International Journal of Advanced Research in Engineering Technology & Science

ISSN: 2349-2819

Impact Factor: 7.10

(Peer-Reviewed, Open Access, Fully Refereed International Journal)

Email: editor@ijarets.org Volume-12 Issue-1 January-2025 www.ijarets.org

ARTIFICIAL INTELLIGENCE FOR PREDICTIVE MAINTENANCE IN MANUFACTURING SYSTEMS

GHANTA SHIVA SAATHWIK

Student, M. Tech in Advanced Manufacturing Systems

Jawaharlal Nehru Technological University, Hyderabad, Telangana State

Abstract

Predictive maintenance, often known as PdM, is a novel method in the field of industrial systems that attempts to improve asset longevity, decrease downtime, and maximise operating efficiency. Artificial intelligence (AI) plays a crucial part in the progression of preventative maintenance (PdM) programs by utilising data-driven insights to anticipate the occurrence of equipment problems and the need for repair before they take place. The purpose of this study is to investigate the application of artificial intelligence (AI) approaches in predictive maintenance, including machine learning, deep learning, and advanced analytics. For the purpose of developing reliable prediction models, the study focusses on the application of artificial intelligence in the processing of real-time data from Internet of Things (IoT)-enabled sensors, past maintenance records, and operating parameters. Methods of critical importance, such as the identification of anomalies, the recognition of failure patterns, and the assessment of remaining usable life (RUL), are investigated. Additionally, alternative solutions are examined, along with problems such as the quality of the data, the integration of the system, and the costs of implementation. The purpose of this article is to show the revolutionary influence that artificial intelligence has had on maintenance procedures by analysing case examples from a variety of sectors. These case studies examine how AI has improved production dependability and reduced costs associated with unexpected downtime. It is clear from these findings that artificial intelligence-driven predictive maintenance has the ability to reimagine the future of technologically advanced production systems.

keywords: *Artificial Intelligence, RUL, Manufacturing*

Introduction

A paradigm change is now taking place in the manufacturing industry, which is being driven by Industry 4.0. This shift is characterised by the convergence of modern technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and Big Data. Within this context, predictive maintenance, also known as PdM, has arisen as an important innovation with the objective of enhancing operational efficiency and reducing unexpected downtime. Reactive maintenance, which handles equipment faults after they have occurred, and preventive maintenance, which depends on set schedules, are two examples of traditional maintenance tactics. Predictive maintenance, on the other hand, makes use of data-driven insights to anticipate failures before they occur. The analysis of enormous volumes of real-time and historical data has made artificial intelligence an essential component in the process of allowing predictive maintenance. Artificial intelligence enables industrial systems to recognise hidden patterns, detect abnormalities, and estimate the remaining usable life (RUL) of equipment by utilising techniques such as machine learning, deep learning, and statistical analysis. These skills greatly improve decision-making, making it possible to undertake maintenance only when it is required, which in turn reduces costs and maximises the utilisation of resources. When it comes to contemporary industrial systems, where unplanned downtime can result in major financial losses, production delays, and quality compromises, the use of artificial intelligence into predictive maintenance is particularly crucial. Real-time monitoring of equipment health is now possible thanks to sensors provided by the Internet of Things (IoT), which opens the door for artificial intelligence to translate raw data into meaningful insights. Nevertheless, in order to fully realise the promise of artificial intelligence in predictive maintenance, it is necessary to overcome difficulties such as data quality, system integration, and cybersecurity considerations. The importance of artificial intelligence (AI) in predictive maintenance, as well as its methodology and the consequences it has for the industrial industry, are investigated in this study. The article focusses on the most important use cases, analyses the advantages and disadvantages of AI-driven maintenance systems, and imagines what the future holds for these systems in an industrial environment that is always changing. The potential of predictive maintenance to solve the constraints of traditional maintenance procedures is one of the reasons why it is gaining popularity. Unanticipated failures are a common consequence of reactive maintenance, which can result in expensive delays and the waste of resources. On the other hand, preventative maintenance may result in unneeded service, which can lead to an increase in operating expenditures. On the other hand, predictive maintenance makes use of insights produced by artificial intelligence to strike a balance, so guaranteeing that maintenance actions are carried out precisely when they are required. The implementation of artificial intelligence in predictive maintenance is in line with the overarching objectives of smart manufacturing, which is characterised by the partnership between networked systems and intelligent algorithms in order to improve both production and efficiency. The study of vast and complicated datasets is made possible by artificial intelligence algorithms such as supervised and unsupervised learning models. These algorithms enables the identification of patterns that human operators would miss. For instance, predictive models might anticipate the breakdown of machines based on minute shifts in vibration, temperature, or pressure that are sensed by Internet of Things sensors. Furthermore, predictive maintenance contributes to sustainability by maximising the utilisation of resources and increasing the lifespan of machinery, which in turn increases the amount of waste produced. Artificial intelligence-driven maintenance provides a means by which businesses that are working towards achieving environmental, social, and governance (ESG) objectives may realise advantages in both their operational and environmental aspects. The application of artificial intelligence in predictive maintenance presents a number of problems, despite the fact that it has many benefits. When it comes to training effective prediction models, it is sometimes necessary to have high-quality datasets that have been labelled. However, collecting such data may be both time-consuming and costly. In addition, the integration of artificial intelligence with legacy systems that are already in place in manufacturing plants might provide both technological and organisational challenges. Concerns have also been raised over the privacy and security of data, particularly in situations when sensitive operational data is exchanged across many networks. The purpose of this study is to offer a complete review of the influence that artificial intelligence on predictive maintenance in industrial systems has had and will continue to have. It examines approaches that are considered to be state-of-the-art, reviews applications that are used in the actual world, and considers strategies available to overcome implementation hurdles. The purpose of this study is to contribute to a better understanding of how cutting-edge technology might influence innovation in contemporary industrial processes by investigating the confluence of artificial intelligence and predictive maintenance.

Method

The dataset that is utilised in this work is one that is available to the public. At the University of California, Irvine's Machine Learning Repository, it was obtained. These are simulated measurements of sensors that are attached to an industrial equipment. The data is synthetic and depicts these readings. The usage of such synthetic data was due to the fact that actual ones are neither widely accessible to the general public nor readily available. In all, there are 10,000 records of various measures contained inside the collection. The measurements are as follows: (1) the temperature of the ambient air (in degrees Kelvin), (2) the temperature of the process (in degrees Kelvin), (3) the rotational speed (in revolutions per minute), (4) the torque (in Newton-meters), (5) a measurement that represents tool wear, (6) the type of product being produced, which is represented by one of the letters (L, M, or H), and (7) failure on a working machine, which is represented by ones or zeros. The procedure is seen in figure 1, above.

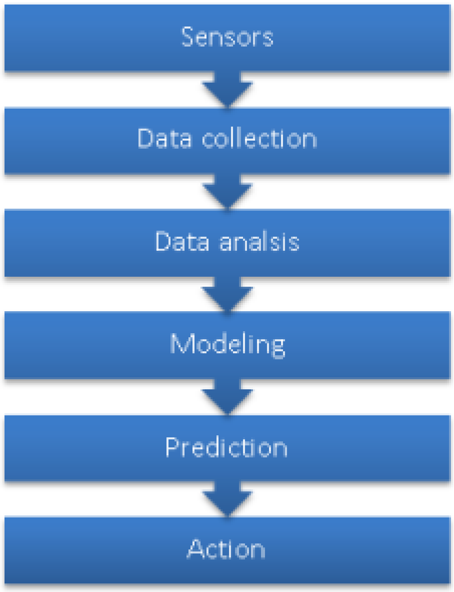

Figure 1. Schematic representation of the process of predictive maintenance

Results and discussions

First things first: in order to construct an effective artificial intelligence model, we need to look at the data to see if there are any signs of correlations between the variables and whether or not these correlations impact the output response. To begin, we do an analysis of the data by employing boxplots and histograms, as seen in figure 2. In terms of temperature values, it is evident that the range is restricted to around 8 K, and the distribution of these values is relatively uniform. With some outliers at the upper end, the speed is centred about 1540 revolutions per minute and is slanted to the left, which indicates that it is lower. Outliers can be seen at both the lower and upper ends of the torque distribution, which is regularly distributed. In terms of wear, it is distributed consistently over the whole range; yet, relatively few instances of big values occur in comparison to other values. As a result, our preliminary assessment is that we anticipate that the most significant impact on machine failure will be exerted by speed and torque, followed by wear.

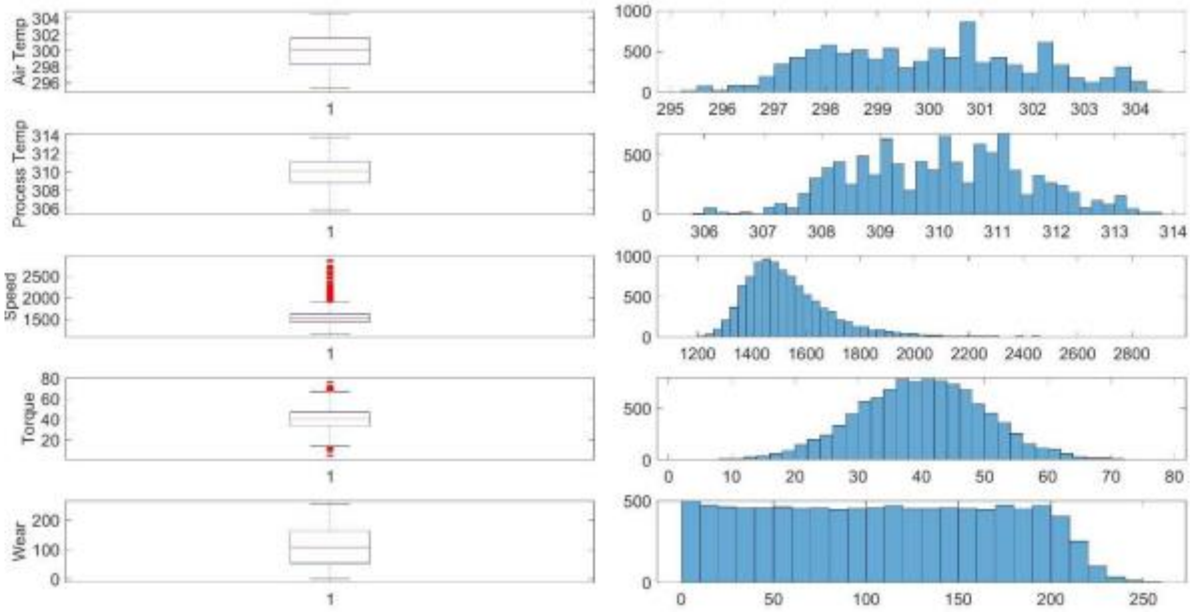

Figure 2. For each variable, boxplots and histograms are presented.

According to the findings of the investigation into the instances of machine failure, there are precisely 339 failure incidences out of 1000 recordings. In terms of the operations of the machine itself, this equates to a likelihood of failure of 3.39 percent; however, this also indicates that there is an imbalance between the number of records that reflect machines that are operating and those that have failed. This will, as a consequence, have an impact on the training process of the artificial neural network, which will be explored in further detail in the next section A presentation of descriptive statistics may be found in Table 1. Without a doubt, it is evident that the average temperatures of the air and the process were nearly same in both the functioning and the failed circumstances. When the other factors, namely speed, torque, and wear, are taken into consideration, it becomes evident that there was a discernible disparity between the mean values of these variables for healthy and failing situations. In addition, it is possible to see that the number of failure occurrences is higher when the machine is run at high torque values and low speed combinations. This may be seen in image 3, above. Although this discovery is in agreement with our previous initial prediction, which said that torque and speed are key elements to failure, it is vital to note that other aspects are equally significant. Because it is difficult to determine the function of each aspect through straightforward data visualisation, we make use of artificial intelligence in order to uncover the hidden connections that exist between the variables that are input and the answer that is generated.

Table 1. Descriptive statistics

Failure	0	1
Group Count	9661	339
Mean (Air_temp) [K]	300.0	300.9
Mean (Process_temp) [K]	310.0	310.3
Mean (Speed) [rpm]	1540.3	1496.5
Mean (Torque) [Nm]	39.6	50.2
Mean (Wear)	106.7	143.8

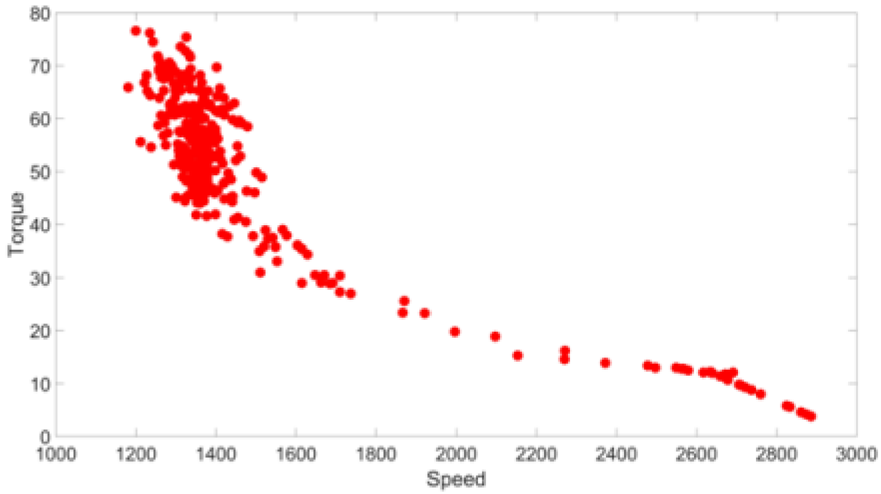

Figure 3. High torque and low speed both result in a higher failure rate.

Modeling

A neural network (ANN) is modelled using the dataset, which is presented in this section. On the basis of the six variables (air temperature, process temperature, rotational speed, torque, wear, and kind of product), an artificial neural network (ANN) is trained to identify the state of the machine as either functioning or failed. We made use of an artificial neural network classifier that was feed forward. Any artificial classifier will be biassed to predict operational events with better accuracy than failed ones since the dataset was imbalanced, which means that the number of failure incidents was around thirty times lower than the number of operating occurrences. The confusion matrix chart, which is seen in figure 4, is the metric that is used to evaluate the accuracy of the prediction. This chart displays the outcomes of training the final artificial neural network (ANN) after a number of trials. In the confusion matrix, the rows are arranged to represent the real class, which is the actual measurements, and the columns are arranged to represent the projected results. Using the validation dataset, the final artificial neural network was able to accurately predict the no-failure condition for 1924 cases, in contrast to 21 cases that were truly failed but were incorrectly forecasted as non-failure throughout the training process. The right-hand side of figure 7 displays a summary of the percentages of each corner that indicate the mix of the values that were actually observed and those that were projected. In accordance with the predictions, a true positive rate (TPR) of 99.5% was achieved in the classification of non-failures, while a true negative rate (TNR) of 68.7% was achieved in the classification of actual failures.

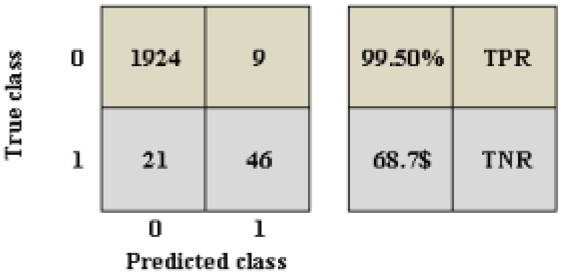

Figure 4. Indicators of confusion matrix results

Performance evaluation

This section provides a description of the actions that were done in order to enhance the adaptive neural network's capacity to forecast failure episodes. that is, TNR. As can be seen in Table 2, two further artificial neural networks (ANNs) have been investigated. NN_1 is the initial network that was mentioned before, and NN_2 and NN_3 are representative of an ANN that has two and three hidden layers, respectively. In addition, the dataset was divided into two sets: the first set was used for training, which comprised eighty percent of the initial dataset, and the second set was used for verifying the findings of the artificial neural network. Over the course of the training phase, the validation dataset was kept hidden from the artificial neural network (ANN) in order to guarantee that the ANN will be able to accurately anticipate the failure condition based only on its own learning experience. We made sure that the dataset was shuffled before we divided it into separate training and validation datasets. This was done because the most recent rows of the original dataset contained entries that were not considered to be failures. This was done in order to guarantee that the data contained inside each dataset was as similar to one another as would be conceivable. Lastly, the values of the predictors were standardised in order to ensure that the learning process of the artificial neural network (ANN) would not be influenced by the variable scale differences that exist amongst the predictors. As can be shown in Table 2, the capabilities of prediction were improved as a result of these activities in terms of TPR and TNR.

Table .2 True positive and negative rates of three ANNs

	NN_1	NN_2	NN_3
TPR	99.5	99.6	99.8
TNR	68.7	72.6	81.4

Prediction

Being that the ANN has been constructed, it is now possible to utilise it to make predictions about the status of the machine based on measures that are predictive. A dataset is utilised as an illustration of the capabilities that the ANN possesses. This dataset contains one hundred records that were taken from the first dataset in which the machine's attempt to retrieve them was unsuccessful. When we sent these records into our artificial neural network (ANN), it suggested that 77 of them had failed, while it incorrectly projected that 23 of them were operational or non-failures. The findings, on the other hand, also offer forecasts regarding the likelihood of failure for each record. Figure 5 illustrates the values of the chance of failure for each of the 23 records that were collected here. Our artificial neural network (ANN) regarded a likelihood of failure that was less than 0.5 to be operational. Considering that it has a success rate of 77% in predicting failure, we might investigate using a lower threshold, such as 0.1. In other words, the artificial neural network (ANN) will receive data from the sensors that are monitoring the machine, and it will display alerts to the administrator of the system if a forecast is greater than a threshold that has been established. It is for this reason that more investigations will be carried out in order to take the necessary remedial steps.

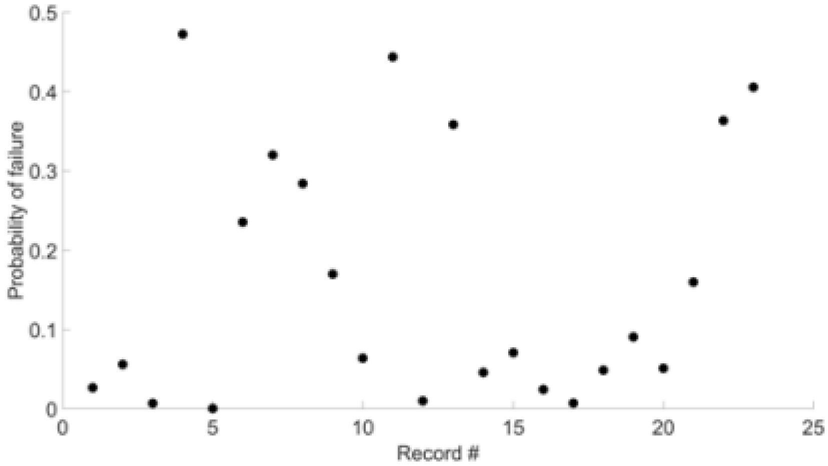

Figure 5. Probability of failure for each wrongfully predicted record

Alternative predictive models

In conclusion, we provide a concise summary of additional models that has the potential to be utilised in the process of forecasting the states of machines. It should be noted that, this overview is limited and serves only to give a general idea of the capabilities of predictive modeling in the field of maintenance. One might consult the following for further information on predictive models: The flowchart-like form of the decision tree model in which inputs and outputs are presented makes it simple to understand what the model is trying to say. An illustration of the decision tree prediction model may be found in Figure 6. This category of prediction models provides the user with an indicator that is both clear and easy to understand. The use of logistic regression is yet another type of prediction model. Failure occurrences are represented by the polynomial equation as a function of process variables, as has been demonstrated in a clear and convincing manner.

$$\begin{aligned}Failure = 1 &+ Type * Air\_Temp + Type * Process\_Temp + Type * Speed + Type \\ &* Torque + Type * Wear + Air\_Temp * Process\_Temp + Air\_Temp * Speed \\ &+ Air\_Temp * Torque + Air\_Temp * Wear + Process\_Temp * Speed \\ &+ Process\_Temp * Torque + Process\_Temp * Wear + Speed * Torque \\ &+ Speed * Wear + Torque * Wear\end{aligned}$$

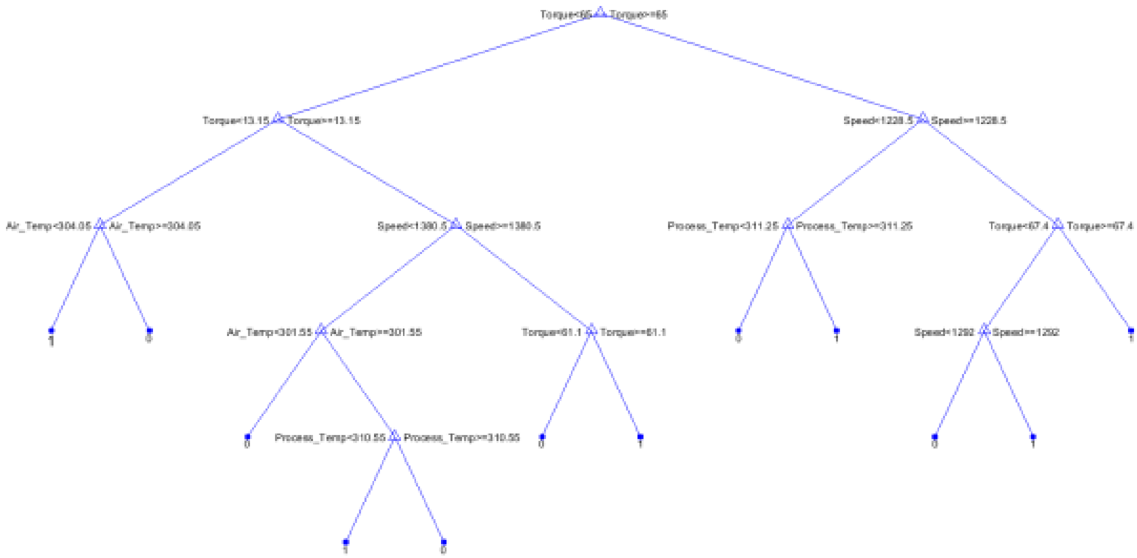

Figure 6. Decision tree

Conclusion

The incorporation of artificial intelligence (AI) into predictive maintenance (PdM) has brought about a sweeping change in the maintenance procedures that are utilised in industrial systems. Industries are able to move beyond traditional maintenance practices and employ proactive, data-driven processes by using modern artificial intelligence techniques such as machine learning and deep learning. Through this change, manufacturers are able to decrease the amount of downtime they experience, maximise the utilisation of resources, and improve their operational efficiency. Predictive maintenance systems that are driven by artificial intelligence are able to deliver accurate failure predictions and actionable insights by analysing real-time data from sensors that are enabled by the internet of things (IoT) and past maintenance records. Not only do these skills contribute to increased dependability and cost savings, but they also help to efforts to reduce waste and extend the lifespan of equipment, which in turn contributes to sustainability. In spite of the enormous promise it possesses, there are still substantial difficulties to overcome, including issues over cybersecurity, integration complexity, and data quality. The implementation of robust data governance, strategic planning for system integration, and investments in secure technology are all necessary in order to overcome these obstacles. The development of artificial intelligence (AI), the stakeholders in the manufacturing industry, and policymakers will need to work together in order to overcome these hurdles and make the most of the benefits of AI-driven maintenance. In conclusion, artificial intelligence-driven predictive maintenance makes a significant contribution to the development of smart manufacturing and Industry 4.0. The use of predictive maintenance is expected to rise as a result of ongoing breakthroughs in artificial intelligence and internet of things technologies. This will, in turn, redefine maintenance paradigms and drive industrial efficiency in a global market that is increasingly competitive. By incorporating artificial intelligence into maintenance procedures, manufacturing systems have the potential to reach higher levels of dependability, cost-effectiveness, and sustainability, so paving the way for a more intelligent and strong industrial future.

References

[1] Joshi A V. 2020 Machine learning and artificial intelligence (Cham: Springer)

[2] Virvou M, Tsihrintzis G A and Tsoukalas L H Advances in Artificial Intelligence-based Technologies Selected Papers in Honour of Professor vol 1

[3] Ognjanovic I 2020 Artificial intelligence in healthcare vol 274

[4] Hassanien A E 2020 Advances in Intelligent Systems and Computing 723 Mohamed Mostafa Editors The International Conference on Advanced Machine Learning Technologies and Applications (AMLTA2018)

[5] Partridge D 2013 Artificial intelligence and software engineering: Understanding the promise of the future

[6] Jackson P C 2019 Introduction to artificial intelligence (Mineola New York: Dover Publications Inc.)

[7] Kamel H 2012 Neural Network Application for Structure Design Optimization of Thin-Wall Structures ASME 2011 International Mechanical Engineering Congress and Exposition, IMECE 2011 vol 9 (American Society of Mechanical Engineers Digital Collection) pp 41–5

[8] Anon File:Artificial neural network.png - Wikimedia Commons

[9]] Hu C, Fan H and Wang Z 2022 Residual Life Prediction and Optimal Maintenance Decision for a Piece of Equipment

[10] Filomena M, Justyna S and Erika T Innovations in Mechanical Engineering [11] Mobley R K 2002 Introduction to Predictive Maintenance

[11] Thomas D S 2018 The Costs and Benefits of Advanced Maintenance in Manufacturing (Gaithersburg, MD)

[12] Matzka S 2020 UCI Machine Learning Repository: AI4I 2020 Predictive Maintenance Dataset Data Set

[13] Mathworks C 2020 Predictive Maintenance Toolbox TM User ' s Guide R 2020 a

[14] Alexandre J, Marques L, Nauber F, Gois José B, Simon X-N and Fong J 2021 Predictive Models for Decision Support in the COVID-19 Crisis

[15] Lughofer E and Sayed-Mouchaweh M 2019 Prologue: Predictive maintenance in dynamic systems