Intelligent predictive maintenance for fault diagnosis and prognosis in machine centers: Industry 4.0 scenario

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Intelligent Predictive Maintenance for Fault Diagnosis and Prognosis in Machine Centers — Industry 4.0 Scenario

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Abstract Fault diagnosis and prognosis in mechanical systems have been researched and developed in the last few decades at a very rapid rate. However, owing to the high complexity of machine centers, research on improving the accuracy and reliability of fault diagnosis and prognosis via data mining remains a prominent issue in this field. This study investigates fault diagnosis and prognosis in machine centers based on data mining approaches to formulate a systematic approach and obtain knowledge for predictive maintenance in Industry 4.0 era. We introduce a system framework based on Industry 4.0 concepts, which includes the process of fault analysis and treatment for predictive maintenance in machine centers. The framework includes five modules: sensor selection and data acquisition module, data preprocessing module, data mining module, decision support module, and maintenance implementation module. Furthermore, a case study is presented to illustrate the application of the data mining methods for fault diagnosis and prognosis in machine centers as an Industry 4.0 scenario.

Keywords Data Mining · Machine Centers · Predictive Maintenance · Industry 4.0

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1 Introduction

In recent years, with the increasing demand for machining quality and manufacturing complexity, the complexity and integration of industrial equipment has been increasing drastically [1]. On the one hand, an unexpected failure can result in a devastating accident and financial losses for the company owing to the interaction behaviors among industrial equipment. On the other hand, early detection and prediction of a fault can prevent it from growing and eventually turning into critical problems [2]. Hence, increasing attention has been paid to condition monitoring, fault diagnosis, and prognosis in modern industry [3].

Simultaneously, machine centers have grown rapidly in automotive, aerospace, die making, and other industries in recent times [4]. As one of the most important and active research areas in Knowledge Discovery in Databases (KDD) over the last few decades, data mining (DM) and related techniques have been widely researched and applied for fault diagnosis and prognosis in machine centers.

It is well known that machine faults can result in consequences that may range from a simple replacement of a cheap bearing to an accident that will cost millions in lost production, injuries, or pollution [5]. It may also bother maintenance engineers to capture the trade-off between improving the system reliability and reducing the total maintenance cost simultaneously.

Accordingly, significant attention has been paid to condition-based maintenance in the literature during the last few decades and to predictive maintenance more recently [6]. A thorough literature overview of both condition-based and predictive maintenance policies has been presented by Jardine et al. [7]. The goal of predictive maintenance is to reduce the downtime and cost of maintenance under the premise of zero failure manufacturing by monitoring the working condition of equipment and predicting when equipment failure might occur. The prediction of a future potential fault enables the planning of maintenance before the fault happens [8].

Considerable progress has been made in fault interpretation, detection, and prediction for machine centers based on DM during the last few decades, especially in specific core components or performance, such as gearbox [9], thermal error [10], and rolling element bearings [11]. However, most of these studies only focused on their own parts or concentration. There remains a lack of systematic application or framework of DM for diagnosis and prognosis in machine centers. Moreover, it is difficult to realize all the advantages of predictive maintenance without the foundation of correlation techniques such as big data and cloud computing. Many manufacturing systems are still not ready to manage big data owing to the high demands on the access and quality of data. Furthermore, the extraction of relevant information from multiple data sources still remains a challenge in many situations [12].

Today, Industry 4.0 is a buzzword in academia. It is widely discussed among practitioners and theorists, and facilitates the creation of a smart factory [13]. It was introduced at Hanover fair in 2011 in Germany to present a new trend toward the networking of traditional industries [14]. Subsequently, many similar projects and programs have demonstrated the concepts of Industry 4.0 such as “intelligent manufacturing system” and “smart manufacturing.” This study aims to formulate a systematic approach and obtain knowledge for fault detection, interpretation, and prediction based on Industry 4.0 concepts.

The remaining part of the paper is organized as follows. Section 2 briefly presents the background of machine centers and classifies fault analysis according to the observed components, monitoring methods, or specific purposes. Section 3 discusses the concepts of Industry 4.0 including its development, components, and definition. Section 4 provides a system framework that includes the entire process of fault analysis and treatment for predictive maintenance in machine centers based on DM and Industry 4.0 concepts. Section 5 presents an Industry 4.0 scenario about backlash error interpretation and prediction to illustrate the realization of predictive maintenance in machine centers. The conclusions and future research are summarized in the last section.

2 Fault Analysis Techniques in Machine Centers

The term “machine center” can be used to describe any computer numerical control (CNC) milling and drilling machine that includes an automatic tool changer and a table that clamps the workpiece in place. According to the orientation of the spindles, they can be divided into two types: vertical and horizontal. Vertical machining centers generally have good precision, whereas horizontal machining centers favor production. The spindle of a vertical machine center is vertically oriented. Generally, a vertical machine center includes several sub-systems that should be monitored. As shown in Fig. 1, it may include a server motor system, ball screw system, guide systems, spindle system, tool magazine, hydraulic system, lubrication system, and cooling system [15, 16]. All these systems have unique functions, and failures occurring at any one of them may cause faults in the entire machine center.

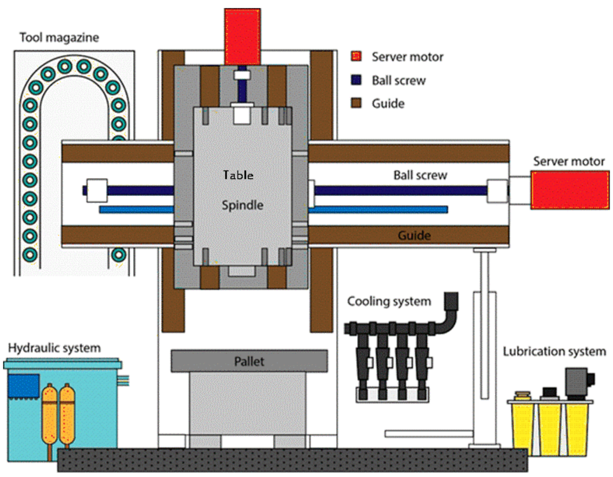

Fig. 1 Components of a machine center

In order to achieve fault diagnosis and prognosis in machine centers, many contributions have been made in this area. Normally, research in this field can be divided into seven groups: geometric measurement analysis, vibration analysis, oil analysis, cutting fluid analysis, energy consumption analysis, temperature analysis, and acoustic emission analysis, according to the observed components, monitoring method, or specific purpose [15-21]. However, the integration of all these techniques and information to form comprehensive, high-efficiency, and intelligent maintenance strategies still remains a challenge till the breakthrough of Industry 4.0.

3 Industry 4.0

Industrial production has continued to progress since its very beginning. Sometimes, the changes were so potent and significant that the term "industrial revolution" had to be coined. Further, the term Industry 4.0 is used to recognize the three previous industrial revolutions.

Today, we are witnessing the fourth industrial revolution, which is also known as Industry 4.0. It combines the strengths of optimized industrial manufacturing with Internet technologies and changes the manufacturing process, maintenance management, and maintenance strategies significantly.

Industry 4.0 is closely related to other technological concepts such as machine-to-machine communication [22], radio frequency identification (RFID) technology [23], cyber-physical systems (CPS) [24], the Internet of Things (IoT), the Internet of Services (IoS), cloud computing [25], computational intelligence (CI), DM, and decision-making/supporting system.

3.1 Components of Industry 4.0

Industry 4.0 is the superposition of several technological developments related to CPS, IoT, IoS, and DM. CPS refers to a new generation of systems with integrated computational and physical capabilities that can interact with humans using many new modalities. The key is the ability to interact with, and expand the capabilities of, the physical world via computation, communication, and control [26]. Furthermore, Industry 4.0 facilitates the development of intelligent and flexible production control systems, which apply information and communication technologies to facilitate machines to intercommunicate and interact. Typically, Industry 4.0 consists of the following four components.

1. CPS
2. IoT
3. Big data (BD) & DM
4. IoS

3.2 Cyber-Physical Systems

As an important component of Industry 4.0, CPS refers to a new generation of systems with integrated computational and physical capabilities that can interact with humans using many new modalities. The key is the ability to interact with, and expand the capabilities of, the physical world via computation, communication, and control [26]. CPS has the ability to transfer the physical world into the virtual one and can be understood as a basic unit. The development and application of identification approaches such as RFID have become the foundation to achieve unique identification of objects. CPS applies multiple sensors using information and communication technologies to collect, store, and parse data.

3.3 Internet of Things

The IoT is defined as the ubiquitous access to entities on the Internet for the extension of the physical world using a variety of sensing, detection, identification, location tracking, and monitoring equipment [27]. It allows "things or objects" to interact with each other and cooperate with their "smart" components to achieve common aims. The IoT can be considered as a network where CPSs cooperate with each other via unique addressing schemes.

3.4 Data Mining

DM can be defined as the process of discovering interesting (non-trivial, implicit, previously unknown, and potentially useful) patterns and knowledge from large amounts of data [28]. It can also be considered as a result of the natural evolution of information technology. The evolution is an essential process, where intelligent methods are applied to extract data patterns and discover knowledge from data [29]. The data sources may include databases, data warehouses, the Web, other information repositories, or data that are streamed into a system dynamically [30]. In other words, DM is the process of answering questions by searching a database for rules, relationships, and patterns not obtained by conventional query tools.

Real-time big data is not just a process of storing a huge amount of data in a database or warehouse. DM enables us to analyze and discover patterns, rules, and knowledge from big data collected from multiple sources. Therefore, we can make the right decision at the right time and right place according to the result of analysis using real-time data.

3.5 Internet of Services

The IoS pursues a similar approach as IoT, but with services instead of physical entities. The integration of these developments promotes the cooperation among all the partners in the entire system. It enables service vendors to offer their services via the Internet. The IoS consists of business models, infrastructure for services, the services themselves, and participants. Services are offered and combined into value-added services by various suppliers. They are communicated to users and consumers, who access them via various channels.

3.6 Definition of Industry 4.0

Based on the literature review, Industry 4.0 can be summarized as a collective term for the technologies and concepts of value chain organizations. Within the smart factories of Industry 4.0, CPSs monitor physical processes, create a virtual copy of the physical world, and thereby make decentralized decisions. Using the IoT, CPSs communicate and cooperate with each other and humans in real time. DM discovers knowledge to support the decision-making process. Using the IoS, both internal and cross-organizational services are offered and utilized by participants of the value chain [14].

4 System Framework based on Industry 4.0 Concepts

As discussed above, monitoring systems in machine centers may require DM methods for fault diagnosis and prognosis according to different monitoring purposes or components. Therefore, a systematic framework based on DM to achieve fault diagnosis and prognosis for machine centers is imperative [31]. As shown in Fig. 2, a system framework is formulated for predictive maintenance in machine centers based on Industry 4.0 concepts. DM and CI have been applied to discover failure information and optimize the solutions, respectively. This system can monitor plant floor assets, link the production and maintenance operations systems, obtain data, collect feedback from a remote customer site, and integrate it into upper-level enterprise applications, discovery hidden information about impending failures, and generate maintenance knowledge. It can also monitor the state of manufacturing processes and predict the condition of the equipment.

The system can make a maintenance decision to prevent the occurrence and development of failures effectively, ensure equipment and personal safety, and reduce the economic loss caused by failures. It can use fault diagnosis, performance assessment of the degrading level, and fault prognosis models to achieve near-zero-breakdown performance and improve the productivity of a company. The framework includes five main modules: sensor selection and data acquisition module, data preprocessing module, DM module, decision support module, and maintenance implementation module. All these modules have clear ordinal relation and specific functions in the system. The framework is based on many key techniques of Industry 4.0 concepts, such as CPS, IoT, IoS, CI, DM, and swarm intelligence (SI), and should be researched and developed for satisfying the industry requirements.

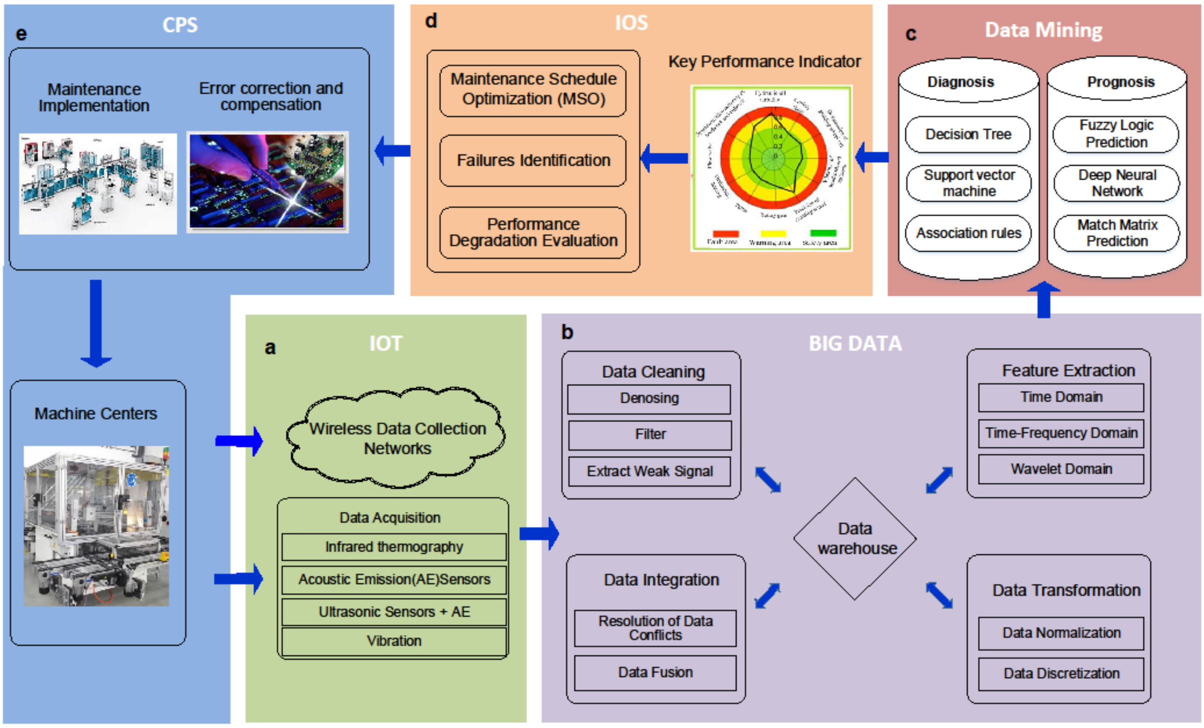

Fig. 2 The framework of fault diagnosis and prognosis in machine centers

(a) Sensor selection and data acquisition module

(b) Data preprocessing module

(c) Data mining module

(d) Decision support module

(e) Maintenance implementation module

4.1 Sensor Selection and Data Acquisition Module

This is the first step to implement diagnosis and prognosis based on DM in machine centers. The task of this module is to select a suitable sensor and optimal data collection strategy to extend the physical world using a variety of sensing, detection, and identification techniques, and connect the objects or enable them to interact with each other. It can be considered as the implementation of IoT. The data acquisition process transforms the sensor signals into domains that have the most information to represent the condition of the equipment or a fusion of several domains. Various sensors such as micro-sensors, ultrasonic sensors, vibration sensors, and acoustic emission sensors can be designed to collect different data. The selection of sensors determines the representation of the machine health by the collected data, considering both the specifications and cost-effectiveness. Moreover, with the increase in the complexity of the machine system, the sensor network is considered as a feasible solution for the diagnosis and prognosis system in machine centers, which may include different kinds of sensors. Sensor fusion achieves significance under this condition. Therefore, obtaining smart sensors is also a prominent research field in condition monitoring [32]. The selection of suitable sensors is the key for the effectiveness of condition monitoring, and a complete data acquisition system can improve the correction and efficiency of diagnosis and prognosis directly.

4.2 Data Preprocessing Module

After the data acquisition module, all the collected data will be stored in the data warehouse for diagnosis and prognosis. However, during the process of knowledge discovery, if there is too much irrelevant and redundant information, such as noise or unreliable data, the training phase will be more challenging. Therefore, it is necessary to preprocess the data before the subsequent step. This challenge is also called as BD in the industry.

Generally, the major steps involved in data preprocessing include data cleaning, data integration, data reduction, and data transformation. Data cleaning is the process of detecting and correcting corrupt or inaccurate records from the database by filling in missing values, smoothing noisy data, identifying or removing outliers, and resolving inconsistencies. Data integration is the process of merging data from multiple data stores. Careful integration can help reduce and avoid redundancies and inconsistencies in the resulting data set. Data reduction provides a reduced representation of the data set that is much smaller in volume and can produce the same (or almost the same) analytical results. There are many dimensionality reduction methods. Among them, a straightforward approach is to apply feature extraction methods to the data set, which extract features that are the characteristics of an incipient failure or fault from preprocessed signals. Generally, the features can be extracted from three domains: time domain, frequency domain, and time-frequency domain. In data transformation, the data are transformed or consolidated into forms appropriate for DM, such that the DM process may be more efficient, and the patterns obtained may be easier to understand [30].

The development of storage media and computation ability results in massive data during the data acquisition process. Data preprocessing can effectively clean the raw data, reduce the dimension of the data, and store it back in the warehouse for knowledge discovery. Therefore, massive data can be converted to features or statistical values as the input variables of the DM process.

4.3 Data Mining Module

DM has the capability to discover hidden links, recognize unknown patterns, and predict future trends by digging through and analyzing enormous sets of data [33]. The functions or models of DM can be categorized according to the task performed [34], such as clustering, classification, decision trees, predication, regression, and association. Generally, the analysis methods of DM can be categorized into three groups: statistics, machine learning, and artificial intelligence (AI) [35].

As the research field of collection, analysis, interpretation, and presentation of data, statistics has an inherent connection with DM. A statistical model is a set of mathematical functions that describe the behavior of objects in a target class in terms of random variables and their associated probability distributions [30]. Hence, it is widely used to model data and data classes during the process of DM. Examples of statistics include regression analysis, cluster analysis, and discriminate analysis.

As a subfield of computer science, machine learning investigates the method by which computers can study and make predictions based on data [36]. Machine learning is employed in a range of computing tasks to learn to recognize complex patterns and make appropriate decisions automatically. Machine learning is usually divided into two main types: predictive or supervised learning, and descriptive or unsupervised learning [37]. In the predictive or supervised learning process, the goal is to form a mapping from inputs x to outputs y, given a labeled set of input-output data $D = \{(x_i|y_i)\}\ i = 1,2,3 \ldots N$, where D is the training set and N is the number of training examples. In descriptive or unsupervised learning, the learning process is unsupervised since there are no classes labeled in the input samples. In this process, only the inputs will be given, $D = \{x_i\}\ i = 1,2,3 \ldots N$, and the goal is to determine interesting patterns and knowledge from large amounts of data. This is a much less well-defined problem, since we are not aware of the kind of patterns to search for, and there is no obvious error metric for evaluating the results.

The third family root of DM is AI, which is built using a heuristic algorithm. It includes several techniques such as genetic algorithm (GA), artificial neural network (ANN), fuzzy logic systems (FLS), and case-based reasoning (CBR). The main idea is to apply human-thought-like processing to statistical problems. It uses techniques for writing computer code to represent and manipulate knowledge, which is exactly apt for computer processing in modern business environment [35]. Currently, owing to the rapid development of deep learning approaches, they also provide feasible methods to deal with the issue of fault prediction, which was once considered as the most challenging problem in the research area of predictive maintenance.

DM benefits from these technologies, but differs from the objective pursued: extracting patterns, describing trends, or predicting behaviors. It is applied in a wide range of domains where large amounts of data are available for the identification of unknown or hidden information [34]. As to the fault diagnosis and prognosis in machine centers, owing to the high complexity and coupling features among a wide range of faults, it is appropriate to apply DM methods in this field.

The DM module in the framework mainly focuses on fault detection, classification, and prediction for predictive maintenance. Fault diagnosis and prognosis strategies have been developed and have achieved extensive utility in a wide range of application domains in recent years. Typically, they can be divided into two major categories: model based and data-driven [38]. A model-based technique depends on the accuracy of the dynamic system model. It utilizes the actual system and model to generate the difference between the two outputs, which is indicative of a potential fault condition. However, in many manufacturing systems, it is difficult to establish a high-accuracy dynamic system model. Data-driven techniques often address only the anticipated fault condition, where a fault model is a collection of constructs such as neural networks and expert systems, which must be trained first with known prototype fault patterns. Generally, if the historical data can be obtained easily, the data-driven technique is useful to identify the fault and evaluate the condition. When only a part of the historical data can be obtained, hybrid techniques that combine the data-driven techniques and model-based techniques can be used to evaluate the current condition of the manufacturing system or products. The semi-supervised learning method can also be used to evaluate the condition and identify faults when only a part of the historical data is available and it is very effective.

This study focuses on the data-driven techniques and hybrid techniques in the fault diagnosis and prognosis module. For example, a deep belief network can be used to identify fault types and recognize fault severity ranking in rolling element bearings [39]. Some common diagnosis and prognosis algorithms are listed in the framework. All these techniques have already demonstrated their ability to deal with certain issues. They are widely applied and can be selected according to the real manufacturing system analysis.

4.4 Decision Support Module

The main purpose of this module is to visualize the result of DM and provide an optimized strategy according to DM. It can also be considered as the application of IoS. Generally, a diagram of key performance indicator (KPI), also called a spider chart, can be used for presenting the situation of equipment. The conditions of equipment can be defined in several levels from zero to one. For example, zero indicates no faults and one indicates complete damage of equipment. In the framework, the KPI may be formed according to the outputs of the DM module. The diagram will enable operators or managers to evaluate the performance visually, and subsequently, an optimized maintenance schedule can be provided according to the result of evaluation.

Maintenance planning and scheduling optimization is a kind of nondeterministic polynomial time (NP) problem and it is always difficult for the decision-makers to capture the trade-off. SI algorithms could be a very good technique to solve this kind of problem. Usually, one may apply GA, particle swarm optimization, ant colony optimization, and bee colony algorithm as decision support methods, and attempt to determine the optimal dynamic predictive maintenance scheduling. All these methods are selectable in the framework to solve maintenance scheduling optimization problems. Furthermore, this module may also include the function of failure identification and the evaluation of performance degradation according to the result of the DM module.

4.5 Maintenance Implementation Module

In this module, maintenance will be implemented after the decision-makers choose the strategy of maintenance. It can be considered as the purpose of CPS. The physical world is transferred into the virtual one for communication, computation, analysis, and decision-making via the previous modules. In this module, we react to the physical world according to the result of those modules and implement maintenance to achieve a certain purpose, e.g., to minimize the cost of maintenance, realize zero-defect manufacturing, or reduce breakdown.

Moreover, this module may also include the function of error correction, compensation, and feedback control based on the results from the maintenance decision support module to continue to run the equipment and process in a normal condition. Different techniques can be used to correct and compensate the errors. ANN has been widely used for the compensation of backlash errors in computer-controlled machine centers. However, the error correction and compensation process is mainly dependent on the types of machines and processes. The module should be integrated with control devices and the maintenance management system.

5 Case Study: Backlash Error Prediction for Green Monitoring in Machine Centers

This case study is from a project called Green Monitoring, which aims to decrease the cost of faults, defects, and maintenance during the manufacturing process via remote condition monitoring and DM. As shown in Fig. 3, the data is obtained from a remote customer site and transported to a DM center for analysis. After a series of DM processes, the result and suggestion will be provided to the customers for maintenance optimization.

In the case study, ANN is applied for fault prediction, and can be used to illustrate the use of DM methods for predictive maintenance in machine centers. The process can be divided into five steps: data acquisition, data preprocessing, DM, fault prediction, and decision support. The technique modifies a time-based behavior model using an ANN, which can map and predict the backlash error in machine centers for failure detection or prediction and maintenance decision support. This case only considers the backlash error as an instance to demonstrate the working of the system and illustrate an Industry 4.0 scenario.

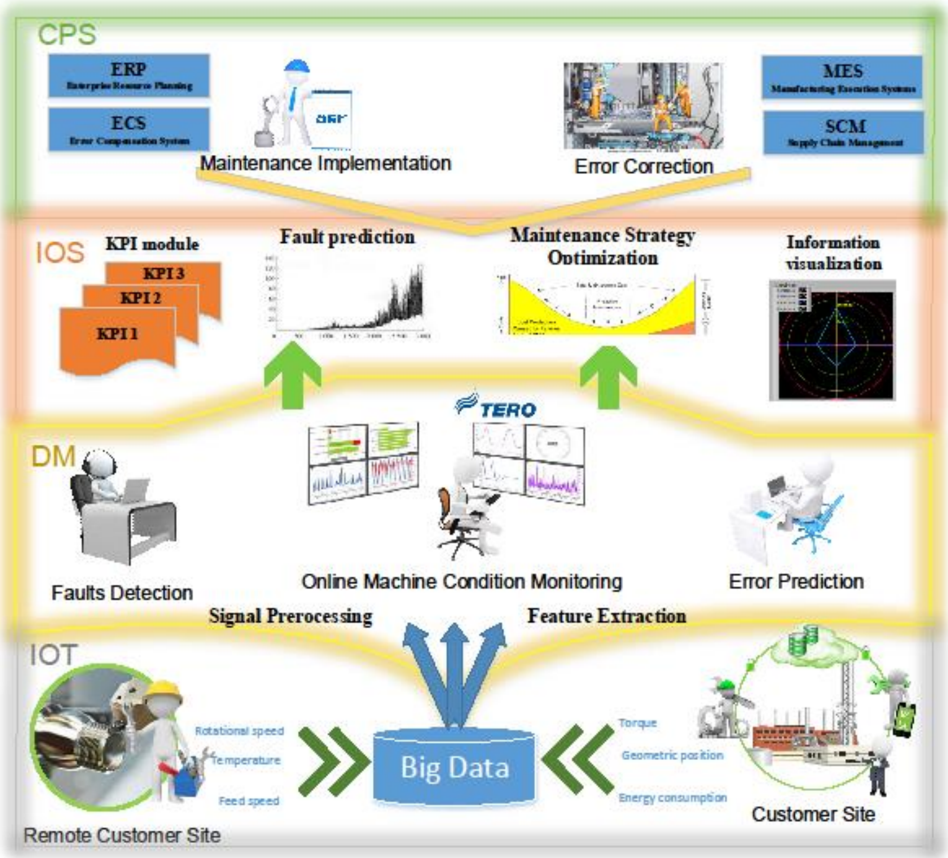

Fig. 3 Green Monitoring System based on Industry 4.0 concepts

5.1 Data Acquisition

Usually, a machine center itself is equipped with many high-precision sensors such as grating, rotary encoder, linear scale, current sensor, and temperature sensor to guarantee accuracy using a closed or half-closed loop control. Therefore, many parameters such as machine temperature, position of the screw and table, torque, and current can be obtained directly from the control system. In this case, the backlash error is calculated according to the axis position of the table (spindle) and ball screw, which are already collected and stored using a rotary encoder and linear scale in the machine center. Therefore, new installation of specific sensors or diagnostic equipment is not required. The form of collected data is shown in Fig. 4. The vertical axis is the position of the table and screw, and the horizontal axis is the sampling units, which can be considered as time.

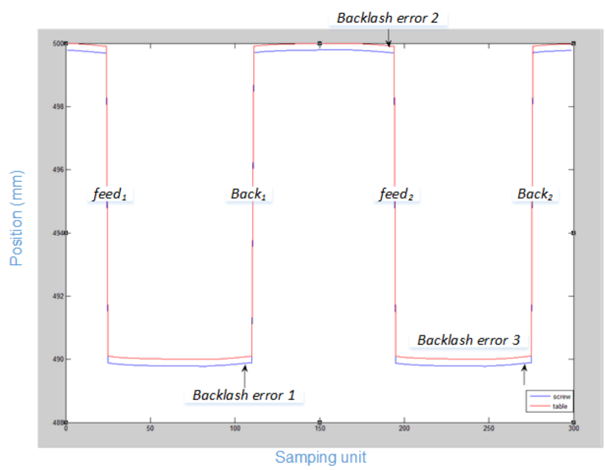

Fig. 4 Axis position of table and screw

5.2 Data Preprocessing

As shown in Fig. 4, three blocks of backlash error can be recognized during a sampling process. Furthermore, the average backlash error during this test can be interpreted according to the change of difference between the position of the table and screw. The position of the screw can be represented as follows:

$$
\begin{aligned}
Screw(t) &= Screw\ (0) + \int_0^t feed(t)\,dt + \int_0^t back(t)\,dt \\
&\quad + \int_0^t backlash(t)\,dt \\
&= Screw\ (0) - feed_1 + backlash_1 + back_1 - \\
&\quad backlash_2 - feed_2 + backlash_3 + back_2 \qquad (1)
\end{aligned}
$$

where

$Screw(t)$: Position of the screw in sample no. t

$Screw(0)$: Initial position of the screw

$backlash$: Backlash error at the t^{th} sample

$feed(t)$: Feed rate at t^{th} sample, which is equal to zero if not under feed movement

$back(t)$: Return rate at t^{th} sample, which is equal to zero if not under return movement

The position of the table can be represented as follows:

$$
\begin{aligned}
Table(t) &= Table\ (0) + \int_0^t feed(t)\,dt + \int_0^t back(t)\,dt \\
&= Table\ (0) - feed_1 + back_1 - feed_2 \\
&\quad + back_2 \qquad (2)
\end{aligned}
$$

where

$Table(t)$: Position of the table in sample no. t

$Table(0)$: Initial position of the table

Subsequently, the overall backlash error in t samples can be calculated as follows:

$$
\begin{aligned}
\int_0^t backlash(t)\,dt &= [Screw(t) - Screw\ (0)] \\
&\quad - [Table(t) - Table\ (0)] \qquad (3)
\end{aligned}
$$

The backlash error extracted from the collected data is stored in the database, which will record the data of all the working days. A new data warehouse for training will be established to record the backlash error every week from the selection of the daily database. A median filter was applied to select the samples and exclude outliers for further DM.

5.3 Data Mining

During the DM process, historical data is leveraged to discover the hidden information or certain characteristics about specific faults. As shown in Fig. 5, we can divide the DM process into two processes: prognosis and diagnosis. The prognosis process is in charge of predicting the fault caused by natural wear and tear, while diagnosis process deals with the difference between current and normal parameters and evaluating the effect of working conditions under certain failures. Subsequently, predictive maintenance can be performed according to the result of prognosis and diagnosis individually or together based on some DM methods of decision support such as association rules and SI.

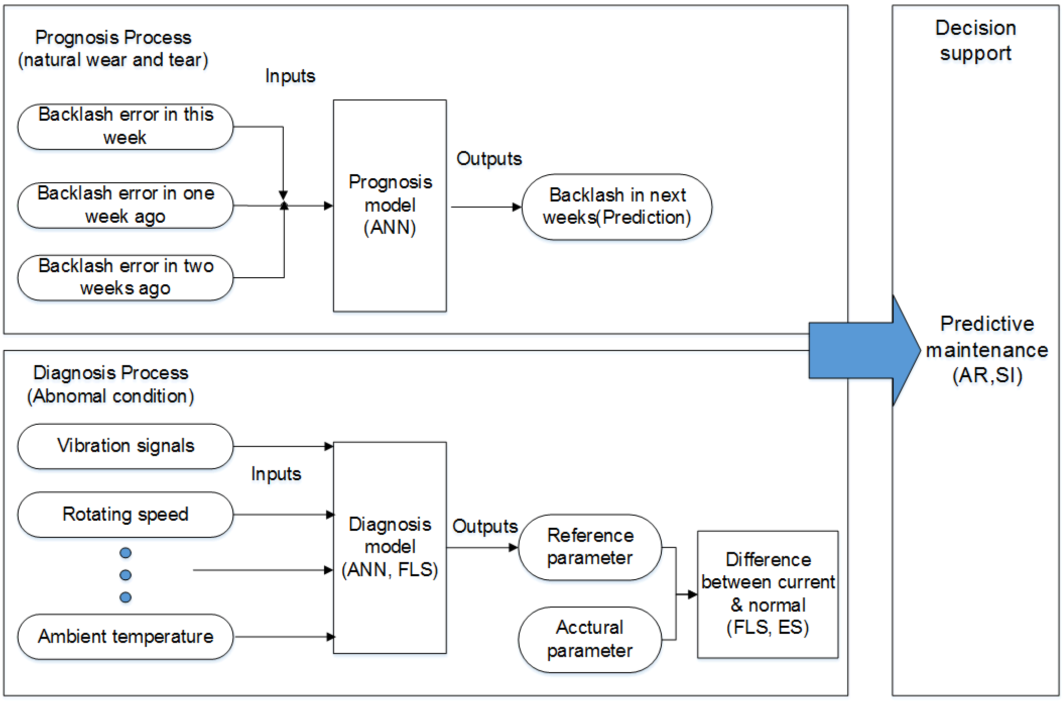

Fig. 5 Data mining process for the diagnosis and prognosis of backlash error in machine centers

This case study mainly focuses on the prognosis process for a backlash error in machine centers. In order to map and track the backlash error under normal working conditions, we applied an ANN, which is inspired by biological neural networks (the central nervous systems of animals, in particular the brain) and applied to estimate approximate functions using a large number of inputs [40]. The inputs in the prediction process are the backlash errors of the last three weeks and the output is the backlash error of the following week. This process includes two processes: training process and prediction process. The ANN was trained and established in the training process to obtain the characteristics of backlash error under ordinary wear and tear for the specific machine center, and the backlash error can be predicted in the prediction process. Subsequently, the maintenance decision can be made according to the prediction result.

5.4 Fault Prediction

After training the network, the data collected from the current condition can be applied as inputs to evaluate and predict the potential fault. In this case, we collected the data of a machine center that ran normally and steadily without any maintenance for 22 weeks until the backlash error exceed the permissible error. During the process of data collection, the equipment operated a series of rigorous procedures to ensure that all the samples are under the same working conditions. Subsequently, the backlash error was calculated from the data and used to train the ANN. The training process can be divided into two phases: network establishment and network testing. In the process of network establishment, 70% of the experiment data was applied to train and adjust the network using the difference between the target and output values. In the testing process, the remaining 30% of data was divided into two groups: validation data and testing data. The validation data was used to estimate the condition of the network's generalization, which indicates that the training would cease when the generalization stops improving. Furthermore, since the testing data has no effect on the training process, an independent assessment can be performed according to the testing results. The maximal training error in this case is approximately 0.6 μm. The model trained in this process can be used as the reference to map the backlash error with time.

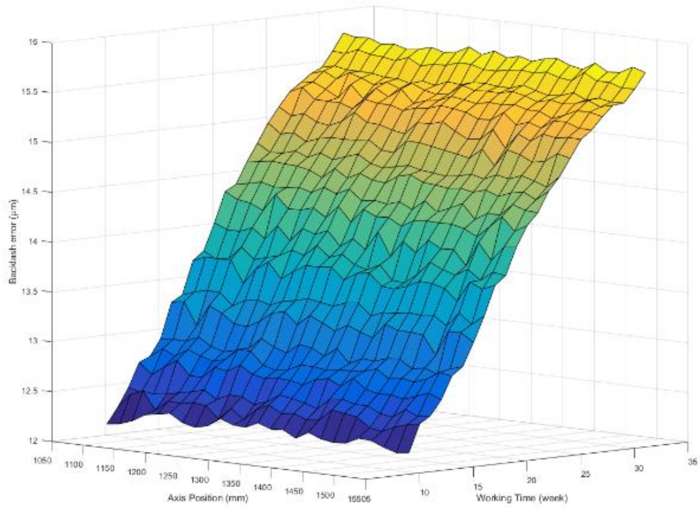

Fig. 6 Prediction result of backlash error

In the prediction results shown in Fig. 6, the backlash errors of the last three weeks can be used as inputs to predict the backlash error of the subsequent week in the ANN model.

5.5 Decision Support

After fault prediction, the result will be recorded and published on the online dashboard for remote condition monitoring and information sharing. All the data and analysis results will be stored in an online data warehouse for data exchange and transport. The recommended maintenance strategy will be formulated in the decision support system according to the prediction or evaluation result. Generally, relevant optimization and association theories are required to capture the trade-off between several factors such as maintenance cost, machining accuracy, and defective percentage, and make the optimal decision. For maintenance strategy, if the backlash error of the following week predicted in the network exceeds the tolerance interval or a certain degree, maintenance shall be implemented in advance. The target is to enable the operation team to utilize real-time data to optimize and prioritize maintenance scheduling.

6. Conclusion

DM will play a very important role in predictive maintenance in machine centers owing to their complexity and high machining precision. The theoretical contribution of this paper could be represented by the collection, classification, and induction of DM approaches applied for fault diagnosis and prognosis in machine centers. Furthermore, the definition of Industry 4.0 provided herein clarifies the basic understanding of the term Industry 4.0 among practitioners.

Moreover, this paper presented a framework to formulate a systematic approach and obtain knowledge based on Industry 4.0 concepts for predictive maintenance in machine centers based on the DM result in fault diagnosis and prognosis. The framework contains the entire process of fault analysis and treatment, which includes sensor and data acquisition, data preprocessing, fault diagnosis and prognosis, performance indicator analysis, and maintenance schedule optimization. DM is applied in the framework to achieve fault diagnosis and prognosis in machine centers. Moreover, a case study about backlash error interpretation and prediction in machine centers is reported and discussed to illustrate the operation of DM for fault diagnosis and prognosis, and it provides a maintenance strategy to machine centers.

However, there still exist some challenges in the application of DM for fault diagnosis and prognosis in machine centers. The main benefits of ANN are fault tolerance, generalization, and adaptability. Nevertheless, the limitation is the lack of an explanation function, which indicates that it is difficult to determine the influence of various factors. GA is a robust, general-purpose search procedure; it can quickly explore large search spaces and determine those regions that have above-average fitness. However, the convergence time to determine global optima will be very long. FLS can be applied where accurate mathematical models are unavailable or difficult to be established, but empirical knowledge of the problem is required to develop an accuracy model of the subsystem. Furthermore, most of the research reviewed in this paper is based on current working conditions or natural wear, which may be related and combined to achieve higher accuracy of fault diagnosis and prognosis. Therefore, a fault diagnosis and prognosis system based on DM in machine centers should be researched and developed further.

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