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Data-driven smart manufacturing

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ABSTRACT

The advances in the internet technology, internet of things, cloud computing, big data, and artificial intelligence have profoundly impacted manufacturing. The volume of data collected in manufacturing is growing. Big data offers a tremendous opportunity in the transformation of today's manufacturing paradigm to smart manufacturing. Big data empowers companies to adopt data-driven strategies to become more competitive. In this paper, the role of big data in supporting smart manufacturing is discussed. A historical perspective to data lifecycle in manufacturing is overviewed. The big data perspective is supported by a conceptual framework proposed in the paper. Typical application scenarios of the proposed framework are outlined.

1. Introduction

Manufacturers are embracing the notion of a convergence between the cyber and physical world. Manufacturing strategies have been developed, such as Industry 4.0 in Germany, Industrial Internet in the US, and the Made in China 2025 initiative. These programs promote the application of modern information technologies (new-IT) in manufacturing, which drives the development of smart manufacturing [1]. Smart manufacturing aims to convert data acquired across the product lifecycle into manufacturing intelligence in order to yield positive impacts on all aspects of manufacturing [2]. In the modern manufacturing industry, data generated by manufacturing systems is experiencing explosive growth, which has reached more than 1000 EB annually [3]. The systematic computational analysis of manufacturing data will lead to more informed decisions, which will in turn enhance the effectiveness of smart manufacturing [4]. In other words, data-driven manufacturing can be regarded as a necessary condition for smart manufacturing. Therefore, data is becoming a key enabler for enhancing manufacturing competitiveness [5], and manufacturers are beginning to recognize the strategic importance of data.

The value of big data does not hinge solely on the sheer volume of data under consideration, but rather on the information and knowledge that lies hidden in it. The emergence of New IT as the Internet of Things (IoT), cloud computing, mobile Internet, and artificial intelligence (AI), can be strategically leveraged and effectively integrated in support of data-driven manufacturing. For example, a number of innovative IoT solutions [6,7] promote the deployment of sensors in manufacturing to collect real-time manufacturing data. Cloud computing [8,9] enables networked data storage, management, and off-site analysis. Analysis results can be easily accessed by users through various mobile devices [10]. Artificial Intelligence (AI) solutions enable "smart" factories to make timely decisions with minimal human involvement [11].

Efforts to explore the applicability of big data in manufacturing have been initiated. A number of studies examining big data in manufacturing, including industrial automation [12], have emerged in recent years. Big data as a driver of industrial competitiveness was investigated in [13]. Dubey et al. [14] illustrate the unique role of big data analytics in sustainable manufacturing. Zhang et al. [15] propose a big data analytics architecture for clean manufacturing and maintenance processes. Other researchers have explored the role of big data in equipment maintenance [16], fault detection [17], fault prediction [18], and cost estimation [19], etc. In light of the inborn intelligence of big data, manufacturing systems must be made more "smart" to achieve the all-round monitoring, simulation, and optimization of production activities.

The rest of this paper is organized as follows. The evolvement history of manufacturing data is reviewed in Section 2. The lifecycle of manufacturing data is discussed in Section 3. The revolutionizing paradigm of big data driven smart manufacturing is presented

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in Section 4, followed by an illustrative case study showcased in Section 5. Finally, conclusions are drawn in Section 6.

2. Historical perspectives on manufacturing data

As shown in Fig. 1, for a long time, information was documented on paper while manufacturing was realized by handicraft, therefore, the integration between information technology and manufacturing technology was neither beneficial nor feasible. Since the advent of ENIAC (i.e., the first electronic computer) in 1940s, the rapid development of information technology (IT) has been driving manufacturing toward informatization. The first numerical controlled (NC) milling machine was developed in the 1950s, which announced that manufacturing entered the NC era. Since the 1960s, the development of integrated circuits has paved the way for the advancement of computer hardware and software. Since the 1980s, TCP/IP, local area network (LAN), World Wide Web (WWW), and search engine emerged one after another to meet the increasing needs for data storage, indexing, processing, and exchange. All of these information technologies were widely applied in manufacturing. As a result, many advanced manufacturing technologies were put forward, such as computer integrated manufacturing (CIM), computer aided design (CAD), manufacturing execution system (MES), computer aided manufacturing (CAM), enterprise resource planning (ERP), and networked manufacturing (NM), etc. Recently, the rise of New IT (e.g., Internet of Things, cloud computing, big data analytics, and artificial intelligence) continues to revolutionize the manufacturing paradigm, leading to a series of new manufacturing concepts, for instance, manufacturing grid, cyber-physical manufacturing system, cloud manufacturing, etc. Due to the deep fusion between IT and manufacturing, the degree of manufacturing smartness is progressively elevated. As a result, the manufacturing data also becomes increasingly richer. The evolution of manufacturing data in four stages is discussed (see Fig. 1).

2.1. Data in the handicraft age

Prior to the First Industrial Revolution, the human society had been in the manual manufacturing stage for a long time. Artefacts were predominantly designed and manufactured by artisans [20]. As the most basic form of manufacturing, handicraft activities were of low complexity. As a result, the data generated in the production process was limited as it existed mostly in the form of human experience. In addition, experience was mostly transmitted verbally from one generation to the next, primarily based on apprenticeships. The key information and data could be easily lost, making production and quality control impossible to achieve. Due to the extremely low quantity and quality, the manufacturing data generated in the handicraft age was neither emphasized nor fully exploited. However, since handcrafting involves a high levels of human creativity, even today, it is used to manufacture luxury products (e.g., jewelry, watch, leather bag).

2.2. Data in the machine age

Generally speaking, the machine age consisted of two phases. As a result of the first industrial revolution, machines were employed as production tools in the early factories, leading to a significant increase in the scale of manufacturing. During this period, the relationship between humans and machines in production was highly complementary (i.e., early machines could only be operated by skilled operators to deliver their functions). Therefore, manufacturers began to emphasize two particular kinds of manufacturing data: worker-related data and machine-related data. Worker-related data (e.g., attendance, productivity, and performance) was used to facilitate decisions about issues such as salary structure, performance benchmarking, and work schedules. Machine-related data was used to support decisions concerning machine maintenance, repair, and replacement. Compared to the handicraft age, nevertheless, the First Industry Revolution introduced no significant changes to the way data was collected, stored, analyzed, transferred, and managed. As a matter of fact, workers still handled data manually based on empirical experience.

As a result of the Second Industrial Revolution (or the Technological Revolution), machine tools and interchangeable parts were widely incorporated into the "new" manufacturing process (e.g., the Bessemer process) in modern factories, leading to significant increases in manufacturing efficiency, and the manufacturing paradigm shifted to the mass production model [21]. The Second Industrial Revolution triggered some notable changes in the way data was processed. In particular, because of the division of work between managers and workers, manufacturing data was increasingly handled by educated managers. Moreover, managers began to employ more systematic methods to document and analyze manufacturing data. The raw data was extensively recorded in written documents (e.g., instructions, logbooks, notes, and charts) rather than stored in human memory. Scientific methods were used to determine the dependency relationships between different datasets. During this period, manufacturers began to exploit manufacturing data for cost reduction, quality control, and inventory management. In particular, statistical models were introduced to analyze a variety of quality-related manufacturing data, such as production planning, throughput yield, product quality, failure rate, raw material consumption, and scrap rate.

In summary, in the machine age, although a larger quantity of manufacturing data was analyzed through scientific methods, data was still handled manually by human operators (i.e., managers), as opposed to computers. Therefore, the utilization rate of manufacturing data remained relatively low.

2.3. Data in the information age

In the information age (or the digital age), information technologies were widely applied in manufacturing processes. As a consequence, the quantity of manufacturing data that companies were able to collect grew exponentially. A number of factors contributed to this growth in data. First, information systems (e.g., CRM, MES, ERP, SCM, PDM, etc.) were widely employed by manufacturers to facilitate production management. Second, computer systems (such as CAD, CAE, CAM, and FEA) were widely used to aid the creation, simulation, modification, and optimization of new products as well as manufacturing processes. Third, industrial robots and automatic machinery were commonly used in modern factories. More and more, electronic devices and digital computers were employed to automatically control production equipment. The evolvements in information technologies paved the way for manufacturers to achieve meeting customer needs better, quicker, and cheaper [22].

In the information age, data was stored in computer systems and managed by information systems. For example, customer data (e.g., home address, phone number, demographics), sales data (e.g., type, quantity, price, and shipping date of finished products), supply chain data (e.g., type, quantity, price and supplier of raw materials), financial data (e.g., assets, real property, tangible property, utility, intangible property, etc.), production planning data, bill of materials, inventory data (e.g., type, quantity, location of material and finished products in the warehouse), and maintenance data are all managed by CRM, MES, ERP, SCM, PLM, etc. Therefore, it could be easily exchanged among different departments or organizations. The efficiency of data analysis was significantly enhanced due to the use of computational models, although analysis results