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Unsupervised Machine Learnig approach for NPP LTO Program

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ABSTRACT

Recent advancements in data-driven analysis methods, represented by those in artificial intelligence and machine learning, are improving the NPP performance ranging from the anomaly detection to the automated operational control of its complex systems. Indeed, the application of these methods can significantly improve the ability to operate safely NPP also in the long-term. In this framework, it is worthy to note that more than 67% of the reactors in operation must face ageing as they are more than 30 years old. This paper focuses on unsupervised Machine Learning (ML) and artificial neural network (ANN) approaches for anomaly detection of SCCs of NPPs. These methods, based on Mahalanobis distance and autoencoder neural networks respectively, are described including tasks of data analysis, monitoring, prognostics etc. Both ML and ANN were tested on anomaly pattern that deviates from nominal/normal plant conditions. LTO condition is also considered. To the aim of this study, the dataset is provided by a digital twin of primary pipe under inner temperature of 300 °C and internal pressure of 15.5 MPa. Finally, the two approaches are compared for performance assessment. The findings suggest that the implemented methodology is able to predict the pipe failure. The transition from time-based maintenance to predictive maintenance demonstrates to support in a profitable way NPP operation and LTO program allowing also to increase the value of nuclear reactor assets by potentially precluding serious consequences due to faults and failures of plant components.

1 INTRODUCTION

Following a 1% drop in 2020 because of the Covid-19 epidemic, worldwide power demand is expected to rise by nearly 4% in 2022 [1]. Considering this outlook and the goal of low-carbon electricity generation, LTO program, can play an important role in clean energy transition in the next decades (Figure 1). In LTO framework critical life-limiting components represent a limit of the life extension of the nuclear power plants (NPPs) [2]. Mitigate ageing by monitoring the health status of the structures, systems, and components (SCCs) represent a key tool to keep high the safety level of the NPPs and save the economic asset.

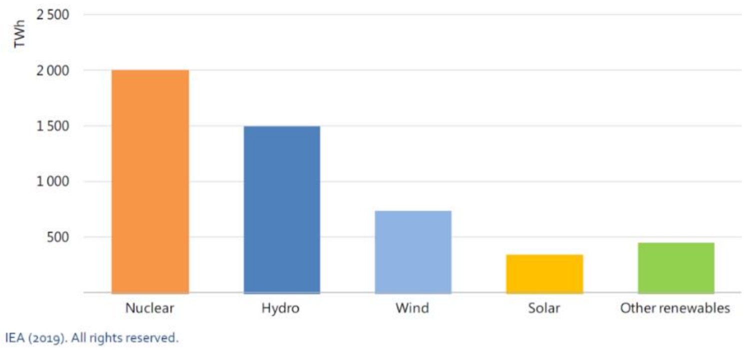

Figure 1: Low-carbon electricity generation in advanced economies by source, 2018

Predictive maintenance based on ML and deep learning (DL) algorithm can improve monitoring and maintenance strategy of SCCs. ML and DL are subsets of artificial intelligence. ML and DL algorithms can perform tasks without being programmed.

DL is itself a sub-category of machine learning and is based on the concept of a neural network. ML and DL are therefore a way to "instruct" an algorithm so that it can learn from several situations. Training involves the use of a large amount of data and sophisticated algorithms to adapt to changing conditions. In general, there are three main forms of machine learning: supervised learning, unsupervised learning, and reinforcement learning.

Unsupervised learning uses data without labels (unstructured). The model may observe the data structure and extract significant information using this method.

Supervised algorithm can make predictions about unavailable or future data based on the labelled training data.

Reinforcement learning aims to create a system that improves its performance by interacting with its environment. Reinforcements, also known as reward signals, are used to increase the performance prediction [3].

These three different approaches are summarized in Figure 2.

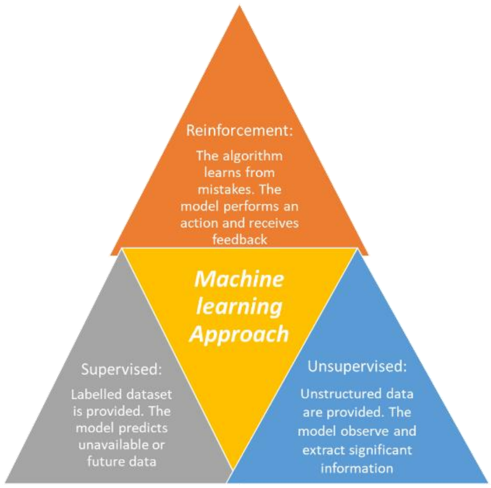

Figure 2: Type of ML approaches

In nuclear industry anomalies or failures are unfrequent events. Setting up a supervised learning approach for predictive maintenance in the absence of run-to-failure data (labelled data) of the components is exceedingly difficult. To this end, unsupervised anomaly detection approach based on ML and DL algorithm is proposed. Anomaly or outlier detection is a technique for recognizing abnormal event that deviates from nominal conditions. In nuclear field, public monitoring data of SCCs are unavailable. As result synthetic dataset is provided by a digital twin of Class I primary pipe implemented through finite element model. The dataset is represented by a timeseries which contains 500 hours of displacement records of aged piping. In order to test the code and verify if it is able to predict the plastic limit, a deviation from nominal pattern is simulated. The most used monitoring platform is SCADA®. It is a computer-based system for collecting and analyzing real-time data. Platform is based on manually threshold setting between normal and anomaly pattern, this needs a deep domain expertise by specialist. These settings might provide to numerous erroneous alarms or missing alerts.

To this end, anomaly detection methodology based on Mahalanobis distance (MD) and autoencoder (AE) are provided. Mahalanobis distance (MD) is a statistical approach used for measuring how distant a datapoint is from the center of a multivariate normal distribution [4]. AE is type of unsupervised neural network. It reconstructs the input from the output by a compression and encoding mechanism. Both techniques are recognized as soundness approaches in different anomaly detection fields [5][6].

2 MATERIALS AND METHODS

AE and MD approaches are applied on class I piping. The pipe is 0.0826 m thick with inner diameter of 0.787 m. The 2D pipe is fully implemented in FE-code. The pipe is made of AISI 304, Young modulus and yield strength values are assumed temperature dependent according with database [7]. The model was set-up with 480 elements; an inner pressure of 15.5 MPa for 500 hours was also applied as initial condition. The 2D FE model represents the digital twin of the considered piping: it has the task of creating a synthetic monitoring data set. Firstly the data are collected and structured in tables, then they are fed to the predictive model for anomalies identification . In the our study, the first 150 hours of the dataset, which represents typical operating conditions, are used to train the model. The remaining set of the dataset are used to test the prediction capability of the model (based on detection of plasticity. An early identification of anomalies makes it possible to schedule a better maintenance, improving the safety of the NPP and preserving the economic asset.

The methodology workflow is represented in Figure 3. The synthetic dataset collects 5 different displacement signals associated of 5 different mechanical configurations taking into account ageing effect. Further, an artificially deviation from nominal conditions is considered in order to test the model and validate if it can predict the plastic limit [3]. The mechanical properties are provided in the Table 1.

AISI-304	% Of Properties Reduction	Young modulus (MPa)	Yield strength (MPa)	Operating temperature (° C)
UNAGED	0	1.76e+11	1.44e+08	300
AGED	5	1.67e+11	1.36e+08	300
AGED	10	1.58e+11	1.30e+08	300
AGED	15	1.50e+11	1.22e+08	300
AGED	20	1.41e+11	1.12e+08	300

Table 1: AISI-304 Properties

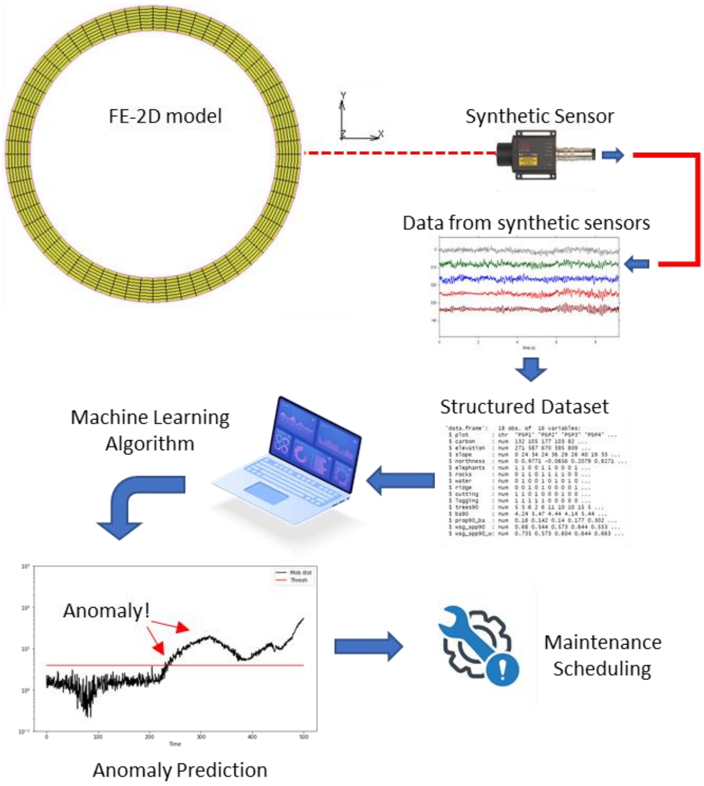

Figure 3: Methodology Workflow

The predictive methodology is based on two different algorithms: mahalanobis distance and autoencoder (special type of neural network). Mahalanobis distance is defined as:

$$D^2\,(\boldsymbol{x},\mu) = (\boldsymbol{x}-\mu)^T \times (\textstyle\sum^{-1}) \times (\boldsymbol{x}-\mu) \qquad (1)$$

Where, D^2 is the square of the Mahalanobis distance, $\boldsymbol{x}$ is the vector of the observation (rows in a dataset, μ is the vector of mean values of independent variables (mean of each column), $\sum^{-1}$ is the inverse covariance matrix of independent variables of a dimension $n \times n$. To classify if an observation is anomaly or not, the inverse of covariance matrix $\sum^{-1}$ is calculated based on normal operation training data which correspond of "health status'' of the pipe. Once calculated the Mahalanobis distance, it is possible to detect the anomaly if the MD of observation point exceeds a certain threshold.
The recommended threshold is 'k' = 5.5 based on the MD distribution shown in Figure 4. The monitoring platform marks the new observation as an anomaly if MD is greater than "k".

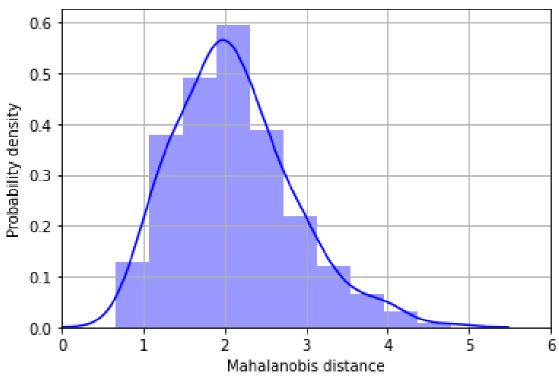

Figure 4: MD distribution

Autoencoders are unsupervised trained artificial neural networks, which networks aim to learn encoded representations of the data, and then re-generate the input data from the encoded representations. The model architecture is represented in Figure 5.
Autoencoder is trained to copy its input to output after compression through a hidden layer (also called latent space or bottleneck) with less neurons than the input and output layers. This hourglass shape forces the neural network to learn to reconstruct the original data with limited information. Autoencoder will extract the essential information based on original data [8][9]. Therefore, given an input dataset x_n, where n= 1,2,…,N, and $x \in R^n$, autoencoder can be described by equation (2) and (3):

$$h(x) = f(W_h x + b_h) \tag{2}$$

$$\hat{x} = g(W_x h(x) + b_x) \tag{3}$$

Where:

h(x)	:	Encoder vector	W_h	:	Encoder weight matrix
$\hat{x}$	:	Decoder vector	W_x	:	Decoder weight matrix
f()	:	Encoding function	b_h	:	Bias vector of encoding phase
g()	:	Decoding function	b_x	:	Bias vector of dencoding phase

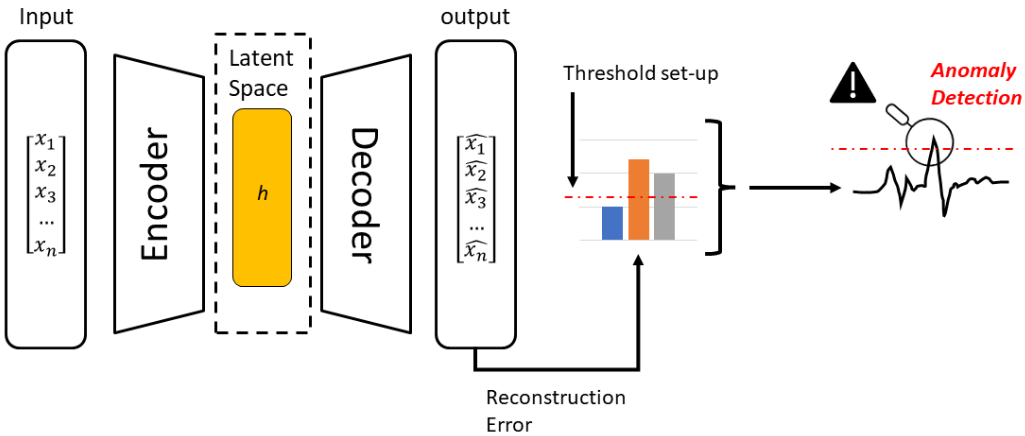

Figure 5: Description of Autoencoder approach

In the model the reconstruction error is evaluated through the MSE loss. The dataset which contains the synthetic records of displacements is divided into training, testing and validation set. No abnormal occurrences are included in the training phase; only data relating to healthy condition are provided to the model. After training phase, the model can detect anomalies.
The model only learned event records that correspond to a healthy condition of component. As results, when the entire dataset is supplied to the model, which also contains anomalous events, large reconstruction error is obtained. The reconstruction error can be considered a measure of the "anomaly" of the input signal. Since the training data contains only normal operating states, the autoencoders are trained to reconstruct what is known as a "normal" signal. As a result, the trained autoencoder is unable to reconstruct the input when it detects an "anomaly" because the correlation between the input variables differs from the typical conditions it was trained on. The MSE loss is shown in Figure 6.

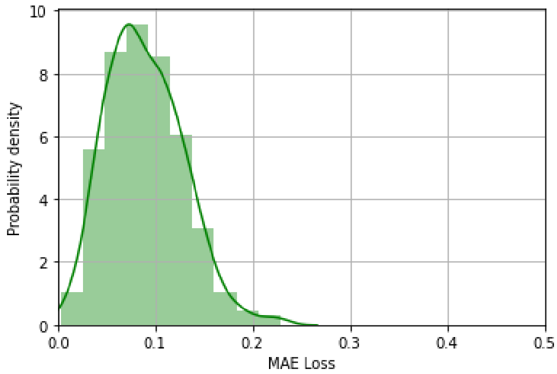

Figure 6: Distribution of MAE loss of training set

From distribution of Figure 6 is set-up a threshold of z = 0.23. Therefore, the neural network will flag the new observation as an anomaly if the value is greater than "z", otherwise no anomaly is detected. The set-up model has 10 nodes in the first layer, 2 nodes in the middle (bottleneck), and 10 nodes in the third layer. After each epoch, 5% of the training data is used for validation.

3 RESULTS AND DISCUSSION

Corrosion, radiation, ageing, and other damage mechanisms are all factors that primary piping is susceptible to when it is in operation. Therefore, it is crucial to manage ageing in order to confirm that piping remaining safety margin is still appropriate. In nuclear field, especially within LTO program, the ability to spot or anticipate abnormal behaviors in advance could be an extremely useful skill. AI-based anomaly detection provides a monitoring system that enables the development of business-impacting technologies like failure prediction and predictive maintenance as part of the decision-making process [3]. In the implemented model, 500 hours of operation have been recorded using the artificial sensors. In addition, unexpected anomaly was implemented in the FE model taking the pipe to reach its plastic limit. The goal was to predict the deviation of nominal pattern in advance. The results of the implemented model based on MD and AE algorithms are shown in Figure 7 and Figure 8.

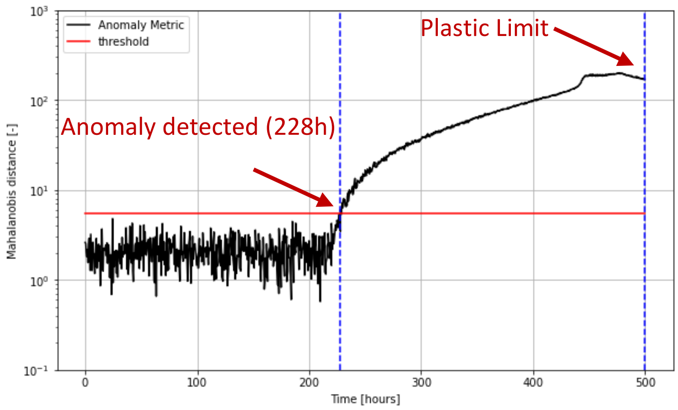

Figure 7: Result of anomaly detection model based on MD distance algorithm

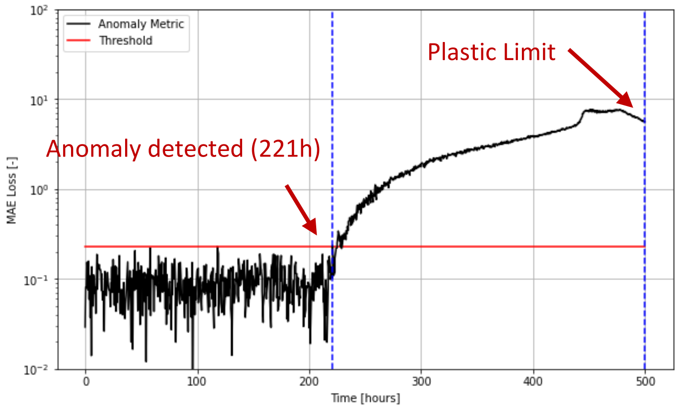

Figure 8:Result of anomaly detection model based on AE algorithm

The red lines in both figures show the calculated threshold. The black line in Figure 7 shows the calculated MD distance, and the black line in Figure 8 shows the reconstruction loss between the input x_n and the predicted output $\hat{x}_n$. The blue dotted lines display the original crossover anomaly and the piping's plastic limit. The plastic limit can be predicted by the MD-based model 272 hours in advance, and by the AE-based model can predict it 279 hours earlier. Both algorithms demonstrated to identify the plastic limit in advance. Nevertheless, the model based on neural networks shows better performance. It detects the anomaly about 7 hours earlier than the model based on the MD algorithm. The main advantages and disadvantages of the two algorithms presented are summarized in the table below [10][11].

	Advantage	***Disadvantage***
Autoencoder	- Unsupervised technique. No information of target labels needed.	- Autoencoder as NN has a black box nature
	- Able to capture nonlinear relationship between variables.	- Prone to overfitting
	- Ability to operate with incomplete information.	- Instead of focusing on gathering the most relevant information, autoencoder learns to get as much data as possible.
Mahalanobis Distance	- Unsupervised technique. No information of target labels needed.	- Unable to capture nonlinear correlation between variables.
	- Easy implementation	- The calculation of MD requires the inverse of covariance matrix ($\sum^{-1}$). If the variables are strongly correlated, it is impossible to compute this.
	- Effective multivariate distance metric	- If normal test instances are different from normal training instances, the false positive rate for such methods will be high

Table 2: Advantage and Disadvantage of Autoencoder and MD algorithm

4 CONCLUSION

This study presented two different algorithms based on ML and DL approaches that were implemented into a 2D FE model in order to predict the behaviour of class I piping.

The main purpose of this work was to demonstrate the potential and benefit coming from the adoption of artificial intelligence in monitoring and predictive maintenance. The autoencoder model-based showed better performance compared to MD model-based. Preventive maintenance frequently results in the premature replacement of components that are still in "good health" because the maintenance interval, particularly for class I components, is quite short for safety and financial reasons. In order to increase the safety margin of NPPs and protect the NPP economic asset, the developed methodology is able to warn users to potential problems in advance. . Indeed, the proposed methodology showed a great potential for predicting components performance for unexpected events, such as piping failure due to thinning, corrosion, etc.; this is of meaningful importance for the life extension of NPP (LTO program). As future development, we will implement a more complete sensor system (pressure, temperature, flow, etc.) and use real or mixed datasets (data augmentation).

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