JOURNAL OF PRODUCTION ENGINEERING VOL. 27, NO. 2 (2024)
DOI: 10.24867/JPE-2024-02-001

Original research article

Journal of Production Engineering

https://jpe.ftn.uns.ac.rs/index.php/jpe
ISSN: 1821-4932 (print), ISSN: 2956-2252 (online)

Development of Artificial Neural Network models for vibration classification in machining process on Brownfield CNC machining center

Pavle Stepanić [a] 0000-0002-6992-0900, **Nedeljko Dučić** [b*] 0000-0001-7351-5898

Nebojša Stanković [b] 0000-0002-1770-9601

[a] *Research and Development Institute Lola L.t.d., Kneza Višeslava, 70A, 11030, Belgrade, Serbia*
[b] *Faculty of Technical Sciences Čačak, University of Kragujevac, Svetog Save 65., 32102, Čačak, Serbia*

ABSTRACT

This study presents the development of artificial neural network models capable of classifying the type of vibration during the step drilling process. Classification refers to recognizing the nature of vibrations during the machining process and categorizing them into two classes: safe and harmful. The data used in the study were obtained from Bosch and collected during the aforementioned machining process on a four-axis horizontal CNC machining center. Several different architectures of artificial neural networks have been developed, and their performance (with a classification success rate of around 96%) has shown that they can be applied as a highly useful tool in predictive maintenance.

ARTICLE INFO

Received: 1 July 2024
Revised: 5 September 2024
Accepted: 12 September 2024

KEYWORDS:
Predictive maintenance;
Vibration;
Step drilling;
Artificial neural networks.

**Corresponding author's.e-mail:*
nedeljko.ducic@ftn.kg.ac.rs

1. INTRODUCTION

Companies that follow the trends of smart production base the success of their business on recording, collecting and processing data in all stages of production, which is the meaning of Industry 4.0. The concept of Industry 4.0, which includes disciplines such as: Internet of Things (IoT), Internet of Services (IoS), Artificial intelligence (AI), and data mining (DM), enables working with big data and exploiting it with the aim of forming an adequate maintenance strategy. K. Wang et al. classify maintenance strategies into three groups: corrective maintenance, preventive maintenance, and predictive maintenance [1]. Corrective maintenance is undertaken to pinpoint and address the root causes of failures in a malfunctioning system. It emphasizes identifying failures based on their manifestations, which may include multiple symptoms. Preventive maintenance refers to scheduled maintenance tasks and inspections performed on equipment or systems to prevent potential issues, ensure optimal performance, and extend their operational lifespan. This approach aims to detect and address minor problems before they escalate into more significant failures or downtime. Predictive maintenance is a proactive approach that utilizes data analysis and machine learning techniques to predict equipment failures and schedule maintenance tasks efficiently. By leveraging advanced technologies such as sensor data and analytical methods, predictive maintenance aims to optimize maintenance processes, prevent failures, and reduce unnecessary maintenance costs [2-4]. This strategy has gained significant traction within the Industry 4.0 framework, enabling effective monitoring of industrial systems to enhance operational efficiency and reduce downtime [5,6]. Machine learning algorithms play a crucial role in predictive maintenance by enabling real-time assessment of equipment health, thereby enhancing safety, reducing hazards, and improving overall equipment performance [7]. These algorithms analyze operating and faulty condition data to predict future machine conditions, facilitating informed decision-making regarding maintenance actions [8,9]. Moreover, the application of machine learning and deep learning techniques in predictive maintenance has been instrumental in addressing key research areas such as failure prediction, remaining useful life (RUL), and root cause analyses (RCA) [10]. Predictive maintenance not only optimizes maintenance schedules but also contributes to sustainable manufacturing systems by minimizing failures that lead to production losses and energy wastage [5,6]. By integrating information from various machines and manufacturing systems, IoT platforms provide crucial support for predictive maintenance, enabling comprehensive data

Published by the University of Novi Sad, Faculty of Technical Sciences, Novi Sad, Serbia.

analysis and decision-making [11]. Furthermore, the implementation of automatic forecasting models based on machine learning approaches enhances the recognition of machine failures and aids in the development of algorithms for preventive and descriptive maintenance [12]. Predictive maintenance in CNC machines technology has become a crucial aspect in the era of Industry 4.0, where advanced technologies like artificial intelligence and machine learning are leveraged to enhance efficiency and reduce downtime [13]. Utilizing machine learning techniques for remaining useful life prediction, such as neural networks, has shown promising results in improving maintenance strategies [14]. For instance, the reliability prediction of CNC machine tool spindles has been enhanced through optimized cascade feedforward neural networks, leading to more accurate predictions and improved reliability [15]. Moreover, fault detection in CNC machinery has been significantly improved through the integration of deep learning and genetic algorithms, enabling early fault detection and prevention of costly downtime and safety risks [16]. Additionally, fault diagnosis of CNC machine tools has been enhanced by optimizing neural networks, which can effectively detect faults based on differences between system output and neural network output [17]. Furthermore, the application of artificial neural networks in predicting CNC machine health has been highlighted as a vital component of condition-based maintenance to prevent malfunctions proactively [18]. Additionally, the prediction of thermal errors in CNC machine tools using artificial neural networks has been proposed as a method to improve machining accuracy by compensating for thermal errors effectively [19]. Predictive maintenance, driven by data-driven approaches and machine learning algorithms, represents the future of maintenance strategies in various industries. By harnessing the power of advanced technologies, organizations can proactively manage their equipment, optimize maintenance processes, and ensure operational efficiency. The integration of advanced technologies like neural networks and machine learning has revolutionized predictive maintenance in CNC machines, enabling more accurate predictions, early fault detection, and proactive maintenance strategies to enhance reliability and efficiency in manufacturing processes.

The motivation behind this research stems from the critical importance of predictive maintenance in CNC machine technologies. Specifically, the focus is on developing artificial neural network models for classifying vibrations during the machining process. These models aim to significantly enhance the predictive maintenance of CNC machining systems by accurately classifying vibration data as either safe or potentially detrimental to the machining process.

2. METHODOLOGY

The primary aim of this research is to develop artificial neural network (ANN) models for classifying vibrations occurring on the spindle housing during the step drilling process. Step drilling is a crucial process in various industries, especially in applications like drilling through printed wiring boards (PWBs) and composite materials. Step drilling involves drilling through holes using several cutting feeds, which is essential for preventing micro-drills from breaking [20]. Research has shown that employing a rapid-feed step-drilling cycle with appropriate steps and feed rates can enhance hole quality and processing efficiency compared to conventional non-step drilling methods [21]. The dataset used for model development originates from the Bosch company database, comprising data collected during the step drilling of an aluminum workpiece on a four-axis horizontal CNC machining center [22]. The process parameters included were: Spindle speed=15000rpm and Feed=100mm/min. The inputs to the ANN models are acceleration values for each of the three axes (X, Y, and Z) separately. The output indicates membership in one of two classes: safe vibrations and harmful vibrations. These outputs are determined based on the database used and information about the dimensional accuracy of the machined parts. Vibrations that caused dimensional inaccuracies in the parts are classified as harmful, while vibrations that did not affect the dimensional accuracy of the part are classified as safe in this specific case. Data acquisition was achieved indirectly by gathering accelerometer data from Bosch CISS sensors installed on the rear end of the spindle housing (Figure 1).

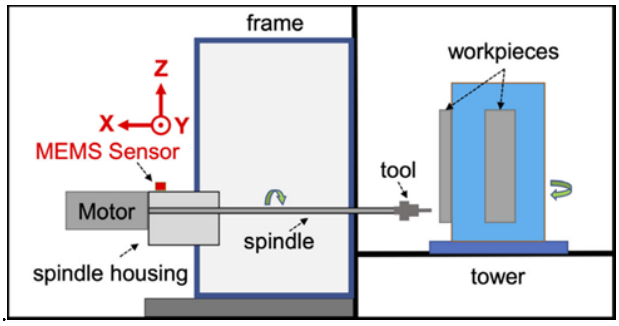

Fig. 1 *Schematic sketch of the experimental setup: 4-axis machining center with mounted sensor [22].*

The rear location remains unaffected by extreme machining conditions such as coolant and material chips, making it feasible to retrofit new sensors onto existing machines ('brownfield machines'). The sensor consistently maintains its position relative to the tool center point, with its three accelerometer axes aligned with the machine's linear motion axis. Using the tri-axial CISS sensor, acceleration data is collected with a sampling rate of 2 kHz. The total number of datasets used is 175.111 samples. Table 1 displays several datasets belonging to the defined classes.

Table 1 – *Dataset (separated samples).*

Acc X, Y and Z axis (mm/s^2)			Safe vibration	Harmful vibration
70	93	-1098	1	0
0	70	-1139	1	0
579	396	-1729	0	1
107	124	-2490	0	1
70	-107	-1059	1	0
…	…	…	…	…

3. ARTIFICIAL NEURAL NETWORK MODEL FOR CLASSIFICATION

To optimize the process parameters and ensure high-quality workpieces, neural networks can be employed. Neural networks have been utilized in various fields for prediction, classification, and data denoising [23]. Specifically, in the context of machining operations like step drilling, neural networks can be trained using frequency spectra reflecting tool and workpiece oscillations to detect manufacturing defects [24]. Process parameters in drilling operations, such as the selection of drilling fluids, play a crucial role in the efficiency and effectiveness of the process. Automated tools utilizing geometric parameters have been developed to predict drilling fluid performance with high accuracy, contributing to the automation of drilling operations [25].

Additionally, noise reduction techniques based on neural networks have been proposed for machining processes, indicating the potential for enhancing the quality of workpieces by reducing unwanted noise during operations [26]. The application of neural networks in predicting machining deviations, such as in gear autonomous machining, demonstrates the capability of these models to improve detection accuracy and operational speed, leading to better quality outcomes in the production of workpieces [27]. Furthermore, neural networks have been used in predicting rotor machining errors, showcasing their nonlinear fitting ability and potential for addressing complex machining challenges [28].

In conclusion, the integration of neural networks in step drilling operations can significantly impact the process parameters and the quality of workpieces. By leveraging neural networks for tasks such as defect detection, fluid selection, noise reduction, and deviation prediction, manufacturers can enhance the efficiency, accuracy, and overall quality of their machining operations.

In this research, several feedforward artificial neural network models were created with varying numbers of hidden layers and neurons in them. Additionally, different training algorithms for artificial neural networks were employed. A sigmoidal activation function was used in the hidden layers of all neural network architectures. Table 2 displays the best-performing artificial neural network models along with information about their basic parameters. All the mentioned Artificial Neural Network (ANN) architectures demonstrated considerable potential in tackling the classification problem, with each showing comparable performance in terms of classification accuracy and success rates. Below, we present a detailed analysis of one specific ANN model using two key evaluation metrics: the Confusion Matrix and the Receiver Operating Characteristic (ROC) curve.

In particular, this ANN model, trained using the Levenberg-Marquardt algorithm, incorporates two hidden layers, each consisting of 12 neurons. The model successfully achieved a Mean Squared Error (MSE) of 0.027, indicating high accuracy in its predictions (as illustrated in Figure 2).

Table 2 - *Developed models of artificial neural networks and their performance.*

Number of hidden layers	Number of neurons in hidden layers	Training algorithm	Performance: Mean squared error (MSE)/Cross Entropy (CE)
1	12	Bayesian Regularization	0.027 (MSE)
1	18	Levenberg-Marquardt	0.028 (MSE)
1	36	Gradient Descent with Momentum	0.11 (CE)
1	48	Scaled Conjugate Gradient	0.046 (CE)
2	24, 12	Bayesian Regularization	0.026 (MSE)
2	12,12	Levenberg-Marquardt	0.027 (MSE)
2	12,12	Gradient Descent with Momentum	0.09 (CE)
2	12,6	Scaled Conjugate Gradient	0.045 (CE)

This low MSE highlights the model's ability to minimize prediction errors, making it a robust tool for solving complex classification tasks.

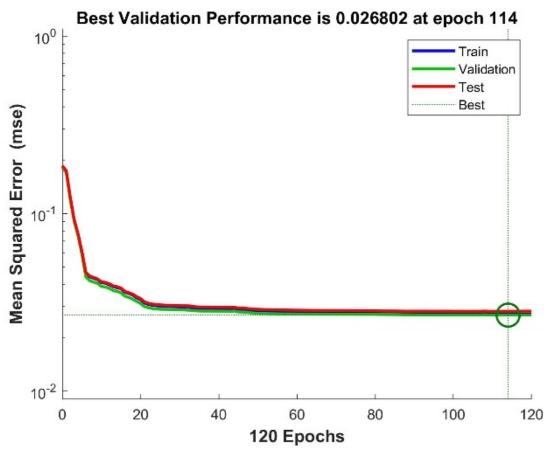

Fig. 2 *Mean Squared Error (MSE)*

The model achieved an overall classification success rate of 95.8% across all stages—training, validation, and testing—as depicted in the Confusion Matrix. This performance metric provides a comprehensive overview of both correct and incorrect classifications at each stage of the neural network's development. The green squares along the diagonal of the matrix represent the correct classifications, while the red squares indicate the misclassifications, highlighting areas for potential improvement (Figure 3). The Confusion Matrix thus serves as a valuable tool for visualizing the accuracy of the model and identifying specific areas where the network may need further refinement or adjustment.

Fig. 3 *Criteria – Confusion Matrix*

The Receiver Operating Characteristic (ROC) performance indicator indicates a true positive and false positive ratio (Figure 4). The true positive ratio for a given class *i* is the quotient of the number of outputs whose actual and predicted value is class *i* and the number of outputs whose predicted value is class *i*. The false positive ratio is the quotient of the number of outputs whose actual class is not class *i* and the predicted value is class *i*, and the number of outputs whose predicted value is not class *i*.

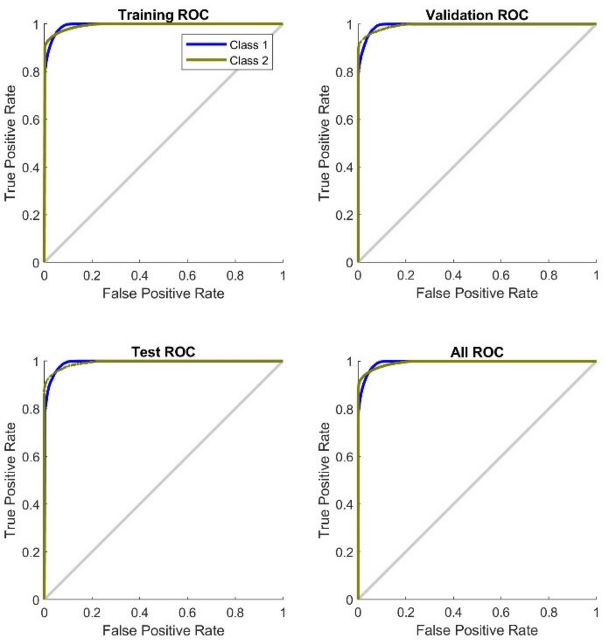

Fig. 4 *Criteria – Receiver Operating Characteristic (ROC)*

4. CONCLUSIONS

This research highlights advancements in predictive maintenance strategies for CNC machining centers by developing artificial neural network (ANN) models for vibration classification during step drilling. Using vibration data from CNC spindle housing, we classified vibrations as safe or harmful, improving maintenance practices. The results show several ANN architectures with strong potential in predicting vibrations during machining. Specifically, an architecture using the Levenberg-Marquardt algorithm with two hidden layers of 12 neurons achieved a Mean Squared Error (MSE) of 0.027 and a classification success rate of 95.8%. These findings demonstrate machine learning's potential in predicting equipment health and preventing costly downtimes. Additionally, integrating IoT and data mining within Industry 4.0 supports better decision-making and proactive maintenance. The outcomes advance smart manufacturing, stressing data-driven approaches to enhance efficiency, reliability, and sustainability. Future work should include larger datasets and compare different machine learning techniques, such as Support Vector Machines (SVM) and K-nearest neighbor (KNN) algorithms, for predictive maintenance and vibration classification.

ACKNOWLEDGMENT

This research has been supported by the research grants of the Serbian Ministry of Science, Technological Development and Innovations, grant No. 451-03-66/2024-03/200066 and grant No. 451-03-66/2024-03/200132.

REFERENCES

[1] Wang, K. S., Li, Z., Braaten, J., & Yu, Q. (2015). Interpretation and compensation of backlash error data in machine centers for intelligent predictive maintenance using ANNs. *Advances in Manufacturing*, vol. 3, no. 1, p. 97-104. DOI: 10.1007/s40436-015-0107-4

[2] Sabat, R. S. (2023). Conditional predictive maintenance of electric vehicles from electrical and mechanical faults. *International Journal for Multidisciplinary Research*, vol. 5, no. 1. DOI: 10.36948/ijfmr.2023.v05i01.1325

[3] Alves, F., Badikyan, H., Moreira, H. A., Azevedo, J., Moreira, P. M., Romero, L., & Leitão, P. (2020). Deployment of a smart and predictive maintenance system in an industrial case study. *IEEE 29th International Symposium on Industrial Electronics (ISIE)*, p. 493-498.

[4] Cavalieri, S., & Salafia, M. G. (2020). A model for predictive maintenance based on Asset Administration Shell. *Sensors*, vol. 20, no. 21, p. 6028. DOI: 10.3390/s20216028

[5] Mohammed, B., Nadia, M., & Mourad, Z. (2022). Multi-criteria analysis of diagnostic and prognostic models for predictive maintenance. *E3S Web of Conferences*, vol. 01041. DOI: 10.46338/ijetae1022_14

[6] Noureddine, R., Solvang, W. D., Johannessen, E., & Yu, H. (2020). Proactive learning for intelligent

maintenance in industry 4.0. *Advanced Manufacturing and Automation IX 9th*, p. 250-257.

[7] Helgo, M. (2023). Deep learning and machine learning algorithms for enhanced aircraft maintenance and flight data analysis. *J. Robotics Spectrum*, vol. 1, p. 90-99.

[8] Pundir, A., Maheshwari, P., & Prajapati, P. (2022, August). Machine learning-based predictive maintenance model. *Proceedings of the 2nd Indian International Conference on Industrial Engineering and Operations Management*, p. 2160-2174.

[9] Selvaraj, K., & Lakshmanan, S. (2021). The machine learning for predictive maintenance in supply chain management. *Journal of Artificial Intelligence and Machine Learning*, vol. 1, no. 1, p. 9-15. DOI: 10.55124/jaim.v1i1.233

[10] Veloso, B., Ribeiro, R. P., Gama, J., & Pereira, P. M. (2022). The MetroPT dataset for predictive maintenance. *Scientific Data*, vol. 9, no. 1, p. 764. DOI: 10.1038/s41597-022-01877-3

[11] Parpala, R. C., & Iacob, R. (2017). Application of IoT concept on predictive maintenance of industrial equipment. *MATEC Web of Conferences*, vol. 02008. DOI: 10.1051/matecconf/20178702008

[12] Martins, J. P. S., Rodrigues, F. M., & Henriques, N. (2020). Modelling system based on machine learning approaches for predictive maintenance applications. *KnE Engineering*, p. 857-871. DOI: 10.18502/keg.v5i6.7105

[13] Adu-Amankwa, K., Attia, A., Janardhanan, M., & Patel, I. (2019). A predictive maintenance cost model for CNC SMEs in the era of Industry 4.0. *The International Journal of Advanced Manufacturing Technology*, vol. 104, no. 9-12, p. 3567-3587. DOI: 10.1007/s00170-019-04094-2

[14] Guerroum, M., Zegrari, M., Masmoudi, M., Berquedich, M., & Elmahjoub, A. (2022). Machine learning techniques for remaining useful life prediction using diagnosis data: A case study of a jaw crusher. *International Journal of Emerging Technology and Advanced Engineering*, vol. 12, no. 10, p. 122-135. DOI: 10.46338/ijetae1022_14

[15] Yan, W., Pin, W., & He, L. (2021). Reliability prediction of CNC machine tool spindle based on optimized cascade feedforward neural network. *IEEE Access*, vol. 9, p. 60682-60688. DOI: 10.1109/access.2021.3074505

[16] Mbilong, P. M., Aarab, Z., Belouadha, F. Z., & Kabbaj, M. I. (2023). Enhancing fault detection in CNC machinery: A deep learning and genetic algorithm approach. *Ingénierie des Systèmes d'Information*, vol. 28, no. 5. DOI: 10.18280/isi.280525.

[17] Rao, J. (2024). Fault diagnosis of CNC machine tools based on neural network optimization. In *Intelligent Computing Technology and Automation*, p. 33-41. DOI: 10.3233/atde231169.

[18] El-Barawany, M., Elminir, H., Elattar, H., & Abdel Hamid, E. (2022). Computer numerical control CNC machine health prediction using multi-domain feature extraction and deep neural network regression. *Journal of Engineering Research*, vol. 6, no. 5, p. 7-12. DOI: 10.21608/erjeng.2022.160627.1100.

[19] Feng, Z., Min, X., Jiang, W., & Fan, S. (2023). Study on thermal error modeling for CNC machine tools based on the improved radial basis function neural network. *Applied Sciences*, vol. 13, no. 9, p. 5299. DOI: 10.3390/app13095299.

[20] Shibata, R., Hirogaki, T., Aoyama, E., Ogawa, K., & Yamashita, T. (2015). Influence of ball screw equipped with counter-balance mechanism on machine tool vibration in step-drilling process. *Manufacturing Science and Technology*, vol. 3, no. 5, p. 266-273. DOI: 10.13189/mst.2015.030512.

[21] Aoyama, E., Hirogaki, T., Ogawa, K., Nojiri, S., & Takeda, Y. (2010). Effect of rapid-feed step-drilling cycle and super-high-speed spindle for high-speed micro drilling in printed wiring boards. *Key Engineering Materials*, vol. 447, p. 836-840. DOI: 10.4028/www.scientific.net/kem.447-448.836.

[22] Tnani, M. A., Feil, M., & Diepold, K. (2022). Smart data collection system for brownfield CNC milling machines: A new benchmark dataset for data-driven machine monitoring. *Procedia CIRP*, vol. 107, p. 131-136. DOI: 10.1016/j.procir.2022.04.022.

[23] Chen, A. C., Jia, W. K., Hwang, F. J., Liu, G., Song, F., & Pu, L. (2022). Machine learning and deep learning methods for wireless network applications. *EURASIP Journal on Wireless Communications and Networking*, vol. 2022, no. 1, p. 115. DOI: 10.1186/s13638-022-02196-2.

[24] Masalimov, K., & Munasypov, R. (2019). Neural networks for diagnostics of metal cutting machine modules. In *7th Scientific Conference on Information Technologies for Intelligent Decision-Making Support (ITIDS 2019)*, p. 95-100.

[25] Okoro, E. E., Alaba, A. O., Sanni, S. E., Ekeinde, E. B., & Dosunmu, A. (2019). Development of an automated drilling fluid selection tool using integral geometric parameters for effective drilling operations. *Heliyon*, vol. 5, no. 5. DOI: 10.1016/j.heliyon.2019.e01713.

[26] Zafar, T., Kamal, K., Mathavan, S., Hussain, G., Alkahtani, M., Alqahtani, F. M., & Aboudaif, M. K. (2021). A hybrid approach for noise reduction in acoustic signal of machining process using neural networks and ARMA model. *Sensors*, vol. 21, no. 23, p. 8023. DOI: 10.3390/s21238023.

[27] Dai, J., & Xie, Q. (2022). Prediction of deviation range of gear autonomous machining relying on failure sign algorithm of firefly neural network. *Mobile Information Systems*, vol. 2022, no. 1, p. 5878748. DOI: 10.1155/2022/5878748.

[28] Mei, Y., Sun, C., Li, C., Liu, Y., & Tan, J. (2022). Research on intelligent assembly method of aero-engine multi-stage rotors based on SVM and variable-step AFSA-BP neural network. *Advanced Engineering Informatics*, vol. 54, p. 101798. DOI: 10.1016/j.aei.2022.101798.