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Ceramic Tool Condition Monitoring in Machining of Inconel 718

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Abstract— There is an in-depth discussion in this paper about the improvement of a system regarding tool wear monitoring in hard turning operation. Acoustic emission (AE) signals from metal cutting processes have been investigated for various purposes, including in-process tool wear monitoring. Hard turning is a machining process Nickel based alloys are difficult-to-machine materials which are widely used in various applications. Tool wear is a major problem in these materials because of their high hardness. The present study is focusing on Inconel 718 with varying HRC (51, 53, and 55) and the tool employed here is ceramic. By using L9 orthogonal array extracted from taguchi method, taking input parameters such as speed, feed, depth of cut and hardness. Taking vibration signal data as an input to ANOVA and Grey relation analysis (GRA) which identifies the optimal and most dominant feature (Root Mean Square(RMS), Crest Factor(CF), Skewness(Sk), Kurtosis(Ku), Absolute Deviation(AD), Mean, Standard Deviation(SD), Variance, peak, Frequency and Time in the tool wear operation.

Keywords— Tool condition Monitoring, Dominant features, Acoustic Emission, Grey relation analysis, Anova

I. INTRODUCTION

Nickel-based super alloys are widely used in aerospace applications due to their magnificent mechanical properties maintained at high temperature and their corrosion resistance. Machining of these alloys is still a challenge, especially in dry machining. Super alloys characteristics like high temperature, tensile and shear strength, work hardening, reduced thermal conductivity, built-up edge formation and the presence of abrasive particles in their microstructures etc. are induce high thermo-mechanical loads at the tool-chip interface resulting in significant wear of the tool [1]. Tool wear strongly influences production costs and affect surface integrity of the component [2,3]. Cutting tool selection is an important factor when machining Ni based alloys. Cemented carbides have been used for decades and the use of multilayer coatings (TiN,TiCN) have improved their suitability for machining Ni-based alloys. Cemented carbide tools should not be used to machine nickel-based alloys at high speed since they cannot withstand the conditions of extreme high temperature and stress in the cutting zone. In general, the recommended cutting speeds range up to 30 m/min for uncoated inserts and up to 100 m/min when machining nickel-based alloys using cemented carbide tools properly coated [4]. Ceramic tool have superior hot hardness and can be used at speeds around an order of magnitude higher than the coated carbide cutting tools. Ceramic tools have been used increasingly in cutting operations of Ni alloys. High cutting speed can be achieved with the use of whisker reinforced ceramics [5].

In metal-cutting processes tool wear is a complex phenomenon occurring in various ways. Normally, the surface finish is mainly affected by a worn tool and therefore there is a need to develop TCM systems that alert the operator to the tool wear state, thereby avoiding undesirable effects [6]. TCM systems that were improved in the past are comprehensively reviewed in a number of articles.

Micheletti [7] discussed different types of sensors for "in-process" measurement of tool wear. Ravindra and Srinivas [8] conducted experiments for sharp tools and various stages of flank wear. To discuss the wear time and wear force relationship in turning, and in estimating tool wear a mathematical model based on multiple regression analysis was developed.

TCM not only reduces the manufacturing expenses by lowering downtime and unnecessary cutting tool changes, but also improves the product quality by eliminating chatter, excessive tool deflection and poor part surface finish[9].

Many methods for TCM had been put forward in the past but not many were universally successful because of the complex nature in machining. The classification of sensors as direct (radioactive, optical, electric resistance, etc) and indirect (AE, spindle motor current, vibration, cutting force, etc) sensing methods are successful methods. Recent studies have concentrated on the improvement of indirect monitoring methods for cutting processes. AE being the most efficient indirect sensing method.

The benefit of using AE to detect tool wear lies in two aspects: its frequency range is very high than the vibrations of machines and environmental noises Most of them use analogue root mean square of the signal to observe tool wear or find out breakages.

Damodara samy [10] discussed the combined effect of radial force, feed force and AE (RMS value) in modeling the tool flank wear for turning operation. AE is considered as a phenomenon whereby transient elastic waves are produced by the rapid release of energy from a localized source or source within the material, or the transient elastic wave so produced. AE signals produced during turning can be continuous or transient/burst type.

Jemielniak et al. reviewed various AE methods [11,12] applied for TCM and put forward that due to a wide sensor dynamic range, AE can find out most of the phenomena in machining, although significant data acquisition and signal processing is required. Dilma [13] also spoke about some AE techniques used for flank wear detection [14,15]. The author discussed that AE can be deemed only suitable as an additional sensing method for growth in reliability of TCMS due to complexity involved in selection of the location for sensor mounting and signal analysis techniques.

Rang Wala and Dornfeld [16] performed sensor integration using AE along with other signals for TCM. The RMS of AE was observed to be sensitive to the degree of flank wear.
Heiple et al. [17] observed AE during turning of the cutting tool as phenomena of heat treatment and observed that the primary source of AE was sliding friction between the tool flank and the work piece. It was finalized that since changes in AE with tool wear were strongly material dependent, the single characteristic change in AE with tool wear is valid for all material was unlikely to exist.

Cho and Komvopoulos [18] found the relationship between AE RMS and changes in tool–work piece contact area due to wear, changes in the interfacial friction coefficient, and the cutting tool material properties resulting from various coating materials. The tool life calculated using AE RMS was in good correlation with that found with maximum wear land width.

Chungchoo and Saini [19] improved a model to relate AE rms in the turning operation with the flank and crater wear. The improved model accurately predicted the flank wear during turning.

In a brief review, Scheffer et al. [20] used AE rms signals along with other signals in order to improve a tool wear monitoring system for hard turning.

Sun et al. [21] developed a tool condition observing system using efficient feature set taken from AE signals along with support vector machine (SVM). The method that is put forward could identify flank wear effectively, and manufacturing losses in industries due to under- or over-prediction of flank wear was lowered. It was seen that ring down count parameter of AE signals showed a significant growth with the tool wear.

Bhuiyan et al. [22] improved a dummy tool holder apparatus in order to fore see tool wear from AE measurement.

Kondala Rao[23] found that dominant features of the coated carbide tool with the help of AE sensing technique. The present paper focusing to study the sequence of dominant features of ceramic tool wear by using AE signals.

II. DOMINANT FEATURE

In various industrial applications, different features are computed. However, it has been identified that, beyond a certain threshold, including additional features leads to a worse performance. However, the selection of features affects various aspects of the recognition process, such as accuracy, learning time, and essential sample size. Vitally, computing more features take to an increase in time and computational space complexity of the recognition process.

Various methods for tool wear monitoring were proposed in the past, but during the feature deriving stage, the most dominant features which correlate well with tool wear and not affected by process conditions are developed from the prepared signals is not specifically mentioned. Hence this project made an attempt to find out the dominant feature for both AE and Vibration Signatures. In this paper, GRA is used as statistical decision tool for identifying the dominant features which are most appropriate in predicting the time series of tool wear in industrial turning machines using an online, real-time, and indirect approach, with data from installed AE and vibration sensors

III. METHODOLOGY

The proposed methods were tested using a single point cutting tool in an industrial high-speed turning machine. AE measurements were taken during a period using an AE sensor. During the measuring period, the tool was periodically extracted from the chuck, and tool wear was measured using ‘Tool Makers microscope’. This yielded a baseline time plot of actual tool wear versus time. Eleven features, commonly used for machinery monitoring in industries, were calculated from the measured AE data. ANOVA was applied to observe the most contributing feature among the eleven features. The GRA method was then used to observe the optimal feature values with the help of Artificial Neural network (ANN).

IV. GREY RELATIONAL ANALYSIS

The Grey Relational Analysis (GRA) which is involved with the Taguchi method represents a new approach to optimization. The grey theory is based on the random uncertainty of small samples which developed into an evaluation technique to solve certain problems of system that are complex and have incomplete information. A system for which the accurate information is completely known is a white system, while a system for which the relevant information is completely unknown is a black system. Any system between these extremities is a grey system having poor and limited information.GRA which is a normalization evaluation technique is extended to affect the complicated multi-performance characteristics.

V. EXPERIMENTAL WORK

A. Work material, Tools and measurement of flak wear

Turning experiments were carried out on a CNC lathe Lokesh TL250 and its capacity 20KW. Experiments were conducted on a round bar (50 mm dia and 10Kg weight) of Inconel 718, hardness (51,53 and 55HRC) with Ceramic insert(TNMG 160408 A65) with tool holder MTJNL 2020K16 without cutting fluid for this investigation.

The flank wear of tool insert was measured using Elshaddai Engineering Equipments make Tool maker's microscope(LT-24) with a magnification of 30x ,with X-Y movement on ball bearing slides with 25mm graduated micrometers and least count 0.001mm. The flank wear was measured for every 120mm length of cut.

B. Cutting conditions

Since the focus of this work has been to find most dominant feature of tool wear with ceramic insert with dry machining, experiments have been conducted at four cutting parameters (speed, feed rate, depth of cut and hardness) were taken with three levels for each cutting parameter were summarized in Table 1.

Table 1 Experimental Factors and their levels

Levels of the experimental factors	Factors			
	Speed, N (rpm)	Feed rate, f (mm/rev)	Depth of cut, d (mm)	Hardness (HRC)
1	50	0.05	0.15	51
2	65	0.075	0.2	53
3	80	0.1	0.25	55

C.Measurement and processing of cutting AE signals

The number of experiments and the combinations of parameters for each run was obtained by using Taguchi's L9 orthogonal array. 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 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 sensed the AE signals in the z-direction.The trained signal is finally sent to laptop with LABVIEW based software for display and storage. The vibration signal data is stored in a excel file for further processing and analysis.

VI. RESULTS AND DISCUSSION

The nine experimental runs were performed based on the combinations from Table 2 with each experimental run carried for a length of 120 mm. All the operations on CNC were performed using numerical control part programming. Tool flank wear measurements have been carried out using high resolution Tool maker's microscope. The tool wear obtained from tool maker's microscope were given in the table 2

The AE signals of Fig.1 have been captured for all the combinations cited in Table 2 cutting speed, feed,depth of cut and hardness of the material.

Various Features were calculated by using Lab View software and MATLAB for each and every signals collected by AE sensors are shown in table.3

These features and corresponding output (tool wear) trained with Neural Network by considering the parameters got high accuracy of 98%. The network diagram and the regression graphs were shown in 2 and 3, from this it is observed that the error is almost all minimised. Based upon the training the performance curves were plotted which were shown in Fig. 4 and Fig.5

Table 2 Manual Tool Wear from Tool maker's microscope

EXP NO	SPEED (m/min)	FEED (mm/rev)	DOC (mm)	HARDNESS (HRC)	Tool Wear (mm)
1	1	1	1	1	0.129
2	1	2	2	2	0.149
3	1	3	3	3	0.14
4	2	1	2	3	0.19
5	2	2	3	1	0.118
6	2	3	1	2	0.116
7	3	1	3	2	0.193
8	3	2	1	3	0.122
9	3	3	2	1	0.111

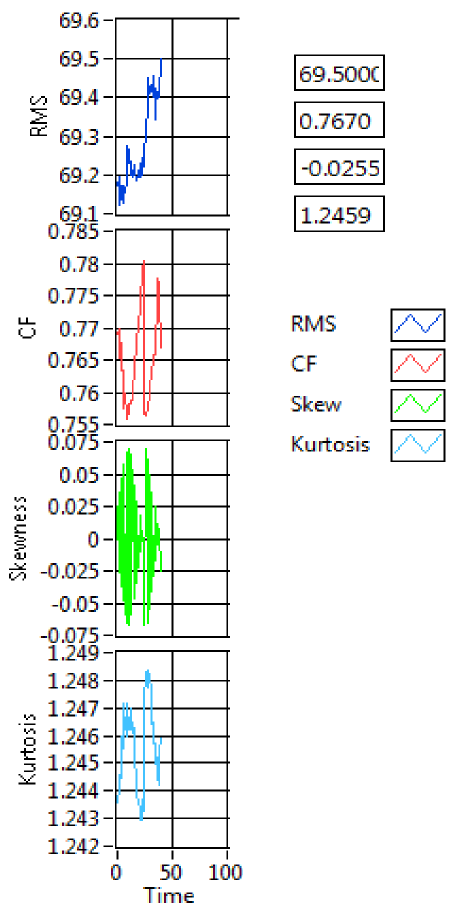

Figure 1 AE signal captured in hard turning

After obtaining satisfactory relation between features and outputs in neural network training, we simulated the results for different variations in the features and obtained the outputs which was presented in table 4.

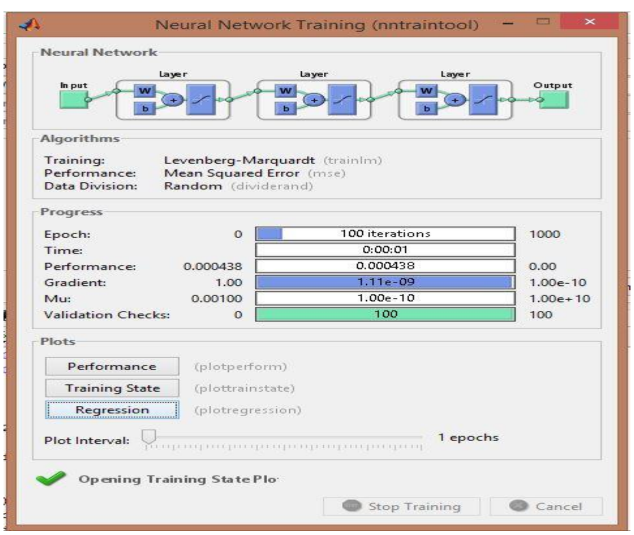

Figure 2 Neural Network for AE Signals

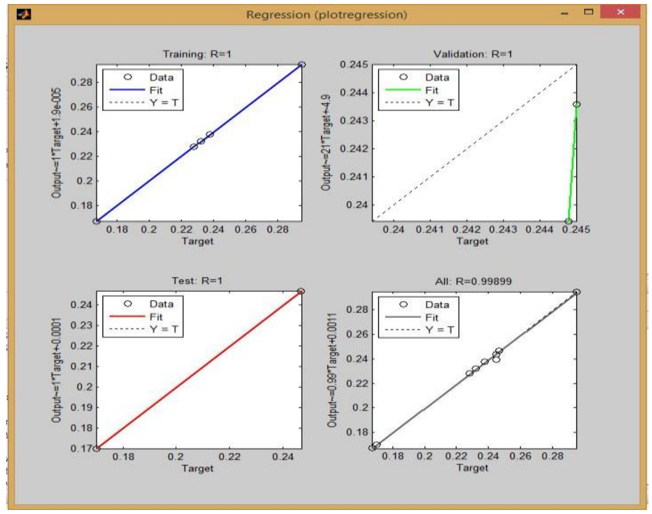

Figure 3 Regression Graph for AE signals

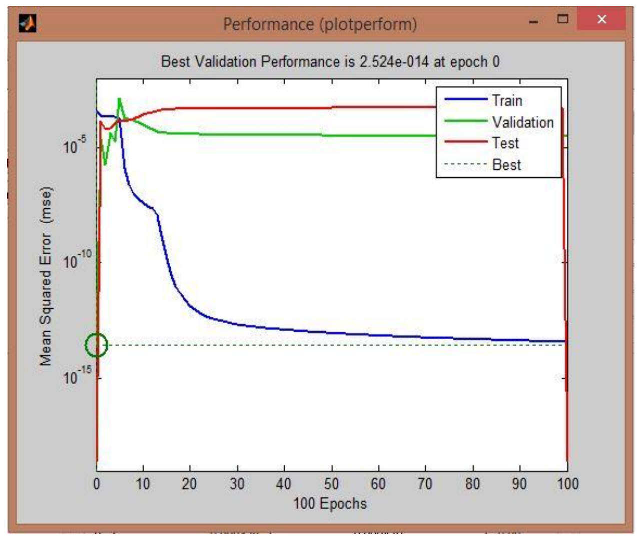

Figure 4 Performance Graph for AE signals

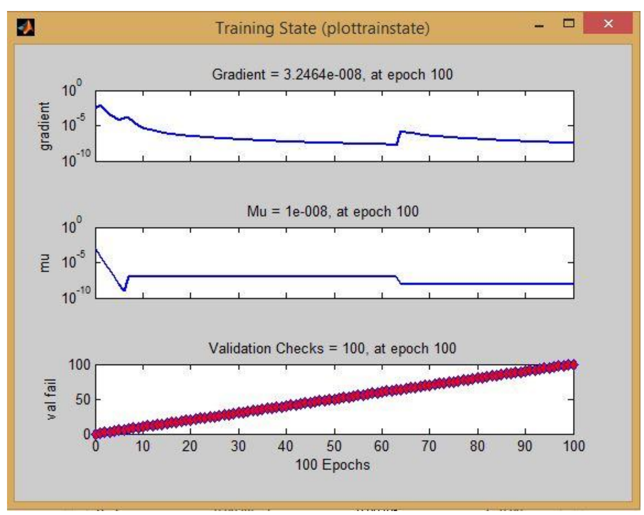

Figure 5 Training State Graph for AE

Table 3 All Features from Acoustic Emission Signals for Ceramic insert

EXP.NO	1	2	3	4	5	6	7	8	9
RMS	19.2333	17.572	19.3092	19.7097	19.4146	15.408	19.365	19.2711	16.3725
CF	0.6653	0.65939	0.6565	0.6638	0.6598	0.6658	0.6658	0.664	0.6566
SKW	0.0454	0.0454	-0.0594	-0.0099	-0.0607	0.0051	0.022	-0.0201	-0.0607
KURT	1.5037	1.5024	1.5095	1.4994	1.5032	1.5024	1.5017	1.5019	1.5079
AD	4.6608	6.6373	0.0992	9.424	0.9653	1.0974	9.3384	0.3959	0.7661
MEAN	16.6857	16.0826	19.152	11.3088	19.9999	18.2684	10.6458	19.3959	18.769
SD	6.748	8.2616	0.1367	9.5982	1.1083	1.4145	9.4382	0.7118	2.7493
VAR	45.536	68.2537	0.0187	92.1252	1.2283	2.0009	89.0798	0.5067	7.5584
PEAK	20.2762	22.0136	19.5547	19.7682	21.8875	19.4507	19.365	21.811	19.5807
FRE	0.005618	0.008	0.047619	0.008403	0.012821	0.032787	0.005882	0.026316	0.020833
TIME	177.9993	125	21.00002	118.9995	77.99704	30.49989	169.9986	37.9997	48.00077

Table 4 Simulated Neural Network Results of ceramic insert for AE

EXP NO	RMS	CF	SKW	KURT	AD	MEAN	SD	VAR	PEAK	FRE	TIME	TW (mm)
1	15.408	0.656	-0.0607	1.499	0.099	10.6458	0.1367	0.0187	19.365	0.00561	21.0000	0.1998
2	15.408	0.656	-0.0607	1.499	4.761	15.3228	4.8674	46.071	20.6893	0.02661	99.4996	0.1734
3	15.408	0.656	-0.0607	1.499	9.424	19.9999	9.5982	92.125	22.0136	0.04761	177.999	0.2167
4	15.408	0.661	-.00765	1.504	0.099	10.6458	0.1367	46.071	20.6893	0.02661	177.999	0.1733
5	15.408	0.661	-.00765	1.504	4.761	15.3228	4.8674	92.125	22.0136	0.04761	21.0000	0.1782
6	15.408	0.661	-.00765	1.504	9.424	19.9999	9.5982	0.0187	19.365	0.00561	99.4996	0.1899
7	15.408	0.665	0.0454	1.509	0.099	10.6458	0.1367	92.125	22.0136	0.04761	99.4996	0.1995
8	15.408	0.665	0.0454	1.509	4.761	15.3228	4.8674	0.0187	19.365	0.00561	177.999	0.2179
9	15.408	0.665	0.0454	1.509	9.424	19.9999	9.5982	46.071	20.6893	0.02661	21.0000	0.2340
10	17.558	0.656	- 0.00765	1.509	0.099	15.3228	9.5982	0.0187	20.6893	0.04761	21.0000	0.2614
11	17.558	0.656	-.00765	1.509	4.761	19.9999	0.1367	46.071	22.0136	0.00561	99.4996	0.1699
12	17.558	0.656	-.00765	1.509	9.424	10.6458	4.8674	92.125	19.365	0.02661	177.999	0.1695
13	17.558	0.661	0.0454	1.499	0.099	15.3228	9.5982	46.071	22.0136	0.00561	177.999	0.2318
14	17.558	0.661	0.0454	1.499	4.761	19.9999	0.1367	92.125	19.365	0.02661	21.0000	0.1694
15	17.558	0.661	0.0454	1.499	9.424	10.6458	4.8674	0.0187	20.6893	0.04761	99.4996	0.1727
16	17.558	0.665	-0.0607	1.504	0.099	15.3228	9.5982	92.125	19.365	0.02661	99.4996	0.2505
17	17.558	0.665	-0.0607	1.504	4.761	19.9999	0.1367	0.0187	20.6893	0.04761	177.999	0.2229
18	17.558	0.665	-0.0607	1.504	9.424	10.6458	4.8674	46.071	22.0136	0.00561	21.0000	0.2038
19	19.709	0.656	0.0454	1.504	0.099	19.9999	4.8674	0.0187	22.0136	0.02661	21.0000	0.1744
20	19.709	0.656	0.0454	1.504	4.761	10.6458	9.5982	46.071	19.365	0.04761	99.4996	0.1903
21	19.709	0.656	0.0454	1.504	9.424	15.3228	0.1367	92.125	20.6893	0.00561	177.999	0.1751
22	19.709	0.661	-0.0607	1.509	0.099	19.9999	4.8674	46.071	19.365	0.04761	177.999	0.1764
23	19.709	0.661	-0.0607	1.509	4.761	10.6458	9.5982	92.125	20.6893	0.00561	21.0000	0.1749
24	19.709	0.661	-0.0607	1.509	9.424	15.3228	0.1367	0.0187	22.0136	0.02661	99.4996	0.1726
25	19.709	0.665	-.00765	1.499	0.099	19.9999	4.8674	92.125	20.6893	0.00561	99.4996	0.2295
26	19.709	0.665	-.00765	1.499	4.761	10.6458	9.5982	0.0187	22.0136	0.02661	177.999	0.2551
27	19.709	0.665	-.00765	1.499	9.424	15.3228	0.1367	46.071	19.365	0.04761	21.0000	0.1863

Table 4 Simulated Neural Network Results of ceramic insert for AE

EXP NO	RMS	CF	SKW	KURT	AD	MEAN	SD	VAR	PEAK	FRE	TIME	TW (mm)
1	15.408	0.656	-0.0607	1.499	0.099	10.6458	0.1367	0.0187	19.365	0.00561	21.0000	0.1998
2	15.408	0.656	-0.0607	1.499	4.761	15.3228	4.8674	46.071	20.6893	0.02661	99.4996	0.1734
3	15.408	0.656	-0.0607	1.499	9.424	19.9999	9.5982	92.125	22.0136	0.04761	177.999	0.2167
4	15.408	0.661	-.00765	1.504	0.099	10.6458	0.1367	46.071	20.6893	0.02661	177.999	0.1733
5	15.408	0.661	-.00765	1.504	4.761	15.3228	4.8674	92.125	22.0136	0.04761	21.0000	0.1782
6	15.408	0.661	-.00765	1.504	9.424	19.9999	9.5982	0.0187	19.365	0.00561	99.4996	0.1899
7	15.408	0.665	0.0454	1.509	0.099	10.6458	0.1367	92.125	22.0136	0.04761	99.4996	0.1995
8	15.408	0.665	0.0454	1.509	4.761	15.3228	4.8674	0.0187	19.365	0.00561	177.999	0.2179
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13	17.558	0.661	0.0454	1.499	0.099	15.3228	9.5982	46.071	22.0136	0.00561	177.999	0.2318
14	17.558	0.661	0.0454	1.499	4.761	19.9999	0.1367	92.125	19.365	0.02661	21.0000	0.1694
15	17.558	0.661	0.0454	1.499	9.424	10.6458	4.8674	0.0187	20.6893	0.04761	99.4996	0.1727
16	17.558	0.665	-0.0607	1.504	0.099	15.3228	9.5982	92.125	19.365	0.02661	99.4996	0.2505
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18	17.558	0.665	-0.0607	1.504	9.424	10.6458	4.8674	46.071	22.0136	0.00561	21.0000	0.2038
19	19.709	0.656	0.0454	1.504	0.099	19.9999	4.8674	0.0187	22.0136	0.02661	21.0000	0.1744
20	19.709	0.656	0.0454	1.504	4.761	10.6458	9.5982	46.071	19.365	0.04761	99.4996	0.1903
21	19.709	0.656	0.0454	1.504	9.424	15.3228	0.1367	92.125	20.6893	0.00561	177.999	0.1751
22	19.709	0.661	-0.0607	1.509	0.099	19.9999	4.8674	46.071	19.365	0.04761	177.999	0.1764
23	19.709	0.661	-0.0607	1.509	4.761	10.6458	9.5982	92.125	20.6893	0.00561	21.0000	0.1749
24	19.709	0.661	-0.0607	1.509	9.424	15.3228	0.1367	0.0187	22.0136	0.02661	99.4996	0.1726
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27	19.709	0.665	-.00765	1.499	9.424	15.3228	0.1367	46.071	19.365	0.04761	21.0000	0.1863

The average grey relational grade of each factor at each level, shown in Table 5. The optimal level for each factor was obtained based on 'higher is better' characteristic. From Table 6, the optimal level in each factor was highlighted. The dominant feature was obtained by taking the maximum value of all factors.. Thus the dominating sequence was RMS, AD, CF, SD, Mean, Ku, Frequency, Variance, Sk, Peak, Time.

ANOVA tests the null hypothesis that the means of each level of parameters are equal and the alternative hypothesis is that at least one of the means is not equal. It is obtained by measuring the sum of squared deviations from the total mean of the grey relational grade. In addition, the F-test was used to identify the turning parameters significance on the output responses. Usually, the change of turning parameter has a significant effect on the output response when the F value is large than the tabulated value. The ANOVA for the overall grey relational grade was shown in Table 7.

Table 5 The normalized values, deviation values and grey relational grades of Ceramic insert for AE signal

	NORMALISED VALUES			ABSOLUTE DIFFERENCE			GREY COEFFICIENTS				
EXP NO	NTW	NSR	NTM	DTW	DSR	DTM	GRC-TW	GRC-SR	GRC-TEMP	TOTAL GRC	GRADE
1	0.669566	0.000118	0.856377	0.330434	0.999882	0.143623	0.602095	0.33336	0.776852	1.712306	0.570769
2	0.95629	0.060011	0.522125	0.04371	0.939989	0.477875	0.919608	0.347225	0.511313	1.778146	0.592715
3	0.486028	1	0.03451	0.513972	0	0.96549	0.49311	1	0.341183	1.834293	0.611431
4	0.957812	0.181778	0.614348	0.042188	0.818222	0.385652	0.92219	0.379299	0.564556	1.866045	0.622015
5	0.904317	0.645499	0.735407	0.095683	0.354501	.264593	0.839372	0.585137	0.653942	2.078451	0.692817
6	0.776558	0.117476	0.143455	0.223442	0.882524	0.856545	0.69114	0.361657	0.368584	1.421381	0.473794
7	0.672176	0.214801	0	0.327824	0.785199	1	0.603993	0.389045	0.333333	1.326371	0.442124
8	0.472763	0.123543	0.028674	0.527237	0.876457	0.971326	0.486743	0.363251	0.33983	1.189823	0.396608
9	0.29738	0.080932	0.004739	0.70262	0.919068	0.995261	0.415759	0.352344	0.33439	1.102492	0.367497
10	0	0	0.044628	1	1	0.955372	0.333333	0.333333	0.343555	1.010221	0.33674
11	0.994346	0.212553	0.212305	0.005654	0.787447	0.787695	0.988818	0.388365	0.388291	1.765474	0.588491
12	0.999021	0.629076	0.764726	0.000979	0.370924	0.235274	0.998047	0.574103	0.680019	2.252169	0.750723
13	0.321627	0.958247	0.002656	0.678373	0.041753	0.997344	0.424314	0.92293	0.333924	1.681168	0.560389
14	1	0.99133	0.270169	0	0.00867	0.729831	1	0.982955	0.40656	2.389515	0.796505
15	0.964336	0.922974	1	0.035664	0.077026	0	0.933421	0.866513	1	2.799934	0.933311
16	0.118517	0.980529	0.025326	0.881483	0.019471	0.974674	0.36193	0.962518	0.339058	1.663506	0.554502
17	0.418071	0.960348	0.568605	0.581929	0.039652	0.431395	0.462138	0.926523	0.536829	1.92549	0.64183
18	0.625639	0.937533	0.413835	0.374361	0.062467	0.586165	0.571846	0.888941	0.460335	1.921123	0.640374
19	0.945526	0.845328	0.748387	0.054474	0.154672	0.251613	0.901755	0.763741	0.665236	2.330732	0.776911
20	0.772317	0.994378	0.965759	0.227683	0.005622	0.034241	0.687112	0.98888	0.935908	2.611901	0.870634
21	0.93748	0.998698	0.901866	0.06252	0.001302	0.098134	0.888857	0.997403	0.835933	2.722193	0.907398
22	0.924214	0.984198	0.009218	0.075786	0.015802	0.990782	0.868379	0.969365	0.335394	2.173138	0.724379
23	0.93998	0.968959	0.32356	0.06002	0.031041	0.67644	0.892826	0.941547	0.425011	2.259384	0.753128
24	0.965206	0.948482	0.896613	0.034794	0.051518	0.103387	0.93494	0.906589	0.828656	2.670184	0.890061
25	0.346635	0.999112	0.053123	0.653365	0.000888	0.946877	0.433514	0.998228	0.345572	1.777314	0.592438
26	0.068501	0.89797	0.785662	0.931499	0.10203	0.214338	0.349284	0.830523	0.699949	1.879757	0.626586
27	0.81581	0.96452	0.977892	0.18419	0.03548	0.022108	0.730791	0.933742	0.957657	2.62219	0.874063

Table 6 Average grey relational grade of AE for each factor at each level for Ceramic insert

LEVEL	Factors										
	RMS	CF	SKW	KURT	AD	MEAN	SD	VAR	PEAK	FRE	TIME
1	**0.529974**	**0.667312**	**0.664354**	**0.684245**	**0.575585**	**0.689963**	**0.703695**	**0.627401**	**0.667997**	**0.609265**	**0.645423**
2	**0.644763**	**0.716267**	**0.617519**	**0.686697**	**0.662146**	**0.645033**	**0.677809**	**0.648951**	**0.638564**	**0.664168**	**0.659786**
3	**0.779511**	**0.570669**	**0.672375**	**0.583306**	**0.716517**	**0.619253**	**0.572745**	**0.677896**	**0.647687**	**0.680814**	**0.64904**

Table 7 Results of ANOVA of Ceramic insert for AE signal

FACTORS	**SUM OF SQUARES**	**DF**	**MEAN SQUARE**	**F-VALUE**	**P-VALUE**	**% CONTRIBUTION**
RMS	0.280805	2	0.140403	26.25579	0.005	38.89885
CF	0.090932	2	0.045466	8.502317	0.0363	12.59647
SKW	0.015802	2	0.007901	1.47747	0.3308	2.188923
KURT	0.025232	2	0.012616	2.359242	0.2105	3.495298
AD	0.098805	2	0.049403	9.238472	0.0317	13.68711
MEAN	0.062654	2	0.031327	5.85822	0.0648	8.679154
SD	0.08657	2	0.043285	8.094426	0.0393	11.99217
VAR	0.011556	2	0.005778	1.080497	0.4215	1.600794
PEAK	0.004086	2	0.002043	0.382073	0.7049	0.566054
FRE	0.023049	2	0.011525	2.15516	0.2317	3.192943
TIME	0.001005	2	0.000502	0.093925	0.9123	0.139154
ERROR	0.02139	4	0.005347			2.963069
TOTAL	0.721886	26				100

VII. *7.CONCLUSIONS*

- Using both Taguchi method and GRA to observe the dominant feature to find the tool wear in TCM has been reported
- Various Features were estimated from the LAB VIEW and MAT LAB software and observed that Mean, Variance, Absolute Deviation and Peak were observed as constant for all the experiments which shows these features are not affecting the tool wear.
- A Neural Network tool in MATLAB was used to train the remaining Features to get the relation between tool wear and the features and observed that around 98 % accuracy.
- Tool wear was calculated by Simulating Neural Network, Features consider as input data from L27 Taguchi orthogonal array.
- The Simulated data was analyzed by Grey relational method and obtained grey grade, which is used to find out the dominant feature for the TCM.
- The dominant features ranking sequence for AE signal were obtained as RMS, AD, CF, SD, Mean, Ku, Frequency, Variance, Sk, Peak, Time**..**
- ANOVA analysis has been carried out for the simulated data and grey codes, identified that the same features ranking Sequence was obtained for AE signal

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