Review of Key Technologies and Progress in Industrial Equipment Health Management

CHENG PENG1,2, (Member, IEEE), ZHAOHUI TANG2, WEIHUA GUi2, QING CHEN1, LONGXIN ZHANG1, XINPAN YUAN1, AND XIAOJUN DENG1
1School of Computer, Hunan University of Technology, Zhuzhou 412007, China
2School of Automation, Central South University, Changsha 410083, China
Corresponding author: Zhaohui Tang (zhtang@csu.edu.cn)

This work was supported in part by the Natural Science Foundation of China under Grant 61871432 and Grant 61771492; and in part by the Natural Science Foundation of Hunan Province under Grant 2020JJ4275, Grant 2018GK4016, Grant 2019JJ6008, and Grant 2019JJ60054.

ABSTRACT Industrial equipment health management is an extension of traditional fault diagnosis, which is a frontier research field of information science. The definition and application area of industrial equipment health management are first clarified, and then technologies related to health management are introduced, including feature analysis, fault diagnosis, fault prognosis and other technologies. The difficulties and bottlenecks of various technologies are expounded through comparative analysis, and a feasible scheme for future health management and integration is also discussed in this article.

INDEX TERMS Industrial equipment, fault diagnosis, failure prognosis, health management.

I. INTRODUCTION
In 2016, according to the prediction of SPS IPC drives in Pittsburgh, industrial intelligent software will become the key to realizing the intelligence of industrial manufacturing [1]. During the interconnected and complex industrial process, many traditional technologies, such as control, driving, interaction, sensing, and communication, will restrict the further intellectualization of industrial production. In fact, all countries in the world, led by the United States, Germany and China, have invested large amounts of manpower, materials and financial resources in transforming the entire existing industrial chain into a manufacturing industry based on industrial big data analysis [2] to construct truly new manufacturing modes, such as intelligent manufacturing and smart cloud manufacturing. Among them, in the 1990s, from intelligent manufacturing systems (IMSs) [3] to manufacturing partly realized intelligence through the adoption of expert systems, neural networks, fuzzy decision-making and other technologies [4] for process design, fault diagnosis, etc., demonstrate great potential and application value.

Equipment health management (EHM) stemmed from the condition-based maintenance (CBM) [5] system formed in the 1970s and is an important support in intelligent manufacturing. In 1998, the US military launched the F-35 joint fighter program with the aim of reducing maintenance manpower, increasing sorties and achieving autonomous support, which created the conditions for the birth of EHM. In 2005, NASA hosted the first international aerospace forum “Integrated Systems Health Engineering and Management (ISHEM)”, which reinforced the importance of equipment health management. In 2006, the paper on equipment health management published by Kalgren et al. [6] became a ground-breaking research literature in computer science. Meanwhile, the American Information Society (AIS) introduced equipment health management as a new discipline that aimed to use monitoring information and combined various models or algorithms to diagnose, evaluate and predict the equipment health status and to find the optimal maintenance time to realize real-time maintenance of the equipment system. To date, there have been more than 5 international SCI journals, approximately 6 volumes of international conference symposiums, and nearly 500 papers published regarding EHM. Moreover, every year, many internationally renowned academic conferences such as prognosis and health management (PHM), ISHEM have related subjects or research topics. Equipment health management technology has been widely studied by industry and academia and has become a hot spot for research combining computers and other disciplines.

With the advent of industry 4.0 era, as a typical method of equipment supervision, fault diagnosis, prediction and health management are developing in full swing, opening up a new direction for the field of intelligent manufacturing. However, to the best of the author’s knowledge, the review of equipment...
health management methods is still scarce or outdated. Therefore, this article makes a systematic and complete review of equipment health management methods, which means to make up for this gap. The main contributions of this article include: (1) This article reasonably divides a whole program of equipment health management into four technical processes, i.e., fault diagnose, fault prognosis, health state evaluation and remaining useful life (RUL) prediction, and reviews them systematically in order; (2) This article verifies the advantages and disadvantages of relevant typical algorithms through simulation experiments, providing the basis for readers to choose; (3) This article points out the problems and the challenges existing in the current health management methods, and gives a comprehensive review through analyzing large amount of references to provide a systematic perspective for researchers as well as a basic tutorial for beginners.

This article is organized as follows. Section 1 introduces the purpose and significance, generation and development process of equipment health management; the related methods of health management are discussed in Section 2, including equipment fault diagnosis, fault prediction, remaining useful life prediction, health status estimation; Conclusions are drawn in Section 3 with discussions on future challenges as well as opportunities for machinery health management.

II. EQUIPMENT HEALTH MANAGEMENT STATUS AND ANALYSIS

With the increasing safety and reliability issues of industrial equipment, many research institutions at home and abroad have started to study equipment health management since the concept was put forward. At present, the main institutions include San Diego National Laboratory, NASA PCoE Laboratory, University of Cincinnati, University of Maryland, University of Pennsylvania, Georgia Institute of Technology, University of South Carolina and other universities as well as National University of Defense Technology, Dalian University of Technology, and Huazhong University of Science and Technology in China. For a variety of different application areas, researchers have proposed many methods related to health management. In general, health management mainly includes data preprocessing, fault diagnosis, fault prognosis, and health status assessment, among which fault diagnosis and prognosis are indistinguishable during feature extraction, and health status assessment is mainly realized through feature evolution analysis and residual life prediction. The specific implementation process is depicted in figure 1, and its main steps include multisource heterogeneous data acquisition and preprocessing, feature analysis, fault diagnosis, fault prognosis, and state estimation and RUL prediction.

A. MULTISOURCE DATA ACQUISITION AND PREPROCESSING

As depicted in figure 2, data acquisition is mainly divided into internal information system data acquisition and real-time monitoring data acquisition. The data sources of the internal information systems include manufacturing execution systems (MES), enterprise resource planning (ERP), manufacturing management System (MMS), and quality management system (QMS). The real-time monitoring data mainly come from the monitoring system and the data of each sensor node. Based on the enterprise bus, data interface, and other secure file transfer modes, data extraction, and data transmission can be realized automatically by configuring the relevant strategies and defining parameters such as the transmission cycle and frequency.

The data acquired from the industrial production process and various management platforms mentioned above, with the characteristics of multiple sources, different structures, and complex attributes, need to be preprocessed, providing the foundation for feature analysis. At present, the method of data preprocessing mainly includes data marking, rule encapsulation, conflict elimination, noise removal and smoothing processing, as shown in figure 2.

However, data acquisition and preprocessing now face the following challenges: the first challenge is the heterogeneity of the communication environment. The production equipment comes from different manufacturers, and the communication interfaces and protocols of these equipment are different, so connectivity cannot easily be achieved. The second is that high bandwidth, high frequency, and large capacity data are increasingly common in real-time monitoring, and big data processing methods are needed. Finally, the data processing of single sensor data or management platforms hardly meets the needs of analysis, and multisource heterogeneous data fusion needs to be considered.
To realize multisensor real-time data acquisition and aggregation, the research group where the author works has built an intelligent monitoring platform for industrial equipment. The structure of the platform is shown in figure 3. The platform consists of sensors, multi-mode gateway, data center and monitoring center. The multimode gateway is responsible for the data acquisition and data parsing from the first line sensor within the industrial equipment. Sensors mainly include temperature sensor, vibration sensor, pressure sensor, flow sensor, acoustic sensor, and light sensor et al. Different types of sensor data parsing rules can be maintained through the monitoring center, and the multimode gateway automatically updates the local data parsing rule library from the server. Once the data are parsed, they will be sent to the data center through the network for unified storage, and then users maintain different data presentation templates and control policies through the monitoring center for different sensor types and components. The monitoring center calls the corresponding data filling template from the data center according to the component type to realize real-time monitoring and control of the equipment and components. It is worth noting that data fusion can also be adopted to extract higher-level decision-making knowledge for data collected by different sensor. The data fusion methods mainly include Dempster-Shafer (D-S) evidence theory and deep confidence network.

B. FEATURE ANALYSIS

1) FEATURE EXTRACTION

Physics-based methods and data-driven methods are mainly adopted in feature extraction. The physics-based approach includes domain knowledge and expertise, such as signal processing techniques. According to different signal types, the time domain, frequency domain, time-frequency domain, Fourier transform, morphological signal processing, spectral analysis, and other methods are mainly used. Feng et al. [7] summarized the application of more than 20 time-frequency analysis methods, including high-order spectrum, linear or nonlinear, and adaptive parameterization or no parameterization methods in mechanical equipment fault diagnosis. Yan et al. [8] reviewed the progress of wavelet theory over the past 10 years and its applications in fault diagnosis of road vehicles and power grids. For the extraction of complex fault signals, Zhiliang et al. [9] combined the indexes of the time domain signal and frequency domain signal to achieve gear fault diagnosis. To reduce noise interference in
the original signal and solve the difficult problem of complex nonlinear and nonstationary signal fault feature extraction, Yang et al. [10] used a Fourier transform to extract the features from the frequency domain signal of the induction motor, which effectively improved the signal-to-noise ratio. Lei et al. [11] extracted high-quality time and frequency domain features by combining empirical mode decomposition (EMD) and Hilbert demodulation. In addition, many scholars from other countries [12], [13] have devoted their efforts to the underlying research of fault signal processing and feature extraction and have proposed efficient processing methods for modal signals, pulse signals, etc., which are significant contributions to the further development of signal processing and fault diagnosis.

The data-driven method mainly adopts machine learning or statistical methods. As a new method in the field of machine learning [14], deep learning [15] has made brilliant achievements in the fields of image and speech recognition due to its strong automatic feature extraction ability. As one of the classic algorithms of deep learning, the deep belief network (DBN) has successfully solved problems such as information retrieval, dimension reduction and fault classification with its excellent feature extraction and training algorithm. Increasing numbers of domestic and foreign scholars have paid attention to this field and made many achievements. Tran et al. [16] achieved a higher fault identification rate in the fault diagnosis of reciprocating compressor valves by combining the DBN and the Teager-Kaiser energy operation (TKEO) algorithm. Shao et al. [17] combined particle swarm optimization (PSO) and DBN and acquired better identification accuracy in the absence of prior fault information for rotary bearings. However, these methods also have obvious shortcomings. When using the DBN algorithm to extract fault features and identify the health status of collected fault signals, most of the signals are frequency domain signals, and when the signals are not periodic, this method fails and is not generic.

2) FEATURE SELECTION

The key to feature selection is how to select vital feature information, filter out redundant and insensitive information, reduce dimensions and ensure that the information entropy is unchanged. At present, the commonly used selection methods are based on single criterion and multiple criteria. The single criterion mainly includes Fisher discrimination, information gain, kernel density estimation, the distance between classes, and manifold learning [18]. However, the single criterion method ignores the influence of other related factors in feature selection and has limitations. For this reason, researchers [19], [20], [21] successively proposed a feature selection method that combines two or three criteria, such as sensitivity, class divergence, and spatial arrangement, as selection criteria to realize constraint mapping of multidimensional feature vectors to low-dimensional spaces, which improves the accuracy and information integrity of feature selection to some extent, but the calculation process is complicated.

3) FEATURE TRANSFORMATION

In terms of feature transformation, Pearson [22] first proposed the principal component analysis (PCA) algorithm, which is mainly used to analyze data with a high linear correlation and decompose the feature parameter space into a low-dimensional principal element space and residual space. However, the PCA algorithm needs to assume that the data sample space is subject to a normal distribution, which may not be consistent with the actual application; therefore, Comon [23] proposed the independent component analysis (ICA) method to transform the data of a multivariable system with a nonnormal distribution into an independent part to isolate the hidden noise and realize dimension reduction. Similarly, ICA ignores the time correlation of data, while the collection of working condition data mostly contains a temporal relation. Therefore, the partial least squares (PLS) algorithm [24] and time series analysis (TSA) algorithm [25] were designed. For the dimension reduction process of the above methods, linear reduction is often adopted, but it is not suitable for nonlinear systems. Li et al. [26] proposed the nonnegative matrix factor (NMF) method to achieve the characteristic data dimension reduction of complex nonlinear systems.

In addition, how to use sensor data obtained from different sources, time and space is a common problem. To quickly and accurately extract, sort out, merge and refine multisensor data, researchers have introduced data fusion methods into the fault diagnosis of complex equipment and made some progress. Among them, there are many studies on neural networks, support vector machines (SVMs), Dempster-Shafer (D-S) evidence theory, fuzzy logic [27], and rough set theory [28]. SVM was adopted to fuse multisensor data for engine fault diagnosis in reference [29]. Literature [30] combined a neural network with D-S evidence theory to realize turbine fault diagnosis. However, the above methods also face the identification, extraction, transformation and other fusion problems of multi-source, heterogeneous, large-scale and cross-domain data in the industrial production process, which needs to be further studied.

C. FAULT DIAGNOSIS

As the basis of equipment health management, fault diagnosis technology mainly evaluates the health status of the equipment system by calculating the statistics of the fault proportion and fault distribution over a period of time. In general, the mechanical manufacturing system is composed of six main independent parts, and different combinations of these parts are used to form different production lines to produce different products. A large number of studies have shown that these 6 components are the most common locations for fault occurrence. The probability of failure occurrence, common fault types and maintenance solutions adopted by enterprises are shown in Table 1. It is not difficult to find that under
TABLE 1. Common fault modules, fault type and maintenance strategy.

| Fault modules & ratio | Fault type & ratio | Maintenance technique & ratio |
|-----------------------|-------------------|------------------------------|
| Machining 6%          | Crack 11%         | Experience & Record 52%      |
| Transmission 31%      | Leakage & Emission 12% | Enterprise Resource Planning 12% |
| Driver 22%            | Vibration 23%     | Manufacturing Execution Systems 4% |
| Hydraulic 16%         | Heat 35%          | Manufacturing Management Systems 8% |
| Power 12%             | Halt 8%           | Quality Management Systems 20% |
| Control 13%           | Disconnection & Deformation 11% | PHM systems 4% |

the existing technical conditions, large enterprises are likely to deploy a PHM system, and small enterprises still mostly adopt traditional fault maintenance methods.

According to different analysis objects and processing methods, fault diagnosis methods include physical-based methods, data-driven methods, and hybrid methods. Physical-based methods can be divided into knowledge-based and model-based methods.

1) MODEL-BASED METHOD
The model-based method is relatively mature in theory for studying the fault mechanism and identifying and revealing the cause of the fault. Bachschmid and Pennacchi [31], Robert [32] and Sekhar [33] successively studied the crack model, mechanism and dynamic behavior of the rotor. Yang et al. [34] classified the fault mode and fault mechanism of the locomotive power supply, Glodez et al. [35] studied the evolution law of gear fault characteristics and revealed the fault mechanism of gears. Jue and Huaping [36] conducted an in-depth study on the failure mechanism of complex electromechanical systems. Jinji [37] studied the vibration mechanism and feature recognition of rotating mechanical arms and proposed the fault self-healing principle. Wang and Shen [38] analyzed the fault characteristics of rail vehicle wheels and proposed three methods to diagnose faults in vehicle wheelsets. The basic research on fault diagnosis is discussed in literature [39], and it is acknowledged that the research on fault diagnosis mechanisms is currently insufficient; the dynamics of fault evolution of complex equipment systems under special working environments need to be further studied. In summary, the model-based diagnosis method is based on systematic mathematical or physical models. The establishment of the model requires a large amount of mathematical and mechanical knowledge; additionally, it is difficult to avoid errors and unknown interference in the modeling process.

2) KNOWLEDGE-BASED METHOD
The knowledge-based fault diagnosis method constructs a knowledge base that relies on domain expert experience and fault information and simulates the process of expert reasoning and matching with the algorithm to realize fault diagnosis. It is widely used in electric power [40], rail transit, and aviation [41]. Due to the parallel processing ability, graphical reasoning process and good fault tolerance of the incomplete fault information of Petri net, Sun et al. [42], Ran and Qiu [43], Luo and Kezunovic [44] and Xie and Tong [45] performed formal reasoning and modeling analysis and realized the diagnosis of grid fault through simulation experiments by using fuzzy Petri net, weighted fuzzy Petri net, directional weighted fuzzy Petri net and hierarchical fuzzy Petri net, respectively. On this basis, Yaxiong et al. [46] proposed a grid fault diagnosis expert system based on the combination of an improved dynamic adaptive fuzzy Petri net and a BP algorithm. In addition, some scholars have carried out research on expert systems based on Fault-tree [48], multiagent [49], knowledge automatic push [50], etc., as well as methods combining multiple technologies [51], which enriched and developed knowledge-based fault diagnosis methods from different perspectives. In summary, the diagnosis results of the knowledge-based method are influenced by the degree and level of expert experience in the knowledge base. In fact, all kinds of decision-making parameters in the reasoning model, such as confidence, threshold, and weight, are given by artificial experience, which leads to poor adaptive and self-learning abilities. Obviously, there are still problems in knowledge acquisition and matching speed.

3) DATA-DRIVEN METHOD
The data-driven method finds the mapping relation between the hidden feature space and fault space through numerical calculation and identifies the normal mode and fault mode of the system to realize fault diagnosis. Machine learning algorithms and statistical methods are generally adopted. Machine learning methods include artificial neural networks (ANNs), Bayesian networks (BNs), support vector machines (SVMs), and hidden Markov models (HMMs). Li and Chenyuan [52] adopted the cross entropy support vector machine (CE-SVM) method to solve the problem of connection line faults in a grid. Fault diagnosis based on the fusion of BN and other methods was proposed in literature [47], which studied fault diagnosis for a high-speed rail for the first time. Zhou et al. [53] designed the gear fault diagnosis method of HMM and improved the range measurement.
Recently, some scholars have proposed semisupervised and nonsupervised learning methods, semisupervised spectral nuclear learning methods [54] and nonsupervised deep learning methods [55] as representative approaches. Statistical methods mainly include the autoregressive moving average (ARMA), gamma process, and Wiener process.

To verify the efficiency and accuracy of the above algorithms, this article takes the open data set of a time series collected during the bearing running period as the research object. The data set contains a total of 1731*3 operating records with three different parameters, including temperature, rotation speed and rotation accuracy, by injecting fault information. The above typical algorithms, such as BN, ANN, HMM and SVM, were used for fault diagnosis testing. The experiment was implemented through MATLAB simulation, and the experimental results were the average of 100 iterations. Figure 4 shows the running time complexity comparison curve, and figure 5 depicts the fault diagnosis accuracy comparison results.

Based on the comparison of the experimental results, the above methods are inseparable from the training and testing of samples. SVM requires fewer training samples and has high calculation efficiency, but it lacks consideration of sparse samples, the determination of the kernel function lacks theoretical support, and the accuracy rate of fault diagnosis is low. BN has a certain processing capacity for incomplete data but needs prior knowledge support. Without prior knowledge, the model cannot be constructed. BN also requires a large number of training samples and has low fault diagnosis accuracy. The interpretation ability and computational efficiency of HMM are good, but the classification accuracy is not high. ANN requires a long training time, but it has strong robustness and fault tolerance to noise, does not rely on prior knowledge, and has strong learning ability, under the same conditions, the classification accuracy is better than other methods.

In summary, fault diagnosis technology based on data-driven methods has achieved a variety of research results. However, on the one hand, in the complex industrial production process, the data produced by industrial equipment come from various sources and types and require complex mathematical operations and a large number of signal processing technologies to extract fault feature information, which is inefficient and costly; on the other hand, the training process is highly dependent on the data samples, which leads to the limited processing abilities of classifiers for dealing with early-stage faults, weak faults, unknown faults, complex faults and intermittent faults. In addition, the existing multisource data fusion methods mainly aim at multisensor data. Therefore, how to efficiently extract the feature information and realize dimension reduction, rapid retrieval, and the fusion of multisource heterogeneous big data is one of the hot spots in current research.

D. FAULT PROGNOSIS

Fault prognosis is an important part of equipment health management technology. It refers to the predictive diagnosis of the future health status of equipment components or systems based on the current or effective historical performance status of the equipment, including the probability of a failure or defect at some point in the future. In essence, fault prognosis is an extension of fault diagnosis. In general, fault prognosis methods can be divided into two categories: model-based methods and data-driven methods.

1) MODEL-BASED METHOD

For the model-based fault prognosis, the future running state of the system is simulated according to the accurate mathematical model of the system, which mainly includes Kalman filtering, particle filtering, and other methods. The Kalman filter method was adopted by Sun et al. [56] to realize fault prediction in complex systems with missing data and to evaluate the fault state. Du et al. [57] proposed a method based on the hybrid adaptive particle filter to solve the fault prediction problem of a three-capacity system. The premise of such methods is to know the fault modes of the components or systems and to build models of the failure mechanisms.
that cause loss or damage to key components of the system and the physical and stochastic processes related to the accumulated effect of the faults. In addition, the fault features that emerge in the operation process are closely related to the model parameters. Therefore, the prediction precision is greatly influenced by the accuracy of the model. At present, the model-based method is mainly used in fault prediction of electromechanical systems, such as rotary mechanical arms; however, for complex industrial equipment systems such as rail transit and power systems, the study of fault prediction is relatively insufficient due to the complexity of the fault modes and mechanisms, and it is difficult or almost impossible to establish mathematical models.

2) M DATA-DRIVEN METHOD

The data-driven prognosis is based on the data collected from a sensor and fits the functional relationship between the implied time and fault trend in the data set to achieve fault prognosis and residual life judgment; the prognosis method mainly includes machine learning and statistical analysis. The representative methods of machine learning include artificial neural networks (ANNs) and other relevant artificial intelligence methods. The aging and health trend prediction of rotating bearings was discussed by Zhu et al. [58] with the self-organizing neural network. Hong et al. [59] proposed a regression neural network method for fault prediction and health evaluation of large-scale storage systems. With the development of artificial intelligence methods, hidden Markov models, support vector machines, decision trees, data mining and other methods have also been applied in fault prognosis. Peng et al. [60] constructed a dynamic behavior model for industrial networking software by mining log documents generated during the operation of an industrial software system and extracting behavioral sequences satisfying custom invariant constraint relations; this model provided the basis for further fault diagnosis and prognosis. Data-driven fault prognosis technology is relatively practical. However, on the one hand, the acquisition cost of typical data, such as fault injection data and simulation experiment data of industrial equipment, is relatively high. On the other hand, the existing methods for dealing with such data are limited, which makes it more difficult to realize fault prognosis technology.

To make a more accurate comparison and analysis, we selected typical algorithms, including ANN, BN, SVM and HMM, for the experiment. The SCADA data set of monitored wind turbine operation collected over 2 weeks was adopted. The dataset contains approximately 90,000 records; among them, normal data records account for 83.6%, abnormal data records account for 15.2%, and unknown error data records account for 1.2%. This article compares the early warning ratio and false alarm ratio: (1) early warning ratio: the proportion of abnormal type records detected by the model but not verified in the total data set records. (2) False alarm ratio: the ratio of the number of records wrongly judged by the model to the number of records in the whole normal data. The experimental results are shown in Fig. 6 and Fig. 7, respectively.

As shown in the above figures, when the amount of data is large, although ANN takes a long time to train, ANN has an associative memory function and can fully approximate the complex nonlinear relationship in the time series, once the training data set reaches a certain scale, the performance of the algorithm tends to be stable, with the highest early-warning ratio and the lowest false alarm ratio. HMM has a certain prediction effect on the incomplete data set, with a higher early-warning ratio, but its premise hypothesis, such as signal conformity with monotony, is not necessarily consistent with practical application, leading to a higher false alarm ratio. BN also needs a large number of training samples, and the predicted results are sensitive to the early distribution; it has uncertainty, with the lowest early-warning ratio and the highest false alarm ratio. The problem of confidence setting and selection was not considered by SVM, the early-warning ratio and false alarm ratio were affected to some extent, and the results were not satisfactory.
For the statistical analysis method, the fault probability density function (PDF) is calculated by the historical fault data and combined with the recently obtained sample data; then, the prediction results with a certain confidence are calculated by the algorithm. It is found that the “bathtub curve” can well describe the failure rule and failure rate during the system life cycle. NASA also classifies complex equipment failures into five constant probabilities. In addition, a large number of experiments found that the system failure was subject to the Weibull distribution over time. Therefore, the Weibull model is widely used in fault predicting of components or equipment [61]. The typical forecasting algorithms include Bayesian networks, fuzzy logic, and some combination of forecasting algorithms. However, the above methods are affected by factors such as equipment process characteristics, production line changes, and efficiency degradation within the life cycle. There are also some other problems: the process of fault prediction is complex, the reliability of the prediction results is low, and the fault false alarm ratio is high. These problems need further study.

E. RUL PREDICTION

The purpose of RUL prediction is to determine the life probability distribution of equipment according to the effective information such as failure mechanism, degradation data, energy efficiency monitoring, condition evaluation, etc. Based on the comprehensive analysis of the correlation of existing literature and the evolution relationship between different methods, and according to the basic principle and technology of RUL prediction, the prediction methods of equipment residual life are generally divided into physical model based method, statistical model based method and machine learning method.

1) PHYSICAL MODEL BASED METHOD

The method based on the physical model adopts stress and damage mechanics analysis to study the life evolution process and rule of equipment caused by physical and chemical changes, and infer its remaining life. The common physical and chemical effects of equipment include wear, corrosion, deformation and fracture. Therefore, the method based on cumulative fatigue damage and fracture mechanics is relatively mature and widely used in failure analysis and RUL prediction. However, for some complex mechanical systems, such as rotating machinery, the generation of damage and fracture is the product of the comprehensive action of electromagnetic, thermal, dynamic and other physical fields, and its internal change mechanism and evolution law are still not easy to understand, so it is difficult to establish a physical model, which greatly limits the application of such methods.

2) STATISTICAL MODEL BASED METHOD

The statistical model-based method fits the effective failure data and performance degradation data into a random coefficient model or a random process model under a probability framework to estimate the conditional probability distribution of the remaining life of the equipment. With the development of monitoring technology, degradation data reflecting system performance or health status are easier to obtain, such as wear and crack data, etc. The remaining life prediction method based on degradation data has received extensive attention and research. These methods include Markov process based method, gamma process based method, inverse Gaussian process based method and Wiener process based method. Although the effects of non monotonicity, nonlinearity, uncertainty and different failure modes on the degradation process are considered, the influence of equipment health status on the degradation process is not thought over.

3) MACHINE LEARNING METHOD

The method based on machine learning uses artificial intelligence technology to learn the degradation mode of equipment from monitoring data. This method has attracted more and more attention in the field of RUL prediction. The number of relevant research literature is only second to the method based on statistical model. According to the level and scale of the machine learning model structure, it is divided into shallow machine learning methods and deep learning methods. Shallow machine learning methods mainly include Artificial Neural Network (ANN), Support Vector Machine (SVM), and Neural Fuzzy System (NFS).

Deep learning is a new technology developed on the basis of neural networks. According to different network structures, there are mainly recurrent neural networks (RNN), convolution neural networks (CNN), deep belief networks (DBN) and deep neural networks (DNNS) are used for RUL prediction. The method based on machine learning has made great progress, but the prediction performance of the model largely depends on the design of model structure and function. In order to obtain valuable features, a lot of time will be spent in feature extraction and selection, and complete prior knowledge is required. The function of the model is usually designed according to the specific situation, which lack of universality.

F. HEALTH MANAGEMENT TECHNOLOGY

Health management technology is mainly based on the above characteristics analyses, fault diagnosis, fault prognosis, and status analysis of industrial equipment. Through the above analyses, all relevant papers in recent years were searched, and the methods were categorized in this article, as shown in the following figures. Fig. 8 shows the variation of publication numbers over the past 20 years regarding the topic of prognosis and health management of industrial equipment. The total number is 373, which was calculated based on a search result from the Web of Science. The number of publications has been increasing rapidly since 2006. The total number of publications from 1999 to 2010 was 100, while the number of publications in the last five years was 198, which is much larger than the total number in the first 10 years. Fig. 9 shows the ratio of approaches adopted in the publications and the components most frequently researched.
In fact, the U.S. military first proposed the concept of equipment health management. Subsequently, the Ministry of National Defense developed and used equipped health management systems, such as the spacecraft integrated health management system, aircraft status monitoring system, engine monitoring system, and integrated diagnosis and prediction system. More than 180 types of helicopters, including the army’s ah-64 apache, uh-60 black hawk, are installed with health management systems. The F35 joint strike fighter equipped with health management software reduced its troubleshooting time by 94% compared with the original and improved the efficiency of maintenance [62]. From the civil aspect, the “Aircraft Status Management” system developed by Boeing has been adopted by many airlines. According to the preliminary estimation by Boeing, the use of the system can decrease airlines costs due to flight delay or cancellation by approximately 25% and improve flight safety and operation efficiency [63]. In the space field, the intelligent maintenance system (IMS) and IMS-based anomaly monitoring sensing software have been designed to perform analysis and health monitoring for the thermal control system of the international space station [64].

In addition, relevant institutions have conducted a large number of studies. In addition to the American universities mentioned above, the US National Laboratory of San Diego, the US Department of Energy, Industry, and Academia establish equipment fault prognosis and health state management centers to develop and test health management technology [65]. The health management architecture based on logical layering proposed by the Boeing Research Center has become the basic idea for the top design of PHM systems [66]. The framework divides the PHM system into seven functional levels: data acquisition layer, data processing layer, state monitoring layer, diagnostic prediction layer, health evaluation layer, decision support layer and display layer. Other countries, such as the Netherlands, have also established a corresponding industrial equipment health management system; the PRoMI system of the Netherlands characterizes the physical state of equipment with continuously measured health status parameters and predicts the residual
life of components through the life model and the expected system load.

In China, the research and application of health management technology started relatively late. In recent years, many universities and scientific research institutions have carried out research on basic algorithms such as equipment health management architecture, related fault diagnosis and prognosis. The department of industry and information and the CALCE research center of the University of Maryland became the first research institution to study the health management of equipment. Research institutions such as the Reliability Engineering Research Institute of Beijing University of Aeronautics and Astronautics, 634 Institute of Aeronautics, Central China University of Science and Technology, and Key Laboratories of National University of Defense have conducted many studies on the law of equipment health recession, fault prediction models and health management technology. In May 2016, Tongji University cooperated with the National Instrument Company of the United States and established an industrial Internet experiment center, which became the first intelligent laboratory with the whole factor of industry 4.0 in China.

The equipment manufacturing industry in China has also begun to pay attention to equipment health management technologies. With the development and breakthrough of data monitoring and fault diagnosis, these technologies have been adopted in practical applications such as command monitoring, space-time monitoring, and macro decision-making. For example, the spatial-temporal monitoring platform developed by the Sany Heavy Industry Company can optimize the transportation process of stirred vehicles by collecting location and oil level data to avoid congestion and reduce waiting and energy consumption. The fault diagnosis system of the pump truck of Zoomlion can quickly locate the fault and find the cause by gathering and integrating the real-time operating data of the hydraulic system of the pump truck. The general intelligent and information control platform developed by the Zhongche Zhuzhou Electric Locomotive Research Institute meets the requirements of vehicle-ground wireless communication, multisource information fusion and intelligent decision-making, which solves the problems of heterogeneous multitype data acquisition, data fusion and collaborative computing among various equipment between the vehicle and ground.

### III. CONCLUSION

The above research results have promoted the development of health management, but they generally have the following problems. First, at present, the data source is single and mainly from real-time sensor data. There are few fusion and calculation methods for other data sources, and the computational efficiency and accuracy of fault diagnosis need to be improved. Second, the results of the equipment health state assessment obtained by the above methods are a qualitative description, that is, healthy or unhealthy. The flexibility, effectiveness, and adaptability are limited because of the absence of quantitative analyses; in fact, the quantitative analyses are more detailed and closer to the actual health state.

Thus, we can conclude that although equipment health management has made great progress and gained remarkable achievements, there is still no effective way to solve the above problems. Therefore, it is urgent to propose new theories and methods to improve the practical application effect of these technologies, and we can predict the main problems that need to be further studied in the future:

The first problem is that under the background of industrial production transformed from automation to intelligence, the realization of intelligent manufacturing is inseparable from the interconnection between the equipment. The Industrial Internet of the United States, Industry 4.0 of Germany, and China Manufacturing 2025 are the core features of intelligence and interconnection, and interconnection is the premise and foundation of intelligence.

To solve this problem, we may face three challenges. First, the heterogeneity of the communication environment. Because the equipment comes from different manufacturers, the communication interfaces and protocols are different, the semantics of the data from different devices are incomprehensible, and the devices cannot communicate with each other, which makes it difficult to achieve interactive collaboration. Second, there is a high bandwidth of data communication. With the development of intelligence, the production site is no longer limited to traditional small-scale data interactions. With the introduction of new technologies such as video analysis, video detection and vibration waveform analysis, the proportion of high-frequency and large-capacity data is becoming common in the industrial field; therefore traditional industrial buses are not available for carrying high-bandwidth data communication. Third, the equipment access is increasingly flexible. Due to rapid equipment upgrades and mobile equipment access, traditional industrial networks cannot meet the flexible, convenient and extensible access requirements of equipment.

The second problem is that the increasing functional requirement and complexity of equipment has made industrial equipment transition from traditional mechanization to the machine of electricity, light, and gas (steam) integration, which brings great challenges to the monitoring and maintenance of industrial equipment and mainly includes three aspects:

First, the heterogeneity of monitoring objects. Due to the diversity of equipment and the complexity of internal unit structures, monitoring objects are typically heterogeneous and manifest through different dimensions, scales, monitoring frequencies, and data presentation requirements; thus, new requirements regarding the openness and adaptability of equipment monitoring are proposed. Most traditional monitoring systems are only suitable for specific equipment with limited monitoring objectives and a low degree of automation, which greatly affects the instantaneity, accuracy, and intelligence of maintenance and reduces the efficiency of equipment.

VOLUME 8, 2020
Second, the dimension of the health indicator is high. The application of physical information systems in the industry has triggered a new industrial revolution, which makes it possible for equipment health management to change from traditional breakdown maintenance to beforehand health assessment and prognosis. Health evaluation results are extended from the traditional “failure or not” to multivalue states (such as subhealth), and the equipment health indicators are becoming high-dimensional; the above leads to the requirement that evaluation and prediction rely on multiple different health indicators, and traditional methods are not suitable.

Third, component relationships are complex, and operational models are difficult to construct. It is difficult to establish an accurate mathematical model for equipment to describe the efficiency change, cost, and energy consumption of the maintenance process due to its various types and complex and mutual influence among components.

Therefore, it is meaningful to study the intelligent monitoring technology of industrial equipment to realize full state, whole process, real-time and intelligent monitoring. It is important to apply health assessment and prediction technology based on multidimensional big data fusion to realize advanced warning and intervention. It is also necessary to conduct research on 3D visual evolution simulation technology to analyze key factors such as efficiency change, fund input and energy consumption, to provide scientific support for operation and maintenance planning and decision-making, and to offer intuitive, clear and friendly interfaces.

ACKNOWLEDGMENT
Prof. Peng completes the experiment and writing of the article. Prof. Tang and Academician Gui give the overall idea of the article and the main development direction at present. Prof. Chen and Prof. Yuan give suggestions and amendments. Thank all the authors for their contributions to this article, editors and reviewers for their hard work.

REFERENCES
[1] SPS: Accessed: Jun. 18, 2020. [Online]. Available: https://www.mesago.de/en/SPS/For_visitors/Facts_figures/index.htm
[2] W. Xue, Q. Li, and Q. Xue, “Text detection and recognition for images of medical laboratory reports with a deep learning approach,” IEEE Access, vol. 8, pp. 407–416, 2020.
[3] T. P. Raptis, A. Passarella, and M. Conti, “Data management in industry 4.0: State of the art and open challenges,” IEEE Access, vol. 7, pp. 97052–97093, 2019.
[4] Y. Hu, S. Liu, H. Lu, and H. Zhang, “Remaining useful life model and assessment of mechanical products: A brief review and a note on the state space model method,” Chin. J. Mech. Eng., vol. 32, no. 1, pp. 130–211, Dec. 2019.
[5] A. K. S. Jardine, D. Lin, and D. Banjevic, “A review on machinery diagnostics and prognostics implementing condition-based maintenance,” Mech. Syst. Signal Process., vol. 20, no. 7, pp. 1483–1510, Oct. 2006.
[6] P. K. B. Roemer, “Defining PHM, a lexical evolution of maintenance and logistics,” in Proc. IEEE Autotestcon, Sep. 2006, vol. 25, no. 4, pp. 353–358.
[7] Z. Feng, M. Liang, and F. Chu, “Recent advances in time–frequency analysis methods for machinery fault diagnosis: A review with application examples,” Mech. Syst. Signal Process., vol. 38, no. 1, pp. 165–205, 2013.
[8] R. Yan, X. Gao, and X. Chen, “Wavelets for fault diagnosis of rotary machines: A review with applications,” Signal Process., vol. 96, pp. 1–15, Mar. 2014.
[9] L. Zhiliang, P. Deng, and Z. Mingjiang, “A review on fault diagnosis for rail vehicles,” J. Mech. Eng., vol. 52, no. 14, pp. 134–146, 2016.
[10] T. Yang, H. Pen, and Z. Wang, “Feature knowledge based fault detection of induction motors through the analysis of stator current data,” IEEE Trans. Instrum. Meas., vol. 65, no. 3, pp. 549–558, Mar. 2016.
[11] Y. Lei, Z. He, Y. Zi, and Q. Hu, “Fault diagnosis of rotating machinery based on multiple ANFIS combination with GAS,” Mech. Syst. Signal Process., vol. 21, no. 5, pp. 2280–2294, Jul. 2007.
[12] S.-H. Wang, T.-M. Zhan, Y. Chen, Y. Zhang, M. Yang, H.-M. Lu, H.-N. Wang, B. Liu, and P. Phillips, “Multiple sclerosis detection based on biorthogonal wavelet transform, RBF kernel principal component analysis, and logistic regression,” IEEE Access, vol. 4, pp. 7567–7576, 2016.
[13] R. Alzubi, N. Ramzan, H. Alzoubi, and A. Amira, “A hybrid feature selection method for complex diseases SNPs,” IEEE Access, vol. 6, pp. 1292–1301, 2018.
[14] A. Elkharar, R. Al-Debsi, and O. Eimea, “Arabic text classification using deep learning models,” Inf. Process. Manage., vol. 57, no. 1, 2020, Art. no. 102121.
[15] M. Limmer, J. Forster, D. Baudach, F. Schüle, R. Schweiger, and H. P. A. Lensch, “Robust deep-learning-based road-prediction for augmented reality navigation systems at night,” in Proc. IEEE 19th Int. Conf. Intell. Transp. Syst. (ITSC), 2016, pp. 1888–1895.
[16] V. T. Tran, F. AliThobiani, and A. Ball, “An approach to fault diagnosis of reciprocating compressor valves using Teager–Kaiser energy operator and deep belief networks,” Expert Syst. Appl., vol. 41, no. 1, pp. 4113–4122, 2019.
[17] H. Shao, H. Jiang, and X. Zhang, “Rolling bearing fault diagnosis using an optimization deep belief network,” Meas. Sci. Technol., vol. 26, no. 11, pp. 423–435, 2015.
[18] C. Peng, Z. Tang, W. Gui, and Q. Chen, “A bidirectional weighted boundary distance algorithm for time series similarity computation based on optimized sliding window size,” J. Ind. Manage. Optim., vol. 13, no. 5, pp. 211–225, 2019.
[19] P. Yang, B. B. Zhou, Z. Zhang, and A. Y. Zomaya, “A multi-filter enhanced genetic ensemble system for gene selection and sample classification of microarray data,” BMC Bioinf., vol. 11, no. 51, pp. 1–12, Jan. 2010.
[20] Z. Liu, J. Qu, M. J. Zuo, and H.-B. Xu, “Fault level diagnosis for planetary gearboxes using hybrid kernel feature selection and kernel Fisher discriminant analysis,” Int. J. Adv. Manuf. Technol., vol. 67, nos. 5–8, pp. 1217–1230, Jul. 2013.
[21] K. Zhang, Y. Li, P. Scarf, and A. Ball, “Feature selection for high-dimensional machinery fault diagnosis data using multiple models and random basis function networks,” Neurocomputing, vol. 74, no. 17, pp. 2941–2952, Oct. 2011.
[22] K. Pearson, “Principal component analysis,” J. Science, vol. 6, no. 2, pp. 559–572, 1901.
[23] P. Comon, “Independent component analysis, a new concept?” Signal Process., vol. 36, no. 3, pp. 287–314, Apr. 1994.
[24] H. Abdi, “Partial least squares regression and projection on latent structure regression (PLS Regression),” Wiley Interdiscip. Rev. Comput. Statist., vol. 2, no. 1, pp. 97–106, 2010.
[25] F. Cong, J. Chen, G. Dong, and F. Zhao, “Short-time matrix series based singular value decomposition for rolling bearing fault diagnosis,” Mech. Syst. Signal Process., vol. 34, nos. 1–2, pp. 218–230, Jan. 2013.
[26] B. Li, P.-L. Zhang, D.-S. Liu, S.-S. Mi, G.-Q. Ren, and H. Tian, “Feature extraction for rolling element bearing fault diagnosis utilizing generalized t-transform and two-dimensional non-negative matrix factorization,” J. Sound Vib., vol. 330, no. 10, pp. 2388–2399, May 2011.
[27] M. Latinovic, I. Dragovic, and V. B. Arsic, “A fuzzy inference system for credit scoring using Boolean consistent fuzzy logic,” Int. J. Comput. Intell. Syst., vol. 11, no. 1, pp. 414–427, 2018.
[28] H. Gao, W. Huang, and X. Yang, “Applying probabilistic model checking to path planning in an intelligent transportation system using mobility trajectories and their statistical data,” Intell. Automat. Soft Comput., vol. 25, no. 3, pp. 547–559, Jan. 2019.
[29] T. P. Banerjee and S. Das, “Multi-sensor data fusion using support vector machine for motor fault detection,” Inf. Sci., vol. 217, pp. 96–107, Dec. 2012.
[30] C. Xu, H. Zhang, D. Peng, Y. Yu, C. Xu, and H. Zhang, “Study of fault diagnosis of integrate of D-S evidence theory based on neural network for turbine,” Energy Procedia, vol. 16, pp. 2027–2032, 2012.
Q. Guangqi, G. Yingkui, and C. Junjie, "Selective health indicator for...

L. Ren, X. Cheng, X. Wang, J. Cui, and L. Zhang, "Multi-scale dense...

B. Li and B. Chenyuan, "Power grid fault diagnosis using cross entropy...

W. Bing, Z. Hongquan, and S. Kai, "Knowledge push fault diagnosis of...

Z. Yang, X. Tianhua, and Z. Yuping, "Study on fault diagnosis method...

M. M. Rashid, M. Amar, and I. Gondal, "A data mining approach for...

W. Yaxiong, X. Min, and Y. Yuyuan, "Grid fault diagnosis based on...

X. Luo and M. Kezunovic, "Implementing fuzzy reasoning Petri-nets for fault section estimation," IEEE Trans. Power Del., vol. 23, no. 2, pp. 676–685, Apr. 2008.

H. Xie and X. Tong, "A method of synthetical fault diagnosis for power systems based on fuzzy hierarchical Petri net," Power System Technol., vol. 36, no. 1, pp. 246–252, 2012.

W. Xayiong, X. Min, and Y. Yuyuan, "Grid fault diagnosis based on improved dynamic adaptive fuzzy Petri net and BP algorithm," J. China Electr. Eng., vol. 35, no. 12, pp. 2008–3017, 2015.

Z. Yang, X. Tianhua, and Z. Yaping, "Study on fault diagnosis method of on-board equipment of high-speed railway signal system based on Bayesian network," J. Railway Eng., vol. 11, pp. 48–53, 2019.

M. Sun, X. Tong, and X. Liu, "Apower system fault diagnosis method using temporal Bayesian knowledgebases," Power System Technol., vol. 38, no. 3, pp. 715–722, 2017.

M. M. Rashid, M. Amar, and I. Gondal, "A data mining approach for machine fault diagnosis based on associated frequency decision," Appl. Intell., vol. 45, no. 3, pp. 638–651, 2019.

G. Niu, T. Han, B.-S. Yang, and A. C. C. Tan, "Multi-agent decision fusion for motor fault diagnosis," Mech. Syst. Signal Process., vol. 21, no. 3, pp. 1285–1299, Apr. 2007.

W. Bing, Z. Hongquan, and S. Kai, "Knowledge push fault diagnosis of multi-sensor integrated hydrogen detection system," Opt. Precis. Eng., vol. 23, no. 6, pp. 1742–1748, 2016.

B. Li and B. Chenyuan, "Power grid fault diagnosis using cross entropy support vector machine and fuzzy integral," J. Motor Control, vol. 20, no. 2, pp. 112–120, 2016.

Z. Zhou, C. Yang, and C. Wen, "Random projection based k Nearest Neighbor rule for semiconductor process fault detection," in Proc. 33rd Chin. Control Conf., Jul. 2014, pp. 3169–3174.

L. Ren, X. Cheng, X. Wang, J. Cui, and L. Zhang, "Multi-scale dense gate recurrent unit networks for bearing remaining useful life prediction," Future Gener. Comput. Syst., vol. 94, pp. 601–609, May 2019.

Q. Guangqi, G. Yingkui, and C. Junjie, "Selective health indicator for bearings ensemble remaining useful life prediction with genetic algorithm and Weibull proportional hazards model," Measurement, vol. 15, no. 6, pp. 69–80, 2020.

S. Wenjun, S. Siyu, and Y. Ruqiang, "Fault diagnosis of induction motors based on sparse automatic coding depth neural network," J. Mech. Eng., vol. 52, no. 9, pp. 65–71, 2016.

D. B. Du, W. Zhang, and C. H. Hu, "A failure prognosis method based on Wavelet-Kalman filtering with missing data," Acta Automatica Sinica, vol. 40, no. 10, pp. 2115–2125, 2014.

K. Zhu, Z. Chen, and Y. Bo, "A new hybrid adaptive particle filter algorithm for fault prediction," J. Inf. Comput. Sci., vol. 9, no. 14, pp. 3939–3946, 2012.

S. Hong, Z. Zhou, E. Zio, and W. Wang, "An adaptive method for health trend prediction of rotating bearings," Digit. Signal Process., vol. 35, pp. 117–123, Dec. 2014.

P. Cheng, Y. L. Ming, and M. J. Feng, "Dynamic modeling of networked software interactive behavior," Acta Electronica Sinica, vol. 41, no. 2, pp. 314–320, 2013.

J. Ben Ali, B. Chebel-Morello, L. Saidi, S. Malinowski, and F. Fnaiech, "Accurate bearing remaining useful life prediction based on weibull distribution and artificial neural network," Mech. Syst. Signal Process., vol. 56–57, pp. 150–172, May 2015.

M. E. Malley, "A methodology for simulating the Joint Strike Fighter’s (JSF)," Prognostics Health Manage. Syst., vol. 34, no. 2, pp. 146–152, 2001.

F. Nasrian, F. Mahdavi Pajouh, and B. Balasundaram, "Detecting a most closeness-central clique in complex networks," Eur. J. Oper. Res., vol. 283, no. 2, pp. 461–475, Jun. 2020.

S. Jinfang, D. Jinying, and W. Bin, "Identifying influential nodes in complex networks based on global and local structure," Phys. A, Stat. Mech. Appl., vol. 541, no. 1, pp. 232–243, 2020.

G. Chassagnon, M. Vakalopoulou, N. Paragios, and M.-P. Revel, "Deep learning: Definition and perspectives for thoracic imaging," Eur. Radiol., vol. 30, no. 4, pp. 2021–2030, Apr. 2020.

A. B. Hamida, A. Benoit, P. Lambert, and C. B. Amar, "3-D deep learning approach for remote sensing image classification," IEEE Trans. Geosci. Remote Sens., vol. 56, no. 8, pp. 4420–4434, Aug. 2018.

CHENG PENG (Member, IEEE) received the M.E. and Ph.D. degrees from the School of Information Science and Engineering, Central South University, Changsha, China. He is currently working as a Postdoctoral Research in automation and control major at Central South University. He is an Associate Professor. His current research interests include big data analysis, industrial equipment health analysis, and software engineering.

ZHAOHUI TANG received the master’s degree in electrical engineering and automation and the Ph.D. degree in control science and control engineering from Central South University. He is currently a Professor and the Ph.D. Supervisor of the School of Information Science and Engineering, Central South University. His current research interests include modeling and optimization control of complex industrial systems, information processing, and application of computer control systems.

WEIHUA GUI was an Academician and an Automation Expert of Nonferrous Metal Industry and the Academic Leader, Doctoral, and Postdoctoral Supervisor of the National Natural Science Foundation Innovation Research Group. His current research interests include automation and informatization of nonferrous metal industry and industrial process automation optimization control of complex industrial systems.
QING CHEN received the Ph.D. degree from the School of Information Science and Engineering, Central South University, Changsha, China. She is currently a Professor with the School of Computer, Hunan University of Technology. Her research interests include industry big data analysis and equipment health state evaluation.

LONGXIN ZHANG received the M.S. and Ph.D. degrees from the School of Information Science and Engineering, Central South University, in 2008 and 2012, respectively. Since July 2013, he has been a Teacher with the School of Computer Science, Hunan University of Technology. His current research interests include industry big data analysis and high-performance computation.

XINPAN YUAN received the M.S. and Ph.D. degrees from the School of Information Science and Engineering, Central South University, in 2008 and 2012, respectively. Since July 2013, he has been a Teacher with the School of Computer Science, Hunan University of Technology. He is currently an Associate Professor. His current research interests include industry big data analysis and text analysis.

XIAOJUN DENG is currently a Professor with the School of Computer Science, Hunan University of Technology. His current research interests include industry big data analysis and industry equipment health management.

* * *