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PREDICTIVE MAINTENANCE THROUGH DATA-DRIVEN APPROACHES

MANTENIMIENTO PREDICTIVO MEDIANTE EL ENFOQUE BASADO EN DATOS

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ABSTRACT: Nowadays, the Industrial Internet promises to transform our world. The melding of the global industrial system that was made possible because of the Industrial Revolution, with the open computing and communication systems developed as part of the Internet Revolution, opens new frontiers to accelerate productivity, reduce inefficiency and waste, and enhance the human work experience. With the emergence of Industry 4.0, smart systems, machine learning within artificial intelligence, predictive maintenance (PdM) approaches have been extensively applied in industries for handling the health status of industrial equipment. This paper focus on the PdM field, describing and specifying, its techniques, applications in the real world, methods and approaches widely used as such its challenges.

KEYWORDS: predictive maintenance; anomaly detection; data-driven.

Resumen: Hoy en día, el Internet Industrial promete transformar nuestro mundo. La fusión del sistema industrial global que se realizó fruto de la Revolución Industrial, con los sistemas de comunicación e informáticos abiertos de comunicación desarrollados como parte de la revolución de Internet, abre nuevas fronteras para acelerar la productividad, reducir la ineficacia y el despilfarro, y mejorar la experiencia de trabajo del ser humano. Con la aparición de la Industria 4.0, los sistemas inteligentes y el aprendizaje automático dentro de la inteligencia artificial, los enfoques de mantenimiento predictivo se han aplicado ampliamente en las industrias para manejar el estado de salud de los equipos industriales. Este artículo se centra en el campo del mantenimiento predictivo, describiendo y especificando sus técnicas, aplicaciones en el mundo real, los métodos y enfoques ampliamente utilizados, así como sus desafíos.

Palabras clave: mantenimiento predictivo; detección de anomalías; data-driven

1 Introduction

Since the outset of the Industrial Revolution, maintenance of engineering equipment in the field has been a challenge. While impressive progress has been made in maintaining equipment in the field in an effective manner, maintenance of equipment is still a challenge due to factors such as size, cost, complexity, and competition [7]. The notions of prediction or prevention didn't exist, as we know in the present, so maintenance suffered from quite a bad image back then [7]. The industrial world, as well as the implications, were very different from the ones we know today. At that time, the industry was prospering, so the consequences on production lines weren't the same (e.g. equipment were not integrated to a more general system) [8, 6]. Several industrial managers overlooked the positive influence of proper maintenance management on their company's activity. Yet, it is a major performance factor and a cause for prompt gains within the company: in terms of productivity as well technology, suitable industrial maintenance management has positive consequences on organizations and their products [8]. In recent years, manufacturing industry has been facing a major shift of the manufacturing requirements (e.g. consumer demand for customized products continues to grow), resulting in a much shorter product life cycle, unlike the traditional mass production of standardized products [17]. These changes are impacting companies, rising the need for adaptation, driving all sectors of the manufacturing activity to move correspondingly. Maintenance activities can impact the entire manufacturing/production cost and quality, and consequently, customer satisfaction [17]. This shift in the maintenance paradigm has led to the research and development of new ways to execute maintenance by considering the operational state of assets and enabled the development of new maintenance approaches, such as, predictive maintenance, a proactive maintenance strategy that tries to predict when a piece of equipment might fail so that maintenance work can be performed just before that happens. Monitoring for future failure allows maintenance to be planned before the failure occurs.

The rest of the paper is organized as follows: Section 2 overviews the maintenance strategies, Sections 3 describes the predictive maintenance techniques and applications. Finally, Section 5 rounds up the paper with a discussion on the topic addressing the open challenges in this field.

2 Maintenance Strategies

Maintenance implementation requires organization, planning and control practices, in order so that it is possible to have a disciplined structure that supports a change of mentality and behavior in maintenance. The maintenance function involves all activities related to the maintenance of good working conditions of equipment, systems and installations, and the performance of corrective interventions whenever failures or breakdowns arise. According to the literature there are three main types of maintenance [12, 2], Reactive, Preventive and Predictive. To these three main types, two more can be added [11], these being, Condition-based and Pro-active maintenance. Figure 1 illustrates the taxonomy of the maintenance strategies.

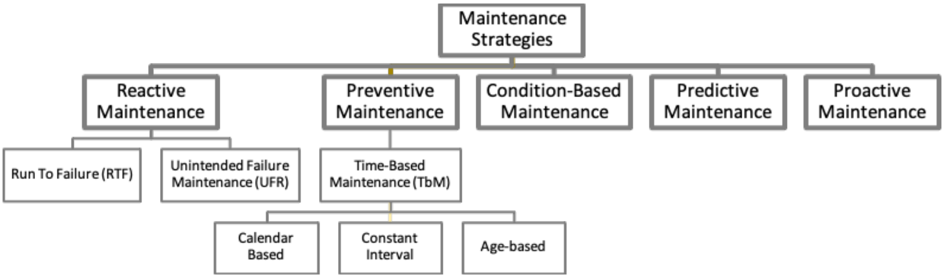

Fig. 1. Maintenance strategies Taxonomy.

- **Reactive Maintenance** (or Unplanned Maintenance): When equipment fails, it must be repaired, or replaced. Reactive Maintenance is the technical activity performed after the occurrence of a malfunction and aims to restore the asset to a condition where it can function as intended, either by repair or replacement. This type of maintenance often leads to worse and more regular breakdowns, as well as costly downtimes [22, 12].
- **Preventive Maintenance** (or Planned Maintenance): Instead of waiting for the malfunction to occur, this type of maintenance is aimed at preventing it from happening. It takes place in a cyclical and scheduled manner, regardless of the condition of the asset and with the aim of preventing damage and minimizing the consequences of equipment breakdowns. Examples of preventive maintenance actions include inspections, periodic overhauls, cleaning and lubricating parts [4, 12].
- **Predictive Maintenance** (PdM): This is the most recent and the one that requires the most technological investment. Concerns monitoring equipment conditions to predict when it is destined to fail. When certain undesirable conditions are detected a repair is scheduled before the equipment actually malfunctions, thus eliminating the need for costly corrective maintenance or unnecessary preventive maintenance. It is based on the physical and operational condition of the equipment, through regular monitoring and testing of the condition and performance of the equipment [12, 4].

To these three main types, two more can be added [11]:

- **Condition-based Maintenance** (CbM): Carried out by assessing the condition of the machine, normally carried out continuously. The component replacement process is based on predictive analysis. Concerns to monitoring the condition of the equipment to assess which maintenance needs to be performed. It occurs only when the data indicates a drop in performance or the first signs of failure. This differentiates it from preventive maintenance, where tasks are performed at regular intervals [20].
- **Pro-active Maintenance** (PbM): is any form of maintenance that is done before any significant breakdowns or failures occur. As opposed to reactive maintenance, it focuses on anticipating and managing machine failures before they take place. Is focused on by undertaking activities that avoid the underlying conditions that lead to machine faults and degradation. Requires to identify the root causes of a failure that can be removed, to determine potential failure locations and to avoid breakdowns caused by deteriorating equipment conditions [9].

3 PdM Techniques and Applications

3.1 PdM Techniques

PdM is a group of emerging scientific technologies that can be used to detect potential failures that may not be evident through a preventive maintenance program. If the equipment's failure characteristics are known, the PdM can detect the failure well in advance and the appropriate actions can be taken in a planned manner. The difficulty is in detecting faults, which are not always noticeable to the user in an initial state. That is why it is so important to find the indicated non-destructive tests to diagnose infrastructure failures [16]. Non-destructive tests are techniques that do not compromise or damage the analyzed equipment:

- **Thermographic and infrared analysis:** Infrared thermography uses special instruments to detect, identify, and measure the heat energy objects radiate in proportion to their temperature and emissivity. Is used to study everything from individual components of machinery to plant systems, roofs, and even entire buildings [10].

- **Oil analysis:** The purpose of oil analysis is to measure the number and size of particles in a given (oil) sample to determine wear and tear on the equipment. The full benefit of oil analysis can only be achieved by taking frequent samples and evaluating data from each machine in the program. Based on the results of the analysis, lubricants can be changed or updated to meet specific operational requirements [23].
- **Wear particle analysis:** While the oil analysis provides information about the lubricant itself, the wear particle analysis provides direct information about the wear conditions within the machinery. The wear particle morphologies of machine lubricants contain valuable information about the wear processes in operation and can reveal the condition of a machine [18].
- **Vibration analysis:** This type of analysis is ideal for equipment and rotating machines, such as compressors, water pumps and engines. Vibration monitoring of plant machinery can provide a direct correlation between mechanical condition and recorded vibration data for each machine in the plant. Used correctly, it can identify specific components of the degrading machine or the failure mode of plant machinery before serious damage occurs [21].
- **Ultrasonic testing:** The instruments intended for ultrasonic tests detect the ultrasonic waves produced by the operation of the machines, as well as the turbulent flow of leakage. It is designed to detect early leaks in compressed air transport systems. They provide quick and accurate diagnosis of problems such as valves in blowby mode, defective steam traps, vacuum and pressure leaks [19].

3.2 PdM Applications

Predictive maintenance can be applicable to all sectors where machines produce significant amounts of data and require maintenance or fine-tuning of their parameters. PdM applications is already gaining traction in some industries such as:

- **Airlines:** The aviation industry is grasping for opportunities to reduce costs. Airlines are no stranger to monitoring sensor data from planes.

Today's analytical capabilities allow them to analyze more data, increasing passenger safety.

- **Transportation:** Although airlines lead the group in terms of the complexity of their equipment, other means of transportation, such as trains, also involve complex machinery that can benefit from predictive maintenance.
- **Ports:** Exposed to adverse conditions, the conditions of port equipment deteriorate rapidly. For instance, cranes are critical components, but are subject to failure. Crane downtime means more waiting time for ships and less processing for ports. Reducing downtime improves service quality and reduces waste at ports [1].
- **Automotive:** Automotive companies operate some of the largest robot parks in the world. In order to reduce inventory costs, automotive companies have developed the Just-In-Time manufacturing methodology since the 1960s and 1970s. As a result, they have fully integrated supply chains. While tight supply chain integration allows for reduced inventory, any reduction in manufacturing efficiency results in a significant supply chain disruption. It is no surprise that automotive companies gain significantly from technology that reduces downtime.
- **High-tech manufacturing:** Operating complex equipment at optimal parameters is the main challenge for improving the efficiency of high-tech manufacturers, such as semiconductor manufacturers. Predictive maintenance systems allow them to operate at a level closer to the ideal parameters.
- **Oil and gas:** Despite the increase in green energy, oil and gas is still one of the largest industries. Both extraction and refining involve expensive equipment that can cause risks to health and the environment in the event of failure. For example, the Deepwater Horizon oil spill in 2010, which resulted in 11 deaths and 5 million barrels of spilled oil, was one of the worst disasters in the past decade [15]. The stakes are high to prevent such disasters with better analysis and maintenance.

4 PdM Data-Driven paradigm

In predictive maintenance scenarios, data should be collected over time to monitor the state of equipment. The goal is to find patterns that can help predict and ultimately prevent failures. There are two main paradigms to deal with this problem, Model-driven and Data-driven. Model-Driven fault prediction (or detection) implies the creation of a model of how the physical system works and how it can break. It is grounded in theory-based hypothesis formation and experiment-based testing.

Data-Driven fault prediction is a new way of thinking enabled by machine learning algorithms that can discover hidden patterns in OT data (sensors, PLCs, SCADA) and IT data (ERP, quality, MES, etc). Because of the continuous improvement of data acquisition ability [5], as well as the exponential growth of data volume [13], data-driven methods have achieved great success and received widespread attention regarding the PdM of industrial equipment. Data-driven PdM system consists of two phases [26]:

- The learning process consisting of the training phase of the model through historical data from the sensor signals;
- The prediction process consists of applying the trained model to predict targets and make decisions.

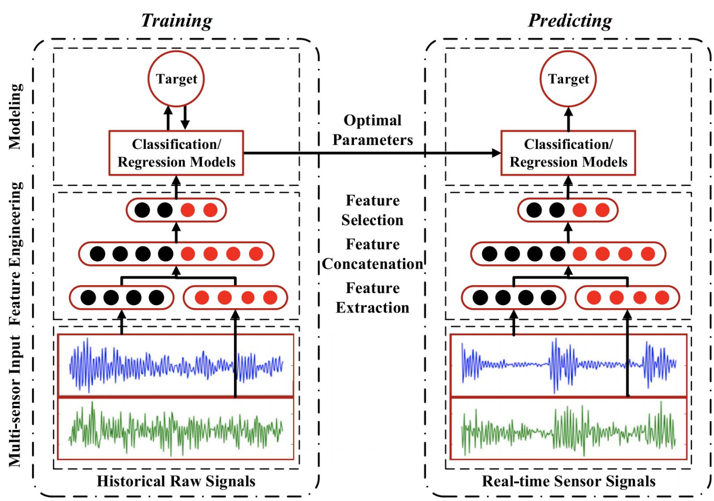

Fig. 2. Data-driven method for PdM from Zhang et al. [26].

In addition, each phase consists of the following three subprocesses:

1. Data acquisition and preprocessing;
2. feature engineering through processes such as feature extraction, concatenation, and selection;
3. model training and predicting, in which a well-trained model will be generated with the optimal parameters.

Most notably, data-driven methods make data acquisition an indispensable part of the PdM process [3], providing valuable information for specific tasks. However, for engineering applications, a customized data acquisition system needs to be established to meet specific requirements. It has been proven that Data analysis at different stages of the machine's life cycle can not only process data or information more effectively, but also achieve transparency of the health status of industrial equipment. Moreover, addressing the obtained data effectively (i.e., whether to use feature engineering or not) is a major challenge for algorithm selection.

The Model building is also a major part of data-driven process, and the selection, training and optimization of the model deserve more attention. In practice, supervised learning has achieved remarkable results in many fields, but it requires data to be recorded correctly, which is also a major challenge for the PdM. With the quantitative trend of industrial big data, and since the process of labeling data is hard and time consuming, unsupervised learning has naturally become a promising research direction.

Machine Learning has been widely used in computer science and other fields, such as the PdM of industrial equipment, which is one of the potential application fields for data-driven methods such as, Logistic Regression, Decision trees, Support Vector Machines and Neural Networks [14, 24]. As a result, although increasingly high-performance algorithms are continually developed, generally, employing simple and efficient methods is considered first. These methods have become a surefire solution for managing the health status of equipment with Remaining useful life (RUL) prediction given insights about when a machine will fail so maintenance can be scheduled in advance; flagging irregular behaviour through Anomaly detection time series analysis; failure diagnosis and recommendation of mitigation or maintenance actions after failure.

5 Discussion – Open Challenges

Predictive Maintenance enables more efficient, longer-term planning for maintenance operations and makes it easier to define operational maintenance goals and to allocate maintenance resources. Examining data from hundreds or thousands of sensors, gathered over months or even years, is well beyond the capabilities of human operators. Furthermore, the mathematical models, which describe an equipment's evolution (and predict potential faults) based on such a wealth of data, are generally prohibitively complex to be used by humans. For data scientists, predictive maintenance has several promising outcomes, including reducing machine downtime and avoiding unnecessary maintenance costs while adding revenue streams for equipment vendors with aftermarket services. However, engineers and scientists face challenges [25] around process and data when applying predictive maintenance technologies into their business operations:

- Being unaware of how to do predictive maintenance;
- Lacking data to create proper predictive maintenance systems;
- Lacking failure data to achieve accuracy;
- Understand failures but not being able to predict them;
- Unable to store or process large amounts of data.

The growing digitalization of companies marks the beginning of a new era for industrial maintenance: the emergence of predictive maintenance. A new generation of smart sensors appeals to an increasing number of manufacturers who wish to improve their maintenance methods. Companies should press well beyond one digital tool and think about how digital and advanced analytical techniques can transform their entire maintenance and reliability system. This means looking end to end for opportunities to make better use of data and apply user-centric design principles to digitize processes. The sustainable impact will require a blend of new digital tools, changes in asset strategy, and improved reliability practices.

Ongoing research into predictive maintenance techniques discussed in this paper promises to deliver technologies that may improve equipment reliability; predict failures before they occur; and contribute to process safety and efficiency. Integrating the predictive maintenance techniques will enable plants to avoid unnecessary equipment replacement, save costs, and improve process safety, availability, and efficiency.

Future work in this field is related to the development of algorithms to tackle predictive maintenance data-driven challenges such as: dealing with large amounts of data, allowing transparency in outputs and the ability to automatically adjust hyperparameters to data distributions.

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