Industrial Symbiosis Improvement with Digital Twins

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Abstract: Digital twins (DTs) are dynamic digital representations of physical systems that accurately depict their behaviour and states through virtual space over their lifetime. They are built on models and computer programs that use real-time data from sensors or IoT devices. DTs serve as a bridge between the physical and virtual worlds, enabling real-time tracking, data analysis, and simulation of various scenarios. They facilitate remote management, immediate intervention, and data-driven decision-making across industries. The implementation of DT principles in industrial symbiosis can optimize resource usage, improve collaboration, and create more sustainable production systems. However, the lack of system integration with information and communication technology tools and the complexity of knowledge sharing within symbiosis networks delay its effective implementation. To establish DTs in IS, a systematic approach is required, involving the specification of exchange processes, determination of bottlenecks, prioritization of integrated parts, and the creation of mathematical models and simulations. The benefits of DTs in IS include reduced time to market, reduced waste and energy consumption, improved performance monitoring, and enhanced collaboration between teams. Future developments needed for IS include addressing the lack of big data for training ML models, ensuring data security, establishing standards and regulations, and overcoming observability and controllability issues.

1 INTRODUCTION

Industrial symbiosis (IS) is a mutually beneficial interaction between different industries/companies for the exchange of waste materials or energy to be used as a source for other companies. That results in the design of a production system that is more resource-efficient and has a reduced environmental impact (Seager et al.,2010). It is an effective strategy for the optimization of resource usage and collaboration improvement in the context of Industry 4.0 (Scafà et al., 2020).

Is also strengthens synergies between humans and machines (Scafà et al., 2020). It encompasses the exchange of waste materials and waste energy between industrial units. Its design could be facilitated by tools based on information and communication technology (ICT) (Grant et al., 2010; Kosmol, 2019) . The implementation of IS can lead to the development of eco-industrial parks (EIPs), where more industries collaborate to create a more sustainable and circular production system (Al-Quradaghi et al., 2020). Therefore, IS is a key component of the circular economy. It promotes the increasing resource efficiency, waste reduction, and environmental sustainability. IS is a shift from the traditional linear economic model to a more circular approach (Feiferytė-Skirienė & Stasiškienė, 2021).

One of the main challenges in the development of IS networks is the lack of system integration by the use of ICT tools. Although the trend of using semantic web technologies to share information and knowledge is constantly increasing. These tools are often not fully incorporated into broader IP activities (Kosmol, 2019). This gap hinders the effective implementation and sustainability of IP business models.

Another major gap lies in the complexity of knowledge sharing within IS networks. Despite being considered as crucial in the implementation and maintenance of IP business models. Knowledge sharing is rarely explored or implemented in depth (Kosmol, 2019). This lack of understanding can delay the development of robust IS networks and limit their potential benefits.

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The design of EIPs for specific industries reveals gaps in the early stages of development. While there are frameworks to guide decision-makers, there is a need for better integration with design software to predict product recycling and its production optimization (Al-Quradaghi et al., 2020). Addressing these gaps could significantly improve the efficiency and sustainability of IS initiatives.

Digital twins (DT) are dynamic digital representations of physical systems. That means a digital representation of devices or processes that accurately represent their current and predicted future states (Gómez-Berbís & Amescua-Seco, 2019). They depict the behaviour and states of real-life objects through virtual space over their lifetime (Verdouw et al., 2021). These virtual replicas are built on a series of models and computer programs that use real-time data from sensors or Internet of Things (IoT) devices (Kaur et al., 2019; X. Zhang et al., 2023) . Moreover, it can be taken that DT is a digital shadow, digital replica or digital mirror of physical systems (Lyu, 2024).

DTs are not just conventional data models or simulations. They make forecasting and optimization by simulating digital models of systems. DTs do this by constantly updating and evolving in response to changes in properties of physical factors (Kang et al., 2021). All parts that are integrated into DT can be visually seen in Figure 1. This dynamic nature differentiates them from static digital models. DTs serve as a bridge between the physical and virtual worlds, allowing for real-time tracking, data analysis, and simulation of various scenarios (Ferrigno & Barsola, 2023). They facilitate remote management, immediate intervention, and data-driven decision-making across industries. These include manufacturing, health care, transportation, and smart agriculture (Kaur et al., 2019; Verdouw et al., 2021). By integrating technologies such as IoT, artificial intelligence, and machine learning, DTs can offer a comprehensive understanding of system behavior, and can foster improved efficiency, optimization, and information selection in cyber-physical systems (Awouda et al., 2024; Fuller et al., 2019).

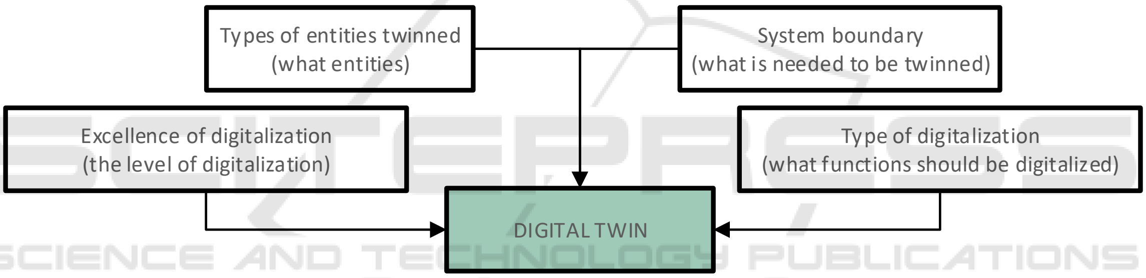

Figure 1: The four forces that make DT.

Sources for analysis of literature were Elsevier data basis. For the searching term "Digital twins for design of industrial symbiosis" appeared 540 raw articles. Related to energy (used filter) are 81. Other searching results for ("Digital twins" AND "industrial symbiosis") can be found 121 articles (Fig.2).

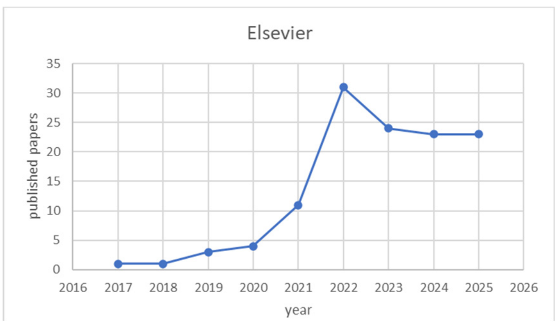

Figure 2: Results shown by searching the Elsevier database for expression — "Digital twins" for design of "industrial symbiosis"

But, anyway, all those articles are not directly connected to the use of digital twins (DTs) in IS or EIP.

2 DIGITAL TWINS

DTs are available in several types. Asset Administration Shell (AAS) DTs are becoming more popular in Industry 4.0, within three different types (J. Zhang et al., 2025). These types of AAS contribute to the systematic engineering of specific components in DTs. Moreover, in manufacturing, DTs can be identified based on the relationship and data flow between the physical object and its digital equivalent. These types are evolving with corporate digital transformation processes, including external data sources such as social media and artificial intelligence solutions. The agricultural sector emerging DTs with levels of complexity. Type classification is based on the sophistication of the twin's capabilities (Pylianidis et al., 2021; Verdouw et al., 2021). Verdóuw et al. (2021) classified different types of DTs with the proposed conceptual framework for their design and implementation in smart agriculture. This framework consists of a control model based on a general system approach and an implementation model based on the Internet of Things Architecture (IoT-A).

DTs can be ranged between simple data-driven models and designed complex simulations enhanced by artificial intelligence. The classification of DTs often depends on their level of sophistication, the degree of their integration with physical systems, and the specific industry where they are used.

DTs are emerged as a key technology in Industry 4.0 and 5.0. They are widely used in equipment and assets in creating virtual representations of physical machines and devices in smart factories. DTs enable real-time monitoring, predictive maintenance, and process optimization (Lampropoulos & Siakas, 2023). IoT devices in smart factories can be connected to DTs for dynamic representation of a physical system through its lifecycle (sensor) data (Catarci et al., 2019). The DTs of systems is modelled the overall production or overall complex systems. They provide real-time automated analysis of data from connected machines, accelerate error detection and make correction. This type of DTs improves overall efficiency and reducing costs in industrial production.

Some research finds the potential of human DTs in the context of human-robot collaboration and augmented reality interfaces in Industry 5.0 ((Zafar et al., 2023)). As Industry 5.0 continues to evolve, DTs would play an increasingly important role in achieving smart, sustainable, and human-cantered manufacturing (Zafar et al., 2023) .

DTs enable real-time visualization, monitoring, and control of workflows. They simulate process parameters (Wang et al., 2024). DTs are integrated with local systems in real-time. This allows the prediction of the status of production and to perform effectiveness analysis of human resources (Ruppert & Abonyi, 2020). They can also be used for predictive maintenance. Integration of artificial intelligence enables them to monitor, diagnose, and optimize different systems (Kerkeni et al., 2025).

DTs are one of the key players in the transformation of manufacturing towards Industry 4.0 and 5.0. They are used for product design, production planning, ergonomics, maintenance, and the entire product lifecycle (Cinar et al., 2020). The integration of advanced technologies like Vision Transformers and DTs can make manufacturing sustainable, stronger, and more personalized (Industry 5.0 goals) (Fantozzi et al., 2025).

DTs can be integrated within real-time localization systems (RTLS). That can predict production status and monitor performances, as well as analyse the effectiveness of human resources (Ruppert & Abonyi, 2020). DTs can serve as independent cloud computing services. That enables scalability and will control simulations through a model DT-as-a-Service (DTaaS) (Borodulin et al., 2017). This showed the importance of cloud platforms for the concept of DTs in smart factories.

Moreover, the integration can be done with the IoT and artificial intelligence. That creates precise digital replicas of production systems. It enables process optimization, the reduction of downtime, and the improvement of maintenance strategies (Fantozzi et al., 2025). The integration of DTs into the industry requires a combination of hardware and software components with high performances. That combination makes a comprehensive virtual presentation of physical objects and processes.

Many authors gave the basic content of DT in different ways. Alam and Sadik (2017) reported that DTs are based on two modules. Those are physical modules (process and communication systems) and digital modules (virtual system—computer models and decision-making). Rodič et al. (2017) divided systems into digital shadows (physical systems) and digital masters (computer models that capture the shadow). Moreover, Lyu (2024) explained differences between expressions digital model, digital shadow and DT. Based on him, the digital model is the presentation of the physical systems without the automatic exchange of data (system simulation). Digital shadow has a single connection with the physical system. It only receives the change of the state of the physical system. Contrary, DT has bidirectional communication between digital and physical systems with changes in both in real-time.

DT can represent part of the physical system (reactor, separation system, or product), or it can represent the whole system.

The main hardware for DTs are sensors, IoT devices, and communication systems to collect real-time data from physical parts (Costantini et al., 2022; Khalyasmaa et al., 2023). Sensors collect information for parameter values like temperature, vibration, and performance metrics (Okpala Charles Chikwendu et al., 2025).

The software, which is used creates advanced computational models. It can contain different simulation tools and artificial intelligence algorithms to process and analyse the collected data (Okpala Charles Chikwendu et al., 2025).

There are several types of software tools for establishing DTs in the manufacturing industry. Each of those types of software has a different purpose or different role in the creation of DTs.

1. Unity3D—This is a tool for real-time 3D system development. It can be chosen because its cross-platform capability and simplified modelling of industrial systems (González-Herbón et al., 2024; Rassolkin et al., 2020). It is used for physical simulations and visualization of DTs (Rassolkin et al., 2020). Similar commercial software are: AspenONE, CATIA®, SolidWorks®, and AutoCAD® for visual representation and FlexSim®, Tecnomatrix®, AnyLogic®, Simio®, Arena®, 3DVIA Composer®, Matlab, ANSYS, Thermoflow, COMSOL, Modelica, etc.

2. The Vuforia SDK as a software development kit is used to simplify augmented reality integration in DTs (González-Herbón et al., 2024).

3. Node-RED is a system integration option for DTs (González-Herbón et al., 2024).

4. The MQTT protocol is used for communication in DT systems (González-Herbón et al., 2024).

5. Object-Z notation is a formal language for realizing the concept of DTs (Barbie & Hasselbring, 2024).

6. A Unified Modelling Language (UML) is used to visualize relationships between DT concepts such as class diagrams (Barbie & Hasselbring, 2024).

Generally speaking, there is no standardized set of software for implementing DTs. Which software will be used depends on the specific requirements of the DT implementation project and the industry in which it is applied.

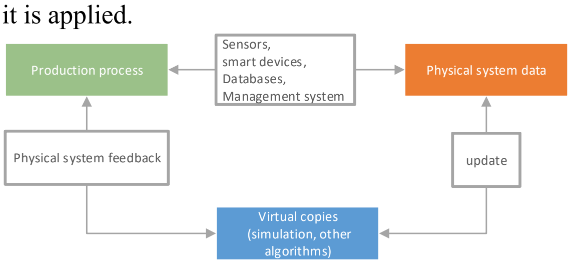

Figure 3: Architecture of DTs.

The connection between physical and virtual systems is done with a communication interface. Its role is connection and conversion of data through sensors, switches, routers, firewalls, hosts, links, databases, intelligent devices and management systems (Fig. 3). That is a two-way street. Communication solutions are IoT, big data, and cloud technologies (Shin et al., 2018).

DTs can have different levels of autonomy in response to physical systems, and they can have different levels of integration of physical systems. Autonomy is directly connected to responses in real-time.

3 DIGITAL TWINS AS AN IMPORTANT TOOL FOR INDUSTRIAL SYMBIOSIS

The implementation of DT principles in industry or systems created by IS can be done only on previously designed models. Lyu (2024) gave differentiation between models created with various methodologies as first principle models (models based on numerical solutions and optimization), statistical models (machine learning based on historical state and behaviour data, neural networks), rule-based and multiagent system based decision-making models, computer-aided engineering (CAE), deep learning models, industrial DT applications (for PALM), IoT, AI-based operational energy-DT (EDT), Data-driven EDT, power industry EDT, generic EDT, etc.

Software that will be used in any of these types of models should provide the following: synchronization rules and template implementation for temporal data, their synchronization, their aggregation, obtain data from sensors and other sources in the physical systems, data conversion, use of behavioural models of DT, implementing visual models, creating multi-images of physical systems (PS), DT data processing and analysis, results visualization, ensure data confidentiality, and DT data storage. All these digital processes with their relations are presented in Fig. 4.

Digital platforms for the implementation of DTs are IoT, Business process Management platforms, analytics & data platforms, and application platforms (Nath, 2021). Moreover, there can be used public clouds like Microsoft Azure, Amazon Web Services (AWS), Google Cloud Platform (GCP), Alibaba Cloud, Oracle Cloud Infrastructure (OCI), IBM Cloud, and Tencent Cloud.

In manufacturing, the collaboration DT is divided into the physical world (shop floor and management floor participants) and the cyber world (DT layers, industrial technology layers and application layers). The shop floor participants are factories machines, workers, monitoring devices, sensors, robotic devices, etc. The management floor participants are people who use operational data such as decision-makers, management department employees, HR, security, and all other human supported departments in administration).

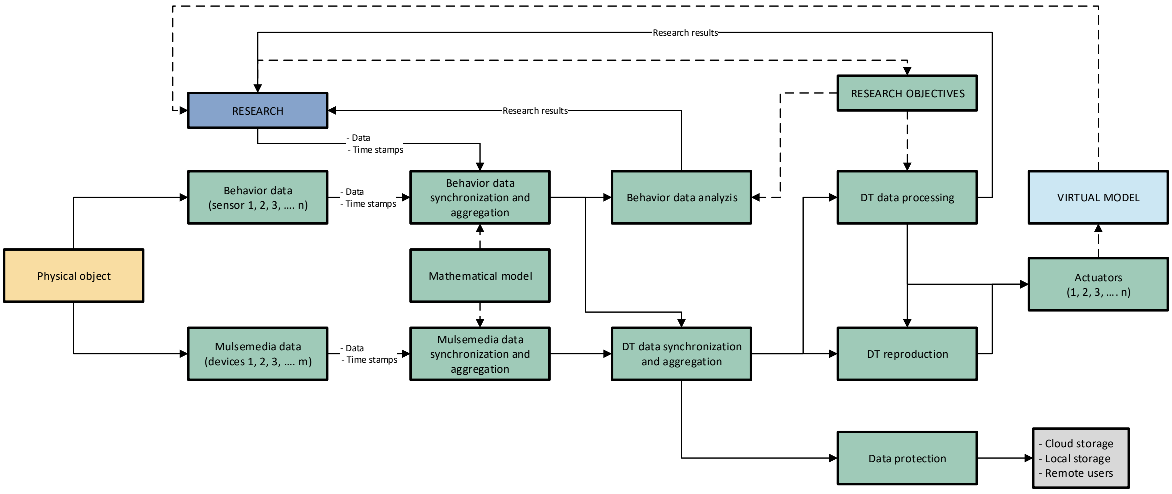

Figure 4: Software system architecture for DTs.

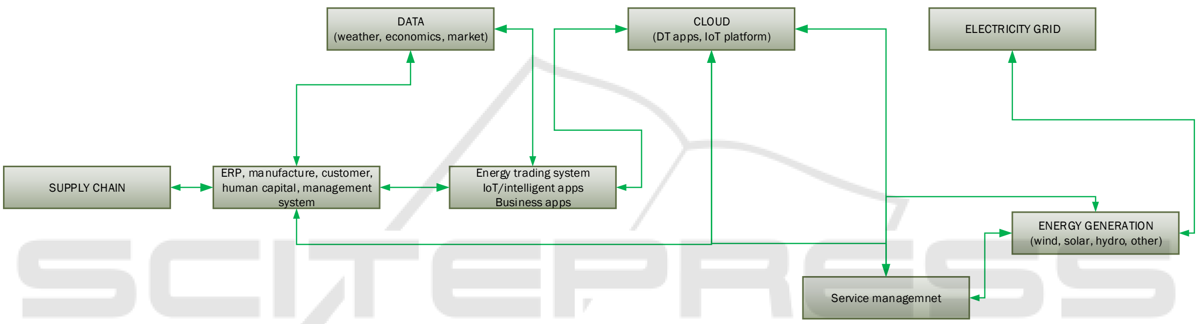

Figure 5. Interaction between different information technologies for creating of DT in industrial symbiosis.

On the other side, in the cyber world, DT layer has models and solutions for autonomous collaborative industrial manufacturing. Here could be found real-time data and predictions of potential risks that are used by decision-makers and sent to the physical system. The industrial technologies layer is included in solutions for collaboration, like blockchain networks (secure exchange of data), AI-based DT technologies (predictive data analytics, predict potential risks, predictive maintenance, etc.), cloud and edge computing technologies for real-time data analysis, and visualization tools for clear and quick understanding of physical systems (Fig. 5). The application layer is the usage of DT for different systems, like the energy industry, rail industry, logistic industry, health care industry, etc.

DTs in manufacturing creates systems at different levels, like unit level (smallest participant/unit), system level (system of a few participants or units connected into a process) and system of systems (SoS) level (connected to several systems or DT levels).

The implementation of DT in the industry is in a low stage. Applications of DT in industry are in general for optimization and predictions for discrete manufacturing; manage, predict, optimize, safety and scheduling of batch processes; predict energy demand and improve energy distribution; improvement and prediction of renewable energy generation; conduct real-time FEM analytics for assessing offshore oil platforms' structural integrity using weather and ocean data; enhance recovery yields in mineral processing and monitor mine tailings and environmental waste in real-time and offer expert recommendations; vehicles supply manufacturers with usage data for design enhancements. Current information about implemented projects of DT in the industry showed partial implementation of specific processes. DT is implemented in water processing for future state of the system prediction, an air separation process for selecting the fastest start up and shut down, beverage processes for rescheduling based on various disturbances, steam turbine subsystems for online performance monitoring, and phosphorus production for minimal energy consumption. Ma et al. (2022) reported about DT implementation in the ceramic industry in China. Implementation in Pharma can lead by DT connections with cognitive sensors and simulations. Based on that, DT is directed to visualization. Visualization is done with smart data management and integration. It uses data visualization, data persistence and processing, and data integration. Integrated data are shown in MES, SCADA, PLC and IBA (Salis et al., 2023).

Logistics is very important in supply chains for industrial processes or in systems like IS. DT can be used in “Logistics 4.0” as part of Industry 4.0. This helps in tracking the movement of goods.

Moreover, control, energy generation and fault diagnostics of wind turbines can be supported by DT.

Iyer et al. (Iyer et al., 2024) showed the system of IS based on the framework of digitalization within Industry 4.0. They connect existing “industrial technologies” based on products and information that are supplied by industry in symbiotic systems. All these information must be sent to the work centre of DT (Park et al., 2020). On the other side, the sustainable smart manufacturing framework suggests using intelligent design, intelligent production, intelligent maintenance and service, and intelligent recovery (Ren et al., 2019).

Determination and creation of DT are done by two teams: business & operations team, and the IT & development team (Nath, 2021). The implementation steps for DT in IS are following:

1. There must have already established IS or EIP.
2. Specification of all processes that connect units in IS or EIP. Determination exchange processes for energy, materials, goods, and services. The whole system is divided into subsystems based on the business model that will be used. (separate system for electricity generation and distribution, separate heat generation and distribution, separate systems for sharing materials, etc.).
3. Determination of bottlenecks and negative factors. Preparing of high-digital DT references.
4. Prioritization of integrated parts and data validation.
5. Creating mathematical models and simulation.
6. Selecting the best model with simulation validation.
7. Determination of the connection points for sensors and all other equipment that is required. Making a list of equipment for further projects.
8. Determination of benefits (added value, economic and quality benefits).
9. The project proposal is analysed for economic, environmental, production and social benefits. If there are benefits (higher incomes), comes the next step. Based on the type of connection, selection of communication technology must be done. If there are no calculated benefits, the whole process returns back to the basics modelling and simulation.
10. Determination of complete business process and operation plan. Decision-making for investment for the DT project.
11. When all processes and connections are determined, the digital (virtual) system is designed.
12. Installation of required equipment (sensors, flowmeters, ethernet, etc.) and establishing two-way connection between physical and digital systems.
13. The first results for the function of created DT. Testing and improvement.
14. Used Business model will lead to creating sub-control centres. Those sub-control centres are control systems of separate companies that are in charge of the supply or distribution of utilities, materials or services.
15. All sub-control centres are connected to the main control centre of IS where the management of IS can be controlled, monitored and take action with decision-making for all units that consist of the IS or EIP.

In case when IS management is responsible for all exchange processes in IS, and no other companies are in charge of specific types of distribution or services, there is only one control centre.

Establishing DTs in the industry, but also in IS must be based on key factors for approving that kind of project. Objective criteria must be set based on the DT’s target to ensure it adds business value. Business values and outcomes broadly include improved life of the asset, process efficiency gains, operational optimization or lower operating costs, new digital revenues, competitive advantages, improvement and customer satisfaction (production units in IS), improved safety, and social goodness, like the reduction of the carbon footprint (Nath, 2021). Moreover, the part of business processes is sending alerts. Yellow (lower importance) and red (high importance) alert for the probability of existing problems in the system. Many monitored parameters are related to the key performance indicators determined for the system.

Senna et al. (2020) determined pillars of energy-DT. The four pillars are factory driver IO, human-machine interaction, energy data modelling & standardization, and data-driven services. As supporting IOT technologies are selected factory driver IO, big data & cloud computing, industrial internet of things (IIoT), AI, DT modelling and simulation, and augmented reality. Major objectives for establishing are energy savings, environmental footprint reduction, and life cycle cost reduction.

IS contain production processes as all processes of exchange and transformation of materials and energy quality; there are storage, recyclability, services, etc. Integration of all these additional segments in DT could be made with specified DTs of storage/warehouses, DT of shipping, DT of recycle system, and DT of specific services based on KPIs related to those services.

4 HOW DT CAN IMPROVE IS

The benefits for the industry gotten by usage of DT are many. *Reduced time to design and to market* (DT utilize digital models to simulate product performance, potentially reducing or eliminating the need for field trials. This is because simulations can identify likely failure scenarios, enabling designers to make necessary product adjustments before production.), *Reduced waste during manufacturing* (determining optimal manufacturing parameters can reduce waste and rejects, leading to a greener and more advanced production process.), *Reduced energy consumption* (DT enables first-time right production, reducing energy consumption per part. It can also identify products with suboptimal energy performance for replacement.), *Reduced raw material consumption* (operating optimally with minimal defects reduces raw material consumption, promoting greener operation.), and *Improved performance monitoring* (High-fidelity 3D models enhance augmented reality, improving product tracking and problem-solving. IoT technologies also offer the advantage of remote monitoring.), *Introduction of numerous virtual sensors* (digital models in DTs allow engineers to measure physical quantities, like temperature and pressure, at locations unsuitable for physical sensors.), *Maintaining optimal operation* (two-way communication between a DT and its physical twin, like a production machine, allows for parameter adjustments in the DT to be applied to the physical counterpart, ensuring optimal operation.), *Reduced cost of maintenance of machinery and elimination of downtime* (By predicting future states using predictive analytics, a DT can anticipate maintenance issues, allowing for preventive maintenance and avoiding costly shutdowns. Optimizing asset operations also reduces maintenance costs.), *Improved warehousing/shipping of finished products* (A DT mirroring warehousing and shipping optimizes operations, further reducing the facility's carbon footprint.), *Improved collaboration between teams* (Digital models linked by a common digital thread improve factory team collaboration by providing a "single source of truth". This minimizes errors and enhances synergies in manufacturing optimization.), *Improved safety* (DT-controlled augmented reality can train staff in hazardous trades safely).

5 FUTURE DEVELOPMENTS NEEDED FOR IS

DTs are not so well presented to the industrial symbiotic systems. There is not enough knowledge in management or engineers that are employed in production plants.

There is a lack of big data for training ML models in DTs of manufacturing processes. ML models are crucial in DTs for autonomous decision-making. They need large, representative data sets, which are scarce in manufacturing due to its heterogeneous nature, unlike uniform consumer industries. Each manufacturing method requires unique data, making it time-consuming and resource-intensive to build large data sets. Challenges include finding, accessing, and transforming data from various sources, along with issues of poor data quality and translation loss.

Data security in DTs is crucial in a connected IIoT environment to protect intellectual property, requiring a focus on privacy, confidentiality, transparency, and data ownership, particularly in business collaborations.

The lack of standards, regulations, and governance in data handling hinders data-centric technologies like DTs. For effective data sharing, interoperability standards are vital, especially between DTs from different organizations. Issues may also occur when DTs at various levels produce different data types without correct conversion.

Reluctance to share strategic knowledge: data is now a key asset, not just a business by-product. Therefore, companies may keep data confidential to maintain their competitive edge, hindering collaboration between organizations' DTs.

Observability and controllability issues: a DT's control system requires processes to be observable and controllable. Sensors need to capture critical quantities effectively, while actuators must execute the DT's commands. Suitable hardware is essential for DT success.

Creating physics-informed ML models enhances accuracy by identifying and removing data outliers, but their complex multi-physics and multiscale nature complicate high-fidelity model development.

Lifecycle mismatch: products like aircraft and cars often last longer than the software used to design, simulate, or analyze them. Unsupported software can render the virtual twin obsolete before its physical version.

Upfront capital outlay: creating reliable DTs requires significant resources affordable only by large corporations. Without resource pooling by industry bodies, DTs may remain inaccessible to smaller businesses for years.

Conventional engineers must learn new ML and AI methods and be assured of their effectiveness to adopt DTs in the factory.

6 CONCLUSIONS

DTs are built on mathematical models and simulation software that use real-time data from sensors or IoT devices. The implementation of DT principles in IS can optimize resource usage, improve collaboration, and create more sustainable production systems. However, the lack of system integration with ICT tools and the complexity of knowledge sharing within symbiosis networks delay its effective implementation. To establish DTs in IS, a systematic approach is required, involving the specification of exchange processes, determination of bottlenecks, prioritization of integrated parts, and the creation of mathematical models and simulations. The benefits of DTs in IS include reduced time to market, reduced waste and energy consumption, improved performance monitoring, and enhanced collaboration between teams. Future developments needed for IS include addressing the lack of big data for training ML models, ensuring data security, establishing standards and regulations, and overcoming observability and controllability issues.

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