# An analysis of feature identification for tool wear monitoring by using acoustic emission

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ABSTRACT. *There is an in-depth discussion in this edition about the improvement of a system regarding tool wear monitoring in hard turning operation. Grinding is a reasonable alternative to hard turning in manufacturing industry, but the reliability of hard turning processes is often unpredictable because of the dominant parameters that occur during tool wear. Here the dominant parameters are being compared to give the highest dominant feature among them. The ongoing study is focusing on Inconel 718 with varying HRC (51, 53, and 55) and the tool employed here is coated carbide. By using L9 orthogonal array extracted from taguchi method taking input parameters such as speed, feed, depth of cut and hardness. Taking acoustic emission (AE) signal data as an input to ANOVA and Grey relation analysis (GRA) which identifies the optimal and most dominant feature in the tool wear operation and also surface operation.*

RÉSUMÉ. *Nous discutons en détail de l'amélioration d'un système de surveillance de l'usure des outils dans les opérations de chariotage dans cet article. La rectification est une alternative raisonnable au chariotage dans l'industrie manufacturière, mais la fiabilité des processus de chariotage est souvent imprévisible en raison des paramètres dominants qui se produisent lors de l'usure des outils. Dans cet article, les paramètres dominants sont comparés pour donner la caractéristique dominante la plus élevée parmi eux. L'étude en cours porte sur l'Inconel 718 avec différents HRC (51, 53 et 55) et l'outil utilisé est le carbure enduit. La matrice orthogonale L9 extrait de la méthode taguchi s'applique en prenant des paramètres d'entrée tels que la vitesse, l'alimentation, la profondeur de coupe et la dureté. Prennant des données du signal d'émission acoustique (AE en anglais) comme données d'entrée pour l'analyse de la variance (ANOVA en anglais) et l'analyse de la relation de gris (GRA en anglais) qui identifie la caractéristique optimale et la plus dominante dans les opérations d'usure des outils et celles de surface.*

KEYWORDS: *hardturning, tool condition monitoring, dominant features, acoustic emission, grey relation analysis.*

MOTS-CLÉS: *chariotage, surveillance de l'état de l'outil, caractéristiques dominantes, émission acoustique, relation de gris.*

DOI:10.3166/TS.34.117-135 © 2017 Lavoisier

## 1. Introduction

Hardness ranging from 45 to 65 Rockwell C (HRC) (Konig *et al.*, 1984) is involved in hard turning operations during cutting of materials. Hence, the hardness of tool materials is usually high. Ceramics, high-speed steels (HSS), cubic boron nitride (CBN) and coated CBN, polycrystalline diamond (PCD), or tungsten carbide (WC) coated with titanium nitride (TiN) are some of the main tool materials included (Konig *et al.*, 1984; Bartarya and Choudhury, 2012). It is possible to cut materials 3in their hardened state as improvements took place in the last few decades in tools and machines. Reduced machining costs, lead time, number of essential machine tools, improved surface integrity, reduced finishing operations and removable of part distortion caused by excessive heat treatment are the benefits of producing components in hardened state (Koshy *et al.*, 2002).

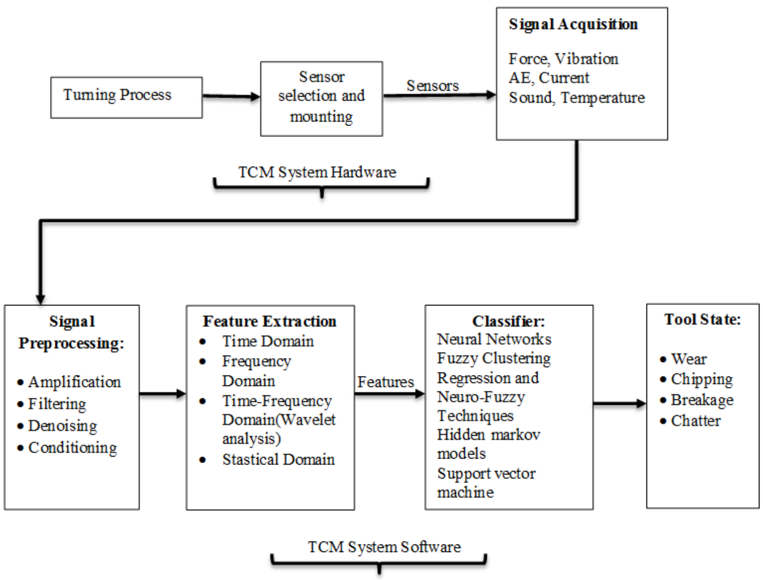


*Figure 1. Tasks performed by TCM*

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 (Chen and Li, 2007). TCM systems that were improved in the past are comprehensively reviewed in a number of articles.

Micheletti (1976) discussed different types of sensors for “in-process” measurement of tool wear. Ravindra *et al.* (1993) 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 art surface finish. Hence, more study has been done in the past 30 years (Li and Mathew, 1990).

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 (Li, 2002; Sata *et al.*, 1973). AE based on TCM systems has been available for approximately 20 years. Most of them use analogue root mean square of the signal to observe tool wear or find out breakages. Damodarasamy and Raman (1993) 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 (ASTM, 1998). AE signals produced during turning can be continuous or transient/burst type. Teti *et al.* (2010) reviewed various AE methods (Teti *et al.*, 2010; Kannatey *et al.*, 1982; Jemielniak and Bombinski, 2006) 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 (2000) also spoke about some AE techniques used for flank wear detection (Moriwaki and Tobito, 1990; Blum and Inasaki, 1990). 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. Rangwala and Dornfeld (1990) 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*. (1994) 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. Komvopoulos and Cho (1997) 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 (2002) improved a model to relate AErms in the turning operation with the flank and crater wear. The improved model accurately predicted the flank wear during turning. In a brief review, Li (2002) spoke that AE-based TCM for turning containing AE generation in turning, different methods used for AE signal measurement and processing, and methodologies for calculating tool wear. Scheffer *et al*. (2003) used AE rms signals along with other signals in order to improve a tool wear monitoring system for hard turning. Sun *et al.* (2005) 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. Sharma *et al*. (2008) and Gajate *et al*. (2010) observed AE, vibration, and force signals in turning process. It was seen that ring down count parameter of AE signals showed a significant growth with the tool wear. Al- Habaibeh *et al*. (2010) and Deiab *et al*. (2009) observed AE signals along with force signals, and the improved systems successfully performed the tool wear monitoring. Xi *et al.* (2010) observed the confusing characteristics of AE signal produced in turning process. It was seen that the strange attractor in phase space and the Poincare shows both have contraction tendency with the tool wear. Bhuiyan *et al*. (2011) improved a dummy tool holder apparatus in order to foresee tool wear from AE measurement. In their recent publication, Jemielniak *et al*. (2012) performed sensor fusion using AE, vibration, and force sensors in order to analyze suitability of different signal features for TCM. This paper has used the AE signals from an embedded sensor for computation of features and forecast of tool wear.

A reduced feature subset, which is an optimal in calculation and clustering least squares errors, is then selected using a new dominant-feature observing algorithm to decrease the signal processing and number of sensors required. Tool wear is then predicted using Artificial Neural network based on the reduced features.

## 2. 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.

## 3. 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 and vibration 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).

## 4. Grey relational analysis

The Grey Relational Analysis (GRA) which is involved with the Taguchi method represents a new way to optimization. GRA is a normalization evaluation technique is extended to affect the complex multi-performance characteristics.

The data obtained from neural networks is to be processed. For this purpose the experimental results are normalized in the range between zero and one. The normalization can be done form three different aspects.

If the target value of original sequence is infinite, then it has a phenomena of "the larger-the – better". The original sequence can be normalized as follows.

$$X_i^*(k) = \frac{X_i^0(K) - \min \quad X_i^0(K)}{\max \quad X_i^0(K) - \min \quad X_i^0(K)} \tag{1}$$

If the expectancy is the smaller-the better, then the original sequence should be normalized as follows.

$$X_i^*(k) = \frac{\max \quad X_i^0(K) - X_i^0(K)}{\max \quad X_i^0(K) - X_i^0(\min \quad K)} \tag{2}$$

However, if there is a definite target value to be achieved, the original sequence will be normalized in the form.

$$X_i^*(k) = 1 - \frac{|X_i^0(K) - X^0|}{\max \quad X_i^0(K) - X_i^0} \tag{3}$$

Or the original sequence can be simply normalized by the most basic methodology i.e., let the values of original sequence be divided by the first value of sequence

$$X_i^*(k) = \frac{X_i^0(K)}{X_i^0(1)} \tag{4}$$

Where

$x_i$*(k) is the value after the grey relational generation (data pre-processing), max $x_i^0$(k) is the largest value of x 0(k), min $x_i^0$(k)is the smallest value of $x_i^0$(k) and $x^n$ is the desired value.

### *4.1. Grey relational coefficient and grey relational grade*

Accordingto data pre-processing, a grey relational coefficient is estimated to express the relationship between the ideal and actual normalized experimental results. They grey relational coefficient can be expressed as follows:

$$\zeta_i(K) = \frac{\Delta_{min}+\zeta.\Delta_{max}}{\Delta_{oi}(K)+\zeta.\Delta_{max}} \tag{5}$$

Where $\Delta_{oi}$(k) is the deviation sequence of the reference sequence $x_o$*(k) and the comparability sequence$x_i$*(k) namely

$$\Delta_{oi}(K) = \| X_0{}^*(K) - X_i{}^*(K)\|$$

$$\Delta_{max} = \max_{\forall j\, \varepsilon i} \; \max_{\forall K} \; \| X_0{}^*(K) - X_i{}^*(K)\|$$

$$\Delta_{min} = \min_{\forall j\, \varepsilon i} \; \min_{\forall K} \; \| X_0{}^*(K) - X_i{}^*(K)\|$$

ζ is distinguishing or identification coefficient ζ ε to [0, 1]. ζ=0.5 is generally used.

After obtaining the grey relational coefficient, we normally consider the average of the grey relational coefficient as the grey relational grade. The grey relational grade is defined as follows.

$$\gamma_i = \frac{1}{n} \sum_{k=1}^{n} \zeta_i\,(k) \tag{6}$$

However, since in real application the effect of each factor on the system is not exactly same. Eq.(6) can be modified as

$$\gamma_i = \frac{1}{n} \sum_{k=1}^{n} W_k.\zeta_i\,(k) \sum_{k=1}^{n} W_k = 1 \tag{7}$$

Where $w_k$ represents the normalized weighting value of factor 'k'. Given same weights. Equations (6) and (7) are equal.

In the grey relational analysis, the grey relational grade identifies the relationship among the sequences. The grey relational grade also indicates the degree of influence. By using grey relation grade the optimal parameters are identified by taking means of the levels.

## 5. Analysis of variance (anova analysis)

ANOVA is a combination of statistical models, and their associated procedures, in which the identified variance in a particular variable is partitioned into components accountable to different sources of variation. ANOVA is used to determine whether the parameters have significant influence on output parameters. The null hypothesis has to be rejected by comparing the F value with tabulated values so that the larger F value indicates the most significance of the parameter for certain confidence level.

## 6. Experimental setup

Based on the literature, a methodology was put forward to study the influence of cutting parameters on tool wear rate in turning round bar of Inconel 718 with coated cemented carbide insert with ISO code (TNMG 160408 MS PR1305).

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 |

The number of experiments and the combinations of parameters for each run was obtained by using Taguchi's L9 orthogonal array. The Computer Numerically Controlled (CNC) lathe machine is utilized for the experimental work. A special tool setup is designed and fabricated to make it possible to differentiate the transient signal generated from chip formation only. One dummy tool setup that has been replicating the conventional tool setup is designed and integrated into the conventional tool setup.

The dummy tool holder and tool-insert arrangement were designed and fabricated to support the AE signal to follow about the same path of energy transmission from sources to the sensor. The dummy tool-insert and tool holder arrangement are placed over the main tool-insert and tool holder arrangement. The dummy arrangement is set in such a way with respect to the main tool setup that it cannot come in contact with the work piece while the main tool cuts the material.

However, the chips that are released during metal cutting would touch the dummy tool insert as it leaves the work piece. Rubber insulation is placed between the tool holders to avoid mutual vibrations. The placement of rubber insulation has helped to dampen the low-frequency signal components arising from plastic deformation and tool wear. Besides the AE sensor and the data acquisition system permits the signal above 50 kHz to pass to storage. It is expected that the whole effect of rubber insulation and data acquisition system could success- fully make the dummy setup signal independent. A piezoelectric AE sensor is placed on the dummy tool holder to store the acoustic emission generated during cutting.

This is placed on the dummy tool holder very close possible to the spot of collision between chip and dummy tool-insert. The detail of whole setup is shown in Fig.2. The signal obtained from the new setup shows the chip formation occurrence only respective to the different cutting conditions. As the sensor is placed in the dummy tool holder, it never comes in contact with the main tool- holder assembly and the sensor transient AE signal does not include the tool fracture signal. Fig. 3 shows The AE signal measuring chain in metal cutting.

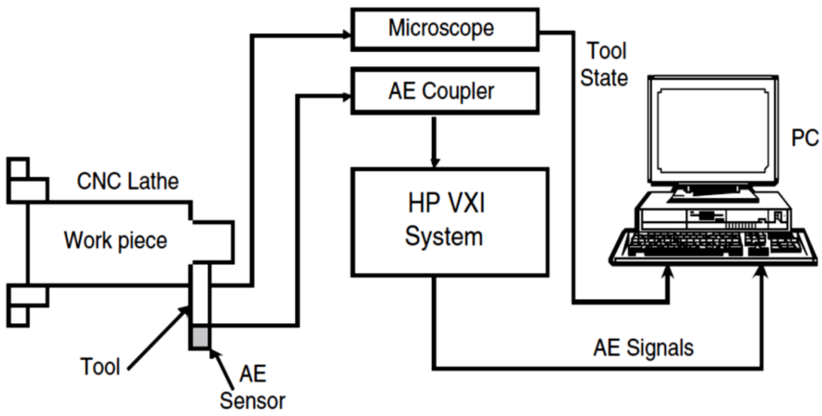


*Figure 2. Experimental set-up scheme*

## 7. Results and discussion

In order to minimize any effect of non-homogeneity on the experimental results, turning operation was first performed on the work piece with CNC lathe. 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 Wear (TW) measurements have been carried out using high resolution Tool maker's microscope. The tool wear criteria were used as per ISO 3685 i.e. the tools were shed after reaching average flank wear (VB avg) of 0.3 mm and /or after reaching depth of cut notch wear (VN) of 0.6mm. The tool wear obtained from tool maker's microscope were given in the table 2.

The AE signals of Fig.3 have been captured for all the combinations cited in Table 2 cutting speed, feed, depth of cut and hardness of the material.

*Table 2. Manual tool wear from tool maker's microscope*

| EXPT.NO | SPEED (rpm) | FEED (mm/min) | DOC (mm) | HARDNESS (HRC) | TW (μm) |
|---|---|---|---|---|---|
| 1 | 50 | 0.05 | 0.15 | 51 | 0.19 |
| 2 | 65 | 0.05 | 0.2 | 55 | 0.175 |
| 3 | 80 | 0.05 | 0.25 | 53 | 0.16 |
| 4 | 50 | 0.075 | 0.2 | 53 | 0.19 |
| 5 | 65 | 0.075 | 0.15 | 51 | 0.145 |
| 6 | 80 | 0.075 | 0.15 | 55 | 0.14 |
| 7 | 50 | 0.1 | 0.25 | 55 | 0.19 |
| 8 | 65 | 0.1 | 0.15 | 53 | 0.17 |
| 9 | 80 | 0.1 | 0.2 | 51 | 0.14 |

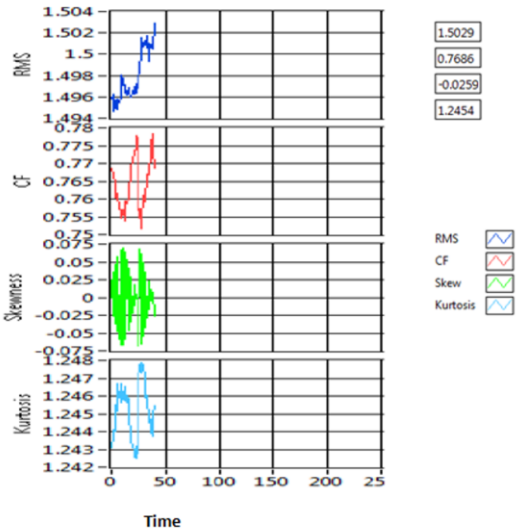


*Figure 3. RMS AE signal captured in turning*

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

These features and corresponding outputs (tool wear, surface roughness and temperature) trained with Neural Network by considering the parameters shown in Fig. 4 and got high accuracy of 98%.

*Table 3. All features from AE signals*

| EXP. NO | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| RMS | 68.8787 | 2.2444 | 1.4047 | 2.3803 | 69.8101 | 2.3779 | 2.3422 | 1.8487 | 2.0611 |
| CF | 0.771 | 0.1516 | 0.1235 | 0.1475 | 0.7618 | 0.1519 | 0.163 | 0.1444 | 0.1522 |
| SKW | 0.024 | -0.1653 | -0.1747 | -0.1744 | 0.0505 | -0.1693 | -0.1177 | -0.148 | -0.1959 |
| KURT | 1.2398 | 7.5238 | 8.7514 | 7.5017 | 1.2494 | 7.4509 | 7.4375 | 7.8118 | 7.4447 |
| AD | 0.0566 | 0.5571 | 2.7992 | 2.3797 | 0.2062 | 0.9636 | 5.263 | 1.8266 | 1.4765 |
| MEAN | 69.0006 | 6.2035 | 14.676 | 11.9495 | 69.8777 | 9.1582 | 12.1636 | 14.8153 | 12.1067 |
| SD | 0.0693 | 0.8359 | 4.2843 | 4.5117 | 0.3045 | 1.6628 | 13.9901 | 3.3876 | 2.6249 |
| VAR | 0.0048 | 0.6988 | 18.355 | 20.3554 | 0.0927 | 2.765 | 195.7221 | 11.4758 | 6.8901 |
| PEAK | 69.1411 | 7.1157 | 23.9898 | 29.5283 | 70.4084 | 10.5943 | 95.8129 | 20.0335 | 14.4455 |
| FRE | 0.022222 | 0.052632 | 0.38095 | 0.10714 | 0.037037 | 0.27273 | 0.5 | 0.2 | 0.15 |
| TIME | 45.00045 | 18.99985 | 2.625016 | 9.333582 | 27.00003 | 3.66663 | 2 | 5 | 6.666667 |

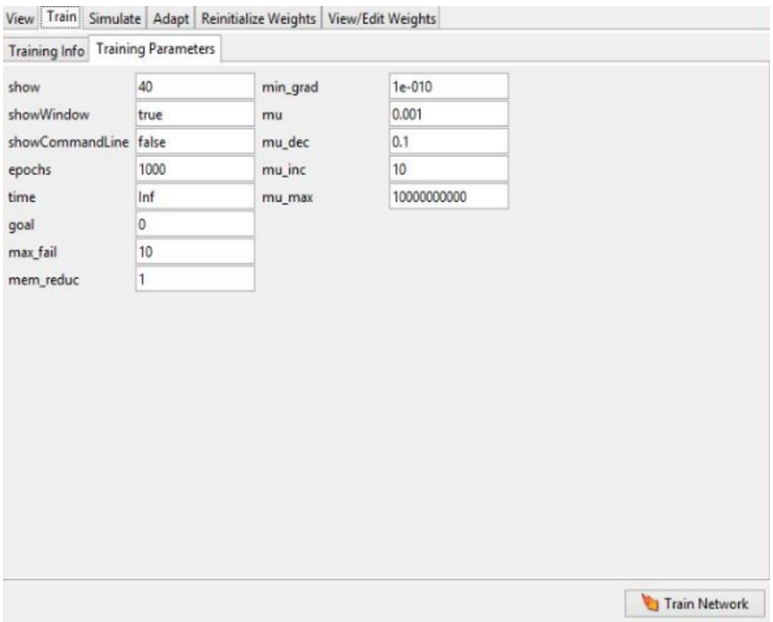


*Figure 4. Training parameters for AE signals*

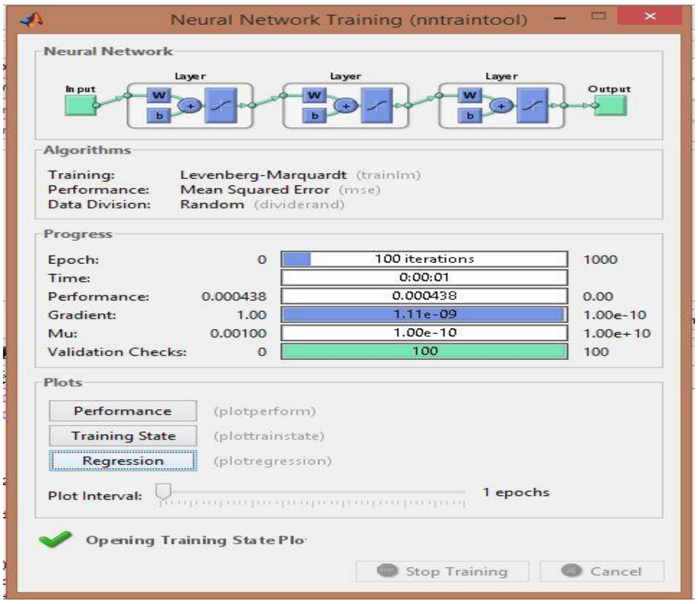


*Figure 5. Neural network for AE signals*

The network diagram and the Regression graphs were shown in 5 and 6, 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. 7 and Fig. 8.

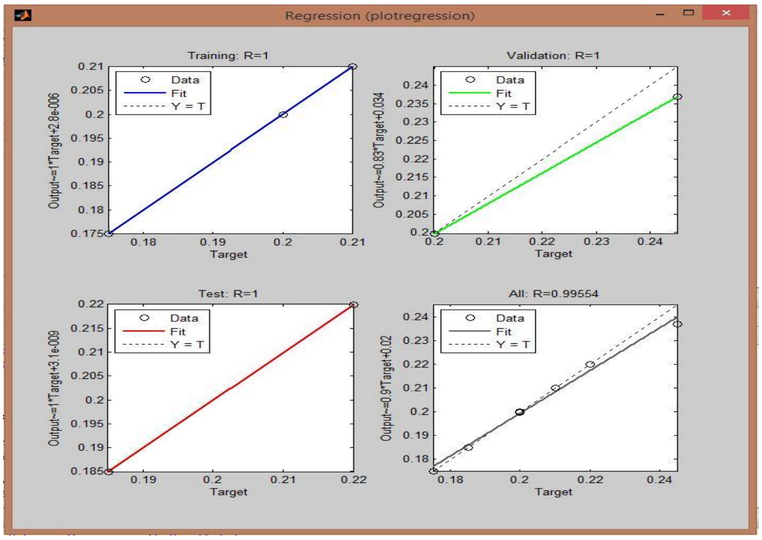


*Figure 6. Regression graph for AE signals*

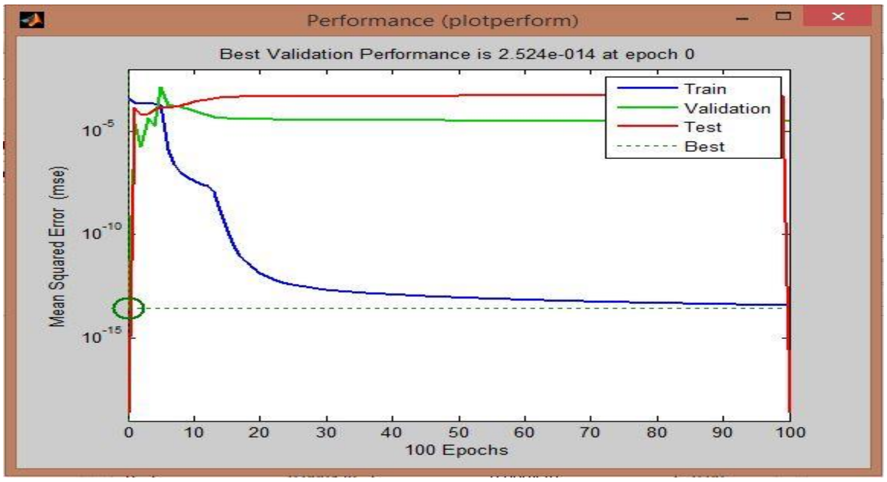


*Figure 7. Performance graph for AE signals*

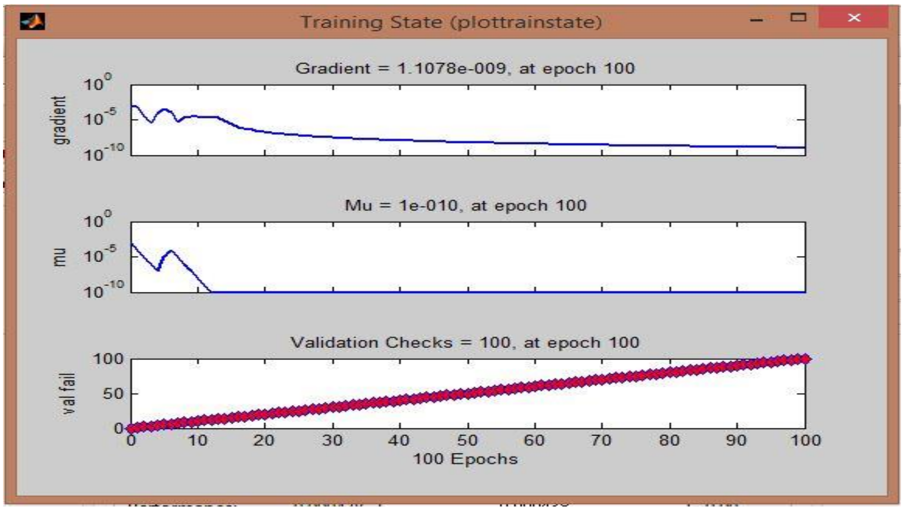


*Figure 8. Training state graph for AE*

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.

*Table 4. Simulated neural network results of coated carbide insert for AE*

| EXP NO | RMS | CF | SKW | KURT | AD | MEAN | SD | VAR | PEAK | FRE | TIME | TW (mm) | SR (µm) | TEMP (°C) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1.4047 | 0.1235 | -0.1959 | 1.2398 | 0.0566 | 6.2035 | 0.0693 | 0.0048 | 7.1157 | 0.02222 | 2 | 0.14 | 0.8898 | 188.68 |
| 2 | 1.4047 | 0.1235 | -0.1959 | 1.2398 | 2.6598 | 38.040 | 7.0297 | 97.863 | 51.4643 | 0.2611 | 25.5003 | 0.1400 | 1.8648 | 180.00 |
| 3 | 1.4047 | 0.1235 | -0.1959 | 1.2398 | 5.263 | 69.877 | 13.990 | 195.72 | 95.8129 | 0.5 | 45.0004 | 0.1899 | 1.8644 | 180.00 |
| 4 | 1.4047 | 0.4472 | -0.0727 | 4.9956 | 0.0566 | 6.2035 | 0.0693 | 97.863 | 51.4643 | 0.2611 | 45.0004 | 0.1714 | 0.7600 | 189.31 |
| 5 | 1.4047 | 0.4472 | -0.0727 | 4.9956 | 2.6598 | 38.040 | 7.0297 | 195.72 | 95.8129 | 0.5 | 2 | 0.19 | 0.7600 | 180.05 |
| 6 | 1.4047 | 0.4472 | -0.0727 | 4.9956 | 5.263 | 69.877 | 13.990 | 0.0048 | 7.1157 | 0.02222 | 25.5004 | 0.1890 | 1.8649 | 180.00 |
| 7 | 1.4047 | 0.771 | 0.0505 | 8.7514 | 0.0566 | 6.2035 | 0.0693 | 195.72 | 95.8129 | 0.5 | 25.5004 | 0.1897 | 0.7600 | 246.92 |
| 8 | 1.4047 | 0.771 | 0.0505 | 8.7514 | 2.6598 | 38.040 | 7.0297 | 0.0048 | 7.1157 | 0.02222 | 45.0004 | 0.1886 | 0.7601 | 180.15 |
| 9 | 1.4047 | 0.771 | 0.0505 | 8.7514 | 5.263 | 69.877 | 13.990 | 97.863 | 51.4643 | 0.2611 | 2 | 0.1896 | 0.7649 | 183.41 |
| 10 | 35.607 | 0.1235 | -0.0727 | 8.7514 | 0.0566 | 38.040 | 13.990 | 0.0048 | 51.4643 | 0.5 | 2 | 0.1867 | 0.7600 | 336.58 |
| 11 | 35.607 | 0.1235 | -0.0727 | 8.7514 | 2.6598 | 69.877 | 0.0693 | 97.863 | 95.8129 | 0.02222 | 25.5004 | 0.1892 | 1.0921 | 180.01 |
| 12 | 35.607 | 0.1235 | -0.0727 | 8.7514 | 5.263 | 6.2035 | 7.0297 | 195.72 | 7.1157 | 0.2611 | 45.0004 | 0.1899 | 1.6101 | 180.01 |
| 13 | 35.607 | 0.4472 | 0.0505 | 1.2398 | 0.0566 | 38.040 | 13.990 | 97.863 | 95.8129 | 0.02222 | 45.0004 | 0.1888 | 0.7600 | 246.72 |
| 14 | 35.607 | 0.4472 | 0.0505 | 1.2398 | 2.6598 | 69.877 | 0.0693 | 195.72 | 7.1157 | 0.2611 | 2 | 0.1421 | 0.7603 | 186.13 |
| 15 | 35.607 | 0.4472 | 0.0505 | 1.2398 | 5.263 | 6.2035 | 7.0297 | 0.0048 | 51.4643 | 0.5 | 25.5004 | 0.1622 | 0.7600 | 180.13 |
| 16 | 35.607 | 0.771 | -0.1959 | 4.9956 | 0.0566 | 38.040 | 13.990 | 195.72 | 7.1157 | 0.2611 | 25.5004 | 0.14 | 1.8169 | 184.96 |

| | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 17 | 35.607 | 0.771 | -0.1959 | 4.9956 | 2.6598 | 69.877 | 0.0693 | 0.0048 | 51.4643 | 0.5 | 45.0004 | 0.1892 | 1.8621 | 326.61 |
| 18 | 35.607 | 0.771 | -0.1959 | 4.9956 | 5.263 | 6.2035 | 7.0297 | 97.863 | 95.8129 | 0.02222 | 2 | 0.1848 | 1.8272 | 180.00 |
| 19 | 69.810 | 0.1235 | 0.0505 | 4.9956 | 0.0566 | 69.877 | 7.0297 | 0.0048 | 95.8129 | 0.2611 | 2 | 0.1677 | 0.7600 | 228.29 |
| 20 | 69.810 | 0.1235 | 0.0505 | 4.9956 | 2.6598 | 6.2035 | 13.990 | 97.863 | 7.1157 | 0.5 | 25.5004 | 0.1884 | 0.7600 | 203.41 |
| 21 | 69.810 | 0.1235 | 0.0505 | 4.9956 | 5.263 | 38.040 | 0.0693 | 195.72 | 51.4643 | 0.02222 | 45.0004 | 0.1874 | 0.7637 | 180.01 |
| 22 | 69.810 | 0.4472 | -0.1959 | 8.7514 | 0.0566 | 69.877 | 7.0297 | 97.863 | 7.1157 | 0.5 | 45.0004 | 0.14 | 1.7646 | 341.8 |
| 23 | 69.810 | 0.4472 | -0.1959 | 8.7514 | 2.6598 | 6.2035 | 13.990 | 195.72 | 51.4643 | 0.02222 | 2 | 0.1400 | 1.8641 | 194.29 |
| 24 | 69.810 | 0.4472 | -0.1959 | 8.7514 | 5.263 | 38.040 | 0.0693 | 0.0048 | 95.8129 | 0.2611 | 25.5004 | 0.1609 | 1.4319 | 180.00 |
| 25 | 69.810 | 0.771 | -0.0727 | 1.2398 | 0.0566 | 69.877 | 7.0297 | 195.72 | 51.4643 | 0.02222 | 25.5004 | 0.1884 | 0.7718 | 185.55 |
| 26 | 69.810 | 0.771 | -0.0727 | 1.2398 | 2.6598 | 6.2035 | 13.990 | 0.0048 | 95.8129 | 0.2611 | 45.0004 | 0.1898 | 0.7604 | 183.87 |
| 27 | 69.810 | 0.771 | -0.0727 | 1.2398 | 5.263 | 38.040 | 0.0693 | 97.863 | 7.1157 | 0.5 | 2 | 0.1751 | 0.8799 | 180.44 |

### *7.1. Grey relation analysis for AE*

The simulated data present in Table 4 were normalised (X*) using the equations (1) and (2). The 'lower is better' criteria were used for surface roughness and hardness because this project aims at lowering the toll wear. The normalised values were given in Table 5. From the normalised values of the response variables, the reference value (R) was found using the equation (3) regardless of the response variables.

If the grey relational grade value is higher, the corresponding factors combination is said to be near to the optimal.

The average grey relational grade of each factor at each level, shown in Table 5, was obtained by taking the average of the grey relational grades for the required factor at the required level. 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 Kurtosis, Frequency, Skewness, Time, Mean, RMS, Peak, Standard Deviation, Absolute Deviation, Variance, Crest Factor.

*Table 5. The normalized values, deviation values and grey relational grades 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 | 1 | 0.882502 | 0.946329 | 0 | 0.117498 | 0.053671 | 1 | 0.809719 | 0.903064 | 2.712783 | 0.904261 |
| 2 | 0.9998 | 9.05E-05 | 0.999994 | 0.0002 | 0.999909 | 5.56E-06 | 0.9996 | 0.333353 | 0.999989 | 2.332942 | 0.777647 |
| 3 | 0.0004 | 0.000453 | 0.999992 | 0.9996 | 0.999547 | 8.03E-06 | 0.333422 | 0.333434 | 0.999984 | 1.66684 | 0.555613 |
| 4 | 0.3714 | 0.999991 | 0.942437 | 0.6286 | 9.05E-06 | 0.057563 | 0.443027 | 0.999982 | 0.89676 | 2.339768 | 0.779923 |
| 5 | 0 | 0.999946 | 0.999658 | 1 | 5.43E-05 | 0.000342 | 0.333333 | 0.999891 | 0.999317 | 2.332542 | 0.777514 |
| 6 | 0.0196 | 0 | 1 | 0.9804 | 1 | 0 | 0.337747 | 0.333333 | 1 | 1.67108 | 0.557027 |
| 7 | 0.0056 | 0.999991 | 0.586377 | 0.9944 | 9.05E-06 | 0.413623 | 0.334582 | 0.999982 | 0.547272 | 1.881836 | 0.627279 |
| 8 | 0.0264 | 0.999937 | 0.999047 | 0.9736 | 6.34E-05 | 0.000953 | 0.339305 | 0.999873 | 0.998098 | 2.337276 | 0.779092 |
| 9 | 0.007 | 0.995592 | 0.978866 | 0.993 | 0.004408 | 0.021134 | 0.334896 | 0.991262 | 0.959447 | 2.285605 | 0.761868 |
| 10 | 0.0652 | 0.999982 | 0.032255 | 0.9348 | 1.81E-05 | 0.967745 | 0.348481 | 0.999964 | 0.340659 | 1.689103 | 0.563034 |
| 11 | 0.015 | 0.699449 | 0.999993 | 0.985 | 0.300551 | 6.98E-05 | 0.3367 | 0.62457 | 0.99986 | 1.96113 | 0.65371 |
| 12 | 0.001 | 0.230615 | 0.999922 | 0.999 | 0.769385 | 7.79E-05 | 0.333556 | 0.393892 | 0.999844 | 1.727292 | 0.575764 |
| 13 | 0.0234 | 0.999982 | 0.587592 | 0.9766 | 1.81E-05 | 0.412408 | 0.338616 | 0.999964 | 0.548 | 1.88658 | 0.62886 |
| 14 | 0.957 | 0.999719 | 0.962074 | 0.043 | 0.000281 | 0.037926 | 0.92081 | 0.999439 | 0.929496 | 2.849746 | 0.949915 |
| 15 | 0.5552 | 1 | 0.999141 | 0.4448 | 0 | 0.000859 | 0.529213 | 1 | 0.998285 | 2.527497 | 0.842499 |
| 16 | 1 | 0.043444 | 0.969301 | 0 | 0.956556 | 0.030699 | 1 | 0.343276 | 0.942154 | 2.285429 | 0.76181 |
| 17 | 0.0142 | 0.002534 | 0.093849 | 0.9858 | 0.997466 | 0.906151 | 0.336519 | 0.333897 | 0.35558 | 1.025997 | 0.341999 |
| 18 | 0.1036 | 0.034122 | 0.999993 | 0.8964 | 0.965878 | 6.8E-06 | 0.358064 | 0.341092 | 0.999986 | 1.699142 | 0.566381 |
| 19 | 0.4456 | 0.999991 | 0.701521 | 0.5544 | 9.05E-06 | 0.298479 | 0.474203 | 0.999982 | 0.626191 | 2.100376 | 0.700125 |
| 20 | 0.0318 | 0.999991 | 0.85529 | 0.9682 | 9.05E-06 | 0.14471 | 0.340553 | 0.999982 | 0.775543 | 2.116078 | 0.705359 |
| 21 | 0.0502 | 0.996624 | 0.999916 | 0.9498 | 0.003376 | 8.41E-05 | 0.344875 | 0.993293 | 0.999832 | 2.338 | 0.779333 |
| 22 | 1 | 0.09078 | 0 | 0 | 0.90922 | 1 | 1 | 0.354806 | 0.333333 | 1.68814 | 0.562713 |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 23 | 0.9988 | 0.000724 | 0.911625 | 0.0012 | 0.999276 | 0.088375 | 0.997606 | 0.333494 | 0.849799 | 2.180899 | 0.726966 |
| 24 | 0.5812 | 0.391901 | 0.999968 | 0.4188 | 0.608099 | 3.15E-05 | 0.544188 | 0.451223 | 0.999937 | 1.995348 | 0.665116 |
| 25 | 0.031 | 0.989302 | 0.965693 | 0.969 | 0.010698 | 0.034307 | 0.340368 | 0.979052 | 0.935791 | 2.255211 | 0.751737 |
| 26 | 0.0028 | 0.999611 | 0.976034 | 0.9972 | 0.000389 | 0.023966 | 0.333957 | 0.999222 | 0.95426 | 2.287439 | 0.76248 |
| 27 | 0.2968 | 0.891435 | 0.99726 | 0.7032 | 0.108565 | 0.00274 | 0.415559 | 0.821605 | 0.994549 | 2.231713 | 0.743904 |

*Table 6. Average grey relational grade of AE for each factor at each level for coated carbide insert*

| LEVEL | Factors | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | RMS | CF | SKW | KURT | AD | MEAN | SD | VAR | PEAK | FRE | TIME |
| 1 | 0.724469 | 0.690539 | 0.65139 | 0.768546 | 0.697749 | 0.721212 | 0.71616 | 0.679515 | 0.726649 | 0.705263 | 0.743774 |
| 2 | 0.653775 | 0.72117 | 0.68501 | 0.663275 | 0.719409 | 0.71959 | 0.703719 | 0.686707 | 0.702779 | 0.748294 | 0.704687 |
| 3 | 0.710859 | 0.677394 | 0.752703 | 0.657283 | 0.671945 | 0.648301 | 0.669224 | 0.722881 | 0.659675 | 0.635546 | 0.640642 |

*Table 7. Results of ANOVA for AE signal*

| FACTORS | SUM OF SQUARES | DF | MEAN SQUARE | F-VALUE | P-VALUE | % CONTRIBUTION | RANK |
|---|---|---|---|---|---|---|---|
| RMS | 0.025325 | 2 | 0.012662 | 0.605128 | 0.5894 | 5.943764 | 6 |
| CF | 0.009082 | 2 | 0.004541 | 0.217016 | 0.8138 | 2.1316 | 11 |
| SKW | 0.047932 | 2 | 0.023966 | 1.145305 | 0.4043 | 11.24957 | 3 |
| KURT | 0.070493 | 2 | 0.035247 | 1.684402 | 0.26947 | 16.54476 | 1 |
| AD | 0.010164 | 2 | 0.005082 | 0.242854 | 0.7952 | 2.38539 | 9 |
| MEAN | 0.031203 | 2 | 0.015601 | 0.745573 | 0.5306 | 7.323269 | 5 |
| SD | 0.010643 | 2 | 0.005321 | 0.254309 | 0.7871 | 2.497911 | 8 |
| VAR | 0.009723 | 2 | 0.004861 | 0.232322 | 0.8027 | 2.281945 | 10 |
| PEAK | 0.02074 | 2 | 0.01037 | 0.495567 | 0.6423 | 4.867624 | 7 |
| FRE | 0.058273 | 2 | 0.029136 | 1.392405 | 0.3476 | 13.67666 | 2 |
| TIME | 0.048798 | 2 | 0.024399 | 1.166001 | 0.3991 | 11.45284 | 4 |
| ERROR | 0.083701 | 4 | 0.020925 | | | 19.64466 | |
| TOTAL | 0.426075 | 26 | | | | 100 | |

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.

## 8. Conclusions

The following conclusions are drawn from the present investigation

- 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 LABVIEW 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 Kurtosis, Frequency, Skewness, Time, Mean, RMS, Peak, Standard Deviation, Absolute Deviation, Variance, Crest Factor.
- 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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