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State of AI-based Monitoring in Smart Manufacturing and Introduction to Focused Section

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Abstract—**Over the past few decades, intelligentization, supported by Artificial Intelligence (AI) technologies, has become an important trend for industrial manufacturing, accelerating the development of smart manufacturing. In modern industries, standard AI has been endowed with additional attributes, yielding the so-called Industrial Artificial Intelligence (IAI) that has become the technical core of smart manufacturing. AI-powered manufacturing brings remarkable improvements in many aspects of closed-loop production chains from manufacturing processes to end product logistics. In particular, IAI incorporating domain knowledge has benefited the area of production monitoring considerably. Advanced AI methods such as deep neural networks, adversarial training and transfer learning have been widely used to support both diagnostics and predictive maintenance of the entire production process. It is generally believed that IAI is the critical technologies needed to drive the future evolution of industrial manufacturing. This survey offers a comprehensive overview of AI-powered manufacturing and its applications in monitoring. More specifically, it summarizes the key technologies of IAI and discusses their typical application scenarios with respect to three major aspects of production monitoring: fault diagnosis, remaining useful life prediction and quality inspection. In addition, the existing problems and future research directions of IAI are also discussed. This survey further introduces the papers in this focused section on AI-based Monitoring in Smart Manufacturing by weaving them into the overview, highlighting how they contribute to and extend the body of literature in this area.**

Index Terms—**Smart manufacturing, Artificial intelligence, Machine learning, Deep learning, Fault diagnosis, Remaining useful life prediction, Quality inspection**

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I. Introduction

Science and technology developments have advanced industrial manufacturing through the stages of mechanization, electrification and digitization over the past 150 years. Industrial intelligentization, i.e., the fusion of advanced manufacturing processes with data and AI technology, which enables intelligent perception, analysis, reasoning, decision-making and control, is believed to be the next stage in manufacturing. Smart manufacturing is the core of industrial intelligentization. In general, it is the organic integration of many existing high-end technologies from a wide range of areas including communication, production, internet, computer science, and is continually absorbing emerging technologies such as the Internet of Things (IoT) and digital twin technologies. Consequently, the definition of smart manufacturing is evolving with the advancement of modern technologies. Currently, smart manufacturing is considered to be the aggregation of various new technologies including AI algorithms, IoT, big data analytics, cloud computing, and Cyber Physical Systems (CPS) [1]. Lee et al. [2] proposed the concept of the industrial intelligence ecosystem composed of four key elements including big data technology, data analytics technology, cloud computing and cyber technologies. Regardless of the specific technologies that may contribute at present or potentially in the future, we define smart manufacturing as self-evolving manufacturing endowed with human intelligence which can not only learn but also learn to learn. Therefore, the potential of smart manufacturing is unlimited and its development may never cease.

Today, smart manufacturing is regarded as the core competitiveness that marks the level of a country's industrial manufacturing abilities. To vigorously support smart manufacturing and promote the competitive advantage of domestic manufacturing industries, almost all the big industrial countries have created their own programs and policies such as China's 'Made in China 2025', the United States' 'Advanced Manufacturing Partnership', Germany's 'Industries 4.0', the United Kingdom's 'High value manufacturing strategy', Japan's 'New robot strategy'.

Intelligent manufacturing is mainly supported by Industrial Artificial Intelligence technologies. Although the corresponding research is still in the early stage, IAI is attracting increasing attention, incurring rapid technical development and making remarkable progress in applications (e.g., [3]). In essence, IAI involves six key techniques: modeling, diagnos-

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tics, prediction, optimization, decision and deployment. They have penetrated all aspects of industrial manufacturing from process quality control to supply chain management, among which real-time monitoring is one typical area benefiting greatly from IAI technologies.

Real-time monitoring involves diagnosis, prediction and inspection of manufacturing process. Taking Fault Diagnosis (FD) as an example, this area has experienced a long history of research and is essential for the safety of smart manufacturing. In general, FD includes state monitoring and fault diagnosis for management and maintenance of equipment (e.g., [4]) and many developed countries took an active part in its development.

Intelligentization is the inevitable trend of industrial manufacturing. The deep integration of AI and advanced manufacturing technologies provides a complete solution to improve the quality and efficiency of products, raise service levels of enterprises and reduce energy consumption considerably. This survey focuses on the field of manufacturing monitoring, concerning the technologies of fault diagnosis, remaining useful life prediction, and quality inspection of IAI. The research status of these technologies is systematically summarized and the corresponding problems faced by IAI along with their possible solutions are also discussed.

In an effort to disseminate current AI advances for intelligent manufacturing, we organized a focused section in IEEE/ASME Transactions on Mechatronics, which will provide a platform for scientists, engineers and industrial practitioners to present their latest theoretical and technological advancements in the design of advanced and/or emerging health monitoring and management, fault diagnosis and prognosis, practical implementation, and various case studies of the AI-based manufacturing applications of these techniques. The focused section received a total number of 42 submissions, among which 16 papers were accepted. The accepted paper are recorded in Table I. In what follows, papers in bold are accepted papers for the focused section. This survey further introduces the papers in this focused section on AI-based Monitoring in Smart Manufacturing by weaving them into the overview, highlighting how they contribute to and extend the body of literature in this area.

This paper is organized as follows. Section II provides an overview of the main concept of IAI from the technical perspectives to typical application scenarios. Following that, IAI technology is discussed in detail specifically under the context of manufacturing monitoring. Section III, IV and V present AI-based fault diagnosis, remaining useful life prediction and quality inspection, respectively. Section VI discusses the existing problems of IAI and Section VII demonstrates future research prospects. Finally, Section VIII concludes this survey. This survey introduces the papers in this focused section on AI-based Monitoring in Smart Manufacturing by weaving them into the overview, and showing how they contribute to and extend the body of literature in this area. These papers are specifically highlighted in the survey by bolding the references to them.

II. An overview of industrial artificial intelligence

To achieve high-quality, efficient, reliable and low-cost multi-objective industrial operations, IAI combines AI technologies and the domain knowledge of standard industrial processes to generate intelligent systems, endowed with the ability of self-perception, self-comparison, self-prediction, self-optimization and self-adaptation. AI technologies including traditional analytics, machine learning and deep learning techniques have been applied to solving problems in computer vision, speech engineering, natural language processing and decision-making. The standard industrial process involves production, decision-making and product service (e.g., design, production, process, assembly, warehousing and logistics, sales), equipment category (i.e., sensors, manufacturing equipment, production lines, workshops, factories) and supplementary category (e.g., operation and maintenance, after-sales, market, emission, energy consumption, environment). IAI as a member of the AI family is developed under the context of industry. We summarize six key technologies of IAI in Figure. 1, namely modeling, diagnostics, prediction, optimization, decision and deployment.

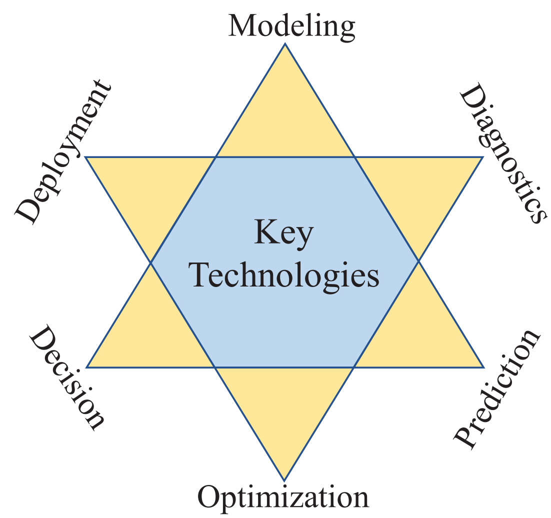

Figure 1. Key technologies of industrial artificial intelligence.

Modeling: Modeling is of great significance in industrial production. Models constructed based on industrial mechanisms and knowledge reveal hidden laws such as the deterioration process of equipment or components, the relationship between process parameters and product quality, the coupling between the status of production line operation and component process. Therefore, these models are able to reflect the core production process of manufacturing industries and indicate the production capacity and competitiveness of enterprises. By describing the manufacturing process as industrial CPS, Yuan et al. [5] proposed a novel method to identify nonlinear coupled system dynamics using a dictionary of mechanistic functions, excavate the switching logics between the subsystems, and reveal the evolution trend of CPS. Due to its desired performance in modeling industrial processes, the developed

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Table I
ACCEPTED PAPER FOR THE FOCUSED SECTION.

Title	Authors
Surrogate-assisted symbiotic organisms search algorithm for parallel batch processor scheduling	Z. Cao, C. Lin, M. Zhou, J. Zhang
Robust deep learning-based diagnosis of mixed faults in rotating machinery	S. Chen, Y. Meng, H. Tang, Y. Tian, N. He, C. Shao
Intelligent fault diagnosis of multi-channel motor-rotor system based on multi-manifold deep extreme learning machine	X. Zhao, M. Jia, P. Ding, C. Yang, D. She, Z. Liu
Vibrational triboelectric nanogenerator-based multi-node self-powered sensor network for machine fault detection	W. Li, Y. Liu, S. Wang, W. Li, G. Liu, J. Zhao, X. Zhang, C. Zhang
Fault detection of electromechanical actuators via automatic generation of a fuzzy index	D. De Martini, T. Facchinetti
An unknown input observer-EFIR combined estimator for electro-hydraulic actuator in sensor fault tolerant control application	S. A. Nahian, T. Q. Dinh, H. V. Dao, K. K. Ahn
Robust wheel wear monitoring system for cylindrical traverse grinding	B. C. Zhang, C. C. Katinas, Y. C. Shin
Ensemble generalized multiclass support vector machine-based health evaluation of complex degradation systems	J. Wu, P. Guo, Y. Cheng, H. Zhu, X.B. Wang, X. Shao
Industrial remaining useful life prediction by partial observation using deep learning with supervised attention	X. Li, X. Jia, Y.L. Wang, S.J. Yang, H.D. Zhao, J. Lee
Machinery health monitoring based on unsupervised feature learning via generative adversarial networks	J. Dai, J. Wang, W. Huang, J. Shi, Z. Zhu
Prognostics of health measures for machines with aging and dynamic cumulative damage	C. Duan, C. Deng
Exploring equipment electrocardiogram mechanism for performance degradation monitoring in smart manufacturing	B. Chen, J. Wan, M. Xia, Y. Zhang
A CNN-based adaptive surface monitoring system for fused deposition modeling	Y. Wang, J. Huang, Y. Wang, S. Feng, T. Peng, H. Yang, J. Zou
Operating mode recognition based on fluctuation interval prediction for iron ore sintering process	S. Du, M. Wu, L. Chen, J. Hu, L. Jin, W. Cao, W. Pedrycz
Parameter identification and non-parametric calibration of the tri-pyramid robot	S. Liao, Q. Zeng, K. F. Ehmann, J. Cao
Magnetic machine perception for reconstruction of non-uniform electrical conductivity based on eddy current model	B. Hao, K. Lee, I. Chang

method has been successfully applied under many contexts such as robotics, smart manufacturing, intelligent power grids. Jin et al. [6] applied variational Bayesian inference to model complex networks with sparse nework topologies, which can be used to decouple manufacturing components.

Diagnostics: Safety is the basic requirement in industrial production since abnormal operations of equipment or production process may lead to the serious drop in product quality, or possibly accidents and casualties. Therefore, sensors are widely used to collect monitoring data in the form of images, videos and time series from manufacturing equipment, production lines and the final products. With enormous data, big data analysis, machine learning, deep learning and other AI-based methods are used to realize intelligent online detection and diagnosis of anomalies in industrial production processes, and to perform causality analysis. These tasks are often solved as supervised or unsupervised classification and clustering problems. For example, a deep learning framework was proposed in [7] to automatically extract the features from noisy sensor signals including vibration, voltage, current, temperature, sound, and force. The framework is robust and flexible, and achieves high-precision diagnosis for several manufacturing components containing bearings, cutter, gearboxes, Lithium batteries.

Prediction: Prediction plays an important role in boosting industrial production. With the rapid development of big data, cloud service and AI technologies, data-driven forecasting methods have been widely used in predictive maintenance, demand prediction, quality prognosis, which helps reduce costs, increase efficiency and improve the quality and safety of industrial manufacturing. In predictive maintenance, both monitoring data and empirical degradation knowledge are used to predict the remaining useful life of industrial equipment, which guides the development of strategies for efficient maintenance [8]. Based on the historical monitoring data of the production line, the manufacturer forecasts the demand to coordinate the production chain, carry out risk management and reduce production waste. Finally, quality prediction is often implemented in high-end manufacturing. Product quality is predicted by analyzing the monitoring data and operation status of the production line. The production process is then optimized to avoid defective products. Notably, the digital twin

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technology as a novel concept shows growing impacts on the quality inspection area in recent years [9], [10].

Optimization: Optimization is a major technique to improve the efficiency of industrial manufacturing, which is divided into equipment level optimization and system level optimization. The parameters of industrial equipment control the manufacturing process, thus influencing the quality of end product. Since many process parameters are not known a priori, they are usually learned from monitoring data using supervised feature screening (e.g., LDA, Fisher score, Lasso) or unsupervised feature screening (e.g., PCA, Laplacian score, autoencoder). Online optimization of process parameters using AI algorithms are crucial to improve the quality and efficiency of industrial processes in real time. Hence, a variety of optimization algorithms have been developed [12]. Normally, a production process involves a series of industrial equipment and a production line is composed of multiple production processes. Based on the monitoring data of equipment and manufacturing processes, the cooperation among production processes is optimized in terms of the desired indices for the whole production line [13].

Decision: Decision making is the key to closing the loop of industrial manufacturing, which is associated with the optimization of industrial process and maintenance of equipment [14]. Decision making takes into account various manufacturing-related factors (e.g., real-time market information, production conditions, operation indices, production instructions, control instructions and operation conditions) to achieve the enterprise objectives by performing optimization and scheduling [15]. For example, **Cao, Z et al.** solved scheduling of a parallel batch processor using the reinforcement learning algorithm SARSA(λ). As for the maintenance of industrial equipment, decision making determines repairing maintenance, preventive maintenance and predictive maintenance, among which predictive maintenance is considered to be one of the 'killer' applications of the industrial Internet. Predictive maintenance can effectively reduce maintenance costs, eliminate production downtime, reduce equipment or process downtime, and improve productivity [16]. Recently, prescriptive maintenance has been a new trend experiencing rapid development. The methods not only predict a failure that may likely happen but also prescribe what can be done to avoid the failure altogether.

Deployment: Deployment is the key to the efficient implementation of IAI by providing technical support platforms. More specifically, the technology of hardware acceleration based on smart chips is the core to deploy AI models. With the rapid growth of data volume, standard computing chips (e.g., CPU) can no longer meet the demand of real-time processing in the stage of online model reasoning. Therefore, it is imperative to invent intelligent chips for the implementation of IAI algorithms. The essence of intelligent chip technologies is the hardware acceleration for model interface, which involves the design of efficient hardware architectures and software compilation tools. Compared with traditional computing chips, smart chips are superior in terms of computing power and reduced energy consumption. The development of intelligent chips has accelerated the spread of IAI applications.

IAI appears to be increasingly important in the rapid development of industrial manufacturing. It has penetrated into many links of the production chain. As shown in Figure 2, typical application scenarios of IAI include quality inspection and process quality control, energy management and energy efficiency optimization, supply chain and intelligent logistics, predictive maintenance of equipment.

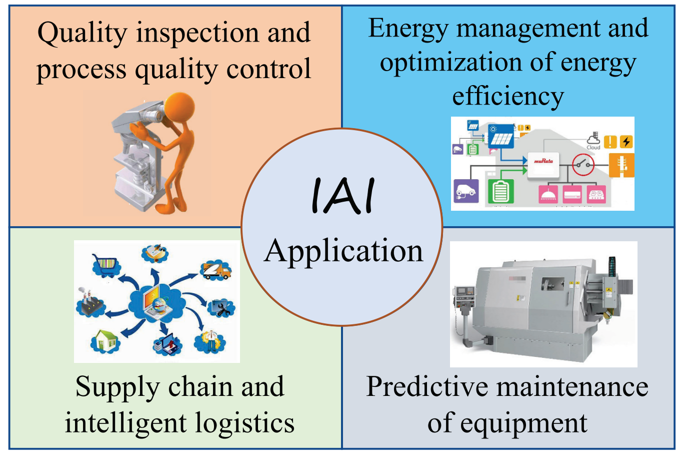

Figure 2. Typical application scenarios of industrial artificial intelligence.

To better demonstrate detailed technologies, IAI is specifically discussed in the context of intelligent monitoring that involves Fault Diagnosis (FD), Remaining Useful Life Prediction (RULP) and Quality Inspection (QI). According to the general framework of intelligent monitoring, the following sections will discuss AI based algorithms for FD/RULP/QI in sequence, and the typical methods are summarized in Figure 3.

III. Fault diagnosis of manufacturing equipment with machine learning

Safety and robustness are critical to industrial manufacturing [17]–[21]. Fault diagnosis aims to prevent the occurrence of possible accidents and casualties by recognizing abnormal operations of production process and equipment from monitoring data. Additionally, highly efficient FD technologies are required to achieve the goals with low maintenance costs, high flexibility, robust performance, desired platform independence and good interpretability.

Machine learning has been a prevalent IAI technique for fault diagnosis. Considering the depth of model structures, machine learning based methods are classified into two categories, i.e., shallow machine learning and deep learning methods. Shallow machine learning methods mainly contain Extreme Learning Machine (ELM), Gaussian Process Regression (GRP), Support Vector Machine (SVM) and Hidden Markov Process (HMM) while deep learning involves the usage of deep neural networks (e.g., Convolutional Neural Networks (CNN), Fully connected Neural Networks (FNN), Long Short-Term Memory (LSTM), Generative Adversarial Networks (GAN) and Graph Neural Networks (GNN)) along with advanced learning strategies (e.g., Transfer Learning (TL)

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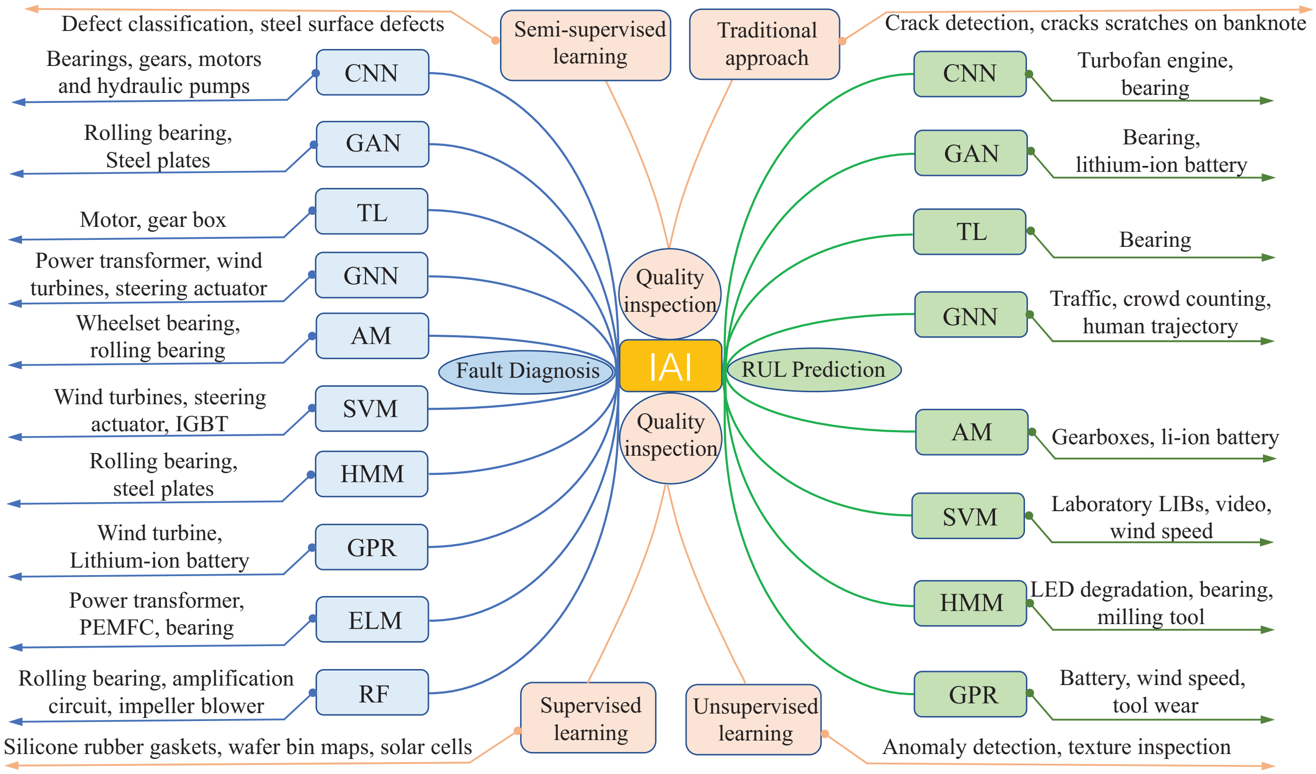

Figure 3. Typical machine learning methods of industrial artificial intelligence and its application.

and Attention Mechanism (AM)). In recent years, deep learning has dominated fault diagnosis and is receiving increasing attention. In addition, other approaches based on advanced control theories are also studied as part of intelligent fault diagnosis.

A. Benchmark datasets

Benchmark datasets are often used to verify algorithm performance and to compare different methods. A variety of benchmark datasets are available online for fault diagnosis including motor bearing datasets with vibration signals [22], [23], bearing datasets with current signals [24], gear fault vibration datasets [25], [26], milling dataset [27], turbofan engine degradation simulation datasets [28].

B. Machine learning based methods

Machine learning based diagnosis methods typically include three steps: feature extraction, feature selection and classification. Feature extraction and selection can be achieved artificially or automatically. Artificial feature extraction and selection benefit from expert experience and, thus, better interpret inherent properties, e.g., system dynamics, whilst automatic feature learning through designed models can extract abstract representations embedded in more complex feature spaces. Notably, these two approaches are often combined in the deep learning framework. The detection of machine failure is often formulated as a classification problem and addressed using learned features.

Chen, S et al. proposed a 1-D CNN-based approach to diagnose both known and unknown faults in rotating machinery under added noise, which reliably identified the nature of the mixed faults. Two neural networks were developed to evaluate rotors and bearings respectively for 48 machine health conditions. One-vs-all classifiers were designed to identify previously unseen fault types. It turns out that the method was robust to noise, thus providing stable performance.

Zhao, X et al. proposed a new FD method for multi-channel motor-rotor system via Multi-manifold Deep Extreme Learning Machine (MDELM) to address multi-channel data. The designed MDELM algorithm combined unsupervised and semi-supervised learning schemes where unsupervised self-taught feature extraction was realized using Extreme Learning Machine based-Modified Sparse Filtering (ELM-MSF) and a Multimanifold Extreme Learning Machine (MELM) classifier with multi-manifold constraints was applied to explore the intra-class and inter-class discriminant feature information to

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accomplish semi-supervised fault classification. The designed MDELM showed outstanding learning efficiency for industrial data from motor-rotor systems.

Li, W et al. developed a multi-node sensor network to detect machine faults using SVM based on mechanical vibration energy. The method applied a multilayered vibrational triboelectric nanogenerator (V-TENG) to extract energy from working machines. The V-TENG generated an output with a power density of 3.33 mW/m3 once triggered by the vibration motion. A Self-powered Vibration Sensor Node (SVSN) was constructed based on a micro control unit integrated with sensors and a wireless transmitter, which was supported by the V-TENG. SVM was employed to build up the three-SVSN network for fault diagnosis by analyzing acceleration and temperature data from the working machine. The developed method was able to recognize different working conditions of the machine accurately.

C. Other approaches

Machine learning based FD are data-driven methods under the end-to-end framework, which do not exploit the physical rules or working mechanisms of the target system. Such methods are highly flexible and applicable to a wide range of platforms. The scenario developed for one scenario is transferable to other scenarios, thus, incurring low maintenance costs. Nevertheless, machine learning based methods are sensitive to noise and in most cases, not understandable by human labors. To offer robust and analyzable FD systems, a variety of techniques have been invented using advanced control theories.

De Martini et al. proposed a FD framework for electromechanical systems based on a Fuzzy Inference System (FIS). Whilst Fuzzy Logic (FL) requires the specification of a large number of fuzzy inference rules in accordance to input variables and Membership Functions (MFs), the developed Fuzzy INDices (F-IND) framework automatically generated the fuzzy rules from the specification of the qualitatively best and worst cases of the MFs of each input variable. The method was applied to electric motors, presenting high computational performance and detection accuracy.

Nahian et al. developed an Unknown Input Observer (UIO)-integrated Extended Finite Impulse Response (EFIR) Estimator (UIOEFIR) to estimate states of Electro-Hydraulic Actuators (EHAs) in sensor Fault Tolerant Control (FTC) applications. This hybrid estimator exploited the UIO structure in the EFIR filter and estimates system states and unknown invoked-sensor-fault value without prior knowledge of states and process or measurement noise. The UIOEFIR estimator contributed to the fault diagnosis algorithm inside a simple sensor FTC architecture of an EHA to detect unknown sensor fault information. The developed method presented outstanding and reliable performance under chaotic environmental conditions.

Zhang, B et al. proposed a robust grinding wheel wear monitoring system applicable to diverse grinding conditions (e.g., varying wheel types and workpiece materials). A novel normalization scheme was applied to extract features of signals collected from the grinding process via power sensors, accelerometers and acoustic emission sensors in order to decouple these features from the factors of the wheel type, workpiece material and grinding parameters. With the selected features, an interval type-2 Fuzzy Basis Function Network (FBFN) was adopted as the wheel wear monitoring model to predict wheel wear under various grinding conditions and estimate variance according to the fluctuation of features, leading to the robust monitoring performance.

IV. Remaining useful life prediction for manufacturing equipment

With the rapid development in sensors, data storage, network transmission and other new technologies, numerous data are generated to monitor key manufacturing equipment. The main part of life prediction research is focused on mining the deterioration information from monitoring data and developing effective algorithms to predict the accurate remaining useful life.

Data-driven RUL prediction techniques are typically divided into two groups, i.e., statistical methods [29] and machine learning based methods [30]. Statistical methods are based on the theory of statistics. Principal component analysis or partial least square methods are commonly utilized to process the data of equipment degradation, establish evaluation indices, and assess the health status of equipment. However, the application of these methods is limited by data quality and strict preconditions of statistical theory. In contrast, machine learning based methods are more flexible and practical, becoming the common techniques utilized for RUL prediction in recent years with great success. Hence, this section mainly discusses machine learning based methods. RUL prediction techniques based on machine learning are composed of feature extraction, health index establishment, feature selection, and remaining useful life prediction. These steps are implemented in very different ways for shallow and deep learning frameworks.

A. Benchmark datasets

Similar to FD, benchmark datasets are applied to test the proposed methods. Some well-known benchmark datasets for RULP include turbofan engine degradation simulation dataset [31], FEMTO bearing dataset [32], IMS bearing dataset [33], milling dataset [34].

B. Machine learning based methods

RUL prediction based on machine learning is attracting growing attention [35], [42]. Similar to fault diagnosis, representative methods of RULP include Support Vector Regression (SVR) [36], [37], HMM, GRP, CNN [38], Deep Belief Networks (DBN) [39], and Recurrent Neural Networks (RNN) [40], [41].

Wu, J et al. proposed a health evaluation method comprised of stacking ensemble learning and a Generalized Multiclass Support Vector Machine (GMSVM) algorithm. Before evaluating the health situation of a degradation system, abnormal value elimination and missing value processing were conducted. Statistical features and Pearson correlation coefficient

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were applied to selected efficient features. The experimental results showed that the GMSVM algorithm achieves high multiclass efficiency with low variance and deviation.

Li, X et al. utilized the supervised attention mechanism using the deep neural network framework to predict the RUL for real-world cutting wheel degradation process with high-resolution image datasets. The IMS-Foxconn dataset originated from Intelligent Maintenance Systems lab and Foxconn Technology Group was introduced, offering a new perspective on the image-based prognostic. The experimental results validated the effectiveness and superiority of the proposed method over traditional DCNN, LSTM and NoSupAtt.

Dai, J et al. developed a new Generative Adversarial Networks (GAN) model to learn a discriminative feature for machinery health monitoring. The proposed model adopted Auto-Encoder (AE) as the generator to learn the data distribution of normal samples embedded in the signal spectrum space and latent representation space. Experiments demonstrated that the high sensitivity to incipient machinery anomaly and the capability in description of machine degradation progression can be achieved.

C. Other approaches

While data-driven methods based on machine learning have been extensively studied, degradation model based methods and model-data fused methods also have unique advantages in that they can mine the deep information in the degradation process of equipment.

Duan, C et al. employed a prognostic model to describe the aging and environment-varying cumulative damage process which included a large number of states and flexible transition mechanisms under varying operational conditions. A matrix-based approximation method was developed to compute important health measures so that the low computational load could be obtained.

Chen, B et al. proposed an Equipment Electro-Cardiogram (EECG) mechanism to collect the entire operating data. An optimization strategy of APL-EECG was adopted to improve the efficiency of an intelligent production line and a preventive maintenance strategy was designed.

V. Quality inspection of industrial products

Quality Inspection (QI) of industrial products plays a significant role in modern industries. Compared with traditional approaches that rely on expert experience, automated quality inspection provides high-quality and high-efficiency monitoring routines. QI methods can be classified into two categories, including machine learning-based approaches (i.e., supervised, semi-supervised and unsupervised learning) and other traditional approaches.

A. Benchmark datasets

A variety of benchmark datasets are available online for QI to verify the developed inspection algorithms and to compare different methods, including road crack datasets [43], datasets for PCB analysis [44], nanofibrous materials datasets [45], steel strip surface datasets [46], X-Ray datasets [47], saliency defects of magnetic tile [48], images of cracks on solar cells [49], non-woven fabric [49].

B. Machine learnng-based methods

Recent advances in the development of AI technologies have driven traditional QI towards intelligent QI in several key industries such as aerospace, automotive, and healthcare. The novel paradigm of AI adoption is to apply advanced machine learning algorithms on quality inspection processes to achieve quality control and process monitoring with high reliability. Supervised, semi-supervised, and unsupervised learning have been the mainstream machine learning algorithms for intelligent QI and quality control, which helps to increase the productivity and profitability of enterprises by reducing the rejection and defect rate of product.

Wang, Y et al. proposed a novel surface monitoring system for fused deposition modeling processes to achieve high defect detection accuracy with high response speed under a cloud-based framework. A heuristic algorithm was proposed to achieve adaptive shooting position planning according to part geometries and a CNN-based model was designed to achieve efficient defect classification with high accuracy.

Du, S et al. designed an Elman neural network with another classification model to predict the operating mode of iron ore sintering processes, according to the data distribution of the burn-through point in fluctuation intervals. Fluctuation intervals were the key features in this study and were used to describe the time-series signals acquired by sensors. In terms of the feature extraction, PCA and the fuzzy information granulation methods were employed to reduce the high-dimensional time-series sensory data and extract the fluctuation interval respectively.

Liao, S et al. predicted the end-effector positions of a 3-DOF over-constrained parallel robot (named Tri-Pyramid Robot). The final positions were calculated by combining a parametric and a non-parametric calibration method. More specifically, the spatial position data of the end-effector were collected on a test-rig using a laser tracker. Then, the structural parameters in the kinematic robot model were identified using the least-squares method. For the non-parametric calibration, non-geometric errors like backlash and link deformations were predicted by using a trained neural network.

Wang et al. [50] applied a lightweight CNN for machine vision inspection to identify and classify defective product without loss of accuracy. For the image data pre-processing, Gaussian filtering and probabilistic Hough transform methods were employed to prevent the influence of noise and remove the unrelated background contents respectively. The developed method, as an online inspection method, demonstrated outstanding performance on defective and defect-free bottle images.

C. Other approaches

In addition to deep learning that dominates the field of surface inspection, traditional statistical and spectral methods are also widely used.

Hao, B et al. proposed a novel field-based sensing method that reconstructs Eddy Current (EC) density field enabling the machine to have adequate perception to locate and quantify features or defects (such as residual stress, corrosion and microstructure abnormity). This work solved the inverse solutions to the EC model, which differs from the forward EC models used in previous studies, to reconstruct the unknown conductivity distribution.

Cao et al. [51] used a knowledge embedded sparse Bayesian regression approach to achieve online machining error predictions of thin-wall workpieces. The proposed Bayesian model was trained to learn the hidden pattern between the machining errors and cutting parameters, cutting location, as well as online measured cutting forces.

Yang et al. [52] adopted a nonsubsampled shearlet transform to decompose the original images into multiple subbands at different directions and scales. A novel column filtering based on envelope gray level gradient was employed to remove the uneven background in the approximation subband, and a shearlet coefficient variance discriminator was used to eliminate interferences of noise and textures in the detail subbands.

Tsai et al. [53] proposed a global Fourier image reconstruction method to detect and localize small defects in nonperiodical pattern images by comparing the whole Fourier spectra of the template with the inspection image. Similarly, Gai et al. [54] used the quaternion wavelet transform and the least squares method to detect cracks and scratches on banknote images.

VI. Existing problems and challenges

Industrial AI can use the high volumes of data generated by production processes to identify hidden patterns, which improves production efficiency and reduces the consumption of manufacturing processes. Whilst significant progress has been achieved in FD/RULP/QI as discussed in above sections, the current stage of the IAI still faces several challenges:

1) *Heterogeneous data*: Datasets generated by industrial equipment, production lines, Manufacturing Execution Systems (MES) and Enterprise Resource Planning (ERP) are complex and heterogeneous in arbitrarily high dimensional spaces. Industrial data have different formats: (a) Vibration, pressure and temperature data are time series; (b) Image data are obtained by infrared nondestructive testing technology; (c) Video and audio data are collected by ultrasonic testing, acoustic emission testing, ray testing and other means; and (d) Documentary data cover logistics, management, operation and service.

2) *Data imbalance*: As sensors have been widely implemented in intelligent plants, one typical challenge that manufacturers and researchers face is the imbalanced data problem. This problem is characterized by the fact that only a fraction of the operational data constitutes machine failure. Furthermore, failure data points are commonly different from one another. On the contrary, normal operational data samples account for the majority of the data and share similar features. As a result, conventional feature extraction and selection methods are not appropriate for imbalanced data. Moreover, the evaluation metrics (e.g., accuracy and area under the curve) can mislead the users due to a biased satisfied model generated from imbalanced training datasets. The model does not learn the features of the failure data as it focuses on the instances of the majority class, i.e., normal data. Most mainstream classifiers such as SVM and ANN learn from balanced datasets but show poor generalization on the test dataset given imbalanced training datasets.

3) *Complexity*: Learning advanced industrial production processes demands enormous datasets and complex learning algorithms. Machine learning algorithms concentrate on achieving high model accuracy without considering the training cost. As for deep learning, models have been trained deeper and deeper in recent years without too many constraints in terms of the great number of training parameters and weights, leading to high computational costs and significant memory requirements. Therefore, real-time data processing is challenging for most machine learning methods. More importantly, proposed machine learning models should self-adapt to diverse application circumstances and able to address various impact factors such as equipment, human operators, target objects, manufacturing techniques, raw material and working conditions.

4) *Uncertainty*: In CPS smart manufacturing processes, uncertainty sources of the final product quality may originate from several stages, including measurement uncertainty from embedded sensors, input uncertainty and modeling errors from manufacturing processes, resource and communication from network system, environmental uncertainties, and subjective uncertainties from experienced experts. Moreover, these uncertainties are accumulated over time during the manufacturing process, especially for those complex components that require multi-stage manufacturing processes. Without considering the effect of these uncertainty sources, the robustness and generalization of machine learning techniques will significantly degrade.

5) *Black box model*: Most of the machine learning methods train models without domain knowledge and expert experiences. They build the so called 'black box' models to describe input-output relationships using data acquired during manufacturing processes. However, despite the significant performance of machine learning, the learning process is not transparent and the learned weights of a model reflect little information about the model's behavior. In the industrial field where the trust of the model is critical for decision makers, the wide implementation of AI platforms can be considered unreliable without model interpretability. For this reason, maintenance decisions of precision instruments/equipment and key components in military, aerospace and other important industrial fields are still based on previous experience and domain experts. Hence, this calls for understandable, explainable and transparent machine learning models of industrial systems, enabling the clear explanation of the results of the system models to human experts/engineers.

VII. Research prospectives

In response to the abovementioned challenges in smart manufacturing, we identify the following aspects which will

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help manufacturers transfer the IAI from laboratory settings to the factory floor:

1) *Feature engineering*: To deal with imbalanced positive and negative samples, methods including data augmentation, knowledge transfer between similar categories by means of transfer learning, and domain adaptive learning can be used for compensation. Moreover, feature enlargement is used to enhance the diversity of training samples. Especially, unsupervised learning and supervised learning based feature selection methods can be combined to embed high dimensional data into low dimensional spaces, from which hidden features and key information are extracted.

2) *Robustness*: In practical applications, it has been recently shown that machine learning models are vulnerable to uncertainties (i.e., data outliers and measurement noise) of the input data which may cause misclassification [56]. It is possible to enhance the robustness of machine learning model via robust loss functions, parameter regularization, and reliable optimizers. Incorporating uncertainty treatment techniques such as probabilistic modeling into neural network structure provides potential solutions in terms of establishing effective tools to analyze proposed models rigorously.

3) *Generalization*: Accelerated learning algorithms based on stochastic optimization and distributed optimization have been proposed to address large amounts of data, strong individuation, and numerous parameters of deep learning models in industrial production. The super parameters and structure of the model are automatically optimized with intelligent optimization algorithms. Ultimately, industrial artificial intelligence algorithms are expected to possess great generalization ability in order to handle various industrial demands such as monitoring, prediction, diagnosis, and optimization in a fast and portable way .

4) *Interpretability*: The interactive mechanism between the expert experience of industrial production and machine learning models should be established in conjunction with the existing IAI methods. Interpretable IAI includes aspects of explainable feature extraction, explainable machine learning architecture and explainable result evaluation. Essentially, the reasoning process and decision making of the models become transparent, and the users can understand, trust, and manage smart manufacturing systems effectively. In 2016, the U.S. Defense Advanced Research Projects Agency (DARPA) proposed an explainable-AI program to emphasize human-computer interaction in IAI [57]. Lundberg et al. [58] proposed tree-based models with a certain level of interpretability based on game theory for feature attributes. In terms of the time-series data acquired by sensors (e.g., acceleration, voltage, current, and temperature), shapelets method proposed by [59] explored a maximally discriminative sub-sequence of a class of time series data. The identified sub-sequence can be considered as interpretable features to domain experts. As for the image, video, and text data, a recent new concept of machine learning termed attention-mechanism [60] evaluates the specific weights associated with the network layers in determining the relative importance of features among the whole image/video/text, thus ensuring prediction results with higher robustness and interpretability.

VIII. Conclusions

Smart manufacturing is expected to be the next generation of industrial manufacturing. IAI that incorporates AI technologies and the domain knowledge of industry is the primary force that supports AI-powered manufacturing. In general, industrial intelligentization is the inevitable trend of development driven by two leading factors. First, advanced technologies including IoT, cloud computing and cyber technologies enable highly efficient data collection, transmission, storage and management, thus accelerating the generation of massive data. As a result, big data form the foundation for industrial intelligentization. Second, AI technologies such as machine learning, deep learning, transfer learning. have seen substantial development over the past few decades. These methods are characterized by two major attributes that strongly promote the development of smart manufacturing. First of all, most AI algorithms are data-driven, enabling them to make the best use of the availability of big data. In addition, IAI technologies are powered by the end-to-end framework, offering satisfactory performance with low demand of domain knowledge that becomes increasingly difficult to learn from highly complex manufacturing systems in modern industries. Hence, IAI makes industrial intelligentization possible by providing the technological backbone. Overall, IAI technologies bring novel manufacturing modes that possess intelligent characteristics such as self-perception, self-comparison, self-prediction, self-adaptation and self-optimization. Consequently, AI-powered manufacturing is equipped with highly efficient and reliable production chains from manufacturing process to end product logistics.

Production monitoring is one of the key links in the complete production chain, which involves fault diagnosis, remaining useful life prediction and quality inspection. With the development of smart manufacturing, IAI technologies have been widely applied in these three areas where machine learning or deep learning based methods are two major technological drivers. In general, FD, RUL and QI apply common AI based methods (e.g., CNN, GAN, attention mechanism, GNN) to accomplish different tasks while these methods are customized with respect to specific applications. Overall, IAI technologies present remarkable performance in production monitoring and show great potential in the future.

It is believed that the future development of IAI will focus on four aspects, i.e., robustness, generalization, interpretability and analyzability. The former two aim to further improve the applicability of IAI technologies in real world applications. More specifically, IAI algorithms should be robust to uncertainties originating from systems, data, environment. In addition, they are expected to be applicable across different domains for diverse tasks such as monitoring, prediction and diagnosis. As a field that emphasizes risk assessment, industrial manufacturing especially requires causality analysis for model reasoning and decision making. The development of interpretable IAI technologies is attracting increasing attention in smart manufacturing. There is also a trend towards using IAI not only for decision support but also as part of a feedback loop with the ultimate goal of autonomous industrial

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plants, which requires both interpretable and analyzable IAI. The developed models should be analyzed like traditional control systems by considering stability and closed loop signal behavior before commissioning. Analyzable IAI promotes the shift from being focused mainly on quality monitoring and equipment maintenance towards comprehensive plant operations in real world.

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