Intelligent Predictive Maintenance (IPdM) for Elevator Service

Through CPS, IOT&S and Data Mining

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***Abstract*— With the rapid economic growth and urbanization development, most of elevator production and service companies have completely changed their service policy opting to eliminate the standard preventive service policy. They now provide some form of predictive service policy and emphasize that they utilize remote monitoring of elevators to detect faults and estimate when components may need to be maintained due to actual usage. However, most of them are not true predictive maintenance policy. They merely a preventive, slightly enhanced, usage-based program. What is the future of elevator production and service companies? This paper will challenge the word "predictive maintenance" and present the framework of intelligent predictive maintenance system for smart elevator service based on industry 4.0 concepts.**

Keywords—Industry 4.0; CPS; IOT&S; Big data/ Data Mining; Elevator service; Smart elevator

I. INTRODUCTION

According to the World Health Organization (WHO) estimates that by 2050 there will be 70 per cent of people living in large cities. With the rapid economic growth and urbanization development, China's elevator industry and university are facing an unprecedented opportunity for research and development. Elevator ownership, annual production and annual growth are all ranked at top one of the world. In the recent decade, the Chinese elevator has kept an average annual growth rate of around 20%, with the volume of elevators, which are being used and registered in Quality Departments throughout the country growing from 346,067 in 2002 to 3,009,268 at the end of 2013. [1]

It is expected that in 2016 the total amount of elevators will be over nearly 4.5 million units in China and the activities of maintenance, repair, update, change of elevators will give service companies tremendous opportunity and economic value. The past five years, the number of various elevator accident has increased doubling. Factors leading to the elevator safety hazards are 16% for the manufacturing quality, 24% related to installation, while up to 60% caused by maintenance and usage of elevators. [2] Therefore, a reliable and safe usage and maintenance of elevator systems is most essential. How to protect the elevator routine maintenance and How to ensure the safety of boarding passengers will be the central questions to elevator industries.

The elevator service business has, and continues, to undergo many changes. Traditional elevator maintenance service is not able to meet the requirement of customers. For example, remote monitoring of elevators appeared in the late 1980s. While remote monitoring would alert the elevator company when an elevator had a breakdown, it did not in and of itself reduce the number of breakdowns. A decade later in the 1990s, the model evolved to usage-based maintenance – a concept based around adjusting the level and frequency of repairs dependent on each elevator's usage. This method had been adapted from the automobile industry, where motor oil was often changed based upon distance travelled. In the elevator industry, this paved the way for gradual progression towards more condition-based maintenance policy.

Each of these developments demonstrated the ongoing industry intent to have completely restructured their service policies aiming to eliminate the standard "preventive maintenance" service. Market competition coupled with cost increases has been a driver for searching new innovative approaches of elevator maintenance service.

With the development of Industry 4.0 concept. It gives more possibilities for elevator industry. A new methodology with the power to take the learnings of these earlier maintenance systems and incorporate the benefits of the new systems and technologies we now have access to, was needed to create a new efficient and effective practice for elevator repairs to enhance overall building efficiency. ThyssenKrupp has cooperated with Microsoft to develop MAX system for predictive maintenance and manage to detect and predict failures of elevators. [3]

Nowadays, many elevator companies will say they now provide some form of "predictive maintenance" service and emphasize that they utilize remote monitoring of elevators to gain visibility of faults and estimate when components may need to be replaced due to actual usage. However, when asked, the typical company representative will explain that their policy monitors the elevator and therefore they know when it "faults" or that they will replace a consumable part before its

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useful life has expired. Is this a "predictive maintenance" policy? Or, is it merely a preventive, slightly enhanced, usage-based policy? [4]

This paper will challenge the word "predictive maintenance" and review what is required to be truly "predictive maintenance". Based on Industry 4.0 concept, the framework of Intelligent Faults Diagnosis and Prognosis System (IFDaPS) is proposed for elevator industry to develop their own predictive maintenance system in the future.

II. CALSSIFICATION OF MAINTENANCE

There are many ways to define maintenance policy. [5-11], In general, the maintenance policy can be classified as two types: (1) Reactive maintenance and (2) Proactive maintenance. We focus on the techniques that are used to do maintenance tasks. The classification of Maintenance is shown in Fig. 1.

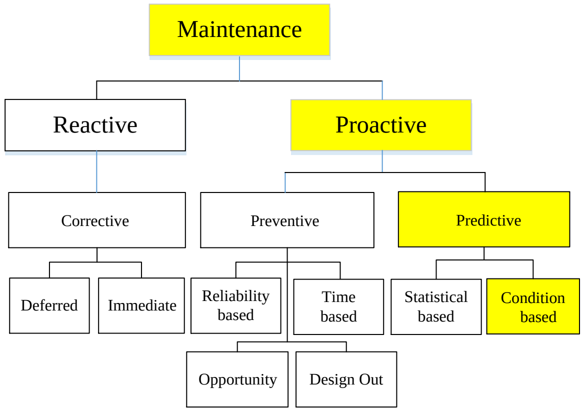

Fig. 1. Classification of Maintenance policy

A. *Reactive maintenance*

Reactive maintenance (also known as "breakdown maintenance") are repairs that are done when equipment has already broken down.

Reactive maintenance focuses on restoring the equipment to its normal operating condition. The broken-down equipment is returned to working within service specifications by replacing or repairing faulty parts and components. Emergency repairs cost to times more than planned repairs, so maintenance plans that rely on reactive maintenance are generally the most expensive. Reactive maintenance is so expensive because shutdowns happen during production runs (instead of pre-scheduled maintenance shutdowns during downtimes); because expedited shipping for spare parts costs much more than regular shipping; and because maintenance staff is often forced to work overtime to repair machinery.

B. *Proactive Maintenance*

Proactive maintenance is a preventive maintenance strategy for maintaining the reliability of machines or equipment. The purpose of proactive maintenance is to view machine failure and similar problems as something that can be anticipated and dealt with before they occur.

Proactive maintenance consists of Preventive maintenance and Predictive maintenance.

C. *Preventive vs Predictive*

1) *Preventive manintenance*

- Definition: Applies a planned maintenance service before a failure occurs.
- Characteristics: Simple, easy to implement, reliable, but low efficient.

2) *Predictive maintenance*

- Definition: Carries on the philosophy "execute at the right time". Service actions take place only when necessary.
- Characteristics: High efficient, reliable, but requires mass data and complicated analytical models

3) *Implementation of predictive maintenance*

The implementation of the predictive maintenance addresses several concerns, customer needs, organizational requirements and feasible technologies. Quickly the predictive maintenance became the desired industry standard in most markets. Some questions are related to implementation of predictive maintenance, for example, Did the standard preventive maintenance simply become something marketed as "predictive" when it really didn't have the necessary elements to be "predictive"? or Was it merely a usage-based policy that fell short of actually "predicting" failures based upon a component's, or a system's, behavioral patterns?

4) *Predictive maintenance for elevators*

Predictive maintenance can be divided two types: Statistical-based predictive maintenance and Condition-based predictive maintenance. Statistical-based predictive maintenance (SBM) depends on statistical data from the meticulous recording of the stoppages of the in-plant items and components in order to develop models for predicting failures, while Condition-based predictive maintenance (CBM, also called Condition-based maintenance) depends on continuous or periodic condition monitoring equipment to detect the signs of failure. There are a slight difference between predictive maintenance and condition based maintenance. CBM is focus on condition monitoring and humans make the decision of maintenance. While predictive maintenance more focuses on data analysis and data mining for support maintenance decision making automatically. Recently, Industry 4.0 will more concern data analysis rather than only condition monitoring.

Condition monitoring is a pre-condition to implement predictive maintenance. Modern elevators are highly intelligent systems running sophisticated, proprietary remote monitoring system producing a wealth of data within every movement, or desired movement. In order to be beneficial in creating the predictive maintenance, the remote monitoring, or M2M (Machine to Machine) data, must allow for immediate access to data, analysis of the elevator's intelligence, component and system trend analysis, analytical models to predict component and system failures based upon established patterns, dissemination of proper knowledge to service operation teams, and accurate inventory predictions. Clearly, any service provider can perform “dumb” remote monitoring. The concepts of Industry 4.0 have help us to develop a predictive maintenance system systematically. I session III, we will introduce the concepts of industry 4.0 and its technical components. In session VI, a detail framework of intelligent predictive maintenance for elevators is presented.

III. Industry 4.0

A. Indystry revolutions

A Manufacturing is and continues to be an essential part of world’s economy. Smart manufacturing will be capable of rapidly adapting their physical and intellectual infrastructures to exploit changes in technology as manufacturing becomes faster, more responsive to changing global markets and closer to customer’s needs.

Industrial production has been changed since it is in very beginning. Often, the changes have been so powerful that the term of revolution has been used to describe it. The name Industry 4.0 recognized the existence of three previous industrial revolutions.

1) Industry 1.0

The first industrial revolution is the term used to describe the change from purely manual work to machine production, which initially affected the cotton-spinning and weaving mills in England from 1770. The great breakthrough came in 1782 with the steam engine invented by James Watt. From this on it was possible to have an energy supply at any location and the manual work was no longer focused

2) Industry 2.0

The second industrial revolution was characterized by the principles of rationalization by Taylor. It is mainly based on the division of labor, standardization, precision manufacturing, and assembly line work. Henry Ford applied the first conveyor belt for the production of the T-Model and achieved pioneering success with it in the automobile manufacturing at the beginning of the 20th century.

3) Industry 3.0

The third industrial revolution was based on the development of the computer and IT technology. This led to numerically controlled machines, such as NC machines and industrial robots, which could be modified much faster than conventional mechanical automated machines. Thus, the flexible automation came into being and systems were characterized by high productivity and flexibility

4) Industry 4.0

Now we are standing on the brink of the fourth industrial revolution, so called Industry 4.0. Information and communication technologies (ICT) are growing together and affecting all areas of life. Devices and systems in our real environment that are controlled by embedded software are integrated into the global communication network, where “internet” is the key term. The real world and the virtual world are clearly growing together.

Industry 4.0, which is buzzwords discussed among practitioners as well as theorists, will facilitates the version of smart factory. [15, 16] It was introduced at Hanover fair in 2011 in Germany to present a new trend towards the networking of traditionally industries such as manufacturing. Similarly, in the United States, an initiative known as the Smart Manufacturing Leadership Coalition (SMLC) is also working on the future of manufacturing [17]. UK has been working on a strategy on “bring manufacturing back to UK” [18]. China adopts “smart Manufacturing” strategy to seek innovation-driven development, which is called “China Manufacturing 2025” or “Made in China 2025” [19]. There many similar programs and projects in the world, such as “Intelligent manufacturing system” from Japan, Canada, European Union, Switzerland and Norway [20]. “Future of Manufacturing” from Norway [21] and “Ubiquitous manufacturing” from South Korea [22].Technical components and definition of Industry 4.0

Industry 4.0 enables the manufacturing of individual and customized products at the same cost of mass production, which are manufactured by a smart factory with high automation and efficiency. For production companies, this specifically means that they are able to overcome predominant interface issues between product development, production and product usage, and thus orient all main value-adding processes towards the customer’s requirements. New development processes, e.g. integrated product and production system development, intensify exchange between departments and companies. Furthermore, industry 4.0 enables intelligent and flexible production control using IT-based intercommunicating and interacting machines, products, services, equipment and tools. M2M communication and networking bridges department boundaries and promotes the company’s orientation towards the customer.

5) Technical components of Industry 4.0

In general, Industry 4.0 may consists of 4 components: 1. Cyber-Physical Systems (CPS); 2. Internet of Things (IOT); 3. Big data & Data Mining (DM); 4. Internet of Service (IOS), seeing Fig. 1.

a) Cyber-Physical Systems (CPS)

An important component is Cyber-Physical Systems (CPS), which transfer the physical world into the virtual one. They can be understood as a basic unit in the system. The development of CPS is characterized by three stages. The first generation of CPS includes identification technologies like RFID tags, which allow unique identification of objects. Storage and analytics have to be provided as a centralized service. The second generation of CPS are equipped with sensors and actuators with a limited range of functions. CPS of the third generation can store and analyze data, are equipped with multiple sensors and actuators, and are network compatible.

b) Internet of thing (IoT)

The Internet of Thing (IOT) allows “Things or Objects” interact with each other and cooperate with their “smart” components to reach common aims. Based on CPS given in section 2.1, CPS can be defined as “Things or Objects”.

Therefore, the IOT can be thought as a network where CPS cooperate with each other through unique addressing schemas.

c) Data mining (DM)

Real-time big data isn't just a process for storing a huge amount of data in a data base or warehouse. Data Mining enables you to analyze and discover patterns, rules and knowledge from big data collected from multiple sources. So you can make the right decision at the right time and right place.

d) Internet of service (IOS)

The Internet of Services (IoS) enables service vendors to offer their services via the internet. The IoS consists of business models, an infrastructure for services, the services themselves and participants. Services are offered and combined into value-added services by various suppliers. They are communicated to users as well as consumers and accessed by them via various channels.

Following the 4 key components of Industry 4.0, a general and explicit definition of Industry 4.0 can be given as the following.

B. Definition of Industry 4.0

Based on the literature review, the general definition of Industry 4.0 is that Industry 4.0 is a collective term for technologies and concepts of value chain organization. Within the Smart Factories of Industry 4.0, CPS monitor physical processes, create a virtual copy of the physical world and make decentralized decisions. Over the IoT, CPS communicate and cooperate with each other and humans in real time. Data Mining discover knowledge to support decision-making process. Via the IoS, both internal and cross-organizational services are offered and utilized by participants of the value chain.

C. Implementation principle of Industry 4.0

Many scenarios of Industry 4.0 have been implemented and tested by research institutes and industries. Their results will affect the design of Industry 4.0. Referring to [12], seven design principles are driven for helping the companies who are interested in development of Industry 4.0 strategy.

a) Interoperability

In Industry 4.0 companies, CPS and humans are connected over the IoT and the IoS. Standards will be a key success factor for communication between CPS of various manufacturers.

b) Virtualization

Virtualization means that CPS are able to monitor physical processes. These sensor data are linked to virtual plant models and simulation models. Thus, a virtual copy of the physical world is created.

c) Decentralization

The rising demand for individual products makes it increasingly difficult to control systems centrally. Embedded computers enable CPS to make decisions on their own. Only in cases of failure, tasks are delegated to a higher level. Nevertheless, for quality assurance and traceability it is necessary to keep track of the whole system at any time.

d) Real-time capability

For organizational tasks, it is necessary that data is collected and analyzed in real time. The status of the plant is permanently tracked and analyzed. Thus, the plant can react to the failure of a machine and reroute products to another machine.

e) Service Orientation

The services of companies, CPS, and humans are available over the IoS and can be utilized by other participants. They can be offered both internally and across company borders. All CPS offer their functionalities as an encapsulated web service. As a result, the product specific process operation can be composed based on the customer specific requirements provided by the RFID tag.

f) Modularity

Modular systems are able to adapt to changing requirements by replacing or expanding individual modules flexibly. Therefore, modular systems can be easily adjusted in case of seasonal fluctuations or changed product characteristics.

g) Security

Industry 4.0 will use ICT technologies for data transmission and processing. The security and privacy of the information shall be emphasised in the data exchange processes using both hardware and software.

IV. Framework of a Predictive Program for Elevator Service

A. Predictive maintenance

Predictive maintenance is a set of activities that detect changes in the physical condition of equipment (signs of failure) in order to carry out the appropriate maintenance work for maximizing the service life of equipment without increasing the risk of failure. It is classified into two kinds according to the methods of detecting the signs of failure: (1) Statistical-based predictive maintenance and (2) Condition-based predictive maintenance. Statistical-based predictive Maintenance (SBM) depends on statistical data from the meticulous recording of the stoppages of the in-plant items and components in order to develop models for predicting failures, while Condition-based predictive Maintenance depends on continuous or periodic monitoring conditions of equipment to detect the signs of failure and make a maintenance decisions using data mining technology.

B. A IPdM (Intelligent Predicitve Mantenance) for Elevator service

Our intelligent predictive maintenance solution (Fig. 2) opens up innovative new possibilities for companies. [13][14] Data generated by Cyber-physical systems (CPS) and transmitted by Internet if Things (IOT) monitoring machine/process condition is automatically reviewed to pick up any patterns that indicate a possible fault through Data Mining systems. This decision use Internet of service (IOS) to allow the onset of a stoppage to be recognized early and corrective measures to be planned and introduced in the most effective way. It also means unplanned downtimes can be avoided and both staff and resources can be employed more effectively. This innovative solution is called Industry 4.0 for Intelligent Predictive Maintenance (IPdM).

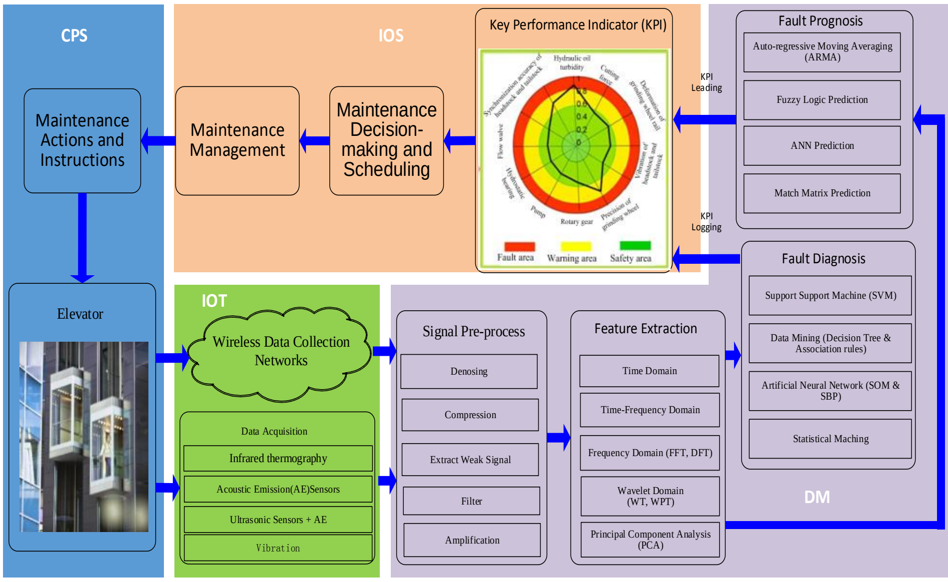

Fig. 2. The framework of Intelligent Predictive Maintenance (IPdM) systems In Industry 4.0.

C. Some key techniques of IPdM systems

IPdM systems based on many key techniques, such as CPS, IOT, IOS, Computational Intelligence (CI), Data Mining (knowledge discovery), Swarm Intelligence (SI), need to be researched and developed for fitting industry requirements. There are six main modules in IPdM: (1) Sensor and data acquisition (2) Signal pre-processing and feature extraction, (3) Maintenance decision-making, (4) key performance indicators, (5) maintenance scheduling optimization and (6) feedback control and compensation.

These modules has been developed at KDL laboratory, NTNU and they are described as the following:

1) Sensor and data acquisition module

It is the first step to implementing an IPdM strategy for machinery diagnostics and prognostics. The task of this module is selecting a suitable sensors and optimal sensor strategy. The data acquisition process transforms the senor signals into domains that are of the most information of the condition of the equipment. Various sensors, such as micro sensors, ultrasonic sensors, vibration sensors, acoustic emission sensors, have been designed to collect different data.

2) Signal pre-processing and feature extraction module

Generally, there are two steps to deal with the signals from sensors. The one is signal processing, which enhances the signal characteristics and quality. The techniques in signal processing include filtering, amplification, data compression, data validation, and de-noising that will improve the signal-to-noise ratio. The other is feature extraction, which extracts features from processed signals that are characteristic of an incipient failure or fault. Generally, the features can be extracted from three domains: time domain, frequency domain and time-frequency domain. All possible signal pre-processing and feature extraction methods are shown in Table 1 and which features could be selected depend on the real machines or system. All these kinds of methods are selectable in IFDPS and which methods are applied can be decided by real machine or system analysis.

3) Maintenance decision-making module.

Maintenance decision-making module offers sufficient and efficient information to maintenance personnel' decision on taking maintenance actions. The models for decision-support could be divided into 4 categories: (1) physical model; (2) statistic model; (3) data-driven Model, and (4) hybrid model. Because PdM strategy mostly depends on the signals and data reflecting the condition of equipment, data-driven model will be in a dominate place. IPdM focus on data-driven and hybrid model.

IPdM focus on the data-driven techniques and hybrid techniques in maintenance decision-making module. If the historical data can be obtained easily, the data-driven is very good to identify the fault and evaluate the condition. When only part of historical can be obtained, the hybrid techniques that combine the data-driven techniques and model-based techniques can be used to evaluate the condition of machine effectively. The semi-supervised learning method also can be used to evaluate condition and identify fault when only part of historical data is available and it is very effective. All these techniques are selectable according to the real manufacturing system analysis. Techniques for maintenance decision-making module can be divided into two main classes: diagnostics and prognostics. Fault diagnostics focuses on detect, isolation and identification of faults when they occur. While prognostics attempts to predict faults or failures before they occur. CI and DM techniques have been increasingly applied to equipment diagnosis and shown improved performance over traditional approaches. However, in practice, it is not easy to apply CI techniques due to the lack of efficient procedures to obtain training data and specific knowledge, which are required to train the models. So far, most of applications in the literature just used experimental data for model training. The intelligent techniques used include Artificial Neural Networks, Fuzzy logic Systems, fuzzy-neural networks, neural-fuzzy systems, evolutionary algorithms and Swarm intelligence. Compared to diagnostics, the no. of papers of prognostics is much smaller. The most used prognostics is to how much time is left before a failure occurs. The time left is usually called Remaining Useful Life (RUL). IPdM evaluate the remaining useful life using data-driven model and try to find the relations between the remaining useful life and the condition of machine or component.

4) Key Performance Indicators (KPI) module

A diagram of KPI also called spider chart or health radar chart is used for indicating the degradation of components. Each radio line shows the component condition of from zero (perfect) to one (damage). The colors shows the levels of the components, such as safe, warning, alarm, fault and defect. The diagram will help operators or mangers to evaluate the performance of the equipment visually.

5) Maintenance schedule optimization module

Maintenance planning and scheduling optimization is a kind of NP problem and the SI algorithms could be a very good technique to solve this kind of problem. IPdM apply Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO) and Bee Colony Algorithm (BCA) and try to find the optimal dynamic predictive maintenance scheduling. All these kind methods are selectable in IPdM to solve maintenance scheduling optimization problems.

6) Error correction, compensation and feedback control module

This module will make error correction, compensation and feedback control based on the results from the maintenance decision-support module.

V. CONCLUSIONS

This paper has proposed a general framework of intelligent predictive maintenance system for elevator service based on the concepts of industry 4.0. The main technical components in the system are CPS, IOT&S, and Data Mining.

The most difficult task in predictive maintenance is data analysis. Once advanced analytical models are applied to real-time remote monitoring data, the integrated maintenance management system provides holistic management providing the organization with a variety of actionable predictions, including failure predictions. The key to success is real-time predictions allowing for real-time decision-making capabilities.

Real-time data driven predictive maintenance is a paradigm shift from traditional reactive, preventive, to usage-based maintenance platforms, which are driven by fault resolution practices versus fault avoidance practices. An intelligent predictive maintenance solution well developed allows for quicker workflow optimization, leaner organizational structure, visibility, collaboration, and improved service margins.

The future work will be focus on the research and develop an efficient data mining and analysis model, which could integrated model-based approaches with data driven methods. We believe that industry 4.0 will give elevator industry and service great opportunities in the near future. The research goal of us is to develop real Elevator 4.0 for make elevator more safe and robust.

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