Digital Twin in Supply Chain and Logistics

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A digital twin is a virtual representation that replicates a physical object or process over a period of time. These tools directly assist in reducing the manufacturing and supply chain lead time to produce a lean, flexible, and smart production and supply chain setting. Digital twin technology creates relatively close connectivity between both the virtual and physical worlds, allowing you to monitor and command systems and components remotely. Moreover, it is now possible to run simulation models to test and forecast resource and process-related changes in various "what-if" scenarios. Hence, organizations are now getting significant benefits from digital twin technology that assists in mapping and analyzing details related to operations performance, product and service innovation, and shorter on time delivery.

Keywords: digital twin ; data-driven technology ; lean manufacturing ; supply chain 4.0

1. Relationship between Logistics 4.0, Supply Chain 4.0 and Industry 4.0

IR 4.0 has led to the digitization in supply chain and logistics has made way for the evolution of logistics 4.0. Various tools and technological settings from the IR 4.0 have been adopted in the supply chain and logistics setting or environment to leverage the benefits. Digital twin technology offers risk free scenario analysis by developing a predictive and prescriptive decision-making platform for the industry players and it is one of the core technological tools in IR 4.0 [1].

Basically, logistics is the sub-component of supply chain and supply chain is the sub-component of production management. A digitally equipped supply chain platform is the backbone for Industry 4.0 to function. I.R 4.0 tools equip the supply chain and logistics processes such as inbound logistics, warehouse management, intralogistics, outbound logistics and logistics routing, etc. I.R 4.0 based protocols and tools such as Smart data management, Internet of things, cloud computing and Blockchain accelerated the supply chain and logistics processes to greater extent. These create an automated, intelligent and increasingly autonomous flow of assets, goods, materials and information between the point of origin and the point of consumption, and the various points in-between are key. Supply chain logistics processes become more efficient, effective, connected, and agile/flexible in order to meet the needs of market [2][3][1][4].

Logistics 4.0 sounds similar to the concept of I.R 4.0. Instead of referring to the digitalization of industrial sector and processes it refers to the digitization of the physical elements and mobility. Moreover I.R tools have improved the visibility, imparted smart utilities, and adopted IoT in logistics. A state-of-the art logistics 4.0 scenario refers to the condition in which it becomes capable of collaborating and integrating with Industry 4.0 procedures and systems. Logistics 4.0 seems like a lucrative value-added proposition for all the businesses that wish to drift away from the complexities of a global supply chain creating supply chain transparency, automation, and real-time tracking [3][1][4][5].

2. Digitalization of Supply Chain and Logistics

Previous conventional supply chain and logistics processes in the industrial scenario had huge paperwork and manual interference. Recent inclusions such as data warehouse and SAP systems have revolutionized the way in which shop floors, warehouses and logistics entities work [4][6]. The static nature of visualizing a supply chain network needed a dynamic way to view it for better decision making, especially the current and future processes related to supply chain and logistics. It is now slowly possible only through effective digital transformation of the supply chain and logistics. Digital transformation is a key driver for Industry 4.0 that creates digitalized, interconnected, smart supply chain, and logistics [6][7]. In global supply chains, it is obvious that countries and logistics providers need to achieve a competitive advantage in terms of digitalization. However, still more studies should focus on measuring the potential for innovation to improve logistics efficiency [8]. In this context, particularly the term 'Logistics 4.0' receives growing attention, in recent years, which in a way accentuates that logistics as a central function plays an important role within the digital transformation of the manufacturing sector and thus, the underlying Industry 4.0 vision [9]. They are built with data-powered digital systems such as the internet of things, big data, and blockchain platforms with hyperledger [10]. However, the environmental issues in the supply chain should also be taken into account [11].

One such example is the digital learning factory that has been built by the Research Center of Vorarlberg University of Applied Sciences for educating students and employees of industrial partners by devising learning scenarios and courses addressing a wide variety of topics related to Industry 4.0 and showcasing the best practicing platform for digitalization. In addition, novel methods and technologies for digital production adopt cloud-based manufacturing, data analytics, and digital twins.

3. Real-Time Data-Driven Simulation Modelling

Use of historical data is becoming outdated and practitioners are looking for real-time data. Therefore, the demographic data acquisition from different supply chain players or stakeholders can also be utilized to obtain information such as the location of truck routes, distribution centers, retail stores, and individual consumers to understand the logistic systems [12]. These data can be directly fed into the Enterprise Resource Planning (ERP) database and production system database to generate a usable XML visual basic file that can be fed into the simulation software to create a digital twin.

To bolsters this, Goodall et al. (2019), [13] constructed a data-driven simulation model to predict material flow behavior in remanufacturing processes by using data from digital production systems (e.g., databases, traceability systems, process plans) to update and automatically modify simulation constructs to reflect the real world or planned system. The information was gathered through a Radio Frequency Identification (RFID) traceability software platform at the factory. Tannock et al. (2007), [14] applied the same concept in the supply chain of a civil aerospace sector. Qiao and Riddick (2004), [15] used a neutral information representation tool based on the extensible markup language (XML), to acquire information integration and exchange along supply chain applications. Similarly, mass customization in manufacturing and supply chain needs data integrated simulation systems. Qiao et al. (2003), [16] built a neutral model of shop information, based on the XML, to exchange data between simulations and perform analysis according to the demand fluctuations in the shop floor.

The product, product family, and related logistic resources like a truck, carriers, distribution centers, production facilities, warehouses can be presumed to be agents that can help create an agent-based model and replicate the behavioral pattern of the supply chain model. Another tool that can be integrated within a Discrete Event or Agent Based simulation models is the geographical information systems that allow use of the geographical maps with exact coordinates. This is further applied to allot location and routes for distribution centers, suppliers, trucks, etc. Product routing, supply chain optimization, Greenfield analysis can also be done using Geographic Information Systems (GIS) acquired from the logistics route database [17].

Discrete Event Simulations is used to adapt and mimic warehouse operations from the producer’s perspective (Finished Product Des-patch & Product Recall), and a system dynamics model can be integrated to display managerial decision making, consumer behavior, and cost associated with these operations [18]. As a result, an integrated or hybrid modeling technique is utilized to virtually represent the dynamic nature of logistics models in terms of functionality as well as the cost incurred. Hybrid simulation modeling can precisely capture complex behavior and changes in model design. Typically, simulation is a representation of a system that is either going to happen in the future or is already present. As a result, a data-driven decision-support system combined with IoT connectivity will aid in feeding real-time data into a virtual real-time prototype [19]. A centralized SCADA (Supervisory Control and Data Acquisition) system acts as the core data hub [20]. As a result, these tools have enabled simulation modeling to obtain data from real-time data warehouses, resulting in a logistics 4.0 environment. As a result, data-driven simulation modeling generates scenario-based patterns that are employed by machine learning algorithms to instruct the models to react to previously established patterns and ascertained solutions.

4. Applications of Reinforced Learning in Supply Chain and Logistics

According to Meng at al. (2013), [19] there are several methods to set up a data-driven feed to simulation setting. One among them is generating XML visual basic code that can feed in the data required for the software given that the software is capable of receiving it. The inclusion of machine learning to build predictive analysis to enable automated logistics route optimization and decision making are enabled with a series of datasets that are utilized to build a descriptive, predictive, and prescriptive analytics platform with the help of regression/correlation-based supervised machine learning (deep learning) algorithms. This action is further validated to and predict behavioral patterns [21][22].

Logistics 4.0 and its self-perception can transform and strengthen conventional logistics. Logistics has been a central pillar of the supply chain for the industry. Extremely competitive and volatile logistics markets and large logistic networks need new approaches, products, and services. Today’s customer behavior is leading to new strategic problems and opportunities. For that, the idea of the cyber-physical system (CPS), wireless networks, the Internet of Things and Services (IOT&S), Big Data/Data Mining (DM), and cloud computing, etc., seems to be the possible technological answer. Its consequent application ultimately leads to the need to revisit some core principles of conventional logistics [9][23]. To connect end-to-end logistics networks and meet complex manufacturing goals, it is very essential to tap the benefits of elements such as IoT (Internet of Things), digital twin simulation models, advanced robots, big data analytics, and virtual/augmented reality [24].

A logistic system needs to be optimized from both inbound and outbound that is possible by intelligent systems, embedded in software and databases from which relevant information is provided and shared through the Internet of Things (IoT) systems, to achieve a major automation degree by creating a network where all processes can communicate with each other, and enhance analytical potentialities throughout the supply chain. This promotes a significant decision-making standard and reaches top quality and becomes more and more flexible and efficient in the near future [25]. Song et al. (2020), [26] applied simulation integrated reinforced learning to study the percentage increase of ride-sharing in taxi service. They used taxi data from Seoul (South Korea) to determine optimal surge rates for ridesharing services over a specific period. The reinforced learning strategy based on centrality that governs the probability of the drivers' destination decision was used. Furthermore, passenger waiting time mediated the reward function.

Shen and Dai (2017), [27] applied the same principle in the container ship controller systems with neural network technique. Abdelghany et al. (2021), [28] introduced an innovative methodology for developing itinerary choice models (ICM) for air passengers. A reinforcement learning algorithm looks for the values of the itinerary choice model's parameters while maximizing a reward function. The negative difference between the estimated and observed system metrics is used to calculate the reward function.

Furthermore, Cavalcante et al. (2019), [29] proposed a new approach to analyze the risk profiles of supplier performance under uncertainty by combining simulation and machine learning integrated digital supply chain twins. These twins improved resilience by learning and designing risk mitigation strategies in supply chain disruption models, re-designing the supplier base, or judging the most important and risky suppliers. Similarly, more studies should be focused on the development of a state-of-the-art IoT-assisted embedded data-driven gateway that feeds online data to run the prebuild hybrid simulation models or digital twins. All the required parameters/variables to simulate the logistic model's dynamic complexity in real-time will be set up in the model to connect to their respective data and create simulation runs. By knowing the rubrics and dynamics of the logistic model, an optimized real-time value-focused application platform can be suggested for future research. Disruptions and related solutions (rewards) are applied to the models that are further integrated with a reinforced learning algorithm that captures the patterns of disruptions and give solutions to the same disruptions. Human intervention is avoided and artificial intelligence takes over.

This research approach can widen up the scope and give insights in building sophisticated AI-based decision support systems for future logistics 4.0. Various real-time industrial problems in the area of (1) Multi-mode transportation network optimization [30], (2) Truck route network scenario planning and optimization [31], (3) Smart Warehouse Bin Pick and Drop [18], Forklift Route Planning and Throughput, Automated Rack Storage and Retrieval [32], and (4) Multiple Criteria based Smart Conveyor Design [33], etc.

Strategic and resilient simulation models or digital twins appear to be an efficient and cost-effective tool for visualizing problems, proposing solutions, and practicing risk-free testing. They can virtually forecast optimal network design, inventory management methods, supply and distribution systems, logistics (micro and macro), and other associated systems [34][35]. Even though demand-specific uncertainties like work in process time, lead time, supply chain queues, delays, etc., can easily be projected using a digital twin [36], there is a need for perfect real-time data monitoring systems [37]. The manual data feed of historical data following the know-how trend has become old. A stochastic mode of what-if analysis with real-time online data is currently needed to analyze disruptions and measure the resilience of a system [38][39]. To attain this, simulation modelling are integrated with IoT to provide dynamic and virtual supply chains along with traceability and tracking options [40]. IoT-based modelling allows supply chains to use virtualizations to actively assist manufacturers in grappling with perishable products, volatile supply fluctuations, safety, and sustainability specifications. Virtualization allows supply chain members to track, manage, schedule, and automate logistics networks remotely and in real-time over the Internet, focusing mainly on physical reality instead of post-data observation [41][42].

While the latest revolution on digital transformational provides new opportunities. Logistics models are now re-evaluated by data-driven platforms. Extracting insights from operational data assists in predicting uncertainties and reduce inefficiencies in logistics operations by making them more resilient and sustainable [43]. But still, these are again just know-how digital twins at that point in time. However, it is also important to measure their behavioral dynamics when subjected to disruptions. Reinforced machine learning has great potential here to absorb humungous patterns of data and create a prescriptive analysis platform for logistics and build better decision support systems.

5. Applications of Digital Twin in Macro Logistics

Reliable plans to outline the trucks' routes are feasible by flexible and strong data-driven decision-making processes both at the operational level or real-time. IoT devices have the capability to enable this with ease. A simulation-based What-if scenario is generated to simulate, predict, optimize, project, and measure resource performance [44]. Global positioning system (GPS) based IoT devices are capable of collecting a large amount of data that were not fully utilized to optimize reaction times, a stochastic truck traveling speed previously. This data can act as a direct feed to the simulation model to allow risk-free truck route optimization according to the process constraints [45]. Simulation strategies like discrete event simulation have been widely used to design flexible and optimal resources. Previously, Meng at al. (2013), [19] developed a Unified Modelling Language-based formal information model to generate simulation models via pre-built Petri nets to address equipment scheduling issues. In another case, a severe traffic problem related to efficiency in urban ports was addressed by Heilig et al. (2017), [46] with the same method in which an algorithm was developed to build a cloud-based decision platform to consider contextual data, including traffic data and the current positions of trucks allowing ports to utilize potentials of digitalization and optimization issues.

6. Application of Digital Twin Technology in the Warehouse Operations (Micro + Macro Scenario)

It can also be applied extensively in warehouse-based scenarios. The best example is the optimization of automated modular conveyor systems in warehouses facing bottlenecks. The unpredictability and intricate dynamics of the process can be captured by time-based simulation modelling. These models are exposed to various scenarios after verification and validation. In addition, if this is made completely data-driven, a cost-effective approach is given to increase performance. This is the future of a stable standalone system of decision support enabled by dynamic digital twin recreations [47].

To mention a few, Sahay and Ierapetritou (2013), [48] formulated a hybrid simulation modelling approach by combining an iterative model with an agent-based simulation model which can decide toward an optimal allocation of resources subjected to multiple problems and constraints. Industry 4.0 has paved the way for a world where smart factories will automate and upgrade many processes through the use of some of the latest emerging technologies. It can ease the automatable and tedious tasks, like the ones performed on a regular basis for determining the inventory and for preserving item traceability [49][50]. Kim et al. (2020), [51] formulated optimal cut-off and pick-up time in the warehouse as per the customer order responsiveness through priority-based job scheduling using flow-shop models that can assist warehouse managers in decision making. The application of stochastic simulation models for uncertain real-life operational environments contributes to the practical gap and novelty.

To conclude on this case, a real-time industrial warehouse problem can be addressed, or a prototype warehouse bin pick up and storage system in the logistics 4.0 lab that is included with few modifications along with problem definitions and solutions. The insights from the study conducted by Fragapane et al. (2019), [52] provided directions in terms of the research objective and also use the process parameters that were used in the statistical model. These methods can tackle many distribution warehouse issues without the restrictions of traditional tools. Hybrid Smart Simulation can abstract distributed autonomous entities that can interact with each other and their environment through space and time, allowing to capture a lot of resource relation attributes such as work time allocation of resources, automated guided vehicle (AGV) work scheduling, congestion (buffer) wait time, process/cycle times, Forklift throughput, worker and machine speeds, resource block behavior, Bin or Rack Storage, Designing Artificial Storage and Retrieval System, etc.

Moreover, a hybrid modelling approach can also be adopted to virtually visualize the dynamic nature of the system or logistics model covering all the functionalities. Complex behavior and changes in model design shall be precisely captured by hybrid simulation modelling. Usually, simulation is a display of a system that is either going to happen in the future or that is already there. So, a data-driven decision support system + IoT integration gateway module will be installed here in feeding real-time data to obtain a virtual real-time prototype. Later, these data patterns are utilized to build a predictive analytics platform with the help of reinforced/supervised machine learning algorithm. A real case logistics system from the industry shall be first recorded and tabulated for primary data taking either Case A or B systems into account.

For example, the product, product family, and logistic resources like a truck, carriers, AGVs, and Conveyors, etc., are presumed to be agents to replicate the behavioral pattern of the system under study. IoT devices assist in obtaining real-time data by directly retrieving data from the resource blocks mentioned above to the embedded cloud server. If not, it can also be retrieved from the Enterprise Resource Planning (ERP) database and production system database to generate a usable XML visual basic or CSV file that are fed into the simulation software. However, the latter has technological constraints if the host firm does not have this setup.

The geographic information system feature in the simulation modelling software shall assist in planning the optimal positioning of the distribution centers, transport routing, milk runs, product routing, and supply chain optimization. After the completion of an empirically verified digital twin, the parameters for disruptions and respective solutions shall be included in the models to analyze different scenario patterns. These patterns are separately retrieved to build Reinforced Learning Algorithms that help create a prescriptive analytic platform that acts as a stepping stone for logistics 4.0 decision support systems.

There are several methods to set up a data-driven feed to simulation software. One among them is generating XML visual basic code that can feed in the data required for the software given that the software is capable of receiving it [19]. Therefore, the series of datasets are utilized to build a descriptive, predictive, and prescriptive analytics platform with the help of regression/correlation-based supervised machine learning (deep learning) algorithms.

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