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Research
AI Energizes Process Manufacturing—Perspective

Cyber–Physical Production Systems for Data-Driven, Decentralized, and Secure Manufacturing—A Perspective

Manu Suvarna [a], Ken Shaun Yap [b], Wentao Yang [c,d], Jun Li [e], Yen Ting Ng [b], Xiaonan Wang [f,*]

[a] Department of Chemical and Biomolecular Engineering, National University of Singapore, Singapore 117585, Singapore
[b] Singapore Institute of Manufacturing Technology, Singapore 138634, Singapore
[c] School of Economics and Management, Tsinghua University, Beijing 100084, China
[d] Zhigui Internet Technology, Beijing 100080, China
[e] China Industrial Control Systems Cyber Emergency Response Team, Beijing 100040, China
[f] Department of Chemical Engineering, Tsinghua University, Beijing 100084, China

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ABSTRACT

With the concepts of Industry 4.0 and smart manufacturing gaining popularity, there is a growing notion that conventional manufacturing will witness a transition toward a new paradigm, targeting innovation, automation, better response to customer needs, and intelligent systems. Within this context, this review focuses on the concept of cyber–physical production system (CPPS) and presents a holistic perspective on the role of the CPPS in three key and essential drivers of this transformation: data-driven manufacturing, decentralized manufacturing, and integrated blockchains for data security. The paper aims to connect these three aspects of smart manufacturing and proposes that through the application of data-driven modeling, CPPS will aid in transforming manufacturing to become more intuitive and automated. In turn, automated manufacturing will pave the way for the decentralization of manufacturing. Layering blockchain technologies on top of CPPS will ensure the reliability and security of data sharing and integration across decentralized systems. Each of these claims is supported by relevant case studies recently published in the literature and from the industry; a brief on existing challenges and the way forward is also provided.

1. Introduction

1.1. Transformation in manufacturing

Value creation in the manufacturing industry has been subject and witness to radical evolution over the past two centuries. Be it the steam-powered factories of the First Industrial Revolution, the application of mass production technology during the Second Industrial Revolution, the automated manufacturing of the Third Industrial Revolution, or—most recently—the digital revolution in manufacturing known as "smart manufacturing," each has disrupted existing manufacturing paradigms and transformed the efficiency, productivity, safety, and profitability of the global manufacturing sector. Manufacturing has been a key pillar in the global economy, and the most recent transformation toward smart manufacturing has intrigued most developed and developing nations. These nations are now transforming their existing manufacturing infrastructure and labor markets to produce personalized and specialized products—with targeted investments in research and development (R&D) and an emphasis on technological innovation [1,2]. Table 1 presents some of the major enterprises and R&D initiatives taken in this direction across the world.

1.2. Enablers of a paradigm shift in manufacturing

The advancement and expansion of information and communication technologies (ICT), wireless networks, and the Internet of Things (IoT) in the last decade have created an unprecedented opportunity to access and use data ubiquitously across various domains and, more specifically, in manufacturing processes [6,7]. Moreover, the rise of artificial intelligence (AI) algorithms, including machine learning, deep learning, reinforcement learning, and knowledge graphs, have fostered the operation and control of manufacturing systems to become more intuitive, intelligent, and informed [3,8]. Technologies such as the Industrial Internet of

* Corresponding author.
E-mail address: wangxiaonan@tsinghua.edu.cn (X. Wang).

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Table 1
Evolution of global smart manufacturing initiatives over the decade [1,3–5].

Country	Initiative	Year of inception
Germany	Industry 4.0	2011
UK	High Value Manufacturing Catapult	2011
USA	Smart Manufacturing Leadership Coalition	2012
Sweden	Production 2030	2013
Republic of Korea	Manufacturing Innovation Strategy 3.0	2014
China	China Manufacturing 2025	2015
Singapore	Industry Transformation Maps	2017
Japan	Connected Industries	2017

Things (IIoT), cloud computing, edge computing, and fog computing have enabled otherwise resource-constrained and dispersed industrial devices and systems to gain powerful computation capabilities with explicit communication and coordination, thereby enabling near real-time data-driven decision-making [9–11]. The application of these computational resources and network-based technologies in driving the shift toward next-generation manufacturing systems is often referred to as "smart manufacturing" or the "factories of the future" [3,7].

Along with the acceptance of this current generation of computation technologies, a strong and sustained market desire and a push for personalized products have contributed equally to the change of trends in manufacturing practices [12,13]. The concept of modularity, which has been adopted by the automobile sector in recent years, is an ideal example. Modularity on the automotive shop floor requires identical automobile components to be mass produced in a conventional assembly line. It is only at the finish (i.e., the last stage of the assembly line) that custom modules are added to give each model/product its unique characteristics. Thus, mass production has become hybridized with customization to allow for the production of unique goods at scale, thereby enabling strategies for "mass customization" by producing highly personalized products in dynamic batch sizes and efficiencies at the cost of conventional assembly lines [14]. In particular, the confluence of modern digital technologies and networks (ICT and AI), along with the drive toward mass customization in producing personalized or customized products, has triggered a disruption in existing manufacturing paradigms and aims to transform global manufacturing into a smarter, more automated, and decentralized version of itself [2,13,15], as represented in Fig. 1.

In this review, we present a broad overview of cyber–physical production system (CPPS) and offer our views on how CPPS will act as key enablers of next-generation manufacturing systems. We do not intend to provide a systematic and detailed review of the literature pertaining to CPPS, nor do we present a thorough review of its enabling technologies, as these are reported elsewhere [16,17]. Rather, we focus on three aspects of smart manufacturing through the lens of CPPS: ① data-driven modeling, ② decentralized systems, and ③ integrated blockchains for data security. We also establish a link among these aspects and explain how one engenders the other. The remainder of this paper is outlined as follows. Section 2 presents a brief introduction and lists essential characteristics of a CPPS with respect to smart manufacturing. Section 3 delves into CPPS-enabled data-driven manufacturing through the real-time data analytics, monitoring, control, and optimization of manufacturing processes. In Section 4, we reflect on decentralized manufacturing, its enablers, and the way forward. Section 5 discusses the role of blockchain-enabled CPPS for traceable, transparent, and secure data management across decentralized manufacturing units. Lastly, the challenges in this roadmap and the conclusive understanding of this study are presented in Sections 6 and 7, respectively. The overall theme of the review, as depicted in Fig. 2, is to bring forth the idea that CPPS will aid in transforming manufacturing to become more data-driven and automated, which in turn will pave the way for decentralized manufacturing. The layering of blockchain technologies on top of CPPS will ensure the reliability and security of the data shared across such distributed systems.

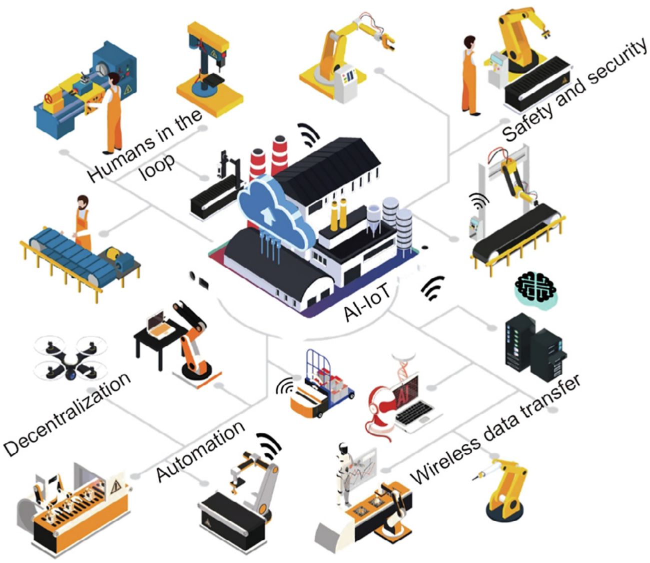

Fig. 1. The future of factories driven by the integration of various cyber technologies with physical systems (machines and humans) for automated and smart manufacturing technologies.

2. Cyber–physical production systems

2.1. Conceptual overview and research impact

Smart manufacturing represents an advanced kind of manufacturing system in which the exchange and analysis of data in real time, across all forms of the product life cycle (including the shop floor, supply chain, and enterprise) [2,6] aids in the improvement of the overall efficiency, productivity, and profitability of manufacturing processes through informed decision-making [8,18]. A CPPS is the interactive and responsive platform of such an automated manufacturing environment, as it amalgamates real-world, dynamic physical processes with cyber systems through a communication–computation–control loop, thereby ensuring real-time acquisition, exchange, process, and feedback of data for efficient and informed decision-making [11,19]. In contrast to the typical automation pyramid that exists in conventional manufacturing (which is a hierarchical system of field sensor–programmable logic controllers–process control–optimization–enterprise decision-making), CPPS offer more decentralized characteristics that enable a multitude of instruments or machines on the shop floor to seamlessly communicate and interact with each other and with human operators, primarily aided by the IIoT and data-driven models [16,17].

Since the inception of this ideology, CPPSs have garnered substantial interest in the manufacturing scientific community. Specific to this review, the visualization of similarities (VOS) viewer, an open-source text mining and visualization program [20], was employed to present a visual representation of the research directions pertaining to CPPS-aided manufacturing. Fig. 3 presents the network plots generated from the viewer, in which three clusters are identified for research topics of interest with respect to CPPS.

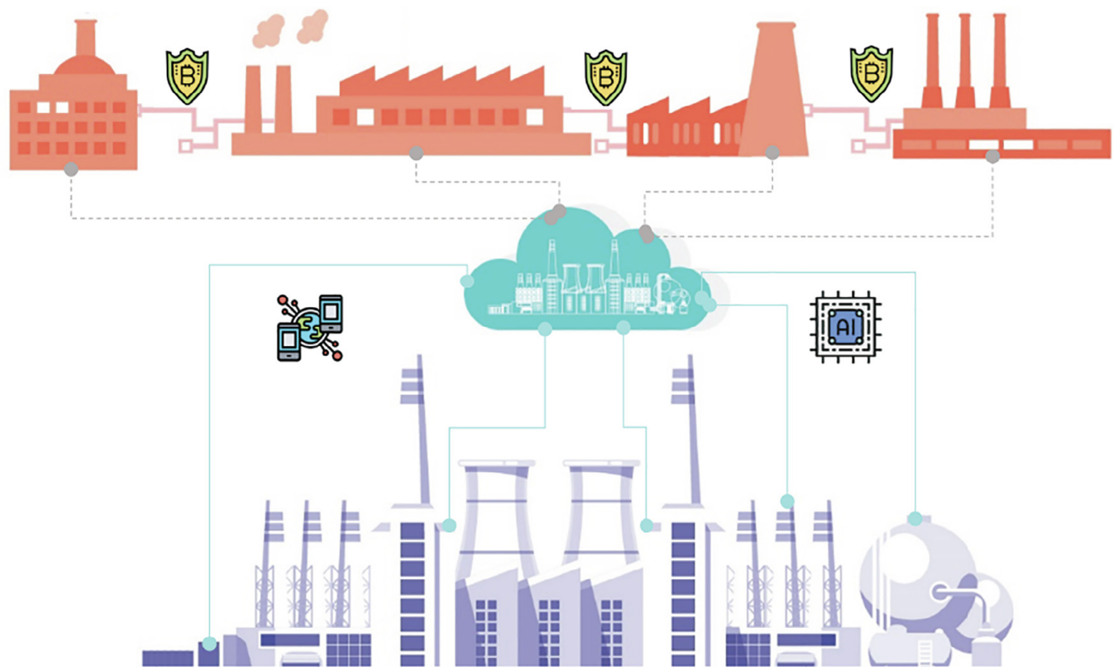

Fig. 2. The structured layers of a smart factory enabled by CPPS, in which data-driven manufacturing enables decentralized manufacturing through automation and connected entities. The subsystems of a decentralized manufacturing system are exclusive to each other, but receive and exchange data with individual entities to make informed decisions. This sharing of data and information necessitates blockchain technology, which in turn enables a transparent and secure smart manufacturing ecosystem.

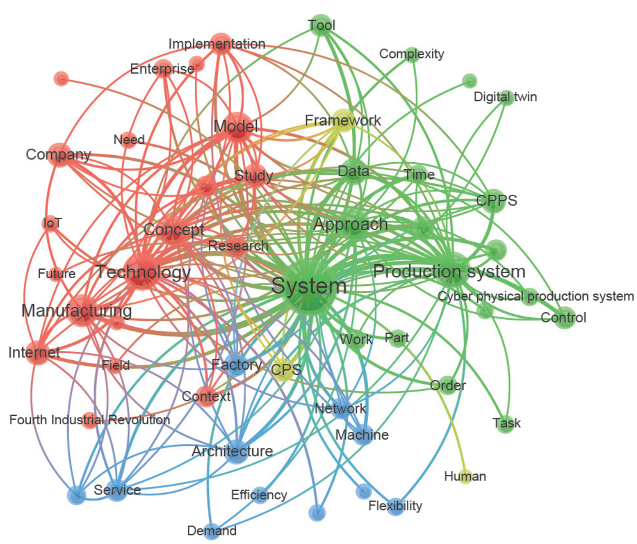

Fig. 3. Network plots as visualized in the VOS viewer. A keyword search for terms such as cyber–physical production systems and manufacturing was performed in the Web of Science for the time period 2015–2019. Based on this filter, the first 50 terms that occurred a minimum of 30 times (in the title, keyword, or abstract) were selected to generate the network plot. In the network plot, the size of the label and its corresponding circle represent the weight (i.e., significance according to the frequency of occurrence in literature) of the topic.

The color of each term is determined by the cluster it belongs to, while the lines represent co-occurrence of the term in the published literature.

The green cluster with the term system as the centroid represents studies on the more basic and essential attributes of CPPS and includes terms such as production system, digital twin, data, and control. The blue cluster with the term architecture as the centroid encompasses the concept of a CPPS as a platform and includes terms such as network, demand, efficiency, and flexibility while the red cluster with technology as the centroid depicts the application of CPPS, as evident through terms such as manufacturing, research, enterprise, and Fourth Industrial Revolution.

2.2. Characteristics of CPPS

2.2.1. Real-time data access and analytics

In manufacturing, conventional production and scheduling tasks have relied on deterministic planning, based on expert human knowledge and experience. However, with the changing paradigms in factories of the future, pervasive sensing objects that are integral to CPPS will foster the real-time access, acquisition, and storage of relevant manufacturing data, both perennially and ubiquitously [11]. Recent developments and applications of seamless and tether-free methods of data acquisition, channelization, transfer, distribution, and storage in a central database through protocols such as message queuing telemetry transport (MQTT), constrained application protocol, simple text-oriented messaging protocol, and extensible messaging and presence protocol [17,21], which are essentially IIoT technologies, have fostered a greater degree of agility and dynamicity for data within manufacturing. Moreover, in addition to data acquisition, transfer, and storage capabilities, data-driven AI models specifically devised from machine learning, or deep learning algorithms that are integral characteristics of CPPS [3], transform the aggregated data into actionable and insightful information. This is done by devising complex multivariate linear or nonlinear relationships (supervised learning) without needing to significantly understand the physical system, or by exclusively identifying underlying patterns in the data itself (unsupervised learning), which would otherwise not be conceivable [6,8]. The application of these analytical models involves the concepts of descriptive analytics, causal analytics, predictive analytics, and prescriptive analytics, the application of which is transforming manufacturing into highly optimized and smart production facilities through planned and informed decision-making.

2.2.2. Decentralized system and interoperable capabilities

The advancement and development of CPPS have not only given rise to highly automated and intelligent manufacturing systems, but also brought forth the notion of decentralized manufacturing. A decentralized manufacturing system has its resources geographically distributed, yet interconnected through central nodes to form collaborative networks that are self-aware and have the capability to make their own decisions [15]. The CPPS thus facilitates the integration of distributed manufacturing resources and functional departments into a single entity and provides visibility for all such entities in the distributed network [22]. In this way, the potential of shared manufacturing is also realized [23]. The concept of shared manufacturing, which is still in its early developmental stage, is based on the sharing economy that promotes peer-to-peer (P2P) collaborations in the utilization of idle capacity and the optimization of resource allocation across the manufacturing network in order to improve production efficiency and thereby enhance manufacturing competitiveness [23]. CPPS thus allows for interoperable collaborations between distributed business applications. On the shop floor, the CPPS autonomously recognizes and responds to dynamic and unexpected situations, such as machine breakdown, an abrupt lack of raw materials, or last-minute demand orders. In this way, the CPPS demonstrates its distinction from the traditional manufacturing enterprise hierarchy, while simultaneously rendering better control of production processes with high quality and flexibility, and mitigating the risk or uncertainty.

2.2.3. Human-in-the-loop CPPS

The confluence of a human workforce in a CPPS aims to blend the worker's experience and expert knowledge, with the computational and cognitive power of a CPPS [24]. Such hybrid systems tend to be symbiotic in nature and present the dimension of adaptive automation, wherein, if one of the entities (human or CPPS) falls short in performing its activities, the latter is expected to step up and aid the former to perform the tasks at hand, according to the expected quality of performance criteria. The concepts of human-in-the-loop and human-in-the-mesh that pertain to human–CPPS interactions for increased flexibility have garnered specific interest in recent years [25,26]. The former combines data-driven models with human knowledge and actions, augmenting the advance of machine intelligence while crediting the human factor as the first in line and master of the production environment. The latter describes the role of humans as one of minimalistic intervention, and acknowledges the CPPS as the lead driver of the production environment. The confluence of human operators and CPPS also increase the scope and convenience of flexible or remote work, while introducing better control and decision-making ability to the human workforce through the cognitive abilities of CPPS [24]. More specifically, these advantages stem from technologies such as AI, augmented reality and virtual reality, and interconnected machines [26,27]. Such synergy would provide human workers with sufficient response time to react and respond, thus alleviating workers' stress or even workload under anomalies and faulty manufacturing conditions.

3. Data-driven modeling in manufacturing

Contemporary manufacturing enterprises, whether small or large in scale, are equipped with a variety of commercial ICT tools and solutions ranging from field sensors to planning and production control (PPC), manufacturing execution systems (MESs), and enterprise resource planning (ERP) in the hierarchy of order [2]. Each tool or solution is responsible for managing the different levels of the enterprise. Through these platforms, data—regardless of whether it is historical or real-time, structured or unstructured—can be collected and leveraged for informed actions and decision-making across the life cycle of the product. These actions could take the form of descriptive, predictive, and prescriptive analytics depending upon the need, with descriptive and predictive analytics having found prominence in recent times. To enable such actions, a fundamental understanding of real-time production is essential. While conventional approaches such as lean manufacturing and six sigma, discrete-event models, and agent-based models have been used in the past for making informed decision making, these methodologies are rigid and meticulous in their formulation. They are not cross-deployable and fail to capture all the intricate dynamics at the enterprise level in real time [3,8]. In contrast, data-driven models powered by machine learning and deep learning algorithms, which are generic in nature and cross-deployable, can ideally source the data generated from the abovementioned systems and leverage it for production monitoring, process control, or real-time optimization as needed. Fig. 4 represents the flow schematic of data-driven modeling for the abovementioned applications within the framework of CPPS [3].

3.1. Real-time process monitoring

Given the pervasive nature of data in modern manufacturing enterprises, it is not only recommended to make use of the data offline, but also online for improved manufacturing operations and data-driven decision-making in real time. In today's demanding manufacturing environments, precise and dependable measurements or estimates of product quality via process monitoring are critical.

Dong and Qin [28] applied and evaluated dynamic-inner principal component analysis (PCA), dynamic-inner partial least square, and dynamic-inner canonical correlation analysis algorithms for the modeling of multidimensional manufacturing time-series data for prediction, diagnosis, and feature analysis. Tennessee-Eastman process data was used to validate the efficacy of these dynamic models, and it was observed that the principal dynamic latent variables were the most predictable components in the whole data space and had the fewest prediction errors. Papananias et al. [29] developed a probabilistic model based on Bayesian linear regression for predictive analytics and advanced control in multistage manufacturing. The model predicted the quality and associated uncertainties of the online process monitoring data, after a training period and was validated against experimental measurements for flatness tolerance. Dong et al. [30] applied a Laplacian-based weighting score to ease the otherwise cumbersome independent component analysis and support vector data description (ICA-SVDD) process that is typically used for multivariate process monitoring. The model was tested on an online hot-rolling process to monitor steel production. It enabled efficient monitoring of the process, which involved non-Gaussian and highly correlated features; reduced the complexity of the SVDD model; and significantly improved the monitoring accuracy. Gajjar et al. [31] proposed sparse PCA, a variant of conventional PCA, which produces the principal component with sparse loading via a variance-sparsity trade-off and significantly improved the interpretability of the principal components for online process monitoring and fault detection. To monitor the transition of manufacturing process variables from steady state to transient state and vice versa, Zhao and Huang [32] proposed an integrated framework by combining cointegration analysis (CA) with slow-feature analysis (SFA), which is an unsupervised dimension-reduction methodology to determine varying latent variables from temporal data. The framework was applied to an industrial-scale multiphase chemical production process, where all the stationary and non-stationary variables were identified *a priori*, followed by the

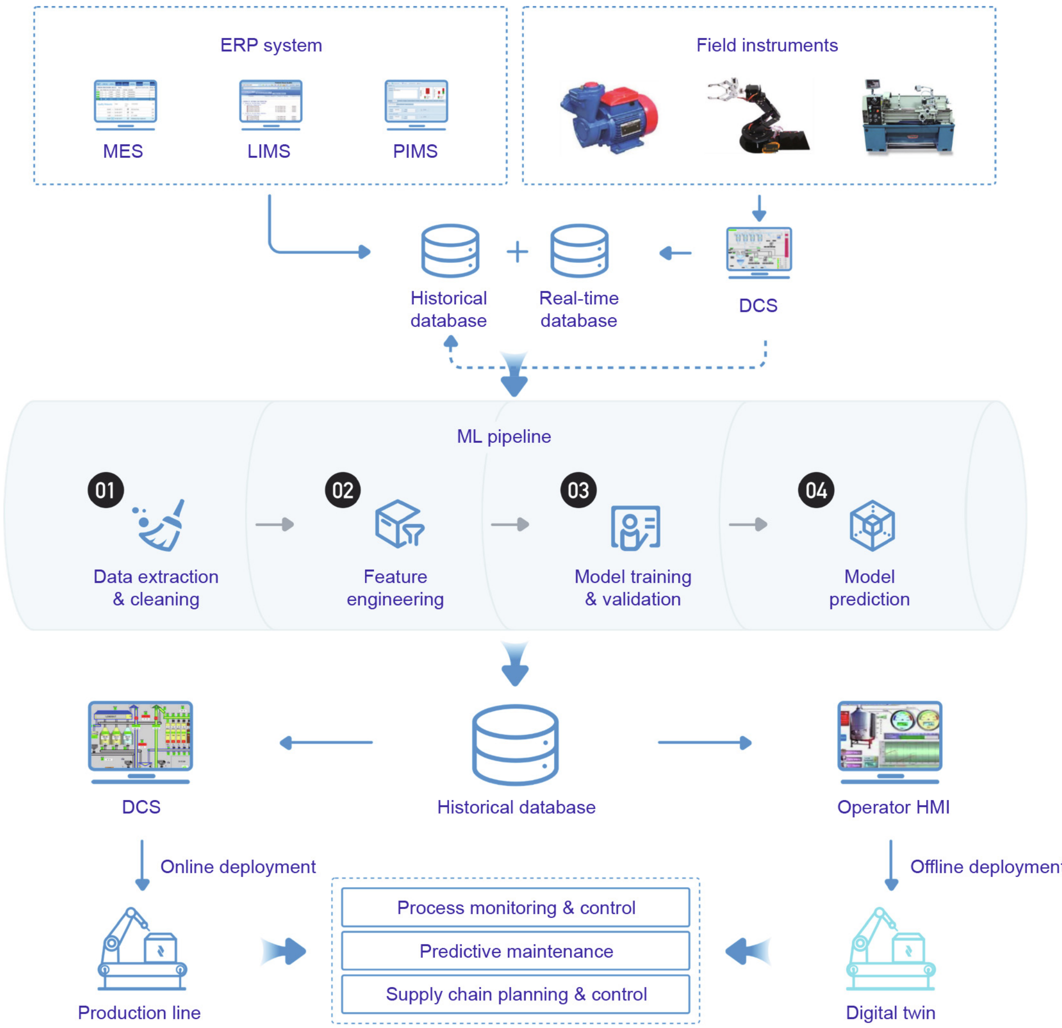

Fig. 4. The data from historical or real-time databases can be sourced and subjected to data-driven modeling via machine learning algorithms. The output of these models can be stored in a separate database and further used for the offline visualization and analysis of production or process parameters via operator human machine interface (HMI) screens, or they can be sent to distributed control systems (DCSs) so that essential control actions can be taken on the production line. ML: machine; LIMS: labratory information management system; PIMS: production information management system. Reproduced from Ref. [3] with permission of John Wiley & Sons, Inc., © 2020.

application of CA and SFA to monitor the variables. Statistical inferences were devised to detect and distinguish the various states of the process variables during changes of operation or at faulty operation states by checking the corresponding deviations, either from steady-state or transient conditions. Shang et al. [33] proposed SFA for the concurrent monitoring of deviations of process variables from operating points (ranges) and the associated process dynamics. Four process monitoring indices were devised based on the derived slow features and their physical interpretations were explained, which made it possible to suitably distinguish whether the changes to process variables in the steady state or under dynamic conditions were normal or faulty. In a related study, Zhong et al. [34] employed unsupervised regularized slow-feature analysis for online product quality estimation of the purified terephthalic acid process. Modified just-in-time learning further improved the online prediction performance by addressing the nonlinearity of the systems. The methodology as a whole could adequately handle the process dynamics by exploring the temporal relationship among the entire set of input variables.

3.2. Data-driven process control and optimization

Conventional manufacturing has resorted to statistical process control for measuring and controlling production quality during the manufacturing process, rather than applying advanced process control such as model predictive control (MPC), which finds extensive application in the hydrocarbon sector, primarily due to the cost versus application constraints and the need for dedicated distributed control system (DCS) architecture [10,35]. However, developing data-driven control systems and deploying them on a CPPS platform offer the possibility of widespread control and optimization throughout the product life cycle in manufacturing enterprises, thereby alleviating the aforementioned constraints.

Wang et al. [35] studied real-time control in a two-machine geometric serial line by developing a Markov chain model to analyze the transient behavior with constraints on the minimum required and maximum allowable residence time. The structural properties of the system were analyzed, and an iterative algorithm was devised to perform real-time control, which improved the system performance by balancing the trade-off between the production rate and the scrap rate. Chen et al. [36] used real-time production data to devise max-plus linear models to emulate the dynamic relations between system input and corresponding system machine status. The max-plus linear model was then layered by time-varying, event-driven MPC to modify the job release plans and thereby address the real-time feedback control problem in order to develop a coherent planning structure, which could eventually be incorporated into the ERP or MES.

Wong et al. [37] devised recurrent neural networks (RNNs)-based MPC (RNN-MPC) for applications in pharmaceutical manufacturing. RNNs aptly simulated the dynamics of a continuous stirred-tank reactor (CSTR) in pharmaceutical manufacturing and enabled a satisfactory closed-loop performance for the MPC of a complex reaction in the CSTR, which are essential to meet the regulations of critical quality attributes. Min et al. [38] proposed a machine learning-based control method to increase the yield of light oil in a petrochemical production unit. They developed the LightGBM model to simulate the production process based on real-time data from the plant and eventually integrated it online with supervisory control and data acquisition, for real-time recommendations and production control. Shang et al. [39] devised a piecewise linear kernel-based support vector cluster (SVC) to formulate the uncertainty of a data-driven robust optimization. The uncertainty set was nonparametric in nature, and aided in solving the mixed-integer linear programming optimization formulation that was specifically designed for production planning in a chemical process plant. Ning and You [40] proposed a data-driven approach for optimization under uncertainty based on multistage adaptive robust optimization and nonparametric kernel density. This data-driven optimization model was applied for the short-term scheduling of multipurpose batch processes, and yielded 31.5% more profits than conventional optimization scheduling applications.

3.3. Section summary

Within the manufacturing framework, the increased adoption of the IIoT has made data acquisition and storage more pervasive than ever before. A gradual question arises as to how to effectively and efficiently make use of all that data in actionable insights, considering the deterministic nature of traditional manufacturing operations, which are currently heavily reliant on human experts. In this context, the more recent "technology push" in the field of AI as a whole and its "market pull" within the context of smart manufacturing have only expanded their application to make use of this massive data generated across the various hierarchical levels in manufacturing. Thus, through CPPS, a dynamic knowledge base for the shop floor, supply chain, and enterprise can be developed, in which data-driven models can learn from historical trends and patterns and aid in taking informed actions and decision-making. Such data-driven practices are more intuitive and data-oriented, and mitigate any negative effects on the production process or decision-making; in this way, they prove advantageous to both the cost and the quality of a production process, thus introducing the "smart" aspect of manufacturing. Through real-time process monitoring, analytics, and the data-driven control of production processes, CPPS also foster new service models such as predictive maintenance, fault diagnosis, and performance optimization, all of which are pushing conventional production-oriented manufacturing toward a more service-based manufacturing.

4. Decentralized manufacturing

Traditionally, manufacturing systems are an integration of heterogeneous systems, characterized by the concentration of capital, materials, and machineries in a single manufacturing facility [41], with decision-making capabilities (e.g., production planning, scheduling, and control) performed at one central node (e.g., computers and servers) [42]. Such a centralized system offer various benefits in terms of ease of control, a simple database design and architecture that permits ease of data management, and adherence to standardized policies and procedures [43]. However, these systems tend to be highly inflexible due to their rigid structure [10], to suffer from bottlenecks in the case of increased demand while operating under limited capacity [44], to be susceptible to whole-system breakdown and failure, and to have maintenance issues, as the whole system depends on its central unit.

The limitations of a centralized system, accompanied by new manufacturing paradigms and the push toward mass customization, are guiding the manufacturing industry toward decentralization. This is described as a P2P system in which all peers communicate symmetrically and perform equal roles [43]. Various decentralized manufacturing concepts and networks exist, including segmented manufacturing, fractal manufacturing, decentralized mini-factories, strategic networks, virtual enterprises, and cluster concepts [15], and offer several advantages. In terms of resources, a distributed structure allows the final products to be manufactured closer to customers, thus reducing the costs associated with production, storage, and transportation [10]; facilitates the acquisition of timelier information [13] and raises its responsiveness to the consumer market, so that decisions can be made promptly and the production-to-sale time can be reduced; distributes workloads across multiple suppliers and machines, so that the failure of one of these components does not cause a total production halt [10]; makes use of excess or idle capacity through resource sharing; supports production scalability to adapt throughputs to the changing demand [45]; and, lastly, enables on-demand production so as to minimize the need to forecast demand and keep large inventories, thus minimizing resource waste [14]. In terms of the network architecture, a decentralized system enhances system diversity and flexibility [15] and minimizes performance bottlenecks by balancing the overall load between all the nodes, as well as by reducing the overall network latency through edge and fog computing [46].

4.1. Technology enablers of decentralized manufacturing

Several technologies have emerged over the years that serve as enablers for the decentralization of CPPS. The rise of ICT cannot be undermined, as it serves as one of the key drivers for CPPS [16]. In particular, in a connected industry, the effective exchange of data between decentralized units (e.g., machines, factories, supply chains) is crucial in order to perform data analysis for near real-time decision-making and control. A key technology in the realization of decentralized control systems is middleware, which is a reusable software layer between the operating system and distributed applications [47]. These technologies facilitate the communication in industrial control systems, as well as the integration of heterogeneous devices and subsystems [47]. Some commonly known middleware architectures include open platform communications unified architecture (OPC UA), data distribution service, and real-time common object request broker architecture. It has been observed that none of these middleware technologies are able to support all the requirements of DCSs [47]. Accordingly, the growth in high-speed Internet, including 5G, as well as the more recent multi-protocols that support industry standards such as Message Queuing Telemetry Transport (MQTT), Eclipse, and RabbitMQ, are of paramount interest to the success of middleware adoption. The middleware technology itself would not cause a redesign in the production structure, but would ensure low latency in the network and supports near real-time communication between decentralized units [46]. This is especially significant in the era of big data and in a landscape where the manufacturing environment is constantly changing. Furthermore, the deployment of radio-frequency identification devices would be vital in providing efficient real-time monitoring and data acquisition of the distributed production lines and supply chain under operational and environmental uncertainties [48].

4.2. Relevant case studies

In a decentralized manufacturing system, job dispatching and resource allocation must be processed in multiple distributed factories, each of which consist of an independent and unique production line. Feasible planning and scheduling methods must be able to tackle the inherent challenges posed by a decentralized manufacturing system. Therefore, ongoing research has been conducted on this specific topic—and a chronological review of the same is presented here. Block et al. [49] introduced a new CPPS-oriented PPC approach for a decentralized MES. The decentralized framework consisted of edge computing, where data acquisition was performed in real time, and stored and evaluated at the edge devices. P2P communication was implemented using Hyper text Transfer Protocol (HTTP) requests via representational state transfer and WebSockets. Li et al. [41] proposed a multi-agent system (MAS)-based approach to achieve global optimal scheduling for distributed manufacturing and resource sharing. The approach comprised an enterprise-level multi-agent subsystem, which included the job, resource, and manager agents; an enterprise alliance; and the mediator and scheduling agents. Experimental investigation showed that the MAS approach increased the scheduling efficiency by up to 35.2%. Vespoli et al. [50] introduced a decentralized scheduling approach for the job sequencing of a constant work-in-progress production line. The approach was validated through a multi-agent simulation, which resulted in an increase in the system's productivity by 4%. Fu et al. [51] proposed a stochastic multi-objective brain storm optimization algorithm to solve the scheduling problem (by minimizing the tardiness and energy consumption) of a distributed manufacturing system comprising multiple factories, each of which consisted of an independent production line. The proposed algorithm was compared with two algorithms, non-dominated sorting genetic algorithm II [52] and multiple-objective genetic local search [53], with a set of test data and outperformed the other two. Kumar et al. [54] developed an agent-based approach for operations planning, which allowed the distribution of decision-making to various functional agents. The approach was applied to solve the complex four operation functions integration problem for an automotive manufacturing firm. The performance of the proposed approach was compared with the firm's existing planning approach, and was found to provide up to 21.6% and 50.8% reduction in production cost and computational time, respectively. However, this work was not performed under dynamic conditions, which was a limitation of the study.

The concept of a distributed MPC (DMPC) with respect to decentralized manufacturing necessitates a special mention, as the individual controllers in the DMPC counter the challenges associated with data transmission issues, the control of a multitude of process variables, and computational complexities in large-scale decentralized plants with their numerous subsystems [55,56]. DMPCs utilize an array of unique controllers to perform the control calculations and actions in distinct processors, while the individual controllers communicate among themselves to achieve the closed-loop process objectives. Farina et al. [57] devised a cooperative iterative DMPC and compared it with a non-cooperative DMPC by emulating the functioning of a real-world natural gas refrigeration plant in a simulation environment. Their work summarized that each individual controller in the DMPC required complete working knowledge of the entire plant as compared with the distributed predictive control (DPC), which could otherwise limit the scalability of such controllers. However, with the easier access to ICT technologies in modern times, along with the push toward digital transformation, this limitation could be overcome by effectively meeting the infrastructure and communication requirements. In the above study, the performance of the DMPC overpowered that of the DPC in all the tested scenarios, proving its robustness in decentralized manufacturing processes. To cope with the latency-related issues in data transfer in decentralized manufacturing, Ravi and Kaisare [58] implemented a distributed MPC framework in which the process variables of one or more sub-entities of the whole plant were measured infrequently and then relayed after an inherent delay. They employed the state augmentation formulation and integrated it with a Kalman filter centralized estimator. This method was able to provide better prediction control and improved the control performance under varying latencies in linear and nonlinear systems. Yin et al. [59] devised a distributed monitoring framework for the absorption column in a post-combustion carbon dioxide (CO_2) capture plant. They modeled the absorption column as five distinct interacting subsystems, and a distributed state estimation network with local estimators was developed for the entire column. The significance of the work was that it relied on an iterative algorithm with novel triggering conditions to ease the trade-off between fast convergence and efficient computation. Their simulation results confirmed that the proposed DMPC could provide good state estimates of the absorption column subsystems.

4.3. Section summary

In an increasingly dynamic and competitive production environment, along with the growing drive toward mass customization, it becomes imperative to allocate the available resources more efficiently and effectively. A decentralized manufacturing system systematically combines the numerous distributed entities as a conglomerate of autonomous and proactive machines or equipment, driven by intelligent AI algorithms. Its system architectures are both scalable and modular and constantly collaborate and mutually interact with each other, aiding the aforementioned cause. Such a system offers numerous benefits, such as flexible architecture, the capability to meet on-demand production, and increased responsiveness to consumer market, among others. Given the inherent nature of such systems to evolve and scale up, along with the evolution and application of digital technologies in manufacturing, the trend toward decentralization will only accelerate. This will aid the transformation in manufacturing, and decentralization will find extensive application in production planning and control, job dispatching, resource allocation, and market-to-customer proximity, as discussed in the preceding section.

5. Efficient and secured data sharing in manufacturing

CPPS-oriented decentralization seeks to evolve communication architecture in manufacturing environments from the currently existing cloud- or Internet-service-based architectures to an architecture in which all the entities involved in the systems communicate and interact with one another (as in a P2P network). As a result, the issues of data security, legitimacy, and trustworthiness come to the fore [60]. The blockchain emerges as a promising technology to address this issue. In the broadest sense, a blockchain can be defined as a digital distributed ledger technology that seamlessly stores all the data exchanges with a time-stamp on them, to ensure legitimate tracking of data. Moreover, all the information in a blockchain is cryptographically stored, ensuring immutability, legitimacy, and trustworthiness [61,62]. Thus, the combination of a blockchain and an Industrial Internet platform promotes the notion of P2P interaction, as well as interaction among the numerous physical entities in CPPS-aided decentralized manufacturing, with trust and in an auditable manner [63].

5.1. Essential features

5.1.1. Reliable access and secure management of edge devices and data sources

Blockchain nodes can be used as entrances for industrial equipment and other data resources to access the Industrial Internet. Based on the blockchain, the decentralized identity and authorization management of industrial equipment can be realized. Dynamic management actions such as device identification, registration, discovery, access, and deletion can also be reliably achieved [64]. Key data such as equipment interconnection, operation records, and data exchange can be recorded on the blockchain to form a trusted edge device access system. Furthermore, the blockchain can effectively monitor the status of equipment connected to the Industrial Internet platform and automatically signal the alarm for security risks and malicious attacks by means of smart contracts [60].

5.1.2. Trusted collection and safe sharing of industrial data

A data management platform based on a blockchain can achieve reliable data collection and secured sharing. This promotes data exchange between different industrial platforms, thereby connecting isolated information and data. A blockchain makes it possible to establish data security and access control, as well as formulating data transmission and authorization rules, in order to carry out data authority management and encryption services [65]. The life-cycle supervision of data can be implemented through data deposit certification, transmission tracking, and user credit evaluation; the blockchain features of anti-tampering, security, and transparency make this function more credible. Such a platform promotes the evolution of the Industrial Internet from equipment and data networks to knowledge and value networks, while realizing cross-industry data sharing, value mining, and security protection. The trusted sharing of data, algorithms, services, and models in different industries and different fields also boosts the application of digital twins and other simulated models in the Industrial Internet with the aid of this platform [62].

5.1.3. Supply-chain management based on blockchains

Based on the Industrial Internet platform, real-time information synchronization among multiple parties can be achieved. Key elements of the industrial supply chain, such as property rights design, service orders, production processes, and product information, can be stored on the blockchain. Based on real data, product evaluation, service, and credit, many value-added services in supply-chain management can be realized, such as shared design requirements, collaborative production, intelligent matching of supply and demand, product anti-counterfeiting traceability, and intelligent operation and maintenance [66,67].

5.2. Recent works on blockchains in manufacturing and case studies

In recent years, the incorporation of blockchains in cyber–physical systems has garnered much interest in the research communities of distributed electrical grid systems, decentralized logistics operations, and decentralized data sharing in healthcare, among others. While the application of the blockchain across various domains is evolving, its application in the manufacturing sector is in an even earlier stage. A few notable works published recently are mentioned below to provide readers with a contextual perspective on the role of the blockchain in smart and decentralized manufacturing, followed by a couple of actual implementations of blockchains in manufacturing, which comprise our ongoing research initiative.

Lee et al. [63] proposed a unified three-level blockchain architecture including a connection net, cyber net, and management net to address the key challenges of interoperability, data sharing and security, automation, and resilience in decentralized manufacturing systems. Leng et al. [68] presented 12 evaluation metrics for the adoption of blockchains in manufacturing based on a "business canvas model." The key focus of their study was how these metrices could support sustainable manufacturing and product life-cycle management within the framework of CPPS-enabled smart manufacturing. Angrish et al. [69] proposed a prototype platform called the FabRec to handle a decentralized network of manufacturing entities, including both cyber and physical, in order to enable automated transparency and smart contracts in such systems, which could be sufficiently verified through an audit trail. They further tested their prototype in a bench-scale test bed platform, which included computing nodes, physical devices such as the Raspberry PI, and a basic computer numerical control machine equipped with Ethereum smart contracts. They concluded that the proof-of-concept study could be leveraged for a large-scale system with further improvements in system design. Pal and Yasar [70] presented a hybrid architecture for manufacturing supply-chain information systems, which consisted of IoT applications and a blockchain-based distributed ledger to support transaction services in a multi-party global apparel business network. Their model comprised an IoT-enabled smart global network with unique addresses to foster interaction and cooperation among participating companies in order to achieve common objectives. The IoT was further layered with a distributed ledger (blockchain) to support confident and reliable transaction services within such global businesses. In a more recent study, Barenji et al. [71] proposed blockchain-enabled fog computing for collaborative design in decentralized manufacturing in order to realize customized production. They first developed machine learning-based clustering algorithms to categorize customer needs and expectations, followed by the fog computing-based integration of the various physical and cyber entities of the production platform. A blockchain layer was devised on this system to improve the data integrity, trust, and security-related issues. For interested readers, a detailed review on the prospects, current technology barriers, and future directions of blockchains for CPPS-aided manufacturing is presented in a recent review article [72].

5.2.1. Accounts receivable and inventory financing

Accounts receivable and inventory financing (ARIF) is a commercial loan based on asset control for warehousing in the manufacturing supply chain. Smart supply-chain management by the Industrial Internet can ensure that the warehouse receipts are taken without re-collateralization. This will assist banks in realizing the supervision and control of goods, thereby reducing loan risks and optimizing industrial efficiency.

The life-cycle management of goods' information can be achieved through the Industrial Internet. Therefore, the ARIF business model has been upgraded from a traditional strong dependence on corporate credit to property-oriented risk management. Such risk management is achieved through the application of blockchain on big data and AI-related technologies. The key technologies are shown in Fig. 5**.** The status of goods can be monitored and controlled through IoT technology in real time. This technology helps to build smart warehouses and logistics systems, record the outbound and inbound information of goods in real time, control the right to pick up goods, and reduce financing risks. More specifically, this technology can perform non-contact identification of the items to be inspected. It has the characteristics of fast reading and writing, small size, strong penetration, large capacity, and high security. GPS helps to track the location of goods in real time and provides video data at key points in time to be noticed. AI technologies such as fingerprints and face recognition help to confirm the identity of the operator and implement authority management. The blockchain helps to connect data from different business systems. Each end of the industrial chain is added to the blockchain

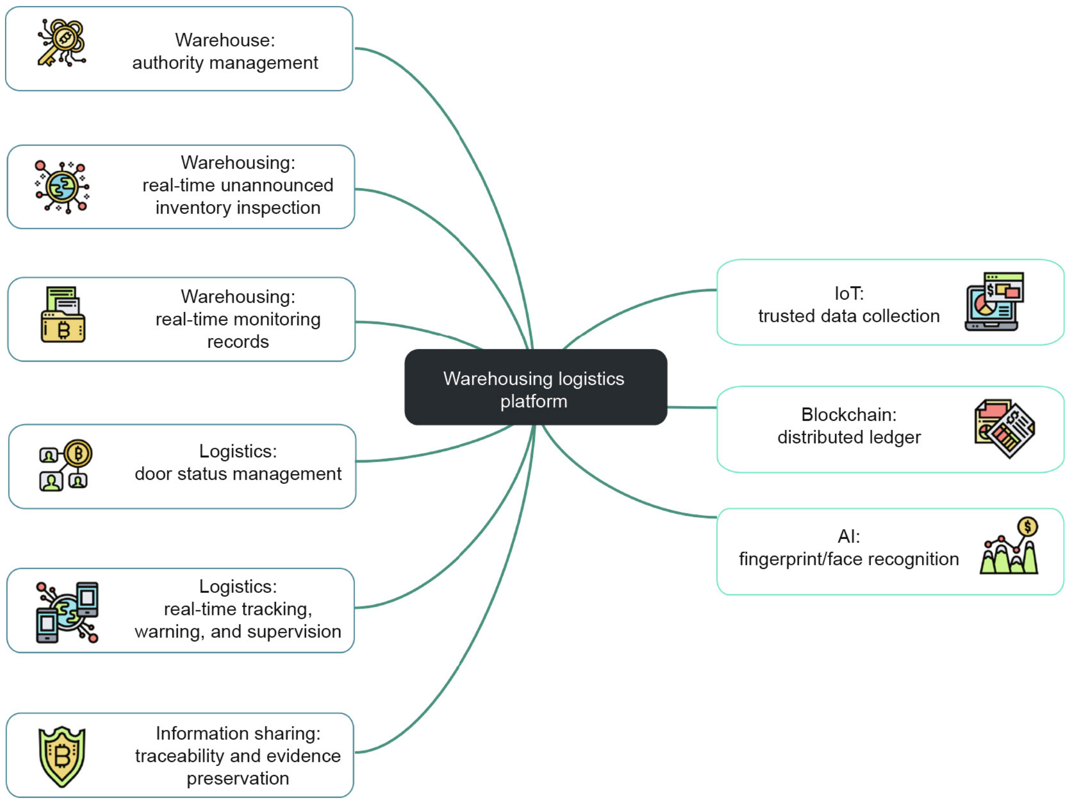

Fig. 5. The key technologies in a warehousing logistics platform for ARIF.

as a peer node to share necessary information. The data is simultaneously recorded on the blockchain and cannot be tampered with, which ensures the authenticity of the data.

5.2.2. The Industrial Internet platform

The Industrial Internet platform connects the data flow between consumption and production, and helps manufacturers organize their resources and production processes flexibly. This helps to realize low-cost, large-scale, and flexible customization as well as experiential consumption, which improve product value and enhance user retention. This "reverse production model," which is driven by users in modern manufacturing, is known as the customer-to-manufacturer (C2M) model. This model can realize the mass production of customized products according to the individual needs of consumers. The process is shown in Fig. 6.

The C2M model innovates the design and production process with a variety of Internet technologies. It merges data from clients, e-commerce platforms, designers, and manufacturers to enrich the database. Meanwhile, market trends can be predicted with the help of massive data and machine learning technology, while a smart production line is then created to achieve flexible manufacturing. Finally, mass production based on customized requirements is realized with the help of the e-commerce platform, which can effectively control production costs. Through the entire length of the supply chain and production network, as described, the blockchain allows the consumer to seamlessly track all the details from raw materials to the final product through the transparent and real-time exchange of data, information, and communication between the customer and the manufacturer [73].

5.3. Section summary

This section presented the potential application of the blockchain within the context of decentralized manufacturing for the management of trust, security and smart contracts application, audits, and the detailed and legitimate traceability of records. Moreover, as CPPS platforms make extensive use of predictive analytics via big data, which is traditionally stored in designated databases, it is of paramount importance that the security of such databases is ensured, specifically when accessed through Internet services. In this context, the significance of the blockchain can be realized in the form of data tracking, evaluation, anti-tampering, and transparency, which are crucial in order to perform data analysis for near real-time decision-making and control. This section described a few recent works on the application of blockchain-enabled CPPS and discussed a couple of real-world applications of blockchain catering to manufacturing practices in logistics, inventory, and mass customization, which are directly linked to our ongoing research endeavors to showcase the potential of blockchain in the future of manufacturing.

6. Challenges and future perspectives

While it is well accepted in the literature that the CPPS is one of the essential pillars in future manufacturing, its concepts, frameworks, and success stories are still in their nascency, and several challenges remain to be addressed and overcome for its successful and widespread implementation. Table 2 summarizes some of these challenges, specifically catered to the theme of this review, as they establish the basis for future research directions.

7. Conclusions

This review collectively draws insights into the role and contributions of CPPS in driving the next generation of manufacturing, commonly referred to as "smart manufacturing" or "factories of the future." First, a brief overview of the prime enablers of this paradigm shift in manufacturing was presented, after which the concept of the CPPS was introduced. A holistic perspective on the

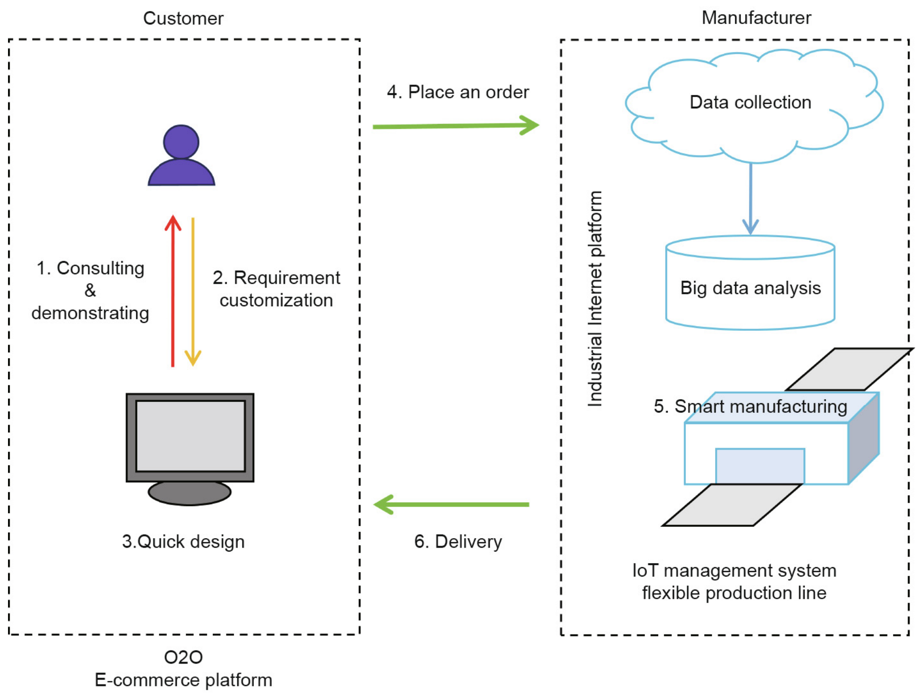

Fig. 6. The C2M business process. O2O: online to offline.

Table 2
Challenges in the transition toward CPPS to enable smart manufacturing.

Domain	Challenges	Authors	Year	Reference
Data exchange and analysis	• When data is processed at edge devices and is not transmitted to the centralized unit of the system, some information is lost by exchanging operational data over the edge computing paradigm, resulting in data degradation. Balancing this trade-off is not straightforward.	Sprock et al.	2019	[74]
	• Currently, most of the data analysis is driven by AI and machine learning capabilities that are still performed at the cloud. The next generation of CPPS must transfer these capabilities to the edge network.	Mocnej et al.	2021	[44]
	• Data heterogeneity remains one of the main problems encountered; it extends beyond the standard syntax and semantics requirement needed for data exchange.	Lu and Asghar	2020	[75]
System complexity	• Interconnected devices often experience communication problems due to mutually incompatible networks. These networks are normally provided by different vendors.	Balador et al.	2017	[47]
	• Each decentralized system could be exposed to dissimilar uncertainty patterns in the market needs, as well as to different operational and environmental conditions.	Mocnej et al.	2021	[44]
	• The system needs to be scalable and flexible, as well as capable of self-adapting and self-organizing, so that it is prepared to integrate new applications under any circumstances.	Mocnej et al.	2021	[44]
Production planning and control	• With the increasing number of product variants, the validity of planning data decreases due to the unavailability of historical data.	Block et al.	2018	[49]
Verification and validation	• Standards and methods for data handling, decision-making, and execution would not be complete without support for verification and validation. For a decentralized system, it remains a challenge to construct a virtual simulation test bed that enables the proposed models to be tested and verified.	Sprock et al.	2019	[74]
	• The challenge of the efficient and optimum utilization of resources increases significantly for decentralized systems under a multi-resource and dynamic environment.	Mocnej et al.	2021	[44]
Security and data privacy	• Governance over valuable data may be lost to the cloud solution provider, which controls a relatively large number of standards and procedures for its own business process.	Helo et al.	2014	[9]
	• With greater interconnectivity and wider resource sharing in decentralized units, susceptibility to malicious attacks and trust and credibility issues increase. To deal with complex interactions in CPPS, as well as trust and consensus among various stakeholders, the peer nodes must be able to handle secure access to resources.	Bodkhe et al.	2020	[46]

role of CPPS in the drive toward smart manufacturing was presented with a focus on data-driven manufacturing, decentralized manufacturing, and integrated blockchain for secure data management, which formed the main themes of this study.

The CPPS as a whole realizes the comprehensive connection and management of end-to-end industrial data, equipment, products, systems, and services. It fosters the online aggregation and configuration of massive industrial resources such as R&D design, manufacturing, operation, and maintenance services, and eventually aims to accelerate the transformation of enterprise organization management through digital transformation. These digital technologies (i.e., big data, cloud computing, the IIoT, and AI) promote the evolution of traditional manufacturing to an intelligent production mode through platform convergence and intelligent application in the CPPS. By transforming enterprises through such intelligent production, CPPS fosters new service models such as predictive maintenance, fault diagnosis, and performance optimization, and thereby pushes conventional production-oriented manufacturing toward service manufacturing. Furthermore, the IIoT-enabled CPPS platform opens up data flow between consumption and production, allowing greater flexibility between manufacturing resources and production processes and leading to personalized customization, which enhances product value and boosts customer satisfaction and engagement. CPPS platforms effectively integrate manufacturers, suppliers, consumers, developers, and other participants, and use information flow to drive technology flow, capital flow, talent flow, and material flow to form platform-based business collaborations, capability sharing, and other open development models. Such platforms realize the dynamic allocation of the resource network and promotes networked manufacturing, which can be decentralized in nature. By layering the CPPS with a blockchain in such decentralized systems, secure access to data flow and control can be established, ensuring data security and trustworthiness, which in turn consolidate data-driven manufacturing. Lastly, key challenges pertaining to various aspects and applications of CPPS were presented, which serve as research challenges to be addressed in order to expedite this journey toward the realization of smart manufacturing in the next few years.

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Authors' contribution

Manu Suvarna: Conceptualization, methodology, writing, review, editing and visualization. Ken Shaun Yap: Methodology, writing, review and editing. Wentao Yang: Methodology, writing, review, editing and visualization. Jun Li: Methodology, writing, review and editing. Yen Ting Ng: Visualization, writing, review and editing. Xiaonan Wang: Conceptualization, writing, review, editing and supervision.

Compliance with ethics guidelines

Manu Suvarna, Ken Shaun Yap, Wentao Yang, Jun Li, Yen Ting Ng, and Xiaonan Wang declare that they have no conflict of interest or financial conflicts to disclose.

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