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The application of machine learning for on-line monitoring Nuclear Power Plant performance

S.A. Cancemi, R. Lo Frano
University of Pisa
Largo Lucio Lazzarino
56122, Pisa, Italy
Salvatore.cancemi@phd.unipi.it, rosa.lofrano@ing.unipi.it

ABSTRACT

The aim of the paper is focused on the development of on-line monitoring strategy and predictive methodology to analyse the performance of the nuclear system and components.

Advancing online monitoring is attracting a lot of interest at nuclear power plants operating today as it involves the transition from traditional monitoring techniques of nuclear power plant, gathering via manually recorded data sheets, to a full embrace of digitalization.

In this research, a conceptual framework for the application of digital twin technology to primary nuclear power plant component prognosis and maintenance process is proposed in order to reduce its failure risk that could, in turn, affects plant operations and safety.

The development of machine learning algorithm for automated diagnostics and prognostics that, for example, may allow the transition from time-based to condition-based maintenance of the nuclear plant, is totally new and innovative. No prior knowledge of machine learning for on-line monitoring of nuclear items performance in the open literature is known.

The methodology uses big data from sensors and logical controllers for training machine learning algorithm to recognize anomalies or useful pattern before components failure.
Due to the limited available data on primary nuclear components, digital twin concept is adopted in order to generate them for different plant conditions through numerical simulation. After that, the trained algorithm is capable to predict the performance of nuclear components anticipating or delaying the planned inspection for their repairing/replacing. This approach may support the plant condition-based predictive maintenance optimization and the development of the "digital twin model" for improved plant safety and availability.

1 INTRODUCTION

The energy sector is responsible for almost 3/4 of today's greenhouse gas emissions, and it holds the key to averting the worst effects of climate change. Reducing global carbon dioxide (CO2) emissions to zero by 2050 is consistent with attempts to keep average global temperatures below 1.5 degrees Celsius over the long run. To achieve net-zero emissions by 2050, the electrical sector must undergo significant changes. In the net zero emission scenario, nuclear power plants are the most important contributors to decarbonizing, with production gradually increasing by 40% to 2030 and doubling by 2050, though its overall share of generation is below 10% in 2050.

To keep the nuclear energy capacity, existing reactor lifetime extensions are under review in many industrialized countries since they are one of the most cost efficient sources of low-carbon energy [1]. Regarding new constructions are expected to increase to around 4.5 GW per year on average from 2021 to 2035. Despite these efforts, nuclear power's share of overall generation in industrialized economies is expected to decline from 18 percent in 2020 to 10% in 2050. In the Net Zero Emission scenario, 2/3 of new nuclear power capacity is installed in rising market and developing states, with the fleet of reactors quadrupling by 2050 [1]. It is clear that the planned nuclear power plant are not sufficiently to ensure the strictly target of net zero emission. To this end, most of the important economies are involved in the long term operation (LTO) program. LTO, is utmost important also owing to the increased interest of operating organizations. Nevertheless, this requires that plant components still work in compliance with technical specifications to which they were built or manufactured [2]. As the operation of nuclear power plant progress, operational costs become a critical issue that should be addressed. Based on report [3] during the lifetime of a nuclear power plant, excluding the capital cost that is the main segment of entire investment (168$/MWh), fuel costs account for only 9$/MWh of the total operating costs, while operation and maintenance costs account for 16.26 $/MWh of the total operating costs. Furthermore, revenue loss due to unplanned maintenance and unexpected failure are essential factors to consider [4]. The Ginna Nuclear Power Plant in New York is the smallest nuclear power plant in the United States, and it has one reactor with a net summer electricity generating capacity of about 581 megawatts. In 2019, the nuclear power plant generated at total of 4,993,693 MWh, achieving an annual average capacity factor of about 98%. Therefore, considering fixed and variable O&M cost of about 16.26 $/MWh [3], O&M costs per year concerning Ginna Nuclear Power plant are about 81 million of dollars. A reduction of only 2% of O&M cost would bring a saving of about 20 million of dollars per year. Updated estimates of power plant capital and operating costs are represented in Figure 1.

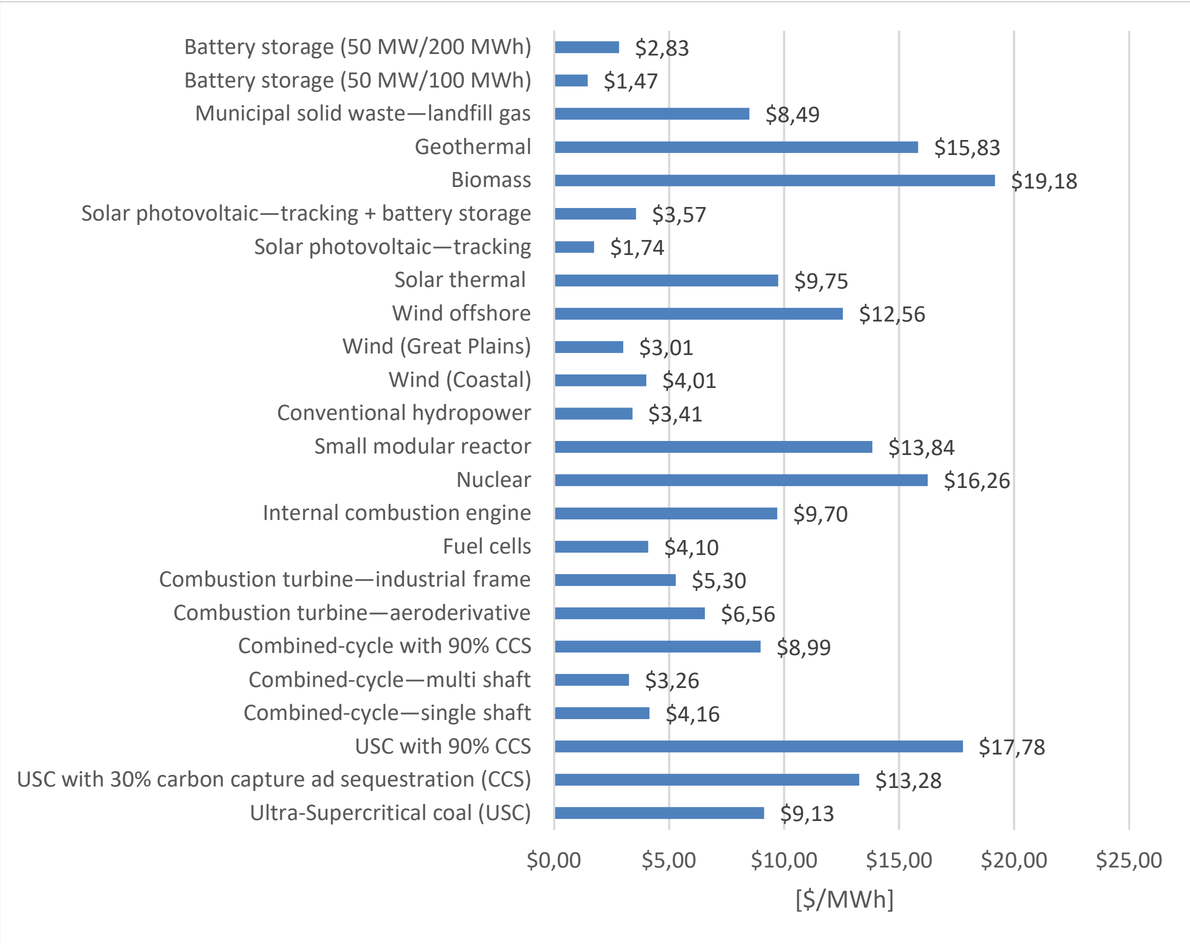

Figure 1: O&M Cost Estimate in USA (2020) [3]

Predictive maintenance could reduce the amount of unplanned outages caused by reactor system failures, as well as the maintenance expenses associated with them. The growth and reliability of predictive machine learning (ML) algorithms had a significant impact on systems, structures and components.

Several study in energy sector use ML technique in predictive maintenance framework. Wang et al. [4] based on deep learning approach in combination with convolutional auto-encoder developed a tool for predicting Remaining Useful Life (RUL) of electric gate valves in nuclear power systems. RUL is calculated by supervised learning approach. The training dataset is provided through sensors installed on the electric valve used to simulate aging and degradation process. A recent study (2020) of Saeed et al. [5] developed on-line fault monitoring technique for a small modular reactor (IP-200) based on convolution neural networks and sliding window technique. The different operating conditions of reactor are implemented and tested by means RELAP5. The authors state that through integration of these two techniques, ML model is able to detect and classify faults at any operating conditions demonstrating robustness of methodology.

Oluwasegun and Jung [6] proposed an innovative approach in order to monitor the health status of Control Element Drive Mechanism (CEDM) of nuclear power plant. The lack of failure data necessary to develop a soundness supervised ML model are calculated by digital twin of CEDM. This approach represents a turning point in the predictive maintenance of critical components, which for reasons of cost and safety cannot run to failure. Similar approach was performed by Aivaliotis et al. [7] for six-axis industrial robot used for welding tasks in the manufacturing field. The authors predict the behaviour of machine and RUL by digital twin of the robot. The lack of failure data as well as the long time needed to record the data to obtain the degradation curves lead the authors to develop synthetic data through a digital/numerical model of the robot such to provide data for training ML algorithm. The developed tool is not able to predict in real-time the RUL for computational cost reasons, but it allows to improve maintenance scheduling and resource planning.

Very few knowledge of machine learning for on-line monitoring in combination with digital twin concept of nuclear items in the open literature are available and no one at commercial level. These challenges make innovative the proposed methodology in order to move from aged-based to condition-based maintenance strategy.

ML is a subset of artificial intelligence; its goal is to use experience to improve automatically the performance of computer algorithms that can be developed for specific applications. Experience in machine learning field is represented by large datasets which contain huge amount of information. Datasets can be described as data gathered from previously recorded observations or live feedbacks (e.g., sensors measurements). ML models can identify useful patterns by the training on data frame. The trained model is thus able to provide predictions and “make” decisions on the events under consideration. The main learning approach is summarized in Figure 2.

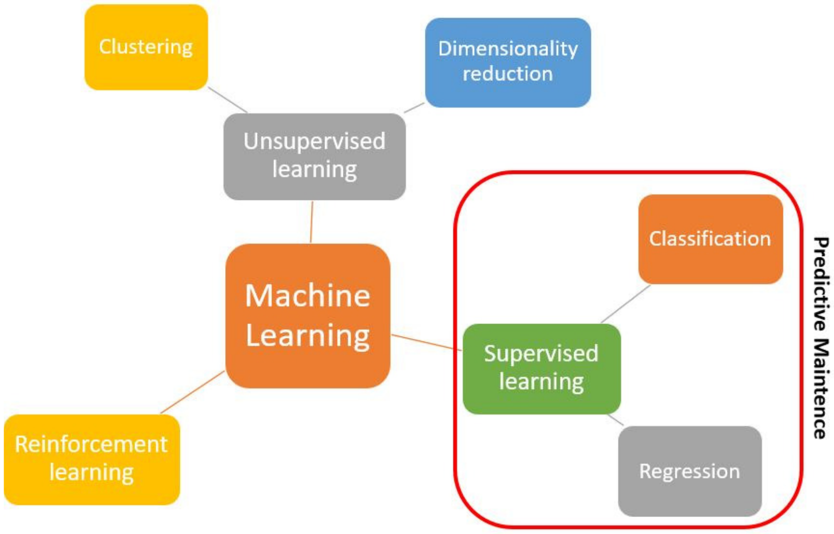

Figure 2: The most important machine learning phases.

Several issues in 4.0 industry are solved by three types of learning approach:

1. Unsupervised learning: In unsupervised learning data without labels or unstructured data are provided. With this approach, the model is able to observe the data structure and extract significant information. This approach cannot rely on a known outcome variable or reward function. Two technique are available for this approach.
    a. Clustering: Clustering is an exploratory technique that allows data to be aggregated within groups (called clusters). The technique allows you to aggregate similar data into clusters by finding relationships between data.
    b. Dimensionality reduction: Dimensionality reduction is an approach used in the pre-processing of features, with the aim of eliminating the "noise" from the data.
2. Reinforcement learning: Reinforcement learning involves several methods in which an algorithm learns strategies automatically. The goal is to get as many rewards as possible, the model performs an action and receives feedback (trial-and-error).
3. Supervised learning: Supervised Learning builds a model from labelled training data, with which the model will make predictions about unavailable or future data. Therefore, the supervised learning means that in the set of samples (or datasets), the desired output signals are already known since previously labelled.
    a. Classification is a method employed in supervised learning. Based on the analysis of previously labelled data, the classifier will predict the labelling of future data classes.
    b. The regression is theoretically comparable to the classification model. In case of regression model the output has a continuous and non-discrete domain.

Predictive maintenance with faulty data of the component is modelled by supervised learning approach. Labelled training data represent healthy and faulty conditions of the component. These recent improvements have enabled industries to study Predictive data-driven Maintenance (PdM) and Leave Reactive (RM) and Preventive Maintenance (PM) procedures.

Aerospace, petroleum and electric industries are investing significantly in PdM development. The development PdM strategy automated, may allow the transition from time-based to condition-based maintenance. The maintenance strategy is shown in Figure 3.

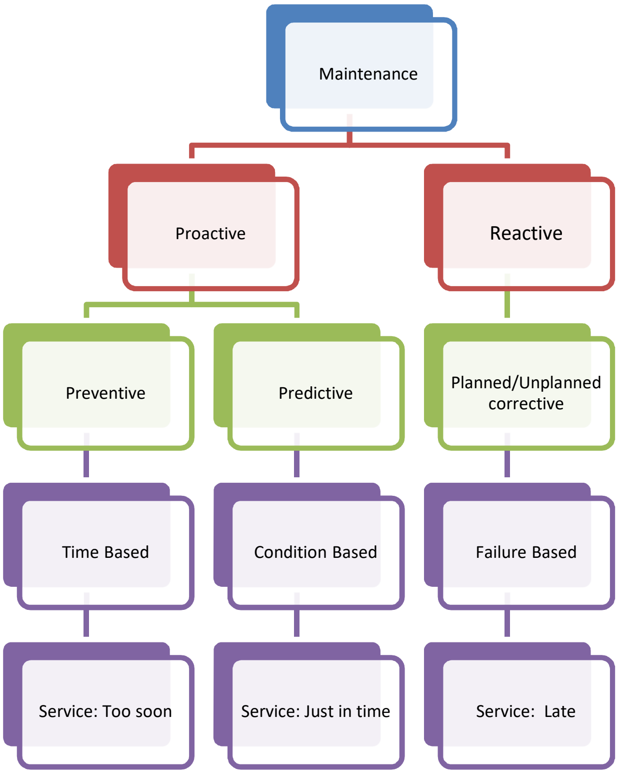

Figure 3: Maintenance Strategy

However, nuclear industry still adopts PM and RM maintenance strategies. Especially for class I components, the maintenance interval is very short for safety and cost reason, regular maintenance often leads to premature replacement of components that are still functional. On other hand, PdM needs historical data and degradation curves provided by on-line health platforms of the components to predict the appropriate time period to initiate the maintenance activity. A common problem related to degradation curve is the lack of failure data. Nuclear industries rarely allow their components to run to failure. Lack of failure data or of good data represents the main limitation of machine learning approach for predictive maintenance [8].

To this end, this study proposes an innovative methodology to support nuclear industry by the use of the digital twin concept to overcome the limitations of lack of failure and/or good data. A digital twin is a digital representation of a physical object or system. It represents one of the main concepts of industry 4.0. It should be highlighted that the digital twin is not just a passive clone of the real system; it's an active and reactive component that can assess constantly the state of its real twin and provide expert advice on how to improve processes, forecast and schedule maintenance, and improve design and overall performance [9].

2 METHODOLOGY

A one-day outage of a 1000-megawatt nuclear power plant causes losses of about 500 k$, a higher availability of just 1% a year compensates the extra costs for management, operation, and maintenance [10]. The predictive maintenance by means digital twins could represent the solution of the unplanned downtime, improving the capacity factor and so, the competitiveness of nuclear energy. The purpose of predictive maintenance is to avoid downtime by predicting when service is required using sensor data. Maintenance would be performed only when it is necessary, rather than at predetermined intervals. The two types of maintenance are represented in Figure 4.

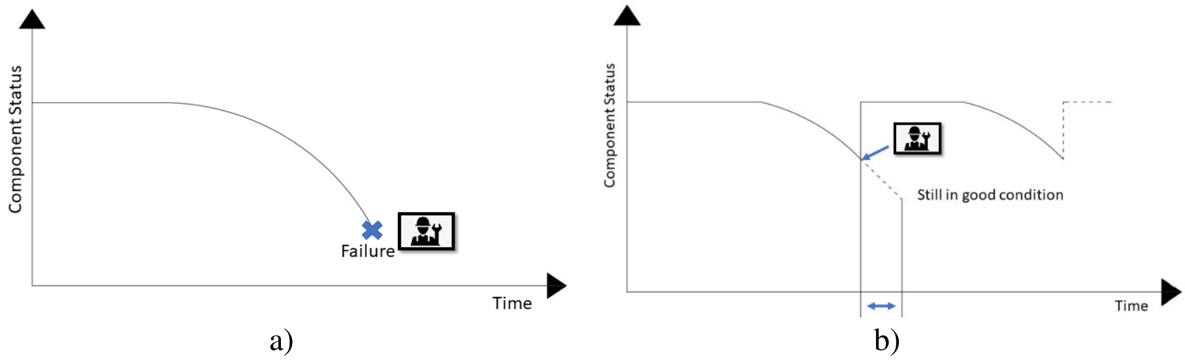

Figure 4: a) Reactive Maintenance, b) Preventive Maintenance [11]

After a component failure, reactive maintenance works on restoring equipment to regular operation replacing or repairing broken parts and components. Reactive maintenance makes sense if parts are cheap and easy to replace, and failure does not affect any high-value assets. Anticipating and managing machine faults is the goal of preventive maintenance. Identifying prospective failure areas, and avoiding failure caused by deteriorating or aging equipment conditions are all part of preventive maintenance. Determining when to do maintenance represent the challenge of preventive maintenance, especially in case of safety-critical equipment for which it is necessary to be conservative in planning.

Predictive maintenance could be the answer to reactive and preventive maintenance as it allows to estimate time-to-failure of structures, systems and components. Optimum time to schedule maintenance is made possible by failure time prediction. Predictive maintenance not only predicts future failures, but also pinpoints issues in sophisticated equipment and supports users in determining which component requires maintenance. The idea of predictive maintenance is represented in Figure 5.

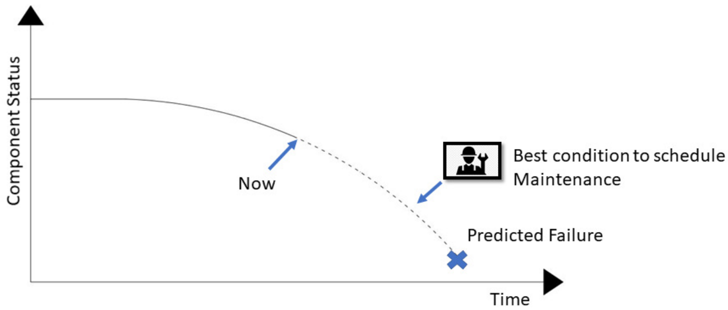

Figure 5: Predictive Maintenance [11]

The main features for developing a good predictive maintenance algorithm are four:

1. Large amount of data quality
    a. Consistency
    b. Accuracy
    c. Compatibility
    d. Completeness
2. Enough fault data
3. Effective prediction of anomalies and failures
4. Capability to predict the RUL

In nuclear power plant is not allowed to run to failure the components for safety and cost reasons. Although a large amount of qualitative data provided by the sensors is available, the lack of failure data makes the predictive maintenance tool ineffective. The predictive algorithm without failure data of the component would not be able to predict warning signs to activate "just-in-time maintenance" since it has not been trained to predict so. Implementing a 3D mathematical model of the component (digital twin) capable of generating failure data under varying operating conditions could represent the solution of lack of failure data.

The workflow of methodology proposed in this study is shown in Figure 6, the reference component of which is a typical primary bent pipe.

The first stage is to gather a wide set of data that represents both normal and faulty operation. As aforementioned, due to unavailability of failure data, the faulty data (synthetic) are generated by a digital twin of component. The synthetic sensors implemented in the 3D model record any variation of component's parameters (e.g., temperature, pressure, flow). The 3D model is modelled by means of multidomain dynamical systems software such as Simulink© or Finite Element codes which allow to simulate several fault conditions and so, may provide failure dataset to train the ML algorithm. For example, in case of piping, ageing degradation can be implemented. Young modulus (E) and yielding strength (σ_y) are the main indicators of the healthy status of the component. The reduction of E and σ_y in function of time and/or temperature based on database [12] can be implemented in a 3D model (digital twin) and the synthetic monitoring system will be able to record the variation of parameters affected by ageing. The purpose is to assess the relationship between extracted features and the degradation path of the component in order to calculate its RUL. The synthetic data aim to simulate different fault conditions under different operating conditions. Sensors of temperature, pressure and flow are implemented in the workflow, but based on the studied component any types of data provided by different types of sensors can be used. The predictive maintenance algorithm uses a combination of generated and data collected by monitoring system as input.

The second stage is represented by the process of the collected data. The data could be structured/unstructured and affected by the noise. At this stage denoising, dataset cleaning, features extractions, features scaling and selection are applied. Simplify datasets, signal analysis (e.g., conversion from time-domain to frequency-domain) and manage the outliers are important steps to build robust ML model.

The obtained results (i.e. cleaned structured data) are fed to ML algorithm for training. Therefore, the trained model is firstly validated, after that it can be used for predictions. The trained model will be able to detect anomalies of component, identify the different type of failure (pipe leakage, blocked inlet, etc) and evaluate the remaining useful life.

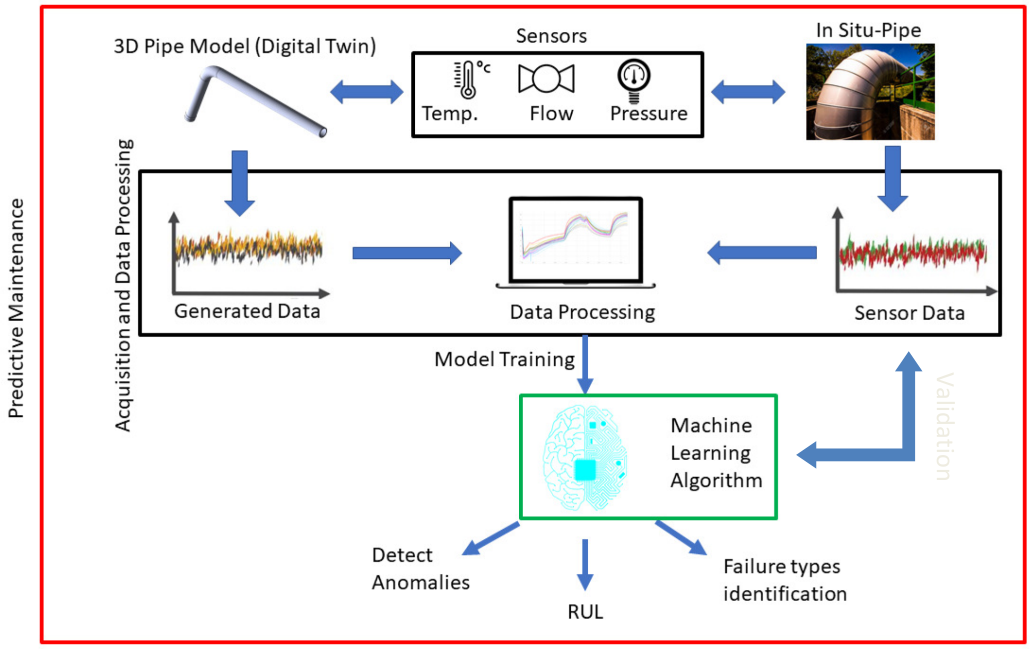

Figure 6: Workflow of predictive maintenance with digital twin approach

3 CONCLUSION

Predictive maintenance and artificial intelligence are becoming an unbreakable combination for smart manufacturing. In terms of maintenance, traditional time/failure based approach involved the use of control and data acquisition systems with a series of set rules and configurations. This approach is based on thresholds on individual parameters (e.g., temperature, pressure), the maintenance is scheduled when an anomaly is reported. However, this approach does not take into account the production context. Unexpected failure and revenue loss due to unplanned maintenance are important concerns to consider. To overcome these limitations the industry are investing resource in order to move from time-based to condition-based maintenance. A lack of available data has slowed development in some industries, including nuclear field.. This paper proposed a new maintenance strategy based on digital twin concept to solve the lack of such data in order ML algorithm is able to predict the behaviour of the component taking into account not only the operational and environmental conditions but also the ageing ones.

At today 46% operating Nuclear Power Plant has lifetime between 30 and 40 years, while 19% is in operation since more than 40 years. Predicting the performance of a no-replaceable component in view of the operational extension of the plant is hence key issue in the LTO program.

4 REFERENCE

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