Condition monitoring on grinding wheel wear using wavelet analysis and decision tree C4.5 algorithm

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***Abstract* -A new online grinding wheel wear monitoring approach to detect a worn out wheel, based on acoustic emission (AE) signals processed by discrete wavelet transform and statistical feature extraction carried out using statistical features such as root mean square and standard deviation for each wavelet decomposition level and classified using tree based knowledge representation methodology decision tree C4.5 data mining techniques is proposed. The methodology was validate with AE signal data obtained in Aluminium oxide 99 A(38A) grinding wheel which is used in three quarters of majority grinding operations under different grinding conditions to validate the proposed classification system. The results of this scheme with respect to classification accuracy were discussed.**

Keywords-Grinding wheel wear, Acoustic emission (AE), Signal pre processing, Discrete wavelet decomposition, Decision tree C4.5 algorithm.

I. 1. INTRODUCTION

Grinding is a Machining processes which is preferable or necessary to obtain the closer dimensional tolerances, surface roughness, or surface-finish characteristics on the material. It is a concluding process that uses a rotating abrasive wheel to level the surface of metallic or nonmetallic materials .Surface grinding is the most familiar of the grinding operations among this category used by medium scale production units too. Grinding wheel characteristics changes during grinding as more material is removed. Due to this reason the effectiveness of grinding process on the work piece were affected depressingly most of the time. Grinding wheel wear may induce grinding burn and bad surface quality which leads to rejection of components and sometimes even serious accidents. Use of the high frequency (range 20kHz to 1MHz) acoustic emission (AE) technique in grinding wheel wear monitoring has been budding over recent decade. Though at the same time as vibration analysis on grinding wheel wear monitoring is well established, the application of AE to this field is still immature.

In addition, there are limited publications on the application of AE to grinding wheel wear monitoring. Unfortunately, existing approaches dealing with wheel wear are based on human experience and dressing interval is roughly determined by means of sparks generation during the process, as a rule by skilled operators. This leads to undesirable impacts on grinding process. Firstly, grinding wheel wear might already happen before dressing process, which usually causes reduction in performance of grinding operation on work piece. Else, if dressing process is carried out in advance of wheel wear, the grinding effectiveness is reduced though the abrasive materials are worn out .Grinding wheel wear monitoring is thus essential in grinding process. Indirect method of grinding wheel condition monitoring depends on machining process factors and sensor signals such as vibration, forces, current, power, temperature, and acoustic emission. Direct method make use of scanning electron microscope to measure grinding wheel surface directly.

While comparing the both the succeeding method have good prediction with more expensive as well and methodology not deployed as in-service ,thus the way is open to go on this path of automated online wheel wear monitoring. A brief review over the past two decades on this specific issue is discussed below.

W.Hundt et al.,(1994) [1] reviewed the usage of Capacitive and piezoelectric sensors have been used for monitoring purposes and concluded with suggesting AE technique is a feasible method. karpuschewski et al.,(1995)[2] provided a new approach for grinding wheel monitoring system which is used to detect the disturbances in the grinding process and the grinding cycle optimization based on the AE and power signals. The monitoring application as a foreground process can perform other tasks, like preprocessing or visualization using dry and wet condition monitoring systems and concludes with a system utilizing data fusion from different sensors, in this case an AE sensor and a power sensor, allied with various methods has been implemented. Furthermore, reliable data acquisition techniques and a graphical user interface can be applied. Amin A. Mokbel et al.,(1999) [3] made an attempt to monitor the condition of diamond grinding wheels using the AE technique and the grinding outcome of hard materials depends on the condition of the grinding wheel such that the abnormal wheel condition on the work piece resulting in an increase in the grinding forces, which affects the surface reliability and strength This was achieved found by measuring the work piece surface roughness Ra value . Subrahmanya and Shin [4] provided a new approach of automated feature selection and sensor fusion combine with parameter-free model training approach for monitoring of wheel problems such as burn, chatter and wheel wear. Grouping of embedded sensor selection algorithm and an approximate estimate of the leave-one-out error for hyper parameter tuning of least squares–support vector machines were proposed.

Rogers LM (1979) [5] discussed about the different sensor technologies and finalized with Piezoelectric sensor technology is particularly suitable for measuring acoustic emission (AE) in machining process monitoring. T.Warren Liao et al.,(2006) [6]reported that the wavelet-based methodology were used to analyze the raw signals taken from different states and conditions of for grinding wheel by acoustic emission (AE) signals in creep feed mode on alumina specimens with a resinoid-bonded diamond wheel using two different conditions. Adaptive genetic clustering algorithm was finally utilized to classify in order to distinguish different states of grinding wheel condition.T. Warren Liao et al., (2005) [7] provided a new approach using a diamond wheel on two ceramic materials with online based by acoustic emission (AE) signal analysis . Preprocessing , signal analysis done by using wavelet analysis and after feature extraction, and classification of dull and sharp wheel is done using minimum distance classifier (MDC). Liao TW [8] given a new methodology for feature extraction and feature selection in sensor-based condition monitoring using acoustic emission signals collected during grinding operations and processed by discrete wavelet decomposition for feature extraction, and then the best feature subsets were found by different feature selection methods such as ant colony optimization and sequential forward floating selection method. classification is done by five algorithms as follows are the nearest mean (NM), k-nearest neighbor (KNN), fuzzy k-nearest neighbor (FKNN, center-based nearest neighbor (CBNN, and k-means-based nearest prototype (KMNP) and it is compared with respect to accuracy. Pawel Lezanski [9] investigated the cutting abilities of aluminum oxide wheel through the external cylindrical grinding process. Back propagation neural network were used for statistical feature selection among the time and spectral features obtained from the multiple sensor system and fuzzy logic decision system were used for grinding wheel condition monitoring. Warkentin and Bauer [10] investigated the relationships between wheel wear of aluminum oxide wheel and various grinding forces for different depths of cut on mild steel and from the findings the trend shows the average normal value force for various depths of 10, 20, and 30 mm for tangential forces it shows slight positive slope. Maximum depths of 40 and 50 mm, the data show a negative slope and piecewise negative slope, respectively. Li .X [11] & A.G. Rehorn et al.,[12] discussed on their review about the betterment of indirect ,online condition monitoring approach which relies on some sensory signals such as forces, power, vibration, and acoustic emission (AE) that highly correlate with the tool condition. T.W. Liao et al., [13] focused on the study of grinding wheel surface condition changes both in the constituting grits and the overall shape of the wheel when more material is removed. Contrasting other cutting tools, a grinding wheel must be prepared after mounted on the machine spindle, first by truing to ensure its roundness, and then by dressing to open up the abrasives. Mokbel and Maksoud [14] analyzed raw AE raw signals obtained during grinding operation from different mild steel specimens using a FFT and correlated the AE frequency amplitudes of various diamond wheel bond , grit sizes, and using various grinding wheel/truing speed ratio conditions with respect to surface roughness (Ra) of the specimens .Kwak and Ha [15] proved that the signal of grinding force in surface plunge grinding of STD11 specimen machined by alumina wheel could be better processed by wavelet de-noising than by FFT filtering. clearly, the of Daubechies wavelet transform approximation coefficients A4 were used for the detection of wheel dressing time in a sudden signal change at the time or frequency domain . Zhensheng Yang & Zhensheng Yang & Zhonghua Yu [16] investigate the raw AE raw signals obtained during surface grinding operation. A preprocessing based on discrete wavelet decomposition is used to seperate the grinding period signals from raw AE signals. Root mean square and variance of each decomposition level are chosen as the feature vector using the same discrete wavelet decomposition. Various grinding experiments were performed to validate the support vector machine classification system. T.W. hwang et al.,(2000)[17] investigated the diamond grinding wheel and studied the wheel wear rate through means of AE technique. The AE signal is extracted at various interval levels during the high speed grinding of silicon nitride using a single layer electroplated diamond wheel. It was found that the raw AE signals contained system frequencies including the rotational spindle frequency and the specimen frequency and conclude that it monotonically increases with wheel wear. Teti R et al., [18] made a review on recent information on tool condition monitoring and present an extensive survey of new sensor technologies, signal processing methods, and decision making strategies using data mining techniques for process monitoring, Future trends and challenges in this field of condition monitoring using sensor were discussed. Alonso et al.,(2008) [19] decomposed two vibration signals (longitudinal and transverse) into the trend and the detrended signals, and extracted from them several statistical features. It appeared that only the RMS and variance of the detrended signals showed a monotonic behavior with tool wear, which meant that the information in the vibration signals about flank wear was mostly contained in the high-frequency components. Further, they extended their technique by applying cluster analysis to group the decomposition of the vibration signals .

Krzysztof Jemielniak & Joanna Kossakowska [20] evaluated the relation of signal features extracted from different wavelet coefficients of raw AE signal during turning operation of Inconel 625. Statistical features of raw signals were automatically extracted from band pass signals using 22 different wavelets and used for tool condition monitoring were mentioned. The optimal wavelet was selected because it obtain the best results after comparison with other wavelet bases.

In the above section the importance of various methodologies for prediction of wheel wear condition is experimentally discussed/proved by means of acquired the raw signals from the experimental set up for different types of wheels/work with various conditions of work environment using different sensors, and signal processing and is done by various methods such as Time domain analysis , frequency domain analysis ,wavelet analysis and so on. After signal processing feature extraction process has been carried out . for classification of wheel condition some of the researches used various data mining and soft computing techniques such as Neuro-fuzzy[9],KNN types[8],Boosted classifiers[7], Adaptive genetic clustering algorithm[26],Support vector machine (SVM)[16] were used. In turn to make an important step towards the on-line condition monitoring in industrial scenario This paper presents a new method of evaluation on grinding wheel wear monitoring system based on discrete wavelet decomposition and data mining technology is introduced to wheel wear diagnosis field, and a new method based on C4.5 decision tree is proposed. In this method, after data collection, preprocessing and feature extraction is done . Then, C4.5 is trained by using the samples to generate a decision tree model with diagnosis knowledge. At last the tree model is used to make diagnosis analysis. To validate the method proposed, two kinds of running states (dull or blunt) simulated on real surface grinder to test C4.5.

II. EXPERIMENTAL SETUP AND EXPERIMENTAL PROCEDURE

A. Experimental setup

The grinding tests were performed on an PRAGA of model 451 surface grinder, white alumina wheel (Aluminium oxide 99 A(38A)) of size 250 x 50 x 76.2 were used(Fig-1) .This grinding wheel contains more than 98% of Aluminium oxide and particularly suitable for machining of alloy and carbon steels with more than 0.5% contents of carbon and hardness above generally 62HRC. The work piece is a steel specimen (AISI 1018) has a dimension of 300 mm in length and 50 mm in width as well as height. The grinding process was monitored by an physical acoustics corporation standard general purpose acoustic emission sensor (R80D) mounted on the side face of the work piece through magnetic force. Its operating frequency was 30kHz-1MHz and the AE signal was collected at 1 MHz sampling rate using a PC-based data acquisition card (Peripheral component Interconnect -PCI-2).

Fig. 1 Experimental set up

B. Grinding Experimental procedure

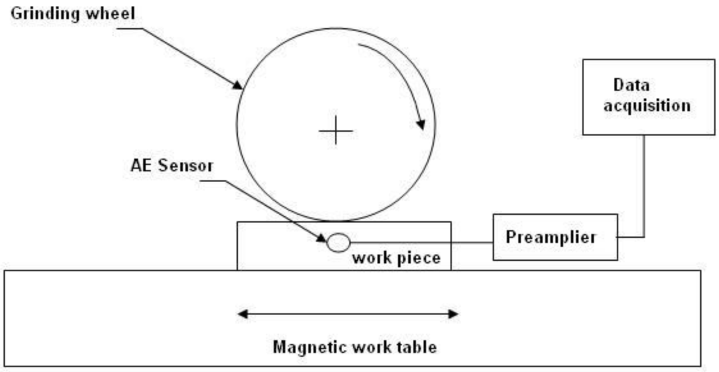

Fig. 2 Schematic view of experiment process

The tests were carried out in 12 different grinding conditions on a specimen. A schematic diagram of the experimental setup is shown in Fig. 2.The process was initially grinded several times prior to the data acquisition to stable the grinding wheel and based on that wheel condition was assigned with experiments keeping grinding parameters include wheel speed as a constant at 2800 rpm and three combinations of depth of cut were used to grind the specimens: first with table traverse speed rate /work piece speed of 12 m/min and 30 μm depth of cut (the high material removal rate condition) as shown in Fig.4 and second condition with 8 m/min and 20 μm depth of cut (the medium material removal rate condition) as shown in Fig.5 and third condition with 4 m/min and 10 μm depth of cut (the low material removal rate condition) as shown in Fig.6 has taken .

Along with the above conditions, experiment was carried out in up grind and as well down grind positions for sharp and blunt conditions of grinding wheel. Each wheel has undergone dressing and truing processes before it was set to run as per the procedure [6]. The importance of truing and dressing procedure is to prepare the wheel more stable and durable through the entire operation. Truing sets the wheel's improper alignment in the machine as well as the wheel's out of balance, Dressing is done to remove the dust particles which has been stored on the surface during grinding. The appropriate coolant was used as per the manufacturer's instruction in the process. After ensuring the grinding wheel contact with work piece during the process, acquisition system would start collecting the signals with high sampling rate of 1 MHz in stable sharp state for 12 different conditions as well after a period, wheel reached a blunt state for 12 conditions and sample collection was continued for both sharp and blunt conditions twice for the same 12 conditions. Every acoustic emission signal segment has 5000 data points, which equal to roughly around a duration of 0.4 grinding wheel revolution. Sample size was selected based on to reduce the processing time and to preserve sufficient amount of information. Sample raw AE signals containing pre and post grinding signal segment along with grinding signal segment in the duration of about 4 seconds were collected. The wheel was blunt or not was decided based on the grinding sounds and sparks with the operator's experience.Fig.2 shows a Raw AE signals containing pregrinding, grinding, and post grinding signal segments.

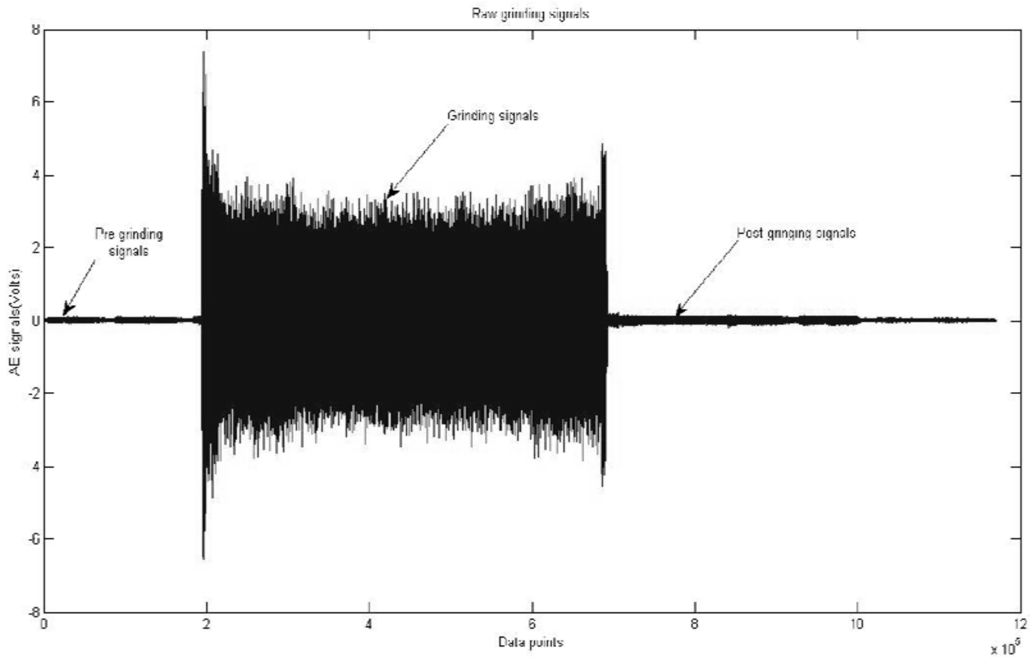

Fig. 3 Raw A.E signals with pre, grinding and post grinding signals

III. DATA PRE PROCESSING

In this grinding process raw signals are sampled at high enough frequency to retain the useful information. Because of high sampling rate time series AE signal data acquisition from the whole grinding process would be in large quantity for a short period of time .This leads to increase the processing time in continuous online Wear monitoring. Preferably, only grinding signals in the process collected to reduce space and to avoid the preprocessing of post and pre grinding signals. To simplify subsequent processing, the grinding signals are characteristically segmented and undergo dimensionality reduction by means of specific transformation functions that also work in the time domain or in the frequency domain.

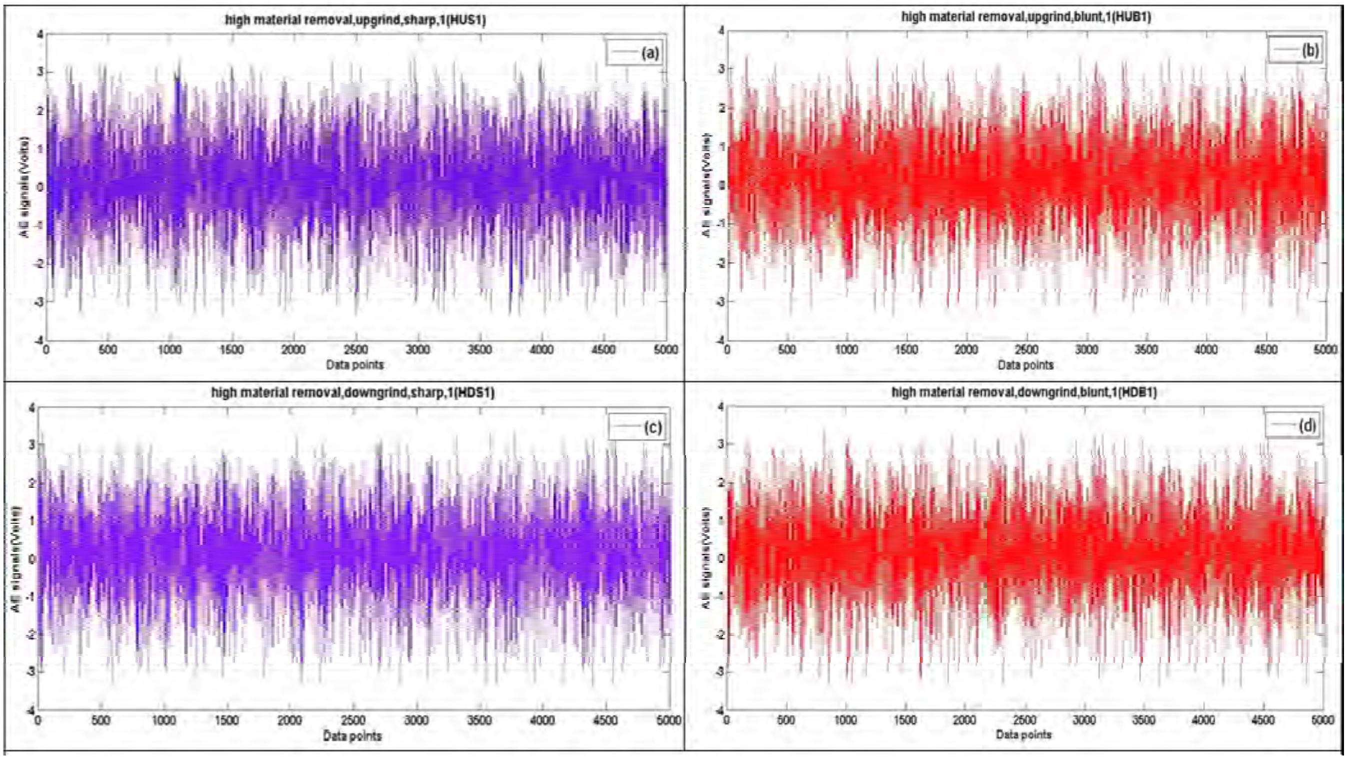

Fig. 4 Raw sample A.E signals with high material removal rate (a) high upgrind sharp (b)high upgrind dull (c) high downgrind sharp (d) high downgrind dull

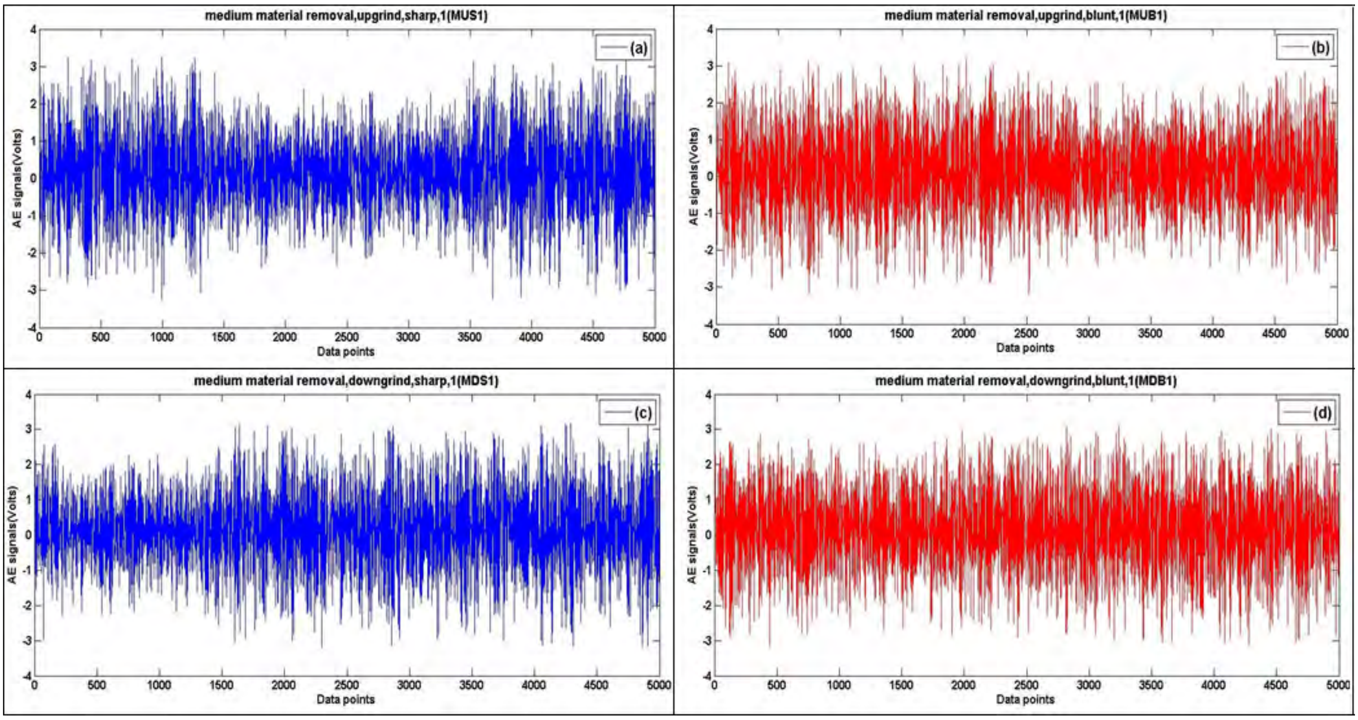

Fig. 5 Raw sample A.E signals with Medium material removal rate (a) medium upgrind sharp (b)medium upgrind dull (c) medium downgrind sharp (d) medium downgrind dull

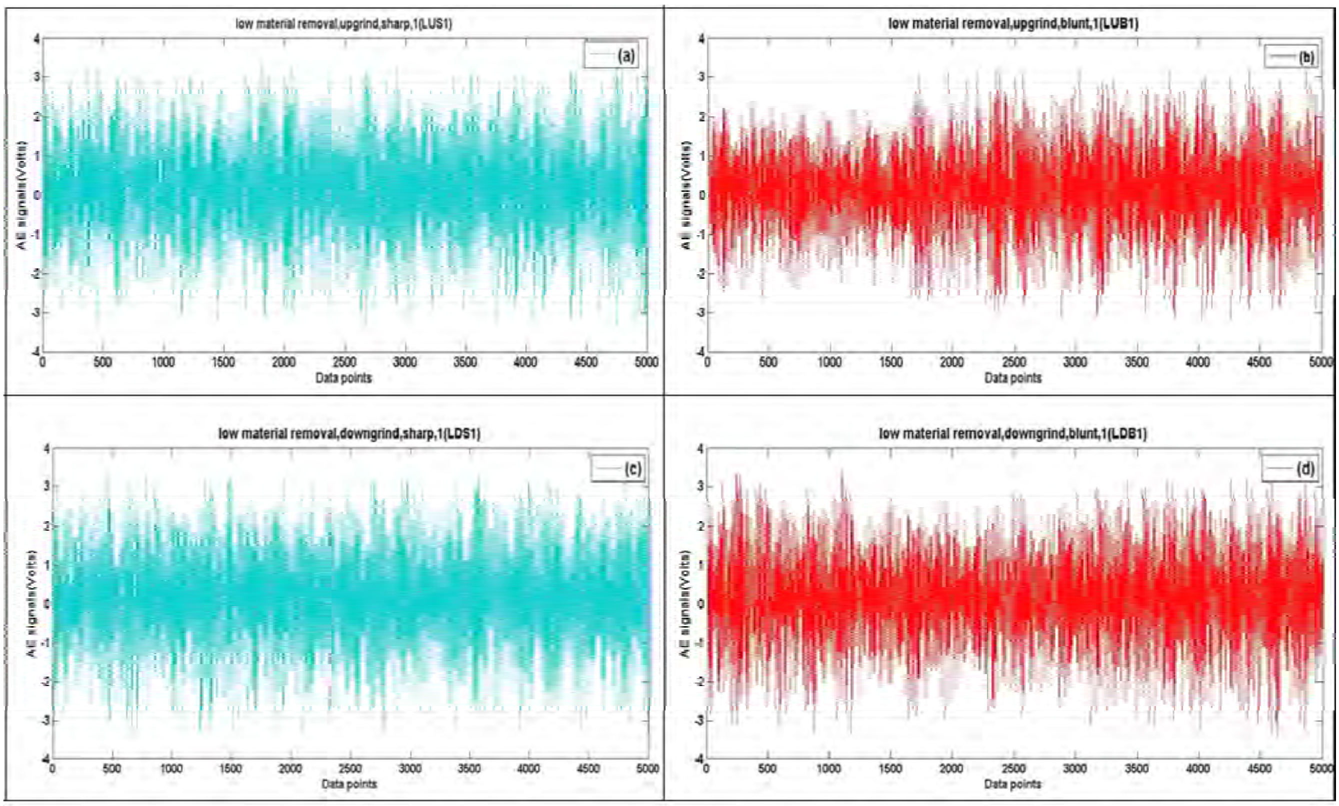

Fig.6 Raw sample A.E signals with Low material removal rate (a) low upgrind sharp (b)low upgrind dull (c) low downgrind sharp (d) low downgrind dull

Commonly used transformation technique in tool condition monitoring is Fast Fourier transform (FFT) to transform the time series data to frequency domain where the signal is used to deduction of sine and cosine waves from the sample. FFT was also execute on sample signals during pre, post grinding and grinding periods. The plots are shown in Fig. 7(a), 7(b) and 7(c). It is observed that the frequency spectrum plot of pre grinding period signals Amplitude levels were raised at frequency domains in the range of 25kHz to 75 kHz. More or less the same range is reflected in of post grinding period signals after mentioned range, frequency spectrums were relatively weak. But as a contrast frequency spectrums of grinding period signals more than the range of pre, post grinding period signals were clearly noticeable for some extent. Moreover, the amplitude is higher than pre, post grinding signals grinding signals at the initial stage of frequency scale.

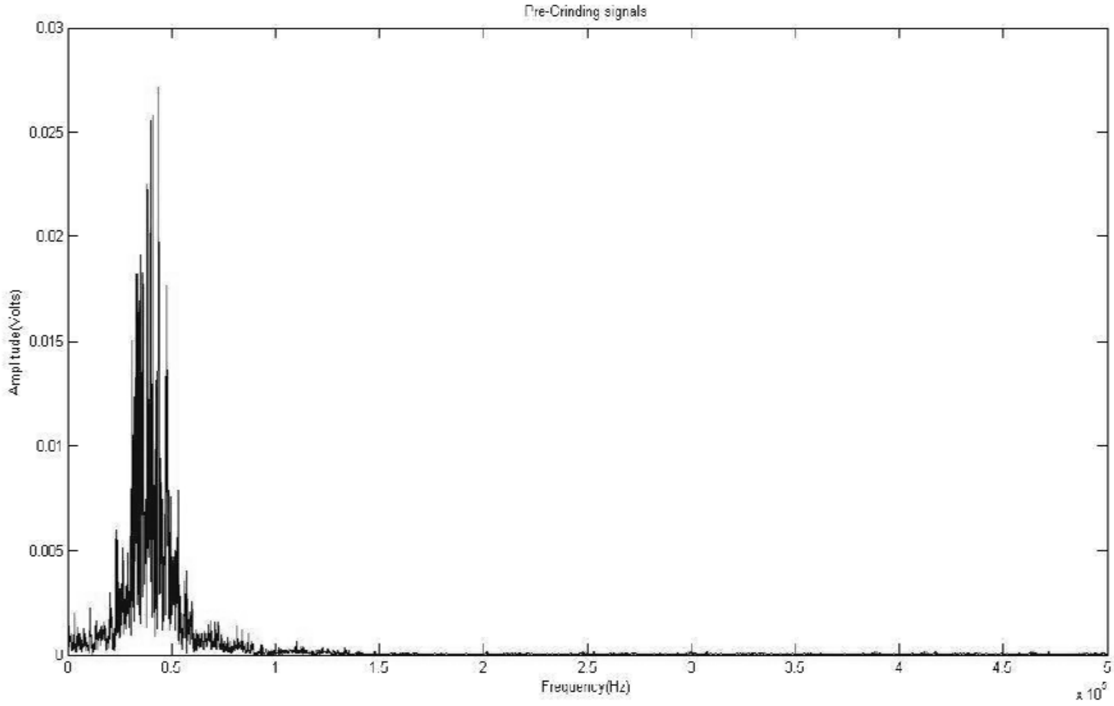

Fig. 7(a) The frequency spectrum plot of Pre grinding period

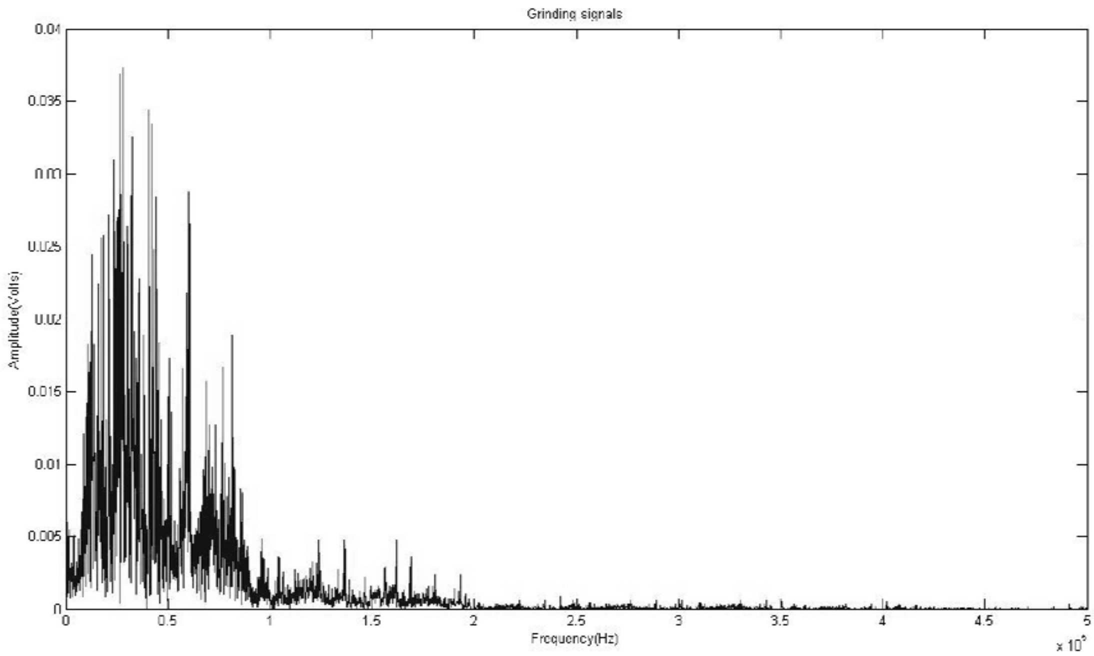

Fig. 7(b) The frequency spectrum plot of grinding period

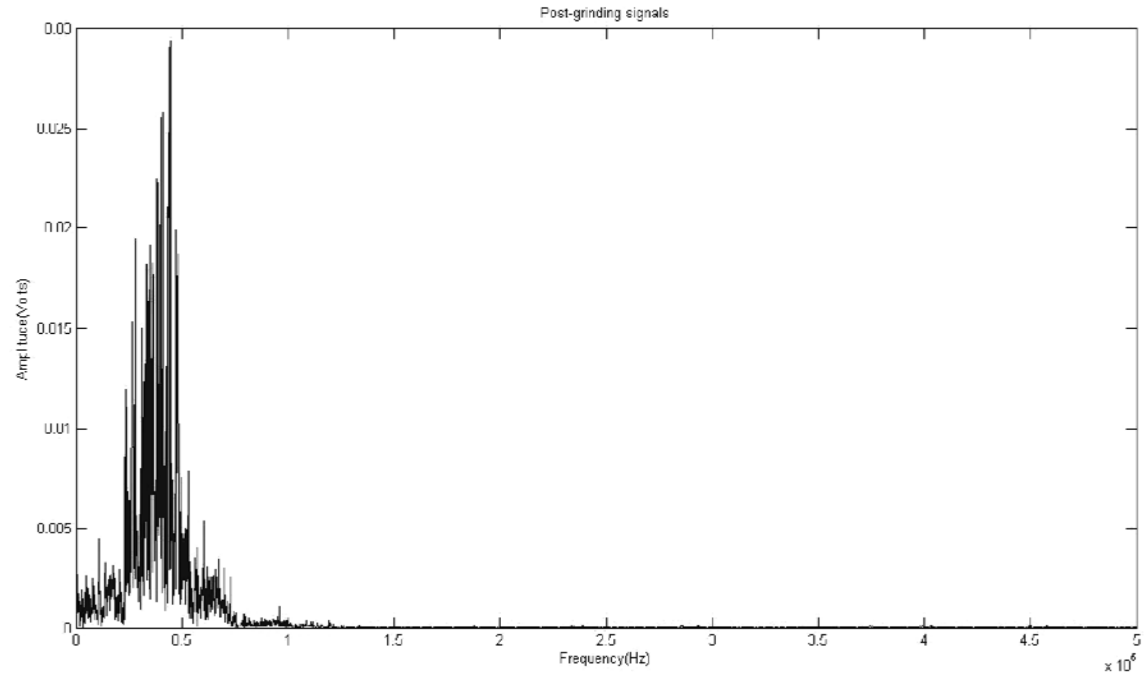

Fig. 7(c) The frequency spectrum plot of post grinding period

These results of FFT helpful us in filtering of pre, post grinding period signals from grinding period signals of the samples and after this filtering the chaste grinding period signals which is shown in Fig.4,5&6 were used as a sample for wavelet decomposition . In this paper we proposed the wavelet transform method for transformation. To obtain this reduction some subset of the transformed coefficients are taken as features .These features form a transformed space and it is used as the input of next process called classification. In Limitation point of FFT, it cannot find the non-stationary transient information from the samples. That is the reason this paper focus on wavelet transform. Versatility and Effectiveness of wavelet transform over Fourier transform is discussed elaborately by Liao et al. [7, 8].

IV. THEORETICAL BACKGROUND OF WAVELET TRANSFORM

Wavelet transform(WT) is a time-frequency decomposition of a sample signal into “wavelet” basic function. Wavelet analysis is widely to decomposing, denoising and signal analysis over an non-stationary signals . At high frequencies WT gives good time and poor frequency resolution, and at the same time at low frequencies it gives good frequency and poor time resolution. Investigation with wavelets proceed with breaking up a signal into shifted and scaled versions of its mother (or original) wavelet, that is obtaining one high frequency term from each level and one low frequency residual from the last level of decomposition[25]. In other words Decomposition of signal is a process of breaking of signals into lower resolution components with respect to levels. There are two categories of this transformation widely used in wavelet: Continuous Wavelet Transform (CWT), Discrete Wavelet Transform (DWT) was discussed in further section.

Sample No.	State	d1	d2	d3	d4	d5	d6	d7	d8	d9	d10	d11	a11
1	HUS1	0.530281	0.590471	0.682582	0.377557	0.148449	0.092084	0.037922	0.03548	0.036563	0.024592	0.002819	0.189114
2	HUS2	0.54619	0.608186	0.70306	0.388883	0.152902	0.094846	0.03906	0.036544	0.03766	0.02533	0.002904	0.194788
3	HDS1	0.525515	0.619356	0.539475	0.30378	0.137655	0.072136	0.034272	0.026914	0.014341	0.008105	0.001259	0.1619
4	HDS2	0.546536	0.64413	0.561054	0.315931	0.143161	0.075022	0.035643	0.02799	0.014915	0.008429	0.001309	0.168376
5	HUB1	0.528951	0.633901	0.581334	0.316398	0.148041	0.079537	0.034576	0.027917	0.018403	0.009845	0.001317	0.163994
6	HUB2	0.555399	0.665596	0.610401	0.332218	0.155443	0.083513	0.036305	0.029313	0.019323	0.010337	0.001383	0.172193
7	HDB1	0.540199	0.647899	0.583796	0.322687	0.148766	0.079715	0.035109	0.030191	0.018914	0.010475	0.002901	0.164259
8	HDB2	0.567209	0.680294	0.612986	0.338821	0.156204	0.083701	0.036864	0.0317	0.01986	0.010999	0.003046	0.172472
9	MUS1	0.54273	0.650721	0.585788	0.328464	0.149058	0.084243	0.037769	0.030868	0.021075	0.013506	0.00404	0.172615
10	MUS2	0.569866	0.683258	0.615077	0.344887	0.156511	0.088455	0.039657	0.032411	0.022129	0.014181	0.004242	0.181246
11	MDS1	0.553256	0.661634	0.599702	0.332474	0.150757	0.092345	0.038469	0.031449	0.022035	0.015588	0.004162	0.180452
12	MDS2	0.575387	0.688099	0.62369	0.345773	0.156787	0.096039	0.040008	0.032707	0.022917	0.016212	0.004328	0.18767
13	MUB1	0.577308	0.702172	0.623705	0.347732	0.152137	0.092427	0.039761	0.032252	0.02621	0.01849	0.005766	0.180543
14	MUB2	0.606174	0.737281	0.65489	0.365118	0.159744	0.097049	0.041749	0.033865	0.02752	0.019414	0.006055	0.18957
15	MDB1	0.582041	0.705322	0.630989	0.355041	0.154421	0.092675	0.039879	0.037806	0.029941	0.020412	0.007107	0.188474
16	MDB2	0.611143	0.740588	0.662538	0.372793	0.162142	0.097308	0.041873	0.039697	0.031438	0.021433	0.007462	0.197898
17	LUS1	0.583606	0.711694	0.635746	0.357459	0.154918	0.09842	0.042728	0.040546	0.030568	0.02495	0.007609	0.194838
18	LUS2	0.612787	0.747279	0.667533	0.375332	0.162664	0.103341	0.044865	0.042574	0.032096	0.026197	0.00799	0.20458
19	LDS1	0.591353	0.717342	0.636824	0.367264	0.163277	0.100436	0.043973	0.046603	0.03072	0.038188	0.008418	0.201262
20	LDS2	0.609093	0.738863	0.655928	0.378282	0.168176	0.103449	0.045292	0.048001	0.031642	0.039333	0.00867	0.207312
21	LUB1	0.593152	0.719077	0.643685	0.368454	0.164353	0.100804	0.045929	0.061444	0.056899	0.040056	0.008607	0.203515
22	LUB2	0.616878	0.74784	0.669433	0.383192	0.170927	0.104836	0.047766	0.063902	0.059175	0.041658	0.008952	0.211655
23	LDB1	0.60102	0.742847	0.660151	0.372431	0.168128	0.102431	0.048704	0.079063	0.068996	0.043117	0.009963	0.211895
24	LDB2	0.631071	0.77999	0.693159	0.391053	0.176535	0.107553	0.05114	0.083016	0.072446	0.045273	0.010461	0.222489

Table 1- Sample RMS feature values extracted from 11 level wavelet decomposition for 3 different conditions of depth of cut

Sample No.	State	d1	d2	d3	d4	d5	d6	d7	d8	d9	d10	d11	a11
1	HUS1	0.383056	0.490521	0.68265	0.377594	0.348484	0.292113	0.279249	0.13548	0.036559	0.02457	0.028192	0.018624
2	HUS2	0.386595	0.496652	0.691184	0.382314	0.35284	0.295764	0.28274	0.137173	0.037016	0.024877	0.028545	0.019024
3	HDS1	0.391548	0.505236	0.70313	0.388922	0.358938	0.300876	0.287627	0.139544	0.037656	0.025307	0.029038	0.013014
4	HDS2	0.395193	0.511552	0.711919	0.393784	0.363425	0.304637	0.291222	0.141289	0.038127	0.025624	0.029401	0.014176
5	HUB1	0.593212	0.717414	0.631052	0.367301	0.148056	0.092355	0.039765	0.03212	0.018378	0.013492	0.00404	0.006453
6	HUB2	0.600627	0.716382	0.63894	0.371892	0.149906	0.093509	0.040262	0.032522	0.018608	0.01366	0.004091	0.006723
7	HDB1	0.61694	0.746111	0.656294	0.381993	0.153978	0.096049	0.041355	0.033405	0.019113	0.014031	0.004202	0.01249
8	HDB2	0.624652	0.755437	0.664497	0.386768	0.155902	0.097249	0.041872	0.033823	0.019352	0.014207	0.004254	0.012471
9	MUS1	0.525568	0.650787	0.539529	0.332507	0.137668	0.079545	0.035112	0.046269	0.030485	0.038145	0.012588	0.016629
10	MUS2	0.532137	0.658921	0.546273	0.336664	0.139389	0.080539	0.035551	0.046848	0.030866	0.038622	0.012745	0.017028
11	MDS1	0.551846	0.683326	0.566506	0.349133	0.144552	0.083522	0.036868	0.048583	0.032009	0.040052	0.013217	0.024078
12	MDS2	0.558744	0.691867	0.573587	0.353497	0.146359	0.084566	0.037329	0.04919	0.032409	0.040553	0.013382	0.023989
13	MUB1	0.542784	0.633964	0.581393	0.316429	0.154934	0.092437	0.043977	0.040289	0.030669	0.024924	0.007107	0.008396
14	MUB2	0.549569	0.641889	0.58866	0.320385	0.15687	0.093592	0.044527	0.040793	0.031053	0.025236	0.007196	0.009101
15	MDB1	0.564496	0.659323	0.604648	0.329087	0.161131	0.096134	0.045736	0.0419	0.031896	0.025921	0.007392	0.030183
16	MDB2	0.571552	0.667565	0.612206	0.3332	0.163145	0.097336	0.046308	0.042424	0.032295	0.026245	0.007484	0.030902
17	LUS1	0.591412	0.719149	0.623767	0.357494	0.150772	0.102441	0.045933	0.031333	0.021033	0.008103	0.009964	0.01336
18	LUS2	0.598805	0.728138	0.631564	0.361963	0.152656	0.103722	0.046508	0.031725	0.021296	0.008204	0.010089	0.018823
19	LDS1	0.620982	0.755106	0.654955	0.375369	0.15831	0.107564	0.04823	0.0329	0.022084	0.008508	0.010462	0.004818
20	LDS2	0.628745	0.764545	0.663142	0.380061	0.160289	0.108908	0.048833	0.033311	0.022361	0.008614	0.010593	0.00765
21	LUB1	0.583665	0.705393	0.64375	0.36849	0.163294	0.100814	0.042733	0.026846	0.018899	0.01047	0.001317	0.04345
22	LUB2	0.59096	0.71421	0.651796	0.373097	0.165335	0.102074	0.043267	0.027181	0.019136	0.010601	0.001334	0.054312
23	LDB1	0.612848	0.740662	0.675937	0.386915	0.171458	0.105855	0.044869	0.028188	0.019844	0.010993	0.001383	0.016813
24	LDB2	0.620508	0.749921	0.684386	0.391751	0.173602	0.107178	0.04543	0.02854	0.020092	0.011131	0.001401	0.017581

Table 2- Sample SD feature values extracted from 11 level wavelet decomposition for 3 different conditions of depth of cut.

A. Continuous wavelet transform

The advantage over the Fourier transform is the continuous wavelet transform had the capability to create a time-frequency signal which contains a very good time and frequency localization. This locate the wavelet transform apart from the Fourier Transform, the effect were accumulation of higher frequency sine waves spread throughout the frequency axis.CWT is widely used to divide a continuous-time function into wavelets. The continuous wavelet transform of a time function z(t) is denoted as :

$$CWT(x,y) = \int_{-\infty}^{\infty} z(t)\psi^{*}_{(a,b)}(t)dt \qquad (1)$$

Where $\psi^{*}_{(a,b)}$(t) is a continuous function in both the time domain and the frequency domain called the mother /original wavelet and * represents operation of complex conjugate.

Further expansion of $\psi^{*}_{(a,b)}$(t) gives

$$\psi^{*}(x,y) = \frac{1}{\sqrt{x}}\psi\left(\frac{t-y}{x}\right) \quad \text{Where} \quad x, y \in \text{R}, x \neq 0 \tag{2}$$

In general mother wavelet gives a source function to generate the translated and scaled version of its sibling wavelets. As given in Equation. (2), the transform signal CWT (a, b) is defined on plane x - y, were a and b are used to change the frequency and the time location of the wavelet. Whenever high frequency resolution is required, the decrement of x will construct a high-frequency wavelet and vice versa is possible. In other side as y increases, the wavelet transverses the length of the input signal, and a increases or decreases in response to changes in the local time and frequency content of the signals.

B. Discrete wavelet transform

Discrete wavelet Transform (DWT) wavelets used in numerical analysis and functional analysis, gives a detailed signals by means of discretely separating the signals into several approximation . DWT is a wavelet transform for which the wavelet ψ(x,y) is discretely sampled. Typically, the DWT can be obtained from discretisation of CWT.As compare with Fourier transforms DWT captures both frequency and location information (location in time).

$$DWT(a,b) = \int_{-\infty}^{\infty} x(t)\psi^{*}_{(i,j)}(t)dt \tag{3}$$

$$\psi^{*}(i,j) = \frac{1}{\sqrt{2^{i}}}\psi\left(\frac{t-2^{i}k}{2^{i}}\right) \tag{4}$$

Where *a* and *b* are replaced by 2^{i} and $2^{i}k$ respectively. After using the filters on the original signal z(t) the decomposition process of low frequency called approximations and high frequency called details were carried out and subsequently it can be iterated with successive approximations being decomposed in turn, though the signal can be split into many lower-resolution components[24].

Compare to discrete wavelet transform (DWT), Continues wavelet transform is computationally slow but it gives surplus information about the signals. But in online condition monitoring less processing time is needed .In many of the condition monitoring studies type of wavelet was chosen without particular reasons and wavelet coefficients were typically treated as separate time domain signals, As like time domain signals each signals characterized by features [18], Zhensheng Yang & Zhonghua Yu [16] pointed out the importance of choosing the wavelet function by considering the factors such as Orthogonality, Compact support and shape of the wavelet transform .

V. WAVELET-BASED DECOMPOSITION AND STATISTICAL FEATURE EXTRACTION

The Daubechies wavelets is an important type of discrete wavelet transform comes under a family of orthogonal wavelets[23] .In general db1(Daubechies wavelets) which is equal to haar wavelets . In this present work using Matlab, “wavedec”1D wavelet decomposition function(command) is used for decomposition of the sample signals. After filtering the grinding signals from raw signal such as pre, post grinding period signals, samples were taken and 11-level wavelet decomposition using haar wavelet is carried out on each AE sample, For an 11 level decomposition, the number of decomposed signals is 12 including the approximation signal a11 Fig.8(a),8(b) shows sample signal contains ‘d1 to d11’& a11 decomposed signals taken for a sharp & blunt grinding conditions. Statistical features such as root mean square(RMS) and standard deviation(SD) of each separate decomposed signal were calculated to represented signal’s useful information and variation among them[19]. As a outcome, for each decomposition, Statistical features RMS and SD is found by and defined as

$$X_{RMS} = \sqrt{\frac{1}{N}\sum_{t=1}^{N} x_{t}^{2}} \tag{5}$$

$$X_{SD} = \sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(x_t - \mu\right)^2} \tag{6}$$

Where x_t is a signal series for t = 1, 2,….., N , N is the number of data points in each decomposition and μ denotes the mean of the sample set.

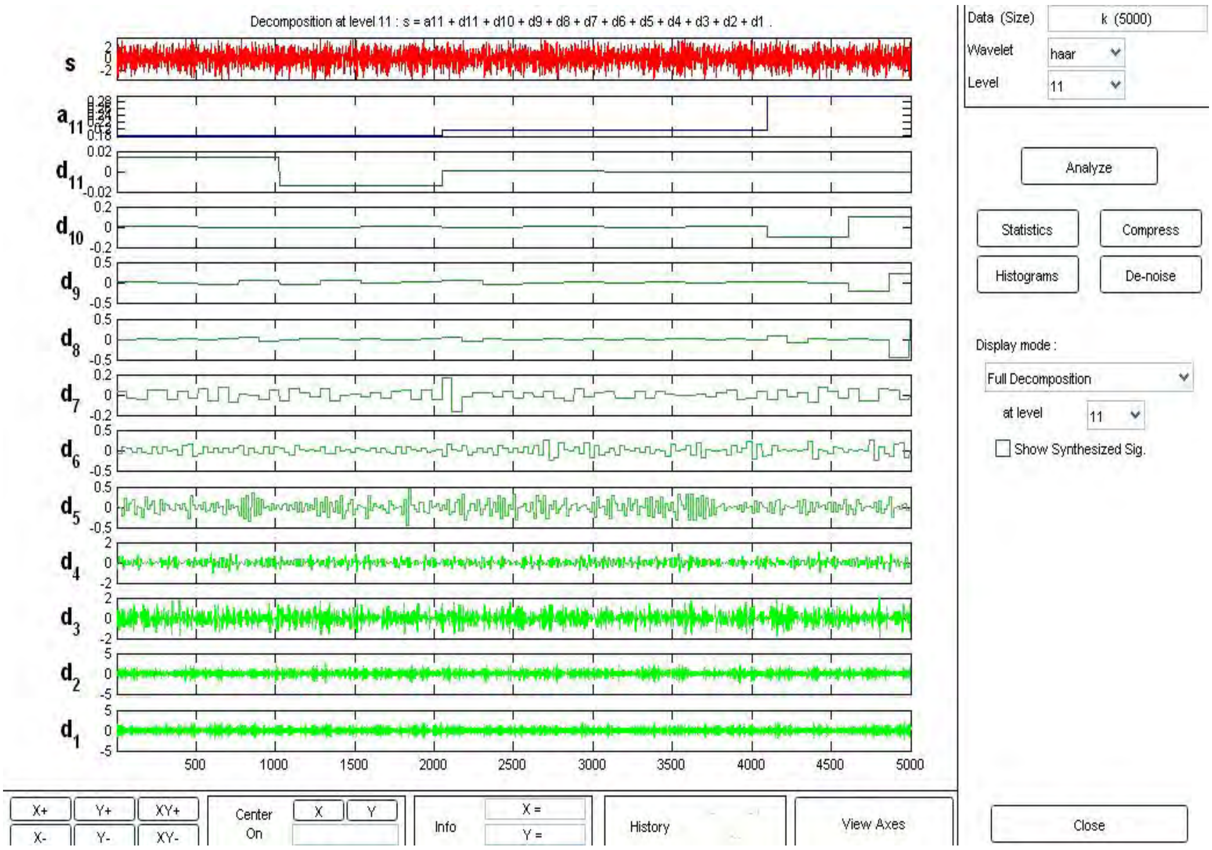

Fig. 8(a) sample wavelet decomposition of AE sample signals taken from sharp wheel condition(MDS1)

For each AE signal segment obtained from each decomposition 12 features are thus extracted. Table 1 gives (24 samples of 12 conditions) 12-root means square (RMS) feature values extracted from the decomposed signals according to the procedure described in this section. Subsequently Table 2 gives 24 samples of 12-standard deviation (SD) feature values extracted from the decomposed signals. From the 24 samples, 12 sample files ends with ‘1’ from the table denotes set-1and rest of 12 sample files ends with ‘2’ from the table denotes set-2 among those files ‘H’ denotes ‘high material removal rate’ of 30µm., ‘M’ denotes ‘medium material removal rate’ of 20µm,‘L’ denotes ‘low material removal rate’ of 10µm., , ‘U’ denotes ‘up grinding position’ ‘D’ denotes ‘down grinding position’ ‘S’ denotes ‘sharp’ and ‘B’ denotes ‘blunt’ condition of grinding wheel (for example MUS1 indicates medium material removal rate of 20µm with up grinding direction and sharp condition grinding wheel).

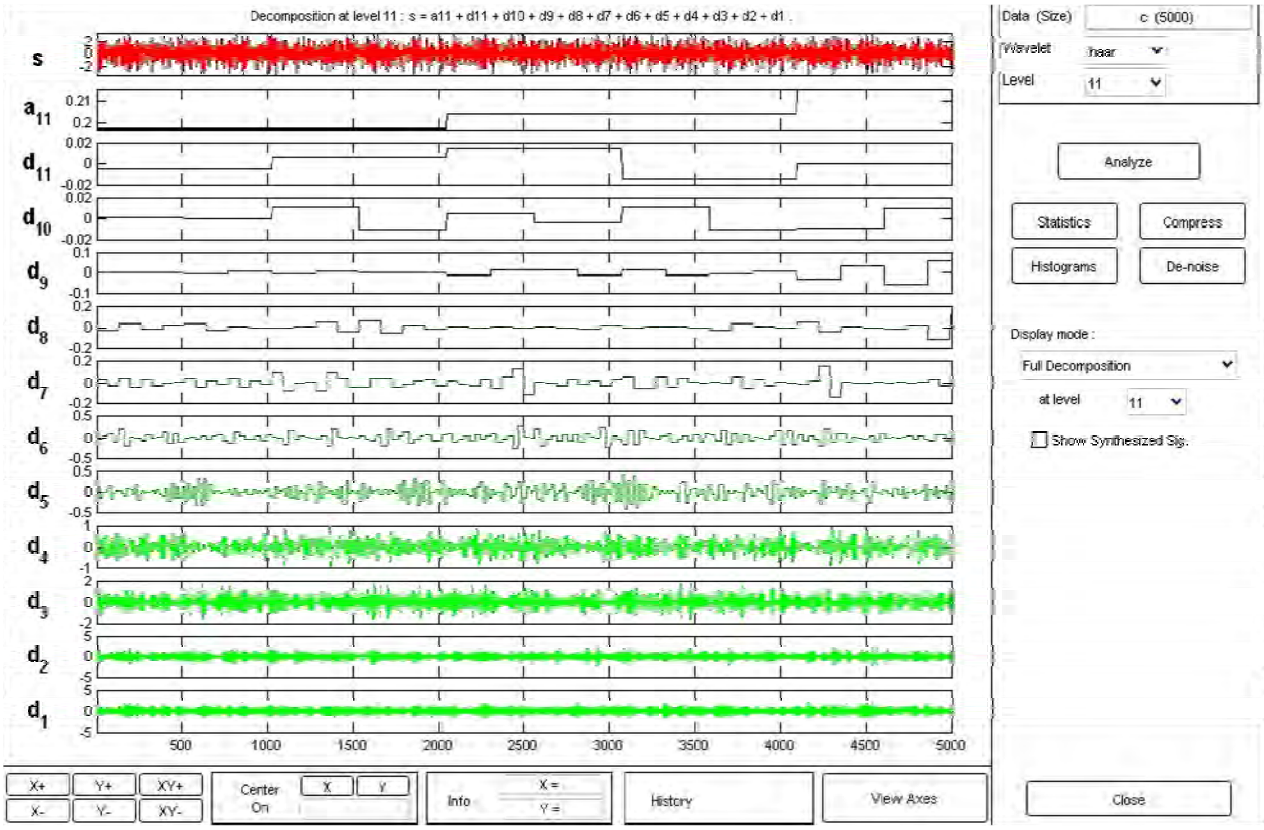

Fig. 8(b) sample wavelet decomposition of AE sample signals taken from blunt wheel condition(MDB1)

VI. THEORETICAL BACKGROUND OF C4.5 ALGORITHM

Decision Tree performs under the category of supervised learning, the ability of the decision tree depends on resolving a complex process into a set of simple processes of determination. The ultimate aim of this dynamic discretisation method is to execute each attribute in every process to select the best test attribute.During creation of the decision tree; a training data set is divided based on certain decision rules until one subset match with particular class label. In the beginning, the decision tree has a single root node for the whole training data set, subsequently for every partition, a new node is supplemented to the decision tree. Sample tree is shown in Fig. 9. Assume D is a training data set and if D is a void set or a set having only single class label, the simplest decision tree is a tree having a leaf of that particular class label. Though, Z is a decision rule and having output $OP_1, OP_2, OP_3, \ldots\ldots\ldots OP_n$, ; each data of D include one of these outputs. Therefore test attribute Z generates a subsets {D1, D2, D3,... Dn} indicating data output OP_n. During each subset of D_i replaces a decision tree relative to the D_i in the above procedure and that is to be the final result of this algorithm.

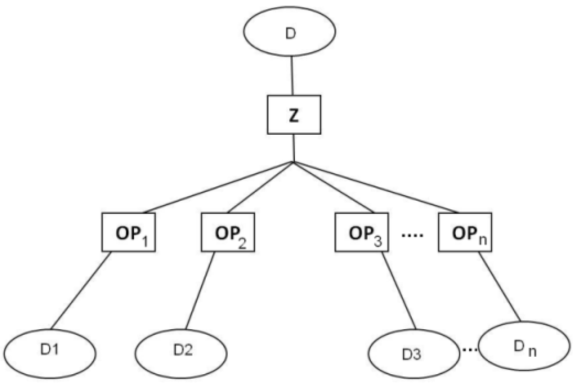

Fig. 9 Sample decision tree model

Quinlan, (1993) [21]given the methodology of test attribute selection criterion of decision tree had an significant importance and how to use information entropy evaluation function calculation based on the information theory as the selection criteria as follows.

Step 1: Determine Info(D) to identify the class label in the training data set D.

$$Info(D) = -\sum_{i=1}^{k}\{[freq(C_i, D)/|D|]log_2[freq(C_i, D)/|D|]\} \tag{7}$$

Where $|D|$ is the number of cases in the training set. C_i is a class, i = 1, 2, ...K, K is the number of classes and $freq(C_i, D)$ is the number of cases included in C_i

Step 2: Calculate the expected information value, $Info(S)$ for test X to partition S

$$Info_X(D) = -\sum_{i=1}^{L}\left[\left(\frac{|D_i|}{|D|}\right) Info(D_i)\right] \tag{8}$$

where L is the number of outputs for test attribute X, S_i is a subset of S corresponding to i th output and S_i is the number of cases of subset S_i.

Step 3: Calculate the information gain after partition according to test Z.

$$Gain\ (Z) = Info_X(D) - Info_X(D) \tag{9}$$

Step 4: Calculate the partition information value Split Info(Z) acquiring for S partitioned into L subsets.

$$Split\ Info(Z) = -\frac{1}{2}\sum_{i=1}^{L}\left[\frac{|D_i|}{|D|}\quad log_2\frac{|D_i|}{|D|} + \left(1-\frac{|D_i|}{|D|}\right)\ log_2\ \left(1-\frac{|D_i|}{|D|}\right)\right] \tag{10}$$

Step 5: Calculate the gain ratio of Gain(Z) over Split Info(Z).

$$Gain\ ratio\ (X) = Gain\ (Z)/Split\ info(Z) \tag{11}$$

The Gain ratio (Z) compensates for the weak point of Gain (Z) which represents the quantity of information provided by Z in the training set. Therefore, an attribute with the highest GainRatio (Z) is taken as the origin node of the decision tree.To reduce the process time and over-training or over-fitting over the sample without affecting the accuracy of results C4.5 algorithm applies negative error post pruning strategy. For each classification node algorithm find an expected error rate based misclassifications at that particular node. The procedure followed here to find error rate based on the upper limit of an a confidence interval for the mean *E/N* of a binomial distribution *B(E/N)* since , proportion of misclassifications is denoted as *E/N* at the node[22].

Many times, algorithm solves the classification problem with continuous attributes in the discretisation process and it has to select the optimal threshold. For a continuous-valued attribute Z, suppose it has ‘m’ values in the training set and the values are sorted in ascending order, i.e., $\{z_1, z_2, ...z_m\}$ $\{z_1 \le z_2 \le ...... \le z_m\}$ a special value z_i, it split the samples into two set $\{z_1, z_2, ...z_i\}$ and $\{z_{i+1}, z_{i+2}, ...z_m\}$.One has Z values up to z_i, the other has Z values greater than z_i and z_i is an optional threshold for discretisation. Therefore, there exist $m-1$ type of partitions / thresholds will exist. For each of these partitions, compute the information gain and choose the partitions that exploit the gain. The boundary value z_j in the optimal partition is selected as the optimal threshold. This procedure is followed for each and every test attribute.

VII. Implementation of Decision tree C4.5 classifier in diagnosis of wheel wear

Consolidated statistical features obtained from table-1 & table -2 with the indication of two common state of wheel conditions such as SHARP & BLUNT class labels instead of notations were given as a input for training and testing of the proposed C4.5 algorithm in preferable percentage.

At initial stage the features taken from the experiment divided into two parts as training sample set for train the algorithm and testing sample set used for test the validity of the classifier. In general random sample about 60% from the feature table were selected for train the algorithm, and the remaining available sample about 40% used as testing set. Ten-fold cross-validation is employed to evaluate classification accuracy. The tree generation starts from single node representing the sample of training data set .The node becomes a leaf when the samples are belong to same class label ,Otherwise, the algorithm split every attribute to select the optimal threshold value and uses the information gain as investigation methodology for select the particular attribute which will separate into individual classes. For each separate interval of the test attribute, separate branch is generated, and consequently the samples were partitioned. This tree generation process is continued until upon a condition is satisfied either the given node sample belong to same class label or non availability of attributes for samples further partitioned or There are no samples for the branch test attribute. In this case, a leaf is created with the majority class in samples. To improve the algorithm accuracy, pruning method is used to trim the unwanted nodes from grown tree. J48 algorithm available in WEKA accomplishment of c4.5 Algorithm is used in this work. The trained C4.5 decision tree shown in Fig-10 contains 7 leaf nodes, uses four test attributes (d7, d9, d10 & d11) .The other test attributes (d1, d2, d3, d4, d5& d6) not shown in model is trimmed by pruning method. In general in a decision tree, a path from root to leaf can be viewed as a classification rule [22]. From this approach, a decision tree represents a set of rules. From the Fig. 10, 7 rules were obtained, including the indication of principal dataset feature and value range of other dataset features. The persuaded rules can be used as diagnosis knowledge to diagnose grinding wheel wear. This classification is done for each grinding condition with respect to different depth of cuts by separation of statistical feature and taken for training & testing of algorithm and follow the above procedures for classification.

State of the wheel	**Overall classification accuracy (%)**	**Average classification Timing (sec)**
High material removal rate	99.15	0.0082
Medium material removal rate	98.95	0.0075
Low material removal rate	96.70	0.0079

Table-3 Diagnosis results of c4.5 algorithm

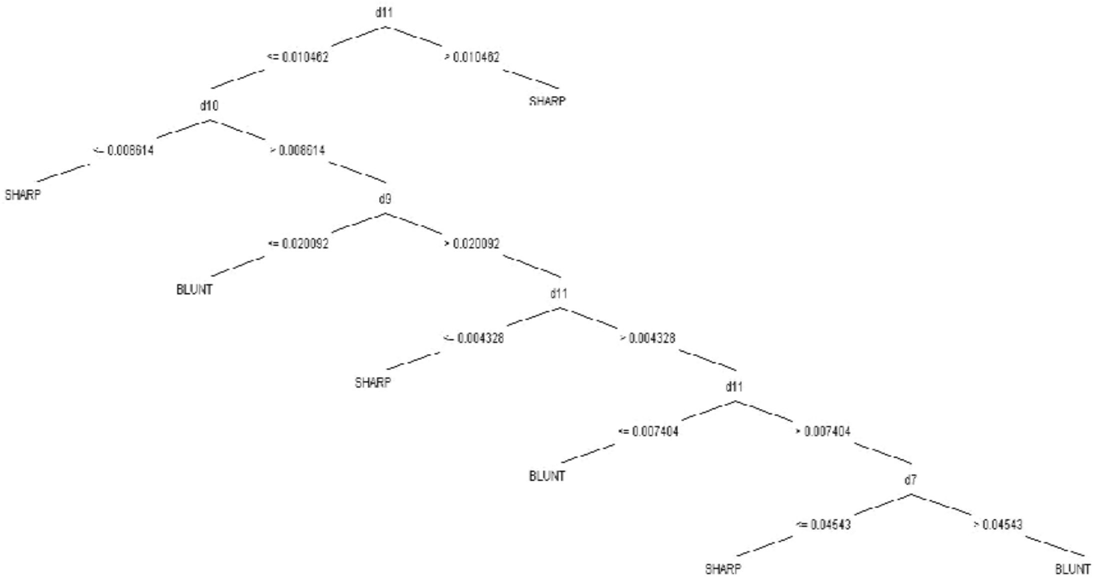

Fig.10 Sample trained decision tree with set of rules for different conditions

As shown in Table -3, Decision tree C4.5 is a good classifier for grinding wheel wear diagnosis. It has high diagnosis accuracy of 99.15% for high material removal condition, about 0.5 percentage points less than medium material removal condition and more than 2% than the low material removal rate . Even though while comparing the classification timings medium material is shows the best.

VIII. CONCLUSIONS

In this proposed study one of the uncomplicated data mining technology decision tree C4.5 is proposed along with wavelet based grinding wheel wear online monitoring field and verified by means classification accuracy of the algorithm by training and testing of sample data taken from the real time experiment. It is proved by the experiment that C4.5 is a good classifier and it can diagnose grinding wheel wear accurately. Acoustic emission signals collected from the experiment processed by filtering and useful information concerning wheel wear was extracted. The root mean square value and standard deviation of each wavelet decomposition signals were extracted to form statistical features. After that statistical features was given as input into the classification algorithm for training and testing . The experimental results show that classification accuracy could reach up to 96.70% with a depth of cut 10 μm, 98.95% with a depth of cut 20 μm and 99.15% at the cut depth of 30 μm. For multiple grinding conditions accuracy was 95.25%. This indicates that the proposed monitoring method has a good performance for grinding wheel wear prediction.

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