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Smart Factory and Industry 4.0: A Survey on Advancements, Technologies, Methods and Perspectives of Digital Transformation in Manufacturing

Haris Karic[1], Arockia Selvakumar Arockiadoss[2], and Daniel Schilberg[1]

[1]Institute of Robotics and Mechatronics, University of Applied Sciences Bochum, Bochum, Germany
[2]School of Mechanical Engineering, Vellore Institute of Technology, Chennai, Tamil Nadu, India

ABSTRACT

Digitalization is fundamentally transforming the manufacturing industry, leading to the development of intelligent factories, known as Smart Factories. These form the core of Industry 4.0 and combine innovative technologies such as the Industrial Internet of Things (IIoT), Cyber-Physical Systems (CPS), Machine Learning (ML), Artificial Intelligence (AI) and Big Data to maximize efficiency, flexibility and resource conservation. This paper provides a comprehensive overview of the Smart Factory as a central element of the Fourth Industrial Revolution (Industry 4.0). It presents key digitalization methods as well as technological innovations and approaches that have been developed over more than a decade of continuous progress in Industry 4.0 and digitalization. Finally, an insight into current research at University of Applied Sciences Bochum is provided, focusing on the application and practical implementation of intelligent technologies in the manufacturing industry. The emphasis is on solution approaches for the realization of smart production processes that equally address technical, social and economic requirements.

Keywords: Smart factory, Industry 4.0, Digitalization, Big data, IoT, Cyber-physical systems, Brownfield projects, Digital transformation, Smart manufacturing, Automation

INTRODUCTION

After more than a decade of technological progress and developments in the context of Industry 4.0, digitalization is progressing steadily. Characterized by the use of innovative technologies and digital networking, the fourth industrial revolution marks a decisive turning point. It is increasingly becoming a key factor for companies to remain successful and fit for the future in a highly competitive market environment (Nikelowski & Wolny, 2020). The systematic planning of a networked factory is made possible through the targeted use of modern methods and tools. This takes into account a variety of framework conditions, integrates all elements of the value chain and at the same time creates the basis for self-controlling and autonomous company processes. The so-called smart factory uses state-of-the-art technologies to not only achieve operational goals efficiently, but also to fulfill social and economic functions by seamlessly connecting the physical and virtual worlds (Nikelowski & Wolny, 2020). As part of the digital transformation, complex, interactive and autonomous systems are being created, for example through the use of brownfield methodology. These enable a more efficient and powerful optimization of existing structures as well as business and production processes by specifically upgrading and integrating existing potential (Nikelowski & Wolny, 2020; Hopkins & Jenkins, 2008; Stock, 2020). With the help of cyber-physical systems, physical devices and processes in established production landscapes can be equipped with computing and network capabilities and connected to a data and knowledge structure that is ultimately integrated into the manufacturing process (Nikelowski & Wolny, 2020; Pedone & Mezár, 2018; Gönnheimer et al., 2022). The use of algorithms for industrial big data and advanced technologies enables the optimization and adaptation of manufacturing processes. In this dynamic development, self-adaptive, self-learning and autonomous systems can help to successfully overcome the challenges of rapid technological progress and increasing product complexity. The integration of information technologies and operational technologies is crucial to achieving the overarching goal of digitalization in established industries. In this context, there is a particular focus on creating conditions that can fulfill not only operational goals but also social and economic functions within a factory (Heuser et al., 2017; Jaspert et al., 2021). This requirement suggests that the redesign of a digital factory must, on the one hand, ensure the smooth technical and economic flow of the production process and, on the other hand, also create optimal working conditions for the personnel in the factory (Bauernhansl et al., 2014; Etz et al., 2020; Wischhusen, 2023).

Smart Factory

The smart factory, a core component of Industry 4.0, is a digitally enhanced production environment where new processes and business models are tested. It represents a significant advancement in traditional factory automation, offering modernization and optimization opportunities for heterogeneous, legacy machine parks. Seamlessly integrating information systems with operational systems, external components and the surrounding environment, the smart factory unites production, maintenance and logistics. Real-time data exchange between decentralized machines, systems and logistics enables autonomous production control, fostering flexible and efficient manufacturing. Key enabling technologies include the Industrial Internet of Things (IIoT), cyber-physical systems (CPS), machine learning (ML) and industrial big data, facilitating dynamic management of object properties. Real-time data from sensors and IoT devices, termed big data due to its volume and velocity, provides insights into machine condition and production progress (Bauernhansl et al., 2014). Data analytics, including descriptive, predictive and prescriptive analysis, further enhances efficiency and flexibility by enabling proactive problem-solving and process optimization. The smart factory's self-organization and decentralization support efficient production of highly individualized products, even in small quantities. This requires real-time data collection, analysis and visualization across the networked value chain, enabling materials, machines, storage and logistics to communicate directly. Decisions are made at the lowest possible level of the automation pyramid, optimizing the value stream and extending beyond individual companies to create innovative value creation networks (Bauernhansl et al., 2014; Jahid et al., 2023; Soori et al., 2023).

Historical Background and Development

Industrial development is a dynamic process that has shaped the transformation of the world of work and production methods over several centuries. From the transition from manual production to mass production to the introduction of intelligent, networked systems in Industry 4.0, technological breakthroughs have significantly changed the way goods are produced and services are provided. The so-called industrial revolution can be divided into four phases, each of which is characterized by groundbreaking innovations and profound upheavals. While the first three phases - Industry 1.0, 2.0 and 3.0 - have already been completed, humanity is currently in the fourth phase, Industry 4.0. The first industrial revolution (from around 1780) ushered in the mechanization of production with the steam engine, making manufacturing independent of natural energy sources possible for the first time. The early industrialization of Industry 2.0 (from around 1830) brought a massive increase in production capacities and advances in telecommunications thanks to electricity and assembly line work. The third industrial revolution (from around 1970) led to the automation of processes with computers and information technology and laid the foundations for digital business models. Finally, the fourth industrial revolution (since the end of the 20th century) through the introduction of the internet and the associated progressive digitalization is networking production systems through the use of modern technologies such as the Internet of Things (IoT), automation, artificial intelligence (AI) and big data. This enables highly flexible smart factories and accelerates globalization. Compared to the long development cycles of previous revolutions, Industry 4.0 is characterized by a rapid innovation dynamic that is fundamentally changing production processes and value chains (Heuser et al., 2017).

Key Technologies of the Smart Factory

Building upon the previous chapter's discussion of industrialization's emergence and phases, this section examines the efficient transformation of existing production facilities into smart factories, driven by increasing digitalization and networking. A comprehensive overview of the current state-of-the-art in smart factory technology is presented, analyzing key components like data generation, analysis and inter-machine communication (Rocha et al., 2023). Transformation methodologies, including the brownfield approach and digitalization frameworks are considered.

Specifically, the greenfield, brownfield and bluefield approaches are detailed, illustrating how these strategies facilitate targeted planning and optimization of digital production transformation while fostering future innovation.

Greenfield: In production facility development, the greenfield approach denotes a complete redesign and implementation from scratch, analogous to building on a "green field." This allows for the elimination of legacy system limitations and the integration of cutting-edge technologies and optimized processes. While offering maximum future-proofing, it necessitates comprehensive analysis, redesign and reorganization, potentially leading to longer project durations and higher costs. This clean-slate approach enables the rethinking of complex systems and the streamlined incorporation of new automation solutions (Hopkins & Jenkins, 2008; Gönnheimer et al., 2022; Jaspert et al., 2021; Etz et al., 2020; Wischhusen, 2023).

Brownfield: The brownfield approach, in contrast to greenfield, focuses on modernizing existing production facilities while preserving core processes and systems. It involves adapting data and processes to a new digital environment rather than implementing a complete overhaul. This approach enables the integration of current technologies into older machinery, regardless of age, potentially through a "big bang" migration requiring meticulous planning and prior validation of existing functionality within the new environment. Primarily aimed at optimizing and expanding existing automation, brownfield offers a cost-effective alternative to complete replacement, improving efficiency and functionality while adhering to current technical and legal standards (Hopkins & Jenkins, 2008; Gönnheimer et al., 2022; Jaspert et al., 2021; Etz et al., 2020; Wischhusen, 2023).

Bluefield: The approach offers a hybrid migration strategy, balancing the benefits of greenfield and brownfield implementations. It selectively integrates existing, proven system components with modern technologies, replacing obsolete elements. This allows for a gradual, non-disruptive transition, avoiding a "big bang" overhaul. By retaining valuable assets and strategically introducing new features, bluefield minimizes risk and optimizes resource allocation. It supports both process modification and new implementation, leveraging existing system knowledge. Data migration can be tailored to specific needs, ranging from selective to full historical transfer. This balanced approach ensures a cost-effective and timely modernization process (Jaspert et al., 2021; Etz et al., 2020; Wischhusen, 2023).

Architecture and Frameworks

After the various transformation methods, this section presents digitalization architectures and frameworks. The increasing global networking of production resources and processes necessitates the adoption of standardized frameworks. These frameworks provide concepts, methods and guidelines for designing future organizational structures, production systems and business processes in the context of Industry 4.0 digital transformation. Standardization frameworks such as the automation pyramid, the Reference Architecture Model Industry 4.0 (RAMI 4.0, 2014) and the Industrial Internet Reference Architecture (IIRA, 2015) are crucial for managing the complexity of this transition and ensuring strategically aligned implementation (Pedone & Mezár, 2018).

The automation pyramid is a central concept in industrial control technology that describes the hierarchical structure of automation systems in production. It is used to systematically classify the various levels, starting with field and process automation at the lowest level right up to strategic company management at the top. This structure enables efficient control and optimization of production processes. At the lowest level, sensors, actuators and controllers monitor the production processes in real time. Above this, control and process control systems coordinate machines and systems in order to optimize production processes. The operations management level comprises manufacturing execution systems (MES), which manage production orders, resources and schedules and thus establish the link between operational control and corporate goals. At the corporate level, strategic decisions are made that influence the entire manufacturing strategy. Here, Enterprise Resource Planning (ERP) systems link business processes, while Production Planning and Control (PPC) handles resource planning, including Material Requirement Planning (MRP I) and Manufacturing Resource Planning (MRP II) (Heuser et al., 2017).

RAMI 4.0 and IIRA are two central reference architectures for Industry 4.0 that differ in their development, structure and application. RAMI 4.0 was developed as part of a politically driven initiative and is based on the smart grid architecture model. It represents a three-dimensional cube model that describes Industry 4.0 components along three axes. The hierarchy axis integrates automation levels up to the enterprise control system, the layer axis comprises six levels for the detailed description of plants and systems and the life cycle and value stream axis follows the IEC 62890 standard by distinguishing between types (design and prototyping) and instances (production and use). RAMI 4.0 enables a step-by-step migration of existing production systems to a networked Industry 4.0 environment and places particular emphasis on end-to-end, lifelong data management. This includes not only physical assets such as machines, but also intangible components such as production plans or control data.

In contrast, IIRA was developed by industry and focuses on the information flows within the Industrial Internet system. The architecture is divided into four viewpoints that represent the different perspectives of the stakeholders. The Business Viewpoint links business objectives with regulatory framework conditions, while the Usage Viewpoint describes the planned use of the system based on typical processes. The Functional Viewpoint defines the functional components, interfaces and interactions, while the Implementation Viewpoint specifies the technical implementation and integration of the components. IIRA primarily considers physical objects and focuses on demand-oriented data collection for specific use cases such as big data analyses or process control (Pedone & Mezár, 2018).

Digitization and Data Transformation

In order to gain a comprehensive understanding of digital transfer and the technological elements that make up a smart factory, the current state of the art in this area is examined in detail below (Rocha et al., 2023).

Cyber-physical systems (CPS) are highly integrated systems that combine physical and digital components, enabling them to work in close cooperation. These systems decentralize and automate processes, particularly in manufacturing environments. By integrating CPS with embedded systems, they can communicate via the internet and utilize online services. CPS use sensors to collect physical data and actuators to influence processes, storing and evaluating this data to interact with both the physical and digital worlds. CPS can be networked with various objects, devices, buildings, transportation means or production facilities and they often feature multimodal human-machine interfaces for communication and control, such as speech or gestures. When CPS interact in production or logistics, they form cyber-physical production systems (CPPS) or cyber-physical logistics systems (CPLS), acting as autonomous, intelligent units. Each unit is represented by a plant agent, which serves as the interface between the Industry 4.0 agent system and the physical plant. CPS are used across industries such as healthcare, transportation, energy and manufacturing, enabling the automation, monitoring and optimization of complex tasks (Heuser et al., 2017; Bauernhansl et al., 2014; Rocha et al., 2023).

The Internet of Things (IoT) refers to a network of physical objects or "things," equipped with unique identities and capable of communicating, exchanging information and coordinating decisions. These objects, integrated with sensors, software and other components, interact with other devices and systems via the internet. IoT technologies enable the harmonization of diverse systems, even from different manufacturers, facilitating communication and automation without external intervention. IoT applications can range from everyday household devices to complex industrial machines. These "smart devices" have electronic intelligence that allows them to perform automated tasks and communicate over the internet. IoT is divided into private and industrial applications. In the private sector, it focuses on enhancing convenience through the networking of devices, such as smart home systems. In the industrial sector, it aims to automate processes, improving efficiency and reducing costs by enabling machines to self-organize. Industrial IoT applications include intelligent manufacturing, networked assets, preventive maintenance, smart grids, smart cities, networked logistics and digital supply chains. IoT technologies are widely used in manufacturing, automotive, retail, healthcare, transportation and logistics. By integrating IoT, businesses can improve process management, enhance productivity, create new revenue streams and optimize operations. This connectivity between the physical and digital worlds increases competitiveness, improves quality control and minimizes losses (Heuser et al., 2017; Jahid et al., 2023; Tran et al., 2022; Baker, 2023).

Digitaltwin: A digital twin is a virtual representation of a physical object, system, plant or process. This technology enables the capture and simulation of complex, dynamic environments. In a "cyber-physical" model, users interact with a digital replica of the production environment, which is continuously updated with real-time data, including static and dynamic information, behavioral patterns and interactions. Digital twins allow for the simulation of real-world objects and processes, enabling scenario testing, impact prediction and risk reduction before physical prototypes are created. This capability enhances decision-making, improves efficiency and fosters innovation. To develop a digital twin, clear framework conditions and precise software definitions are needed to ensure accurate replication of real-world objects in terms of status, properties and processes. With advancements in artificial intelligence and machine learning, digital twins will play an increasingly vital role across industries, offering greater precision, knowledge and agility for decision-making and innovation (Soori et al., 2023(12,16)).

Blockchain technology has established itself as a key innovation in the areas of digital currencies and business processes. It is based on a decentralized database that enables secure replication, sharing and synchronization of data regardless of location or organization. A key feature is the lack of a central administrator, as consensus algorithms control transaction validation in a peer-to-peer network. All transactions are stored in an immutable blockchain that is continuously expanded. The decentralized network protects the stored data from manipulation and unauthorized modification. A blockchain network can consist of anywhere from a few to millions of nodes. Transactions are only permanently recorded in the ledger once a consensus has been reached by the majority of nodes. In smart factory environments, blockchain can play a key role by enabling secure, transparent storage and management of data. Its security features, such as distributed consensus, cryptography and smart contracts, help to ensure data integrity, confidentiality and authentication. Smart contracts can also automatically detect and defend against security threats (Perera et al., 2020; Rajasekaran et al., 2022; Masood et al., 2023).

Artificial intelligence (AI) is a subfield of computer science focused on replicating aspects of human cognition through computational models. It encompasses methods that enable machines to perceive, understand and process information, as well as learn from data to improve performance over time. AI is generally classified into weak AI, which assists humans in specific tasks and strong AI, which aims for autonomous decision-making with human-like capabilities. Key advancements include machine learning (ML) and deep learning (DL), both of which drive modern AI applications (Baker, 2023).

Machine learning is a branch of AI that enables systems to identify patterns in data and make predictions or decisions without explicit programming. Based on training datasets, ML algorithms refine their models iteratively, adapting to new information. Depending on human involvement, learning can be supervised or unsupervised. ML is widely applied in robotics, anomaly detection in industrial processes and autonomous vehicles, utilizing various data types, including text, images and sensor inputs (Baker, 2023; Esposito et al., 2019).

Deep learning is an advanced subset of ML that relies on artificial neural networks (ANNs) with multiple layers to process large datasets. It mimics biological neural networks, where information flows through interconnected neurons, weighted based on learned importance. Deep learning algorithms, such as convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, enhance capabilities in image recognition, natural language processing and predictive analytics (Baker, 2023).

Robotics According to DIN 8373 (1996), industrial robots are defined as manipulators with at least three programmable axes. This broad definition has led to various designs, which are mainly categorized into industrial and service robots. Industrial robots are versatile, programmable machines used for handling, assembly or processing tasks in industrial environments, such as automotive manufacturing. They typically consist of a manipulator (robot arm), control unit and effector (tool or gripper). Service robots, as defined by the International Federation of Robotics (IFR) based on ISO 8373:2012, provide semi- or fully autonomous services that enhance the well-being of people and equipment but do not involve manufacturing processes. Examples include pool cleaners, vacuuming robots and lawnmowers (Etz et al., 2020).

Gateways serve as interfaces between incompatible systems by utilizing hardware or software components to enable communication. The term originates from computer science and information technology. Non-compliant networks operate with different communication protocols and addressing methods, requiring protocol conversion to facilitate data exchange. In this process, incoming data is translated by the gateway before being forwarded to the target network. A common example is a DSL router or network switch that connects a local area network (LAN) to the Internet. Additionally, gateways enable interoperability between mobile networks with varying architectures (Etz et al., 2020).

Radio Frequency Identification (RFID) Radio Frequency Identification (RFID) is a key technology for tracking products and material flows in manufacturing. It enables the electronic assignment of digital identities to physical objects and facilitates machine-to-machine (M2M) communication using tags and readers. As a passive technology, RFID tags lack intrinsic intelligence; they respond to interrogation signals from a reader, which transmits the data to a database for object identification within a range of 10 cm to 200 meters. RFID tags can be active (battery-powered), passive (battery-free) or semi-passive (battery-assisted). High Frequency (HF) and Ultra High Frequency (UHF) RFID systems ensure precise product tracking. The integration of RFID with sensor technology and communication protocols like ZigBee, Bluetooth and Wireless LAN has advanced the Internet of Things (IoT). Modern RFID systems enhance data transparency, optimize material flow and improve process planning, leading to greater efficiency and cost savings in manufacturing and logistics (Heuser et al., 2017; Bauernhansl et al., 2014; Baker, 2023; Zhong et al., 2013).

Message Queue Telemetry Transport (MQTT) IBM has developed the MQTT message protocol, which is specially designed for data transmission in applications in the consumer market. It is currently widely used, for example in office and home automation and in the healthcare sector. MQTT is also attractive for low-power and low-latency applications, especially those based on wireless devices (e.g. smartphones). The protocol is designed to "transport" data. Therefore, no differentiation/organization of data types is provided in the protocol specification. The MQTT architecture is based entirely on the publish/subscribe model. For example, a client cannot freely read variables, but must wait for the system to publish the information. According to the MQTT specification, the device can participate in the data exchange either as a server or as a client. The server is the message broker that manages and transmits the messages. It forms the center of the architecture to which all clients are related. The MQTT server is also referred to as a broker. On the other hand, a client can act as a publisher (sender) and/or subscriber (destination) of messages (Silveria & Sestito, 2019).

Mobile technology 5G, the fifth generation of mobile communication technology, offers significant advancements over its predecessor, 4G, particularly in speed, capacity, latency and connectivity. With speeds up to 20 Gbit/s (Enhanced Mobile Broadband, eMBB), 5G vastly outperforms 4G. It also features a latency of under 1 millisecond and 99.9999% reliability (ultra-reliable low-latency communication, uRLLC), enabling applications like augmented reality, virtual reality and autonomous driving. Additionally, 5G supports high device density, with up to 1 million devices per square kilometer (massive machine type communication, mMTC). In industrial settings, 5G enables efficient integration of numerous sensors and devices, reducing infrastructure costs. It is particularly beneficial for sensors that create digital twins of plant components. However, to ensure coverage and reliability, private networks using licensed spectrum and specialized equipment are required. 5G also features network slicing, allowing the division of applications into separate logical networks for efficient resource use (Jahid et al., 2023; Soori et al., 2023; Ahrend et al., 2021; Capgemini, 2023).

Research University of Applied Sciences Bochum

The BO Smart Factory research initiative at Bochum University of Applied Sciences aims to implement the production process for assembling pico satellites with the help of a prototype smart factory system. In collaboration with the space project at Bochum University of Applied Sciences, the automated assembly of the satellites is carried out in predefined assembly steps. The manufacturing system developed will be equipped with the advanced technologies described in this paper in order to further develop the current state of the art and research. The manufacturing process will be realized by the coordinated cooperation of traditional industrial robots, collaborative robots and mobile robots (AMRs). The brownfield methodology is used to plan the production system, in combination with a HOT approach. The V-model is used to develop the production processes, supplemented by agile methods from software development. In future, the project will offer companies the opportunity to automate and digitalize their heterogeneous production facilities and processes in a real test environment. This test environment also serves to test new processes, business models and methods in the context of Industry 4.0, with a focus on the sustainable implementation of efficiency measures under realistic conditions. The test environment addresses current challenges facing companies, such as demographic change, a shortage of skilled workers and high investment costs with limited expertise. It enables the realistic simulation of a modern factory system that can then be integrated into the company's operational structures (Gönnheimer et al., 2022; Capgemini, 2023; Reich et al., 2022; Wee et al., 2016).

CONCLUSION

This paper provides an overview of the digital transformation towards a smart factory within the context of Industry 4.0, comparing methods, explaining technologies and presenting frameworks and guidelines for digitalization. It highlights the impact of digitalization on the labor market, emphasizing the growing automation of work processes. Driven by digitalization and globalization, product life cycles and innovation cycles are shortening to maintain competitiveness. In the future, robots and software will increasingly perform tasks previously done by humans in production, administration and services. Emerging technologies such as artificial intelligence, quantum computing and blockchain will unlock new business areas and transform existing models. The paper also discusses research at Bochum University of Applied Sciences, which addresses these challenges and supports companies in their digital transition. In collaboration with industry, the university is developing guidelines implemented in its prototype smart factory, providing a test environment for companies to trial digital components in production. This smart factory utilizes cutting-edge technologies to develop digital solutions for industrial production, advancing the vision of intelligent factories. The work underscores that the digital transformation has technological, economic and social implications, necessitating sustainable and innovative development.

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