Arch. Metall. Mater. **66** (2021), 3, 901-909

DOI: 10.24425/amm.2021.136396

MOGANAPRIYA CHINNASAMY[1], RAJASEKAR RATHANASAMY[1*], GOBINATH VELU KALIYANNAN[2], PRABHAKARAN PARAMASIVAM[1], SARAVANA KUMAR JAGANATHAN[3,4,5]

A FRONTIER STATISTICAL APPROACH TOWARDS ONLINE TOOL CONDITION MONITORING AND OPTIMIZATION FOR DRY TURNING OPERATION OF SAE 1015 STEEL

This research study intends to develop an online tool condition monitoring system and to examine scientifically the effect of machining parameters on quality measures during machining SAE 1015 steel. It is accomplished by adopting a novel microflown sound sensor which is capable of acquiring sound signals. The dry turning experiments were performed by employing uncoated, TiAlN, TiAlN/WC-C coated inserts. The optimal cutting conditions and their influence on flank wear were determined and predicted value has been validated through confirmation experiment. During machining, sound signals were acquired using NI DAQ card and statistical analysis of raw data has been performed. Kurtosis and I-Kaz coefficient was determined systematically. The correlation between flank wear and I-Kaz coefficient was established, which fits into power-law curve. The neural network model was trained and developed with least error (3.7603e-5). It reveals that the developed neural network can be effectively utilized with minimal error for online monitoring.

Keywords: Coated inserts, Microflown sensor, flank wear, I- Kaz, Neural network

1. Introduction

In recent years, the manufacturing sector has seen many transformations. The emphasis is on cost savings, quality growth, elimination of downtime, failure, and waste. Owing to environmental health objectives of machining, dry hard turning has positive effect in manufacturing [1]. The machining attributes can be increased by versatile characteristics of cutting tools such as hot strength, wear resistance, thermal and chemical stability. In recent times, the hard coating of tool inserts has been intensively studied. Several depositions and coating methods for friction reduction and wear protection for cutting tools have been reported [2,3].

At present, coating materials such as TiN, TiCN, TiAlN, and so on are often used on cutting tools due to improved behavior of tribology, higher resistance to oxidation at high temperatures [4,5]. The mechanical properties of inserts are significantly enhanced by these coatings. The author has conducted tests to evaluate the machinability of AISI 420C stainless steel through TiAlN ultrafine coated cutting tool under various cutting conditions. The cutting speeds were found to control the life of the tool rather than other parameters [6,7].

In the hard machining process, Yigit et al. measured the influence of input parameters with 10.5 mm thick multilayer insert to reduce tool wear and surface roughness through optimization [8]. Using PCBN wiper tool in steel AISI H13, the author employed RSM for optimizing material removal rate as well as machine life, cutting force, and minimal surface roughness [9]. Taguchi method was employed to optimize various input parameters to reduce surface roughness, energy usage, and enhance material removal rate [10] . Gupta et al. used grade 2 titanium alloy containing cubic nitride boron (CBN) inserts using cutting fluids to optimize their input through particle swarm and bacterial foraging algorithm [7,11].

Today, research focuses on the development of completely automated online tool condition monitoring system (TCMs) which are capable to recognize the tool's state under minimum human supervision without interruption of the machining process. The effort is finally directed towards developing an automated control system that should have the ability to detect,

[1] KONGU ENGINEERING COLLEGE, DEPARTMENT OF MECHANICAL ENGINEERING, PERUNDURAI – 638060, TAMIL NADU STATE, INDIA
[2] KONGU ENGINEERING COLLEGE, DEPARTMENT OF MECHATRONICS ENGINEERING, PERUNDURAI – 638060, TAMIL NADU STATE, INDIA
[3] BIONANOTECHNOLOGY RESEARCH GROUP, TON DUC THANG UNIVERSITY, HO CHI MINH CITY, VIETNAM
[4] FACULTY OF APPLIED SCIENCES, TON DUC THANG UNIVERSITY, HO CHI MINH CITY, VIETNAM
[5] DEPARTMENT OF ENGINEERING, FACULTY OF SCIENCE AND ENGINEERING, UNIVERSITY OF HULL, HU6 7RX, UNITED KINGDOM

* Corresponding author: rajasekar.cr@gmail.com

analyze, learn through knowledge, and correct errors [12]. Typical TCMs framework requires the following elements to replicate human intervention [12]:

- Sensor technologies
- Feature extraction.
- Decision making algorithm

Valuable information on the process and state of the cutting tool can be provided through sound generated duting machining. Some researchers considered the sound to be a source of knowledge about the machining operation, tool, and machine. They also utilized sound signals to monitor tool wear [13]. Teti et al. examined different sound-measuring techniques to bring flank-wear measurements and proposed that audible sound energy is one of the most realistic among various sensing techniques [14]. Tool condition can be monitored from sound signals, cutting force, vibration signals, acoustic emission, temperature, surface finish etc. To the best of authors knowledge, tool condition monitoring with very near field acoustic sensor (Microflown sensor) is not found elsewhere in the literature. This work focuses on optimiztion of turning parameters and coating material to enhance tool life and design of tool condition monitoring system with I-Kaz coefficeints using Artificial Neural Network.

2. Materials and methods

The overall workflow of research work is depicted in Fig. 1.

2.1. Coating and machining

Thin-film coatings were performed on cutting tool inserts in an industrialized coating unit (Oerlikon Balzers Ltd., Pune, India). TiAlN and TiAlN/WC-C coatings were synthesized through the cathodic arc evaporation technique. SAE 1015 mild steel cylindrical bars were used as work material and the machining was carried out by using TiAlN/WC-C, TiAlN coated and pure carbide tool inserts in JOBBER XL CNC turning center. The cutting parameters were selected based on literature as shown in Table 1. For the prescribed cutting parameters, the L_{27} orthogonal array was selected based on the design of experiments. Correspondingly, twenty-seven experiments were conducted for selected design. Flank wear of tool was measured for each run through profile projector. The average of three values was recorded in Table 2. For optimizing the output response (tool wear), smaller the better criteria were considered [15] . Taguchi's parameter design approach was used to investigate the effect of process parameters on flank wear as depicted in Table 2.

TABLE 1

Cutting Parameters

Workpiece: Mild steel (50 mm diameter, 110 mm length)
Machining time: 10 minutes
Coolant: No coolant, dry cutting environment

Parameter/ Level	1	2	3
Coating	Uncoated	TiAlN	TiAlN/WC-C
Cutting speed (rpm)	500	550	600
Feed rate (mm/rev)	0.05	0.1	0.15
Depth of cut (mm)	1	1.5	2

2.2. Online tool condition monitoring system

In this research experiments, sound generated during machining was recorded through a novel sound sensor- Microflown-PU sensor.

Fig. 2 shows the basic concept of measurement of sound pressure. It is suitable to measure particle velocity and sound

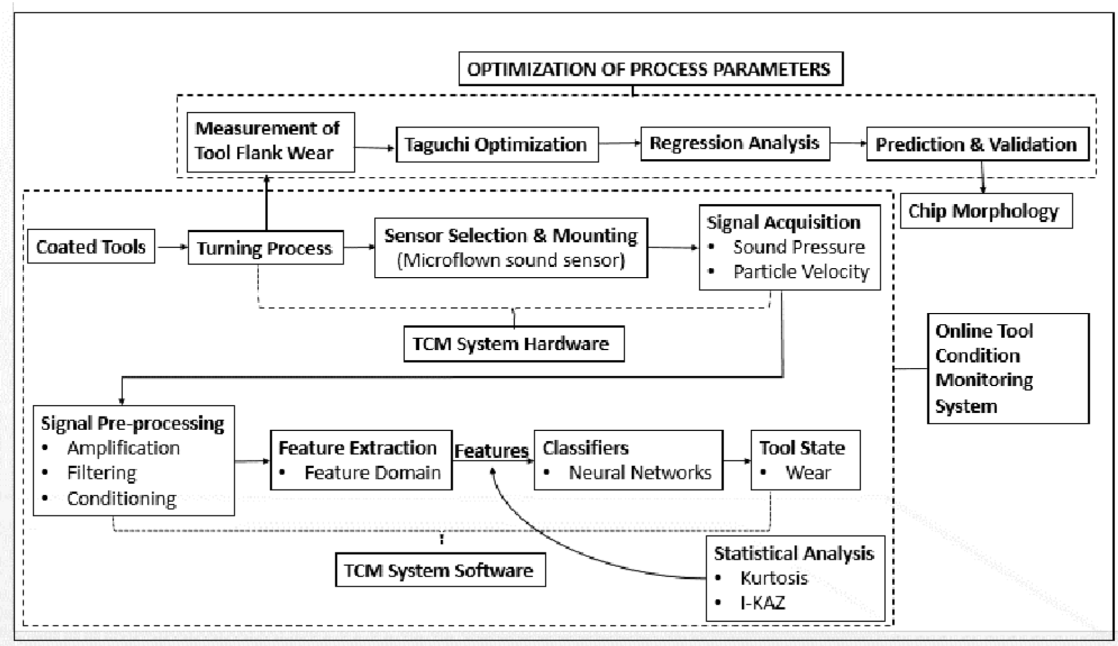

Fig. 1. Methodology and TCM frame work

TABLE 2

Experimental Design

S.No	Coating	Cutting speed (rpm)	Feed rate (mm/rev)	Depth of cut (mm)	Flank wear (mm)
1	Uncoated	500	0.05	1	0.025900
2	Uncoated	500	0.1	1.5	0.029000
3	Uncoated	500	0.15	2	0.033000
4	Uncoated	550	0.05	1.5	0.031000
5	Uncoated	550	0.1	1	0.026000
6	Uncoated	550	0.15	2	0.033241
7	Uncoated	600	0.05	2	0.036390
8	Uncoated	600	0.1	1	0.020000
9	Uncoated	600	0.15	1.5	0.026210
10	TiAlN	500	0.05	2	0.039000
11	TiAlN	550	0.1	1.5	0.027000
12	TiAlN	550	0.15	2	0.028000
13	TiAlN	550	0.05	1	0.025128
14	TiAlN	600	0.1	1	0.022000
15	TiAlN	600	0.15	2	0.030000
16	TiAlN	600	0.05	1.5	0.029000
17	TiAlN	500	0.1	1	0.022325
18	TiAlN	500	0.15	1.5	0.027000
19	TiAlN/WC-C	500	0.05	1.5	0.024750
20	TiAlN/WC-C	500	0.1	1	0.015000
21	TiAlN/WC-C	500	0.15	2	0.021000
22	TiAlN/WC-C	550	0.05	2	0.028000
23	TiAlN/WC-C	550	0.1	1	0.015000
24	TiAlN/WC-C	550	0.15	1.5	0.018000
25	TiAlN/WC-C	600	0.05	1	0.020110
26	TiAlN/WC-C	600	0.1	1.5	0.019000
27	TiAlN/WC-C	600	0.15	2	0.025000

pressure during machining process and it can differentiate the signals of good and faulty tool significantly. Data acquisition from sensor was carried out through NI LabVIEW as shown in Fig. 3. Fig. 4 depicts the LabVIEW program for data acquisition in frequency response. The acquired signals were statistically analyzed in terms of kurtosis and I-Kaz coefficient.

Nuwai laid the groundwork for I-Kaz method, who studied random or non-deterministic signal features. To categorize the deterministic features, the r^{th} order of moment M_r is used often.

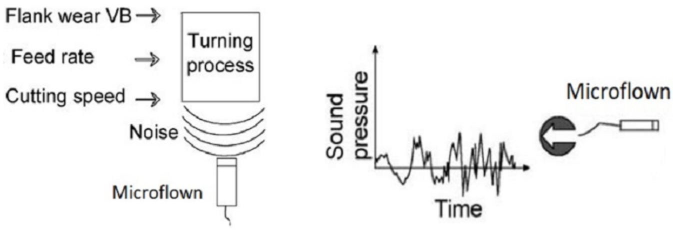

Fig. 2. Basic Concept of Measurement

Fig. 3. Microflown Data Acquisition Setu

The r^{th} order of the moment, M_r for the discrete sign in the frequency band can be expressed as:

$$M_r = \frac{1}{N}\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^r \tag{1}$$

where, N – Number of data points, X_i – Data at instantaneous points, $\bar{X}$ – Mean.

Initially, signals are obtained using LAB-View, n number of values by a combination of sound pressure and particle velocity were gained. The kurtosis K for discrete data can be expressed as :

$$K = \frac{1}{N\sigma^4}\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^4 \tag{2}$$

where σ – Variance.

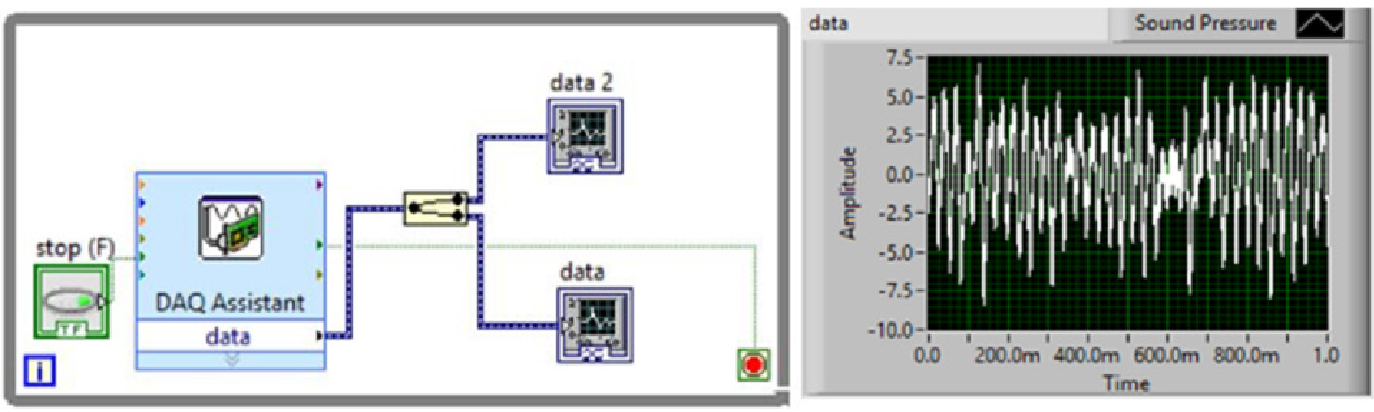

Fig. 4. Lab VIEW program for Data Acquisition

The I-Kaz coefficient calculates the distance of any data point from the centroid of signal to determine the degree of dispersion in data distribution. The coefficient I-Kaz shall be as follows:

$$I - Kaz\,2D\,Coef = \sqrt{\frac{1}{N}\left(M^{I}\right) + \frac{1}{N}\left(M^{II}\right)} \qquad (3)$$

where, M^I and M^{II} – the moment in the channel I and II

By substituting equations 1, 2 in 3, I-Kaz coefficient can be framed as depicted in equation 4 and it is denoted by the symbol Z_2^{∞}.

$$Z_2^{\infty} = \frac{1}{N}\sqrt{K_I S^I + K_{II} S^{II}} \qquad (4)$$

where, K_I and K_{II} – Kurtosis of signal in ch-I and ch-II; S^I and S^{II} – Standard deviation of signal in ch-I and ch-II.

2.3. Artificial Neural Network Design

The analysis of tool condition using different types of networks and implementation of neural network (NN) in monitoring system were studied by several authors. The output and quantity of neurons in each hidden layer were affected in terms of NN's uniqueness [16]. Seventy percent of samples were used for training and thirty percent were used for testing and confirmation purposes for the remaining samples. The Levenberg-Marquardt (TRAINLM) training algorithm provided the highest performance among several training algorithms. The network was calibrated to its error value during the training process.

As the adaption learning feature, LEARNGDM was considered. The learning factor for LEARNGDM was selected as 0.01 and dynamic constant of 0.9 has been used to develop network learning process. Another significant part of hidden layer transfer function is that it directly influences the results of NN. TANSIG sigmoid function was used for hidden layer transfer. The validation data were used for assessment and training process was completed until generalization ceased to improve. The output of mean square error (MSE) was used. A lower MSE value indicates better network efficiency. Zero MSE indicates that the NN forecast was not defective.

3. Results and discussion

3.1. Machining and Optimization

Machining experiments were performed based array and corresponding flank wear was measured and tabulated as shown in Table 2. Minimal tool wear values are preferred and hence, smaller the best is considered for this analysis as depicted in equation 5 [15].

$$\text{S/N ratio} = -10\,\text{Log}_{10}\,[\text{mean of sum of squares of measured- ideal}] \qquad (5)$$

From Fig. 5, the optimal condition of cutting parameters were identified by selecting the largest S/N ratio. As depicted in Table 3, the optimum cutting parameters for dry machining of SAE 1015 steel were found as follows: coating – TiAlN/WC-C, cutting speed – 600 rpm, feed rate – 0.1 mm/rev, and depth of cut – 1 mm. Response and ranking of each factor following to signal to noise ratio are depicted in Table 4.

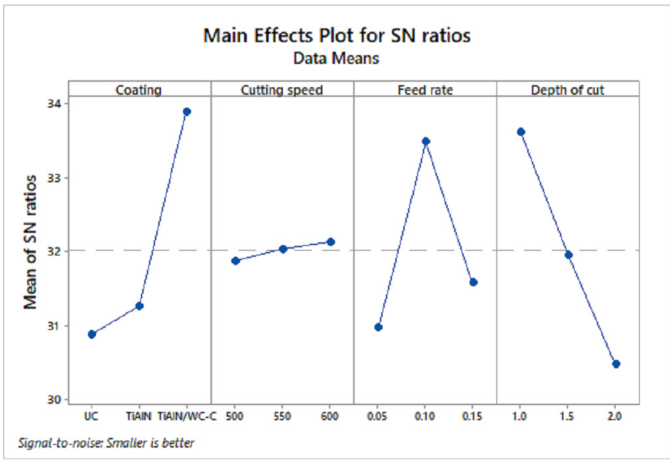

Fig. 5. S/N plot of input parameters

TABLE 3

Optimized Parameter

Parameter	Optimized Setting
Cutting speed	600 rpm
Feed rate	0.1 mm/rev
Depth of cut	1 mm
Coating	TiAlN/WC-C

TABLE 4

Signal to Noise Ratio- Response table

Level	Coating	Cutting speed (rpm)	Feed rate (mm/rev)	Depth of cut (mm)
1	30.88	31.87	30.97	33.61
2	31.26	32.03	33.48	31.94
3	33.89	32.13	31.58	30.48
Delta	3.00	0.26	2.51	3.13
Rank	2	4	3	1

From Table 5, it was determined that the depth of cut effects tool wear by 52.15%, followed by coating, which contributes by 38.92%. Feed rate influences tool wear by 17.76% whereas, cutting speed affects tool wear in lesser dimension (0.53%). The results are inline with previous studies [17]. The depth of cut has a significant effect on flank wear and the flank wear was steadily increased with increase in depth of cut. The bilayer tool (TiAlN/WC-C) exhibited second uppermost contribution, because of the presence of an intermediate layer of carbonitride and hard carbon-top layer (WC-C), which increases the tool's wear resistance (TiAlN / WC-C).

TABLE 5

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value	% Contribution
Regression	5	0.000870	0.000174	61.05	0.000	—
Cutting speed	1	0.000005	0.000005	1.67	0.021	0.54
Feed rate	1	0.000128	0.000128	44.84	0.000	13.76
Depth of cut	1	0.000485	0.000485	170.28	0.000	52.15
Coating	2	0.000362	0.000181	63.55	0.000	38.92
Error	21	0.000060	0.000003			
Total	26	0.000930				

The regression equations for flank wear were as follows

UC = 0.02376 – 0.000010 Cutting speed – 0.05652 Feed rate + 0.011014 Depth of cut (6)

TiAlN = 0.02251 – 0.000010 Cutting speed – 0.05652 Feed rate + 0.011014 Depth of cut (7)

TiAlN/WC-C = 0.01544 – 0.000010 Cutting speed – 0.05652 Feed rate + 0.011014 Depth of cut (8)

Regression equations for the categorical parameters were obtained as prescribed in equations 6-8. Flank wear was predicted using a response optimizer at optimized setting as depicted in Table 6. The output response was predicted as 0.0146295 mm. The confirmation experiment was performed at an optimized setting and the flank wear was measured as 0.01528 mm, which is closer to predicted value. The normal probability plot shows that the residues have fallen on inclined line as depicted in Fig. 6. Residuals were found to be uniformly distributed. Residual vs. fitted value indicates that residue is not patterned and scattered across field. The residual frequency was small and residual was below ±0.0024. The influence of cutting speed, depth of cut on tool wear and feed rate, depth of cut on tool wear are portrayed in Fig. 7.

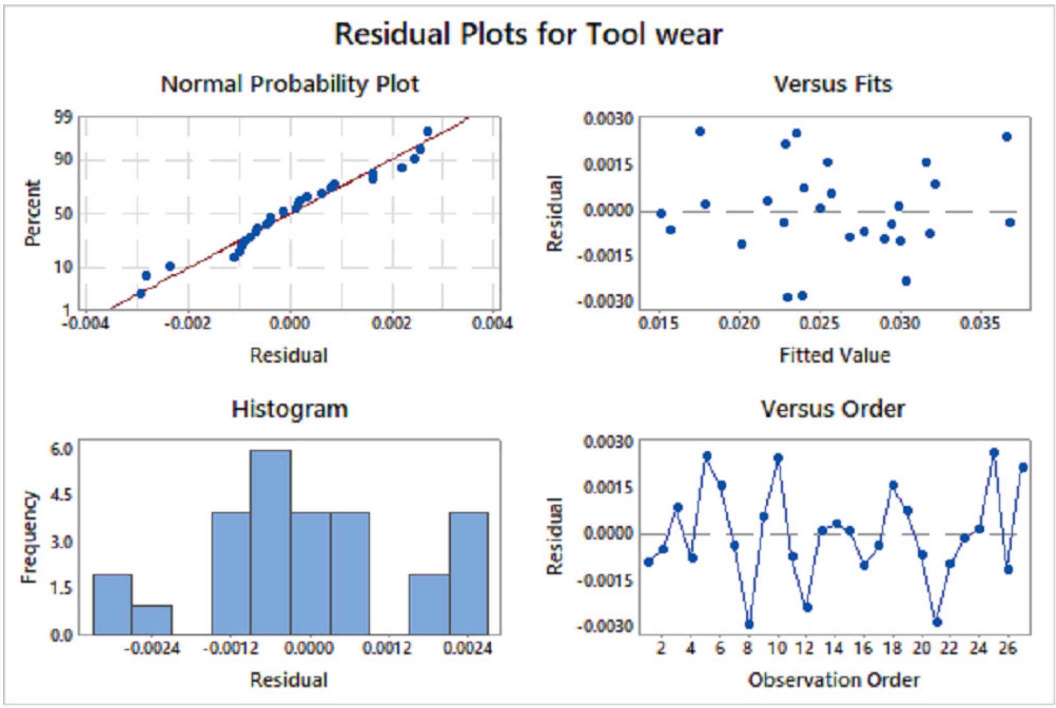

Fig. 6. Normal Probability and Residual plot

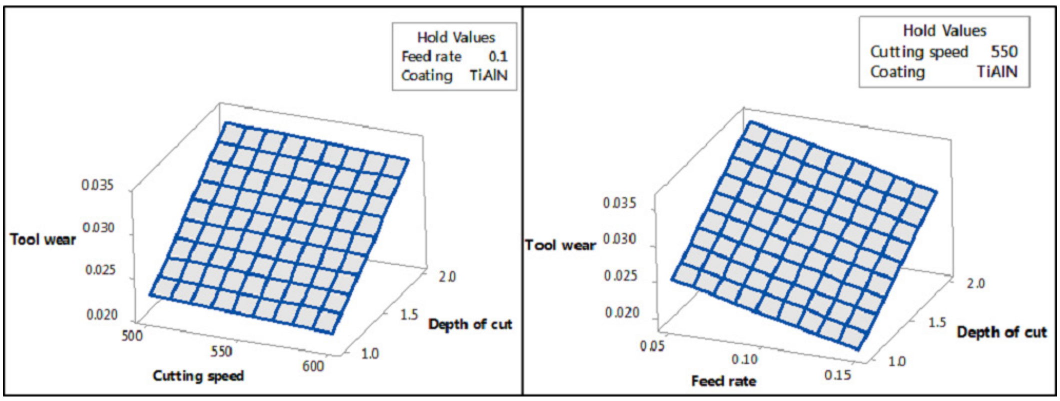

Fig. 7. Effect of cutting speed, feed rate and depth of cut on tool wear

TABLE 6

Prediction at Optimized setting

Fit	SE Fit	95% CI	95% PI
0.0146295	0.0008081	(0.0129490, 0.0163100)	(0.0107375, 0.0185214)

It shows that tool wear increases rapidly with an increase in depth of cut and holds at nominal value for an increase in cutting speed. An increase in depth of cut follows the same trend whereas, a lower feed rate produces higher tool wear than a higher feed rate.

3.2. Design of online tool condition monitoring

The frequency-domain response was generated through a signal analyzer via vibration and sound toolkit of the LabVIEW platform. The sample responses for sound pressure captured during machining were depicted in Fig. 8. At every point of machining, it obtains signals and stores signals simultaneously frame by frames in online mode through the developed LabVIEW program as shown in Fig. 9.

The measured sound pressure and particle velocity signals are processed and amplified. The pile of processed data was sta-

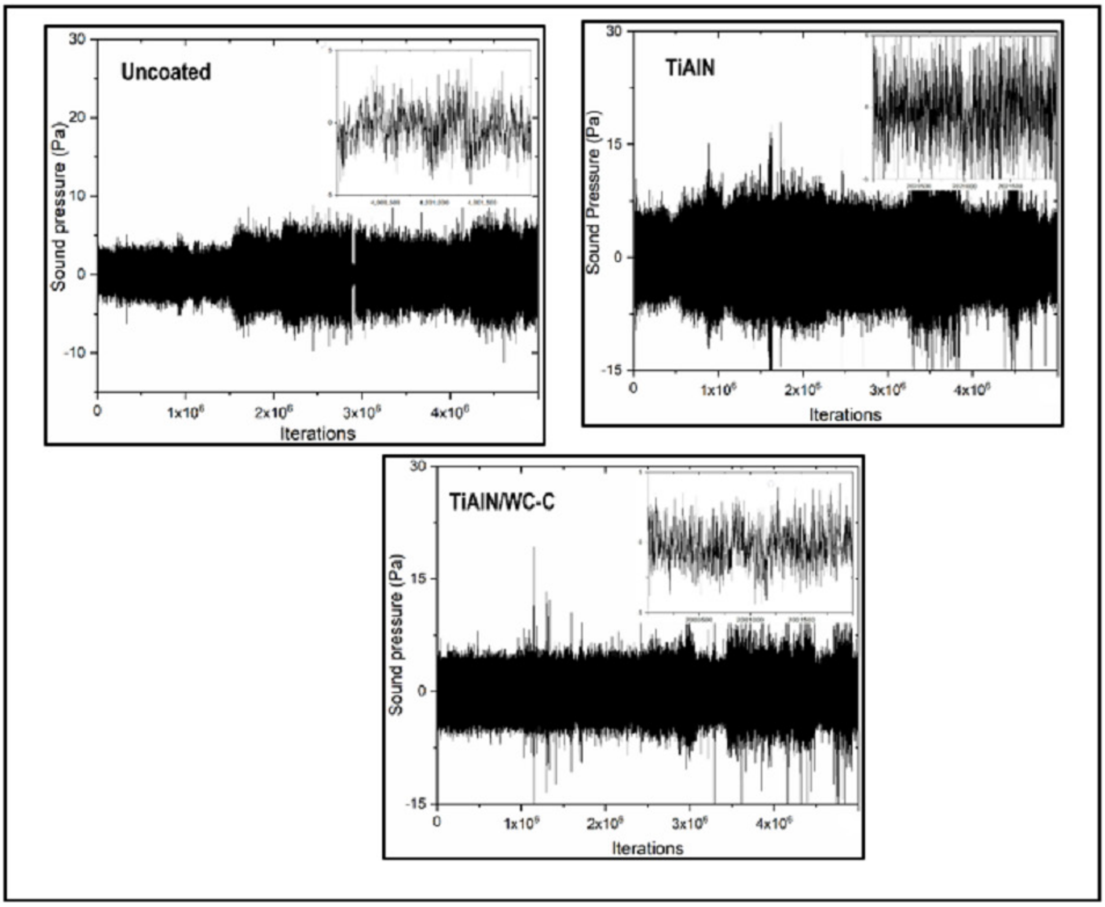

Fig. 8. Sample generated signals fron UC, TiAlN, TiAlN/WC-C tools

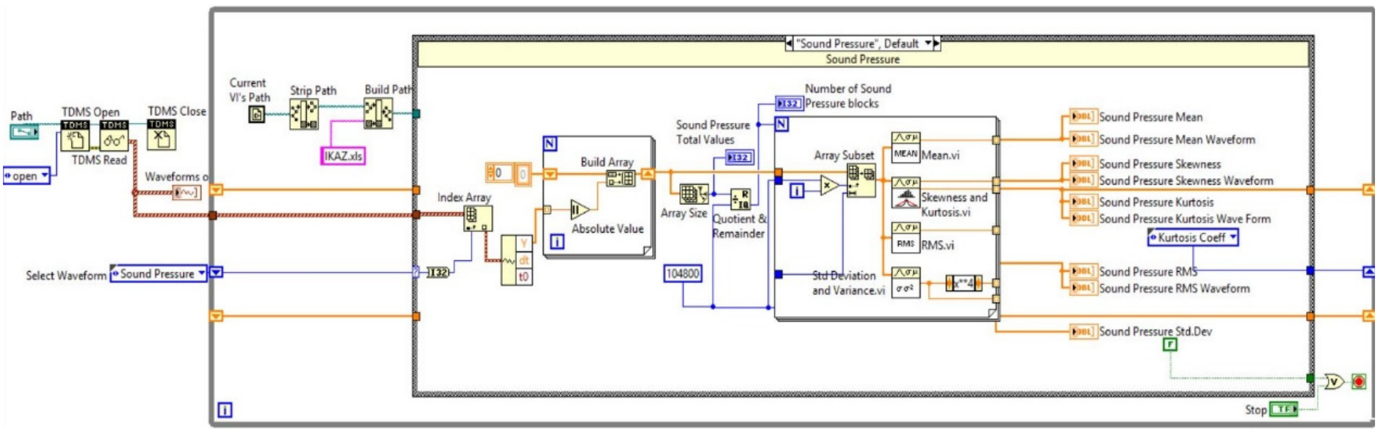

Fig. 9. Program for Kurtosis and I-KAZ Coefficient

tistically analyzed through the I-Kaz coefficient. Kurtosis coefficient was calculated using the equation systematically through the generated program as depicted in Fig. 9. 10,000 iterations or cycles are generated for every 10 seconds, for a period of 10 minutes, 60, 00,000 iterations are recorded. All the iteration values are divided into samples and kurtosis values are calculated for respective samples. By substituting kurtosis coefficient in equation 4, I-Kaz coefficient values were determined for every experiment. Flank wear was measured for every 10,000 cycles. From the results of I-Kaz statistical analysis method, the relation between I-Kaz coefficient (Z_2^∞) with resultant flank wear was established. Fig. 10 illustrates the variation of flank wear and I-Kaz for 100000 cycles. Flank wear and Ikaz coefficient follow a reversible trend in such a way that, an increase in flank wear leads to a decrease in the I-Kaz coefficient. This decline in the coefficient of I-Kaz Z_2^∞ with flank wear is following the trend of power-law curve. It can be expressed as

$$Z_2^\infty = a(VB)^{-n} \tag{9}$$

where Z_2^∞ is a two-dimensional I-Kaz coefficient, a and n are constants which depend on cutting parameter, and VB is denoted for flank wear.

I-Kaz and tool wear correlation graph are plotted for the selective experiments (one set of data for uncoated (Exp. no. 7), single layer (Exp. no. 18), and bi-layer coated inserts (Exp. no. 24)). The correlation between the I-Kaz statistical approach and tool wear is shown in Fig. 10. It can be concluded that I-Kaz and flank wear are inversely proportional to each other and follows the power-law curve and the results are in line with previous work [18,19]. It can be seen that uncoated inserts have a lower I-Kaz coefficient whereas, TiAlN/WC-C has a higher I-Kaz coefficient which states that bilayer coated inserts have the lower flank wear compared to the uncoated inserts.

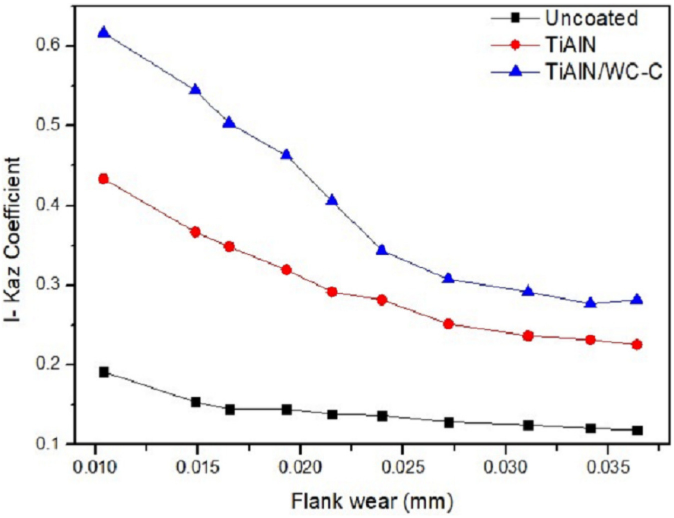

Fig. 10. Flank wear and I-KAZ Coefficient

3.3. Artificial Neural Network (ANN)

A four-layer feed-forward neural network with a back-propagation algorithm has been developed. The network consists of four layers with input, hidden, and output layers. In total, 10, 00,000 I-Kaz values are taken for Neural Network data processing. Out of total values, 7, 00,000 values are used for training, and 3, 00,000 values are used for testing. The number of learning steps for complete training was set at 1000 based on the time to convergence. As the errors are significantly low in comparison with one hidden layer, this model has been developed with two hidden layer network. The input neuron is I-Kaz coefficients and the output neuron is flank wear.

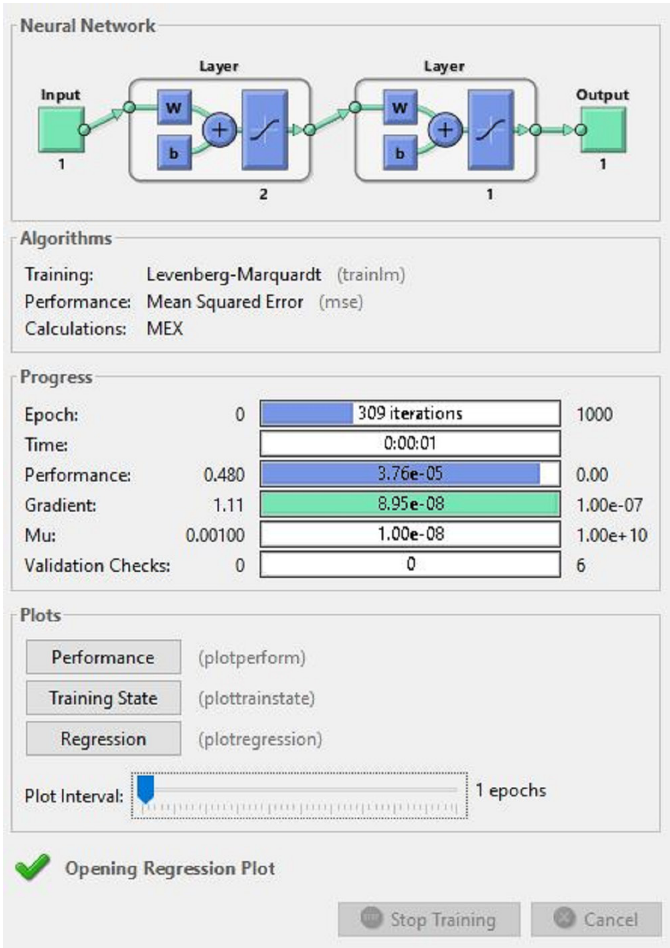

Fig. 11. Neural Network

The corresponding neural network and custom neural network is shown in Fig. 11 and 12. The learning of the neural network was executed through the feed-forward Levenberg-Marquardt algorithm process of learning and it was stopped at 309 iterations.

The best training performance is shown in Fig. 13. The Levenberg-Marquardt algorithm performs better than other algorithm. The best training performance was obtained at 309 epochs. Fig. 14 shows the regression plot generated from training the neural network shows the linearity of the given data and the respective regression equation is also generated (Output = 1.4*Target + 0.024). The neural network model developed has better (almost 0.94933) coefficient values close to 1 as depicted in Fig. 13.

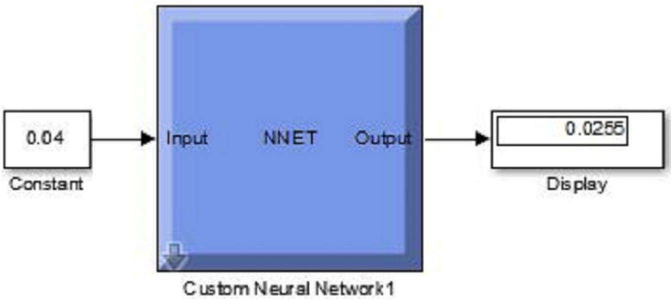

Fig. 12. Custom Network

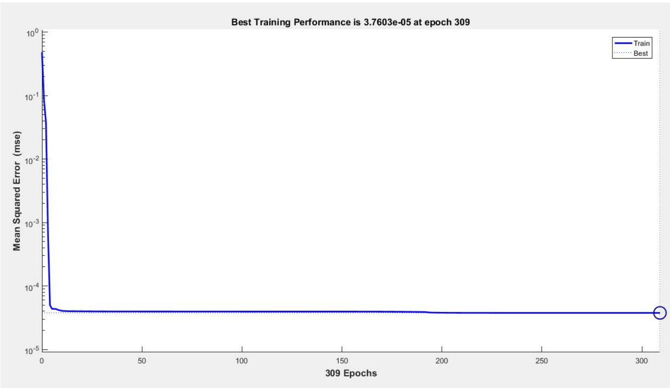

Fig. 13. Mean Square for Training

This value showed that the model could effectively predict the tool state. ANN was given training up to 1000 epochs, showing a least MSE value of 3.7603e-5 as shown in Fig. 11. This portrays that the developed estimator has a minimal error.

4. Conclusion

Dry machining of SAE 1015 steel was performed by employing uncoated, TiAlN, TiAlN/WC-C coated inserts. Flank wear was measured as output response and the input parameters have been optimized through the Taguchi design of experiments. The depth of cut had a significant effect on flank wear. A novel very near field acoustic sensor – Microflown sensor was used to acquire sound signals during the machining operation. The raw data were processed and analyzed using LabVIEW software. The relation between flank wear and the statistical data was established using kurtosis and I-Kaz coefficient. From the results, it was observed that flank wear and I-Kaz coefficient follow the trend of the power-law curve. The artificial Neural network model was trained, validated, and tested with the least mean square error value of 3.7603e-5. The developed neural network can be efficiently employed with minimal error for monitoring tool conditions online.

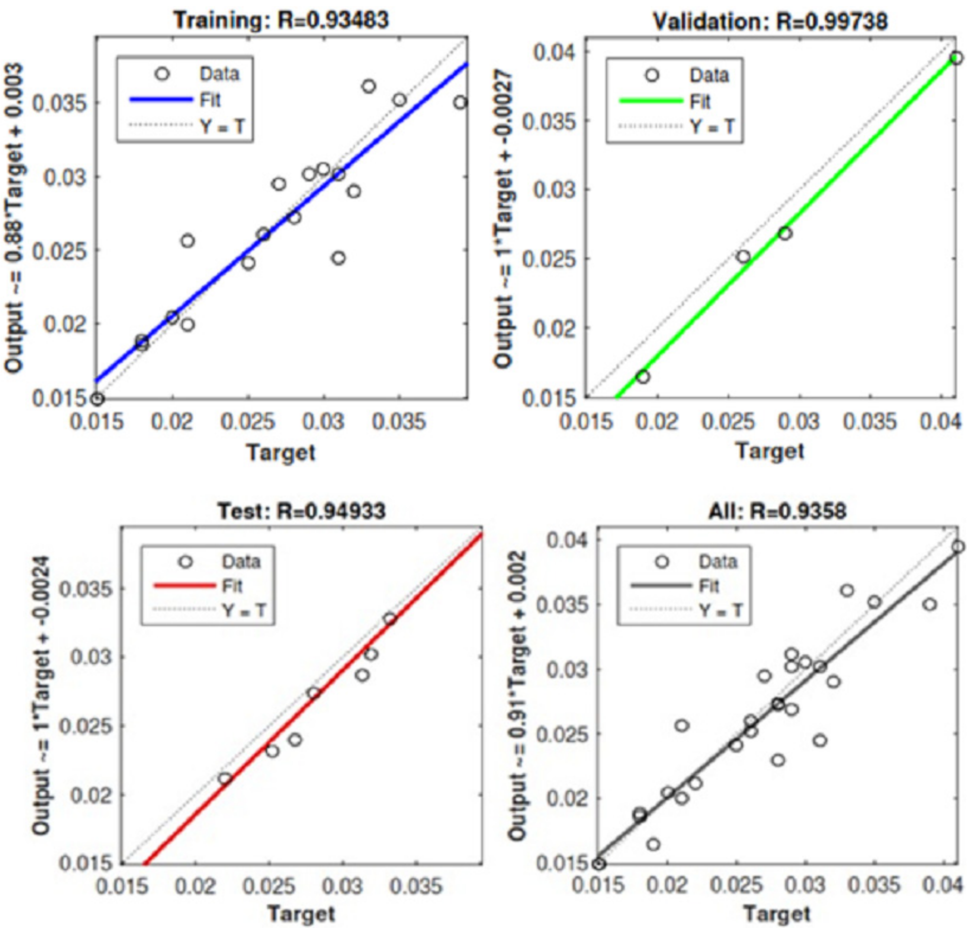

Fig. 14. Regression Plot

REFERENCES

[1] M. Noordin, V. Venkatesh, S. Sharif, J. Mater. Process. Tech. **185** (1-3), 83-90 (2007). DOI: https://doi.org/10.1016/j.jmatprotec.2006.03.137

[2] C. Moganapriya, M. Vigneshwaran, G. Abbas, A. Ragavendran, V.C. Harissh Ragavendra, R. Rajasekar, Mater. Today, Proceeding (2020).

[3] A.M. Ravi, S.M. Murigendrappa, P.G. Mukunda, T. Indian I. Metals **67** (4), 485-502 (2014). DOI: https://doi.org/10.1007/s12666-013-0369-0

[4] A.P. Kulkarni, V.G. Sargade, Mater. Manuf. Process **30** (6), 748-755 (2015). DOI: https://doi.org/10.1080/10426914.2014.984217

[5] C. Moganapriya, R. Rajasekar, K. Ponappa, R. Venkatesh, S. Jerome, Mater. Today. Proceeding **5** (2), 8532-8538 (2018). DOI: https://doi.org/10.1016/j.matpr.2017.11.550

[6] G.C. Rosa, A.J. Souza, E.V. Possamai, H.J. Amorim, P.D. Neis, Wear **376**, 172-177 (2017). DOI: https://doi.org/10.1016/j.wear.2017.01.088

[7] A. Alok, M. Das, Measurement **133**, 288-302 (2019). DOI: https://doi.org/10.1016/j.measurement.2018.10.009

[8] R. Yigit, E. Celik, F. Findik, S. Koksal, Int. J. Refract. Hard. Met. **26** (6), 514-524 (2008). DOI: https://doi.org/10.1016/j.ijrmhm.2007.12.003

[9] R. Horváth, Á. Drégelyi-Kiss, G. Mátyási, Acta Polytech. Hung. **11** (2), 137-147 (2014).

[10] R. Kumar, P.S. Bilga, S. Singh, J. Clean Prod. **164**, 45-57 (2017). DOI: https://doi.org/10.1016/j.jclepro.2017.06.077

[11] M.K. Gupta, P. Sood, V.S. Sharma, J. Clean Prod. **135**, 1276-1288 (2016). DOI: https://doi.org/10.1016/j.jclepro.2016.06.184

[12] S. Pai, T. Nagabhushana, Handbook of Research on Emerging Trends and Applications of Machine Learning, 2020 IGI Global.

[13] A.K. Jain, B.K. Lad, J. Intell. Manuf. **30** (3), 1423-1436 (2019). DOI: https://doi.org/10.1007/s10845-017-1334-2

[14] R. Teti, K. Jemielniak, G. O'Donnell, D. Dornfeld, CIRP Ann. **59** (2), 717-739 (2010). DOI: https://doi.org/10.1016/j.cirp.2010.05.010

[15] C. Moganapriya, R. Rajasekar, K. Ponappa, R. Venkatesh, R. Karthick, Arch. Metall. Mater. **62** (3), 1827-1832 (2017). DOI: https://doi.org/10.1515/amm-2017-0276

[16] H.B. Ulas,T. Indian I. Metals **67** (6), 869-879 (2014). DOI: https://doi.org/10.1007/s12666-014-0410-y

[17] S. Thangarasu, S. Shankar, T. Mohanraj, K. Devendran, P. I. Mech. Eng. C.-J. Mec. **234** (1), 329-342 (2019).

[18] J.A. Ghani, M. Rizal, M.Z. Nuawi, C.H. Che Haron, M.J. Ghazali, M.N.A. Rahman. Trans. Tech. Publ. 2010.

[19] S. Oraby, D. Hayhurst, Int. J. Mach. Tools Manuf. **44** (12-13), 1261-1269 (2004). DOI: https://doi.org/10.1016/j.ijmachtools.2004.04.018