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Digital Twins for Decision Making in Supply Chains

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Abstract This paper studies utilization of digital twins (DTs) as a decision support tool in supply chains (SCs) by providing a framework. DT is an emerging technology-based modelling approach reflecting virtual representation of an object or system that can help organizations monitor operations, perform predictive analytics, and improve their processes. For instance, it may provide a digital replica of operations in a factory, communications network, or the flow of goods through a SC system. In this paper, by focusing on SC systems, we explore the critical decisions in SCs and their related data to track, to make right decisions within DTs. We introduce six main functions in SCs and define frequent decisions that can be taken under those functions. After defining the required decisions, we also identify which data/information would help to make correct decisions within those DTs.

Keywords • Digital Twin • supply chain • decision problems • decision support

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Introduction

Decision making is a process of choosing one alternative from a set of alternatives to achieve a desired goal. This process requires *(i)* identification of alternatives, and *(ii)* evaluation of level of satisfaction of needs by each alternative, which comprises the sequential activities of model building, data collection, analysis, and interpretation of analysis outcomes (Harris, 1980). Decision support tools ensure this process to be systematic and replicable.

In this study, our focus is on decision problems in SCs. In recent years, the most frequently confronted decision problems are related with disruptions in SCs. For instance, by the recent COVID-19 outbreak, serious disruptions took place in SCs in many countries. Hence, SC managers have started to question their SC management styles by the results of those disruptions (Alicke et al., 2021). While for years companies have focused on eliminating redundancy in sourcing to reduce costs and increase efficiency, the recent global pandemic has changed that sole perspective, and the importance of the resilient SC designs has become one of the significant focus topics. According to a survey by McKinsey and Company's which is employed for senior SC executives from across of industries and geographies, 93% of respondents declared that they intended to make their SCs far more flexible, agile, and resilient (Alicke et al., 2021). Another survey by Barclays (2021) which is applied for 700 US manufacturing professionals shows that 25% of professionals had to change their supply chains in response to the pandemic. A report from UK's Business Insights and Conditions Survey (BICS) shows that wholesale, retail, and manufacturing industries would like to rethink their SC management to overcome the bottlenecks they encountered during the global pandemic and the EU Brexit (Office for National Statistics, 2022).

According to a Statista's report (Buchholz, K., 2021), SC disruptions tend to increase again after the crisis in pandemics, especially in Europe and US. Due to those uncertainties and challenges in SCs, which are new in many aspects, it is well understood that past experiences cannot be relied upon to generate solutions. Hence, the big question is, how all those uncertainties and complex SC problems can be handled, particularly in terms of design, planning and execution in the network.

A SC Digital Twin (DT) might be a solution for those challenges which is a versatile tool with extensive implementation potential in wide range of decision-making problems. DT is a virtual replica of an object or system to help organizations to monitor operations, perform predictive analytics, and improve processes. While it could be a digital replica of operations in a factory, communications network, or the flow of goods through a supply chain system, it could also be a replica of a physical object such as an airplane, a space craft, or a wind turbine, etc. A DT consists of three main components: an actual system, a detailed simulation model of that system (virtual system) and a data link in between (Jones et al., 2020).

Recent developments in the areas of internet of things (IoT), big data, artificial intelligence (AI), cloud computing technologies have enabled effective realization of DTs for systems of concern. According to Gartner's Emerging Technologies and

Trends Impact Radar 2022, DT technology will have a high impact on existing products and markets in 1-3 years (Gartner Insights, 2021). SC systems can also benefit from DTs capabilities in many ways. According to DHL Logistics Trend Radar given in Figure 1, it is foreseen that DT would be one of the emerging approaches within 5-10 years for Logistics systems (DHL Insights, 2022).

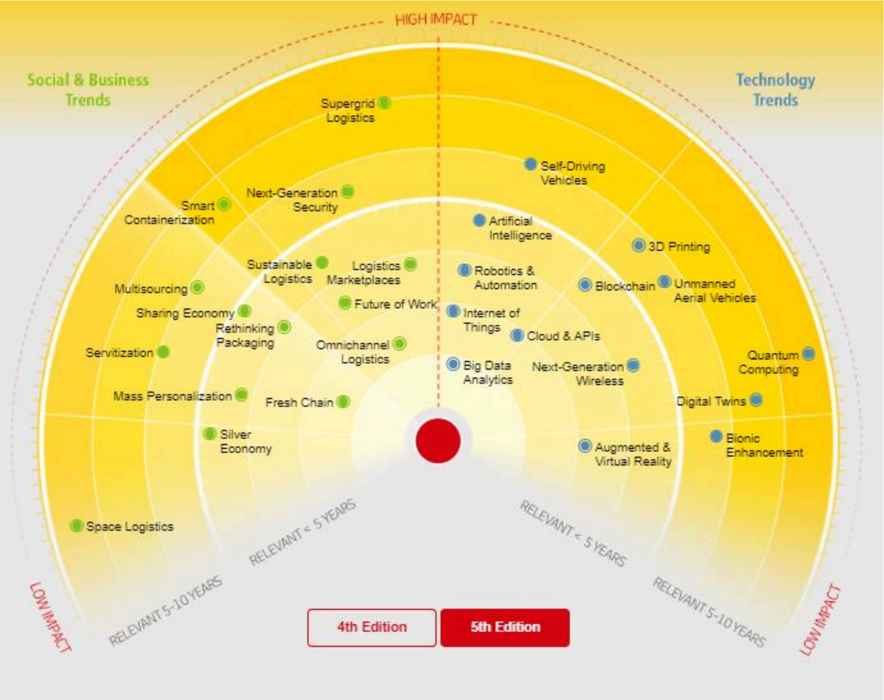

Fig. 1. DHL Logistics Trend Radar (source: DHL Insights, 2022)

DT can provide advantage for SCs by creating value in the following dimensions (Moshood et al. 2021):

Descriptive Value: Due to real time data flow from physical system, DT may provide immediate and real-time visualization of the system of concern. Thus, real-time state of the SC system can be monitored, which provides visibility.

Analytical and Predictive Value: DT paves the way for conducting an enhanced what-if analysis on the simulation model, which might not be reasonable to apply directly on the real system. This capability can be utilized efficiently in complex problem solving and optimization purposes.

Diagnostic Value: DT can process excessive data in SC systems. By applying big data analytics and machine learning algorithms embedded in DT, hidden patterns, complex relationships, and abnormalities can be identified.

In this paper, by considering the values above, we investigate how DTs could be utilized as a decision support tool for different decision-making processes in SCs. Accordingly, the main research question of the work can be summarized to be:

RQ: How do SC systems benefit from DT as a decision support tool?

The rest of this work is organized as follows. In Section 2, we outline different categories based-on decision problems in SCs. Then, we discuss the contribution of DTs on those decision problems in Section 3. Finally, we conclude the work in Section 4.

Decision-Making in Supply Chains

Decisions in SC systems can be grouped in three categories based on their period and impact level on systems. These categories are strategic, tactical, and operational (Ravindran, 2016).

Strategic decisions are mainly related with the design of SC systems. They are usually considered for long time periods (e.g., for several years) and, as a result they are subject to high level of uncertainty. Strategic decisions generally have greater impact on systems and require more resources than other decision types. Examples of strategic decisions for SCs are the number and locations of plants and warehouses, choice of suppliers and other partners.

Tactical decisions are made for a time horizon of moderate length (e.g., generally monthly, or quarterly decisions) and are subject to less uncertainty relative to strategic decisions. Examples of tactical decisions for SCs are production planning decisions (e.g., how much to produce and when?), transportation mode selection decisions, etc.

Operational decisions are short-term decisions (e.g., generally made on a daily/weekly basis). They involve lower expenditure of funds and lower level of uncertainty. Weekly or daily production schedule decisions, setting due dates for customer orders are examples of operational level decisions in SCs.

The decision-making needs of organizations mostly depend on their organizational structures. In this study, we consider functional organizational structure and its decision levels to classify decision processes of SCs. We consider the following functional areas while defining the possible decision mechanisms within DTs:

- Planning
- Procurement
- Manufacturing
- Inventory
- Warehousing and Material Handling
- Transportation

We identify different decision problems that might contribute to efficiency of SCs. We consider an already established SC system, where we ignore decision problems such as initial number of plants and their locations in this study. In decision making within DTs, data tracking is the most important process for a correct decision making. Therefore, DTs are typically built on data-driven decision-making process structure (Provost et al., 2013; Ivanov et al., 2021). By tracking those data and correctly embedding the related intelligent decision-making algorithms in DTs, those decisions can be taken effectively. In this paper, along with the critical decisions in SCs, we provide a list of data types which could help for taking those decisions. Note that, data that has fixed structure (e.g., warehouse dimensions, etc.) are not taken into consideration.

By the help of recent technological developments such as embedded sensors, RFID, and Industry 4.0 technologies, it is possible to track real time data through end-to-end SCs. Consequently, DT enables real-time monitoring of the systems. High fidelity models in DT enables through analysis of problems. Recent developments in big data analytics and machine learning techniques add more power to DT's capabilities. By the help of these capabilities, hidden patterns, correlations, and abnormalities can be explored. As a result, data tracking capability and possession of high-fidelity capable models make DT a powerful decision support tool. DT can track the past, monitor, and conduct analysis for the present, predict the future of systems in concern. Establishing decision making frameworks with relevant data tracking in DT, facilitates solutions of decision problems for SCs. All those decision-making frameworks along with the required data to track within the DT are summarized in Figure 2. The details of Figure 2 layers are discussed in below sub-titles. In those sub-titles we also discuss on why those decisions are considered as well as what the challenges and required data tracking processes are.

Planning

An important tactical level problem in planning is to decide the amount and timing of production. Demand forecasting is the starting point of production planning efforts. It requires accurate data about demand and analysis of the data with appropriate models. Hence, this effort is challenging due to its nature. Recent COVID-19 pandemic and continuing global crisis have increased uncertainties in every stage of SCs (Association for Supply Chain Management, 2021). Consequently, demand forecasting has become a challenging task. Similar circumstances are also valid for customer requirements which tend to be highly stochastic during disruptions. Another challenge in this decision area is to predict availability of transportation lines, because of unpredicted congestions in ports/airports and fuel shortages. Moreover, wide-scale shortages of critical basic materials are still an ongoing issue due to the latest disruptions. Thus, forecasting the availability of materials becomes another challenging point in planning of SCs.

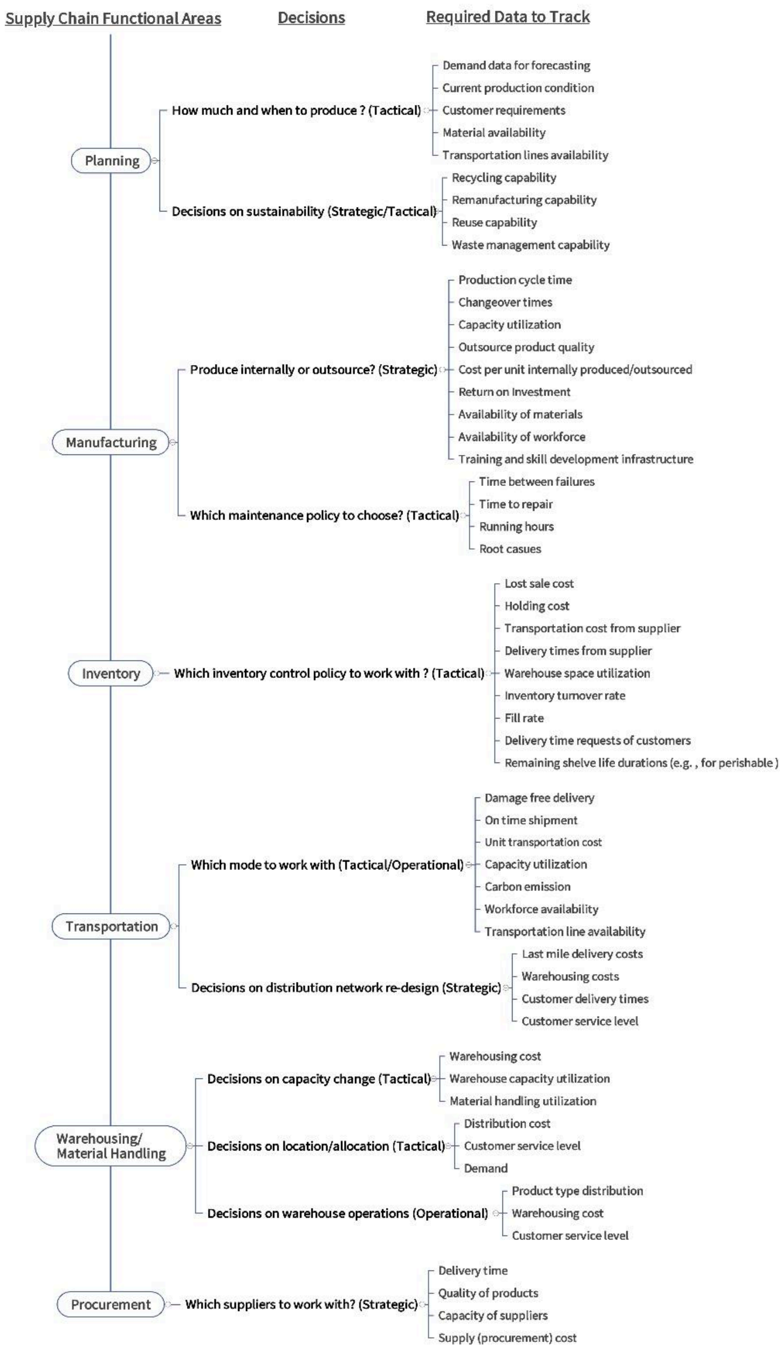

Fig. 2. Supply Chain Decision Problems and Data Requirements

Decisions on planning for sustainability requires identifying recycling/remanufacturing/reusing and waste management capabilities of the system. This identification process requires real-time system state data. Also, solution to this decision problem necessitates experimenting with different capability levels and observing system behaviors. Therefore, a data collection tool and a detailed representation of system behavior would be vital for this decision process.

Manufacturing

The main manufacturing decision is to choose between inhouse manufacturing or outsourcing. As discussed earlier, supply chain disruptions have been among the biggest challenges for manufacturing especially during COVID-19 pandemic. As a result, shortages of critical basic materials and skilled labor create bottlenecks in manufacturing. One reason for the skilled labor shortage is aging population. Senior workers are retiring, and their knowledge and experience leave with them. Difficulty in employee retention is other reason of labor shortage (Khan et al., 2016). Thus, training and skill development capability of SC system is becoming an important issue to overcome this challenge.

Other data requirements such as production cycle time, changeover times, capacity utilization, which are listed in Figure 2 are also vital for a data-driven decision process. Another challenge is deciding on maintenance policies for shop floor, which have potential to improve capacity utilization, production cycle time and reduce production costs. This challenge necessitates real-time state data collection from shop floor and algorithms to generate maintenance policies.

Inventory

Inventory control policy selection is a prominent strategic level decision for SC systems. This decision problem requires data such as inventory turnover rate, fill rate, lead times, customer requirements, warehouse space utilization which are listed in Figure 2. Limited visibility of inventory may result with insufficient customer satisfaction and increased inventory cost management. Improving end to end visibility in SCs can be realized by accession to necessary data (Moshood et al., 2021). Then, the real time data collection from SCs could be achieved for the solution of decision problems of concern. Uncertainties in transportation costs and customer delivery requests are some of other challenges to deal with in inventory related decisions, effectively.

Transportation

Distribution mode selection and distribution network re-design decisions are other set of decision problems considered under transportation problems (Engebrethsen et al., 2019; Yadav et al., 2022). Mode selection is a decision problem in choosing the best option, among the possible transportation methods (air, land, water, pipeline, cable, space, etc.). Transportation cost has a large share in total cost of SCs. Hence, those modes can be changed dynamically in SC operations. Development of data-driven transportation algorithms taking into consideration, real-time transportation prices, customer expectations, delivery time requests, carbon emission amounts, etc. would be critical in this step.

Decision-making on distribution network re-design may be required when inefficiencies in the current distribution network are detected. This might be understood by tracking of transportation cost related data such as last mile delivery costs, unit transportation costs, etc. as well as delivery related data such as delivery times from suppliers, damage free delivery, on time shipment, capacity utilization of vehicles, etc. In addition, environmental concerns and regulations may necessitate tracing of carbon emission of assets (Chen et al., 2016). By accomplishing an end-to-end visibility in SC systems, accessibility and visibility to all those transportation related data could be realized.

Warehousing/ Material Handling

Decisions on warehousing capacity, location/allocation of supplier/demand changes, and decisions on warehouse operations are considered under the warehousing and material handling topic. Those decisions would require real-time data tracking of: distribution and warehousing costs, warehouse capacities and their utilizations, material handling devices utilizations, demand distribution as well as current customer service expectations, etc. Again, accomplishing an end-to-end visibility would provide accessibility to those data.

Decisions on warehouse operations would require product type distribution, warehousing cost, and customer service-related data. Warehouses generally have operations for receiving, put-away, storage, picking, sorting, packing, and shipping. Because of increased e-commerce usage, many warehouses involve in extensive return operations as well. Picking is the most-costly operation in warehouses (Kembro et al., 2018). Product type distribution, warehousing cost and customer service level might be the possible data requirements for that decision problem. Real time data tracking from SC system enables a detailed analysis over those operations. Thus, the main challenge for this problem is to construct visibility over the system.

Procurement

A leading strategical level decision problem in procurement area is to choose which supplier/suppliers to work with. That decision would also play significant contribution on SC resilience to alter disruptions. For instance, by predicting a possible disruption, a new supplier selection policy can be applied. Hence, it starts with identifying the right supplier, then continues with keeping track of the supplier performance which in return yields continual supplier management (Zimmer et al.,2016). This decision problem requires data about suppliers (e.g., delivery times, quality of products delivered, capacity and cost). Limited visibility on procurement process makes it challenging for companies to make decisions about their purchases and suppliers. Thus, lack of visibility through SC system is an important issue to overcome in the procurement subject. Establishing visibility in SC system provides easy access to information on delivery times of suppliers, quality of products delivered and cost information.

DT for Decision Making Framework in SC Systems

By the help of DT, enterprises can access real-time data and information about internal and external processes, easily. It has been observed that organizations having business models involving real-time data monitoring, regular risk review and incident management strategies implemented before COVID-19 pandemic experienced less chronic disruptions in their SCs during pandemic (Association for Supply Chain Management, 2021).

End-to-end visibility of the SCs guarantees collection of high-quality data from real system. Thus, the data requirements that are listed in Figure 2 would become critical in increasing capabilities of DT. Then, current, and historical data can be used for decision problems defined in each functional area.

By the analytical abilities of DTs, different scenarios of actions can be experimented for the SC system. For instance, various levels of shortages (e.g., material, workforce, energy, etc.) can be examined with respective impacts on SC systems to forecast future actions. Likewise, decision problems on sustainability, transportation mode selection, warehouse layout, maintenance policies for shop floor can also be considered in decisions by experimenting on different cases. Due to its high-fidelity simulation model, DT also enables analysis on different resolution levels of SC systems. This ability eliminates requirements for multiple models required for different resolution decision problems.

Due to skilled labor shortages, training, and skill development capability in SCs become a critical issue. Also, this capability is important for work safety purposes. Detailed simulation model by DT can also be used for training, skill development purposes and work safety training.

By the help of DT big data analytics capabilities, hidden patterns, complex relationships, and abnormalities can be identified. This capability may provide early warnings for the disruptions ahead. Then, SC system can take necessary precautions in advance. Also, for decision problems like selection of maintenance policies in manufacturing and material handling areas, diagnostic capabilities of DT provide necessary inputs to SC system.

As a result, DT with its data-tracking and analysis capabilities, can provide significant decision support for SC systems in different levels and functions.

Conclusion

In this study, we investigate how DTs can be utilized as decision support tool for different decision-making processes in SCs. To facilitate efficient decision processes in SCs, we present a decision-making framework with relevant decisions and data to track within DT. Functional organizational structure of enterprises and decision levels as strategic, tactical, and operational are proposed to define different decision problems in SCs. Then, data requirements for solving those problems are listed in Figure 2. We discuss detailed data tracking capability and possession of high-fidelity, as well as highly capable models of DTs, while creating a powerful decision support tool in SCs. We also discuss the recent technological and IT developments which makes it possible to realize DTs in SCs by integrating intelligent decision algorithms aiming to reduce the impacts of disruptions. As a future work, we intend to apply this framework for a real case industry SC.

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