



Federal Ministry
for Economic Affairs
and Energy



中国国家标准化管理委员会
Standardization Administration of the P.R.C.



中华人民共和国工业和信息化部

The Standardisation Roadmap of Predictive Maintenance for Sino-German Industrie 4.0/ Intelligent Manufacturing

*Sino-German Industrie 4.0/Intelligent Manufacturing
Standardisation Sub-Working Group*



STANDARDIZATION
COUNCIL
INDUSTRIE 4.0



Implemented by

giz Deutsche Gesellschaft
für Internationale
Zusammenarbeit (GIZ) GmbH

Imprint

Publisher

Federal Ministry of Economic Affairs and Energy
Department of Public Relations
11019 Berlin
www.bmwi.de

Text

Standardization Council Industrie 4.0
DKE Deutsche Kommission Elektrotechnik
Elektronik Informationstechnik in DIN und VDE,
60596 Frankfurt am Main

Design and production

AKRYL digital agency, Hamburg

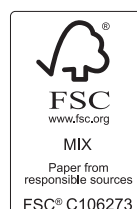
Status

April 2018

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Introduction

Efficient production significantly relies on the availability of the production equipment. In order to guarantee the intended usage of such equipment and to avoid unplanned downtimes, the status of the equipment and its components need to be monitored and assessed. This process is called Condition Monitoring.

Modern automation system components are more and more equipped with sensors and capabilities for self-monitoring. These functions may gather data that can be used to determine the component status. However, the components are delivered from different vendors and are based on different technologies. Thus, a uniform solution for accessing the

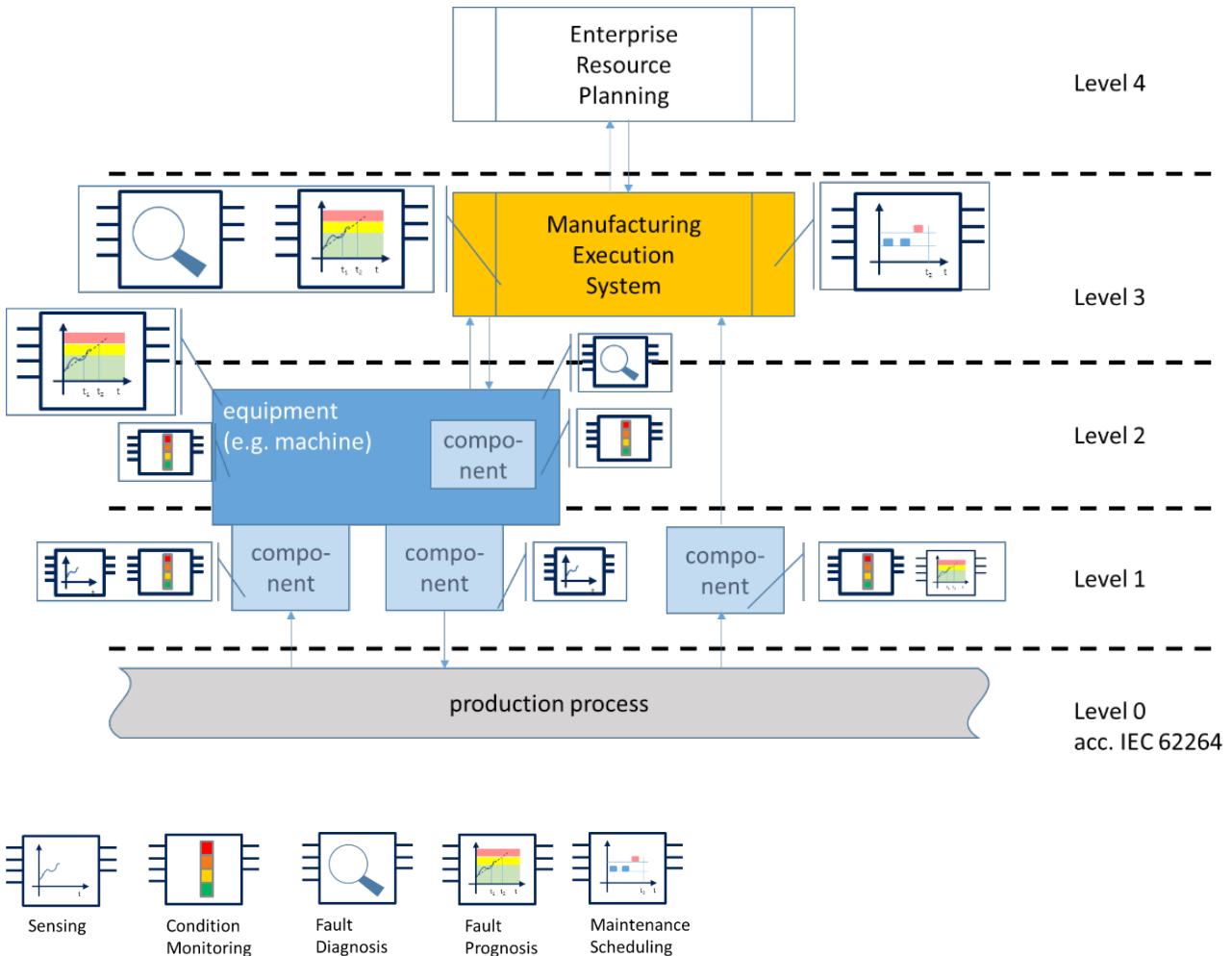


Figure 1: Positioning of condition monitoring, prediction, and maintenance scheduling in a production system (principle).

Based on the assessment and with knowledge of the intended processes to be carried out, a prediction of the remaining error-free operation of the equipment can be made, and possible activities for maintenance can be planned. This process is called Predictive Maintenance. Changes of the production workflow can also be initiated, targeting on re-organization of the equipment usage. Figure 1 shows a principle system structure with condition monitoring and prediction functions.

A main prerequisite for such prediction is the availability of status information of the equipment or component. Mo-

data and calculating status information is currently not available. This significantly impedes the efforts for an introduction of predictive maintenance solutions.

Due to the heterogeneity and the technological design of the networks the components are connected to, it is rather impossible to transfer all relevant raw data to a cloud-based status calculation and prediction solution.

From the status description above, a demand for Standardisation can be derived. Providing an appropriate infrastructure, consisting of components with uniform interfaces, is of utmost importance. Such an approach will support an easy composition of complex condition monitoring and predictive maintenance solutions. It will allow aggregating

the single information – derived from raw data using analytics methods – with respect to the functional structure of the equipment or plant.

This document discusses the actual status of related technologies and approaches, reflects actual development trends, identifies Standardisation needs, and proposes a roadmap for further Standardisation activities for predictive maintenance in Intelligent Manufacturing and Industrie 4.0.

This roadmap focuses on the predictive maintenance in the intelligent manufacturing process, which is different from traditional troubleshooting, PHM's emphasis and scope. The

connotation of PHM which originated in the field of military and aerospace is so broad. In the background of intelligent manufacturing, the predictive maintenance in this roadmap collects the raw data using the condition monitoring, fault diagnosis and other methods, which processes the data and provides support for failure prediction.

Several countries have started the research or application of predictive maintenance in many different fields. This roadmap currently only includes related work in China and Germany.

Part 1: Current Status of Predictive Maintenance

1.1 Current status of predictive maintenance in China

On account of the manufacturing method change which is led by the intelligent manufacturing technology of the Cyber-physical systems, such as intelligent equipment and factory; the industrial value chain system is rebuilt. Leading this development is the new manufacturing model, such as network crowdsourcing, collaborative design, mass customization, accurate supply chain management, life cycle management, and e-commerce. With a new manufacturing model new manufacturing fields which are expanded by the intelligent terminal products, such as wearable intelligent products, the intelligent household and intelligent cars. The new generation of information technology is closely cooperating with the manufacturing industry, which is bringing about a far-reaching industry revolution. This new industrial revolution allows the formation of a new production mode, industrial form, business model and economic growth point.

China's economy is stepping into a new era. The development of intelligent manufacturing is the best way to integrate the development of the emerging industries with the upgrading of traditional industries. At the same time, it has an important and far-reaching impact on deepening the integration of manufacturing and the internet, while strengthening the foundation of the real economy. „Made in China 2025” makes the intelligent manufacturing a priority. In order to build manufacturing power, it puts a special emphasis on the following points:

Accelerate the development of intelligent manufacturing equipment and products. The organization develops intelligent manufacturing equipment and intelligent production lines with the function of depth perception, intelligent decision and auto-execute, such as the high-grade CNC machine tool, industrial robots and additive manufacturing equipment. It breaks through intelligent core devices, such as new sensors, intelligent measure instrument, industrial control systems, servo-motors & driver and the speed gearbox. All of these will promote engineering and industrialization. We will accelerate the intelligent reconstruction of production equipment, such as machinery, aviation, ship, automobile, light, textile, food and electronic industry. We will further improve the capacity of the precise and agile manufacturing. We will plan and promote product design and manufacture, such as intelligent vehicles, intelligent construction machinery, service robots, intelligent household, intelligent lighting appliance and wearable devices.

Advance manufacturing process intelligence. In priority fields, we will try to build intelligent plants/digital workshops. This will help accelerate the application of new technology and equipment in the productive process, such as the intelligent human-machine interaction, the industrial robots, the intelligent logistics management and the additive manufacturing. All of this will help us with simulation optimization, digital control, real-time state monitoring and adaptive control of the manufacturing process. We will promote the integration of key links, such as group management and control, design and manufacture, integration of manufacturing and marketing, business and financial connection. This allows us to carry out intelligent control by the means of accelerating the popularization and application of the product life-cycle management, customer relationship management and supply chain management systems.

We will speed up the construction of intelligent detection and supervision systems in key industries, such as the civil explosive, dangerous chemicals, food, printing and dyeing, rare earth, pesticides, in order to improve the level of intelligence.

The intelligent factory, which is composed of industrial robot and large numerical control machine, is the result of deeper integration of the information technology and the automation technology. It is also an important carrier of intelligent manufacture. One of the most pressing issues in the field of intelligent manufacturing is how to avoid unexpected downtime in the production process and ensure production efficiency of the intelligent plant.

In the end of the 1990s, the United States introduced on-condition maintenance in the field of civil products industry. Through analyzing the reliability factors in each part of the mechanical equipment, scientific determination of the maintenance work item is possible. This enables an optimization of maintenance works by determining a reasonable maintenance period. Maintenance work will be limited to what is required, which leads to greater reliability of the mechanical equipment and also saves maintenance time and reduces costs. The aim is to monitor the device status of equipment in real-time or near real-time, and to determine the best time for maintenance according to the actual condition of the equipment, so as to improve the availability of the equipment and the reliability of the task. In the field of civil technology, predictive maintenance technology has been widely used in the monitoring and managing the

health of important equipment and engineering facilities, such as automobiles, civil aircraft, bridges, complicated constructions, and nuclear power stations.

The predictive maintenance technique emphasizes the reliability of equipment and the failure effect of equipment as the main basis for the formulation of the maintenance strategy. On the basis of structural evaluation and analysis of the failure effect of equipment, the comprehensive fault effect and the information about failure mode which is taking operation economy as the starting point, presents a maintenance strategy for security, operation economy and maintenance cost savings. The predictive maintenance technique has the ability to diagnose the potential faults of the system and to protect them in advance. Therefore, it can effectively improve the functioning of intelligent devices, increase the reliability and availability of intelligent devices, and reduce the maintenance cost of intelligent equipment and manufacturing cost of production system. Compared with traditional breakdown maintenance and periodic maintenance technology, the predictive maintenance technique, which takes the feature recognition, life prediction, fault analysis, maintenance planning as the core technologies, is characteristically networked, intelligent, and in real-time. Thus, more and more scholars and experts have paid attention to it.

However, currently there are still some bottleneck problems in the predictive maintenance technology, which seriously affect its application in the industrial field. For example, the research on the actual system is not sufficient, and the prediction model cannot adequately reflect the equipment characteristics. The degree of digitalization and availability of digital information of major equipment is low. The accumulated data cannot effectively support various data-driven algorithms. The operational state and potential failures supported by running data identification system still need experts, and the potential of deep learning algorithms have not been fully explored. In addition, there are the pressing problems of how to merge that result of predictive maintenance into operational maintenance management of the production process and how to evaluate the effectiveness of predictive maintenance. Predictive maintenance technology is still far away from real industrialization and commercialization.

A number of conferences are held regularly in China to gather the researcher to discuss the recent advances on predictive maintenance. For example, Chinese Conference on Machinery condition monitoring, diagnosis, and maintenance is held by Chinese Society for Vibration Engineering every two years. International conferences are held and sponsored by China Universities and research institutes, such as International Conference on Sensing, Diagnostics, Prognostics, and Control, Prognostics and System Health Management Conference.

Similar research activities have been held in universities and research institutes for many years, e.g. Tsinghua University, Beijing Aerospace and Aviation University or China Academy of Engineering Most of them are involved with specific industries and therefore need deep know-how to such specific areas. We seldom see a department of a university or an institute, which has the comprehensive and diverse configuration or distribution of segment areas in the topic we are discussing. From this point of view, the multi-discipline overlap and knowledge fusion is necessary.

In the industry, there are some traditional companies, which are involved in the business of data collection, conditioning monitoring, and fault diagnosis. For example, they operate in such areas of large size architecture/bridge health management, high power electrical machine monitoring. Some recently emerging startups are attracting investments. They are utilizing AI, big data analysis, and cloud computing technologies to development high efficient algorithms, with the potential to solving problems innovatively. In era of Intelligent Manufacturing/Industrie 4.0, we can see a wave of data driven companies, and the most applicable area could be predictive maintenance.

There are also several alliance or consortium organizations in China. For example, the China Sci-Tech Automation Alliance (CSAA) has been operating a working group on these topics for many years. They are actively developing an operation guideline for general purpose predictive maintenance.

1.2 Current status of predictive maintenance in Germany

Reducing downtime and saving operational costs has been a goal of a multitude of activities in Germany. Depending on the industries, several – mainly individual – approaches have been developed. They focus on condition-based maintenance approaches, but also incorporate prediction aspects. Especially for industries with continuous operation, e.g. oil and gas, chemicals, and power plants, condition-based approaches show a higher interest. Since continuous operation is combined with high equipment costs, a further demand is put on predictive maintenance and maintenance planning. In the industries listed above, the term asset management has been introduced.

Asset management can be seen from a general, more management-oriented, viewpoint, and from one closely related to the shop floor. While the first one is supported by ERP systems, the second one is also called Plant Asset Management. This term is in focus of organizations like NAMUR, an organization supporting end users in oil and gas, chemicals, pharmaceuticals, and similar industries. NAMUR has published several recommendations [NE107, NE158] that cover

basic principles of plant asset management, the relation to manufacturing execution systems (MES), and functions for self-diagnosis of components, e.g. field devices. The adoption of the before mentioned recommendations is rather high in the industries listed. However, there are still many individual solutions and legacy products used in the market.

In discrete manufacturing industries, the situation is similar. A wide range of individual solutions exists, strengthened by the broad market of suppliers for systems, devices and components. Many of these suppliers offer individual solutions for the monitoring and for the maintenance of their individual products. This leads to higher efforts for integration, not only for the end users, but also for system suppliers like machine vendors. Depending on the individual components used, uniform solutions for condition monitoring and prediction are hard to achieve. Several industries, e.g. automotive, tend to integrate the specific solutions into their MES, thus offering a close link between the measurements and monitoring functions and the maintenance planning and execution. In other industries, i.e. machine building, machine vendors need to integrate the solutions of the suppliers into machine-specific tools and products. The end users often have to integrate the solutions provided by the machine vendors into their own systems. Defining interfaces to existing systems and for visualization is also in the focus of different activities. This includes, for example, a recently started workgroup 7.26 from VDI/GMA.

An approach to harmonize the solutions for condition monitoring and to reduce effort and cost of their engineering and operation was started by VDMA. Reference architecture has been defined, considering different viewpoints [VD582]. The main goal of this activity was to provide a uniform definition of a condition monitoring function block with well-defined interfaces, applicable at different levels of the automation architecture.

While many of the technologies and solutions focus on condition monitoring and malfunction detection, they can be seen as inputs for prediction. It is important to generate reliable information of the components in a manufacturing system. Thus, status and condition monitoring directly at the components has gained importance as well. From a technological level, the current developments towards (industrial) CPS and the adoption of Industrial Internet of Things (IIoT) in manufacturing systems can be seen as enablers. The effort of integrating such components into manufacturing systems is steadily decreasing, reducing the psychological barrier to do so. The increasing computing power of such devices supports the deployment of condition monitoring in industry.

Furthermore, the ability to access and to compute larger amounts of data enables the introduction of new functions, like big data analytics, for better determining conditions,

since historical and statistical data or even data from the internet can be integrated. This gives a push to both data-intensive applications and better prediction methods – applicable not only at the MES level, but down to equipment, machines and components as well. While the methods of computing larger data sets are becoming more widely available, the models for predictions are not accessible at the same level. Often they do exist at the manufacturer or the integrator, but are not made available for the end users.

Industrie 4.0 will allow a uniform and structured access to information representing the components and the system as a whole. It organizes the information in different partial models of Industrie 4.0 components, accessed via semantically well-defined properties [I4OAS]. This allows, for example, providing the models mentioned above, and providing condition monitoring functions and data as well as prediction functions and data for appropriate applications belonging to different views. Thus, it can be expected that diagnostics, condition monitoring, and prediction will be made available via the asset administration shells of the Industrie 4.0 components. On one hand, this will reduce the engineering efforts, and on the other hand, it will open up business opportunities for providers of such functions, tools and solutions. Interoperability is the key point here, supported by uniform and unique semantic definitions and by uniform access via Industrie 4.0 conformant services.

The importance of condition monitoring and predictive maintenance can be recognized not only from solutions available at the market and from activities in Standardisation groups, but also from discussions and roundtable activities at fairs (e.g. Hanover Fair, SPS/IPC/Drives in Nuremberg), from articles in automation-related journals, and from workshops and conferences. An example is the conference “Predictive Maintenance 4.0”, organized by VDMA based on a yearly schedule. In February 2018, the 3rd edition will be held.

1.3 Development trend of predictive maintenance related technologies

Market driver:

The core targets of Intelligent Manufacturing/Industrie 4.0 are higher quality, lower cost, higher efficiency and sustainability. As reliability and stability are quite essential to equipment and production system, we hope to reach the goal of near-zero failure operation. The response to any potential failure should ideally be predictive in rather than a response to failure.

There are some other market drivers for predictive maintenance. First of all, lack of experienced operators, which means we must convert knowledge and experiences of aged

professionals to model and software. Second, the emergence of service oriented business model ask for the value creation throughout the whole life cycle of equipment and production system. For this to work sufficiently, predictive maintenance is one of the most important value point of all. Finally, more and more available data, more powerful computing capability locally and cloud-based services, and more advanced algorithms make it possible than ever.

Challenges:

However, there are still severe challenges we have to face nowadays. Almost any model needs training, either offline or online. Furthermore the lack of enough data sometimes makes it difficult. Data security issues even prevents custo-

mer share their data with external service provider. Finally, limited knowledge of machine model, complexity of production system and operation environment decrease the effectiveness of software algorithm.

Enabling technologies:

Fast development of ICT technologies, including industrial big data analysis, AI, IoT, cloud computing, edge computing, 5G communication, etc. are powerful enablers to predictive maintenance. IoT and 5G make it possible to gather necessary data, cloud and edge computing lead to powerful and sufficient data process capability, data analytics and AI will offer more applicable and intelligent algorithms.

Part 2: Key Functions and relevant Technologies in Predictive Maintenance

2.1 Introduction

There is a multitude of different technologies existing already now, which are applicable to predictive maintenance. Future developments in ICT will bear additional potential technologies for predictive maintenance. Since technology cycles will shorten, the maturity and the application prerequisites will need to be thoroughly evaluated before integration into predictive maintenance solutions.

The overall functional structure for predictive maintenance will, however, stay rather fixed (see Figure 2). The determination of the current state of relevant components needs to be conducted using sensing functions. Based on this, a calculation of the state of health and a condition status assessment can be performed. This is a prerequisite for fault diagnosis and for defining repair measures on the one hand, and for fault prediction and for defining maintenance actions on the other. Finally, all the maintenance measures need to be seamlessly integrated into a maintenance management solution at the Manufacturing Operation Management level. Independent of the specific functionalities, a systematic approach should be introduced, in order to establish a predictive maintenance system.

This functional structure covers both approaches, on-site and remote maintenance. The technological developments, especially the communication and data processing solutions, will enhance the usage of remote monitoring and maintenance.

In the following sections, key aspects of relevant functionalities are discussed.

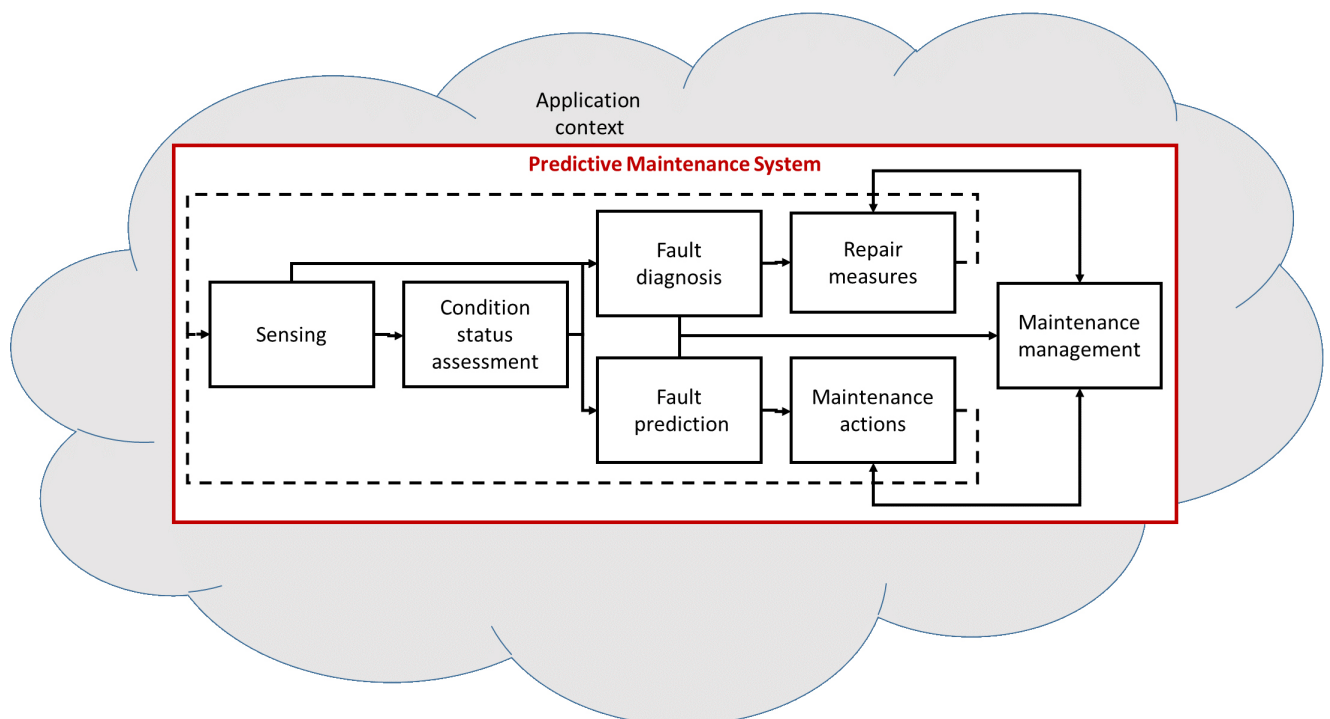


Figure 2: The principle functional structure for predictive maintenance

2.2 Sensing Technologies

The key issues in sensing technologies are two-fold: sensing modality and sensor placement strategy. Overcoming these issues is necessary to acquire the most representative information of machinery status.

A variety of sensing techniques have been instrumented to acquire machinery conditions. According to the correlation between sensing parameters and machinery conditions, these sensing techniques can be categorized into direct sensing and indirect sensing methods. Direct sensing techniques (e.g., tool-maker's microscope, radioactive isotopes) measure actual quantities that directly indicate machinery conditions. Since the defects usually occur internally in the machinery, direct sensing is usually performed by disassembling the machinery structure, or interrupting the normal operations. On the contrary, with the symptoms (e.g., the increases of vibration, friction or heat generation) caused by machinery defect, indirect sensing techniques can measure the auxiliary in-process quantities (e.g., force, vibration, and acoustic emission, etc.) that indirectly indicate machinery conditions. Compared with direct sensing, indirect sensing methods are less costly and enables continuous detection of all changes (e.g. tool breakage, tool wear, etc.) to signal measurements without interrupting machinery normal operation. Take machining tool as an example, the pros and cons of direct sensing and indirect sensing methods are summarized in Table 1.

The sensors are getting smarter with scalable networking capability (e.g. smart Internet of Things). In general, the more sensors one places on manufacturing equipment, the more comprehensive information one obtains to best represent the equipment conditions. Nevertheless, in practice, the number of sensors is typically limited and subject to issues such as cost, installation, etc. Therefore, given only a limited number of sensors, the sensor placement locations are needed to be optimized so as to obtain as much information of manufacturing equipment as possible. Different optimization strategies are developed including heuristic approaches, classical and combinatorial optimization.

Besides automatically determining the state of a component by sensors, manual inspection will remain a possible alternative, especially with respect to the know-how of the inspecting persons. Thus, an interface for the integration of results from manual inspections should be provided.

Table 1: Comparison between direct sensing and indirect sensing techniques in machine tools

Category	Sensing techniques	Pros	Cons
Direct sensing	Microscope, CCD camera, Electrical resistances, Radioactive isotopes	Accurate, direct indicators of tool conditions	High cost, limited by operating environment, mainly for offline or intermittent monitoring
Indirect sensing	Cutting force, vibration, sound, acoustic emission, temperature, spindle power, displacement	Less complex, low cost, suitable for continuous monitoring in practical applications	Indirect indicators of machinery conditions

2.3 Condition monitoring

Derivation of condition and status information is based on data collection. The data gathered will be used as inputs for calculation of a component's status, often called health state. The health state depends from the actual conditions, perhaps combined with historical data. Actual conditions can be measured from direct or indirect sensing functions. Typically, an evaluation is performed by comparing a measured or calculated condition status with thresholds or reference values. In addition, a current system state or other context information may be integrated. In order to assess the status, it may be necessary to perform pre-processing functions, for example for filtering, data correction, eliminating of overlaying trends, etc.

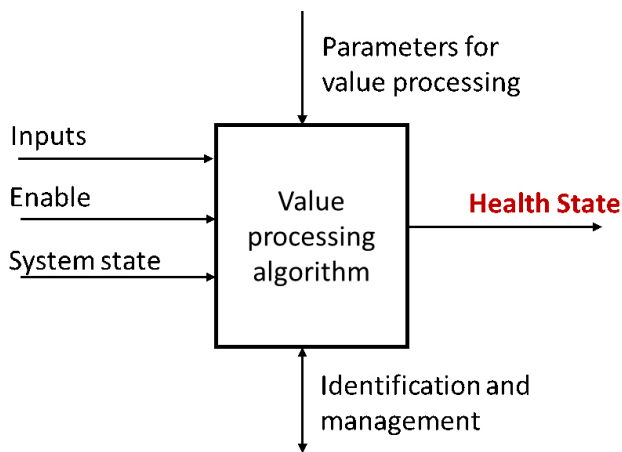


Figure 3: Determining of health state of a component by processing actual input values

Depending on the application, different algorithms can be used for value processing (Figure 3). The variety spans a range from simple arithmetic functions, statistical functions, differentiation, integration, up to transformation functions like FFT. With the increasing computing power of the components, such algorithms may be deployed to components of the automation and even sensor levels. Data-driven approaches can be used for condition monitoring as well. Common to data-driven approaches is the modeling of desired system output (but not necessarily of the mechanics of the system) using historical data. Such approaches encompass “conventional” numerical algorithms, like linear regression or Kalman filters, as well algorithms that are commonly found in the machine learning and data mining communities. The latter algorithms include neural networks, decision trees, and Support Vector Machines.

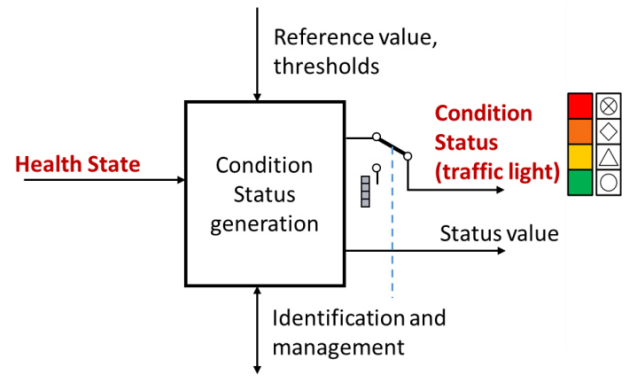


Figure 4: Assessment of Condition Status

Because of the broad functional diversity, it is important to provide a uniform way of interpretation for the calculated condition status. A suitable way is to map the condition status to application-depending value ranges, represented by the thresholds or reference values. The ranges can have colors assigned, thus creating a traffic light status (Figure 4).

The calculation of a component's condition status may not be sufficient to provide a condition status for a whole equipment or system. Thus, it is necessary to combine different condition status values or traffic lights. For example, as in Figure 5, the condition status of a machine tool is displayed, aggregated from single condition states of its functional components like spindle drive, feed axis, pneumatics, and fluid technology. The structure of this combination is given by the functional structure of the equipment or system. It may span several logical levels, e.g. several combination functions may be aggregated in a sequence, finally forming a tree. The combination function itself may range from a simple logical or-function, more complex logical functions, parameterized or weighted inputs, up to complex aggregation functions.

It is important to distinguish this functional aggregation from the physical deployment of the components. When defining the deployment structure, the logical interconnections of the functional aggregation are transformed into physical communication paths.

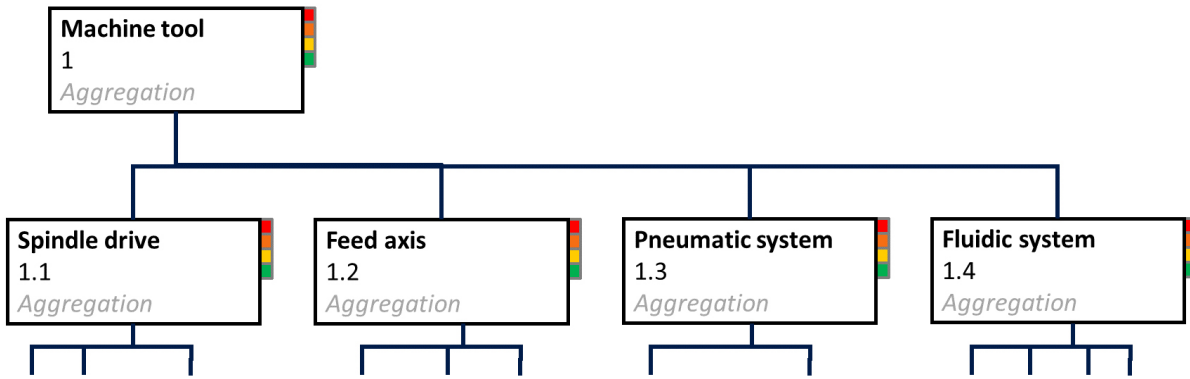


Figure 5: Functional aggregation of components' condition status information

2.4 Fault diagnosis

The scope of fault diagnosis includes, for example, machine, electronics, and communication network. The methods used for it are slightly different. The fault diagnosis may be subdivided into fault detection, fault location, fault isolation and fault recovery.

The fault diagnosis method can be classified in qualitative/quantitative manner, according to the methods based on the analysis model, based on the qualitative empirical knowledge, or be based on the data driven methods. The related methods for the fault diagnosis can also be applied to the status monitoring process, and the method that based on data-driven can also be used for life prediction. Figure 6 shows the classification of common fault diagnosis methods.

The method based on an analytical model includes state estimation, parameter estimation and equivalent space. These methods need to describe the exact mathematical model in the process, and the modeling is an in-depth understanding of the mechanism structure in the process, whose ideal state is to get the exact model. In practice, there are often relations that cannot be explicitly modeled, e.g. complex behavior, which can reduce the diagnostic effects.

The method based on qualitative empirical knowledge includes the expert system, which is a typical method. At the same time, the expert system is widely used in the field of the hydraulic machinery, electric power and engine. The data-driven method includes statistical methods, signal processing method, and quantitative artificial intelligence method. This kind of method has a wide range of applications and is adaptable, and it is especially suitable for the fields, where precise models are difficult to obtain. The data-driven method includes statistical analysis methods such as grey theoretical methods, time series analysis methods

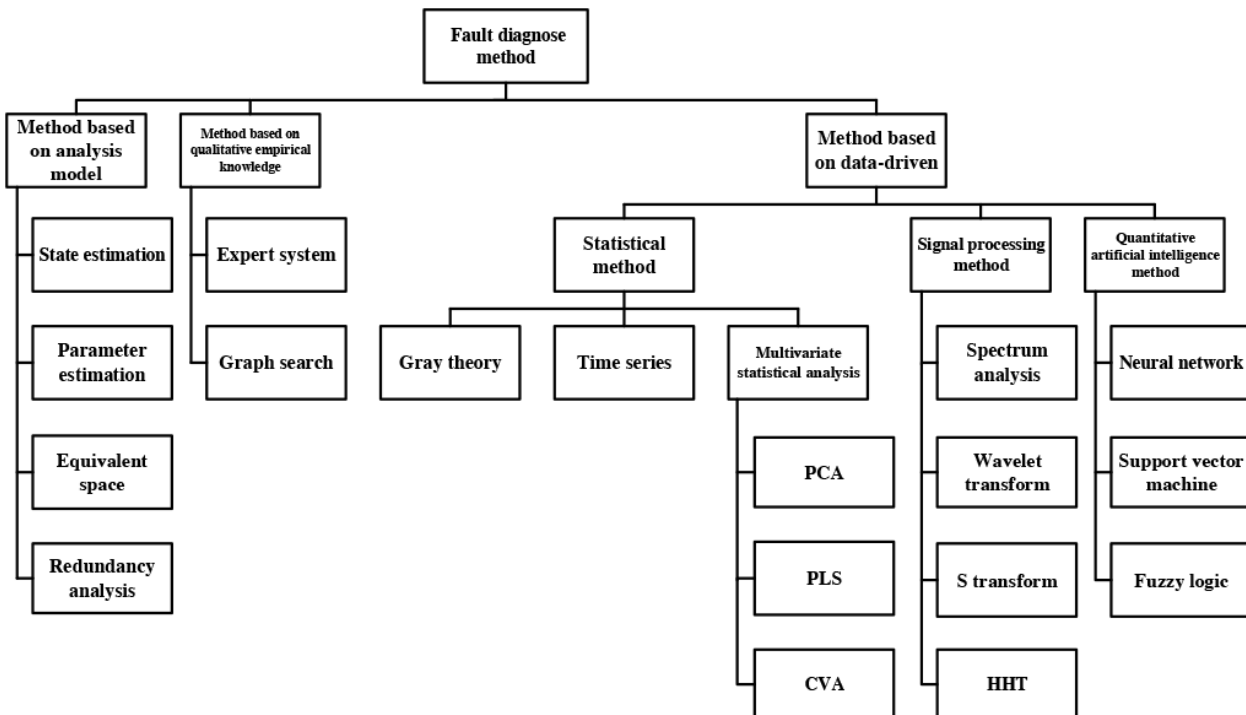


Figure 6 Classification of fault diagnosis methods

and multivariate statistical analysis methods. The representative multivariate analysis method includes PCA (principal component analysis), which will map the data to another space by changing the base for the purpose of dimensionality reduction, but it is not ideal for complex nonlinear systems. PCA method is often applied to process industry, such as chemical engineering and the fault diagnosis of IC equipment in FDC process. The mathematical tools that are applied, include principal component analysis (PCA) and canonical variate analysis (CVA). The fault diagnosis based on signal processing is widely used in the signal field of vibration signal and other characteristics, such as motor, rotary machinery and internal combustion engines. The tools that are applied include wavelet transform, HHT and Kalman filter.

It is worth noting that the analytical methods used are similar, because there is an internal relationship among state monitoring, fault diagnosis and life prediction.

2.5 Fault prognosis

Fault prognosis focuses on predicting the fault and remaining life of a device or system based on monitoring and assessing data. The method of remaining life research can be divided into two kinds: one is to estimate or predict the average remaining life; the other is to find the probability distribution of the remaining life.

There are many factors affecting equipment life. For example, in the manufacturing, assembly, testing, shipping and installation and debugging process, any link may affect the reliability of the parts. Operating and maintenance environment, such as the size of the equipment production load, the operating environment (temperature, humidity and dust), as well as the level of maintaining the equipment and the responsibility of maintenance personnel, can affect the remaining life of the equipment. Therefore, fault prognosis is a very challenging task, which needs the above methods for comprehensive application. The basic process of fault prognosis is shown in Figure 7.

Life prediction mainly includes four methods: methods of insurance and warning devices, data-driven methods, failure physical model methods, and fusion prediction methods.

Fault prognosis is feasible from a technical point of view. With the development of sensors, microprocessors, compact nonvolatile memory, battery technology, and wireless telecommunications networks technology, the implementation of sensor modules and automatic data recorders, fault prognosis is possible. The signal and information processing unit theory, which is the core of the fault prognosis system, has made significant progress. Especially the mathe-

tical model of fault prognosis is becoming more intelligent and practical. Based on accurately predicting the life of key parts, the fault prognosis combines with automatic identification technology, such as radio frequency identification (RFID), which is used to locate the parts in the supply chain. According to the requirements, it can quickly obtain and provide replacement parts for the on-time supply.

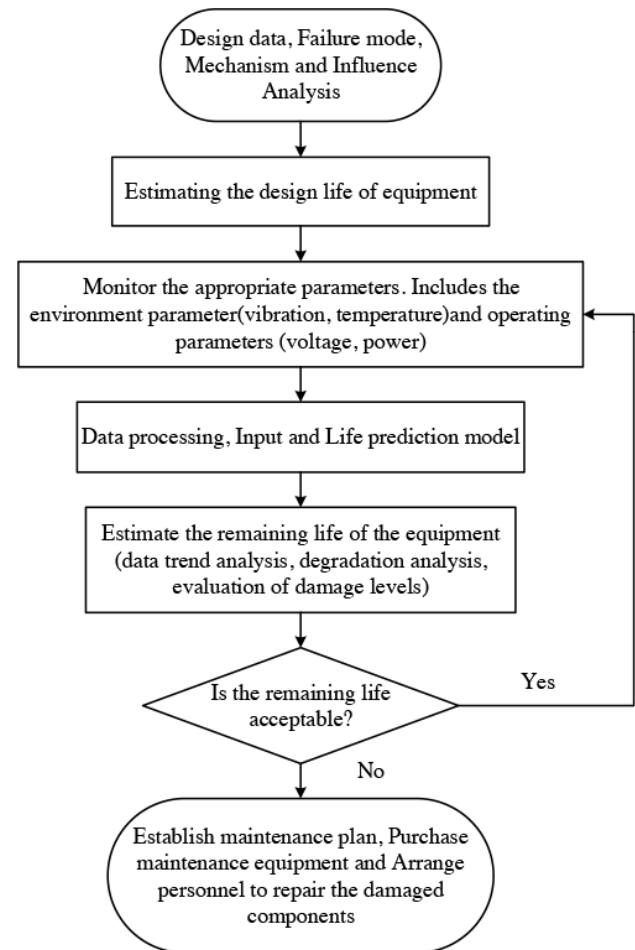


Figure 7 Basic Process of Fault Prognosis

2.6 Maintenance management

Maintenance management is the basic task of implementing a machine maintenance plan. Predictive maintenance determines how fast the degradation is expected to progress from its current state to functional failure and offers a cost-effective maintenance strategy. The relationship among the cost, time to failure and reliability of machines is shown in Figure 8. When time to failure equals zero, the system will go into breakdown status. The reliability of the system decreases as the time to failure of the system approaches to zero. The performance cost of system increases while the maintenance cost decreases. Thus, the total cost, as the sum of the performance cost and the maintenance cost, decreases firstly, and then increases. Predictive maintenance with the capability of precisely predicting the time to

failure and reliability of the system can provide useful information for the decision making of an economical maintenance schedule.

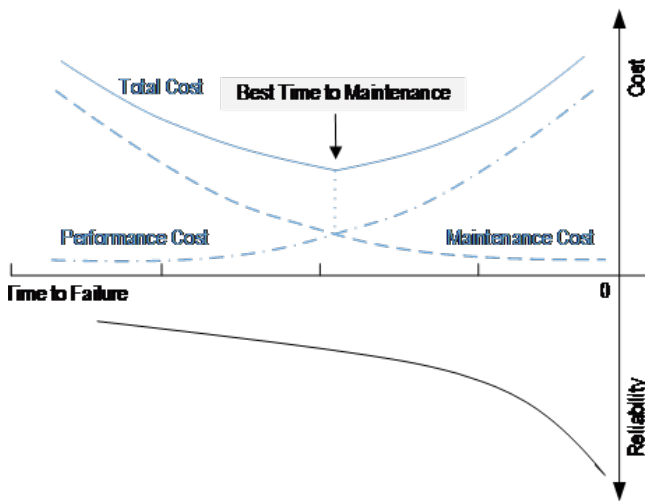


Figure 8 The relationships among time to failure, reliability and cost

Additionally, predictive maintenance needs to consider the types of resources required for organizational maintenance, including people, spare parts, tools and time. The main content of maintenance management is the closed-loop control of planning, implementation, inspection, analysis (PDCA).

However, this best time may not always be achievable, due to the overall application schedule. Therefore, it needs to be integrated into a Manufacturing Operation Management (MOM). MOM plays an important role in supporting continuous improvements in manufacturing efficiency, quality control, cost savings, consistency, safety and agility across the extended value chain. MOM functions can create significant additional value from people and existing industrial automation system investments by enabling streamlined end-to-end business to manufacturing processes and providing valuable real-time data in support of rapid and empowered decision making across operations.

Modern MOM software solutions continue to develop and mature, with some leading full scope Manufacturing Execution System (MES) and Enterprise Resource Planning (ERP) suppliers extending their offerings. Typical functionalities of MOM include: APS, MRP, MES, WHM, APC, OEE, APQP, SPC/SQC, Historian, etc. While MES stands at the central position, it normally includes manufacturing execution and part of quality execution and compliance. Predictive maintenance or equipment health management is part of MOM and getting more and more important. The standard IEC 62264 defines structures, functional areas, activities, objects and attributes suitable for MOM. Especially the functional area of maintenance management is of interest here. Using this standard, a predictive maintenance

solution can access relevant functional components of MOM using standardized interfaces and transactions.

2.7 System aspect

The specific algorithms for status calculation and prediction vary depending on the specific functions a component provides. The idea of the function block, as introduced in VDMA [VD582], allows to encapsulate and to hide details of the algorithms, while enabling to set up complex predictive maintenance solutions with aggregation of data along the functional hierarchy of a system. Furthermore, it protects the intellectual properties of the algorithm developer.

In order to cope with the increasing flexibility and heterogeneity of future manufacturing systems, it is necessary to provide a systematic approach for predictive maintenance. This calls for the development of a predictive maintenance platform (see Annex B as an example) or even a complete eco system. Its overall architecture shall be modular, enabling to easily add or enhance functional components for sensing, condition status assessment, diagnosis, and prediction. Besides these functional components, it shall comprise means for a flexible deployment of such functions to different resources. For example, a sensing function determining data from an electric drive may be implemented inside the drive itself, but also at a dedicated monitoring component connected to field level network, to an edge or fog component, or directly to a cloud. The different deployment options can be chosen with respect to computing capabilities, available context data (e.g., production schedule), or cost.

Thus, a predictive maintenance solution shall provide necessary abstractions in components and interfaces in order to be adaptable to different industries and application domains. On the other hand, the configuration effort shall be kept minimal. For example, it should support plug & produce operations and, perhaps, also self-adaptation.

This requires the clear distinction between the single function, its aggregation along the functional hierarchy, and its deployment to a certain resource. From a system architect's view, it is envisaged to apply systematic design principles, e.g. the viewpoint concept according to ISO/IEC/IEEE 42010 [ISO42]. Separating business and functional viewpoints from implementation and communication viewpoints supports the required flexibility. The architectural aspects shall be supported by organizational measures, e.g. methods for identification, versioning, dependency tracking, etc. Since this roadmap is mainly focusing on predictive maintenance in the context of intelligent manufacturing and Industrie 4.0, the definitions, concepts and specifications set up in this context shall be applied.

Part 3: Use case

Case 1: Condition monitoring and fault diagnosis of robot gearbox

User background and problems:

At present, industrial robots widely used in automobile welding and other fields for more than five years, the gearbox develops problems, e.g. tooth breakage and wear. Although it is not possible to trigger a robot fault alarm, the repeated positioning accuracy is difficult to guarantee. Consequently, the welding failure rate increases. In the past, the maintenance engineer periodically judged the operation of the gearbox by the noise of each gearbox of the robot, and decided whether to change the decelerator. The assessment is relatively subjective and the gearbox is expensive. Therefore it is difficult for the factory to evaluate the necessity and effectiveness of the replacing the equipment.

Predictive maintenance methods:

The sensors such as temperature and vibration are deployed on the key parts of the equipment, to detect and test the equipment state in real time. The data is uploaded in real time through the industrial wireless Internet, and through the switch, the vibration and temperature data are cleaned by means of data processing methods such as filtering, then the eigenvalue is uploaded to the cloud platform. Using the technology of deep learning neural network, before the system is put into operation, the storage and training of the robot fault data of permutation combinatorial grouping test such as fault type, life time and undertaking, making the parameters of the system converge to a set of parameters. Then the measured data corrected parameters are continuously used, which makes the system analysis ability continuously optimized and the judgment more accurate.

Application Effect:

The condition monitoring and fault early warning of robot gearbox based on wireless communication is provided to the users. Through the analysis and training of off-line storage data, the training and correction of measured data, diagnosing equipment failure and predicting life cycle, the defective rate of the robot welding process is reduced, the yield of product is enhanced, and the product quality is improved.

Case 2: Wind turbine intelligent real-time online condition monitoring system

User background and problems:

Wind turbines run with many unpredictable operating conditions that can cause turbine operation failure. If it is possible to detect and deal with the fault as soon as possible, the availability is increased and the maintenance cost is reduced. The traditional vibration sensor cannot analyze the transmission chain in real time. The vibration data acquired can only obtain the vibration amplitude overrun of the turbine, which cannot accurately reflect fault point and failure cause. Even if the condition monitoring system is installed at a later stage, the majority of products are not able to synthetically analyze and diagnose the overall condition information of the fan in real time.

Methods/Means of Predictive Maintenance:

The solution of condition monitoring system allows the integration from sensor to acquisition analysis software to be extended. Through multi-channel vibration data real-time acquisition, the flow algorithm is used to calculate and analyze it in real time. According to the factory parameters of the equipment, the faults and problems of wind turbine drive train system can be detected in advance. Additionally, the turbine condition data is provided to the main control system real-time online, so an intelligent control system can be realized.

Application Effect:

Wind turbine manufacturers are supported in providing early fault warning and diagnosis for installation of the unit. By providing relevant condition data in real time, product safety and reliability can be improved, and can be extended into after-sale warranty. Furthermore, it can reduce the maintenance workload, the labor intensity and the maintenance cost. Finally, it provides a basis for optimization and manage the assets of the wind farm.

Case 3: Using a data-driven early warning method to discover the precursor characteristics of equipment failures

User background and problems:

The small steam turbine in a generator unit of a power plant has no alarm or warning before the failure of the sensor. In the past, a multilevel threshold is preset on the monitoring sensor to realize the early warning. However, this method has high requirements for equipment management personnel, and the preset threshold is not accurate due to the aging of equipment, which is can easily cause false negatives. The users intend to find out the data characteristics that build an early indicator of a fault.

Predictive maintenance methods:

By using neural network based technology, historical data of the equipment before the failure is used as training input. The approach is based on the multi-sensor data fusion analysis mechanism, and the operation state characteristics of the equipment are extracted from the historical data. In the production process, the abnormal state of the equipment operation is recognized in real time by the establishment of its status feature model.

Application Effect:

It provides user enterprises with effective means to realize the early warning and monitoring of equipment by operation data.

Part 4: Predictive maintenance

Standardisation requirements

4.1 Current standards analysis

At present, predictive maintenance has obtained some research results and application cases in the field of military industry and aerospace. From a standardized point of view, ISO, IEEE, MIMOSA, SAE, FAA and the United States military have made and developed the standards and norms. In different fields, there are some standards and norms such as CBM/IVHM/PHM/HUMS. The overall status is shown in the following Table 2.

Table 2 - Standards and norms related to predictive maintenance

Standard Organization	Technical Committee	Typical Standard	Category
ISO	TC108	CM&D	
MIMOSA	---	OSA-CBM, OSA-EAI	CBM
	G-11r	CBM	
SAE	HM-1	IVHM	IVHM
	E-32	EHM	
IEEE	SCC20	IEEE Std-1232	PHM
	PHM	IEEE Std-1636	
SAE	HM-1	HUMS	
FAA	---	AC-29C MG-15	HUMS
U.S. Army	---	ADS-79-HDBK	
IEC	TC 56	IEC 60300, IEC 60706, IEC 60812	
	TC 65	IEC 62541 (OPC UA), IEC 62264 (MES), IEC 61158, IEC 62904	

ISO/TC108 (Technical Committee for Standardisation of Mechanical Vibration, Shock and State Monitoring) is in charge of basic technology research in this field. ISO Standardisation work has been intensively concentrated in mechanical fields, and formed the CM&D series standard, such as: ISO 2041 „Vibration, Shock and Condition Monitoring Vocabulary“, ISO 13372 „Machine Condition Monitoring and Diagnostic Vocabulary“, ISO 13379-1 “Machine Condition Monitoring and Diagnostic--Data interpretation and diagnostic techniques--Part 1: General”, and ISO 13381-1 “Machine Condition Monitoring and Diagnostic--Prediction--Part 1: General Guide”. ISO 13374-3:2012 and ISO 13374-4:2015 is the second edition. In addition, ISO 18434-1 “Condition monitoring and diagnostics of machines -- Thermography -- Part 1: General procedures” and ISO 18436 “Condition monitoring and diagnostics of machines -- Requirements for qualification and assessment of personnel” is also related to predictive maintenance. The product data expression and exchange of industrial automation system integration is defined respectively in ISO 10303-11, 21, 28, which is closely related to predictive maintenance. In the above analysis, a lot of work has been done on predictive maintenance by ISO, which is relatively more systematic. At present, it is the leading in Standardisation in this field.

The SCC20 Coordinating Committee for Standardisation is responsible for IEEE Standardisation. IEEE Std 1232 and IEEE Std 1636(SIMICA) series standards are relatively representative. IEEE Standardisation focuses more on the general description of testing and diagnostic information. IEEE 1636.2 maintenance activity information exchange standard draft uses XML technology to provide a possible exchange channel. This is also the much-needed technology to build large systems and intelligent factories.

Other international organizations have also developed relevant standards for industry and strong application color, for example, MIMOSA (Mechanical information management open standard alliance) develops OSA-CBM and OSA-EAI. OSA-CBM develops a standard framework for the implementation of on-condition maintenance, and provides a standard information transfer method for CBM (based on state maintenance). OSA-EAI defines an open architecture for enterprise application integration, including reliability, maintainability and asset management. SEA and FAA has also proposed some standards in particular areas, such as HUMS systems of helicopter field, IVHM/ISHM system of aerospace and commercial aircraft field.

IEC/TC65 is the core organization of international intelligent manufacturing Standardisation, which is organizing international experts to develop standards of state monitoring, life cycle management and intelligent equipment management, such as IEC 62890 “Measurement, Control, Automation Systems and Product life cycle Management in the Industrial Process” and IEC/TC65E WG10 „intelligent equip-

ment management”. Although some reference and practical meaning exists between the above standards and the standards proposed in this project, for now international standards for predictive maintenance are not developed in the context of intelligent manufacturing. See appendix for the list of existing standards.

With respect to condition monitoring as an important part within the functional chain for predictive maintenance, a Standardisation activity is ongoing in IEC TC65E. The Working Group 11 “Condition Monitoring” is currently defining IEC 62904, based on the work carried out in VDMA 24582.

IEC 62904 Part 1 will contain basic terminology and models, including semantic property descriptions based on IEC 61360 definitions, compatible to eCl@ss and Industrie 4.0. Part 2 is planned as a TR with use cases and requirements, guidelines and examples. The set of documents is accomplished by IEC 62904 Part 3 Technology Mappings. In these parts, the mapping of the concepts from part 1 to specific technologies will be defined. They will include mappings to IEC 61131-3 (PLC programming), to IEC 62541 (OPC UA), to IEC 62264 (MES), to IEC 61158 (Fieldbus), and to IEC 61131-9 (IO-Link). Other parts may follow.

In IEC, other technical committees are working on topics relevant for predictive maintenance as well. However, they focus on different application domains. For example, the standards IEC 61800-7-1 Adjustable speed electrical power drive systems - Part 7-1: Generic interface and use of profiles for power drive systems - Interface definition discusses applications in drive systems, while IEC 61850-90-3 Communication networks and systems for power utility automation - Part 90-3 is focusing on condition monitoring diagnosis and analysis in power grids and substation automation.

The related standards discussed here are listed in Annex A. However, it is not closed list.

On the basis of the above analysis, the current system of standard of the whole predictive maintenance framework is not yet fully established. There is certain correlation degree between the work of the Standardisation organizations and the industry background, and Standardisation work will be some overlap. Predictive maintenance technology is now relatively mature and has a large number of best practices. However, under the background of intelligent manufacturing and Industrie 4.0, new technologies, e.g. data analytics and artificial intelligence, are still not reflected accordingly.

4.2 Standardisation requirement and suggestions

At present, more extensive research has been carried out in

the field of predictive maintenance and health management in the world. The research requirements and objectives mainly focus on the production and application field of high-tech equipment such as aviation, aerospace, ship and weapons. The complexity and reliability of products in these fields is high, therefore the demand for predictive maintenance is clear and strong. There is a gap between theoretical research and practical application. To overcome this, a systematic, clear analysis and guidance for predictive maintenance is still needed.

Due to the rapid development of new technologies such as artificial intelligence, big data and cloud computing, and in order to better adapt to the needs of intelligent manufacturing, future predictive maintenance Standardisation should allow the easy integration of such technologies and thus enabling their usage.

The main vision for Standardisation in predictive maintenance is to **provide a standardized infrastructure**. This infrastructure shall integrate the different functional entities described in chapter 2. It shall focus on providing a systematic and functional view of predictive maintenance, and shall provide appropriate interfaces to relevant functionalities like sensing, health state calculation, prediction, and maintenance management. This should include access to information of the entity, originating from different stages of its life cycle. Thus, a common framework shall be established, leaving room for easy embedding of new technologies. This will allow for future developments, and will be a basis for application domain specific specialization and implementation.

Therefore, Standardisation of predictive maintenance should include the following steps:

1. Establish a common approach for condition monitoring
2. Provide operational guidelines for prediction of remaining life
3. Provide interfaces to manufacturing operations management

The introduction of predictive maintenance based on a standardized infrastructure will change the business of equipment manufacturers. Since they have knowledge how to maintain their products, they might deliver software and provide services to support this. Standardisation will also provide benefits for system integrators and end users by introduction of well-defined interfaces and system structure. Furthermore, it will provide new alternatives for professional service provider by delivering advanced algorithms as components into the infrastructure.

For implementation of this infrastructure in Intelligent Manufacturing and Industrie 4.0 systems, e.g. embedding predictive maintenance functionalities as partial model into the administration shell of Industrie 4.0 components, additional documentations and specifications need to be considered.

Summary

This roadmap describes current standards and approaches for predictive maintenance, and discusses enabling technologies. It also shows the complexity of the task of predictive maintenance. Considering this, it becomes clear, that there are many different topics to be addressed in order to introduce a generalized and standardized approach for predictive maintenance of intelligent manufacturing and Industrie 4.0.

Therefore, Standardisation should focus on providing a standardized infrastructure for predictive maintenance. It

should consist of a set of single standards setting basic terminology and models, defining an overall structure using modularity approaches with well-defined interfaces. It shall be supported by domain-specific standards and by specifications for mapping to already existing standards. This calls for a close cooperation between different Standardisation organizations. Finally, a guidance for technology mapping or application integration should be included.

Annex A. The list of current standards and guides for predictive maintenance

A.1 International standards

- ISO 13374-1:2003 Condition monitoring and diagnostics of machines -- Data processing, communication and presentation -- Part 1: General guidelines
- ISO 13374-2:2007 Condition monitoring and diagnostics of machines -- Data processing, communication and presentation -- Part 2: Data processing
- ISO 13374-3:2012 Condition monitoring and diagnostics of machines -- Data processing, communication and presentation -- Part 3: Communication
- ISO 13374-4:2015 Condition monitoring and diagnostics of machine systems -- Data processing, communication and presentation -- Part 4: Presentation
- ISO 13381-1:2015 Condition monitoring and diagnostics of machines -- Prognostics -- Part 1: General guidelines
- ISO 13372:2012 Condition monitoring and diagnostics of machines -- Vocabulary
- ISO 18434-1:2008 Condition monitoring and diagnostics of machines -- Thermography -- Part 1: General procedures
- ISO 10303-11:2004 Industrial automation systems and integration -- Product data representation and exchange -- Part 11: Description methods: The EXPRESS language reference manual
- ISO 10303-21:2016 Industrial automation systems and integration -- Product data representation and exchange -- Part 21: Implementation methods: Clear text encoding of the exchange structure
- ISO 10303-28:2007 Industrial automation systems and integration -- Product data representation and exchange -- Part 28: Implementation methods: XML representations of EXPRESS schemas and data, using XML schemas
- ISO 2041:2009 Mechanical vibration, shock and condition monitoring -- Vocabulary
- ISO 13379-1:2012 Condition monitoring and diagnostics of machines -- Data interpretation and diagnostics techniques -- Part 1: General guidelines
- ISO 13381-1:2015 Condition monitoring and diagnostics of machines -- Prognostics -- Part 1: General guidelines
- IEEE Std 1232-1:1997 IEEE Trial-Use standard for artificial intelligence exchange and service tie to all test environments (AI-ESTATE): Data and knowledge specification
- IEEE Std 1232-2:1998 IEEE Trial-Use standard for artificial intelligence exchange and service tie to all test environments (AI-ESTATE): Service specification
- IEEE Std 1232-3:2014 IEEE Guide for the use of artificial intelligence exchange and service tie to all test environments (AI-ESTATE)
- IEEE Std 1636-1:2007 IEEE Trial-Use standard for software interface for maintenance information collection and analysis (SIMICA): Exchanging test results and session information via the extensible markup language (XML)
- IEEE Std 1636-2:2010 IEEE Trial-Use standard for software interface for maintenance information collection and analysis (SIMICA): Exchanging maintenance action information via the extensible markup language (XML)
- IEEE Std P1856:2017 IEEE Draft standard framework for prognostics and health management of electronic systems
- IEC 62890:2016 Life-cycle management for systems and products used in industrial-process measurement, control and automation
- IEC 60300-3-14:2004 Dependability management - Part 3-14: Application guide - Maintenance and maintenance support
- IEC 60706-2:2006 Maintainability of equipment - Part 2: Maintainability requirements and studies during the design and development phase
- IEC 60812:2006 Analysis techniques for system reliability - Procedure for failure mode and effects analysis (FMEA)
- IEC 61158: Digital data communications for measurement and control -- Fieldbus for use in industrial control systems
- IEC 62541: OPC unified architecture
- IEC 62904 Industrial-process measurement, control and automation - Uniform representation of condition monitoring functions
- ISO/IEC 62264 Enterprise/Control System Integration
- OSA-CBM UML Specification 3.3.1: 2010 Interface
- OSA-CBM UML Specification 3.3.1: 2010 Information
- OSA-EAI Basic Terminology Dictionary 3.2.3: 2012
- OSA-EAI CCOM UML Diagrams: 2012

AC 21-29C:2008 Detecting and Reporting Suspected Unapproved Parts

US Army ADS-79C-HDBK: 2005 Aeronautical design standard handbook for condition based maintenance systems for US army aircraft

A.2 German Standards

VDMA 24582: Fieldbus neutral reference architecture for Condition Monitoring in production automation. 2013

NE 107: NAMUR-Recommendation Self-Monitoring and Diagnosis of Field Devices. 2017.

NE 123: NAMUR-Recommendation Service and Maintenance of the Physical Layer of Fieldbuses, 2008.

NE 129: NAMUR-Recommendation Plant Asset Management. 2009.

NA 157: NAMUR Arbeitsblatt Documentation Requirement on Instrumentation from Maintenance Perspective. 2015.

NE 158: NAMUR-Recommendation Health Monitoring of PCS Assets. 2016.

VDI 2890: Planned maintenance – Guide for the drawing up of maintenance lists. 1986.

VDI /VDE 2650 Part 2: Requirements regarding self-monitoring and diagnosis in field instrumentation - General faults and fault conditions. 2006.

VDI/VDE 2651 Part 1: Plant asset management (PAM) in the process industry - Definition, model, task, benefit. 2017.

VDI/VDE 3543: Diagnosis of electric drives. 2007.

VDI 2879: Maintenance - Inspection of installation and buildings with UAV (unmanned aerial vehicle). 2017.

VDI 2882: Obsolescence Management. 2016.

VDI/VDE 2883 Part 1: Maintenance of photovoltaic installations - Basics. 2017.

VDI 2885: Standardized data for maintenance planning and determination of maintenance costs - Data and data determination. 2003.

VDI 2886: Benchmarking applied to maintenance. 2003.

VDI 2887: Quality management in maintenance. 1998.

VDI 2888: Maintenance condition monitoring. 1999.

VDI 2889: Methods and systems for condition and process monitoring in maintenance. 1998.

VDI 2890: Planned maintenance - Instruction on creating of maintenance lists. 2017.

VDI 2891: Maintenance relevant criteria for purchase of machines. 2008.

VDI 2892: Management of maintenance spare parts. 2006.

VDI 2893: Selection and formation of indicators for maintenance. 2006.

VDI 2894: Planning of manpower for maintenance. 1987.

VDI 2895: Organisation of maintenance - Maintenance as a task of management. 2012.

VDI 2896: Controlling of maintenance within plant management. 2013.

VDI 2897: Maintenance - Application of lubricants in plants - Objectives and organisation. 1995.

VDI 2898: Utilisation of EDP for maintenance - Requirements and criteria. 1996.

A.3 Chinese Standards

GB/T 22393-2015: Condition monitoring and diagnostics of machines—General guidelines

GB/T 22394.1-2015: Condition monitoring and diagnostics of machines—Data interpretation and diagnostics techniques—Part 1: General guidelines

GB/T 20921-2007: Condition monitoring and diagnostics of machines - Vocabulary

GB/T 22281.1-2008: Condition monitoring and diagnostics of machines - Data processing, communication and presentation - Part 1: General guidelines

GB/T 22281.2-2011: Condition monitoring and diagnostics of machines - Data processing, communication and presentation - Part 2: Data processing

GB/T 25742.1-2010: Condition monitoring and diagnostics of machines - Data processing, communication and presentation - Part 1: General guidelines

GB/T 25742.2-2013: Condition monitoring and diagnostics

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GB/T 23713.1-2009: Condition monitoring and diagnostics of machines - Prognostics - Part 1: General guidelines

GB/T 19873.1-2005: Condition monitoring and diagnostics of machines-Vibration condition monitoring-Part 1: General procedures

GB/T 19873.2-2009: Condition monitoring and diagnostics of machines - Vibration condition monitoring - Part 2: Processing, analysis and presentation of vibration data

GB/T 25889-2010: Condition monitoring and diagnostics of machines - Acoustic emission

GB/T 2298-2010: Mechanical vibration, shock and condition monitoring - Vocabulary

GB/T 27758.1-2011: Industrial automation systems and integration - Diagnostics, capability assessment and maintenance applications integration - Part 1: Overview and general requirements

GB/T 27758.2-2015: Industrial automation systems and integration—Diagnostics, capability assessment and maintenance applications integration—Part 2: Descriptions and definitions of application domain matrix elements

GB/T 26221-2010: Condition - based maintenance system architecture

GB/T 30831.1-2014: Condition monitoring and diagnostics of machines - Thermography - Part 1: General procedures

Annex B. Predictive Maintenance Platform (example)

With respect to the requirements for a systematic approach for predictive maintenance, this annex contains an example for a predictive maintenance platform.

User background and problems:

With the intensification of market competition, more and more car manufacturers put forward new quality requirements, which lead manufacturers of auto parts to continue improving the quality control of the production process to meet the needs of machine manufacturers. For example, in manufacture of the automobile hub, leading enterprises are committed to building the digital workshop of wheel production. However, the operation and maintenance of manufacturing equipment (such as machining centers, robots, and injection molding machines) will directly affect the

product quality and progress. At the same time, there are many sub-centers of the company in the country. In order to guarantee that the quality of production is easy to be controlled, the equipment forecasting maintenance platform is need to be established to monitor the equipment operating state of all production plants and to achieve that the maintenance resources is deployed efficiently.

Predictive maintenance methods:

A) Condition monitoring

Condition monitoring is the basis of predictive maintenance platform, usually performs state monitoring of key failure points by means of external sensing terminal. With the improvement of intelligent degree of equipment, partial equipment can provide state monitoring data of the ontology. Therefore, the state data acquisition from the equipment also becomes an important data sources.

The modeling method that based on function blocks is based on the function to analyze the equipment and find the coupling relationship between input and output of each function. Find the functions. Coupling between input and output. A potential implementation is technology mapping to OPC UA and fieldbus. With the application of this technology, it can clearly define the function of the equipment and realize the functional condition monitoring of the equipment.

B) Data transmission

The predictive maintenance platform can support different communication media (fieldbus, wired and wireless network, etc.), communication interface (Modbus RTU/Modbus TCP, Profibus, etc.), and support external standard output interface (OPC UA, etc.), as well as redundant and multi-way data acquisition, etc. It can achieve the interconnection between the equipment of different types and models whose core is this platform.

C) Fault diagnosis and life prediction

The platform can provide the functions of fault diagnosis and life prediction, and cover a variety of failure physics and life prediction models. It can select one or more models quickly and accurately for equipment type and failure mechanism. With the support of deep learning and artificial intelligence, the platform can realize the self-optimization of the model, and constantly improve the confidence of life prediction.

D) Maintenance decision

A joint optimization model of predictive maintenance and spare parts management is constructed by using fault pre-

diction results. With maintenance interval, maintenance threshold and spare parts order threshold as optimal variables, with minimum total cost of equipment maintenance cycle as optimization goals, the expert knowledge base is set up. Comparing the cost of the potential loss caused by the temporary unrepaired and the immediate maintenance, it can provide the predictive maintenance decision recommendations.

Application effect:

The predictive maintenance platform is under construction and the data collection and integration within the device

has been completed. The problem is how to combine device data with the operating state of the device, which requires a lot of data and research. But the platform provides the technical basis for the operation and maintenance of equipment and control of enterprises (with multiple sub-centers). By constructing the platform, the enterprises will achieve the optimal allocation of manufacturing and maintenance resources, which, with the quality control measures, will greatly enhance the quality of the product.

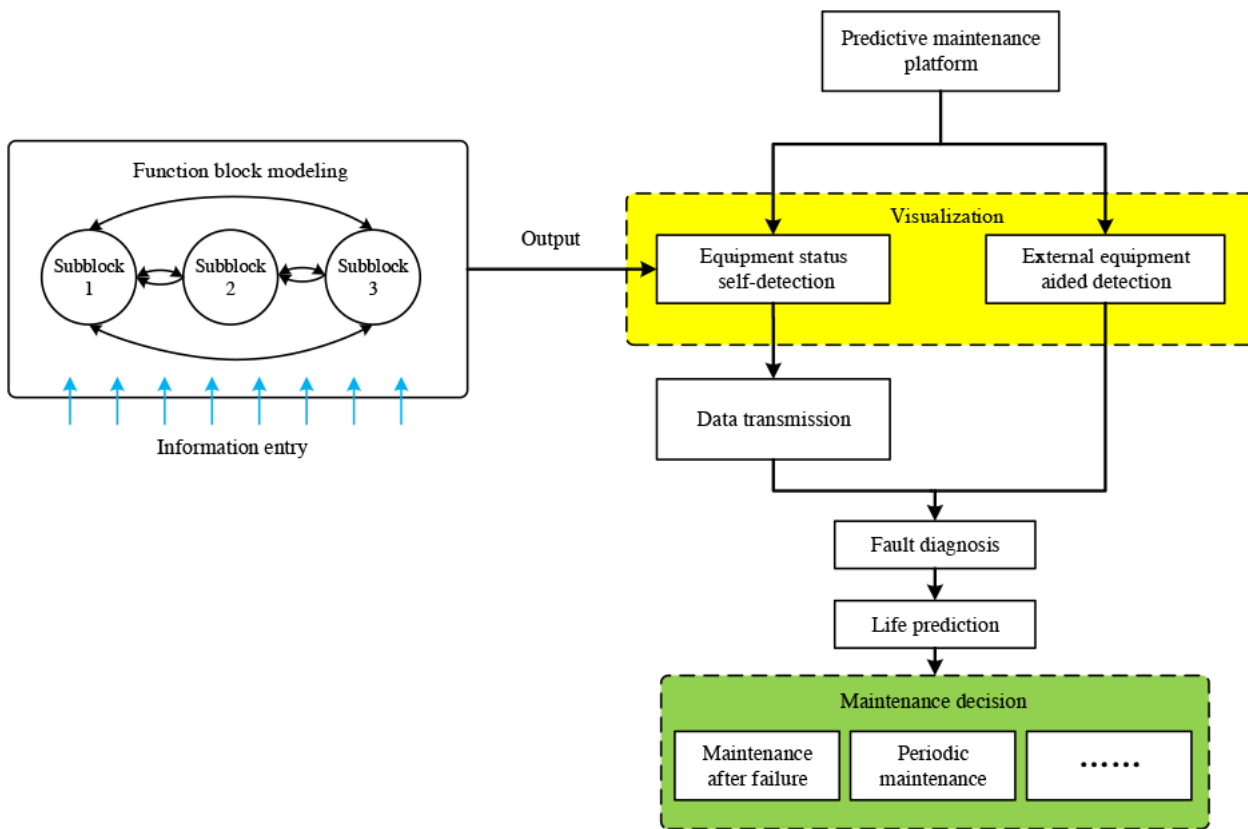


Figure B.1 Example of Predictive Maintenance Platform Function

Annex C. The list of abbreviation

AI, Artificial Intelligence	MOM, Manufacturing Operation Management
APQP, Advanced Product Quality Plan	MRP, Material Requirement Planning
APS, Advanced Planning and Scheduling	NAMUR, Normen Arbeitsgemeinschaft Mess- und Regelungstechnik
CBM, Condition Based Maintenance	OEE, Overall Equipment Effectiveness
CCD, Charge Coupled Device	OPC UA, OPC Unified Architecture
CM&D, Condition Monitoring and Diagnostics of Machines	OSA-CBM, Open System Architecture - Condition Based Maintenance
CNC, Computer Numerical Control	OSA-EAI, Open System Architecture - Enterprise Application Integration
CPS, Cyber Physical System	PCA, Principal Component Analysis
CSAA, China Sci-tech Automation Alliance	PCS, Process Control System
CVA, Canonical Variate Analysis	PDCA, Planning, Implementation, Inspection, Analysis
DD, Data Driven	PHM, Prognostics and Health Management
ERP, Enterprise Resource Planning	PLC, Programmable Logic Controller
FAA, Federal Aviation Administration	PLS, Partial Least Squares
FDC, Fault Detection and Classification	PoF, Physics of Failure
FFT, Fast Fourier Transformation	RFID, Radio Frequency Identification
GMA, Association of German Engineers	RTU, Remote Terminal Unit
HHT, Hilbert-Huang Transform	SAE, Society of Automotive Engineers
HUMS, Health and Usage Monitoring Systems	SEA, Systems Engineering Association
ICT, Information Communications Technology	SIMICA, Software Interface for Maintenance Information Collection and Analysis
IEEE, Institute of Electrical and Electronics Engineers	SPC, Statistical Process Control
IIoT, Industrial Internet of Things	SQC, Statistical Quality Control
IM, Intelligent Manufacturing	SPS/IPC/DRIVES, Exposition and Fair for PLCs, Industrial PCs, Drive Systems, and Automation and Control
ISHM, Integrated System Health Management	TCP, Transmission Control Protocol
ISO, International Organization for Standardization	VDI, Verein Deutscher Ingenieure
IVHM, Integrated Vehicle Health Management	VDMA, Verband Deutscher Maschinen- und Anlagenbauer
MES, Manufacturing Execution Systems	WHM, Web Host Manager
MIMOSA, Mechanical Information Management Open Standard Alliance	

XML, Extensible Markup Language

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