The benefits of predictive maintenance in manufacturing excellence: a case study to establish reliable methods for predicting failures.

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Abstract

In the course of manufacturing excellence, decision makers are consistently confronted with the task of making choices that will enhance and meet the plant's requirements. To this end, it is essential to maintain machines and equipment in a timely manner, which can prove to be one of the primary challenges. Predictive maintenance (PdM) technology can enable real-time maintenance, providing numerous benefits such as reduced downtime, lower costs, and improved production quality. This article tries to demonstrate efficient physical parameters used in PdM field. The paper presents a case study operated in industrial production process to compare between the most used algorithm in predicting equipment failures. Future research can improve prediction accuracy with other artificial intelligence tools.

1. Introduction

Over the past few decades, the manufacturing industry has experienced significant changes in its industrial strategies in production and in maintenance processes. Lee et al. [1] and other authors state that the manufacturing paradigm changes towards predictive manufacturing, the role of maintenance function within manufacturing needs to be refined as a value creation function for achieving more sustainable operations.

The preventive maintenance (PdM) approach is a common strategy in maintenance management to avoid failures, as it provides maintenance actions based on a schedule. This approach is not optimal in terms of costs, as it does not consider the dynamic state of the production equipment; often it leads to too much or too little maintenance that causes unnecessary replacements or unproductivity in the production process [2].

According to the ISO 13381-1 standard [3], predictive maintenance is defined as a maintenance strategy that uses the condition monitoring of an item and the application of appropriate techniques and analysis to detect a change in the item's condition, which is indicative of a failure. The primary objective of predictive maintenance is to determine the appropriate maintenance activities needed to prevent equipment failures before they occur. This approach involves the monitoring of equipment health through the use of various technologies such as vibration analysis, thermal imaging, and oil analysis, among others. By analyzing the data collected from these monitoring techniques, it is possible to predict when equipment failure may occur and take corrective action before the equipment fails.

Predictive Maintenance is a condition-based maintenance strategy that carries out maintenance action when needed, avoiding unnecessary preventive actions or failures. Machine learning (ML), in the form of advanced monitoring and diagnosis technologies, has become increasingly attractive [4].

Maintenance function has undergone a constant evolution over the past few decades with the aim of improving availability and reducing breakdowns. The new PdM function aims not only to reduce
breakdowns, but also to anticipate them to guarantee better machine performance. Figure 1 shows this evolution since the emergence of corrective maintenance.

Predictive maintenance usually adopts a condition-based approach that involves frequent monitoring of system components to assess equipment status, predict its future trajectory, and develop maintenance plans based on the expected changes in equipment status and possible failure modes. Currently, predictive maintenance encompasses various activities, including monitoring equipment condition, diagnosing faults, predicting residual life, and making informed decisions about maintenance.

2. Literature Review

2.1. Predictive Maintenance:

Predictive Maintenance is a Conditional Maintenance Strategy (CBM) that performs maintenance actions when needed, avoiding unnecessary preventive actions or failures [4]. According to Sezer et al [5] Machine Learning-based predictive maintenance: A cost-oriented model for implementation), the PdM is based on historical data, models and domain knowledge. This type of maintenance is intended to predict trends, behavior models and correlations through statistical or machine learning models to anticipate pending failures in advance to improve the decision-making process for the maintenance activity by primarily avoiding time stop.

Predictive maintenance (PdM) is able to assess the condition of equipment to detect signs of failure and anticipate them, PdM could also brings several potential benefits in terms of dependability and cost performance and other benefits. Different approaches are proposed in the literature. Initially grounded in data, physics models, or existing knowledge, these approaches face persistent challenges and limitations. Specifically, there is a need to overcome the reliance on a specific context, incorporate data and business knowledge while accounting for the unique challenges of applying established solutions to new situations, address difficulties related to data analysis, and effectively manage uncertainties [6].

In order to conduct a detailed study on the different methods used in PdM, our research team conducted a literature review on this topic. The result shows that more than 25 of recent research have used models based on Random Forest (RF), Deep Learning (DL) and Artificial Neural Network (ANN).

In the manufacturing field, Wang [7] put forward the system function model of predictive maintenance is shown in the Fig. 2. Predictive maintenance defined by the model includes data acquisition and processing, state identification, fault identification and location, health prediction, maintenance management and maintenance execution.

2.2. Artificial Neural Network:

Artificial Neural Network (ANN) is a machine learning model inspired by the structure and function of biological neurons in the human brain. ANN typically consists of several layers of interconnected nodes,
or artificial neurons, which are designed to simulate the behavior of biological neurons in the human brain. The basic structure of an ANN includes an input layer, one or more hidden layers, and an output layer (Fig. 3).

The input layer receives the input data and passes it through to the hidden layers, where the data is processed through a series of mathematical computations that involve weights and biases assigned to the nodes. The hidden layers help to extract and learn relevant features and patterns from the input data.

It is commonly used in predictive maintenance, which is a technique that uses data analysis to predict when maintenance on machinery or equipment is needed, in order to avoid unplanned downtime and reduce costs. ANN model is used in predictive maintenance to analyze sensor data from machinery and equipment and predict when maintenance will be required.

Safoklova et al. [8] say that using Artificial Neural Networks (ANN) is essential for processing vast amounts of data obtained from product condition monitoring systems. This helps predict potential solutions for product maintenance. One effective method of optimizing maintenance and repair is integrating with Aircraft Health Monitoring (AHM), which involves leveraging the use of ANN as a tool. The use of an ANN is provided as a maintenance tool. Predictive maintenance with an artificial neural network is part of the MRO strategy "Before the fault is detected.

2.3. Deep learning:

Deep learning is a subfield of machine learning that involves the use of neural networks with multiple layers to learn and model complex patterns in data. It is based on the idea that the network can learn to recognize features and make predictions by processing large amounts of data.

The degradation of machine tools was quantified using a generative deep learning approach. This approach was used to predict future degradation and the results were used in scheduling algorithms. The quantification was done using HI [9].

In the context of predictive maintenance, deep learning can be used to analyze data from sensors, machines, and other sources to detect potential problems before they occur. This can help reduce downtime, improve efficiency, and save money. Scientific researchers have been exploring various deep learning techniques for predictive maintenance.

2.4. Random Forest:

RF model is a machine learning algorithm that is commonly used for classification and regression tasks. It is an ensemble learning method that combines multiple decision trees to make predictions. In a Random Forest, multiple decision trees are trained on different subsets of the data, using a random subset of features at each node of the tree. Each tree produces a prediction, and the final prediction is determined by aggregating the individual predictions of all the trees.

2.5. Comparison between the most used predictive models
In this section, a previous research paper produced by our team research in 2022 [10] made a comparison between the most used models in maintenance prediction. Table 1 shows the number of research papers used those models to study the benefits of predictive maintenance. The results of this literature paper shows that between 2016 and 2021, the majority of researchers in predictive maintenance focused on ANN more than DL or RF.

<table>
<thead>
<tr>
<th>Models</th>
<th>Number of research papers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random Forest</td>
<td>1</td>
</tr>
<tr>
<td>Deep Learning</td>
<td>4</td>
</tr>
<tr>
<td>Artificial Neural Network</td>
<td>1</td>
</tr>
</tbody>
</table>

3. Case Study: A Comparative study in PdM

Equipment data used in predictive maintenance case study:

The industrial equipment studied here consists of several sensors, including air temperature, process temperature, rotational speed, torque, and tool wear duration. These sensors provide six parameters that can be used for failure prediction, as shown in Table 3. It is worth noting that the prediction model was developed using a set of synthetic data that contains no missing values.

Table 3: The five sensor parameters of the studied industrial equipment

<table>
<thead>
<tr>
<th></th>
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</thead>
<tbody>
<tr>
<td>Min 296</td>
<td>306</td>
<td>1168</td>
<td>8</td>
<td>0</td>
</tr>
<tr>
<td>Max 304</td>
<td>313</td>
<td>2886</td>
<td>72</td>
<td>253</td>
</tr>
</tbody>
</table>

The number of data used in this case study of maintenance prediction consists of 10,000 data, divided between equipment failure data and no-failure state data. Table 4 shows the distribution of data according to the six studied parameters.

Table 4: Equipment status type and number in the studied period
As described in the abstract, a case study was conducted in the field of predictive maintenance to study the most effective models used in prediction of failures especially among those models described before in the literature review section. To do this, the study was limited to comparing two models that are currently used, Neural Networks and Random Forest. The figure 2 shows that the case study was based on a real equipment failure database, which consists of 10,000 data points distributed across several sensor data and different types of failures. The case study approach is based on training ANN and RF models using this data, and then making a prediction based on a table of 80 rows to predict potential failures based on the learned data. The last step of the approach is calculating accuracy ratio of the learning models.

The case study shows that both models studied are powerful in predicting failures based on data from 5 different sensors. However, the model based on RF appears to be more effective both to predict failure or no failure and the type of failure. The table 5 shows the accuracy rate for the two studied models.

Table 5. Calculation of the accuracy ratio of the two studied model

<table>
<thead>
<tr>
<th>Failure/no failure</th>
<th>Failure</th>
<th>Type of failure</th>
</tr>
</thead>
<tbody>
<tr>
<td>RF</td>
<td>70</td>
<td>67</td>
</tr>
<tr>
<td>ANN</td>
<td>67</td>
<td>66</td>
</tr>
<tr>
<td>Accuracy ratio</td>
<td>88%</td>
<td>84%</td>
</tr>
</tbody>
</table>

4. Conclusion

Predictive maintenance is a proactive maintenance strategy that uses data analysis techniques to predict when equipment failure is likely to occur. By monitoring equipment in real-time and analyzing historical data, predictive maintenance can identify patterns and predict potential problems before they happen.

This paper presents scientific research about predictive maintenance and its benefits in industrial performance. The study shows also that more than 10 parameters are used in failure prediction. According to this review, parameters of vibration and temperature are utilized in more than 80% in industrial case studies. The presented case study compares in section 3.2 between the models utilized in prediction of failures.
The real challenge involved in this case study is that the implementation of predictive maintenance depends on several factors, such as data reliability, real-time data processing, and other technical challenges. Another challenge is how to offer a simplified predictive maintenance model to small and medium-sized enterprises (SMEs) that do not have technical and financial resources to implement PdM. Further research studies could treat those challenges to propose a new simplified model of PdM.

Declarations

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Data set used in the case study are based on the archive of Machine Learning Center of UCI California, USA based on the publication of Stephan Matzka, School of Engineering - Technology and Life, Hochschule fur Technik und Wirtschaft Berlin, 12459 Berlin, Germany, stephan.matzka@htw-berlin.de.


Competing Interest:

Authors of this paper have no financial interests and have no relevant financial or non-financial interests to disclose.”

Author Contributions:

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Meddaoui Anwar, Hachmoud Adil and Hain Mustapha. The first draft of the manuscript was written by Meddaoui Anwar and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Figures

Figure 1

Evolution of the maintenance function
Figure 2

Architecture of predictive maintenance (Wang, 2021)

Figure 3

The structure of an ANN model