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Supply Chain 4.0 and the Digital Twin Approach: A Framework for Improving Supply Chain Visibility

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Abstract

The emergence of Industry 4.0 has led to an increased level of complexity in supply chain operations. As a result, innovative approaches are required to improve visibility. Conventional approaches such as optimisation and simulation are no longer adequate for ensuring visibility across the entire supply chain. The aim of this study is to explore the potential of digital twins (DT) within the domain of supply chain management. A comprehensive DT framework is formulated utilising the Genetic Algorithm (GA). The results emphasise the potential of DT in promoting data-driven decision-making, improving visibility, and optimising SC operations. This study attempts to fill the current gaps in knowledge, offering significant insights for stakeholders in the supply chain.

Keywords: Digital twin; Industry 4.0; Supply chain management; Visibility; Genetic Algorithm; Resilience

1. Introduction

Over the past decade, the evolution of Industry 4.0 (I4.0) has significantly transformed supply chain operations, marking a pivotal shift towards digitalization [1]. While the implementation of I4.0 has undoubtedly enhanced the efficiency of supply chain processes by enabling better monitoring, optimization, and management of inventory, production, and distribution, it has simultaneously introduced a new set of intricate challenges [1-3]. These challenges encompass the management of extensive data, cybersecurity vulnerabilities, the imperative need to enhance the skill sets of the workforce, and the critical requirement for seamless interoperability among diverse systems within the supply chain [3]. Organisations are actively leveraging cutting-edge technologies like IoT, cloud computing, and notably, Digital Twins (DT) to tackle these issues and to gain a competitive advantage in the dynamic market landscape [1]. Digital twins, which essentially represent real-time simulations mirroring the behaviour of physical systems, hold the promise of substantially improving visibility, optimisation, and decision-making capabilities within the supply chain [4]. However, a comprehensive framework for the seamless integration of DTs into supply chain management is still underdeveloped, revealing a considerable gap in understanding their full potential [5]. Defined as an integrated multi-physics, multi-scale, probabilistic simulation of complex products or systems, DTs leverage the best available physical models, sensor data updates, historical information, and more, to replicate the lifecycle of their physical counterparts [6].

By bridging the virtual and physical realms, DTs facilitate remote system monitoring and the execution of simulations for various hypothetical scenarios, offering a pathway for enhanced operational efficiency [1, 4]. Although the applications of DTs have been explored in diverse industries like aerospace and healthcare, a comprehensive framework

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for their integration within the supply chains remains elusive [5, 7]. This gap emphasizes the critical need for a more thorough comprehension of digital twins in the context of supply chain complexities.

The aim of this paper is to develop a comprehensive framework for the integration of digital twins within the domain of supply chains. The emphasis is on providing useful recommendations based on evaluations of existing literature, case studies, and empirical results. This framework will provide organizations with the opportunity to leverage digital twin technology and revolutionise their supply chain operations in the Supply Chain 4.0 Era and beyond. It will also, serve as a valuable tool for supply managers to potentially enhance supply chain efficiency through demand forecasting, and disruption management. The scientific contribution is to address existing research gaps by developing a comprehensive framework that facilitates the assimilation of digital twins in the domain of supply chain management.

2. Literature Review

In the era of Supply Chain 4.0, the emergence of the "Digital Twin" technology stands as a pivotal advancement, offering a bridge between the physical and digital realms of supply chain management. While its potential is vast, its practical applications and benefits have not been fully explored. Clarification of the digital twin technological landscape in supply chain contexts is the goal of this review. Through a meticulous review of existing studies, this review not only provides a comprehensive understanding but also identifies the critical research gaps.

2.1. Historical Context and Evolution

The fourth industrial revolution's concept of supply chain 4.0 denotes the digitalization of the production process. Automation is replacing human methods in this period to increase operational effectiveness and satisfy individual demand [8]. A key component of this transformation, digital twin technology creates a digital counterpart of physical objects to enable real-time monitoring and optimisation [9]. In 2002, Grieves coined the term DT which subsequently evolved from ‘conceptual ideal for product lifecycle management (PLM)’, ‘the mirrored space model’, and ‘the information mirroring model’, to today’s slightly varying definitions of a DT.

2.2. The Role and Potential of Digital Twins

Supply chain management (SCM) activities are being transformed as a result of digital twins [10]. Digital twins have been used by various industries, most notably aviation, to increase operational effectiveness [11]. Rolls Royce has used DTs in the context of offshore wind energy. They developed a standalone DT by creating a 3D CAD model of a turbine and importing it into a game engine for realistic visualization [11]. BMW is creating a comprehensive DT of a whole factory to replicate 31 factories, which is expected to result in 30% more effective planning processes [12]. However, there are difficulties when integrating digital twins into SCM, particularly when it comes to data storage, security, and real-time data processing [13].

2.3. Existing Frameworks and Their Limitations

Several academic studies have put forth models for incorporating digital twins into SCM. These frameworks support a range of functions, including manufacturing and logistics. However, a thorough, specific framework addressing the complexity of SCM is noticeably lacking. Park, Son, and Noh (2020) [14] proposed an architectural framework for a cyberphysical logistics system for digital twin-based supply chain control in 2020. This paradigm places a focus on DTs' integration into the supply chain, improving the management and control of logistics operations. Shao [15] developed a framework for a digital twin in manufacturing that uses a distinct strategy, focussing on the scope and needs of integrating DTs into the manufacturing sector. This framework offers insightful information about the possible use of DTs in SCM, notably in the manufacturing sector. [16] proposed a manufacturing blockchain of things in 2020 to set up a data- and knowledge-driven digital twin manufacturing cell. This architecture improves the security and effectiveness of supply chain operations by integrating blockchain technology with DTs. Defraeye [17] created a digital fruit twin based on mechanistic modeling to simulate the thermal behavior of mango fruit across the cold chain. Lugaresi [18] developed a method for automatically discovering manufacturing systems and generating appropriate digital twins to accurately assess systems. Yi [19] explores the application framework of DT-based smart assembly process design, in realizing smart assembly for complex product enterprises. However, one of the challenges is how to reconstruct a multiscale high-fidelity DT model to optimize the assembly process. This literature review found a lack of a comprehensive framework to integrate digital twins into supply chain processes.

3. Methodology

The Digital Twin (DT) model is created with Python for ease of integration of the physical twin onto the DT and using several variables, such as lead times, transportation costs, and manufacturing and inventory costs. These variables help businesses optimize their operations, reduce costs, enhance customer service, and adapt to changing market conditions while considering the complexities of the supply chain ecosystem [20]. The model is optimised through the utilisation of a Genetic Algorithm (GA). Compared to other algorithms, GA offers better flexibility, is less likely to get stuck in local optima, and is often robust to noise and uncertainties computational efficiency [21, 22]. The DT framework is shown in Fig. 1.

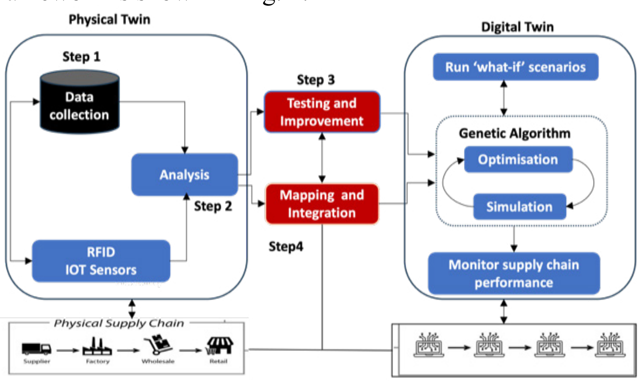

Fig. 1. Digital twin framework

3.1. Case Study

The study relates to a manufacturing supply chain with three major components; suppliers, manufacturers, and retailers. The dataset used in this study has been obtained from Kaggle, a well-known platform for open datasets. It relates to a business that manufactures beauty products. The dataset provides a thorough understanding of the dynamics of the supply chain involving three manufacturers, three retailers, and one supplier.

3.1.1. Key Components of the Dataset

- Orders from Retailers to Manufacturers: It Provides information on the size and regularity of the orders that each of the three retailers place with the manufacturers.
- Manufacturers to Retailers: It includes details like the quantity of goods transported, the mode of transportation employed, the cost of transportation, and lead times.
- Supplier to Manufacturers: It contains details such as the quantity of materials supplied, the frequency of supply, the mode of transportation, and related costs.

3.2. Digital Twin Development

This section details the Digital twin (DT) development and supply chain integration process. The Digital Twin (DT) development process requires supply chain integration of several components. This study created a model to improve industrial supply chain efficiency. This model uses transportation, inventory, demand, and capacity data to adjust to unanticipated demand spikes or supply chain disruptions.

3.2.1. Step 1: Assumptions

Several fundamental assumptions have been made to simplify the model and lessen the computational complexity associated with developing Digital Twins (DT). These assumptions are:

- All variables, including demands, cost, capacities, and lead times, are known and fixed.
- The cost of production is the same for all goods.
- Products can be kept without worrying about decaying for an unlimited amount of time.
- Prices for products remain consistent across all retailers.
- Supplier, producer, and retailer capacities are fixed.
- Transportation, inventory, and penalty costs are all straight lines.
- There are consequences for unmet demand even when there are no backorders.
- The model is concentrated on a single product category.

3.2.2. Step 2: Data Collection

The gathering and preparation of data is the first step in the creation of the digital twin (DT). This study makes use of historical data obtained from Kaggle. Demand, inventory levels, and product quantities are all included in this dataset.

3.2.3. Step 3: Model Design

The next step is to create the Python-coded digital twin (DT) model. It includes classes and structures for a variety of supply chain elements, including inventory, transportation, suppliers, manufacturers, and retailers, each of which behaves according to its characteristics. For instance, whereas inventory maintains item placements, transportation coordinates pick-ups and deliveries. The DT maximises an objective function that includes inventory costs, transportation costs, and fines for unmet demand. The simulation and optimisation of the supply chain activities are determined by the model's architecture. The model uses the GA algorithm to find solutions to disruptions and bases its operation on equation (1), which is covered in more detail in subsequent sections.

$$\text{Min } f = \sum_{m \in M} \sum_{t \in T} I_{mt} x_{smt} + \sum_{r \in R} \sum_{t \in T} I_{rt} W_{rt} + \sum_{m \in M} \sum_{r \in R} \sum_{t \in T} \sum_{v \in V} T_{mrv} y_{mrv} + \sum_{r \in R} \sum_{t \in T} P_{rt} z_{rt} \quad (1)$$

Where the parameters are:
- C_{sm}: Capacity of manufacturer m ∈ M for supplier s ∈ S
- C_{mr}: Capacity of retailer r ∈ R for manufacturer m ∈ M
- D_{rt}: Demand at retailer r ∈ R in time period t ∈ T
- I_{mt}:Inventory cost at manufacturer m ∈ M in time period t ∈ T
- L_{rt}:Inventory cost at retailer r ∈ R in time period t ∈ T
- W_{rt}:Inventory level at retailer r ∈ R in time period t ∈ T
- T_{mrv}: Transportation cost from manufacturer m ∈ M to retailer r ∈ R using transportation mode t ∈ T
- P_{rt}:Penalty for losing demand at retailer r ∈ R in time period t ∈ T
- L_{mrv}: Lead time from manufacturer m ∈ M to retailer r ∈ R using transportation mode v ∈ V
- Cap_v:Capacity of transportation mode v ∈ V

Other sets:
- T: Time Periods
- V: Transportation methods

The constraints are:

Supply capacity: $x_{smt} \leq C_{sm}$ for all s ∈ S, m ∈ M, t ∈ T
Manufacturing capacity: $\sum_{s \in S} x_{smt} \leq \sum_{r \in R} \sum_{v \in V} y_{mrtv}$
Retail capacity: $\sum_{v \in V} y_{mrtv} \leq C_{mr}$
Transportation capacity: $y_{mrtv} \leq Cap_v$
Inventory: $W_{rt} = W_{r(t-1)} + \sum_{m \in M} \sum_{v \in V} y_{mr}(t - L_{mrv})v - D_{rt} + z_{rt}$
Demand satisfaction: $\sum_{m \in M} \sum_{v \in V} y_{mr}(t - L_{mrv})v + z_{rt} = D_{rt}$

Equation (1), represents the objective function which is to minimize the total costs, which is a combination of inventory costs at both manufacturer and retailer levels, transportation costs, and penalties for lost demand. While the constraints imply that; for each supplier, the supply capacity (possibly the amount of product supplied) should not exceed a certain predefined capacity. For a given product and time, the total amount taken from all suppliers should not exceed the total amount that goes into manufacturing for all manufacturing locations and all vehicles or routes. For each product, retail location, time, and vehicle, the amount transported should not exceed the vehicle's capacity.

3.2.4. Step 4: Model Testing and Refinement

Once the model has been implemented, it undergoes testing to verify its fidelity in representing the various functions and activities of the supply chain. This process entails executing the model and conducting a comparative analysis between the obtained outcomes and the factual data derived from the supply chain.

3.2.5. Step 5: Integration into the Supply chain

The simulation model is integrated into the supply chain framework as the final step.

3.3. Digital Twin Operation and Functionality

The created model is a sophisticated supply chain management tool that, when combined with real-time data, can become a DT. It monitors inventory levels, sales, and product movement throughout the supply chain. The DT's capacity to forecast demand, which uses historical data and sophisticated algorithms to inform distribution choices and reduce stockouts and excess inventory, is a standout feature. In addition to monitoring, the DT simulates various events, such as changes in demand or interruptions in supply, to help managers make data-driven decisions for cost and service optimisation. A genetic algorithm is used to choose the best product distribution plan during disruptions.

3.4. Monitoring Capabilities

The DT for the supply chain is structured modularly and hierarchically to mimic real-world operations. It encompasses key supply chain components: suppliers, manufacturers, and retailers, each with distinct functionalities. Key features include; inventory management, transport mechanism, supplier dynamics, manufacturer dynamics, retailer dynamics, and visualization. The DT offers dynamic charts for real-time monitoring, depicting inventory levels, demand, and other parameters, enhancing stakeholder understanding of supply chain performance (Fig. 2).

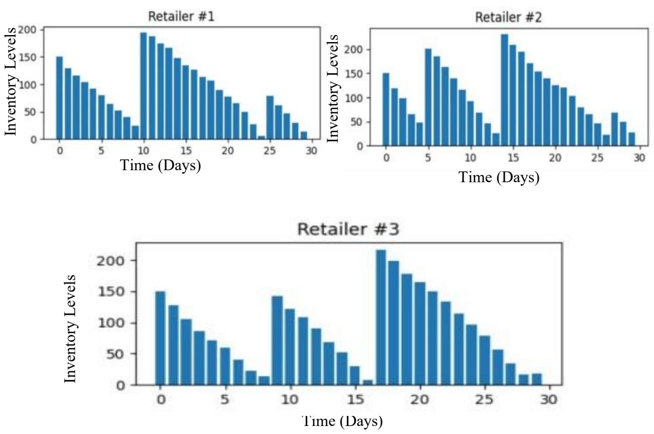

Fig. 2. Inventory levels of retailers for 30 days shown by DT

3.5. Scenario Analysis Outcomes

In the conducted scenario analysis, a complex real-world case was examined involving three distinct retailers and manufacturers, each located at different distances, adding logistical intricacies to the supply chain. All manufacturers sourced raw materials from a single supplier and maintained separate inventory systems for raw materials and finished goods, emphasizing the importance of efficient inventory management due to space constraints. The bar charts (Fig. 3) depict inventory levels for manufacturers and retailers, showcasing the dynamic interplay of demand, production, and supply. Key insights include demand-supply synchronization, inventory management, logistical challenges, and benefits and risks.

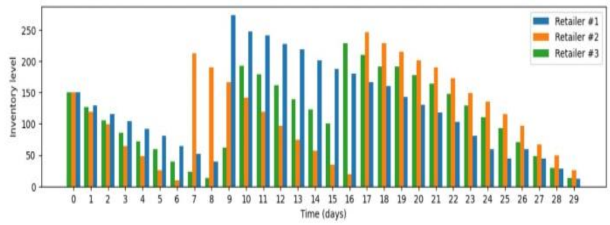

Fig. 3. Inventory levels of manufacturers and retailers

3.6. Disruption Management and Genetic Algorithm Performance

Supply chain disruptions, stemming from various causes, pose significant challenges for businesses. Key parameters for our Digital Twin's disruption management include:

- **Population Size (POP_SIZE = 400):** Represents the initial set of solutions. A larger size offers diverse solutions but demands more computational power.
- **Mutation Probability (MUTATION_PROB = 0.3):** Introduces random changes in solutions, ensuring the algorithm explores a broad solution space and avoids local optimums.
- **Crossover Probability (CROSSOVER_PROB = 0.95):** Facilitates the generation of new solutions by combining existing ones, promoting solution diversity.
- **Elitism (ELITISM = 0.01):** Ensures the top 1% of solutions transition to the next generation unchanged, preserving optimal solutions.

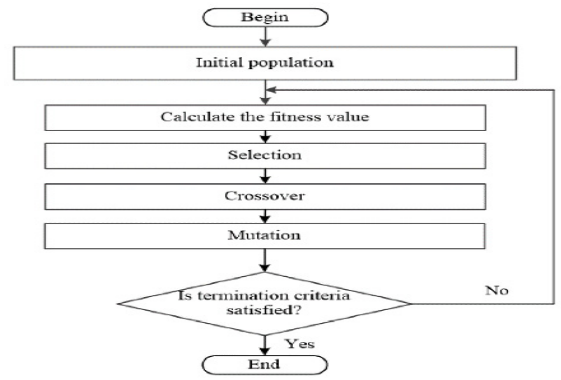

Fig. 4. GA flow chart

4. Results and Discussion

This section presents the outcomes of the research focused on the development of a model (that can potentially be Digital Twin (DT)) for supply chain management. The empirical results highlight the model's potential in enhancing supply chain visibility and efficiency. The 40-day inventory levels displayed in real-time bar charts demonstrate the flexibility of the Digital Twin. These graphic representations provide a glimpse into the complex dynamics of inventory management.

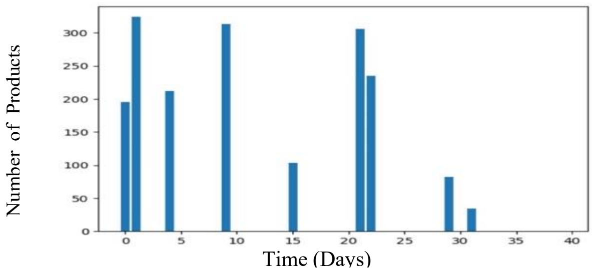

Fig 5. Dynamic inventories

The bar chart shows the products in transit. It provides a thorough understanding of the dynamics of movement throughout the supply chain. Such immediate tracking makes sure that stakeholders are continually informed about the progress of their product, improving operational transparency and assisting in well-informed decision-making.

4.1. Comparative Analysis: With and Without GA

Two different scenarios—one with and one without the Genetic Algorithm (GA) in the event of a disruption—were examined to further highlight the benefits of the integration.

4.1.1. Without Genetic Algorithm

Without the usage of GA, the bar chart depicting merchant inventory levels during a disruption exhibits substantial changes. Periods, where inventory levels fall below the ideal levels, are visible and signal potential missed sales. In this case, the system's reactive response makes it difficult for it to adapt to the supply chain's unforeseen and unexpected changes. For instance, from day 25 to day 29 some of the retailers did not have any inventory as shown in Fig. 6. Also, Fig. 7 shows an increased number of deliveries without the DT utilising the GA algorithm resulting in more cost of delivery.

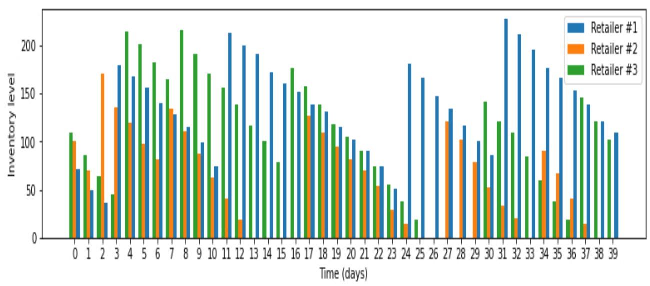

Fig. 6. Inventory levels of retailers without using GA during disruption

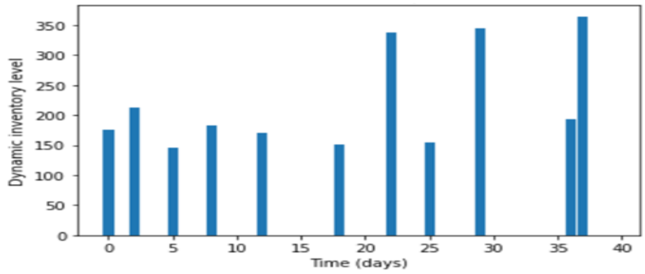

Fig. 7. Dynamic inventory level without using GA algorithm

4.1.2. With Genetic Algorithm

The bar chart showing inventory levels with GA integration, in sharp contrast, reveals a more stable inventory dynamic. The system, directed by the GA, manages to maintain inventory levels that are closer to the ideal thresholds even in the face of disturbances. The GA's proactive changes ensure that there are few lost sales and that the product distribution plan is more effective. As shown in Fig. 8, the inventory levels of the retailer has been improved significantly as compared to Fig. 6 where some days had zero inventory. Also, Fig. 9 shows that fewer deliveries were done as compared to Fig. 7 when the DT did not use the GA, and this resulted in less cost for delivery.

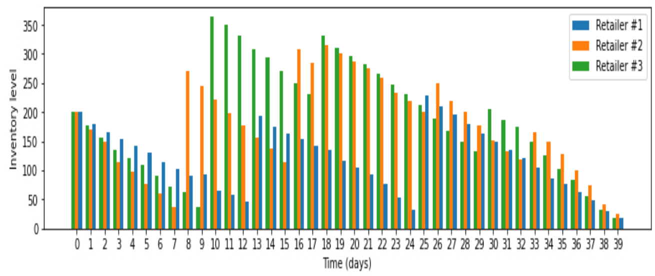

Fig. 8. Inventory levels of retailers with GA during disruption

The comparative analysis underscores the transformative potential of the Genetic Algorithm. By optimizing decision-making during disruptions, the GA not only minimizes operational hiccups but also ensures customer satisfaction by preventing stockouts.

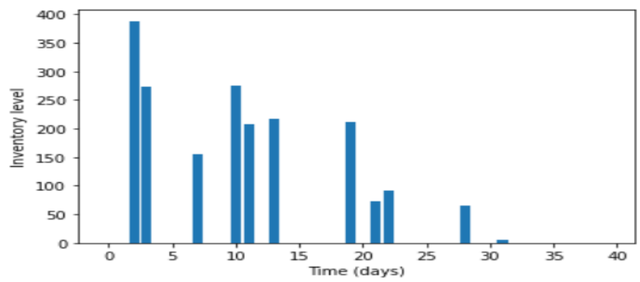

Fig. 9. Dynamic inventory level with GA algorithm

5. Theoretical and practical implication

The theoretical implications of this GA-based Digital Twin (DT) model are significant. The use of the GA enhances the capabilities of the model by efficiently finding solutions to disruptions and optimizing the objective function that includes inventory costs, transportation costs, and fines for unmet demand. This contributes to the theoretical advancement of supply chain optimization and management methodologies. However, there are practical challenges and limitations associated with implementing this GA-based Digital Twin model. Firstly, the integration and management of data from multiple supply chain elements can be complex and require robust data integration and governance frameworks. Secondly, scalability can be a challenge, especially as supply chains grow larger and more intricate. Managing a Digital Twin that accurately represents the entire supply chain while considering diverse behaviours and interactions among elements requires substantial computational resources and expertise. Thirdly, the implementation of the GA algorithm itself can pose challenges. Fine-tuning the algorithm parameters, handling convergence issues, and ensuring the algorithm's effectiveness in finding optimal solutions to disruptions and optimizing the objective function require specialized knowledge and skills in optimization and algorithm design. Finally, there may be organizational barriers such as resistance to change, limited technological infrastructure, and resource constraints that could hinder the successful deployment and adoption of the GA-based Digital Twin model within a real-world supply chain environment.

6. Conclusion and Future Research

This study developed a GA-based DT model to simulate various scenarios and actively manage the supply chain. By using the proposed model, the supply chain's visibility in the face of disruptive events is strengthened. The study's demonstration of the integration of digital twins into supply chain management promises improved operational visibility, agility, and adaptability, representing advancement in the field. Although the existing framework provides a reliable answer for supply chain management, there are several directions for further study. Future research may consider a variety of goals, such as maximizing supplier dependability or reducing transportation costs. while the current paper provides a foundation for understanding our framework, the lack of empirical evidence is a limitation. Further studies should be done to validate the benefits of the framework and address potential obstacles in real supply chain contexts. The accuracy and responsiveness of the Digital Twin can be further improved with the use of real-time data.

CRediT author statement

Shehu Sani & Alireza Zarifnia: Conceptualization, Methodology, Software. **Alireza Zarifnia**: Data curation, Writing- Original draft preparation. **Shehu Sani & Alireza Zarifnia**: Visualization, Investigation. **Konstantinos Salonitis & Jelana Milisavljevic-Syed**: Supervision. **Shehu Sani & Alireza Zarifnia**: Software, Validation. **Shehu Sani & Alireza Zarifnia:** Writing- Reviewing and Editing.

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