Acoustic Emission based Tool Condition Monitoring System in Drilling

Karali Patra, *Member, IAENG*

Abstract—**This paper describes the development of a tool wear monitoring system using AE signals acquired during drilling on mild steel work-piece. The acquired AE signals were filtered through digital band pass filter to avoid the affects of low frequency vibration. The filtered AE signals were analyzed in time-domain and time-frequency domain to extract features which are sensitive to drill wear. Root means square (RMS) value which is also a representative parameter for total AE energy of the signal has shown increasing trend with increasing drill wear. In time-frequency domain, wavelet packet transform has been applied to the AE signals, and RMS values of the wavelet coefficients in selected frequency bands are considered as the monitoring features which also show similar increasing trends. The relationships among the features and wear values are found to be non-linear. Artificial neural networks (ANN) are efficient tools to map such non-linear relationships if effectively trained through experimental data. An ANN model trained through back propagation learning algorithm has been developed here to correlate the extracted features to tool wear at different cutting conditions. Experimental results show that drill wear prediction of ANN model based on wavelet packet features is more accurate compared to that based on time domain features.**

Index Terms— **Drilling, tool wear, acoustic emission, artificial neural network, wavelet packet**

I. INTRODUCTION

It is important to develop a tool condition monitoring (TCM) system to increase productivity and promoting automation in metal cutting process. Many attempts have been made in the past to develop such systems using signals from various sensors such as dynamometer, current, accelerometer, acoustic emission (AE), speed, etc. But the successes of different sensor based systems are limited due to the complexity of tool wear process. The research is still ongoing for improved TCM system with applications of advance signal processing techniques and artificial intelligent models. Among various sensing methods, AE is one of the effective means for sensing tool wear. Acoustic emission (AE) in metal cutting is a transient elastic wave generated by dislocation in the primary shear zone and sliding friction in the secondary shear zone. As the cutting tool wears, additional friction between the tool flank and the work-piece also creates AE [1]. Iwata & Moriwaki [2] were the first to use an AE signal to monitor tool wear condition. Power spectrum of AE signal up to 350 kHz increases with the increase of tool wear and then becomes stable. The total count of AE events, i.e., the number of occurrences of AE, was found to be closely related to the tool wear. Since then many attempts were made to establish AE-based tool wear or fracture monitoring systems [3-4], which were mainly confined to turning process. Application of AE-based methods for tool condition monitoring of turning tools are reviewed in [5].

Only few attempts have been made to apply AE-based methods for TCM of drilling process. Braun et al. [6] proposed a point process for extracting drill wear sensitive features from the acoustic signals in the frequency range of 0-25 kHz. Konig et al. [7] discussed the advantages of using AE in monitoring drill wear, especially that of small drills. The acquired signal was analyzed in the frequency range of 1-5 kHz. Quandro & Branco [8] performed drilling tests with HSS drills with and without TiN coating, and monitored the AE signal in the range of 100-1000 kHz. Velayudham et al. [9] applied wavelet packet transform to determine tool wear monitoring indices from the acoustic emission signals in drilling of composite materials. Gomez et al [10] correlated AE mean power to the torque obtained during drilling and related this feature to different degree of drill wear. The main objective of the present work is to develop an effective tool wear monitoring system based on artificial neural network (ANN) using AE signals acquired during drilling experiments on mild steel work-piece by high speed steel drill bits.

II. EXPERIMENTAL PROCEDURE

Drilling experiments have been performed at different ranges of cutting speed, feed-rate and drill diameter as shown in Table 1. The schematic diagram of the experimental set-up for the drill wear monitoring system is shown in Fig. 1. The drilling was performed using column type drilling machine (HMT make). During each drilling operation, AE signal was acquired through an AE sensor (Dunegan Engineering Company Inc. Make, SE900-MWB) which was fitted to the work-piece in the vertical direction. The analog sensor outputs were converted to digital signals by an A/D board (Measurement Computing make, PCI–DAS 4020/12) fitted to an IBM PC. An inverted metallurgical microscope (RADICAL make, model RMM77B) has been used to measure the drill flank wear each time a drilling experiment was performed.

Manuscript received December 16, 2010; revised March 5, 2011.

Dr. K. Patra is an Assistant Professor in the Department of Mechanical Engineering, Indian Institute of Technology Patna, Patna-800013, India (phone: +91-612-2552012; fax: +91-612-2277384; e-mail: kpatra@iitp.ac.in).

ISBN: 978-988-19251-5-2
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

TABLE 1
EXPERIMENTAL CUTTING CONDITIONS

Cutting tool	Drilling parameters	Work-piece
Two-fluted twist drill Diameter: 8, 10 and 12 mm Tool material: High speed steel (HSS)	Spindle speed: 630, 900 and 1250 rpm Feed rate: 0.1, 0.16 and 0.25 mm/rev Dry cutting	Material: Mild steel

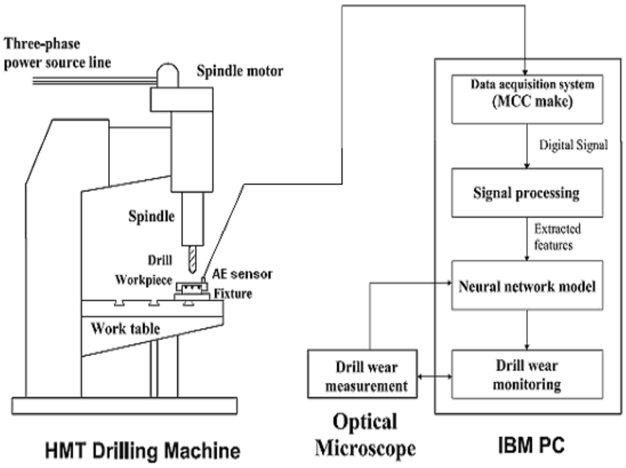

Fig. 1. Schematic view of the experimental set-up

III. SIGNAL ANALYSIS AND FEATURE EXTRACTION

It has been observed from literature that Acoustic emission (AE), which is a transient signal, is mostly analyzed in the frequency range of 100-1000 kHz. Therefore, AE analysis requires high sampling rate, noise filtering, huge data storage and memory retrieval, and speed of processing and analysis. There is also example of the AE sensor signal analysis in the low frequency (1-5 kHz) range [7]. The present work tries to extract wear sensitive features from the analysis of AE sensor signals at low frequency range to avoid huge data storage and retrieval memory requirements for high frequency analysis. The acquired AE signals were filtered through Chebyshev-1 band pass (500 Hz - 50 kHz) digital filter. Time-domain representation of the filtered AE signal for a particular case is shown in Fig. 2, and the FFT plot of the corresponding signal is shown in Fig. 3. Most of the AE signal energy is concentrated in 1 kHz to 5 kHz frequency range, as shown in the FFT plot. The time-domain representation and the FFT plot of the vibration signal acquired during the same drilling experiment are shown in Fig. 4 and Fig. 5, respectively. It is seen that the vibration signal is mainly concentrated to frequency range lower than 500 Hz. So the lower limit of the Chebyshev-1 band pass has been taken as 500 Hz to avoid the affect of low frequency vibration in the acquired AE signal. The upper limit is set at half of the sampling rate, i.e., 50 kHz.

A. Time-domain feature

RMS value of the AE signal (AE_{rms}) under each cutting condition is determined. The variation of RMS value with average flank wear under a particular cutting condition is shown in Fig. 6. It (AE_{rms}) shows an overall increasing trend with the average flank wear. Hence, this feature has been selected as one of the input parameters in drill wear monitoring system.

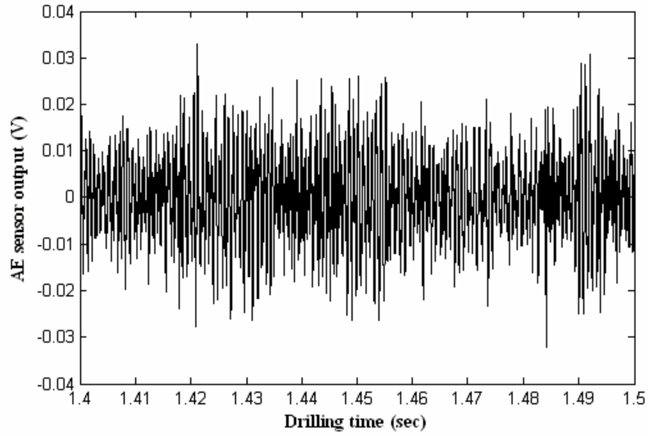

Fig. 2. Time-domain representation of AE signal

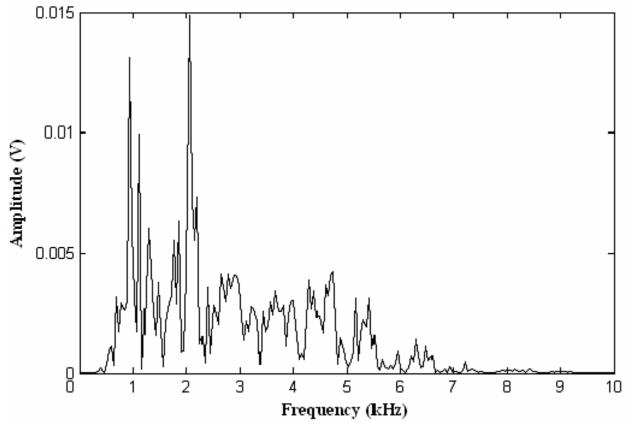

Fig. 3. FFT plot of AE signal

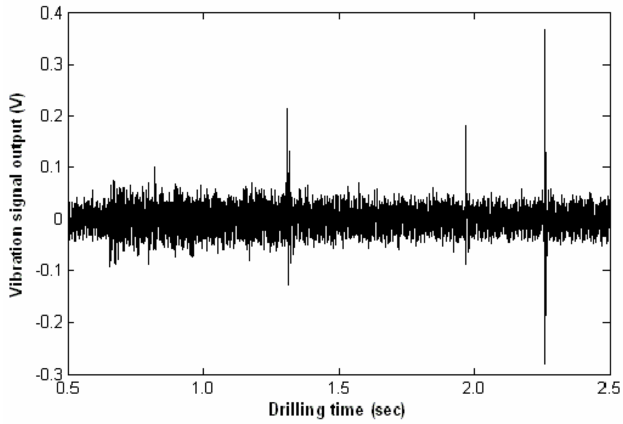

Fig. 4. Time-domain representation of vibration signal

ISBN: 978-988-19251-5-2
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

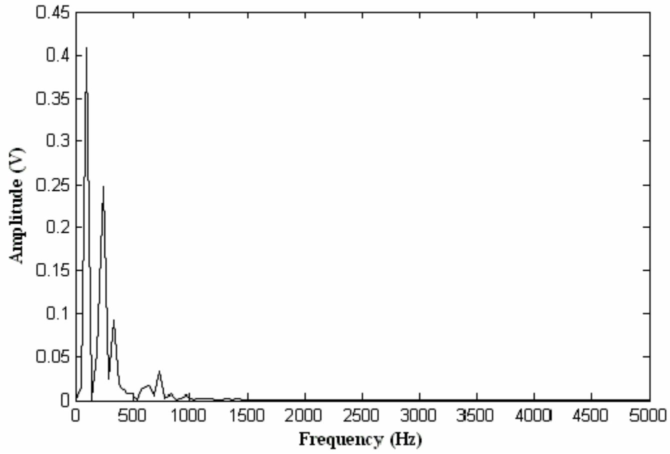

Fig. 5. FFT plot of vibration signal

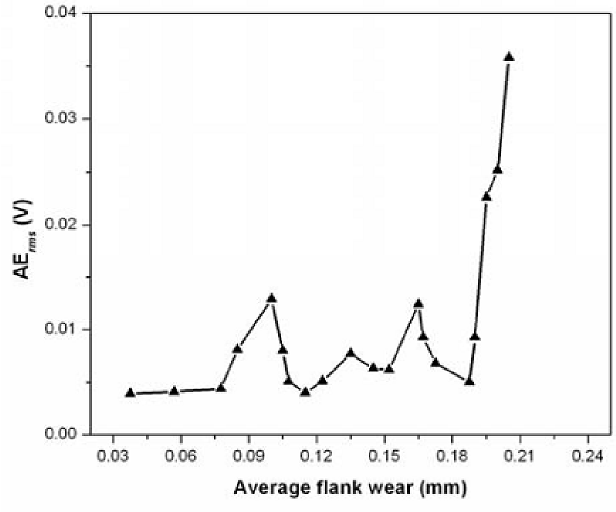

Fig. 6. Variation of RMS value of AE with average flank wear

B. Wavelet packet features

The filtered AE signal from each drilling experiment was decomposed into optimum number of wavelet packets. The extracted feature from each optimum packet shows an overall increasing trend of similar nature with average flank wear as shown in Fig. 7. These features, listed below, are the RMS values of the wavelet coefficients in each of the optimum packets.

- AWC_{10} is the feature of packet (1,0), i.e. frequency band (0-25 kHz)
- AWC_{20} is the feature of packet (2,0), i.e. frequency band (0-12.5 kHz)
- AWC_{30} is the feature of packet (3,0), i.e. frequency band (0-6.25 kHz)
- AWC_{31} is the feature of packet (3,1), i.e. frequency band (6.25- 12.5 kHz)

From the FFT plot of the AE signal, shown in Fig. 3, it is observed that the AE signal is mostly concentrated in packet (3,0) and in packet (3,1). Hence, AWC_{30} and AWC_{31} are selected from these four features.

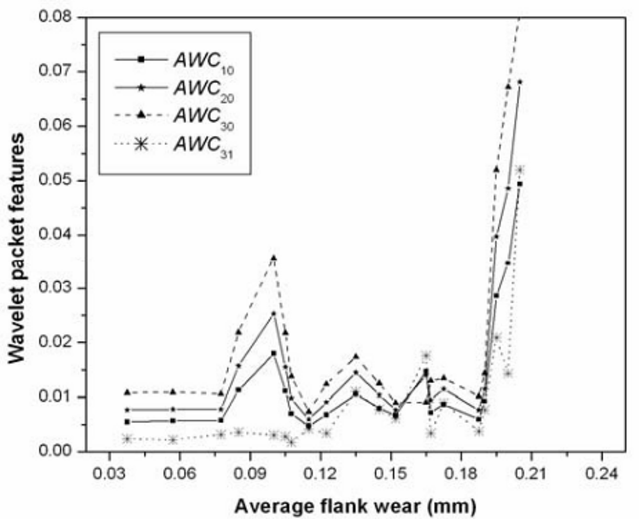

Fig. 7. Wavelet packet features vs. average flank wear

IV. ANN MODEL FOR DRILL WEAR MONITORING

Due to the complexity of the drill wear mechanism, it is very difficult to achieve online monitoring of wear based on analytical wear model. The present trend in tool wear monitoring is in the direction of applying artificial neural network (ANN) techniques which can very efficiently map the nonlinear relationship between different sensor signals and the tool wear. Artificial neural network is a collection of simple, interconnected nodes, which operate in parallel and store the knowledge through connecting weights between the adjacent layers of nodes. Artificial neural network models have become very popular in industry because of their classification and prediction capabilities [11]. Neural network may be seen as an attempt to automate the process of building a monitoring system. In principle, neural network can be trained to model the non-linear dependencies of manufacturing process parameters with tool wear and failure.

The ANN model applied here is the most widely tested multilayer feed forward network with back propagation learning. This model is trained and tested with datasets produced during the drilling experiments as described in section 2. Two data sets, dataset#1 and dataset#2, have been prepared from time-domain feature and wavelet packet features, respectively, from 75 numbers of drilling experiments under different cutting conditions as shown in Table 1. Four input parameters and one output parameter form a pattern in dataset#1, whereas five input parameters and one output parameter form a pattern in dataset#2; and there are 75 such patterns in both data sets. Four input parameters for dataset#1 are drill diameter (D), cutting speed (V), feed-rate (f) and RMS value of AE (AE_{rms}). For dataset#2, first three input parameters, i.e., D , V and f are same to those of the dataset#1 and other two input parameters are the extracted wavelet packet features (AWC_{30} and AWC_{31}). For both datasets, the values of the output parameter, i.e., the average flank wear, are same. Topologies of neural networks for both datasets are shown in Fig. 8 and Fig. 9, respectively. All the input and output

ISBN: 978-988-19251-5-2
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

parameters in both datasets are normalized in the range of 0.1 to 0.9. The normalization is done using the following equation.

$$x_{norm} = 0.1 + 0.8\left(\frac{x - x_{\min}}{x_{\max} - x_{\min}}\right) \qquad (1)$$

where, $x_{\max}$ is the maximum value of any parameter in the dataset under consideration, $x_{\min}$ is the minimum value of the parameter, x is the actual value of the parameter for any pattern, and x_{norm} is the corresponding normalized value. For both datasets, the first 65 data patterns have been used for training the networks, while the remaining 10 patterns have been used for testing these trained networks.

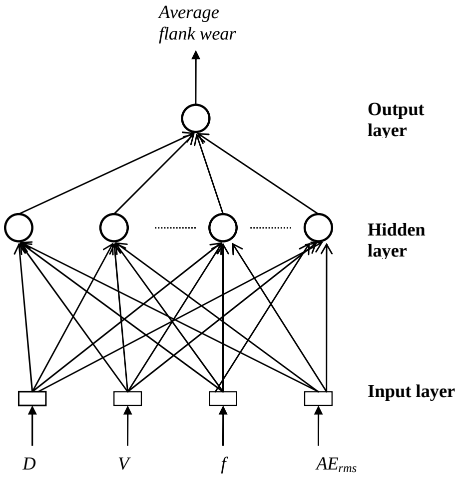

Fig. 8. Topology of neural network for dataset#1 (time-domain approach)

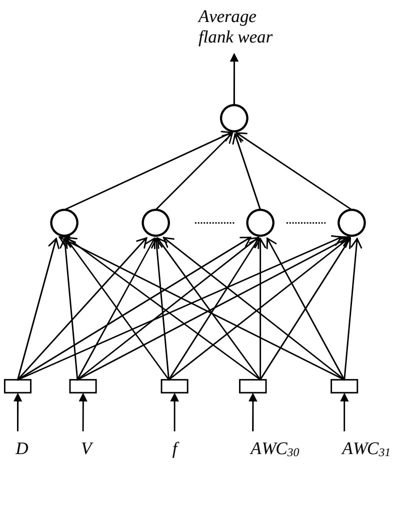

Fig. 9. Topology of neural network for dataset#2 (wavelet packet approach)

V. RESULTS AND DISCUSSION

ANN models are evaluated for different numbers of hidden nodes, as well as at different learning rates (LR), to arrive at the best possible performance of the same in terms of mean prediction error. The best ANN architecture using dataset#1, i.e., patterns containing time-domain feature and process parameters is found to be 4-5-1. The best architecture for wavelet packet approach (dataset#2) is found to be 5-15-1. The comparison of the wear prediction performances of these two approaches are shown in Table 2. The mean error of wear prediction by the wavelet packet approach is 9.41%, whereas the same by time-domain approach is 15.32%.

TABLE 2
COMPARISON OF TOOL WEAR PREDICTION PERFORMANCES

Dataset	Best ANN architect-ture	Learning rate (LR)	Iterations	Mean square error in training	Predicted error (%)
Dataset#1	4-5-1	0.3	200000	0.01221	15.32
Dataset#2	5-15-1	0.4	250000	0.01044	9.41

The prediction performances of both approaches for each of the 10 testing cases are plotted against the experimentally measured values of flank wear as shown by Fig. 10 and Fig. 11, respectively.

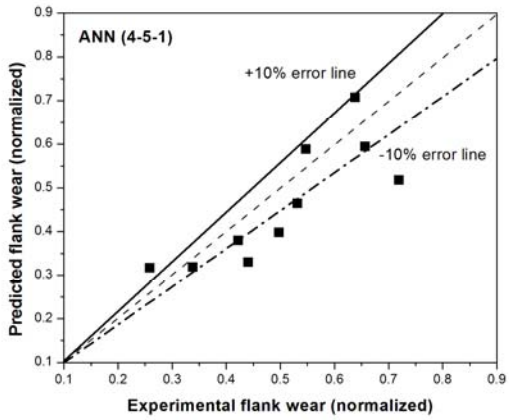

Fig. 10. Predicted vs experimental flank wear for dataset#1 (time-domain approach)

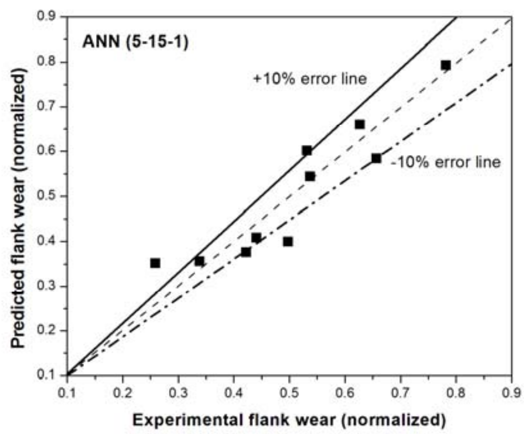

Fig. 11. Predicted vs experimental flank wear for dataset#2 (wavelet packet approach)

From the above figures, it has been seen that maximum numbers of testing patterns from wavelet packet approach (dataset#2) are predicted within 10% error line, as compared to the same from time-domain approach (dataset#1). This may be due to the fact that compared to the time-domain features, the wavelet packet features are less sensitive to cutting condition and external noises [12].

VI. CONCLUSION

The experimental results presented in this paper clearly re-affirmed the applicability of AE sensor as an effective means for drill wear monitoring. The results have also justified the need of using one of the most advance methods in signal processing technique, i.e. wavelet packet transform for feature extraction from the acoustic emission signal. Considering the complexity of the drill wear process, the performance of the proposed ANN model based on the extracted features through the wavelet packet is reasonably good. Hence, it has been concluded that ANN model based on wavelet packet features from the AE sensor can be applied as drill wear monitoring system for automated drilling process.

ACKNOWLEDGMENT

The experimental works for this paper were conducted at Mechanical workshop of Mechanical Engineering department, Indian Institute of Technology (IIT) Kharagpur during PhD study by the author. The author is grateful to his supervisors, Dr. Surjya K. Pal and Dr. K. Bhattacharyya for their supports. The author also acknowledges the support of the technical staffs of IIT Kharagpur during the drilling experiments.

REFERENCES

[1] S. Y. Liang and D. A. Dornfeld, “Tool wear detection using time series analysis of acoustic emission,” Journal of Engineering for Industry, Transactions of the ASME, Vol. 111, pp. 199-205, 1989.
[2] K. Iwata and T. Moriwaki, “An application of acoustic emission measurement to in-process sensing of tool wear,” Annals of CIRP, Vol. 25, No.1, pp. 21-26, 1977.
[3] R. Teti and D. Dornfeld, “Modeling and experimental analysis of acoustic emission from metal cutting,” Journal of Engineering for Industry, Transactions of the ASME, Vol. 111, pp. 229-237, 1989.
[4] X. Li and Y. Zhejun, “Tool wear monitoring with wavelet packet transform – fuzzy clustering method,” Wear, Vol. 219, pp. 145-154, 1998.
[5] X. Li, “A brief review: acoustic emission method for tool wear monitoring during turning,” International Journal of Machine Tools & Manufacture, Vol. 42, pp. 157-165, 2002.
[6] S. Braun, E. Lenz and C. L. Wu, “Signature analysis applied to drilling,” Journal of Mechanical Design Transactions of the ASME, Vol. 104, pp. 268-276, 1982.
[7] Kutzner K Konig, and U. Schehl, “Tool monitoring of small drills with acoustic emission,” International Journal of Machine Tools & Manufacture, Vol. 32, No. 4, pp. 487-493, 1992.
[8] A. L. Quadro and J. R. T. Branco, “Analysis of the acoustic emission during drilling test,” Surface and Coating Technology, Vol. 94-95, pp. 691-695, 1997.
[9] A. Velayudham, R. Krishnamurthy, and T. Soundarapandian, “Acoustic emission based drill condition monitoring during drilling of glass/phenolic polymeric composite using wavelet packet transform,” Materials Science and Engineering: A, Vol. 412, pp. 141–145, 2005.
[10] M. P. Gómez, A. M. Hey, J. E. Ruzzante, and E. D´Attellis C. E. Carlos, “Tool wear evaluation in drilling by acoustic emission,” Physics Procedia, Vol. 3, pp. 819–825, 2010.
[11] D. E. Dimla, P. M. Lister and N. J. Leighton, “Neural network solutions to the tool condition monitoring problem in metal cutting- a critical review of methods,” International Journal of Machine Tools & Manufacture, Vol. 37, No. 9, pp. 1219-1241, 1997.
[12] Y. Wu and R. Du, “Feature extraction and assessment using wavelet packets for monitoring of machining processes,” Mechanical Systems and Signal Processing, Vol. 10, No. 1, pp. 29-53, 1996.