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REVIEW ARTICLE

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Smart manufacturing systems for Industry 4.0: Conceptual framework, scenarios, and future perspectives

Abstract Information and communication technology is undergoing rapid development, and many disruptive technologies, such as cloud computing, Internet of Things, big data, and artificial intelligence, have emerged. These technologies are permeating the manufacturing industry and enable the fusion of physical and virtual worlds through cyber-physical systems (CPS), which mark the advent of the fourth stage of industrial production (i.e., Industry 4.0). The widespread application of CPS in manufacturing environments renders manufacturing systems increasingly smart. To advance research on the implementation of Industry 4.0, this study examines smart manufacturing systems for Industry 4.0. First, a conceptual framework of smart manufacturing systems for Industry 4.0 is presented. Second, demonstrative scenarios that pertain to smart design, smart machining, smart control, smart monitoring, and smart scheduling, are presented. Key technologies and their possible applications to Industry 4.0 smart manufacturing systems are reviewed based on these demonstrative scenarios. Finally, challenges and future perspectives are identified and discussed.

Keywords Industry 4.0, smart manufacturing systems, Internet of Things, cyber-physical systems, big data analytics, framework

1 Introduction

Information and communication technology (ICT) is currently undergoing rapid development. Many disruptive technologies, such as cloud computing, Internet of Things (IoT), big data analytics, and artificial intelligence, have emerged. These technologies are permeating the manufacturing industry and make it smart and capable of addressing current challenges, such as increasingly customized requirements, improved quality, and reduced time to market [1]. An increasing number of sensors are being used in equipment (e.g., machine tools) to enable these equipment to self-sense, self-act, and communicate with one another [2]. Through these technologies, real-time production data can be obtained and shared to facilitate rapid and accurate decision making. The connection of physical manufacturing equipment and devices over the Internet together with big data analytics in the digital world (e.g., the cloud) has resulted in the emergence of a revolutionary means of production, namely, cyber-physical production systems (CPPSs). CPPSs are a materialization of the general concept cyber-physical systems (CPS) in the manufacturing environment. The interconnection and interoperability of CPS entities in manufacturing shop floors together with analytics and knowledge learning methodology provide an intelligent decision support system [3]. The widespread application of CPS (or CPPS) has ushered in the fourth stage of industrial production, namely, Industry 4.0 [4].

Industry 4.0 has elicited much interest from the industry and academe [5]. A recent literature survey identified the basic concept, perspectives, key technologies, and industrial applications of Industry 4.0 and examined its challenges and future research trends [6,7]. However, no work has established a systematic framework of smart manufacturing systems for Industry 4.0 that can guide academic research and industrial implementation. Motivated by this situation, this study proposes a conceptual framework for Industry 4.0 smart manufacturing systems. The framework covers a wide range of topics, including smart design, smart machining, smart monitoring, smart control, smart scheduling, and industrial implementation. A number of demonstrative scenarios are presented, and

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current challenges and future research directions are discussed.

Although extensive effort continues to be exerted to make manufacturing systems smart, smart manufacturing systems do not have a widely accepted definition. In Industry 4.0, CPPSs can be regarded as smart manufacturing systems. CPPSs comprise smart machines, warehousing systems, and production facilities that have been developed digitally and feature end-to-end ICT-based integration from inbound logistics to production, marketing, outbound logistics, and service [3]. Smart manufacturing systems can generally be defined as fully integrated and collaborative manufacturing systems that respond in real time to meet the changing demands and conditions in factories and supply networks and satisfy varying customer needs [8]. Key enabling technologies for smart manufacturing systems include CPS, IoT, Internet of Services (IoS), cloud-based solutions, artificial intelligence (AI), and big data analytics.

The rest of this paper is structured as follows. Section 2 presents a framework for Industry 4.0 smart manufacturing systems. Section 3 provides several demonstrative scenarios. Section 4 discusses current challenges and future perspectives, and Section 5 presents the conclusions.

2 Smart manufacturing systems for Industry 4.0

The Industry 4.0 concept in the manufacturing sector covers a wide range of applications from product design to logistics. The role of mechatronics, a basic concept in manufacturing system design, has been modified to suit CPS [9]. Smart product design based on customized requirements that target individualized products has been proposed [10]. Predictive maintenance [11] and its application in machine health prognosis are popular topics in Industry 4.0-based CPS [12]. Machine Tools 4.0 as the next generation of machine tools has been introduced in machining sites [13]. Energy Management 4.0 has also been proposed for decision-based energy data and has transformed energy monitoring systems into autonomous systems with self-optimized energy use [14]. Moreover, the implication of Industry 4.0 technologies on logistic systems has been investigated [15]. The entire range of applications cannot be discussed in a single paper. Therefore, this paper only presents design, monitoring, machining, control, and scheduling applications.

Figure 1 presents a framework of Industry 4.0 smart manufacturing systems. The horizontal axis shows typical

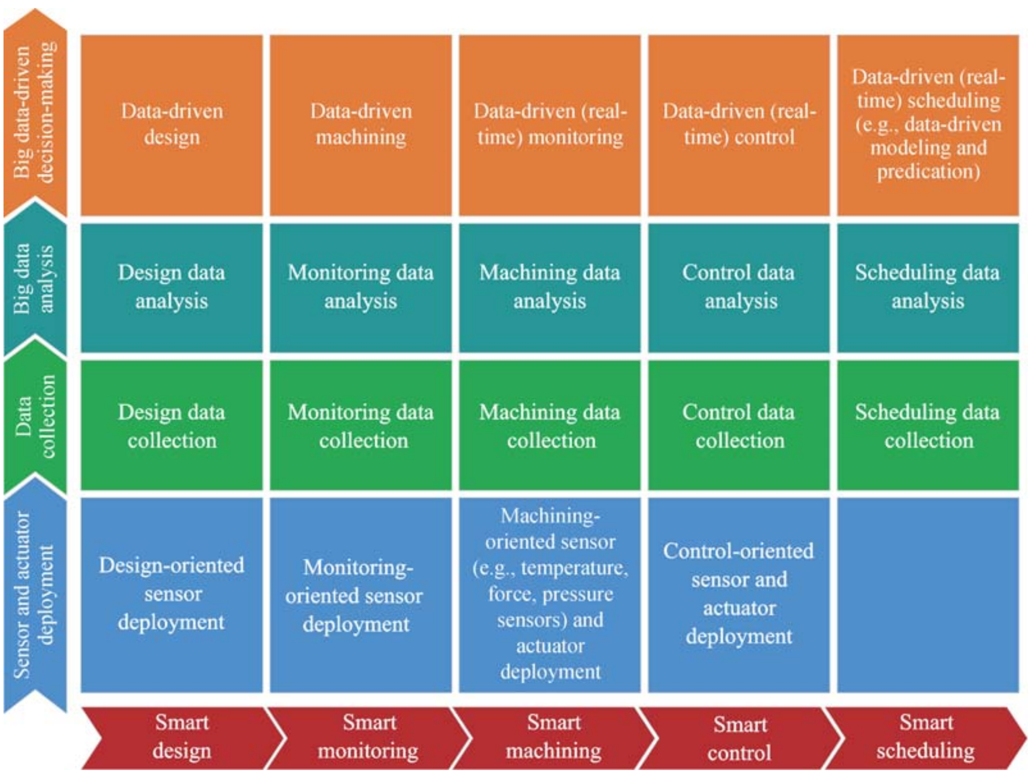

Fig. 1 Conceptual framework of Industry 4.0 smart manufacturing systems

issues in Industry 4.0, including smart design, smart machining, smart monitoring, smart control, smart scheduling, and industrial applications, which are the focus of this work. The vertical axis shows issues in another dimension of Industry 4.0 ranging from sensor and actuator deployment to data collection, data analysis, and decision making. In Industry 4.0, data gathering and analysis are the main sources of the smartness of activities shown on the horizontal axis.

• Smart design. Traditional design has been upgraded and has become smart due to the rapid development of new technologies, such as virtual reality (VR) and augmented reality (AR). Hybrid prototyping using VR techniques has been introduced to additive manufacturing. Design software, such as computer-aided design (CAD) and computer-aided manufacturing (CAM), can now interact with smart physical prototype systems in real time via 3D printing integrated with CPS and AR [16]. Thus, engineering changes and physical realizations could be combined to achieve a smart design paradigm.

• Smart machining. In Industry 4.0, smart machining can be achieved with the aid of smart robots and other types of smart objects that can sense and interact with one another in real time [17]. For example, CPS-enabled smart machine tools can capture real-time data and transfer them to a cloud-based central system so that machine tools and their twined services can be synchronized to provide smart manufacturing solutions. In addition, self-optimization control systems provide in-process quality control and eliminate the need for post-process quality inspection [18].

• Smart monitoring. Monitoring is an important aspect in the operation, maintenance, and optimal scheduling of Industry 4.0 manufacturing systems [19]. The widespread deployment of various sensors has made smart monitoring possible. For example, data on various manufacturing objects, such as temperature, electricity consumption, vibrations, and speed, can be obtained in real time. Smart monitoring provides not only a graphical visualization of these data but also alerts when abnormality occurs in machines or tools [20,21]. CPS and IoT are key technologies that enable smart monitoring in Industry 4.0 smart manufacturing systems.

• Smart control. In Industry 4.0, high-resolution, adaptive production control (i.e., smart control) can be achieved by developing cyber-physical production control systems [22]. Smart control is mainly executed to manage various smart machines or tools physically through a cloud-enabled platform [23]. End users can switch off a machine or robot via their smartphones [24]. Decisions can then be timely reflected in frontline manufacturing sites, such as robot-based assembly lines or smart machines [25].

• Smart scheduling. Smart scheduling mainly utilizes advanced models and algorithms to draw information from data captured by sensors. Data-driven techniques and advanced decision architecture can be used to perform smart scheduling. For example, distributed smart models that utilize a hierarchical interactive architecture can be used for reliable real-time scheduling and execution [26]. Production behavior and procedures can then be carried out automatically and effectively because of the well-established structures and services. With the aid of data input mechanisms, the output resolutions are fed back to the parties involved in different ways [27].

• Industrial applications. Industrial applications that target different industry implementations of various solutions are the ultimate goal of Industry 4.0 and may revolutionize manufacturing systems. The solutions provided by Industry 4.0 are sufficiently flexible to support customized configuration and development according to the uniqueness and specific requirements of several industries, such as the food industry that includes a large number of perishable products. Thus, dynamic manufacturing networks are provided opportunities to manage their supply and business modes [28]. With the support of configurable facilities from layers of smart design and manufacturing and smart decision making, applications can achieve a holistic perspective by considering practical concerns, such as production efficiency, logistics availability, time constraints, and multiple criteria [29].

Several of the key research topics within this framework are summarized as follows.

• Smart design and manufacturing. Research at this level encompasses smart design, smart prototyping, smart controllers, and smart sensors [30,31]. Real-time control and monitoring support the realization of smart manufacturing [32]. Supporting technologies include IoT, STEP-NC, 3D printing, industrial robotics, and wireless communication [33].

• Smart decision-making. Smart decision making is at the center of Industry 4.0. The ultimate goal of deploying widespread sensors is to achieve smart decision making through comprehensive data collection. The realization of smart decision making requires real-time information sharing and collaboration [34]. Big data and its analytics play an important role in smart decision-making tasks, such as data-driven modeling and data-enabled predictive maintenance [35]. Many technologies, including CPS, big data analytics, cloud computing, modeling, and simulation, contribute to the realization of smart decision making [36–38].

• Big data analytics. CPS and IoT-based manufacturing systems involve the generation of vast amounts of data in Industry 4.0 [39], and big data analytics is crucial for the design and operations of manufacturing systems [41]. For example, by using the big data analytics approach, a holistic framework for data-driven risk assessment for industrial manufacturing systems has been presented based on real-time data [41]. Such a topic has been widely reported to support production optimization and manufacturing CPS visualization [42–44].

• Industrial implementations. Industrial applications are the ultimate aim of Industry 4.0. Almost all industries, including manufacturing, agriculture, information and media, service, logistics, and transportation, can benefit from the new industrial revolution. Many new opportunities will be available for industrial parties [45]. Companies may focus on their core business values or challenges, which could be upgraded or addressed with Industry 4.0-enabled solutions.

3 Demonstrative scenarios

3.1 Smart design: User experience (UX)-based personalized smart wearable device

ISO 9241-210 defines UX as "a person's perceptions and responses resulting from the use and/or anticipated use of a product, system, or service" [46]. In the Industry 4.0 environment, the two typical emerging tendencies in the product development stage are 1) customers become actively involved in the product design process to co-create personalized products with improved UX and satisfaction, which is known as the manufacturing paradigm of mass personalization [47] and 2) products themselves become smart and able to communicate with other things in their lifecycle as defined in the IoT [48]. Both aspects aim to improve UX during the product development stage. However, only a few studies have discussed the establishment of such a smart design for personalization. To bridge these gaps, this scenario provides a systematic means to develop a series of personalized wearable products by considering the aforementioned factors.

The conceptual framework of the proposed co-creation model is shown in Fig. 2 (derived from Ref. [49]). It consists of physical, cyber, and UX layers. The physical layer stands for physical products (e.g., wrist band) and services (e.g., application (app) subscription), the cyber layer stands for web-based virtual co-design resources (e.g., CAD models and product configuration systems), and the UX layer stands for the cognitive and affective behaviors of users (e.g., feedback and emotions) during product development.

Smart design adopts state-of-the-art design methodologies (e.g., adaptable design [50] and innovative design thinking [51]) to guide the user interactive conceptual design process. A product configuration system with a graphical user interface is also developed to enable the co-creation process. To prototype the personalized parts, 3D scanners are utilized to capture the specific features of a user, and the geometric parameters are optimized in CAD software for subsequent 3D printing. A smart sensor platform (e.g., Raspberry Pi [52]) is implemented in the prototyping product to test its smart functions (e.g., heart rate and breathing frequency) with apps in smart mobile devices. Sensor data are then mashed up into an IoT platform for further data analytics and tracking of the status of the product (e.g., location and usage time). Meanwhile, UX is captured during product development and prototype product testing stages. For the former, marketing strategies (e.g., questionnaire and focus group) and digital equipment

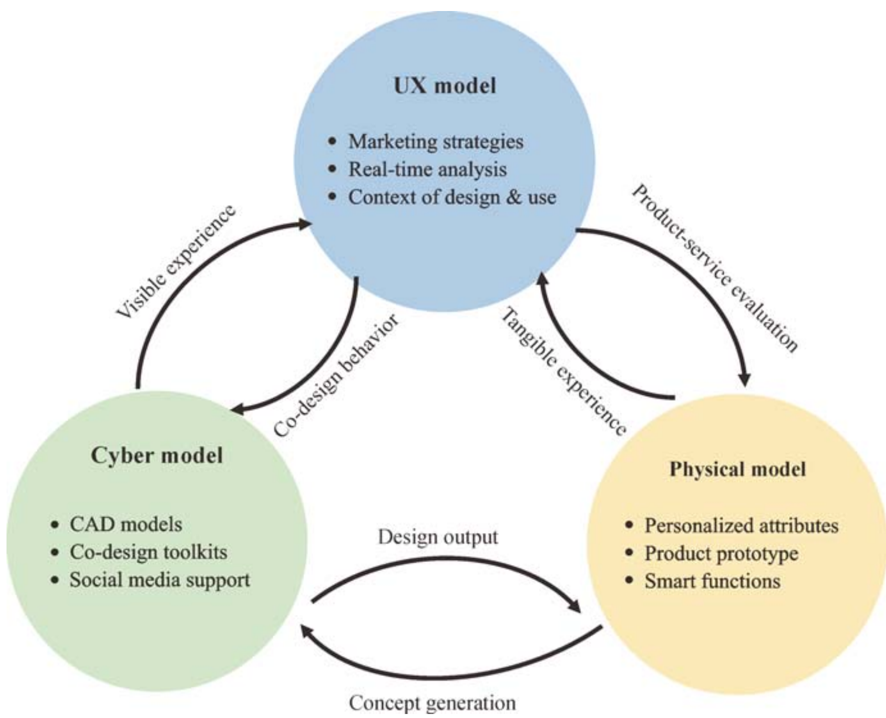

Fig. 2 Conceptual framework of the proposed product development process

(e.g., eye tracker and video camera) are utilized to reflect the perceptions of users toward the co-design process. For the latter, the experiences of users are recorded by digital equipment (e.g., VR headset and eye tracker) and through marketing strategies.

Smart design processes are pre-designed in a series of human participation experiments that are conducted to 1) determine the relationship between UX and user preference in the scope of common products (designed by the designer), modularized products (co-design), and personalized products (designed by the user); 2) discover which method achieves improved UX in a certain context, i.e., product design visualization (e.g., VR and AR) or product design rapid prototyping (e.g., 3D printing); 3) determine the relationship between the smart attributes and UX of a smart wearable product; 4) discover user behavior in the co-design human-computer interaction process; and 5) provide useful guidelines to engineer-to-order companies for customer-centric product development optimization.

3.2 Smart machining: CPS-based smart machine tools

After smart design, CPS-enabled smart machine tools are used to produce physical products. CPS are can bring together virtual and physical worlds to create a truly networked world in which intelligent objects communicate and interact with one another [53]. In Industry 4.0, production systems evolve into CPPS, which comprise smart machines, warehousing systems, and production facilities that have developed digitally and feature end-to-end ICT-based integration [4].

Smart machine tools can be regarded as combinations of different CPS (as shown in Fig. 3). Radio frequency identification devices (RFID) tags are attached to critical components, such as spindles, bearings, and cutting tools, so that physical objects can be uniquely identified. Various sensors (accelerometers, dynamometers, AE sensors, etc.), cameras, and data acquisition devices are deployed in the machine tools to collect real-time machining data on each critical component and machining process.

Communication service deals with the integration, communication, and management of real-time machining data collected from smart machine tools. Although different data communication technologies (Ethernet, RS 232, 4G network, Bluetooth, etc.) can be utilized to transmit real-time data depending on different data acquisition devices, the formats of various data originating from different machine controllers and sensors pose significant challenges to data integration and management. Additionally, after gathering all the data, a digital twin for each critical component needs to be modeled to comprehensively represent its physical attributes and real-time status simultaneously. Standardized data communication protocols and information modeling methods are used to address these issues. MTConnect is an open, royalty-free communication standard intended to enhance the data acquisition capabilities of devices and applications and move toward a plug-and-play environment to reduce the

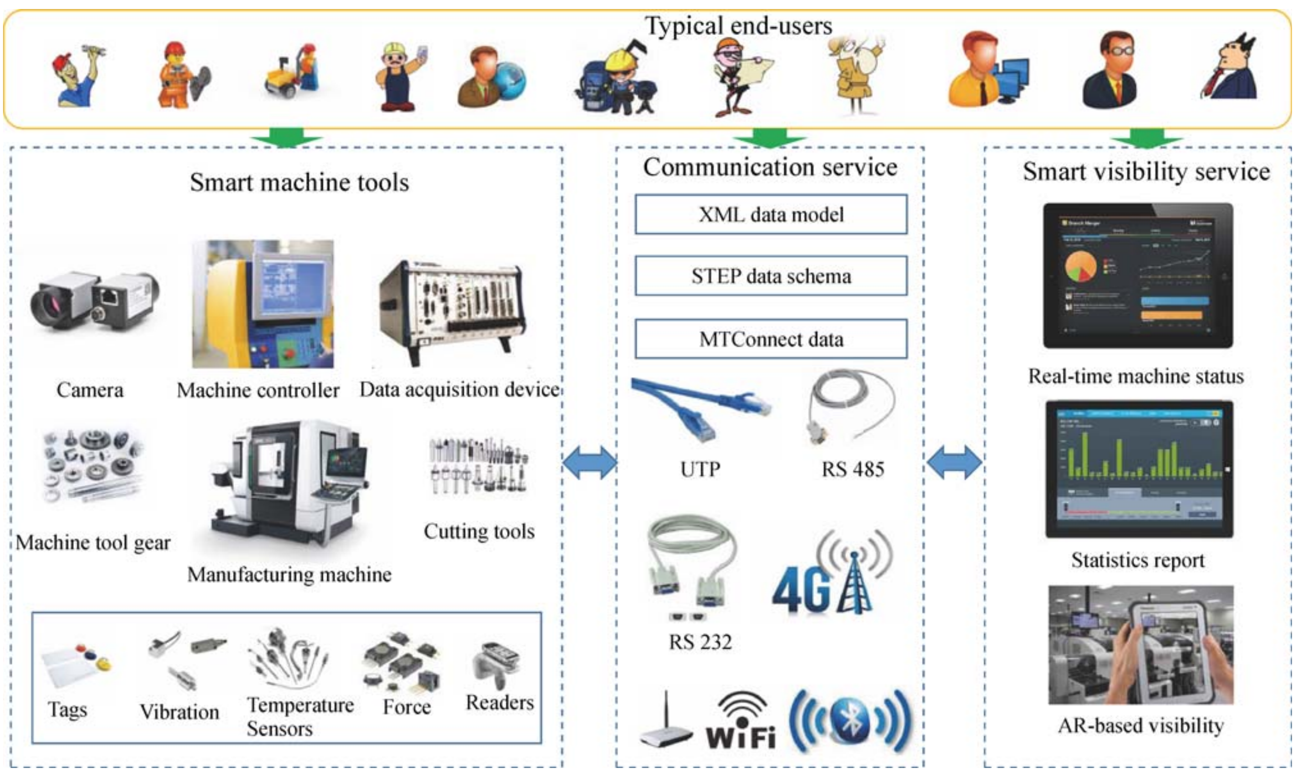

Fig. 3 CPS-enabled smart machine tools

cost of data integration [54]. MTConnect can translate data collected from different devices into the XML data format, which can be used by most software applications. ISO 10303, also known as STEP, is an ISO standard that describes product data throughout the life cycle of a product independent of any particular system. On the basis of these standards, communication service creates digital twins for the critical components and provides well-formatted real-time data to various applications through the Internet.

Smart visibility service is an application that takes advantage of real-time data provided by the communication service. Given the availability of real-time data from field-level devices on the Internet, the real-time status of each critical component of smart machine tools can be remotely visualized from mobile devices, such as tablets and smartphones. Statistical reports on machine tool status can be directly accessed by business management systems, such as enterprise resource planning (ERP), thus enabling seamless communication between field-level manufacturing devices and high-level decision-making systems. Detailed historical data would be available if each critical component is saved in the cloud and locally by recording the real-time data provided by the communication service. Then, prognostics and health management (PHM) algorithms can be applied to assess the health state of certain components so that proactive maintenance can be achieved and machine failure can be avoided. AR can visualize machining processes. Combining AR technology with real-time manufacturing data collected during machining processes will enable intuitive and effective interactions between users and smart machine tools.

3.3 Smart monitoring: Energy consumption monitoring

Energy-efficient production is a concern of many industrial enterprises in Industry 4.0 manufacturing systems. A machining workshop contains many machining equipment (e.g., machine tools), as shown in Fig. 4. The X axis denotes time (in h), and the Y axis denotes power consumption (in kW). Currently, energy prices are soaring, and environmental protection is a major concern of many countries.

Each piece of machining equipment usually has a fixed energy consumption characteristic. Several energy demands, such as the power for starting a machine tool, idle power, the power for starting the spindle, cutting power, and the power of the machine function (tool change, work piece handling), during machining operations are usually fixed. Some portions cannot be expressed using formulae. For example, the power for starting the spindle may have complex expressions, which increase the difficulty of calculating the energy demand and subsequent optimization. Furthermore, a workshop experiences power fluctuations that result in difficulties in establishing an energy consumption model. To achieve energy-efficient production, the machining energy consumption must be monitored in real time.

Owing to the widespread deployment of various sensors, energy consumption data can be collected in Industry 4.0. Machine learning methods can be applied to the collected data to determine the energy demand characteristics. Deep neural network (DNN) is a machine learning method that focuses on the analysis of large datasets. It can be utilized to extract the energy consumption characteristics or trends

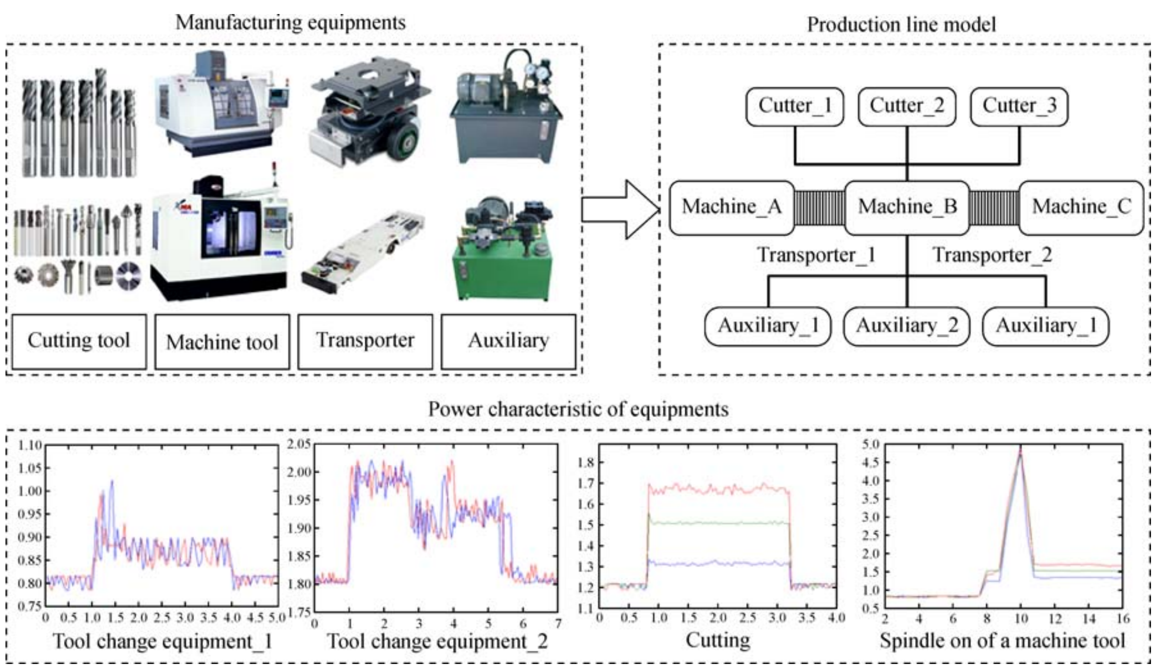

Fig. 4 Energy-efficient manufacturing

of manufacturing equipment on the basis of data obtained from energy consumption monitoring.

Input and output determination is the first procedure in DNN. The input includes machine tools, cutting tools, materials of parts to be machined, parameters, machining strategies, transporters, and auxiliaries. The output is the energy consumption of each stage during machining processes. Different cutting tools possess different parameter ranges (e.g., cutting velocity and feed rate). The machine tool, cutting tool, and material jointly determine the cutting energy consumption, which thus becomes a variable energy demand. The relationship between the combination and cutting of energy consumption can therefore be established via DNN.

3.4 Smart control: Cloud-based numerical control

Smart control in Industry 4.0 manufacturing systems is significant because a machine tool and its control system have become highly sophisticated. For example, a current computer numerical control (CNC) system can be used by an operator, who in turn uses the human-machine interface (HMI), switches, and buttons to manipulate the machine and make it perform a machining job. Each control system of the machine tool operates independently, thus creating an "information isolated island" problem. In a cloud manufacturing environment, a new and innovative form called control system as a service (CSaaS) is provided. Users of CSaaS are not limited to machine operators but include machine supervisory vendors and even end users of the product to address the emerging demands in new business models.

A cloud-based smart control system is illustrated in Fig. 5. CNC control is used as an example to illustrate the key concepts. All non-real-time tasks are executed in the cloud. Machining jobs are scheduled and distributed among connected machine tools in consideration of their capability and availability, which are treated as local manufacturing resources. A local operator can start machining by logging a part program. The cloud can

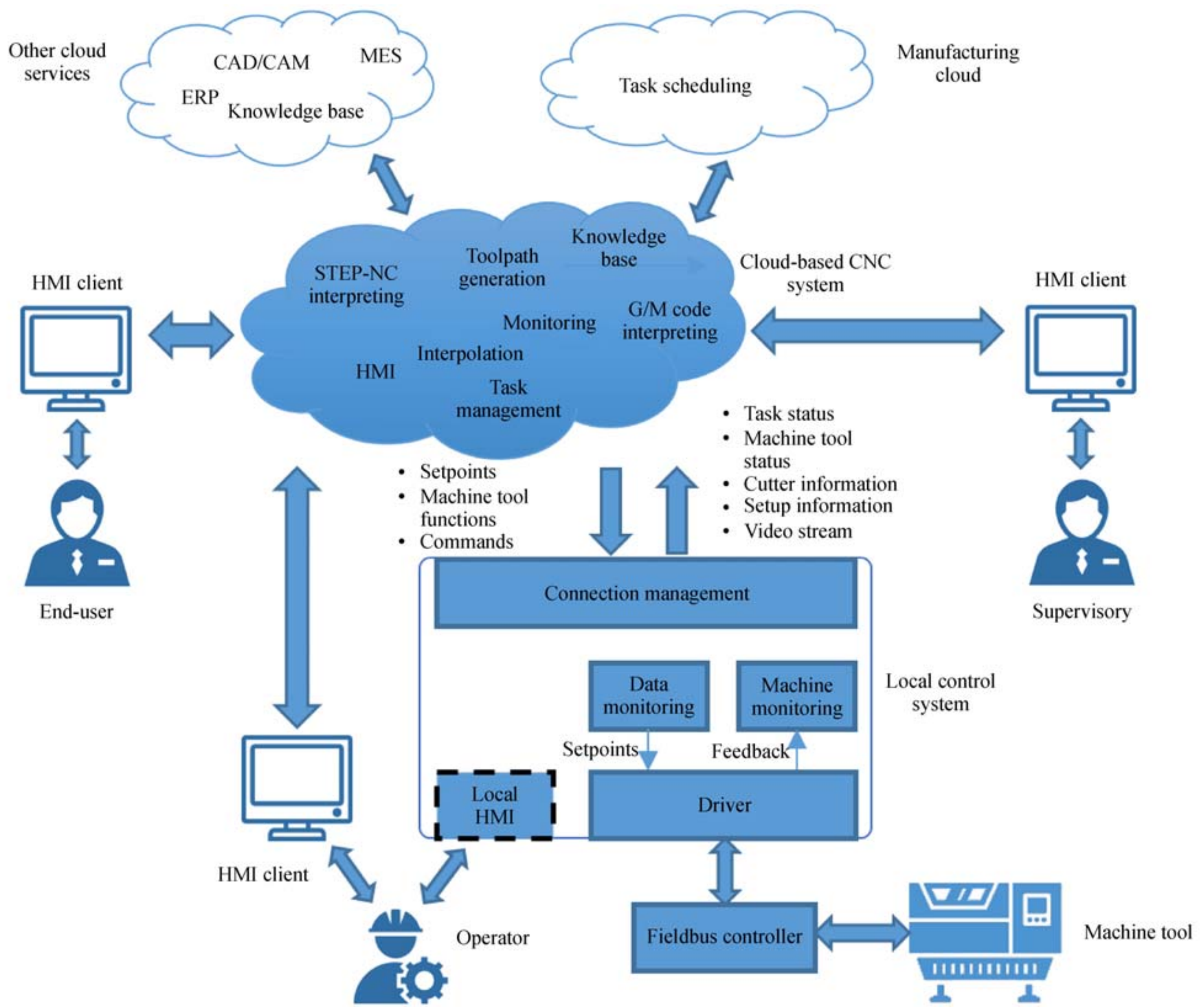

Fig. 5 Cloud-based smart control system

interpret the part program whether it is in G/M code or in STEP-NC. If it is a STEP-NC part program, the cloud will generate a tool path from the STEP-NC part program. During the tool-path generation process, offline optimization tasks, such as optimization of cutter selection and re-sequencing of the working steps and cutting parameter, can be performed with the help of a knowledge base or other optimization services.

Interpolation is also executed in the cloud, so the computational power of the cloud is fully used. If no adaptive control is involved, then the generation of setpoints by the interpolator is independent of the feedback control of the machine tool. The local control system is responsible for ensuring that the axes follow the setpoints precisely.

In the local control system, the connection management takes charge of managing the Internet connection between the cloud and the local. Data monitoring is responsible for observing the data received and coping with any transmission errors. Proper setpoints are fed to drives and transformed into a pulse command, which is finally transmitted through the fieldbus and executed by the motors. The feedback from the encoder is used by the machine monitoring module. By combining the information from other sensors, the machine monitoring module provides the status of the machining and machine tool. Although HMI is provided by the cloud, in the local control system, a simple HMI still displays basic information for the operator to control the machine tool in the case that the cloud service is unavailable.

The information from a machine tool, including current axis positions, setup, and cutter status, is transmitted to the cloud to be used when the tool paths are generated. The progress of the machining tasks and the status of the machine tool (e.g., operation status and warning information) are transmitted to the cloud by the local control system.

3.5 Smart scheduling: Machine scheduling in smart factories

Smart machine scheduling can be achieved based on smart machines, smart monitoring (e.g., energy consumption monitoring), and smart control system from the cloud. Machine scheduling is a classical problem that has been studied for decades [55], and in Industry 4.0, a number of new characteristics and requirements exist (Fig. 6). Machines in Industry 4.0 are endowed with a certain degree of intelligence and can communicate with one another by deploying various sensors and wireless communication devices (e.g., RFID). In this case, machines are, to a large extent, transparent in the sense that data of each part of a machine can be conveniently collected in real time. Optimal machine scheduling can be performed by extracting useful information (such as operating status and energy consumption) from the

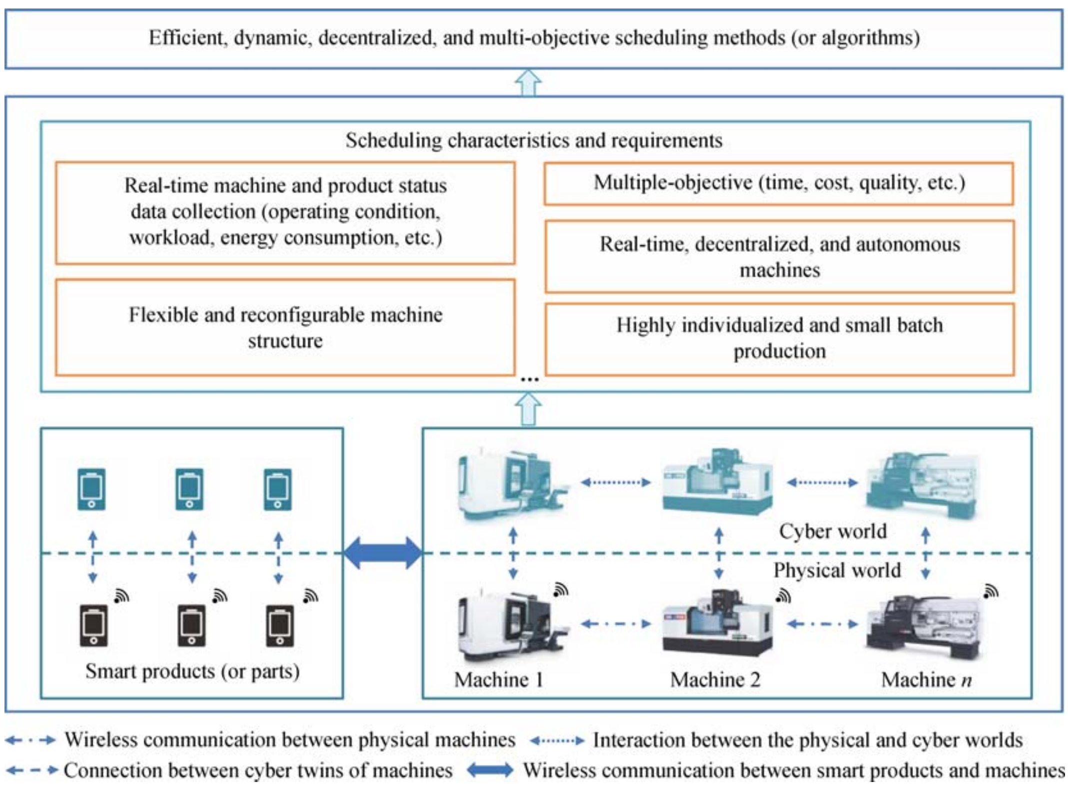

Fig. 6 Machine scheduling in Industry 4.0

collected data. This situation presents many advantages and eliminates several barriers in machine scheduling, such as machine breakdown [56] and unavailability [57], because machine breakdown or unavailability can be foreseen in the Industry 4.0 manufacturing environment. Another main difference between machine scheduling in Industry 4.0 and traditional machine scheduling is that products (or parts) are smart and can communicate with machines, which brings new advantages and challenges.

In the Industry 4.0 manufacturing environment, each machine is a CPS entity that can communicate with others in physical and virtual worlds (Fig. 6). The essence of machine scheduling in Industry 4.0 is the scheduling of collaborative CPS [58]. The complexity of machine scheduling in Industry 4.0 originates from the typical characteristics of CPS, such as autonomous (e.g., self-aware, self-predict, and self-compare), decentralized, and real time [59].

As a result, machine scheduling in Industry 4.0 requires efficient, dynamic, and decentralized scheduling methods [60]. In fact, machine scheduling in Industry 4.0 can be well supported by enhancing a machine into a CPS with comprehensive perception. AI, such as multi-agent systems, provides an effective instrument for machine scheduling in an Industry 4.0 smart factory [61–63]. In Industry 4.0 manufacturing systems, scheduling models and algorithms are implemented in the cyber space of CPS (e.g., cloud); they interact with physical machines and cooperatively drive production.

3.6 Industrial implementation: Smart 3D scanning for automated quality inspection

Material inspection and quality control in a smart production environment are challenges in Industry 4.0. An Industry 4.0 smart factory is established by merging the physical world of shop floor equipment with the virtual world of ICT. Under this circumstance, manufacturers should be aware that producing a single product must remain profitable. Therefore, revolutionary changes in smart machines and other smart equipment on the shop floor should be conveyed by smart quality control to ensure the delivery of best-quality products to customers. Customers also desire to have access to real-time quality data to ensure that the final products satisfy their requests. For this task, a novel technology that can speed up quality inspection processes with high accuracy and backward traceability is required [64].

A common technology to execute the quality inspection of processing materials and measure the quality of final products is the coordinate measuring machine (CMM). However, current CMM technologies cannot provide fast quality assessment for individual products nor measure complex geometric parts of manufactured products. Accordingly, technologies in metrology have changed in the past few decades from stand-alone and fixed CMM equipment to portable measuring devices. Advanced optical machine vision technologies are also adopted to perform inspection tasks by introducing 3D laser scanning for quality inspection. These changes have not only brought inspection right to the production line as close to the part as possible, but have also made it automated with high accuracy.

Figure 7 shows the principle of 3D scanning for automated quality inspection. The process begins by scanning an object and creating 3D files of points called point clouds as raw input. Unreliable range measurements (outliers) are removed through a filtering process. Then,

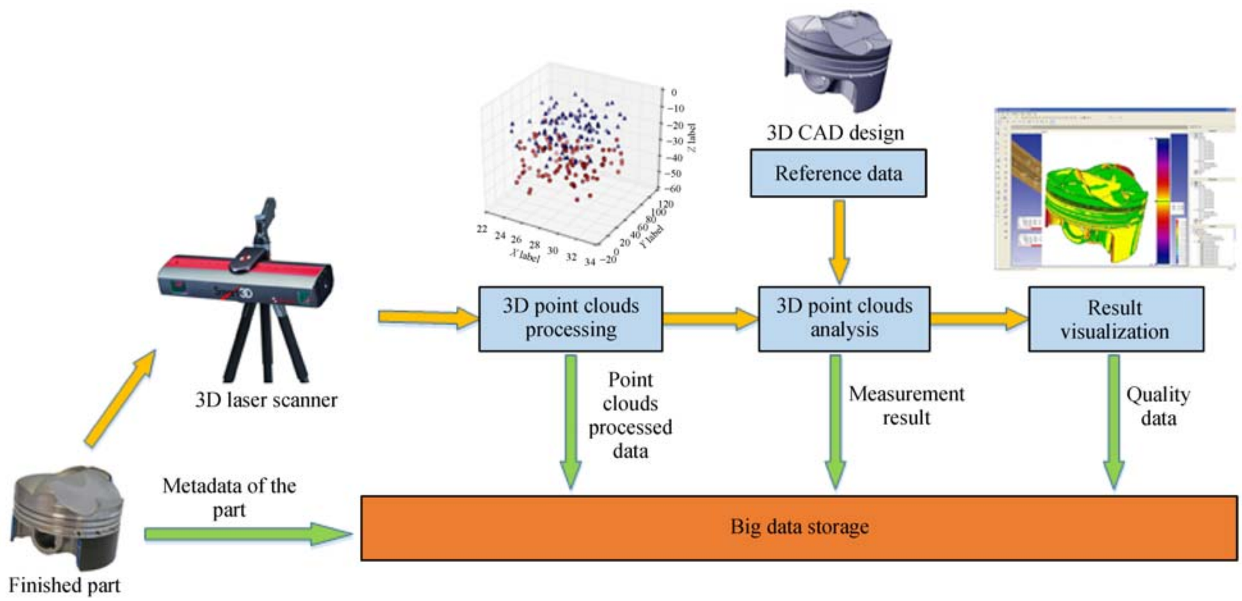

Fig. 7 Smart 3D scanning for automated quality inspection

point clouds are analyzed and compared with those in the initial design [65]. The results are visualized with different colors to show the degree of quality of each segment of the part. The data gathered from each process are stored in a large data storage. By using big data analytic tools, control charts, mathematical statistics knowledge, and intelligent algorithms, the data are processed to provide valuable information for manufacturers and customers. This system is also connected to the Internet to provide real-time online quality data on the processing parts or finished workpiece for customer access.

Automated quality inspection using 3D scanning provides accurate quality results, is fast and easy to implement, reduces the time consumed by the inspection process, and is suitable for all materials; moreover, the final part/product can be compared with the initial design to ensure fitting performance with other parts [66]. However, this technology possesses drawbacks, such as high cost of the device, limited point per second scanning volume, and need for high-capability hardware for data processing.

Table 1 summarizes the advantages and disadvantages of each individual project in the demonstrative cases.

4 Current challenges and future perspectives

Most manufacturing systems use typical machinery to accomplish various processes according to planned production logics. Manual and paper-based working mechanisms are commonly utilized to support these processes [67]. Several challenges exist in the use of these mechanisms. First, working efficiency is low because all the operations, interactions, and executions on shop floors are time consuming when large amounts of manpower are used. For example, machine operators, technical engineers, chief engineers, and shop floor supervisors usually need to meet to discuss and establish a solution when designs are reengineered. Such meetings usually last for more than half a day because information or data need to be shared and current situations need to be analyzed to establish a suitable solution. Second, data collection is mainly based on paper sheets or record cards. Various workers have to write down critical data, such as working pieces, quality data, and WIP level [21]. Workers are usually busy with operating machines and reluctant to spend time on data recording, which is not a value-adding process [68]. Third, shop floor managers have to use data to make manufacturing decisions, such as production planning and scheduling. These decisions are prone to become unreasonable and unpractical when they are based on data from a large number of paper sheets or cards because dealing with a large number of paper sheets and cards is time consuming and tedious; moreover, the information obtained is always not up to date. To keep pace with the Industry 4.0 era, real-time data collection is required for most manufacturing companies. IoT and CPS can provide possible solutions to these issues. The future of

Table 1 Summary of demonstrative scenarios

Scenarios	Advantages	Disadvantages
UX-based personalized smart wearable device	• Users are actively involved in the co-creation process for personalization. • User experience can be readily obtained/analyzed in a real-time design context. • Product change can be rapidly prototyped for design innovation in a cyber-physical manner.	• The application scope of the model is limited to highly modularized or discreet manufacturing systems (e.g., automobile and bicycles), rather than integral or continuous processes (e.g., chemical process and natural gas).
CPS-based smart machine tools	• Users can control the machine tool in real time by using cloud-based services. • Real-time status can be reflected in the user interface.	• System reliability is based on the stability of communication networks. • Information confidentiality is an issue on the part of end users.
Energy consumption monitoring	• Energy consumption can be tracked and visualized in real time. • Decision making/optimization can be based on energy consumption.	• Smart sensors should be equipped to machines. • Data transmission relies on multiple channels.
Cloud-based numerical control	• Control of the machine is servicelized. • Highly sophisticated algorisms can be applied. • Service is flexible and can be updated and upgraded easily. • The process know-hows can be well protected.	• Concerns on cyber security and service availability may exist.
Machine scheduling in smart factories	• Machines are optimally scheduled based on real-time information. • Any disturbances can be tracked and traced in real time.	• Advanced decision-making models are required. • Real-time data processing models are necessary.
Smart 3D scanning for automated quality inspection	• Quality inspection can be automatically executed. • Quality data can be visualized in real time for decision making.	• Data storage and processing may be an issue if the volume of real-time information is large.

real-time data collection in manufacturing systems may be carried out as follows.

• IoT-enabled data collection. Typical IoT technologies, such as RFID and barcoding, can be embedded into various manufacturing resources. In this manner, they are converted into smart manufacturing objects (SMOs) that can intelligently interact and communicate with one another so that real-time production data can be captured and collected in real time.

• Smart sensors. With the rapid development of cutting-edge technologies, smart sensors can now integrate multi-functional capabilities to collect real-time data on temperature, force, pressure, and humidity. These sensors are attached to various SMOs so that manufacturing operations and production lines or working stations can be synchronized with physical operational and information flows.

• CPS-based smart machines. In the future, machines will be converted into smart objects by taking advantage of CPS technology. Smart machines can send their working status in real time to a central cloud-based "manager" that can monitor their states through a visualization approach.

Currently, manufacturing companies are facing challenges in visualizing and displaying various manufacturing services. Information visibility plays an important role in precise decision making in Industry 4.0. Several challenges exist when implementing manufacturing virtualization and visualization. First, manufacturing objects should be visualized in real time to ensure production quality and safety. However, the closed-circuit television (CCTV) system, which is the only option, cannot reflect the status of a working machine. Manufacturing resources should be virtualized into various services so that they can be shared as a service. Virtualization approaches and sharing models have been rarely reported and investigated. Finally, the visibility of various manufacturing objects requires a new data modeling approach that can combine heterogeneous data into a standardized format. Afterward, such data can be displayed for different end users who are concerned about the different visibility of different equipment. However, these research gaps have been rarely studied in existing literature.

To fill these gaps, future research should emphasize the following aspects.

• AR-enabled real-time visibility. Applying AR technology to manufacturing can result in real-time visibility of working machines. With the data from smart machines, the AR interface can reflect the status of a machine and its processing behavior through a visualized model in real time. AR-enabled real-time visibility allows end users to visualize machine data that are projected onto a real machining scene [69].

• Cyber virtualization modeling. Various physical manufacturing resources are modeled by the cyber virtualization approach so that their capability and status can be reflected in a cloud platform, which is going to be shared within an alliance. This modeling approach uses data from smart machines and sensors to build a standardized service that can be displayed and visualized by other users who can benefit from the service.

Decision making in smart manufacturing systems for Industry 4.0 requires information and knowledge, which can be mined from large amounts of production data. In a recent survey, 55% of the respondents felt that decision making is not viewed at senior levels of their organizations [70]. Faced with the big data from manufacturing sites, several challenges should be addressed. First, decision models need a long time to establish a solution when large amounts of data are used. Various objectives are utilized for different purposes, such as optimization of production planning and scheduling [71]. However, precise data input is lacking when decision making is carried out. Second, decision making in Industry 4.0 always targets manufacturing resource sharing, which can make full use of manufacturing equipment and services. A new manufacturing paradigm is thus needed.

Future decision making should focus on two directions.

• Decision-making models driven by big data analytics. These models can excavate useful information and knowledge from large amounts of production data to support specific decision making. Advanced technologies or algorithms, such as deep machine learning, can be integrated into these models where big data analytics are encapsulated as services [43]. Such services may be deployed in a cloud platform so that they can be downloaded easily by end users for daily decision making.

• Cloud manufacturing. With the support of cloud technology and IoT, cloud manufacturing can transform various manufacturing resources into services so that end users can request services on demand in a convenient pay-as-you-go manner [72]. Moreover, CPS integration into cloud manufacturing enables remote monitoring and execution of manufacturing operations. Thus, physical machinery and virtualized services are implemented to support manufacturing activities and decision making [37]. The networked manufacturing services allow for smart decision making through a collaborative and intelligent full sharing and circulation of manufacturing capabilities and services.

5 Summary

Industry 4.0 holds the promise of increased flexibility, mass customization, increased speed, improved quality, and enhanced productivity in manufacturing and thus enables companies to cope with various challenges, such as increasingly individualized products, shortened lead time to market, and high product quality. This paper presents the conceptual framework of Industry 4.0 smart manufacturing systems and showcases several key technologies and demonstrative scenarios. On the basis of the demonstrative scenarios, related key technologies, such as

Internet of Things, CPS, cloud manufacturing, and big data analytics, are reviewed. Current challenges and future perspectives are also highlighted to inspire researchers and practitioners when they embark on Industry 4.0.

The significant contributions of this work are as follows. First, a systematic framework for Industry 4.0 smart manufacturing systems is proposed. The framework covers many relevant topics, such as design, machining, monitoring, control, and scheduling. It provides an important reference for academicians and practitioners to rethink the essence of Industry 4.0 from different perspectives. Second, key perspectives are reviewed under the framework by combining several studies carried out by the authors. Future research directions in terms of data collection, virtualization, and decision making are also provided. This work is expected to provide the manufacturing industry insights into implementing Industry 4.0 in the near future.

Nomenclature

AR	Augmented reality
CAD	Computer-aided design
CAM	Computer-aided manufacturing
CCTV	Closed-circuit television
CMM	Coordinate measuring machine
CNC	Computer numerical control
CPPS	Cyber-physical production systems
CPS	Cyber-physical systems
CSaaS	Control system as a service
DML	Deep machine learning
DNN	Deep neural network
ICT	Information and communication technology
IoT	Internet of Things
ISO	International Organization for Standardization
PHM	Prognostics and health management
RFID	Radio frequency identification
SMOs	Smart manufacturing objects
UX	User experience
VR	Virtual reality
XML	Extensible markup language

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