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Digital Twins: Enabling Interoperability in Smart Manufacturing Networks

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Abstract: As Industry 4.0 networks continue to evolve at a rapid pace, they are becoming increasingly complex and distributed. These networks incorporate a range of technologies that are integrated into smart manufacturing systems, requiring adaptability, security, and resilience. However, managing the complexity of Industry 4.0 networks presents significant challenges, particularly in terms of security and the integration of diverse technologies into a functioning and efficient infrastructure. To address these challenges, emerging digital twin standards are enabling the connection of various systems by linking individual digital twins, creating a system of systems. The objective is to develop a "universal translator" that can interpret inputs from both the real and digital worlds, merging them into a seamless cyber-physical reality. It will be demonstrated how the myriad of technologies and systems in Industry 4.0 networks can be connected through the use of digital twins to create a seamless "system of systems". This will improve interoperability, resilience, and security in smart manufacturing systems. The paper will also outline the potential benefits and limitations of digital twins in addressing the challenges of Industry 4.0 networks.

Keywords: industrial internet of things; (IIoT); interoperability; digital twin; industry 4.0; smart manufacturing; artificial intelligence (AI); machine learning (ML); universal translator

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1. Introduction

Industry 4.0 technologies offer manufacturers the opportunity to enhance their competitiveness by integrating capabilities such as sensing, big data analytics, and cloud computing into the factory floor. However, interoperability has become a key challenge for the development of these technologies within automation, summarised very well by Körner et al. [1] and visually portrayed below in Figure 1.

To establish interoperability between physical items such as sensors and enterprise assets, Industry 4.0 calls for the integration of various components and services found within a traditional factory or in a non-traditional manufacturing environment. This type of integration, often referred to as horizontal integration, involves connecting enterprises, smart factories, smart devices, and processes for manufacturing control [2]. The concept of a digital twin can safely be regarded as the literal meaning of digital transformation, enabling the transition of traditional legacy manufacturing systems into smart, modern facilities capable of capitalizing on data insights to call themselves 'smart factories.' Legacy devices in factories can use externally applied sensors to build data-driven insights, with no inherent interconnectivity issues [3]. Like many Industry 4.0 innovations, AI algorithms form the basis of the digital twin. In addition, IIoT (Industrial IoT), actuators, and data analytics are crucial for success.

This paper aims to examine the challenges associated with enabling interoperability in manufacturing scenarios. The focus will be on clarifying the differences between syntactic and semantic interoperability, and the need for data homogenization. Additionally, this paper will present the various types of digital twins and their relevant categorizations within the automation pyramid as shown above in Figure 1, as well as assessing the barriers to their deployment. The paper will also analyse how digital twins can meet the challenge of providing an interoperable system across multiple sites if needed. As a key enabling technology, edge processing will be reviewed and the deployment of machine learning algorithms in smart manufacturing will also be assessed.

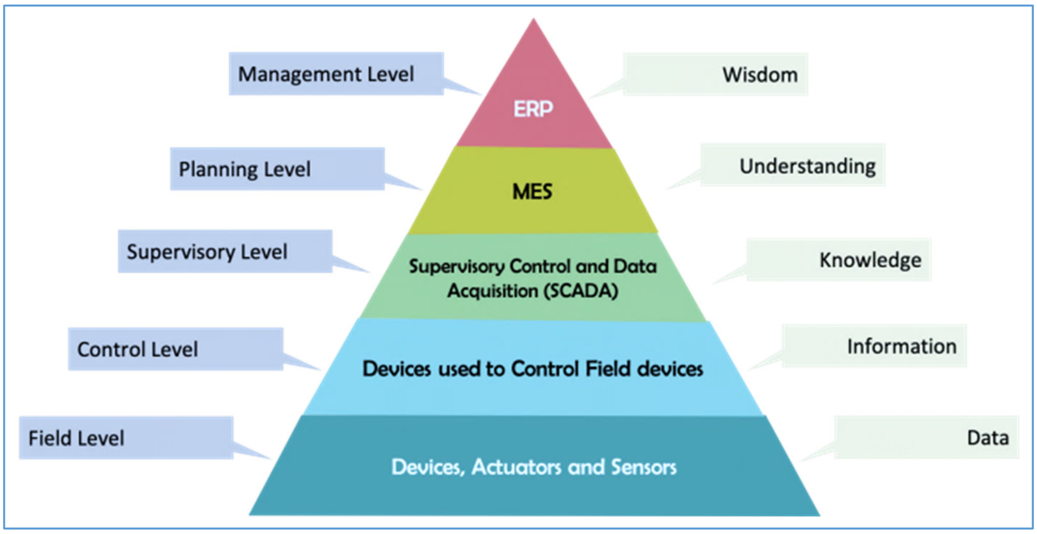

Figure 1. Automation pyramid (adapted from [1]).

Finally, this paper will discuss the deployment of a digital twin framework towards delivering a "system of systems". This discussion will include the benefits of integrating such an approach within a manufacturing facility and outline the impacts that such an approach would bring to the broader manufacturing sector. By the end of this paper, readers will have a thorough understanding of the challenges associated with enabling interoperability in manufacturing scenarios and how digital twin technology, edge processing, and machine learning algorithms can help to overcome these challenges. Additionally, readers will gain insight into the benefits of deploying a digital twin framework and its integration within manufacturing facilities.

2. Interoperability in Manufacturing

Interoperability can be defined as the capacity of two or more products, programs, or systems to communicate and understand one another's data. Currently, there is no one agreed definition of interoperability that fits all projects and uses cases. However, the IEEE defines interoperability as "the ability of two or more systems or components [from different manufacturers/vendors] to exchange information and to use the information that has been exchanged". Harvesting inputs from numerous sensors, a substantial amount of data can be gathered in mere moments. Manufacturing architectures have evolved into interconnected networks of automation devices, services, and businesses as a result of recent developments in manufacturing technology, including cyber-physical systems, industrial internet, AI (artificial intelligence), and machine learning. The rising requirement for interoperability at all levels of the manufacturing ecosystem is one of the difficulties that have come about as a result of this growth. To help operators maximise performance, industrial IoT (IIoT) links the factory floor to the company, boosting visualisation, data analysis, and holistic insights. Data synergy, or the integration of data from various sources to produce value, is a crucial part of the industrial IoT [4]. There are several challenges associated with achieving interoperability in manufacturing, including the following:

- Technical Complexity: Manufacturing systems often consist of a variety of different equipment, machines, and software applications from different vendors, each with its own data format and communication protocols. Achieving interoperability between these systems can be technically complex and challenging.

- Data Incompatibility: Incompatible data formats and standards can make it difficult to integrate different systems and share data between them. Data formats, protocols, and standards can vary widely across different manufacturing systems, leading to incompatibility issues.
- Security Risks: Interoperability between different systems and devices can increase the risk of security breaches, as it creates more opportunities for hackers to exploit vulnerabilities.
- Lack of Standardisation: There is currently no single standard for achieving interoperability in manufacturing, which can lead to confusion and incompatibility issues between different systems and devices.
- Cost: Achieving interoperability can be expensive, as it often requires significant investment in hardware, software, and personnel resources.
- Legacy Systems: Many manufacturing systems and equipment are older and may not have been designed with interoperability in mind. Retrofitting these systems to achieve interoperability can be costly and time-consuming.
- Organizational Resistance: Achieving interoperability often requires changes in business processes and workflows, which can be met with resistance from employees and management.

Nowadays, interoperability is more of a need than a desirable quality, especially when smart things start to take the form of widespread technology. Interoperability is crucial both between smart devices from various manufacturers and between smart devices and current infrastructures [5]. According to Tolk, the technological architecture of smart objects must be specifically tasked to facilitate interoperability to accomplish the delivery of interoperability [6]. Figure 2 below displays a summary of the six levels of conceptual interoperability and their alignment with the expected interfacing architecture of the data sharing between various interoperable platforms.

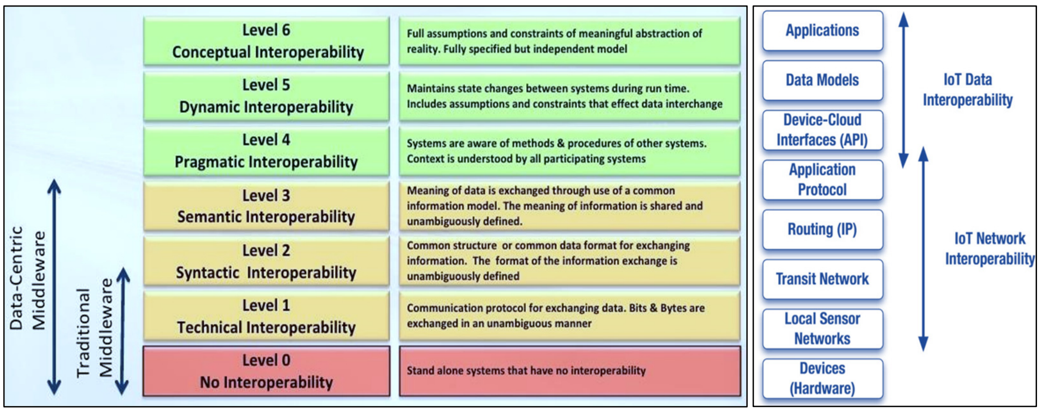

Figure 2. The interfacing levels of the interoperability model (adapted from [6]).

2.1. *Backwards and Forward Compatibility*

In manufacturing domains heavily reliant on legacy systems, interoperability challenges arise due to poorly integrated and isolated databases and systems. Engineers and administrators spend a significant amount of time chasing information across these disparate systems. Backwards and forward compatibility is crucial for the evolutionary path towards Industry 4.0, as they extend the lifespan of machines and enable old and new machinery to coexist. Compatibility also ensures companies can benefit more from their digital strategy [7]. Most large-scale production facilities use outdated systems and machinery, making it difficult to adapt to new developments. Wired networks for operations technology (OT), information technology (IT), and security are physically segregated in factory setups, with only a small portion of industrial plants implementing wireless technologies at scale and combined IT and OT networks. Integrating older technology infrastructure into a smart manufacturing environment is challenging as it requires updating technology while taking into account interdependencies. The deployment of digital intelligence to older equipment requires expertise in both legacy configurations and modern digital solutions, increasing complexity and reducing the system's steadfastness.

2.2. Semantic Interoperability

As the manufacturing industry advances and integrates more IoT protocols, edge computing models, and cyber-physical systems into their factory floor, they face the challenge of becoming proficient integrators of these technologies. The complexity of the data generated by these systems makes deploying AI solutions a challenge. Semantic interoperability is also complicated by the fact that data formats may not be compatible between different systems. Therefore, manufacturers often have to extract and collect data, and then convert or transform it to be used in a new system, an example of the complexity of managing semantic interoperability is shown in Figure 3 below. The complexity of data formats for AI/M adds an additional challenge to algorithm deployment [8]. As a result, manufacturers need to carefully consider their approach to data management and standardization to ensure that they can effectively deploy AI solutions to enhance their operations [9,10].

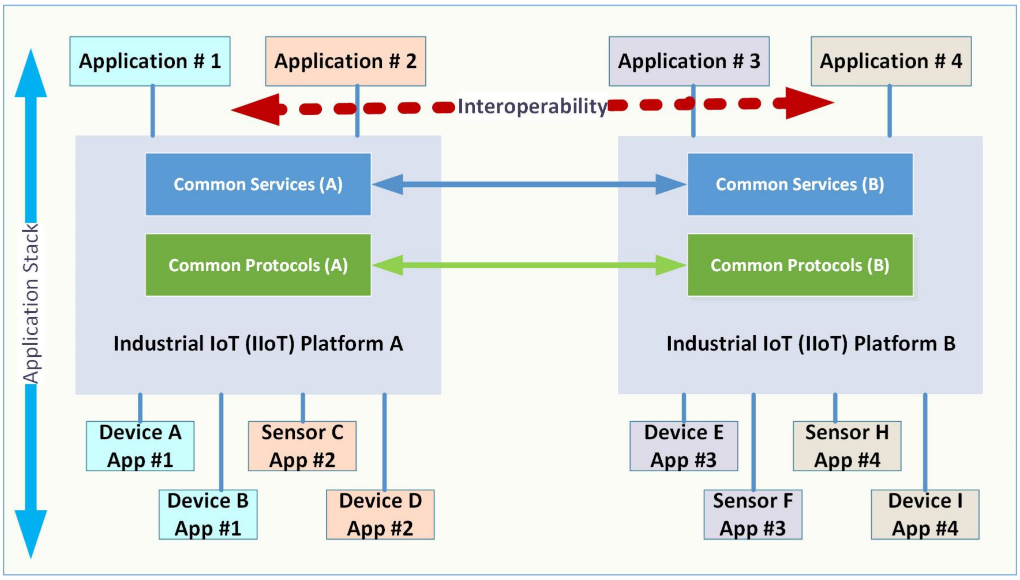

Figure 3. Schematic of semantic interoperability between different IoT platforms.

2.3. Syntactic Interoperability

In the manufacturing industry, a significant challenge is the lack of system compatibility. With vendors offering a wide range of technologies and parts, many of which are incompatible with other systems, it creates an interoperability problem [4]. To enable communication and data exchange between two or more systems, mapping and bridging between them are necessary. Syntactic interoperability focuses on the structure of the syntax of the data and how it is presented in machine-readable formats. As stated by Veltman in 2001, it pertains to the various systems' ability to understand and process the data [10]. While many companies are exploring avenues of automation, most are still relying on existing Wi-Fi or Ethernet network infrastructures that present data in bespoke formats specific to those protocols and not easily compatible with industry protocols commonly used on factory floors. Therefore, integrating systems with different syntactic interoperability can be challenging, and it requires careful consideration of how to standardize data representation to ensure compatibility as shown below in Figure 4 [8].

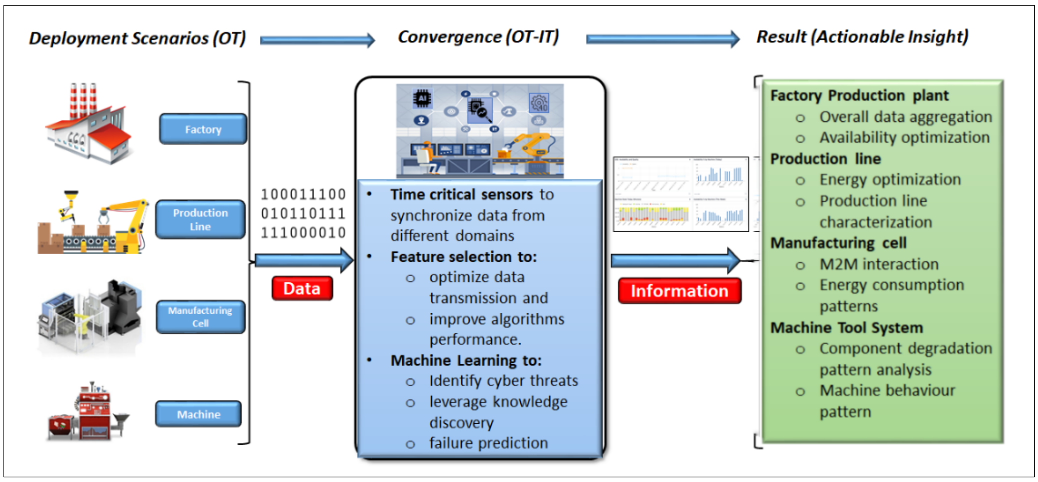

Figure 4. Interoperability of different entities in smart manufacturing.

2.4. Homogenising Data for Interoperability

To achieve data interoperability in manufacturing, it is essential to have a system that provides comprehensive semantic data homogenization, which arranges data into specific categories and conveys contextual information to all users. This is crucial to ensure that all data packets are easily discoverable and that selective access to specific information can be defined while fulfilling the demands of all participants equally. A homogeneous data set is required to meet the interoperability requirements of modern production and logistics, from the operation of a single system to the development of a cross-sector Industry 4.0 solution. A comprehensive semantic data homogenization system must provide full access control to all data packets generated and arrange data into specific categories such as warning or status messages. For instance, raw data from a machine is easy to understand for staff involved in the process, but contextual information is required for software systems to display the data uniformly, especially when the software receives raw data from different assets. In a large and complex digital twin system that includes entities from multiple domains, each with its semantics, persistent information will contain domain-specific information from heterogeneous subsystems. Heterogeneous information sets inherently incorporate disparate syntactic and semantic standards that must be accommodated for system interoperability. To achieve this, translators and gateways are necessary so that information from different and incompatible domains can be normalized when needed for holistic knowledge. Manufacturers who hope to remain competitive in the future market need to leverage IoT to increase productivity, uptime, and efficiency. However, many are still relying on unconnected legacy machines, and failure to adopt data synergy made possible by an IIoT connected factory can lead to being left behind by competitors [11].

3. Digital Twins

A digital twin is a virtual model that replicates a physical system or process, providing real-time data and feedback on its performance. Digital twins enable manufacturers to monitor and analyse the behaviour of physical assets in real-time, enabling them to optimise performance, reduce downtime, and improve efficiency. It is a virtual representation that acts as the real-time digital counterpart of a physical thing or process. The term "digital twin" was coined by Dr Michael Grieves in 2002 at the University of Michigan.

> *"Only when we get it to where it performs to our requirements do we physically manufacture it? We then want that physical build to tie back to its digital twin through sensors so that the digital twin contains all the information that we could have by inspecting the physical build."* Dr Michael Grieves, 2002.

While digital twins are most certainly used in manufacturing today, the use cases span across many industry verticals. Over the last few years, as the world has become more connected, data has become more readily available, richer, and more accurate. The proliferation of IoT equipment has meant data is harvested from a wide array of networked sensors, creating a detailed map of any enterprise asset or series of assets. A digital twin creates a virtual representation of a process, system, service, product, or other physical thing using virtual or augmented reality, 3D graphic modelling, and data modelling. The physical world is mirrored in this digital duplicate. Real-time updates are used to preserve its exact duplicate status. Due to its many benefits, including the elimination of errors and cost optimisation in any system, digital twin (DT) technology is regarded as the foundation of smart manufacturing. From the literature, it is clear how the evolution of the digital twin has been deployed over the years, falling into one of three subcategories [11,12]:

- Digital Model: A manual data exchange between a physical object and a digital object is required, and therefore changes in the physical object are not reflected in real-time.
- Digital Shadow: Data from the physical object is automatically transferred to the digital counterpart, but not the other way around. Therefore, changes in the physical object can be viewed digitally but not vice-versa.
- Digital Twin: A two-way data exchange between physical and digital objects is involved. Therefore, the changes in the physical/digital objects affect each other.

Digital twins can be even further categorised in their deployments of various types, according to their creation, integration level, application, and hierarchy level of the digital twin. After reviewing the literature, a summary of the relevant terminologies of a digital twin is shown below [12–14]. In manufacturing, DTs can be divided into three levels from a hierarchical viewpoint [13]. A digital twin environment (DTE) is a logical setting in which hardware, software, and occasionally both interact to imitate a whole system or a portion of a system. A virtual clone of a tangible system, process, or product is created by digital twins. By using data analysis, the replica, for instance, may forecast when a machine will break down, enabling businesses to boost production through predictive maintenance [14].

- Part/Component Twin: the smallest unit on the industry floor and is based on a geometric, functional, and operational model of the unit-level physical copy.
- System level: DT is the composition of many unit-level DTs in a production floor, interconnected for wider information flow and efficient resource allocation.
- System of Systems (SoS) level: Formed when multiple system-level DTs are connected, bringing different departments such as logistics, design, service, maintenance etc. together into one twinned model. This is outlined below in Figure 5 [13].

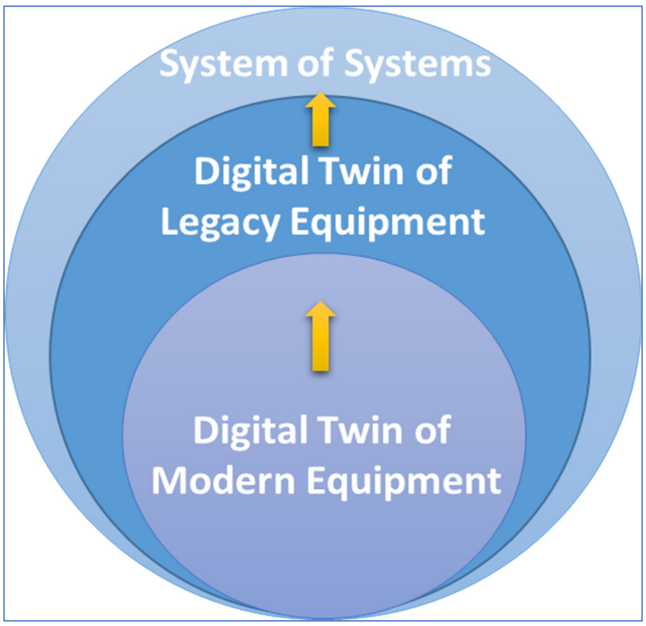

Figure 5. Progression toward a system of systems for digital twins.

As per Grieves and Vickers [14], DT can be classified into two types when it is developed during the life cycle of the product—at the prototype stage and the production stage. In a system known as the digital twin environment; both sorts of DTs are combined and used for various purposes. (DTE).

- Digital twin prototype (DTP) is the collection of information needed to generate a physical model from the virtual version. This consists of design documents, CAD files etc. The product cycle starts from the creation of the DTP, tested rigorously, before creating its physical twin. The DTP helps identify unwanted outcomes which are impossible to identify with traditional prototyping.
- Digital twin instance is linked to its physical replica throughout the duration of its life. To identify and predict the performance of a physical system after it has been constructed, data collected at the physical layer is communicated to the virtual space and vice versa. With the available data, it can be investigated if the prediction model is as expected or not.

3.1. Applications of Digital Twins

Digital twins can also be classified as per their applications. According to Singh, [12] the applications are also broadly divided into two categories, prediction and interrogation. In a predictive DT, future behaviour and performance of its physical copy are speculated. While in interrogative DT, the past and present state of the physical copy is examined. DTs can also be classified as per the focus of the application, which is either product, process, or performance [4,15,16]:

- Product DT analyses the product in different conditions and ensures that the physical product is acting as expected. This virtual validation of the product leads to rapid prototyping and reduced development time.
- Production DT is used to validate the processes through simulation and analysis, before beginning actual production, which paves the way for the creation of a flexible production approach. The product and production DT data can be utilised to track and maintain the equipment.
- Performance DT is used for decision-making through data collection and analysis. Performance DT incorporates product and production performances and therefore it optimises the functioning of the industry floor according to the obtainability of the industry resources. This creates an option to boost the performance of both production and product DT using a feedback loop.

The sophistication level of digital twins can be expressed in terms of autonomy, intelligence, learning and fidelity. According to the quantity and quality of data collected from the physical twin and its surroundings, DTs can have multiple properties:

- Partial Digital Twins consist of only a small amount of data from their physical counterpart.
- Clone Digital Twins consist of a significant amount of data from the physical system useful for making prototypes.
- Augmented Digital Twins use the collected data from the asset along with the historical data and derive useful information using data analysis.

Finally, when classifying DTs, the sophistication level of the virtual representation of the DT model allows for DTs to be further divided into four levels.

- Pre-digital Twin is the first level where the DT is created before the physical system to analyse prototype designs and rule out any technical risks by virtual commissioning.
- Digital Twin is the second level when the data is collected from the physical copy relating to the performance, robustness, and maintenance. The virtual model uses the collected data to assist in the design and development of the physical system along with decision-making and arranging maintenance.
- Adaptive Digital Twin is third level which imparts an adaptive interface between the physical and the digital world. Using ML techniques, it learns from the experiences of the human operators, allowing for real-time decision-making.

- Intelligent Digital Twin has additional capabilities along with features from the second and third levels. It can detect patterns in the manufacturing floor using reinforcement learning, allowing for more precision and efficient handling of the system.

3.2. Edge Computing: Enabling the Digital Twin

Smart manufacturing is more than just collecting massive data sets through a myriad of disparate connected devices. At its core, smart manufacturing is the potential to be able to use the collected data efficiently to decide, predict, and take actions in real-time to optimise the manufacturing output. As the adoption of digital technologies in manufacturing grows, it will increase the requirements for more localised decision-making, storage capabilities, and analysis at the edge, known as edge computing. Although the idea of edge computing is not new, it has recently emerged as the essential component of smart manufacturing, which aims to quicken the process of digital transformation [17]. Edge computing enables manufacturers to transform enormous amounts of machine-generated data into meaningful and useful information [8]. It accomplishes this by using Internet of Things (IoT) devices that are networked, such as environmental sensors, alarms, or motor driven units. This makes it possible for big data analytics to materialise right at the source of the data. A robotic arm or conveyor system are examples of an operational technology (OT) computing framework that is nearest to the IoT sensed data collection sources. As they frequently exist the farthest from the core of the information technology (IT) computing framework, these are considered as being at the "edge". The IoT gateway anchors an open source software platform, e.g., IOTech's Edge Xpert [18] or KepWare [19], which is often the preferred method to provide a way to link the sensed devices, enable localised decision-making, and relay the relevant device information for further analysis at the cloud. These edge platforms must be able to support industrial protocol standards such as OPC UA, CAN bus, etc., and may also need to support different wireless protocols such as cellular, WiFi, Bluetooth or Zigbee, LoRa, etc. An edge platform imparts the following key functions [20]:

- Interoperability—provides the required protocol conversion for communications to be acknowledged between devices unable to communicate with each other.
- Localised processing—facilitates the unloading of computing jobs from smart devices by caching information and functioning as a private cloud suitable for remote access.
- Quality of service—increases the efficacy of available network bandwidth while decreasing endpoint bottlenecks.
- Security—provides advanced security solutions compared to those implemented on each endpoint, hence building a better defensive strategy for the entire network within the factory.
- Local storage—saves transmission costs by just transmitting the necessary data to the cloud. In certain cases, it is advantageous to have the edge device act as the computing node to record data and make localised analytical decisions.

As the manufacturing sector transitions from single-domain digitalised sites to cross-domain digitalised sites, the focus will shift to a system of systems approach where pivotal points of interoperability can be used to inform and interact at a large scale. The "system of systems" endeavour that utilises digital twins interoperating with one another needs a consistent IoT platform strategy, based on open specifications, strong resiliency principles, security, and standardisation, as when multiple networking technologies are involved, standards are needed to regularise the interactions between devices and sites.

3.3. Barriers to Digital Twin Integration in the Smart Manufacturing Sector

It can be said that no industry stands to benefit more from IoT advancements when compared to the manufacturing sector. Using edge devices, integrating data storage and edge computing within industrial appliances, manufacturing data can be collected allowing for improvement in predictive maintenance and energy efficiency [21]. This will reduce overall costs and maintain the preferred reliability and production time. Some of the main advantages to adopting a digitalising strategy and deploying digital twins in manufacturing are listed below:

1. Preventive maintenance: IoT capabilities will improve operational intelligence, which is essential to smart manufacturing. This sector will gain from the availability of numerous sensors able to provide real-time information regarding equipment performance. The data can aid in predicting and preventing equipment malfunction when integrated with machine learning (ML) and artificial intelligence (AI).
2. Enhanced process efficiencies and troubleshooting: Interoperability and digital transformation work together to improve manufacturing process efficiencies. For example, using deep learning neural networks and advanced visual recognition, robotic systems can accurately and quickly scan connected objects for quality control in real time. Specialised equipment can be fixed remotely by specialists using augmented reality (AR), made possible by 5G networks' high bandwidth and low latency support.
3. Increased security with built-in security features: Interoperability and digital transformation will provide increased security with built-in security features, integrating security into the core network architecture and allaying manufacturers' security fears about adopting IoT [22].
4. Sandbox scenario testing: The charm of digital twinning is that it enables businesses to construct specialised, virtual replicas of their web infrastructure and to do predictive research tailored to their requirements. Employing digital twins to assess the viability of system applications and data architecture can help businesses intending to implement new systems or migrate to the cloud.
5. System Scalability: There is little doubt that there are huge opportunities for large-scale digital twins, which can assist manufacturing sites greatly by enhancing asset maintenance, increasing company transparency, and improving and deepening decision-making.

4. Digital Twins: Enabling Interoperability in Manufacturing

Smart manufacturing approaches informed by continuous data monitoring will enable companies to tailor production runs to better match consumer stipulations [5]. The following are some examples of the manufacturing use cases accomplished by the upcoming Industrial IoT and edge computing solutions:

- Predictive maintenance and equipment safety—e.g., a pump installed with edge computing capabilities can determine if an established threshold has been surpassed, using basic analytics, and shut itself in milliseconds. Applying an edge computing device to perform this function will result in zero decision latency without any requirement for internet connectivity.
- Production flow monitoring and optimisation—-to compile the data on a local gateway and send overall equipment effectiveness (OEE) patterns and alerts to the operational staff, edge computing can do near real-time analytics across a variety of data obtained from sensors installed within the floor.
- Supply chain optimisation—any industrial facility's supply chain processes must be optimised, which calls for the use of optimisation algorithms and data analytics that can quickly adjust supply-chain goals inside business systems such as ERP, SCM, etc.

Machine Learning in Smart Manufacturing

Industries often collect large amounts of raw data from different types of sensor networks [23,24]. The massive heterogeneous data is often then sent to the cloud where an information dashboard is expected. This presents an enormous challenge to clean and homogenize the raw data to make it suitable for analysis. The availability of the data is often taken for granted by the industries and it is expected to provide a real-time predictive analytic model with a dump of data which is often insufficiently exploited by companies.

The use of current machine learning (ML) approaches is anticipated to be an appealing solution to address manufacturing security challenges due to the large amounts of data, high computing power, and large storage capacity that have been deployed in factories through the connection of smart devices and machinery. Machine learning coupled with real-time data analysis is gaining huge popularity as mainstream support for the provision of on-the-spot (or near immediate) relevant information and actionable insights in strategic monitoring.

Artificial intelligence's branch of machine learning relies on the notion that computers can discover patterns in data and make judgments without much human input. Many studies have been carried out on how to make machines learn by themselves. A recent study by Cadavid et al. [9] presents a wide variety of ML applications in Industry 4.0. However, these ML applications generally focus on aspects of the production process itself, such as planning and scheduling, smart maintenance, quality control, etc. [25]. An overview of the multitude of ML types is shown below in Figure 6.

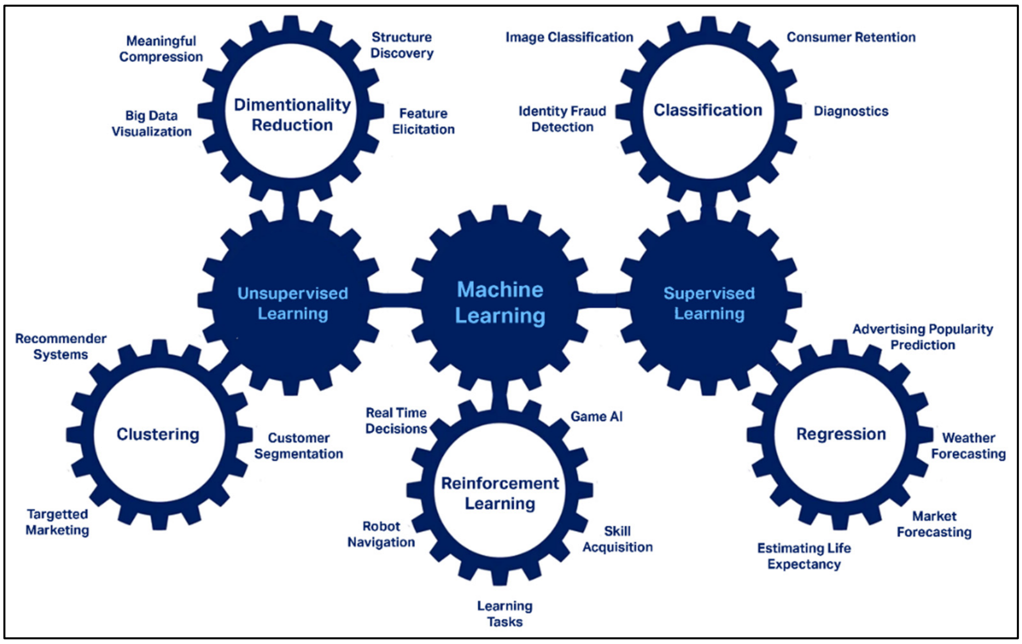

Figure 6. Types of machine learning.

By analysing and transforming stored data into knowledge that can be used to generate predictions, ML approaches are intended to extract knowledge from existing data. Making decisions that can be put into action more quickly and precisely than a human can is what machine learning in manufacturing refers to. Forecasting and comprehending anomalies or outliers are two areas where this proves to be eminently sensible. Forecasting can add value in some stages of the production process. There is a good possibility that forecasts can be made with enough historical data and context regarding the choices and procedures used in relation to the data. A human analyst may find the data from a single machine to be overwhelming, which is where ML might be useful [9]. Five domains have been identified where ML has a big influence.

1. Predictive maintenance. The amount of downtime can be considerably decreased by using historical data from maintenance logs to estimate how a machine will react under a future payload and whether it will need to be changed based on what previously resolved that issue.
2. Predictive quality. Significant cost savings can be achieved by anticipating and reducing costs.
3. Scrap reduction. It is possible to reduce waste and increase product quality by using measurements to predict behaviour across product requirements.
4. Increasing yield/throughput. Knowing if and when a machine or process will not conform to a set of requirements enables proactive action to be taken to bring it back into compliance, lowering the number of quality passes.

5. Demand and inventory forecasting. It is possible to estimate the demand for and movement of essential parts with a complete understanding of factory operations and the production data, leading to significant inventory savings [5,26–30].

5. A Digital Twin Framework for Interoperability

Digital twins are unique because no two businesses will have the same digital twin architecture as their assets; processes and facilities will differ. The beauty of a digital twin is that it is a mirror of the physical workspace. As the business grows and changes, so too will the digital counterpart. Understanding systems, their architecture, behaviours, and how they interact with other systems depends on conceptual models. Such models must be codified and standardised in a way that is reusable for various use cases encountered in the field in a world where millions and billions of interconnections are implemented daily in dynamic ways. By modelling information, professionals can develop standardised models depicting the fundamental components of systems and intelligent machines, resulting in better modularity and reuse. A digital twin system's primary goal is to speed the holistic understanding of the real world for the best decision-making. The "world" can be a structure, utility, community, nation, or another environment. Not simply the isolated connection between two subsystems, but all information transmitted across connected systems must assist the digital twin's overall goal: the development of a common interoperability mechanism, in which each system contributes to the collective intelligence of the whole and where one system may easily consume and respond to information from another system [31]. Below in Figure 7 is a diagram that captures the concept of an interoperable system as outlined.

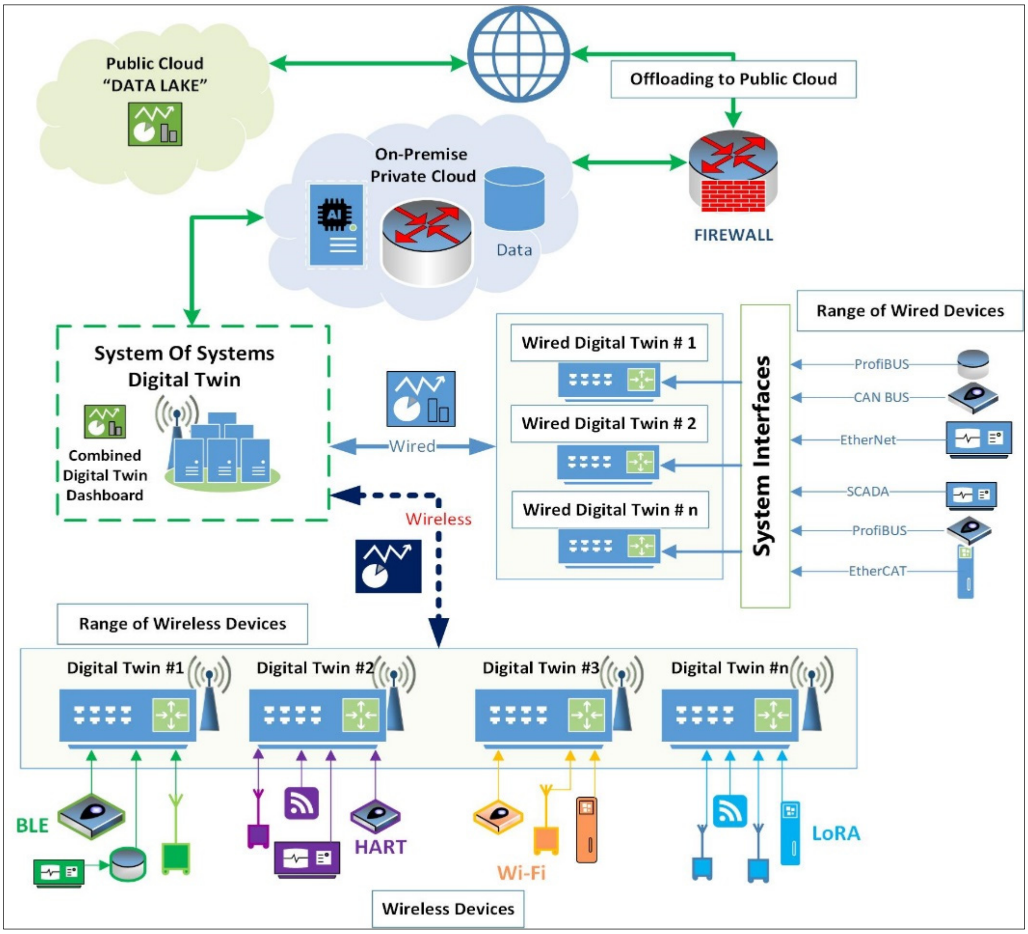

Figure 7. Conceptual digital twin framework towards a system of systems.

According to the 2017 EU report, European Interoperability Framework, "The focus is on releasing machine readable data for use by others to stimulate transparency, fair competition, innovation and a data-driven economy" [32].

Manufacturing businesses with legacy production systems and functional PLC code must find a method to integrate a verified manufacturing approach into their current processes if they are to tackle the demands of Industry 4.0. By bridging the gap between the factory floor and the company, industrial IoT improves visualisation, data analysis, and holistic insights, enabling operators to maximise the effectiveness of crucial operations. Data synergy, or the integration of data from various sources to produce value, is a crucial part of the industrial IoT. The aforementioned deployment methodology can be applied to both modern and antiquated production facilities, with little disturbance to ongoing installations. This architecture offers a real-time enabled framework for vertical and horizontal integration, making it easier for various sensors and systems to communicate with one another. For manufacturing, the transition towards interoperability can improve policies and standard practices through the following:

1. Improved supply chain management, resulting in reduced costs, increased efficiency, and faster delivery times [33].
2. Enhanced quality control processes, leading to improved product quality, reduced waste, and increased customer satisfaction [34].
3. Increased regulatory compliance, through standardized data collection, sharing, and analysis, reducing costs and improving transparency [35].
4. Informed decision-making through better data analytics, providing insights into operations, products, and customers [36].
5. Greater innovation and collaboration, enabling the development of new products, services, and business models that meet evolving market needs [37].

Interoperability can foster greater innovation and collaboration, enabling the development of new products, services, and business models that meet evolving market needs. By collaborating with different partners and stakeholders, manufacturers can gain new perspectives, share best practices, and leverage technology to create innovative solutions that drive business growth. Given these benefits, policymakers and standard-setting organisations can promote interoperability to enhance the manufacturing ecosystem's sustainability and transparency. By facilitating the integration of different systems and promoting data sharing and analysis, they can create a more efficient, responsive, and resilient manufacturing industry that can adapt to changing market needs and drive economic growth.

6. Conclusions

The transition to Industry 4.0 can be a daunting process for many manufacturing organisations, particularly those with complex legacy systems that have been in place for decades. As manufacturers progress further along the digital transformation journey, it becomes increasingly clear that real-time knowledge and data-based decision-making will be necessary on a large scale, requiring a significant amount of automation. Fortunately, the advent of the Internet of Things (IoT) has made it possible to integrate legacy equipment via a digital twin. With the help of IoT devices, manufacturers can gather data from their legacy systems and use it to inform decisions and improve operations. By using IoT devices to gather data from legacy equipment and integrating it into a digital twin, manufacturers can optimise their operations and improve their bottom line through data-driven decision-making. The further integration of multiple digital twins into one system or "system of stems" brings not only additional insights through the data gathering but the capacity to allow legacy equipment to interact and better inform the decision-making process of more modern equipment also connected to the overall digital system.

The adoption of a "system of systems" approach can provide manufacturers with a more robust and comprehensive digital infrastructure for the manufacturing industry. By integrating data from various sources and leveraging advanced analytics, manufacturers can gain valuable insights into their operations and make informed decisions in real-time.

This approach can also help to improve product quality and reduce defects by integrating quality control systems. Early identification of quality issues can lead to prompt corrective actions and better product consistency, ultimately resulting in increased customer satisfaction. Implementing a "system of systems" approach can give manufacturers a competitive edge by enhancing their operational efficiency, flexibility, and responsiveness. This can lead to greater productivity and profitability in the long run, positioning manufacturers to meet the changing demands of the marketplace.

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