Computers & Industrial Engineering 191 (2024) 110145

Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

Digital twin model with machine learning and optimization for resilient production–distribution systems under disruptions

Roberto Rosario Corsini [a,*], Antonio Costa [a], Sergio Fichera [a], Jose M. Framinan [b]

[a] University of Catania, DICAR Department, Catania, Italy
[b] University of Seville, Industrial Management, Laboratory of Engineering for Environmental Sustainability, School of Engineering, Seville, Spain

ARTICLE INFO

Keywords:
Supply chain
Digital twin
Resilience
Disruption
Time to recover
COVID-19

ABSTRACT

Inspired by a real-life problem in the semiconductor industry, we introduce a novel digital twin model for a company subject to the adverse effects of unpredictable disruptions. Specifically, this company manufactures a product using a raw material provided by an external supplier, whose lead times may abruptly change due to disruptive events. The Smoothing Order-Up-To rule is adopted by the company as a replenishment policy. It is characterized by three control parameters, which must be optimized to enhance the resilience of the system. To this end, the digital twin learns from the real production–distribution data and periodically self-adjusts the replenishment parameters based on the evolution of the external environment. The digital twin architecture combines data analytics, simulation modeling, machine learning, and a metaheuristic. More specifically, an Artificial Neural Network learns from the manufacturer's operations and generates predictive models. These are embedded in a Particle Swarm Optimization, which provides the optimal combination of the replenishment parameters. An experimental campaign was performed to demonstrate that the digital twin outperforms the traditional strategy in which the replenishment parameters are kept unchanged. The numerical results show that the digital twin strongly improves the manufacturer's performance, in particular in terms of time-to-recover and time-to-survive, used to measure the resilience of the system subject to disruption.

1. Introduction

Disruptions in production–distribution systems have become a topic of great interest among academics and practitioners. According to Katsaliaki et al. (2021), the number of papers on disruption has increased by 30 % since 2015. Disruptions can interrupt the normal flow of goods and materials among supply chain (SC) nodes for a certain period and can be caused by natural disasters, such as earthquakes, hurricanes, and pandemics, or by human actions, such as industrial accidents and operational mistakes. Given the global nature of SCs and the presence of suppliers located in regions of high uncertainty and instability, even a small disruption can have dangerous and cascading effects on the entire SC (Snyder et al., 2016). During a disruptive event, the transportation of goods may be subject to long delays and suppliers might not be able to satisfy orders in time. Consequently, the production capacity of manufacturing systems might be reduced due to the lack of raw materials (Novoszel & Wakolbinger, 2022). The interest in disruptions has exponentially increased due to the COVID-19 pandemic (Ivanov & Dolgui, 2022; Birkel et al., 2023) since, to face the global pandemic, governments have imposed lockdowns or severe restrictions that minimized human interactions. As a result, people were forced to stay at home and the availability of workers was scarce. Furthermore, the impact of COVID-19 on transportation and logistics was remarkable, as cross-border travels were forbidden and some ports were blocked in many countries (Dolgui & Ivanov, 2021; Ciapetti & Le Pira, 2022; Ramani et al., 2022). The COVID-19 pandemic then emphasized the need for production–distribution systems to ensure the normal flow of products and to provide goods and services to stakeholders without delay (Spieske et al., 2023). To this end, the concept of resilience, which is defined as the capability of the system to recover to normal functionality as soon as possible from disruptions with the lowest deterioration of performance (Llaguno et al., 2021), and its declinations (robustness, flexibility, and recovery) assume a key role in managing production–distribution systems under disruptive events (Ivanov & Dolgui, 2021b; Habibi et al., 2023). Several strategies can be deployed to improve SC resilience, including the following (Ivanov, 2021): i) implementing redundancies (such as e.g. multiple sourcing or product substitution programs), ii) designing recovery flexibility and

* Corresponding author at: DICAR Department, University of Catania, Via S. Sofia, 54, 95125 Catania, Italy.
E-mail address: roberto.corsini@unict.it (R.R. Corsini).

https://doi.org/10.1016/j.cie.2024.110145
Received 26 September 2023; Received in revised form 22 February 2024; Accepted 8 April 2024
Available online 10 April 2024

Table 1
State of the art on the DT application to enhance the replenishment strategy.

Source	Type of system	Static replenishment policy	Digital Twin method	Type of disruption	Key Performance Indicator
Badakhshan and Ball (2022)	Three-echelons SC	OUT policy	Inductive learning	Demand, capacity and payment disruption	Inventory level, fill rate and cash conversion cycle
Badakhshan et al. (2022)	Three-echelons SC	OUT policy	Inductive learning	–	Cash conversion cycle
Kurian et al. (2023)	Four-echelons SC	Human decision, Sterman policy and OUT policy	LightGBM algorithm	–	Bullwhip effect, fill rate and inventory cost
Li et al. (2023)	General SC	SOUT policy	Damped trend forecasting	–	Bullwhip effect
Liu and Nishi (2023)	Three-echelons SC	OUT policy	Random forest + Evolutionary algorithms	–	Total cost and fill rate
Maheshwari and Kamble (2022)	Three-echelons SC	OUT policy	Agent-based simulation	–	Total cost
Preil and Krapp (2022)	Four-echelons SC	–	Monte Carlo tree search	–	Total cost
Priore et al. (2019)	Three-echelons SC	SOUT policy	Inductive learning	Fast-changing and chaotic scenarios	Bullwhip effect
Ren et al. (2023)	Single-echelon retailer	Different state-of-art heuristics	Integrated-Bayesian and Separate.lasso approaches	Non-stationary demand	Total cost
Theodorou et al. (2023)	Single-echelon retailer	OUT policy	Gradient boosted regression tree model	–	Total cost
Tian et al. (2024)	Single-echelon warehouse	–	Advantage Actor-Critic + Proximal Policy Optimization	–	Total cost
The present paper	Production-distribution system of a manufacturer	SOUT policy	Artificial Neural Network + Particle Swarm Optimization	Delivery lead times	Fill rate, inventory and backlog level, time-to-recover and time-to-survive

contingency plans (such as e.g. backup supply or transportation), and iii) augmenting end-to-end SC visibility (such as e.g. data-driven, real-time monitoring and visibility systems).

Given the challenges arising from the disruptive effects on SCs, finding the most suitable inventory level is recognized as a cornerstone of effective production–distribution systems management (Simchi-Levi et al., 2018), as companies can respond to unexpected events that disrupt the flow of goods and materials by keeping appropriate inventory levels, therefore enhancing their resilience (Pathy & Rahimian, 2023; Yan, 2023). In this context, balancing the need to guarantee a target level of customer service while minimizing inventory costs becomes crucial for the manufacturer's performance (Snyder et al., 2016; Badakhshan & Ball, 2022). Achieving this balance requires a careful analysis of factors such as demand variability and lead time, among others. Among the several replenishment policies existing in the literature, the Smoothing Order-Up-To policy (SOUT) is widely recognized by academics and practitioners for its ability to reduce the bullwhip effect (Gaalman, 2006; Disney & Lambrecht, 2008; Schmitt et al., 2017). Inspired by the traditional Order-Up-To (OUT) policy, SOUT is controlled by three replenishment parameters to smooth the gap between the target and current inventory and work-in-progress levels. To increase the effectiveness of SOUT, several papers have been devoted to determining the most suitable combination of these controllers to achieve an effective trade-off in performance (Lin et al., 2018; Disney et al., 2021).

An aspect that deserves immediate attention is that the conventional approach to the design of replenishment policies typically involves a static strategy. This strategy entails selecting parameters that remain fixed until modifications are deemed necessary, which may occur after a significant amount of time has passed, possibly even after the point of irreversibility. However, in a dynamic scenario characterized by disruptions, a continuous adjustment of these parameters may be required to cope with the changing environment. In this regard, digitalization with innovative technologies represents a new opportunity to increase the resilience of production–distribution systems (Novoszel & Wakolbinger, 2022). More specifically, Digital twin (DT) modeling has proven to be a valuable data-driven strategy in supply chain and operations management (SCOM) for managing disruptions and improving manufacturer's performance (Dolgui & Ivanov, 2022, Ivanov, 2023). A DT is a virtual representation of a physical system or process and can simulate the flow of goods, services, and information in production–distribution systems, enabling companies to gain real-time insights into their operations and identify areas for improvement (Latsou et al., 2023; Singh et al., 2023). The use of DTs has the potential to revolutionize the industry by providing companies with the ability to predict and mitigate the impact of disruptions and to improve decision-making by offering a more comprehensive understanding of the production–distribution system (Ivanov et al., 2019). The advantages of using DT models have become increasingly clear with the outbreak of COVID-19, as companies need to continuously adapt their replenishment strategies to the volatility of the environment (Ivanov and Dolgui, 2021a).

The concept of DTs has garnered significant interest in the literature, with researchers focusing on developing systematic reviews or theoretical and conceptual frameworks to explore the potential applications of this emerging technology (see e.g. Ivanov and Dolgui, 2021a, 2021b; Bhandal et al., 2022; Corsini et al., 2022a; Kamble et al., 2022; Nguyen et al., 2022). With the increasing availability of data and advances in technology, the potential applications of DTs are vast, and future research is likely to focus on their practical implementation and effectiveness in real-world scenarios (Ivanov, 2023). Table 1 summarizes the existing applications of DTs or data-driven frameworks with different replenishment policies, providing information on i) the type of production–distribution system under study, ii) the static replenishment policies being compared, iii) the DT method proposed in the literature, iv) the type of disruption, if considered by the authors, and v) the Key Performance Indicators (KPIs). Firstly, the table reveals that the OUT (or SOUT) replenishment policy is widely used as a generalizable replenishment policy in the literature, working as a static rule for the comparison with proposed DT or data-driven frameworks. Furthermore, it can be noted that the majority of the literature proposed new DT models without addressing occurrences of disruptive events (Badakhshan et al., 2022; Maheshwari and Kamble, 2022; Preil and Krapp, 2022; Kurian et al., 2023; Li et al., 2023; Liu and Nishi, 2023; Theodorou et al., 2023; Tian et al., 2024). For instance, Maheshwari and Kamble (2022) developed a DT model comprising an agent-based simulation model to replicate the physical system and integrate the information on demand, orders, and shipments. Another example is the work of Kurian et al. (2023), where they employed a Machine Learning (ML)-based DT framework to mimic human decision-making on order quantity in a beer game environment. They proposed a LightGBM algorithm, trained with data collected from simulated beer games, demonstrating that the proposed DT enhances system performance compared to human decisions, Sterman, and OUT replenishment policies.

On the other hand, some papers promote new DT frameworks to deal with unpredictable disruptive events (Priore et al., 2019; Badakhshan and Ball, 2022; Ren et al., 2023). Priore et al. (2019) were the first to investigate the effectiveness of a dynamic framework for periodically identifying the best replenishment rule for a node in an SC. They developed a simulation model to study key variables that can impact SC performance and assess the influence of inventory strategies in different disrupted scenarios. An inductive learning algorithm was used to learn from the information gathered in the simulation model and establish a set of decision rules for reducing the bullwhip effect in SCs. Similarly, Badakhshan and Ball (2022) introduced a DT framework based on Discrete-Event Simulation (DES) simulation and a decision-tree-based ML algorithm to enhance SC resilience. They also considered the financial aspects of SCs and evaluated the impact of payment, demand, and capacity disruptions on the performance of the entire SC. Recently, Ren et al. (2023) aimed to find a dynamic inventory policy based on Integrated-Bayesian (IB) or Separate-Lasso (SL) approaches for a single-echelon retailer dealing with non-stationary customer demand characterized by different unpredictable distributions for different periods.

Although the mentioned papers shed some light on the benefits arising from the application of DT to optimize the replenishment strategy in SCs under disruptions, some relevant aspects remain unexplored and should be investigated in depth. In particular, the mentioned works only addressed adjusting some of the parameters of the replenishment policy among a discrete range of values and did not consider performance indicators related to SC resilience (such as the Time-To-Recover and Time-To-Survive indicators). The present paper aims to fill the gap in the literature by proposing a new DT model, which embeds data analytics, simulation modeling, ML, and metaheuristic algorithm for the optimization, for production–distribution systems subject to sudden peaks of delivery lead times caused by disruptive events. This paper is inspired by some studies conducted in a semiconductor company, which was severely affected by the global pandemic. In fact, from the second half of 2020, the semiconductor SC was characterized by a 'chip shortage' and higher shipping costs, forcing many automobile companies to partially close some production lines (Wu et al., 2021; Mohammad et al., 2022) or to rise the final price of vehicles (by approximately \$5000 in the US) (Ramani et al., 2022). According to Voas et al. (2021), this shortage impacted an estimated 964,000 vehicles in 2021, resulting in an anticipated loss of \$61 billion in revenue for the automotive sector. Furthermore, Mohammad et al. (2022) highlighted that the 'chip shortage' also affected other industries, such as computers, communication, and industrial sectors among other. In particular, the authors pointed out that this disruption led to a sharp increase in lead times within the computer industry, reaching up to 120 days, consequently causing the rise in material prices. So far, literature dealt with such a kind of disruption under a twofold perspective, by considering disruption profiles yielded by a fast-changing demand (see e.g. de Arquer et al., 2022) or by sudden reductions in the production capacity (see e.g. Cao et al., 2022; Katsoras and Georgiadis, 2022). Since the unpredictable and unique scenario of the COVID-19 pandemic clearly affected the global SCs and the logistic service providers (LSPs) were overwhelmed accordingly, in this paper we suppose that the effects of such disruption have a detrimental impact on the production capacity of both suppliers and logistic providers, which in turn causes a drastic increase in the delivery lead times.

Hence, the present paper focuses on analyzing the manufacturer dynamics, i.e., the semiconductor company that must face sudden peaks in delivery lead times due to unpredictable disruptive events. The manufacturer is further divided into the manufacturing plant and the warehouse, which plays a critical role in the manufacturer dynamics by placing orders to the supplier while respecting a Minimum Order Quantity (MOQ) constraint, which is a realistic assumption for global SCs (Tuncel et al., 2022). Continuous adjustment of the replenishment policy is crucial for the manufacturer's performance since any

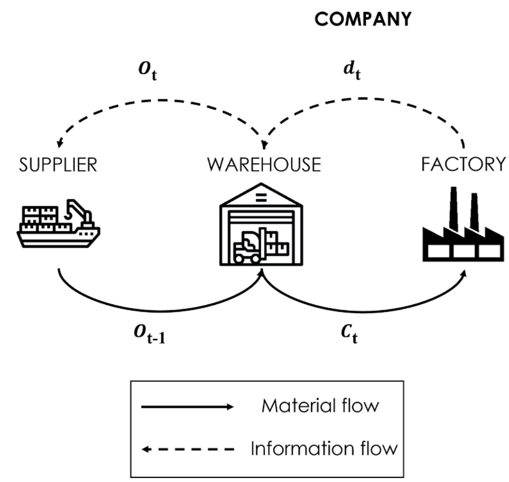

Fig. 1. Production-distribution model.

unfulfilled production demand could lead to production blocks. In contrast to the SC literature, the optimization procedure of the proposed DT model considers all control parameters related to the SOUT replenishment policy, i.e., the forecasting smoothing factor, the proportional controller, and the safety stock factor, varying them over continuous ranges. To assess the manufacturer's ability to withstand disruptive phenomena, the production–distribution system under study is subject to sudden peaks in delivery lead times. To emulate this non-stationary trend of delivery lead times, we employed COVID-19 data regarding people unable to work and forced to stay at home due to government restrictions. We adapted this trend to delivery lead times with an appropriate scale, assuming that the abrupt peaks in delivery lead times are a consequence of the shortage of workers during the pandemic. The manufacturer's performance was evaluated using different indicators, being the main objective to maximize the fill rate, which means that the production demand is always satisfied, and no production blocks occur. Other key performance indicators were considered, including inventory performance (i.e., net stock and backlog levels), Time-To-Recover (TTR) and Time-To-Survive (TTS), the latter two introduced by Simchi-Levi et al. (2015) to measure SC resilience. Experimental analyses were conducted to compare the benefits of using the DT versus the conventional and static strategy usually adopted by academics and practitioners.

To sum up, among the several strategies that can be implemented to improve SC resilience, our paper focuses on augmenting end-to-end visibility for SC and, particularly, on model-based decision-making support (see e.g. Ivanov and Dolgui, 2021a). More specifically, our paper aims to propose and validate a DT model that improves the resilience of a make-to-stock production system by reducing its time-to-recover and increasing its time-to-survive in the presence of large peaks in the delivery lead times due to external disruption. The structure of the paper is as follows: Section 2 presents the problem statement, along with the simulation model based on discrete-time difference equations and key performance indicators. Section 3 outlines the rationale for the DT model, while Section 4 deals with the experimental campaign and presents the statistical analysis of the results. Section 5 points out the theoretical and managerial implications. Finally, in Section 6, the conclusions of the work and directions for future research are provided.

2. Problem statement

The scope of this paper is to develop an adaptive replenishment model based on a DT architecture able to increase the resilience of the production–distribution system against disruptive events. In this study, we consider an external supplier and the company, which, in turn, is composed of the raw materials warehouse and the production plant (as depicted in Fig. 1). Our focus is on the warehouse, which needs to issue orders to the supplier to satisfy the demand for raw materials from the production plant. The assumption of the problem can be summarized as follows:

- The problem consists of a periodic-review inventory system and the time unit of the problem is one day. This hypothesis corresponds to an environment often encountered in practice (van Donselaar et al., 2021). Furthermore, fixed-interval ordering has become a common practice in supply chains to facilitate freight consolidations and logistics/production scheduling (Marklund, 2011). Therefore, periodic-review inventory systems play an important role in warehouse operations in order to save order and shipment costs (Dreyfuss & Giat, 2019);
- The semiconductor manufacturing sector is particularly representative of a stable component demand since it is well-known that the semiconductor sector is capacity-constrained (see e.g. Habla et al., 2007), with plants operating close to their maximum utilization. From the perspective of the component warehouse, this saturated scenario produces a non-correlated, stable, demand of components, which can be captured with the independent and identically distributed (i.i.d.) demand. Furthermore, the i.i.d. demand is quite often assumed in the SC literature to describe a stable demand pattern (see in this regard e.g. Zhao & Katehakis, 2006, Zhou et al., 2007, Kiesmüller et al., 2011 or Zhu et al., 2015). For these reasons, in the problem at hand, the production demand is stochastic and characterized by a stationary behaviour described with the normal distribution, i.e., N(μ_d, σ_d), where μ_d is the mean and σ_d is the standard deviation (i.i.d. process) (Framinan, 2022);
- The lead time to deliver the raw materials from the warehouse to the production plant is negligible;
- The supplier lead time is stochastic (Wang and Disney, 2017) and described with normal distributions, i.e., N(μ_{LT}, σ_{LT}), where μ_{LT} is the mean and σ_{LT} is the standard deviation;
- The system under investigation is subject to disruptive events that involve unpredictable peaks in the supplier delivery lead time for a certain amount of time. To model these peaks in delivery lead times, we adapted COVID-19 data related to the unavailability of workers with an appropriate scale, assuming that the long delivery lead times are a consequence of the shortage of workers during the pandemic;
- The warehouse adopts the SOUT replenishment policy to issue orders to the external supplier (Framinan, 2022; Fussone et al., 2023), consisting of adding a proportional controller to the standard Order-Up-To (OUT) policy and hence also denoted as Proportional Order-Up-To (POUT) policy in the inventory management literature (see e.g. Wang and Disney, 2017);
- The exponential smoothing method is employed by the SOUT policy to forecast future demand. This methodology is widely used in the literature on SC dynamics (see e.g. Disney et al., 2021) and similar strategies have also been applied to semiconductor supply chain problems (see e.g. Diaz et al., 2022);
- The order placed by the manufacturer to the supplier must be at least of a minimum size (i.e., MOQ constraint, see Zhu et al., 2015);
- The nonnegative condition of orders is considered since the returns of finished products in case of overstock are not allowed (Chatfield & Pritchard, 2013).

The objective is to measure the effectiveness of the DT architecture to enhance the resilience of the system under disruptions. The main goal is to maximize the fill rate (*FR*), in order to meet the production demand. Unsatisfied demand will be considered as backlog quantity. In addition, other performance indicators are evaluated, i.e., the standard deviation of the fill rate (σ_{FR}), the average value of the net stock level ($\overline{I_+}$), the standard deviation value of the net stock level (σ_{I_+}), the average value of the backlog level ($\overline{B}$) and the standard deviation of the backlog (σ_B), the time-to-recover ratio (TTR_{ratio}), the time-to-survive ratio (TTS_{ratio}). In this work, the manufacturing operations are emulated by a simulation model based on discrete-time difference equations, which is a technique widely diffused in SC dynamics literature (Warburton and Disney, 2007; Ponte et al., 2017; Corsini et al., 2023a; Framinan, 2022). The nomenclature of the production–distribution model is formalized in Table 2, which reports the indexes, the endogenous parameters (i.e., parameters that can be adjusted by the decision-maker), the exogenous parameters (i.e., parameters that are intrinsic features of the production–distribution system), the variables and the performance measures. Section 2.1 is devoted to delineating the dynamics of the production–distribution system under study. Section 2.2 describes how the disruption is modelled, while Section 2.3 deals with the key performance indicators considered in this work.

Table 2
Nomenclature of the production–distribution model.

Indexes			
T	Time period	TR	Time of review
TH	Time horizon	WP	Warm-up period
Endogenous Parameters			
α	Forecasting smoothing factor	ε	Safety stock factor
β	Proportional controller		
Exogenous Parameters			
μ_d	Mean of stationary customer demand	μ_{LT}	Mean of delivery lead time
σ_d	Standard deviation of stationary customer demand	σ_{LT}	Standard deviation of delivery lead time
DD	Duration of the disruptive interval	MOQ	Minimum Order Quantity
TD_1	Starting time of the disruptive interval	TB_1	Earliest backlog within the disruptive interval
TD_2	Ending time of the disruptive interval	TB_2	Latest backlog withing the disruptive interval
Variables			
C_t	Units of raw materials delivered by the warehouse at time *t*	O_t	Order quantity placed by the warehouse at time *t*
d_t	Production demand at time *t*	R_t	Units of raw materials arriving from the supplier at time *t*
$\widehat{d}_t$	Forecasted production demand at time *t*	TI_t	Target inventory at time *t*
LT_t	Delivery lead time at time *t*	TW_t	Target delivery work in progress at time *t*
$O_{t,SOUT}$	Order quantity defined by SOUT at time *t*	W_t	Delivery work in progress at time *t*
Performance measures			
FR	Fill rate	$\overline{B}$	Average backlog quantity
σ_{FR}	Standard deviation of the fill rate	σ_B	Standard deviation of the backlog quantity
$\overline{I_+}$	Average net stock level	TTR_{ratio}	Time-to-recover ratio
σ_{I_+}	Standard deviation of the net stock level	TTS_{ratio}	Time-to-survive ratio

2.1. Manufacturer's operations

Orders are placed by the manufacturer to the supplier to fulfil the production demand for raw materials, using the SOUT replenishment policy. SOUT aims at meeting the forecasted demand, $\widehat{d}_t$, while filling two gaps: i) the gap between the target inventory, TI_t, and the current inventory level, I_t; ii) the gap between the target delivery work in progress, TW_t, and the current delivery work in progress, W_t (Disney and Lambrecht, 2008; Fussone et al., 2023). The order quantity with the

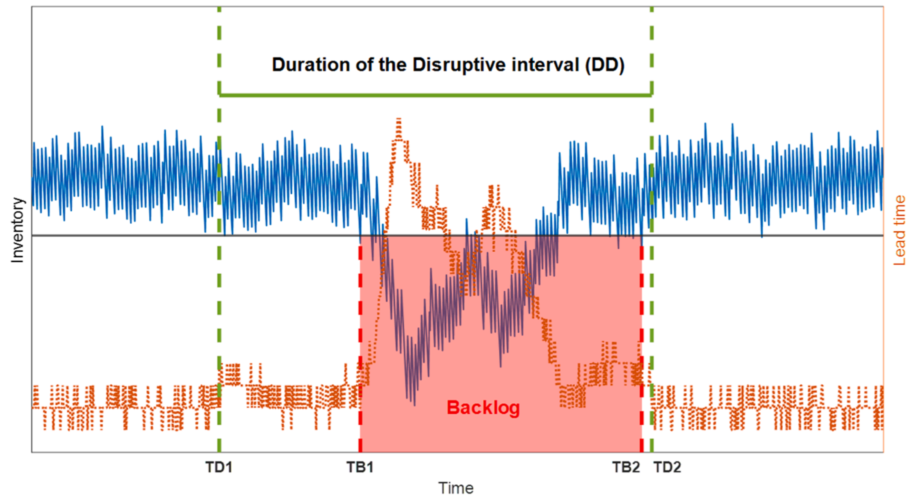

Fig. 2. Plot of non-stationary delivery lead time due to disruptions.

SOUT strategy, $O_{t,SOUT}$, is calculated as follows:

$$O_{t,SOUT} = \widehat{d}_t + \beta \bullet (TI_t - I_t + TW_t - W_t) \tag{1}$$

In the given equation, β is the proportional controller, i.e., a replenishment parameter that is used to adjust the order quantity appropriately. The value of β is within the range of [0.1, 1] (Priore et al., 2019). If β is set to 1, it is equivalent to the traditional Order-Up-To (OUT) policy. The exponential smoothing methodology is used to compute the forecasted demand, $\widehat{d}_t$ (Costa et al., 2022b), which takes into account the variable demand, d_t, and the forecasted demand of the previous day, $\widehat{d}_{t-1}$. This data is weighted by the forecasting smoothing factor, α, as follows:

$$\widehat{d}_t = \alpha \bullet d_t + (1 - \alpha) \bullet \widehat{d}_{t-1} \tag{2}$$

The target inventory, TI_t, is determined by multiplying the forecasted demand, $\widehat{d}_t$, by the safety stock factor, ε (Framinan, 2022):

$$TI_t = \varepsilon \bullet \widehat{d}_t \tag{3}$$

On the other hand, the target work in progress, TW_t is calculated as follows:

$$TW_t = \mu_{LT} \bullet \widehat{d}_t \tag{4}$$

where $\widehat{d}_t$ is the forecasted demand, and μ_{LT} is the mean value of the delivery lead time LT_t, which is a time-varying parameter. In summary, SOUT is characterized by three different endogenous parameters: i) α, i. e., the forecasting smoothing factor; ii) β, i.e., the proportional controller; iii) ε, i.e., the safety stock factor. The company needs to calibrate these replenishment parameters based on its objectives to determine the appropriate quantity of raw materials to order. However, the ordered quantity must also comply with the minimum order quantity (MOQ) constraint, which can influence the selection of the parameters' values, as it may require ordering a larger quantity of raw materials than what is actually needed. The problem of determining a control policy for single-item, periodic review inventory systems with stochastic demand and MOQ has been previously addressed in the literature, starting with the seminal work by Robb and Silver (1998). The properties of optimal inventory policies for such a system have been investigated by Zhao & Katehakis (2006), but these are typically too complicated to implement in practice (Zhou et al., 2007) and different heuristic (i.e., approximated) procedures have been proposed in the literature (see e.g. Zhou et al., 2007; Kiesmüller et al., 2011; Zhu et al., 2015; Shen et al., 2019; or Zhu, 2022). In our case, we implement a simple heuristic where an order is placed if the size required (according to the SOUT policy) is equal to or higher than half of the MOQ, otherwise, no order is issued in this period. Note that this 'rounding-up' policy is commonly adopted in the industry (Robb & Silver, 1998). More specifically, O_t the order placed is calculated as follows:

$$O_t = \begin{cases} \max_t \{O_{t,SOUT}, MOQ\} & \text{if } O_{t,SOUT} \geq (MOQ/2) \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

The company orders are shipped by the supplier with stochastic delivery lead times. The variable R_t indicates the quantity of raw materials arriving at time t from the supplier to the warehouse, which corresponds to the orders that have been issued at time $t - LT$ (Framinan, 2022). Therefore, the inventory level I_t is calculated as follows:

$$I_t = I_{t-1} + R_t - d_t \tag{6}$$

When the inventory level is not enough to meet the demand for raw materials from the production system (i.e.,$d_t > I_{t-1} + R_t$), then, a backlog scenario occurs and the inventory level, I_t, becomes negative. The delivery work in progress, W_t, represents the quantity of ordered raw materials that the company has not yet received. It is calculated as follows:

$$W_t = W_{t-1} + O_{t-1} - R_t \tag{7}$$

Regarding the quantity of raw materials delivered from the warehouse to the production system, C_t, the delivery lead time is negligible. C_t is equal to d_t, if the inventory level is enough to satisfy the demand arising from the production system. Otherwise, the production system will receive the available inventory level, i.e., $I_{t-1} + R_t$:

$$C_t = \max_t \left\{ \min_t \{I_{t-1} + R_t, d_t\}, 0 \right\} \tag{8}$$

2.2. Disruption

During the COVID-19 pandemic, the unavailability of workers due to lockdowns, quarantine measures, and other restrictions imposed by governments to control the spread of the virus were the major reasons for these disruptions. As a result, many businesses have struggled to maintain their operations and meet customer demands, leading to delays in lead times and delivery schedules. For this motive, to replicate the non-stationary delivery lead times caused by disruptions, we used COVID-19 data collected from the website https://health.google.com/covid-19/open-data/explorer related to the people who were forced to stay at home due to government restrictions. We adapted this trend to the delivery lead time with an appropriate scale, assuming that the sudden increase in delivery lead time is caused by the scarcity of

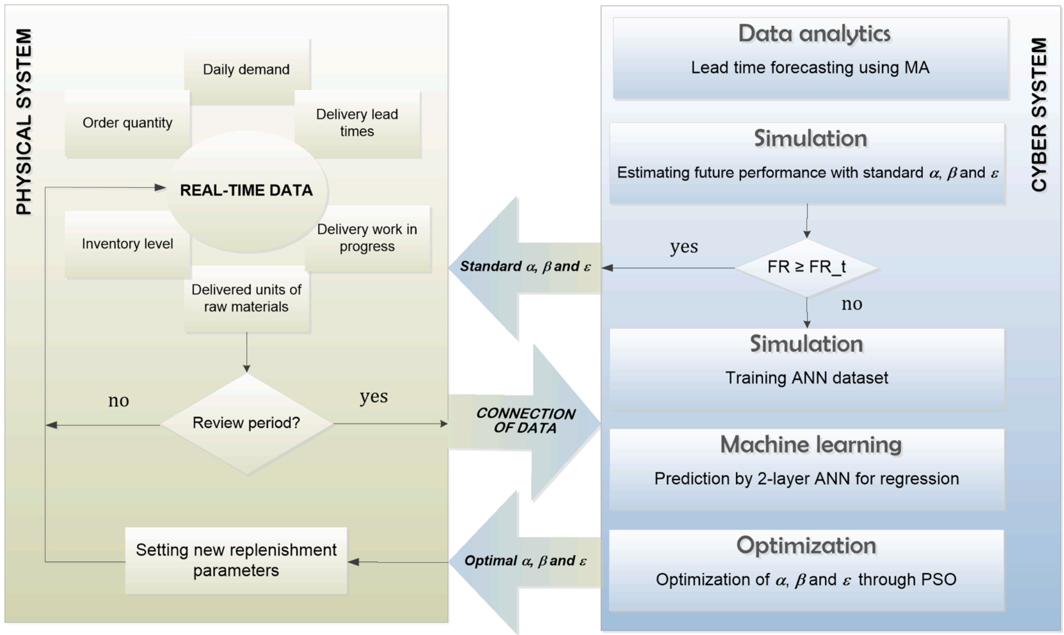

Fig. 3. Flow chart of the DT model.

available workers during the pandemic.

In SC dynamics, the 'up' state is typically used to define SCs characterized by normal functioning, while the 'down' state is when disruptions negatively impact SC operations (Snyder et al., 2016). In the proposed model, disruptions can occur randomly during the simulation run and the system abruptly moves to the 'down' state for a specific duration, resulting in non-stationary delivery lead times. Fig. 2 shows an example of disruption in the simulation, in which the evolution of the delivery lead time is depicted by the orange line, while the inventory level is represented by the blue line. From the graph, it can be observed that, in the initial phase, the manufacturer operates in the "up" state and delivery lead times assume a stationary trend. Suddenly, due to the disruptive event, the system moves to the "down" state, and an abrupt peak of delivery lead times occurs, which lasts for a certain interval. The 'down' state is characterized by the starting time of the disruptive interval, TD_1 (that is the time in which the disruption occurs), the ending time of the disruptive interval, TD_2, and the duration of the disruptive interval, $DD = TD_2\text{-}TD_1$, which is the time interval characterized by non-stationary delivery lead times due to the disruptions. Furthermore, it is noteworthy to denote the earliest and latest backlog situations within DD, as TB_1 and TB_2, respectively. After this disruptive interval, the system returns to the "up" state, and the delivery lead times return to the initial values.

2.3. Performance indicators

In this paper, we distinguish two groups of performance indicators:

i) the indicators universally employed to assess the performance of production–distribution systems (see e.g. the book by Hopp and Spearman, 2011), i.e., the fill rate (FR), the standard deviation value of the fill rate (σ_{FR}), the average value of the net stock level ($\overline{I_+}$), the standard deviation value of the net stock level (σ_{I_+}), the average value of the backlog level ($\overline{B}$) and the standard deviation value of the backlog level (σ_B);
ii) and those related to the resilience of the system, the time-to-recover (TTR) and the time-to-survive (TTS). Although they have been introduced in a general manner as SC resilience indicators (see e.g. Simchi-Levi et al., 2015; Gao et al., 2019), we are not aware of papers using them to evaluate a production–distribution system, which, in our view, constitutes one novelty of our paper and serves to complement the evaluation conducted using more traditional indicators.

In SC dynamics, the fill rate (FR) measures the ability of the SC to fulfil the customer demand (Ponte et al., 2017; Corsini et al., 2022b; Corsini, 2023). In this problem, the customer is represented by the production system, which requires raw materials from the company warehouse. The FR is calculated as the ratio between the units delivered by the warehouse to the production system and the production (customer) demand:

$$FR = \frac{1}{TH - WP}\left(\sum_{t=WP+1}^{TH} \frac{C_t}{d_t}\right)\% \tag{9}$$

Where TH is the time horizon of the simulation run and WP is the warmup period that must be excluded in the calculation of the performance indicators. The average value of the net stock level ($\overline{I_+}$) is used as a surrogate measure of the holding costs incurred by the company. The net stock level consists of only positive values of the inventory level (I_t); thus, $\overline{I_+}$ is calculated as:

$$\overline{I_+} = \frac{1}{TH - WP}\left(\sum_{t=WP+1}^{TH} \max_t\{I_t, 0\}\right) \tag{10}$$

Also, the average value of the backlog level ($\overline{B}$) is measured to evaluate the costs incurred by the warehouse of the company due to a stock-out situation. The backlog level consists of only the negative values of the inventory level (I_t); thus, $\overline{B}$ is calculated as:

$$\overline{B} = \frac{1}{TH - WP}\left(\sum_{t=WP+1}^{TH} \min_t\{I_t, 0\}\right) \tag{11}$$

The standard deviation value of the fill rate, σ_{FR}, net stock level, σ_{I_+}, and backlog, σ_B, are calculated to evaluate the variability of the KPIs along the time horizon. In particular, the standard deviation of the net stock level, σ_{I_+}, is a relevant indicator to consider since the higher σ_{I_+}, the higher the safety stock needed to achieve a given service level (Framinan, 2022).

TTR and TTS are also considered as post-processing key performance indicators to measure the resilience of the production–distribution sys-

Table 3
Results of the calibration of the replenishment parameters.

σ_d/μ_d	*MOQ*	α	β	ε	*FR*	$\overline{I_+}$
0.1	500	0.2	0.9	0.1	100 %	380.20
0.1	1000	0.2	0.8	0.3	100 %	670.00
0.1	1500	0.2	0.9	0.4	100 %	885.81
0.3	500	0.1	0.6	0.2	100 %	491.84
0.3	1000	0.1	0.8	0.3	100 %	668.92
0.3	1500	0.1	0.7	0.6	100 %	1086.85

tem (Simchi-Levi et al., 2015). TTR and TTS are defined by Gao et al., 2019 as 'the time duration between the disruption and the time when the supply chain recovers to full functionality', and as 'the initial time interval after disruption during which the supply chain is still capable of serving normal demands', respectively. Therefore, the TTR measures the number of days until the latest negative inventory level (or backlog) occurs within the disruptive interval, while TTS indicates the number of days in which the inventory level remains nonnegative before that the warehouse experiences a backlog situation. In order to include the duration of the disruptive interval (i.e., *DD*), we propose two novel variants of conventional performance measures, which are hereinafter denoted as TTR_{ratio} and TTS_{ratio} and calculated as follows:

$$TTR_{ratio} = \frac{TB_2 - TD_1}{DD}\% \tag{12}$$

$$TTS_{ratio} = \frac{TB1 - TD1}{DD}\% \tag{13}$$

A TTR_{ratio} value close to 100% implies that the manufacturer was not able to recover to full functionality before the conclusion of the disruptive interval, while a TTR_{ratio} value close to 0% indicates that the manufacturer restored full functionality immediately after the occurrence of the disruption. On the other hand, a TTS_{ratio} value close to 100% means that the manufacturer was able to maintain full functionality within the whole disruptive interval despite the effect of disruption, while a TTS_{ratio} value close to 0% indicates that the manufacturer experienced a backlog situation immediately after the occurrence of the disruption.

3. Digital twin model

The DT was defined by Ivanov (2023) as a virtual system that comprises: "(i) a digital visualization of a physical supply chain and its elements (e.g. firms, flows, and products) in a computer model, (ii) digital technologies providing data about the physical object (e.g. sensors, blockchain, clouds), and (iii) descriptive, predictive and prescriptive analytics for decision-making support". The use of DT technology in production–distribution systems management can bring numerous benefits, such as increasing the operational efficiency of the system, improving its resilience and reducing costs. In this problem, the DT model is designed with a twofold objective: i) to identify potential disruptions that might cause delays in the delivery lead time; and ii) to periodically determine the optimal values of the replenishment parameters by considering the changing delivery lead times. Conforming to the definition of Ivanov (2023), the proposed DT consists of the Physical System (PS), which represents the real-world production–distribution processes, and the digital counterpart, denoted as Cyber System (CS), which is the virtual replica of the PS. In DT applications for production–distribution systems management, PS and CS interact through a bidirectional data flow by means of digital technologies (e.g., sensors or clouds). The physical system continuously generates the real data that are collected and processed by the CS. In this work, the CS consists of a combination of a simulation model, data analytics with the Moving Average (MA) technique, an Artificial Neural Network (ANN) as an ML model, and Particle Swarm Optimization (PSO) as a metaheuristic algorithm for the optimization procedure. Fig. 3 provides an overview of the proposed DT architecture, which is described in detail in the following subsections.

3.1. Physical system

The PS provides the real-time data arising from the operations conducted by the production–distribution system. At each review period (e.g., one month), the CS is triggered by the PS to optimize the replenishment parameters used by the company. As for data connection, semiconductor firms are usually equipped with digital technologies in terms of ERP, IT hardware and software, sensors and automation both in the production bays and in the logistic/handling activities. In this case,

Table 4
Results from the comparison between SP and DT.

σ_d/μ_d	*MOQ*	Strategy	*FR*	σ_{FR}	$\overline{I_+}$	σ_{I_+}	$\overline{B}$	σ_B	TTR_{ratio}	TTS_{ratio}
0.1	500	SP	89.55 %	31.59 %	315.78	188.68	44.37	149.79	98.17 %	11.01 %
		DT	98.49 %	15.48 %	410.38	205.30	3.97	36.10	81.90 %	24.24 %
	RPD		***9.99 %***	***−51.02 %***	*29.96 %*	*8.81 %*	***−91.06 %***	***−75.90 %***	***16.57 %***	***120.13 %***
0.1	1000	SP	93.87 %	39.94 %	589.85	218.89	22.39	126.07	93.80 %	25.21 %
		DT	99.04 %	31.38 %	683.74	246.70	2.70	28.5	79.23 %	31.95 %
	RPD		***5.51 %***	***−21.43 %***	*15.92 %*	*12.71 %*	***−87.96 %***	***−77.03 %***	***15.53 %***	***26.71 %***
0.1	1500	SP	95.58 %	25.44 %	800.79	335.66	16.46	102.65	94.07 %	24.84 %
		DT	99.18 %	13.63 %	913.30	327.97	2.54	30.63	80.87 %	28.72 %
	RPD		***3.77 %***	***−46.42 %***	*14.05 %*	***−2.29 %***	***−84.58 %***	***−70.16 %***	***14.03 %***	***15.60 %***
0.3	500	SP	91.04 %	37.19 %	416.81	342.70	33.81	105.25	95.17 %	23.80 %
		DT	98.89 %	31.05 %	521.47	376.52	2.77	27.80	72.12 %	31.86 %
	RPD		***8.62 %***	***−16.50 %***	*25.11 %*	*9.87 %*	***−91.80 %***	***−73.59 %***	***24.22 %***	***33.85 %***
0.3	1000	SP	93.77 %	22.35 %	597.84	468.54	22.77	89.95	94.75 %	26.92 %
		DT	99.13 %	13.22 %	748.37	465.18	2.36	31.61	80.35 %	29.26 %
	RPD		***5.72 %***	***−40.85 %***	*25.18 %*	***−0.72 %***	***−89.63 %***	***−64.86 %***	***15.20 %***	***8.70 %***
0.3	1500	SP	97.02 %	33.72 %	982.15	493.56	9.60	64.89	83.25 %	36.95 %
		DT	99.39 %	30.73 %	1085.90	492.52	1.80	25.14	65.78 %	38.15 %
	RPD		***2.44 %***	***−8.87 %***	*10.56 %*	***−0.21 %***	***−81.30 %***	***−61.26 %***	***20.98 %***	***3.25 %***

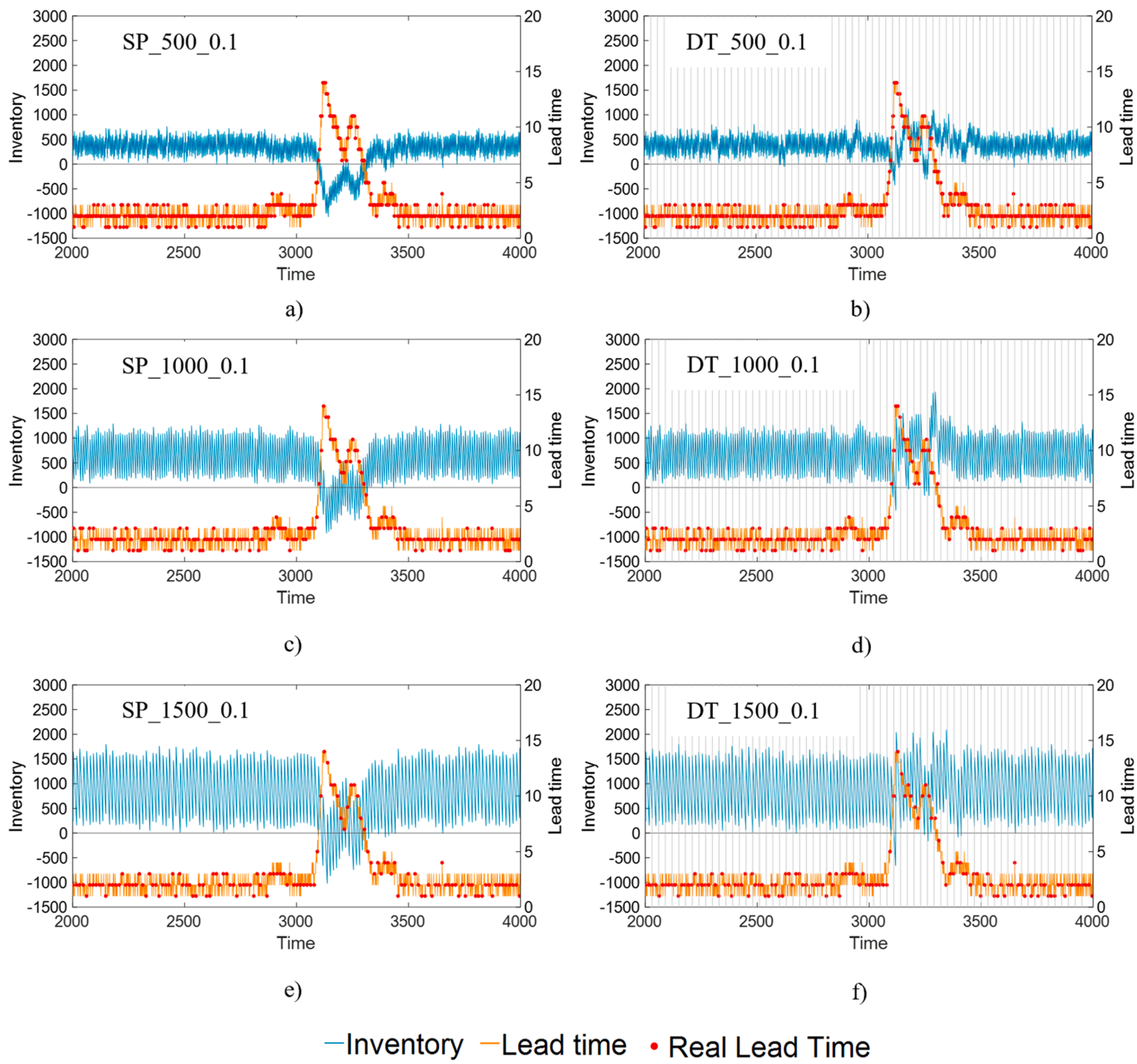

Fig. 4. Inventory levels for SP and DT approaches at varying MOQ when $\sigma_d/\mu_d = 0.1$.

the data from the PS are instantly retrievable through the ERP systems and transmitted to the CS. As shown in Fig. 3, the data transmitted from PS to CS consists of the inventory and work-in-progress levels, order quantities, delivered units of raw materials, delivery lead times and daily demand. The objective of this study is to assess the effectiveness of the proposed DT before its implementation within real-life company operations. Therefore, to evaluate the potential advantages offered by the DT, we adhered to the common practice in the SCOM literature of replicating the real-time operations and decision-making processes of the PS using a simulation model (Ivanov and Dolgui, 2021; Badakhshan and Ball, 2022).

3.2. Cyber system

The CS integrates data analytics, simulation, ML, and optimization to identify the optimal replenishment parameters at each review period in the PS. As shown in Fig. 3, the structure of the CS is the following:

- The initial phase of the CS involves data analytics, where data (more specifically, delivery lead times) from the PS is gathered and future delivery lead times are predicted using the MA technique.
- Subsequently, the data from PS and the forecasted delivery lead times are used as input data for the simulation model outlined in Section 2. In this step, the simulation model estimates the manufacturer's performance until the next review period (e.g., the next month) based on the standard values of α, β and ε.
- The standard values are kept unchanged if they enable the system to achieve an estimated future fill rate greater or equal to the target fill rate; therefore, the subsequent ML and optimization procedures are skipped. Otherwise, they are required to determine the optimal values of the replenishment parameters.
- The ANN dataset is trained during each review period to be reactive to sudden shifts in delivery lead times due to disruptions. This training dataset is generated by assessing various replenishment parameter combinations through the simulation model. Since the primary goal is to minimize the inventory level while maintaining the target fill rate, these combinations are paired with the estimated future fill rate and inventory levels.
- Once input (i.e., different combinations of α, β and ε) and output (i.e., estimated future fill rate and inventory level) training data are available, the 2-layer ANN is employed to generate two distinct surrogate models for fill rate and inventory level (hereinafter

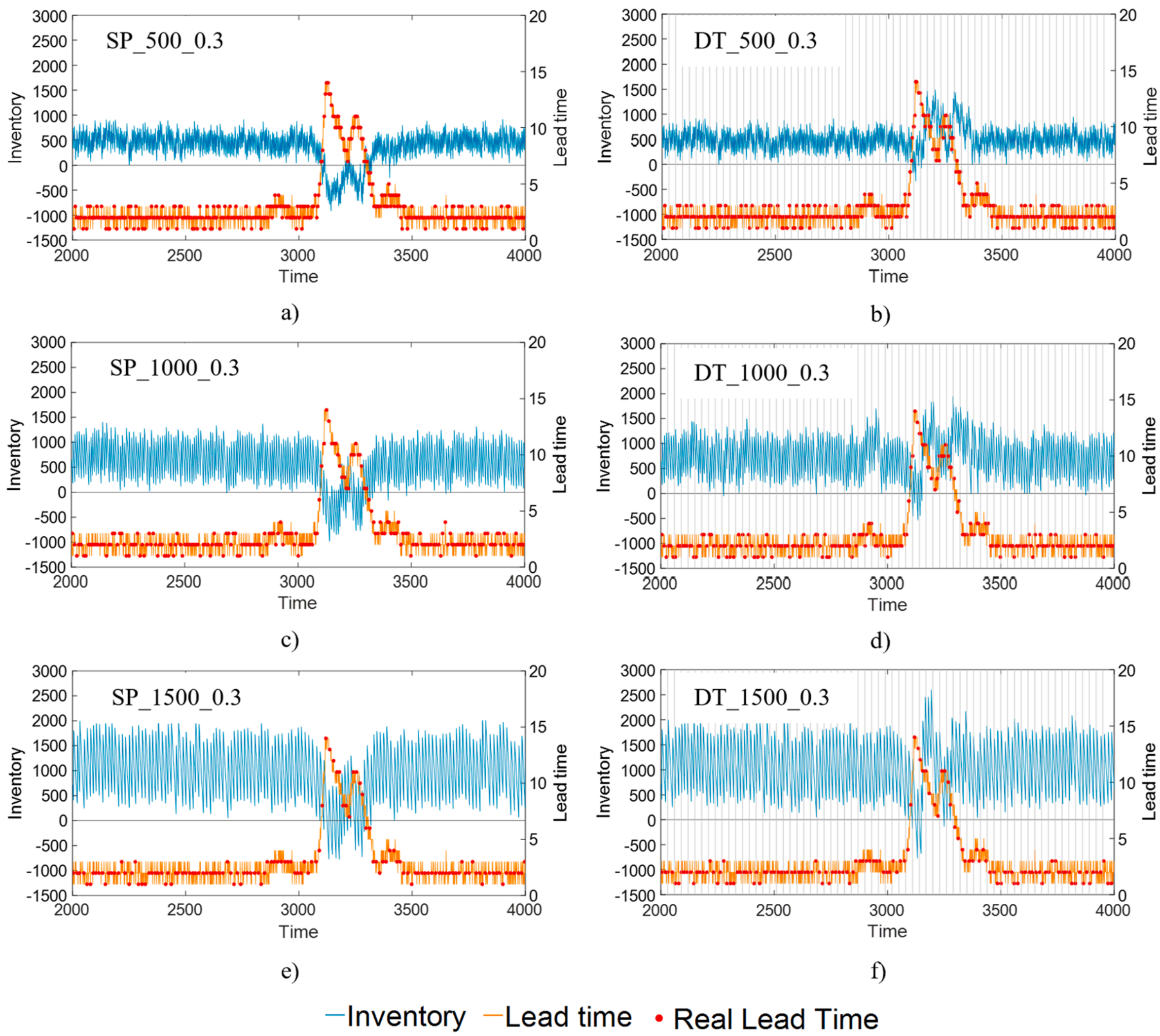

Fig. 5. Inventory levels for SP and DT approaches at varying MOQ when $\sigma_d/\mu_d = 0.3$.

denoted as FR_{ANN} and $\bar{I}_{ANN}$, respectively). These models will be used to predict the values of the fill rate and inventory level in the next step.

- Then, the two surrogate models are integrated into a PSO metaheuristic to select the optimal replenishment parameters that minimize the provided objective function. Specifically, the ANN surrogate models predict both FR_{ANN} and $\bar{I}_{ANN}$ for each particle, i.e., candidate solution, during the evolutionary path of PSO. The optimal triplet of parameters determined by the PSO is then utilized in the PS.

The architecture of ANN and PSO are described in the following subsections.

3.2.1. Artificial Neural network

The ANN is utilized as the ML algorithm to create a predictive model of the manufacturer dynamics. The use of ANNs for generating surrogate models or metamodels of production–distribution systems is a well-established practice within the relevant literature. Can and Heavey (2012) were among the first to emphasize the potential of ANNs as substitutes for discrete event simulation models. Their work demonstrated that the surrogate models generated by ANNs, when applied to various analogous problems such as inventory control or production lines, allow them to maintain high accuracy and significantly improve the computational efficiency. Moreover, in recent years, there has been a growing trend towards integrating ANN models with metaheuristic algorithms, wherein surrogate models are employed to evaluate the fitness function of diverse candidate solutions. These integrations have shown notable success since they facilitate the expedited evaluation of possible solutions. For this reason, the combination of ANN and metaheuristic algorithms is growing particularly in decision-making contexts for production–distribution systems (Nezamoddini et al., 2020; de Paula Vidal et al., 2022; Liu and Nishi, 2023).

ANN is inspired by the structure and function of the human brain, which consists of billions of neurons interconnected with each other in a complex neural network, where each neuron can process and transmit information to other neurons. Similarly, an ANN is composed of nodes or neurons that are interconnected through links in the network (Sharma & Garg, 2020). This study makes use of two distinct multilayer feedforward ANNs for the fill rate and the average inventory level. The ANN models include an input layer, two hidden layers, and an output layer. The input layer has three nodes that represent the replenishment parameters, namely α, β, and ε. The number of neurons in the hidden layers varies based on the output of the ANN model. Particularly, we developed two-hidden layers five-neurons per layer for the fill rate output, and two-hidden layers fifteen-neurons per layer for the inventory level output. The neurons of the hidden layers are interconnected using weighted links. These links are characterized by weights and biases, which in turn allow neurons to feed forward the input data to the final layer. An

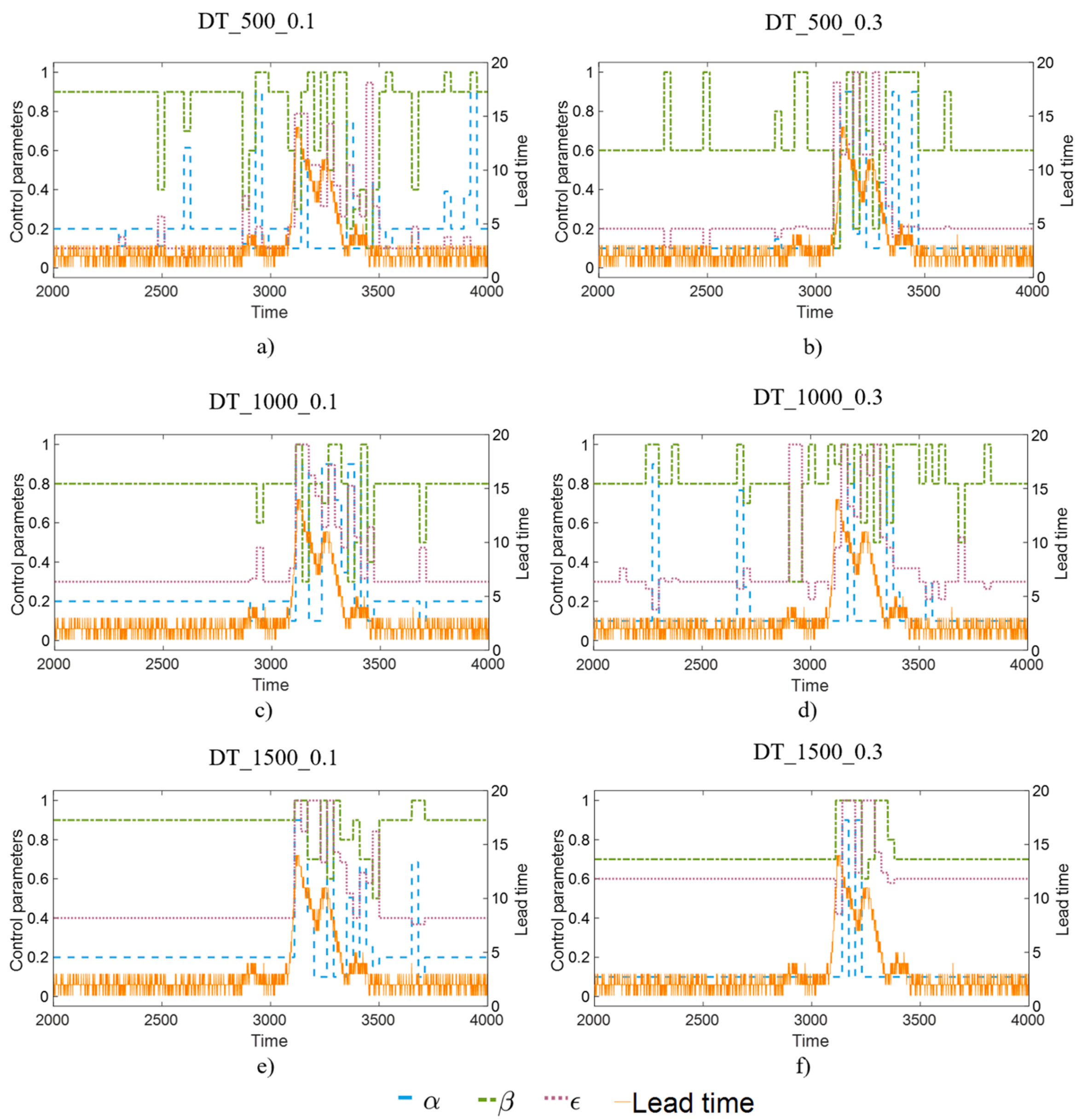

Fig. 6. Replenishment parameters' values selected by the DT strategy.

activation function, specifically a log-sigmoidal activation function, is employed to determine whether each neuron of the network should be activated based on the weighted sum of signals from the input (Narayan, 1997). The output of the activation function is denoted as f(x) and can be expressed as follows:

$$f(x) = 1/(1 + e^{-x}) \tag{14}$$

where x is the weighted sum of the input signals. The output layer of the ANN model generates a single response variable. The weight values in the ANN model are adjusted using the Levenberg-Marquardt Back-propagation (BP) algorithm, which minimizes the mean square error. The BP algorithm trains the neural network using an approximate descendent procedure for iteratively adjusting the weights to minimize the cost function of the neural network (Costa et al., 2022a). To prevent the overfitting of the prediction model, k-fold cross-validation is used for the validation phase. This statistical procedure splits the input data into k equal-sized groups, in which k-1 groups are used for training, and the remaining group is used for validation (Refaeilzadeh et al., 2009). After a series of trial-and-error attempts, the 10-folds cross-validation was selected and 70 %, 15 %, and 15 % of the dataset have been assigned to training, validation and testing procedures, respectively. These ANN configurations have been chosen after a preliminary test phase in which a different number of layers, each one including a varying number of neurons, has been carried out. Indeed, we selected the ANN configurations able to generate a reliable surrogate model in a reasonable computational time.

3.2.2. Optimization problem

For each review period, the goal of the manufacturer is to have the possible maximum fill rate with the lowest inventory. Formally, this problem can be defined as a constrained single-objective optimization problem and can be stated as follows: find the best combination of replenishment parameters (i.e., α, β, ε), denoted as x, i.e.:

$$x = \begin{bmatrix} \alpha \\ \beta \\ \varepsilon \end{bmatrix} \forall LB_\alpha \le \alpha \le UB_\alpha, LB_\beta \le \beta \le UB_\beta \text{ and } LB_\varepsilon \le \varepsilon \le UB_\varepsilon \tag{15}$$

so the following objective function is minimized:

$$\textbf{\textit{Minimize}}\, Y(x) = |\bar{I}|(1 + viol(x))^{n} \tag{16}$$

where $viol(x)$ is defined as follows:

$$viol(x) = 1 - \min(1; FR) \tag{17}$$

In other words, $viol(x)$ measures the deviation of the FR from the maximum possible fill rate (1.0 or 100 %), and it is introduced as a penalty factor in the objective function that minimizes the absolute value of the inventory (note that, in our model, a negative inventory represents the backlog orders and therefore taking out the absolute value would imply maximizing the backlog). Finally, n is a penalty exponent that, in our experiments, is set to 10. Note that, although both indicators (inventory and fill rate) are weighted in the objective function, the use of the penalty function coupled with the fact that, for a given scenario, the maximum fill rate is bounded in practice, leads to favoring solutions with the highest fill rate and, among them, those with lesser inventory.

3.2.3. Particle swarm optimization

The optimization problem has been addressed by a PSO, which makes use of the two ANN prediction models in terms of FR_{ANN} and $\bar{I}_{ANN}$ to evaluate the objective function of each candidate solution. Hence, the PSO plays a key role in identifying the optimal values of α, β, and ε, which in turn will be employed by the PS until the next review period. The PSO metaheuristic is a population-based optimization technique inspired by the social behaviour of birds and fish (Kennedy & Eberhart, 1995). The swarm denoted by $\boldsymbol{X}$ holds a population of particles, i.e., candidate solutions, characterized by a position $x_i(k)$ and a velocity $v_i(k)$, at each iteration k. In the problem under investigation, each position $x_i(k)$ consists of a combination of the 3 replenishment parameters to be optimized, i.e., α, β, and ε, as expressed in Equation (15). Hence, at each iteration, the swarm $\boldsymbol{X}$ gathers the position vectors $x_i(k)$ of each particle i as follows:

$$\boldsymbol{X} = [\, x_1(k) \quad x_2(k) \ \cdots \ x_i(k) \quad \cdots \quad x_m(k)\,] \tag{18}$$

Where m is the dimension of $\boldsymbol{X}$. The velocity $v_i(k)$ supports the movement of the particle i from the position $x_i(k)$ to the next position $x_i(k+1)$ in the solution space and is part of the velocity of the swarm, $\boldsymbol{V}$, defined as:

$$\boldsymbol{V} = [\, v_1(k) \quad v_2(k) \ \cdots \ v_i(k) \quad \cdots \quad v_m(k)\,] \tag{19}$$

In addition to position and velocity, each particle has a memory that allows it to remember the best local position achieved so far, p_i, and the corresponding objective value, p_best_i. Likewise, the swarm has a memory that records the best global position, represented by g and the related objective value, g_best.

Algorithm 1 shows the PSO pseudo-code. The algorithm begins by loading the ANN prediction models, which are used to compute the objective function of the swarm, $Y(\boldsymbol{X})$. Therefore, two different predictive models are required, one for the fill rate and another one for the inventory level. PSO begins by randomly generating an initial swarm and its associated velocity. PSO evolutionary mechanism consists of updating the position and the velocity of each particle. Regarding the position, each particle learns from its own experience, represented by the best local position p_i, and also communicates with the other particles to learn from the best global position achieved by the swarm, g. Therefore, at each iteration k, the velocity of each particle is updated by the following equation:

$$v_i(k) = w(k) \bullet v_i(k-1) + r_1 \bullet C_1 \bullet (p_i - x_i(k-1)) + r_2 \bullet C_2 \bullet (g - x_i(k-1)) \tag{20}$$

where r_1 and r_2 are two random numbers in the range of [0 1], C_1 and C_2 are two positive constants denoted as acceleration coefficients, $w(k)$ is the inertia coefficient, which decreases at each iteration, by a coefficient b, as follows:

$$w(k) = b \bullet w(k-1) \tag{21}$$

Therefore, the position of the particle is updated by the following equation:

$$x_i(k) = x_i(k-1) + v_i(k) \tag{22}$$

After computing the evolutionary mechanism of the swarm, the objective function, $Y(\boldsymbol{X})$ is evaluated for each candidate particle in the swarm. Furthermore, at each iteration, p_i and g are updated as described in Algorithm 1. The PSO operations are stopped when the maximum number of iterations, K, is reached. The global best particle g represents the output of the algorithm, which is the optimal set of replenishment parameters to be adopted for the replenishment tasks.

Algorithm 1 Pseudo-code of PSO

```
Procedure PSO
    Initialize parameters (e.g. K, m, C1, C2 and so on).
    Load ANN predictive models for fill rate and average inventory level.
    Generate the initial swarm, X, and the initial general velocity of the
    swarm, V.
    Compute Y(X).
    For each particle, set p_i equal to the objective value of the initial position.
    Set g equal to the best p_i in the swarm. Save p_best and g_best
    For k = 1 to K
        Update the inertia coefficient according to Eq. (21).
        For i = 1 to I
        Update the velocity of the particle, v_i(k), according to Eq. (20).
        Update the position of the particle, x_i(k), according to Eq. (22).
        Evaluate the objective function for each position of the particle, Y
        (x_i).
            If Y(x_i) < p_best_i
                p_i = x_i(k)
                p_best_i = Y(x_i)
                If Y(x_i) < g_best
                    g = x_i(k)
                    g_best = Y(x_i)
                End if
            End if
        End for
    End for
    Return g and g_best
End procedure
```

4. Experimental results

In this paper, two strategies are compared: the ‘static parametric’ (SP) strategy, in which the replenishment parameters are predetermined and remain unchanged over time, and the ‘digital twin’ (DT) strategy. To compare the two approaches, six different scenarios were defined based on different values of MOQ and demand variability, which is calculated as the ratio between the standard deviation value and the mean value of the production demand (σ_d/μ_d). MOQ is varied at three levels, i.e., i) $MOQ = 500$; ii) $MOQ = 1000$; iii) $MOQ = 1500$, while σ_d/μ_d is varied at two levels, i.e., i)$\sigma_d/\mu_d = 0.1$; ii)$\sigma_d/\mu_d = 0.3$. The MOQ values were set based on the studies conducted in a semiconductor company, while the values of σ_d/μ_d are conforming with the relevant literature (Priore et al., 2019; Costa et al., 2022b). In these scenarios, the mean production demand, μ_d, the mean delivery lead time, μ_{LT}, and the standard deviation of the delivery lead time, σ_{LT}, are set to 100, 2, and 0.5, respectively. The delivery lead times in the simulation are restricted to integer values. The time horizon of the simulation, TH, and the warm-up period, WP, are set to 4,000 and 2,000 days, respectively. To estimate the average values with higher confidence, the experimental campaign is conducted with 50 replications. For each replication, the disruptive events randomly occur in the interval between 2,000 and 3,400 (i.e., $TD_1 \in$ [2,000, 3,400]), and the duration of the disruptive interval, DD, is 600 days. Finally, in the DT architecture, the review period, TR, is set to

Table 5
Prediction accuracy of ANN models.

σ_d/μ_d	*MOQ*	*Fill Rate (FR_{ANN})*				*Inventory level ($\bar{I}_{ANN}$)*			
		R^2	*MAE*	*MSE*	*MAPE*	R^2	*MAE*	*MSE*	*MAPE*
0.1	500	99.96 %	0.0042	0.0001	3.56 %	99.98 %	11.98	261.62	13.85 %
0.1	1000	99.94 %	0.0058	0.0001	2.43 %	99.97 %	16.50	515.94	12.78 %
0.1	1500	99.96 %	0.0065	0.0001	2.64 %	99.98 %	22.52	863.65	18.69 %
0.3	500	99.92 %	0.0058	0.0001	2.34 %	99.96 %	16.05	475.25	13.71 %
0.3	1000	99.93 %	0.0078	0.0002	3.17 %	99.94 %	28.83	1483.48	19.54 %
0.3	1500	99.94 %	0.0078	0.0001	2.83 %	99.96 %	28.29	1503.43	18.58 %
	Average	99.94 %	0.0063	0.0001	2.83 %	99.96 %	20.70	850.56	16.19 %
	Min	99.92 %	0.0042	0.0001	2.34 %	99.94 %	11.98	261.62	12.78 %
	Max	99.96 %	0.0078	0.0002	3.56 %	99.98 %	28.83	1503.43	19.54 %

30 days (Priore et al., 2019). The DT architecture was developed in Matlab®2022b on a workstation equipped with an INTEL i9-9900 3.6 GHz 10 core CPU, 32 Gb DDR4 2666 MHz RAM and Win 10 PRO OS. On average, this architecture, which includes simulation, data analytics, training of ANNs and optimization using PSO, takes approximately 8.67 s to select the optimal values of the SOUT parameters.

The experimental resolution approach used to evaluate the effectiveness of the two strategies consists of two steps. Firstly, the 'standard values' are calibrated through a Full-Factorial Design Of Experiments (FF-DOE) to identify the most suitable set of control parameters for each of the six experimental scenarios without any disruptive event. Then, the experimental comparison between the two strategies is executed for the six experimental scenarios under disruption. The key performance indicators of the two strategies are compared in terms of Relative Percentage Deviation (RPD) (Corsini et al., 2023b). In this work, *RPD* refers to the improvement/worsening of performance provided by DT compared to the results from SP. Therefore, *RPD* is calculated as:

$$RPD = \left| \frac{KPI_{DT} - KPI_{SP}}{KPI_{SP}} \right| \% \tag{23}$$

4.1. Calibration of the replenishment parameters

The manufacturer's performance is strongly influenced by the values of the three control parameters (i.e., the forecasting smoothing factor α, the proportional controller β and the safety stock factor ε). The forecasting smoothing factor α is used to balance the exponential smoothing methodology, which is employed for forecasting the production demand (see equation (2). The proportional controller β is directly involved in the SOUT replenishment policy, which aims to smooth the gaps between the inventory and work-in-progress levels with the relative target values (see Eq. (1)). The safety stock factor ε is needed to define the target inventory value (see Eq. (3)). Therefore, the manufacturer needs to periodically select the most suitable set of replenishment parameters to improve its performance.

To properly calibrate α, β and ε, and identify the standard values, an FF-DOE is defined. The factor α varies in the range [0.1, 0.9] with discrete intervals of 0.1. It cannot be equal to 0 and 1 since it is involved in a 'smoothing' technique (Corsini et al., 2023a). The parameter β is in the range [0.1, 1] with discrete intervals of 0.1. The scenario in which β is equal to 0 is excluded since, in this case, the order quantity $O_{t,SOUT}$ should always be equal to the forecasted demand $\hat{d}_t$. On the other hand, as in the work of Priore et al. (2019), β equal to 1 is included since it represents the classical Order-Up-To (OUT) policy. Finally, the factor ε varies in the range [1, 20]. This range was normalized in [0, 1] with discrete intervals of 0.1. The total number of FF-DOE combinations is equal to 9·10· $=$ 990. With 50 replications for each combination, the total number of simulation runs is $990 \cdot 50 = 49{,}500$. For the sake of brevity, we report in Table 3 only the results related to the most suitable combination for each experimental scenario. The first two columns indicate the values of the demand variability and MOQ, the other three columns report the best replenishment parameter values (standard values), and the last two columns show the performance related to the combination. Note that the values of *FR* and $\overline{I_+}$ are averaged over the 50 replications. The best combination for each experimental scenario is the one that minimizes $\overline{I_+}$ while keeping *FR* equal to 100 %. These values will be adopted by the traditional strategy as the predetermined set of replenishment parameters that are kept unchanged over time and by the DT model as 'standard values'.

4.2. Experimental comparison between the two strategies

In this section, we compare the manufacturer's performance based on the SP and DT strategies. The two strategies were compared on the six scenarios described in Section 4. Table 4 displays the results of the eight KPIs considered in this paper. For each KPI, the related values are averaged over the 50 replications. The first two columns represent the values of the two independent variables, i.e., *MOQ* and σ_d/μ_d, which characterize the experimental scenarios. The third column indicates whether the manufacturer adopts the SP or DT strategy. The last 8 columns show the values of each KPI, i.e., the fill rate (*FR*), the standard deviation of the fill rate (σ_{FR}), the average value of the net stock level ($\overline{I_+}$), the standard deviation value of the net stock level (σ_{I_+}), the average value of the backlog level ($\overline{B}$), the standard deviation of the backlog (σ_B), the time-to-recover ratio (TTR_{ratio}) and the time-to-survive ratio (TTS_{ratio}). Finally, *RPDs* are reported for each experimental scenario and shown in italics. *RPDs* are also shown in bold when DT provides a performance improvement compared to SP. Fig. 4 and Fig. 5 show the dynamics of the inventory levels and delivery lead times for one illustrative replication of each experimental scenario. In each simulation run, lead time is generated on each day and is depicted by the orange line in the graphs. However, the company will only experience 'real' delivery lead times when an order is placed. These 'real' lead times assigned to each order are indicated in the graph with red dots. The inventory levels are represented by blue lines. Each figure is labelled to indicate the strategy employed by the manufacturer, the *MOQ* and σ_d/μ_d values. For instance, Fig. 4-a) is labelled by "SP_500_0.1", which denotes that: i) the 'static parametric' (SP) strategy is considered; ii) $MOQ = 500$; iii)$\sigma_d/\mu_d = 0.1$. The figures related to DT also show the review periods, shown with grey vertical lines.

Looking at Table 4, it becomes evident that the DT strategy improves the manufacturer's performance in terms of *FR*, σ_{FR}, $\overline{B}$, σ_B, TTR_{ratio} and TTS_{ratio}. It is worth noting that, when this data-driven strategy is employed, the value of *FR* is close to 100 % for each scenario. Interestingly, it can also be observed that the DT strategy ensures the lowest values of TTR_{ratio} and $\overline{B}$ close to 0, indicating that the DT strategy enables production–distribution systems to quickly recover to full functionality and reduce the negative effects of the backlog situation, thus being generally resilient to disruptive events. Also, the TTS_{ratio} of the DT strategy is higher than the SP strategy, demonstrating that the production–distribution system with DT has more chances to survive the effect of disruptive events. Finally, the great benefits provided by the DT strategy are also confirmed by the performance in terms of standard

Table 6
Comparison between SP and DT in terms of average net stock level.

σ_d/μ_d	*MOQ*	Strategy	α	β	ε	*FR*	$\overline{I_+}$	σ_{I_+}
0.1	500	SP	0.8	0.3	0.6	98.49 %	940.44	305.51
		DT	–	–	–	98.49 %	410.38	205.30
		RPD				*−0.01 %*	***−54.85 %***	***−32.80 %***
0.1	1000	SP	0.7	0.3	1	99.01 %	1144.08	406.45
		DT	–	–	–	99.04 %	683.74	246.70
		RPD				*0.01 %*	***−40.70 %***	***−39.90 %***
0.1	1500	SP	0.9	0.8	0.7	99.17 %	1331.33	511.54
		DT	–	–	–	99.18 %	913.30	327.97
		RPD				*0.00 %*	***−31.40 %***	***−35.89 %***
0.3	500	SP	0.1	0.2	0.8	98.91 %	1045.72	328.2
		DT	–	–	–	98.89 %	521.47	376.52
		RPD				*−0.01 %*	***−47.70 %***	*14.72 %*
0.3	1000	SP	0.1	0.6	0.7	99.11 %	1180.89	401.25
		DT	–	–	–	99.13 %	748.37	465.18
		RPD				*0.02 %*	***−36.63 %***	*15.93 %*
0.3	1500	SP	0.3	0.6	0.9	99.38 %	1486.16	550.72
		DT	–	–	–	99.39 %	1085.90	492.52
		RPD				*−0.01 %*	***−26.00 %***	***−10.57 %***

deviation values of *FR* and $\overline{B}$. Fig. 4 and Fig. 5 show that the sudden peak in the delivery lead time deteriorates the manufacturer's performance with the SP strategy, leading to negative inventory levels. SP can only recover to full functionality from a disruption when operations of the production–distribution system return to the 'up' state. Fig. 4 and Fig. 5 also demonstrate how production–distribution systems with the DT strategy can swiftly respond to sudden increases in delivery lead time. In fact, the DT strategy promptly adjusts the values of the replenishment parameters, allowing the production–distribution system to recover to full functionality from disruption even when production–distribution operations are in the 'down' state. Therefore, stock-out scenarios only occur during the initial unpredictable peak in the delivery lead time. These findings are reinforced by Fig. 6, which illustrates the replenishment parameter values over the time horizon. This in-depth investigation is valuable in demonstrating the effectiveness and robustness of the DT strategy. In fact, the graph shows that the optimization module of the DT strategy is activated when the production–distribution system experiences a sudden increase in delivery lead time. As shown in Fig. 6, we detect in some cases an increase of α (which may be indicative of the system being prepared for a higher responsiveness by giving a higher weight to the more recent periods). Also, β tends to decrease to try to meet the required demand (even if this would eventually lead to a higher inventory), since the main goal of the system is to maintain a high service level. Finally, ε tends to increase for analogous reasons in order to avoid backlogs. Nevertheless, such trends do not always happen, as the system is constantly correcting the values of the parameters according to the current inventory situation and the forecasts, so excess inventory and forecasting errors in one period are later compensated by properly adjusting the parameters.

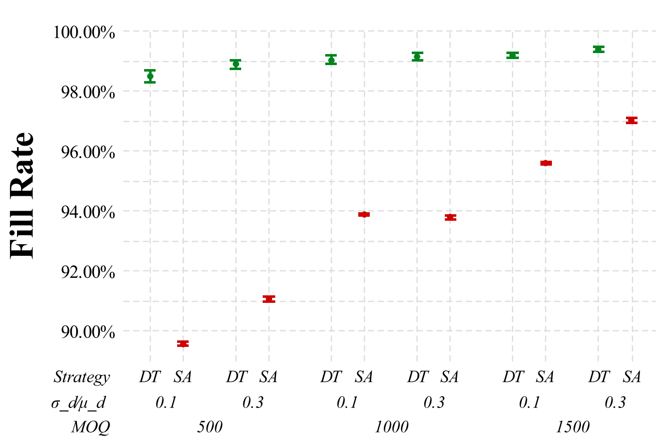

Fig. 7. Interval plot for the fill rate.

One of the main factors contributing to the effectiveness of the DT lies in the high prediction accuracy of the ANN models for the fill rate FR_{ANN} and the inventory level $\bar{I}_{ANN}$. Table 5 presents the average values of the coefficient of determination (R^2), Mean Absolute Error (*MAE*), Mean Square Error (*MSE*), and Mean Absolute Percentage Error (*MAPE*) of the two ANN models across each experimental scenario. The last three rows of the table display the overall average, minimum, and maximum values for each prediction accuracy indicator. The high prediction accuracy of both surrogate models is demonstrated by the overall average values of R^2, which are close to 100 %, and *MAPE*, which remains below 20 %. Furthermore, considering the scale and range of data values, the *MAE* and *MSE* exhibit low values, confirming the robustness of the ANN predictive models.

Another discussion should be dedicated to inventory-related performance. The results of Table 2 show that the SP strategy results in a reduction of the average net stock level and its standard deviation (in some scenarios). Intuitively, it may seem that SP should be preferable if the company needs to reduce the holding costs incurred by the inventory level. However, this performance is caused by long periods of stock-out and implies a lower fill rate. To make a fair comparison in terms of inventory-related performance, we conducted a final comparison between SP and DT in terms of $\overline{I_+}$ and σ_{I_+}. In this new experimental phase, the replenishment parameters were calibrated again for the SP strategy, but this time, the disruption in terms of delivery lead time was included in the simulation runs. Then, the combinations of replenishment parameters that achieved the same *FR* of the DT under disruption were selected. Table 6 shows that the six configurations of replenishment parameters calibrated under disruptive events for the SP strategy allow gaining almost the same performance as the DT strategy in terms of *FR*. On the other hand, as expected, the last columns show the highest values of inventory level of the static strategy compared to the DT strategy. This demonstrates that, in Table 2, manufacturers with SP achieve the lowest values of $\overline{I_+}$ since the warehouse is not able to satisfy the production demand in time. A similar trend is revealed for σ_{I_+}, except for scenarios with $MOQ = 500$ and 1000, and $\sigma_d/\mu_d = 0.3$.

Finally, Fig. 7 is provided to graphically compare the two strategies in terms of *FR* and to assess the influence of the two experimental factors, i.e., *MOQ* and σ_d/μ_d. As mentioned earlier, it is remarkable that the DT strategy outperforms the static strategy in maximizing the *FR*. Furthermore, it is noteworthy that *MOQ* has a significant influence on the *FR*. Higher values of *MOQ* allow production–distribution systems to achieve a higher fill rate, particularly for the SP strategy. This suggests that higher *MOQ* leads the company to higher inventory levels, which act as a safety stock for unexpected peaks in delivery lead times. This trend is also observable for the other performance measures in Table 2. On the other hand, demand variability also affects the performance of manufacturers as well, but its impact is less significant compared to *MOQ*. The influence of demand variability is consistent with the findings of the work of Costa et al. (2022b). It is worth specifying that the variability of the interval plots arises from the 50 replications of each experimental scenario, and not from σ_{FR}, which is the standard deviation of *FR* in the time horizon of the simulation.

5. Theoretical and managerial implications

An experimental campaign was conducted to compare static and DT strategies based on experimental scenarios including different levels of minimum order quantity and demand variability. The main findings of this comparison hold implications for both professionals in practice and researchers in supply chain theory, as delineated below.

5.1. Implication for managers

The outcomes of the experimental campaign highlight the potential of the DT strategy in aiding companies to promptly respond to disruptive events. These events are often unpredictable, leading to unavoidable reduction of inventory levels during the initial periods. Nevertheless, the results reveal that the DT strategy allows the manufacturer to achieve fill rate values close to 100 %. The DT strategy may enable production–distribution systems to rapidly recover full functionality from disruptions, even while the system is in the 'down' state, as evidenced by the time-to-recover ratio indicator (TTR_{ratio}). Furthermore, the time-to-survive ratio indicator (TTS_{ratio}) demonstrates that the manufacturer that adopts the DT strategy can still meet the production demand despite disruptions. As for the holding costs, the DT strategy requires higher inventory levels to achieve a fill rate close to 100 % in an uncertain environment. However, a new experimental comparison was conducted to demonstrate that the performance of the static approach in terms of inventory level is influenced by long backlog periods. The experiments underscore that the proposed DT strategy represents a fundamental shift from conventional strategies, as it offers the potential for more agile and responsive production–distribution systems management. By enabling real-time updates and dynamic modifications, companies can better manage disruptions, improving their ability to react to unexpected events and minimize the risk of production blocks. In summary, the results of this work strongly suggest managers to implement DT systems for an intelligent replenishment approach, thereby enhancing the resilience of the company and effectively coping with disruptive events, which are increasingly frequent and unpredictable in today's business landscape.

5.2. Implications for researchers and academicians

Traditional replenishment strategies, typically considered in supply chain literature, exhibit several limitations. One significant limitation is their reliance on pre-determined parameters that may become inadequate over time due to disruptions. This can lead to suboptimal replenishment strategies, which may result in stock-outs during disruptive scenarios. Therefore, there is a need for more sophisticated, data-driven replenishment strategies capable of adjusting replenishment parameters in response to the dynamic external environment and enhancing the resilience of production–distribution systems. The analysis of the experimental results reveals that the static strategy fails to respond adequately to increased delivery lead times, resulting in long stock-out periods. As for the dynamic control of the replenishment parameters shown in Fig. 6, even if general trends can be observed, it is not possible to formulate a universal rule that could be implemented with good results. One of the contributions of our paper is to demonstrate that the proposed DT approach effectively addresses this extremely complex, highly interrelated problem, which otherwise would be challenging to tackle efficiently. Furthermore, the proposed DT architecture is also efficient in terms of computational time since the ANN predictive models are embedded in the PSO algorithm to evaluate each candidate combination of replenishment parameters.

6. Conclusions

In this work, we propose a new DT strategy for production–distribution systems subject to sudden and unforeseen disruptions leading to increased delivery lead times. Inspired by the semiconductor industry, our focus is on the warehouse operations of the manufacturer, that issues orders to an external supplier and meets the demand from the production system. Both production demand and delivery lead time are stochastic and normally distributed. However, the production–distribution system can be impacted by disruptive events, resulting in unpredictable peaks in delivery lead time for a certain period. To issue orders, the warehouse adopts the SOUT policy, which is characterized by three replenishment parameters, namely the forecasting smoothing factor, the proportional controller, and the safety stock factor. Usually, the previous literature adopts a static strategy in which the values of these replenishment parameters are predetermined and remain unchanged during experiments.

Unlike the conventional approach, this paper presents a novel DT model designed to periodically identify the best replenishment parameters. One of the novelties lies in the digital component, which integrates the simulation model, Artificial Neural Network, and Particle Swarm Optimization algorithm. The simulation model enables the DT to accurately emulate real-world scenarios related to the production–distribution systems affected by disruptions, facilitating data-driven decision-making processes. First, the simulation model is used to assess whether the standard replenishment parameters are still suitable for assuring a satisfying performance in the future. Otherwise, the simulation model estimates the performance of several combinations of replenishment parameters to generate a training dataset for ML. Based on these training data, two distinct ANN models in terms of fill rate and inventory level have been developed to calculate the objective function of several candidate solutions in reasonable computational times. Finally, the integration of the metaheuristic optimization algorithm empowers the DT to efficiently explore vast solution spaces and identify the best replenishment parameters, enabling the manufacturer to achieve enhanced performance metrics.

To demonstrate the efficacy of the DT model compared to the conventional approach, we conducted an experimental campaign, varying two crucial factors: the minimum order quantity and demand variability. The results of this experimental study highlight the significant effectiveness of the DT model in enhancing supply chain resilience against the unpredictable effects of disruptions. Specifically, the DT model showcased a remarkable improvement in various supply chain performance metrics, such as fill rate or backlog quantity, and resilience indicators, i.e., time-to-recover and time-to-survive, outperforming the conventional methods and pointing out its ability to swiftly recover full functionality from adverse events. In conclusion, the results obtained through our experimental campaign validate the superiority of the DT model as a strategic tool for intelligent replenishment operations and suggest that supply chain managers must implement it to improve the performance and resilience of production–distribution systems and to face the effects of unforeseen disruptions. As for supply chain theory, the present paper brings out the limitation of the conventional approach when the production–distribution system is subject to sudden peaks in delivery lead times. For this reason, it emerges the need for more sophisticated and data-driven replenishment approaches to cope with the external dynamic environment.

This study could inspire other applications of DT strategies in production–distribution contexts. Therefore, several directions for future research could be outlined. First, the proposed DT for production–distribution systems can be further tested under various other effects arising from the COVID-19 pandemic. These effects may include unexpected changes in customer demand, sudden loss of production capacity, and other related uncertainties. In this manner, we can provide new insights into the robustness and effectiveness of the proposed DT in addressing real-world challenges of supply chains and manufacturing systems caused by unpredictable disruptions. Furthermore, the application of the DT strategy could be extended to different supply chain structures, such as three- or four-echelon supply chains, to study the impact in terms of the bullwhip effect. Finally, hybrid manufacturing/remanufacturing systems could also benefit from the DT strategy to increase their performance.

CRediT authorship contribution statement

Roberto Rosario Corsini: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Antonio Costa:** Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Writing – original draft, Writing – review & editing. **Sergio Fichera:** Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Writing – original draft, Writing – review & editing. **Jose M. Framinan:** Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgements

This work was supported by the University of Catania with Project PIACERI 2020/22 – GOSPEL / 59722022261, the EU Commission (H2020) with Project ExPliCit - EXploring PLausIble CIrcular fuTures (101086465 — HORIZON-MSCA-2021-SE-01-01) and the Spanish Ministry of Science and Innovation with Project ENSURE – ENterprise-wide SUstainable REsilience" (PID2022-142062OB-I00).

References

Badakhshan, E., & Ball, P. (2022). Applying digital twins for inventory and cash management in supply chains under physical and financial disruptions. *International Journal of Production Research, 1–23*. https://doi.org/10.1080/00207543.2022.2093682

Badakhshan, E., Ball, P., & Badakhshan, A. (2022). Using digital twins for inventory and cash management in supply chains. *IFAC-Papers OnLine, 55*(10), 1980–1985. https://doi.org/10.1016/j.ifacol.2022.09.689

Bhandal, R., Meriton, R., Kavanagh, R. E., & Brown, A. (2022). The application of digital twin technology in operations and supply chain management: A bibliometric review. *Supply Chain Management: An International Journal.*. https://doi.org/10.1108/SCM-01-2021-0053

Birkel, H., Hohenstein, N. O., & Hähner, S. (2023). How have digital technologies facilitated supply chain resilience in the COVID-19 pandemic? An exploratory case study. *Computers & Industrial Engineering, 183*, Article 109538. https://doi.org/10.1016/j.cie.2023.109538

Can, B., & Heavey, C. (2012). A comparison of genetic programming and artificial neural networks in metamodeling of discrete-event simulation models. *Computers & Operations Research, 39*(2), 424–436. https://doi.org/10.1016/j.cor.2011.05.004

Cao, E. Z., Peng, C., & Cao, Z. (2022). Risk propagation decision-making for product and supply chain change systems under COVID-19: An assessment-to-control support scheme. *IEEE Transactions on Computational Social Systems*. https://doi.org/10.1109/TCSS.2022.3215260

Chatfield, D. C., & Pritchard, A. M. (2013). Returns and the bullwhip effect. *Transportation Research Part E: Logistics and Transportation Review, 49*(1), 159–175. https://doi.org/10.1016/j.tre.2012.08.004

Ciapetti, L., & Le Pira, M. (2022). Disruption of global and regional supply-chains in the aftermath of Covid-19 pandemic. Analyses and forecasts. *Research in Transportation Economics, 93*, Article 101209. https://doi.org/10.1016/j.retrec.2022.101209

Corsini, R. R. (2023). Adaptive production control of two-product closed-loop supply chain dynamics under disruptions. *Journal of Industrial and Production Engineering, 40*(8), 638–660. https://doi.org/10.1080/21681015.2023.2256962

Corsini, R. R., Costa, A., Cannella, S., & Framinan, J. M. (2023a). Analysing the impact of production control policies on the dynamics of a two-product supply chain with capacity constraints. *International Journal of Production Research, 61*(6), 1913–1937. https://doi.org/10.1080/00207543.2022.2053224

Corsini, R. R., Costa, A., Fichera, S., & Framinan, J. M. (2022a). A new data-driven framework to select the optimal replenishment strategy in complex supply chains. *IFAC-PapersOnLine, 55*(10), 1423–1428. https://doi.org/10.1016/j.ifacol.2022.09.590

Corsini, R. R., Costa, A., & Framinan, J. M. (2023b). An adaptive product changeover policy for a capacitated two-product supply chain in a non-stationary demand environment. *International Journal of Management Science and Engineering Management, 1–12*. https://doi.org/10.1080/17509653.2023.2219644

Corsini, R. R., Fichera, S., & Costa, A. (2022b). Assessing the Effect of a Novel Production Control Policy on a Two-Product, Failure-Prone Manufacturing/Distribution Scenario. In Selected Topics in Manufacturing (pp. 1-20). Springer, Cham. 10.1007/978-3-030-82627-7_1.

Costa, A., Buffa, G., Palmeri, D., Pollara, G., & Fratini, L. (2022a). Hybrid prediction-optimization approaches for maximizing parts density in SLM of Ti6Al4V titanium alloy. *Journal of Intelligent Manufacturing, 1–23*. https://doi.org/10.1007/s10845-022-01938-9

Costa, A., Cannella, S., Corsini, R. R., Framinan, J. M., & Fichera, S. (2022b). Exploring a two-product unreliable manufacturing system as a capacity constraint for a two-echelon supply chain dynamic problem. *International Journal of Production Research, 60*(3), 1105–1133. https://doi.org/10.1080/00207543.2020.1852480

de Arquer, M., Ponte, B., & Pino, R. (2022). Examining the balance between efficiency and resilience in closed-loop supply chains. *Central European Journal of Operations Research, 30*(4), 1307–1336. https://doi.org/10.1007/s10100-021-00766-1

de Paula Vidal, G. H., Caiado, R. G. G., Scavarda, L. F., Ivson, P., & Garza-Reyes, J. A. (2022). Decision support framework for inventory management combining fuzzy multicriteria methods, genetic algorithm, and artificial neural network. *Computers & Industrial Engineering, 174*, Article 108777. https://doi.org/10.1016/j.cie.2022.108777

Diaz, M. F. L., Ehm, H., & Ismail, A. (2022, December). Simulated-Based Analysis of Recovery Actions Under Vendor-Managed Inventory Amid Black Swan Disruptions in the Semiconductor Industry: A Case Study from Infineon Technologies AG. In 2022 Winter Simulation Conference (WSC) (pp. 3513-3524). IEEE. 10.1109/WSC57314.2022.10015305.

Disney, S. M., & Lambrecht, M. R. (2008). On replenishment rules, forecasting, and the bullwhip effect in supply chains. *Foundations and Trends® in Technology, Information and Operations Management, 2*(1), 1–80. https://doi.org/10.1561/0200000010

Disney, S. M., Ponte, B., & Wang, X. (2021). Exploring the nonlinear dynamics of the lost-sales order-up-to policy. *International Journal of Production Research, 59*(19), 5809–5830. https://doi.org/10.1080/00207543.2020.1790687

Dolgui, A., & Ivanov, D. (2021). Ripple effect and supply chain disruption management: New trends and research directions. *International Journal of Production Research, 59*(1), 102–109. https://doi.org/10.1080/00207543.2021.1840148

Dolgui, A., & Ivanov, D. (2022). 5G in digital supply chain and operations management: Fostering flexibility, end-to-end connectivity and real-time visibility through internet-of-everything. *International Journal of Production Research, 60*(2), 442–451. https://doi.org/10.1080/00207543.2021.2002969

Dreyfuss, M., & Giat, Y. (2019). Allocating spares to maximize the window fill rate in a periodic review inventory system. *International Journal of Production Economics, 214*, 151–162. https://doi.org/10.1016/j.ijpe.2019.04.017

Framinan, J. M. (2022). Modelling supply chain dynamics. *Springer, Cham.*. https://doi.org/10.1007/978-0-387-39940-9_565

Fussone, R., Dominguez, R., Cannella, S., & Framinan, J. M. (2023). Bullwhip effect in closed-loop supply chains with multiple reverse flows: A simulation study. *Flexible Services and Manufacturing Journal, 1–29*. https://doi.org/10.1007/s10696-023-09486-x

Gaalman, G. (2006). Bullwhip reduction for ARMA demand: The proportional order-up-to policy versus the full-state-feedback policy. *Automatica, 42*(8), 1283–1290. https://doi.org/10.1016/j.automatica.2006.04.017

Gao, S. Y., Simchi-Levi, D., Teo, C. P., & Yan, Z. (2019). Disruption risk mitigation in supply chains: The risk exposure index revisited. *Operations Research, 67*(3), 831–852. https://doi.org/10.1287/opre.2018.1776

Habibi, F., Chakrabortty, R. K., & Abbasi, A. (2023). Evaluating supply chain network resilience considering disruption propagation. *Computers & Industrial Engineering, 183*, Article 109531. https://doi.org/10.1016/j.cie.2023.109531

Habla, C., Driebel, R., Monch, L., Ponsignon, T., & Ehm, H. (2007). A short-term forecast method for demand quantities in semiconductor manufacturing. In 2007 IEEE International Conference on Automation Science and Engineering (pp. 94-99). IEEE. 10.1109/COASE.2007.4341724.

Hopp, W. J., & Spearman, M. L. (2011). *Factory physics*. Waveland Press.

Ivanov, D. (2021). Introduction to supply chain resilience: Management, modelling, technology. *Springer Nature*. https://doi.org/10.1007/978-3-030-70490-2

Ivanov, D. (2023). Conceptualisation of a 7-element digital twin framework in supply chain and operations management. *International Journal of Production Research, 1–13*. https://doi.org/10.1080/00207543.2023.2217291

Ivanov, D., & Dolgui, A. (2021a). A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0. *Production Planning & Control, 32*(9), 775–788. https://doi.org/10.1080/09537287.2020.1768450

Ivanov, D., & Dolgui, A. (2021b). OR-methods for coping with the ripple effect in supply chains during COVID-19 pandemic: Managerial insights and research implications. *International Journal of Production Economics, 232*, Article 107921. https://doi.org/10.1016/j.ijpe.2020.107921

Ivanov, D., & Dolgui, A. (2022). The shortage economy and its implications for supply chain and operations management. *International Journal of Production Research, 60* (24), 7141–7154. https://doi.org/10.1080/00207543.2022.2118889

Ivanov, D., Dolgui, A., Das, A., & Sokolov, B. (2019). Digital supply chain twins: Managing the ripple effect, resilience, and disruption risks by data-driven optimization, simulation, and visibility. *Handbook of Ripple Effects in the Supply Chain, 309–332*. https://doi.org/10.1007/978-3-030-14302-2_15

Kamble, S. S., Gunasekaran, A., Parekh, H., Mani, V., Belhadi, A., & Sharma, R. (2022). Digital twin for sustainable manufacturing supply chains: Current trends, future perspectives, and an implementation framework. *Technological Forecasting and Social Change, 176*, Article 121448. https://doi.org/10.1016/j.techfore.2021.121448

Katsaliaki, K., Galetsi, P., & Kumar, S. (2021). Supply chain disruptions and resilience: A major review and future research agenda. *Annals of Operations Research, 1–38*. https://doi.org/10.1007/s10479-020-03912-1

Katsoras, E., & Georgiadis, P. (2022). An integrated System Dynamics model for Closed Loop Supply Chains under disaster effects: The case of COVID-19. *International Journal of Production Economics, 253*, Article 108593. https://doi.org/10.1016/j.ijpe.2022.108593

Kennedy, J., & Eberhart, R. (1995). Particle swarm optimization. In Proceedings of ICNN'95-international conference on neural networks (Vol. 4, pp. 1942-1948). IEEE. 10.1109/ICNN.1995.488968.

Kiesmüller, G. P., De Kok, A. G., & Dabia, S. (2011). Single item inventory control under periodic review and a minimum order quantity. *International Journal of Production Economics, 133*(1), 280–285. https://doi.org/10.1016/j.ijpe.2010.03.019

Kurian, D. S., Pillai, V. M., Gautham, J., & Raut, A. (2023). Data-driven imitation learning-based approach for order size determination in supply chains. *European Journal of Industrial Engineering, 17*(3), 379–407. https://doi.org/10.1504/EJIE.2023.130601

Latsou, C., Farsi, M., & Erkoyuncu, J. A. (2023). Digital twin-enabled automated anomaly detection and bottleneck identification in complex manufacturing systems using a multi-agent approach. *Journal of Manufacturing Systems, 67*, 242–264. https://doi.org/10.1016/j.jmsy.2023.02.008

Li, Q., Gaalman, G., & Disney, S. M. (2023). On the equivalence of the proportional and damped trend order-up-to policies: An eigenvalue analysis. *International Journal of Production Economics, 265*, Article 109005. https://doi.org/10.1016/j.ijpe.2023.109005

Lin, J., Spiegler, V. L., & Naim, M. M. (2018). Dynamic analysis and design of a semiconductor supply chain: A control engineering approach. *International Journal of Production Research, 56*(13), 4585–4611. https://doi.org/10.1080/00207543.2017.1396507

Liu, Z., & Nishi, T. (2023). Data-driven evolutionary computation for service constrained inventory optimization in multi-echelon supply chains. *Complex & Intelligent Systems, 1–22*. https://doi.org/10.1007/s40747-023-01179-0

Llaguno, A., Mula, J., & Campuzano-Bolarin, F. (2021). State of the art, conceptual framework and simulation analysis of the ripple effect on supply chains. *International Journal of Production Research, 60*(6), 2044–2066. https://doi.org/10.1080/00207543.2021.1877842

Maheshwari, P., & Kamble, S. (2022). The Application of Supply Chain Digital Twin to Measure Optimal Inventory Policy. *IFAC-PapersOnLine, 55*(10), 2324–2329. https://doi.org/10.1016/j.ifacol.2022.10.055

Marklund, J. (2011). Inventory control in divergent supply chains with time-based dispatching and shipment consolidation. *Naval Research Logistics (NRL), 58*(1), 59–71. https://doi.org/10.1002/nav.20441

Mohammad, W., Elomri, A., & Kerbache, L. (2022). The Global Semiconductor Chip Shortage: Causes, Implications, and Potential Remedies. *IFAC-PapersOnLine, 55*(10), 476–483. https://doi.org/10.1016/j.ifacol.2022.09.439

Narayan, S. (1997). The generalized sigmoid activation function: Competitive supervised learning. *Information sciences, 99*(1–2), 69–82. https://doi.org/10.1016/S0020-0255(96)00200-9

Nezamoddini, N., Gholami, A., & Aqlan, F. (2020). A risk-based optimization framework for integrated supply chains using genetic algorithm and artificial neural networks. *International Journal of Production Economics, 225*, Article 107569. https://doi.org/10.1016/j.ijpe.2019.107569

Nguyen, T., Duong, Q. H., Van Nguyen, T., Zhu, Y., & Zhou, L. (2022). Knowledge mapping of digital twin and physical internet in Supply Chain Management: A systematic literature review. *International Journal of Production Economics, 244*, Article 108381. https://doi.org/10.1016/j.ijpe.2021.108381

Novoszel, L., & Wakolbinger, T. (2022). Meta-analysis of supply chain disruption research. *Operations research forum, 3*(1), 1–25. https://doi.org/10.1007/s43069-021-00118-4

Pathy, S. R., & Rahimian, H. (2023). A resilient inventory management of pharmaceutical supply chains under demand disruption. *Computers & Industrial Engineering, 180*, Article 109243. https://doi.org/10.1016/j.cie.2023.109243

Ponte, B., Wang, X., de la Fuente, D., & Disney, S. M. (2017). Exploring nonlinear supply chains: The dynamics of capacity constraints. *International Journal of Production Research, 55*(14), 4053–4067. https://doi.org/10.1080/00207543.2016.1245884

Preil, D., & Krapp, M. (2022). Artificial intelligence-based inventory management: A Monte Carlo tree search approach. *Annals of Operations Research, 1–25*. https://doi.org/10.1007/s10479-021-03935-2

Priore, P., Ponte, B., Rosillo, R., & de la Fuente, D. (2019). Applying machine learning to the dynamic selection of replenishment policies in fast-changing supply chain environments. *International Journal of Production Research, 57*(11), 3663–3677. https://doi.org/10.1080/00207543.2018.1552369

Ramani, V., Ghosh, D., & Sodhi, M. S. (2022). Understanding systemic disruption from the Covid-19-induced semiconductor shortage for the auto industry. *Omega, 113*, Article 102720. https://doi.org/10.1016/j.omega.2022.102720

Refaeilzadeh, P., Tang, L., & Liu, H. (2009). *Cross-validation. Encyclopedia of database systems, 5*, 532–538.

Ren, K., Bidkhori, H., & Shen, Z. J. M. (2023). Data-driven inventory policy: Learning from sequentially observed non-stationary data. *Omega, 123*, Article 102942. https://doi.org/10.1016/j.omega.2023.102942

Robb, D. J., & Silver, E. A. (1998). Inventory management with periodic ordering and minimum order quantities. *Journal of the Operational Research Society, 49*(10), 1085–1094. https://doi.org/10.1057/palgrave.jors.2600622

Sharma, M., & Garg, R. (2020). An artificial neural network based approach for energy efficient task scheduling in cloud data centers. *Sustainable Computing: Informatics and Systems, 26*, Article 100373. https://doi.org/10.1016/j.suscom.2020.100373

Shen, H., Tian, T., & Zhu, H. (2019). A two-echelon inventory system with a minimum order quantity requirement. *Sustainability, 11*(18), 5059. https://doi.org/10.3390/su11185059

Simchi-Levi, D., Schmidt, W., Wei, Y., Zhang, P. Y., Combs, K., Ge, Y., Gusikhin, O., Sanders, M., & Zhang, D. (2015). Identify risks and mitigating disruptions in the automotive supply chain. *Interfaces, 45*(5), 375–390. https://doi.org/10.1287/inte.2015.0804

Simchi-Levi, D., Wang, H., & Wei, Y. (2018). Increasing supply chain robustness through process flexibility and inventory. *Production and Operations Management, 27*(8), 1476–1491. https://doi.org/10.1111/poms.12887

Singh, G., Rajesh, R., Daultani, Y., & Misra, S. C. (2023). Resilience and sustainability enhancements in food supply chains using Digital Twin technology: A grey causal modelling (GCM) approach. *Computers & Industrial Engineering, 179*, Article 109172. https://doi.org/10.1016/j.cie.2023.109172

Snyder, L. V., Atan, Z., Peng, P., Rong, Y., Schmitt, A. J., & Sinsoysal, B. (2016). OR/MS models for supply chain disruptions: A review. *IIE Transactions, 48*(2), 89–109. https://doi.org/10.1080/0740817X.2015.1067735

Spieske, A., Gebhardt, M., Kopyto, M., Birkel, H., & Hartmann, E. (2023). The future of industry 4.0 and supply chain resilience after the COVID-19 pandemic: Empirical evidence from a Delphi study. *Computers & Industrial Engineering, 181*, Article 109344. https://doi.org/10.1016/j.cie.2023.109344

Theodorou, E., Spiliotis, E., & Assimakopoulos, V. (2023). Optimizing inventory control through a data-driven and model-independent framework. *EURO Journal on Transportation and Logistics, 12*, Article 100103. https://doi.org/10.1016/j.ejtl.2022.100103

Tian, R., Lu, M., Wang, H., Wang, B., & Tang, Q. (2024). IACPPO: A deep reinforcement learning-based model for warehouse inventory replenishment. *Computers & Industrial Engineering, 187*, Article 109829. https://doi.org/10.1016/j.cie.2023.109829

Tuncel, O., Taneri, N., & Hasija, S. (2022). Why are minimum order quantity contracts popular in practice? A behavioral investigation. *Manufacturing & Service Operations Management, 24*(4), 2166–2182. https://doi.org/10.1287/msom.2021.1061

van Donselaar, K., Broekmeulen, R., & de Kok, T. (2021). Heuristics for setting reorder levels in periodic review inventory systems with an aggregate service constraint. *International Journal of Production Economics, 237*, Article 108137. https://doi.org/10.1016/j.ijpe.2021.108137

Voas, J., Kshetri, N., & DeFranco, J. F. (2021). Scarcity and global insecurity: The semiconductor shortage. *IT Professional, 23*(5), 78–82. https://doi.org/10.1109/MITP.2021.3105248

Wang, X., & Disney, S. M. (2017). Mitigating variance amplification under stochastic lead-time: The proportional control approach. *European Journal of Operational Research, 256*(1), 151–162. https://doi.org/10.1016/j.ejor.2016.06.010

Warburton, R. D., & Disney, S. M. (2007). Order and inventory variance amplification: The equivalence of discrete and continuous time analyses. *International Journal of Production Economics, 110*(1–2), 128–137. https://doi.org/10.1016/j.ijpe.2007.02.021

Wu, X., Zhang, C., & Du, W. (2021). An analysis on the crisis of "chips shortage" in automobile industry——Based on the double influence of COVID-19 and trade

Friction. In Journal of Physics: Conference Series (Vol. 1971, No. 1, p. 012100). IOP Publishing. 10.1088/1742-6596/1971/1/012100.

Yan, X. (2023). An analysis of the role of order quantity in supply chains with uncertainties from demand and/or supply. *Computers & Industrial Engineering, 183*, Article 109447. https://doi.org/10.1016/j.cie.2023.109447

Zhao, Y., & Katehakis, M. N. (2006). On the structure of optimal ordering policies for stochastic inventory systems with minimum order quantity. *Probability in the Engineering and Informational Sciences, 20*(2), 257–270. https://doi.org/10.1017/S0269964806060165

Zhou, B., Zhao, Y., & Katehakis, M. N. (2007). Effective control policies for stochastic inventory systems with a minimum order quantity and linear costs. *International Journal of Production Economics, 106*(2), 523–531. https://doi.org/10.1016/j.ijpe.2006.06.020

Zhu, H. (2022). A simple heuristic policy for stochastic inventory systems with both minimum and maximum order quantity requirements. *Annals of Operations Research, 309*(1), 347–363. https://doi.org/10.1007/s10479-021-04441-1

Zhu, H., Liu, X., & Chen, Y. F. (2015). Effective inventory control policies with a minimum order quantity and batch ordering. *International Journal of Production Economics, 168*, 21–30. https://doi.org/10.1016/j.ijpe.2015.06.008