed a game theoretic model to identify the optimal production quantity and carbon emission reduction for a manufacturer that received advance payment from its downstream SC member, the retailer, in return for offering a price discount. Wu et al. (2020) applied incentive contracts as a credit guarantee mechanism that was provided by a distributor for its cash-constrained suppliers. It was shown that the incentive contracts not only provide financing for cash-constrained suppliers, but also help the distributor to acquire ideal suppliers.

For mixed financing in the SCs, Zhang, Xu, and Chen (2020) presented a game theoretic model to address a financing problem in a closed-loop SC consisting of a financially constrained manufacturer and a retailer. The objective of the developed model was to determine the remanufacturing and pricing decisions for the manufacturer that had access to trade credit financing from the retailer and bank financing. Cai, Chen, and Xiao (2014) developed a mathematical model to identify the optimal order quantity and financing decisions for a retailer that had access to bank financing and trade credit financing from its supplier. Chen, Zhou, and Zhong (2017) developed a mathematical model to determine optimal ordering, advertising, and financing decisions for a retailer that had access to trade credit financing from its supplier and bank financing.

Some studies in SC finance literature have considered SC disruptions. Supply and production disruptions are the most studied disruptions. Gupta and Chutani (2020) employed the Stackelberg game to model a SC financing problem under production capacity disruptions. Razavian et al. (2021) developed an optimisation model to identify the optimal financial decisions in a SC in presence of supply disruptions. Choi and Shi (2022) showed that the supply guarantee deposit payment scheme improves the profitability of a SC under production disruptions. Huang (2021) identified the optimal advance payment, discount rate, and payment timeline in a dyadic SC including a buyer and a capital-constrained supplier under supply disruptions. Shi and Mena (2021) studied the impact of SC members' net working capital on SC resilience in presence of supply disruptions. In summary, these papers do not consider financial flow disruptions.

The occurrence of the COVID-19 has drawn more attention to financial disruptions in addition to the physical disruptions in SC finance literature. Moretto and Caniato (2021) collected empirical data through a focus group with industry experts to identify the required adaptations for SC finance in the post-COVID-19 era. They highlighted the need for innovative SC finance solutions that include new actors, collaborations, credit risk assessment methods, and social and environmental performance indicators. Caniato, Moretto, and Rice (2020) found that during financial disruptions large firms reduce their CCC by extending payables to their suppliers rather than assisting cash-starved suppliers. Hofmann et al. (2021) discussed SC finance solutions that can help firms and their SC partners to stabilise their liquidity and net working capital in presence of financial disruptions. Röck, Hofmann, and Rogers (2020) highlighted the importance of enhanced transparency in SCs in the post-COVID-19 era to provide SC members with greater insights into their operations and help them to make informed decisions. In summary, these papers employed empirical research methods. There is lack of studies which applied simulation and machine learning to manage disruptions.

Literature on SC finance under disruptions mostly focus on physical flow disruptions such as supply and production disruptions. There is limited research on the impact of financial flow disruptions on SC performance. Moreover, the application of integrated simulation and machine learning to manage disruptions in the literature is scarce. To fill these gaps, this study firstly investigates the impact of financial flow disruptions, i.e. payment, in addition to the physical flow disruptions, i.e. supply and demand, on SC performance and secondly presents an integrated simulation-machine learning framework to minimise the impact of the disruptions on SC performance. Such an integrated framework ensures that financial resources are fairly distributed among SC members which in turn improves the resilience of a SC to physical flow disruptions as implementing resilient strategies requires sufficient financial resources.

### 2.3. SC digital twins

The digital twin of a SC is a digital model that represents the physical SC network in real-time and provides end-to-end SC visibility (Ivanov et al. 2019a). SC digital twins possess two main characteristics. First, they are updated in real-time or near real-time through connectivity to the real SC, external systems and databases. second, they incorporate optimisation and data analytics into SC simulation models. These features make SC digital twins descriptive, predictive and prescriptive (Burgos and Ivanov 2021).

Several studies reported the benefits of applying SC digital twins. Baruffaldi, Accorsi, and Manzini (2019) developed a digital twin of a warehouse management system to enhance the efficiency of the operation. Dolgui, Ivanov, and Sokolov (2020) stated that SC digital twins are one of the key enabling technologies for implementing reconfigurable SC networks. Ivanov and Dolgui (2021) and Yevgenievich Barykin et al. (2020) discussed the role of SC digital twins in managing the disruption risks in SC networks. Tae Park, Son, and Noh (2020) presented a digital twin of an automobile parts SC to reduce the bullwhip effect and the ripple effect. Ho et al. (2021) developed a SC digital twin to enhance traceability in an aircraft SC. Spindler, Kec, and Ley (2021) reduced production lead time in a pharmaceutical SC by using a SC digital twin. Burgos and Ivanov (2021) developed a SC digital twin to improve the resilience of food supply chains to disruptions caused by the COVID-19 pandemic. Priore et al. (2019) employed a SC digital twin to reduce the bullwhip effect in SCs. Blackhurst, Das, and Ivanov (2021) elaborated on the interplay between SC resilience and digital technologies. Dolgui and Ivanov (2022) discussed the role of 5G technology in enhancing intelligence, visibility, transparency, dynamic networking, and connectivity in SC digital twins. Ivanov (2021b) presented a framework to unlock the potential of end-to-end SC visibility for resilience management in presence of pandemic disruptions.

Literature on SC digital twins is still in its infancy and more research on deploying SC digital twins is required. Much of the literature developed conceptual frameworks and there is limited research on the application of the SC digital twins in practice (Badakhshan and Ball 2021; Kritzinger et al. 2018). To the best of our knowledge, there is no study on applying SC digital twins to minimise the impact of disruptions in physical and financial flows on SC performance. To fill the gap, in this study, a SC digital twin which integrates a simulation model, DES, and a decision tree algorithm is developed to minimise the impact of demand, capacity, and payment disruptions on SC performance.

## 3. Inventory and cash management

Based on the gaps discussed in the literature, this study now examines how inventory and cash management impact the financial performance of SCs.

### 3.1. Ordering policy

In this study, we have applied the order-up-to (OUT) policy developed by Mosekilde, Larsen, and Sterman (1991) to calculate the amount to order for each SC member. The amount to order is defined as follows:

$$\mathrm{OP_t} = \mathrm{Max}\left(0, \bar{D} + \alpha\left(\underbrace{\mathrm{DI} - \left(\overbrace{\mathrm{INV_t} - \mathrm{B_t}}^{\mathrm{NI}}\right)}_{\mathrm{INV\ GAP}}\right) + \beta\left(\underbrace{\mathrm{DWIP} - \mathrm{WIP_t}}_{\mathrm{WIP\ GAP}}\right)\right) \quad (1)$$

To determine the amount to order (OP), each member seeks to meet the forecasted demand of its downstream member and also bridge the gaps between inventory and work-in-process (WIP) with their corresponding desired values. We used an average function to forecast the demand.

To calculate the inventory gap, the net inventory (NI) which is the difference between the inventory and unfilled orders (B) is deducted from the desired inventory (DI). Similarly, the WIP gap is calculated by subtracting the actual WIP from the desired WIP. The WIP represents the orders that have been sent by the supplier but still have not been delivered. The desired inventory and the desired WIP are constant values that are specified by each SC member. As the inventory and WIP gaps are not filled entirely in a review period, smoothing replenishment rules are used to give an appropriate weight (i.e. $\alpha$ and $\beta$) to the gap terms (Disney et al. 2007). A high $\alpha$ value shows an aggressive policy to replenish the discrepancy between the desired inventory and the current net inventory. In the case of $\beta$, a high value indicates that all pending delivery orders have been considered, when deciding on the amount of order to be placed with the upstream member.

In Expression (1), controllable parameters including desired inventory (DI), desired WIP (DWIP), inventory proportional parameter ($\alpha$), and WIP proportional parameter ($\beta$) allow us to change the dynamic behaviour of the SC. Indeed, amending these parameters leads to a set of ordering patterns ranging from order variance amplification known as the bullwhip effect to smoothing the order variance (Disney et al. 2007). The next section explains how impacts on the SC financial performance is modelled.

### 3.2. Impact of ordering policy on cash conversion cycle (CCC)

The CCC is the length of time that it takes for a company to convert resource inputs into cash flows collected from customers (Stewart 1995). The CCC is one of the pivotal metrics used to measure the efficiency of cash flow management in SCs (Zhao et al. 2015). The CCC for a firm is composed of three factors including days inventory outstanding (DIO), days sales outstanding (DSO), and days payable outstanding (DPO) and is calculated as follows:

$$\mathrm{CCC} = \mathrm{DIO} + \mathrm{DSO} - \mathrm{DPO} \quad (2)$$

To determine DIO, the value of average inventory which is the product of inventory position (I) and sales price per unit (SP) is divided by the daily cost of goods sold (COGS) that is a product of unit cost (UC) and the average demand (D) divided by 365. Dividing COGS by 365 assures the expression of DIO in days since both average inventory and COGS are expressed in the currency unit (£). Therefore, DIO can be calculated as:

$$\mathrm{DIO} = \frac{\text{Average Inventory value}}{\mathrm{COGS}/365} = \frac{I \bar{\times} SP}{\mathrm{UC} \times \mathrm{D}/365} \quad (3)$$

To calculate DSO, The average accounts receivable (AR) is expressed in terms of demand, backlog (B) and inventory level. The credit collection policy of the firm is indicated by m; $0 \leq m \leq 1$. It would be equal to zero if all value of the sales is in the form of advanced cash payment and would be 1 if all sales are in the form of credit.

$$\begin{aligned}\mathrm{DSO} &= \frac{\text{Average AR value}}{\mathrm{Revenue}/365} \\ &= \frac{\mathrm{m} \times \min(\mathrm{SP} \times (\mathrm{D}+\mathrm{B}),\ \mathrm{SP} \times \mathrm{I})}{\mathrm{SP} \times \mathrm{D}/365} \\ &= \frac{\mathrm{m} \times \min(\mathrm{D}+\mathrm{B},\mathrm{I})}{\mathrm{D}/365} \end{aligned} \quad (4)$$

To measure DPO, The average accounts payable (AP) is expressed by order quantity (q) and sales price of the

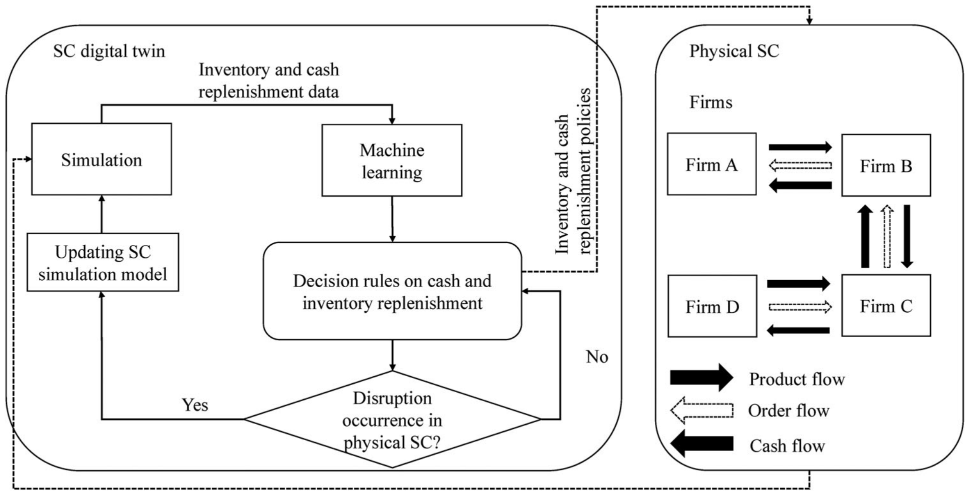


**Figure 1.** SC digital twin framework.

upstream member (USP). The credit purchase policy of the firm is represented by n; $0 \leq n \leq 1$. It would be equal to zero if all purchasing is in the form of advanced cash payment and would be 1 if all purchasing uses credit.

$$\mathrm{DPO} = \frac{\text{Average AP value}}{\mathrm{COGS}/365} = \frac{n \times \mathrm{USP} \times q}{\mathrm{UC} \times D/365} \tag{5}$$

The lower the CCC, the more successful the firm is in managing cash. For example, Amazon is a role model in the effective management of cash possessing a CCC of −25 days in 2020. That is to say, Amazon collected cash from customers 25 days before it paid it to suppliers. Apple is another example with a CCC of −70 days (Desai 2018). In crisis times, such as the COVID-19 pandemic, firms may face various uncertainties and therefore seek to reduce their CCC. This may be achieved by choosing a credit purchase policy, n, close to 1 and making all the value of the purchase in the form of credit. This prolongs the CCC for their suppliers. It should be emphasised that this is a firm-centric view. From a SC centric point of view, suppliers are squeezed. In other words, SC members that increase their credit purchase, reduce their CCC at the expense of increasing the CCC for their suppliers. This may not impact midstream members of a SC as they impose the same payment policy on their suppliers. Although the upstream members of the SC have to bear the brunt of credit purchase increases. In such circumstances, upstream members may face liquidity constraints that threaten the very nature of a SC's existence.

## 4. SC digital twin

To address the inventory and cash management problem, simulation in combination with machine learning has the potential to provide an effective way of decision making. Therefore, in this study, we develop a SC digital twin framework that integrates simulation and machine learning. Figure 1 shows the developed SC digital twin framework. The simulation model represents the physical SC by considering the dynamics in the product, order, and cash flows and generates the inventory and cash replenishment data to be inputted into the machine learning model. The machine learning model then generates decision rules for setting the inventory and cash replenishment policies. When disruptions in the flows of the physical SC happen the simulation model is updated and a new set of data is fed into the machine learning model to give new decision rules for setting inventory and cash replenishment policies. Finally, the inventory and cash replenishment policies are outputted to the physical SC to inform decision making of the firms.

### 4.1. *Machine learning and decision tree algorithms*

Machine learning (ML) is one of the subfields of artificial intelligence that focuses on the development of algorithms capable of learning from data. The term machine learning (ML) was first coined by Arthur Samuel in 1952 and most of the foundational research on ML algorithms was conducted in the 1980s. The ML rose to prominence in the 2020s due to data abundance and advancements in data storage and computing power. The main ML techniques are: (1) supervised learning, (2) unsupervised learning, and (3) reinforcement learning. A supervised learning algorithm uses labelled data to create a model that is able to make predictions given new data. An unsupervised learning algorithm uses unlabelled data to discover hidden patterns in data. A reinforcement learning algorithm uses a reward system to enforce a model to learn how to make decisions.

Inductive learning is a supervised learning technique that discovers decision rules from data. The decision rules are generally in the form of if–then-else statements that build a decision tree. This allows users to easily comprehend the decision-making process. The inductive learning algorithm extracts the decision rules by examining a training dataset with m examples that are represented as an attribute-value table. The attributes refer to the features or inputs of the problem and the value refers to the output of the problem that is going to be predicted. Inductive learning techniques split the training dataset into n sub-tables. One table for each possible output value. Thereafter, combinations of the attributes are derived and for each combination of the attributes, the number of occurrences of the combination in the rows of the sub-tables is counted. Then, the combinations of the attributes are sorted based on the number of occurrences in descending order and the decision rules are extracted accordingly.

The research seeks to provide guidelines to assist decision-makers in setting out inventory and cash replenishment policies by generating decision rules. This helps the decision-makers in understanding the decision making process. Inductive learning is able to generate decision rules, unlike most machine learning techniques which are generally considered as black-box systems (Priore et al. 2019). Therefore, we need to employ inductive learning. There is a wide range of inductive learning algorithms such as ID3(Quinlan 1979), CART (Breiman et al. 1984), C4.5 (Salzberg 1994), CHAID (Kass 1975), and MARS (Friedman 1991). C4.5 and CART are the most applied inductive learning algorithms and are among the top 10 data mining techniques owing to their capability in making a good trade-off between learning speed and error rate (Lim, Loh, and Shih 2000; Wu et al. 2008; AlMana and Aksoy 2014).

In this study we employ the CART algorithm which uses the concept of Gini impurity to sequentially select the nodes of the decision tree. The Gini impurity is the measurement of the likelihood of incorrect classification of new, random data if it were given a random class label according to the class distribution in the dataset. The Gini impurity for a dataset that contains $D$ rows and $n$ classes is expressed by Equation (6).

$$\mathrm{Gini}(D) = \sum_{i=1}^{n} p_i(1-p_i) = 1 - \sum_{i=1}^{n} {p_i}^2 \qquad (6)$$

Where $p_i$ is the probability of samples belonging to class $i$ at a given node. The Gini impurity is lower-bounded by zero and this is obtained when all records belong to the same class. To find the best attribute, feature, for the first split of the decision tree, root node of the decision tree, the Gini impurity for each feature is calculated and the feature with the lowest Gini impurity is selected as the best feature for splitting the data. This process would continue for each subsequent node until the maximum depth of the decision tree is reached. The maximum depth of a decision tree is a hyperparameter that could be set by the user. If the maximum depth of a decision tree is not specified, the nodes will be expanded until all leaf nodes contain only one class. For more details on the CART algorithm, the reader is referred to (Breiman et al. 1984; Wu et al. 2008; AlMana and Aksoy 2014).

### *4.2. SC structure and simulation model*

In this study, a single-product serial SC is considered. This is a three-echelon SC with one manufacturer, one wholesaler, and one retailer, see Figure 2. This represents a typical FMCG SC. The distribution lead time between SC members is 1 week and there is no distribution lead time between the retailer and customer as the customer collects its order from the retailer. The production capacity of the manufacturer is 35,000 products per week. Customer demand is stochastic and follows a uniform distribution in the range of [5000, 10,000] products per week. If the retailer cannot fulfil customer demand in full using its inventory, the unmet order is backlogged. This negatively impacts the service level of the supply chain which is the ratio of the retailer sales rate to customer demand. The sales term is mixed cash and credit sales with credit purchase policy of 0.1. This means that each SC member pays 90% of its order value in cash and the remaining 10% is paid after the trade credit period which is set to be 4 weeks.

We assume that the three SC nodes operate according to periodic-review inventory policy with a review period of 1 week. This means every week each SC member reviews its inventory and WIP and places an order with its upstream member. The sequence of events for each SC member is as follows: (1) Delivery of the products that were ordered the previous week are received (lead time = 1) and added to the inventory. We consider unlimited storage capacities for SC members. (2) The inventory is used to meet orders received from downstream members and also backlogs (if they exist). (3) Products are sent downstream and the inventory positions (both net inventory and WIP) are updated and, if necessary, a backlog is generated. Note that the backlogs are allowed, and they will be cleared as soon as inventory becomes available. (4) A non-negative order is issued to the upstream member using the ordering policy outlined in Section 3.1.

We applied DES methodology to represent the dynamics of the studied SC. The simulation model is developed

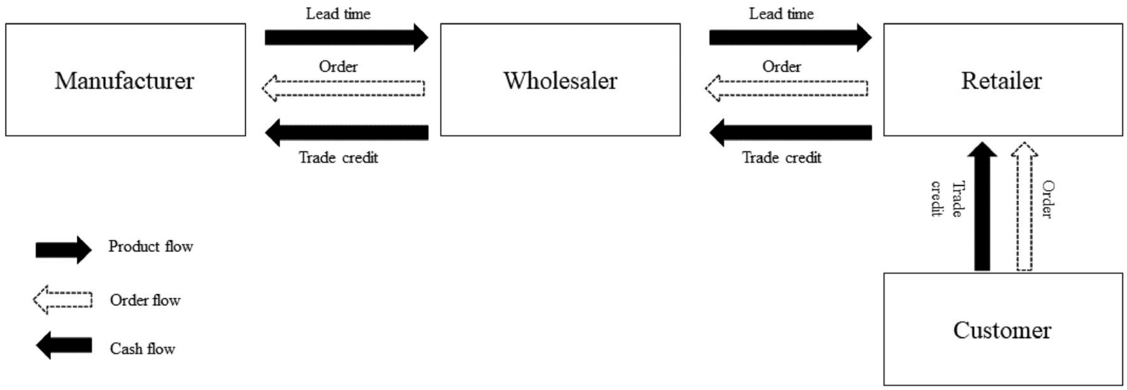


**Figure 2.** SC structure.

using Simpy library in python to analyse the impact of supply, demand, and financial disruptions on SC financial, customer, and operational performances. For financial performance, CCCs of the SC members are analysed. For customer performance, the service level is considered. For operational performance, inventory levels at the facilities, and production levels at the manufacturer are assessed. The time window considered for simulation is 52 weeks, one year, with a warm-up period of 12 weeks. To verify the developed model the simulation run monitoring and output data analysis were used. To validate the output results of the simulation, 100 replications have been performed for each set of the simulation parameters to reduce the output randomness. For testing the results of the replications are compared. Moreover, the developed model demonstrates the existence of the bullwhip effect if the parameters of the model are set in accordance with the Beer distribution game assumptions (Sterman 2000).

## 5. Results and discussion

### 5.1. Scenarios

Four scenarios are designed to investigate the impact of disruptions in financial and physical flows on SC performance. Inventory and WIP proportional controllers for all SC members are set to be 0.5 and 0.2, respectively. The credit purchase policy ($n$) and credit collection policy ($m$) for all SC members are set to be 0.1. Retailer desired inventory and desired WIP are set to be 15,000. Wholesaler and manufacturer desired inventory and desired WIP are set to be 20,000 and 25,000, respectively.

#### 5.1.1. Scenario 0. No disruption scenario

This scenario serves as a baseline scenario and shows the performance of the FMCG SC when the SC is free from disruptions. The impact of disruption events is compared with the results obtained from a no disruption scenario. Figure 3 shows the customer demand that follows a uniform distribution in the range of (5000, 10,000). As we move towards the upstream of the SC, demand volatility decreases. For instance, manufacturer production varies in the range of (6262, 8050). This shows that the order-up-to (OUT) policy is efficient in smoothing the demand throughout the SC. Inventory levels at the upstream of the SC are higher than the downstream as the upstream members have higher desired inventory and desired WIP. The higher inventory levels at the upstream of the SC results in a higher CCC for the upstream members as inventory plays a pivotal role in determining the CCC. The means of CCCs are 11.4, 15.6, and 20.3 weeks for the retailer, wholesaler, and manufacturer, respectively. Under a no disruption scenario supply chain service level remains 100% throughout the simulation.

#### 5.1.2. Scenario 1. Payment disruption

In this scenario, the retailer and wholesaler increase their credit purchase policies ($n$) from 0.1 to 1. That is to say, they move from 10% payment after trade credit to 100% payment after the trade credit period in an attempt to improve their financial position by increasing financing from SC partners. Table 2 shows the impact of the credit purchase increase on SC performance. The 95% confidence intervals (CIs) for the mean of the CCCs for SC members that are calculated from 100 simulation runs are reported. The credit purchase increase leads to a decrease in the CCC for the retailer and an increase in the CCC for the manufacturer compared to the no disruption scenario. The longer the disruption time, the higher the impact on the mean of CCCs for the manufacturer and retailer. A 20 week credit purchase increase reduced the mean of CCC for the retailer by 41%. While, it increased the mean of CCC for the manufacturer by 40%. The 20 week credit purchase increase did not have a significant impact on the mean of CCC for the wholesaler. This shows that increasing the credit purchase highly impacts

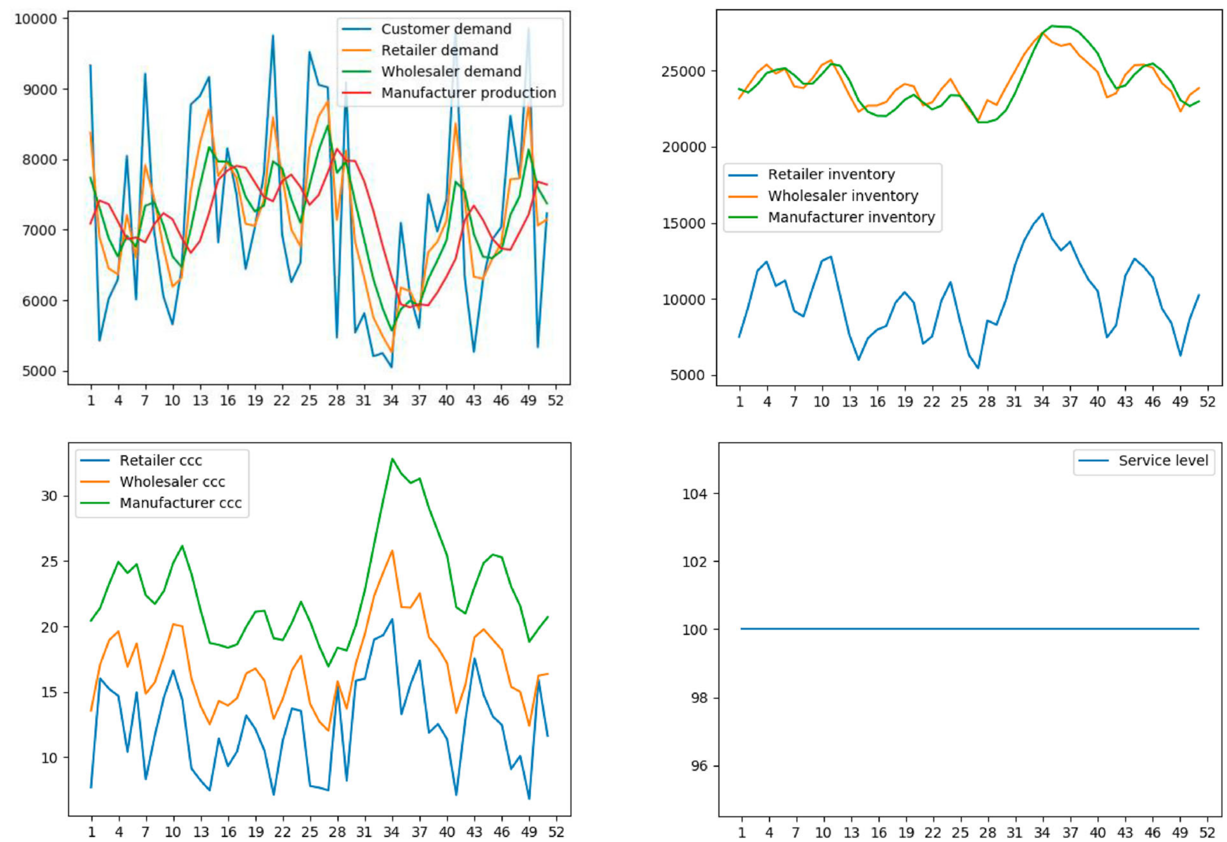


**Figure 3.** Experiment results: No disruption scenario.

**Table 2.** Impact of financial disruption time on SC performance.

| | Performance indicator 95% CI | | | |
|---|---|---|---|---|
| Disruption time | Mean service level | Mean retailer CCC | Mean wholesaler CCC | Mean manufacturer CCC |
| 5 | [100 ± 0] | [10.7 ± 0.74] | [15.4 ± 0.59] | [22.2 ± 0.68] |
| 10 | [100 ± 0] | [9.6 ± 0.79] | [15.1 ± 0.58] | [25.6 ± 0.57] |
| 15 | [100 ± 0] | [8.1 ± 0.61] | [15.6 ± 0.41] | [27.2 ± 0.46] |
| 20 | [100 ± 0] | [6.7 ± 0.75] | [15.2 ± 0.60] | [28.4 ± 0.71] |

the CCC of the SC members that are either trading with customers, i.e. retailer, or suppliers, i.e. manufacturer. This result was expected as the impact of credit purchase increase by midstream SC members, i.e. wholesaler, is offset by credit purchase increase from the downstream members, i.e. retailer. Similar to the no disruption scenario, the mean SC service level in this scenario remains at 100% as there is no disruption in the physical flow throughout the SC.

### *5.1.3. Scenario 2. Demand and capacity disruptions*

In this scenario, there is an increase in customer demand and a decrease in manufacturer production capacity. From week 25 to week 45, customer demand follows a uniform distribution in the range of (10,000, 15,000) and manufacturer capacity drops to 17,500 products per week. Figure 4 illustrates the impact of demand growth and capacity reduction on SC performance. Similar to scenario 0, the order-up-to (OUT) policy reduces the variability of the demand as we move towards the upstream of the SC. The variability of the manufacturer production is in the range of (8018, 10,957) which is significantly lower than the variability range of the customer demand in the same time period. The inventory levels of all SC members falls after the disruption and also results in a fall in their CCCs. The mean of CCC for the retailer, wholesaler, and the manufacturer are 7.9, 11.9, and 14.8, respectively. Compared to the no disruption scenario, the mean of CCC for the retailer, wholesaler, and manufacturer dropped by 31%, 24%, and 27%. The mean service level during the disruption period is 94%.

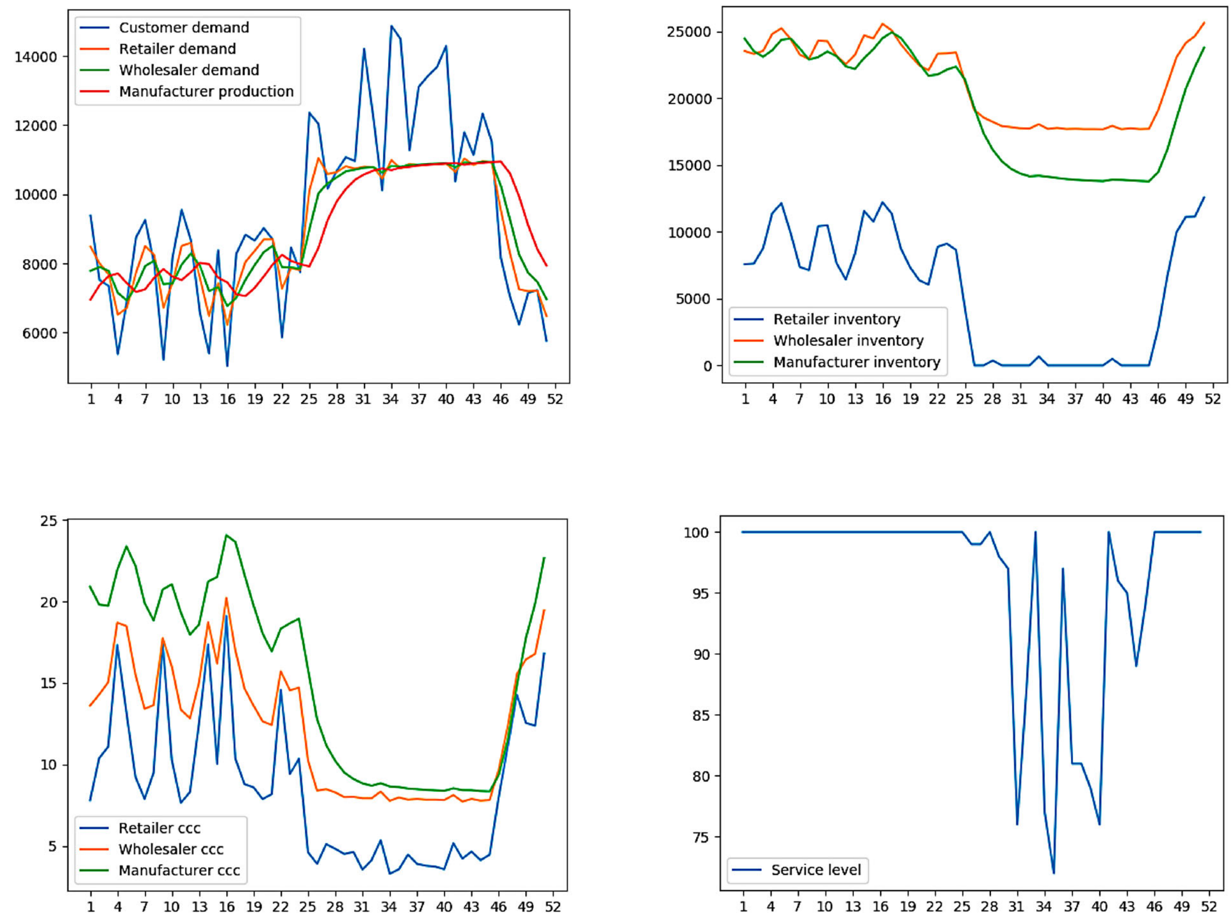


**Figure 4.** Experiment results: Demand and capacity disruptions.

#### *5.1.4. Scenario 3. Demand, capacity and payment disruptions*

This scenario combines scenarios 1 and 2 to investigate the impact of simultaneous disruptions in physical flow, i.e. demand and capacity disruptions, and financial flow, i.e. payment disruption, on supply chain performance. Lower inventory levels for the supply chain members compared to the no disruption scenario leads to a fall in the CCC of the members during the disruption period. The mean of CCC for the retailer, wholesaler, and the manufacturer are 7.7, 12, and 17.1 weeks, respectively. Compared to the no disruption scenario, the mean of CCC for the retailer, wholesaler, and manufacturer dropped by 32%, 23%, and 16%. The means of CCCs obtained in this scenario are closer to the values in scenario 2 than the values in scenario 1. This shows that the inventory level plays a more significant role than the credit purchase policy in determining the CCC for SC members. In other words, the CCCs of the SC members are more impacted by the disruptions in physical flow than the disruptions in the financial flow. Similar to scenario 2, the mean service level during the disruption period is 94% due to the demand and capacity disruptions. To compare performance indicators of the three scenarios, Table 3 presents the summary of the results obtained from each scenario. Table 3 reports the 95% CIs for the mean of the performance indicators that are calculated from 100 simulation runs for each scenario.

### *5.2. Decision tree algorithm*

#### *5.2.1. Example generator and dataset*

The example generator provides the decision tree algorithm with the necessary information so that it is able to generate the decision rules. We consider three classes to represent the level of CCC for the manufacturer: (1) low represents the manufacturer CCC less than 12 weeks; (2) moderate refers to the manufacturer between 12 and 24 weeks; and (3) high represents the manufacturer CCC more than 24 weeks.

In the previously described SC, we consider the following explanatory attributes to determine the class of manufacturer CCC: (1) Attributes that are directly used to calculate manufacturer CCC including manufacturer inventory, wholesaler demand, manufacturer

**Table 3.** Summary of performance indicators for each scenario.

| Performance indicator 95% CI | Scenario 0 No disruption | Scenario 1 Payment disruption | Scenario 2 Demand and capacity disruptions | Scenario 3 Demand, capacity and payment disruptions |
|---|---|---|---|---|
| Mean retailer inventory (number of products) | [9383 ± 457] | [9834 ± 410] | [5801 ± 881] | [5551 ± 874] |
| Mean wholesaler inventory | [23953 ± 258] | [24125 ± 230] | [21564 ± 565] | [21414 ± 562] |
| Mean manufacturer inventory | [23497 ± 328] | [23895 ± 293] | [19819 ± 830] | [19493 ± 827] |
| Mean service level (%) | [100 ± 0] | [100 ± 0] | [94 ± 1.35] | [94 ± 1.31] |
| Mean retailer CCC (weeks) | [11.4 ± 0.67] | [6.7 ± 0.75] | [7.9 ± 0.88] | [7.7 ± 1.1] |
| Mean wholesaler CCC | [15.6 ± 0.54] | [15.2 ± 0.60] | [11.9 ± 0.83] | [12 ± 0.98] |
| Mean manufacturer CCC | [20.3 ± 0.64] | [28.4 ± 0.71] | [14.8 ± 1.19] | [17.1 ± 1.11] |

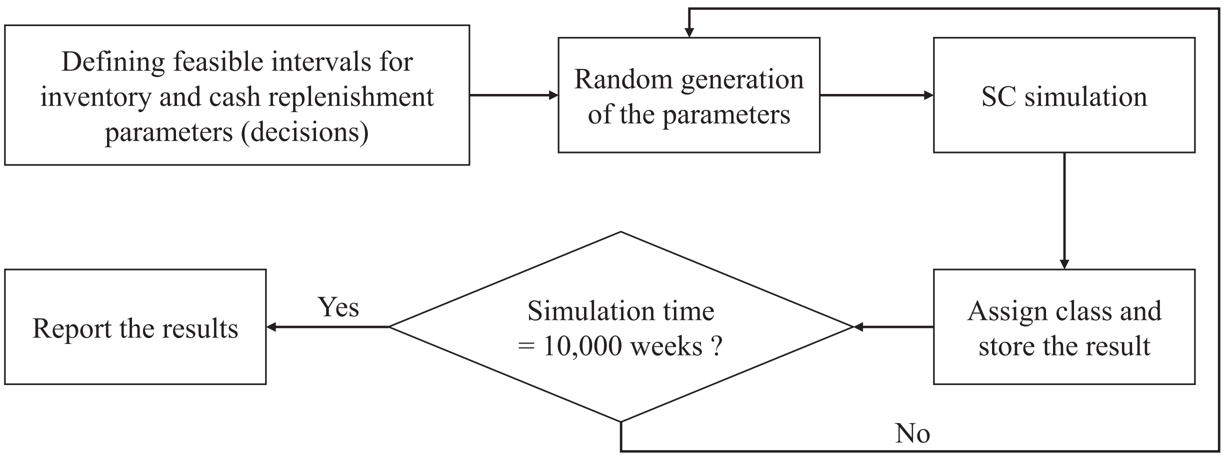


**Figure 5.** Flow diagram of the example generator.

credit collection policy, manufacturer credit purchase policy, manufacturer backlog, and manufacturer production; (2) inventory policies of all SC members including desired inventory, desired WIP, inventory proportional controller ($\alpha$), and WIP proportional controller ($\beta$); and (3) customer demand.

Figure 5 illustrates the procedure to generate examples for the decision tree algorithm. Firstly, feasible intervals for inventory and cash replenishment parameters, policies, are defined within the simulation model. The inventory and WIP proportional controllers follow a uniform distribution in the range [0, 1] and the desired inventory and desired WIP follow a uniform distribution in the range of [0, 30,000] which equals 3 times maximum customer demand. This is in line with prior works in the literature (e.g. Dominguez, Framinan, and Cannella 2014). Thereafter, the simulation model is run for 10,000 weeks and the values of the 19 explanatory attributes and corresponding class for manufacturer CCC are recorded for each week. Table 4 shows an extract of the generated examples.

### 5.2.2. Accuracy of the decision-tree algorithm

To obtain the cash management knowledge from the training dataset and structure it through a decision tree, we employ the CART algorithm in the Scikit-learn library. The 10-fold cross-validation method is used to validate the results. This randomly divides the example set into 10 subsets, 9 of which are used for knowledge extraction. This process is repeated ten times and average results are reported, which defines the so-called hit ratio. This metric represents the accuracy of the decision-tree algorithm. Figure 6 displays the hit ratio for different sizes of the training dataset (between 500 and 10,000 examples). As expected, the hit ratio improves as the number of examples increases. Nonetheless, this indicator stabilises in a narrow range, approx. 83–86%, over 500 examples. The slight variability is mainly explained by the randomness of the examples chosen by the cross-validation method. Overall, it is observed that the decision tree algorithm is capable of capturing the complex relationships between inventory and cash replenishment decisions that impact financial performance of the upstream SC member, the manufacturer.

### 5.2.3. Insights on the impact of inventory and cash replenishment decisions on CCC

In this section, the knowledge-based control systems obtained from 10,000 examples for no disruption scenario, scenario 0, and demand, capacity and payment disruptions scenario, scenario 3, using a decision tree algorithm are discussed. This includes extracting

**Table 4.** generated examples for the decision tree algorithm.

| | Attributes | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Example | A1:CD | A2:RDI | A3:R$\alpha$ | … | A15:MCCP | A16:MCPP | A17:MI | A18:MP | Class |
| 1 | 5441 | 386 | 0.15 | … | 0.52 | 0.79 | 21878 | 10968 | Moderate |
| … | … | … | … | … | … | … | … | … | … |
| 5000 | 9995 | 2991 | 0.92 | … | 0.44 | 0.57 | 18473 | 5166 | High |
| … | … | … | … | … | … | … | … | … | … |
| 9999 | 6251 | 19319 | 0.51 | … | 0.21 | 0.78 | 14608 | 12620 | Low |
| 10000 | 7801 | 29404 | 0.92 | … | 0.38 | 0.89 | 35955 | 994 | High |

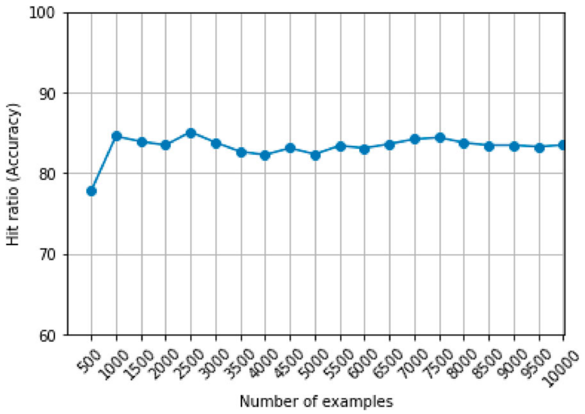


**Figure 6.** Relationship between accuracy and number of examples in the training dataset.

decision rules from 18 inventory and cash replenishment attributes. The attributes are the inventory and cash replenishment decisions of the SC members.

The accuracy of the decision rules obtained from a decision tree highly depends on its design. The accuracy of a decision tree on training data increases as the depth of the tree grows. While its accuracy on test data will not improve beyond a certain depth. If the design of a decision tree becomes too complex which means increasing the depth beyond a level that improves the accuracy of training data and not the test data, the decision tree will overfit the training data which means that the decision rules extracted from the tree are ineffective rather than informative. The overfitting of a decision tree could be prevented by tuning the hyperparameters of the tree which is known as pruning. There are 12 hyperparameters in a decision tree algorithm among which the max depth of the tree plays a pivotal role in overfitting prevention. To find the optimal max depth of the decision tree, in this study, we first create a full tree without setting any max depth. This results in a decision tree with depth 8. We, then use Grid search which is a hyperparameter tuning technique to find the max tree depth that produces the highest accuracy on training data known as the optimal max depth of the tree. We found the optimal max depth of the tree to be 4. Therefore, the max depth of the decision tree was selected to be four. Figures 7 and 8 represent the decision tree with max depth 4 for no disruption and demand, capacity and payment disruptions scenarios, respectively. Figure 7 shows the branches generated from the four upper attributes including manufacturer inventory, wholesaler desired WIP, wholesaler desired inventory and wholesaler proportional inventory controller. The class variable at the bottom of each box indicates the class of CCC for the manufacturer. Classes low, moderate and high are represented by green, purple and brown boxes, respectively. Various combinations of the four attributes result in different decision rules, policies. In Figure 8, under the demand, capacity and payment disruptions scenario, the decision tree algorithm uses the wholesaler WIP proportional controller to generate the decision tree in addition to the four attributes that were used in Figure 7.

In total, 16 decision rules were distracted for each scenario. As an illustration, Table 5 reports some of the rules for the no disruption scenario. Next to each rule, the ratio of the number of examples properly classified over the total number of examples that verify the conditions of the rule known as the hit ratio is reported. For instance, rule 3 states that if the manufacturer inventory is less than 5283, wholesaler desired WIP is less than 10,092, and wholesaler desired inventory is more than 18,469 the level of CCC for the manufacturer is predicted to be low which means the CCC for the manufacturer is between 4 and 12 weeks.

The order of relevance of the factors, attributes, can be deduced from a decision tree. The higher the attribute in the decision tree, the more significant it is in explaining the target. For instance, in the decision tree depicted in Figures 7 and 8, manufacturer inventory is the most relevant attribute in explaining the level of manufacturer CCC. This was expected as it is well known that the inventory level plays a key role in determining the CCC. More unexpected is the finding that under no disruption scenario wholesaler desired WIP is the second most relevant factor in explaining the manufacturer CCC and under the demand, capacity and payment disruptions scenario, the wholesaler desired WIP and wholesaler desired inventory are the second most relevant factors in explaining the manufacture CCC. The proportional

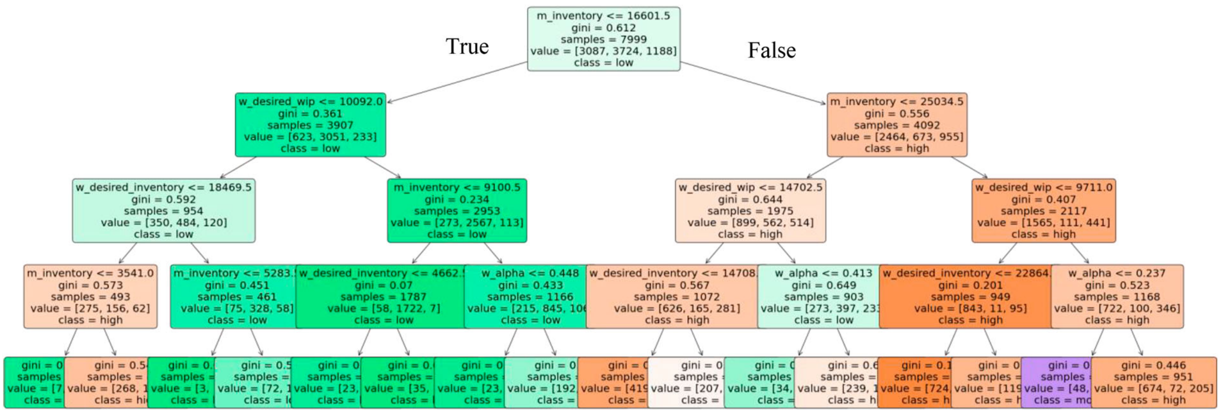


**Figure 7.** Decision tree for no disruption scenario.

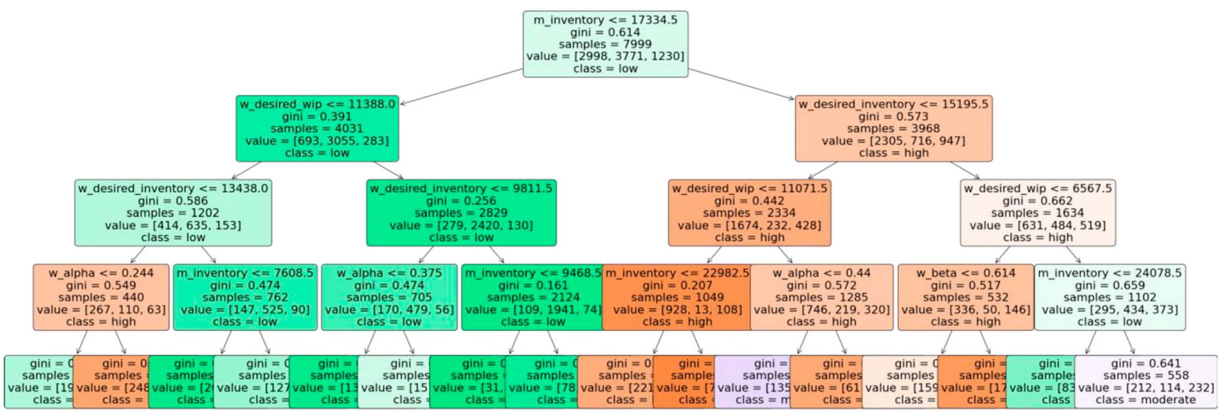


**Figure 8.** Decision tree for demand, capacity and payment disruptions scenario.

**Table 5.** Extract of decision rules.

| Rule | If | Then | Hit ratio |
|---|---|---|---|
| 1 | m_inventory < = 16601 and w_desired_WIP < = 10092 and w_desired_inventory < = 18469 and m_inventory < = 3541 | low | 52/59 |
| 2 | m_inventory < = 16601 and w_desired_WIP < = 10092 and w_desired_inventory < = 18469 and m_inventory > 3541 | high | 268/434 |
| 3 | m_inventory < = 16601 and w_desired_WIP < = 10092 and w_desired_inventory > 18469 and m_inventory < = 5283 | low | 136/139 |
| … | | | |
| 15 | m_inventory > 16601 and m_inventory > 25304 and w_desired_WIP > 9711 and w_alpha < =0.237 | moderate | 141/217 |
| 16 | m_inventory > 16601 and m_inventory > 25304 and w_desired_WIP > 9711 and w_alpha > 0.237 | high | 674/951 |

controllers of the wholesaler inventory and wholesaler WIP are other significant explanatory attributes. This reveals that the ordering policy of the lower echelon of the supply chain, i.e. wholesaler, greatly impacts the manufacturer CCC. This is in line with the finding by Badakhshan et al. (2020) that showed this by modelling cash flow bullwhip in SCs. Moreover, comparing the manufacturer inventory recommended in decision rules obtained from Figure 7 and Figure 8 reveals that the manufacturer needs to keep higher inventory in the demand, capacity and payment disruptions scenario than in the no disruption scenario to keep its CCC below 12 weeks. This is in line with the findings by (Ivanov et al. 2019b) that recommend increasing inventory throughout the SC as a proactive strategy for dealing with SC disruptions.

### *5.2.4. Centralised planning vs. decentralised planning*

In this section, the performance of the supply chain operating in a centralised manner planning using the decision rules obtained from the decision tree algorithm is compared with the decentralised alternative. To this end, we run several simulation runs of 1000 weeks. In the decentralised case, there is no integrated planning and each supply chain member sets its inventory and cash replenishment policy individually. While, in the centralised case, there is an integrated planning framework

**Table 6.** 95% CI for the mean of manufacturer CCC under no disruption scenario.

| Policy | Run1 | Run 2 | Run 3 | Mean |
|---|---|---|---|---|
| Decentralised | [21.28 ± 0.35] | [21.61 ± 0.36] | [20.75 ± 0.35] | 21.21 |
| Centralised (rule 1) | [9.77 ± 0.26] | [10.32 ± 0.25] | [10.19 ± 0.26] | 10.09 |
| Centralised (rule 2) | [9.98 ± 0.24] | [10.38 ± 0.29] | [10.15 ± 0.28] | 10.17 |
| Centralised (rule 3) | [10.33 ± 0.27] | [10.18 ± 0.27] | [10.42 ± 0.28] | 10.31 |
| Centralised (rule 4) | [11.78 ± 0.29] | [11.25 ± 0.28] | [11.84 ± 0.28] | 11.62 |
| Reduction | (11.51) | (11.43) | (10.60) | (11.12) |

**Table 7.** 95% CI for the mean of manufacturer CCC under demand, capacity, and payment disruptions scenario.

| Policy | Run1 | Run 2 | Run 3 | Mean |
|---|---|---|---|---|
| Decentralised | [17.84 ± 0.38] | [18.32 ± 0.37] | [18.11 ± 0.37] | 18.09 |
| Centralised (rule 1) | [9.19 ± 0.22] | [9.38 ± 0.25] | [9.33 ± 0.24] | 9.30 |
| Centralised (rule 2) | [8.38 ± 0.25] | [8.82 ± 0.25] | [8.59 ± 0.24] | 8.60 |
| Centralised (rule 3) | [8.72 ± 0.28] | [8.84 ± 0.27] | [9.20 ± 0.26] | 8.92 |
| Centralised (rule 4) | [8.41 ± 0.25] | [8.71 ± 0.27] | [8.70 ± 0.27] | 8.61 |
| Centralised (rule 5) | [9.14 ± 0.21] | [8.88 ± 0.23] | [8.94 ± 0.24] | 8.99 |
| Centralised (rule 6) | [11.47 ± 0.29] | [11.43 ± 0.29] | [11.27 ± 0.26] | 11.39 |
| Reduction | (9.46) | (9.61) | (9.52) | (9.49) |

that selects inventory and cash replenishment policies for SC members so as to keep the manufacturer CCC at the low level, i.e. below four weeks while keeping the mean service level above 98%. In no disruption scenario, eight decision rules that are represented by green boxes at the end node of the decision tree in Figure 4 lead to the low level CCC for the manufacturer. Four of these decision rules generate a mean service level of less than 98% and are excluded from further analysis. We run four simulation models that represent the four decision rules that lead to a low level for manufacturer CCC while keeping the mean service level above 98%. We choose the inventory and cash replenishment policies for the supply chain members in line with the rule that results in the lowest value for the manufacturer CCC.

In the demand, capacity and payment disruptions scenario, eight decision rules that are represented by green boxes at the end node of the decision tree in Figure 7 lead to the low level CCC for the manufacturer. Two of these decision rules generate a mean service level of less than 98% and are excluded from further analysis. We run six simulation models that represent the six decision rules that lead to a low level for manufacturer CCC while keeping the mean service level above 98% and choose the inventory and cash replenishment policies for the supply chain members in line with the rule that results in the lowest value for the manufacturer CCC.

Tables 6 and 7 report the 95% CIs for the mean of CCC for the manufacturer obtained from three simulation runs of the decentralised and centralised planning cases for no disruption and the demand, capacity and payment disruptions scenarios. Each run includes 100 replications. The values to the parameters of the simulation model in the decentralised case are set to be equal to those explained in section 5.1 and in the centralised case are set to be equal to the recommended caps by the decision tree algorithm shown in Figures 4 and 5. In both scenarios, centralised planning significantly decreases the CCC of the manufacturer compared to decentralised planning. In presence of centralised planning, the mean CCC for the manufacturer under the no disruption scenario and the demand, capacity and payment disruptions scenario dropped by 11.12 and 9.49 weeks, respectively.

Under both centralised and decentralised planning, the value of the mean of CCC for the manufacturer in the demand, capacity and payment disruptions scenario is lower than the value in the no disruption scenario. Under centralised planning, the mean of CCC for the manufacturer in the demand, capacity and payment disruptions scenario is 12% lower than in the no disruption scenario. Under decentralised planning, the mean of manufacturer CCC in the demand, capacity and payment disruptions scenario is almost 15% lower than in the no disruption scenario. The reason for these is the lower inventory at the manufacturer which is caused by the increase in customer demand.

From rules 1–4 shown in Table 6 and from rule 1 to rule 6 shown in Table 7, the recommended inventory to be held by the manufacturer increases which results in a growing CCC for the manufacturer. Although the rate of CCC growth is significantly lower than that of inventory growth. For instance, under the no disruption scenario the maximum recommended inventory to be held by the manufacturer in rule 4 is 25,034 which is 51% higher than the recommended value in rule 1. While, the mean of CCC for the manufacturer obtained from rule 4 is 15% higher than the one obtained from rule 1.

It is important to note that we used the t-test technique to statistically verify that each centralised policy outperforms each decentralised policy. We have tested the significance of the difference between the means of manufacturer CCC in each centralised planning policy and decentralised planning policy, and obtained a *p*-value much lower than 0.05 in all cases. Thus, we reject the null hypothesis (equality of means in decentralised and centralised planning cases).

To sum up, our results show how upstream members of the SC may suffer from a longer CCC compared to their SC peers under no disruption and the demand, capacity and payment disruptions scenarios. This is caused by the inventory strategies of the SC members which are mostly set in a decentralised manner. We demonstrate that centralised planning using machine learning techniques offers a promising solution for reducing the CCC for upstream members of the SCs.

## 6. Concluding discussion

SC disruptions create imbalances in flows of products and money into SCs. The COVID-19 pandemic is a recent example of a SC disruption that has challenged SCs around the globe. The shopping behaviour of the customers has changed dramatically and an unprecedented increase in demand put SCs under huge strain. Manufacturing sites and distribution centres experienced shutdowns or were forced to operate at reduced capacity due to the measures imposed by governments around the world to contain the spread of the virus. From the product flow perspective, this has caused unpredictability in inventory levels and shortages at some SC members and consequently reduced service levels to the customers (Ivanov and Das 2020). From the financial flow perspective, this has resulted in more credit purchase and less cash purchase throughout the SCs that in turn increased the average accounts receivable for upstream members and the average accounts payable for the downstream members of the SCs (Errico, De Noni, and Teodori 2022). Therefore, the cash conversion cycle (CCC) for downstream members decreased while it increased for upstream members.

To manage inventory and cash in SCs under disruptions in physical and financial flows, this work developed a SC digital twin framework. The developed framework answers two research questions: (1) What are the impacts of disruptions in physical and financial flows on SC performance? and (2) How can a SC digital twin help in identifying the inventory and cash replenishment policies that minimise the impact of the disruptions on SC performance? To answer the first question, the framework used discrete-event simulation (DES) which is a widely-used tool for modelling SC disruptions to examine the impact of disruptions on SC performance. To answer the second question, the framework employed the decision tree algorithm which generates decision rules to assist decision-makers in setting out inventory and cash replenishment policies that minimise the impact of the disruptions on SC performance.

### 6.1. Theoretical contribution

This study makes two main contributions. Firstly, it extends the literature on SC simulation with disruption risks (e.g. Ivanov and Rozhkov 2020; Li and Zobel 2020; Llaguno, Mula, and Campuzano-Bolarin 2021) and literature on SC finance under disruptions (e.g. Razavian et al. 2021; Choi and Shi 2022; Shi and Mena 2021) through incorporating financial flow disruptions in addition to the physical flow disruptions. We examined the impact of three disruption scenarios on SC performance, i.e. (1) credit purchase increase, (2) demand increase and capacity reduction, and (3) simultaneous credit purchase increase, demand increase and capacity reduction. Our simulation results showed that the credit purchase increase imposes a longer CCC on the furthest upstream member of the SC, although it reduces the CCC for the furthest downstream member of the SC. The midstream member of the SC is not impacted by this disruption. Under demand increase and capacity reduction, the CCCs for all SC members dropped which is mainly caused by a reduction in inventory levels at SC members. Finally, under the simultaneous credit purchase increase, demand increase and capacity reduction, the CCCs for all SC members dropped. The reduction for the downstream member was significantly higher than the reduction for the upstream member. This was because in this scenario the downstream SC member, retailer, is the only member that reduces cash payment to the wholesaler while the cash they receive from the customer remains unchanged. On the other hand, the upstream member, the manufacturer, is the only SC member that does not reduce cash payment to its supplier although the cash they receive is reduced by the wholesaler. Moreover, we observed that the CCCs for all SC members under the simultaneous credit purchase increase, demand increase and capacity reduction scenario are lower than the CCCs under the no disruption scenario. Here, the downstream member of the SC, retailer, benefited more from it than the upstream members of the SC, i.e. manufacturer.

Secondly, this study presents a SC digital twin framework that integrates simulation and machine learning to identify the inventory and cash replenishment policies that minimise the impact of the physical and financial disruptions on SC performance. Such integrated framework is absent from the literature on SC simulation with disruption risks (e.g. Olivares-Aguila and ElMaraghy 2020; Chauhan, Perera, and Brintrup 2021), literature on SC finance under disruptions (e.g. Moretto and Caniato 2021; Hofmann et al. 2021), and literature on SC digital twins (e.g. Ho et al. 2021; Spindler, Kec, and Ley 2021). The SC digital twin framework inputs the data generated by the simulation to the decision tree algorithm to identify actions that reduce the CCC for the upstream member of the SC, manufacturer, that is most impacted by disruptions in physical and financial flows. The reason for employing the decision tree algorithm, instead of other machine learning techniques, is that, unlike most machine learning techniques which are generally considered as black-box systems, the decision-tree algorithm enables the understanding of the decision-making process (Priore et al. 2019).

In light of this, we have obtained insights on the impact of the relevant inventory and cash replenishment decisions on the CCC of the manufacturer. Our results show that the ordering policy of the lower echelon of the manufacturer in the SC, i.e. wholesaler greatly impacts the CCC for the manufacturer. We also show that centralised planning in which inventory and cash replenishment decisions of a SC are made in an integrated manner, rather than individually by each SC member, is an effective strategy for dealing with disruptions in the financial flow of SCs. In particular, we show that centralised planning reduces the CCC for upstream members of the SCs under both disruption free and the demand, capacity and payment disruptions scenarios.

### 6.2. Managerial implications

The first step for practitioners wishing to minimise the impact of disruptions in physical and financial flows on their SC performance using the presented SC digital twin framework would be to replicate the known real-world SC system in a controllable environment, e.g. through a simulation model. This process includes considering the disruptions in the physical and financial flows of the SC in the simulation model and studying the impact of the disruptions on SC performance. The simulation model enables exploration of a wide range of scenarios and investigate the suitability of various inventory and cash replenishment policies in each scenario.

Secondly, in the next step, the generated data by the simulation model can be translated into knowledge by a machine learning algorithm, which could establish a set of decision rules for setting inventory and cash replenishment policies to minimise the impact of disruptions in physical and financial flows on the SC performance. This creation of decision rules or policy settings will allow practitioners not just to have a tool set to explore disruptions, as in the paragraph above, but to standardise ways of working for on going planning rather than having to continually manually search for solutions.

Thirdly, we have illustrated this process in a simulated case study. The decision tree algorithm has proven to successfully identify the inventory and cash replenishment policies that reduce the CCC for the upstream member of the SC, manufacturer, that is most impacted by disruptions in physical and financial flows with an average accuracy of 85%. This demonstrates that practitioners can achieve tangible performance improvements using the developed framework

Finally, the presented SC digital twin framework also demonstrates the superiority of centralised planning over decentralised planning to practitioners using standard data and metrics. We show that centralised planning significantly decreases the CCC of the manufacturer compared to decentralised planning under both no disruption and demand, capacity and payment disruptions scenarios. Overall, these outcomes illustrate the potential for how practice could be changed to derive better policy setting to achieve higher performance in companies in context of their SCs.

### 6.3. Limitations and future research

To consider directions for future research, the limitations of this work are as follows. Firstly, in this paper, the anchoring and adjustment heuristic (Tversky and Kahneman 1974) was employed as an inventory ordering policy. Future research may consider other replenishment policies such as reorder point-order quantity (Q,r). The decision tree algorithm might recommend different inventory strategies for SC members in presence of other inventory ordering policies. Secondly, the objective of this work is to minimise the CCC for the upstream member of the SC, manufacturer. Future work can minimise the CCC for more than one SC member by considering multiple objectives rather than a single objective. Thirdly, the performance of the other machine learning techniques can be compared with the performance of the decision tree algorithm in improving SC financial and operational performance. Fourthly, the performance of the optimisation algorithms such as GA might be compared with the performance of the machine learning techniques in improving SC financial and operational performance. Another research topic is to define other metrics rather than the CCC to measure SC financial performance. Fifthly, we showed the effectiveness of centralised planning to deal with disruptions in the financial flow of SCs. Future research can study the effectiveness of other solutions such as collaboration among SC members to secure third-party financing, public cloud SC finance, and private cloud SC finance for dealing with disruptions in the financial flow of SCs. Finally, an integrated framework including machine learning and optimisation might be developed to find actions that improve SC resilience to disruptions.

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## Data availability statement

The data that support the findings of this study are available from the corresponding author, Ehsan Badakhshan, upon reasonable request.

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