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Expanding the Scope of Manufacturing Digital Twins to Supply Chain

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Abstract. The rapid emergence of digital technologies is revolutionising the manufacturing industry, with digital twins (DTs) emerging as a transformative innovation. DTs, virtual counterparts of physical entities or systems, hold immense potential for optimizing and overseeing manufacturing processes. By proposing a three-dimensional classification framework that considers DT integration levels, supply chain (SC) structural hierarchies, and SC processes, this study examines the evolution of manufacturing DTs to encompass the SC. An analysis of existing literature reveals a significant gap in extending manufacturing DTs to the SC system level without incorporating structural and process aspects of DT models. The paper also investigates the key performance objectives, including efficiency, resilience, and sustainability, as well as the challenges associated with DT implementation. The insights provided in this paper contribute to a better understanding and practical application of DTs in the dynamic contexts of manufacturing and the SC.

Keywords. Digital twins, manufacturing systems, supply chain process, supply chain structure, sustainability, resilience.

1. Introduction

The rise of Industry 4.0 has brought about a significant digital transformation in manufacturing processes. Digital twins (DTs) play a crucial role in driving this transformation, consisting of a physical object or system, a virtual replica, and the connecting data [1]. DTs enable an interactive and dynamic relationship between the physical and virtual entities, emphasizing real-time bidirectional data flow. DTs a viable solution across a multitude of sectors, including manufacturing, aviation, healthcare, maritime and shipping, urban management, and aerospace and power plant management.

Implementing DTs is a complex undertaking that necessitates interactions among humans, technology, and processes [2], as the modelling process, which incorporates personnel, equipment, materials, and the environment, is dynamic and subject to evolution over time [3]. Applying DTs is not straightforward. It involves interaction among humans, technology, and processes [2]. The modelling process, which includes elements such as personnel, equipment, materials, and environment [3], is not static and changes over time. The structure of SC is multi-scale in nature, and the interconnections among the SC entities are not simply linear and may involve return processes. The direction, type and volume of SC flows are dynamic and human-related, further complicating analysis. These factors highlight the potential value of a framework to guide the design and implementation of DTs across SC hierarchy. These factors indicate

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the necessity for a framework to guide DT design in SC hierarchies. The potential of DT to sustainability lies in its ability to handle a wide scope beyond efficiency, offering scalability for system-level enhancements.

Therefore, this paper delves deeper into the exploration of the multifaceted nature of DTs within multi-level and multi-scale manufacturing systems. We start by reviewing the evolution of DTs and their deployment in manufacturing systems, while considering DT integration levels, SC structural hierarchy, and SC processes. Following this, we discuss the performance objectives in use and identify the challenges and prospects associated with implementing DTs in manufacturing systems. There is a particular emphasis on sustainability and resilience in the paper, motivated by the scarcity of literature in this space.

2. Scaling up manufacturing DTs to SC system level

DTs can facilitate the interaction at components or parts, products or service, machine, processes, and the system integration in SC systems. DTs can be viewed from multiple perspectives, such as hierarchical level, life-cycle phase, functional use, the maturity level and data flow of DTs [4]. Based on the data integration levels, DTs can be categorised into three groups [4]: (1) digital model, with no automated data exchange; (2) digital shadow, allowing one-way data flow from physical to digital entities; and (3) digital twin, enabling bidirectional data flow between physical and digital entities. Our use of the term "DT" specifically refers to the two-way flow of data between virtual models and physical objects.

Current studies focus more on DT implementation at machine, product, or shop floor level [5], where the integration of multiscale nature of SC system is considered less [6]. However, a big picture of smart manufacturing and I4.0 requires the scope of DT application to be expanded beyond the boundary of manufacturing systems but with the inclusion of business partnership in the context of SC. Therefore, our study emphasises the analysis of DT implementation in manufacturing systems by prioritising the examination of SC processes and structural hierarchy (see **Figure 1**), which implies the supplier and customer relationship management and the complexity of SC systems.

Given the complexity of interconnected SC entities, this study defines a SC as a network of sub-systems that evolve over time into new SC structures. The complexity and evolution of these structures depict how SCs deliver products or service and generate desired performance. The DT-enabled SC system can be considered as a complex and dynamic Cyber-Physical system (CPS), where the DT synchronisation across SC hierarchy can achieve high-level interoperability [6]. Understanding the spatial-temporal dynamics of SC structures and processes, DTs can be implemented at the SC system level to simulate, analyse, predict, monitor, and optimise SC behaviours [7].

We consider four basic structural hierarchy levels in SC systems [8]: (1) SC block, representing a specific business function; (2) SC module, a collection of blocks that fulfil a particular business function and may involve geographic changes; (3) SC member, referring to firm-level operators comprising one or more modules; and (4) SC system, which represents the interconnected network of SC members.

Extending from product life cycle, our study considers SC system and utilises the Supply Chain Operation Reference (SCOR) model as a basis for investigating DT implementation, spanning entire SC. The SCOR model identifies six primary processes: plan, source, make, deliver, return, and enable (Council, 2017). These processes are designed to prioritise cross-functional operations and coordinate flows of materials, products, and potentially energy, water, and other resources within the SC [8, 10]. Across the SC structural hierarchy, SC processes manifest at different scales and scopes within operational units or "blocks" through the entire SC to deliver the products and service. By integrating DTs of these processes, organisations can enhance their operational efficiency and achieve a seamless coordination of various functions involved in the SC.

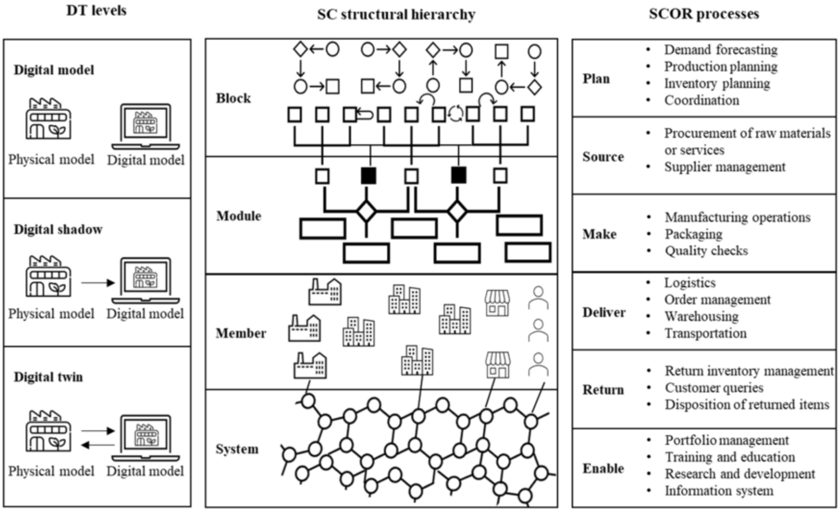

Figure 1. Dimensions of DTs in manufacturing and SC systems

3. Implementation of DTs in SC context

The scalability of implementing DTs in manufacturing systems to encompass the SC level plays a pivotal role in the umbrella concepts of smart manufacturing and Industry 4.0 [11, 12]. This emphasises the significance of extending the application of DTs beyond individual manufacturing units to achieve a holistic and interconnected approach throughout the entire SC.

In extant studies, DT technology has been employed across various industries, infusing technical functionalities into product design, flow shop design, scheduling, planning, assembly, logistics, and more [13]. However, clusters of DTs applications tend to operate in isolation, focusing on the application scenarios (e.g., job-shop scheduling, smart manufacturing, virtualising manufacturing system, product assembly process, alternative manufacturing), enabling technologies and techniques (e.g., information models) [14], and functionalities (e.g., information management, data analysis, manufacturing operation management) [15, 16]. Yet, these propositions often focus on individual process such as logistics planning ("plan") [17] and manufacturing production ("make") [6, 18], rather than holistic solutions that interconnects complex SC processes. In general, "plan" (e.g., job-shop scheduling), "make" (e.g., micromachining), and "enable" (e.g., optimisation techniques) are the dominant SCOR processes investigated.

Literature indicates a scarcity in system-level applications of DTs in SC context, neglecting SC complexity in structural hierarchy. The focused areas of DT application are generally based on the individual SC structural levels in "blocks" (e.g., machine tools, turbomachinery, rotating machinery fault diagnosis) [19–21], "modules" (e.g., logistics and assembly) [18, 22], and "members" (e.g., the manufacturer) [11, 20]. For instance, Bao et al.[22] examined the ontology of assembly workshops ("modules"), focusing on simulating assembly resources and tasks but without addressing the embeddedness of assembly "blocks" or extend to the SC level ("systems"). Similarly, Park et al.[17] introduced a DT information model that encompasses the entire manufacturing abstraction, focusing on the "members" level of application but without connections with SC partners and the embeddedness of SC structural hierarchy.

Existing research on DTs in SC context suggests their potential for SC-level integration with systematic thinking but lacks enabling methods and techniques for achieving bidirectional data integration across multiscale SC structures and processes. For instance, Ivanov et al.[7] introduced the concept of data-driven, cyber-physical SCs without proposing a technical pathway. Serrano-Ruiz, Mula and Poler highlighted DTs as an enabler for SC resilience and sustainability within the I4.0 framework but did not emphasise model fusion across multiple levels and scales. While Aheleroff et al.[2] proposed architectural models for DT application, but lacked clear representation of elements and scopes of the system development lifecycle dimension (referring to SC system in this study). In general, these propositions of DT models overlook comprehensive multiscale integration of SC structures and processes and underemphasise DT design for desired performance (e.g., resilience and sustainability).

4. Performance objectives of DT-enabled manufacturing and SC systems

DTs in manufacturing and SCs can strategically align with key performance (e.g., sustainability development and system resilience) [13]. Efficiency, resilience, and sustainability emerge as major objectives of DT application, especially in the agri-food SC context [23]. However, the lack of comprehensive modelling supporting these metrics limits the scope and depth of performance objectives.

The integration of DTs helps to manage disruption risks and fosters SC resilience [7, 24]. DTs enhance resilience by improving asset management, maintenance, and mitigating equipment failures and production disruptions. The use of what-if scenario analysis through DTs aids in SC coordination and enables proactive and predictive management in the face of SC challenges such as bullwhip effects, ripple effects, and disruptions [7]. Resilience, measured in terms of recovery speed or the magnitude of loss from financial or operational perspectives, reflects SC business aspects rather than specific DT attributes. The literature lacks a universal resilience framework of DTs that can be implemented across SC structure hierarchy and processes in different industries. Therefore, there is a gap in quantifying resilience enhancement to validate the superiority of DT-enabled manufacturing systems.

DTs significantly contribute to sustainability in smart manufacturing, enabling real-time monitoring, predictive maintenance, and dynamic simulations that reduce waste and resource consumption [25]. By promoting collaboration and transparent lifecycle management, DTs support eco-friendly practices, carbon emission reduction, and the attainment of Sustainable Development Goals (SDGs) [26]. However, capturing the sustainability benefits of DTs poses challenges due to limited integration of sustainability into DT models, lack of empirical evidence, and the absence of a universal sustainability measurement framework. This hampers the simulation of sustainability practices across different scales and scopes, making it difficult to align sustainability measures with complex structural hierarchy and processes.

5. Challenges of DT implementation in manufacturing and SC systems

Despite the potential benefits of DTs in manufacturing systems, their successful implementation presents challenges. Firstly, data quality and management are critical. DTs depend on accurate, comprehensive data, but uncertainties in manufacturing make data collection difficult [18]. High-quality data necessitates appropriate sensors and data management practices. While technologies like IoT have eased data collection, real-time data accessibility remains challenging in industrial practices. Secondly, designing and measuring resilience attributes for DTs is complex. Manufacturing systems and SCs are dynamic and susceptible to disruptions, and resilience attributes must account for this variability. To ensure consistency across industries, a generic framework is needed, yet developing this framework is complicated by issues with data availability and accuracy. Thirdly, sustainability considerations are vital for achieving SDGs. Although ISO standards for DTs exist, there are no standard guidelines for incorporating sustainability into DTs consistently, limiting performance measurement, especially at SC scale. Complexities of sustainability dimensions, evolving goals, regulations, and data availability challenges add further complications. Finally, DT implementation involves organizational changes, requiring new skills and continuous adaptation of organisational structures [27]. These dynamic alterations necessitate comprehensive change management strategies and a learning-oriented culture to ensure smooth transitions and effective navigation of this transformative journey.

6. Conclusions

DTs have significant potential for Industry 4.0, highlighting the importance of system integration. While recent advancements focus on SC level frameworks, systematic integration with SC structural hierarchy and processes is still lacking. The recognition of KPIs for DT implementation, particularly resilience and sustainability, is increasing. However, developing a standard assessment framework remains challenging due to the complex nature of SC and DTs. Data quality, management, and organizational changes present additional challenges. Nevertheless, DTs hold promise in transforming manufacturing, driving innovation, enhancing competitiveness, and promoting sustainable smart manufacturing and SC systems aligned with SDG principles.

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References

[1] Tao, F., Xiao, B., Qi, Q., Cheng, J., Ji, P., Digital twin modeling. J. Manuf. Syst. (2022).

[2] Aheleroff, S., Xu, X., Zhong, R.Y., Lu, Y., Digital Twin as a Service (DTaaS) in Industry 4.0: An Architecture Reference Model. Adv. Eng. Inform. (2021).

[3] Zhuang, C., Tian, M., Liu, J., Hui, X., The connotation of digital twin, and the construction and application method of shop-floor digital twin. Robot. Comput.-Integr. Manuf. (2021).

[4] Kritzinger, W., Kritzinger, W., Karner, M., Traar, G., Henjes, J., Sihn, W., Digital Twin in manufacturing: A categorical literature review and classification. IFAC-Pap. (2018).

[5] Zhang, H., Qi, Q., Tao, F., A multi-scale modeling method for digital twin shop-floor. J. Manuf. Syst. (2022).

[6] Park, K.T., Son, Y.H., Noh, S.D., The architectural framework of a cyber physical logistics system for digital-twin-based supply chain control. Int. J. Prod. Res. (2020).

[7] Ivanov, D., Dolgui, A., Das, A., Sokolov, B., Digital Supply Chain Twins: Managing the Ripple Effect, Resilience, and Disruption Risks by Data-Driven Optimization, Simulation, and Visibility. Handb. Ripple Eff. Supply Chain. (2019).

[8] Zhang, J., Zhang, J., Brintrup, A., Calinescu, A., Kosasih, E.E., Sharma, A., Sharma, A., Supply Chain Digital Twin Framework Design: An Approach of Supply Chain Operations Reference Model and System of Systems. (2021), from https://doi.org/10.48550/arXiv.2107.09485.

[9] Council, S.C., Supply chain operations reference model. Overv. SCOR Version. 12(0), (2017).

[10] Ivanov, D., Sokolov, B., Kaeschel, J., A multi-structural framework for adaptive supply chain planning and operations control with structure dynamics considerations. Eur. J. Oper. Res. (2010).

[11] Jiang, P., Leng, J., Leng, J., Wang, D., Shen, W., Pan, Q.-K., Li, X., Li, X., Liu, Q., Liu, Q., Chen, X., Chen, X., Digital twins-based smart manufacturing system design in Industry 4.0: A review. J. Manuf. Syst. (2021).

[12] Kokkonen, K., Hannola, L., Rantala, T., Ukko, J., Saunila, M., Rantala, T., Preconditions and benefits of digital twin-based business ecosystems in manufacturing. Int. J. Comput. Integr. Manuf. (2022).

[13] Bhandal, R., Meriton, R., Kavanagh, R.E., Brown, A., The application of digital twin technology in operations and supply chain management: a bibliometric review. Supply Chain Manag. (2022).

[14] Aivaliotis, P., Georgoulias, K., Arkouli, Z., Makris, S., Methodology for enabling Digital Twin using advanced physics-based modelling in predictive maintenance. Procedia CIRP. (2019).

[15] Dai, S., Zhao, G., Yu, Y., Zheng, P., Bao, Q., Wang, W., Wang, W., Wang, W., Ontology-based information modeling method for digital twin creation of as-fabricated machining parts. Robot. Comput.-Integr. Manuf. (2021).

[16] Zhang, H., Yan, Q., Wen, Z., Information modeling for cyber-physical production system based on digital twin and AutomationML. Int. J. Adv. Manuf. Technol. (2020).

[17] Park, K.T., Lee, J.-H., Kim, H.J., Kim, H.-J., Kim, H., Noh, S.D., Digital twin-based cyber physical production system architectural framework for personalized production. Int. J. Adv. Manuf. Technol. (2020).

[18] Stavropoulos, P., Papacharalampopoulos, A., Sabatakakis, K., Mourtzis, D., Metamodelling of Manufacturing Processes and Automation Workflows towards Designing and Operating Digital Twins. Appl. Sci. 13, 1945 (2023).

[19] Ghosh, A.K., Ullah, A.M.M.S., Ullah, A.S., Teti, R., Kubo, A., Developing sensor signal-based digital twins for intelligent machine tools. J. Ind. Inf. Integr. (2021).

[20] Wang, J., Ye, L., Gao, R.X., Li, C., Zhang, L., Zhang, L., Digital Twin for rotating machinery fault diagnosis in smart manufacturing. Int. J. Prod. Res. (2019).

[21] Xie, R., Chen, M., Liu, W., Jian, H., Shi, Y., Digital Twin Technologies for Turbomachinery in a Life Cycle Perspective: A Review. Sustainability. (2021).

[22] Bao, Q., Zhao, G., Yu, Y., Dai, S., Wang, W., The ontology-based modeling and evolution of digital twin for assembly workshop. Int. J. Adv. Manuf. Technol. (2021).

[23] Singh, G., Rajesh, R., Daultani, Y., Misra, S.C., Resilience and sustainability enhancements in food supply chains using Digital Twin technology: A grey causal modelling (GCM) approach. Comput. Ind. Eng. 179, 109172 (2023).

[24] Serrano-Ruiz, J.C., Mula, J., Poler, R., Smart Master Production Schedule for the Supply Chain: A Conceptual Framework. First Comput. (2021).

[25] He, B., Bai, K.-J., Digital twin-based sustainable intelligent manufacturing: a review. Adv. Manuf. 9, 1–21 (2021).

[26] Hassani, H., Huang, X., MacFeely, S., Enabling Digital Twins to Support the UN SDGs. Big Data Cogn. Comput. (2022).

[27] Rosen, R., Wichert, G. von, Lo, G., Bettenhausen, K.D., About the Importance of Autonomy and Digital Twins for the Future of Manufacturing. IFAC-Pap. (2015).