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Keyword: Industrial Internet of Things, Big Data, Artifical Intelligence, Smart Factory.

***Abstract*—Thanks to the rapid development and applications of advanced technologies, we are experiencing the fourth industrial revolution, or Industry 4.0, which is a revolution towards smart manufacturing. The wide use of cyber physical systems and Internet of Things leads to the era of Big Data in industrial manufacturing. Artificial Intelligence algorithms emerge as powerful analytics tools to process and analyze the Big Data. These advanced technologies result in the introduction of a new concept in the Industry 4.0: the smart Factory. In order to fully understand this new concept in the context of the Industry 4.0, this paper provides a survey on the key components of a smart factory and the link between them, including the Industrial Internet of Things, Big Data and Artificial Intelligence. Several studies and techniques that are used to enable smart manufacturing are reviewed. Finally, we discuss some perspectives for further researches.**

1. Introduction

In Industry 4.0, the future factory will be more conscious and intelligent to independently perform complex tasks, i.e, "smart factory". The smart factory integrates advanced technologies like Industrial Internet of Things (IIoT), Big Data, Artificial Intelligent (AI) to optimize performance, quality, controllability and transparency of manufacturing processes. It now becomes the heart of Industry 4.0 and attracts a lot of interest from governments, enterprises and researchers. An extensive review on technologies for manufacturing systems based on the smart factory concept has recently been scanned in [2].

The IIoT refers to the use of Internet of Things (IoT) technology to enhance industrial manufacturing processes. A vital characteristic in the IIoT is that sensors are embedded in all the components related to the manufacturing process. These sensors play the role of eyes for collecting data from the entire manufacturing process and the product life cycle. Along with the wireless sensor networks, they make the data collected from smart manufacturing systems grow exponentially, leading to the concept of Big Data.

The massiveness, complexity and heterogeneity of Big Data requires advanced computing technologies. It is now performed efficiently due to the availability of AI. In the past, the computers were programmed to perform a specific task. Now, the AI makes it intelligent with the ability of correctly interpreting external data, learning from data, and using those learnings to achieve specific tasks through flexible adaptation. The use of AI can revolutionize the industrial manufacturing process with a large number of application such as predictive quality analytics, automation, insightful identification of engineering systems.

Becoming a Smart Factory is a long-term and complex process, requiring a deep insight into advanced technologies that are integral to this process. This paper aims to provide a survey of techniques and applications of IIoT, Big Data and AI in Industry 4.0. The challenges and emerging topics of these crucial components in smart manufacturing are summarized. The rest of the paper is organized as follows. In Section 2, we present the background and techniques of the IIoT. Section 3 explains the concept of Big Data and presents the applications of AI in Industry 4.0. Section 4 is devoted to some perspectives for further researches on the application of IIoT and AI in the smart factory. The conclusion is given in Section 5.

2. The Industrial Internet of Things

Based on a large number of modern technologies such as cyber-physical systems, cloud computing, mobile technologies, and radio frequencey identification (RFID), the IIoT harnesses the sensor data and incorporates Big Data into machine-to-machine communication and automation technologies that have existed in industrial settings for years [25]. As a result, it enables creating new business models by improving productivity, exploiting analytics for innovation, maximizing operational efficiency, optimizing business operations, and protecting systems. The advantages of IIoT in the intelligence manufacturing and smart factories are discussed broadly in the literature, see, for example [23] and [38].

The first essential basic platform for the IIoT is the Internet of Things (IoT), which is a network of physical devices embedded with sensors, actuators, electronics, software, and the network connectivity that enables these objects to connect and exchange data. The IoT is a bridge between the digital domain and the physical domain. Recently, the arising of novel communication infrastructures such as 5th generation (5G) wireless mobile communication and Low-power Wide-area (LPWA) networks is also a significant contribution to the IIoT. Yang et al. [37] provided an extensive review of the IoT in the smart manufacturing.

Another state-of-the-art technology of the IIoT is Cyber-Physical System (CPS). The CPS contains networked interactions that are designed and developed with physical inputs and outputs, along with their cybertwined services such as control algorithms and computational capacities [38]. It is now considered as one of the most significant advances in the development of computer science, information and communication technologies. Herterich et al. [8] investigated the influence of the CPS on industrial services in manufacturing. Several defining characteristics, design techniques and the applications of the CPS have been presented in [11, 20].

3. Big Data and Artificial Intelligence in industrial applications

In a smart factory, a large number of sensors is used to collect data. These sensors turn physical conditions of an object into electrical signals. These signals are then passed to a programmable logic controller for futher actions. Each component involving in smart manufacturing has a capability of communicating and sharing data based on new network technologies. The rapid development of advanced IIoT technologies makes the process of data acquisition and storage increasingly easy and convenient, promoting the era of industrial Big Data.

In the literature, the first definition of Big Data focuses on enlisting its characteristics, leading to '3V', namely, Volume, Velocity and Variety [24]. These characteristics are then extended by adding multiple features like Veracity, Volatility, and Value [31]. Other dimensions of Big Data like Vision, Validation, Variability have been recently mentioned in [2]. The core feature of Big Data is that they require to be analyzed, i.e Big Data analytics. Without being analyzed, Big Data have not much value. Big Data analytics refers to the process of collecting data, transfering data into centralized cloud data centers, preprocessing data, analyzing data, and visualizing data. It helps enterprises planning, handling numerous problems of fault detection and diagnosis, optimization and control, management, transportation, fully understanding the potential of data-driven marketing, production analysis and a new product recommendation. The applying of Big Data analytics results in a 15% - 20% increase in return on investment for retailers [22]. Recently, AI, a key factor that makes a smart factory "smart", emerges as a powerful tools in Big Data analytics.

The AI refers to the intelligence demonstrated by machines. This is a set of algorithms that enables a machine to perform complex tasks by perceiving working environment and taking actions to maximize the possibility of successfully achieving the predetermined goals. Nowadays, the term "Artificial Intelligence" is ubiquitous and its application has been witnessed in a large number of areas of everyday life. In industrial manufacturing, the AI also provides significant improvement in designing automatic robot, making decision, monitoring and scheduling the production process, predictive maintenance and analytics. It can be said that the manufacturing and factories in Industry 4.0 cannot be "intelligent" or "smart" without AI.

In the literature, machine learning (ML) algorithms are applied to a large number of applications such as classification of health monitoring systems, detection of faults after the occurrence of certain failures, predictions of the future working conditions and the remaining useful life [1]. The advantages and challenges of typical techniques of the ML like Support Vector Machine, Random Forest, Bayesian Networks, and Artificial Neural Network in a wide range of industrial areas have been illustrated in [26, 36]. Gao et al. [6] discussed the strengths and weaknesses of the machine learning methods for fault prognostic. To overcome the limitation of traditional machine learning methods, a number of deep learning algorithms have been recently investigated. The Convolutional Neural Network, the Deep Belief Network and the Stacked Auto Encoder have been applied to several fault diagnostics such as bearing, gearbox, wind generator and wind turbine [9, 13]. Deep learning algorithms such as the Recurrent Neural Network (RNN) and the Support Vector Regression have been proposed for predictive analytics in [34]. Wang et al. [33] conducted a comprehensive review of applications of deep learning algorithms for smart manufacturing.

Another algorithm of the AI which also has a great impact on Industry 4.0 is the reinforcement learning (RL). The major contribution of RL to smart manufacturing is perhaps in Robotics, which is discussed broadly in [12]. Levine et al. [15] and Mnih et al. [19] utilized deep RL to tackle a wide variety of motion planning for industrial robots directly from sensory inputs. Then, these studies were improved in [18] to avoid the computational effort of the learning problem. Deep reinforcement learning with a smooth policy update has been applied to robotic cloth manipulation in [29]. The RL algorithms also significantly contribute to scheduling, which is the process of arranging, controlling and optimizing work and workloads in a production process. A large number researches on the scheduling problem have been conducted in the literature, see, for example, [14, 35]. According to the discussion in [27], there are two main approaches in real-time scheduling from previous studies, involving the multi-pass simulation approach and the machine learning approach. The authors have pointed out several drawbacks of these two methods and then proposed a RL-based model for real-time scheduling for a smart factory.

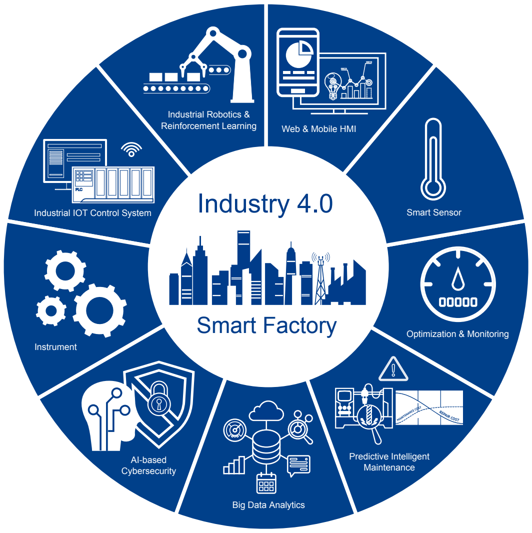

Fig. 1: A framework for the smart factory

4. Opportunities for Industrial Internet of Things, Big Data, and Artificial Intelligence in the Smart Factory

In previous sections, we presented the concepts, applications and current studies of IIoT, Big Data and AI for smart factories in the Industry 4.0. Figure 1 provides a framework for the smart factory, in which IIoT, Big Data and AI are three key components. In this section, we discuss some opportunities and futher perspectives of these important factors in intelligent manufacturing.

4.1 Monitoring production process

Production monitoring is an important task in smart manufacturing because it enables enterprises to detect timely abnormalities in production lines and then reduce waste. Recently, machine learning algorithms have been proposed for the use within Statistical Process Monitoring (SPM). This approach converts the monitoring problem to outlier detection problem or a supervised classification problem which classifies future observations as either in-control or out-of-control. From this point of view, the idea of using One-Class Support Vector Machines for detecting abnormality in [28] can be developed further for applying.

The use of IIoT technologies for the large production lines operating continuously creates real-time data. Moreover, the data in smart manufacturing are nowadays collected with a high frequency, high dimension and large variety which should not be treated straightforwardly. Therefore, advanced models for real-time Big Data monitoring are required. Recently, the Topological Data Analysis (TDA) emerges as a powerful tool to extract insights from high-dimensional, incomplete and noisy data of varying types such as images, 3D Scan, graph, point clouds, and meshes. The core idea of TDA is to find the shape, the underlying structure of shapes or relevant low dimensional features of high-dimensional data. As a result, the problem of treating the complex structure and massive data is brought to simpler problems. The first successful application of TDA in the manufacturing domain is conducted in [7]. In this study, the authors applied the Mapper algorithm, a tool in TDA, for predictive analysis of a chemical manufacturing process data set for yield prediction and a semiconductor etch process data set for fault detection. In general, there are still very few studies on this promising approach and further researches need to be carried out to discover its numerous applications to smart manufacturing. For instance, the deep learning algorithms such as long short-term memory (LSTM) and RNN for Topological Data should be developed to monitor the smart manufacturing process.

4.2 Product Lifecycle Management

Product lifecycle management (PLM) refers to the succession of strategies for managing all data relating to the design, production, support and ultimate disposal of manufactured goods. From this point of view, monitoring production process could be considered as a component of PLM. The PLM brings tremendous benefits to manufacturing industries for improving product quality, reducing prototyping costs, identifying potential sales opportunities and revenue contributions, maintaining operational serviceability, and reducing environmental impacts at end-of-life. Venkatasubramanian [32] reported that the petrochemical industry in the U.S. incurs approximately \$20 billions in losses due to poor management of equipment and processes which lead to such abnormal situations. Similarly, U.S. manufacturers spend over \$7 billions annually recalling and renewing over 2000 defective products. All of these costs are associated with the PLM. A key factor in PLM is prognostic and diagnostic monitoring. By comparing various existing approaches for prognostic and diagnostic in PLM, the author concluded that no traditional single method is adequate to handle all the requirements for a desirable diagnostic system. The application of the intelligent systems framework for this complex problem is then suggested. In this sense, the use of IIoT, Big Data and AI is a basic platform to design such intelligent PLM systems. The IIoT based PLM systems will be the first place where all product information from marketing and design comes together while the AI algorithms process these information and output a form suitable for production and support. As an example, Karasev and Sukhanov [10] recently designed a PLM system using multi agent systems models. In general, developing the AI based PLM systems in smart manufacturing is attractive for future research.

4.3 Predictive maintenance

Another application of IIoT, Big Data and AI in intelligent manufacturing is the predictive maintenance or just-in-time maintenance. The benefits and advantages achieved by the development of a comprehensive predictive maintenance are shown in [5]. In the past, the maintenance was regularly scheduled at fixed intervals, leading to some limitations. It could be a large amount of money in lost productivity while process must be halted to fix the failures when a machine breaks before the maintenance. Otherwise, time and another amount of money would be wasted if the machine does not need any maintenance at the moment. Even, unnecessary maintenance operations may increase the failure rate because of installed defective items or human negligence. The advanced IIoT technologies allows engineering to carry out timely predictive maintenance. In particular, the sensors are applied to different piece of equipments to continuously update the individual equipment health. The AI tools can process this gathered data to monitor and forecast overloads, machinery failures, or related problems based on learning algorithms. The appropriate time that a machine need to be maintained will be determined exactly. The Online Learning, Transfer Learning and Domain Adaption are the trends for predictive maintenance and prognosis in Industry 4.0 [4].

4.4 Cybersecurity

The exponential growth of IIoT also brings a significant challenge related to the cybersecurity problem in designing and implementing the smart factory. It would result in severe and heavy consequences if hackers could gain access to control networks or malware and worms could invade and destroy the operating systems of a factory. The cybersecurity is now a major concern in many researches. Twenty-four risk assessment methods developed for or applied in the context of a supervisory control and data acquisition system have been selected and examined in [3]. Tuptuk and Hailes [30] provided a large number of real reported attacks against smart manufacturing systems and existing active and passive countermeasures with their limitations. In general, several traditional existing cybersecurity solutions have become obsolete [16]. The machine learning and deep learning algorithms for regression, classification and clustering are poweful tools to detect and identify different classes of network attacks. For example, the method for network intrusion detection based on nested one-class support vector machines presented in [21], the method for anomaly detection in time series based on LSTM networks presented in [17] could be applied and developed for futher applications to the cybersecurity problem in intelligent manufacturing.

5. Conclusion

The IIoT, Big Data and AI are three key components of a smart factory. The wide use of electronic sensing devices, wireless sensor networks and other advanced technologies in the IIoT make the process of collecting, transforming and storing data from all statges of production process easier and more convenient, promoting the era of big manufacturing data. The AI provides powerful analytics approaches for the insight into these Big Data. By extracting insightful information from the unprecedented amount of data, the AI algorithms bring numerous benefits to the smart factory such as optimizing the production process, enhancing the product quality, reducing cost and securing. Despite of a large number of studies contributing to the applications of these technologies to intelligent manufacturing, there are still many challenges for further researches. The new advanced inventions in IIoT and AI will make a decisive contribution to the development of Industry 4.0.

References

[1] H Ahuett-Garza and T Kurfess. A brief discussion on the trends of habilitating technologies for industry 4.0 and smart manufacturing. *Manufacturing Letters*, 15:60–63, 2018.

[2] V Alcácer and V Cruz-Machado. Scanning the industry 4.0: A literature review on technologies for manufacturing systems. *Engineering Science and Technology, an International Journal*, 2019.

[3] Yulia Cherdantseva, Pete Burnap, Andrew Blyth, Peter Eden, Kevin Jones, Hugh Soulsby, and Kristan Stoddart. A review of cyber security risk assessment methods for scada systems. *Computers & security*, 56:1–27, 2016.

[4] Alberto Diez-Olivan, Javier Del Ser, Diego Galar, and Basilio Sierra. Data fusion and machine learning for industrial prognosis: Trends and perspectives towards industry 4.0. *Information Fusion*, 50:92–111, 2019.

[5] Susana Ferreiro, Egoitz Konde, Santiago Fernández, and Agustín Prado. Industry 4.0: Predictive intelligent maintenance for production equipment. In *European Conference of the Prognostics and Health Management Society*, pages 1–8, 2016.

[6] Robert Gao, Lihui Wang, Roberto Teti, David Dornfeld, Soundar Kumara, Masahiko Mori, and Moneer Helu. Cloud-enabled prognosis for manufacturing. *CIRP annals*, 64(2):749–772, 2015.

[7] Wei Guo and Ashis G Banerjee. Identification of key features using topological data analysis for accurate prediction of manufacturing system outputs. *Journal of Manufacturing Systems*, 43:225–234, 2017.

[8] Matthias M Herterich, Falk Uebernickel, and Walter Brenner. The impact of cyber-physical systems on industrial services in manufacturing. *Procedia CIRP*, 30: 323–328, 2015.

[9] Olivier Janssens, Viktor Slavkovikj, Bram Vervisch, Kurt Stockman, Mia Loccufier, Steven Verstockt, Rik Van de Walle, and Sofie Van Hoecke. Convolutional neural network based fault detection for rotating machinery. *Journal of Sound and Vibration*, 377:331–345, 2016.

[10] VO Karasev and VA Sukhanov. Product lifecycle management using multi-agent systems models. *Procedia Computer Science*, 103:142–147, 2017.

[11] Siddhartha Kumar Khaitan and James D McCalley. Design techniques and applications of cyberphysical systems: A survey. *IEEE Systems Journal*, 9(2):350–365, 2015.

[12] Jens Kober, J Andrew Bagnell, and Jan Peters. Reinforcement learning in robotics: A survey. *The International Journal of Robotics Research*, 32(11):1238–1274, 2013.

[13] Yaguo Lei, Feng Jia, Jing Lin, Saibo Xing, and Steven X Ding. An intelligent fault diagnosis method using unsupervised feature learning towards mechanical big data. *IEEE Transactions on Industrial Electronics*, 63 (5):3137–3147, 2016.

[14] Matheus Leusin, Enzo Frazzon, Mauricio Uriona Maldonado, Mirko Kück, and Michael Freitag. Solving the job-shop scheduling problem in the industry 4.0 era. *Technologies*, 6(4):107, 2018.

[15] Sergey Levine, Chelsea Finn, Trevor Darrell, and Pieter Abbeel. End-to-end training of deep visuomotor policies. *The Journal of Machine Learning Research*, 17(1):1334–1373, 2016.

[16] Tariq Mahmood and Uzma Afzal. Security analytics: Big data analytics for cybersecurity: A review of trends, techniques and tools. In *2013 2nd national conference on Information assurance (ncia)*, pages 129–134. IEEE, 2013.

[17] Pankaj Malhotra, Lovekesh Vig, Gautam Shroff, and Puneet Agarwal. Long short term memory networks for anomaly detection in time series. In *Proceedings*, page 89. Presses universitaires de Louvain, 2015.

[18] Richard Meyes, Hasan Tercan, Simon Roggendorf, Thomas Thiele, Christian Büscher, Markus Obdenbusch, Christian Brecher, Sabina Jeschke, and Tobias Meisen. Motion planning for industrial robots using reinforcement learning. *Procedia CIRP*, 63:107–112, 2017.

[19] Volodymyr Mnih, Adria Puigdomenech Badia, Mehdi Mirza, Alex Graves, Timothy Lillicrap, Tim Harley, David Silver, and Koray Kavukcuoglu. Asynchronous methods for deep reinforcement learning. In *International conference on machine learning*, pages 1928–1937, 2016.

[20] László Monostori, Botond Kádár, T Bauernhansl, S Kondoh, S Kumara, G Reinhart, O Sauer, G Schuh, W Sihn, and K Ueda. Cyber-physical systems in manufacturing. *CIRP Annals*, 65(2):621–641, 2016.

[21] Quoc Thong Nguyen, Truong Thu Huong, Kim Phuc, Minh Kha Nguyen, Philippe Castagliola, and Salim Lardjane. Nested one-class support vector machines for network intrusion detection. In *2018 IEEE Seventh International Conference on Communications and Electronics (ICCE)*, pages 7–12. IEEE, 2018.

[22] J Perrey, D Spillecke, and A Umblijs. Smart analytics: How marketing drives short-term and long-term growth. *McKinsey Quarterly*, pages 00425–3, 2013.

[23] Matthew NO Sadiku, Yonghui Wang, Suxia Cui, and Sarhan M Musa. Industrial internet of things. *International Journal of Advances in Scientific Research and Engineering*, 3, 2017.

[24] Seref Sagiroglu and Duygu Sinanc. Big data: A review. In *Collaboration Technologies and Systems (CTS), 2013 International Conference on*, pages 42–47. IEEE, 2013.

[25] Maicon Saturno, Vinícius Moura Pertel, Fernando Deschamps, and E de FR Loures. Proposal of an automation solutions architecture for industry 4.0. In *Proceedings of the 24th International Conference on Production Research*. ICPR Poznan, 2017.

[26] Michael Sharp, Ronay Ak, and Thomas Hedberg Jr. A survey of the advancing use and development of machine learning in smart manufacturing. *Journal of Manufacturing Systems*, 2018.

[27] Yeou-Ren Shiue, Ken-Chuan Lee, and Chao-Ton Su. Real-time scheduling for a smart factory using a reinforcement learning approach. *Computers & Industrial Engineering*, 2018.

[28] Kim Phuc Tran, Truong Thu Huong, et al. Data driven hyperparameter optimization of one-class support vector machines for anomaly detection in wireless sensor networks. In *Advanced Technologies for Communications (ATC), 2017 International Conference on*, pages 6–10. IEEE, 2017.

[29] Yoshihisa Tsurumine, Yunduan Cui, Eiji Uchibe, and Takamitsu Matsubara. Deep reinforcement learning with smooth policy update: Application to robotic cloth manipulation. *Robotics and Autonomous Systems*, 112:72–83, 2019.

[30] Nilufer Tuptuk and Stephen Hailes. Security of smart manufacturing systems. *Journal of manufacturing systems*, 47:93–106, 2018.

[31] Muhammad Fahim Uddin, Navarun Gupta, et al. Seven v's of big data understanding big data to extract value. In *American Society for Engineering Education (ASEE Zone 1), 2014 Zone 1 Conference of the*, pages 1–5. IEEE, 2014.

[32] Venkat Venkatasubramanian. Prognostic and diagnostic monitoring of complex systems for product lifecycle management: Challenges and opportunities. *Computers & chemical engineering*, 29(6):1253–1263, 2005.

[33] Jinjiang Wang, Yulin Ma, Laibin Zhang, Robert X Gao, and Dazhong Wu. Deep learning for smart manufacturing: Methods and applications. *Journal of Manufacturing Systems*, 2018.

[34] Peng Wang, Robert X Gao, and Ruqiang Yan. A deep learning-based approach to material removal rate prediction in polishing. *CIRP Annals*, 66(1):429–432, 2017.

[35] Wen-Hsiang Wu, Wen-Hung Wu, Juei-Chao Chen, Win-Chin Lin, Jungpin Wu, and Chin-Chia Wu. A heuristic-based genetic algorithm for the two-machine flowshop scheduling with learning consideration. *Journal of Manufacturing Systems*, 35:223–233, 2015.

[36] Thorsten Wuest, Daniel Weimer, Christopher Irgens, and Klaus-Dieter Thoben. Machine learning in manufacturing: advantages, challenges, and applications. *Production & Manufacturing Research*, 4(1):23–45, 2016.

[37] Hui Yang, Soundar Kumara, Satish TS Bukkapatnam, and Fugee Tsung. The internet of things for smart manufacturing: A review. *IISE Transactions*, (just-accepted): 1–35, 2018.

[38] Ray Y Zhong, Xun Xu, Eberhard Klotz, and Stephen T Newman. Intelligent manufacturing in the context of industry 4.0: a review. *Engineering*, 3(5):616–630, 2017.