PRINT ISSN 1119-8362
Electronic ISSN 2659-1502

Full-text Available Online at
https://www.ajol.info/index.php/jasem
https://www.bioline.org.br/ja

J. Appl. Sci. Environ. Manage.
Vol. 28 (2) 459-465 February 2024

Artificial Neural Network-Based Tool Wear Prediction in Turning AISI 1040 Medium Carbon Steel Blanks

***NTUKIDEM, BI; ACHEBO, JI; OZIGAGUN, A; UWOGHIREN FO; OBAHIAGBON, KO**

Department of Production Engineering,[2]Department of Chemical Engineering, University of Benin, Benin City, PMB 1154, Nigeria.

**Corresponding Author Email: ntukidembenson55@gmail.com*
Co-Authors Email: joseph.achebo@uniben.edu; andrew.ozigagun@uniben.edu; frank.uwoghiren@uniben.edu; kess.obahiagbon@uniben.edu

ABSTRACT: The objective of this paper was to investigate the Cutting Speed, Feed Rate and Depth of Cut to predict Tool wear during Turning of AISI 1040 Medium Carbon Steel Blanks using Artificial Neural Network Approach. The significance of the cutting parameters was investigated using the Analysis of Variance and results revealed the feed rate as the most influential factor, followed by the interaction of cutting speed and depth of cut. The Artificial Neural Network model exhibited notable correlation coefficients (R) in training (0.81301), validation (0.99932), and test (0.99922) datasets, with an overall coefficient of 0.86662, affirming the model's efficacy in predicting tool wear. The minimum predicted tool wear (0.1007mm) was observed at a 0.50mm depth of cut, cutting speed of 200m/min, and feed rate of 0.15mm/rev, demonstrating a close alignment with the observed data. The ANN predictions effectively capture the intricate relationship between tool wear and process parameters, substantiated by high correlation coefficients.

DOI: https://dx.doi.org/10.4314/jasem.v28i2.18

Cite this paper as: NTUKIDEM, B. I; ACHEBO, J. I; OZIGAGUN, A; UWOGHIREN F. O; OBAHIAGBON, K. O. (2024). Artificial Neural Network-Based Tool Wear Prediction in Turning AISI 1040 Medium Carbon Steel Blanks. *J. Appl. Sci. Environ. Manage.* 28 (2) 459-465

Dates: Received: 22 December 2023; Revised: 03 February 2024; Accepted: 18 February 2024 Published: 28 February 2024

Keywords: Turning; Tool wear; Analysis of Variance; Artificial Neural Network.

Machining encompasses the removal of undesired material from a workpiece to attain a desired shape or surface finish. This precise process achieves specified dimensions by gradually eliminating excess material using a cutting tool. Turning, executed on a lathe machine, is a machining method where a single-point cutting tool eliminates surplus material from the surface of a rotating cylindrical workpiece. The cutting tool is linearly fed in a direction parallel to the axis of rotation and this engagement with the workpiece induces friction which gradually leads to wear on the tool surface. Machining, being a heat-generating activity, can intensify wear due to elevated temperatures. Additionally, the workpiece material might contain abrasive particles, contributing to the gradual erosion of the cutting tool's surface during the cutting process. The continuous formation and removal of chips in cutting exposes the tool to dynamic loads, influencing its wear characteristics. In essence, tool wear is an inevitable outcome during machining which according to Bartarya and Choudhury (2012), has a major effect on the cutting edge geometry, machined surface quality and workpiece dimensions. The progression of tool wear is a gradual phenomenon influenced by various factors such as tool and workpiece materials, tool geometry, process parameters, cutting fluids, and machine tool characteristics. As tool wear progresses, the cutting

**Corresponding Author Email: ntukidembenson55@gmail.com*

tool loses its cutting edge and ability which causes an increase in cutting force and power consumption resulting in chatter vibration and poor surface integrity (Demirpolat *et al*., 2023). Ultimately, tool wear culminates in the abrupt failure of the cutting tool and as highlighted by Palanisamy *et al*. (2008), it results in productivity loss, part rejection, and subsequent economic setbacks. Twardowski and Wiciak-Pikuła (2019) affirm that it is quite important to effectively predict tool wear during machining as it facilitates timely tool replacement thereby avoiding the consequences of tool wear. Numerous authors have endeavored to predict and mitigate tool wear through diverse modeling approaches. Suresh and Basavarajappa (2014) employed the response surface methodology to formulate mathematical models, investigating the impact of machining parameters on both surface roughness and tool wear. The findings highlighted abrasion as the primary contributor to tool wear under elevated cutting conditions. The cutting speed emerged as the most influential parameter on tool wear, indicated by a significant F-value of 711.21. Following closely, the feed rate exhibited considerable influence with an F-value of 422.86, while the depth of cut had the least impact, reflected by an F-value of 237.86.Mgbemena*et al*. (2016) utilized the Taguchi technique, employing an L9 orthogonal array, to optimize turning parameters for minimizing tool wear and maximizing metal removal rate while turning AISI 1080 carbon steel. Through the analysis of variance (ANOVA), they assessed the impact of turning parameters on Metal Removal Rate (MRR) and Tool Wear Rate (TWR). The results highlighted the depth of cut as the most influential parameter for MRR, while cutting speed and feed rate were deemed the most significant for TWR. The optimal machining conditions for maximum metal removal rate and for minimizing tool wear rate were identified at a cutting speed of 140 rpm, a feed of 0.30 mm/rev, and a depth of 0.75 mm. The study concluded that AISI 1018 low carbon steel exhibited a maximum MRR of 35.29 mm^3/s and a minimum TWR of 0.21 mm/s. Gouarir *et al*. (2018) introduced an advanced strategy called in-process tool wear prediction system integrating machine learning and an adaptive control system. This system employs a force sensor to monitor tool flank wear progression and a Convolutional Neural Network (CNN) for predicting tool wear, achieving a reported prediction accuracy of 90%.Kong *et al*. (2018) presented a robust model for predicting tool wear width, combining the Gaussian Process Regression (GPR) model with the radial basis function kernel principal component analysis (KPCA_IRBF). The GPR model not only predicts tool wear values but also offers an equivalent confidence interval, allowing for quantitative modeling of Gaussian noises and accurate tool wear monitoring. Experimental validation confirmed the effectiveness of this approach, demonstrating superior prediction accuracy compared to artificial neural networks (ANN) and support vector machines (SVM). Twardowski and Wiciak-Pikuła (2019) utilized a neural network model to forecast tool wear by considering cutting forces and mechanical vibrations. In their study, they noted that the accuracy of predicting tool wear values was significantly influenced by the proper selection of the number of neurons in the hidden layer and the activation function in the ANN model. The correlation coefficient derived from the analysis of cutting forces exceeded that from the analysis of vibration accelerations. Although wear prediction based on cutting force components yielded slightly better results than vibration accelerations, the authors concluded that, for difficult-to-cut materials, both cutting forces and vibration acceleration serve well in assessing tool wear. Abbas *et al*. (2021) employed four process parameters: depth of cut, cutting speed, feed rate, and cutting length to investigate their impact on crater and flank wear as well as surface roughness during the machining of Ti6Al4V alloy with carbide inserts. ANOVA results from the experimental data indicated that cutting length and depth of cut exerted the most significant influence on the crater and flank wear of the cutting tool, while cutting speed had a minor effect on tool wear. Further analysis revealed that at high speeds, flank wear was predominantly caused by abrasion, while increased cutting length accelerated crater wear. Baig *et al*. (2021) formulated a tool wear prediction model based on vibration signatures during the turning of EN9 and EN24 steel alloys. They employed an Artificial Neural Network (ANN) for predicting flank wear, utilizing a Levenberg–Marquardt model with hyperbolic tangent sigmoid and logarithmic sigmoid transfer functions for 15 neurons. Flank wear was measured using a tool maker's microscope. The model demonstrated effectiveness, producing optimal results with a regression coefficient of 0.9964, showcasing close correlation between the predicted values and experimental observations. Ghosh *et al*. (2022) employed the Taguchi method to optimize Tool wear and Material Removal Rate (MRR) during the turning of mild steel AISI 1018. Cutting parameters such as speed, feed, depth of cut, and types of cutting fluids (three levels each) were considered, using two vegetable-based cutting fluids and a semi-synthetic water-emulsified cutting fluid. Taguchi S/N ratio, Orthogonal Analysis and ANOVA were utilized to identify the factors with the most and least influence on the response parameters. Experimental results indicated that the statistically dominant parameters affecting tool wear were cutting speed (67.07%) and depth of cut (24.13%). The authors concluded that the optimal combination for tool wear involved cutting speed (250 rpm), feed (0.08mm/rev), and depth of cut (1.5 mm), using mustard oil as the cutting fluid, resulting in a tool wear of 0.085 mm. Khan *et al*. (2022) investigated the turning of AISI D2 steel with prime inserts, finding that cutting speed had the highest impact on tool wear (55.38%), followed by feed rate (13.72%) and depth of cut (11.43%). Maximum tool wear, attributed to crater wear, was observed at high feed rates and depths of cut.Demirpolat *et al*. (2023) conducted an experimental study to explore the impact of cutting parameters and two different environmental conditions on the turning behavior of AISI 52100 bearing steel. The study considered Minimum Quantity Lubrication (MQL) and dry conditions, examining tool flank wear, surface roughness, cutting force, and chip shape. The findings revealed that the most significant increase in flank wear (34%) occurred under dry and high-cutting speed conditions, especially with an increased depth of cut. Additionally, a notable rise in flank wear was observed at a low depth of cut (0.2 mm) as the feed rate increased from 0.1 to 0.3 mm/rev in both dry and MQL conditions. However, machining at low cutting speed in the dry environment resulted in lower flank wear compared to the combined MQL and high cutting speed condition. The minimum flank wear occurred at a feed rate of 0.1 mm/rev, a depth of cut of 0.2 mm, a cutting speed of 30 m/min, and with the MQL combination. The study concluded that cutting environmental conditions significantly affect tool flank wear progression and that MQL-assisted machining effectively protects against tool flank wear and crater wear during the turning of AISI 52100. The present study engages three key process parameters namely the cutting speed, feed rate and depth of cut to predict Tool Wear during turning of AISI 1040 medium carbon steel blanks using Artificial Neural Network approach.

MATERIALS AND METHODS

AISI 1040 steel, characterized by its ductility and ease of machining, is a medium carbon steel featuring a substantial carbon content. Boasting a machinability rating of 60, it finds utility in the automotive industry and the manufacturing of machine components like axles, gears, and crankshafts. Its robust strength, coupled with excellent wear and fatigue resistance, makes it well-suited for use in high-stress applications. Twenty (20) AISI 1040 steel cylindrical blanks measuring 200 x 50mm were employed in the experiments conducted using a CNC lathe machine. Carbide turning inserts were utilized for the machining process, during which tool flank wear manifested on the cutting tool's flank face due to heightened friction between the tool and the workpiece. Measurement of the flank wear was carried out using a Mitutoyo vertical profile projector PJA3000. Tables 1 and 2 display the chemical composition and properties of AISI 1040 medium carbon steel, while table 3 illustrates the range of process parameters obtained from literature.

Table 1: Chemical Composition of the AISI 1040 Steel

S/N	Element	Composition (%)
1	Iron (Fe)	98.6-99
2	Manganese (Mn)	0.60-0.90
3	Carbon (C)	0.370-0.440
4	Sulfur (S)	≤ 0.050
5	Chromium (Cr)	0.07

Table 2: Mechanical Properties of the AISI 1040 Steel

S/N	Properties	Value
1	Tensile strength	620 MPa
2	Yield strength	415 MPa
3	Bulk modulus	140 GPa
4	Shear modulus	80 GPa
5	Tensile strength	620 MPa
6	Hardness, Brinell	201

Table 3: Process parameters and their ranges

Parameter Ranges	Process Parameters		
	Depth of cut (mm)	**Cutting speed (m/min)**	**Feed rate (mm/rev)**
	0.25	150	0.10
	0.50	200	0.15
	0.75	250	0.20

The experiments, which aimed to predict and minimize tool wear, were conducted following the Central Composite Design Matrix (CCD) outlined in table 4 which also contains the experimental results for the tool wear.

Table 4: Experimental Data Set

std	run	Depth of Cut (mm)	Cutting Speed (m/min)	Feed Rate (mm/rev)	Experimental Tool Wear (mm)
1	1	0.25	150.00	0.10	0.4
5	2	0.25	150.00	0.20	0.23
16	3	0.50	200.00	0.15	0.09
7	4	0.25	250.00	0.20	0.32
19	5	0.50	200.00	0.15	0.49
2	6	0.75	150.00	0.10	0.41
11	7	0.50	115.91	0.15	0.32
6	8	0.75	150.00	0.20	0.47
10	9	0.92	200.00	0.15	0.09
12	10	0.50	284.09	0.15	0.15
18	11	0.50	200.00	0.15	0.36
8	12	0.75	250.00	0.20	0.24
15	13	0.50	200.00	0.15	0.66
4	14	0.75	250.00	0.10	0.85
13	15	0.50	200.00	0.07	0.26
3	16	0.25	250.00	0.10	0.39
14	17	0.50	200.00	0.23	0.39
20	18	0.50	200.00	0.15	0.47
17	19	0.50	200.00	0.15	0.26
9	20	0.08	200.00	0.15	0.49

Modelling using ANN: Utilizing a predictive model, the Artificial Neural Network is employed to predict tool wear outcomes. During the network training process, a feed-forward backpropagation algorithm is utilized along with a hyperbolic tangent (tan-sigmoid) transfer function for the input layer to compute the layer output based on the network input. Additionally, a linear (purelin) transfer function is employed for the output layer. The optimal architecture of the neural network is illustrated in figure 1.

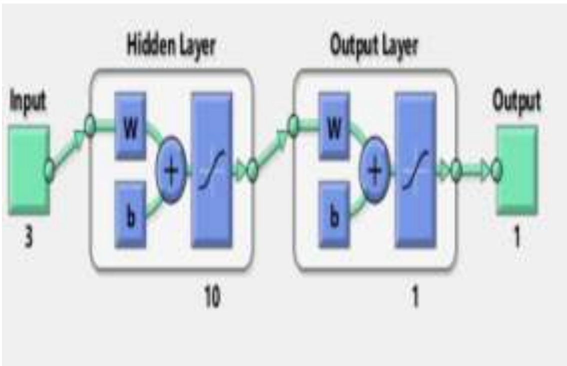

Fig 1: ANN architecture for Tool wear

The number of hidden neuron was set at 10 neurons per layer and the network performance was monitored using the mean square error of regression (MSEREG). The selected optimization training algorithm is Levenberg-Marquardt optimization while the network training function is Trainlm.For this study, 60% of the data was employed to perform the network training, 25% for validating the network while 15% was used to test the performance of the generated network. The network properties for tool wear is presented in figure 2

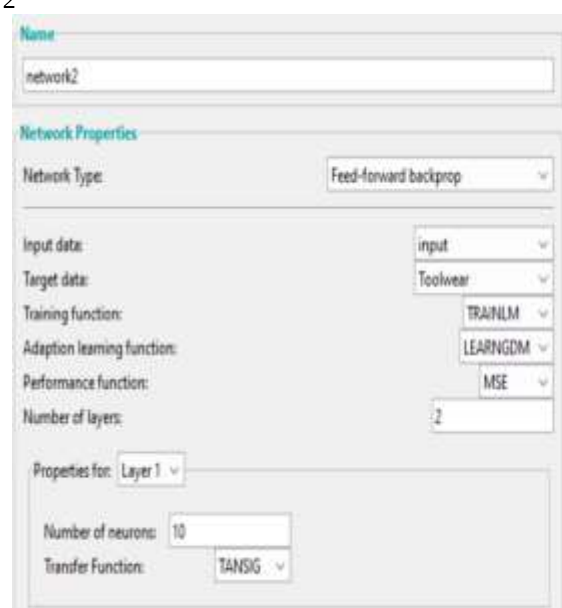

Fig 2.: ANN properties applied for predicting Tool wear

The neural network diagram for predicting tool wear is presented in figure 3 showing the selected network training settings.

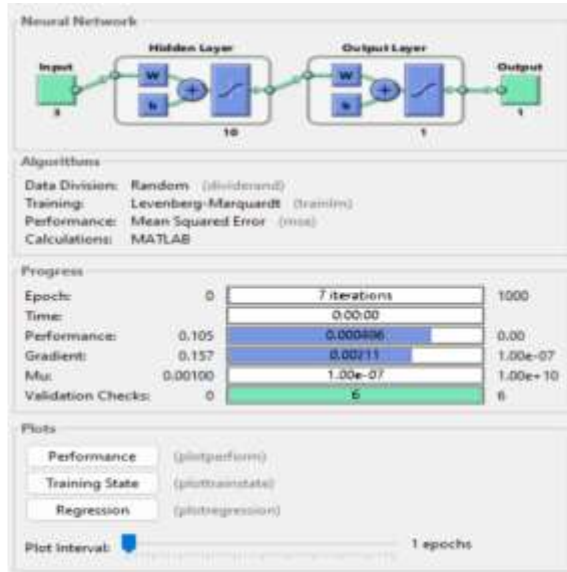

Fig 3: Network training diagram for predicting tool wear

Figure 4 presents the performance curve for the trained network. The plot displays the error of the neural network as a function of the training epochs and shows the performance of the neural network during training and validation. The training curve shows how the error decreases during the training process as the neural network adjusts its weights and helps to detect overfitting. The best validation performance of 0.015365 occurs at epoch 1 which indicates that the model achieved its highest performance on the validation data set after the completion of the first epoch of training though seven (7) epochs were used in the iteration process. It also suggests that the mean squared error reduces significantly after one epoch.

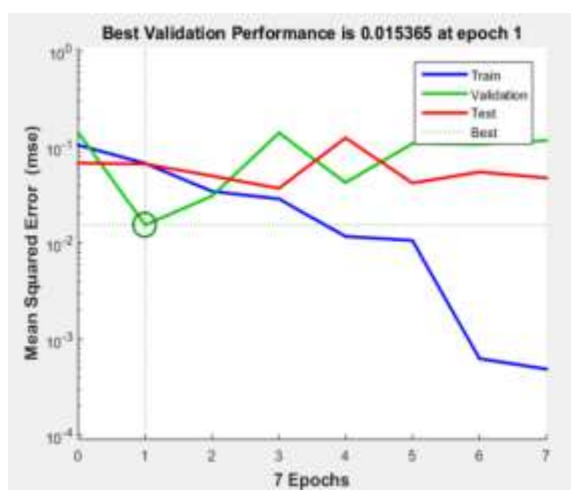

Fig 4: Performance curve for trained network to predict tool wear

RESULTS AND DISCUSSION

The experimental results from table 4 were evaluated with an analysis of variance (ANOVA) to determine the extent of influence the process parameters have on the tool wear. The ANOVA result is given in table 5.

Table 5: ANOVA table for the Tool Wear

Source	Sum of Squares	Df	Mean Square	F Value	p-value Prob> F	
Model	0.57	9	0.064	10.32	0.0006	Significant
A-depth of cut	3.556E-003	1	3.556E-003	0.58	0.4652	
B-cutting speed	0.021	1	0.021	3.44	0.0935	
C-feed rate	0.069	1	0.069	11.25	0.0073	
AB	0.049	1	0.049	7.94	0.0182	
AC	6.845E-006	1	6.845E-006	1.110E-003	0.9741	
BC	1.551E-003	1	1.551E-003	0.25	0.6269	
A^2	0.15	1	0.15	24.20	0.0006	
B^2	0.021	1	0.021	3.44	0.0935	
C^2	0.22	1	0.22	34.93	0.0001	
Residual	0.062	10	6.169E-003			
Lack of Fit	0.014	5	2.746E-003	0.29	0.9020	not significant
Pure Error	0.048	5	9.592E-003			
Cor Total	0.63	19				
R-Squared = 0.9028, Adj R-Squared = 0.8153, Pred R-Squared = 0.7187						

The R-Squared value of 0.9028 estimates that about 90% of the observed variation can be explained by the model's inputs. The Predictive R-Squared value of 0.7187 is in reasonable agreement with the Adjusted R-Squared value of 0.8153. From the ANOVA table, the most influential parameter on the tool wear is the feed rate with an F-value of 11.25 and P-value of 0.0073. This is followed by the interaction of the depth of cut and cutting speed which have an F-value of 7.94 and P-value of 0.0182.

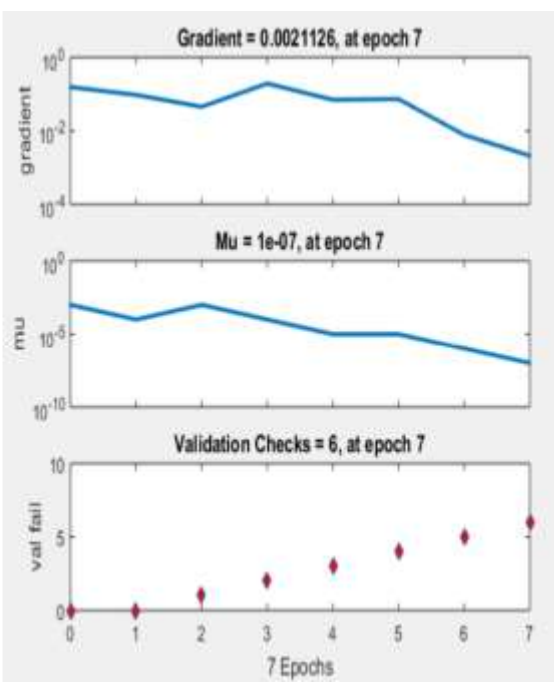

Fig 5: Neural network gradient plot for predicting tool wear

ANN Results: The gradient plot of the neural network for predicting tool wear which indicates the number of epochs used up during the training process is presented in figure 7.

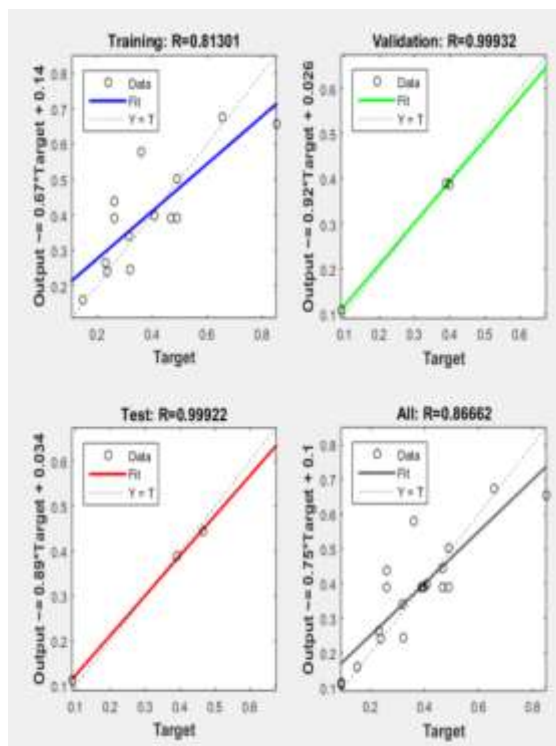

Fig 6: Regression plot of training, validation and testing for tool wear

It is observed that during the training of the network, seven (7) epochs were used and the gradient value of 0.0021126 was observed at epoch 7. The model also undertook six validation checks and a damping parameter value of 1e-07 (0.0000001) occurred at epoch 7. The regression plots (training, validation and testing data set) of figure 6 show scatter plots of the predicted outputs against the actual target outputs. They are evaluated using the correlation coefficient "R" which assesses to what degree the predictions made by the neural network align with the actual target values.

Table 6: ANN Tool Wear prediction

run	Depth of Cut (mm)	Cutting Speed (m/min)	Feed Rate (mm/rev)	Experimental Tool Wear (mm)	ANN predicted Tool wear (mm)
1	0.25	150.00	0.10	0.4	0.40796
2	0.25	150.00	0.20	0.23	0.20198
3	0.50	200.00	0.15	0.09	0.1007
4	0.25	250.00	0.20	0.32	0.34337
5	0.50	200.00	0.15	0.49	0.4907
6	0.75	150.00	0.10	0.41	0.40515
7	0.50	115.91	0.15	0.32	0.32884
8	0.75	150.00	0.20	0.47	0.48451
9	0.92	200.00	0.15	0.09	0.10581
10	0.50	284.09	0.15	0.15	0.14397
11	0.50	200.00	0.15	0.36	0.3907
12	0.75	250.00	0.20	0.24	0.24441
13	0.50	200.00	0.15	0.66	0.64381
14	0.75	250.00	0.10	0.85	0.84341
15	0.50	200.00	0.07	0.26	0.26742
16	0.25	250.00	0.10	0.39	0.38109
17	0.50	200.00	0.23	0.39	0.38655
18	0.50	200.00	0.15	0.47	0.3907
19	0.50	200.00	0.15	0.26	0.2907
20	0.08	200.00	0.15	0.49	0.49131

The correlation coefficients (R) for the training, validation, and test datasets were 0.81301, 0.99932, and 0.99922, respectively, while the overall correlation coefficient for all datasets was 0.86662. This collective R value of 0.86662 implies a strong positive correlation between the neural network's predictions and the actual target values, indicating the network's effectiveness in predicting tool wear. The experimental and ANN predicted results for tool wear are provided in table 6.

The experimental and predicted results of the ANN were juxtaposed and the outcome shown in figure 7, illustrates the accuracy of the network's predictions. Remarkably, there is a substantial correlation between the results obtained through the ANN predictions and the experimental determinations. The experimental minimum tool wear was 0.09mm, while the minimum value predicted by the ANN was 0.1007mm.

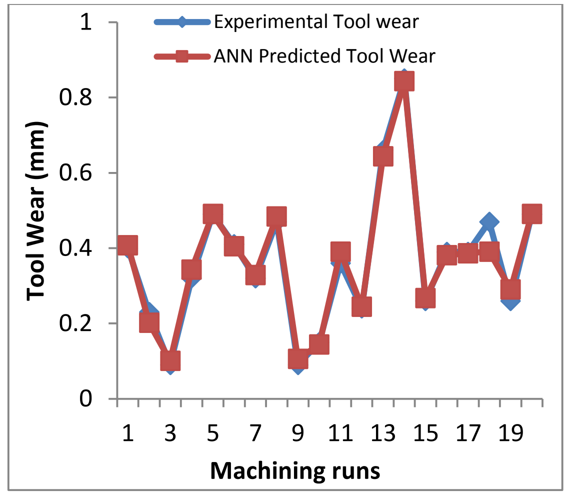

Fig 7: Comparison of Experimental values and ANN prediction

*Conclusion***:** This study focused on predicting tool wear in turning AISI 1040 carbon steel, highlighting the feed rate as the most influential parameter. Experimental results showed increased tool wear with higher depth of cut and cutting speed. The ANN predictions closely aligned with experimental values, affirming the model's effectiveness. This research lays the groundwork for optimizing turning operations, emphasizing the ANN model's potential for precise tool wear prediction with specific process parameters. Integration with optimization algorithms can further enhance turning parameters.

REFERENCES

Abbas, AT; Al Bahkali, EA; Alqahtani, SM; Abdelnasser, E; Naeim, N; Elkaseer, A (2021). Fundamental Investigation into Tool Wear and Surface Quality in High-Speed Machining of Ti6Al4V Alloy. *Mat.* 14(23): 7128.DOI: https://doi.org/10.3390/ma14237128

Baig, RU; Javed, S; Khaisar, M; Shakoor, M; Raja, P (2021). Development of an ANN model for prediction of tool wear in turning EN9 and EN24 steel alloy. *Adv. Mech. Eng*. 13(6): 1-14. DOI:10.1177/16878140211026720

Bartarya, G; Choudhury, S (2012). State of the art in hard turning. *Int. J. Mach. Tools Manuf*. 53:1–14. DOI: https://doi.org/10.1016/j.ijmachtools.2011.08.019

Demirpolat, H; Binali, R; Patange, AD; Pardeshi, SS; Gnanasekaran, S (2023). Comparison of Tool Wear, Surface Roughness, Cutting Forces, Tool Tip Temperature, and Chip Shape during Sustainable Turning of Bearing Steel. *Materials (Basel)*16(12): 4408. DOI: https://doi.org/10.3390/ma16124408

Ghosh, S; Mandal, MC; Das, K; Mondal, N; Ray, A (2022). Optimization of Cutting parameters of AISI 1018 Low Carbon Mild steel in turning using green cutting fluid by Taguchi Method. *J. Mech. Eng*. 1(1): 62-67. DOI: 10.56697/JMEP.2022.1108

Gouarir, A; Martinez-Arellano, G; Terrazas, G; Bernardos, P; Ratchev, S (2018). In-process Tool Wear Prediction System Based on Machine Learning Techniques and Force Analysis. Procedia CIRP77: 501-504. DOI:10.1016/j.procir.2018.08.253

Khan, SA; Ameer, MF; Uddin, GM; Anwar, S; Farooq, MU; Alfaify, A (2022). An in-depth analysis of tool wear mechanisms and surface integrity during high-speed hard turning of AISI D2 steel via novel inserts. *Int. J. Adv. Manuf. Technol*. 122(9-10): 4013–4028. DOI: https://doi.org/10.1007/s00170-022-10151-0

Kong, D; Chen, Y; Li, N (2018). Gaussian process regression for tool wear prediction. Mech. Syst. *Signal Proc*. 104, 556–574. DOI: https://doi.org/10.1016/j.ymssp.2017.11.021

Mgbemena, C; Etebenumeh, G; Ashiedu, F (2016). Effect of turning parameters on Metal Removal and Tool Wear rates of AISI Low Carbon Steel. *Nig. J. Tech*. 35(4): 847-854. DOI: http://dx.doi.org/10.4314/njt.v35i4.20

Palanisamy, P; Rajendran, I; Shanmugasundaram, S (2008). Prediction of tool wear using regression and ANN models in end-milling operation. *Int. J. Adv. Manuf. Technol*. 37: 29-41.DOI: https://doi.org/10.1007/s00170-007-0948-5

Suresh, R; Basavarajappa, S (2014). Effect of process parameters on tool wear and surface roughness during turning of hardened steel with coated ceramic tool. *Procedia Mater. Sci.* 1450-1459. DOI: https://doi.org/10.1016/j.mspro.2014.07.464

Twardowski, P; Wiciak-Pikuła, M (2019). Prediction of Tool Wear Using Artificial Neural Networks during Turning of Hardened Steel. *Mat.* 12(19): 3091.DOI: https://doi.org/10.3390/ma12193091