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Incorporating supply and production digital twins to mitigate demand disruptions in multi-echelon networks

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ABSTRACT

In today's globalized environment, supply chain (SC) and manufacturing operations are intrinsically linked to satisfy consumer demand. Faced with rising preferences for personalized goods, convenience, and price competitiveness, many companies pivot towards e-commerce strategies and product family approaches to offer wider product varieties and shorten delivery times. This is evident in the fast-moving consumer goods (FMCG) industry, where multi-echelon networks are often utilized to optimize inventory and lower costs. While these methods can fulfill consumer expectations, decreased network resilience is a key obstacle, leaving supply networks vulnerable to supply and demand disruptions. Hence, a holistic approach is required to mitigate disruptions impacts in multi-echelon networks. As a digital enabler, digital twin (DT) technology can manage disruptions in SC networks and manufacturing shop floors. However, these solutions typically operate in silos without context considerations, resulting in illogical solutions. To overcome these challenges, this study proposes a novel supply and production (S&P) DT system to enhance resilience and disruption management in multi-echelon networks. A four-tier technology stack is introduced first, then resilience evaluation, SC replanning, and shop floor rescheduling methods are explored. Based on this, a DT-enabled disruption mitigation mechanism is proposed and featured in an F&B-oriented demand spike disruption case study. Results show the role of the hybrid S&P DT system in improving demand fulfillment rate and reducing production make span to enhance operational continuity.

1. Introduction

Supply and demand fluctuations often exert significant tolls on industries, resulting in substantial profit losses. As companies typically rely on multi-echelon supply chain (SC) networks optimized for efficiency and cost-effectiveness in resource allocation and inventory replenishment, the rise of e-commerce strategies and increased consumer price-sensitivity has led to stretched SCs that are susceptible to demand disruptions. This is evident in industries such as consumer packaged goods (CPG) (Leahy, 2011), which are heavily influenced by purchasing trends and operational costs. Additionally, increased popularity in e-markets and price sensitivity has led to weakened performance within the industry as a whole (Kopka et al., 2020), reversing decades of exponential growth due to value-creation models that supported product innovation, brand development, partnership distribution, and cost efficiency. Hence, there is an increased emphasis on SC resilience to maintain overall profitability during disruptions.

To streamline SC operations within multi-echelon networks, hybrid supply and production (S&P) facilities are utilized to efficiently distribute work-in-progress (WIP) and finished goods to downstream entities. Here, network and shop floor functional processes are intrinsically linked in these facilities and are bottlenecks owing to their centrality within the system. The complexity of resource distribution is exacerbated by the bullwhip effects arising from demand spikes in downstream retailers and consumers. While many existing studies aim to address this issue by emphasizing on risk management (Adobor, 2019), improving demand forecasts (Abolghasemi et al., 2020), and simulating disruption scenarios (Moosavi and Hosseini, 2021), mitigation processes remain tedious and error-prone, often reliant on the experience of managers and planners. Therefore, to mitigate disruption impacts, there is a need to integrate resilience evaluation, SC planning, and shop floor operations holistically for hybrid S&P facilities in such

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complex networks.

As a prevailing technology in both SC and manufacturing, DT is a potential enabler to overcome disruptions through heterogeneous data handling, bi-directional connectivity, simulation, and decision support capabilities to facilitate informed decision making (Nguyen et al., 2022) (Lim et al., 2020a). However, existing DT systems often operate in silos with focus on specific SC and production tasks without context considerations, resulting in limited solution effectiveness when managing disruptions.

Furthermore, while DT fundamentals in SC and manufacturing domains remain similar, emphasis on functional modules and technology levels of their components differ based on desired outcomes to improve SC resilience and manufacturing robustness. For instance, shop floor operations require real-time asset connectivity and high-fidelity simulation whereas SC operations require end-to-end (E2E) network visualization and process simulation. Hence, there is a need to establish an integrated system capable of representing and optimizing operational activities in hybrid S&P facilities.

A key motivation behind this study is to reduce disruption impacts experienced by S&P sites in fast-moving consumer goods (FMCG) industries, which can be quantified by time and cost savings. Given the sectors' reliance on high-volume low-cost product family brand sales and multi-echelon networks to satisfy consumer demand, there is an emergent requirement to aid FMCG enterprises in adapting to contemporary shifts in consumption preferences such as personalized products and faster delivery lead times. Thus, the S&P DT system is designed to bolster the resilience and competitive edge of FMCG enterprises by bridging SC and manufacturing domains to support resource allocation through network resilience evaluation, SC replanning, and shop floor rescheduling.

Aiming to fill these research gaps, an S&P DT architecture is first proposed to mitigate impacts from demand fluctuations. Designed as a scalable platform that integrates the functional modules from SC network and shop floor operations, capabilities such as cyber-physical connectivity, multiple simulation-based representations, and decision support mechanisms are leveraged to enhance network resilience and manufacturing robustness. Through end-to-end (E2E) network visibility, functional task allocation, and solution generation capabilities, the system can provide a reusable and efficient method to overcome downstream disruptions. Next, 11 KPIs are presented to assess overall network resilience and estimate the Time to Recovery (TTR), after which a constraint-based replanning model can derive feasible mitigation strategies to maintain operational efficiency based on disruption type. Subsequently, the rescheduling module factors in shop floor limitations to generate optimal production schedules.

The effectiveness of the S&P DT system is demonstrated in an FMCG food and beverage (F&B) industrial case study to overcome a demand spike disruption, with results reflecting increased resilience and robustness in S&P operations.

To the best of the authors' knowledge, this paper is amongst the first to introduce DT-enabled synchronization mechanisms towards mitigating demand disruptions in complex multi-echelon S&P networks. It also addresses DT-related research calls (Lim et al., 2020a) to encompass multiple engineering life cycles phases. Key research contributions include:

(1) the integration of SC and shop floor functional aspects to create a scalable DT technology stack,
(2) establishing a systematic approach towards mitigating demand disruptions through resilience evaluation, replanning, and rescheduling mechanisms,
(3) demonstrating industrial relevance through an FMCG F&B industrial use case with considerations to guidelines, protocols, context, and site constraints.

This study serves to drive new concepts such as the Physical Internet (PI) paradigm (Leung et al., 2022) to enhance global mobility of goods. The rest of the article is organized as follows. Section 2 reviews recent DT advancement in SC and manufacturing domains and distinguishes between the two types of DT. Section 3 presents the methodology to integrate SC and manufacturing workflows and showcases a holistic DT framework. Section 4 describes mechanisms for disruption mitigation while section 5 implements the strategy through an industrial use case. Section 6 concludes the study.

2. Related work

This section reviews recent DT advancements relevant to the S&P domain. Given that DT systems are often customized to specific stakeholder needs and requirements, key components in the context of disruption management typically include resilience evaluation, SC replanning, and operational rescheduling. First, the technical disparities between SC and manufacturing DTs are highlighted, emphasizing the fundamental functions vital for S&P facilities. Next, DT developments in SC domains are surveyed, focusing on strategies for resilience and planning. Lastly, DT-enhanced scheduling systems in the manufacturing domain are explored.

2.1. Connotations and reference models for supply chain digital twins

The Industry 4.0 paradigm has galvanized many manufacturing-oriented DT solutions for a wide range of applications such as product family design and optimization (Lim et al., 2020b), shop floor reconfiguration (Zhang et al., 2021a), and decision support systems (Sun et al., 2021). Within SC domains, DT is also regarded as pivotal towards enhancing network visibility, planning, resilience, and disruption management (Ivanov and Dolgui, 2021), (Busse et al., 2017). Although DT systems typically include cyber-physical connectivity, simulation, and decision support capabilities, their functionalities may defer based on industrial needs. From a S&P facility perspective, E2E visibility, resilience and risk evaluation, SC planning, production scheduling, and disruption mitigation are crucial attributes in which the DT system needs to support. Table 1 highlights recent industrial DT advances to enhance S&P operations, which encompass supply network, shop floor, and warehouse aspects. While SC-related DT studies seldom focus on production planning and scheduling operations, shop floor-/-warehouse-oriented DT studies do not consider global E2E visibility, network risk evaluation, and disruption management.

With FMCG industries such as F&B and e-commerce leveraging complex multi-echelon networks to optimize inventory levels, consequences of market fluctuations resulting in bullwhip effects can result in tremendous inefficiencies (Sucky, 2009). Thus, DT-enhanced disruption mitigation mechanisms and functional module integration will be a key focus in this study.

2.2. DT-enabled SC resilience evaluation and planning

Disruption management starts with resilience evaluation involving network performance analysis and recovery effort cost calculation (Aguila and ElMaraghy, 2019). SC DT can provide end-to-end (E2E) visibility, contingency plan simulation, and decision support (e.g., inventory and capacity management) (Ivanov and Dolgui, 2021), (Burgos and Ivanov, 2021). As such, DT systems are also adapted for replanning operations, with Bhandal et al. reviewing DT-enhanced operations from network and business perspectives (Bhandal et al., 2022) and Rahmanzadeh et al. showcasing an open SC management for production planning via DT networks (Rahmanzadeh et al., 2022).

To establish reconfigurable SC networks, Wang et al. used DT-enabled modeling, optimization, and collaboration approaches for retail operations during the pandemic (Wang et al., 2022) while Dolgui et al. leveraged DT, dynamic SC meta-structures, and autonomous services to support structural, process, and plant aspects (Dolgui et al.,

Table 1
Functionality comparison of recent DT works to enhance S&P facility operations.

DT focus aspect	Reference	Industry	Core DT-driven Functionalities				
			E2E visibility	Risk and resilience evaluation	SC planning	Production planning	Disruption mitigation
Supply network	(Aguila and ElMaraghy, 2019) (Park et al., 2021)	Automotive		✔			✔
	Lee and Lee (2021)	Construction		✔	✔		
	Wang et al. (2022)	E-commerce	✔				
	Burgos and Ivanov (2021)	Food & Beverage	✔	✔	✔		
	(Moshood et al., 2021) (Ivanov and Dolgui, 2021)	Generic	✔	✔			✔
	Busse et al. (2021)	Maritime	✔				✔
	Rahmanzadeh et al. (2022)	Textile			✔		
Shop floor	(Qin and Lu, 2021) (Zhang et al., 2018)	Aerospace			✔	✔	
	(Park et al., 2020) (Gallego-García et al., 2019) (Agostino et al., 2020)	Automotive			✔	✔	
	Min et al. (2019)	Petrochemical			✔	✔	
	Lu et al. (2019)	Remanufacture				✔	
Warehouse	Pan et al. (2021)	3PL	✔		✔	✔	
	(Wong et al., 2021) (Lim et al., 2022a)	Cargo/Freight			✔		✔
	Leung et al. (2022)	E-commerce			✔	✔	
	Zhang et al. (2020)	Paint & coating			✔	✔	

2020). Serrano-Ruiz et al. leveraged DT to implement zero-defect manufacturing management models to maximize SC service levels (Serrano-Ruiz et al., 2021). In a make-to-order environment for personalized automotive parts, Park et al. leveraged on distributed DT to overcome bullwhip and ripple effects for a hybrid supply and manufacturing network (Park et al., 2021).

2.3. DT-enabled dynamic shop floor scheduling

Shop floor scheduling is a continuous challenge closely related to efficiency, sustainability, and costs. Qin and Lu reviewed DT's role for robust scheduling in self-organizing manufacturing systems to realize mass personalization (Qin and Lu, 2021). To improve system responsiveness, Fang et al. proposed a DT-driven job shop scheduling method with dynamic parameter updating (Fang et al., 2019), and Zhang et al. presented a 5D machine DT for dynamic scheduling of hydraulic valves via prediction, detection, and evaluation methods (Zhang et al., 2021b). Similarly, Zhang et al. established a smart production-logistics system to aid scheduling efficiency for an engine manufacturer (Zhang et al., 2018). To perform localized and robust scheduling practically, Zhang et al. designed a bi-level multi-agent scheduling approach for a distributed workshop (Zhang et al., 2021c). Liu et al. integrated DT and super network models of an aeroengine gear production workshop to optimize schedules through feature similarity matrix, similarity calculations and relationship mapping (Liu et al., 2021).

Through genetic algorithm approaches, Yan et al. addressed constraint influences due to finite transportation conditions for flexible job shop scheduling (Yan et al., 2021) and Negri et al. proposed a sim-heuristics framework for robust scheduling (Negri et al., 2021). Liu et al. utilized a combined NSGA-II, simulated annealing, and multi-objective particle swarm optimization approach for hot rolling scheduling (Liu et al., 2019). Meanwhile, constraints from FMCG domains have led to mixed integer linear programming (MILP) being a viable approach. Elzakker et al. increased computational efficiency through a two-stage make-and-pack ice cream production (van Elzakker et al., 2012). Elekidis et al. utilized two MILP decomposition strategies to achieve significant changeover time reduction (Elekidis et al., 2019), whereas Georgiadis et al. used two MILP models via mixed discrete-continuous time representation to minimize make span and changeover time (Georgiadis et al., 2020).

Existing methodologies for resilience evaluation, planning and scheduling in SC networks are often conducted in silos with limited context considerations. While DT demonstrates potential towards disruption management in SC and manufacturing domains, no DT-enabled framework and mechanism exists to support S&P facility operations. Hence, a SCOR-compliant and scalable S&P DT system is proposed to mitigate demand-based disruptions seamlessly through resilience evaluation, replanning, and rescheduling mechanisms.

3. Managing supply and production operations in multi-echelon networks

To overcome the research gaps mentioned and capitalize on the data interdependencies between supply network and shop floor functions to support context-based solution generation, a S&P DT framework is proposed to facilitate disruption management. Existing SC and manufacturing operational procedures are leveraged to design a modular DT technology stack for both scalability and customizability.

3.1. Interdependencies between supply and production operations

Based on functional modules of typical S&P facilities, an operational workflow integrating SC and shop floor operations is modeled as shown in Fig. 1. From the multi-echelon network, work-in-progress (WIP) and finished goods (FG) are requested from upstream entities such as manufacturing plants and port warehouses. These goods are pushed to the S&P site where assembly, repackaging, and customization works are performed. Customer demand for products from the various downstream entities such as regional/local distribution centers, retailers, and customers (via e-commerce) are collated and distributed to each S&P site. To manage the downstream distribution requirement and the upstream push inventory, the S&P workflow, comprising of strategic, tactical, and operational layers, highlights the interconnectivity among supply, manufacturing, and distribution aspects.

From the perspective of an individual S&P facility, Fig. 1 depicts the information flow driving S&P operations starting from new customer orders to goods delivery. Between each process, essential functional modules are highlighted, along with details of their specific roles in relation to SC, production, and warehouse operations. Starting with the *strategic layer*, the business model strategies module facilitates evaluation of value drivers and implementation of business model strategies (e.g., make-to-stock, make-to-order) (Liu et al., 2022), (Beemsterboer et al., 2017). Meanwhile, the network optimization module provides end-to-end (E2E) visibility, TTR estimation, network expansion metrics, and relevant multi-echelon distribution policies. In the *tactical layer*, data from preceding modules along with historical trends and market

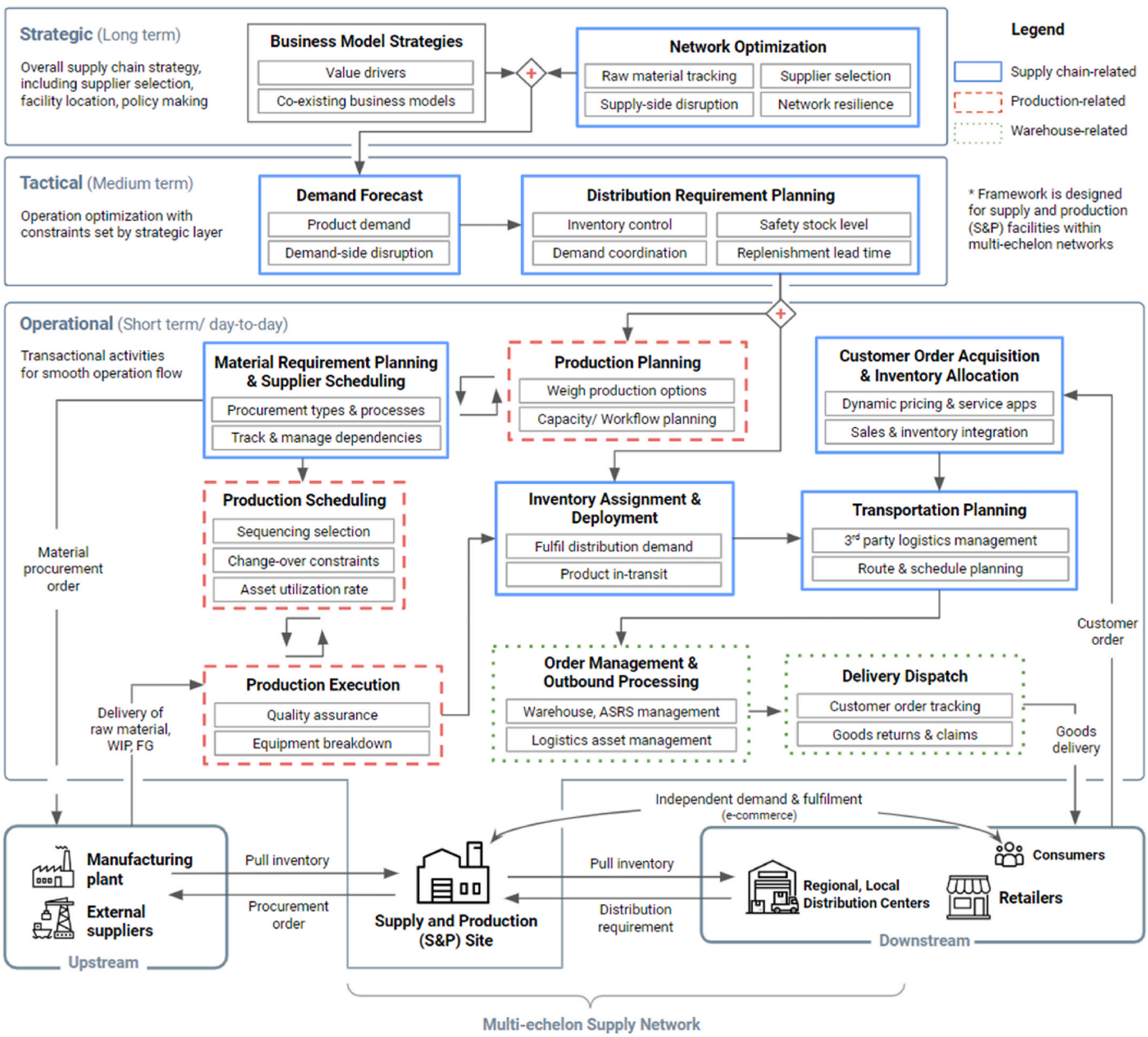

Fig. 1. Interdependencies between SC and Production functional modules.

conditions allow the demand forecast module to predict purchase sentiments and demand for each product family. Based on predicted demand variability, inventory stock levels and distribution flow are handled by the distribution requirement planning (DRP) module. This module uses a time-based approach to mitigate the bullwhip effect and ensure the operational continuity of downstream entities. Network simulations can be utilized to assess disruption severity based on the performance indicators affecting lead time and cost. Lastly, the *operational layer* manages functions ranging from WIP procurement to order delivery. With the expected demand and product allocation from the DRP module, the production planning module estimates the required level of product mix and matches them to available resources with considerations to production capacity and methods. The material requirement planning and supplier scheduling module manages WIP replenishment quantities and supplier networks. In the event of supply disruptions, alternative suppliers can be sourced through the network optimization module to fulfill prioritized orders.

New orders are typically received via the enterprise resource planning (ERP) system, where the required inventory is traced and allocated to an S&P facility. Here, the customer order acquisition and inventory allocation module optimizes stock levels and storage costs to satisfy demand efficiently. From the required FG quantity, the production scheduling module generates an optimized schedule based on asset utilization, production constraints such as changeover sequences, and order priorities. In addition, it is constantly refreshed in accordance with the production execution module via the manufacturing execution system (MES) to facilitate shop floor disruptions such as equipment maintenance and resource availability. The inventory assignment and deployment module plans and distributes the FG in accordance to the DRP with considerations to prioritized downstream entities. Next, the transportation planning module manages both internal and third-party logistics by coordinating the routes and schedules of logistical assets. The order management and outbound processing module retrieves the FG, ensures that the orders are correct before dispatch, and manages warehouse and logistical assets. Finally, the delivery dispatch module provides order tracking and facilitates reverse logistics. While specific functional modules can be managed via enterprise software, these solutions often operate in silos and do not have context considerations. Thus, the following subsection highlights a DT framework to facilitate S&P operations in multi-echelon networks for disruption management.

3.2. DT-enabled technology stack for S&P operations

A DT-based supply and production (S&P) technology stack is proposed, as shown in Fig. 2, to enhance SC network resilience and shop floor robustness. As e-commerce activities necessitate real-time inventory visibility and demand sensing to keep pace with demand fluctuations, third-party logistics (3PL) provider management, and scenario-based fulfilment strategies, DT technologies can support these requirements from an operational perspective through bi-directional connectivity, simulation, and decision support functionalities. Utilizing the hierarchical data-information-knowledge-wisdom (DIKW) framework, with asset-model data used as a fundamental input source, this modular DT stack is designed to be customizable based on specific industry needs. As such, the large amounts of heterogeneous data and considerations between both SC and manufacturing aspects can be managed systematically.

The *connectivity tier* establishes cyber-physical connectivity for both the production shop floor and multi-echelon supply network. For facility aspects, raw data pertaining to physical entities are acquired through IoT techniques and digital enterprise solutions (e.g., ERP, MES), whereas for SC aspects, upstream and downstream networks are geo-mapped to reflect distribution entities and major transit access routes/modes based on industry type. Performance attributes for S&P aspects within shop floor and supply operations are required as well and discussed in subsequent sections.

Next, the *representation tier* is designed to refine and structure these data into useful information sources. Through a cloud computing gateway, sensor data is processed and temporarily stored within the data lake, with relevant data pertaining to disruptions stored in the database for record keeping. Meanwhile, the structured data are tabulated before classification and storage into the database. While NoSQL databases can

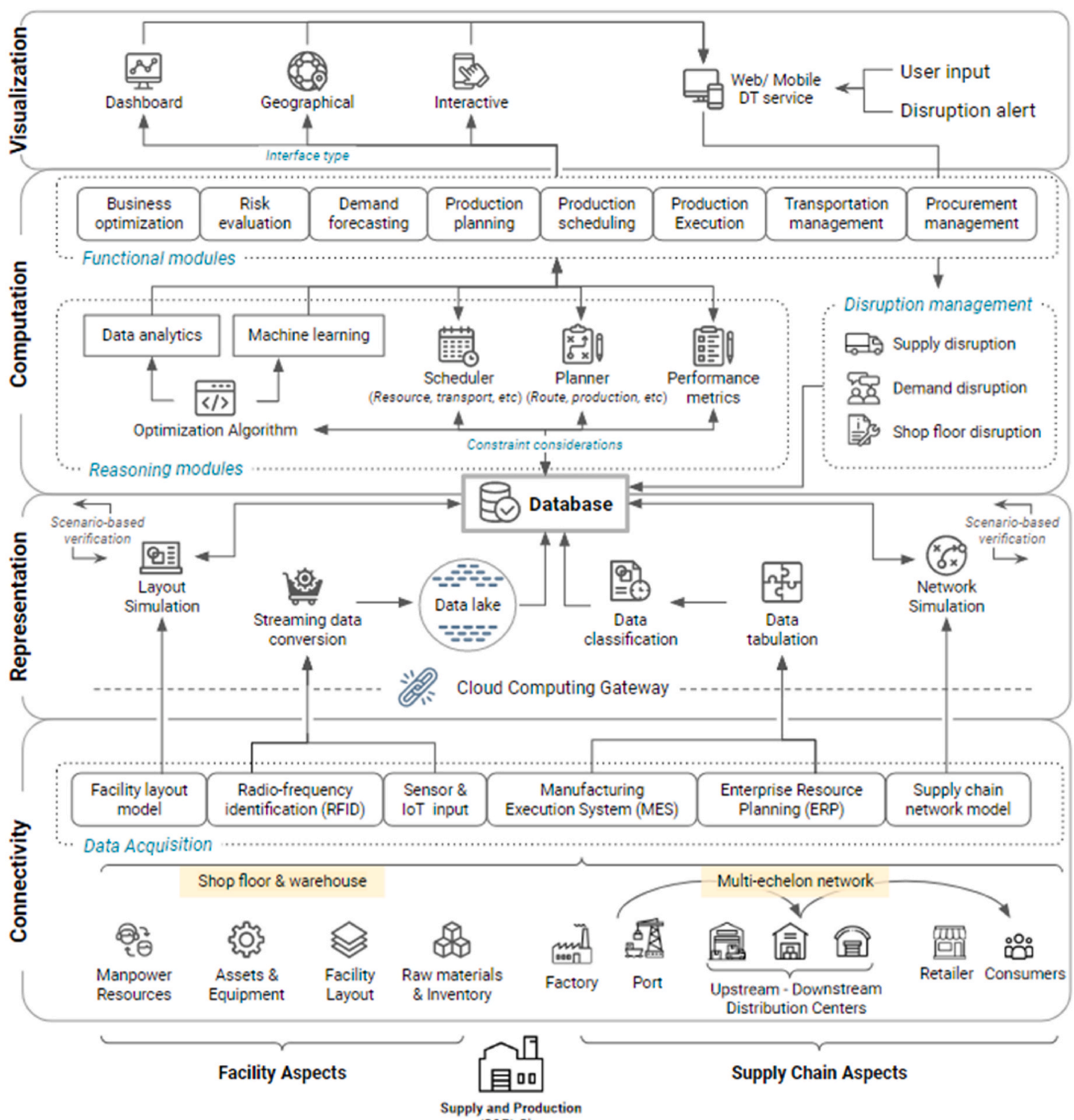

Fig. 2. Digital Twin technology stack for disruption mitigation.

process heterogeneous data storage and retrieval, many enterprise solutions still rely on relational databases due to the ease of set up and analytics derivation from predefined structures. Simulation remains an essential component of the S&P DT framework for specific scenario visualization and evaluation. After retrieval of updated events, multiple simulation tools can be utilized to provide a detailed outlook of potential outcomes, notably with dynamic and discrete event simulations being commonly used in facility settings, and agent-based simulations used in SC network settings. Alternatively, potential solutions generated from the computation tier can also be verified accordingly to provide crucial insights towards expected performance with context considerations via a co-simulation approach (Pulshashi et al., 2020). From the representation tier, E2E visibility can facilitate resource tracing throughout the supply network, while having a high-fidelity shop floor layout can support production reconfiguration. As such, disruptions during transportation can be tracked via GPS trackers for fleet management whereas the delivery status from 3PL providers can be updated via collaborative portals.

The *computation tier* derives knowledge by retrieving relevant information via APIs to optimize functional tasks. Facility constraints and industrial protocols for S&P operations are embedded in optimization algorithms to enhance replanning and rescheduling workflows for disruption mitigation, whereas performance metrics track the status of these operational workflows. Meanwhile, big data analytics and machine learning (ML) techniques serve to identify and evaluate disruption impacts via anomaly detection, pattern recognition, and trend prediction techniques. As such, reasoning modules are designed to support SC network, shop floor, and warehouse domains in areas such as inventory management (Williams and Tokar, 2008), (Saha and Ray, 2019), (Guo et al., 2019), business continuity (Kegenbekov and Jackson, 2021), and logistics (Ansari et al., 2018). To achieve the 8 key functional modules, learned knowledge is transformed into wisdom for disruption management. While existing enterprise solutions (highlighted in Section 5) can be utilized, the module customization and integration are crucial towards automatic solution generation. As such, this tier enables the DT system to provide feasible (simulation-verified) recommendations for stakeholders to make well-informed decisions.

Lastly, the *visualization tier* features essential benchmarks and computational results through front-end interfaces for clarity and conciseness. Dashboard, geographical, and interactive visuals can facilitate KPI display, SC network monitoring, and operator usage respectively, and changes can be implemented via web/mobile services for mobility. With Industry 5.0 emphasizing on a human-centric workforce, incorporating data from manpower resources into the framework can be achieved through human digital twins (Berti et al., 2023). This expansion broadens DT capabilities to allow for operational improvements in areas such as fatigue management and skillset allocation. By encompassing S&P domains within a modular architecture, the context-aware DT system can enhance SC resilience and mitigate SC-related disruptions. In the next section, functional modules critical towards disruption mitigation are discussed and optimization approaches are elaborated.

4. Synchronizing SC resilience, replanning, and rescheduling for disruption mitigation

Leveraging the proposed S&P DT framework, another key contribution of the study involves the synchronization of disruption recovery processes. Designed to equip planners with a strategic tool to mitigate demand disruptions and enhance network resilience, this computational process is deployed in three stages. An overview of this mitigation process is illustrated in Fig. 3, comprising of strategic, tactical, and operational objectives as part of the SCOR model.

Resilience assessment and network redesign. From a strategic standpoint, a simulation-enhanced network assessment is used to evaluate different network configurations based on specific disruption scenarios. Outcomes are assessed based on a set of KPIs to estimate TTR, disruption impacts, network resilience, and solution feasibility.

Cross-functional SC planning. From a tactical and operational stance, a synchronized replanning mechanism then distributes product demand to each upstream S&P facility based on capacity and derives a balanced sourcing plan to downstream DCs. Optimal inventory levels for each SKU (per defined period) are determined so that the total relevant cost is minimized while satisfying production constraints.

Production rescheduling. Based on these previous requirements, this rescheduling mechanism is designed for individual S&P facilities to optimize the design cost such as penalty cost, lost sale, order tardiness, changeover cost, and total production time. Operational constraints such as production recipe, machine connection, and equipment availability are considered, after which a daily production schedule is derived for manufacturing execution.

This study uses MILP approaches for replanning and rescheduling operations, which are elaborated in the sub-sections below. Additionally, subsequent operational level workflows including transportation planning and last-mile delivery can also be validated via simulations for a more nuanced approach to enhance resilience across these multi-faceted S&P facilities.

4.1. Resilience evaluation of multi-echelon networks

Network resilience highlights the ability of a SC to effectively withstand and recover from disruptions, and its evaluation is critical towards disruption mitigation. It is linked to the SCOR-based performance KPIs, covering reliability, responsiveness, cost, asset management efficiency,

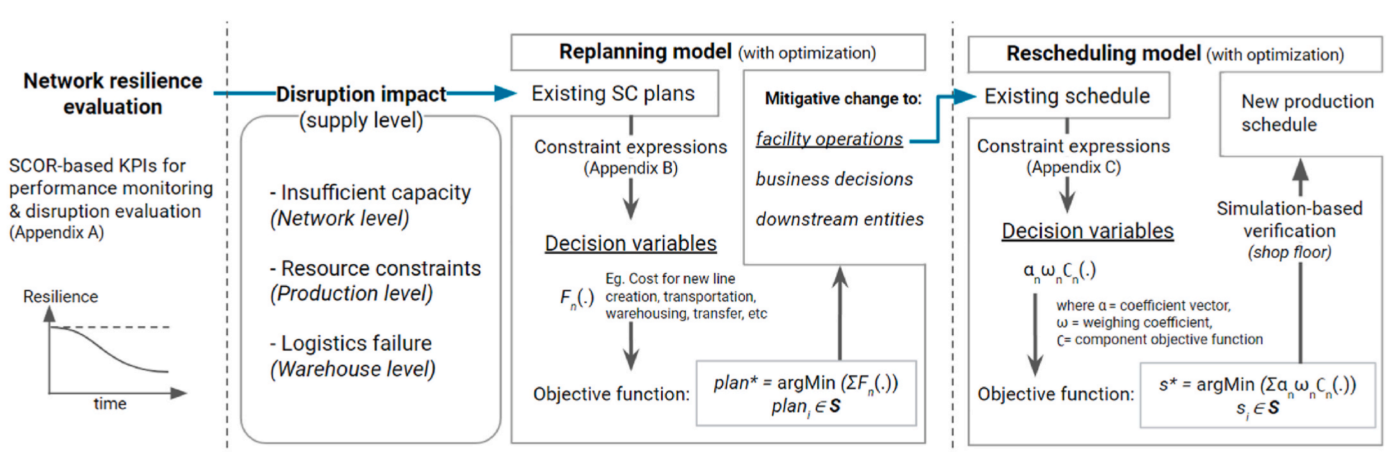

Fig. 3. Three-stage disruption mitigation process for supply and production (S&P) facilities.

and agility. Evaluating disruption impacts starts with network route assessment and profit planning. Next, DRP is analyzed based on replenishment lead time, independent DC demand, distribution requirement, and order assumption. As FMCG enterprises are sensitive towards demand variations, the ability to facilitate urgent production increases and factor new raw material requirements are key competitive differentiators. The point in which demand variation translates into a disruption largely depends on many factors including but not limited to the size of the focal company, industry norms, and government regulations. As a general guide, any event which adversely affects the ability to deliver sales orders can be considered as a disruption. Following that, the material requirement planning (MRP) module derives required quantities for raw materials, work-in-progress (WIP), and FG from order type and forecast data, whereas downstream transportation efficiency is assessed via the inventory assignment and deployment module. Depending on the network structure and disruption type, both agent-based and discrete event simulations can be suitable options for scenario planning to facilitate strategy formulation.

KPIs can track performance factors pertaining to total profit, service level, fill rate, cycle times, and average inventory (Eddoug et al., 2018), (Vidalis et al., 2014). Through 11 KPIs, complex multi-echelon network health and TTR are estimated as such. (1) *Capacity utilization* compares actual asset use time to available production time. (2) *Delivery performance to customer commit date* facilitates punctual WIP and goods delivery. (3) *Frequency for days before next shipment* highlights the average time between consecutive orders. (4) *Inventory days of supply* shows the average time between resource procurement and finished product sales. (5–7) *Cycle times* for order delivery, fulfillment, picking/packing process provide the period between two consecutive order placements and having a shorter cycle time means having increased efficiency. (8) *Overall value-at-risk* metric estimates the potential SC losses and mitigation benefits. (9–10) *Percentage of orders delivered in full* and *perfect order fulfillment* measures delivery performance. (11) *Total supply chain cost* covers the expense incurred for SC functions. Meanwhile, mitigating solutions are evaluated via specific KPIs. E.g., capacity-reduction disruptions are linked to inventory, manufacturing, or transportation aspects and require resilience analysis or reiteration of the DRP algorithm. Details on KPI formulas can be found in Appendix A and simulation-based assessments can be used to evaluate the resilience as highlighted by Moosavi and Hosseini (2021).

The role of performance indicators to categorize disruption impacts is a prevailing topic (Pettit et al., 2013), (Zhang et al., 2021d) and are typically customized for specific use cases. As such, the 11 KPIs presented are used to monitor the essential attributes featured in this FMCG case study. Meanwhile, impacts from affected KPIs and potential mitigation outcomes can be visualized via simulation-based stress testing to aid inventory reallocation or sourcing strategies. For instance, demand spikes from downstream DC will lead to lower order fulfilment KPI at that DC and thus affect overall network resilience. Here, the S&P DT system can provide updated context information for TTR estimation and analytical support to evaluate disruption impacts as well as the mitigation outcomes required to restore affected KPIs.

4.2. Strategic replanning for multi-echelon networks

From the network resilience assessment, disruption impacts (e.g., fulfillment rate decrease, logistics delays, resource shortages) and analysis of potential mitigation approaches are identified. Adjustment plans for site capacities, demand distribution, and other S&P attributes are formulated based on the estimated TTR via an iterative DT-enabled feedback loop aimed at aligning product demand, resource availability and production constraints. For instance, to restore order fulfillment KPIs affected by demand spikes, in-transit inventory shifts between DCs or increases in production capacity can be considered. As such, capacity adjustments as well as costs associated with manufacturing, transportation and prebuilds must be factored in the new production plan. Production replanning consists of long-term (yearly) and short-term (monthly) considerations pertaining to allocation flexibility and demand requirements respectively. Following the manufacturing capacity of each SKU, short-term mitigating plans leverage long-term business objectives to replan production orders for S&P facilities in the multi-echelon network.

The process starts with having updated in-transit/on-hand inventory and transport arrival/departure times from the warehouse in-bound execution module, where inventory assignment module logics is exercised to create inter-site transfer orders. Next, the customer order acquisition & inventory allocation module plans shipment routes from production plants or regional/local DCs depending on stock availability or predefined logics. Shipments are then assigned to respective sites via order delivery tables, where the transportation planning module provides delivery cost optimization, in/out-bound inventory and duration updates. Delivery costs are categorized as fixed, tier (depending on volume/weight), or system-based (minimum cost for specific vehicles/orders). Through the DRP demand distribution process, the production requirements of relevant sites are derived with consideration to the updated demand forecasts and factors such as consumable inventory availability, production capacity, and associated costs in relation to manufacturing, inventory, transportation.

Here, a dynamic demand and production planning model for multi-objective replanning is proposed to fulfill demand using updated parameter settings and production constraints (e.g., resource capacity, minimum lot size, and firm zone computation via Lot Size Key (LSK) and Planning Time Fence (PTF). The hybrid S&P DT consolidates relevant data from various planning levels and sources for the model to support demand distribution and production planning (capacity modifications, prebuild quantity, etc.) while balancing demand-inventory levels as well as factors such as product shelf-life requirements.

This module is developed using a mathematical model via MILP method. With *plan∗* and $plan_i$ as the optimal and feasible plans, and *S* is the feasible plan solution space, components $F_{1\text{-}4}$ represents the cost associated with adding new production capability, adjusting available capacity, sourcing, and inventory reallocation.

Objective:

$$plan* = argMin(F_1(.) + F_2(.) + F_3(.) + F_4(.)) \tag{1}$$

$$plan_i \in S$$

where

$$F_1(.) = \sum_t^T \sum_n^N \sum_j^J LC_{tj}^n c_j^{CR} \tag{2}$$

$$F_2(.) = \sum_t^T \sum_l^L \sum_j^J \sum_j^J LT_{tljj} X_{lj} c_{jj}^{LT} \tag{3}$$

$$F_3(.) = \sum_t^T \sum_n^N \sum_j^J \sum_i^I TR_{tji}^n c_{ji}^n \tag{4}$$

$$F_4(.) = \sum_t^T \sum_n^N \sum_j^J \sum_{t_1}^t \left(PBC_{t_1j}^n - PB_{t_1j}^n\right) w_j^n \tag{5}$$

The objective of the model is to minimize the total cost of line creation, line transfer, transportation between sites, and inventory holding cost. In Eq. (2), LC_{tj}^n represents a new line creation in plant *n* in month *t* for the SKU *j*; c_j^{CR} is the cost of adding a new line for the SKU *j*. In Eq. (3), LT_{tljj} is the logical decision variable for line transfer from SKU *j* to *j'* for line *l* in month *t*; X_{lj} is the logical parameter indicated line *l* producing SKU *j*; c_{jj}^{LT} is the transfer cost from SKU *j* to *j'*. In Eq. (4), TR_{tji}^n is the logical decision variable for delivery quantity of SKU *j* from plant *n* to site *i* in month *t*; c_{ji}^n is the transportation cost from plant *n* to DC *i* for SKU *j*. In Eq.

(5), $(PBC^{n}_{t_1j} - PB^{n}_{t_1j})$ indicates the remaining prebuild products to be consumed at site *n*, for product *j* in each month *t* (where $PBC^{n}_{t_1j}$ and $PB^{n}_{t_1j}$ are prebuilt product quantity of SKU *j* created and consumed at plant *n* for month t_1, respectively; w^{n}_{j} is the holding cost per item of the prebuild SKU *j* in site *n*.

To further map out SC network and shop floor constraints from an industrial context, 17 planning constraints relevant to the FMCG sector are selected and highlighted in Appendix B. Next, the requirements are passed on to stakeholders (e.g., Resource management, production planner) and rescheduling is required for new capacity changes to S&P facilities. As the optimization model cannot realize granular aspects such as production cycle time variation and equipment failure rate, simulation-based verification is used to evaluate solution feasibility. Here, the network simulation (AnyLogistix) and shop floor simulation (Plant Simulation) have been implemented.

4.3. DT-enabled dynamic production re-/scheduling

Due to the new planning requirements arising from demand disruptions, it is essential to reschedule production operations to satisfy short term shortfalls. By establishing an alternative workflow sequence to enhance manufacturing efficiency based on the replanning insights, parameters such as make span, changeover costs, and missed production penalties (lost sale) can be reduced via the optimization of asset assignment, order sequences, and production order start-times, thus achieving optimal resource utilization. Using the advanced planning and scheduling (APS) module, bill-of-materials (BOM), minimum order quantity (MOQ), and master production schedule (MPS), the planning horizon for FG and WIP batch orders is calculated. Backlogs and asset availability from the MES will set the conditions for sequence optimization and work order assignments. As such, factors such as production constraints, large product varieties, due dates, and satisfaction levels are considered.

This multi-objective rescheduling model uses a MILP approach to minimize lost sale penalty, job tardiness, and make span. The objectives of the scheduling optimization are given in Eq. (6), where s^* and s_i as optimal and feasible schedules respectively and *S* represents the feasible schedule space. To enhance model flexibility when choosing the objective, vector of logical parameters α_1, α_2, α_3 is used. $\alpha_i = 1$ indicates the objective *i* is included in the model objective; $\alpha_i = 0$ otherwise. ω_1, ω_2, ω_3 are weighting coefficient parameters associated with three objectives: lost sale -$C_1(.)$, changeover cost - $C_2(.)$, makespan-$C_3(.)$, where $\omega_1 + \omega_2 + \omega_3 = 1$.

Objective:

$$s^* = arg\ Min\ (\alpha_1\omega_1 C_1(.) + \alpha_2\omega_2 C_2(.) + \alpha_3\omega_3 C_3(.)) \tag{6}$$

$$s_i \in S$$

where

$$C_1(.) = \sum_i max\left(0, min\ \left(o^k_{i\_end} - d_i\right)\right) * \rho_i * D_i, \forall i \in N \tag{7}$$

$$C_2(.) = \sum_r \sum_i \sum_{j(j\neq i)} \tau_{ijr}\chi_{ijr}, \forall r \in R, \forall i, j \in N, i \neq j \tag{8}$$

$$C_3(.) = max\left(o^k_{i\_end}\right), \forall i \in N \tag{9}$$

In Eq. (7), d_i is the due date of operation *i* and $o^k_{i\_end}$ indicates the end time of operation *i* of work order *k*, D_i is demand of operation *i* within the planning time fence (PTF), ρ_i is the penalty cost rate of operation *i* due to tardiness, *N* is total number of operations. As such, if the demand D_i is large the penalty for tardiness also becomes higher. Eq. (8) represents the total changeover time between operations of different materials on the same equipment. τ_{ijr} is the changeover cost from operation *i* to *j* scheduled on resource *r*, and χ_{ijr} is a binary variable specifying that operation *j* is scheduled after order *i* on resource *r*. In Eq. (9), production time is obtained via the latest end time.

Note that objective function and constraints of the rescheduling optimization model vary depending on specific requirement and condition of each production in practice. In this study, common cost functions and constraints are highlighted mainly for reference purpose and detailed in Appendix B. Through DT-enabled connectivity between S&P functional modules, an iterative process facilitates the rescheduling mechanism to generate updated production sequences. The optimal production schedule can also be verified via shop floor simulation before implementation.

By integrating the network resilience, replanning, and rescheduling mechanisms, disruption impacts on S&P entities within the multi-echelon network are systematically mitigated across all planning levels. The S&P DT supports E2E connectivity and visualization, simulation, and computational capabilities to determine cost effective optimal solutions. In addition, this system serves as a testbed to support the design, testing, and validation of new SC rules and policies on existing operational processes. Subsequently, an industrial case study featured to showcase the effectiveness of the work.

5. Case study

In this section, the proposed S&P DT system and mitigative mechanisms are showcased to demonstrate the effectiveness in configuring and optimizing the multi-echelon network of an FMCG corporation via retail and e-commerce channels. A domestic Go-To-Market strategy is devised to launch 100 household F&B products from a multi-echelon SC network.

A simplified network comprising two S&P facilities with regional (upstream) and local (downstream) DCs is replicated to service retailers closer to customer location clusters, partially supported by 3PL providers. Each S&P facility is tasked with manufacturing specific product families and can be treated as a storage and retrieval site for finished products based on the distribution plan. Demand from customer clusters is fulfilled by pre-allocated S&P and DC sites depending on order size and can be altered to overcome disruptions in an agile manner.

From the perspective of a single S&P facility, Fig. 4 provides an overview of the SC network, with the S&P site pulling inventory from both the manufacturing plant and suppliers for production and redistribution. Next, these FG are pushed to the designated regional/local DCs whereas consumers can also pull inventory directly from the S&P site. Through cross-echelon and transshipment flow, the FG are distributed downstream to the local DCs and subsequently, retailers and consumers. For ease of demonstration, the inventory push to a regional DC is applied. For cases with multiple regional DCs, the replanning process is repeated for each of them and consolidated for rescheduling afterwards.

This case study uses 12 months of historical data from Jul 2021 to Jun 2022, including a demand spike disruption event occurring from Aug 2021 to Sep 2021. Using a fulfillment level (aka service level) threshold of 95%, the derived solution is benchmarked against the actual fulfilment demand in the same timeframe for analysis. Here, SC operations are performed as such.

(1) Historical sales data from order fulfilment records is used to forecast customer demand across the entire network, with the predicted demand consolidated across DCs. The overall demand is factored to calculate the quantity requirements of each inventory SKU and assigned to the relevant production sites based on the capacity and cost. These requirements are used to derive optimal production and material plans before being scheduled for production. Finally, the FGs are delivered to the corresponding DCs in accordance with the distribution plan.

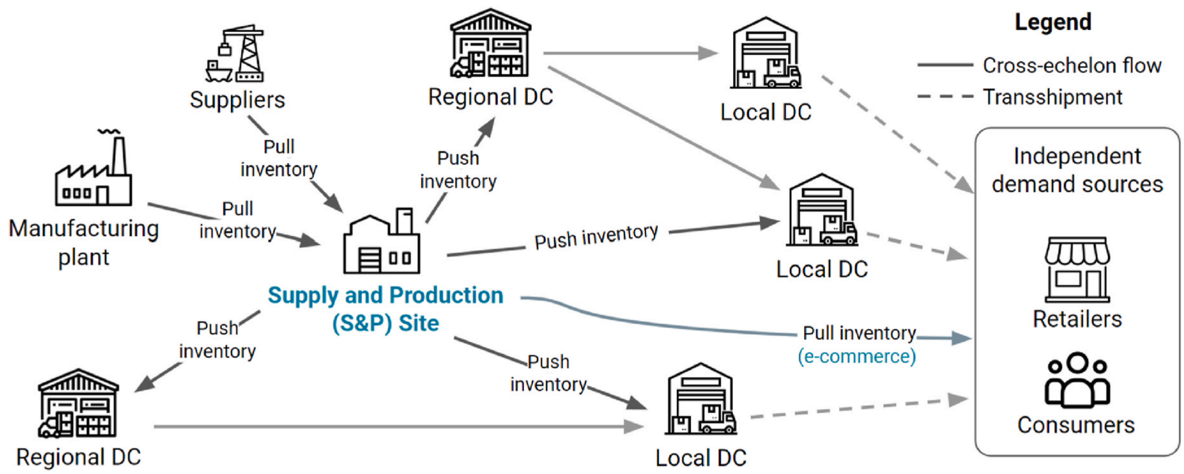

Fig. 4. Simplified view of the multi-echelon network from an S&P facility's perspective.

(2) The process of order fulfillment begins with the receipt of customer orders through various sales channels (including e-commerce). These orders are allocated to either the regional or local DCs based on factors such as order size, customer profile, and inventory levels.

The mitigation mechanism is built on the DT system and streamlines functional operations while reducing disruption impacts. The planning rules for ingredient sourcing, inventory and transportation are mapped to achieve an optimal balance between various KPIs such as operating cost, inventory level, and customer service. Historical data of customer demand, facility capacity, strategic planning, and production scheduling that reflects SC network disruptions is used to evaluate the DT-enabled mitigation system. Fig. 5 illustrates the data parameters and software functional modules critical towards establishing a S&P DT system. The modules are connected via APIs and a common database while adhering to the SCOR process model for industrial relevance. In addition to elements of SC DT from previous studies (Lim et al., 2022b) such as E2E visualization and functional task management, a mechanism to respond to demand spike (capacity-affecting) events is implemented.

5.1. Resilience evaluation and time to Recovery (TTR) estimation

Network resilience evaluation initiates the mitigative process after demand spikes are detected. The historical disruption featured here is accessed using KPIs described in Section 4a to ascertain DC's inability to fulfil the demand orders from the overall value-at-risk metric. The network is modeled using AnyLogistix with disruption details entered in the agent-based simulator (Orozco-Romero et al., 2020) to track the impact propagation. From the model, capacity constraints for DC throughput are projected and impacts are estimated based on overall fulfillment rate and required capacity to achieve the capacity vs demand target. Details of constraints include *capacity*, where delivery orders are halted when the receiving DC has reached maximum capacity; *throughput*, where goods dispatch/reception are delayed till the next day when throughput exceeds the daily limit (prioritized outbound orders); and *lane*, where transportation costs are raised when total shipment volume per lane exceeds the daily limit. As such, relevant constraints such as inventory policy, sourcing strategy, and mitigation process are considered. Historical records reveal that one of the upstream DCs was operated with a setting throughput rate (TR) of 50%. The setting is based on the historical and prediction demand indicated the required TR of this DC to achieve the overall network fulfilment rate of 95%.

However, it is observed that the fulfilment rate drops significantly during the demand spike period (i.e., from Aug 2021 to Sep 2021). In real-life, responding to the disruption, a new demand estimation needs to be made. In this case study, the actual demand is used as the estimated demand during and after the disruption was detected. Among many

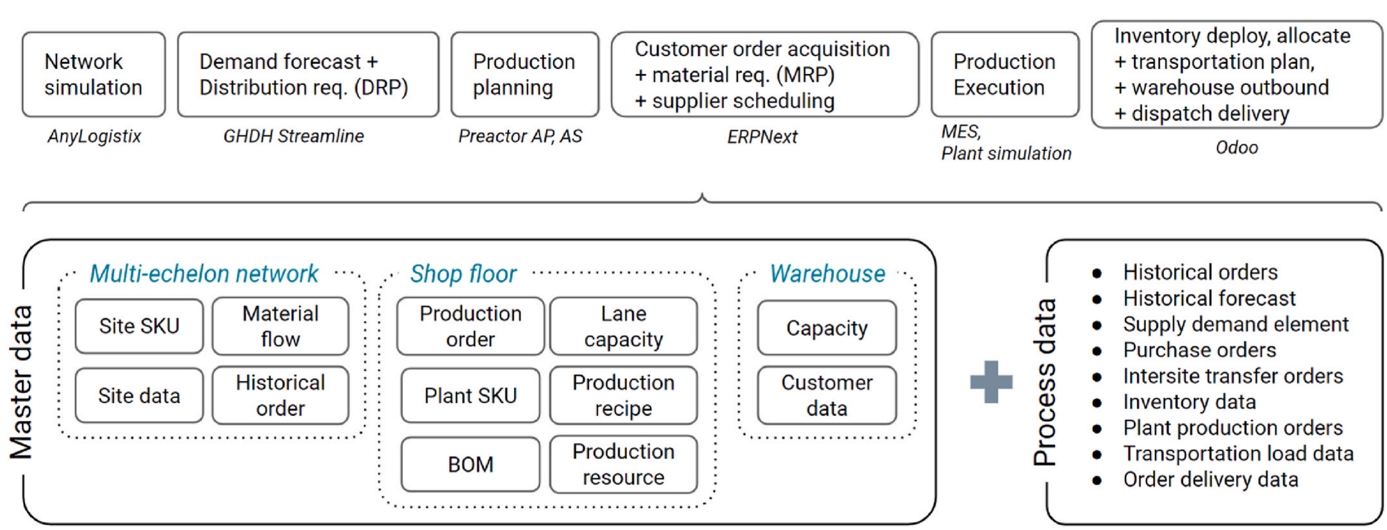

Fig. 5. Data parameters required for functional modules within the digital twin system.

responding strategies, throughput adjustment at DCs was picked for analysis. As such, the TR of the DC is adjusted from its current setting level, 50% upto 100% with the increment of 10%. The target is to identify the TR level that enables the desired overall fulfilment rate.

Fig. 6 shows the simulation results on the DC throughput with a TR of 50% and 100% against the actual demand. The simulation period is chosen based on the estimation of the disruption duration. It shows that the overall fulfillment rate is estimated to decrease to 87.25% if no action is taken. Additionally, with the TR of 100%, the network is still not able to completely fulfill the daily demand, especially in the early weeks of Sep 2021 (Fig. 6). However, a TR of 100% is sufficient for the network to achieve the required overall fulfilment rate in the consideration period. The simulation result highlights an increase in overall average fulfillment rates from 87.25% to 96.67%, thus adhering to the predefined threshold of 95%. Fig. 7 shows the comparison of the long-run, high-level (monthly) simulation results between original scenario versus the implemented mitigation action. While the disruption impact is not fully resolved from the adjustments, there are significant improvements in demand fulfillment between the original and mitigated scenarios. Fig. 7 also illustrates that similar smaller scale disruptions will occur in future (as shown from Apr to Jun-22 period), which can be avoided with the current mitigative action in place.

Based on the network resilience evaluation outcome, capacity levels of S&P facilities are estimated and simulated to validate their feasibility. As the DCs are already operating at full capacity, S&P facility production rates must increase to support greater sourcing quantities. Instead of having high inventory levels and uneven production utilization rates, a capacity replanning model is used to optimize the manufacturing, storage, and distribution of FG with considerations to demand spike impacts, available capacity, TR of DCs, and other relevant parameters.

5.2. DT-driven supply and production replanning

Following the network resilience assessment which highlights the impact from demand spike events on capacity and fulfillment rates, the replanning process aims to fulfill the estimated demand with considerations to capacity, production, and distribution requirements of each S&P facility. DT retrieves the updated information (e.g., new production requirement, maximum capacity limit, inventory policies) and provides feasible production adjustments through the dynamic production optimization model as described in Section 4b. The simulation module identifies the ideal TR of the DC to achieve the targeted fulfilment rate, which is factored in the MILP-based model. After which, the required production capacity as well as the optimal make-to-order and make-to-stock (prebuild) combination is determined to fulfill new demand requirements with respect to the production constraints (e.g., line transfer and upgrades, manpower overtime and shift allocations), as shown in Appendix B.

To achieve the adjusted capacity level, the replanning mechanism leverages information such as manufacturing requirement, inventory level, and capacity limitations to determine the optimal production plan. As such, this helps to align the capacity adjustments from the multi-echelon network level to the operational level of individual S&P facilities. Fig. 8 highlights the capacity adjustment outcomes (green) as compared to the original scenario (blue) with respect to the new production requirement (red), demonstrating the mitigative capabilities of S&P DT system. Model parameters can also be updated to ascertain production outcomes to facilitate replanning efforts.

5.3. DT-enabled production re-scheduling

Using the updated production plan from the replanning model in Section 5b, this rescheduling mechanism factors in production requirements based on current shop floor constraints (e.g., material requirement, outstanding reworks, equipment, and labor availability) to minimize production time (make span) and changeover costs. The data obtained from the DT system is processed via the multi-objective production scheduling module optimizes order assignments and sequences for three making and three packing lines running 24/7. Through the CPLEX solver, production operations are rescheduled on a weekly basis as shown in Fig. 9 based on the updated parameters. As with all shop floor activities, actual implementation is still dependent on factors such as model run time. A snapshot of the derived schedule is showcased in Fig. 10, and results are updated to the S&P DT.

While certain shop floor production constraints can be reflected in the schedule optimization, other factors such as temporary storage, dwelling time, and equipment efficiency cannot be captured by the optimization model. As such, the feasibility of the updated schedule is validated through a discrete event simulation model using the Plant Simulation before actual implementation.

From the simulation, current and subsequent SKU, WIP, and FG work orders can be monitored and visualized, including resource usage and processing/changeover/starving durations. At the same time, different layout configurations and production scenarios can allow manufacturers to analyze potential disruptions during manufacturing. Fig. 11 depicts a snapshot of the simulation model that considers equipment downtime and servicing procedures to enhance the schedule quality. The simulation results, such as cycle times, form part of the KPI to benchmark between the actual, predicted impact, and mitigation scenarios.

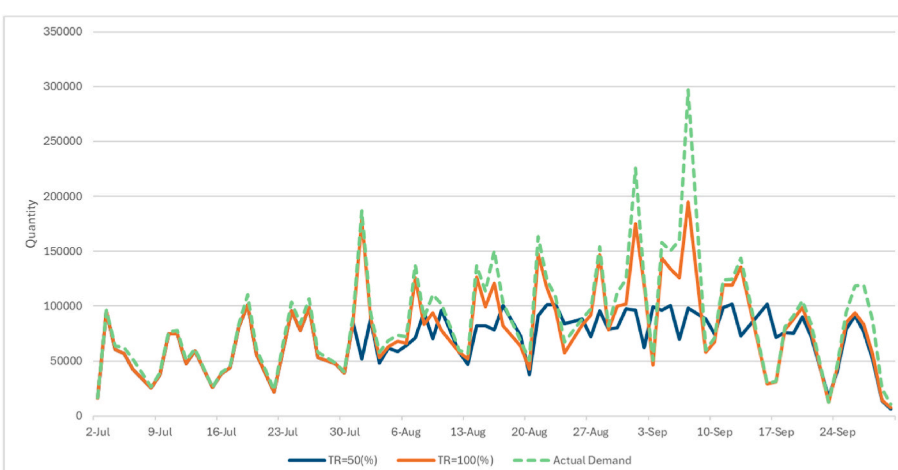

Fig. 6. Total throughput rate comparison across the identified demand spike event.

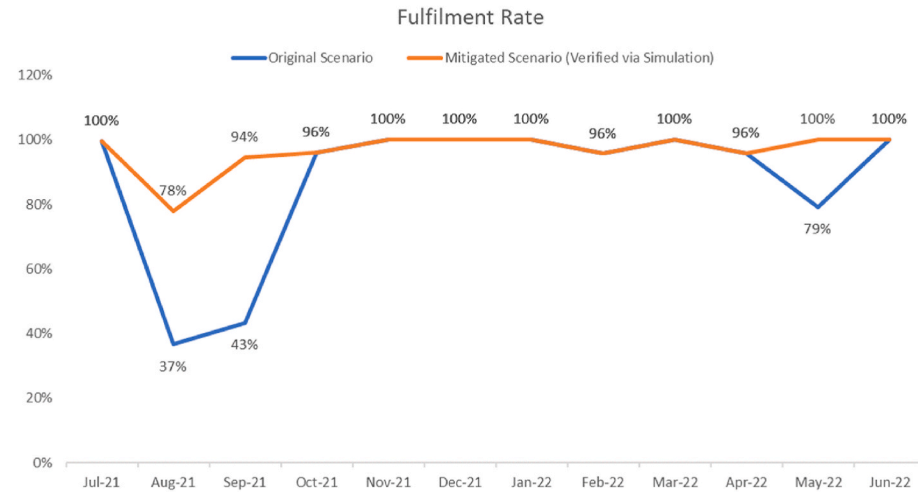

Fig. 7. Comparison between fulfillment rate forecasts of original and mitigated scenarios.

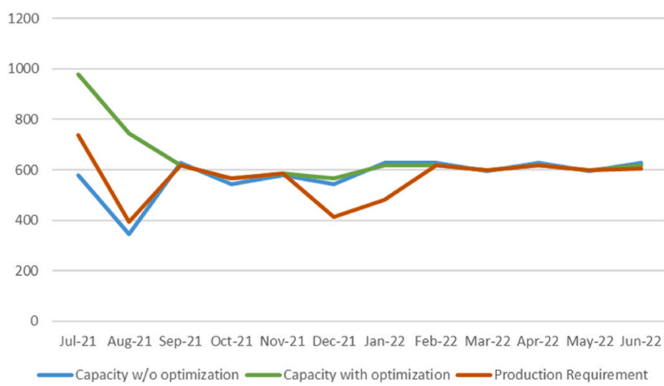

Fig. 8. Production capacity replanning based on new production requirement.

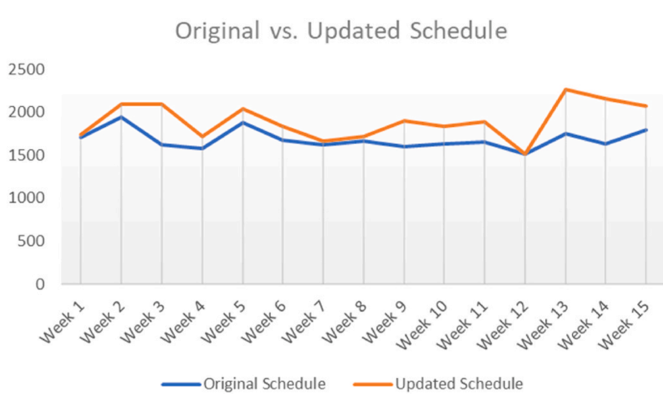

Fig. 9. Comparison of manufacturing outputs based on shop floor constraints.

5.4. Discussion and limitations

This case study demonstrates the effectiveness of DT-enabled mechanisms to evaluate resilience and conduct replanning and rescheduling operations to support S&P facilities in multi-echelon networks. Taking advantage of existing functional modules for network, planning and scheduling operations, the impacts of disruption can be evaluated and mitigated via workflow integration in a comprehensive and user-friendly manner. Emphasizing on planning and scheduling optimization through network and shop floor constraint considerations, the S&P DT increased working efficiency for both regular planning and disruption management. Impacts from the demand spike event which decreased fulfillment rate to 87.25% were mitigated by improving the overall fulfillment rate to 96.67%, exceeding the predefined fulfillment rate threshold of 95%. The mitigation approach was generated across the supply network, stretching from strategic to operational levels in a seamless manner. Likewise, advanced analytics such as descriptive, predictive, prescriptive, diagnostic, and cognitive analytics can achieve E2E visibility, purchase sentiments and market forecasts, scenario-based visualizations, network bottleneck evaluation, business and operation assessments and modernization respectively. These contextual insights, paired with recommendation frameworks, can enhance business models to pivot towards niche markets and serve to retain and expand customer bases.

By facilitating the rapid translation of raw data to recommendations, this S&P DT system enables cross-domain knowledge access between SCM planners and shop floor operators to better allocate resources between PLM manufacturing and distribution stages. Simulation-verified recommendations derived for replanning and rescheduling operations enable users to overcome experience gaps and expedite decision making while knowledge generated from disruptions can be reused for similar events. As S&P facilities from the same organization operate similarly, DT can also serve as a knowledge sharing platform to derive specific site insights for customized regional growth, further signifying its potential from strategic, methodological, and practical perspectives.

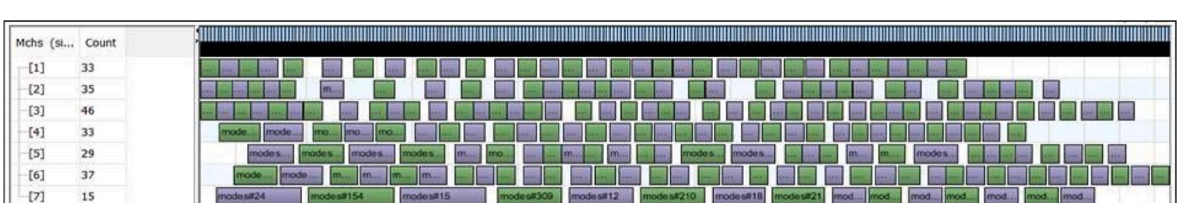

Fig. 10. Optimized workflow schedule based on capacity adjustment from the replanning mechanism.

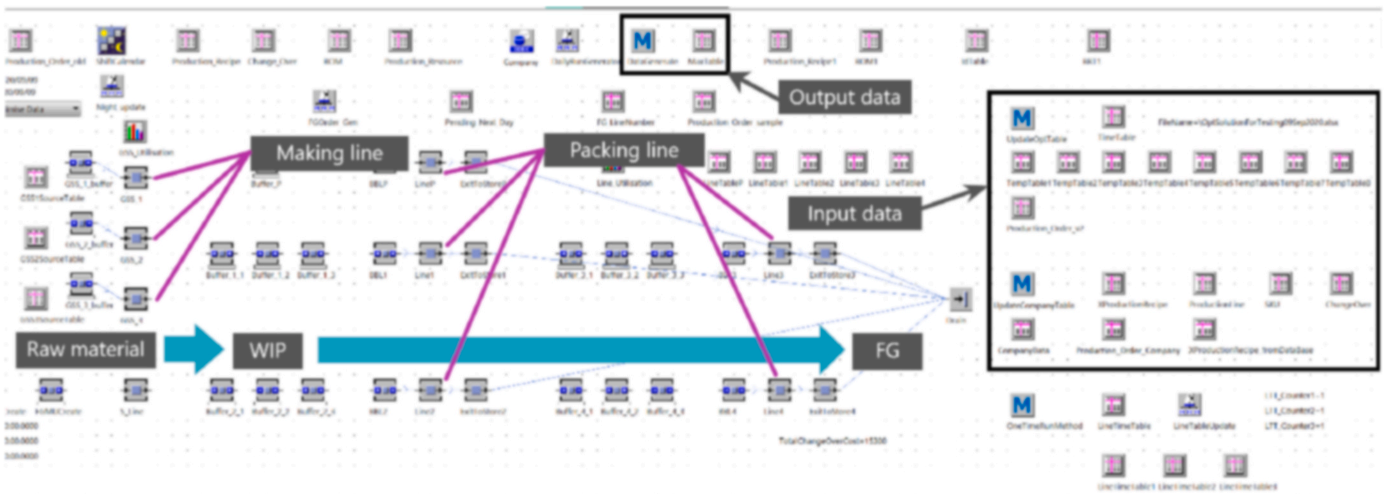

Fig. 11. Shop floor simulation is used to verify the feasibility of derived schedule.

Despite those advantages, the study still has some limitations. For instance, it mainly emphasizes the integration of S&P system functionalities and information flow to mitigate demand disruptions, thus omitting the comparison between various algorithmic techniques. Nevertheless, the modular DT structure proposed allows integration of alternative reasoning modules, reducing the need for companies to conduct expensive and disruptive overhauls of critical modules necessary for solution generation. Meanwhile, the case study does not include any disruption identification aspects, and disruptions featured are based on historical data. Enterprise solutions are also utilized to fulfill last-mile transportation objectives such as 3PL management, which may not be optimized for the FMCG F&B industry.

5.5. Managerial Insights

Through the hybrid S&P DT system, companies are empowered to proactively address disruptions stemming from downstream triggers, such as demand spikes. This systematic approach integrates resilience assessment, SC replanning, and shop floor rescheduling operations, providing stakeholders with the following managerial insights.

For senior executives and SC managers, resilience evaluations can be conducted periodically to reflect the overall state of the multi-echelon network and determine TTR in the event of SC disruptions. The identified 11 KPIs highlighted in Section 5a provide a holistic overview of network health, allowing for strategizing in various disruption scenarios. With E2E visibility and functional task management as supported by the DT system, decisions can be refined to optimize overall fulfillment rates.

Functional planners and SC domain specialists in procurement, sales forecasting, and resource allocation, among other areas of the S&P facility, also stand to benefit from the DT-enabled SC replanning. This approach refines capacity planning in alignment with production needs, harmonizing strategies to achieve optimal make-to-order and make-to-stock (prebuild) combinations to fulfill demand requirements with respect to existing production constraints. Additionally, potential upgrades to the multi-echelon network can be recommended after identifying bottlenecks via network configuration analyses. By representing expert knowledge within the computational layer, optimization processes can be streamlined effectively.

On the production front, shop floor operators and supervisors can leverage the S&P DT system to support rescheduling efforts, factoring in on-ground constraints. Here, optimized production scheduling can substantially reduce make span, changeover costs, tardiness, lost penalties, and other associated factors. Leveraging the simulation-based verification approach, feasibility checks can be used to evaluate the generated solutions, ensuring that the adjustments are validated before implementation.

While optimization techniques might vary across industries, the modular design of the DT system ensures adaptability for individual S&P facilities. These techniques can thus be customized and augmented to suit diverse product types for enhanced outcomes. For instance, the KPIs used can be expanded or tweaked based on overarching business objectives, and the optimization strategies for SC replanning and shop floor rescheduling can be updated without facing compatibility issues. In essence, the hybrid S&P DT system equips companies to methodically navigate disruptions, especially those stemming from volatile demand patterns. Through the pipeline process of resilience assessment to replanning and rescheduling operations, valuable managerial insights can be obtained in each process beneficial to stakeholders within the multi-echelon SC network.

6. Conclusion

Increasing competitive market nature and turbulent environments have resulted in high impact SC disruptions, especially within the FMCG industry. Here, the use of complex multi-echelon networks to optimize inventory levels, in conjunction with product family paradigm and e-commerce business strategies, can fulfill consumer demand for lower-priced personalized goods and convenience. However, supply networks are left susceptible to both supply and demand disruptions due to increased product variants and domain-specific constraints. While DT has been adopted in many SC and manufacturing applications due to its robust capabilities, solutions generated for S&P facilities have limited feasibility due to the lack of context considerations for other entities and constraints within the supply network. To overcome these challenges, this study presents a DT-enhanced system for S&P facilities to mitigate disruptions using a three-layered generic technology stack that integrates various technologies such as simulations and other cyber-physical aspects with respect to S&P operations. A novel mitigative process flow consisting of resilience evaluation, replanning, and rescheduling mechanisms can aid facility managers in practical decision making by highlighting vulnerabilities and reducing disruption impacts.

To demonstrate DT's quick response capabilities towards strengthening resilience, impacts from a demand spike disruption were minimized in an F&B-oriented FMCG case study. This activity-based costing approach analyzes the impact propagation and fully considers industry-specific constraints throughout replanning and rescheduling operations. Downstream situational awareness, together with real-time resource monitoring, disruption scenario simulation, and decision-making support systems can generate contextual solutions such as network bottleneck resolution and production workflow reconfiguration to satisfy production demand. This DT-driven mitigative approach can also be adopted for other critical S&P entities within the network to enhance operational continuity as well as to manage long tail and queuing delay types in a swift and accurate manner to minimize potential revenue losses.

While the proposed system can generate feasible solutions to mitigate demand-based disruptions in complex FMCG networks, the main emphasis remains in critical S&P functional modules and other network aspects have not been explored. Thus, some potential research directions include 1) designing multi-disruption decision support systems with wider SC and shop floor scopes, 2) incorporating fourth-party logistics (4PL) management with cost and environmental emphasis, 3) DT-driven design and optimization of next-generation hyper-personalized products, 4) integrating additional business model elements within DT-enabled decision support systems to achieve optimal outcomes, and 5) establishing human-in-the-loop automatic solution generation systems with inclusion of human DTs.

CRediT authorship contribution statement

Kendrik Yan Hong Lim: Conceptualization, Methodology, Writing – original draft. **Le Van Dang:** Conceptualization, Methodology, Validation, Writing – review & editing. **Chun-Hsien Chen:** Supervision.

Data availability

The authors do not have permission to share data.

Appendix A. KPI calculation for SC resilience evaluation

The 11 Level 1 KPIs reflect the five core attributes.

Attribute	KPI description		Formula Calculation
Reliability	Perfect order fulfillment		[SUM Perfect Orders]/[SUM Number of Orders]
	% of Orders Delivered in Full		[SUM number of orders delivered in full/SUM number of orders delivered] x 100%
	Delivery Performance to Customer Commit Date		[SUM number of orders delivered on the original commitment date]/[SUM number of orders delivered] x 100%
Responsiveness	Source cycle time	Order receipt to pick order release	Weighted_Delivery_Time = (SUM [Quantity x Delivery Time])/[SUM Quality] Weighted_Delivery_Time/[SUM Number of Orders Delivered] in days
		Order release to warehouse to goods issue	Weighted_Delivery_Time = SUM [Quantity x Delivery Time]/[SUM Delivery_time] Weighted_Delivery_Time/[SUM Number of Orders Delivered] in days
		Goods issue to goods receipt	Weighted_Delivery_Time = SUM [Quantity x Delivery Time]/[SUM Delivery_time] Weighted_Delivery_Time/[SUM Number of Orders Delivered] in days
	Frequency (synchronization)		DBNx = SUM [Qty x TMC x Interval]/SUM [Qty x TMC]
Cost	Cost to serve		TSCMC = Transportation Cost + Warehouse handling Cost + Warehouse storage Cost + Production Cost + material Cost
Asset management efficiency	Capacity utilization		[SUM of inventory movement]/Total Capacity
	Inventory days of supply		[5 point rolling average of gross value of inventory at standard cost]/[Annual Cost of Goods Sold (COGS)]/365 in days
Agility	Value at Risk		Supply Chain Risk VAR ($) = VAR $ (Plan) + VAR $ (Source) + VAR $ (Make) + VAR $ (Deliver) + VAR $ (Return)

Appendix B. Supply chain replanning constraints

There are 17 constraints applied within the dynamic replanning mechanism. These constraints reflect typical stipulations experienced by the FMCG industry.

1. Inventory production and retrieval must satisfy demand distribution.

$$W^n_{existing} + W^n_{new} + PB^1_{tj} \geq DM^1_{tj}, \forall n \in N, t \in T, j \in J$$

Where

- $W^n_{existing} = \sum_l^L D_{tlj} X^n_l \alpha_{tl} + X^n_l DT_{tlj} C_{jMax}$ is the total capacity of existing lines in plant n which is count from existing lines and transferred lines
- $W^n_{new} = \sum_{t'=1}^{t} D^n_{t'j} C_{jMax}, \forall j \in J, n \in N$ is capacity from all new lines in plant n

2. Number of actual working days is constrained by the line availability.

$$D_{tl} + \sum_j^J DT_{tlj} = D^0_t\left(0, sign\left(t - T^{Start}_l\right)\right), \forall t, l$$

$$D_{tl} + \sum_j^J DT_{tlj} = D^0_t\left(0, sign\left(T^{End}_l - t\right)\right), \forall t, l$$

3. Transfer can only occur from a default SKU to other SKUs

$$\sum_{j}^{J} X_{lj} LT_{tljj'} = \sum_{j'}^{J} LT_{tljj'}, \forall t, l, j$$

4. When transfer occurs, production on the line is paused for the next k months (including the transfer month). The following Eq. refers to the transfer month, next Eq. ensures a closed line in the next (k-1) months.

$$D_{tl} + \sum_{j}^{J} DT_{tlj} \leq D_t^0 \left(1 - \sum_{j}^{J} \sum_{j'}^{J} LT_{tljj'}\right), \forall t, l$$

$$D_{tl} + \sum_{j}^{J} DT_{tlj} \leq D_t^0 \left(1 - \sum_{j}^{J} \sum_{j'}^{J} LT_{max\ \{1, t-k-1\} ljj'}\right), \forall t, l$$

5. Cannot produce the default SKU after transferring has been made.

$$D_{tl} \leq D_t^0 \left(1 - \sum_{t_1=1}^{t} \sum_{j}^{J} LT_{tljj'}\right), \forall t, l$$

6. DT_{tlj} can only available when transfer has occurred for a specific SKU.

$$DT_{tlj} \leq D_t^0 \left(1 - \sum_{t_1=1}^{t} \sum_{j}^{J} LT_{t_1 ljj'}\right), \forall t, l, j$$

7. Sum of demand in all plants equals to total demand from all DCs for the SKU j, in month t.

$$\sum_{n}^{N} DM_{tj}^{n} = \sum_{i}^{I} d_{tji}, \forall t \in T, j \in J$$

8. Within a planning period, only allow to add p_j^n line of SKU j to plant n.

$$\sum_{t=1}^{T} LC_{tj}^{n} \leq p_j^n, \forall j \in J, n \in N$$

9. Line can only be transferred from one SKU to another SKU.

$$LT_{tljj'} X_{lj} = 0, \forall t, l, j, j'$$

10. If a new line was created, the total of operating days in a month must not be more than the available days of that month.

$$D_{tj}^{n} = D_t^0 \sum_{t'=1}^{t} LC_{t'j}^{n}, \forall j \in J, t \in T, n \in N$$

11. In each plant, only allow to add maximum $p_0 \in N$ new line for each SKU per month.

$$\sum_{j=1}^{J} LC_{tj} \leq p_0, \forall t \in L, n \in N$$

12. Transportation from all plants should add up to total demand from DCs.

$$\sum_{n}^{N} \sum_{i}^{I} TR_{tji}^{n} = d_{tji}, \forall t, j$$

13. Total demands should be delivered.

$$\sum_{n}^{N} \sum_{i}^{I} TR_{tji}^{n} = DM_{tj,}^{n}, \forall t, j, n$$

14. First month consumed prebuilds should less than the initial inventory at a plan.

$$PB^n_{1j} \le Q^n_j$$

15. Inventory consumed should be less than availability and inventory level should be sufficient for filling advanced demand of q_0 months ahead.

$$\sum_{t_1}^{t}\left(Q^n_j + PBC^n_{t_1j} - PB^n_{t_1j}\right) \ge PB^n_{tj}, \forall t, j, n$$

$$\sum_{t_1=max(1,t-q_0)}^{t} PBC^n_{t_1j} + Q^n_j \ge PB^n_{tj}, \forall t, j, n$$

16. Inventory should be all consumed at the end.

$$\sum_t^T \sum_j^J PBC^n_{tl} + Q^n_j - \sum_t^T \sum_j^J PB^n_{tl} = 0, \forall t, j, n$$

17. Prebuild creation is determined from new production, consumed prebuilt, and demand.

$$PBC^n_{tj} = W^n_{existing} + W^n_{new} + PB^n_{tj} - DM^n_{tj}, \forall t \in T, j \in J, n \in N$$

Table
A1 Notation for replanning constraints

Index	Description
T	Planning period
L	List of available production lines from all plants
T^{Start}_l	Available start time of line l
T^{End}_l	End available time of line l
J	List of all SKUs
X^n_l	Logical variable defined if line l is belong to plant n
X_{lj}	Logical variable defined if line l make SKU j
d_{tji}	Demand in month t, of SKU j, from DC i
$c^{LT}_{j_1j_2}$	Transfer cost of a line from SKU j_1 to SKU j_2
c^{CR}_j	Cost of adding a new line of SKU j
D^0_t	Capacity days (calendar day) of month t
α_{tl}	Capacity of line l in month t
C_{jMax}	Maximum capacity of a line with SKU j
c^n_{ji}	Transportation cost of SKU j, from plant n to DC i
w^n_j	Warehouse cost of SKU j on plant n
Q^n_j	Inventory level of SKU j at plant n
Decision Variables	**Description**
$LT_{tljj'}$	Line transfer for line l in month t, which is transferred from SKU j to j'
LC^n_{tj}	Line creation for plant n in month t for SKU j
DM^1_{tj}	Distributed demand of SKU j on month t for plant n
D_{tl}	Number of days without capacity adjustments for line l in month t
DT_{tlj}	Number of days that transferred line l operates in month t
D^n_{tj}	Number of days a new line in plant n operates in month t for SKU j
PB^n_{tj}	Prebuild quantity consumed by plant n in month t for SKU j
PBC^n_{tj}	Prebuild quantity created by plant n in month t for SKU j
TR^n_{tj}	Delivery quantity from plant n in month t for SKU j

Appendix C. Supply chain rescheduling constraints

There are five constraints applied within the rescheduling mechanism. These constraints reflect typical stipulations experienced within S&P facilities.

1. For each job k, WIP (work-in-progress, blending) operation must completed before the FG (finished goods, filling)

$$o^k_{i\_end} < o^k_{j\_start}, \forall k \in K, \forall i, j \in N$$

$$pos\left(o^k_{i\_end}\right) = 0, pos\left(o^k_{j\_start}\right) = 1$$

2. An operation can be scheduled once only

$$\sum_r \sum_i A^k_{ir} \chi^k_{ir} = 1, \forall r \in R, \forall i \in N, \forall k \in K$$

3. If operation *i* and *j* are scheduled next to each other on resource *r*, start time of next operation is equal to end time of the previous operation plus the changeover time between them. It also ensures that a resource can execute only one operation at a time.

$$\chi_{ijr} m^k_{ir\_end} + t_{ijr} = \chi_{ijr} m^k_{jr\_start}, \forall r \in R, \forall i, j \in N, \forall k \in K$$

4. Each operation should be scheduled on its designed resources and a WIP operation after completed should be assigned to packing line based on the resource connection.

$$\sum_p \sum_q \sum_i \sum_j A^k_{ip} \chi^k_{ip} A^k_{jq} \chi^k_{jq} R_{pq} = 1, \forall p, q \in R, \forall i, j \in N$$

$$pos\left(o^k_i\right) = 0, pos\left(o^k_j\right) = 1$$

5. Start time of an operation on resource *r* must later than the earliest available time

$$m^k_{ir\_start} \geq T^0_r, \forall r \in R, \forall i \in N, k \in K$$

Table A2 Notation for rescheduling constraints

Index	Description
R	Total number of resources
R_{pq}	Logical parameter indicating the product linkage from resource p to resource q
N	Total number of operations, including blending and filling
K	Total number of jobs. A job has two operations, blending and filling
t_{ijr}	Changeover time from operation i to operation j scheduled on resource r
τ_{ijr}	Changeover cost from operation i to operation j scheduled on resource r
P_i	Processing time of operation i
d_i	Due date of operation i
ρ_i	Penalty cost rate of operation i due to tardiness
D_i	Demand of operation i within the production time fence (PTF)
T_t	Production time fence (PTF)
$pos(o^k_i)$	Position of operation i, from job k; $pos(o^k_i) = 0$ for blending, $pos(o^k_i) = 1$ for filling
$(\mathtt{C}_1, \mathtt{C}_2, \mathtt{C}_3)$	Component objective function of lost-sale, changeover cost and production time
$(\alpha_1, \alpha_2, \alpha_3)$	Coefficient vector for $\mathtt{C}_1, \mathtt{C}_2, \mathtt{C}_3$. $\alpha_i = 1$ for objective i, $\alpha_i = 0$ otherwise for $i = 1, 2, 3$.
$(\omega_1, \omega_2, \omega_3)$	Weighting coefficient for component objective functions, where $\omega_1 + \omega_2 + \omega_3 = 1$
A^k_{ir}	Binary variable specifies if operation i of job k can be scheduled on resource r
T^0_r	Earliest availability time of resource r
Decision Variables	**Description**
χ^k_{ir}:	Binary variable, $\chi^k_{ir} = 1$ if operation i of job k is scheduled on resource r
χ_{ijr}:	Binary variable, specifies operation j is scheduled after order i on resource r
$o^k_{i\_start}$:	Indicates start time of operation i of job k
$o^k_{i\_end}$:	Indicates end time of operation i of job k
$m^k_{ir\_start}$:	Indicates start time of operation i of job k on machine r
$m^k_{ir\_end}$:	Indicates end time of operation i of job k on machine r

References

Abolghasemi, M., Beh, E., Tarr, G., Gerlach, R., 2020. Demand forecasting in supply chain: the impact of demand volatility in the presence of promotion. Comput. Ind. Eng. 142, 106380 https://doi.org/10.1016/j.cie.2020.106380. Apr.

Adobor, H., 2019. Supply chain resilience: a multi-level framework. Nov Int. J. Logist. Res. Appl. 22 (6), 533–556. https://doi.org/10.1080/13675567.2018.1551483.

Agostino, Í.R.S., Broda, E., Frazzon, E.M., Freitag, M., 2020. 'Using a digital twin for production planning and control in industry 4.0', in *Scheduling in industry 4.0 and cloud manufacturing.* In: Sokolov, B., Ivanov, D., Dolgui, A. (Eds.), International Series in Operations Research & Management Science. Springer International Publishing, Cham, pp. 39–60. https://doi.org/10.1007/978-3-030-43177-8_3.

Aguila, J.O., ElMaraghy, W., 2019. Supply chain resilience and structure: an evaluation framework. Procedia Manuf. 28, 43–50. https://doi.org/10.1016/j.promfg.2018.12.008.

Ansari, S., Başdere, M., Li, X., Ouyang, Y., Smilowitz, K., 2018. Advancements in continuous approximation models for logistics and transportation systems: 1996–2016. Jan Transp. Res. Part B Methodol. 107, 229–252. https://doi.org/10.1016/j.trb.2017.09.019.

Beemsterboer, B., Land, M., Teunter, R., Bokhorst, J., 2017. Integrating make-to-order and make-to-stock in job shop control. Mar Int. J. Prod. Econ. 185, 1–10. https://doi.org/10.1016/j.ijpe.2016.12.015.
Berti, N., Finco, S., Guidolin, M., Battini, D., 2023. Towards Human Digital Twins to enhance workers' safety and production system resilience. Jan. IFAC-Pap 56 (2), 11062–11067. https://doi.org/10.1016/j.ifacol.2023.10.809.
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. Feb Supply Chain Manag. Int. J. 27 (2), 182–206. https://doi.org/10.1108/SCM-01-2021-0053.
Burgos, D., Ivanov, D., 2021. Food retail supply chain resilience and the COVID-19 pandemic: a digital twin-based impact analysis and improvement directions. Aug Transp. Res. Part E Logist. Transp. Rev. 152, 102412. https://doi.org/10.1016/j.tre.2021.102412.
Busse, C., Schleper, M.C., Weilenmann, J., Wagner, S.M., 2017. Extending the supply chain visibility boundary: Utilizing stakeholders for identifying supply chain sustainability risks. Jan Int. J. Phys. Distrib. Logist. Manag. 47 (1), 18–40. https://doi.org/10.1108/IJPDLM-02-2015-0043.
Busse, A., Gerlach, B., Lengeling, J.C., Poschmann, P., Werner, J., Zarnitz, S., 2021. Towards digital twins of multimodal supply chains. Apr Logistics 5 (2), 25. https://doi.org/10.3390/logistics5020025.
Dolgui, A., Ivanov, D., Sokolov, B., 2020. Reconfigurable supply chain: the X-network. Jul Int. J. Prod. Res. 58 (13), 4138–4163. https://doi.org/10.1080/00207543.2020.1774679.
Eddoug, K., ElHaq, S.L., Echcheikh, H., 2018. Performance evaluation of complex multi-echelon distribution supply chain. Apr. In: 2018 4th International Conference On Logistics Operations Management (GOL). IEEE, Le Havre, pp. 1–10. https://doi.org/10.1109/GOL.2018.8378091.
Elekidis, A.P., Corominas, F., Georgiadis, M.C., 2019. Production scheduling of consumer goods industries. Dec Ind. Eng. Chem. Res. 58 (51), 23261–23275. https://doi.org/10.1021/acs.iecr.9b04907.
Fang, Y., Peng, C., Lou, P., Zhou, Z., Hu, J., Yan, J., 2019. Digital-twin-based job shop scheduling toward smart manufacturing. Dec IEEE Trans. Ind. Inform. 15 (12), 6425–6435. https://doi.org/10.1109/TII.2019.2938572.
Gallego-García, S., Reschke, J., García-García, M., 2019. Design and simulation of a capacity management model using a digital twin approach based on the viable system model: case study of an automotive plant. Dec Appl. Sci. 9 (24), 5567. https://doi.org/10.3390/app9245567.
Georgiadis, G.P., Mariño Pampín, B., Adrián Cabo, D., Georgiadis, M.C., 2020. Optimal production scheduling of food process industries. Mar Comput. Chem. Eng. 134, 106682. https://doi.org/10.1016/j.compchemeng.2019.106682.
Guo, S., Choi, T.-M., Shen, B., Jung, S., 2019. Inventory management in mass customization operations: a review. Aug IEEE Trans. Eng. Manag. 66 (3), 412–428. https://doi.org/10.1109/TEM.2018.2839616.
Ivanov, D., Dolgui, A., 2021. A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0. Jul Prod. Plan. Control 32 (9), 775–788. https://doi.org/10.1080/09537287.2020.1768450.
Kegenbekov, Z., Jackson, I., 2021. Adaptive supply chain: demand–supply synchronization using deep reinforcement learning. Aug. Algorithms 14 (8), 240. https://doi.org/10.3390/a14080240.
Kopka, U., Little, E., Moulton, J., Schmutzler, R., Simon, P., 2020. What Got Us Here Won't Get Us There: A New Model for the Consumer Goods Industry. Aug.
Leahy, R., 2011. Relationships in fast moving consumer goods markets: the consumers' perspective. Apr Eur. J. Mark. 45 (4), 651–672. https://doi.org/10.1108/03090561111111370.
Lee, D., Lee, S., 2021. Digital twin for supply chain coordination in modular construction. Jun Appl. Sci. 11 (13), 5909. https://doi.org/10.3390/app11135909.
Leung, E.K.H., Lee, C.K.H., Ouyang, Z., 2022. From traditional warehouses to Physical Internet hubs: a digital twin-based inbound synchronization framework for PI-order management. Feb Int. J. Prod. Econ. 244, 108353. https://doi.org/10.1016/j.ijpe.2021.108353.
Lim, K.Y.H., Zheng, P., Chen, C.-H., 2020a. A state-of-the-art survey of Digital Twin: techniques, engineering product lifecycle management and business innovation perspectives. J. Intell. Manuf. 31 (6), 1313–1337. https://doi.org/10.1007/s10845-019-01512-w.
Lim, K.Y.H., Zheng, P., Chen, C.-H., Huang, L., 2020b. A digital twin-enhanced system for engineering product family design and optimization. J. Manuf. Syst. 57, 82–93. https://doi.org/10.1016/j.jmsy.2020.08.011.
Lim, K.Y.H., Dang, L.V., Chen, C.-H., Chew, K.H., 2022a. Cost-optimal pathfinding model for multi-echelon logistics network design and optimization: a fourth-party logistics (4PL) perspective. In: Moser, B.R., Koomsap, P., Stjepandić, J. (Eds.), Advances in Transdisciplinary Engineering. IOS Press. https://doi.org/10.3233/ATDE220677.
Lim, K.Y.H., Dang, L.V., Ng, C., Qijian, C., Chen, H., 2022b. Disruption mitigation in complex hybrid supply and production FMCG networks: a digital twin approach. In: *12th Conference On Learning Factories, CLF2022*, SSRN Electronic Journal. https://doi.org/10.2139/ssrn.4074145.
Liu, L.-L., Wan, X., Gao, Z., Li, X., Feng, B., 2019. Research on modelling and optimization of hot rolling scheduling. Mar. J. Ambient Intell. Humaniz. Comput 10 (3), 1201–1216. https://doi.org/10.1007/s12652-018-0944-7.
Liu, Z., Chen, W., Zhang, C., Yang, C., Cheng, Q., 2021. Intelligent scheduling of a feature-process-machine tool supernetwork based on digital twin workshop. Jan J. Manuf. Syst. 58, 157–167. https://doi.org/10.1016/j.jmsy.2020.07.016.
Liu, Z., Li, M., Zhai, X., 2022. Managing supply chain disruption threat via a strategy combining pricing and self-protection. May Int. J. Prod. Econ. 247, 108452. https://doi.org/10.1016/j.ijpe.2022.108452.
Lu, Y., Min, Q., Liu, Z., Wang, Y., 2019. An IoT-enabled simulation approach for process planning and analysis: a case from engine re-manufacturing industry. May Int. J. Comput. Integr. Manuf. 32 (4–5), 413–429. https://doi.org/10.1080/0951192X.2019.1571237.
Min, Q., Lu, Y., Liu, Z., Su, C., Wang, B., 2019. Machine learning based digital twin framework for production optimization in petrochemical industry. Dec. Int. J. Inf. Manag. 49, 502–519. https://doi.org/10.1016/j.ijinfomgt.2019.05.020.
Moosavi, J., Hosseini, S., 2021. Simulation-based assessment of supply chain resilience with consideration of recovery strategies in the COVID-19 pandemic context. Oct. Comput. Ind. Eng. 160, 107593 https://doi.org/10.1016/j.cie.2021.107593.
Moshood, T., Nawanir, G., Sorooshian, S., Okfalisa, O., 2021. Digital twins driven supply chain visibility within logistics: a new paradigm for future logistics. Apr. Appl. Syst. Innov. 4 (2), 29. https://doi.org/10.3390/asi4020029.
Negri, E., Pandhare, V., Cattaneo, L., Singh, J., Macchi, M., Lee, J., 2021. Field-synchronized Digital Twin framework for production scheduling with uncertainty. Apr. J. Intell. Manuf. 32 (4), 1207–1228. https://doi.org/10.1007/s10845-020-01685-9.
Nguyen, T., Duong, Q.H., Nguyen, T.V., Zhu, Y., Zhou, L., 2022. Knowledge mapping of digital twin and physical internet in Supply Chain Management: a systematic literature review. Feb. Int. J. Prod. Econ. 244, 108381 https://doi.org/10.1016/j.ijpe.2021.108381.
Orozco-Romero, A., Arias-Portela, C.Y., Saucedo, J.A.M.-, 2020. The use of agent-based models boosted by digital twins in the supply chain: a literature review. In: Vasant, P., Zelinka, I., Weber, G.-W. (Eds.), Intelligent Computing and Optimization, Advances in Intelligent Systems and Computing. Springer International Publishing, Cham, pp. 642–652. https://doi.org/10.1007/978-3-030-33585-4_62.
Pan, Y.H., Wu, N.Q., Qu, T., Li, P.Z., Zhang, K., Guo, H.F., 2021. Digital-twin-driven production logistics synchronization system for vehicle routing problems with pick-up and delivery in industrial park. Aug. Int. J. Comput. Integr. Manuf. 34 (7–8), 814–828. https://doi.org/10.1080/0951192X.2020.1829059.
Park, Y., Woo, J., Choi, S., 2020. A cloud-based digital twin manufacturing system based on an interoperable data schema for smart manufacturing. Dec. Int. J. Comput. Integr. Manuf. 33 (12), 1259–1276. https://doi.org/10.1080/0951192X.2020.1815850.
Park, K.T., Son, Y.H., Noh, S.D., 2021. The architectural framework of a cyber physical logistics system for digital-twin-based supply chain control. Oct. Int. J. Prod. Res. 59 (19), 5721–5742. https://doi.org/10.1080/00207543.2020.1788738.
Pettit, T.J., Croxton, K.L., Fiksel, J., 2013. Ensuring supply chain resilience: development and implementation of an assessment tool. Mar. J. Bus. Logist. 34 (1), 46–76. https://doi.org/10.1111/jbl.12009.
Pulshashi, I.R., Bae, H., Sutrisnowati, R.A., 2020. 'Container-Based coloured petri-net Co-simulation framework'. Feb.. In: 2020 IEEE International Conference on Big Data and Smart Computing (BigComp), pp. 393–395. https://doi.org/10.1109/BigComp48618.2020.00-43.
Qin, Z., Lu, Y., 2021. Self-organizing manufacturing network: a paradigm towards smart manufacturing in mass personalization. Jul. J. Manuf. Syst. 60, 35–47. https://doi.org/10.1016/j.jmsy.2021.04.016.
Rahmanzadeh, S., Pishvaee, M.S., Govindan, K., 2022. Emergence of open supply chain management: the role of open innovation in the future smart industry using digital twin network. Jan. Ann. Oper. Res. https://doi.org/10.1007/s10479-021-04254-2.
Saha, E., Ray, P.K., 2019. Modelling and analysis of inventory management systems in healthcare: a review and reflections. Nov. Comput. Ind. Eng. 137, 106051 https://doi.org/10.1016/j.cie.2019.106051.
Serrano-Ruiz, J.C., Mula, J., Poler, R., 2021. Smart master production schedule for the supply chain: a conceptual framework. Nov. Computers 10 (12), 156. https://doi.org/10.3390/computers10120156.
Sucky, E., 2009. The bullwhip effect in supply chains—an overestimated problem? Mar. Int. J. Prod. Econ. 118 (1), 311–322. https://doi.org/10.1016/j.ijpe.2008.08.035.
Sun, W., Lei, S., Wang, L., Liu, Z., Zhang, Y., 2021. Adaptive federated learning and digital twin for industrial internet of things. Aug. IEEE Trans. Ind. Inform. 17 (8), 5605–5614. https://doi.org/10.1109/TII.2020.3034674.
van Elzakker, M.A.H., Zondervan, E., Raikar, N.B., Grossmann, I.E., Bongers, P.M.M., 2012. Scheduling in the FMCG industry: an industrial case study. Jun. Ind. Eng. Chem. Res. 51 (22), 7800–7815. https://doi.org/10.1021/ie202106k.
Vidalis, M., Vrisagotis, V., Varlas, G., 2014. Performance evaluation of a two-echelon supply chain with stochastic demand, lost sales, and Coxian-2 phase replenishment times. Int. Trans. Oper. Res. 21 (4), 649–671. https://doi.org/10.1111/itor.12057.
Wang, L., Deng, T., Shen, Z.-J.M., Hu, H., Qi, Y., 2022. Digital twin-driven smart supply chain. Mar. Front. Eng. Manag. 9 (1), 56–70. https://doi.org/10.1007/s42524-021-0186-9.
Williams, B.D., Tokar, T., 2008. A review of inventory management research in major logistics journals: themes and future directions. Aug. Int. J. Logist. Manag. 19 (2), 212–232. https://doi.org/10.1108/09574090810895960.
Wong, E.Y.C., Mo, D.Y., So, S., 2021. Closed-loop digital twin system for air cargo load planning operations. Aug. Int. J. Comput. Integr. Manuf. 34 (7–8), 801–813. https://doi.org/10.1080/0951192X.2020.1775299.
Yan, J., Liu, Z., Zhang, C., Zhang, T., Zhang, Y., Yang, C., 2021. Research on flexible job shop scheduling under finite transportation conditions for digital twin workshop. Dec. Robot. Comput.-Integr. Manuf. 72, 102198 https://doi.org/10.1016/j.rcim.2021.102198.
Zhang, Y., Guo, Z., Lv, J., Liu, Y., 2018. A framework for smart production-logistics systems based on CPS and industrial IoT. Sep. IEEE Trans. Ind. Inform. 14 (9), 4019–4032. https://doi.org/10.1109/TII.2018.2845683.
Zhang, K., et al., 2020. Digital twin-based opti-state control method for a synchronized production operation system. Jun. Robot. Comput.-Integr. Manuf. 63, 101892 https://doi.org/10.1016/j.rcim.2019.101892.

Zhang, C., Xu, W., Liu, J., Liu, Z., Zhou, Z., Pham, D.T., 2021a. Digital twin-enabled reconfigurable modeling for smart manufacturing systems. Int. J. Comput. Integr. Manuf. 34 (7–8), 709–733. https://doi.org/10.1080/0951192X.2019.1699256.
Zhang, M., Tao, F., Nee, A.Y.C., 2021b. Digital twin enhanced dynamic job-shop scheduling. J. Manuf. Syst. 58, 146–156. https://doi.org/10.1016/j.jmsy.2020.04.008.
Zhang, J., Deng, T., Jiang, H., Chen, H., Qin, S., Ding, G., 2021c. Bi-level dynamic scheduling architecture based on service unit digital twin agents. J. Manuf. Syst. 60, 59–79. https://doi.org/10.1016/j.jmsy.2021.05.007.
Zhang, A.N., Wagner, S.M., Goh, M., Asian, S., 2021d. Quantifying supply chain disruption: a recovery time equivalent value at risk approach. Int. J. Logist. Res. Appl. 1–21. https://doi.org/10.1080/13675567.2021.1990872.