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BIG DATA ROLE IN SMART MANUFACTURING

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Abstract: *In the digital age, information technologies are widely applied in production processes. As a result, the amount of production data that companies collect has increased exponentially. The efficiency of data analysis has been significantly improved due to the use of calculation models. Manufacturers have started using data to promote some advanced production models such as mass customization and smart manufacturing systems. With the IoT, cloud computing, artificial intelligence, and other technological advances, big data came and was big data. The paper addresses the main aspects of literature related to data-driven smart manufacturing: data types, manufacturing data lifecycle, data-driven smart manufacturing framework, and applications.*

Key words: *big data, smart manufacturing, manufacturing data lifecycle, data-driven smart manufacturing framework, data -driven intelligent personalization.*

1. INTRODUCTION

Advances in internet technology, the Internet of Things (IoT), cloud computing (CC), big data (BD), and artificial intelligence (AI) have profoundly affected manufacturing. The volume of data collected is constantly increasing. Big data offers an extraordinary opportunity to transform the manufacturing paradigm of today into smart manufacturing. Big Data allows companies to adopt data-driven strategies to become more competitive. Smart manufacturing aims to transform the data acquired throughout the product lifecycle into intelligence, to have a positive impact on all aspects of manufacturing [1,2].

This paper reviews the main aspects of literature related to data-driven smart manufacturing: from data types, manufacturing data lifecycle, data-driven smart manufacturing framework, to some applications.

2. TYPES OF DATA

In general, large data generated by manufacturing processes can be classified into the following categories:

Management data collected from production information systems (MES, ERP, CRM, SCM, and PDM). Information systems possess a variety of data that are related to product planning, order dispatch, material management, production planning, maintenance, inventory management, sales and marketing, distribution, customer service, and financial management.

Equipment data collected from industrial IoT smart factories, including data related to real-time performance, operating conditions, and maintenance history of manufacturing equipment.

User data collected from Internet sources, such as e-commerce platforms and social networking platforms. This type of data includes user demographics, user profiles, user preferences over products/services, and user behavior.

Product data collected from smart products and product-service systems, IoT technologies, including product performance, user context, environmental data, and user biological data.

Public data collected from governments through open databases. Such data sets deal with data related to intellectual property, civic infrastructure, scientific development, environmental protection, and health care. For manufacturers, public data can be used to ensure that manufacturing processes and manufactured products comply strictly with government regulations and industry standards.

In production, efficient analysis of large data allows manufacturers to deepen their understanding of customers, competitors, products, equipment, processes, services, employees, suppliers, and regulators. Therefore, Big Data can help manufacturers make more rational, responsive, and informed decisions and increase their competitiveness in the global market.

3. MANUFACTURING DATA LIFECYCLE

Data are a key factor for intelligent manufacturing. However, data are useful only if they are 'translated' into the content and context of concrete information that users can directly understand [3]. In general, before obtaining concrete information from the data, the data must go through several steps: collection, transmission, storage, preprocessing, filtering, analysis, extraction, visualization, and application [1]. A typical manufacturing data lifecycle is illustrated in figure 1.

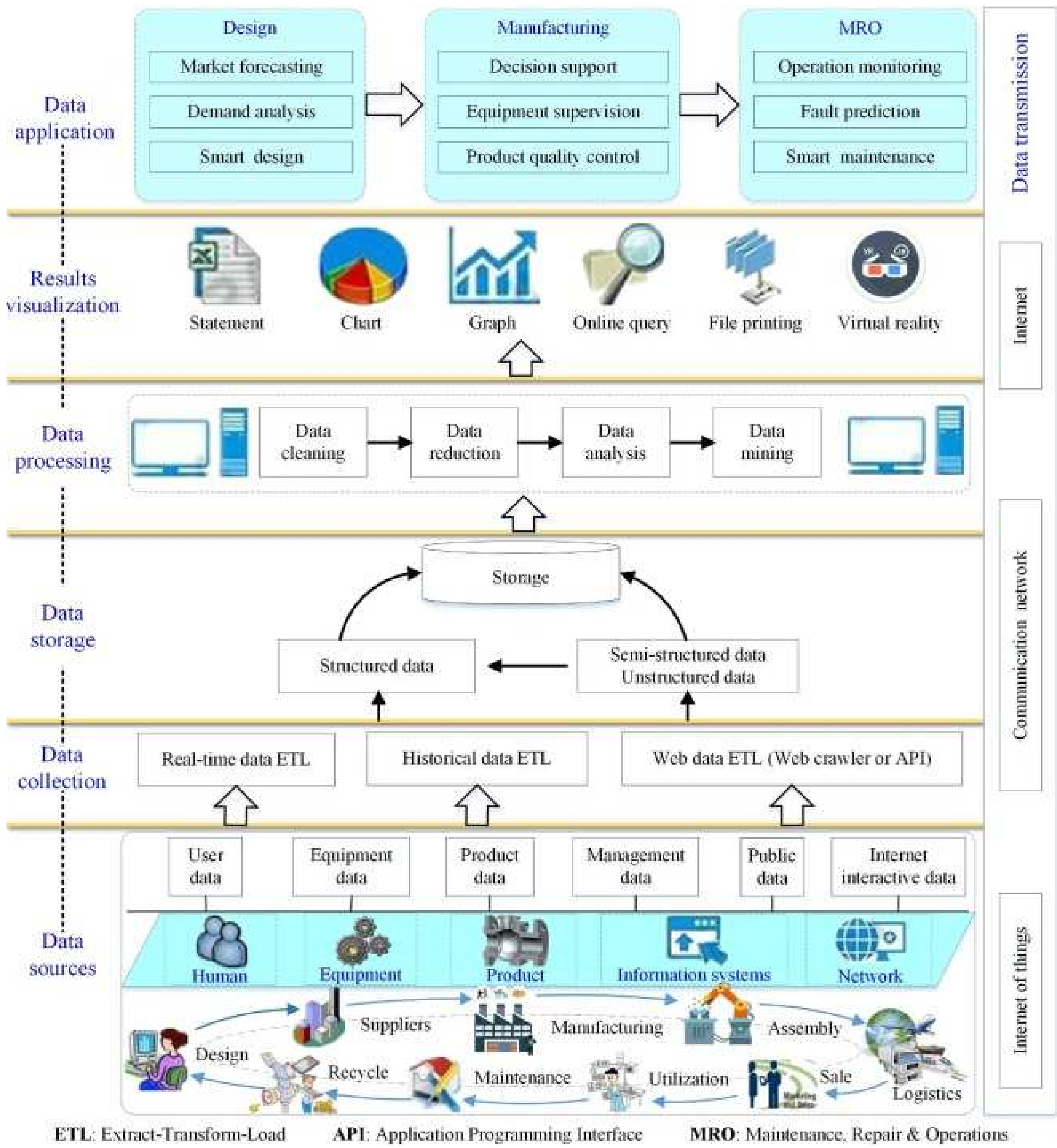

Fig. 1. Manufacturing data lifecycle [1]

Manufacturing data comes from different sources: equipment, products, human operators, information systems, and networks.

Data from different sources is collected in a variety of ways. Above all, it is collected through IoT, whereby equipment and product data can be instantly collected through intelligent sensors, RFID, and other detection devices, making it possible to monitor equipment [4].

The large amount of data collected from manufacturing processes must be safely stored and efficiently integrated. In general, different types of manufacturing data can be classified into structured data (figures, symbols, tables etc.), semi-structured (trees, graphs, XML documents etc.) and unstructured data (journals, audio, videos, images etc.) [5]. Traditionally, manufacturing companies have focused primarily on storing structured data, as it is difficult to directly manage unstructured data in company databases. Object-based storage architecture allows data collections to be stored and managed as objects. This provides a more flexible solution for the integration of semi-structured and unstructured data. Also, through cloud computing, data storage can be achieved in a highly cost-effective, energy-efficient, and flexible way.

Data processing refers to a series of operations performed to discover knowledge from a large volume of data. Data must be converted into information and knowledge for producers to make informed and rational decisions. Above all, data must be carefully pre-processed to remove redundant, misleading, duplicate, and inconsistent information. Data reduction is the process of transforming the massive volume of data into orderly and significant forms [6]. After data reduction, cleaned and simplified data is exploited through data analysis and data mining to generate new information.

The visualization is intended to clearly transmit and communicate information by graphical means, allowing end-users to understand the data in a much more explicit way. Real-time data can be viewed online through user-friendly terminals.

Data transmission plays a key role in maintaining communications and interactions between distributed manufacturing systems and resources.

Recent advances in IoT, the Internet and communications networks have substantially strengthened the technological foundation of real-time, reliable, and secure transmission of different types of data.

Data applications have entered almost all aspects of manufacturing and day-to-day operations in manufacturing enterprises. Firstly, during the conception phase, new perspectives about customers, competitors, and markets are revealed through data analysis. Based on the understanding developed through data analysis, conceptualists can accurately and quickly translate customer voices into product characteristics and quality requirements. Second, during manufacturing, the manufacturing process and equipment are monitored and tracked in real time. Data can facilitate control and improvement of product quality.

4. INTELLIGENT DATA-BASED MANUFACTURING FRAMEWORK

Manufacturing data are collected, stored, processed, and analyzed through large data technologies. As a result, the degree of intelligence in manufacturing can be significantly increased. As shown in Figure 2, the intelligent data-driven manufacturing framework consists of four modules, namely: manufacturing module, data driver module, real-time monitoring module, and problem processing module [1].

Method of manufacture: this module hosts different types of manufacturing activities. It consists of a variety of information systems and manufacturing resources, which can be summarized as human-machine-material-environmental. The inputs of this module are raw materials, while the outputs are finished products. During the input-output transformation process, various data are collected from human operators, manufacturing equipment, information systems, and industrial networks.

Data Driver Module: this module provides the driving force for intelligent production at the different stages of the manufacturing data lifecycle. As input, data from the manufacturing module is transmitted to cloud-based data centers for further analysis. Subsequently, explicit information and actionable recommendations derived from different types of raw data are used to direct actions (product design, production planning, and execution) into the manufacturing module. The real-time monitoring module and problem processing module are also powered by the data driver module.

Real-time monitoring mode: this module plays a role in monitoring the manufacturing process in real time to ensure product quality. Driven by the data driver module, this module allows us to analyze the real-time operating status of production units. As a result, manufacturers can be aware of changes in the manufacturing process to develop optimal operational control strategies. For example, when a machine is empty, the material is distributed, and a trajectory is tracked. The manufacturing process can be adjusted according to specific defects in the quality of the product.

As a result, the real-time monitoring module can make manufacturing facilities work more efficiently.

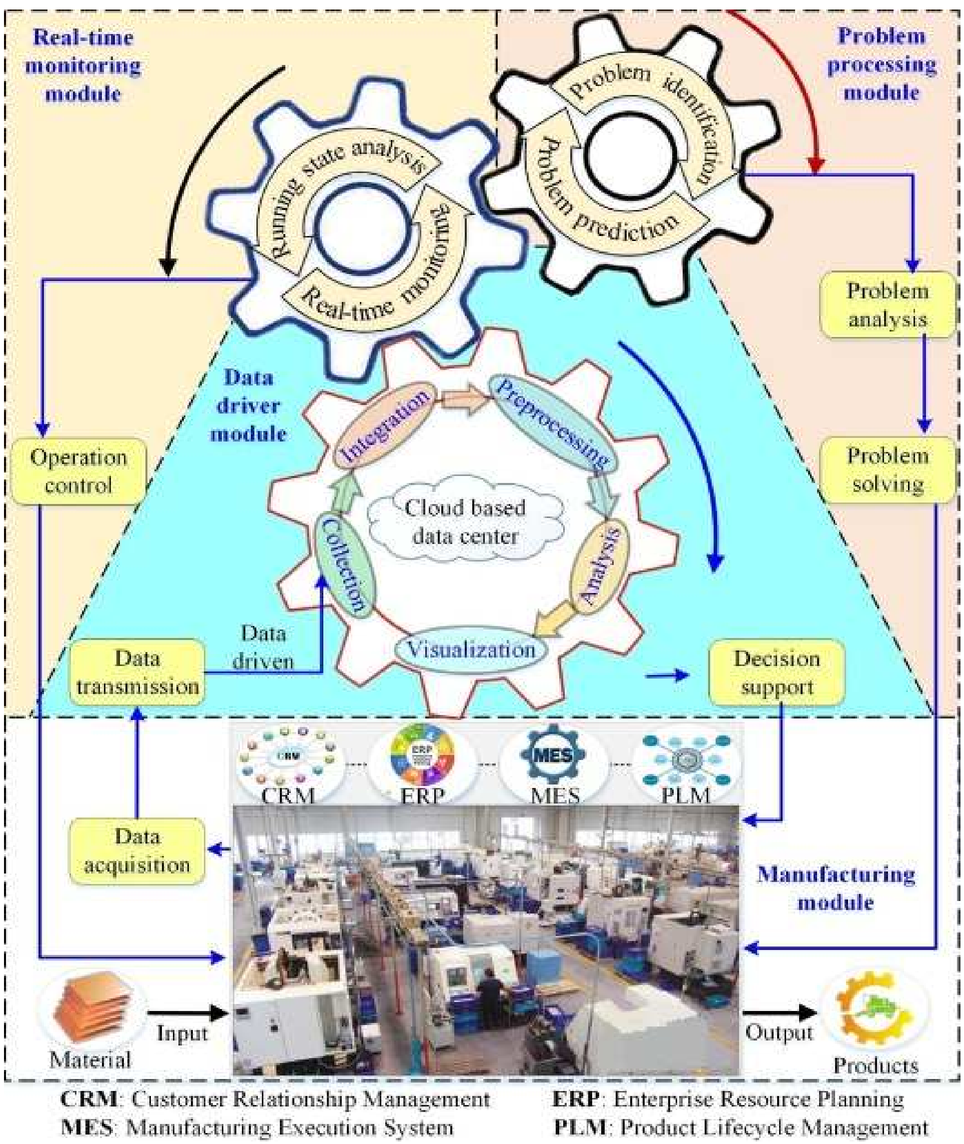

Fig. 2. Intelligent Data-Based Manufacturing Framework [1]

How to process problems: this module works to identify and predict emerging problems (equipment failures or quality defects), to diagnose the root causes, to recommend possible solutions, to estimate the effectiveness of the solution, and to assess the potential impact on other manufacturing activities. Based on real-time information and analysis of historical and ongoing data provided by the data driver module, human operators or artificial intelligence applications can make informed decisions not only to address current problems, but also to prevent similar problems from occurring in the future. Proactive maintenance enabled by this module will improve the proper functioning of manufacturing processes.

The latest research shows that the digital twin (DT) can enhance intelligent personalization driven by data in the context of smart manufacturing, defining a new framework for it [7]. The integrated framework is shown in figure 3.

The digital twin expands data sources in the virtual space, which will significantly improve customization capabilities in terms of quality and reliability. The smart customization module involves manufacturing systems, customized products, and user environments. Manufacturing systems and user environments interact with the customized product throughout the product lifecycle, from the design stage to the use stage. IoT technology allows manufacturing systems to continuously monitor the manufacturing process so that manufacturing plans and parameters can be adjusted in a timely manner to maximize equipment efficiency. Additionally, the customized product can adapt to changing customer behavior by interacting with user environments. By monitoring the natural environment, the social environment, the operating conditions of the product, and the user context, the products can be updated to meet the dynamic needs of customers.

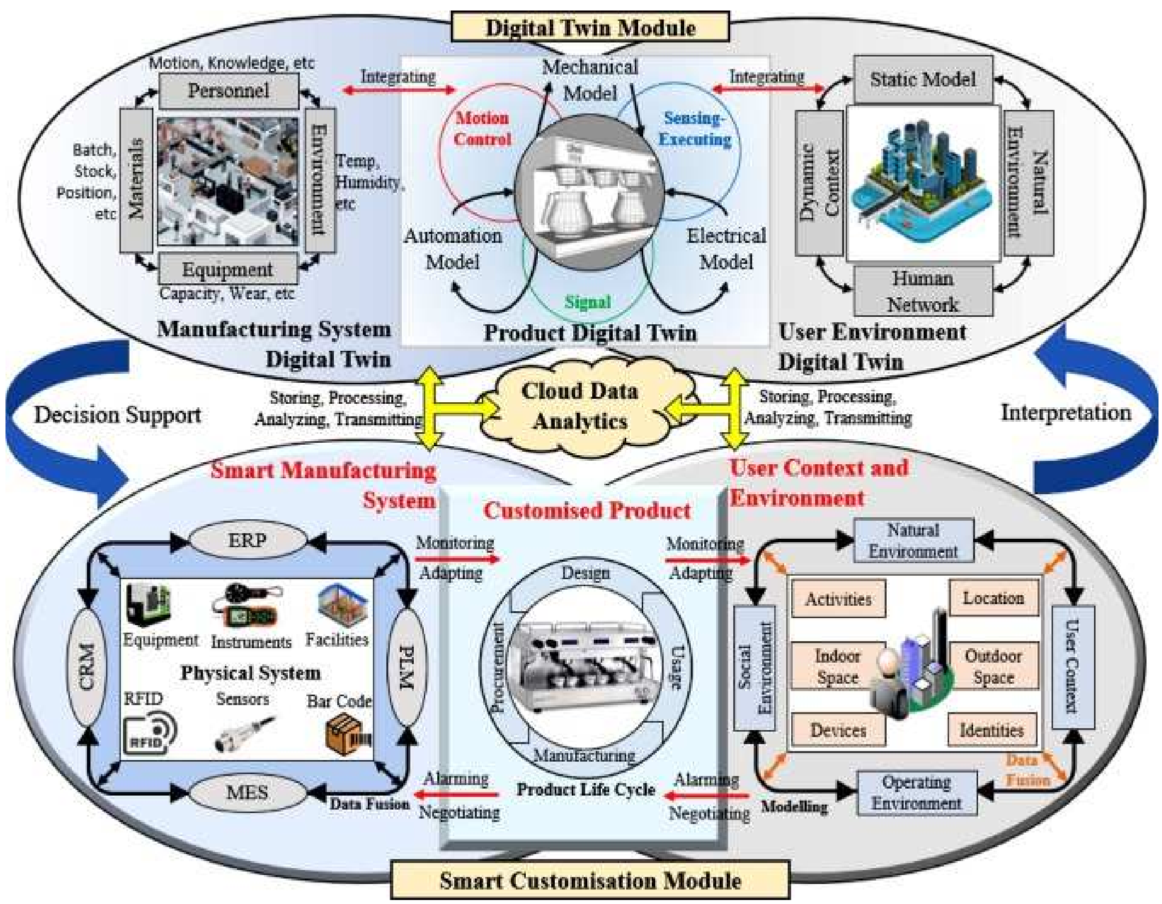

Fig. 3. Intelligent Personalization Framework of Digital Twins and Data-Driven [7]

Real-time data collected from user environments can help conceptualists explore more opportunities to offer personalized features or services. In the smart customization module, the extraordinary data generated by the physical product, manufacturing systems, and physical environments will be uploaded to the virtual space to support the construction of the twin digital module.

5. DATA-DRIVEN SMART MANUFACTURING APPLICATIONS

5.1 Applications in the manufacturing process

Some of the most promising applications that can be implemented during the manufacturing process include applications to enable smart design, smart planning, material distribution and tracking, manufacturing process monitoring, quality control, and intelligent equipment maintenance (Fig. 4.).

Design determines most of the production costs of a product. In the age of big data, product design is moving towards data-based design.

Even before starting to manufacture a product, production planning is necessary to determine the production capacity of a production unit, as well as the availability of resources and materials. Large data analysis can make production planning and workshop scheduling smarter.

The distribution of materials is determined by production planning and the actual progress of production, as well as by various on-site emergency requirements. In the ideal scenario, the right material should be delivered to the right equipment at the right time so that it can be processed through the right operations.

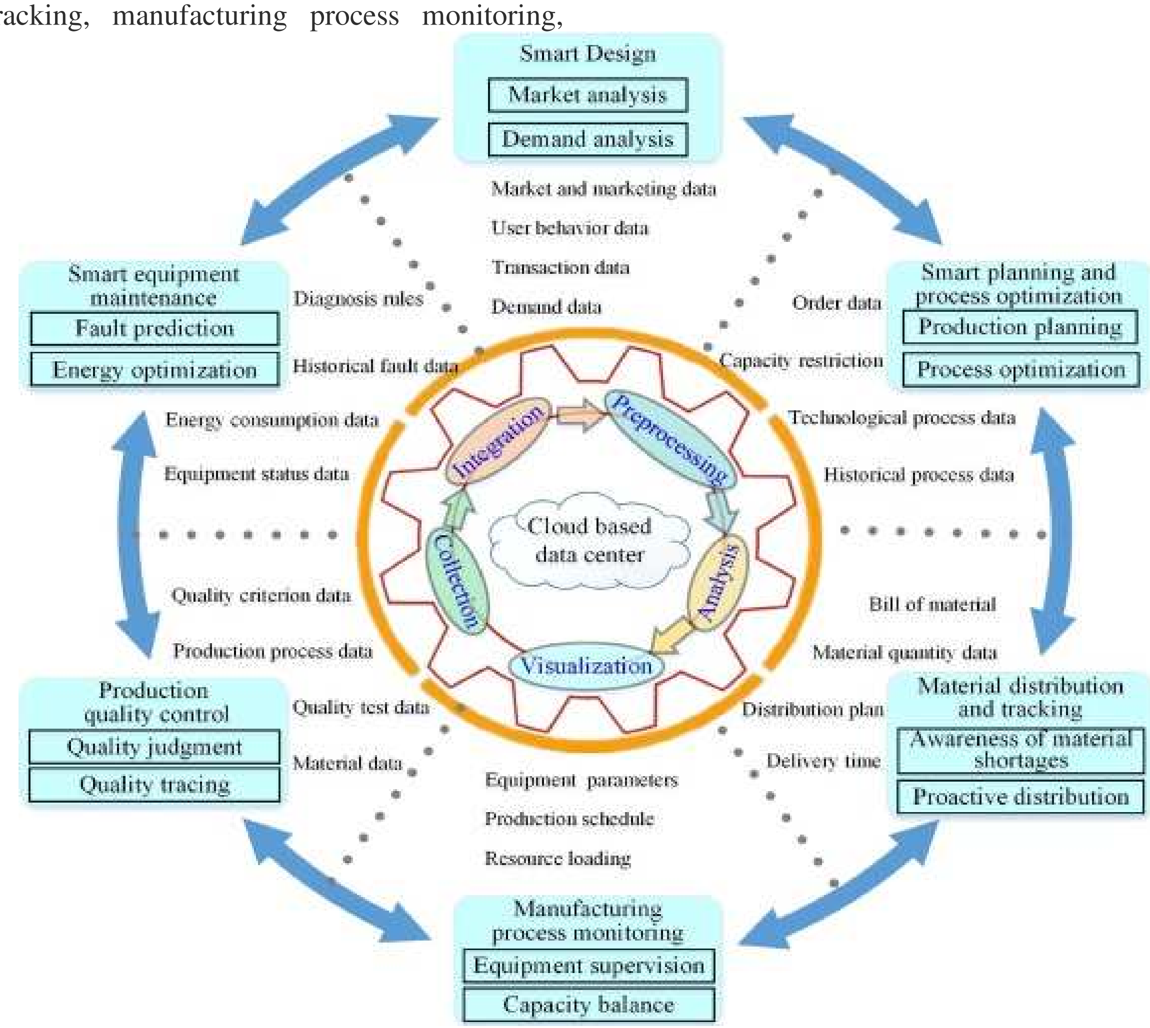

Fig. 4. Intelligent Data-Based Manufacturing Application [1]

The manufacturing process consists of several factors of production. These factors (e.g., manufacturing equipment, material, environment, and technological parameters) can affect the manufacturing process and influence changes in product quality. In addition, they can interact with each other. Therefore, it is particularly important to monitor different steps of the manufacturing process in real time.

For intelligent production, various data-driven quality control techniques are developed. Large data analysis can serve as a global quality monitoring tool, an early warning of quality defects, and a rapid diagnosis of root causes.

Data analysis can accurately predict and diagnose equipment failures and component life. This information can be used to make informed maintenance decisions.

5.2 Applying a model-driven framework in a production scenario

To extend the current state of Big Data Analytics (BDA) in the field of smart manufacturing, this study advocates the use of the large amount of data generated by modern manufacturing stations (mainly CNC machines), recorded by sensors associated with the manufacturing line [8].

BDA can provide valuable data insights to improve manufacturing operations and product quality. To explore this, the Model-based Big Data Analytics-as-a-Service (MBDAaaS) framework was applied in a real production scenario, focusing on machine fault detection.

In Figure 5, a schematic representation of the MBDAaaS methodology is given. The selected MBDAaaS framework offers the possibility of guiding the user through the configuration in five steps [9]. In the first step, a declarative model provides configuration requirements for data representation and preparation. In the second step, services compatible with the specifications of the declarative model are selected from the catalog based on the annotations that map these services to the requirements included in the declarative model. In the third step, a Big Data consultant defines a platform-independent workflow encompassing the various services of the Big Data campaign. In the fourth step, the MBDAaaS compiler transforms the service composition into a platform-dependent workflow called a deployment model. Finally, in the fifth step, the target platform executes the designed analysis.

CNC machines, placed in any high-tech manufacturing environment, can record a large amount of data regarding the health of the machine and the performance of the entire manufacturing process. In Industry 4.0, Cyber-Physical Systems (CPS), Internet of Things (IoT) and cloud-based solutions support the evolution of machine tools, moving toward a type of machine known as the smarter, better connected Machine Tool 4.0 available on a large scale, more adaptive and autonomous [10]. Health prognostics and management, process optimization and analytics algorithms can be applied to take data from the machine-tool 4.0 and contribute to intelligent decision making.

Real-time analytics are essential for monitoring machine health. In addition, real-time stream processing enables the immediate analysis of various types of data and, consequently, enables the detection of threats.

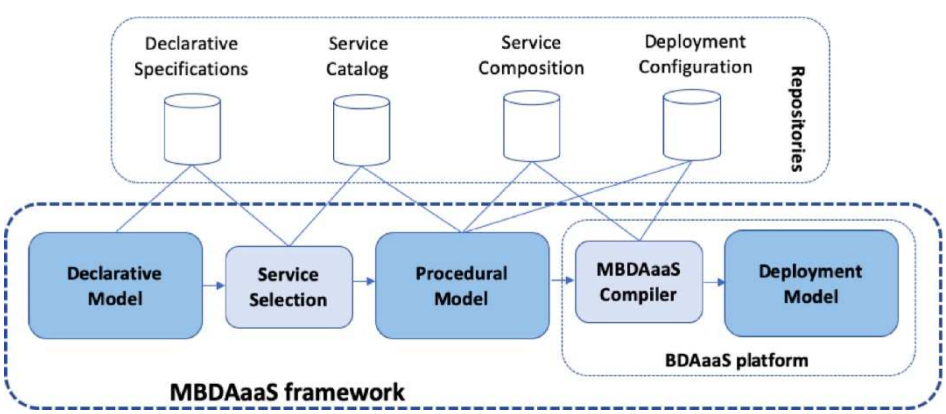

Fig. 5. MBDAaaS Methodology [9]

To apply the MBDAaaS framework in the industrial scenario described, it was integrated into the enterprise network following its security standards.

This study contributes to enriching the knowledge developed in the field of BDA for smart manufacturing by customizing the MBDAaaS framework [9] for the industrial domain of manufacturing. In the field of smart manufacturing, BDA provides interpretive results that are useful for making strategic decisions.

6. CONCLUSION

The volume of data generated over the life cycle of products, which is dynamically changing, is increasing. Data collected can be used to increase production efficiency. This paper provided information on data types, manufacturing data lifecycle, data-driven smart manufacturing framework, and some applications.

Future research will be aimed at developing the intelligent data-driven manufacturing framework for a smart manufacturing system in the automotive industry, adapted to intelligent customized manufacturing.

7. REFERENCES

[1] Tao, F., Qi, Q., Liu, A., Kusiak, A. *Data-driven smart manufacturing*, J Manuf. Syst, 48, 157-69, 2018.

[2] Tao, F., Cheng, J., Qi, Q. et al. *Digital twin-driven product design, manufacturing and service with big data*. Int J Adv Manuf Technol, 94, 3563–76, 2018.

[3] Lee, J., Lapira, E., Bagheri, B., Kao, H.A. *Recent advances and trends in predictive manufacturing systems in big data environment*. Manuf Lett, 1(1), 38-41, 2013.

[4] Zhang, Y, Zhang, G, Wang, J, Sun, S, Si, S, Yang, T. *Real-time information capturing integration framework of the Internet of manufacturing things*. Int. J Comp Int Manuf, 28(8), 811-22, 2015.

[5] Gandomi, A, Haider, M. *Beyond the hype: big data concepts, methods, and analytics*. Int J Inf Manage, 35(2), 137-44, 2015.

[6] Huang, J, Li, Y.F, Xie, M. *An empirical analysis of data preprocessing for machine learning-based software cost estimation*. Inf. Softw Technol, 67, 108-27, 2015.

[7] Wang, X., Wang, Y., Tao, F., Liu, A. *New paradigm of data-driven smart customisation through digital twin*. J Man. Syst, 58, 270-80, 2021.

[8] Corallo, A., Crespino, A.M., Lazoi, M., Lezzi, M. *Model-based Big Data Analytics-as-a-Service framework in smart manufacturing: A case study*. Robot Comput Integr Manuf, 76, 2022.

[9] Ardagna, C.A., Bellandi, V., Bezzi, M., Ceravolo, P., Damiani, E., Hebert, C. *Model-based Big Data Analytics-as-a-Service: take big data to the next level*. IEEE Trans Serv Comput, 14(2), 516-29, 2021.

[10] Xu, X. *Machine Tool 4.0 for the new era of manufacturing*. Int J Adv. Manuf. Technol, 92, 1893–900, 2017.

ROLUL BIG DATA IN FABRICAȚIA INTELIGENTĂ

În era digitală, tehnologiile informaționale sunt aplicate pe scară largă în procesele de producție. În consecință, cantitatea de date de producție pe care companiile le colectează a crescut exponențial. Eficiența analizei datelor a fost îmbunătățită semnificativ datorită utilizării modelelor de calcul. Producătorii au început să utilizeze date pentru a promova unele modele avansate de producție, cum ar fi personalizarea în masă și sistemele de fabricație inteligente. Odată cu IoT, cloud computing, inteligența artificială și alte progrese tehnologice, a venit și era datelor mari. Lucrarea abordează principalele aspecte din literatură referitoare la fabricația inteligentă bazată pe date: tipuri de date, ciclul de viață al datelor de fabricație, cadrul fabricației inteligente bazată pe date și aplicații.

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