DIGITALIZED CONDITION MONITORING AND HEALTH MANAGEMENT SYSTEM FOR ELECTRIC MOTORS

Paper No. PCIC energy EUR23_19

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Abstract - Electric motors, as the main power source in electrification, play a vital role in global industrial production. The digitalized predictive maintenance system utilizes health data generated from condition monitoring tools gathered from motor operations to predict failure trend and probability. Compared to reactive maintenance, the predictive maintenance supports scheduled maintenance plan before the failure occurs. It is critical to prevent significant impacts of accidental failures in operating motors by adapting new condition-based monitoring and health management digital system.

The article introduces digital transformation of condition monitoring and health management system for industrial motors. It identifies the common failures of electric motors, followed by proposing new ways for analyzing motor operating characteristics, health data and systems to quantify failure trend and development. Subsequently the authors establish asset lifecycle management methodologies for maintaining the motors' reliable operations and minimizing the impact to production.

Index Terms — Digitalization, Digital twin, Electric motor, Condition-based monitoring, Prognostics, Health management, Lifecycle management.

I. INTRODUCTION

As one of the main power sources that drives various industrial equipment, the electric motor's reliable operation is crucial to the safety and reliability of process-based large-scale industrial production, such as petroleum, chemical, oil and gas, mining and power generation. The failure of motors' key components may cause equipment malfunction or even damage, resulting in interruption and chain reaction of failure in the entire production process, resulting in huge economic losses [1-4].

With the continuous promotion and application of advanced technologies such as IIoT, big data, and industrial artificial intelligence [5-6], monitoring the operational status of fix assets often requires many monitoring points, high sampling frequency and long data collection period. The amount of data to be processed by the motor health management system has shown an exponential growth. Big data such as hundreds of Terabits or even Petabits is not uncommon. Mechanical big data has become an important resource for revealing the evolutionary process and nature of mechanical failures [7-8]. The massive data on the industrial internet platform has important value. The scale of the data volume and the ability to explain and utilize will also become critical for motor health management [9-12].

Therefore, a large amount of motor operating status data is obtained through online and offline methods. Predictive analysis is established by mining the information embedded in the health data. It assists technicians to recognize, manage and solve various problems from a predictive perspective. It is particularly important to deduce and predict the trend and rate of fault development to achieve targeted maintenance [13-14]. Therefore it reduces efficiency and economic losses caused by unplanned incidents of production lines or units.

The practices of digital transformation of industrial motor condition monitoring and health management system are introduced. Common faults of electric motors are firstly presented. New methods for analyzing motor operating characteristics, health data, and healthy systems are then presented to quantify fault trends and developments. Subsequently, an equipment lifecycle management approach was established to ensure reliable operation of motors and minimize the impact on production. Following a case study in a real scenario, the conclusions are drawn at the end of the paper.

II. MOTOR HEALTH MANAGEMENT

A. General Concept

The Prognostics and Health Management (PHM) system utilizes important operational parameters of the equipment collected through sensors and control systems. By monitoring and analyzing the evolution of such real-time data over a period of time, the system deduces motor failure development process and trend based on certain defined rules and algorithms. The system enables predictive maintenance to reduce the probability of catastrophic failures. Specifically, the system is able to: (1) trigger early warnings for the failure of equipment of concern to avoid unexpected accidents; (2) provide operators the necessary information for predictive maintenance; (3) reduce maintenance frequency and costs; (4) present historical data that can provide feedback for operation improvement.

The necessary conditions for monitored items in PHM are as follows:

1. Common equipment failures which affect the safe operation of equipment, and the failure rate is high.
2. High failure detection operability. Generally, the detection can be done by removing parts such as the cover of junction box when the equipment is

either running or shut down, without compromising health & safety guidelines.
3. The detected results can be quantified to evaluate the fault level.

Other items affecting equipment health can be covered during regular routine maintenance or overhaul.

B. Determination of Motor Health Characteristic Parameters

The working condition of the motor is normally under harsh environment. For example,

1. The motor deployed in the petrochemical industry is in a relatively confined environment with insufficient air flow for dissipating the generated heat. The ambient temperature is often around 40 °C. Or it is often installed in open air area and exposed to direct sunlight.
2. Some motors are installed in open ground close to coastal region. The climate near sea is humid. The salty air is corrosive, endangering the durability of the motor.
3. The motor is used for belt conveyor lines, hoists, or elevators etc., suffering frequent start-up/stop and large load fluctuation.
4. The motor is exposed to heavy particulate air pollution.
5. The motor uses variable frequency power with insufficient harmonic control.

The common faults of motors are excessive vibration, high bearing operating temperature, abnormal sound, low winding insulation resistance, high winding temperature, uneven three-phase current, rust or loose parts, overheating of terminals, etc. Apart from equipment manufacturing and installation related reasons, the faults can be related to previously mentioned harsh conditions and improper maintenance. These faults most likely lead to bearing and winding failures. In addition, burnt leads or cracked components also occur frequently. Statistics show that bearing damage and winding burndown account for 80% of the total damage, while both bearings and windings have fatigue and aging phenomena. Therefore, bearings and windings constitute the main components of interest in reflecting the health of the motors. The power quality (e.g., harmonics) and maintenance behavior also have impact on motor operation, which can be used as reference factors for motor health status and life cycle prediction.

The fault diagnosis mainly focuses on the characteristic parameters of components. The first component is the bearing. (1) The vibration acceleration envelope value (gE) can comprehensively reflect the degree of bearing defects. It can be used as a predictive parameter for the health status and development trend of rolling bearings; (2) The bearing vibration spectrum can be used to further analyze the fault location and fault degree of the bearing, and can be used as a detailed parameter for life cycle prediction in the middle and late stages of the incurred fault; (3) The parameter of the bearing operating environment affects the speed of failure development. The bearing operating temperature can be used as a reference parameter for life cycle prediction; (4) The bearing vibration speed affects the fault development speed and can be used as a reference parameter for life cycle prediction; (5) The abnormal sound from running bearing is used to assist in judging the degree of fault.

The second component is the winding. The winding is composed of coils, inter-turn insulation, ground (core) insulation, lead wires, terminals, etc. The inherent parameters are: (1) Through three-phase and historical data comparison, the three-phase DC resistance R is used for judging the reliability of the electrical connection. It's also regarded as a reference parameter for inter-turn faults. (2) Three-phase inductance L, impedance Z, I/F, and phase angle φ are used for comprehensive judgment of turn-to-turn faults. (3) Comparing to the historical data (or factory data), the ground capacitance C is used to determine the main parameters of ground insulation aging. (4) The insulation resistance R, absorption ratio (or polarization index) can be used to judge the moisture and pollution of the winding. (5) The current and voltage spectrum can be used to comprehensively analyze the dynamic and static unevenness of the stator and rotor air gap, loose windings, rotor bar defects, electromagnetically induced vibration, heat generation, etc.

The third component is the squirrel cage rotor. (1) Three-phase inductance curve is the main parameters for judging the defects of squirrel-cage rotor such as broken bars and thin bars. (2) Combined with the three-phase inductance curve, the current spectrum is main parameters for comprehensively judging the of squirrel-cage rotor defects. (3) The vibration spectrum is used as reference parameters for rotor failure to determine the rotor defects such as unbalance, looseness, and oil film oscillation of sliding bearings.

The natural frequency measurement of other parts such as shafts, casings, components, etc., and the measurement of power harmonics can also be used as a reference for fault diagnosis.

C. Operational Health Stages and Determination of Evaluation Indexes

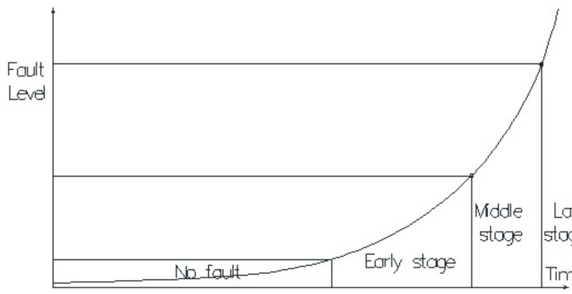

Fig. 1 Stages of motor faults

Operational Health Stage: Regardless of the aging of the motor winding or the fatigue of the bearings, it is a gradual process (sudden failures caused by abnormality are not in the scope of this article). General speaking, after a long period of good operation, the signs of failure are gradually formed and slowly expanded. It enters the early stage of failure. As the degree of failure gradually expands, the speed of development gradually accelerates, entering the middle stage of failure, and then entering the late stage, as shown in Fig. 1. The stage division mainly considers two factors, one is the severity of the fault, refer to relevant standards or experience. The second is the length of time left to deal with the fault. In the late stage of the fault, although it can continue to operate for a period of time, it should be dealt with immediately to avoid great losses until failure occurred.

Evaluation index: According to relevant standards and experience, a reference index can be determined according to specific projects. For each piece of equipment, it should be combined with the operating environment (temperature, vibration, installation method, etc.), working conditions (load rate, operation mode, etc.) and similar products. The operating experience should be properly adjusted, i.e., the evaluation indicators should be continuously revised and improved the accuracy in the process of equipment health management. The suggested reference indicators (but not limited to) are listed in Table I.

TABLE I
Operational Health Evaluation Index

	Surveilled Items	Normal operation	Early	Middle	Late
Online (Temperature Vibration)	Bearing Vibration Velocity/mm/s	≤2.3	>2.3~4.5	>4.5~7.1	>7.1
	Bearing Vibration Acceleration Envelope gE	≤4	>4~7	>7~10	>10
	Rolling Bearing Temperature/℃	≤65	>65~85	>85~95	>95
	Plain Bearing Temperature/℃	≤65	>65~75	>75~85	>85
	Winding Temperature/℃ (Class F)	≤85	>85~105	>105~135	>135
Online (Electrical Signal)	Current Fluctuation/%	≤3	>3~5	>5~10	>10
	Current Unbalance/Dev%	≤2	>2~3	>3~5	>5
	Squirrel Cage Rotor State/db	≥54	< 54~48	< 48~40	< 40
	Voltage Total Harmonic Distortion/THD	≤2	>2~3	>3~5	>5
Offline (Regular Static Physical Examination)	DC Resistance Unevenness/%	≤2	>2~5	>5~10	>10
	Inductive Resistance Roughness/%	≤10	>10~20	>20~30	>30
	Reactance Roughness/%	≤10	>10~20	>20~30	>30
	Three-phase Phase Angle Unevenness (Low Voltage)	≤1.3	>1.3~2	>2~5	>5
	Three-phase Phase Angle Unevenness (High Voltage)	≤1.3	>1.3~3.5	>3.5~8	>8
	I/F(Low Voltage)	≤1.3	>1.3~2	>2~5	>5
	I/F(High Voltage)	≤1.3	>1.3~3.5	>3.5~8	>8
	Winding Pollution Index (Low Voltage)	≤1	>1~2	>2~3	>3
	Winding Pollution Index (High Voltage)	≤1.3	>1.3~2.5	>2.5~3.5	>3.5

D. Health Data Management

The equipment health management is mainly health data management, including data acquisition, current inspection data, historical data of previous inspections, and inspection time intervals. Unless intermediate repairs affect data changes, such as replacing winding coils and bearings, but even so, since the operating environment of the equipment has not changed, the change law of historical data is still of reference value for subsequent health analysis. For this reason, it is necessary to establish a set of data files that can manage, compare and analyze historical data for equipment health management.

The health management data file should have the following functions: (1) It can regularly record the basic data of the equipment, and these data are related to the comparative analysis and spectrum analysis; (2) It can record the location, name, etc. of the equipment, so that the equipment is unique; (3) According to the different detection time, record each detection data, combined with the fault degree standard, automatically judge and mark the fault state according to the color, and can be distinguished according to the detection time; (4) It can compare and analyze the historical data, and can also compare and analyze the detection data of the same equipment (that is, it can compare and analyze both vertically and horizontally); (5) It is possible to store the source files of each detection (such as spectrum, curves, etc.), to compare and analyze the source file data when necessary.

III. CONDITION MONITORING SMART SERVICES SYSTEM ARCHITECTURE

The platform architecture of Condition Monitoring Smart Services is shown in Fig. 2. It comprises six layers: Access Layer, Communication Layer, Platform Layer, Algorithm Layer, Application Layer and UI (User Interface) layer. The system is capable to provide online monitoring for all rotating machines such as motors, compressors, fans and pumps, etc. It is based on standard communication protocols, sharing speed, vibration and temperature data along with asset locations through the IoT Edge hardware.

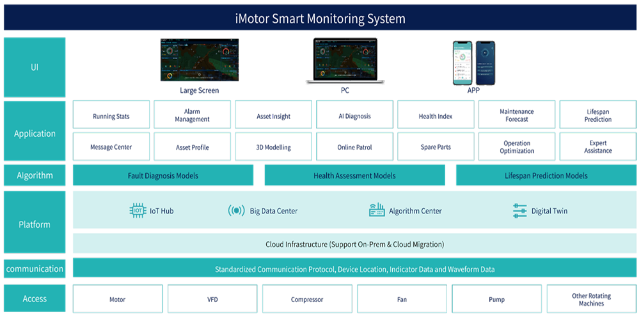

Fig. 2 Condition monitoring smart services platform architecture

Built on the cloud infrastructure and using Spring Cloud microservices, the platform consists of four kay functional centers: IoT Hub, Big Data Center, Algorithm Center and Digital Twin. The algorithm center can provide fault diagnosis, health assessment and lifespan prediction using various AI models.

A range of applications are implemented including alarm management, AI diagnosis, health index, asset profile, 3D modeling, maintenance forecast, expert assistance, message center, spare parts and more. The user interface covers, large screen, PC and mobile APP.

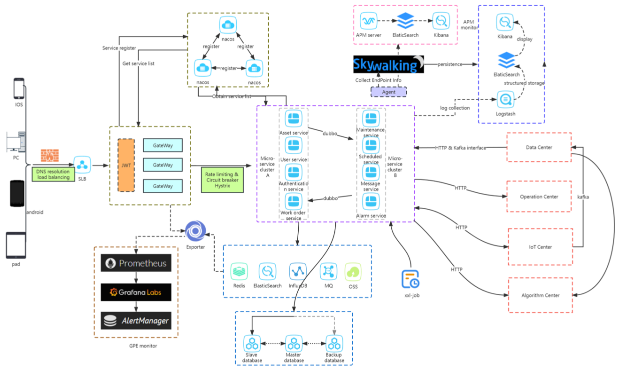

Fig. 3 Condition monitoring smart services software architecture

The Condition monitoring smart services software architecture based on PHM concept is illustrated in Fig. 3. The PHM is constructed based on the microservice architecture, including configuration center, gateway, business service, log collection, scheduled tasks, service monitoring, etc., The core data processing is supported by the business capabilities of each middle platform. The modules of the software architecture are:

1. The Configuration and Registry Center use Nacos to configure and register individual services.

2. The gateway adopts Spring Cloud Gateway for load-balancing and various services routing
3. Microservices business include device service, work order service, user service, authentication service, maintenance service, message service and alarm service. It can run multiple instances. The communication service between services chooses the Dubbo protocol.
4. The scheduled tasks (xx-ljob) are used to execute health reports, inspection reports, device statistics, etc.
5. The message components include SMS, push APP, and MQ.
6. The ElasticSearch search engine is for documentation, expert collaborating chat storage, and device-related searches.
7. MySQL, Redis and PostgreSQL are general business data store.
8. The construction of middle platform in the software architecture comprise of 3 function types. IoT middle platform includes receiving sensor data for reporting and forwarding to business systems. The big data middle platform consists of IoT data, algorithm data, health computing and other related data capabilities and providing data services. The algorithm middle platform contains vibration data spectrum analysis, intelligent trend alarm calculation to provide diagnostic analysis capabilities.

IV. FUNCTION AND ALGORITHM

Based on fast, reliable IoT, big data technology and industrial artificial intelligence, it's achievable to build a complete predictive maintenance with real-time health assessment, intelligent status warning, accurate fault diagnosis and accurate fault prediction as the core of the motor intelligent predictive maintenance and health management system. The functions of the system are to realize the equipment management concept of motor life cycle health management and predictive maintenance.

A. Intelligent Status Warning

Based on various information such as life cycle stage of the motor, the accuracy of motor management and maintenance, etc., a hierarchical early warning system is built. It provides absolute quantity index early warning and relative quantity index early warning to solve the monitoring of dominant problems. The big data analysis and industrial artificial intelligence early warning are able to realize the monitoring of potential hidden problems such as early weak faults. Each early warning method can be accessed and configured separately. Through the dynamic combination of each alarm method, the missing alarm and false alarm can be greatly reduced, and the number of repeated alarm push notifications can be dramatically reduced to meet the satisfaction of users for precise and intelligent early warning.

B. Accurate Fault Diagnosis

The motor intelligent predictive maintenance and health management system provides professional vibration analysis spectrum tools based on the idea of data service integration, including statistical analysis of real-time monitoring of vibration signals, waveform diagram, spectrum diagram, envelope spectrum, refinement spectrum and more than 10 kinds of analysis spectrum. For example, Fig. 4 shows the vibration signal analysis. Combined with the motor diagnosis knowledge base and related equipment information, it can realize the diagnosis and analysis of the health status of the motors.

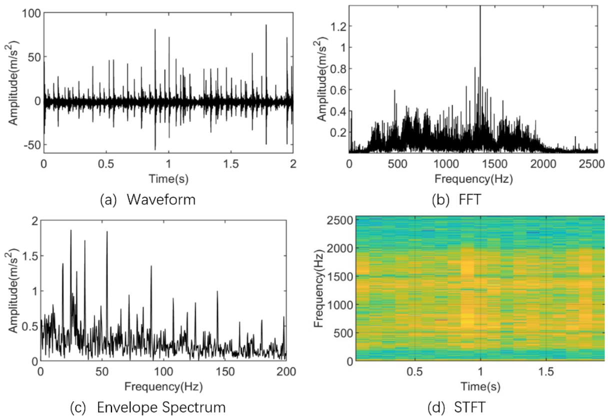

Fig. 4 Vibration signal analysis

C. Intelligent Motor Fault Diagnosis Driven by Knowledge Map

The diagnosable components can be identified from the motor operational status. The health condition indicators are extracted from the vibration, temperature and other signals. The fault symptoms are predicted from the feature trend and vibration frequency domain. Through information extraction, cloud storage and cloud computing with the information visual mapping, it can construct a knowledge map of equipment faults for visual display of knowledge of equipment fault analysis mechanism. It can build a logical reasoning engine for fault identification based on the knowledge map to achieve intelligent diagnosis of common motor faults (Fig. 5.).

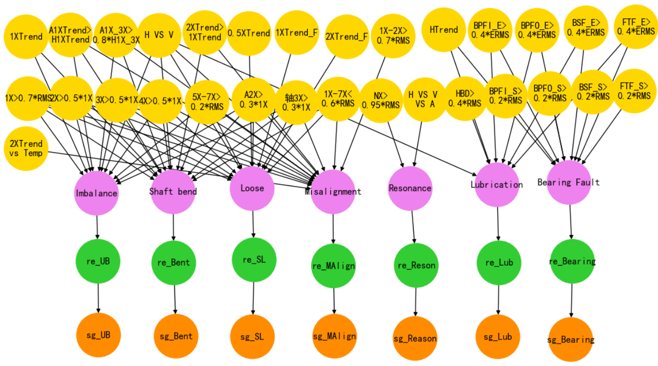

Fig. 5 Motor diagnosis knowledge graph

D. Motor Life Prediction Based on Exponential Degradation Model

Rolling bearings and three-phase windings, as two important components of the motor, are the focus of motor life prediction. The gradual fatigue of the rolling bearing determines the fatigue life of the bearing. The parameters that can be detected and quantified are the acceleration envelope value and the maximum acceleration envelope value of a single component in the vibration spectrum. The gradual aging of winding insulation materials, affected by heat, electricity, chemistry, machinery, etc., determines the aging life of winding insulation. The parameters that can be detected and quantified are ground capacitance C, three-phase inductance, three-phase impedance, three-phase I/F. The local items such as discharge and DC leakage have their own emphasis and need to be comprehensively evaluated. In addition, the gradual growth faults, such as wear and looseness of rotating parts, cracking of squirrel cage rotor bars, etc., can be measured and evaluated through vibration signals (e.g., vibration speed, acceleration) and electrical signals (e.g., squirrel cage rotor status indicators).

Regardless of the fatigue of the bearing or the aging of the winding insulation material, they all follow the gradual and slow decay from the intact stage to the early stage of failure, and the rapid decay from the middle stage to the late stage of the fault. Combined with the basic law of component or material fatigue and aging, in order to simplify the analysis, it is relatively simple and easy to roughly describe the later life law according to the exponent function [15]. The simplified mathematical model is as follows:

$$Y = A_0 + X^t \tag{1}$$

Where

- Y aging evaluation index parameters;
- A_0 the initial value of the evaluation parameter or the previous detection value (when new);
- X state parameters (select the target parameters that have the greatest impact on the current equipment operation or specific target parameters in the health parameters), which are related to both the operational condition and the original state. The development speed and so on are all changing. Each physical examination determines a current X value, combined with the previous X value to judge its change law, and then assigns X to the current forecast calculation. Therefore, the closer to the late period from the mid-term, the more meaningful the forecast is;
- t time node (The bearing data can be collected by hours, and the winding data can be counted by months).

V. CASE STUDY

The Fig. 6 shows the horizontal vibration velocity trend of an environmental protection fan motor operated in a petrochemical company.

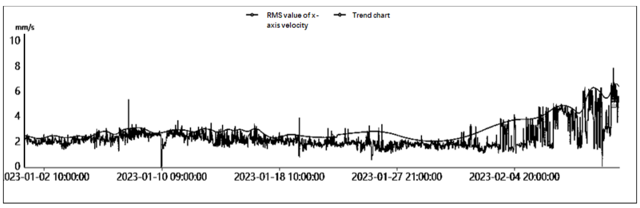

Fig. 6 A fan motor vibration velocity trend chart

It can be seen from the trend chart that the previous operation data of the fan is relatively stable. The effective value of the vibration speed in the horizontal direction is 2.0 mm/s at 11 am on January 31, 2023. After 175 hours of operation on February 7, 2023, the effective value of the vibration velocity is observed to reach 4.85 mm/s and is gradually increasing. The warning alarm is triggered. According to this growing trend, the exponential simplified model is used to fit the vibration trend of the motor, and it is obtained by using Levenberg-Marquardt method [16]

$$Y = 1.05 + 1.007733^t \tag{2}$$

Referring to the ISO10816-3 standard [17], we set the high alarm threshold of 7.1 mm/s as the target value for maintenance. According to Equation (2) and using a safety factor of 0.8, the predicted time to reach the 7.1 mm/s threshold is 105 hours. It can be seen from the trend chart that after the similar amount of hours of operation, the actual vibration speed reaches 6.6 mm/s, which is close to the 7.1 mm/s threshold. The case illustrates the effectiveness of the motor life prediction based on the exponential degradation model in equation (1).

VI. CONCLUSIONS

1) The motor health management is the data source of predictive maintenance. The management of historical motor health data is the key to motor health management. The real-time online monitoring or regular health checks on equipment is essential for the safe operation of the equipment, along with timely collection of the first-hand information on the health status of the equipment.

2) Based on digital technologies such as IIoT, big data, and artificial intelligence, the motor health management system obtains production monitoring data and operating data through intelligent means of deploying advanced sensors and edge computing units. It can intelligently perceive and warn the real-time running status of the motor panoramically. At the same time it realizes the intelligent diagnosis and identification of common faults of the motor, accurately locate the fault, analyze the root cause of the fault, and provide reference for customers to make maintenance decisions.

3) By collecting the motor operation data, the motor's PHM system can monitor trends of fault propagation in deterioration and predict motor failures in advance. It can predict equipment operating life on a rolling basis, transforming traditional temporary and unplanned maintenance into planned maintenance. As a result of implementing PHM, the operators improve efficiency by reducing unplanned downtime. They are able to change conventional motor management system into an intelligent predictive maintenance solution.

NOMENCLATURE

IIoT	Industrial Internet of Things
gE	Envelope value
R	Three-phase DC resistance
L	Three-phase inductance
Z	Three-phase impedance
I/F	Frequency doubling current change ratio
φ	Phase angles
C	Capacitance to ground

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VIII. VITA

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