Building a Smart and Intelligent Factory of the Future with Industry 4.0 Technologies

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Abstract. Manufacturing industries are facing new market challenges driven by high demand for personalized products and shorter product lifecycle. To cope with these challenges, a wide range of advanced Industry 4.0 technologies such as the Internet of Things (IoT), big data analytics, and artificial intelligence (AI) have been adopted to improve the capability and effectiveness of manufacturing processes. Consequently, the new research field towards smart and intelligent manufacturing paradigm needs to be defined. Besides, only implementing new methodologies and technologies is inadequate. There is also a need to trigger the skilled workforce and manufacturing engineer’s competency through education and training. This paper discusses the transformation of manufacturing paradigm, correspondence research topics, and identifies the essential skills required.

1. Introduction

The industrial revolution, in manufacturing domain, can be seen as the technology that responds to human need of products and services. In the past, markets have changed from mass production to mass customization. The trend currently shifted to mass personalized products where each individual has their preference for a product. Manufacturing industries are challenges to produce one single product without losing profits. This drift pushes manufacturing companies to adopt a new paradigm (Figure 1).

![Figure 1. Manufacturing paradigm shift [1]](image-url)
To dealing with this trend, many Industry 4.0 technologies have been adopted in manufacturing to improve manufacturing capabilities and process effectiveness to reduce costs. There are nine technologies, among others, are recognized as the driver of Industry 4.0 revolution. Internet of Things (Industrial Internet), big data analytics, and artificial intelligence are technologies currently dominated the manufacturing transformation to reach the vision of smart and intelligent manufacturing. This approach has expanded manufacturing study to the next level driven by computer science and information and communication technologies (ICT). Accordingly, new disciplines in manufacturing need to be identified. Furthermore, technologies need a capable person to use and operate. Thus, rely on technology only is inadequate for building smart and intelligent factory. Therefore, the skills required for operator and engineer also need to be defined. This paper discusses in detail these two requirements.

The answers to those two questions will be the main contributions of this paper. The rest of the paper are organized as follows. Section 2 discussed the transformation toward intelligent and smart manufacturing. The recent development of new topics related to Industry 4.0 technologies is presented in Section 3. Section 4 described new workforce competencies mandatory for technology adoption. To conclude, Section 5 highlighted the findings and research contributions.

2. Manufacturing transformation

The concept of intelligent manufacturing using artificial intelligence has been introduced since 1978 [2] following the invention of Programmable Logic Controller (PLC) and the beginning of automation in manufacturing. Later, it is known as Industry 3.0. The word “intelligent” in manufacturing refers to the intelligent capability of human body [3]. It senses the surrounding condition, thinks and makes decisions based on previous experience and knowledge, and takes action to possess the desired circumstances. Artificial intelligence, expert systems, and agent-based approaches are driving this development.

During the past decade, sensor technologies, computer science, and information and communication technologies overgrew to an advanced level. Under the core technology of Cyber-physical Systems (CPS), the new industrial revolution (Industry 4.0) was announced for the first time in Germany, 2011 [4]. With the vision of smart manufacturing [5], a wide range of Industry 4.0 technologies is adopted to reach a high level of manufacturing flexibility, improved productivity, and better product quality.

Nowadays, the terms of smart manufacturing and intelligent manufacturing are used interchangeably [6]. Smart and intelligent factory turned every single object on the shop floor into smart object that able to be sensed, monitored, and controlled to keep them running in an optimized condition. Hence, an accurate forecast of future conditions can be made. Besides, any failures can be detected far before it happened and fixed automatically by self-diagnostics and self-adjustment systems.

3. New direction in manufacturing

The integrations of different Industry 4.0 technologies into manufacturing domain are demanding new requirements such as real-time process monitoring capability (visualization), hardware and software modularity, manufacturing resource virtualization, equipment interoperability, service orientation, and system decentralization [7]. To enable those functionalities, cyber-physical systems (CPS), as the main driver of Industry 4.0 technologies, merry the actual processes on the physical world with computational intelligence in the cyber and digital world. In the context of manufacturing, Cyber-physical Production Systems (CPPS) [8] [9] has been introduced to monitor the whole manufacturing processes in shop floor and improve the effectiveness of the processes.

Figure 2 shows the principle work of CPPS where the behaviour of physical processes monitored through different kind of sensors and send the data captured to the cyber computational space.
Through big data and analytics, those processes are investigated to find the optimal condition setting. The result then sent back to the physical machines and equipment via a controller. This principle can be applied for any machines and equipment on shop floor. To improve the visibility of, real-time visualization of manufacturing processes through Digital-twin technology is equipped. The digital-twin visualizes manufacturing processes in real-time and able to simulate the behaviour of future processes.

![Figure 2. CPPS working principle](image)

Although many attempts and methods have been developed for years to find effective industrial processes, the wide range of Industry 4.0 technologies has opened new horizons for further optimization. Consequently, many new topics have appeared recently in manufacturing. Some of those new directions are presented below.

### 3.1. Industrial internet

Industrial internet of things is applied through the installation of different sensors. Radio frequency identification (RFID) can be tagged on materials and semi-finished products to track them during processing. Smart sensors, sensors with microcontrollers, are placed on the edge of machines and equipment. Wireless sensor networks (WSN) integrate different sensors to work simultaneously. Beside, standardized protocols such as OPC-UA\(^1\) and MTConnect\(^2\) are required to read data from machine controllers. Figure 3 shows sensor installation on CNC machine tool and the equipment to capture data.

![Figure 3. Machine tool sensors and data capturing devices](image)

### 3.2. Big data and analytics

\(^1\) [https://opcfoundation.org/](https://opcfoundation.org/)
\(^2\) [https://www.mtconnect.org/](https://www.mtconnect.org/)
Sensors on machines and other devices generate a large amount of data (big data). These data will have no meaning without mining the information insight. The mining process can be decomposed into four activities, i.e., generation, acquisition, analytic and data storage. Machine learning algorithms have been widely used to solve the optimal condition of manufacturing processes [11]. Deep learning methods also gained attention in manufacturing to solve more complex problem [12]. One of the most use cases application is prognostics and health monitoring of physical machines. The maintenance strategy has been transformed from reactive maintenance to preventive maintenance, predictive maintenance, and now many researchers are developing prescriptive maintenance. With the prescriptive maintenance, intelligent agents embed on machines and equipment to avoid predictive failures.

![The Evolution of Maintenance Strategies](image)

Figure 3. The evolution of maintenance strategies

3.3. Knowledge-based system and machine reasoning

Machine learning and deep learning have limitations since the input and the desired output are clearly defined. Also, data should be adequately large for training and testing. Hence, it is difficult to solve a complex problem with limited data. The integration of AI and knowledge engineering creates a machine-reasoning system that combines machine learning and deep learning with reasoning. This enables machines to understand implicit relationships between different things.

Ontologies and semantic web technologies have significant roles in knowledge representation, rule-based system and reasoning [13]. Semantic manufacturing [14] becomes a new discipline to study the intensive knowledge methodologies for knowledge acquisition and sharing of technical and business information in highly sophisticated manufacturing enterprises. Ontologies have been applied for enriching product data [15], manufacturing resources virtualization [16], enterprise collaboration [17], etc. Moreover, AutomationML (AML)\(^3\) is distinguished as the standardized data exchange format between manufacturing engineering tools. With more data generated during manufacturing processes, an ontological approach to big data analytics, known as Ontology-based Data Access (OBDA) [18], are another challenging field.

3.4. Robot Collaboration

Human roles in manufacturing will be decreased as more jobs are to be given to intelligent robots. However, some critical work will still rely on human. To work simultaneously, robots need to be programmed to work collaboratively either with human or other robots. Multi-robot collaboration, such as swarm robotics [19], and human-robot collaboration [20] which include Human-machine interactions (HMIs) are two exciting topics that gained much attention recently. To enable these collaborations, machine vision technologies and machine learning techniques are highly implemented.

\(^3\) https://limblecmms.com
\(^4\) https://www.automationml.org
3.5. Cloud manufacturing

Mirroring the definition of cloud computing, cloud manufacturing provides a pool of distributed manufacturing resources that can be consumed to run manufacturing processes or activities based on the pay-as-use concept [21]. To enable this model, machines and manufacturing devices need to be virtualized and encapsulated as services. The main benefits of cloud manufacturing include reducing initial investment in hardware and software procurement for cloud users and increasing equipment utilities and additional profits for manufacturing providers. This new manufacturing paradigm transforms manufacturing industries from product-oriented to service-oriented manufacturing. Although some companies have practically provided these services, many of their activities are still performed manually. Smart agents to read request for quotation in different CAD files and to search for matching services that can work autonomously have not been well defined.

3.6. Biologicalization

Another new topic appeared recently is the use of biological knowledge to optimize production system, known as biologicalization, the biological transformation in manufacturing [22]. Every single object in manufacturing can be seen as an organism that needs to communicate with each other and adapt to changing conditions. Three-level of biological transformation is defined: bio-inspired, bio-integrated, and bio-intelligent manufacturing [23]. In bio-inspired manufacturing, various concepts and intelligent algorithms have been developed based on biological phenomena. Bio-integrated manufacturing tries to substitute chemical processes with biological processes such as using microorganism for machining. Lastly, bio-intelligent manufacturing embeds intelligent communicating machines where products and processes are communicated and self-adapted. This inspiration still needs further research agenda.

4. Workforce 4.0

Industry 4.0 technologies necessitate highly skilled and smart worker to operate. Next-generation of automation in manufacturing required operator which able to work simultaneously with machines and robots. A symbiosis between human and automation system has been defined as human cyber-physical systems, known as Operator 4.0 [24]. Different kind of operators with correspondence technological skills need specific knowledge and practical training. Augmented reality (AR) is one of the technologies that widely used for training operators [25] and product quality inspection [26]. On the other hand, manufacturing engineers will work intensively with a large amount of data and the digital model of factory equipment. New skills on how to use advanced analytics to monitor, control, and optimize production processes is indispensable. The requirements for data scientist and data engineer that specific in manufacturing domain need to be investigated. Hence, academic institutions are demanded to construct the right curriculum for future manufacturing engineering disciplines.

5. Conclusion and Future Work

Smart manufacturing of Industry 4.0 technologies has transformed manufacturing industries into digital manufacturing with advanced intelligence. This paper presented a short review of the transformation of manufacturing paradigm, identified new topics that gained great attention from industry people and academia, also discussed new required skills for the workforce. However, this paper discussed only described the big picture of the broad topics. For future work, the research will focus on developing strategies for adopting those technologies mainly in small and medium industries.

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