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Predictive Degradation Modelling Using Artificial Inteligence: Milling Machine Case Study

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Abstract

Predictive degradation modelling using artificial intelligence involves employing artificial intelligence techniques to anticipate the deterioration or aging of systems, equipment, or materials over time. This approach is particularly valuable in various industries such as manufacturing, healthcare, energy, and transportation, where the timely prediction of degradation can enable proactive maintenance, reduce downtime, and enhance overall system reliability. In degradation modelling, the first hitting/passage time refers to the moment when degradation stochastic process or degradation random variable reaches a predetermined threshold or specific value for the first time, which is crucial in predicting the remaining useful life and making informed decisions regarding maintenance schedules and asset management strategies. Units that fail before reaching a degradation threshold often indicate premature failures, which is a significant concern in reliability analysis as it suggests that the units did not degrade as expected and failed earlier than anticipated. To address this challenge in this article, the first hitting degradation value is introduced to be modelled through artificial intelligence technics. Furthermore, the milling machine degradation data is used to model the machine status using LSTM model, and the degradation trend is predicted using sequential models to forecast the machine status.

Keywords: degradation modelling, artificial intelligence, long short term memory (LSTM), first hitting/passage time, first hitting degradation value

1. Introduction

In contemporary industries, the application of artificial intelligence (AI) to predict and model the degradation of systems, equipment, or materials has emerged as a crucial aspect of proactive maintenance strategies. Timely and accurate predictive degradation modelling allows for anticipatory measures, facilitating proactive maintenance, minimizing downtime, and elevating overall system reliability (Gorjian et al., 2010). This paradigm shift is particularly significant across diverse sectors including:

- healthcare: which aims to present a comprehensive look at the tools and methods currently in use for detecting and forecasting worsening conditions in patients admitted to hospitals, particularly emphasizing the present and forthcoming contributions of AI in this area (Malycha et al., 2022);
- energy: like degradation prediction of proton exchange membrane fuel cell based on artificial intelligence (Vichard et al., 2020) and battery degradation diagnosis based on AI (Li et al., 2022);
- transportation: like pavement management systems (PMSs) which have a primary role in determining pavement condition monitoring and maintenance strategies (Shtayat et al., 2022);
- engineering: degradation modelling involves predicting the deterioration of a system or component over time. This is crucial in engineering applications to estimate the remaining useful life of assets. AI, particularly machine learning algorithms, can enhance degradation modelling by analysing large datasets to predict when maintenance or replacement is needed, optimizing asset management and reducing

downtime. The combination of degradation modelling and AI can lead to more accurate predictions and cost-effective maintenance strategies (Shahraki et al., 2017);

- manufacturing: modern manufacturing systems are growing more intricate, dynamic, and interconnected. Factory operations encounter intricate nonlinear and stochastic processes due to numerous uncertainties and interconnections. The latest advancements in AI, particularly machine learning, offer significant promise in revolutionizing the manufacturing sector using advanced analytic tools to handle the substantial volumes of manufacturing data, often referred to as Big Data. In contemporary manufacturing, data like images for identifying surface defects and sequences indicating machine wear are demanding progressively sophisticated hierarchical representation, which can break down complexity into smaller components, enabling more efficient data management (Arinez et al., 2020).

Concurrently, smart manufacturing has experienced groundbreaking opportunities in its transition to Industry 4.0 through the implementation of data-driven methods. The pivotal roles of machine learning and deep learning are evident in the development of intelligent systems that cater to descriptive, diagnostic, and predictive analytics, specifically in the realms of machine tools and process health monitoring (Nasir and Sassani, 2021).

In the evolution of Artificial Neural Networks (ANNs), until the 1990s, they were primarily limited to three layers. The breakthrough came in 2009 with the parallelization of ANN training using Graphical Processing Units (GPUs), leading to the development of deep learning models with hundreds of hidden layers. Each neuron in the network transforms incoming data into a distinct output signal, allowing the network to learn complex relationships between inputs and outputs as the depth increases. Convolutional layers, introduced in 1982, form a crucial part of neural networks, especially in image processing. Convolutional Neural Networks (CNNs) leverage these layers to detect features like edges and colors in lower layers, progressing to interpret more complex features like faces and text in higher layers. Furthermore, Recurrent Neural Networks (RNNs) process sequential data, while Long Short-Term Memory (LSTM) networks address the gradient instability problem in RNNs, making them suitable for handling temporal data (Nash et al., 2018).

In the realm of predictive maintenance, numerous studies have explored the application of AI techniques, particularly LSTM models, for degradation modelling (Carvalho et al., 2019; Çınar et al., 2020; Wen et al., 2022). Notable contributions have been made in various domains, emphasizing the potential of these models in providing accurate predictions. This paper builds upon these foundations, focusing specifically on milling machine dataset, and introduces novel methodologies for predicting degradation trends using sequential models.

In degradation modelling, the "first passage time (FPT)" or "first hitting time (FHT)" refers to the time it takes for a system's degradation process to cross a specified threshold level for the first time. This concept is important in predicting the remaining useful life (RUL) of assets and understanding the progression of degradation over time. By analysing the FPT in degradation modelling, engineers can better estimate when maintenance or replacement actions may be required to ensure the continued functioning of the system. However, systems that fail before reaching a degradation threshold often indicate premature failures, which can be a significant concern in reliability analysis as it suggests that the system did not degrade as expected and failed earlier than anticipated. Understanding the reasons behind these premature failures is crucial for improving the reliability and performance of systems and components. Analysing such cases can help identify weaknesses in the design, manufacturing process, or operating conditions that lead to early failures.

The primary objective of this paper is to harness the power of AI, specifically utilizing LSTM models, to predict and model the degradation of milling machines. By doing so, we aim to provide an effective tool for industry professionals to foresee the deterioration trends in machine performance. This proactive approach will empower organizations to conduct timely maintenance interventions, thereby increasing the longevity and reliability of milling machines. The motivation behind this research stems from the imperative need for advanced predictive degradation models in industries where the efficient operation of machinery is paramount. The timely prediction of degradation in milling machines is essential for ensuring optimal performance, preventing unexpected breakdowns, and subsequently reducing operational disruptions.

The contribution of the paper lies in introducing First Hitting Degradation Value (FHDV) and its distribution. This paper attempts to apply LSTM models to milling machine degradation data, showcasing their efficacy in accurately modeling machine status. Additionally, we extend this by employing sequential models to forecast the degradation trends, offering valuable insights into the future performance of milling machines. Through these contributions, we aim to advance the field of predictive maintenance and offer practical solutions for enhancing operational efficiency in manufacturing contexts.

The rest of this paper is organized as follows. Section 2 presents the methodology of FHDV. Section 3 describes the milling machine case study. A numerical and performance analysis is illustrated in section 4. Lastly, concluding remarks and outlooks for future work are presented in Section 5.

2. Model description

In degradation modelling, the first time that the degradation level crosses a failure threshold is associated to the failure time (Kahle et al., 2016; Shahraki et al., 2017). In the framework of degradation modelling with stochastic processes the failure time is often associated to the first hitting time (FHT) of the failure threshold of the stochastic process. The exact formula for the first hitting time depends on the specific degradation model or stochastic process used to describe the system's deterioration over time. One common approach involves the use of a stochastic differential equation (SDE) or a continuous-time Markov process (Galván-Núñez and Attoh-Okine, 2018).

Let $X = \{X_t\}_{t\geq 0}$ be a time series representing the degradation level of a system and a be the failure threshold. Then the failure time (first hitting time variable) associated to X is defined as follows:

$$T = \inf\{t > 0: X_t \geq a\},$$

where inf denotes the infimum, and the set $\{t > 0: X_t \geq a\}$ represents the collection of times when the degradation level surpasses a predefined threshold "a".
The schematic of FHT distribution is depicted in Figure 1.

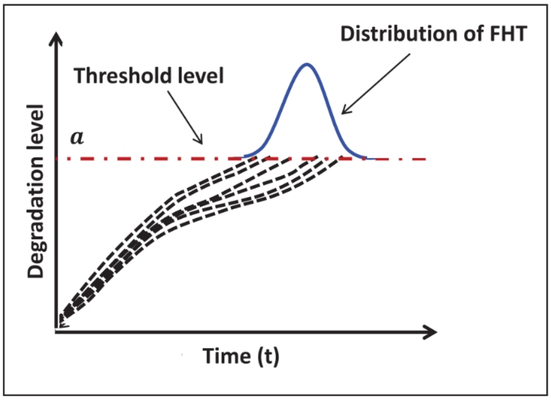

Fig. 1. FHT distribution.

However, the system might fail before reaching degradation threshold, when there are multiple causes to failure, especially, in case of competing risks. Competing risks refer to situations where an individual or system can fail due to multiple mutually exclusive causes. In reliability analysis, this often involves considering different types of failure modes or events that may lead to the end of the system lifetime (Austin et al., 2016). To address these types of failure which happen before reaching predetermined degradation threshold the first hitting degradation value is introduced as follows.

Let $S = \{S_t\}_{t\geq 0}$ be the health indicator of the system which is the aggregation of the different degradation causes and failures. For instance in a series system, if every component is subject to its own degradation the failure occurs when at least one of the degradation indicators reaches the failure level. In this framework, the entire system fails while other components degradation level has not reached their failure threshold. Likewise the FHT, the first hitting degradation value (FHDV) could be introduced as follows:

$$D_t = inf\{X_t: S_t = Failure\},$$

where S_t is the system status at time t, and D_t represents the first degradation value at which the system status is "Failure". Predicting the FHDV involves modelling the degradation process and estimating the degradation level at which a certain probability of failure is reached. This can be done using statistical models, reliability analysis, or machine learning approaches, depending on the complexity and characteristics of the degradation process.

The FHDV distribution is depicted in Figure 2. As it is visible some failures happened before reaching the predetermined degradation threshold, which is common in daily life. This paper is aimed at predicting the probability of different status of S_t based on the observed degradation values.

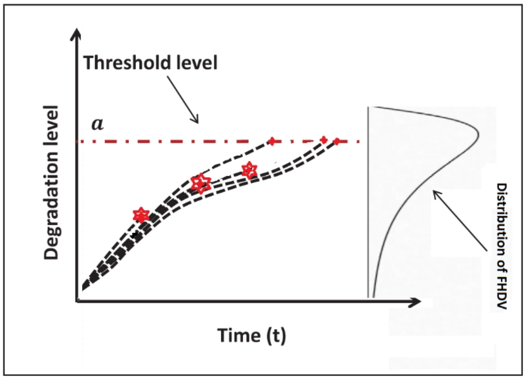

Fig. 2. FHDV distribution.

3. Data Description

This paper considers the milling machine dataset, which is a valuable resource for researchers and practitioners interested in predictive maintenance and machine learning applications in industrial settings. This dataset, contributed by (Matzka, 2020), is part of the AI4I 2020 Predictive Maintenance Competition. The dataset comprises a comprehensive collection of sensor data obtained from an industrial milling machine. It includes various operational parameters and sensor readings, providing a rich source of information for developing and testing predictive maintenance algorithms. Predictive maintenance is a crucial aspect of industrial operations, aiming to anticipate equipment failures and schedule maintenance activities proactively, thus minimizing downtime and optimizing productivity. This dataset includes unique identifier, product ID, product type, air and process temperature in Kelvin (K), rotational speed (rpm), torque (Nm) and tool wear (min). A schematic of a milling machine is depicted in Figure 3.

Fig. 3. Milling machine scheme.

In the mentioned dataset, the milling machine might fail because of five independent competing risks, including:

1. Tool wear failure (TWF): the tool will be fail at a randomly selected tool wear time between 200 - 240 mins (120 times in our dataset), where its first hitting time is introduced as follows:

   $T_{TWF} = inf\{t > 0: tool\ wear > 200\}.$

2. Heat dissipation failure (HDF): heat dissipation causes a process failure, if the difference between air and process temperature is below 8.6 K and the tools rotational speed is below 1380 rpm. This is the case for 115 data points, where its first hitting time is introduced as follows:

$T_{HDF} = inf\{t > 0: |air\ temp. - process\ temp.| < 8.6K\ \&\ tool\ rotational\ speed < 1380rpm\}.$

3. Power failure (PWF): the product of torque and rotational speed (in rad/s) equals the power required for the process. If this power is below 3500 W or above 9000 W, the process fails, which is the case 95 times in our dataset, where its first hitting time is introduced as follows:

   $T_{PWF} = inf\{t > 0: power < 3500W\ or > 9000W\}.$

4. Overstrain failure (OSF): if the product of tool wear and torque exceeds 11000 (min*Nm) the process fails due to overstrain. This is true for 98 datapoints, where its first hitting time is introduced as follows:

   $T_{OSF} = inf\{t > 0: tool\ wear * torque > 11000\}.$

5. Random failures (RNF): each process has a chance of 0.1 % to fail regardless of its process parameters. This is the case for only 5 datapoints, less than could be expected for 10,000 datapoints in our dataset, where its first hitting time is introduced as follows:

   $T_{RNF} = inf\{t > 0: S(t) = Failure\}.$

Figure 4 demonstrates the distribution of different failure modes by a histogram plot on its left side (a) and a heatmap involving correlation between different failure modes and also the final machine status on its right side (b). The heatmap illustrates the relationship between various types of failure modes (TWF, HDF, PWF, OSF, RNF) and instances of machine failure. Each cell on the heatmap shows the correlation coefficient between two factors, varying from -1 to 1. A positive coefficient signifies a direct relationship, whereas a negative one implies an inverse connection. The heatmap indicates that specific failure modes are more strongly linked to machine failures. Recognizing these associations is essential for pinpointing the primary contributors to machine failures in manufacturing operations. Furthermore, it shows that the correlation between different pairs of failure modes is significantly close to zero, which enrich the hypothesis of independent failure modes.

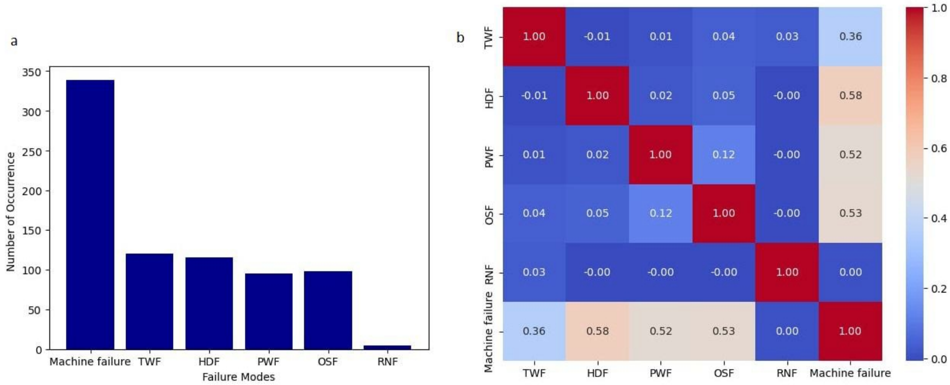

Fig. 4. (a) distribution of different failure modes; (b) correlation between different failure modes.

Finally, based on the different hitting times associated to different failure modes the FHT of the machine is given by,

$$T_s = \min(T_{TWF}, T_{HDF}, T_{PWF}, T_{OSF}, T_{RNF}).$$

This paper attempts to consider the final system status regardless of its failure type and is aimed at predicting it only by FHDVs. Those are going to be fed to the model as inputs and the machine status is going to be predicted.

4. Application and performance analysis

In this section, the machine status is attempted to be predicted using a sequential model like LSTM to consider the sequential dependencies between degradation values.

The “Tool wear (min)” variable in the milling machine dataset represents the time the current tool has been in use (tool wear) in minutes. Without loss of generality, this variable is considered as the degradation value, and based on this variable, the machine status (failure or not) is going to be predicted. Furthermore, the density function of FHDVs is depicted in Figure 5.

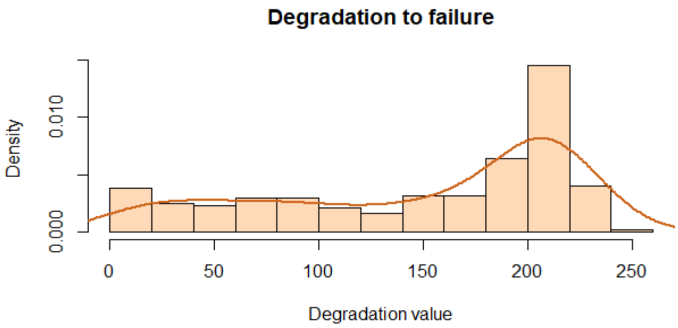

Fig. 5. Density function of degradation values at system failure time.

Based on the depicted boxplot in Figure 6, the machine status is an imbalanced variable. Therefore, the synthetic minority oversampling technic (SMOTE) is considered to address this issue (Chawla et al., 2002).

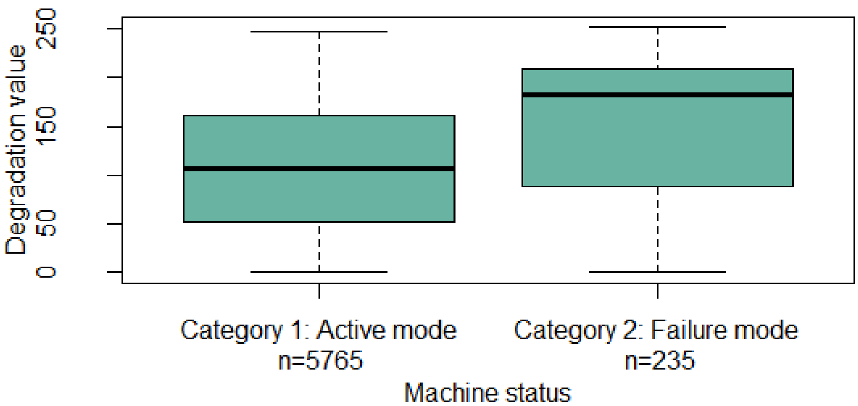

Fig. 6. Machine status boxplot.

After balancing data using SMOTE, the LSTM algorithm is used to predict the machine status based on the degradation values, considering sequential dependencies between them. After training the LSTM algorithm on 80 percent of balanced data, the history plot considering binary cross entropy loss function, accuracy, precision, recall and F1 score is depicted in Figure 7.

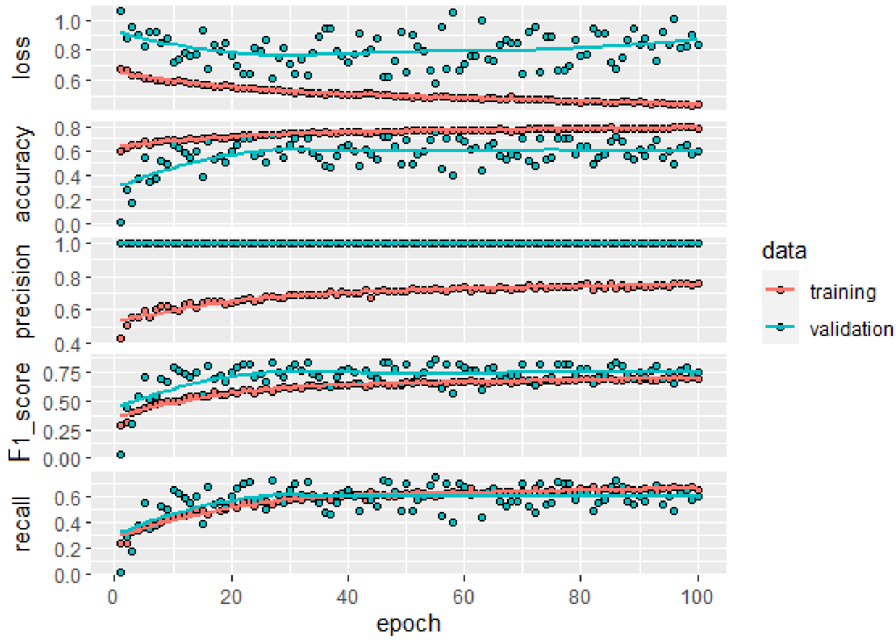

Fig. 7. Training history plot for LSTM algorithm.

Table 1 shows the results of applying the trained model on the rest of data (20 percent) as test data.

Table 1. Different metrics for LSTM model evaluation.

Metrics	Train	Test
Accuracy	0.76	0.80
Precision	0.71	0.96
Recall	0.90	0.83
F1 Score	0.79	0.89

It is visible that the LSTM model, considering the sequential dependency between degradation values, could predict the machine status in a significant manner. Based on machine status predictions, predictive maintenance could be applied to prevent the sudden failures.

It is worth noting that the future trend of the degradation path could be estimated and afterwards the machine status could be forecasted based on the predicted degradation values.

5. Conclusions

In conclusion, this study delved into the realm of degradation modelling, particularly focusing on the first hitting degradation values within the context of stochastic processes and reliability analysis. Leveraging the AI4I predictive maintenance dataset, the FHDVs have been considered to predict the final status of the milling machine through a sequential AI model, called LSTM. By employing the LSTM model, we successfully predicted machine status, considering sequential dependencies among degradation values.

For future works, the FHDVs could be considered in the presence of competing risks, when there are multiple causes to failure. The FHDVs could be surveyed through some appropriate stochastic processes. Also, it would be valuable to explore the extension of the proposed approach to diverse industrial datasets, allowing for a broader validation of its effectiveness across various manufacturing contexts. Further research might focus on optimizing the LSTM architecture parameters and exploring alternative advanced deep learning models to enhance prediction capabilities. The integration of real-time data streams and continuous model refinement could be considered to adapt the predictive maintenance system dynamically. Lastly, collaborating with industry partners to implement and assess the proposed methodology in real-world manufacturing settings would offer valuable feedback and practical insights.

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