Artificial Neural Network Model for Predicting Excavator Downtime

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Keywords: Excavator Downtime, Artificial Neural Network, Pareto Analysis.

Abstract: Previous research shows the significance of maintenance in enhancing performance levels and reducing system costs of equipment. This paper aims to develop a quantitative model for predicting the failure rate of excavators using artificial neural networks (ANN). As an input to the ANN, the duration times of 590 excavator downtimes measured over 198 days at the mining site in Serbia were used to obtain a classification of failures longer than an hour based on the previous 14 days, in aim to prevent potential indirect financial losses which could be over 15000€/hour. A Pareto analysis of the observed data was also performed and showed the technological type of downtime as the most frequent. The results show that the ANN modeling is suitable for mapping the non-linear relationship between excavation activities and the failure rates of excavators. The results showed that the proposed ANN model provides an accurate estimating tool for the early planning stage to predict failure rates of excavators. Future research avenue proposal is directed at monitoring and forecasting the exact duration of excavator downtime in real-time.

1 INTRODUCTION

Earthwork operations, which require the use of heavy construction equipment for material placement, transportation, excavation, and disposal, are crucial both to infrastructure and building projects (Jassim et al., 2017). The situation is similar in the mining sector (Velikanov et al., 2017).

Heavy construction and mining equipment also has huge impact on the environmental e.g. air and water pollution (Jung et al., 2009; Li et al., 2023; Waluś et al., 2018). As society and science and technology advance, the problem of energy scarcity and severe environmental contamination has gained more attention (Liu et al., 2022). Also, heavy machinery operation activities possess high risk (Duarte et al., 2021).

When it comes to efficient usage, maintenance strategies of heavy machinery have to be examined. As much as possible continuous usage of mining machinery is necessary to reap the full benefits of mechanization (Spasojević Brkić et al., 2023). Heavy machinery maintenance is a specialized field with unique requirements. Not only is it critical to select the right machine for the job, but it's also critical to maintain and consider the necessary supplies to keep these machines running. A proper maintenance program has the potential to improve the performance and lifespan of machinery. However, an unplanned failure still accounts for about 46% of significant equipment repairs in the United States (Lazarević et al., 2018).

Accordingly, efficient usage of heavy machinery equipment and failure minimization is crucial. Special emphasis should be put on excavators (D. Edwards et al., 2019; D. J. Edwards and Holt, 2008; Lingard et al., 2013; Spasojević Brkić et al., 2023).

This paper aims to predict extended periods of excavator downtimes by analysing past instances of downtime. The paper's structure comprises the subsequent sections: an overview of prior research, a comprehensive explanation of the methodology employed, the research outcomes, specifically, the results of ANN training and Pareto analysis, and a final analysis of the obtained results along with a suggestion for future research.

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Brkić, V., Mihajlović, I., Perišić, M. and Janev, N.
Artificial Neural Network Model for Predicting Excavator Downtime.
DOI: 10.5220/0012792100003764

In *Proceedings of the 21st International Conference on Smart Business Technologies (ICSBT 2024)*, pages 74-79
ISBN: 978-989-758-710-8; ISSN: 2184-772X

2 PREVIOUS RESEARCH

According to Gransberg et al. (2006), for proper maintenance of heavy machinery, the data from its history card has to be collected. Previous studies reveal that early detection of equipment faults is a very beneficial way to increase the reliability of equipment such as excavators availability (Rosaler et al., 2007). This is because it reduces maintenance costs, increases plant and personnel safety, lowers insurance rates, minimizes downtime, and increases availability (Rosaler et al., 2007). Numerous efforts have been made to date to comprehend the underlying causes of heavy machinery injury accidents; however, the studies that are now accessible seldom analyse downtime types and frequency and typically do not collect data in a systematic manner (Spasojević Brkić et al., 2023).

It appears that there is a significant amount of research available on excavators operations, but there is limited data on downtime and its acquisition procedures. As a result, risk calculation tends to be more qualitative, despite the expectation of high risks. In a recent study by Spasojević-Brkić et al., (2022), an analysis was conducted on the downtime of bulldozers. The authors discovered that certain maintenance tasks, such as heating repair, oil change, bulldozer cleaning, screw replacement, tonsil adjustment, filter replacement, part repairment, hose replacement, and bearing replacement, were the most common causes of failures from a risk perspective.

On the other hand, many authors rely on quantitative data and various types of Failure Modes, Effects, and Analysis (FMEA) for their research (Karasan et al., 2018; Kumar and Kumar, 2016; Misita et al., 2021; Zeng et al., 2020). Accordingly, a more precise method of analysing safety and critical effects has emerged, which involves the use of Pythagorean fuzzy sets (Karasan et al., 2018). This method stands out for its utilisation of functional analysis methods FMEA and Failure Modes, Effects, and Criticality Analysis (FMECA) to minimise maintenance expenses for the excavator and enhance monitoring and maintenance procedures (Kumar and Kumar, 2016). Zeng et al. (2020) conducted reliability and FMEA analyses using excavator failure data. The results of these analyses were used to design appropriate maintenance protocols.

In a study conducted by Misita et al. (2021), the researchers applied the Fuzzy FMEA method to analyse the downtime of hydraulic excavators over a year. The objective was to identify the primary factors contributing to downtime, which is crucial for risk assessment and management.

Chronologically, in the late sixties, Birnbaum (1969) recognized the significance of classical binary measures for assessing the importance of components. He categorized these measures into three distinct categories. In the late 1970s, a new diagram called the binary decision diagram was developed. It was known for its ease of implementation and simplicity in calculations (Akers, 1978). The practical application of this methodology is demonstrated by the studies conducted by Ibáñez-Llano et al. (2010), Xing and Levitin, (2013), Zang et al. (1999). In addition to Akers, (1978), Barlow and Wu, (1978) also define the system state function for coherent systems with multiple states.

In a more recent study, Lisnianski et al. (2010) explored the complexities of systems with varying performance levels and multiple failure modes. They provided a comprehensive overview of the tools and methods used in the field of reliability assessment, optimisation, and implementation (Lisnianski et al., 2010).

Guoping et al. (2013) combined Failure Tree analysis and ANN in order to establish the fault diagnosis of the excavator's hydraulic system. Andraș et al. (2021) use computer simulation in order to predict material failure time for a bucket wheel excavator boom.

Recent advancements in research have led to the development of a sophisticated policy that efficiently allocates resources to ensure the maintenance of critical systems Zhang (2020). There have been proposed two types of measures that are crucial in prioritising critical parts in the maintenance schedule Ahmed and Liu (2019). Several models have been developed to analyse the reliability of systems and their components across different states, ranging from optimal functioning to complete failure (Dao and Zuo, 2016).

Pantelic et al. (2020) proposed corrective actions for reducing risk levels of the most critical mechanical and electrical failure modes of bucket wheel excavators by applying FMECA.

In a recent study by Liu et al. (2022), the authors propose a planned maintenance interval for key components of the hydraulic excavator, considering the performance and maintenance costs. They also suggest the implementation of a reliability-based system to enhance the overall reliability of the excavator.

Besides listed publications, it can still be stated that previous research is scarce and accordingly it is not easy to predict failure rates. Previous research agrees on the fact that more research work should be done to explore better excavator states and find the effects to structural changes, product performance, and reliability improvement in future studies. This paper explores the potential of artificial intelligence usage in predicting and classifying data to determine the duration of downtime for excavators and prevent it.

3 METHODOLOGY

Before effectively processing the data, a thorough examination of its structure is highly important. In this study, Pareto analysis was employed to distinguish the significant minority from the insignificant majority, based on the utilisation of the Pareto principle, also referred to as the 80/20 rule (Pyzdek, 2021).

Subsequently, an ANN was developed on the structured data. The performance of the network in the frame of the ANN is significantly impacted by the selection of adequate activation functions (Parhi and Nowak, 2020). The identification of the optimum activation function in ANN is a significant concern due to its direct correlation with the level of success achieved (Ertuğrul, 2018). This paper explores the utilisation of an ANN to classify excavator downtimes. We utilised two different activation functions: the Refilcted Linear Unit (ReLU) and sigmoid. One reason why ReLU is considered very efficient is because it activates a specific number of neurons at a time, rather than all of them simultaneously (Sharma et al., (2020). On the other hand, given that it is non-linear, the sigmoid function is the most frequently utilised activation function. The sigmoid function is responsible for transforming values within a range of 0 to 1 (Sharma et al., 2020). It can be described as (Sharma et al., 2020):

$$f(x) = \frac{1}{e^{-x}} \tag{1}$$

The primary focus of this paper is to forecast instances of excavator downtimes. Initially, the main causes of downtimes were identified using Pareto analysis. Subsequently, an artificial neural network was developed to accurately predict the occurrence of downtime.

The research involved 10 excavators, all of which experienced periods of downtime. The data set used did not contain any missing data or outliers. The performance evaluation metric in this research is accuracy (Zhou et al, 2019). ANN was trained using MATLAB 2019b.

4 RESULTS

The utilised dataset includes a total of 590 unplanned excavator downtimes that have been systematically gathered over a period of 198 days at the mining site in Serbia. These downtimes have been classified into six distinct categories, namely: technological, mechanical, electrical, third-party impact, organisational, and meteorological impact, as in Spasojevic Brkic et al. (2023). Table 1 shows the percentage frequency of all types of downtime utilised in this study.

Table 1: Dataset downtime types.

Downtime type	Number of downtimes	%
Technological	510	86,44
Mechanical	68	11,53
Electrical	6	1,02
Third party impact	3	0,51
Organisational	2	0,34
Meteorological impact	1	0,17

Based on the data collected, a Pareto analysis of the downtime was conducted and is presented in Figure 1.

Following Pareto analysis, the aforementioned dataset was utilised to train ANN model. The ANN was trained to classify days with downtime exceeding one hour, due to the fact that one hour of downtime could generate indirect financial losses over 15000€ (Pantelic et al., 2020). Roughly 20% of days in the training dataset are classified as days with downtime.

The selected variables for classification were based on the duration of downtime observed in the preceding 14 days. Figure 2 illustrates the architecture of the ANN that was used for data classification. The network is composed of one input layer with 14 input streams (one for every 14 days of data acquisition) and two hidden layers, with the first layer containing 40 neurons and the second layer containing 20 neurons. The activation functions used in the first and second hidden layers are ReLU and sigmoid, respectively. The output layer consists of a single neuron that utilises a linear activation function.

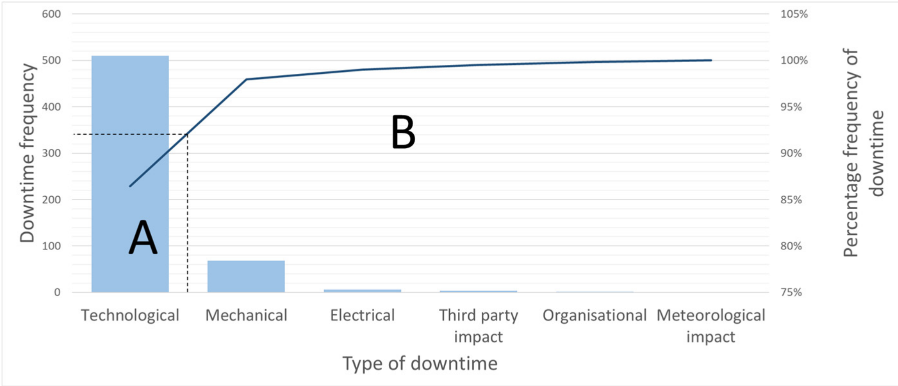

Figure 1: Pareto analysis of the downtime

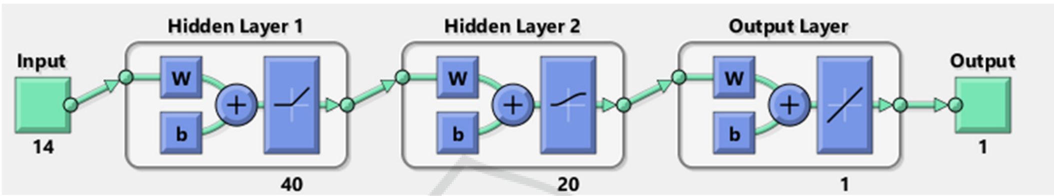

Figure 2: Architecture ANN.

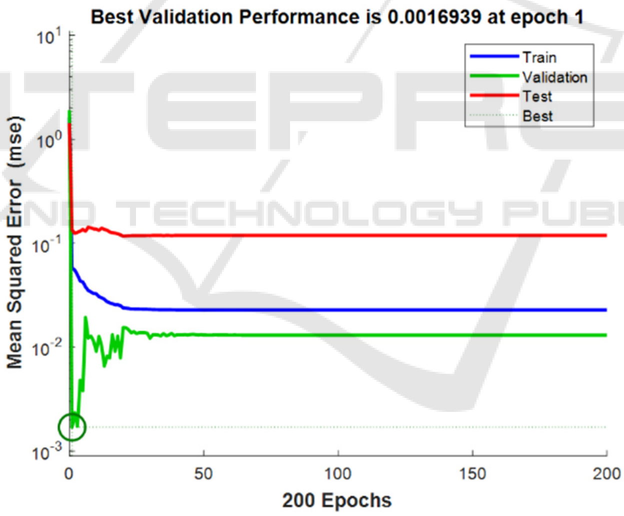

Figure 3: ANN performances.

Figure 3 shows convergence curves obtained during training, testing, and validation of the network, obtained on corresponding datasets. As it can be seen all the curves converge under the 1·10-1 value.

The classification accuracy of the network is shown in Table 2. In comparison to a previous study by Zhou et al (2019), this paper presents an improved performance of the proposed ANN. The accuracy achieved is 85.5%, surpassing the accuracies of 72.14%, 80.12%, and 87.64% obtained in three datasets in the previous study.

Table 2: Classification accuracy.

Train accuracy	Test accuracy
0.9343	0.8750

5 CONCLUSIONS

The present study analyses the occurrences of excavator stoppages over 198 days. According to the analysis, the stoppages that occur most frequently are of technological origin and fall under the category identified as zone A, which has a significant impact, accounting for 86.44% of the total number of stoppages in the Pareto diagram. Zone B encompasses the frequency of all other failures, which is significantly lower, forming only 13.56% of the total number of downtimes. Overall, the Pareto analysis not only provided a clear picture of the downtime landscape but also directly influenced the development of the ANN model by guiding feature selection and focusing model training on the most significant downtime types. This strategic integration of analytical insights into model development is crucial for enhancing predictive accuracy and operational efficiency. Further, the training of an ANN was performed to accurately predict downtime lasting longer than hour. The network's predictions are based on an analysis of downtimes that occurred within the preceding 14-day period. Input was collected from data recorded over a period of 198 days. The training accuracy was 93.43%, the test accuracy was 87.50%, and the validation accuracy was 100%. These results suggest that the constructed network performs exceptionally well, with a very high level of accuracy. Furthermore, the Best Validation Performance is 0.0016939, which suggests an exceptionally small error value. To enhance the content of this research, it would be useful to gather additional data. A potential avenue for future investigation involves the real-time monitoring and prediction of excavator failures, including the ability to accurately forecast the duration of such failures. The proposal for future research in the field of excavator maintenance is highly relevant and has the potential to bring about significant advancements. The focus of this research is on monitoring and predicting the precise duration of excavator downtime in real-time, which could have far-reaching implications. Ultimately, the article offers a strong basis for constructing a predictive model for excavator failure rates through the utilization of artificial neural networks.

ACKNOWLEDGEMENTS

This research was supported by the Science Fund of the Republic of Serbia, #GRANT No. 5151, Support Systems for Smart, Ergonomic and Sustainable Mining Machinery Workplaces – SmartMiner and the Ministry of Science, Technological Development and Innovation of the RS according to the Agreement on financing the scientific research work of teaching staff at accredited higher education institutions in 2024, no. 451-03-65/2024-03/200105 of February 5, 2024. years.

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