Application of Artificial Intelligence Techniques in Monitoring Drilling Processes

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1 Introduction

Tool wear and tool breakage are two important aspects of the metal cutting 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.

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. There are two methods for online tool condition monitoring in machining processes. These methods have been classified into direct (optical, radioactive and electrical resistance, etc.) and indirect (acoustic emission, motor current, cutting force, vibration, etc.) sensing methods according to the sensors used. Recent investigations focus on the development of the methods which monitor the cutting process indirectly by measuring parameters such as tool vibration, force cutting, acoustic emission, motor current, etc.

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.

In order to improve the decision about the tools condition the majority of applications rely on various signal sources at the same time and merge them after filtering out unavoidable noises inherent to cutting and extracting the features carrying information about the . Obvious solutions for fusion of the sensory signals are the artificial neural networks and fuzzy rule-based systems.

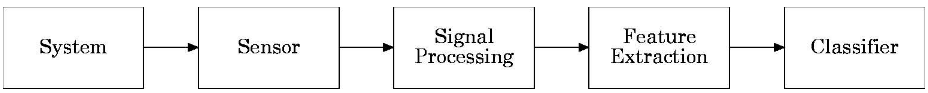

Fig. 1. The signal processing chain of a tool monitoring system

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An artificial neural network 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: 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.

Fuzzy logic is a convenient way to map an input space to an output space. The mapping provides a basis from which decisions can be made. The process of fuzzy inference involves membership functions, fuzzy logic operators, and if-then rules. A membership function is a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1. There are two types of fuzzy inference systems Mamdani-type and Sugeno-type.

2 Overview of the Various Signals Generated by Machining

Forces and Torque in Cutting Processes. Torque, drift and feed force with the strain measurement are all measures of cutting forces and are strongly depend on the tool wear. These dynamic parameters generally increase as the tool gradually wears due to the increasing friction between tool and workpiece.

Monitoring the torque and thrust force is the most common method to collect information about the amount of tool wear in drilling. Cutting forces are affected by experimental conditions such as cutting speed and feed, workpiece material and type of the tool.

AE Signal Associated with a Cutting Process. Machine tool operators have for a long time used their ears as a means of monitoring the cutting process. Skilled machine tool operators are able to judge the change of the tool condition especially the variation of tool wear and an emerging tool failure. They are also able to predict surface the finish simply by listening to the cutting process. The term acoustic emission refers to the release of strain energy in the form of elastic waves associated with the deformation in the frequency range of $20 - 2000$ kHz [1].

The various sources of acoustic emission in machining are listed below:

- plastic deformation and shear of work material
- deformation and sliding friction at the chip-tool surface
- sliding friction at the tool flank
- chip breaking and their impact on the cutting tool or workpiece
- normal and abnormal wear of the tool
- mechanical and thermal crack of the tool

In conventional machining, acoustic emission is largely due to rubbing and friction at shear zone. In the precision machining, however, it is believed that the majority of AE signal generation is generated through the interaction of the tool tip with microstructural features of the workpiece, such as voids, inclusions, grain boundaries, and bulk dislocation interactions in the shear zone [2,3,8].

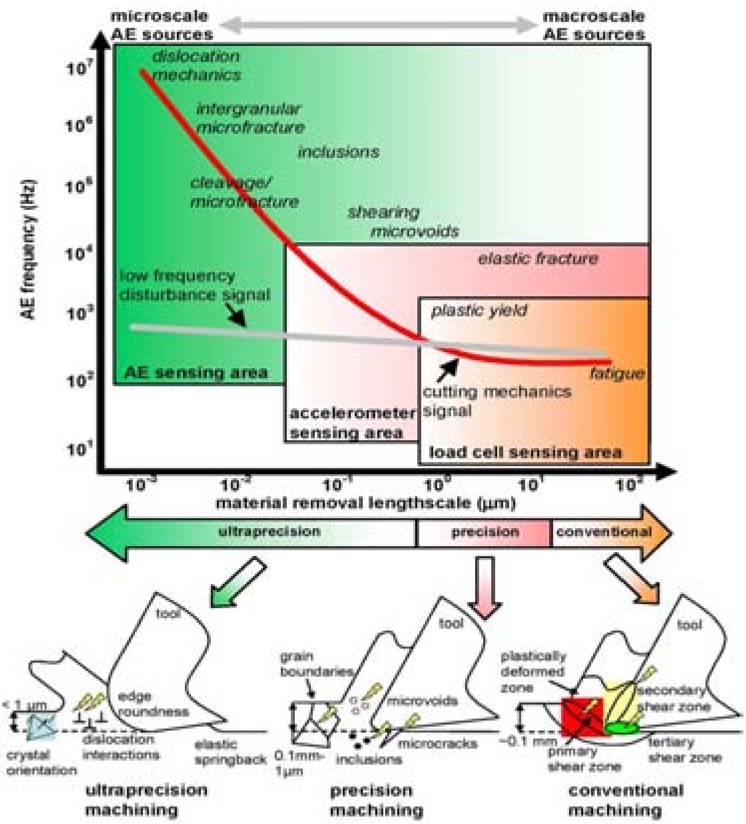

Fig. 2. AE sources at various stages of material removal

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 other one is the increase of the density and event counts (the number of events) exceeding a certain threshold.

Iwata and Morikawi [10] 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 [7]. 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 [5] 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.

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 120 μm and remained constant above that, but the data showed a significant degree of scatter. Inasaki and Yonetsu [5] 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 0.1 mm^2. In case of significantly worn tool this shift decreases. However, by filtering out the frequencies below 300 kHz the effect of wear can be reduced and even the detection of microcracks was reported.

In a recent paper R. Teti, K. Jemielniak, G. O'Donnell, D. Dornfeld [11] give an overview of the different approaches to tool condition monitoring. They also compare them from various points of view. Beside force base detection special attention is given to acoustic emission based systems and signal fusion techniques applied in current experimental setups.

Hase [4] describes the application acoustic emission monitoring of the tool condition in a high precision turning environment they have found that Sensing contact of cutting tool and workpiece would be possible with high precision of 0.1 μm using the AE technique, the amplitude of the AE signal increases as the spindle rotating speed and the cutting depth increase, adhesion of the workpiece material to the rake face of the cutting tool (the formation of built-up edge) can be identified by detecting a high frequency AE signals of more than 1 MHz. The same results were achived by S. Min, J. Lidde, N. Raue, D. Dornfeld [9].

Vibration Generated by Machining Processes. Vibrations in machining can be divided into two groups: dependant and independent of the manufacturing process itself. Independent vibration include forced vibration caused by machine components, e.g. unbalance of rotating parts, inertia forces of reciprocating parts and kinematic inaccuracies of drives. Vibration dependant on metal cutting can demonstrate a number of characteristics as a function of the process, e.g. interrupted cutting. The varying cutting forces that occur during metal cutting may result from non-homogeneity and properties variations in the work material. Tool engagement conditions during machining play a notable role in the vibration produced. The self excited vibration characteristic known as chatter is the most renowned type of vibration in machining and it leads to surface finish deterioration and decrease of tool life. Chatter occurs due to the waviness regeneration caused by material surface and tool interaction at particular spindle rotational frequencies, and by mode coupling where relative vibration between workpiece and tool.

3 Drill Condition Monitoring

3.1 Description of the Solution

Drill wear was classified 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.

Drilling operation represents approximately 40% of all machining operation. Therefore the role of monitoring tool condition became important, especially in case of small twisted drills with diameter in the $0.5 - 5$ mm range. Drill wear can be classified in outer corner wear, flank wear, land wear, crater wear, two types of chisel edge wear and chipping on the cutting edges. Corner wear is the best performance index of drill life. As wear cannot be measured directly in the process, indirect measuring methods have to be applied. For this purpose process

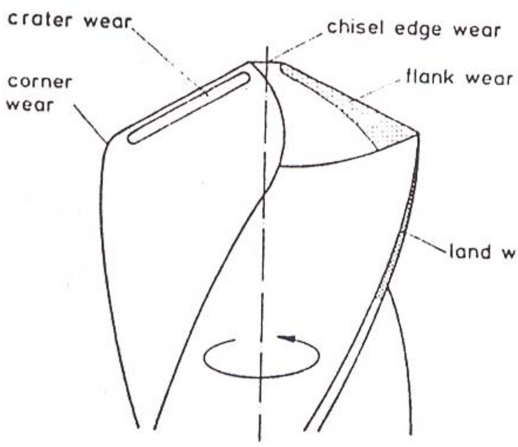

Fig. 3. Various types of wear on a twist drill

signatures like cutting and trust force, torsional vibration, acoustic emission, etc. can be used.

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.

For the fusion of sensory signals neural networks is the obvious solution. 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. In the output layer, the number of perceptrons is determined by the number of possible classes and their coding.

In our case for monitoring the drill condition the following features have been used:

- rms value of the power in the band 0 – 300 Hz
- rms value of the power in the band 300 – 600 Hz
- rms value of the power in the band 600 – 1000 Hz
- rms of the power in the band 1000 – 1500 Hz
- rms of the power in the band 1000 – 1500 Hz
- rms of the power in the band 1500 – 2000 Hz

3.2 Experimental Setup

The experimental drill monitoring system was set up on a manually operated conventional milling machine.

For capturing the acoustic emission and the vibration signals an AKL 85 and a KD 91 broadband sensor were attached to the workpiece close (50 mm) to the

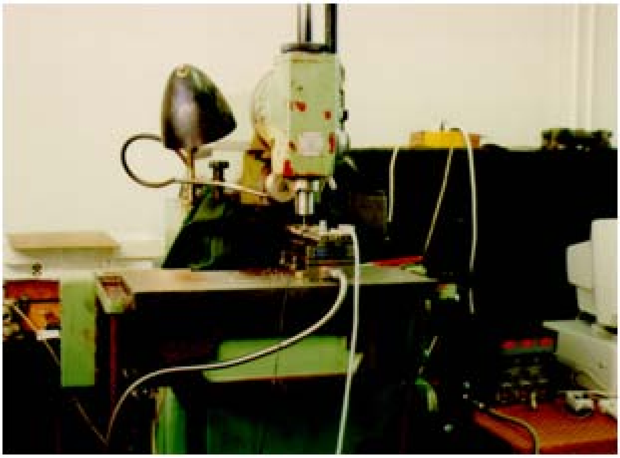

Fig. 4. Experimental setup of the drilling process

actual cutting zone. The feed force was measured by a Kistler dynamometer. The signals were amplified by charge amplifiers.

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

3.3 Experimental Results

The aim of experiments was finding suitable features for tool wear and failure detection. As the experiments proved, the torsional vibration resulted in dominant frequencies in both the AE and the low frequency vibration spectrum. 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.

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.

The behaviour of the low frequency vibration signal as function of the tool wear was also investigated. A rather similar pattern signalling excessive tool wear and tool failure was found. As it can be seen in Fig.7 there is a dominant frequency in the spectrum in the neighbourhood of 6.5 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.

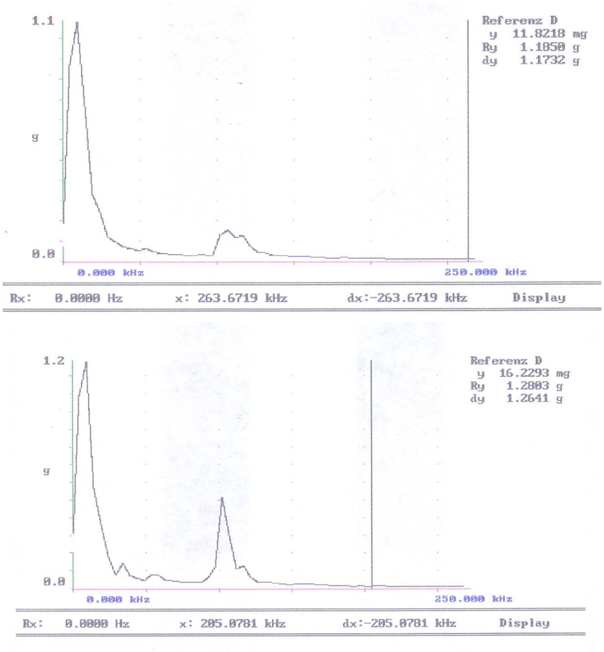

Fig. 5. AE spectrum of sharp and worn 1.5 mm diameter twist drill (material KO36 feed 25 mm/min, 2500 rev/min)

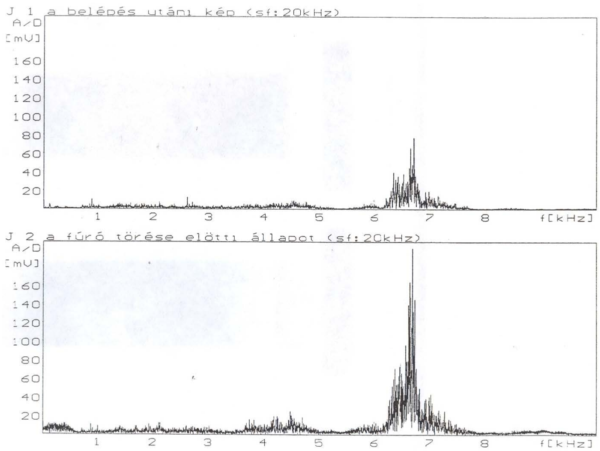

Fig. 6. Vibration spectrum of 1.5 mm diameter twist drill (material KO36 feed 25 mm/min, 2500 rev/min)

The third signal measured during the machining experiments was the feed force. In the subsequent figure the AE average value shown together with the value of the feed-force. 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.

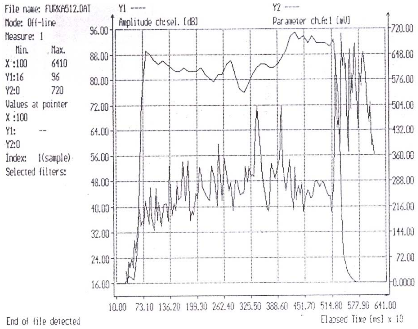

Fig. 7. AE activity and feedforce during tool failure

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.

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 tables below summarise the correct recognition rates, that was achieved, by the two networks in the various sensor fusion experiments.

Table 1. Correct recognition rate of the multilayer feedforward network

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

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

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

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

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

Table 4. Recognition rate using fuzzy reasoning

Tool condition	Recognition Rate
Initial	61%
Normal	89%
Acceptable	81%
Severe	76%
Tool failure	100%

4 Conclusion

An on-line drill wear/failure monitoring system was developed and evaluated in this study. On the basis of these 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.
– The single category based classifier has the advantage over the multilayer feedforward network the in can learn unsupervised which is advantageous in an industrial environment.

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