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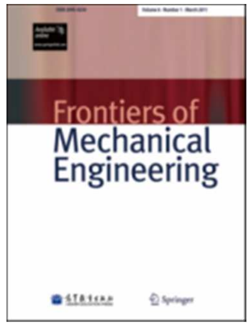

Smart manufacturing systems for Industry 4.0: a conceptual framework, scenarios and future perspectives

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

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Abstract The rapid development of information and communications technology (ICT) has brought about many disruptive technologies such as cloud computing, Internet of Things (IoT), and big data. These technologies are nowadays penetrating almost all industries, with no exception to the manufacturing industry. The fusion of these state-of-the-art technologies and manufacturing brings together the physical and virtual worlds through Cyber-Physical Systems (CPS), which marks the advent of the fourth stage of industrial production – Industry 4.0. The widespread application of CPS in manufacturing environments makes manufacturing systems smarter and more autonomous. In order to advance research and implementation of Industry 4.0, we present a conceptual framework of smart manufacturing systems for Industry 4.0, and showcase some demonstrative scenarios covering topics such as smart design, smart machining, smart control, smart monitoring, and smart scheduling. Based on the demonstrative scenarios, key technologies such as IoT, CPS, and big data analytics for Industry 4.0 smart manufacturing systems are reviewed. Current challenges and future perspectives are also highlighted.

Keywords: Industry 4.0, Smart manufacturing systems, Internet of Things, Cyber-Physical Systems, Big data analytics, Framework.

1 Introduction

Today, technologies – in particular, information and communications technology (ICT) - are undergoing exponential growth, and many disruptive technologies such as cloud computing, Internet of Things (IoT), big data analytics, as well as artificial intelligence are continuously emerging. These new technologies are nowadays penetrating manufacturing and serving as key enablers for the manufacturing industry to address current challenges such as increasingly customised requirements, higher quality, and shorter time-to-market [1] by converting manufacturing systems onto a smart level. For example, by being deployed sensors (e.g. machine tools), manufacturing equipment can self-sense, self-act, and can also communicate with each other [2]. In addition, enabled by these technologies, it is possible to capture and share real-time production data, which could be used for rapid and accurate decision-making. In particular, the connection of physical manufacturing equipment and devices over

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the Internet together with big data analytics in the digital world (e.g. the cloud) brings about a revolutionary production pattern – Cyber-Physical Production Systems (CPPS), which is a materialization of the general concept of Cyber-Physical Systems (CPS) in the manufacturing environment. The widespread applications of CPS (or CPPS) mark the advent of the fourth stage of industrial production – Industry 4.0 [3].

Industry 4.0 has aroused numerous interest in both industry and academia [4]. However, currently there is no systematic framework of smart manufacturing systems for Industry 4.0 that could be clearly identified in both practices and academic research so that future implementations could be guided. Motivated by this situation, this paper proposes a concept framework for Industry 4.0 smart manufacturing systems, covering a wide range of topics such as smart design, smart machining, smart monitoring, smart control, smart scheduling, and industrial implementation. A number of typical demonstrative scenarios are illustrated. Finally, the current challenges and future research directions are also discussed.

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

2. Smart manufacturing systems for Industry 4.0

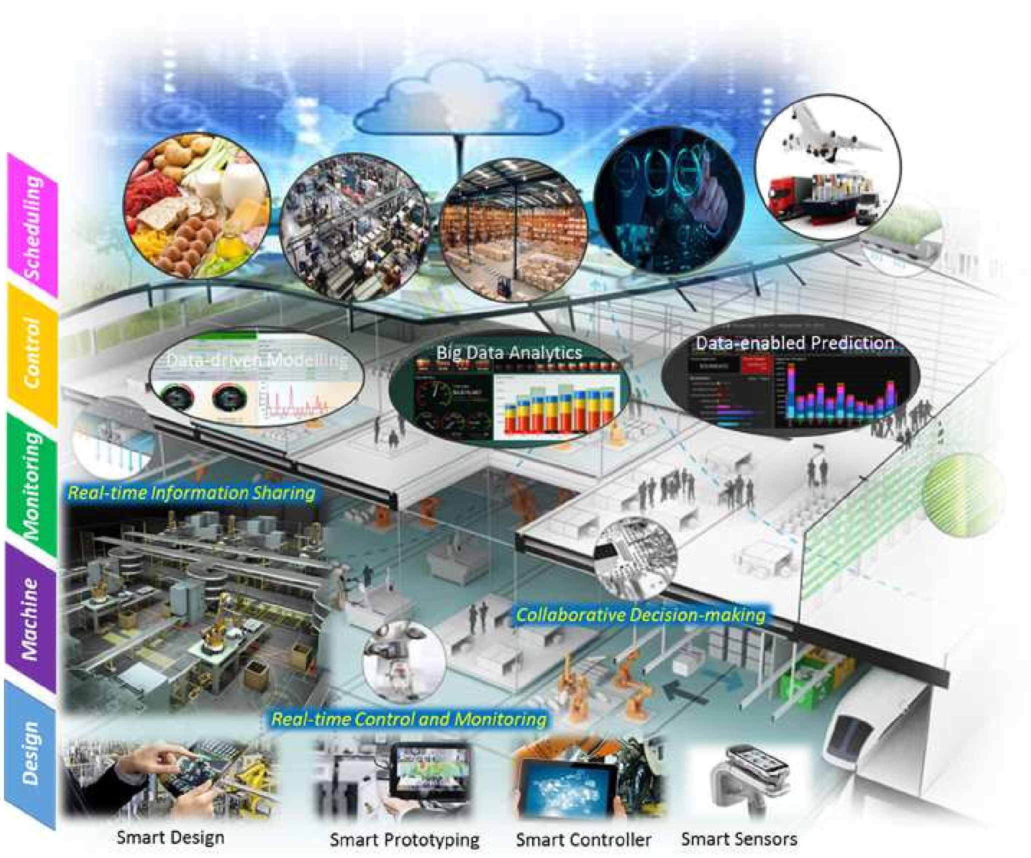

Fig. 1. A concept framework of Industry 4.0 smart manufacturing system

Fig. 1 presents a framework of Industry 4.0 smart manufacturing systems in which research topics are categorized into smart design, smart machining, smart monitoring, smart control, smart scheduling, and industrial applications.

1) Smart design. With the rapid development of new technologies such as Virtual Reality (VR)

and Augmented Reality (AR), traditional design will be upgraded and enter into a smart era. Design software such as CAD and CAM is able to interact with physical smart prototype systems in real time enabled by 3D printing that is integrated with CPS and AR [5]. Thus, the engineering changes and physical realizations could be twined to achieve a smart design paradigm.

2) Smart machining. In Industry 4.0, smart machining can be achieved with the help of smart robots and various other types of smart objects that are capable of real-time sensing and interacting with each other [6]. For example, CPS-enabled smart machine tools are able to capture the real-time data and send it to a cloud-based central system so that machines tools and their twined services could be synchronized to provide smart manufacturing solutions.

3) Smart monitoring. Monitoring is an important aspect for operations, maintenance, and optimal scheduling of Industry 4.0 manufacturing systems [7]. The widespread deployment of various types of sensors makes it possible to achieve smart monitoring. For example, data and information of various manufacturing objects such as temperature, electricity consumption, and vibrations & speed can be obtained in real time. Smart monitoring not only provides a graphical visualization of these status, but also gives some alerts if some abnormality occurs to machines or tools [8, 9]. CPS and IoT are key technologies that enable smart monitoring in Industry 4.0 smart manufacturing systems.

4) 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 [10]. Smart control is mainly executed to physically manage various smart machines or tools through a cloud-enabled platform [11]. End-users are able to switch off a machine or robot via their smart phones [12]. The decisions could then be timely reflected in frontline manufacturing sites such as robot-based assembly lines or smart machines [13].

5) Smart scheduling. Smart scheduling layer mainly includes advanced models and algorithms to draw on data captured from sensors. Data-driven techniques and advanced decision architecture can be used for smart scheduling. For example, in order to achieve real-time, reliable scheduling and execution, distributed smart models using a hierarchical interactive architecture can be used [14]. Production behaviours and procedures will be carried out automatically and effectively given the well-established structures and services. With the help of data input mechanisms, the output resolutions are fed back to parties involved through different ways [15].

6) Industrial applications. Industrial applications targeting different industry implementation of various solutions are the ultimate purpose for Industry 4.0, which may give profound revolutions to manufacturing systems. According to the uniqueness and specific requirements from some industries such as food industry which includes a large number of perishable products, solutions provided by Industry 4.0 are much more flexible to support customised configuration and development. Thus, dynamic manufacturing networks provide the opportunities for them to manage their supply and business modes [16]. Under the support of configurable facilities from layers of smart design and manufacturing as well as smart decision-making, the applications could achieve a holistic perspective by considering practical concerns such as production efficiency, logistics availability, time constraints, and multiple criteria [17].

Research topics within this framework are summarized as follows:

- Smart design and manufacturing. Research in this level encompasses smart design, smart prototyping, smart controller and smart sensors [18, 19]. Real-time control and monitoring supports the realization of smart manufacturing [20]. The supporting technologies include IoT, STEP-NC, 3D printing, industrial robotics, wireless communication, and so forth [21].

- 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 [22]. Big data and its analytics play an important role in smart decision-making such as data-driven modelling, data-enabled predictive maintenance, etc. [23]. Many technologies such as CPS, big data analytics, Cloud computing, modelling and simulation can contribute to the realization of smart decision-making [8, 24-26].
- Big data analytics. CPS and IoT-based manufacturing systems mean generation of vast amounts of data in the era of Industry 4.0 [27], and big data analytics is thus crucial for manufacturing systems design and operations [28]. For example, by using the big data analytics approach, a holistic framework for data-driven risk assessment for industrial manufacturing systems was presented based on real-time data [29]. Such topic has been widely reported to support production optimization and manufacturing CPS visualizations [23, 30-32].
- Industrial implementations. Industrial applications are the ultimate aim of Industry 4.0. Almost all Industries can be beneficial from the new industrial revolution, including manufacturing, agriculture, information and media, services, logistics, transportation, etc. A large number of new opportunities will be available for industrial parties [33]. Companies may focus on their core business value or challenges which could be upgraded or addressed by using Industry 4.0-enabled solutions.

3. DEMONSTRATIVE SCENARIOS

3.1. Smart Design: UX-based Personalized Smart Wearable Device

In the Industry 4.0 environment, two typical emerging tendencies in the product development stage are: 1) customers become more actively involved in the product design process to co-creating personalized products with better UX and satisfaction, which is known as the manufacturing paradigm of mass personalization [34]; 2) products themselves become smart, which are able to communicate with other things in their lifecycle as defined in the term of Internet of Things (IoTs) [35]. Few works deal with the lifecycle tracking of smart end products. Aiming for bridging these two gaps, this scenario provides a systematic way to develop a series of personalized wearable products by taking into account those factors.

The conceptual framework of the proposed co-creation model is shown in Fig. 2. It consists of three layers: physical layer, cyber layer, and user experience layer. Physical layer stands for the physical products (e.g. wrist band) and services (e.g. app subscription), cyber layer stands for the web-based virtual co-design resources, e.g. CAD models and product configuration system, and user experience layer stands for the user's cognitive and affective behaviors (e.g. feedback, emotions) during the product development process.

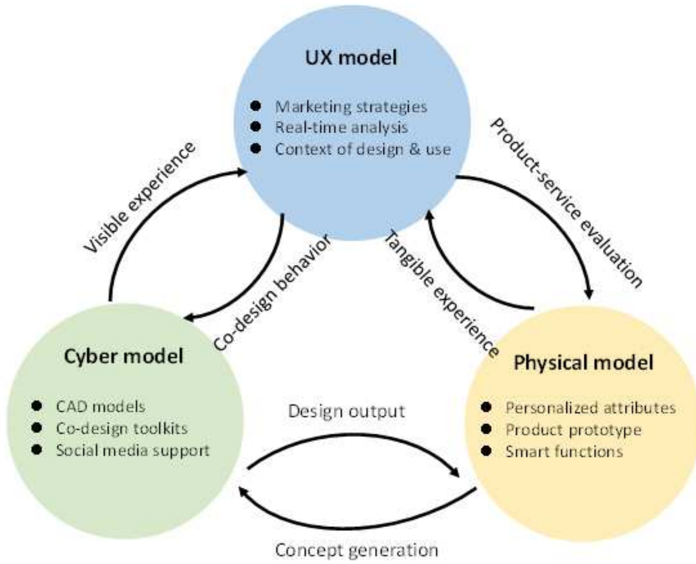

Fig. 2. Conceptual framework of the proposed product development process

Smart design adopts the state-of-the-art design methodologies (e.g. adaptable design [36], innovative design thinking [37]) to guide the user interactive conceptual design process. Also, a product configuration system with graphical user interface is developed to enable the co-creation process. In order to prototype the personalized parts, 3D scanners are utilized to capture the specific features of the user and the geometric parameters are optimized in the CAD software for later 3D printing. Smart sensor platform (e.g. Raspberry Pi [38]) is implemented in the prototyping product to test its smart functions (e.g. heartrate, breathe frequency) with Apps in the smart mobile devices. The sensor data is then mashed-up into the ThingWorx IoT platform [39] for further data analytics and tracking the status of the product (e.g. location, usage time, etc.). Meanwhile, the UX is captured both during the product development stage and prototype product testing stage. For the former one, both marketing strategies (e.g. questionnaire, focus group) and digital equipment (e.g. eye tracker and video camera) are used to reflect users' perceptions towards the co-design process. For the latter one, their experiences are recorded by the digital equipment (e.g. virtual reality headset, eye tracker) and marketing strategies.

Smart design processes are pre-designed in a series of human participation experiment, which is then conducted in order to: 1) find out the relationship between UX and user preference in the scope of common product (designed by designer), modularized product (co-design) and personalized product (designed by user), 2) discover which method achieves better UX in a certain context, i.e. product design visualization (e.g. virtual reality, augment reality) or product design rapid prototyping (e.g. 3D printing), 3) find out the relationship between smart attributes and UX of a smart wearable product, 4) discover the 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

Fig. 3. CPS-enabled Smart Machine Tools

After the smart design, CPS-enabled smart machine tools are used for producing physical products. CPS are capable of bringing together the virtual and physical worlds to create a truly networked world in which intelligent objects communicate and interact with each other [40]. In the context of Industry 4.0, production systems are developed into CPPS, which comprise smart machines, warehousing systems and production facilities that have developed digitally and feature end-to-end ICT-based integration [3].

Smart machine tools can be treated as combinations of different CPS (as shown in Fig. 3). RFID tags are attached to critical components such as spindles, bearings and cutting tools so that the 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 of each critical component as well as the machining processes.

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 used to transmit real-time data depending on different data acquisition devices, various data formats coming from different machine controllers and sensors pose significant challenges for the data integration and management. Additionally, having all the data gathered, a digital twin for each critical component needs to be modelled to comprehensively represent its physical attributes and real-time status at the same time. To address these issues, standardized data communication protocols and information modelling methods are used. 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 cost of data integration [41]. It has the ability to translate the 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 capable of describing product data throughout the life cycle of a product independent of any particular system. Based on these standards, the communication service creates digital twins for the critical components and provides the well-formatted real-time data to various applications through the internet.

Smart visibility service is one of the applications that take advantage of the real-time data provided by the communication service. Having the real-time data from field-level devices available on the internet, the real-time status of each critical component of the smart machine tools can be remotely visualized from mobile devices such as tablets and smart phones. Statistics reports of the machine tool status are directly accessed by business management systems such as ERP, enabling seamless communication between field-level manufacturing devices and high-level decision making systems. Detailed historical data if each critical component are saved both in the cloud and locally by recording the real-time data provided by 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. Augmented Reality (AR) is able to 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

In the context of Industry 4.0 manufacturing systems, energy efficient production is a concern of many industrial enterprises. There is lots of machining equipment (e.g. machine tools as shown in Figure 4) in a workshop. Currently, energy prices are soaring and environmental protection is a major concern of many countries.

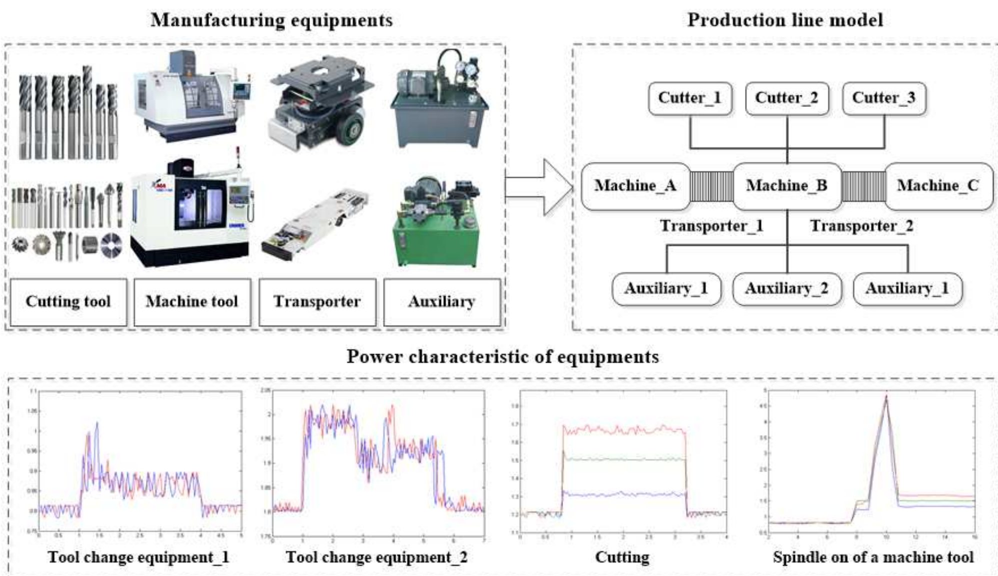

Fig. 4. Energy Efficient Manufacturing

Each piece of machining equipment usually has a fixed energy consumption characteristic. Some energy demand processes such as the power for starting a machine tool, the idle power, the power of spindle start, the cutting power, and the power of machine function (tool change, work piece handling) during machining operations are usually fixed. Some portions cannot be expressed using formulae. For instance, the spindle start power may have complex expressions, which increase the difficulty for calculating energy demand and subsequent optimization. Furthermore, there are power fluctuations in a workshop, resulting in difficulties in establishing the energy consumption model. In order to achieve energy-efficient production, it is necessary to real-time monitor the machining energy consumption.

In the context of industry 4.0, due to the widespread deployment of various sensors, energy consumption data can be collected. Machine learning methods can be applied to the collected data to get the energy demand characteristics. Deep neural network (DNN) is a kind of machine learning method focusing on large datasets analysis. It can be used to extract the energy consumption characteristics or trends of manufacturing equipment based on the obtained data from energy consumption monitoring.

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

3.4. Smart Control: Cloud-based numerical control

Smart control under Industry 4.0 manufacturing systems is significant since machine tool and its control system has been becoming more and more sophisticated. For example, a current CNC system can be used by an operator, who uses the Human Machine Interface (HMI), switches and buttons to manipulate the machine to do a machining job. Each control system of the machine tool operates independently forming an "information isolated island" problem. In a cloud manufacturing environment, a new and innovative form termed as Control System as a Service (CSaaS) will be offered. The users of the CSaaS are not limited to the machine operators but also the machine supervisory vendors and even the end-users of the product in order to suit the emerging demands in the new business models.

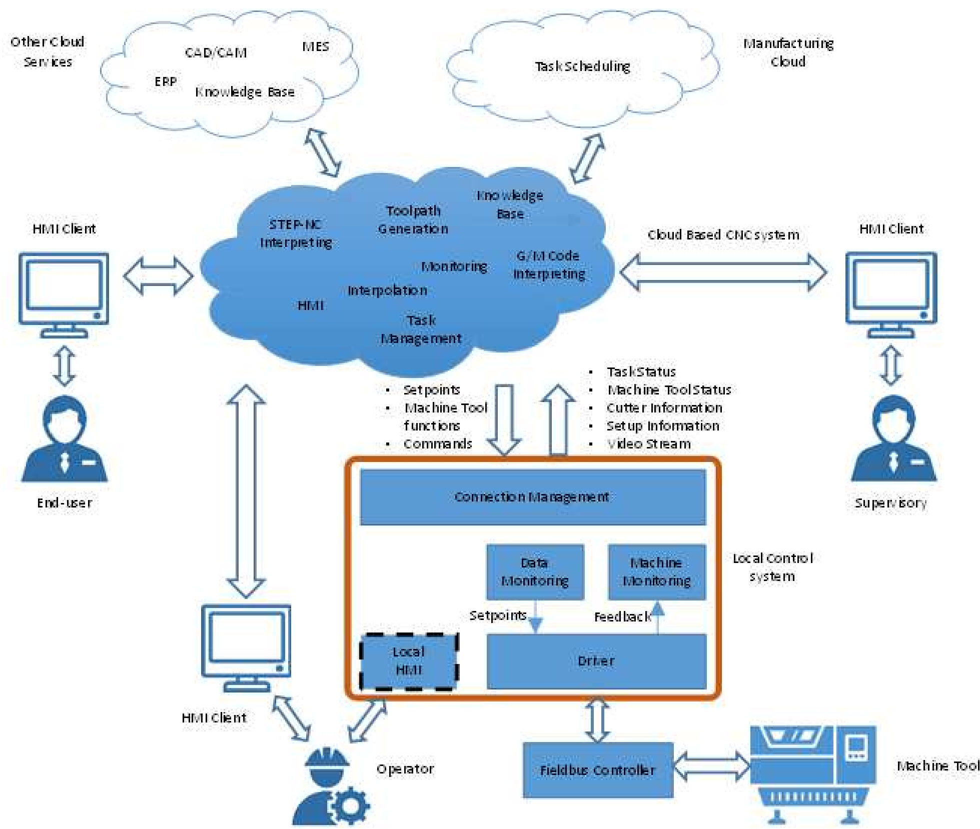

Fig. 5. Cloud-based Smart Control System

A cloud-based smart control system is illustrated in Fig. 5 which takes CNC control for example to illustrate the key concepts. All of the non-real-time tasks will be executed in the cloud. Machining jobs are scheduled and distributed among connected machine tools taking into account their capability and availability, which are treated as local manufacturing resources. A local operator is also able to start a machining by logging a part programme. The cloud is able to interpret the part programme no matter it is in G/M code or in STEP-NC. If it is a STEP-NC part programme, the cloud will generate the tool-path from the STEP-NC part programme. During the tool-path generation process, the offline optimization such as the optimization on the cutter selection, re-sequencing the working steps, and the cutting parameter can be performed with the help of a knowledge base or other optimization services.

The interpolation is also executed in the cloud, therefore the computational power of the cloud can be fully used. If no adaptive control is involved, the interpolator's generating the setpoints is independent with the feedback control of the machine tool. It is the local control system's responsibility to make sure 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. The data monitoring is responsible for observing the data received and coping with any transmission errors. The proper set-points will be fed to drives and be transformed into the pulse command which is finally transmitted through fieldbus and executed by the motors. The feedback from the encoder will be used by machine monitoring module. Combining the information from other sensors, the machine monitoring module will provide the status of the machining and the machine tool. Although the HMI is provided by the cloud, in the local control system there is still a simple HMI displaying basic information for the operator to control the machine tool in case that the cloud service is not available.

The information from a machine tool is transmitted to the cloud, including current axis positions, setup and cutter statues, which will 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, warning information) will be transmitted to the cloud by the local control system.

3.5. Smart Scheduling: Machine Scheduling in Smart Factories

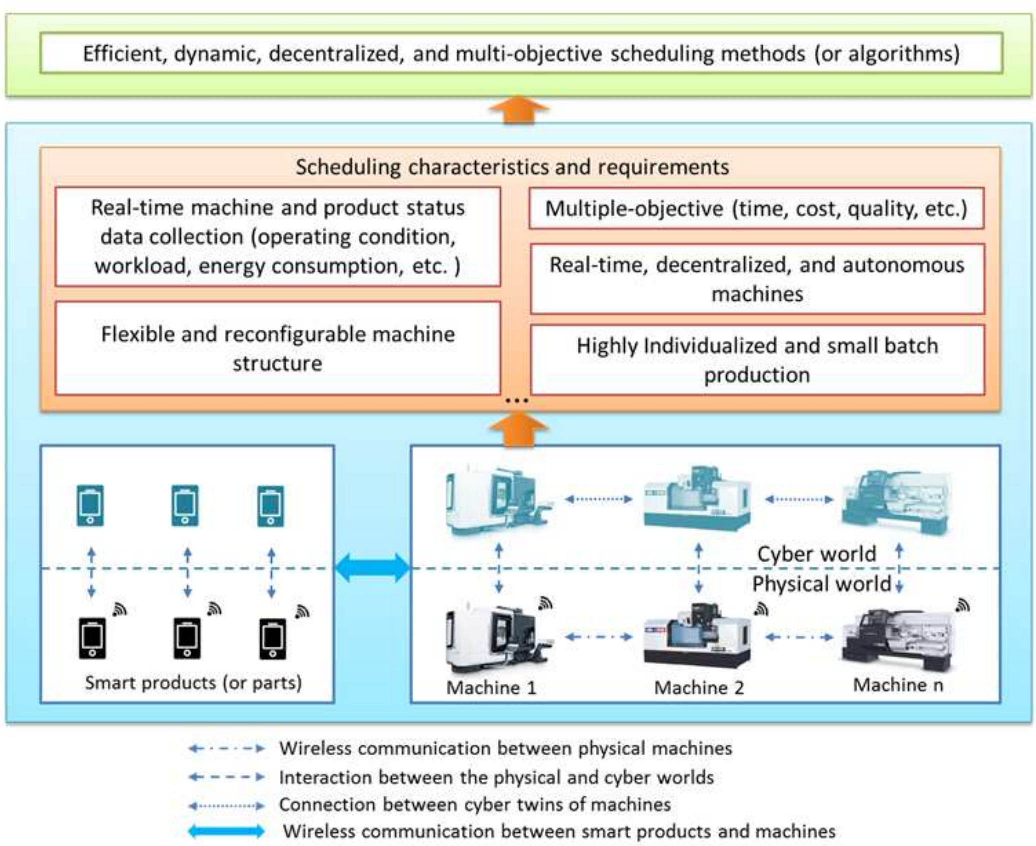

Fig. 6. Machine scheduling in Industry 4.0

Based on smart machines, smart monitoring (e.g. energy consumption monitoring), and smart control system from cloud, smart machine scheduling can be achieved. Machine scheduling is a classical problem that has been studied for decades [42], and in the context of Industry 4.0, there are a number of new characteristics and requirements (Fig.6). In Industry 4.0, machines are endowed with a certain degree of intelligence and can communicate with each other by being deployed 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 parts of a machine can be conveniently collected in real time. By extracting useful information (such as operating status, energy consumption) from the collected data, one can make optimal machine scheduling. This will bring many advantages and eliminate some barriers for machine scheduling such as machine breakdown [43] and unavailability [44] since whether a machine will break down or will be unavailable 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 as well as challenges.

In the Industry 4.0 manufacturing environment, each machine is a CPS entity, which can communicate with each other in both the physical and virtual worlds (Fig. 6). The essence of machine scheduling in Industry 4.0 is scheduling of collaborative CPS [45]. The complexity of machine scheduling in Industry 4.0 comes from the typical characteristics of CPS such as autonomous (e.g. self-aware, self-predict, self-compare), decentralized, and real-time [46].

As a result, machine scheduling in Industry 4.0 necessitates efficient, dynamic, and decentralized scheduling methods [47]. In fact, by enhancing a machine into a CPS with comprehensive perception, machine scheduling in Industry 4.0 will be well supported. Artificial intelligence such as multi-agent systems provide an effective instrument for machine scheduling in an Industry 4.0 smart factory [48-50]. In Industry 4.0 manufacturing systems, scheduling models and algorithms are implemented in the cyber space of CPS (e.g. cloud), which interact with the 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 is one of the big challenges towards Industry 4.0. An Industry 4.0 smart factory is established by merging the physical world of shop floor equipment with 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 best-quality products to be delivered to customers. In addition, 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 [51].

A common technology to execute quality inspection of processing materials as well as to measure the quality of final products is coordinate measuring machine (CMM). However, current CMM technologies are incapable of providing fast quality assessment for individual products as well as to measure complex geometric parts of manufactured products. Accordingly, technologies in metrology have changes in the past few decades from stand-alone and fixed CMM equipment to portable measuring devices. Moreover, advanced optical machine vision technologies are also adopted to perform better inspection tasks by introducing 3D laser scanning for quality inspection. These have brought inspection not only right to the production line, as close to the part as possible, but also more automated with higher accuracy.

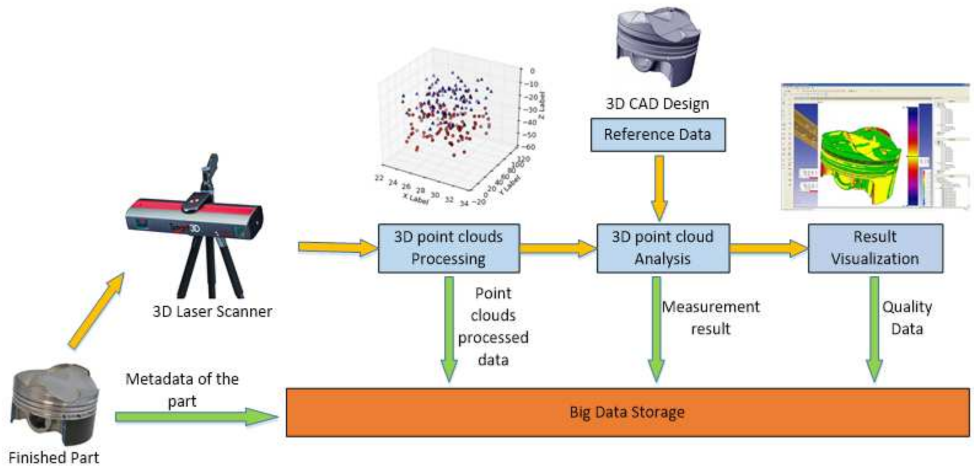

Fig. 7. Smart 3D-scanning for Automated Quality Inspection

Fig. 7 shows the principle work of 3D scanning for automated quality inspection. This process begins with scanning an object and creating 3D files of points, called point clouds, as raw input. By means of filtering process, unreliable range measurements (outlier) are removed. Then point clouds are analyzed and compared with initial design [52]. Finally, the results are visualized with different colors to show the degree of quality of each segment of the part. Data gathered from each process is stored in big data storage. By using big data analytic tools, control chart, mathematical statistics knowledge and intelligent algorithm, the data can be processed to provide valuable information for manufacturers and customers. This system is also connected to the internet to provide real-time quality data of the processing parts or finished workpiece online for customer access.

4. CURRENT CHANLLENGES AND FUTURE PERSPECTIVES

Most manufacturing systems are using typical machinery to accomplish various processes according to planned production logics. Manual and paper-based working mechanisms are commonly used to support these processes [53]. Several challenges exist under this mechanism. Firstly, the working efficiency is low because all the operations, interactions, and executions on shop floors are time-consuming when using large amounts of manpower. For example, machine operators, technical engineers, chief engineers, and shop floor supervisors are usually gathering to discuss a solution when there are any reengineered designs. It is common that such meetings will take more than half a day when a group of people have to share information or data first and then to look at the current situations for working out a suitable solution. Secondly, data collection is mainly based on paper sheets or record cards. Various workers have to write down some critical data such as working pieces, quality data, and WIP level [9]. Workers are usually busy with operating machines and reluctant to spend time in putting these data which are none value-adding processes [54]. Thirdly, shopfloor managers have to use some data to make manufacturing decisions such as production planning and scheduling. Unfortunately, these decisions are prone to be unreasonable and unpractical based on the data from large number of paper sheets or cards. That is because it is very time- and labor-consuming when dealing with huge number of paper sheets and cards where the information obtained is always lagged. In order to keep pace with the Industry 4.0 era, real-time data collection is required for most manufacturing companies. IoT and CPS are able to provide possible solutions to them. The future of real-time data collection in manufacturing systems may be carried out as follows:

- IoT-enabled data collection. Typical IoT technologies such as RFID and Barcode can be embedded into various manufacturing resources. In this way, they are converted into smart manufacturing objects (SMOs) which are able to intelligently interact and communicate with each other 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 are able to integrate multi-functional abilities to collect real-time data about temperature, force, pressure, and humanity. They are attached to various SMOs so that the manufacturing operations along with the production lines or working stations could be synchronised with physical operational flows 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 are able to send out their working status in real time to a central cloud-based 'manager' which can monitor their states through a visualization approach.

Currently, manufacturing companies are facing challenges to visualize and display various manufacturing services. Information visibility plays an important role in precise decision-making in Industry 4.0. Currently, there are several challenges when implementing manufacturing virtualization and visualization. First of all, manufacturing objects should be visualized in real time to ensure production quality and safety. Unfortunately, the CCTV system is only the options which are not able to reflect the status of a working machine. Moreover, manufacturing resources should be virtualized into various services so that they could be shared as a service. The virtualized approach and sharing models are rarely reported and investigated. Finally, visibility of various manufacturing objects requires new data modelling approach that is able to combine heterogeneous data into a standardized format. After that, such data can be displayed for different end-users who are concerned about different visibility of different equipment. However, these research gaps have rarely been studied in existing literature.

In order to fulfil the gaps, future research should put more emphasis on the following aspects:

- AR-enabled real-time visibility. Applying AR technology to manufacturing is able to achieve real-time visibility of working machines. With the data from smart machines, the AR interface can reflect the status of a machine as well as the processing behaviours 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 [55].
- Cyber virtualization modelling. Various physical manufacturing resources are modelled by the cyber virtualization approach so that their ability and status can be reflected in a cloud platform which is going to share within an alliance. This modelling approach uses the data from smart machines and sensors to build up a standardized service which could be displayed and visualized by other users who can be beneficial from the services.

Decision-making in smart manufacturing systems for Industry 4.0 requires information and knowledge which can be mined from large amounts of production data. A recent survey reveals that 55% of respondents felt that decision-making is not viewed at senior levels of their organizations [56]. Facing the big data from manufacturing sites, several challenges should be addressed. Firstly, decision models need such a long time to work out a solution when using large number of data. Various objectives are used for different purposes such as optimization of production planning and scheduling [57]. Unfortunately, it lacks of precise data input when carrying out these decision-making. Secondly, decision-making under Industry 4.0 always targets manufacturing resources sharing which could make full use of the manufacturing equipment and services. New manufacturing paradigm is needed then.

Future decision-making will focus on two directions:

- Big data analytics driven decision-making models. These models are capable of excavating useful information and knowledge from large amounts of production data to support specific decision-making. Advanced technologies or algorithms such as deep machine learning (DML) will be integrated into these models where big data analytics are encapsulated as services [31]. 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 [58]. Thus, physical machinery and virtualized services are implemented to support manufacturing activities and decision-making [25]. The networked manufacturing services enable 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 customisation, increased speed, better quality, and improved productivity in manufacturing, and thus enables companies to cope with various challenges such as increasingly individualized products, shortened lead-time to market, and higher product quality. This paper first presents a conceptual framework of Industry 4.0 smart manufacturing systems, and then showcases some of the key technologies and some demonstrative scenarios. Based on the demonstrative scenarios, this paper then reviews related key technologies such as Internet of Things, Cyber-Physical Systems, cloud manufacturing, and big data analytics. Current challenges and future perspectives are also highlighted so that academia and practitioners can be inspired when they are embracing Industry 4.0.

Significant contributions of this paper are as follows. Firstly, a systematic framework for Industry 4.0 smart manufacturing systems is proposed, covering a number of relavant topics such as design, machining, monitoring, control, and scheduling. This framework provides an improtant reference for academia and practitioners to rethink the essence of Industry 4.0 from different perspectives. Secondly, combining some research carried out by the authors, this paper reviews the key perspectives under the framework. Insights for the future research directions of data collection, virtualization, and decision-making are provided. Hopefully, this paper can provide manufacturing industry with some insights into implementing Industry 4.0 in the near future.

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