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State-of-art and maturity overview of the nuclear industry on predictive maintenance

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Abstract. In order to ensure as continuous as possible nuclear energy production, it is necessary to guarantee the availability of all equipment involved in the production chain, in all its complexity. The safety of all these equipments is based on a good command of the maintenance policy with very specific conditions related to the demanding regulations of the nuclear field. It is about having facilities that are safe, available with a good quality and a limitation to radiological risk.

Today, with the advancement of digital technology, substantial improvements have occurred in the tools that can be applied in the maintenance and monitoring of Structures, Systems and Components (SSCs), enabling an understanding of equipment performance far beyond that available only a few decades ago. Therefore, predictive maintenance becomes a subject of prior interest for the nuclear industry.

In this paper, we will emphasize the incentives and obstacles of predictive maintenance deployment in a nuclear context. The objectives here are to draw a clear picture of what can be the practices of predictive maintenance in the nuclear industry context and to identify the requirements and the needs to implement a predictive maintenance model on the lifecycle management of a nuclear facility.

Keywords: lifecycle management · predictive maintenance · nuclear system

1 Introduction

Nuclear energy is one main source of electricity worldwide and the safe operation of nuclear industry is generally acknowledged as contributing to society's success and promoting economic performance. However, managing nuclear energy production is very complex. In order to maintain a stable energy, it is necessary to guarantee the availability of all the equipment involved in this production chain. IAEA (International Atomic Energy Agency) provides a PLiM (Plant Life Management) program for long-term operation, which aims at identifying all of the factors and requirements for the overall life cycle of the plant for all [17]. One of the important factor of this program is the maintenance prioritization. Maintenance in nuclear industry remains a major challenge for operators: a majority of

nuclear power plant (NPP) systems are aged. The inherent risk of the activity imposes strict regulations and compliance. This consumes money time and hard efforts. We need to put in front of it reliable means, methods and tools to respond to it. The regulatory activities on maintenance are defined by various authorities and institutions working for nuclear safety. Among the standards referred to the maintenance, we have NF EN 13306 which defines the types of maintenance and organization of maintenance, the IAEA safety standards especially for the operation, maintenance and safety of NPP [15,17].

The research interest regarding maintenance strategy to optimizing availability/reliability, minimizing risk and cost has been growing up time by time. According to Web of Science, since 1975, 18857 journals and articles discussing maintenance in nuclear context are found using the keywords “Maintenance” and “Nuclear”.

However, there is a wide gap concerning the implementation of maintenance in research and practice. Although many models, methods, and strategies have been proposed, most of the nuclear industries in the world are still using traditional approaches [23]. These traditional approaches help in minimizing the risk of failure. Nevertheless, they do not guarantee a full availability of all the critical equipments. At the same time, we are now facing the development of industry 4.0 strategy linked with the emergence and maturity of digital. Known as the fourth Industrial Revolution, it is characterized by the widespread use of digital and physical environments called Cyber Physical Systems. This convergence achievement of information technologies, Internet Of Things (IoT), big data, cloud, communication systems (SCADA), Cybersecurity, data analytic, with additional accelerators, such as Artificial Intelligence and cognitive science makes it possible to **improve the traditional maintenance strategies with the Predictive Maintenance (PdM)** [13,24]. Regarding NF EN 13306 standard, the PdM is a “Condition-based maintenance carried out following a forecast derived from repeated analysis or known characteristics and evaluation of the significant parameters of the degradation of the item”. The condition based maintenance is a “preventive maintenance which include assessment of physical conditions, analysis and the possible ensuing maintenance actions”. Its implementation requires a large number of concepts and tools such as Industrial IoT [6], data mining, cloud, big data, and artificial intelligence [24].

Nevertheless, deploying such technologies in nuclear industry is not an easy task due to the regulatory constraints. Also, the maturity of PdM in nuclear facilities is not the same compared to other industries. The nuclear industry can be seen as a conservative one that is usually strictly regulated [16]. Also, the equipment involved in the production chain are very specifics, with very long lifespans. The current fleet of NPP is old, with a majority of plants built and commissioned during the 70s and 80s and an initial lifespan of around 40 years. In addition, of this ageing effect, the equipments that make up the facility are diverse, varied and do not have the same level of criticality. Some systems are very critical, with highly regulated owing to the risks associated with plant accidents and radiation exposure to the public. The objective of this paper is to

establish an overview of maintenance practices in the nuclear industry to evaluate its maturity and to identify opportunities and threats for PdM deployment.

The paper is structured as follow: section 2 is dedicated to the related works of maintenance in nuclear facilities. Section 3 introduces the PdM as a whole. Section 4 focuses on PdM in a nuclear context by identifying the current evolution. Section 5 makes a critical analysis of the maturity of PdM in the nuclear industry and introduces further research directions.

2 Maintenance in nuclear facilities

As seen in the introduction, 18857 articles were found in the Web of Science database considering “Maintenance” and “Nuclear” keywords. The process for relevant papers collections and selections consisted of three main phases. First, we have filtered 18857 articles by categories, considering only papers that are closed to our research area. Then, we keep papers written in English that are journals and proceedings and removed duplicated articles. At least, a total of 8882 research papers were short-listed for classification. In order to deepen our investigation of the short-listed papers, VOSviewer software [22] was used to carry out an analysis of the co-occurrence of authors keywords (Figure 1a).

Firstly, we can highlight a cover of keywords around maintenance, CBM, PdM, fault diagnosis in the NPP. This cluster shows the scientific orientation on the NPP over the last ten years. Then a second group of keywords around ITER remote maintenance, remote handling is observed. ITER (International Thermonuclear Experimental Reactor) is an international nuclear fusion research and engineering megaproject aimed at replicating the fusion processes of the sun to create energy on the Earth. A final keyword overlay around the maintenance is visible. This cluster is linked to all the other ones and is very representative. It can be understood that the focus on the maintenance in nuclear industry is not only on nuclear fission (NPP) but also on nuclear fusion, and the topics are the same and centered on the PdM, optimization, remote maintenance, equipments availability, fault diagnosis.

From this state of the art, we observe that whatever the industry, the challenges remain the same on the maintenance strategies and methods. IAEA highlight the importance of the Reliability Centered Maintenance (RCM) in a nuclear facility optimization [15] as demonstrated by EDF in France [9]. The RCM was introduced in the late 1960 by the airline industry [15]. The core of the RCM philosophy is that maintenance will be performed only after evaluating the consequences of failures at component level. It deals with optimization of preventive maintenance activities considering failure consequences. The RCM approach is system-oriented and may be implemented free of a company’s organizational culture. It helps in establishing system boundaries and developing a critical equipment list. An equipment is said to be critical if it performs a function or if its failure can affect functioning of equipment that impacts nuclear safety, prevention of release of radioactivity to the environment, personnel safety

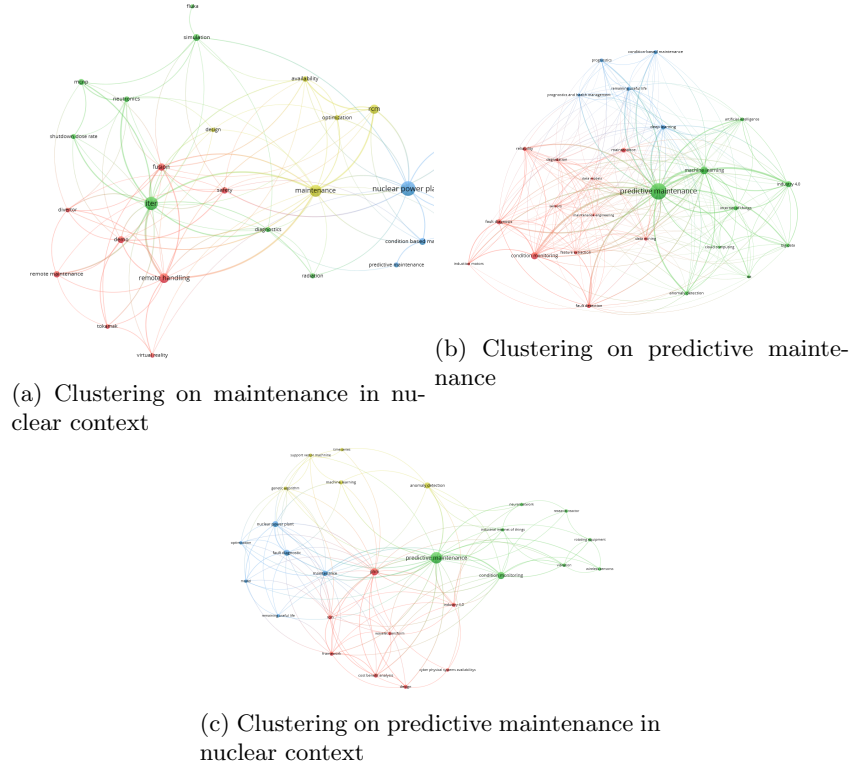


Fig. 1: Clustering of co-occurrence of authors keywords. source: VOSviewer Clustering

and continued power production. Thus the RCM facilitates the decision making on the type of maintenance to be implemented for each equipment.

The maintenance in nuclear industry are how to perform to the optimum level of the capability of equipments and plants. The literature describe several aspects of maintenance. They may be grouped into the technical aspect, commercial one and management one. This implies that maintenance decisions need to be made in a framework that takes into account these issues from an overall business perspective.

The overall maintenance strategies can be categorize in two types. **Corrective maintenance** is carried out after failure detection and aims to restore an asset to a condition in which it can perform its intended function [18]. In the literature, authors identify two types of corrective maintenance: the planned and the unplanned corrective maintenance [18]. **Preventive maintenance** aims at doing the maintenance just before a component fails so the system downtime and the emergency will not happen, by scheduling machine repairs or rebuilds [24].

Two types of preventive maintenance are discussed in the literature [17]: the **time-based maintenance (TBM)** aiming at performing periodic maintenance on the equipment and the **condition-based maintenance (CBM)** carried out in response to a significant deterioration in a machine as indicated by a change in a monitored parameter of the machine condition.

The procedure for performing corrective or preventive maintenance in a nuclear environment is complex. Indeed, it requires a lot of preparation up, given the regulatory safety aspects. First of all, the maintainers must assess the radiological environment, the chemical risks of the process and facility concerned by the maintenance. Then, it is necessary to examine the operating procedure. This allows to optimize the intervention time since this time is very limited and strongly correlated to the radiation exposure. Often, given the complexity of some processes, the failure is difficult to detect.

Maintenance is thus becoming more complex and detecting failures is becoming harder and more time-consuming. The labor cost to carry out maintenance has also been increasing. As a result, maintenance will continue to evolve and the two main drivers for this are (i) technology and (ii) management.

3 Predictive maintenance as a whole

The literature highlight many research areas related to PdM. As in the previous case, web of science is used for relevant articles collection. 3750 articles were found using the key word “Predictive maintenance”. We filtered the most relevant ones using the same process as in the maintenance section. At least, a total of 2453 research papers were short-listed for classification.

Figure 1b draws up three main clusters around PdM literature. The first one is on the maintenance management. It includes all the research studies related to the reliability, fault detection, fault diagnosis, maintenance engineering for maintenance optimization. The second cluster covers research topics on the PdM techniques and tools. This cluster is the most representative one, as it is linked to all the others clusters. It can be understood that PdM in the literature is an association of three main research field: maintenance management, IoT and artificial intelligence. The last cluster relies on the prognostics, health management and the remaining useful life (RUL). Very present in the literature, it is a part of PdM which aims at equipment health monitoring.

PdM has the potential to make the production more reliable and improve service provisioning. However, the maturity for a proper implementation of PdM in research and in practice is not the same. That is why we conducted a multi-case study to underline the conditions and technological aspects for implementing a PdM system in practice. We found that PdM initiatives are triggered by severe impacts of failures on revenue and profit. Furthermore, successful PdM initiatives require that some pre-conditions are fulfilled: Data must be available and accessible. Also, the support by the management is very important. We identified four important factors for PdM implementation: Data integration (highly facilitated

by Cloud-based mechanisms), failure detection (enabled by advanced analytics), PdM operations execution (supported by data-driven process automation) and the visualization [19].

It is important to note that the failure modelling approaches for PdM are a bit common to the maintenance and fault computing. PdM also relies on two distinct approaches:

- **The first approach** is the probabilistic approach. It is based on a statistical and reliability analysis. The input data is retrieved from the Computerized Maintenance Management Information System (CMMIS) software. The CMMIS centralizes maintenance information and facilitates maintenance operations processes. Moreover, the CMMIS optimizes the use and equipment availability.
- **The second approach** is the deterministic approach. It is characterized by the use of some sensors data combined with data mining techniques and artificial intelligence algorithms to predict a machine failure.

The second approach was of great interest to the researchers because it made it possible to optimize maintenance costs better than the first approach. When CBM was introduced in 2002, many implementation methods were developed. These methods involved at measuring certain process parameters from sensor data. The most used methods at the beginning of CBM are: Vibration analysis, Acoustics analysis, Lubrication oils analysis, Corrosive analysis, and Thermal analysis or Infrared thermography [5, 20].

As methods have evolved since 2010, new PdM techniques have emerged. A new method called Prognostic and Health Management (PHM) was introduced [2, 24]. The PHM is an engineering process where algorithms are used to detect anomalies, diagnose faults and predict RUL. Moreover, the financial benefits such as operational and maintenance cost reductions and extended lifetime are achieved with this method [21].

To implement a PHM, many steps are required. Author of [2] addresses the Open System Architecture for Condition-Based Maintenance (OSA-CBM), and draws up six steps for performing a PHM based on ISO 13374: Data acquisition (Access to digitized sensors), Data manipulation (perform single and/or multi-channel signal transformations), State detection or Fault Detection, Diagnosis step, Prognostics assessment and Advisory generation [2, 5, 7, 24]. The architecture system for the PHM includes a database which stores data at each step and a Human Machine Interface for visualization.

CBM and PHM are sometimes confused: CBM includes data acquisition, data processing, fault detection and isolation, and failure diagnostics. Whereas PHM is more a prognosis, an estimation of the RUL and a decision-making process for the implementation of PdM and associated logistics [6, 24].

The predictive modelling techniques used in diagnostic and prognostic functionalities of PHM can be categorized into three: physical modelling (data-based models), artificial intelligence methods (machine learning and deep learning) and statistical-based methods [1, 6, 8, 24].

4 Predictive maintenance in a nuclear context

The state of the art on maintenance has shown that sometimes, a maintenance intervention can be complex especially when a failure is not anticipated. That is why nuclear industry is today moving towards PdM to overcome this problem. The explosion of digital technologies has enabled the collection of sensor data to better model the failure of an equipment. However, is this industry enough mature in deploying such maintenance strategy?

In this sense, we made a literature review based on Web Of Science. 90 articles have been found considering the combination of the following keywords: “predictive maintenance” and “nuclear”. By using the same process as seen previously for relevant papers collection, we finally get a total of 44 research papers. VOSviewer software makes it possible to analyze the co-occurrence of authors keywords.

Overall, Figure 1c draws up all the topics covered in the literature around PdM in the nuclear industry. We identify four main clusters. First, we observe a grouping of keywords around the PHM, characterizing thus the relevant topics. Those keywords (RCM, RUL, wavelet transform, condition monitoring, maintenance, availability, machine learning) show the research orientation of the PHM in nuclear industry. We can also see a significant link between the PHM and the RCM standard. It can be understood that PHM highly impact on the RCM. The second cluster covers various topics around PdM. The topics are: condition based monitoring, industrial IoTs and so one. It is the most representative cluster because it is highly correlated to all the other clusters. The third cluster gathers different topics around the NPP: optimization using fault diagnosis, remaining useful file. Finally, the last cluster includes all the machine learning techniques for PdM implementation. These are: genetic algorithm, support vector machine, neural network and anomaly detection.

The specificity of PdM in nuclear industry lies in its implementation. First of all, equipment instrumentation is governed by regulations that are highly correlated to the radiation exposure and various risks associated with the facility. The location of the sensors on the equipment depends mainly on the risk associated with the process. This is why a risk analysis on the overall process must first be carried out before any intervention. Second, data is often subject to military regulations requiring authorization before any accessibility. Also, predictive models must be in line with the expectations of the process experts and their deployment should be in accordance with the confidentiality rules as defined by the operator and the various safety authorities.

It is important to note that before the introduction of PdM, the nuclear industry, as in all production industries, used traditional techniques such as Infrared Thermography, Ultra sound analysis, Motor current signature analysis, Oil analysis, and Partial discharge to maintain all the facilities. Also, the CMMIS data is mainly used to compute the risk associated with operating the facility, expressed in terms of various statistic metrics related to the different levels of failure to the facility (e.g. core failure frequency), or its environment (e.g. societal

or individual risk) [14, 17]. However these techniques were not enough efficient in predicting a failure. This gave rise to the PdM methods proposed by [12]

PdM has positively impacted the RCM standard in nuclear industry. This positive impact is justified by a good improvement in plant productivity and a reduction in maintenance costs. In [13], authors state that a correct implementation of RCM analysis based on PdM in NPP could bring great benefits in many aspects. Moreover, it is considered to be the best maintenance strategy [13]. Three main lines of research stand out when referring to PdM in the nuclear industry.

The first line is based on the **appropriate methods and techniques used**. The concepts are almost the same as what we saw in the previous section. Many researchers have made a state-of-art of PdM techniques in nuclear industry. Among them, Hashemian was more interesting. He describes three PdM techniques in identifying the onset of equipment failure in NPP: sensor-based technique, test-sensor-based technique and test-signal-based technique [5].

The second line focuses on the **development of Machine learning algorithms for PdM**. The topics were centered on the continuous machine learning for abnormality identification to aid condition-based maintenance [3, 4] and prediction of the RUL of a component [3]. The models work as PHM models and the anomaly detection method is the most used in the reality.

The last line focuses on **data acquisition through the Wireless sensor architecture and applications**. This topic is of great interest to many researchers especially Hashemian [11, 12]. He reported a research and development program to implement wireless sensors for equipment condition monitoring and other application. He proposed an architecture system which integrate a signal in the existing wireless sensors and news wireless sensors for a holistic view of the equipment health and process. He also proposed some wireless sensors for PdM of rotating equipment [11, 12].

In the same way, authors of [10] developed a PdM architecture for nuclear infrastructure using machine learning. They developed the architecture in two parts: a data acquisition part (Offline modelling) and a representation learning part (Online evaluation) with the integration of machine learning algorithms.

5 Critical analysis and conclusions

The research literature conducted in this paper enhance various research aspect of maintenance in nuclear. To come with clear and constructive outcomes, we moved from exploring the maintenance in the nuclear industry with special focus on PdM as a whole and PdM in nuclear industry.

The first finding of this literature study is the **gap in the use of PdM technologies between industries**. In fact, the maturity is not the same. All the papers that introduced PdM using AI in the nuclear industry are very recent in comparison with the airline industry. In order to maintain and optimize their facilities, nuclear operators use traditional methods based on failure probability

analysis, failure modelling, most often computed using data retrieved from CM-MIS. These analyses contributed in computing some classic performance criteria such as MTBF, MTTR. All these methods help in minimizing the risk of failure. Nevertheless, they do not guarantee a full equipment availability. **RCM has become a mandatory standard** that has been implemented by the entire NPP in the world. It allowed them to have a solid methodology to optimize the efficiency of their facilities. PdM technologies are mainly used at NPP; not at the whole fuel cycle.

On the modelling part, most of researchers used some simulated data to implement some machine learning algorithms for PdM. The problem here is that we are not sure to get the same performance on real data. Also many ad-hoc algorithms haven been proposed. **The algorithms are very specific to each equipment** of a nuclear plant; thus do not include a generality.

The information system for PdM has also taken an important part in this scientific literature. The proposed architecture do not integrate nuclear requirements. The architecture for deploying PdM in nuclear context is not well explained: there is no information about how or where the sensors are placed in the equipment, how they communicate with Supervisory control and data acquisition system, and how a PdM solution could be deployed in a manufacturing execution system. Furthermore there is no distinction between cloud or on premise PdM software solution. Some old wireless technologies for vibration analysis, acoustics analysis are mentioned in many studies. Not enough studies have been done on the new wireless technologies such as IIoT or 5G.

This study reveals also **a methodological gap for the deployment and implementation of PdM in nuclear context.** This methodology shall include all the nuclear stakeholders intended to create, manage and exploit PdM technologies. This methodology included in the lifecycle management will increase the speed of deployment and reduce the cost of this technology.

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