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ADVANCES IN SMART FACTORY AUTOMATION: INTEGRATING ROBOTICS, IOT, AND CYBER-PHYSICAL SYSTEMS

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Abstract: Industry 4.0 sees the modern manufacturing being transformed due to the combination of automation and robotics, Internet of Things (IoT), Cyber-Physical Systems (CPS), and artificial intelligence (AI). The present paper gives a detailed view of how all these technologies together ensure smart factories through improved efficiency in operations, quality of products, and real-time decision-making. Automation and AI-based analytics are able to optimize production processes, whereas advanced robotics and human-robot collaboration enhance flexibility, safety, and precision of tasks. IoT and CPS provide a continuous connection between physical objects and computerized systems, which contribute to the massive data collection and monitoring and prediction regulating control. The Digital Twin technology also enhances the process simulation, lifecycle optimization, and intelligent manufacturing management. By combining insights into recent developments, applications, and technological trends, the present paper demonstrates that the digital transformation is crucial in the formation of future manufacturing ecosystems and outlines the essential issues and research opportunities to apply smart manufacturing industrial automation in the future.

Keywords: Automation, Smart Factories, Industry 4.0, Robotics, IoT, Cyber-Physical Systems (CPS), IIoT, Edge Computing.

1 INTRODUCTION

The Manufacturing automation in Industry 4.0 is shifting toward mass production and mass customization via human–robot collaboration. The diverse human–robot collaboration methodologies and their suitability for diverse manufacturing methods are discussed [1]. The benefits of cutting expenses in corporate processes have been demonstrated in a number of studies. the business automation process through the use of robots, but also tries to reduce business management costs through faster activities and more efficient processes that may support many businesses in the future. automation processes with business process management systems or focus on the conceptual application of IoT-based technology [2][3]. Smart automated inspection machines and adopting industrial automation in the textile manufacturing sector. Moreover, profitability is analyzed under uncertain demand scenarios when significant demand data are unavailable. We consider both triangular and trapezoidal demand patterns and their effects on total supply chain profit.

Robotics is a multi-disciplinary domain which deals with study and use of robots. The word robot derived from 'robot', meaning 'forced labour', was first used by Czech writer in 1921 is play ' Rossum's Universal Robots (RUR)'. Lead by science fiction, robots were considered as futuristic machines. Through technological advancements in various fields of electronics, mechanical, computer, information technology, scientists and engineers have been striving hard to practically realize these machines [4]. Conceptually, the IoT is a combination of virtual domains that use the internet to exchange information. Various real-world applications have adopted IoT-based technologies that have made life easy [5][6]. The wide applications of the IoT include smart healthcare, smart agriculture, automatic security systems, smart factories, and smart industries [7]. The smart industry has initiated an extremely positive effort by integrating IoT technology in the industrial domain. As predicted, advanced technologies and industry could solve numerous problems by implementing pervasive security countermeasures through the effective implementation of the IoT.

The smart factory is a concept that makes intelligent use of robotics, automation, embedded systems, and information systems toward Industry 4.0. [8] It is considered a transformation from classical (standard) to intelligent manufacturing heading towards digital manufacturing and digital twin models supported by many emerging technologies such as Cyber-Physical Systems (CPS), Internet of Things (IoT), Big Data, cloud computing, and advanced AI, The combination of physical and virtual spaces is referred to as cyber-physical systems (CPSs), and it aims to create a communicative interface between the digital and physical worlds by integrating computation, networking, and physical assets [9][10]. While the definition of CPS may vary based on perspectives and backgrounds, it is well-understood that the interconnection between the physical world is represented by hardware (e.g., sensors, actuators, robots) and cyber software (communication, networking and internet). CPS is at the core of Industry 4.0.

1.1 Structured of the paper

This paper is organized to cover key aspects of automation in smart factory. Section 2 explores Automation in smart factory, while Section 3 discuss Robotics in smart manufacturing. Section 4 examines CPS and IOT in smart factory manufacturing. Section 5 provides a literature review of recent technologies and trends, and Section 6 concludes and future directions for smart factory automation.

2 AUTOMATION IN SMART FACTORY

The automation of production processes. In the intermediate stage, the focus shifts to strengthening real-time data collection and process management through sensor networks and the Industrial Internet of Things (IIoT) [11]. In the advanced stage, artificial intelligence (AI)-driven predictive analytics and autonomous decision making are employed to optimize processes and maximize productivity. Recent studies have emphasized the technological integration of IoT, IIoT, and Industry 4.0 as the core enabler for smart manufacturing.

2.1 Factory Autonomous Systems

The factory automation systems to fix this kind of problem, the modern control theories involved with state-space and dynamic programming as the core was proposed and widely used in the engineering domain, particularly in aerospace. Therefore, information and communication technology (ICT), including sensor technology, computer, and intelligent technology, communication technology, and control technology, was developed to solve system automation problems. However, due to the increasing complexity of system functions and the diversification of system decision-making, automation technology could not fully meet production needs [12]. The demand for developing autonomy became increasingly vital to alleviate the dependence on human-related interactions, on the other hand, to improve the ability of individuals and systems to complete tasks independently. The development process of the automation system.

The studies in the field of artificial intelligence (AI) are developed and widely discussed in the scientific community. These studies consider the theoretical aspects of the AI technologies and their applications in many areas of our society [13]. The methods of machine learning (ML) are a group of methods often used in AI, which allow for the prediction of new properties of data based on known properties discovered from the training data. One of the specific areas of ML is deep learning (DL).

2.2 Smart Automation of PLC & SCADA

The PLCs and communication interfaces that work with the thinger.io local server IoT platform are being studied. The research aims to demonstrate low-cost embedded platforms based on PLCs using Arduino and Raspberry Pi, which provide communication functions, variable pre-processing and control schemes, to note the programming limitations of traditional PLCs so that the Arduino and Raspberry Pi powered processors come forward as industrial solutions. A proposal comes about using open source hardware and software for SCADA (Supervisory Control and Data Acquisition) systems [14]. The system is composed of four segments: the master terminal unit (MTU), communication protocol, remote terminal unit (RTU), and field devices. The Modbus TCP facilitates data exchange among all the elements including the SCADA platform, which is on a different subnet than the process controllers to keep them safe from external network access.

3 ROBOTICS IN SMART MANUFACTURING

Robotics in manufacturing are well-known for enhancing productivity and product quality due to their durability, accuracy, and flexibility. DTs can describe, control, and display robotic systems' behaviour in real time, enabling the intelligent perception, simulation, understanding, prediction, and optimization of manufacturing processes [15].

3.1 Automation of Tasks

Task automation automates tasks using technology that humans would otherwise perform. Task automation has the potential to improve efficiency, reduce errors, and free up time for more complex and creative work, therefore becoming significantly important. Automating tasks can improve efficiency by reducing the time and effort required to complete them, allowing users to focus on more high-level and value-added tasks. Task automation also increases accuracy due to being less prone to errors and mistakes than manual tasks, which can improve quality and user satisfaction. Currently, task automation is being used in a wide range of industries, including manufacturing, healthcare, finance, and customer service.

- **Web Task Automation & Intelligent Agents:** The user browses annotated websites and selects samples, and d.mix's sampling mechanism generates the underlying service calls that yield those elements [16][17]. The limitations of this system are that the coexistence of two different sampling strategies confused the tool on how to separate a dataset; in a user study.
- **Mobile Task Automation & Intelligent Agents:** The "Worker-to-Robot Replacement Time" refers to the estimated duration needed to fully replace a human worker with a robotic system in a specific role.
- **Desktop Task Automation & Intelligent Agent:** The early task automation systems and intelligent agents which were developed were mostly desktop-based. The first task automation system using the programming-by-demonstration approach was Pursuit by Modano and Myers which enables users to create abstract programs directly containing variables, loops, and conditionals within the interface.

3.2 Innovations in Design: AI-Driven Robotics

Technology related to robotics is a fast-growing area that integrates many different areas like mechanical engineering, electronics, and computer science, and its ultimate goal is to create machines that can mimic, help or completely take over human workers in carrying out certain activities [18]. The foremost thing that comes to mind when designing a robot is the work that needs to be done in different challenging environments, for example in congested areas or around several obstacles, along with the possibility of increasing the structural complexity to suit different tasks and unpredictable environments. Moreover, machines will have to constantly read and analyze vast amounts of intricate data before they can come up with the right decisions through their perception.

- **Autonomous Navigation & Decision-Making:** The autonomous collision avoidance of ships must be developed. In this regard, artificial intelligence has developed rapidly in recent years, and the combination of robot technology and control technology has provided a new solution to the problem of path planning for ships and intelligent collision avoidance [19].
- **Human-Robot Interaction (HRI):** Human–robot interaction (HRI) is a fast-growing research field in robotics and seems to be most promising for robotics' future and its effective introduction into more and more areas of everyday life. HRI research covers many fields and applications.

3.3 Integration with Digital Twins

The Digital Twin (DT) has become increasingly prominent in recent years, being widely discussed in the literature on Industry 4.0 and conversations within large companies, particularly in the IT and digital sectors [20]. The term "Digital Twin" is evocative and partially self-explanatory, although not entirely accurate. As a result, two outcomes have emerged. Firstly, the concept has gained significant popularity across various application areas, surpassing its initial domains, such as aerospace engineering [21], robotics, manufacturing, and IT Furthermore, there is a lack of consensus concerning the exact definition of the term, its areas of application, and the minimum requirements to distinguish it from other technologies.

- **Real-Time Data Synchronization:** Time synchronization was applied on the basis of paired timestamps from the peripheral and central nodes, with random timing variation reduced via a linear least squares' regression algorithm [22]. The central node (or an offline algorithm, in our study) then multiplexes the received data from the peripheral nodes.
- **Process Optimization:** Manufacturing processes transform raw materials into finished products and are broadly categorized in additive manufacturing (material is added layer by layer to create a shape where manufacturing data (process-relevant data, CAD models, systems, algorithms, and alike) are openly available for analysis and application across different workspaces.

4 CPS AND IOT IN SMART FACTORY MANUFACTURING

CPS can be considered a new generation of digital systems and their impact on the acceleration of technological progress is huge. A CPS arises from a tight integration of a cyber system and a physical process. It is defined as a system that deeply joins the capacity of computing and communication to control and interact with a process in the physical world [23]. Through the feedback loop between computing and the process, real-time interactions are increased with the physical system to monitor or control the physical entity in a secure, efficient, and reliable way in real time [24]. The building of CPSs in mobile robotics is particularly interesting. In designing and implementing advanced robotic heterogeneous hardware platforms for controlling an ever-larger multi-agent system, several challenges appear.

4.1 Digital Twin Technology

DT, as a tool for smart asset management, offers the opportunity to integrate physical objects with their virtual counterparts throughout their life cycle to replicate their real-world behaviour. A technology trend report identified DT as one of the top four emerging technologies among a selection of fifteen. It is a revolutionary and innovative technology that enables a quicker and more efficient management, monitoring.

- **Understand Digital Twin:** DT is founded on some current technologies, including, but not limited to, 3D modelling, system simulation [25], and functional and behavioral prototyping. It has been used in aerospace and astronautics for implementation in as-built and next-generation aircrafts for years.
- **Digital Twin for Smart Cities:** DTs hold significant potential for transforming the current urban governance model toward the development of smart cities and the rapid advancement of DT technology within smart cities is making valuable contributions to their development s automation and the benefits of IDP and RPA in insurance claims [26].
- **Technological Drivers of Digital Transformation:** AI), cloud computing, and big data analytics, has accelerated the digitalization of different systems and processes across various sectors including architecture, engineering, and construction Through digital transformation and integrated adoption of technologies [27].

4.2 Smart Decision-Making Through CPS

Smart Cities have emerged as a beacon of innovation, integrating advanced technologies to enhance the quality of life for residents while addressing pressing urban challenges [28]. At the heart of this transformation lie Cyber–Physical Systems (CPSs), which seamlessly integrate physical components with computational and communication capabilities to monitor, control, and optimize various aspects of urban life. In recent years, the concept of Symbiotic CPSs.

4.3 Architecture and Components of CPS in Manufacturing

Developing CPS for industrial applications, either designing new industrial CPS from scratch ("greenfield") or upgrading existing physical systems ("brownfield"), is a challenging undertaking. The development is especially challenging because the consequences of a failing industrial CPS are typically severe, e.g., with respect to safety, productivity, cost, or company reputation. Smart integration Strategies for Digitalization.

4.3.1 Internet of things (IoTs)

AI and the internet of things (IoTs) have started redefining the face of the pharmaceutical landscape and have, therefore, become transformational technologies [29]. AI consists of all those broad-ranging technologies, from machine learning to natural language processing, among other things, to afford advanced analytics with automation capabilities, thereby connecting data exchange with real-time monitoring without the involvement of any device or manual interference. Put together, these technologies can enable a quantum leap in operational effectiveness, quality of products, and regulatory compliance from the conventional, inefficient manual process followed in the industry.

4.4 Manufacturing Automation of IoT-Driven Transformation

This evolution not only enhances operational performance but also introduces new opportunities for innovation and growth in the manufacturing sector. These technologies can streamline the obtaining and processing of real-time the integration of cloud computing with IIoT enabled large-scale data storage and processing, allowing manufacturers to leverage big data analytics [30] for predictive maintenance and tool condition monitoring [31]. This period also saw the emergence of edge computing, where data processing was moved closer to the source (e.g., sensors) to reduce latency and improve real-time decision-making.

4.5 IoT Integration with Robotics and CPS in Smart Factories manufacturing

The strength of lies its recognition of the profound impact of the Fourth Industrial Revolution, or Industry 4.0, on the higher education system and, specifically, the training of future engineers for yet-to-exist professions [32]. It underscores the importance of nurturing soft skills for competitive professionals. The enumerated soft skills, including IT skills, information literacy, teamwork, flexibility, adaptability, learning, and cognitive skills, form a comprehensive framework for addressing the demands of the Fourth Industrial Revolution.

4.6 AI-Powered IoT Analytics in Smart Factory Automation

Artificial Intelligence (AI), the Internet of Things (IoT), and Digital Twins (DT) are interconnected technologies that enhance decision-making, automation, and system optimization across various domains AI refers to the development of algorithms and systems that enable machines to perform tasks that typically require human intelligence, such as learning, reasoning, and problem-solving. IoT involves a network of physical devices embedded with sensors, software, and connectivity, allowing them to collect and exchange data over the internet [33][34]. AI-powered DT can simulate different scenarios, such as occupancy patterns or equipment failures, to identify potential inefficiencies and suggest proactive maintenance measures. Together, these technologies create smarter, more sustainable buildings that adapt in real-time to changing conditions.

5 LITERATURE REVIEW

Recent studies in this section show that the Automation in Smart Factories. Table 1 summarizes recent studies on Automation in Smart Factories, highlighting study, key findings, challenges, and future directions.

Raffik, Balamurugan and Pandian (2025) discusses edge computing architecture and deployment models, its hardware and software components, and networking infrastructure. The objectives to review are to analyze how edge computing facilitates real-time decision-making in automated industrial processes. The discourse is then fully addressed around the different core technologies, advantages, concerns, real-life instances, and future trends toward increasing efficiencies, lowering latencies, and making smart manufacturing possible [35].

Chinnasamy et al. (2025) proposes novel technique in smart manufacturing system based on cloud computing with IIoT in energy efficiency using machine learning. Here the smart manufacturing process has been analysed based on IIoT with cloud computing network, where the energy efficiency is analysed using virtual machine-based reinforcement markov chain based linear regression. Experimental analysis has been carried out in terms of latency, energy efficiency, task response time, accuracy. proposed technique obtained 97% of Latency, 95% of Energy efficiency, 98% of Accuracy, 94% of Task response time [36].

Bi et al. (2025) discusses the relevance of Internet of Things (IoT) to Sustainable Mechatronics. The impact of IoT on sustainable mechatronic systems is discussed, and the focus is on how IoT is used to empower mechatronic systems by integrating with more smart things over Internet. IoT-based reference architecture is presented, and critical enabling technologies are explored. Functional Requirements (FRs) of sustainable mechatronic systems are defined in terms of openness, scalability, dynamics, privacy, and security. Satisfying these FRs require IoT-based solutions in data acquisition, transmission, processes, and utilization [37].

Amiri, Steindl and Hollerer, (2024), which included vendors, integrators, and asset owners, focused on secure and safe infrastructures, system architectures, and risk management. Our findings revealed limited industry awareness and usage of the Reference Architecture Model Industry (RAMI) 4.0, emphasizing the need for an economically viable, holistic approach to integrated security and safety by design. Moreover, we introduced a comprehensive ontology for safety, security, and operation requirements in the IT/OT convergence. Building on top of these works, we introduce a model-based engineering approach to implement integrated safety and security while designing industrial Cyber-Physical Systems (CPS). We model these systems precisely using System Modeling Language (SysML) 2.0 specification and verify the requirements [38].

Jochman et al. (2024) explores the integration of augmented reality into robotic manufacturing systems, emphasizing the enhancement of connectivity, real-time data processing, and interactive visual interfaces. Utilizing HoloLens 2 headsets equipped with OPC UA clients, the system establishes a direct interface between operators and the digital and physical components of the manufacturing environment. The architecture employs augmented reality to facilitate sophisticated operational control and visualization, ranging from robotic additive manufacturing to complex tasks like robotic sanding and screwing with integrated camera systems [39].

Onu, Pradhan and Madonsela (2024) explores recent information technology solutions and prospects of IoT integration and DT technology within smart manufacturing environments rough a comprehensive review of literature and expert insights, this research posits the potential of these technologies in optimizing manufacturing processes, enhancing productivity, and enabling predictive maintenance strategies. Additionally, the study explores the critical role of data analytics in ensuring seamless integration and efficient functioning of IoT and DT systems. This is a contribution to the body of literature on smart manufacturing [40].

Monteiro and Garcia (2023) Things" in industrial areas, find a technology ready to assist in monitoring and tracking the performance of various assets in industrial automation. This article focuses on the development of a microprocessor device created to monitor control valves with spring/diaphragm pneumatic actuators, commonly found in industrial process control installations. The proposed Industrial Internet of Things (IIoT) device is currently being developed and tested in the Industrial Process Control Laboratory of Escola Polytechnical of the University of Sao Paulo (LCPI-EPUSP) [41]

TABLE I. COMPARATIVE REVIEW OF EMERGING TECHNOLOGIES IN SMART MANUFACTURING AND INDUSTRIAL AUTOMATION"

References	Study On	Approach	Key Findings	Challenges / Limitations	Future Direction
Raffik, Balamurugan, and Pandian (2025)	Edge computing in industrial automation	Architecture analysis, component study, real-world applications	Enables real-time decision-making, reduces latency, improves efficiency in smart manufacturing	Concerns related to hardware-software integration, network infrastructure	AI-based analytics, energy-efficient devices, seamless interoperability
Chinnasamy et al. (2025)	Energy-efficient smart manufacturing using IIoT and cloud	ML-based virtual machine with Markov chain regression	Achieved 97% latency, 95% energy efficiency, 98% accuracy, 94% response time	Complex modeling, potential scalability issues	Optimized integration of ML with IIoT and cloud for improved energy models
Bi et al. (2025)	IoT and sustainable mechatronics	IoT-based reference architecture and FRs	IoT improves openness, scalability, and dynamic adaptability of mechatronics	Challenges in meeting privacy and security FRs	Focus on IoT solutions for efficient data processes and system interoperability
Amiri, Steindl, and Hollerer (2024)	Secure architectures in CPS and RAMI 4.0	SysML 2.0-based model engineering	Developed integrated model for safety and security, low RAMI 4.0 adoption noted	Lack of awareness of RAMI 4.0, fragmented security designs	Holistic model-driven security and safety in CPS systems
Jochman et al. (2024)	Augmented Reality (AR) in robotic manufacturing	AR via Hololens 2 and OPC UA clients for control and visualization	Enhanced interaction, optimized workflows, real-time data control	Hardware dependency, integration cost	Broader use of AR in additive manufacturing and visual interfacing
Onu, Pradhan, and Madonsela (2024)	IoT and Digital Twin (DT) in smart manufacturing	Literature review and expert analysis	Optimizes manufacturing, improves predictive maintenance, highlights analytics role	Data privacy, IP rights, AI ethics not fully addressed	Explore ethical AI, data ownership frameworks, fair use standards
Monteiro and Garcia (2023)	IIoT for control valve monitoring in industry	Development of custom IIoT microprocessor device	Efficient asset tracking in pneumatic actuator systems	Currently under testing, lab-scale implementation	Field validation, scalability for industrial deployment

6 CONCLUSION AND FUTURE WORK

The recent rapid changes of Industry 4.0 have also resulted in highly intelligent, connected, and autonomous production spaces of traditional manufacturing. The paper has discussed the underlying technologies behind this change, which include automation, robotics, IoT, CPS, AI and Digital Twins, and their combined ability to improve productivity, flexibility and decision making in smart factories. The AI-based analytics and advanced control architecture created by the modern-day automation systems have provided real time monitoring, predictive optimization and less human reliance to achieve routine operations. The use of robotics, which has been enhanced by advancements in sensing, pathways, and human robot interaction, remains to reinvent the way things are done and the safety of the workplace. Simultaneously, IoT and CPS offer the architectural support of the uninterrupted communication of physical objects and cyber systems to coordinate the workflows, obtain massive amounts of data and control processes in real time. Digital Twin integration also enhances the process of simulation-based planning, lifecycle management, and ongoing optimization of different industrial processes. These technologies combined create the basis of the smart factory ecosystem and reflect the bright future of contemporary manufacturing.

The future research step should be to enhance the security, scalability and interoperability of IoT- and CPS-based manufacturing systems as factories become inter-networked. Higher levels of AI models such as self-learning and federated learning techniques are required to manage data paucity and privacy issues in industrial context. The Digital Twin should also be improved to make autonomous decisions, coordinate multi-agents, and predictive analytics in real-time in future research. Also, it will be needed to expand safe and effective human-robot collaboration system to facilitate the shift to more flexible, human-oriented, and resilient smart manufacturing systems.

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