Proceedings of the 8th European Conference of the Prognostics and Health Management Society 2024 - ISBN – 978-1-936263-40-0

Anomaly Detection of a Cooling Water Pump of a Power Plant Based on its Virtual Digital Twin Constructed with Deep Learning Techniques

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Abstract

This paper aims to explore the use of recent approaches of deep learning techniques for anomaly detection of potential failure modes in a cooling water pump working in a gas-combined cycle in a power plant. Two different deep learning techniques have been tested: neural networks and reinforcement learning. Two virtual digital twins were developed with each family of deep learning techniques, able to simulate the behavior of the cooling water pump in the absence of pump failure modes. Each virtual digital twin consists of several models for predicting the expected evolution of significant behavior variables when no anomalies exist. Examples of these variables are bearing temperatures or vibrations in different pump locations. All the data used comes from the SCADA system. The main features and hyperparameters in the virtual digital twins are presented, and demonstration examples are included.

1. Introduction

The early anomaly detection of failure modes in a power plant is a key factor in mitigating their effects on its operation, maintenance, and, in general, potential costs not planned. This problem has been studied intensively in the scientific literature for some time. Today, the availability of a large amount of data and the development of different machine learning techniques have propitiated their increasing use for early anomaly detection. References (Chavan & Yalagi, 2023), (Pang, Shen, Cao, Van Den Hengel (2021)), or (Nassif, Talib, Nasir & Dakalbab (2021)) are some examples of literature reviews in this area.

Also, anomaly detection with respect to the expected normal behavior is a crucial input for a data-driven, efficient prognostics and health management program (PHM) as is inferred from references (Maior, Araújo, Lins, Moura &. Droguett, 2023), (Ochella, Shafiee & Dinmohammadi, 2021) and (Calvo-Bascones, Sanz-Bobi & Welte, 2021). These references are based on machine learning techniques as the main tools to reach their objectives.

In line with these principles, this paper presents a digital twin of a cooling water pump (CWP) working in a power plant able to emulate normal behavior through a set of characteristic variables when the pump is in normal operation. The variables predicted are those that were considered important for the detection of anomalies that could cause failure modes. The digital twin was developed using two different families of deep learning techniques (Bishop & Bishop, 2024): neural networks and reinforcement learning. The use of reinforcement learning techniques in this field is less known, and this paper explores its potential by comparing the results obtained with a more extended method based on deep neural networks.

The paper is organized as follows: Section 2 describes the foundations of the study. Section 3 presents the digital twins developed and the methodology used. Section 4 shows the anomaly detection results based on the digital twins. Finally, Section 5 presents the more relevant conclusions reached.

2. Study foundations

The objective of the analysis presented in this paper is to detect anomalies as soon as possible in the behavior expected for a Cooling Water Pump (CWO) working in a combined cycle of a power plant. Even when the paper is focused on the case of a CWP, the idea is to develop a procedure that can be easily extended to other components in the power plant. A CWP (Bowman & Bowman, 2021) is an important component whose objective is to cool the steam from the water turbine in an enthalpic process that contributes to the improvement of the water-steam cycle efficiency in the power plant. The process of monitoring if the pump is working as expected in normal behavior for any working condition is based on the consideration of the most typical failure modes that could appear in this type of pump. A Failure Mode and Effects Analysis (FMEA) (Huang, You, Liu & Song, 2020) suggested the main observable variables that could indicate the presence of an anomaly and that can be summarized by monitoring the vibrations in the pump axes, temperature in bearings, and currents in the electrical motor. As it is known, all of these potential failure modes have an important critical impact on keeping the pump in healthy condition.

This information has been used to support the development of a virtual digital twin to predict, in any working condition, the expected values of the vibrations in the axes of the pump, the temperature in its main bearings, and the currents in the electrical motor. This virtual digital twin is based on several models that characterize the relationships between variables to monitor for possible anomalies and the working conditions of the power plant. The list of variables predicted by the models developed follows:

- Prediction of vibration in axis X
- Prediction of vibration in axis Y
- Temperature of the bearing on the electrical motor side
- Temperature of the bearing on the pump side
- Temperature of pump thrust bearing
- Current in the electrical motor

The inputs to all the models correspond with the power generated by the steam turbine of the combined cycle power plant, which is the most important flow to cool, and the temperature in the electrical motor representing the work developed by the pump. The CWP is a high-pressure pump that is horizontal, centrifugal, and multistage. The pump and its motor are mounted on a common structural steel bedplate. Its behavior is monitored from a control room of the power plant where the variables measured in the CWP are accessible.

3. DIGITAL TWIN MODELS

Two redundant virtual digital twins (Jones, Snider, Nassehi, Yon & Hicks, 2020) were developed for the CWP. Both aim to simulate the CWP when it works in normal conditions. The emulation of the expected values for anomaly detection of the target variables is based on a double redundant strategy that uses two different families of deep learning algorithms supporting the models cited: deep learning neural networks and deep reinforcement learning. The datasets used for the creation of the models behind the digital twin correspond to three years of the CWP operation that here will be called year 1, year 2, and year 3. Year 1 will be used for learning the relationships to model, and the other two years will be used for checking the behavior of the digital twin of the pump, simulating its behavior. Python is the programming language used in both versions of the CWP digital twin.

The following subsections will present the results reached by these two types of algorithms.

3.1. CWP digital twin based on Deep Learning Neural Networks (DLNN)

As previously mentioned, six models were created using deep learning neural networks. The procedure followed was similar in all the cases; for this reason, only one case will be described as an example of the method followed. If the whole set of models is used, more than one type of anomaly related to one failure mode could be detected. The example case described here is the estimation of the bearing temperature at the mechanical axis on the side of the connection to the electrical motor. The dataset used for training is Year 1. The input variables were the power generated by the steam water and the temperature in the electrical motor, which represents the working conditions of the CWP. After preprocessing and scaling the data, the *Optuna* open software tool (Akiba, Sano, Yanase, Ohta & Koyama, 2019) was used to find a convenient architecture and hyperparameters of the deep learning neural network. Tables 1 and 2 present the main characteristics of the neural network architecture and the most significant hyperparameters.

Table1. Deep Learning Neural Network. Architecture

Layer	Layer type	Number of neurons	Activation function
1	Dense	40	Sigmoid
2	Dense	25	Sigmoid
4	Dense	1	Sigmoid
4	Output	1	Linear

Table 2. Algorithm Implemented

Language	Python
Main Library	Keras and Tensorflow
Loss function	Mean Squared Error
Optimiser	Adam, learning_rate=0.001, epsilon=1^{e-8}
Training	Epochs=500, steps per epoch=100

Figure 1 shows the result of the relationship learned between the input and output variables based on data from Year 1. Both real and predicted values of the bearing temperature are very close. Their difference or error is in Figure 2. It shows that the most part of the error is the interval [-1, 1] ºC. It suggests a good simulation performance for this part of the digital twin. The axis X is in samples separated by 10 minutes.

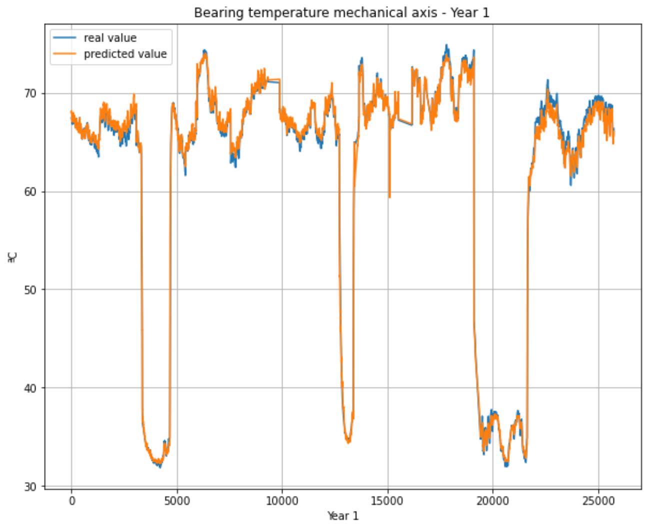

Figure 1. Real and predicted values for the bearing temperature using Year 1 data.

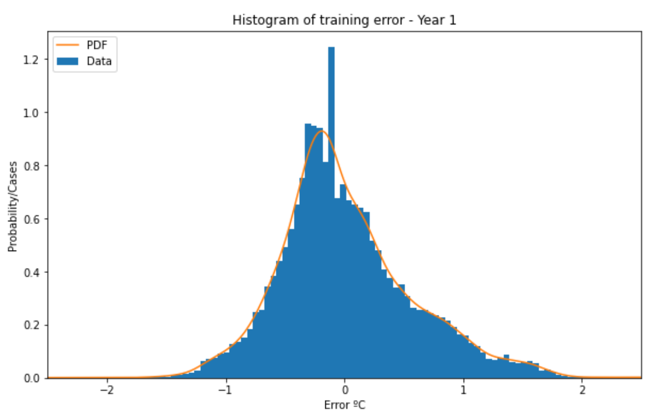

Figure 2. Error observed between real and predicted values for the bearing temperature using Year 1 data.

As a confirmation of the goodness of the model obtained to predict the bearing temperature, Figure 3 presents how good the prediction of this variable is when data used were not included during the creation of the model. Once again, the real and predicted values are very close, concluding that the model created is valid to simulate the bearing temperature in the normal behavior of the CWP. Also, this confirms that no overfitting issues are present. The errors observed are in the same range of values observed with the training dataset, and the same conclusion is reached for the Year 2 dataset. This confirms that this model can be used as a virtual twin of part of the CWP.

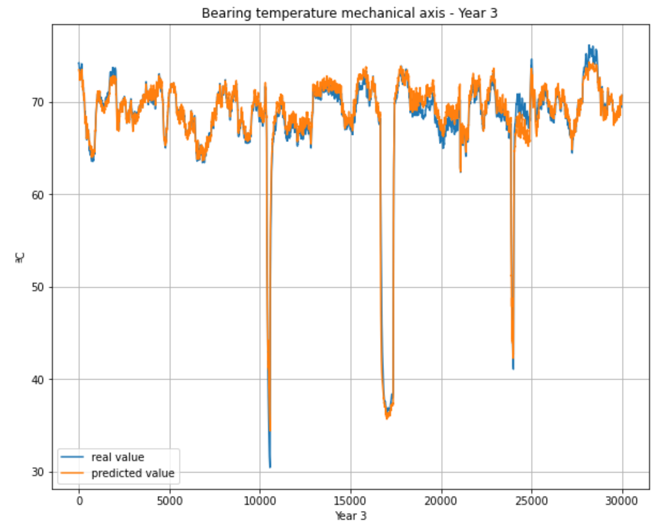

Figure 3. Real and predicted values for the bearing temperature of the dataset Year 3 not used in training.

3.2. CWP digital twin based on Deep Reinforcement Learning (DRL)

Once the CWP digital twin was developed using DLNN, a completely different type of algorithm was studied to cover the same objective. The idea was to explore Reinforcement Learning (RL) techniques for elaborating a digital twin of the CWP. At present, these techniques are not used very often in diagnosing industrial processes, and the number of publications about them is very limited.

Reinforcement Learning (Sutton & Barto, 2018) is a technique where an agent acts in an environment. It has a state, and it can make an action. After each action, the environment provides it with its new state and a reward corresponding to how good the action was. Therefore, the agent learns the parameters of a Quality function and makes new actions according to it. The agent has a multidimensional state space and a multidimensional action space. Figure 4 represents a schema of the basic cyclic process used in RL.

Figure 4 represents the correspondence between the main elements of RL. The objective is to build the same models described for the case DLNN. Here, the state is the input data used by the models. The action is the prediction of the behavior of the pump, considering its different working conditions. The environment gives a reward to penalize how far the prediction is from the real value and gives a new state, which is the new entrance data. The action space is continuous because a real value represents it. There are several RL algorithms; however, due to the continuous nature of the problem to be managed, a Twin Delayed Deep Deterministic Policy Gradient algorithm (TD3) was selected. Details of the method and a pseudocode can be found in (Fujimoto, van Hoof & Meger, 2018).

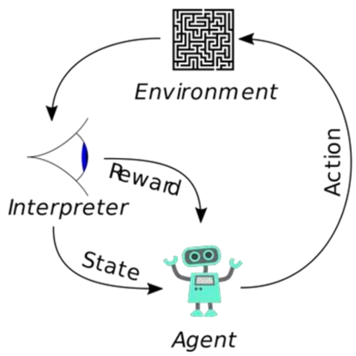

Figure 4. Basic learning cycle of Reinforcement Learning.

With the TD3 algorithm, the agent needs two deep neural networks to decide on its action. The PolicyNetwork determines an action to take. It takes the input data and returns the action, and the Q_network determines the Q_value of the action. It takes the input data and the action and returns the Q_value. During the training phase of the algorithm, the gradient for training the Q_network is calculated based on a linear combination between the reward and the prediction of the algorithm. The PolicyNetwork is trained based on the variation of the Q_network. The Q_Network weights are initialized between -3 and 3. The PolicyNetwork weights are initialized between -0,3 and 0,3. The networks are composed of three linear dense layers with a *relu* activation function.

Table 3. TD3 Hyperparameters

Algorithm Hyperparameter	Value
Training episodes	100
Steps per episode	100
Exploration factor	0.1
Replay buffer size	1032
Batch size	1024
Delayed steps for updating the policy network and target networks	10
Size of hidden layers for networks	64
Learning rate Q_network	3e-4
Learning rate Polocy_network	3e-4
Reward scale	100.

Table 3 presents the values used for the main hyperparameters of the TD3 algorithm. *Keras* and *tensorflow* were used for the implementation of the TD3 algorithm. The reward in RL is essential to guide the correct learning process. The reward design is based on a function of 6 levels depending on the absolute difference between the real and predicted values observed for the output variable of the model. The reward ranges from 100 for differences lower than 0.001, till -1500 for differences higher than 0.3.

Figure 5.a shows the result of the relationship learned between the input and output variables based on data from Year 1. Both real and predicted values of the bearing temperature are very close. Their difference or error is in Figure 5.b It shows that the most part of the error is the interval [-1, 1] ºC. It suggests a good simulation performance for this part of the digital twin.

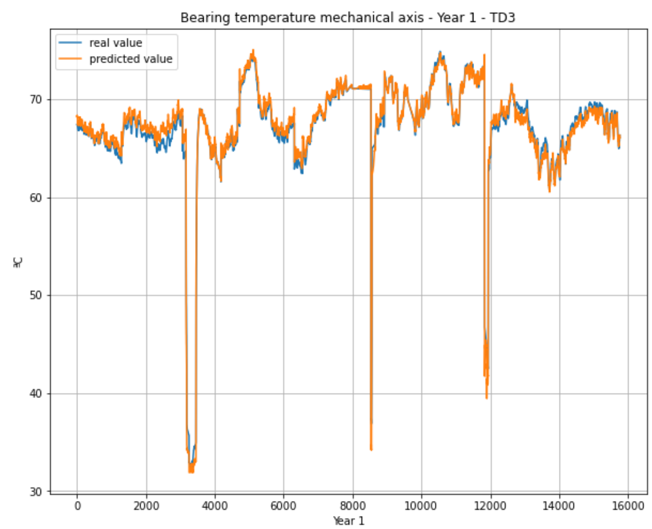

Figure 5.a. Real and predicted values for the bearing temperature using Year 1 data and TD3 algorithm.

Figure 5.b. Error observed between real and predicted values for the bearing temperature using Year 1 data and TD3 algorithm.

Figure 6 confirms the model goodness using RL to predict the bearing temperature when the data used, Year 2, were not included in the model training process. Once again, the real and predicted values are very close, concluding that the model created with the RL algorithm TD3 is also appropriated to simulate the bearing temperature in the normal behavior of the CWP. The errors observed are in the same range of values observed with the training dataset, and the same conclusion is reached for the Year 3 dataset. This confirms that this model can be used as a virtual twin of part of the CWP.

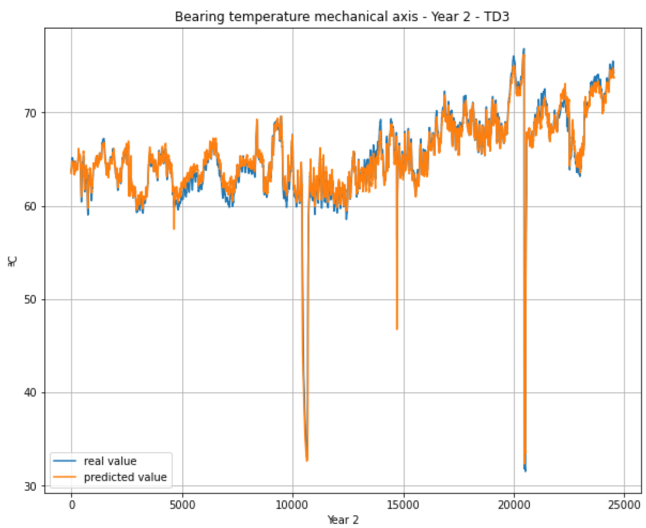

Figure 6. Real and predicted values for the bearing temperature using Year 2 data and TD3 algorithm.

3.3. Comparative results of both CWP digital twins: DLNN and DRL

Once both virtual digital twins were obtained to simulate the CWP performance, one of the objectives of this study was reached, which was the comparison between the use of DLNN and DRL techniques. As mentioned, the use of DRL for this type of problem is not too extended. The results obtained have demonstrated that DRL is a reasonable option in terms of simulation of the behavior of a real industrial component. Table 4 shows the mean and standard errors obtained in °C degrees in all the cases studied with both deep learning methods. It can be observed that the values are within the accuracy of any temperature sensor used in industry, and both methods can be used with similar confidence for detecting deviations concerning the normal behavior expected.

However, the main objective of this study is the early detection of possible anomalies that can cause failures. The next section will show how the digital twins can be used for that.

Table 4. Mean and standard errors obtained

	Year 1	Year 2	Year 3
Mean_DLNN	0,03600	-0,26709	0,16897
Std_DLNN	0,71556	1,36557	1,24222
Mean_TD3	-0,14583	-0,04837	-0,04837
Std_TD3	0,68032	0,04842	0,99234

4. Anomaly detection and risk assessment

The digital twins described in the previous section and their good performance permit the application of a redundant strategy for robust anomaly detection. It is important to note that the algorithms used for both digital twins are completely different, even when they observe the same information. It seems clear that if both coincide in detecting an anomaly in the behavior expected, its certainty should be high. Also, if both observe normal behavior. In the case of a discrepancy, careful monitoring must be observed for the new coming data. Redundancy is key for preventing false alarms in anomalies detected.

Another important point to note is that the digital twins were developed to learn the normal behavior in the CWP operation expressed by several values of variables observed in the SCADA system. If, for some of these variables, the value observed is not similar to the value predicted by the digital twin, then an abnormal behavior is present that has to be investigated. In fact, the variables observed and predicted were selected as direct indicators of the presence of possible failure modes.

The models obtained by DLNN and DRL techniques simulate very well the normal behavior expected for the output variables; however, they show small discrepancies between real and predicted values, such as those presented in Table 4. In order to prevent false alarms in both cases, confidence bands, according to the error observed in the training models, were defined for monitoring new data differently from those used for training. These confidence bands were adopted around the ±3 times the standard deviation of the error observed in training. Any new prediction inside these bands means that there is no behavior different from this expected for the variable predicted.

Figure 7 shows an example of the upper and lower confidence bands (straight lines) for the error observed in the prediction of Year 3 data that were not used for learning. In this figure, the error is inside the confidence bands, concluding that the temperature in this pump bearing is as expected and no anomaly is present. The same approach of confidence bands is applied to any model inside each digital twin.

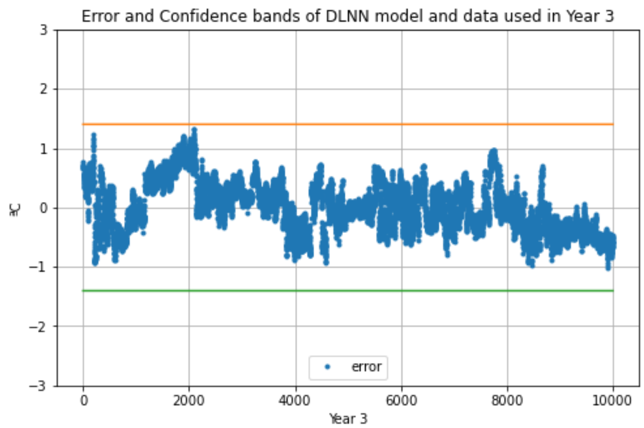

Figure 7. Error inside confidence bands: the behavior observed is similar to the expected one.

The main objective of this section is to present the ability of both digital twins to detect anomalies. In order to reach this goal, an artificial abnormal behavior was introduced in Year 3, simulating an increase in the temperature in the bearing studied in the previous section that could be the result of an incipient failure mode due to the wearing of balls in the bearing or weak lubrication. In this case, only an isolated possible failure mode is considered, leaving the problem of simultaneous failure modes open for further studies. Figure 8 shows the predicted and real values of the bearing temperature in the mechanical axis of the CWP digital twin based on DLNN. In the right part of the figure, there is a significant deviation between real and predicted values that alert about abnormal temperature behavior for the observed working conditions.

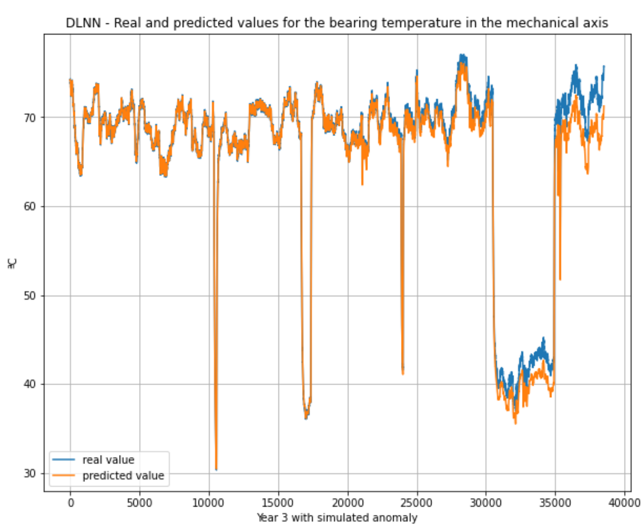

Figure 8. Real and predicted values by the DLNN digital twin. An anomaly is detected at the end of the period.

The deviation with respect to the normal behavior is observed in detail in Figure 9, where the confidence bands of the error are also represented. On the left part of the figure, there is a very clear deviation with respect to the normal behavior expected, meaning that the temperature in the bearing is higher than normal for the current working conditions. Also, it is possible to observe the current fingerprint of the detected anomaly, keeping only the information in Figure 9 that is out of the upper confidence band. This is presented in Figure 10, where an increase of about 2.5 ºC degrees in the last 50 days (6000 samples) is observed, and its trends will be called "risk of the failure mode" in this paper. This information is precious for an approach to implement a data-driven maintenance program.

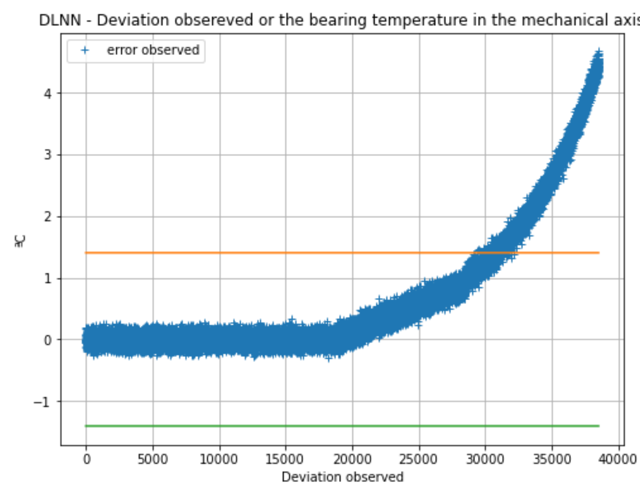

Figure 9. Error inside confidence bands: the behavior observed is similar to the expected one. DLNN case.

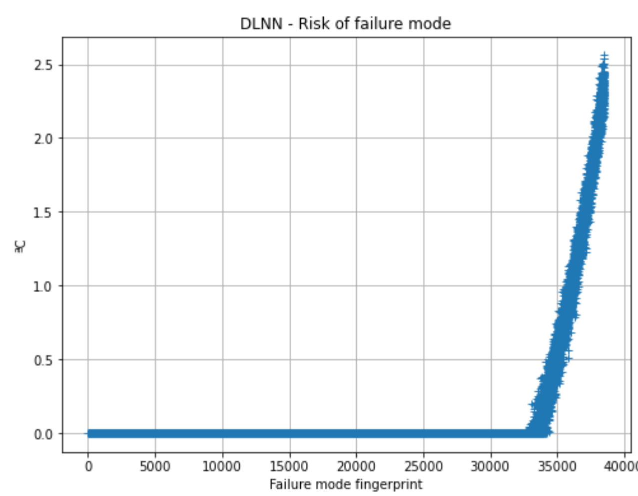

Figure 10. Risk of failure mode based on DLNN digital twin.

The performance of the digital twin based on DRL is similar to that described for the digital twin based on DLNN. Figures 11, 12, and 13 present these results.

Figure 14 presents the superposition of the risk presented in Figures 10 and 13. The objective is to check if some digital twin detects the anomaly condition presented earlier. According to this figure, both virtual digital twins are able to detect the anomaly at the same time. The error observed from the DLNN digital twin seems to be slightly higher, but in any case, it is not significant in ºC units. This confirms the reliability and robustness of the method for anomaly detection based on these digital twins built using different deep learning techniques.

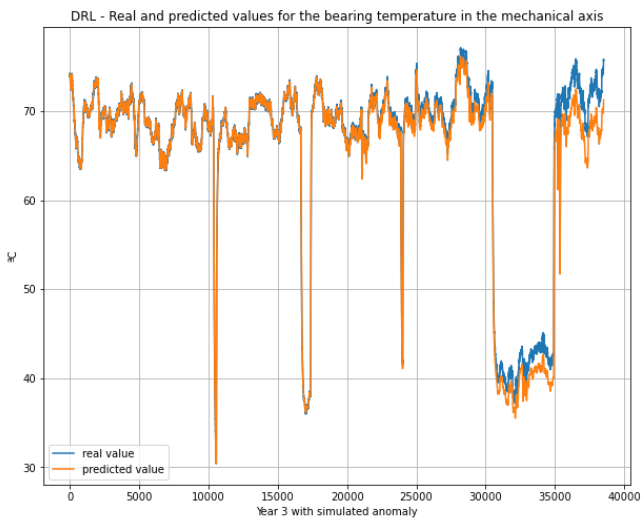

Figure 11. Real and predicted values by the DRL digital twin. An anomaly is detected at the end of the period.

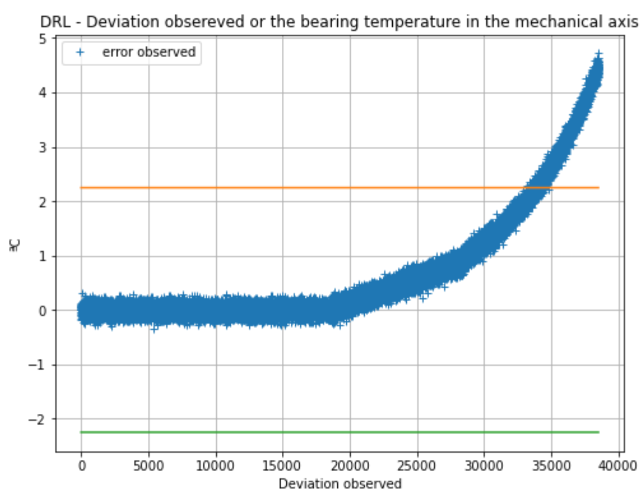

Figure 12. Error inside confidence bands: the behavior observed is similar to the expected one. DRL case.

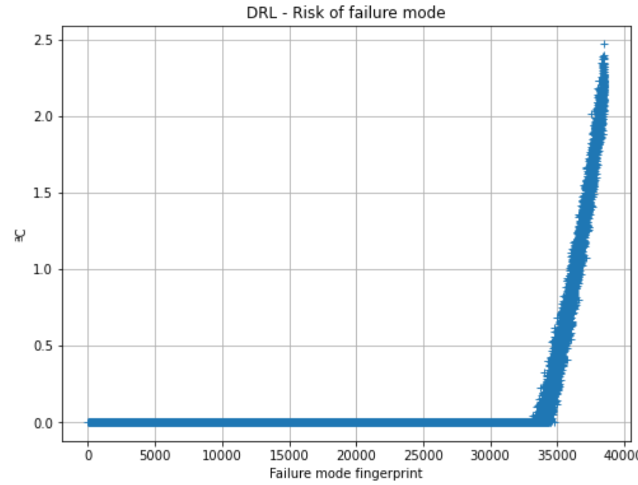

Figure 13. Risk of failure mode based on DRL digital twin.

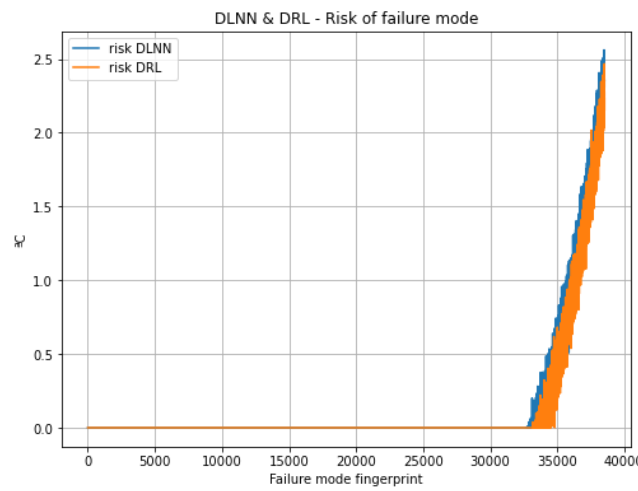

Figure 14. Comparison of risks observed with DLN and DRL digital twins.

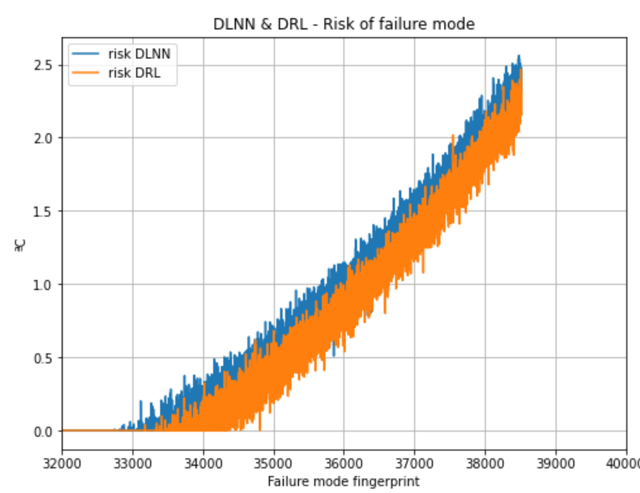

Figure 15. Zoom of the interest zone of Figure 14.

5. CONCLUSION

This paper has presented two virtual digital twins for anomaly detection in a CWP. The objective of creating two digital twins was double. First, the performances between DLNN and DRL were compared because the use of DRL is not well-known yet in this field, and it could have some advantages over the well-known DLNN method because it would need less data for training. The conclusion is that DRL techniques can be used as an alternative option for the DLNN. Second, using two digital twins based on different techniques could robust the anomaly detection process, preventing false alarms. This was verified and confirmed with an example of isolated failure. Additionally, the fingerprint of the detected anomaly can be used as an indicator of risk for a failure mode and alert maintenance people about this fact, giving the basis for a data-driven approach supporting the maintenance and asset management of industrial processes.

The results of this paper open several future studies, such as the analysis of the performance of the digital twins when several failure modes appear simultaneously and the propagation of their effects. Also, the use of the profiles of the risk of failure modes and their integration in maintenance promises to implement new maintenance plans.

ACKNOWLEDGEMENT

The study has been developed with the scientific and economic support of the ENDESA Chair of Artificial Intelligence Applications to Data-driven Maintenance.

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Miguel A. Sanz-Bobi is currently a Professor with the Computer Science Department, and also a Researcher with the Institute for Research and Technology (IIT), both within the Engineering School, Comillas Pontifical University, Madrid, Spain. He shares his time between teaching and research in topics related to the artificial intelligence field applied to diagnosis and maintenance of industrial processes. He has been the main researcher in an important number of industrial projects related to the diagnosis of industrial processes, incipient detection of anomalies based on models, knowledge acquisition and representation, and reliability and predictive maintenance. All these projects have been based on a combination of artificial intelligence, new information technologies, and machine learning techniques.

Sarah Orbach is currently a student in the Engineering School CentraleSupelec. She mainly studied physics and computer science. During a gap year, she did two internships. The first one in collaboration to an Open Source web development project and the second in artificial intelligence with the Institute for Research and Technology (IIT) within the Engineering School, Comillas Pontifical University, Madrid, Spain. She is now specializing in bioengineering.

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