Mathematical modelling of dominant features identification for tool wear monitoring in hard turning by using Acoustic emission

D. Kondala Rao[a], Kolla Srinivas[b], Md. Hasheer SK[c], and K. Hari Prasad[d]

[a,b,c,d] Faculty of Mechanical Engineering, R.V.R. J.C. College of Engineering, Guntur, Andhra Pradesh, India

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Abstract: In machining processes generally tool wear will be obtained with varying proportions. In the present work, the number of dominant features, which affect the tool wear, are studied and computed on Inconel 718 as work material with varying hardness (51, 53&55HRC) levels. The condition monitoring was done on three tools namely uncoated carbide, coated carbide and ceramic tools. By using L9 Taguchi's orthogonal array, speed, feed, depth of cut (DOC) and hardness are considered as input operating parameters. By indirect method of Acoustic emission (AE) technique, signals were collected using Lab VIEW software and dominating features were calculated using the MATLAB. The features were trained in neural network and got the relation between tool wear, surface roughness, temperature and features. The simulated data was analyzed by Grey relational analysis (GRA) and the dominating features ranking sequence was obtained for all the three tools and same ranking was also observed with ANOVA. Since there are no common influencing features among these three tools and hence further investigation continued with statistical mathematical modeling. With Akaike information criterion a mathematical model is developed to find the dominant features. By mathematical modeling the sequence in evaluating tool wear was found to be Kurtosis, Frequency, Variance, Mean and RMS and also a relation between tool wear and dominant features was developed which can be readily used by layman for calculating the tool wear.

Keywords: Hard turning, Tool wear Monitoring, Dominant features, AE, GRA, Akaike

1. Introduction

Hard turning has emerged as a recent new technology that can be used for products with a hardness value of 45 HRC or greater in finishing operations. With the advancement of various super hard cutting tool materials along with correct machine tools, the turning of hardened steel to around 45 HRC is called soft machining. Turning of more than 45 HRC of hardened steel is known as fast machining and examples of hardened steels which are commonly used in engineering applications like dies and molds, automotive and machine tool parts. There are number of ways by which tool wear develops in machining processes. Damaged tools definitely affect the finishing of surface and hence it is necessary to establish tool wear monitoring (TWM) systems by means of which the operator takes corrective steps to improve the quality of products. TWM systems are also termed as tool condition monitoring (TCM) systems. Number of articles have reviewed the enhancements to be made in TCM systems.

Apart from reducing downtime, by avoiding unnecessary tool changes, products cost also reduced extensively by using effective TWM. By proper TCM the product quality improves. It eliminates tool deflection & chatter. For the last 35 years (LI Dan, 1990;Garikapati, 2020) much research has been taken place in TCM. Due to complex nature of machining processes, even though many advanced methods have been put forward, only few were successful. Based on the classification of sensors, the successful methods used were direct techniques which uses radioactive electrical resistance & optical concepts etc. Whereas indirect methods use Acoustic emission (AE), Vibration, Cutting force, Spindle motor current concepts etc. Recent studies have focused on how best indirect monitoring methods could improve the quality of processes. The most efficient indirect method which was emerged in recent times was AE

In traditional machining, tool wear can be tracked using various indirect variables sensitive to the wear of the equipment. The widely used indirect parameters are the three cutting force components as stated by (Teti, 2010). (Moriwaki, 1990; Shankar, 2020; Vasanth, 2017) operated within the 100 kHz and 1MHz frequency ranges. Therefore, the correct frequency range of AE signal was experimentally tested to track the wear of the instruments. (Blum, 1990) observed the relationship between the AE waves and the cutting phase with in the frequency range between 100 kHz to 300 kHz. (Narayanan, 1994; Vasanth 2018) prepared a method for the coated tool life estimation based on AE measurements and analysis. (Ravindra 1997;Battula, 2020) and (Byrne, 1995) investigated the acoustic emission in metal cutting for tool quality monitoring. The carbide tool coated with multilayers was used to machine C60 steel and tool wear was tracked by the AE signals detection and analysis. The prospect of using AE methods as a wear tracking technique for online applications has been examined. A research by (Dalpiaz, 1988; Latchoumi, 2016) found that there was no definite pattern with tool wear in the AE parameters, but rather a general random activity with unexpected variations in the phase of deterioration phenomena. Through their pattern study, (Emel, 1995) have identified 100 kHz to 1 MHz was the most accurate frequency range through their pattern study.

Catastrophic device failure was detected by (Jemielnaik, 1998) by the development of statistical signal processing algorithm to classify kurtosis signal from acoustic emission, skew and RMS. They concluded that when compared with RMS, kurtosis and skew were better markers of catastrophic instrument failure. To know when the failure has occurred, reference signals are obtained at the same time by measurement of cutting force. Using acoustic emission signals along with vibrations & cutting forces, models were developed by (Sharma, 2006) to estimate tool wear. The predicted tool and actual tool wear values were found and established a close relationship between them. Roll bearing deterioration was tracked by (Eftekharnejad, 2011) by using vibration & AE techniques and the results were compared. Because of wide range of frequency when used AE signal for tool condition monitoring it was thought to be superior when compared with that of vibration technique and ambient noise. It also does not interfere with the process.

2. Dominant Feature

A significant number of features are measured in many industrial applications. However, it has been found, that the inclusion of additional features above a certain threshold contributes to a worse result. In addition, the prime features influence other aspects of the recognition process, such as learning time, precision and the sample size which is most important. Moreover, measuring additional features contributes to the process of identification of increase in complexity, computing space and time.

In this work an attempt is made to define the dominant characteristics for tool wear by using acoustic emission technique. In industrial turning machines, tool wear prediction time series could be obtained by selecting dominant features. GRA is used as a software resolution method to select features. This is achieved by an online, indirect real time approach with AE sensors installed. The suggested method is tested on an automated high-speed turning machine using a single point cutting tool. The baseline time plot of real wear versus time of the device is taken. Eleven features were calculated from the measured AE data, commonly used for machinery monitoring in industry. The GRA method is then used with the aid of Artificial Neural Network (ANN) to pick the dominant function.

A high-speed milling machine ball nose cutter tool wear was estimated by identification of dominant features with measurement of AE signals by (Zhou, 2006). The results showed that with dominant features, the tool wear was predicted more effectively. A relationship between kurtosis, skew and tool wear was proposed by (Kannatey-Asibu, 1982). Fisher's linear discriminate analysis was used by (Zhu, 2010) to select cutting force features for tool wear monitoring. Correlation-based feature selection technique was adopted by (Binsaeid, 2010) to estimate the influence of the features from multiple sensor signals.

3. Methodology

The proposed method is tested using a single point cutting tool in an industrial high-speed turning lathe machine Lokesh TL250. Acoustic emission measurements are noted over a period using AE sensor. During the measuring period, the tool is periodically removed from the chuck, and tool wear is measured using Tool Makers microscope. Eleven features, generally used for machinery monitoring in industries, are calculated from the measured data. The optimal feature values were observed using the grey relational analysis along with ANN. Among the eleven features obtained, the most contributing features were identified by applying ANOVA.

3.1. Machining Parameters and their Levels

Taguchi L9 orthogonal array is used to carryout the number of experimental runs and the variations of each run. The turning experiments are performed on LOKESH TL250 Computer numerical control (CNC) lathe. The cutting parameter values along with their levels are presented in Table 1.

Table 1 Parameter values and levels during experimentation.

Level	Operating parameters			
	Speed (m/min)	Feed (mm/rev)	Depth of cut (mm)	Hardness (HRC)
1	50	0.050	0.15	51
2	65	0.075	0.20	53
3	80	0.100	0.25	55

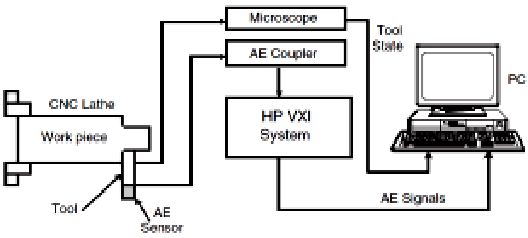


Figure 1 Experimental set-up scheme

4. Experimental Setup

The schematic of the experimental setup developed in this work is depicted in the Figure 1. A Lokesh Machines Limited, 20kW, CNC lathe was used for machining. Inconel 718 Nickel based alloy of of hardness 51,53 and 55HRC was used as the work material. TNMG160408MS SW05 uncoated carbide cutting tool insert, TNMG160408MU PR1305 (PVD) mega coated carbide cutting tool insert, TNMG160408 A65 ceramic tool insert and MTJNL 2020K16 Tool holder were used. Acoustic emission sensor with a frequency range of 50 kHZ- 400 kHZ was used to capture the signals due to flank wear.

4.1 Measurement and processing of AE signals during cutting

The AE signals have been recorded at various stages of cutting until failure of the tool. The AE signals were measured using a Kistler 8152C AE piezoelectric sensor which has been mounted on top of the tool holder with magnetic clamp (Kistler 8443B), and placed possibly near to the tool-insert. The AE sensor has a frequency range from 50 kHz to 400 kHz 1 Hz to 10 kHz and sensitivity of the sensor is 57 dBref 1V/(m/s). A KISTLER 5125C type coupler is used to pass the signal through. The sensor captures the AE signals in the z-direction. The trained signal is finally sent to system with LabVIEW based software for display and storage.

5. Results and Discussion

Experiments were conducted and using AE signals data, the analysis was carried out and the results are obtained. The flank wear of tool is determined using Tool maker's microscope, the surface roughness of the work pieces was measured by using Taly surf and temperature was measured by Infrared thermometer were given in the table 2,3 & 4. In this work, for every 120mm length of cut the tool flank wear was measured for each work piece.

Table 2 Data obtained for Uncoated carbide insert for Inconel 718

EXP NO	Speed (m/min)	Feed (mm/rev)	DOC (mm)	Hardness (HRC)	Tool Wear (mm)	Surface Roughness (µm)	Temperature (°C)
1	1	1	1	1	0.245	1.13	199
2	1	2	2	2	0.185	1.06	180
3	1	3	3	3	0.200	1.19	222
4	2	1	2	3	0.200	0.96	180
5	2	2	3	1	0.200	1.06	390
6	2	3	1	2	0.220	0.94	181
7	3	1	3	2	0.210	1.03	197
8	3	2	1	3	0.175	0.85	180
9	3	3	2	1	0.200	0.98	330

Table 3 Data obtained for Coated carbide insert for Inconel 718

EXP NO	Speed (m/min)	Feed (mm/rev)	DOC (mm)	Hardness (HRC)	Tool Wear (mm)	Surface Roughness (µm)	Temperature (°C)
1	1	1	1	1	0.190	1.150	315
2	1	2	2	2	0.175	0.960	230
3	1	3	3	3	0.160	1.702	180
4	2	1	2	3	0.190	0.924	180
5	2	2	3	1	0.145	0.972	410
6	2	3	1	2	0.140	0.760	240
7	3	1	3	2	0.190	1.264	190
8	3	2	1	3	0.170	0.842	190
9	3	3	2	1	0.140	1.865	400

Table 4 Data obtained for Ceramic insert for Inconel 718

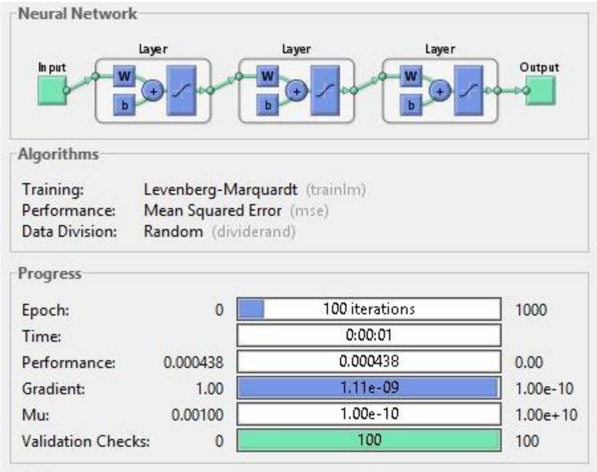
EXP NO	Speed (m/min)	Feed (mm/rev)	DOC (mm)	Hardness (HRC)	Tool Wear (mm)	Surface Roughness (µm)	Temperature (°C)
1	1	1	1	1	0.129	2.2818	200
2	1	2	2	2	0.149	2.3402	201
3	1	3	3	3	0.140	2.2884	202
4	2	1	2	3	0.190	2.3438	203
5	2	2	3	1	0.118	2.0687	194
6	2	3	1	2	0.116	2.0440	194
7	3	1	3	2	0.193	2.3662	203
8	3	2	1	3	0.122	2.1324	210
9	3	3	2	1	0.111	5.4356	232

5.1 Evaluation of Various features for Inconel 718

Various features were calculated by using Lab VIEW software and MATLAB for each signal collected by AE sensor. These features and corresponding outputs (tool wear, surface roughness and temperature) trained with neural network by considering the parameters got high accuracy of 98%. Based upon the training the above performance curves were plotted. After obtaining satisfactory relation between features and outputs in neural network training, the simulated results were optimized based on Grey relation analysis. Using Anova the optimized values are verified for consistency.

5.2 Artificial Neural Network for AE

The obtained features were trained in neural network by considering the parameters shown in Fig.2,3,4 & 5 and got maximum accuracy of 98%.



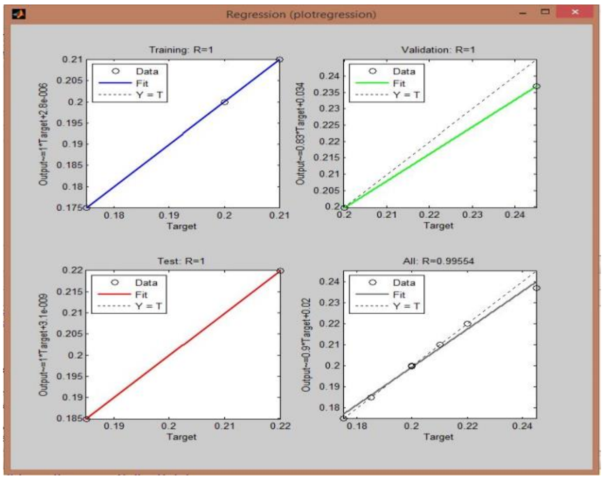
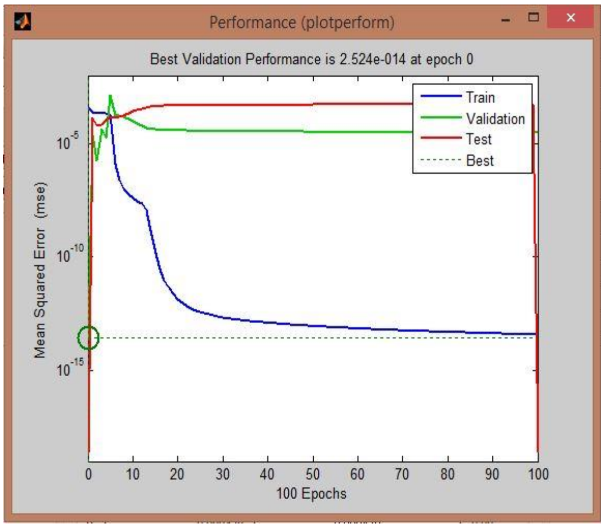


Figure 2 Neural Network for AE Signals

Figure 3 Regression Graph for AE signals



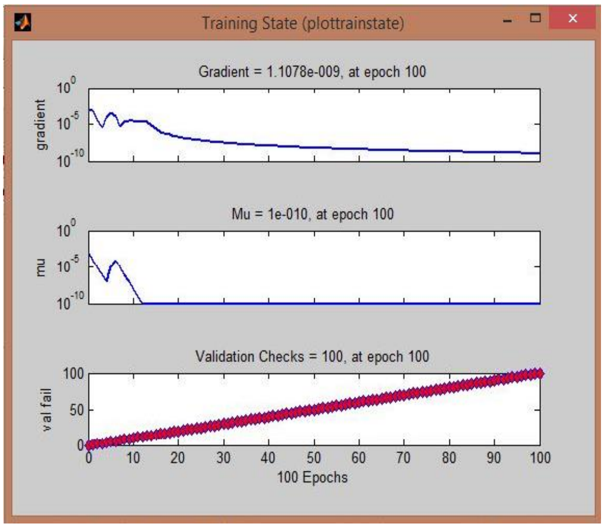


Figure 4 Performance Graph for AE signals

Figure 5 Training State Graph for AE

5.3 Grey relation Analysis for AE

If the value of grey grade is greater, the combination of corresponding factors is said to be near to the optimal. The average grey grade of each factor was attained by taking the average grey grade for the appropriate factor at the required level. The optimum level for each factor was reached on the basis of the ' greater is better' characteristic. The pattern of the grey grade of the experimental runs was graphically described in Fig.6. Thus, the dominating sequence for Uncoated carbide was Skewness (SKW), TIME, Standard Deviation (SD), Root mean square (RMS), Variance (VAR), MEAN, Frequency (FRE), Absolute Deviation (AD), PEAK, Kurtosis (KURT), Crest Factor (CF). Similarly, the dominating sequence for Coated carbide was KURT, SKW, FRE, TIME, PEAK, RMS, VAR, MEAN, CF, AD, SD. And the dominating sequence for Ceramic insert was RMS, AD, CF, SD, MEAN, KURT, FRE, VAR, SKW, PEAK, TIME.

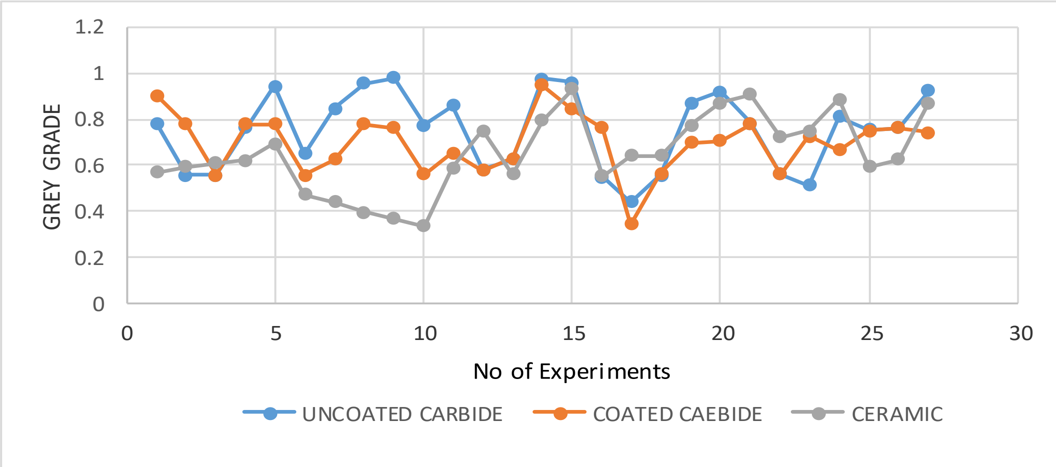
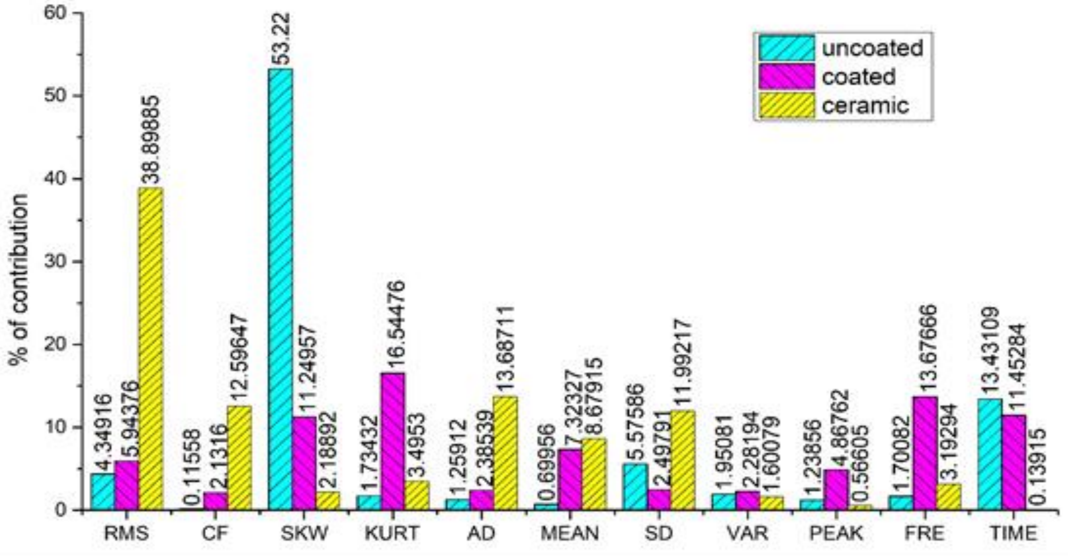


Figure 6 GRA grades of experimental trails for AE

5.4 Anova Analysis for AE

According to this analysis and percentage contribution, a factor with a high percentage contribution, there is a greater effect on the performance of tool wear. Thus, the domina sequence again supported by ANOVA is same as GRA results. From ANOVA sequence of percentage contribution of each feature was shown in Fig.7.



5.5 Mathematical model for tool wear based on Acoustic Emission technique

All together there are eleven independent features and one dependent feature. The dependent feature is tool wear and the all other are independent in experimental. To find out the dominant features amongst all the eleven independent features we have carried out the Akaike's Information Criteria (AIC).

The first five dominant features in our findings are Kurtosis, Frequency, Variance, Mean, RMS based on these five features neglecting the other six features which are contributing less to the tool wear we have calculated a mathematical model as a ready use for any experimentor. Based on these five dominant features the mathematical model is

$$Y = a_0 + a_1X_1 + a_2X_2 + a_3X_3 + a_4X_4 + a_5X_5 \text{ ----------------------- } (1)$$

$$TW = a_0 + a_1(KURT) + a_2(FRE) + a_3(VAR) + a_4(MEAN) + a_5(RMS) \text{--------- } (2)$$

Where

a_0 is the intercept and a_1, a_2, a_3, a_4, are the statistical constants which are calculated by method of least squares.

Table 5 AIC values from Acoustic Emission

	Df	Sum of Sq	RSS	AIC
<none>		0.0033496		-228.86
- avgkurt	1	0.00032939	0.0036790	-228.33
- avgfre	1	0.00037996	0.0037296	-227.96
+ avgvar	1	0.00010803	0.0032416	-227.74
+ avgmean	1	0.00005939	0.0032902	-227.34
+ avgrms	1	0.00004137	0.0033082	-227.19
+ avgskw	1	0.00003977	0.0033098	-227.18
+ avgad	1	0.0000854	0.0033411	-226.93
- avgpeak	1	0.00064756	0.0039972	-226.09
- avgcf	1	0.00066502	0.0040146	-225.97
- avgtime	1	0.00113409	0.0044837	-222.99
- avgsd	1	0.00214775	0.0054973	-217.48

Using R- Programming the least squares method formula is calculated as lm(formula = avgtw ~ avgkurt + avgfree + avgvar + avgmean + avgrms) i.e

TW = -4.273e-17+1.734e-33avgkurt+1.000e+00 avgfree+1.916e-19avgvar+7.471e-19 avgm ean-5.065e-1 9avgrms ------- (3)

By plotting the points the residual versus leverages is given as

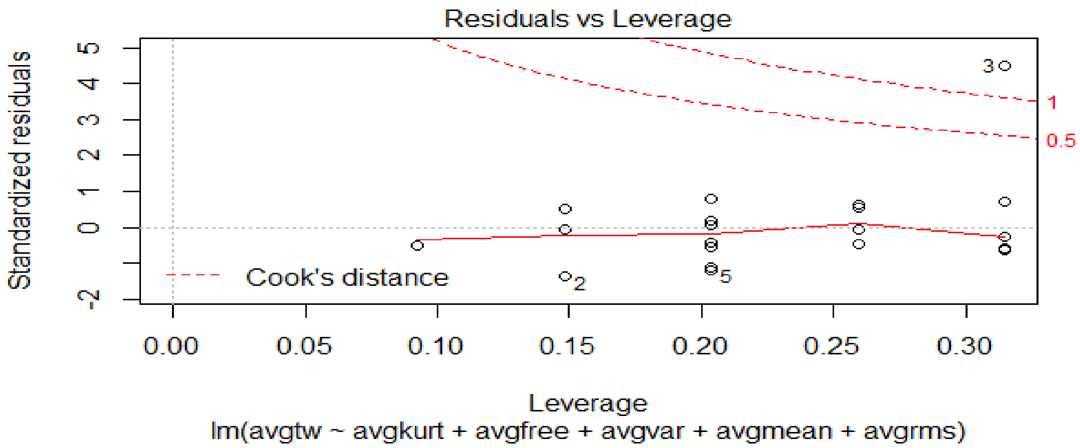


Figure 8 Variation of residuals and leverage of features from AE signals

6. Conclusions

AE signals were collected from the LabVIEW software and the features were measured from the acquired signals using the MAT LAB software. By using neural network to train the features for the relationship between tool wear, surface roughness, temperature and features and has been found to be approximately 98 percent accurate. The output parameters were determined by simulation of neural network where all features were considered as input data from L27 orthogonal array. The simulated data was evaluated using the Gray Relational Approach and the Gray Grade obtained, which is used to assess the dominant function of the tool condition monitoring. The dominant features of the AE signal series of Uncoated, Coated carbide and Ceramic insert were obtained using Gray relational analysis. Although ANOVA analysis was supported out for the neural network simulated statistics and Gray codes, it was observed that same Features rating sequence was obtained for the AE signal. Dominant features are varied for tool wear of three tools in AE. The Mathematical model developed for tool wear based on dominant features obtained by Akaike information criteria for AE technique. Based on mathematical model for features of AE it was observed KURTOSIS, FREQUENCY, VARIANCE, MEAN, RMS are considerable dominant features.

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