Handbook of Research on Industrial Advancement in Scientific Knowledge

Vicente González-Prida Diaz
Universidad de Sevilla, Spain & Universidad Nacional de Educación a Distancia (UNED), Spain

Jesus Pedro Zamora Bonilla
Universidad Nacional de Educación a Distancia (UNED), Spain

A volume in the Advances in Human and Social Aspects of Technology (AHSAT) Book Series

IGI Global
DISSEMINATOR OF KNOWLEDGE

Published in the United States of America by
IGI Global
Information Science Reference (an imprint of IGI Global)
701 E. Chocolate Avenue
Hershey PA, USA 17033
Tel: 717-533-8845
Fax: 717-533-8661
E-mail: cust@igi-global.com
Web site: http://www.igi-global.com

Library of Congress Cataloging-in-Publication Data

Names: Gonzalez-Prida, Vicente, 1975- editor. | Zamora Bonilla, Jesus P., editor.
Title: Handbook of research on industrial advancement in scientific knowledge / Vicente Gonzalez-Prida Diaz and Jesus Pedro Zamora Bonilla, editors.
Description: Hershey PA : Information Science Reference, [2019] | Includes bibliographical references.
Identifiers: LCCN 2018017254| ISBN 9781522571520 (hardcover) | ISBN 9781522571537 (ebook)
Subjects: LCSH: Technological innovations--Management.
Classification: LCC HD45 .T383 2019 | DDC 658.5/14--dc23 LC record available at https://lccn.loc.gov/2018017254

This book is published in the IGI Global book series Advances in Human and Social Aspects of Technology (AHSAT) (ISSN: 2328-1316; eISSN: 2328-1324)

British Cataloguing in Publication Data
A Cataloguing in Publication record for this book is available from the British Library.

Chapter 8
Towards an Industry 4.0-Based Maintenance Approach in the Manufacturing Processes

J. Roberto Reyes García
University of Twente, The Netherlands

Alberto Martinetti
University of Twente, The Netherlands

Juan M. Jauregui Becker
University of Twente, The Netherlands

Sarbjeet Singh
Luleå University of Technology, Sweden

Leo A. M. van Dongen
University of Twente, The Netherlands

ABSTRACT

Maintenance is one of the key application areas of Industry 4.0. Every day, maintenance managers and technicians face the challenge of ensuring maximum machine reliability and availability, while minimizing the utilization of materials consumed by maintenance and repairs. As productivity is pressured to further improve, finding a successful balance between these aspects is becoming increasingly difficult. Therefore, integrating condition-monitoring systems with predictive and prescriptive maintenance principles, a new Industry 4.0-based maintenance can be obtained that enables maintenance engineers to better deal with this challenge. In this context, Maintenance 4.0 expands existing maintenance functions by the integration of Industry 4.0 technologies, like internet of things, cyber physical systems, augmented reality, and 3D printing. This chapter presents the main maintenance areas that are supported and enabled by Industry 4.0 technologies and introduces an Industry 4.0-based predictive maintenance approach for the manufacturing industry.

DOI: 10.4018/978-1-5225-7152-0.ch008

INDUSTRY 4.0 AND MAINTENANCE

The term Industry 4.0 (I4.0) refers to a new technological vision on how management of manufacturing and production processes can be redefined through the implementation of advanced information technologies, robotics and monitoring devices (Kagermann, Wahlster, & Helbig, 2013) (Deloitte AG, 2015) (Gottorp Jeppesen, 2015). The "4.0" designation suggests that the world is now facing the fourth industrial revolution.

Figure 1 illustrates the transformation of manufacturing industry through the four industrial revolutions moments.

The First Industrial Revolution ran from 1760 to 1840; it was driven by the introduction of mechanical production facilities with the help of water and steam power to replace manual labor. It includes the adoption of structured chemical manufacturing and iron production processes. In general terms, it can be summarized as the rise of factory systems.

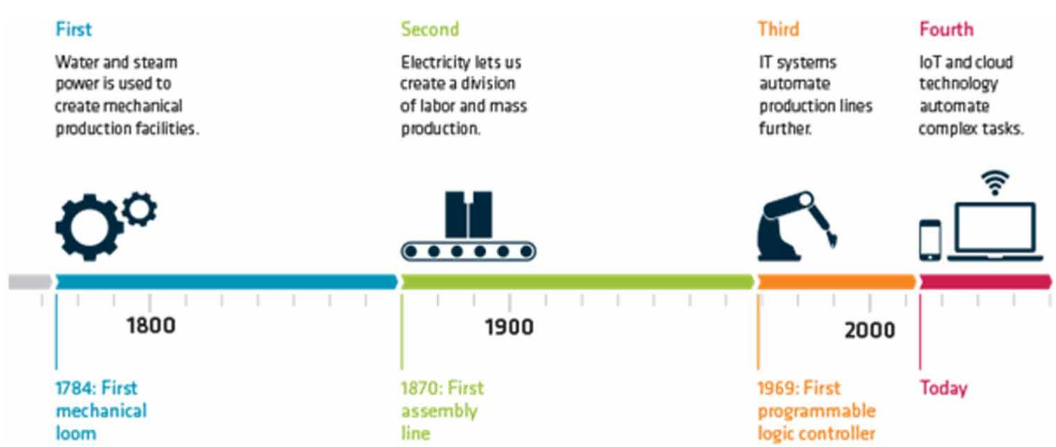
The Second Industrial Revolution, also known as the Technological Revolution, ran from 1870 to 1914 and was driven by the introduction of the division of labor and mass production with the help of electrical power. The factory systems were developed to allow mass production through assembly lines. This booming period was characterized by inventions that radically changed the life style: telegraph and telephone, typewriter, lightbulb, high voltage electric current, first car, first plane and compressed-air brake.

The Third Industrial Revolution, known as the Digital Revolution, started in the 1960's and marked the change from analogue and mechanical technology to digital technology that further automates production.

Programmable Logic Controller (PLC) is universally considered the main expression of this radical change in production manufacturing. It enabled to automate several processes reducing the human involvement.

Finally, the Fourth Industrial revolution started in 2010 and is based on Cyber-Physical Systems (CPS) and the use of the internet to create networks in the production environment and bring services to the customers and the organizations themselves (Kagermann, Wahlster, & Helbig, 2013) (Deloitte

Figure 1. Industrial revolutions' timeline
Source: *Gottorp Jeppesen, 2015*



AG, 2015) (PwC, 2016) (Geissbauer, Vedso, & Schrauf, 2016) (Bruurmijn, 2016) (Sniderman, Mahto, & Cotteleer, 2016) (Khan & Turowski, 2016).

In general terms, I4.0 is a new production paradigm in which manufacturing industry and production processes will be redefined through the implementation of advanced information technologies, robotics, monitoring devices, and the internet (Kagermann, Wahlster, & Helbig, 2013) (Deloitte AG, 2015) (Sniderman, Mahto, & Cotteleer, 2016). Moreover, Industry 4.0 enables new business models focused on services. In the very short future, there will be millions of intelligent production facilities that are all across connected, and they will provide huge quantities of data (big data) about their own operating conditions and product statuses in the cloud (BDI, 2016). All that big data can be used to optimize products and the process themselves. Moreover, smart algorithms can link existing (historical) data to new (incoming) information and predict disturbances caused by the new operational conditions.

Besides, big data provides a foundation for offering both to the workers of the production facilities and to the customers, personalized data-based services in addition to the physical end-product. For instance, operators can collect and analyze data about the total amount of raw materials they get for all of the machines they are responsible for, and use it to generate new services, such as an automatic reconfiguration planning that can cope with the lack of materials. Customers on the other hand, can use the data to get services such as personalized reports in their own IT system, with the information of the possible delays and new forecasted delivery time of their products.

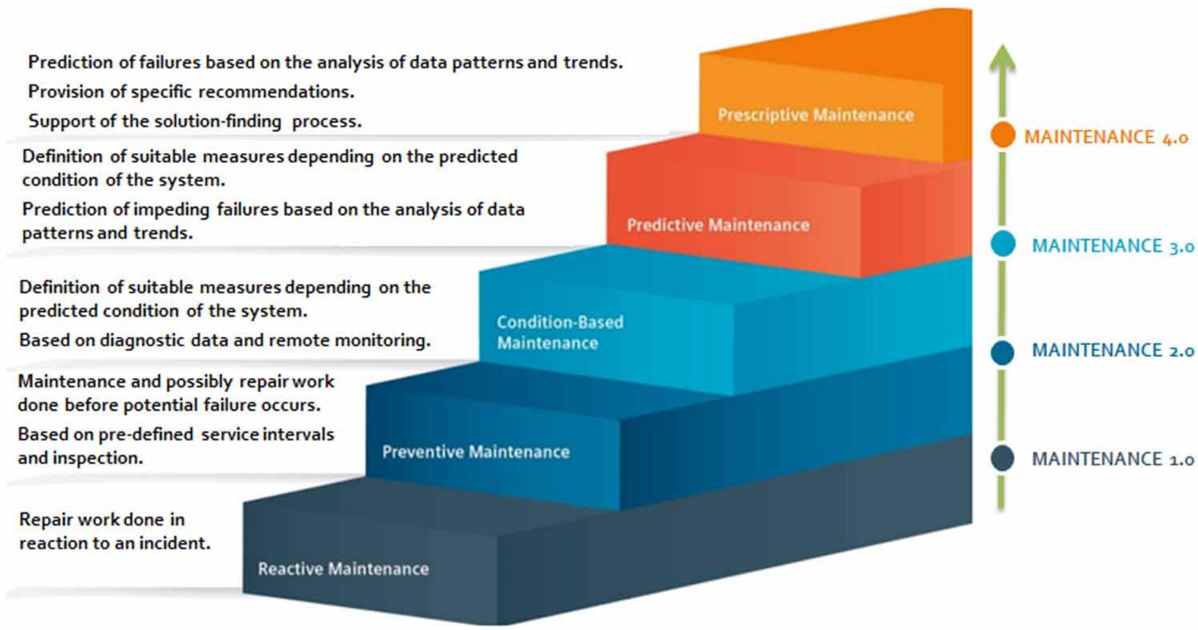
Maintenance 4.0

One of the key challenges for I4.0 relates to the goal of producing tailored and customer-specific solutions (Deloitte AG, 2015). For this to be possible, manufacturing systems must possess a high degree of flexibility, availability and reliability, which are considerations that can now be achieved by means of a good maintenance strategy and management. Therefore, the field of maintenance plays an important role to raise the potential of I4.0. Besides, maintenance is one of the application areas of I4.0 (Kans, Galar, & Thaduri, 2015).

Maintenance is a complex process that essentially involves the planning, organization, implementation and monitoring of all the technical and administrative processes associated with inspecting, servicing, repairing and enhancing machines and systems. In the context of I4.0, the maintenance function is often denoted as Maintenance 4.0, Smart Maintenance or e-Maintenance (Fumagalli, Macchi, Colace, Rondi, & Alfieri, 2016). Maintenance 4.0 refers to a form of self-learning and smart systems that predicts failures, makes diagnosis and triggers maintenance by making use of the Internet of Things (IoT) (MacDougall, 2014). Smart maintenance has enormous potential in terms of information and innovation, by making use of real time data regarding the overall status of the machine, its main components, the availability of spare parts, and the tracking of the maintenance staff performance (Kranz, 2017). Figure 2 shows the evolution of the maintenance function and the place of Maintenance 4.0.

For creating a Maintenance 4.0 policy, I4.0- and IoT- technologies are a crucial enabler (MacDougall, 2014) (Fraunhofer IPA, 2016) (Roubaud, 2017). With these technologies, faults and fluctuations that were invisible before, can be now detected and sometimes even predicted. Instead of solving a problem after it happens, with Maintenance 4.0 systems, production engineers will be alerted ahead of time in order to take the necessary actions to ensure no problem occurs at all (Roubaud, 2017).

Figure 2. Maintenance evolution
Source: *Adapted from Kalt & Rosenberger, 2015*



MAINTENANCE AREAS SUPPORTED AND ENABLED BY INDUSTRY 4.0 TECHNOLOGIES

Information availability in the manufacturing sector can be significantly improved, which in turn can be used to develop optimized (predictive) maintenance strategies (Fraunhofer IPA, 2016). That is particularly possible by means of the technologies and best practices coming along with I4.0 (e.g. increasing standardization, overall lowering of the cost of the monitoring technologies, evolution in the market of solutions' providers, migration to cloud models) (i-scoop, 2017).

Furthermore, the value of large volumes of data generated in the production floor is not limited to helping maintenance personnel to predict and prevent breakdowns. Once the data has been processed and disseminated by the smart maintenance service, it can also be used to enable continuous improvements to machinery and systems (ACATECH, 2015). Particularly, four maintenance areas can benefit from the Industry 4.0 approach and its technologies: 1) Condition Monitoring (CM) & Condition Based Maintenance (CBM); 2) Predictive Maintenance (PdM); 3) Prescriptive Maintenance (RxM).

Condition Monitoring (CM) and Condition-Based Maintenance (CBM)

In order to maintain its functionality for critical mechanical systems, their condition should be periodically evaluated to decide upon the required maintenance activities to be performed. In this regard, Condition Monitoring (CM) and, consequently, Condition-Based Maintenance (CBM) are suitable for maintenance activities based on constant monitoring of an asset.

The trigger for the CBM activity is a measured parameter that is indicative of the machine condition. This may be a performance indicator, or a diagnostic measurement that gives early warning of deterioration, and is termed condition monitoring CM (Starr, et al., 2010). Therefore, CM can be referred as the heart of CBM (Campos & Prakash, 2006).

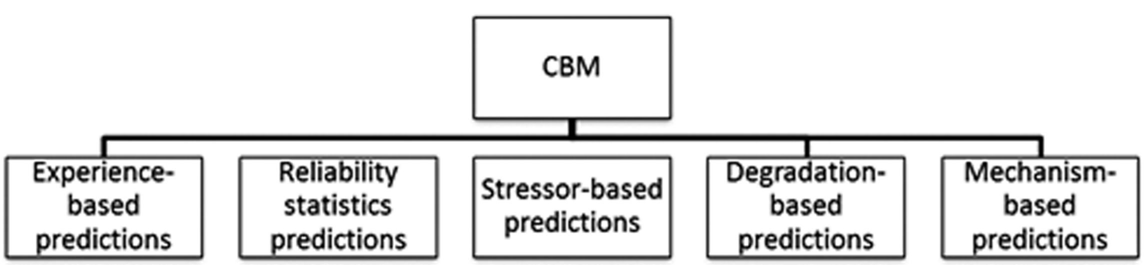
CM is the process of monitoring a parameter of condition in machinery (e.g. vibration or temperature), in order to identify a significant change which is indicative of a developing fault (ISO, 1993) (IAEA, 2007) (Tiddens, Braaksma, & Tinga, 2016). On the other hand, in CBM, once the timing of equipment failure is known, action can be taken to prevent or delay failure. CBM dictates that maintenance should only be performed when certain indicators show signs of decreasing performance or upcoming failure. In CBM, sensors are installed in the system to monitor its components and perform maintenance based on the monitored system's health (Jardine, Lin, & Banjevic, 2006) (Nain & Varde, 2013) (Lee, Wu, Zhao, Ghaffari, & Liao, 2014) (Farrar & Lieven, 2007). Similar to CM, CBM consist of three steps (Jardine, Lin, & Banjevic, 2006), where actually the first two make reference to the CM process (ISO, 1993) (IAEA, 2007):

1. **Data Acquisition:** Is the process of capturing relevant condition information which can indicate the health status of the system. This data can be very versatile ranging from temperature, oil analysis, vibration data, humidity data, etc.
2. **Data Processing:** Cleaning the data from errors/noise and analysing the data to improve its understanding and interpretation. The processing of data is very dependent on the type of data. For example, analysis of vibration data and oil data apply different techniques.
3. **Maintenance Decision Making:** Based on processed data a decision must be made whether maintenance is required. Decision support can be divided into diagnostics and prognostics. In the former is focussed on detection, isolation and identification of faults when they occur. The latter focuses on predicting faults before they occur.

Additionally, CBM allows preventive and corrective actions to be scheduled at the optimal time, thus reducing the total cost of ownership and of maintenance as well (Starr, et al., 2010) (IAEA, 2007). However, CBM also implies extra costs to the maintenance cycle which would not exist in other forms of maintenance. In particular, CBM is highly effective where safety and reliability is the paramount concern such as the aircraft industry, semiconductor manufacturing, nuclear, oil and gas industry (Fiix®, 2017).

In the context of providing decision-making support for maintenance actions, CBM can be referred as a prognostics maintenance technique (Jardine, Lin, & Banjevic, 2006). In this regard, Tiddens et al. (Tiddens, Braaksma, & Tinga, 2015) propose a framework consisting of five maturity levels of prognostics, which can also be representative as a CBM classification as shown in Figure 3.

Figure 3. Prognostics classification framework



The proposed levels are:

1. Experience based predictions of failure times are based on knowledge and previous experience outside (e.g. Original Equipment Manufacturer) or within the company.
2. Reliability statistics prediction analyses are based on historical (failure) records of comparable equipment without considering component specific (usage) differences.
3. Stressor based predictions are based on historical records supplemented with stressor data (e.g. temperature, humidity) to include environmental and operational variances.
4. Degradation based predictions are based on the extrapolation of a general path of a prognostic parameter, a degradation measure, to a failure threshold. The prognostic parameter is inferred from sensor readings. The prediction includes the current state of degradation and results in an expected lifetime of a specific system in a specific environment.
5. Mechanism based predictions are based on direct sensing of the critical failure mechanisms of individual components. It results in an expected lifetime of a specific system in specified conditions.

In general, the various types of CBM usually found in practice are (Jardine, Lin, & Banjevic, 2006) (IAEA, 2007) (Tiddens, Braaksma, & Tinga, 2016) (Fiix®, 2017):

- **Vibration Analysis:** Rotating equipment such as compressors, pumps, motors all exhibit a certain degree of vibration. As they degrade, or fall out of alignment, the amount of vibration increases. Vibration sensors can be used to detect when this becomes excessive.
- **Infrared:** IR cameras can be used to detect high temperature conditions in energized equipment.
- **Ultrasonic:** Detection of deep subsurface defects such as boat hull corrosion.
- **Acoustic:** Used to detect gas, liquid or vacuum leaks.
- **Oil Analysis:** Measure the number and size of particles in a sample to determine asset wear.
- **Electrical:** Motor current readings using clamp on ammeters.
- **Operational Performance:** Sensors throughout a system to measure pressure, temperature, flow, etc.

Predictive Maintenance (PdM)

The common premise of Predictive Maintenance (PdM) is that regular monitoring of the actual mechanical condition, operating efficiency, and other indicators of the operating condition of machines and process systems, will provide the data required to ensure the maximum interval between repairs and minimize the number and cost of unscheduled outages created by machine failures (Mobley, 2002). PdM is a condition-driven preventive maintenance program, but unlike CBM, PdM goes a step further and once data is coming from equipment in real-time (or near real-time), advanced analytics are used to identify asset reliability risks that could impact business operations (Bellias, 2017).

Simply stated, PdM is a philosophy that, uses the actual operating condition of plant equipment and systems to optimize total plant operation (Mobley, 2002). Typically, predictive maintenance decreases the total machine downtime by 30% to 50% and increases machine life by 20% to 40% (ACATECH, 2015).

Similar to CBM, when predictive maintenance is working effectively, maintenance is only performed on machines when it is required. That is, just before failure is likely to occur. This brings several cost savings (Fiix®, 2017):

- Minimizing the time that the equipment is being maintained;
- Minimizing the production hours lost to maintenance; and
- Minimizing the cost of spare parts and supplies.

In addition, a well-known best practice in industry is to CM in conjunction with some form of PdM to determine a machine's current maintenance status. Explicitly, one can say that any form of maintenance of machinery is based on an indication that a problem is about to occur. As a consequence, both the CM and PdM of machinery will (Smith, 2016):

- Avoid any unexpected catastrophic breakdowns that would otherwise have expensive or dangerous consequences;
- Reduce the number of overhauls on machines to a minimum, thereby reducing maintenance costs;
- Eliminate unnecessary interventions with the otherwise consequent risk of introducing faults on smoothly operating machines;
- Allow spare parts to be ordered in timely manner, thus eliminating costly inventories;
- Reduce the intervention time, thereby minimising production loss via unanticipated time delays, because the specific fault to be repaired is known in advance, enabling any overhauls to be scheduled when it is most convenient.

However, when implementing PdM, cost savings also come at a price. Some CM techniques can be expensive and could require experienced personnel in data analysis in order to be effective. Besides, despite the fact that of PdM has existed for many years, the massive investments in technology typically needed to handle the massive volumes of data required, had limited deployment to only the largest organizations.

Conversely, the decreasing cost of sensors, computing power, and bandwidth, coupled with increasing technological advancements, has made PdM a much more viable option, and one that could be feasible to scale on a broad level across facilities and organizations of all sizes (Coleman, Damodaran, Chandramouli, & Deuel, 2017). Besides, with the increasing effect of big data instrumentation and the IoT, more conditional, usage and wear data exists on assets today. This, enables PdM to utilize smart and connected technologies that unite digital and physical assets, which makes small-scale applications also possible (Watts, 2016).

It is of outmost importance to realize that simply gathering the information from sensors and systems is not enough to yield the benefits of PdM. The ability to aggregate and then analyze data can be crucial to predicting malfunctions, but this often requires new capabilities for creating, handling, and making use of data (Coleman, Damodaran, Chandramouli, & Deuel, 2017). Fortunately, with the boost of Industry 4.0 and its technologies, PdM analytics capabilities are increasingly growing in tandem with the growth of connectivity and data, enabling organizations to make sense of the data they collect.

Computerized Maintenance Management Systems (CMMS)

In response to the lack of an actual link between maintenance solutions and monitoring techniques (S.Takata, et al., 2004), advanced manufacturing systems have introduced the use of CM applications for maintenance purposes in order to gain awareness of equipment condition and to identify failures ahead of time (M.Mori, M.Fujishima, Komatsua, Zhao, & Liu, 2008). Real-time monitoring of machine tools and equipment together with visualization and data analysis, under the umbrella of collaboration between the two systems, can lead to condition-based maintenance techniques (Mourtzis, Vlachou, Milas, & Xanthopoulos, 2016).

Today, a new generation of cloud-based Computerized Maintenance Management Systems (CMMS) can digitally capture asset information in real-time to help predict maintenance issues, improve maintenance staff efficiency, assist with regulatory compliance, and manage inventory and budgets (Lachance, 2016). CMMS can be effective for any organization that is constantly working on reactive maintenance and unable to do preventive maintenance, frustrated with tracking and managing spare parts inventory, having difficulty with providing documentation for regulatory compliance, or wasting time on costly manual processes for tracking maintenance (eMaint, 2017). These new systems are scalable, meaning they easily capture today's data and are also designed to capture the demands of tomorrow's data before it is even known what that data is or how large their demands will be. CMMS are also easy to use and will help the organizations to save time, money and a lot of headache. Cloud-based systems are growing in popularity because individual operators can now access the system online. A cloud-based CMMS solution works by storing asset data, automating work order and request processes, monitoring equipment using predictive maintenance, scheduling maintenance work and resources, recording inventory levels, and providing management with reports in order to make data-driven decisions, all in a cloud-based environment (Lachance, 2016).

There are quite a lot of advantages when it comes to cloud-based maintenance management applications. Simply, anything that is cloud-based means that the application is hosted through the internet; these applications are often utilized in CMMS tools. Five of the main advantages are listed below (Chan, 2017):

- **Ease of Use:** First of all, the application and data are stored within a cloud service then can accessed just about anywhere. Wherever a mobile device is available, there's access. This is especially handy if the application is specifically designed for a mobile usage.
- **Backup:** When using a cloud-based system, and it has been done correctly, the server hosting the information is often hosted between multiple locations. Meaning that if locally hosted information is ever lost, then there's still a backup of all the data in a secure location.
- **Real-Time Collaboration:** When using a cloud-based application, it means that anything anyone does is immediately related to the group at large. This means that if someone is editing a document, then others who have access can also edit it in real-time while also seeing what the first edits are impacting. This level of transparency and immediacy really bolsters a team environment and allows for collaborations that simply traditional applications can't match.
- **Always Updated:** The greatness that comes with cloud-based computing is that the data and software is hosted off-site. This means that up-time is constant and that updates to bugs and errors can be rolled out instantly. Making sure that the applications are running smoothly and allowing users to focus on what matters: their work.
- **History:** When any changes are made within a cloud-based maintenance management application, they'll have a time stamp to when any updates have taken place. This gives users the full picture of what happened if something goes wrong or if there's the need to look back on all the maintenance that have been performed on a given asset, time frame, or by whom.

Prescriptive Maintenance (RxM)

As industry adopts Software-as-a-Service (SaaS) and cloud-based systems such as CMMS, there is greater opportunity to take control of operations, quality and safety to move beyond preventive or predictive maintenance. In fact, the ability to connect assets and feed information into a central system gives organizations the power to turn data into powerful insights and automatically take corrective, preventive or predictive action (eMaint, 2017).

With the digitization of the industry and the advancement of computing and visualization technologies, a new era is emerging in the fields of maintenance, the so-called prescriptive maintenance (Matyas, Nemeth, Kovacs, & Glawar, 2017). The concept of prescriptive maintenance extends beyond the mere prediction of failures; based on the analyses of historical data and incoming real-time data, required maintenance measures are predicted by a system and a course of action is prescribed. This allows for a flexible maintenance strategy in which maintenance is only applied when and where it is needed. This virtually eliminates the traditional preventive maintenance schedule (Kovacevic, 2017). Don't just predict problems, prescribe a solution. That is the premise behind Prescriptive Maintenance (RxM) (Kennedy, 2017).

By evolving from time based, to condition based, to predictive and prescriptive maintenance, companies are evolving their maintenance systems from being simply efficient to becoming truly strategic. Beyond maintenance, cognitive systems can integrate maintenance and operations data with other data sources, such as quality, warranty and engineering data, to become critical to how entire companies operate. RxM means moving from planned preventive maintenance to proactive and smart maintenance planning (Khoshafian & Rostetter, 2015). Though RxM is still in its infancy, many thought leaders are considering its potential to become the next level of reliability and maintenance best practice (Kennedy, 2017).

Prescriptive maintenance requires that various asset management and maintenance systems are well integrated. For example, a predictive maintenance solution might recommend that a piece of equipment get overhauled based on analysis of vibration and temperature readings, but a prescriptive system would kick off a work order to field technicians based on this information and oversee the entire maintenance workflows (Bellias, 2017). Thus, when a change in the equipment occurs, prescriptive maintenance will not only show what and when a failure is going to happen, but why it is happening. Taking it one step further, prescriptive maintenance will take the analysis and determine different options and the potential outcomes to mitigate any risk to the operation (Kovacevic, 2017).

Several key business drivers are stimulating interest in Rx strategies and driving solution development. For example:

- **Automation:** As more automation is used in manufacturing, the speed of response required in dealing with maintenance issues is going to get faster (Miklovic, n.d.).
- **Economics:** Decisions as to what's the best option from an economic standpoint are getting more complex. "It just isn't enough to know what can fail or when it might fail … it requires having enough information to understand the options for maintenance as well as the financial implications of each option" (Miklovic, n.d.).
- **Workforce Changes:** Older workers are retiring, and newer, younger workers expect smart, assistive tools to help them do their job (Kennedy, 2017).
- **Operating Conditions:** Assets not only fail by their own means, but also by the manner in which they are operated (Kennedy, 2017). For example, a pump manufacturer will recommend specific

operating design conditions such as discharge pressure and temperature, but there is a lot of variability in process operating conditions and also in the composition of the fluids. Prescriptive analytics can consider these conditions and make recommendations accordingly.

- **Asset Performance:** A higher level of sophistication is required in the way asset and process data are organized (Kennedy, 2017). With the Industrial Internet of Things and Services (IIoTS), analytics platforms are unique in their ability to ingest years of operational data and massive quantities of unconventional data scattered through different systems of record.

On the other hand, the volume of available data for maintenance decisions has increased significantly with the growing popularity of condition monitoring, multisensory technologies and cloud computing. Therefore, one major problem for developing data based prescriptive maintenance measures is the lack of formalized data structures (Matyas, Nemeth, Kovacs, & Glawar, 2017). Even when organizations are successful with PdM, they may still not be able to move to prescriptive maintenance. There are numerous barriers, but a few have been listed below for consideration (Kovacevic, 2017);

- **Cost:** While the cost of the sensors, data storage, and analytical engines come down, there is still a cost in the hardware and software. Also, there will be some learning costs that are incurred when organizations are still using traditional maintenance techniques while prescriptive maintenance is being tested and validated.
- **Regulations:** Certain regulations may not allow the traditional maintenance approach to fade into the past. Take, for example, the requirements to replace or rebuild pressure relief valves (PRVs). Even though there is evidence that the life of the asset may not impact the reliability of it, PRVs must still be replaced on a time-based frequency. As a result, prescriptive maintenance may not be allowed in place of traditional maintenance activities when dealing with regulatory bodies.
- **Culture:** Depending on the level of trust in technology in an organization or the long-held beliefs of what maintenance is and how it should be done, there may be significant hurdles to overcome with the company culture to implement prescriptive maintenance.

So, one should keep in mind that, as stated by James Kovacevic, founder of *High Performance Reliability*, and author of *A smarter way of preventive maintenance*: *Prescriptive Maintenance can be a powerful approach to maintenance if done properly. However, we are just at the beginning of the journey with it, and we will likely see it transform how maintenance is performed in the years to come.*

INTRODUCTION TO AN INDUSTRY 4.0-BASED PREDICTIVE MAINTENANCE APPROACH FOR THE MANUFACTURING INDUSTRY

The importance of the maintenance function is nowadays widely recognized in industrial organizations. Due to its influence on the production system and on other areas such as quality and safety, but especially as a consequence of its financial impact, companies are looking upon the maintenance function more cautiously. Industry experience shows that selecting an effective and efficient maintenance strategy can have a significant effect on the performance of production systems and on reducing overall expenses (Al-Najjar & Alsyouf, 2004) (Alsyouf, 2007) (Pintelon & Parodi-Herz, 2008) (Georgescu, 2010). Moreover, increasing profits in larger amounts by means of savings in unnecessary maintenance expenditures has been claimed as easier and more likely to happen than by increasing sales (Wireman, 2007).

Since failures can be reduced to a minimum level, improving the performance of the maintenance function will mainly reflect in increased availability and higher productivity. Differences between carefully maintained systems and systems that are badly or not maintained at all, are also reflected in the cost and quality of the final product. Therefore, it is essential not to neglect the performance of the maintenance actions and look for its continuous improvement.

Every day, maintenance managers and technicians face the challenge of ensuring maximum machine reliability and availability, at the same time as keeping the costs and amount of materials consumed by maintenance and repairs to a minimum. However, this is a demand that existing maintenance concepts are usually unable to satisfy. Based on CM systems and predictive to prescriptive maintenance principles, an Industry 4.0-based maintenance approach enables maintenance engineers to deal with such demand.

With this approach, firstly the root-causes of failures are identified. Secondly, data from sensors monitoring machine condition is automatically reviewed to pick up any patterns that indicate a possible fault. And thirdly, all retrieved data is processed and analysed by specialized software. This allows 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.

Founded on predictive capabilities, the employment of an Industry 4.0-based predictive maintenance approach aims at reducing unscheduled downtime and saving cost by increasing the machines' reliability. At a glance, usually two pillars are needed for a successful implementation of a PdM programme: 1) a condition monitoring system (CMS); and 2) a suitable computerized maintenance management system (CMMS). Additionally, a third component is proposed here, the utilization of a simplified Mechanism Based Failure Analysis (sMBFA). Figure 4 shows the three components for an Industry 4.0-based predictive maintenance approach for the manufacturing industry.

Simplified - Mechanism Based Failure Analysis

The first step in this approach is to follow a method based on the physics of failure as suggested by Tinga (2012). The procedure is called the Mechanism Based Failure Analysis (MBFA). The premise of the method is that by understanding and modelling the component failure mechanisms that lead to a system failure, the time to failure for a given usage profile can be calculated accurately. Then, that information can be utilized to assess the optimal maintenance interval. To carry out the sMBFA, the 5 steps shown in Figure 5 need to be followed.

Step 1: *Define the problem*. The first step in the analysis is the problem definition, starting with the specification of a failure. In this step, normally a functional failure is described. Then, that failure is used as the top event in the fault tree analysis that will be developed in the next step.

Step 2: *Determine the failure modes*. The next step in the failure analysis procedure is the execution of a Fault Tree Analysis (FTA) to identify all failure modes that could possibly lead to the failure defined in the first step. The resulting fault tree should indicate all possible underlying events (root causes) that may be responsible for the occurrence of the top-level event.

Step 3: *Determine priorities in the failure modes*. Since the number of failure modes is considerable, a selection of the most critical modes must be made. This selection is usually made based either

Figure 4. Industry 4.0-based Predictive Maintenance approach proposed for the manufacturing industry

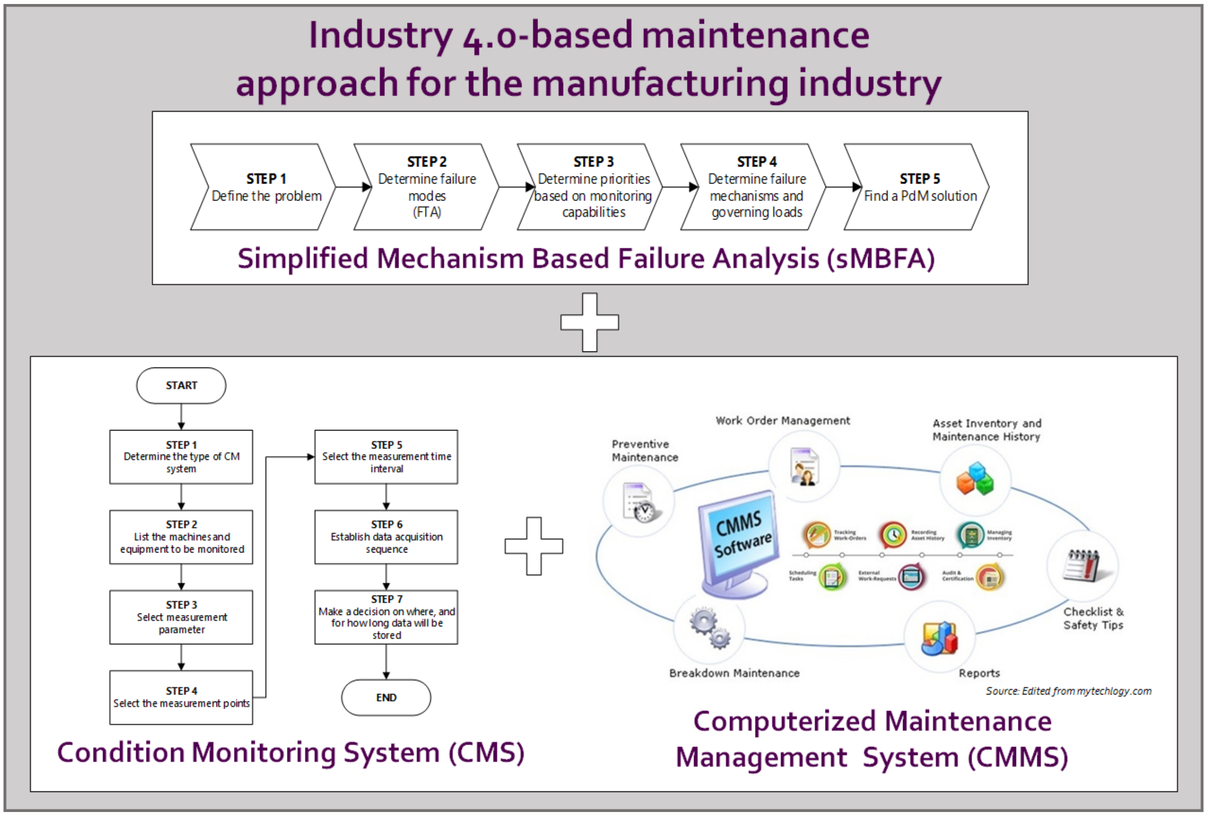
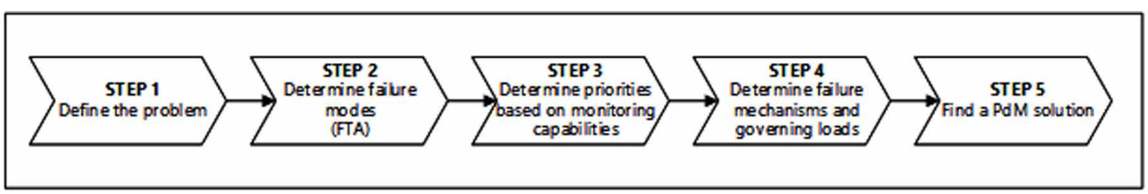


Figure 5. Basic steps of the sMBFA
Source: Based on Tinga, 2012



on costs or on failure frequency (which is related to availability and safety). However, in this case, the interest lays on establishing a PdM programme, therefore, the prioritization is based on the capabilities to monitor the failures.

Step 4: *Determine the failure mechanisms and governing loads.* The next step in the failure analysis is the assessment of the failure mechanisms causing the various failure modes. This final deepening step of a root cause analysis is essential, since it provides valuable insight in the possible solutions for the problem. In addition to the failure mechanisms, the governing loads that eventually because failures can also be determined. Reduction of this load will yield an increase of the system service life, whereas monitoring of this load enables the prediction of upcoming failures.

Step 5: *Find a PdM solution*. As explained before, the final goal of this analysis is towards the implementation of a PdM-FTA. In this context, the solutions should be limited to those that involve the monitoring and prediction of failures. All other solutions are out of the scope of this study.

By following a sMBFA, and since the failure mechanism and governing loads have been determined, it is generally rather easy to decide whether the loads or the capacity of the system constitute the root cause. For capacity problems, a modification of the system should be considered, while for loading problems the usage and associated loading of the system should be reduced.

Although, in this case, the main focus of the sMBFA technique should be on setting up a monitoring program for the usage, loads or condition that may aid to make the failures predictable and carry out a maintenance activity in response. Therefore, once the sMBFA has helped to find the components to be monitored, the CMS should be focused on those components. Then, the CMMS should be used to analyze the data collected by the CMS, and to deliver information that helps to predict failures and make decisions on when to do maintenance.

Condition Monitoring (CM) Programme

A Condition Monitoring (CM) programme is usually established to ensure that the satisfactory operation of a stand-alone machine occurs. And, despite the fact that a simple CM programme does not mean to achieve an Industry 4.0 maintenance setting, CM is the consecutive step to go through the transformation process, and only after successfully implementing a CM environment, the goals of an Industry 4.0-based maintenance approach can be pursued.

In the following steps, a logical progression is considered in the establishment of a typical CM programme. Therefore, depending on the type of machine being monitored, and the impact of any form of plant failure regarding these machines within the production environment, the steps described below might be used in establishing a workable CMS. Figure 6 shows an overview of the implementation process of the CMS.

Step 1: Determine the type of CMS necessary, namely periodic or permanent, and that best meets the needs of the plant or asset in question.

Step 2: List all the machines, equipment, or components to be monitored. This could be based on the importance of those machines within the overall production line.

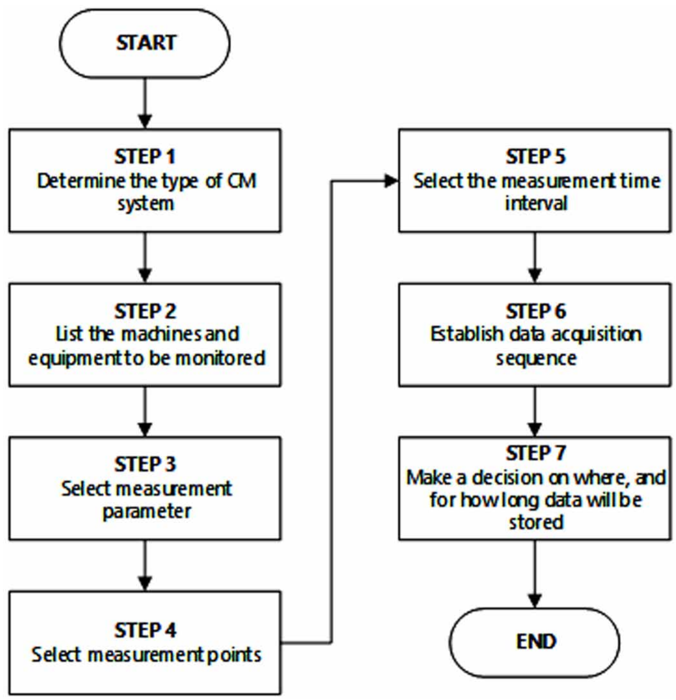
Step 3: Select the most appropriate measurement parameter. For example, temperature, vibration, humidity, pressure. This could be based, for example, on the costs, feasibility, existing monitoring devices, or the easiness for installation, processing, or analysis of the data or signals.

Step 4: Select the strategic measurement locations on the machine(s). Accordingly, when a periodic (i.e. offline) monitoring system is employed, the number of points at which measurements are made is limited only by the requirement of keeping measurement time to a minimum.

Step 5: Selecting the time interval between these measurements. The selection of the time interval between measurements requires knowledge of the specific machine. Some machines develop faults quite quickly, while others run trouble-free for years.

Step 6: Establish an optimum sequence of data acquisition. The sequence in which data is acquired must be planned so that data can be acquired efficiently. For example, the data collection may be planned

Figure 6. Basic steps for the establishment of a typical CM programme in the manufacturing industry



on the basis of plant layout for the type of data required, or on the sequence of components in the machine, such as from its driver-to-driven components.

Step 7: Make a decision on where to store the collected data, how much data will be collected, and for how long it will be stored. Depending on the machine and on the production needs, the data could be stored in a local server or in the cloud. It should be kept in mind that the CM programme is planned to be the base of an Industry 4.0-based maintenance strategy. Therefore, all collected data should have a purpose.

Finally, an important aspect to take into consideration, is the fact that the early detection of faults can only be carried out successfully by comparison with a reference spectrum. CM techniques employed during transient operating environments of the machine (i.e. when the machine is running up to full speed, or the opposite when slowing down from full speed) differs significantly from the techniques employed during steady-state operating conditions (Smith, 2016). For that reason, it is essential that a careful investigation is undertaken to ensure that specific condition monitoring techniques are selected, which will be appropriate for the conditions of measurement.

Computerized Maintenance Management System (CMMS)

A CMMS is computer software designed to simplify maintenance management (MicroMain Co., 2017). CMMSs are vital for the coordination of all activities related to the availability, productivity and maintainability of complex systems (Labib, 2008). A CMMS is intended to help facilities managers track assets, schedule repairs, monitor work orders, mange costs, and adhere to compliance standards (Service

Channel, 2017). Therefore, in parallel to a CM programme, a CMMS should be available in the organization in order to have a successful PdM programme (Hart, 2017).

A CMMS contains current and historical repair information for every piece of equipment maintained. This information is intended to help maintenance workers do their jobs more effectively (for example, determining which machines require maintenance and which storerooms contain the spare parts they need) and to help management make informed decisions (for example, calculating the cost of machine breakdown repair versus preventive maintenance for each machine, possibly leading to better allocation of resources) (Ayala, 2016).

Furthermore, CMMSs can be effective for any organization that is constantly working on reactive maintenance and unable to do preventive maintenance, frustrated with tracking and managing spare parts inventory, having difficulty with providing documentation for regulatory compliance, or wasting time on costly manual processes for tracking maintenance (eMaint, 2017).

The capacity of CMMSs to handle vast quantities of data purposefully and rapidly has opened new opportunities for maintenance, facilitating a more deliberate and considered approach to managing assets. Some of the benefits that can result from the application of a CMMS are (Labib, 2008):

- **Resource Control:** Tighter control of resources.
- **Cost Management:** Better cost management and audibility.
- **Scheduling:** Ability to schedule complex, fast-moving workloads.
- **Integration:** Integration with other business systems.
- **Reduction of Breakdowns:** Improved reliability of physical assets through the application of an effective maintenance programme.

Moreover, the latest generation of CMMSs are designed to work seamlessly in fully connected organizations, collecting all sorts of useful information and distributing it to every member of the team who needs it. Figure 7 shows an overview of the capabilities of common CMMSs. At the smallest scale, that

Figure 7. An example of the usual components of a CMMS software
Source: *Edited from mytechlogy.com*

means that maintenance techs and other workers can access schedules, records, and other info on the fly thanks to mobile device compatibility (Daniel, 2016).

Nowadays, many CMMSs are available in the market. Good CMMSs serve also as powerful management tools. By tracking and summarizing maintenance info automatically, they let decision makers take a real-time look at how your equipment is performing. CMMS can provide actionable information on improvements to be made in the maintenance procedures and warn about upcoming problems before they become critical. In addition, with the boost of Industry 4.0, CMMSs are focusing now on new areas as a direction for future development (Fiix®, 2017). For example:

- Mobile CMMS applications. Maintenance workers spend most of their time outside the office fixing machines and taking care of buildings. So making the CMMS available in the field on their mobile phone is essential. With a mobile app, technicians can record what they are doing as they are doing it, take pictures of the work, and request help onsite.
- Easy-to-use CMMS software. Many established CMMS companies make products that are very difficult to use. The interface hasn't changed since the late 1990's and many unnecessary, complicated features have been added to the product. Nowadays, more innovative CMMS companies are trying to simplify the maintenance process and to make the software easy to use.
- Fast CMMS data entry. The majority of CMMS projects that fail do so because it is too difficult and time consuming to enter data into the system. The next frontier in CMMS design centres around designing intuitive, efficient ways to enter data into the system.
- Cloud-based CMMS. New CMMS companies are mostly focused on providing a private CMMS for their clients, which runs online, through the cloud. The CMMS provider takes care of all the IT, security, and backups, making this a great option for modern maintenance teams.

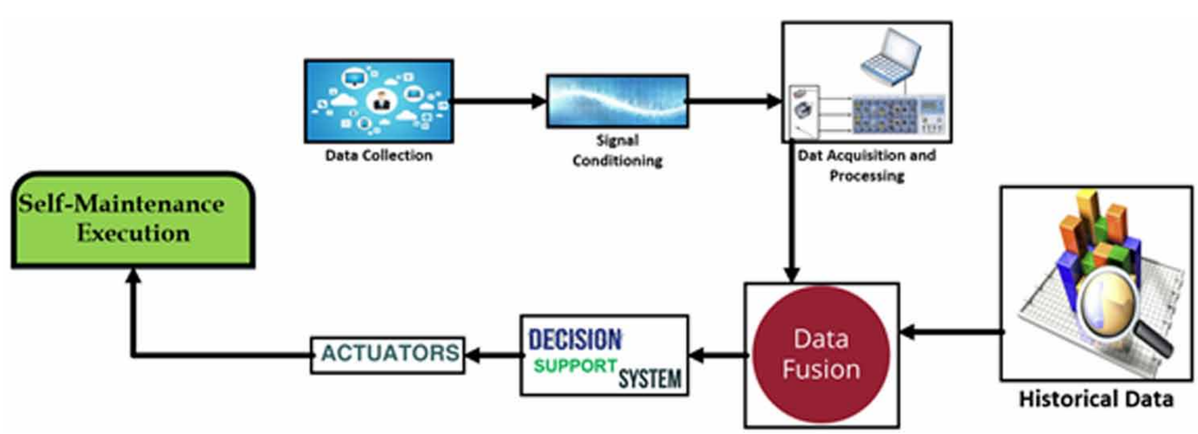
THE FUTURE STEP OF THE INDUSTRY 4.0: SELF- MAINTENANCE TECHNIQUES

As discussed, Industry 4.0 has brought a new technological shift by implementing cutting-edge information technologies, machine learning and monitoring devices in the controlling of manufacturing and production systems. It is also often viewed that Industry 4.0 demands progress in new maintenance concepts with the use of smart devices, such as micro and Nano sensors, controllers, actuators and algorithms like Neural Networks, Fuzzy Logic, Match Matrix, Bayesian Network etc. This is due to the evolution in the number of physical resources that are required to operate well beyond their expected life, and the prerequisite to design equipment with added prominence on reliability and maintainability. In I4.0, the manufacturing and production systems often encounter a collection of applications that increase time-to-repair, and increase management overheads. In order to address these maintenance issues, it is necessary to develop systems that support advanced intelligent maintenance systems or smart maintenance technologies. Self-maintenance machines can be a good option with the capabilities of condition monitoring, diagnosing, repair planning and executing in order to extend the life and performance of equipment. The objective of this section of chapter is to discuss the idea and issues of self-maintenance and scenarios where self-maintenance can be successfully implemented. The concept of self-maintenance systems was initiated in 1990s with the objective of designing a system that applies embedded intelligence together with built-in sensors and actuators. More precisely, self-maintenance is the capability of a system to provide self-monitoring and diagnostic tools to manage equipment usage and to address maintenance, renovation or repair. The objective of Self-maintenance system is to offer real time, fast and accurate maintenance systems with required capabilities to deal with faults and failures in an innovative way (Figure 8).

The need of self-maintenance machines is becoming a prerequisite in certain cases such as offshore wind turbines, aerospace sector, toxic industrial environment and the nuclear industry where it becomes nearly impossible to deal during emergency issues where during the event of a fault, there is very less possibility to access the site thereby strengthening the need for self-maintenance strategies. In time critical situations self-maintenance system can compensate the failure of subsystems by reconfiguring the parameters in an autonomous manner, increasing reliability and safety of the products with substantial saving of time and money (Sarbjeet et. al., 2014). There is great potential of self-maintenance to support the progress of high reliable systems as unsuitable maintenance planning, too much or too little can produce either high costs or abridged reliability (Endrenyi and Asgarpoor 2001). With the passage to time even the finest systems degrade due to use and wear therefore well-organized maintenance scheduling is critical for unremitting reliability of a production system (Jardine et al. 2006). The emerging fields of autonomic computing and artificial immune systems are using the concept of robustness, sustainability, resilience, and autonomy to achieve higher reliability (Lee et al. 2011). The self-maintenance techniques take into account most of the systems and components listed as essential for CBM and CMMS, such as different smart sensors for efficient gathering and processing of information to analysis and decision making, wireless sensor networks, adaptive system, end-user systems and processes;

- **Self-Maintenance and Data Acquisition Systems:** Data acquisition systems in self-maintenance machines are used. It serves as an essential component for binding together a wide variety of products, such as sensors to provide the alarms when critical parameters are exceeded. It is the process of sampling signals from machines sensors and converting them into digital numeric values that can be operated by a computer. However, in order for this approach to be effective it is necessary to identify 'what needs to be monitored and why'. In fact, only the critical components triggering downtime should be monitored, thereby reducing the amount of irrelevant data collected and anal-

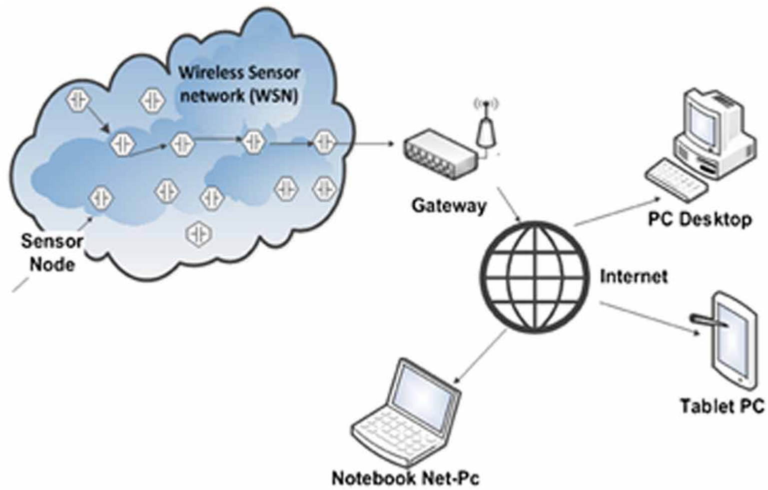
Figure 8. Architecture of Self-maintenance system
Source: *Modified from Sarbjeet et al., 2014*



ysis. Thus, a significant constituent of a self-maintaining system is the planning and ranking tools used by maintenance staff and planning processes to mitigate the costs of the implementation.

- **Smart Sensors:** The technology of Smart sensors in Industry 4.0 monitors the truthfulness of the system and predict network failures. Smart sensors in self-maintenance machines uses microprocessor to collects real-time data for analyzing variety of tasks including self-diagnostics and decision making. Sensors execute an input function and actuators an output function that is used to govern external device. The development of advanced network components allows the network to heal itself based on the measurements of sensors. Smart sensors intermittently monitor the condition of the machine by analyzing the data obtained from the sensing element. The data from sensors of these system can identify the cause of failure and trends can be predicted. Self-maintenance systems can make systems more reliable, reconfigurable and adaptable, particular for systems with critical component failure rate by fusing adaptive systems with modular designs.
- **Wireless Sensor Network (WSN):** Wireless sensor network (WSN) is network of nodes to sense and control the environment facilitating interaction between persons or computers and the surrounding environment (Verdone et al. 2008). Wireless Sensor Network (Figure 9) monitor conditions, such as temperature, sound, vibration, and pressure etc. and pass data to a main location. The sensor nodes are capable of performing processing, gathering information and communicating with other connected nodes in the network. It is used in many industrial applications for machine health monitoring and generated an increasing interest from industrial and research perspectives (Hac 2009; Raghavendra et al. 2004).
- **Adaptability to Frequent Changes in Operating Regime:** The self-maintenance systems should be knowledge-based and adaptive to frequent changes in operating characteristics of the machine and process with negligible additional cost of sensors or intrusive access. The adaptive agent of self-maintenance system can compensate the failure of subsystems by reconfiguring the parameters in an autonomous manner and minimize expensive human intervention. In future, the self-maintenance techniques should be aware of the varying operating regimes in order to strongly select prognostics models to assure prediction accuracy (Lee et al. 2011). Intelligent adaptive control approach for self-maintenance have already been applied for investigating control using fuzzy logic control of material processing in sheet metal forming (Hinduja et al. 2000) and electro-chemical machining (ECM) (Keasbury et al. 2004). The expensive heavy equipment, such as offshore wind turbines, aerospace components, aircraft propellers etc. are expensive to shut down or repair.
- **End-User Systems and Processes**: It seems that self-maintenance pivots around the point that maintenance operators are kept out of the loop but in actual the effectiveness and security of the self-maintaining system is highly dependent on an effective interaction with maintenance staff and collaborative structures. It can be a dicey statement that a self-maintenance system is a plug-in and forget system because it needs efforts while planning, implementing and evaluation. The implementation of self-maintenance systems needs the support of architecture of CMMS and CM systems—especially allowing the maintenance staff to interact with the self-maintenance systems. This will demand CMMS and CM systems to allow for effective integration of new tools, information types, media and processes (Bjorling and Uday 2009).

Figure 9. Wireless sensor network (WSN)
Source: *Sarbjeet et al., 2014*



CONCLUSION AND FUTURE RESEARCH

Industry 4.0 accepts the challenge of addressing new concepts of maintenance with numerous efforts on its implementation in various systems. Intelligent Maintenance Systems have brought new paradigm shift to an in-machine renovation and repair. The concept of CBM may have a significant effect on labor cost and maintenance downtime with some condition monitoring modules fabricated into existing systems. As per our perception, techniques can propose real-time, fast and accurate maintenance system with required capabilities to deal with faults and failures in an innovative way even without human intervention (in case of self-maintenance) in order to increase the overall dependability. The discussed solutions can minimize unnecessary and costly preventive maintenance, optimize maintenance scheduling, reduce lead-time for spare parts and resources all of which can result in significant cost savings. It has been concluded that the aim is to have fully automatized system in order to make a machine capable of reconfiguration, compensation, and, in the last stage, self-maintenance.

Future research of Maintenance 4.0 needs to focus on system integration between machines, infrastructures and personnel. A cooperative environment, where operators can benefit from data gathered with sensors and from information elaborated with Artificial Intelligence, will lead to more efficient solutions. Until now, we monitor the machines and we take decisions; next step will encompass the ability of the machines to learn from situations in order to increase the overall antifragility of the system (Martinetti et al., 2018).

REFERENCES

ACATECH. (2015). *Smart Maintenance for Smart Factories: Driving Industrie 4.0 through smart maintenance*. Munich: Acatech.

Al-Najjar, B., & Alsyouf, I. (2004). Enhancing a company's profitability and competitiveness using integrated vibration-based maintenance: A case study. *European Journal of Operational Research*, *157*(3), 643–657. doi:10.1016/S0377-2217(03)00258-3

Alsyouf, I. (2007). The role of maintenance in improving companies' productivity and profitability. *International Journal of Production Economics*, *105*(1), 70–78. doi:10.1016/j.ijpe.2004.06.057

Ayala, L. (2016). Cybersecurity Lexicon. New York: Apress. doi:10.1007/978-1-4842-2068-9

BDI. (2016, October 10). *What is Industry 4.0?* Retrieved from BDI The Voice of German Industry: https://english.bdi.eu/article/news/what-is-industry-40/#container

Bellias, M. (2017, March). *The evolution of maintenance*. Retrieved from IBM - Internet of Things blog - The evolution of maintenance: https://www.ibm.com/blogs/internet-of-things/maintenance-evolution-prescriptive/

Bjorling, S. E., & Uday, K. (2009). *ICT concepts for managing future challenges in E-maintenance*. San Sebastian: COMADEM.

Bruurmijn, M. (2016). Industry 4.0 Transforms Business Models. *D!gitalist Magazine*. Retrieved from http://www.digitalistmag.com/iot/2016/10/25/industry-4-0-transforms-business-models-04585110

Campos, J., & Prakash, O. (2006). Information and communication technologies in condition monitoring and maintenance. In A. M. Dolgui (Ed.), *Information Control Problems in Manufacturing* (pp. 3–8). Elsevier.

Chan, R. (2017). *5 Advantages of Cloud-based Maintenance Management Applications*. Retrieved from UpKeep Maintenance Management: https://onupkeep.com/blog/5-advantages-cloud-based-maintenance-management/

Coleman, C., Damodaran, S., Chandramouli, M., & Deuel, E. (2017). *Making maintenance smarter: Predictive maintenance and the digital supply network*. Deloitte University Press.

Daniel. (2016). *MyTechlogy: Why So Many Businesses Are Investing in CMMS Software*. Retrieved December 2017, from https://www.mytechlogy.com/IT-blogs/13556/why-so-many-businesses-are-investing-in-cmms-software/#.Wl58TKinGM-

Deloitte, A. G. (2015). *Industry 4.0 - Challenges and solutions for the digital transformation and use of exponential technologies*. Zurich: Author.

eMaint. (2017, July). *Moving Towards Smart Maintenance with Prescriptive Analytics*. Retrieved from eMaint, a Fluke company: https://www.emaint.com/moving-towards-smart-maintenance-prescriptive-analytics/

Endrenyi, J., & Asgarpoor, S. (2001). IEEE/PES Task force on impact of maintenance strategy on reliability. *IEEE Transactions on Power Systems*, *16*(4), 638–646. doi:10.1109/59.962408

Farrar, C., & Lieven, N. (2007). Damage prognosis: The future of structural health monitoring. *Phil. Trans. R. Soc. A*, *365*(1851), 623–632. doi:10.1098/rsta.2006.1927 PMID:17255054

Fiix®. (2017). *Condition based maintenance and monitoring software*. Retrieved August 2017, from fiixsoftware: https://www.fiixsoftware.com/condition-based-maintenance/

Fraunhofer, I. P. A. (2016). *Maintenance at Fraunhofer IPA: Maximized availability at minimized costs*. Fraunhofer Institute for Manufacturing Engineering and Automation IPA.

Fumagalli, L., Macchi, M., Colace, C., Rondi, M., & Alfieri, A. (2016). A Smart Maintenance tool for a safe Electric Arc Furnace. *IFAC-PapersOnLine, 49-31*, 19-24.

Geissbauer, R., Vedso, J., & Schrauf, S. (2016). *Global Industry 4.0 Survey: Building the digital enterprise.* PwC.

Georgescu, D. D. (2010). The maintenance management for lean organization. *Economia. Seria Management*, *13*, 437–446.

Gottorp Jeppesen, B. (2015, January 14). *Realizing the Fourth Industrial Revolution*. Retrieved 2017, from https://mjolner.dk/tech/realizing-fourth-industrial-revolution/

Hac, A. (2009). *Wireless sensor network designs*. Etobicoke: Wiley.

Hart, D. (2017). *Implementing a "Best Practices" Predictive Maintenance Program: Avoiding the 10 Most Common Pitfalls.* Emerson Automation Solutions - White paper, Emerson Reliability Consulting, Watertown.

Hinduja, S., Atkinson, J., Lau, D. K., Labib, A. W., & Agirrezabal, P. (2000). An intelligent controller for improving the quality of deep drawn components. *Annals of the CIRP*, *49*(1), 109–112. doi:10.1016/S0007-8506(07)62933-3

i-scoop. (2017). Retrieved from Predictive maintenance and asset management with IIoT: https://www.i-scoop.eu/industry-4-0/predictive-maintenance-asset-monitoring/

IAEA. (2007). *Implementation Strategies and Tools for Condition Based Maintenance at Nuclear Power Plants*. IAEA.

ISO. (1993). *ISO/TC 108/SC 5: Condition monitoring and diagnostics of machine systems*. International Organization for Standardization.

Jardine, A., Lin, D., & Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mechanical Systems and Signal Processing*, *20*(7), 1483–1510. doi:10.1016/j.ymssp.2005.09.012

Kagermann, H., Wahlster, W., & Helbig, J. (2013). *Securing the future of German manufacturing industry: Recommendations for implementing the strategic initiative INDUSTRIE 4.0.* Frankfurt: Final report of the Industrie 4.0 Working Group.

Kalt, F., & Rosenberger, P. (2015, October). *Stairway to heaven*. Retrieved from Siemens AG - The Magazine - Stairway to heaven: https://www.siemens.com/customer-magazine/en/home/mobility/stairway-to-heaven.html

Kans, M., Galar, D., & Thaduri, A. (2015). Maintenance 4.0 in Railway Transportation Industry. In K. Koskinen, H. Kortelainen, J. Aaltonen, T. Uusitalo, K. Komonen, J. Mathew, & J. Laitinen (Eds.), *Proceedings of the 10th World Congress on Engineering Asset Management (WCEAM 2015) - Lecture Notes in Mechanical Engineering* (pp. 317-331). Springer.

Keasbury, V., Labib, A. W., Atkinson, J., & Frost, H. (2004). Intelligent control of electrochemical machining (ECM). *Proceedings of 34th international MATADOR conference*, 475–480.

Kennedy, S. (2017, May). *RxM: What is prescriptive maintenance, and how soon will you need it?* Retrieved from RxM: What is prescriptive maintenance, and how soon will you need it?: https://www.plantservices.com/articles/2017/rxm-what-is-prescriptive-maintenance-and-how-soon-will-you-need-it/?show=all

Khan, A., & Turowski, K. (2016). A Survey of Current Challenges in Manufacturing Industry and Preparation for Industry 4.0. *Proceedings of the First International Scientific Conference "Intelligent Information Technologies for Industry"*.

Khoshafian, S., & Rostetter, C. (2015). *Digital Prescriptive Maintenance: Disrupting Manufacturing Value Streams through Internet of Things, Big Data, and Dynamic Case Management*. Pegasystems, Inc.

Kovacevic, J. (2017). *What is Prescriptive Maintenance?* Retrieved from High Performance Reliability, Inc.: https://hpreliability.com/what-is-prescriptive-maintenance/

Kranz, M. (2017). *Building the Internet of Things: Implement New Business Models, Disrupt competitors, and transform your industry*. John Wiley & Sons.

Labib, A. (2008). Computerised Maintenance Management Systems. In K. Kobbacy & D. Murthy (Eds.), *Complex System Maintenance Handbook* (pp. 416–435). Springer-Verlag London Limited. doi:10.1007/978-1-84800-011-7_17

Lachance, P. (2016). Cloud-based Maintenance Systems May be the next Game Changer. *Lodging Engineer Magazine,* (23), 30-31.

Lee, J., Ghaffari, M., & Elmeligy, S. (2011). Self-maintenance and engineering immune systems: Towards smarter machines and manufacturing systems. *Annual Reviews in Control*, *35*(1), 111–122. doi:10.1016/j.arcontrol.2011.03.007

Lee, J., Wu, F., Zhao, W., Ghaffari, M., Liao, L. S., & Siegel, D. (2014, January). Prognostics and health management design for rotary machinery systems - Reviews, methodology and applications. *Mechanical Systems and Signal Processing*, *42*(1-2), 314–334. doi:10.1016/j.ymssp.2013.06.004

MacDougall, W. (2014). *INDUSTRIE 4.0 Smart Manufacturing for the Future*. Berlin: Germany Trade and Invest.

Martinetti, A., Chatzimichailidou, M., Maida, L., & van Dongen, L. A. M. (2018). Safety I-II, Resilience and Antifragility Engineering: A debate explained through an accident occurred on a Mobile Elevating Work Platform. *International Journal of Occupational Safety and Ergonomics*, 1–27. doi:10.1080/10803548.2018.1444724 PMID:29473459

Matyas, K., Nemeth, T., Kovacs, K., & Glawar, R. (2017, April). A procedural approach for realizing prescriptive maintenance planning in manufacturing industries. *CIRP Annals - Manufacturing Technology, 66*, 461–464.

MicroMain Co. (2017, November). Retrieved from What is a CMMS?: https://www.micromain.com/what-is-a-cmms/

Miklovic, D. (n.d.). *What Comes After Predictive Maintenance?* Retrieved from http://blog.lnsresearch.com/what-comes-after-predictive-maintenance

Mobley, R. K. (2002). *An Introduction to Predictive Maintenance*. Elsevier Inc.

Mori, M., Fujishima, M., Komatsua, M., Zhao, B., & Liu, Y. (2008, May). Development of remote monitoring and maintenance system for machine tools. *CIRP Annals*, *57*(1), 433–436. doi:10.1016/j.cirp.2008.03.108

Mourtzis, D., Vlachou, E., Milas, N., & Xanthopoulos, N. (2016). A cloud-based approach for maintenance of machine tools and equipment based on shop-floor monitoring. *48th CIRP Conference on MANUFACTURING SYSTEMS - CIRP CMS 2015, 41*, 655 – 660.

Nain, A., & Varde, P. (2013). Fuzzy Rule-Based Approach for Diagnostics in Nuclear Plant Diesel Generators. In S. Chakraborty, & G. Bhattacharya (Eds.), *Proceedings of the International Symposium on Engineering under Uncertainty: Safety Assessment and Management (ISEUSAM - 2012).* Springer.

Pintelon, L., & Parodi-Herz, A. (2008). Maintenance: An Evolutionary Perspective. In K. A. H. Kobbacy & M. D. N. Prabhakar (Eds.), *Complex System Maintenance Handbook*. London: Springer-Verlag London. doi:10.1007/978-1-84800-011-7_2

PwC. (2016). *Industry 4.0: Building the digital enterprise - 2016 Global Industry 4.0 Survey.* PwC.

Raghavendra, C., Sivalingam, K., & Znati, T. (2004). *Wireless sensor networks*. New York: Springer. doi:10.1007/b117506

Roubaud, J. (2017, October 6). *How Predictive Maintenance Fits into Industry 4.0*. Retrieved from Engineering.com: https://www.engineering.com/AdvancedManufacturing/ArticleID/15798/How-Predictive-Maintenance-Fits-into-Industry-40.aspx

Sarbjeet, S., Diego, G., David, B., & Sten-Erik, B. (2014). Self-maintenance techniques: A smart approach towards self-maintenance system. *International Journal of System Assurance Engineering Management*, *5*(1), 75–83. doi:10.100713198-013-0200-7

Service Channel. (2017). Retrieved from What is CMMS?: https://servicechannel.info/what-is-cmms/

Smith, G. T. (2016). *Machine Tool Metrology: An Industrial Handbook*. Springer International Publishing. doi:10.1007/978-3-319-25109-7

Sniderman, B., Mahto, M., & Cotteleer, M. (2016). *Industry 4.0 and manufacturing ecosystems: Exploring the world of connected enterprises*. Deloitte University Press.

Starr, A., Al-Najjar, B., Holmberg, K., Jantunen, E., Bellew, J., & Albarbar, A. (2010). Maintenance Today and Future Trends. In K. Holmberg, A. Adgar, A. Arnaiz, E. Jantunen, J. Mascolo, & S. Mekid (Eds.), *E-Maintenance* (pp. 5–37). Springer. doi:10.1007/978-1-84996-205-6_2

Takata, S., Kirnura, F., Houten, F., Westkamper, E., Shpitalni, M., Ceglarek, D., & Lee, J. (2004). Maintenance: Changing Role in Life Cycle Management. *CIRP Annals*, *53*(2), 643–655. doi:10.1016/S0007-8506(07)60033-X

Tiddens, W., Braaksma, A., & Tinga, T. (2015). The adoption of prognostic technologies in maintenance decision making: a multiple case study. *The Fourth International Conference on Through-life Engineering Services, Procedia CIRP 38*, 171 – 176.

Tiddens, W. W., Braaksma, A. J., & Tinga, T. (2016). Towards Informed Maintenance Decision Making: Identifying and Mapping Successful Diagnostic and Prognostic Routes. In R. W. R. W. Grubbström & H. H. Hinterhuber (Eds.), *19th International Working Seminar on Production Economics* (pp. 439-450). Innsbruck, Austria: Academic Press.

Tinga, T. (2012). *Mechanism Based Failure Analysis: Improving maintenance by understanding the failure mechanisms*. Enschede: World Class Mainteannce.

Verdone, R., Dardari, D., Mazzini, G., & Conti, A. (2008). Wireless sensor and actuator networks. er. *International Journal of System Assurance Engineering Management*, *5*(1), 75–83.

Watts, L. (2016). *The Key to Implementing a Successful Predictive Maintenance Strategy*. London: Presidion.

Wireman, T. (2007). *How to calculate return on investment for maintenance improvement projects.* Retrieved November 2017, from Reliability.com: A culture of reliability: https://vestapartners.com/how-to-calculate-the-roi-on-your-next-maintenance-project/

KEY TERMS AND DEFINITIONS

Computerized Maintenance Management Systems (CMMS): A computerized database that stores and manages all the information necessary for maintenance operations.

Condition Monitoring (CM): The set of processes and activities meant to track parameters of a machine or an infrastructure.

Condition-Based Maintenance (CBM): Maintenance policy focused on the condition of the system based on conditions and remote monitoring.

Cyber-Physical Systems (CPS): Environment where physical and digital components are tightly interconnected.

Industrial Internet of Things and Services (IIoTS): The use of internet of things technologies (machine learning, big data, etc.) to enhance manufacturing and industrial processes.

Internet of Things (IoT): The infrastructure that connects physical devices.

Predictive Maintenance (PdM): Maintenance policy focused on the predicted condition of the system based on impending failures as results of data, patterns, and trends analysis.

Prescriptive Maintenance (RxM): Maintenance policy focused on PdM actions, empowered with provision of specific recommendations towards a solution-finding process.

Software-as-a-Service (SaaS): Business model based on offering software licensed on subscription and, generally, centrally hosted.