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Tool wear monitoring of micro-milling operations

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ABSTRACT

The mechanical removal of materials using miniature tools, known as micro-mechanical milling processes, has unique advantages in creating miniature 3D components using a variety of engineering materials, when compared with photolithographic processes. Since the diameter of miniature tools is very small, excessive forces and vibrations significantly affect the overall quality of the part. In order to improve the part quality and longevity of tools, the monitoring of micro-milling processes is imperative. This paper examines factors affecting tool wear and a tool wear monitoring method using various sensors, such as accelerometers, force and acoustic emission sensors in micro-milling. The signals are fused through the neuro-fuzzy method, which then determines whether the tool is in good shape or is worn. An optical microscope is used to observe the actual tool condition, based upon the edge radius of the tool, during the experiment without disengaging the tool from the machine. The effectiveness of tool wear monitoring, based on a number of different sensors, is also investigated. Several cutting tests are performed to verify the monitoring scheme for the miniature micro-end mills.

1. Introduction

The miniaturization of components has become increasingly important for various modern technologies, in order to meet the demands for shrinking component size and high accuracy. Miniature systems can provide portability, disposability, lower material and power consumption, lower sample requirements, higher heat transfer, and the capability of better process integration and automation. Several researchers (Hesselbach et al., 2004; Masuzawa, 2000) have reached the consensus that the fabrication of 3D structures with high aspect ratios and complex geometry, utilizing a variety of materials, is important. Hence, micro-mechanical machining is gaining greater importance, due to the ability of fabricating complex 3D structures, the high material removal rate, and the capability of machining a variety of engineering materials, especially metallic alloys.

There are several critical issues associated with micro-mechanical milling operations that arise mainly from the miniaturization of the components, tools and processes. Miniature tools are more likely to experience relatively large vibrations and forces, due to size, reduced stiffness, and the size effect. Because of the miniature size of the end mills, these vibrations can be detrimental to the longevity of tools and part tolerances. Also, it is very difficult to detect wear, damage to cutting edges, or even tool breakage due to sensor limitations at the micro-scale. As a result, the monitoring of micro-milling operations is critical to avoid excessive tool wear and to maintain part tolerances and surface quality.

Several researchers have conducted investigations into monitoring of machining processes, especially in the macro-realm, using various variables and sensors. Matsushima et al. (1982) and Deyuan et al. (1994) have used motor current and power for detecting tool wear and breakage. Altintas (1992) and Kim et al. (1999) presented the use of current drawn by feed drive motors for milling process monitoring. Youn et al. (1994) and Dornfeld et al. (2006) investigated the feasibility of using acoustic emission (AE) and cutting force signals for the detection of tool breakages, small fractures and wear of the cutting tools in turning. Others, like Saglam and Unuvar (2003), Kuljanic and Sortino (2005) and Tlusty (1978), have used force signals to detect tool failure and breakage in milling. Among these sensing methods, the accurate measurement of cutting forces provides the most effective method for monitoring tool conditions, since it yields higher signal-to-noise ratios and best represents the state of the machine tools and machining operations (Chae and Park, 2007).

The most common method of measuring cutting forces in machining operations is through the utilization of table dynamometers or piezoelectric load cells. Tansel et al. (2000), Tansel et al. (1993, 2000) have used a neural-network-based usage estimation method for monitoring end mills with a diameter bigger than 1 mm. They have used force signals with different features, such as root mean square, mean, maximum, segmental average

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based and wavelet transformation-based values. Ghosh et al. (2007) fused several signals (i.e. cutting forces, spindle vibration, and spindle current) via a neural network to estimate the average flank wear of the main cutting edge in a milling operation. However, the majority of the machine tool monitoring research work has been directed at the macro-domain. Despite years of research, reliable, versatile and practical methods are not yet available for the monitoring and controlling of high-speed machining processes, especially for micro-machining operations. Moreover, the use of a neuro-fuzzy algorithm, such as the adaptive neuro-fuzzy inference system, for monitoring micro-milling processes has not been thoroughly investigated.

This study examines a tool wear monitoring method using various sensors, such as force and AE sensors and accelerometers, for micro-milling operations. In order to monitor tool conditions effectively in the micro-realm, where the rotational speed is high and the cutting mechanism is complex, sensor fusion is needed to overcome the difficulties associated with the low-frequency bandwidth of the sensors and the complexity of micro-machining processes (Vogler et al., 2003). Sensor fusion through an adaptive algorithm can provide a higher frequency bandwidth and redundancy of various sensor signals. A high-power optical microscope was used to measure the actual tool conditions during the experimental machining tests. The sensor signals were collected and then fused through the neuro-fuzzy algorithm, which had been previously trained using a set of carefully gathered training data, to determine the tool condition and the amount of wear for different cutting conditions, such as different feed rates and spindle speeds. To verify the effectiveness of the sensor fusion and monitoring scheme, different combinations of sensor signals were tested for various experimental micro-milling tests. The methodology has also been extended to estimate high-frequency bandwidth cutting forces.

The paper is organized as follows: in Section 2, micro-milling operations and their uniquely associated aspects, which can significantly affect tool wear, are described. In Section 3, the experimental setup used for performing the cutting test, measuring and gathering data, and observing the actual tool condition is explained. Section 4 discusses the methodology that is used to construct the monitoring scheme. In Section 5, the results of the proposed monitoring method for different signals and conditions are presented. Several challenges and limitations of the method are discussed. Lastly, Section 6 provides a summary of our findings.

2. Micro-milling

Micro-machining operations are different from conventional machining in several aspects, making the monitoring of the process even more important. In macro-machining, the feed per tooth is generally much larger than the tool edge radius; and, the cutting models are based on the assumption of a sharp tool that completely removes the surface of the workpiece without any elastic recovery or plowing. In micro-machining, due to the small edge radius of the tool and very low feed rates, this assumption is no longer valid. The edge radius of the tool in micro-milling is comparable to the chip thickness and causes a large negative rake angle. This negative rake angle then causes plowing and elastic recovery of the surface, as shown in Fig. 1(a) . If the depth of cut is less than a certain value, called the minimum chip thickness, the material is just squeezed underneath the tool. After the tool passes the material, the material is plowed with no chip formation and part of the plowed material recovered elastically. Fig. 1(b) depicts micro-milling operations where each flute goes through both shearing and plowing during machining, resulting in fluctuations of and increases in cutting forces (Malekian et al., 2008a,b) and accelerated tool wear, since increases in the cutting forces significantly affect tool wear. Other aspects of the micro-machining operations that can be attributed to severe tool wear are elastic recovery of the workpiece, dynamic deflections and runout of the tool, and low feed instability.

The elastic recovery of the material in micro-scale affects the tool wear in two ways: the cutting forces, and an increase in the contact area between the tool and workpiece at the flank face of the tool, as can be observed in Fig. 1(a). This increased area causes more friction and rubbing and consequently more flank wear of the micro-tools.

Elastic recovery of a workpiece can be obtained through either indentation or scratching tests using hardness indenters and measuring the elastic recovery of the workpiece using either a profilometer or interferometer (Malekian et al., 2008b). We found the average elastic recovery of the studied aluminum workpiece was approximately 10% by using a scratch test and measuring the scratch with a profilometer (Mitutoyo Surf-test 201). Knowledge about the elastic recovery of the workpiece can be helpful in understanding and estimating the flank wear in micro-scale.

Since micro-tools are very small in diameter, the tool deflection due to cutting forces can be quite significant. Furthermore, even a very small spindle or tool runout can affect the tool engagement and cutting forces considerably. Finding the dynamics of the tool tip in micro-scale, however, is challenging. Unlike macro-scale machine tools, performing the impact hammer test in micro-mills is not possible due to the fragility of the miniature tools. One of the methods to identify the dynamics at the tool tip is through the receptance coupling (RC) method (Mascardelli et al., 2008), which mathematically couples substructure dynamics as shown in Fig. 2. In the RC method, the dynamics of the machine, spindle and tool holder are measured through experimental modal analysis; and, the dynamics of the tool are obtained with finite element analysis. The frequency response functions are then assembled based on the compatibility and equilibrium conditions. The tool tip dynamics can be

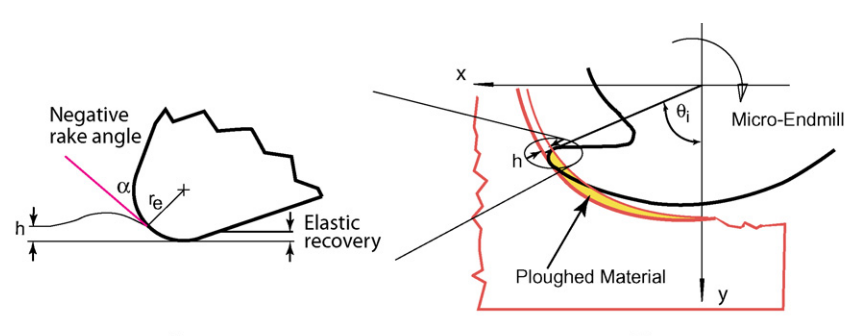


Fig. 1. Micro-end milling operations: (a) tool and workpiece and (b) top view.

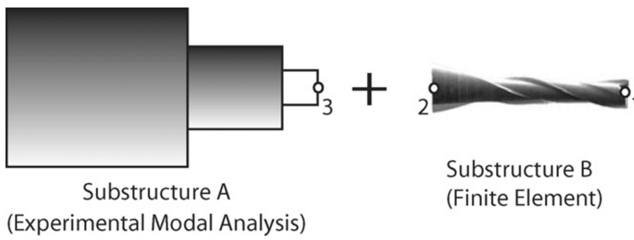


Fig. 2. Receptance coupling.

acquired as:

$$G_{11} = \frac{X_1}{F_1} = H_{11} - H_{12}(H_{22} + H_{33})^{-1}H_{21} \quad (1)$$

where G and H denote the assembled and substructure dynamics, respectively. The dynamics of the tool can be utilized to find the deflection of the tool due to the cutting forces.

Tool deflection due to the dynamics of the tool tip and tool runout affect the tool wear in several ways. Because of these effects, the cutting forces usually increase since the cutting process is not uniform for different flutes with some engaging more with the workpiece and removing more material in one revolution. Tool wear happens much faster for the flutes that engage more, while the other flutes remain intact. In addition, tool vibration cause intermittent impacts on the tool, which can be strong enough to chip the cutting edges or even break the micro-tool.

Vibration can also occur at much lower axial depths of cut, independent of the regenerative effect, as shown in Fig. 3. Low feed rate vibration is caused when rapidly increasing thrust forces, due to plowing, cause a flute of a micro-end mill to leave the workpiece many times over the course of a tool revolution due to the transitions from shearing-dominated cutting to plowing-dominated cutting. The abrupt change in the thrust forces at the transitions can cause a wide band of excitation of the micro-end mill, which can lead to significant vibrations. However, if the axial depth of cut is small enough, the thrust forces may not grow large enough to cause low feed rate vibrations. Fig. 3 shows the tool vibrations and frequency spectra for four slotting operations simulated using the model described by Jun et al. (2006). Each simulation was of a slotting operation in pearlite with a 508 μm diameter two-fluted end mill, a 10 μm axial depth of cut and a critical chip thickness of 0.4 μm. As can be seen in the figure, at low feed rates, such as 0.2 μm per flute, unstable vibration was present at a frequency of 73.2 kHz. However, at higher feed rates, there was significantly less vibration. This indicates that tool wear and the subsequent increase in the edge radius of the micro-tool will cause increased vibrations resulting in poor part quality.

The effects of the all aforementioned aspects on tool wear are extremely difficult to determine quantitatively in micro-scale, since most of these characteristics are not well understood; and, their influence on the tool wear is not yet known. Therefore, real-time adaptive monitoring of the cutting process is necessary to predict the onset of instability or tool breakage and make the required adjustments to the cutting conditions to account for changes in tool geometry, due to tool wear and any additional unknown initial process parameters.

3. Experimental setup

Often micro-CNC machines, like the majority of micro-machine tools, are based on conventional ultra-precision machines that have high rigidity and a temperature-controlled environment. Recently, there has been significant interest in building small-scale machine tools to fabricate micro-sizes (Vogler et al., 2002; Kim et al., 2002). The miniaturization of micro-machines has several benefits, such as portability and reduction in energy, space, materials and costs. The micro-CNC machining centre platform that was used

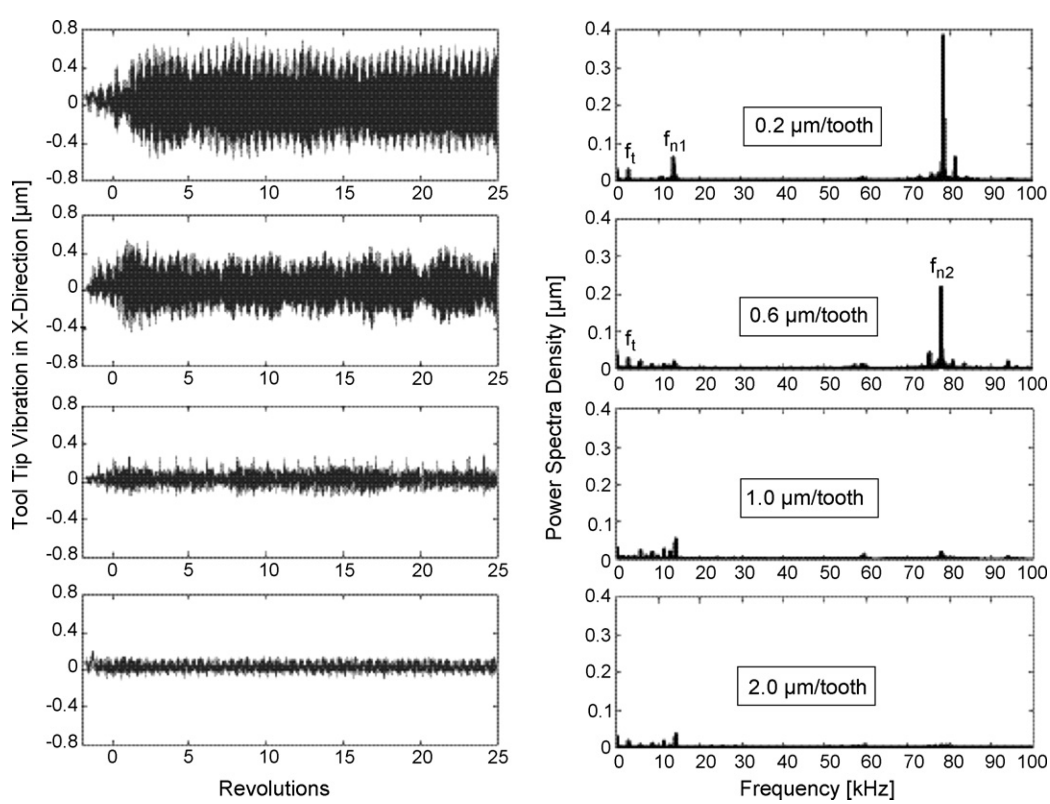
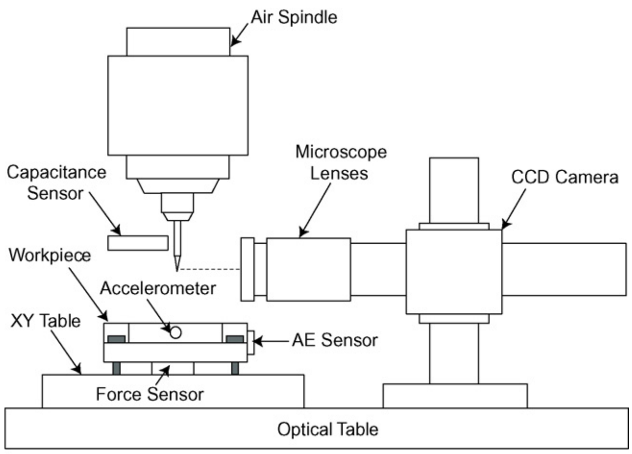
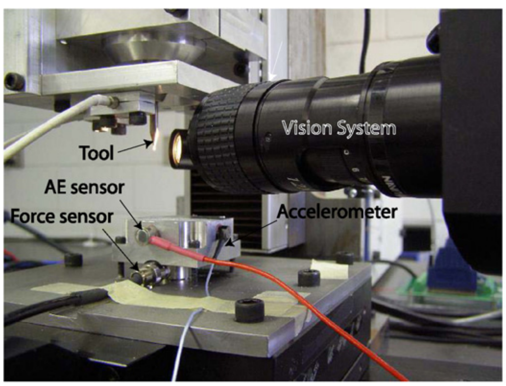


Fig. 3. Low feed instability effect from machining of pearlite (Jun et al., 2006).



(a) Schematics



(b) Pictorial View

Fig. 4. Experimental setup: (a) schematics and (b) pictorial view.

for the micro-milling experiments was a conventional 3-axis vertical column-and-knee type machine. The micro-machining centre consisted of a spindle, stages, frames and a control system. It was specified to meet the functional requirements of machining operations, like travel, minimum resolution, velocity, accuracy and load capacity. A 300 W electric motor spindle (NSK Astro 800E) was used to achieve the required torque for machining various engineering materials. The three linear tables were equipped with cross-roller linear bearings and stepper motors (Parker Daedal 10600, 402LN, ζ Drive). The control interface (National Instrument PXI7240 and PXI1250) provided the control and data acquisition. The machining centre was situated on top of a vibration isolation table (Ealing 10×4) to prevent ground vibrations to the machine. The experimental setup is illustrated in Fig. 4.

Several sensors, including a miniature 3-axis force sensor, an AE sensor, accelerometers and capacitance sensors, and an optical vision system were used to monitor tool conditions. A Kistler piezoelectric force sensor (9017B) was used to measure the micro-cutting forces. The charge signals generated from the force sensor were fed into the charge amplifiers (Kistler 9025B), which converted the charge signals into voltage signals. Since the 3-axis piezoelectric force sensor was sandwiched between the workpiece and the XY stage with the preloads, calibration of the force sensor was imperative. The calibration was performed using a modal impact hammer (Dytran 5800SL) to verify the force measurement. The frequency response function (FRF) between the applied force from the impact hammer and the force sensor was acquired in order to have unity gain, as shown in Fig. 5. The frequency bandwidth of the force sensor was found to be up to 2000 Hz. The forces were preprocessed by subtracting air cutting forces (i.e. peak-to-peak air cutting forces were approximately 0.01 N) from the measured cutting forces through synchronization at each revolution of the spindle using capacitance sensors (Lion Precision C4-D, RD20-2).

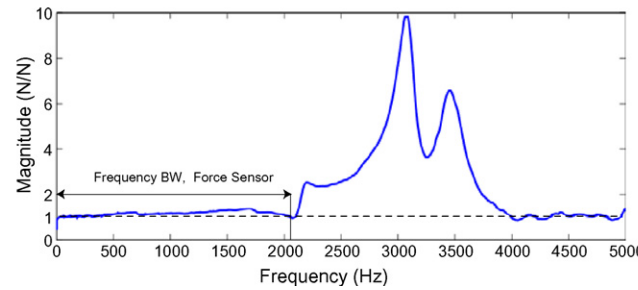


Fig. 5. Calibration of the force sensor in *X* direction.

In order to capture more features of the system under study, the vibration measurements were obtained through the use of two miniature accelerometers (Kistler 8778A500), with frequency bandwidth between 10 Hz and 10 kHz. The accelerometers were attached to the workpiece to measure vibration signals in both the *X* and *Y* directions. Furthermore, an AE sensor (Physical Acoustics Nano30) was used for capturing high-frequency vibrations. The bandwidth of the AE sensor was up to 10 MHz. The sensor signals were first fed through anti-aliasing filters (Krohn-Hite 3364) and logged into the data acquisition system.

The micro-tools used in this study were tungsten carbide (WC) micro-end mills with micro-grains (i.e. <600 nm) with a hardness of 2800 HV. The carbide micro-end mills were coated with titanium aluminum nitride coating (TiAlN) materials with the thickness of approximately 2 μm. The cobalt binding content was approximately 8% by weight. Due to the inherent fragility and costs associated with micro-tools, we utilized 500 μm diameter flat micro-end mills for our experimental cutting tests; however, micro-tools with smaller diameters (200 and 100 μm) can also be used. Additional sets of training data will be needed to formulate the neuro-fuzzy model in order to monitor micro-milling processes with other tools. The tool overhang length was 20 mm from the collet; and, this value remained constant in order not to change the dynamics during the experiments. The scanning electron microscopy (SEM) picture of the tip of the 500 μm diameter carbide end mill (Mitsubishi MS2JSD0050) is shown in Fig. 6.

As can be observed in Fig. 4, a high-power zoom lens (Navitar 12x and 2x lenses) with a reticle mounted on a charge coupled device

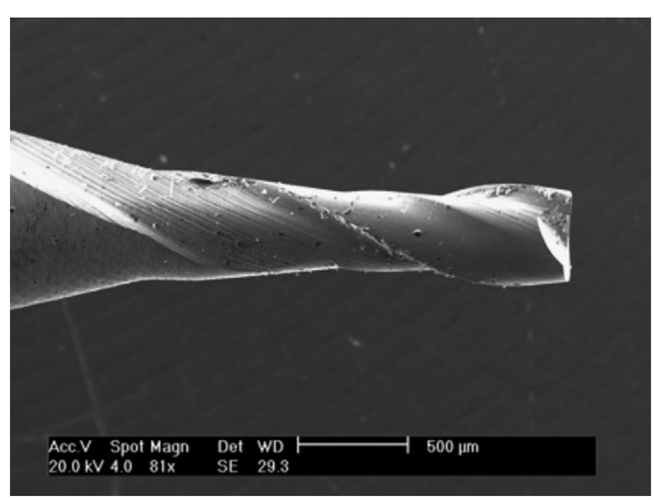


Fig. 6. Tip of the micro-end mill with two helical flutes and 500 μm in diameter.

(CCD) camera (Keyence 2600) was used to detect tool wear without disengaging the tool from the tool holder. This vision system was calibrated using a 10 μm resolution lined calibration scale (Edmund Scientific 036528) at different zoomed magnifications. The vision system, with the aid of the reticle, measured the edge radius of the in situ tool to determine the tool condition; therefore, there was no necessity to disengage the tool.

The 3-axis micro-machining centre with micro-flat end mills, which had been developed in-house, was used for performing several cutting experiments to gather tool wear data. The data consisted of signals captured by different sensors attached to the workpiece; and, the tool condition was deduced from the edge radius, which was measured in situ with the aid of the vision system.

4. Methodology

The aim of this study was the development of accurate and reliable monitoring of tool wear in micro-milling operations. Since the rotational speed of spindle in micro-machining is usually high and the cutting mechanism is complex, the fusion of various sensor signals via an inference system is necessary to increase the bandwidth of the sensors to achieve higher accuracy in monitoring.

An adaptive neuro-fuzzy inference system (ANFIS) model was selected to provide the means for fusing the different sensor signals and give the state of the tool under different cutting conditions. This fusion is accomplished through a set of fuzzy rules that transforms the inputs, i.e. the sensor signals and the cutting parameters (feed rate and rotational speed), to weights. The neuro-fuzzy method has been used for different applications for both engineering and scientific purposes; however, the application of the method to the monitoring of micro-end milling processes has not yet been reported. The amalgamation of different signals increases the accuracy of the measurement and compensates for the incomplete data of various sensors, resulting in the increase of frequency bandwidth. The integration of sensors is particularly necessary for high rotational speed cutting.

In this research, several sensors were used to detect the tool condition through the utilization of the neuro-fuzzy method. Compared to other inference algorithms, such as the artificial neural network, which requires the appropriate selection of the number of nodes and layers, in most cases, through trial and error, the neuro-fuzzy method is efficient to implement (Bose and Liang, 1995).

The outputs of these sensors along with the cutting conditions are applied to a fuzzy logic model to provide guidance to the operator when performing the machining. Finding the proper membership functions and the coefficients is, however, not an easy task. The neuro-fuzzy method uses a learning algorithm to find the unknowns in the fuzzy inference engine (Jang, 1997). Fig. 7 shows a typical neuro-fuzzy structure with n inputs, x_1 to x_n, and m membership functions in each fuzzy set. For a first order Sugeno fuzzy model, a typical fuzzy rule is:

$$\text{If } (x_1 \text{ is } A_{11}) \text{ and} \ldots (x_n \text{ is } A_{n1}) \text{ then}$$
$$f_1 = p_{11}x_1 + \ldots + p_{1n}x_n + r_1 \quad (2)$$

where p, q and r are coefficients of a linear relationship, and A is a nonlinear function to be determined during the training process.

The entire system architecture consists of five layers: a fuzzyfication layer, a product layer, a normalizing layer, a defuzzyfication layer and a total output layer, as depicted in Fig. 7. The neuro-fuzzy algorithm uses a supervised learning algorithm to determine a nonlinear model of input and output functions, i.e. the adaptive nodes. We used the hybrid method, which uses the gradient descent and least-squares methods to identify the coefficients (p, q and r in Eq. (2)). Fig. 8 depicts the schematics of the monitoring procedure.

The signals from different sensors were passed through anti-aliasing filters and were logged by the data acquisition system. A window of 20 revolutions was captured for each set of data. The signals were then preprocessed to extract features. The tool condition was observed during the collection of experimental data using the vision system. The acquired sensor signals, cutting parameters and the edge radius of the tool were used for training the neuro-fuzzy algorithm. After the training, the inference system could estimate tool conditions from the experimental sensor signals and cutting conditions in real time. The results from the monitoring algorithm can alert an operator to change a micro-tool before catastrophic failure and resulting damage to the part.

4.1. Sensor signals

The fusion of various sensors provides higher frequency bandwidth compared with the use of just one sensor. This is especially true for micro-milling operations, where the spindle rotates at high speeds with multiple fluted cutters for various cutting geometries.

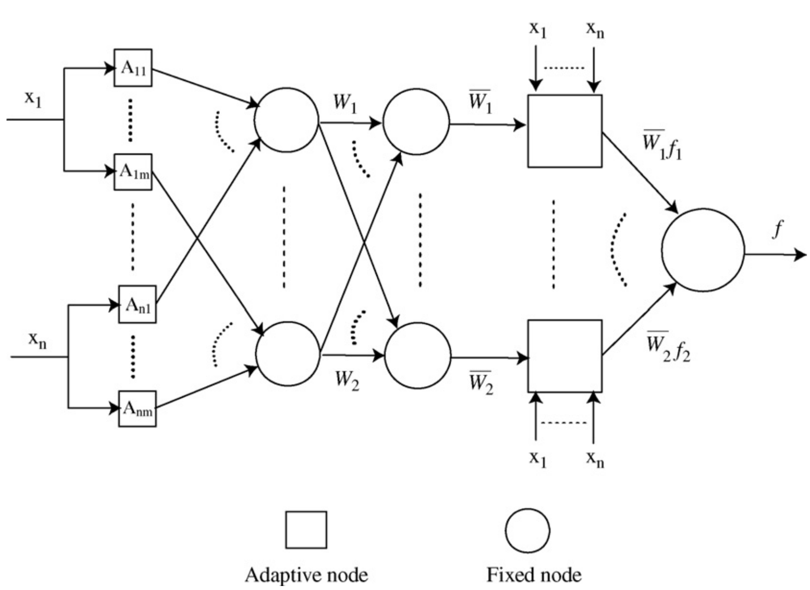


Fig. 7. Adaptive neuro-fuzzy inference system (ANFIS) structure (Jang, 1997).

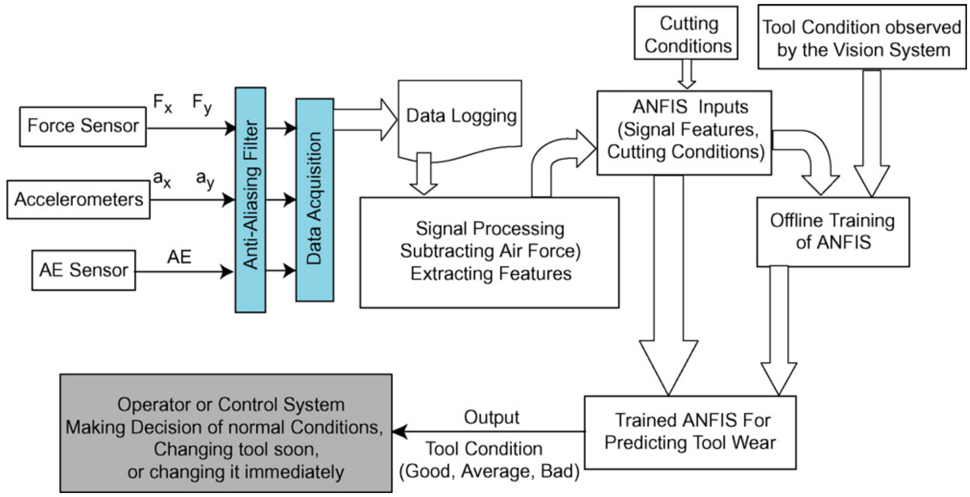


Fig. 8. Schematic of the neuro-fuzzy method for tool condition monitoring.

For example, a 160,000 rpm spindle with two fluted micro-end mills represents the tooth passing frequency of 5333 Hz. Typically, three harmonics signals are required to capture the machining operations accurately; therefore, one force sensor cannot truly represent the micro-milling operations. Other sensors with higher frequency bandwidths, such as accelerometers and/or AE sensors, are needed. Fig. 9 depicts the frequency bandwidths of the different sensors used in this research on the logarithmic scale. Fusing force signals with signals from other sensors can aid us in the capture and monitoring of high-frequency machining operations.

The signals were captured after anti-aliasing filtering (cutoff frequency of 50 kHz) for a short period of time during each cutting test. The sampling rate was chosen to be 100 kHz, and 20,000 samples were captured for each channel. All signals were preprocessed by subtracting air cutting signals through synchronization at each revolution of the spindle using a capacitance sensor. The features of the signals, such as root mean square (RMS), peak-to-peak and mean values, were extracted for use in the inference system. It was found that the best feature of the signals in this study was RMS, since it was a good representation of the energy of the cutting mechanism and avoided sudden signal jumps or outliers in the signal, although the usage of the peak-to-peak value for the force signal did not significantly change the accuracy. Different combinations of signals were fused via the neuro-fuzzy method to determine the best combination that could predict the tool conditions with accuracy.

4.2. Tool condition measurements

Using the microscope, we took a picture of the in situ tool, in order to determine the tool condition after each cutting test, without disengaging the tool from its holder. The edge radius was used to monitor the tool condition, since it is an appropriate indicator of the amount of tool wear in micro-scale. The wear land depth alone is used, in many cases, to measure the amount of tool wear for macro-scale milling operations. In micro-scale milling, however, the tool wear characteristic is different, and the wear land depth is very difficult to measure; therefore, the change in the edge radius is preferred.

In this study, it has been shown that the edge radius of the tool was sufficient for the monitoring of the micro-tool conditions. The edge corner radius of the tool was measured by counting pixels from the vision system and comparing the number with the scale on the reticle. The output was assigned a 0 (good tool), 0.5 (average tool) or 1 (bad tool), corresponding to an edge corner radius of less than 2 μm, between 2 and 5 μm, and greater than 5 μm, respectively. Since different flutes may have different tool wear, we only selected one flute with proper marking for the radius measurements. Fig. 10 illustrates a good tool and a worn tool using the vision system.

To convert the output of the neuro-fuzzy algorithm from quantitative values to linguistic values, we used the membership functions shown in Fig. 11. Since it is difficult to define certain boundaries between different tool conditions, due to the uncertainties involved, trapezoidal membership functions have been chosen. As a result, the tool condition can be defined with a certain percentage of two different conditions in the intersection regions. This gives more suitability and robustness to the condition assignment of the tool.

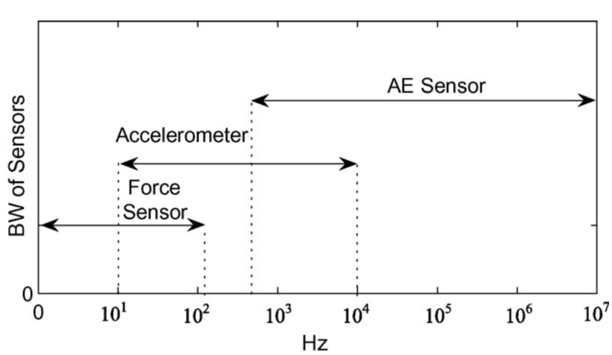


Fig. 9. Frequency bandwidths of different sensors.

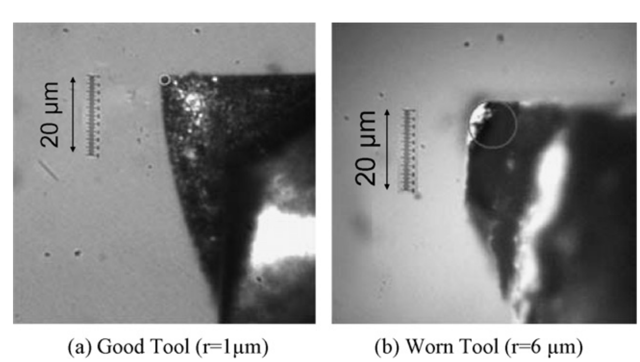


Fig. 10. Edge radii of good and worn tools: (a) good tool (r = 1 μm) and (b) worn tool (r = 6 μm).

Table 1
Cutting conditions and the number of experiments performed.

Rotational speeds (krpm)	Feed rates (μm/flute)	Number of tests with good tool	Number of tests with average tool	Number of tests with bad tool
10	0.5	20	20	15
10	2	20	20	15
10	10	20	20	15
80	0.5	20	20	15
80	2	20	20	15

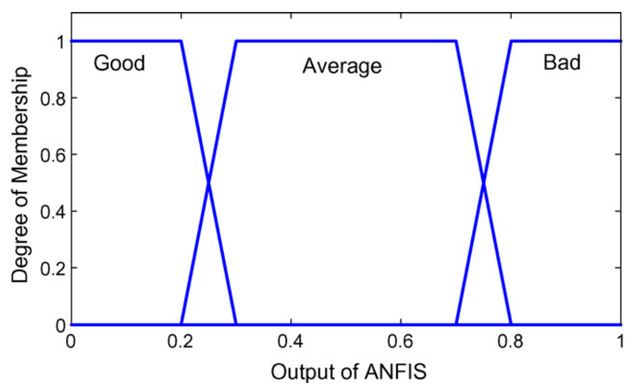


Fig. 11. Output membership functions.

4.3. Training

The neuro-fuzzy algorithm needed to be trained with a proper set of training data, in order to be able to estimate tool wear based on the input–output data. The inputs were the features of the sensor signals and the cutting conditions, so that the algorithm could determine the tool state at different feed rates and rotational speeds. The output was the tool condition based upon the edge corner radius measured by the vision system. In order to achieve effective training of the neuro-fuzzy algorithm, several experimental cutting tests were conducted under controlled environments, and the cutting signals were gathered for each test. For each cutting test, the data were logged after a length of cut of about 10 cm. The machining was performed on aluminum 7075 with a 100 μm depth of cut and full immersion cutting conditions. Since different wear characteristics in micro-milling are strongly dependent on feed rates (i.e. amount of uncut chip thickness) and the measured signals are distorted at high rotational speed, due to sensor dynamics, the focus of this paper was tool condition monitoring at different feed rates and spindle speeds. Therefore, a large range of depths of cut was not considered in this study. Table 1 summarizes the rotational speeds and feed rates under which the cutting was performed. It should be noted that the critical chip thickness of aluminum 7075 is about 0.7 μm (Malekian and Park, 2007); therefore, we tested both the shearing and plowing dominant cutting regimes, as shown in Table 1.

After each test, the edge corner radius of the tool was measured using the microscope and CCD camera, so that a tool condition could be assigned as an output. With the provision of the input–output data, the neuro-fuzzy algorithm can be trained, and the unknown parameters can be identified. Fig. 12 depicts the inputs, membership function, and the function of the fuzzy inference system for tool monitoring after the training.

Once we acquired the neuro-fuzzy model through training, the fuzzy inference system was ready to be employed to estimate tool wear with the provided inputs, which were captured signals and cutting conditions. The results from the monitoring method can guide an operator or control system in making decisions regarding tool change.

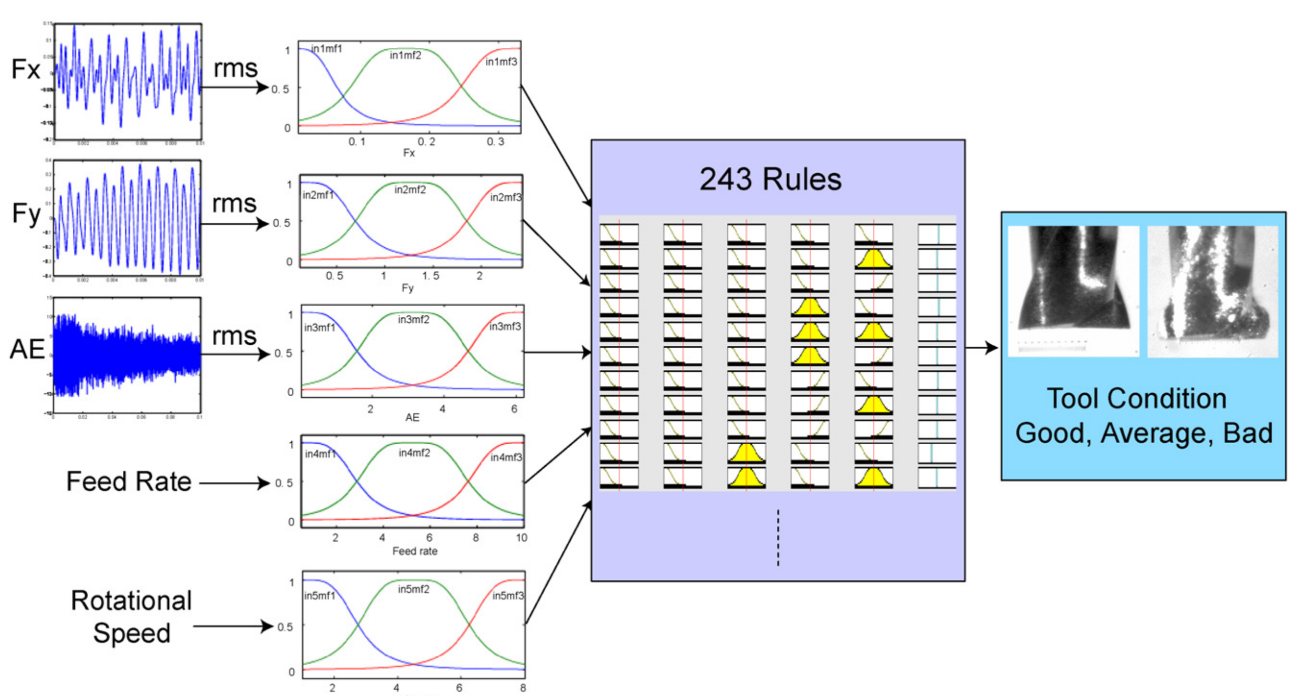


Fig. 12. Fuzzy inference system for tool monitoring.

5. Results and discussion

In this section, the ability of the constructed neuro-fuzzy method for tool wear monitoring is examined, and the effects of fusing different signals are investigated and compared. Based on the effectiveness of the neuro-fuzzy algorithm in the fusion of different signals, it can be decided which combination of signals should be chosen. There are also several challenges associated with the monitoring of micro-milling operations, such as built-up edge and inconsistent longevity of various tools. The neuro-fuzzy method has been extended to estimate the cutting frequencies at the high-frequency bandwidth from for the spindle rotating from 60,000 to 150,000 rev/min with the two fluted micro-end mill.

5.1. Effectiveness of different sensor fusions

After collecting training data and extracting signal features, the neuro-fuzzy algorithm was trained; and, the unknown parameters of membership functions, the set of rules and the output weights were identified, as shown in Fig. 11. It was observed that, among triangular, trapezoidal and bell-shaped membership functions, the best results were obtained when bell-shaped membership functions were chosen for the neuro-fuzzy model. Triangular membership functions also worked well in this case, with a little less accuracy; however, trapezoidal membership functions usually caused erroneous results. To see the effects of fusing different sensor signals, various combinations of signals were used as part of the input data. The inputs also included the feed rate and rotational speed as the cutting conditions.

After the neuro-fuzzy algorithm was trained, a set of independently collected testing data, which were not a part of the training, were used for verification. The testing data were collected under different cutting and tool conditions. Table 2 shows the conditions under which the testing data were gathered.

The forces, acceleration and AE signals for new and worn tools are shown in Fig. 13 for comparison: the cutting conditions were a rotational speed of 80,000 rpm and a feed rate of 2 μm/flute. Since the tooth pass frequency and harmonics were beyond the frequency bandwidth of the force sensor, the captured force signals were amplified. The AE sensor and accelerometers, however, were able to measure the signals correctly, due to their higher bandwidths. The peak-to-peak magnitudes for the force signals increased for a worn tool, but not significantly. The AE sensor signal did increase noticeably from the new tool to the worn tool.

The cross-correlation of different signals presents the relationships between different signals, as depicted in Eq. (3), where *f* and *g* are two arbitrary time-dependent real signals:

$$C_{fg}(t) = \int_{-\infty}^{+\infty} f(u)g(u-t)du \qquad (3)$$

Table 2
Testing data with different tool and cutting conditions.

Test case	Rotational speed (krpm)	Feed rate (μm/flute)	Tool conditions
1	10	0.5	Good
2	10	2	Good
3	10	10	Good
4	80	0.5	Good
5	80	2	Good
6	10	0.5	Average
7	10	2	Average
8	10	10	Average
9	80	0.5	Average
10	80	2	Average
11	10	0.5	Bad
12	10	2	Bad
13	10	10	Bad
14	80	0.5	Bad
15	80	2	Bad

Table 3
Cross-correlation chart for different signals.

Signals	F_x	F_y	A_x	A_y	AE
F_x	1	0.915	0.769	0.791	0.705
F_y	0.915	1	0.817	0.859	0.661
A_x	0.769	0.817	1	0.97	0.721
A_y	0.791	0.859	0.97	1	0.754
AE	0.705	0.661	0.721	0.754	1

Table 3 shows the normalized cross-correlation of different signals. The cross-correlations between F_x and F_y, and also between A_x and A_y, were very close to 1, which means that the signals contained nearly the same information. Therefore, we have used the resultant force and acceleration as inputs of the neuro-fuzzy model. The cross-correlations between the AE and other signals were the smallest ones, meaning that the AE signal contained more information that was independent from the other signals. This may have been because the AE signal can capture high-frequency vibrations that cannot be captured by other sensors. The fusion of independent signals may provide accurate monitoring schemes.

The following sections examine the effectiveness of sensor fusion for the monitoring scheme. We first examined only the force signals in the monitoring of tool wear of micro-milling operations. The force and AE signals were then investigated; and lastly, force, acceleration and AE signals were studied.

5.1.1. Monitoring using only force signals

We examined the usage of force signals as the only input sensor signals. As a result, the inputs of the neuro-fuzzy model were forces in the *X* and *Y* directions, feed rate and rotational speed. The training trend was very fast, and the error reached a constant value after about 8 epochs. In this case, there were 81 rules in the fuzzy inference system. After the training, the testing data was applied to the algorithm to determine its validity. Fig. 14 shows the actual outputs (tool condition) versus the outputs obtained from the neuro-fuzzy algorithm. There are three different regions in the picture: good, average and bad. There are also some transition regions, which are shown as shaded regions. These regions correspond to the transition lines in Fig. 11, in which the tool condition can be described by a certain percentage of two different regions.

Although the outputs of the neuro-fuzzy model were not too different from the actual outputs, the algorithm wrongly predicted tool wear estimation for 4 out of 15 cases (the circled points in Fig. 14), especially when the cutting speed (both feed rate and rotational speed) was low. This may have resulted from the different cutting mechanism at low feed rates or the effects of the built-up edge. Both of these issues can change the regular cutting forces and affect the tool wear estimation via force signals alone. Furthermore, the limited bandwidth of the force sensor may limit the accuracy of the monitoring scheme.

5.1.2. Monitoring using force and AE sensor signals

The AE and force signals were fused to provide tool wear monitoring. In this case, the number of fuzzy rules increased to 243, and the training time increased to more than 3 times that of the previous case (force signals only). The outputs of the neuro-fuzzy algorithm for the testing data versus the actual outputs in this case can be seen in Fig. 15. It can be observed that the agreement between the actual and neuro-fuzzy outputs was better (e.g. one error out of 15 test samples) than the force signals alone, especially for low-speed machining. This may be a direct result of the AE sensor's

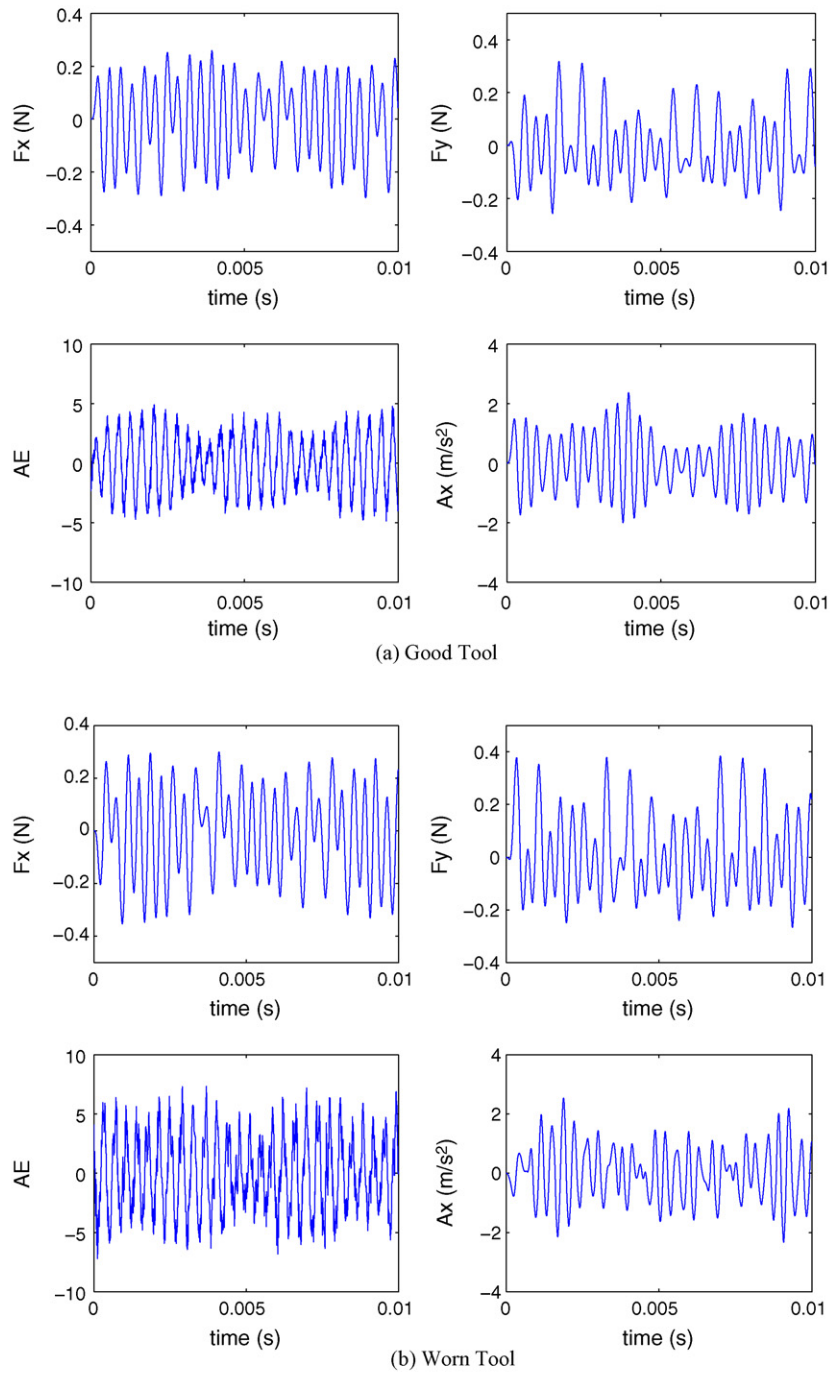


Fig. 13. Sensor signals: (a) good tool and (b) worn tool.

capture of high-frequency vibration, which cannot be measured by the force sensor, due to its low-frequency bandwidth. Therefore, the inclusion of the additional sensor improved the accuracy of the monitoring algorithm.

5.1.3. Monitoring using force, AE and accelerometers

We also analyzed the monitoring scheme using the resultant force, acceleration and AE signals as the inputs. In this case, there are 243 fuzzy rules; and, the outputs of the neuro-fuzzy algorithm versus the actual outputs for testing data are in good agreement (e.g. no error), as shown in Fig. 16. As mentioned earlier, the rotational speed of 80,000 rpm causes distortion of forces; however, the accelerometers and AE sensor can provide correct measurements, due to their higher frequency bandwidth. It seems that using other sensors, such as accelerometers and AE sensors, in addition to force sensors can increase the bandwidth of measurement and capture more features of the system, resulting in a more accurate estimation of the tool wear in micro-milling operations.

5.1.4. Comparison of different sensor fusions

To observe the effectiveness of combining sensor signals, we investigated the training errors of different combinations of fused signals, as illustrated in Table 4. F_r and A_r represent resultant force and acceleration, respectively. The training error is obtained from

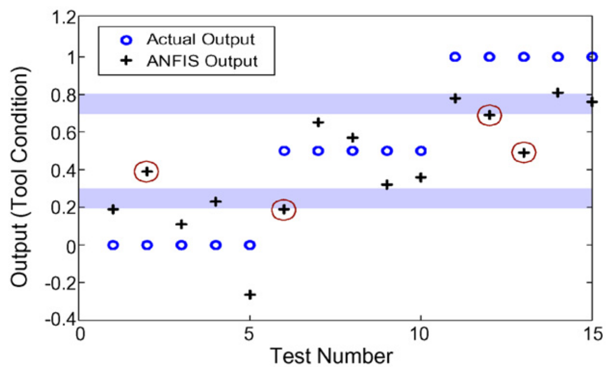


Fig. 14. Results of neuro-fuzzy method for tool state where F_x and F_y are inputs.

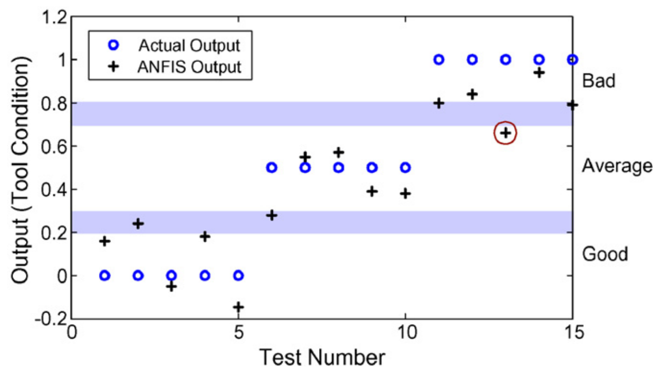


Fig. 15. Results of neuro-fuzzy method for tool state where F_x, F_y and AE are inputs.

Eq. (4):

$$e_t = \sum_{i=1}^{N} (O_{\mathrm{Actual}_i} - O_{\mathrm{ANFIS}_i})^2 \quad (4)$$

where N is the number of training data, O_{Actual} is the actual output of training data, and O_{ANFIS} is the neuro-fuzzy output of training data after training.

The training errors and the accuracy of the monitoring directly correlate with each other when we analyzed the test cases using the trained neuro-fuzzy algorithms. From Table 4, it can be concluded that decreased training errors and a better monitoring algorithm result from increasing the number of inputs from 1 to 2 and from 2 to 3, and fusing different kinds of signals.

It was observed from the above-mentioned results that the effectiveness of the neuro-fuzzy algorithm for tool wear monitoring improved when the number of signals using various sensors was increased. Although the use of force sensors can give an approximate estimation of the tool condition, a more robust and reliable monitoring of micro-milling operations at high rotational speeds and various feed rates requires different sensors with different bandwidths.

Table 4
Training error using different input signals.

Input signals	Training error	Input signals	Training error
F_x	0.1805	F_x and F_y	0.1534
F_y	0.1817	A_x and A_y	0.1570
F_r	0.1793	F_x and AE	0.1465
AE	0.1767	F_r and AE	0.1421
A_x	0.1890	F_r and A_r	0.1535
A_y	0.1905	A_r and AE	0.1446
A_r	0.1879	F_x, F_y and AE	0.1303
		F_r, A_r and AE	0.1228

5.2. Estimation of cutting forces using the neuro-fuzzy algorithms

Force measurement and prediction is important in micro-machining operations, since excessive forces cause severe tool vibration, breakage and large tool deflections. Due to the insufficiency of the frequency bandwidth of the force sensors, the accurate measurement of the cutting forces is not possible at high rotational speeds. If the dynamics of the force sensor is not known, then compensation cannot be performed. The neuro-fuzzy method can be employed in these circumstances for cutting force prediction, since it can be trained for different cutting conditions and rotational speeds. The same methodology is used to estimate the cutting forces at high rotational speeds.

For the force estimation algorithm, signals from the force sensor, accelerometer and AE sensor are captured and their RMS values are computed. These values and the cutting conditions, i.e. the rotational speed and the feed rate, are the inputs of the algorithm. While it is feasible to estimate the RMS of the actual forces with only one or two sensor signals, it has been observed that increasing the number of signals improves the accuracy of the force estimation by the neuro-fuzzy model. The output is the RMS value of the actual cutting forces, which can represent the magnitude of the forces and can be considered as a criterion for monitoring purposes.

In order to train the neuro-fuzzy algorithm, a set of cutting experiments with different cutting conditions (rotational speeds and feed rates) were performed carefully, and the data were gathered. The depth of cut was selected as 50 μm. The rotational speeds were varied from 60,000 to 150,000 rev/min., and feed rates were selected from 1 to 10 μm/flute. In total, 80 different cutting experiments were performed; and, the signals were collected and processed, and their RMS values were calculated. Seventy-three

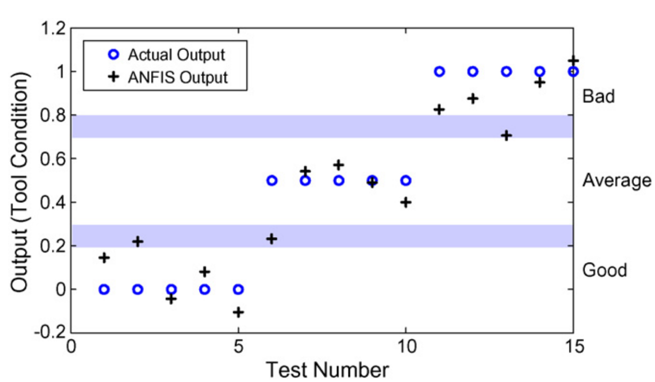


Fig. 16. Results of the neuro-fuzzy method for tool state where F_x, A_x and AE are Inputs.

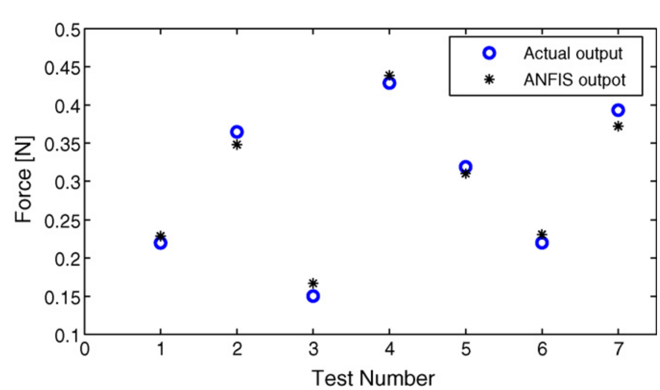


Fig. 17. Actual and neuro-fuzzy method results for RMS of the cutting force.

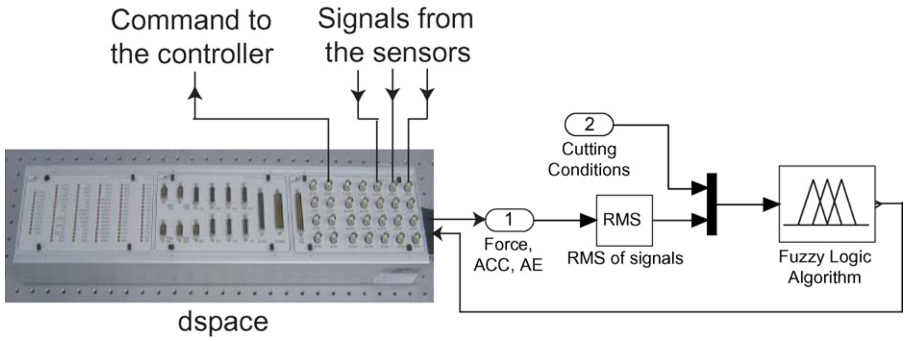


Fig. 18. Real-time implementation of the monitoring scheme.

data sets were used to train the neuro-fuzzy algorithm, and the remaining data were utilized for verification. The outputs of the training data were acquired through the force compensation using the Kalman filter (Park and Altintas, 2004). These outputs can also be obtained via the simulation of the micro-cutting forces.

Fig. 17 shows the actual and neuro-fuzzy outputs of the testing data of Table 5. As can be observed, there was good agreement between the two outputs; and, the neuro-fuzzy algorithm was able to effectively predict the RMS of the actual forces, based on the measured signals. By constructing this measurement scheme, it is feasible to accurately estimate the cutting forces during micro-milling operations. The information will be used for compensating the tool deflection errors and defining the optimal cutting parameters.

5.3. Discussion

It was observed that the neuro-fuzzy algorithm could effectively monitor the amount of wear and tool condition in micro-end mills via fusion of various signals, which increases the monitoring frequency bandwidth. There are many issues related to micro-mechanical milling, including the complex machining mechanism, tool dynamics, instabilities, temperature effects, and nonlinearities, which make it necessary to use sensor fusion and high-performance inference systems for monitoring the processes. In addition, built-up edge formations and the effect of coating materials may affect the overall monitoring scheme, as well as large stock variations in micro-tools and excessive vibrations.

Another cause for tool wear and breakage is that, due to the high temperature that arises locally during the machining of aluminium, the cobalt present as a binder in the carbide migrates toward the tool surface and combines with aluminium, and it is then removed with the chip (Nouari et al., 2005). Adhesion due to the presence of cobalt on the tool surface and chipping are consequences of this localized depletion of cobalt, which makes carbide tools more brittle.

The computational efficiency of the neuro-fuzzy algorithm is high, and it can manipulate a great amount of training data. Although the training time increases exponentially with the increase of the number of inputs, a long training time is not usually a problem since the training is done off-line. If the number of inputs increases drastically, the clustering method should be used to decrease the training time and the amount of required training data. After the off-line training, the neuro-fuzzy algorithm can be used on-line to predict tool wear.

The on-line monitoring scheme can be implemented using a real-time open architecture system (dSpace™, ACE1103PX4CLP), as shown in Fig. 18. The system interfaces with Matlab/Simulink™, where the trained neuro-fuzzy algorithm is embedded in the system. The real-time system captures the analog signals from the sensors. The algorithm converts the sensor signals into the RMS values for the prescribed time; and, the inputted cutting conditions are fed into the inputs of the neuro-fuzzy algorithm, which determines whether the monitoring of the process is acceptable or not. The output of the fuzzy inference system can provide the controllers with the necessary commands (continue cutting, change feed rate or depth of cut, or shut down the machining centre). The real-time monitoring of the micro-machining operations is the subject of future investigations.

During the measurements of the corner edge radii using the vision system, the lighting can influence the accuracy of the edge radii. In our experiments, we used two halogen lights with minimal reflection adjustments. In the neuro-fuzzy analysis, the depths of cut, engagement of the tool and workpiece material are assumed to be constant. For a more comprehensive work, these parameters can be added to the inputs of the algorithm. In spite of the above-mentioned limitations, sensor fusion via the neuro-fuzzy algorithm provides an effective method of manipulating complex phenomena, such as micro-end milling operations at high rotational speed. The neuro-fuzzy algorithm fuses different signals, according to a nonlinear process to increase the bandwidth and determine the tool and process conditions. The neuro-fuzzy algorithm can also effectively provide an estimation of the magnitude of the cutting forces. This is another example of using a neuro-fuzzy method in dealing with complex engineering or scientific phenomena, such as micro-milling operations.

Table 5
Testing data with different cutting conditions.

Test number	Rotational speed (krpm)	Feed rate (μm/flute)
1	60	4
2	75	6
3	90	2
4	105	8
5	120	5
6	135	3
7	150	7

6. Summary

The monitoring of micro-milling processes is critical, because of the very fragile nature of micro-tools and the susceptibility of the processes to vibrations and forces. It is difficult to detect damage to cutting edges or even broken tool shafts, especially for micro-tools with diameters of less than 1 mm. In this study, various sensors and a vision system were utilized to monitor micro-milling operations. Since micro-milling operations are often performed at high rotational spindle speeds, the fusion of various signals with different bandwidths provides an effective means to monitor the tool wear of micro-end mills.

Several cutting experiments were performed, and the amount of wear was observed after each test with a vision system that measured the edge corner radius of the tool. The collected sensor signals and the edge radii were analyzed off-line and were applied to a neuro-fuzzy method to train and determine the membership functions and rules. Once the neuro-fuzzy algorithm was trained, the cutting signals could be interpreted to determine the tool wear through on-line analysis. Comparison between the actual tool wear and the simulated results from the neuro-fuzzy method showed good agreement, especially when the force, acceleration and AE signals were fused together. The trained model can be readily used to monitor micro-milling operations and provide warnings to an operator, in order to minimize tool breakage and violation of part tolerances. Furthermore, the method can be extended to estimate the high-frequency bandwidth cutting forces.

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