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Framework and case study of cognitive maintenance in Industry 4.0

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Abstract: We present a new framework for cognitive maintenance (CM) based on cyber-physical systems and advanced artificial intelligence techniques. These CM systems integrate intelligent deep learning approaches and intelligent decision-making techniques, which can be used by maintenance professionals who are working with cutting-edge equipment. The systems will provide technical solutions to real-time online maintenance tasks, avoid outages due to equipment failures, and ensure the continuous and healthy operation of equipment and manufacturing assets. The implementation framework of CM consists of four modules, i.e., cyber-physical system, Internet of Things, data mining, and Internet of Services. In the data mining module, fault diagnosis and prediction are realized by deep learning methods. In the case study, the backlash error of cutting-edge machine tools is taken as an example. We use a deep belief network to predict the backlash of the machine tool, so as to predict the possible failure of the machine tool, and realize the strategy of CM. Through the case study, we discuss the significance of implementing CM for cutting-edge equipment, and the framework of CM implementation has been verified. Some CM system applications in manufacturing enterprises are summarized.

Key words: Cognitive maintenance; Industry 4.0; Cutting-edge equipment; Deep learning; Green monitor; Smart manufacturing factory
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1 Introduction

Machine tools are important in the development of modern industry. High-end machine tools support advanced manufacturing, and it is very important for manufacturing enterprises to improve their market competitiveness by increasing the value of these tools during their limited service life. Due to the high accuracy, complex structure, and various fault types, the maintenance of high-end machine tools has always been a major problem in engineering applications.

In recent years, to maximize the service value of high-end machine tools in their limited service life and avoid equipment downtime as much as possible, preventive maintenance strategies have been significantly developed. Cognitive maintenance (CM) is similar to intelligent predictive maintenance, but CM focuses mainly on technologies that are related to big data, computational intelligence (CI), and self-maintenance. The cognitive maintenance strategy is a trend in the future development of equipment maintenance. It will be well integrated into the framework of Industry 4.0 development. At the same time, the progress of Industry 4.0 technology is an inevitable condition for the development of CM. CM has

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changed the traditional maintenance strategy, not only greatly reducing the time and labor cost of equipment maintenance, but also outperforming the traditional strategy in equipment maintenance.

In Industry 4.0, a vast number of sensors are used in the production process for monitoring equipment operation status and conditions. A large amount of data is collected constantly and in real time. CM is based on deep data mining algorithms, which are used to analyze the collected massive data to determine machine health and decide maintenance actions for equipment. Currently, although big data and artificial intelligence (AI) technologies are developing rapidly, there are still some unknowns in the application of preventive maintenance. Therefore, CM is not widely used in the industry, and only a small part of total maintenance expenditure is applied in the field of CM. There is still a long way to go to make the new maintenance strategy of CM viable.

2 Framework of cognitive maintenance

The Industry 4.0 era is marked by intellectualization; the interconnection of all things constitutes a physical global information system, and the form of enterprise services is integrated into the cloud service system of intelligent manufacturing. More and more manufacturing enterprises have introduced high-end equipment such as machining centers. The development of the Internet of Things (IoT) enables enterprises to monitor status and process data of high-end equipment at a deeper level (Wang Y et al., 2017). These conditions provide a basis for the establishment of a CM system. The goal of developing CM is to maximize the continuous failure-free running time of equipment, avoid failure downtime, and minimize planned downtime. In smart factories, the IoT avoids the emergence of information islands. Communication can be achieved among machines and between machines and people. All kinds of factory data are collected, including sensor data of key equipment, production process data, and enterprise resource management data. The CM system combines these multisource data with advanced predictive models and analysis tools to diagnose preventable equipment faults. With the development of technology and the application of some advanced intelligent learning methods, the accuracy of the CM system can be greatly improved.

Monitoring sensor systems requires advanced data analysis and decision-making technologies to improve the accuracy of maintenance results. Therefore, it is important to study the general framework of the CM system. In Fig. 1, a technical framework for fault diagnosis and monitoring of industrial

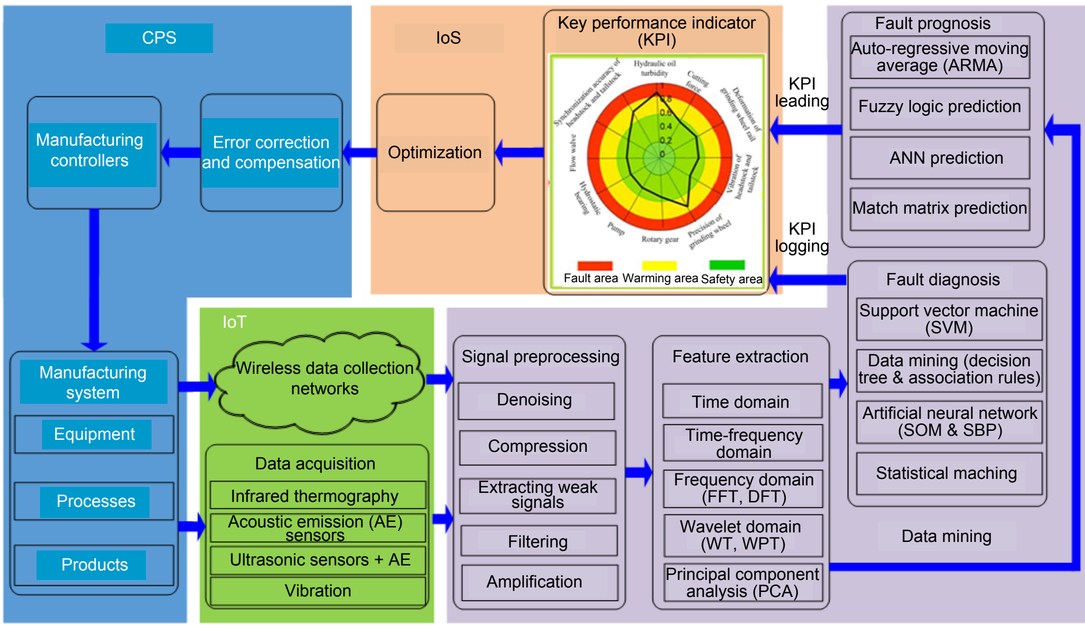

Fig. 1 General framework of the cognitive maintenance (CM) system

equipment is proposed, based on data mining and intelligent decision-making technology.

CM is guided by the development of Industry 4.0, and can be well integrated into the framework of Industry 4.0. It can become the direction for enterprises to realize intelligent manufacturing innovation. In the framework of intelligent manufacturing, a large amount of data is collected and transmitted in the physical information system and IoT. Machine/Process health is automatically monitored. The application of AI and data mining technologies can further simplify the discovery of any abnormal situation or machine failure (Yu and Kumbier, 2018). The decision of fault diagnosis can authorize professional maintenance staffs to take appropriate measures for impending anomalies through the Internet of Services (IoS), such as stopping the machine before it fails or performing effective and safe CM. In this way, we can deal with the impending faults as soon as possible and ensure healthy and continuous operation of the equipment. The system framework for CM includes four modules, i.e., cyber-physical system, IoT, data mining, and IoS.

1. Cyber-physical system

The word "cyber" implies the integration of computation, communication, and control, and it is a virtual space. "Physical" indicates a real space; that is, natural and human-made systems are governed by the laws of physics and operating in continuous time. In a cyber-physical system (CPS), the cyber (virtual) and physical (real) systems are tightly integrated at all scales and levels. CPS is an important component of the Industry 4.0 system; it integrates computation and physical processes, uses embedded computers and networks to compute process data, communicate with each other, and control the physical processes, and receives feedbacks on how physical processes affect computations and vice versa. The application of CPS in intelligent manufacturing has attracted great attention in the industry. Significant progress has been made in information systems and control technologies (Lee et al., 2015).

The CPS module plays an important role and builds up the foundation of a CM system. The major responsibility of the CPS module is to give the manufacturing system the function of perception, i.e., the ability to perceive its own state and the state of the surrounding environment. Equipment, production process, and products constitute a complete manufacturing system, in which production conditions are monitored by connecting the corresponding sensors and equipment. According to the type of data to be monitored, appropriate sensors are selected, such as using vibration sensors to monitor motor or spindle vibration, using sound sensors to monitor the noise in the manufacturing process, and using thermal sensors to monitor the temperature of coolant. A computer vision system can also be used to monitor the manufacturing process, such as an electronic fence.

2. Internet of Things

The IoT enables all ordinary objects within the enterprise to perform independent functions to realize inter-connection and interoperability. The function of the IoT module is mainly data transmission. The data collected by sensors on the device is transmitted to local databases or cloud data centers through the IoT for subsequent module calls. Some of the equipment in the factory is equipped with a supervisory control and data acquisition (SCADA) system to monitor the equipment itself. In the data mining module, the equipment's sensor data and SCADA data can be fused to mine interesting rules in depth, and the health status of the equipment can be further analyzed and diagnosed.

3. Data mining

The data mining module is the key and difficult point in the implementation of the CM system. The causes of equipment failures are determined and degradation of equipment or components is predicted based on strong data analysis and processing capabilities. Some small enterprises are not able to implement a CM system because they lack big data collection and deep data analysis or data mining skills. In our CM system implementation scheme, there are three main steps to bring data mining into full play: (1) preprocessing all kinds of collected signals; (2) analyzing and extracting signal features; (3) diagnosing and predicting faults.

The data-driven technology based on computational intelligence and deep learning has been successfully used in CM systems.

4. Internet of Services

In this module, the interesting patterns of data mining are applied mainly in the form of service. IoS provides three service functions: (1) indicating the performance; (2) formulating and optimizing maintenance plans; (3) correcting and compensating for faults.

One of the main objectives of implementing a CM system is to correct and compensate for faults. This function requires the support of the data mining module and the connected CPS module. Specifically, interesting patterns of the data mining module should be used to modify the equipment and components in the CPS to ensure orderly operation of the manufacturing system.

For detailed information on CM, readers can refer to Wang (2014) and Zhang and Wang (2014).

3 Deep learning for cognitive maintenance

3.1 General overview

The application of AI technology in a CM system is difficult because of the lack of effective methods to acquire training data and professional knowledge in related fields required for training an AI model. Traditional machine learning methods have been developed based on a foundation of a small amount of data. These methods have limited ability to process raw data, so the application effect of such a CM system is unsatisfactory. Building a machine learning system requires decades of elaborate design and a large amount of professional data. We need to design a feature extraction and selection system that can easily transform the original data into an appropriate representation for further analysis. A learning module is usually a classifier that can detect and classify the patterns and rules of input data.

In recent years, deep learning technology has developed rapidly, and has become a new trend in the field of computational intelligence. Applications of deep learning in equipment maintenance have been constantly studied and explored. Deep learning technology is a branch of computer intelligence and consists of a series of algorithms for data analysis and processing, including high-level representation of features and attributes of modeling, approximation, and image extraction. Extracting stratification characteristics or formulation from target data is the fundamental feature of deep learning. Although deep learning appeared relatively late, the advantages of deep learning technology in data processing guarantee a rapid development.

Different researchers have studied deep learning technology from different aspects. Schmidhuber (2015) summarized the research progress of neural network deep learning and distinguished shallow and deep learning methods according to the depth of the confidence allocation path. Among many machine learning algorithms, the greatest advantage of deep learning is that the feature extraction system is not acquired artificially, but through the self-learning process for the original data. In the domain of machine vision and voice recognition, the application of various deep learning algorithms is very successful. Deep learning technology has also performed well in the fields of biomedicine, high-energy physics, and genetic inheritance. Currently, many types of deep learning algorithms, for example, deep belief network (DBN), long- and short-term memory network (LSTM), and deep forward neural network (DFNN), have been applied successfully in CM. In the following, some of the state-of-the-art research is briefly described.

Tamilselvan and Wang (2013) presented a multisensor health diagnosis approach based on the DBN, and successfully applied it to assess the degradation of aircraft engines and electric power transformers. Compared with other classification algorithms, such as support vector machine (SVM), self-organizing map (SOM), and back propagation neural network (BPNN), DBN has better performance in health diagnosis of complex systems.

Wang L et al. (2017) proposed an approach based on a deep neural network to evaluate the conditions of wind turbine gearboxes and identify their impending failures. Gan et al. (2016) presented a diagnostic neural network with a hierarchical structure by collecting restricted Boltzmann machines (RBMs) to detect fault patterns in rolling bearings. In the hierarchical network, two decision layers were designed to identify fault types and evaluate the degradation, separately. Jia et al. (2016) suggested a deep forward neural network to process fault data and automatically provide accurate diagnosis results for rotating machinery.

3.2 Superiority of deep learning for cognitive maintenance

Vanishing gradients are the basic problem in training artificial neural networks. Various types of deep learning algorithms have been proposed and developed in the last few decades. According to Deng (2014), a deep learning algorithm refers to a wide class of intelligent computation and machine learning techniques with structures of many layers to process nonlinear information. These techniques aim to obtain better accuracy. In this subsection, five deep learning architectures are studied, i.e., deep neural network with back-propagation (DNN), stacked auto-encoder (SAE), DBN, LSTM, and convolutional neural network (CNN).

These deep learning algorithms can remove some "bottlenecks" that conventional methods face during the implementation of predictive maintenance. They will be introduced in theory and practical applications based on a literature review to highlight the superiorities of deep learning approaches in certain areas of predictive maintenance. A guidance is offered to select a suitable deep learning model for a different practical application. Table 1 lists the superiority of the five types of deep learning algorithms in predictive maintenance.

Table 1 Superiority of deep learning for predictive maintenance

Architecture	Superiority for cognitive maintenance
DNN	DNN has a more hierarchical structure. So, it is more capable of modeling or abstracting representation of things, and can simulate more complex models.
SAE	Fault characteristics mining is implemented, features or hidden information about failures from the raw input data are extracted, and are subsequently divided into different levels. The dimensionality is reduced and discriminative information about failures is discovered when the input dimensionality is large.
DBN	The DBN model is a viable predictive maintenance approach when the target condition exceeds historical data. In addition, it can discover discriminative information about failures when the input dimensionality is large.
LSTM	LSTM is a time recursive neural network and can be used to predict important events with a relatively long interval and delay in time series.
CNN	CNN has a strong capacity for discovering knowledge behind large data, especially image-based data. Complex patterns for machine health monitoring can be constructed by stacking convolutional layers.

1. DNN

DNN, an evolutionary version of BPNN, improves the recognition rate of past events to a significant extent; DNN has been widely used in fault diagnosis and prediction. DNN's multi-layer perceptron avoids the disadvantage of inability to simulate XOR logic. At the same time, more layers make the network more capable of depicting complex situations in the real world. The advantage of the DNN algorithm in equipment maintenance lies in the modeling of highly complex target problems. Evidence can also be found in practical applications (Din and Marnerides, 2017). For example, Wang L et al. (2017) employed DNN to deal with the lubricant oil pressure in a wind turbine gearbox and subsequently detected coming failures. In Li L et al. (2017), a DNN with multiple hidden layers was applied for fault classification in a semi-conductor manufacturing process. The results also showed that DNN is more competitive in terms of convergence speed and outperforms other conventional approaches, such as multilayer perceptron, SVM, and logistic regression.

2. SAE

SAE has been successfully applied to dimensionality reduction in different engineering fields (Shin et al., 2013; Zabalza et al., 2016). Due to the clear hierarchical relationship between each two layers, SAE has the capacity to implement fault characteristics mining, extract features or hidden information about failures from the raw input data, and divide them into different levels. Actually, dimensionality reduction is one of the most original applications of deep learning, which is also one of the early motivations for developing auto-encoders (Hinton and Salakhutdinov, 2006).

Models of smaller physical spaces require less memory, runtime, and computational load for the system. In general, for predictive maintenance, SAE is superior in obtaining important variations and detecting the discriminative patterns of failures when the dimensionality of the input data is large. Some practical applications based on a literature review also support the theoretical speculation. In Jia et al. (2016), SAE was used to deal with massive fault data and evaluate the health condition of the rolling bearings and planetary gearboxes in rotating machinery. Galloway et al. (2016) directly trained a deep neural network of SAE with spectrograms constructed from raw vibration data instead of using feature extraction. The results showed that SAE can learn the response of the tidal turbine under variable loading conditions and identify faults within the turbine's generator. According to a comparison with other feature-based methods such as SVM, decision tree, and K-nearest neighbor (KNN) classifiers, which are trained after extracting features from vibration data, SAE has even better fault classification performance.

3. DBN

As a type of energy-based model, DBN is constructed by training and stacking several RBM layers, making the learning process correspond to the energy function and making its shape have ideal properties (Bengio, 2009). Gan et al. (2016) applied a DBN with two layers to identify the non-stationary property of vibration signals. The results showed that DBN can discover the weak links in a mechanical system and provide effective information about failures. Compared with BPNN and SVM, DBN can also provide better accuracy and efficiency. The comparison results demonstrated that DBN performs better in fault location and classification than BPNN and SVM.

Tamilselvan and Wang (2013) applied DBN to separately evaluate the health state of an aircraft engine and electric power transformer. In the experiment, they compared the diagnostic performance of DBN with those of SVM, BPNN, and SOM. The results showed that in complex systems, DBN has better diagnostic performance than other classification methods. In addition, DBN has demonstrated outstanding performance in applications such as prediction of chaotic time series (Kuremoto et al., 2014), short-term prediction of drought (Chen et al., 2012), traffic flow prediction (Huang et al., 2014), financial business prediction (Ribeiro and Lopes, 2011), and retrieval term prediction (Ma et al., 2014). Kuremoto et al. (2014) successfully employed DBN to predict the Lorenz chaos with its well-known "butterfly effect," which indicates sensitive dependence on the initial conditions of chaos. In Ma et al. (2014), DBN was applied to predict retrieval terms and descriptive texts. For comparison, the authors tested it with some other methods such as multi-layer perceptron and SVM. The experiments showed that DBN has much higher predictive accuracy than the others. In Section 4, a novel application of DBN to predict backlash errors in a machining center will be introduced. This case study can also verify the theoretical speculation. In general, due to the pre-training process through unsurprised learning, DBN has superiority in discovering discriminative information about failures when the input dimensionality is large.

4. LSTM

As a type of recurrent neural network (RNN), LSTM is constructed by stacking memory cells, which can keep information of previous inputs in the output. LSTM is an outstanding tool for mimicking time series and has been successfully applied in various applications, such as speech recognition (Graves et al., 2013), information retrieval (Palangi et al., 2016), protein disorder prediction (Hanson et al., 2016), handwriting recognition, and processing acoustic sequences (Sak and Senior, 2017).

As reported by Zhao et al. (2016), much machinery data is obtained from sensor data, which is highly time-dependent in nature. In predictive maintenance, LSTM is also a popular and useful model for discovering temporal information from sequential data, especially when the issue is highly related to time series. For example, Zhao et al. (2016) successfully implemented LSTM to forecast tool wear in a high-speed computerized numerical control (CNC) machine. They also compared LSTM with other approaches such as linear regression, SVM, and multi-layer perception (MLP). The results showed that LSTM can learn meaningful representations from raw signals and has better performance than conventional methods in issues where high temporal dependency is involved.

In de Bruin et al. (2017), LSTM was applied to classify fault groups and to predict the faults over time for a railway track circuit. Malhotra (2016) proposed an LSTM-based encoder-decoder model to predict the remaining useful life (RUL) of a pulverizer mill from a time-series dataset generated by multiple sensors. The experiment also demonstrated the outstanding performance of LSTM.

5. CNN

CNN is a kind of hierarchical multi-layer model with a very strong capacity to discover knowledge in big data, especially for image-based data, because vision is highly hierarchically organized (Cheng et al., 2018). For predictive maintenance, in some scenarios, the information or signs of failure can also be perceived from data in a two-dimensional (2D) format, for example, pictures or a frequency spectrum. According to Zhao et al. (2019), filters in convolutional layers can extract local features from raw data and further build complex patterns for machine health monitoring by stacking these convolutional layers, which makes CNN an ideal tool when the target is image-based data.

3.3 DBN model for cognitive maintenance

3.3.1 DBN model construction

DBN is an unsupervised deep neural network model; it is composed of multiple neurons and its basic components are RBMs (Hinton and Salakhutdinov, 2006). It also belongs to a probability generation model. Data is abstracted layer by layer from low level to high level through the DBN model. In this way, the essential characteristics of data can be deeply mined. RBM is a kind of neural perceptron. Each RBM is a two-layer network model consisting of the visual layer and hidden layer. There are connections between the layers of neuron nodes, and no connections within the layers. The visual layer represents the input data samples, and the hidden layer is equivalent to the feature extractor.

Fig. 2 shows a DBN model stacked by three RBMs. Among them, the first visual layer (v_1) is the initial input data, which forms RBM1 with the first hidden layer (h_1); the first hidden layer (h_1) acts as the second visual layer (v_2), which forms RBM2 with the second hidden layer (h_2); the second hidden layer (h_2) acts as the third visual layer (v_3) and RBM3 consists of v_3 and h_3.

RBM training is an important stage in the process of building a DBN model. Hinton (2002) proposed the contrastive divergence (CD) algorithm, which is widely used in RBM training. The whole training process of DBN is divided into two stages, unsupervised pre-training and supervised fine-tuning.

3.3.2 DBN for cognitive maintenance

The DBN model for CM is shown in Fig. 3. The expert system extracts historical data from the data warehouse for training and creates diagnostic models. Combining the fault diagnosis model with the input data, the training of a DBN model is completed. The structure of a DBN model includes multiple RBM layers and one decision-making layer. We use the previously mentioned CD algorithm to complete the training of the RBM model. The decision-making layer realizes fault clustering, fault identification, and potential fault prediction. According to the results of fault prediction, decision support is provided for a manufacturing system, and appropriate maintenance planning and error compensation are formulated for the manufacturing system.

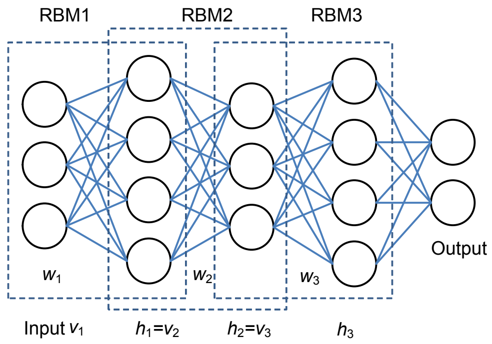

Fig. 2 Deep belief network (DBN) model construction

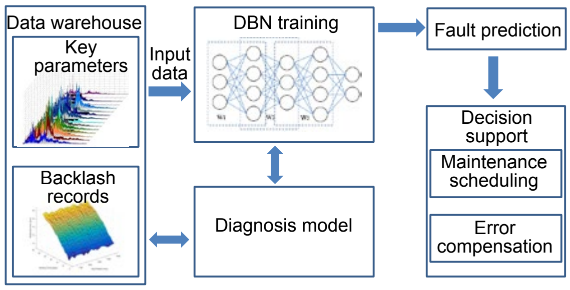

Fig. 3 Deep belief network (DBN) for cognitive maintenance

4 Case study

4.1 Project framework

A machining center involves typical high-tech mechanical equipment. Its development reflects a country's level of design and manufacturing. Shutdown of a machining center will bring great loss to an enterprise. Developing online CM to ensure the sustainable operation of machine tools has become an important way for enterprises to improve their market competitiveness. In the process of health monitoring of equipment, a CM system collects equipment operation status data through various sensors and integrates large data analysis, cloud computing, and advanced intelligent technology to diagnose and predict equipment faults. To implement a CM system in numerical control (NC) machining equipment, the Norwegian University of Science and Technology (NTNU) led the research on the Green Monitor Project, which was supported by the Norwegian Research Council. A software development company (ICB in Bulgaria) and a maintenance company (Kongsberg Terotech, KTT) participated in the research as cooperative units. The project took the machining center as the research object, monitored the condition of the machining center online, and used an intelligent data mining algorithm to predict the degradation of machines and to make maintenance decisions.

In the Green Monitor Project, the participants used their respective advantages. As shown in Fig. 4, NTNU used its own research advantages, proposed a framework for project implementation based on Industry 4.0, focused on CM, and monitored and maintained a five-axis vertical machining center as research objects. As a software service company, ICB provided software assistance for the whole project and developed an integrated platform for the IoT and cloud services. KTT provided maintenance services for machining centers to ensure their continuous and healthy operation. The machining center is the core of machinery manufacturing enterprises. The reason that we choose a machining center as the testing platform is that the state data of the machining center is easy to obtain. It can directly collect the process data in an NC control system, but indirectly collect the state data in a production process by installing relevant sensors on the equipment. The significance of this project is to analyze remote monitoring data in the production process through the intelligent in-depth learning data analysis model to generate an appropriate online maintenance strategy to minimize the cost loss caused by downtime, failure, and so on. The whole project is divided into four sub-systems:

1. CPS for monitoring the condition of equipment

To enable the existing manufacturing equipment to have the functions of self-perception, environmental monitoring, and information sharing, it is necessary to integrate physical equipment with the information system. In the Green Monitor Project, we chose some sensors and controllers to form a data acquisition system that interconnects all hardware devices through a wireless network and makes them part of CPS. Sensors and the data collection process are shown in Fig. 5. To collect data from different data sources of equipment, the system needs to install three different types of adapters to achieve different types of data acquisition, decoding, conversion, and transmission. The functions of each adapter are shown in Table 2.

In the process of data acquisition, when the data of the equipment itself does not meet the needs of the upper system, additional sensors are needed to collect data. In this project, energy consumption data, oil

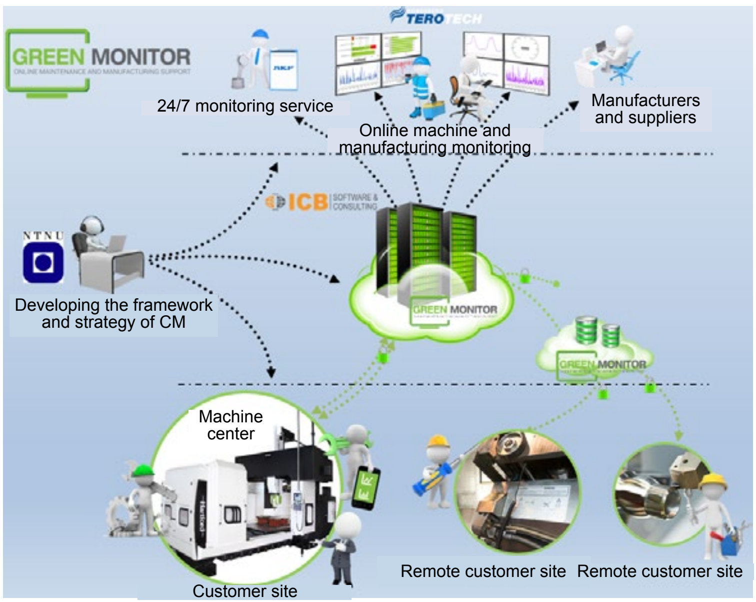

Fig. 4 Structure of the cognitive maintenance (CM) system in the Green Monitor Project

status, and temperature data are collected through specific sensors. The subsystem of data acquisition is composed of a programmable logic controller (PLC) and sensors. The PLC controls the collection of sensor data, and then transfers the data to the data acquisition server through the adapter. The types and functions of the data acquisition controller and sensors used in this project are given in Table 3.

2. IoT and cloud computing system

IoT enables all ordinary objects within the enterprise to perform independent functions to realize interconnection and interoperability. The function of the IoT module is mainly data transmission. In Fig. 6, the IoT system includes two network levels, that is, a machine network and a client network. The data collected by sensors mounted on the device is transmitted to local databases or cloud data centers through the IoT for subsequent system calls.

3. Data mining system

This module uses deep learning to analyze the backlash errors. The details of backlash error analysis are described in the next subsection.

4. IoS and optimization system

This system uses the industry Internet to connect the equipment with the maintenance company (KTT) to make maintenance decisions, for example, selection of a maintenance strategy and maintenance schedule optimization (Li Z et al., 2017a).

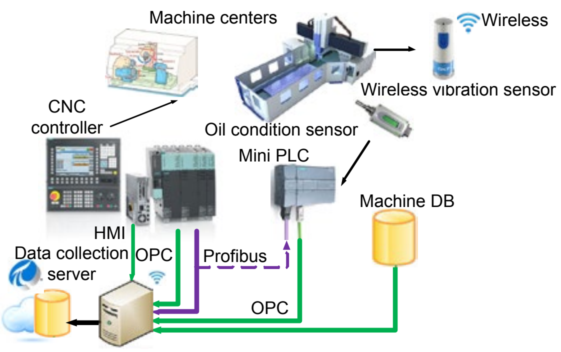

Fig. 5 Equipment and data collection system

Table 2 Adapters and functions

Adapter	Function
RPC Sinumerik adapter	Obtaining machine status and messages; completing file transfer and decoding (for example, backlash data)
PLC interface (machine)	Acquiring machine control data
OPC UA interface	Collecting status, energy data, oil data, etc.

Table 3 Data acquisition controller and sensors

Equipment	Function
SIMATIC ET 200SP open controller	Acting as a data acquisition controller
Energy meters	Providing energy consumption data
Oil sensors	Acquiring oil condition data
Temperature sensors	Acquiring temperature data

4.2 Backlash error prediction

The backlash error will seriously affect the positioning accuracy of the machining center. So, backlash error prediction in the machine center was selected as a case study in the Green Monitor Project (Wang et al., 2015). We used the DBN method to diagnose this error. Table 4 gives a list of needed parameters for the DBN prediction model. The DBN prediction model was presented in Li Z et al. (2017b).

In the course of the experiment, we established a prediction model in the 31^{st} week to predict future backlash errors. This means that the data collected after the 31^{st} week is not used as training data. In many cases, a machine center may not have failures; for example, some machine centers may run normally for several years without any failure. However, potential serious failures may cause economic costs and personal safety disasters. Therefore, it is urgent to study some new models to accurately predict these potential risks. By superposing four RBMs, we established a DBN model to predict the backlash error. Table 5 gives the parameters required for the DBN model.

In the process of model training, the data samples were classified into two categories. We used 70% of the data as the training dataset and the rest as the verification/testing dataset. Fig. 7 shows the training results of the DBN model, and Fig. 8 presents the

Table 4 Inputs for prognosis

Parameter	Meaning
W	Number of weeks
T_1	Coolant temperature
T_2	Machine temperature
T_3	Ambient temperature
TRQ	Torque of machine
P	Position of axis
$\text{backlash}_{W-1, P-1}$	Backlash error ($(W-1)^{\text{th}}$ week, $(P-1)^{\text{th}}$ position)
$\text{backlash}_{W-2, P-2}$	Backlash error ($(W-2)^{\text{th}}$ week, $(P-2)^{\text{th}}$ position)

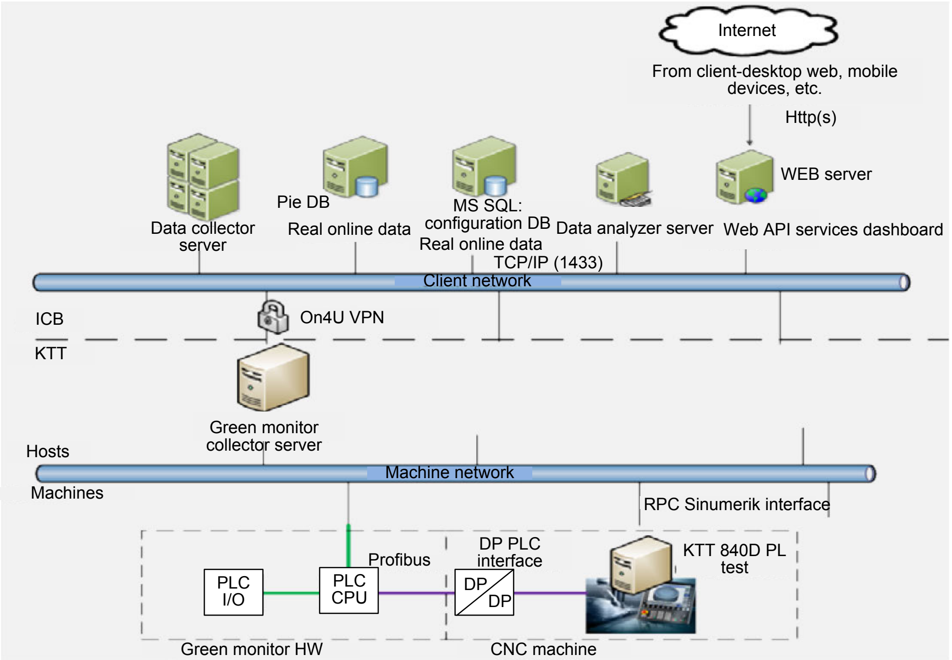

Fig. 6 Industry IoT and cloud computing structure

Table 5 DBN structure parameters

RBM	Hidden layer	Number of neurons	Learning rate	Number of epochs
1	Bernoulli	50	0.01	500
2	Bernoulli	50	0.01	500
3	Bernoulli	30	0.01	300
4	Bernoulli	30	0.01	300

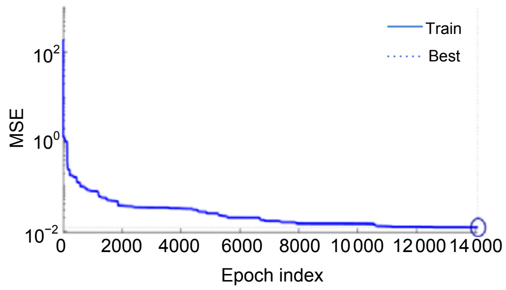

Fig. 7 Training results of deep belief network (DBN)

prediction of the backlash error in the 3D space. We can see that the mean-squared error (MSE) of the backlash error in the whole training period reaches 0.012 205 at the 14 076th epoch.

Fig. 9 shows a comparison of two sets of predictions. Comparison of actual and predicted backlash errors is shown in Fig. 9. The MSE and maximum error (ME) of backlash error prediction in the 32nd and 33rd weeks are given in Table 6. In practice, we set the maximum permissible error (MPE) to 15.8.

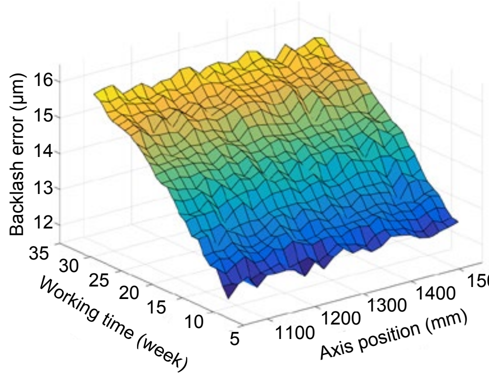

Fig. 8 Prediction results from deep belief network (DBN)

Table 6 Comparison of the prediction results

Week	MSE	ME
32nd	0.0103	0.1807
33rd	0.0141	0.2276

MSE: mean-squared error; ME: maximum error

At this point, we can judge whether there is a possibility of failure according to the value of the predicted backlash error. In this case, the occurrence of equipment failure is predicted two weeks in advance; that is, we can predict the occurrence of failures in the 33rd week. In this way, we can take some maintenance measures in the 32nd week so that the backlash error in the 33rd week does not exceed the MPE.

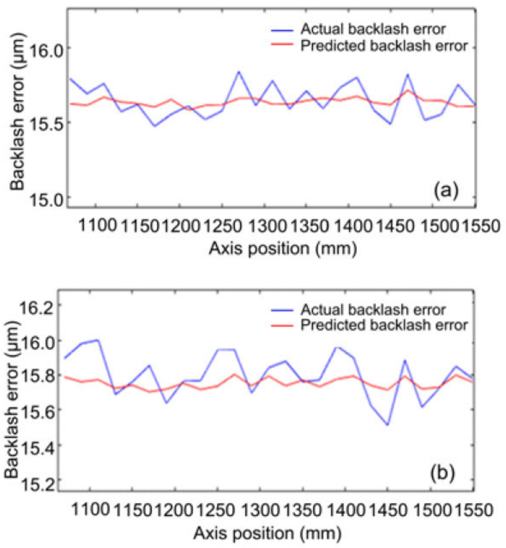

Fig. 9 Comparison of the backlash error: (a) 32nd week; (b) 33rd week

5 Conclusions

Choosing a proper maintenance strategy and implementing the correct maintenance process are the key to successful maintenance of the enterprise. In the era of large data, AI techniques have developed rapidly, and advanced intelligent methods have matured gradually. Although advanced intelligent methods play a crucial role in the equipment maintenance system, they are not a determining factor for the success of the maintenance strategy. Different enterprises have different levels of equipment maintenance. Knowing the organization's maintenance requirements and the level of maintenance procedures should be the first step in running CM projects. Then prototypes are made with appropriate equipment to determine rules and gain knowledge. The main prototype of the device should be highly integrated into the operation, and some necessary periodic failure rules should be established to create a benchmark prediction algorithm.

This study is based on the contributions of predecessors to cognitive maintenance of machining centers. We put forward the framework of intelligent preventive maintenance for enterprises, and presented a method of CM system application. The core of this method is data mining and deep learning technology. The unique advantages of deep learning technology play a key role in the implantation of a CM plan for complicated equipment. In the case study, we illustrated an example of an enterprise, the Green Monitor Project, in which cognitive maintenance was one of the core modules. The implementation of the Green Monitor Project offered some experience that can be used for reference in the promotion of cognitive maintenance system in enterprises. To implement a cognitive maintenance system, the following steps are required: First, the scope of the project is determined by defining business objectives. Second, within the scope of the project, we can see that the number of key devices or subsystems reduces, but all the parameters and properties of the equipment have been fully understood. Finally, it should be tested quickly on smaller datasets to obtain the first prediction result. A large data platform is an effective and easy channel for monitoring sensor data. An appropriate data infrastructure should be designed to achieve automation process monitoring, data acquisition, and data analysis. We can see that the core link in the CM system is the data mining module, and the integration of advanced data mining algorithms, especially deep learning algorithms, will be promising in Industry 4.0. These are research hotspots and key factors for success.

Compliance with ethics guidelines

Bao-rui LI, Yi WANG, Guo-hong DAI, and Ke-sheng WANG declare that they have no conflict of interest.

References

Bengio Y, 2009. Learning deep architectures for AI. *Found Trends Mach Learn*, 2(1):1-127. https://doi.org/10.1561/2200000006

Chen JF, Jin QJ, Chao J, 2012. Design of deep belief networks for short-term prediction of drought index using data in the Huaihe river basin. *Math Probl Eng*, 2012:235929. https://doi.org/10.1155/2012/235929

Cheng J, Wang PS, Li G, et al., 2018. Recent advances in efficient computation of deep convolutional neural networks. *Front Inform Technol Electron Eng*, 19(1):64-77. https://doi.org/10.1631/FITEE.1700789

de Bruin T, Verbert K, Babuška R, 2017. Railway track circuit fault diagnosis using recurrent neural networks. *IEEE Trans Neur Netw Learn Syst*, 28(3):523-533. https://doi.org/10.1109/TNNLS.2016.2551940

Deng L, 2014. A tutorial survey of architectures, algorithms, and applications for deep learning. *APSIPA Trans Signal Inform Process*, 3, Article e2.

Din GMU, Marnerides AK, 2017. Short term power load forecasting using deep neural networks. Int Conf on Computing, Networking and Communications, p.594-598. https://doi.org/10.1109/ICCNC.2017.7876196

Galloway GS, Catterson VM, Fay T, et al., 2016. Diagnosis of tidal turbine vibration data through deep neural networks. Proc 3rd European Conf of the Prognostics and Health Management Society, p.172-180.

Gan M, Wang C, Zhu CA, 2016. Construction of hierarchical diagnosis network based on deep learning and its application in the fault pattern recognition of rolling element bearings. *Mech Syst Signal Process*, 72-73:92-104. https://doi.org/10.1016/j.ymssp.2015.11.014

Graves A, Mohamed AR, Hinton G, 2013. Speech recognition with deep recurrent neural networks. IEEE Int Conf on Acoustics, Speech and Signal Processing, p.6645-6649. https://doi.org/10.1109/ICASSP.2013.6638947

Hanson J, Yang Y, Paliwal K, et al., 2016. Improving protein disorder prediction by deep bidirectional long short-term memory recurrent neural networks. *Bioinformatics*, 33(5): 685-692. https://doi.org/10.1093/bioinformatics/btw678

Hinton GE, 2002. Training products of experts by minimizing contrastive divergence. *Neur Comput*, 14(8):1771-1800. https://doi.org/10.1162/089976602760128018

Hinton GE, Salakhutdinov RR, 2006. Reducing the dimensionality of data with neural networks. *Science*, 313(5786): 504-507. https://doi.org/10.1126/science.1127647

Huang WH, Song GJ, Hong HK, et al., 2014. Deep architecture for traffic flow prediction: deep belief networks with multitask learning. *IEEE Trans Intell Transp Syst*, 15(5): 2191-2201. https://doi.org/10.1109/TITS.2014.2311123

Jia F, Lei YG, Lin J, et al., 2016. Deep neural networks: a promising tool for fault characteristic mining and intelligent diagnosis of rotating machinery with massive data. *Mech Syst Signal Process*, 72-73:303-315. https://doi.org/10.1016/j.ymssp.2015.10.025

Kuremoto T, Kimura S, Kobayashi K, et al., 2014. Time series forecasting using a deep belief network with restricted Boltzmann machines. *Neurocomputing*, 137:47-56. https://doi.org/10.1016/j.neucom.2013.03.047

Lee J, Bagheri B, Kao HA, 2015. A cyber-physical systems architecture for Industry 4.0-based manufacturing systems. *Manuf Lett*, 3:18-23. https://doi.org/10.1016/j.mfglet.2014.12.001

Li L, Dai GL, Zhang Y, 2017. A membership-based multidimension hierarchical deep neural network approach for fault diagnosis. 29th Int Conf on Software Engineering and Knowledge Engineering, p.197-200. https://doi.org/10.18293/SEKE2017-074

Li Z, Wang Y, Wang K, 2017a. A data-driven method based on deep belief networks for backlash error prediction in machining centers. *J Intell Manuf*, p.1-13. https://doi.org/10.1007/s10845-017-1380-9

Li Z, Wang Y, Wang K, 2017b. Intelligent predictive maintenance for fault diagnosis and prognosis in machine centers: Industry 4.0 scenario. *Adv Manuf*, 5(4):377-387. https://doi.org/10.1007/s40436-017-0203-8

Ma Q, Tanigawa I, Murata M, 2014. Retrieval term prediction using deep belief networks. *J Nat Lang Process*, 22(4): 225-250. https://doi.org/10.5715/jnlp.22.225

Malhotra P, Tv V, Ramakrishnan A, et al., 2016. Multi-sensor prognostics using an unsupervised health index based on LSTM encoder-decoder. https://arxiv.org/abs/1608.06154

Palangi H, Deng L, Shen YL, et al., 2016. Deep sentence embedding using long short-term memory networks: analysis and application to information retrieval. *IEEE/ACM Trans Audio Speech Lang Process*, 24(4):694-707. https://doi.org/10.1109/TASLP.2016.2520371

Ribeiro B, Lopes N, 2011. Deep belief networks for financial prediction. Int Conf on Neural Information Processing, p.766-773. https://doi.org/10.1007/978-3-642-24965-5_86

Sak H, Senior AW, 2017. Processing Acoustic Sequences Using Long Short-Term Memory (LSTM) Neural Networks That Include Recurrent Projection Layers. US Patent 962 010 8. http://www.freepatentsonline.com/9620108.html

Schmidhuber J, 2015. Deep learning in neural networks: an overview. *Neur Netw*, 61:85-117. https://doi.org/10.1016/j.neunet.2014.09.003

Shin HC, Orton MR, Collins DJ, et al., 2013. Stacked autoencoders for unsupervised feature learning and multiple organ detection in a pilot study using 4D patient data. *IEEE Trans Patt Anal Mach Intell*, 35(8):1930-1943. https://doi.org/10.1109/tpami.2012.277

Tamilselvan P, Wang PF, 2013. Failure diagnosis using deep belief learning based health state classification. *Reliab Eng Syst Saf*, 115:124-135. https://doi.org/10.1016/j.ress.2013.02.022

Wang KS, 2014. Key technologies in intelligent predictive maintenance (IPdM)—a framework of intelligent faults diagnosis and prognosis system (IFDaPS). *Adv Mater Res*, 1039:490-505. https://doi.org/10.4028/www.scientific.net/AMR.1039.490

Wang KS, Li Z, Braaten J, et al., 2015. Interpretation and compensation of backlash error data in machine centers for intelligent predictive maintenance using ANNs. *Adv Manuf*, 3(2):97-104. https://doi.org/10.1007/s40436-015-0107-4

Wang L, Zhang ZJ, Long H, et al., 2017. Wind turbine gearbox failure identification with deep neural networks. *IEEE Trans Ind Inform*, 13(3):1360-1368. https://doi.org/10.1109/TII.2016.2607179

Wang Y, Ma HS, Yang JH, et al., 2017. Industry 4.0: a way from mass customization to mass personalization production. *Adv Manuf*, 5(4):311-320. https://doi.org/10.1007/s40436-017-0204-7

Yu B, Kumbier K, 2018. Artificial intelligence and statistics. *Front Inform Technol Electron Eng*, 19(1):6-9. https://doi.org/10.1631/FITEE.1700813

Zabalza J, Ren JC, Zheng JB, et al., 2016. Novel segmented stacked autoencoder for effective dimensionality reduction and feature extraction in hyperspectral imaging. *Neurocomputing*, 185:1-10. https://doi.org/10.1016/j.neucom.2015.11.044

Zhang ZY, Wang KS, 2014. Wind turbine fault detection based on SCADA data analysis using ANN. *Adv Manuf*, 2(1):70-78. https://doi.org/10.1007/s40436-014-0061-6

Zhao R, Wang JJ, Yan RQ, et al., 2016. Machine health monitoring with LSTM networks. 10th Int Conf on Sensing Technology, p.1-6. https://doi.org/10.1109/ICSensT.2016.7796266

Zhao R, Yan RQ, Chen ZH, et al., 2019. Deep learning and its applications to machine health monitoring. *Mech Syst Signal Process*, 115(15):213-237. https://doi.org/10.1016/j.ymssp.2018.05.050