Application of Neural Network Based Sensor Fusion in Drill Monitoring

Gy. Hermann

Budapest Polytechnic

John Neumann Faculty of Informatics

Abstract: The detection of tool failure is crucial point in intelligent manufacturing. The lifetime of large cutting tools can be forecasted but the failure of small sized tools is nearly unpredictable. A number of signatures accompanying excess wear or emerging failure are investigated. The application of sensor fusion by means of neural networks to the monitoring of small drills is described and the experimental results are discussed.

Keywords: Tool monitoring, acoustic emission, tool vibration, sensor fusion, neural networks

1. Introduction

Various methods for tool wear sensing have been proposed and evaluated in the past but none of them proved to be universally successful due to the complex nature of the cutting processes. The applied indirect methods suffer from the fact that not only the wear but other process parameters also influence the measurement results. These are the workpiece and tool materials, the geometry of the cutting tool and the technological parameters: cutting speed, feed and depth of cutting.

Since approximately 40% of the machining operations are drilling operations, the monitoring of the drill condition is an important task. This is especially true for twist drills that are mostly used in producing holes in the 1-20mm diameter range. The economic importance of the task is emphasised by the large scatter of the tool life of small twist drills.

2. Monitoring of the drilling process

Tool wear and tool breakage are two important aspects of the metalcutting process that are not well understood. Tool wear has a strong effect on both the dimensional accuracy and the surface finish of the workpiece. Wear can reach values that lead to catastrophic failure of the tool, resulting in high forces which in turn may damage the workpiece or even the machine tool. This fact stresses the importance of tool monitoring.

Tool failure is a sudden event, that needs to be predicted in due course in order to prevent any major damage resulting in economic losses. In drilling, the wear pattern changes along the cutting edge, due to the differences in the drill bit geometry and due to the differences of the cutting conditions along the cutting edge. Brinksmeier[3] has classified drill wear into seven types: the outher corner wear, the flank wear, land wear, crater wear, two types of chisel edge wear and chipping on the cutting edges. Out of the various wear patterns the outer corner wear is considered as the most appropriate performance index of drill life [2].

It is evident that the wear characteristics cannot be measured directly in the process. Therefore, only indirect measuring methods can be applied. Increasing wear at the outher corner or margins excite torsional vibration in the worn drill, causing a periodic change in the length of the tool due to its spiral form, resulting in chip thickness variation. The cutting speed at the outher corners of the vibrating drill is several times higher than in a stable process. The wear-induced vibration can be detected using acoustic emission sensors.

3. AE signal in the cutting process

The term acoustic emission (AE) refers to the elastic stress wave generated as a rapid release of strain energy within a solid material in association with the deformation and fracture generated during metalworking processes. It was rediscovered by manufacturing engineers as a very promising signature to detect an emerging tool failure. The distinct sources of acoustic emission can be identified in metal cutting as:

(1) plastic deformation and shear of work material

(2) deformation and sliding friction at the chip-tool surface

(3) sliding friction at the tool flank-workpiece interface and

(4) chip breaking and their impact on the cutting tool or workpiece

(5) normal and abnormal wear of the tool

(6) mechanical and thermal crack of the tool

There are two types of acoustic emissions: the high amplitude, somewhat erretic, low frequency type called the burst emission which is generally associated with surface events, such as slip line formation and surface microcracks and the lower amplitude, steady and high frequency type called continuous emission that is generally associated with internal mechanism activity.

In recent years many researchers have investigated AE signals from metal cutting processes and their feasibility for in-process monitoring of tool conditions. The majority of the publications deal with the monitoring and supervision of turning and milling. One important goal of studying the AE from metal-cutting processes has been understanding the toolwear related AE variations and evaluating their capability for in-process monitoring of the tool condition. Two possibilities have been identified. One is the increase of the level AE energy (the RMS value of the signal) with increase of the flank wear. The otherone is the increase of the density and event counts (the number of events) exceeding a certain threshold.

Iwata and Morikawi[17] observed that the RMS voltage of the AE signal increased significantly as the carbide tool wore during the machining of carbon steel workpiece. They reported that flank wear has a more significant effect on the average RMS value than the change of cutting speed. Later it was found that cutting speed has a major influence in increasing the average RMS level and that the magnitude of the average AE signal increases abruptly as the tool wear penetrates through the coating of coated tools.

The relationship between the mean value of the AE signal and the flank was also studied by Kannetey-Asibu and Dornfeld[13]. They observed that the AE level change decreases or stops when the flank wear reaches some intermediate value. This phenomenon was attributed to the rapidly developing crater wear. Therefore they suggested the skew of the statistical distribution of the RMS value as a better indicator of the tool wear. Another interesting observation of this group was that the frequency spectrum contains dominant frequencies at 80 and 150 kHz and that the power spectrum amplitude at these frequencies increases with the tool wear.

Inasaki and Yonetsu[9] have found that the AE amplitude is independent of the depth of cut and the feed per revolution but increases continuously with the increasing cutting speed. For constant cutting speed, AE increases approximately linearly with the flank wear over the whole range of the cutting speed. The authors reported that the flank wear estimated using the AE signal and the optically measured values showed very good agreement, with less than 15% deviation.

König, Ketteler and Klumpen[14] studied acoustic emission for turning, drilling and milling as function of tool wear. They observed an increased AE activity over the whole spectrum as the tool wore and a typical steep increase was found at the end of the tool life.

Tool wear has also a significant effect on the density of pulse events in the AE signal. Iwata and Moriwaki[10] observed that the pulse count per cut increases with increasing flank wear up to about 120um and remained constant above that, but the data showed a significant degree of scatter. Inasaki and Yonetsu[9] found sudden increase in the even count rate after a tool developed extensive flank wear and at the same time an increase in the standard deviation of the count rate at this point. This phenomenon was attributed to the development of microcracks in the tool. Although the pulse event count seems to be well correlated to flank wear, many problems inhibit the usage of this relationship in process monitoring. The major problem is that a system based on this principle has to be calibrated for each specific machining condition and the selection of the threshold level for the pulse event count is somewhat arbitrary.

Tool fracture results in a sudden increase of the AE amplitude as it was already observed by Inasaki and Yonetsu[9]. Analysis of the data from cutting experiments using various speeds, feeds and depth of cuts also showed that the ratio of the AE amplitude before and after the breakage exceeds 1.8. Using this ratio they were able to detect edge chipping with fracture are of about 0.1mm^2. In case of significantly worned tool this shift decreases. However by filtering out the frequencies below 300kHz the effect of wear can be reduced and even the detection of microcracks was reported.

4. Signal processing and sensor fusion techniques

Automatic monitoring of the manufacturing processes relies on signal processing. Fast Fourier Transform (FFT) and spectral analysis are the most commonly applied frequency domain signal processing techniques in engineering. However FFT has many weaknesses. The first one is that the frequency resolution of the entire frequency spectrum depends on the sampling frequency and the number of data points. The second weakness is representation of the entire spectrum, with the addition of harmonic signals, by assuming that the data window is repeated indefinitely. A third weakness is the existence of considerable noise in the transformation due to the large degree of freedom of the system. Therefore FFT analysis has to be repeated many times and their result must be averaged in order to get a smooth output.

The time series methods have been proposed to overcome the shortcomings of the FFT and to have a forecasting capability. This approach estimates a difference equation that represents the stochastic characteristics of the signal. The dominant frequencies can be computed from the estimated model without having any dependence between the resolution and the number of datapoints. Mainly the order of the difference equation is less than half of data set's size. The main disadvantage is that time series techniques can not identify transition points in the signal within the data window. In order to estimate transition in a given system a forecast over one or several steps can be made and the accuracy of the estimation evaluated. A considerable change of the estimation accuracy indicates transition in the system.

Obvious solution for fusion of sensory signals is the artificial neural network. It consists of a number of identical processing units usually structured in two to four layers. The fundamental processing element is the perceptron, which calculates the weighted sum of its input, and passes the result through a non-linear threshold function. The threshold function can be a simple signum function, a hyperbolic tangent or the sigmoid. The non-linear behaviour of the threshold function allows a neural network to extend the reach of pattern classification capabilities into the domain of generalised non-linear functions.

The neural network structure used in our investigations was a multilayer feed-forward neural network that uses the backpropagation learning algorithm. The input layer has one node for each feature extracted from the raw signature. The output layer, where the classification emerges, consists of one or more perceptrons. The actual number of output nodes depends on the number of possible classes in the data set as well as on the way the different classes are coded. For instance one output node is needed for a twoclass problem if output value +1 corresponds to the first class and output value -1 to the second class. In problems that involve a larger number of classes one output node will be assigned to each class or a binary coding will be applied. Layers between the input and output layers are called hidden layers. Between the various nodes there are weighted connections through which the processing unit communicate with each other.

The neural network described above represents a complex non-linear function. The learning algorithm adjusts the parameters of the non-linear function, by modifying the weights of the connections, until the classification error is minimised. There are two important situations in which a neural network is particularly useful. The first case is when non-linear decision function is needed to separate two classes of data from each other. The second case is when the data neglects the normality conditions.

The earliest effort for integrating information from several sensors to monitor machining performances is the work by Matsushima and Sata[16]. Their objective was to automatically recognise the cutting state and detect tool failure. A linear discriminant function was used to integrate the cutting parameters, speed and feed rate, with features from the power spectrum of the cutting force. Dornfeld and Pan[5] applied linear discriminant functions to integrate event rate from an AE sensor with the machining parameters to detect chip formation during turning. Balakrishnan[1] used a discriminant function technique to combine cutting force and acoustic emission for tool monitoring. The majority of these approaches suffer from the time consuming training procedure and the high sensitivity to process conditions.

Application of neural network in monitoring metalcutting processes was first proposed by Rangwala and Dornfeld[]. They used a back-propagation network to classify sharp and worn tools in turning. The state of the tool was divided into two classes: sharp with wear land less than 0.25 mm and worn where the wear was between 0.5 and 0.75 mm. They sampled the force and the AE signals simultaneously at a rate of 1kHz and 5MHz respectively. The power spectral density of the signal was found by calculating the square of the absolute of FFT of the sensory signals. The network was used as learning and pattern recognition device, and was able to successfully associate sensor signal pattern with the appropriate decision on tool wear. The neural network was able to filter out noise in the sensor data and this enhanced their ability for successful pattern association tasks over a wide range of machining conditions. Chryssolouris and Domroese[5] performed simulation in order to assess the learning capabilities of these networks as the decision-making component in a tool condition monitoring system. Choi[4] demonstrated the feasibility of a neural network in real-time tool wear monitoring. Noori-Khajavi and Komanduri[18] measured the torque and the thrust force in drilling and fused features extracted from these signals to classify the tool state.

Jammu[11] applied a single category-based classifier to detect tool failure in turning. They used the RMS value of ultrasonic energy, low frequency vibrations in X and Y directions, the X and Z feed motor currents and the coefficients of the ARX model for the velocities as input signals to the network. Various network structures (SCBC, ART2, Kohonen) have been compared from the point of their effectiveness.

5. Experimental setup and data collection

The experimental set-up for evaluating the proposed on-line tool monitoring system was built around a conventional milling machine. The acoustic emission and the vibration were captured respectively by an AKL 85 sensor (equivalent to of Bruel&Kjaer) and a KD 91 broadband sensor having 0.4 mV/m.s2 sensitivity and a resonance frequency around 50 kHz attached to the workpiece within 50 mm distance from the actual cutting zone. The signals were amplified by charge amplifiers (models and 2635). For measuring the feed force a Kistler dynamometer (type) was used and its signal was again amplified by a Kistler charge amplifier (type).

The acoustic emission signal was directly processed by a Krenz broadband spectrumanalyzer with 2MHz bandwidth and at the same time the RMS value was sampled by a data acquisition board on an IBM personal computer. Also the force and vibration signals were processed using the same data acquisition board, but with a much lower sampling rate.

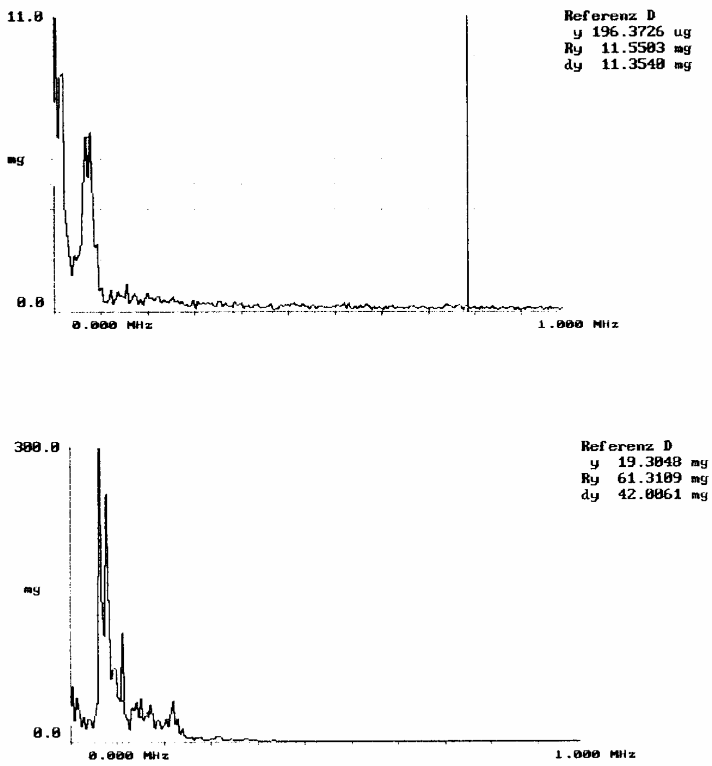

Fig.1. AE spectrum of sharp and worn 1.5mm diameter twist drill (material KO36 feed 25mm/min, 2500 rev/min)

The first series of experiments aimed at finding appropriate features for tool wear and failure detection. It was assumed that the torsional vibration described in paragraph result in dominant frequencies in both the AE and the low frequency spectrum. The experiments showed the correctness of our assumption. The power spectrum of the AE signal has a dominant frequency around 80 kHz and shows dramatic increase at the end of the tool life. One can also notice the appearance of a new peak at 100 kHz in the spectrum of the worn tool (Fig.1).

The experiments showed no significant influence of the cutting parameters and the workpiece material on the place of the dominant frequencies in the AE spectrum, only their amplitude was effected.

We also investigated the behaviour of the low frequency vibration signal as function of the tool wear. Here we have found a rather similar pattern signalling excessive tool wear and tool failure. As it can be seen in Fig. 2 there is a dominant frequency in the spectrum in the neighbourhood of 8 kHz. The amplitude of this peak shows close correlation with the condition of the tool. Moreover it was found that the frequency of this peak is independent of the machining parameters (revolution, feed) and the material of the workpiece.

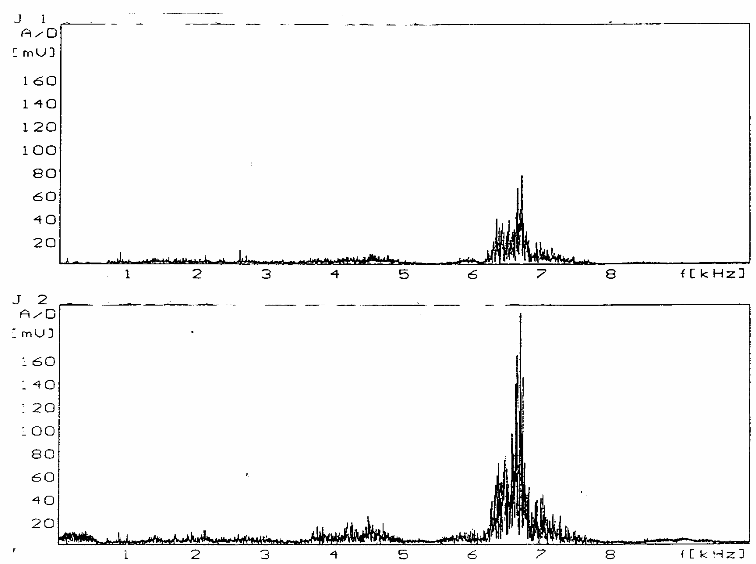

Fig.2. Vibration spectrum of a 1.5 mm twist drill
(material K036, feed 25mm, 2500 rev/min)

The third signal measured during the machining experiments was the feed force. In the subsequent figures the AE average value is given together with the value of the feedforce. One can notice the increase of the AE activity as the tool wears. This trend in the AE activity can be observed even after the toolbreak when the force falls back to a low value.

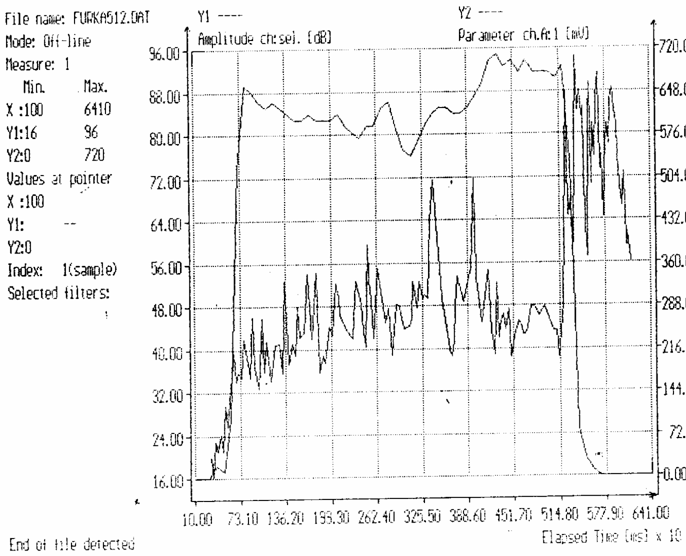

Fig. 3. AE activity and feedforce during tool failure

However at the end of a cut similar signature can be observed even under normal cutting conditions. This can lead to incorrect recognition of the tool conditions. To avoid recognition mistakes, information about the signal trend is incorporated in the decision process.

6. Signal processing

Through signal processing the envelope of the AE signal was derived by band pass filtering, full wave rectifying and averaging. The processed AE signal reflects tool breakage's, but also contain other events that can be mistaken for tool failure. If AE signal used by itself for tool breakage detection it would produce an unacceptable number of false alarms, depending on the threshold level. The number of false alarms can be reduced by increasing the threshold level, but the system may miss some of the tool breakages.

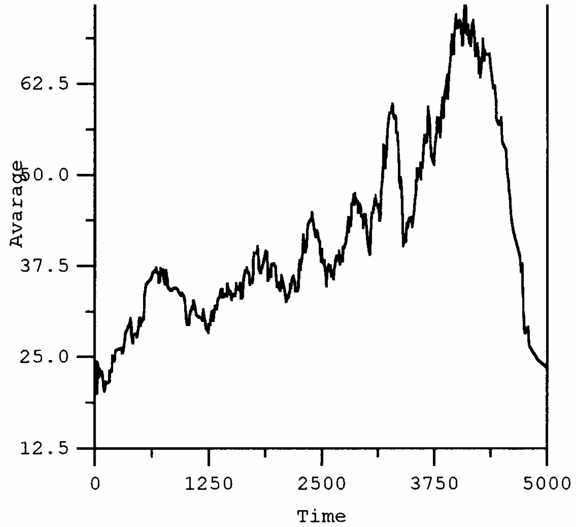

Fig.4. The processed AE signal in case of tool failure

The amplitude of lower frequency vibration is also sensitive to tool failure. The vibration signals in the 5-8 kHz range can also be effectively used for monitoring the tool condition. However this signal alone would also lead to some missrecognitions.

Feedforce is used already for a long time as a signature for detecting tool failure. The specific signal pattern associated with tool breakage can be recognised with simple means. However any changes in the cutting load due to different cutting variables, hard spots, chip entanglement etc. will manifest itself in the signal on a rather similar way. This type of noise may be significant when machining parts with complex geometry. In order to reduce the effect of this noise we have introduced a fourth order ARMA model and used its residuals as features for detecting tool failure.

7. Detection results

In our experiment for sensor fusion two types of networks has been used: multilayer feedforward network and the single category based classifier which is actually a weighted majority based decision-maker. The following tables summarise the correct recognition rates, that was achieved, by the two networks with various sensor fusion during the experiments.

Sensor Combination	Correct Recognition Rate
RMS AE + Force	94%
RMS AE + Vibration	72%
Vibration + Force	85%

Table 1. Correct recognition rate of the multilayer feedforward network

Sensor Combination	Correct Recognition Rate
RMS AE + Force	96%
RMS AE + Vibration	75%
Vibration + Force	89%

Table 2. Correct recognition rate of the single category based classifier

Number of Input Features	Correct Recognition Rate
2	94%
4	96%
6	96%
8	82%

Table 3. the influence of the number of input features on the correct recognition rate is given in case of a single category based classifier.

8. Conclusions

An on-line drill wear/failure monitoring system was developed and evaluated in this study. On the basis of this investigations the following conclusions can drawn:

- By applying a neural network in combination with an AR time series model a considerable improvement in the correct tool condition recognition rate can be achieved.
- The AE RMS + Force signal based tool wear detection system is insensitive to the changes of the cutting conditions and can operated over a wide range of cutting parameters.

- It was recognised that for tool wear detection a relatively small neural network works well.

Acknowledgement

I am grateful to professor Mátyás Horváth for his suggestions during the whole project and gratefully acknowledges the support by the Hungarian National Research Fund OTKA in the project T 034212.

References

[1] Balakrishnan, P., Trabelsi, H., Kannatey-Asibu, Jr.E. and Emmel, E.
A Sensor Fusion Approach to Cutting Tool Monitoring
Advances in Manufacturing Systems Integration and Processes
Proc. 15th NSF Conf. on Production Research and Technology, SME
University of California, Berkeley p. 101-108

[2] Braun, S., Lenz, E., Wu, C.L.
Signature Analysis Applied to Drilling
Transactions of the ASME, Journal of Mechanical Design 1981

[3] Brinksmeier, E.
Prediction of Tool Fracture in Drilling
Annals of the CIRP Vol. 39/1/90

[4] Choi, G.S., Wang, Z.X., Dornfeld, D.A. and Tsujino, K.
Development of an intelligent On-Line Tool Wear Monitoring System for Turning Operations
Proc. Japan-USA Symposion on Flexible Automation, ISCIE, Kyoto, Japan

[5] Chryssolouris, G., and Domrose, M.
Sensor Integration for Tool Wear Estimation in Machining
Proc. for Sensors and Control for Manufacturing, ASME 1988, p. 115-123

[6] Dornfeld, D.A. and Pan C.S.
Determination of Chip Forming States Using Linear Discriminant Function Technique with Acoustic Emission
Proc 13th. NAMRC, SME, p. 299-303

[7] Dornfeld, D.
Neural Network Sensor Fusion for Tool Condition Monitoring
Annals of the CIRP Vol. 39/1/90 p.101-103

[8] Inasaki, I., Aida, S., Fukuoka, S.
System for Cutting Tool Failure Using an Acoustic Emission Sensor
JSME International Journal, Vol. 30, No. 261, 1987 pp.523-528

[9] Inasaki, I. Yonetsu, S.
In-Process Detection of Cutting Tool Damage by Acoustic Emission
Proc. 22nd International Machine Tool Design and Research Conference
Manchester University UK(1981) p.261-268

[10] Iwata, K., Morikawi, T.
An Application of Acoustic Emission Measurement to In-Process Sensing of Tool Wear
Annals of the CIRP Vol. 25/1/1977 p. 21-26

[11] Jammu, V.B., Danai, K., Malkin,S.
Unsupervised Neural Network for Tool Breakage Detection in Turning
Annals of the CIRP Vol. 42/1/1993 p.67/70

[12] Kanai, M. Kanda, Y.
Statistical characteristics of drill wear and drill life for the standardised performance test
Annals of the CIRP, 27(1), 61-66(1978)

[13] Kannatey-Asibu, E., Dornfeld, D.A.
A Study of Tool Wear Using Statistical Analysis of Metal-Cutting Acoustic Emission
Wear 76(1983) pp.247-261

[14] König, W., Ketteler, G., Klumpen, T.
Process monitoring in turning, milling, drilling and grinding processes
Proceeding 8th International IMEKO Symposium on Technical Diagnostics, September 23-25, 1992 Dresden, FRG pp. 433-446

[15] Lan, M.S., Dornfeld, D.A.
In-Process Tool Fracture detection
Transactions of the ASME Journal of Engineering Materials and Technology
April 1984 pp.111-118

[16] Matsushima, Sata
Development of Intelligent Machine Tool
Journal Faculty of Engineering, Univ. of Tokyo
Vol 35. p.395-405

[17] Moriwaki, T.
Application of Acoustic Emission Measurement to Sensing of Wear and Breakage of Cutting Tool

Bull. Japan Soc. of Prec. Eng., Vol. 17, No. 3, 1983

[18] Noori-Khajavi,A., Komanduri,R.
On Multisensor Approach to Drill Wear Monitoring
Annals of the CIRP Vol. 42/1/1993 pp.71-74

[19] Rangwala,S. Dornfeld. D.A.
Integration of Sensors via Neural Networks for Detection of Tool Wear States
Intelligent and Integrated Manufacturing Analysis and Synthesis
ASME WAM, p. 1090-120

[20] Schehl, U.
Werkzeugüberwachung mit Acoustic-Emission beim Drehen, Fraesen und Bohren
Doctoral thesis RWTH Aachen 1991

[21] Souquet,P., Gsib,N., Deschamps,M., Roget,J., Tanguy,J.C.
Tool Monitoring with Acoustic Emission Industrial Results and Future Prospects
Annals of the CIRP Vol. 37/1/1988

[22] Tansel, I.N., McLaughlin, C.
On-Line Monitoring of Tool Breakage with Unsupervised Neural Networks
Trans. of NAMRC, SME pp-.364-370

[23] Tansel, I.N., Mekdeci, C., Rodriguez, O., Uragun, B.
Monitor Drill Conditions with Wavelet Based Encoding and Neural Networks
International Journal of Machine Tools and Manufacture
Vol. 33, No.4, p. 559-575

[24] Tönshoff,H., Wulfberg,J., Kals,H., König,W., Luttervelt,C.
Development and Trends in Monitoring and Control of Machining Processes
Annals of the CIRP, 1988 37/2 pp.611-621