Intelligent Predictive Maintenance (*IPdM*) system – Industry 4.0 scenario

K. Wang
Knowledge Discovery Laboratory, Department of Production and Quality Engineering, Norwegian University of Science and Technology, Norway

Abstract

Industry 4.0 is a collective term for technologies and concepts of value chain organization. Based on the technological concepts of Radio Identification (RFID), Cyber-Physical Systems (CPS), the Internet of Things (IoT), Internet of Services (IoS), and Data Mining (DM), it facilitates the vision of the Smart Factory. Within the modular structured Smart Factories of Industry 4.0, CPS monitor physical objects and processes to create a virtual copy of the physical world and make decentralized controls and decisions. Over the Internet of Things, Cyber-Physical Systems communicate and cooperate with each other and humans in real time. Via the Data Mining and Internet of Services, both internal and cross-organizational services are offered and utilized by participants of the value chain. Although Industry 4.0 is currently a top priority for many industries, research institutes, and universities, a generally accepted definition of the term does not exist. This paper provides a definition of Industry 4.0 and identifies some main principles for implementation. In order to clearly understand what Industry 4.0 looks like, we will show an Intelligent Predictive Maintenance (*IPdM*) system for reaching Zero-Defect Manufacturing (ZDM).
Keywords: Industry 4.0, smart manufacturing, predictive maintenance, computational intelligence, zero-defect manufacturing

1 Introduction

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 customers' needs.

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Industrial production has been changing since 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.

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 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.

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 twentieth century.

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.

Now we are standing on the brink of the fourth industrial revolution, the 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 the buzzword among practitioners as well as theorists, will facilitate the version of smart factory [1, 2]. It was introduced at Hanover fair in 2011 in Germany to present a new trend toward the networking of traditional 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 [3]. UK has been working on a strategy on “bring manufacturing back to UK” [4]. China adopts “smart Manufacturing” strategy to seek innovation-driven development, which is called “China Manufacturing 2025” or “Made in China 2025” [5]. There are many similar programs and projects in the world, such as “Intelligent manufacturing system” from Japan, Canada, European Union, Switzerland, and Norway [6]. “Future of Manufacturing” from Norway [7] and “Ubiquitous manufacturing” from South Korea [8].

Industry 4.0 is closely related to other technological concepts, such as Machine-to-Machine (M2M) communication [9], radio frequency identification (RFID) technology [10], Cyber-Physical Systems (CPS) [11], the Internet of Things (IoT), the Internet of Services (IoS) [12], Cloud Computing [13], Computational Intelligence (CI), Data Mining (DM), and Decision-making/supporting system.

However, most industries and research institutions do not clearly understand what Industry 4.0 is and what it will be. This paper focuses on the gap in research.

The author adopts an understandable definition of Industry 4.0 and uses a solution of intelligent predictive maintenance system to show how to implement a scenario of Industry 4.0.

The paper is organized as follows. Section 1 offers a comprehensive overview of Industry 4.0. The main components and definition of Industry 4.0 are given in Section 2. Section 3 describes the six principles when a company wants to implement Industry 4.0, which will be of great benefits for developing the new Industry 4.0 scenarios more quickly. Intelligent predictive maintenance as a core function of Industry 4.0 to be used for explaining what the Industry 4.0 looks like. In Section 5, we list some ongoing Industry 4.0 projects based on the development of the framework of Intelligent Predictive Maintenance. Conclusions and future research are summarized in Section 6.

2 Industry 4.0 key components

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 toward 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 toward the customer. In general, Industry 4.0 may consist of four components: (1) Cyber-Physical Systems (CPS); (2) Internet of Things (IoT); (3) Big data & Data Mining (DM); (4) Internet of Service (IoS); see Fig. 1.

2.1 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.

2.2 Internet of Things (IoT)

The Internet of Things (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 of as a network where CPS cooperate with each other through unique addressing schemas.

2.3 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.

2.4 Internet of Services (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 four key components of Industry 4.0, a general and explicit definition of Industry 4.0 can be given as the following.

2.5 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 discovers 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.

3 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 [2], seven design principles are driven for helping the companies who are interested in development of Industry 4.0 strategy.

3.1 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.

3.2 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.

3.3 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.

3.4 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.

3.5 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.

3.6 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.

3.7 Security

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

4 Intelligent predictive maintenance

4.1 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 (also called Condition-based Maintenance, CBM) depends on continuous or periodic monitoring conditions of equipment to detect the signs of failure and make a maintenance decisions. Our intelligent predictive maintenance solution (Fig. 1) opens up innovative new possibilities for companies. Data generated by CPS and transmitted by IoT monitoring machine/process condition is automatically reviewed to pick up any patterns that indicate a possible fault through Data Mining systems. This decision uses 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*).

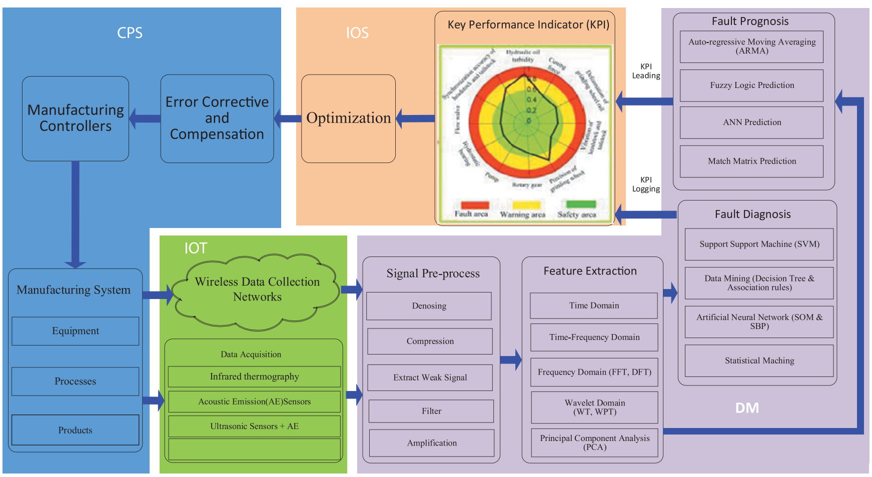

Figure 1: The framework of Intelligent Predictive Maintenance (*IPdM*) systems in Industry 4.0.

4.2 The framework and 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 have been developed at KDL laboratory, NTNU, and they are described in the following.

4.2.1 Sensor and data acquisition module

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

4.2.2 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 these kinds of methods are selectable in IFDPS and which methods are applied can be decided by real machine or system analysis.

4.2.3 Maintenance decision-making module

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

IPdM focuses 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 detection, isolation, and identification of faults when they occur. On the other hand, 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 the 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 number of papers of prognostics is much smaller. The most used prognostics is how much time is left before a failure occurs. The time left is usually called remaining useful life (RUL). *IPdM* evaluates the RUL using data-driven model and tries to find the relations between the RUL and the condition of the machine or component.

4.2.4 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 from zero (perfect) to one (damage). The colors show 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.

4.2.5 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* applies Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Bee Colony Algorithm (BCA) and tries to find the optimal dynamic predictive maintenance scheduling. All these methods are selectable in *IPdM* to solve maintenance scheduling optimization problems.

4.2.6 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.

5 Implementation of *IPdM*

Based on Industry 4.0: *IPdM* solutions, we have successfully run the following projects within European, Norwegian, and Chinese industries and universities. Due to the limited scope of the paper, we only give a short description of the projects.

(1) Zero defect manufacturing [11]

Project IFaCOM (Intelligent Fault Correction and self-Optimizing Manufacturing system) is funded by EU (Large-scale integrating collaborative project (IP) FP-2011-NMP-ICT-FoF) to reach a predictive maintenance strategy in smart factories.

(2) Windsense [12]

A Norwegian National research project called INDSENSE (Add-on instrumentation system for wind turbines) developed a system that reduces wind turbines' unforeseen operational shutdown and thereby increases the uptime of the power plant.

(3) Green Monitoring

In this project, NTNU has cooperated with a Norwegian machinery maintenance company and Bulgaria software company to successfully create an innovative product – a Centralized Condition-Based Maintenance and Manufacturing Support System (CCMMSS) – that helps in greening the production processes of industrial manufacturing enterprises.

(4) MonitorX

Norwegian Research Council (NFR) under the program of ENERGIX has supported project MonitorX (optimal remaining useful life of hydropower equipment based on condition monitoring and risk technology). NTNU will cooperate with ENERGI NORGE AS, SINTEF Energy, Comillas Pontifical University in Spain, and 13 Norwegian industries. Industry 4.0 concepts will be implemented in the project in order to reduce maintenance cost and increase operation efficiency in Norwegian Hydro power stations.

(5) Industry 4.0 Laboratory in SSPU

Shanghai Second Polytechnic University (SSPU) work together with NTNU, SAP, and other Chinese and Norwegian companies to develop a test bed of Industry 4.0 in Shanghai for showing how to design an Industry 4.0 system or China manufacturing 2025 system. The products of the smart factory demonstration are innovative electrochemical glass for smart building.

6 Conclusions

The paper contributes to the ongoing discussion focusing on Industry 4.0 within both the academic and industry. By providing a general definition of Industry 4.0, the paper creates a common understanding of the term, which is needed for a reasonable academic discussion about the topic. The design principles derived from four basic Industry 4.0 components support academics in identifying, describing, and selecting Industry 4.0 scenarios in the context of further investigations.

The paper's practical contributions are twofold: First, the definition given for Industry 4.0 helps clarify the basic understanding of the term of Industry 4.0 among practitioners. Second, the seven design principles can be applied for implementing Industry 4.0 scenarios in companies. They help identify potential use cases and offer guidance during implementation. The paper presents an Industry 4.0: Intelligent predictive maintenance solution, which allows practitioners to have an effective guidance when they are going to implement Industry 4.0 in different industries from manufacturing factories to energy sectors.

Researchers and practitioners should challenge their utility by identifying, describing, and selecting Industry 4.0 scenarios. Since Drath and Horch [13] underline that "Industry 4.0 is a phenomenon that will come inevitably, whether we want it or not." Therefore, both academics and practitioners should use the Industry 4.0 concepts to make future intelligent and integrated manufacturing and production processes.

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