

Intelligent cutting tool condition monitoring in milling

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ABSTRACT

Purpose: of this paper is to present a tool condition monitoring (TCM) system that can detect tool breakage in real time by using a combination of neural decision system, ANFIS tool wear estimator and machining error compensation module.

Design/methodology/approach: The principal presumption was that the force signals contain the most useful information for determining the tool condition. Therefore, ANFIS method is used to extract the features of tool states from cutting force signals. The trained ANFIS model of tool wear is then merged with a neural network for identifying tool wear condition (fresh, worn).

Findings: The overall machining error is predicted with very high accuracy by using the deflection module and a large percentage of it is eliminated through the proposed error compensation process.

Research limitations/implications: This study also briefly presents a compensation method in milling in order to take into account tool deflection during cutting condition optimization or tool-path generation. The results indicate that surface errors due to tool deflections can be reduced by 65-78%.

Practical implications: The fundamental limitation of research was to develop a single-sensor monitoring system, reliable as commercially available system, but much cheaper than multi-sensor approach.

Originality/value: A neural network is used in TCM as a decision making system to discriminate different malfunction states from measured signals.

Keywords: Tool condition monitoring (TCM); Wear; Tool deflection; ANFIS; Neural network; End-milling

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1. Introduction

Detection of cutting tool condition is essential for faultless machining in flexible manufacturing systems (FMS). An unmanned flexible manufacturing system (UFMS) is the most developed type of FMS. Such a system replaces human operators with robots, thus reducing labour costs and preventing human errors. In such an automated and unmanned machining system, a computerized system must have capabilities for monitoring and controlling the machining process to perform the role of a human

operator. Tool condition monitoring (TCM) is a fundamental requirement for the control of the machining process. The main goal of the development of TCM systems is to increase productivity and hence competitiveness by maximizing tool life, minimising downtime, reducing scrap and preventing damage. What was the traditional ability of the operator to determine the condition of the tool based on his experiences and senses is now the expected role of the monitoring system. The role of the operator is typically supervisory. Usually, the operator is also responsible for loading into and unloading parts from several

machines in a manufacturing cell, meaning that his time of reaction to a problem with any machine will not be sufficient for the speed at which machining operations take place on modern machine tools. Each tool condition monitoring (TCM) system consists of sensors, signal conditioners/amplifiers and a monitor [1]. The monitor uses a strategy to analyse signals from the sensors and to provide a reliable detection of tool and process failures. It can be equipped with a signal visualisation system and is connected to the machine control. Many studies have been conducted on the monitoring of malfunctions and abnormal cutting states of machine tools [2]. With regard to the monitoring of cutting tool states, two main factors are tool wear and failure. Tool failure has become more important recently since hard tools are frequently used in the cutting process.

There are two techniques for tool wear sensing: direct and indirect. The direct technique includes the measuring of the actual wear by using radioactive analyses of the chip. Generally, direct measurements are avoided because of the difficulty with online measurements. For indirect methods of TCM, the following steps are to be followed: the use of single or multiple sensors [3] to capture process information; the use of signal processing methods to extract features from the sensor information; the use of decision-making strategy to utilize extracted features for the prediction of tool failure. The indirect technique includes the measuring of cutting forces, torque, vibration, acoustic emission (stress wave energy), sound, temperature variation of the cutting tool, power or current consumption of spindles or feed motors, and roughness of the machined surface [4]. The recent trend in TCM is the multi-sensor approach which is termed sensor fusion/sensor integration/sensor synthesis. The idea is to gather information from several sensors to make a comprehensive estimate of tool wear. The application of TCM in industry has mostly relied on robust and reliable sensor signals such as force, power and AE. They are relatively easy to install in existing or new machines, and do not influence machine integrity and stiffness.

Recent studies show that force signals contained the most useful information for determining the tool condition [5]. However, in many cases the use of force sensors is not practical for retrofit applications and the spindle power signal is often used as an alternative.

Several different approaches have been proposed to automate the tool monitoring function. These include classical statistical approaches as well as fuzzy systems and neural networks. For instance, Iqbal [6] has developed an approach based on the least-squares regression for estimating tool wear in machining. Haber [7] has measured the flank wear of the cutting tool using computer vision. The capacity of artificial neural networks to capture nonlinear relationships in a relatively efficient manner has motivated Chien and Tsai [8] to apply these networks in developing tool wear prediction models. But in such models, the nonlinear relationship between sensor readings and tool wear embedded in a neural network remains hidden and inaccessible to the user [9]. In this study, we attempt to solve this situation by using the Adaptive Neuro-Fuzzy Inference System (ANFIS) to predict the flank wear of the tool in end-milling processes. This model offers the ability to estimate tool wear as its neural network based counterpart providing also an additional level of transparency that neural networks fail to provide. Then, a neural network is used as a decision making system to predict the condition of the tool. In this study, the cutting forces are used as the indicator of the tool flank wear variation.

2. Problem definition

End-milling is an interrupted cutting process, which means that each cutting tooth generates a cyclic cutting force ranging from negative to maximum force, and back to negative. This force is graphed as a series of peaks (Figure 1).

Cutting parameters and tool conditions affect the magnitude of the resultant force. Therefore, the resultant force F_R , generated from the X and Y directions, is used in this experiment for detecting the tool state. If the tool condition is good, the peak measurement of each tooth's force should be roughly the same during one revolution of the tool. If a tooth is broken, it generates a smaller peak force because it carries a smaller chip load. As a result, the tooth that follows a broken tooth generates a higher peak force as it extracts the chip that the broken tool could not. One main force principle can be used to detect tool condition: Maximum peak force in each revolution should be different in good tools and in broken tools [10]. Maximum peak force of a broken tool must be larger than that of a good tool.

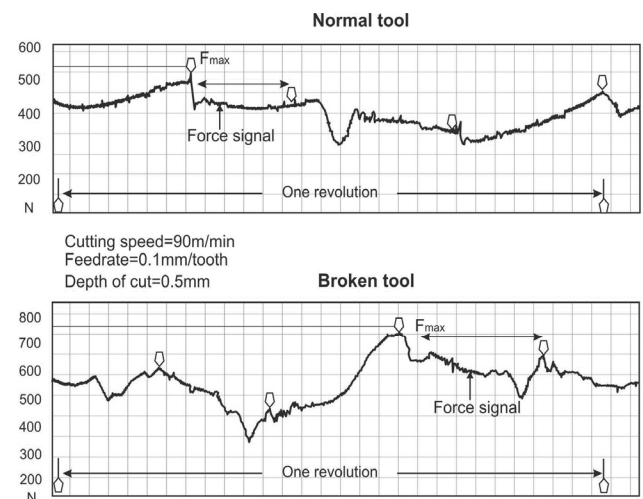


Fig. 1. Cutting force signal of a good tool and a damaged tool

Figure 1 illustrates the diagram of undamaged and broken tools. Applying these principles, an in-process tool breakage monitoring system was developed for end-milling operations. The cutting forces and the machining parameters were selected as input factors.

3. Methodology and system components

The proposed approach consists of three main steps. In step 1, an ANFIS model of tool wear is developed from a set of data obtained during actual machining tests performed on a Heller milling machine using a Kistler force sensor. The trained ANFIS model of tool wear is then merged subsequently in step 2 with

a neural network for estimating tool wear condition (fresh, worn). Tool deflection that occurs during machining and especially when flexible tools, such as end mills are used, can result in dimensional errors on workpieces. Therefore, finally in step 3, an error compensation module is used that modifies the cutting conditions, compensates for the machining errors due to tool deflection and tool wear, without degrading the production performance and the machined accuracy. The compensation strategy allows the on-line optimization of feed rates or the tool path trajectory in order to achieve a specified tolerance. Figure 2 shows the basic architecture of the proposed system.

3.1. ANFIS based tool wear predictor

The relationship between the machining parameters/sensor signals and flank wear is first captured via a network and is subsequently reflected in linguistic form with the help of a fuzzy logic based algorithm. The estimation design process consists of a linguistic rule construction, the partition of fuzzy subsets and the definition of the membership function shapes. It uses training examples as input and constructs the fuzzy if-then rules and the membership functions (MF) of the fuzzy sets involved in these rules as output. This process is called a training phase. Two different membership functions, the triangular and the trapezoidal, were adopted during the training process of ANFIS in this study in order to compare the prediction accuracy of flank wear according to the two membership functions. After training the estimator, its performance was tested under various cutting conditions.

Generally, a worn tool is not a catastrophic event and when detected, it is usually possible to continue machining to the end of the current operation.

This is a typical TCM system where the sensor is used to collect the signals during milling through a data acquisition module.

The signal processing module analyses the machining signals for extracting features sensitive to tool wear.

The features, together with the machining parameters, constitute the data set to be used as input to the decision system and the estimator. The main purpose of the decision system and the estimator is to map the input features to the current state of tool, i.e. the amount of tool wear. A multi-layer perceptron neural network with the backpropagation algorithm is used in TCM as a decision system due to its ability of learning [11], noise suppression and parallel processing.

The advantages of the multi-layer perceptron are described in [12].

A random pattern classifier module divides the data into a training and a testing set.

The training set is used for learning purposes while the testing set is used for testing the decision system performance.

ANFIS modelling algorithm

Using a given input/output data set, the ANFIS method constructs a fuzzy inference system (FIS) whose membership function parameters are adjusted by using the backpropagation algorithm. This allows fuzzy systems to learn from the data they are modelling.

The FIS structure is a network-type structure, which maps inputs through input membership functions and associated parameters, and then through output membership functions and associated parameters to outputs.

Figure 3 shows the fuzzy rule architecture of ANFIS when the triangular membership function is adopted. The architectures shown in Figure 3 consist of 31 fuzzy rules.

The process variables are force sensor readings (F_R), cutting speed (v), feed rate (f), depth of cutting (A_D/R_D), machining time and flank wear (w_B). The domain of definition of these variables is normalized in the range (0,1), where 1 corresponds to the maximal value of that variable.

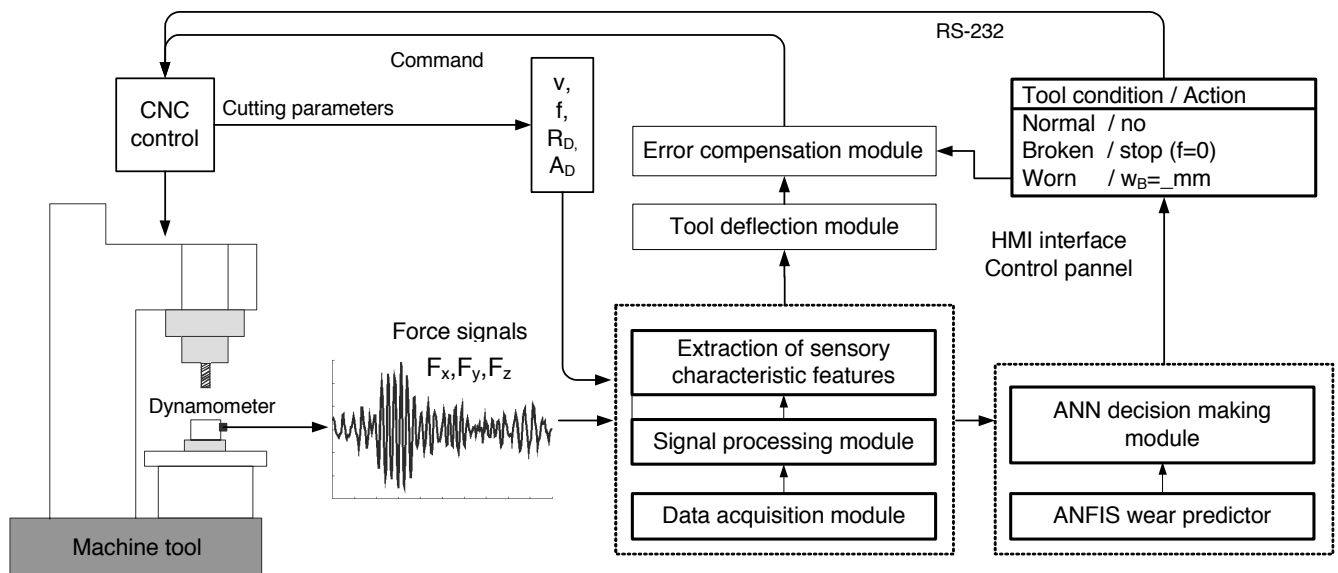


Fig. 2. Architecture of tool condition monitoring system

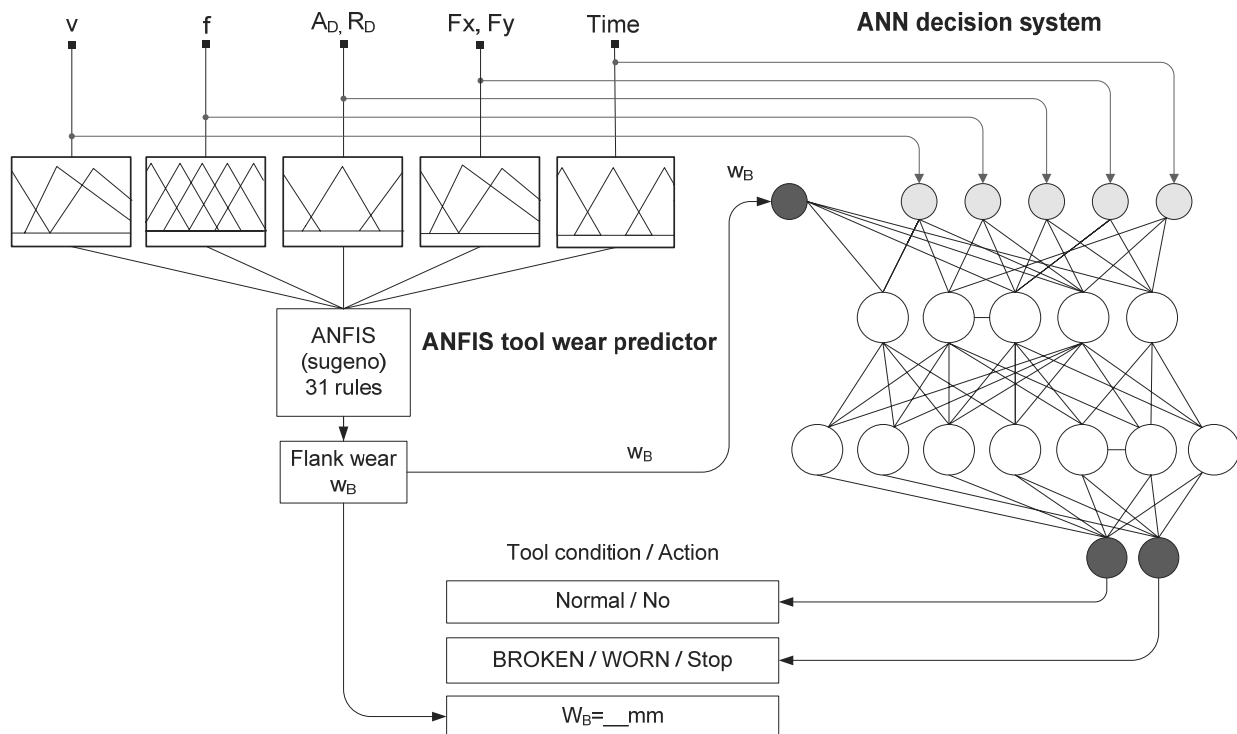


Fig. 3. Components of TCM (In-process ANFIS predictor and ANN decision system)

For a first-order Sugeno fuzzy model, a typical rule set with 31 fuzzy rules can be expressed as:

Rule i :

IF (v is A_i) AND (f is B_i) AND (A_D/R_D is C_i) AND (F_R is D_i) AND ($Time$ is E_i) THEN

$$w_{Bi} = p_i v + q_i f + r_i A_D/R_D + s_i F_R + t_i Time$$

where $i=1...31$; p_i, q_i, r_i, s_i and t_i are linear parameters and A_i, B_i, C_i, D_i, E_i are nonlinear parameters.

The ANFIS architecture is explained in detail in [13]. ANFIS applies two techniques in updating parameters.

For the premise parameters that define the membership functions, ANFIS employs gradient descent to fine-tune them.

For each consequent parameter that defines the coefficients of each output equation, ANFIS uses the least-squares method to identify parameter. This approach is thus called Hybrid Learning method because it combines the gradient descent method and the least-squares method [14].

ANFIS modelling algorithm

The modelling process starts by selecting a data set (input-output data pairs) and dividing it into a training data set and a testing data set. The training data set is used to find initial premise parameters for the membership functions by equally spacing each of the membership function. A threshold value for the error between the actual and the desired output is determined. Consequent parameters are found by using the least-squares method. Then, an error for each data pair is found. If this error is larger than the threshold value, update the premise parameters

using the gradient descent method as the following ($Q_{next} = Q_{nov} + \eta d$, where Q is a parameter that minimizes the error, η the learning rate, and d is a direction vector). The process is terminated when the error becomes less than the threshold value. Then, the testing data set is used to compare the model with the actual system. During training in ANFIS, 150 sets of experimental data were used to conduct 500 cycles of learning.

The findings are analysed and discussed in Section 5.

The neural decision-making system was developed with Matlab software. The neural network used to predict the cutting tool condition is shown in Figure 3. It has tool-breakage detection capability and is based on pattern recognition. The neural network stores a number of reference force patterns that are characteristic of tool breakage. When a tool tooth breaks, the cutting force suddenly rises for a while and then drops to zero. The system continuously monitors the signal for a break pattern. If the pattern is identified, a break is declared within 10 ms of the breakage.

Four steps were required to develop a neural decision system. In step 1, the network architecture and prediction factors were selected. The network had two hidden layers and used a set of 5 normalized inputs for tool condition prediction: (1) cutting speed, (2) feed rate, (3) depths of cut, (4) forces, (5) tool wear. The output layer consisted of only two neurons: (1) normal and (2) broken/worn.

In step 2, the learning rate, momentum factor and the number of hidden layers/hidden neurons were defined. The number of hidden neurons was set at 12, the learning rate was set at 1, and the momentum item was 0.4. The number of training/testing cycles was 1700.

In step 3, the data set was divided into the training and the testing set. 200 data points were used in this study. Good tools collected half of these and broken tools collected the rest. All the data were scaled.

It is very difficult to mimic the moment of chipping or breaking in an experiment. Therefore, in this study, first, the normal tool cuts a part of the workpiece. After confirming that the system classified normal cutting state, the cutter was retracted to remove one insert. After that, it was checked whether the monitoring system classified abnormal cutting state. The same process was repeated with the cutter whose one side worked and the other was broken. The broken side of the tool possessed varying degrees of breakage (0.5 mm x 0.5 mm; 1.5 mm x 1.5 mm; 1.5 mm x 2 mm). The damage was limited to the cutting edge. Damage observed on the rake surface, such as crater wear, was quite limited. There were six cutting passes performed for the down milling cases and four cutting passes performed for the up milling cases. Within these cutting passes performed, the wear propagation was almost linearly related to the cutting time for both the down milling and the up milling. For the cases of down milling, the width of flank wear was about 0.1mm after the first cutting pass. After the sixth cutting path, the width of flank wear was about 0.3 mm. For up milling, the development of tool wear was more rapid compared with that for down milling. The width of flank wear was over 0.2 mm even after the first cutting pass. After the fourth cutting pass, it reached as high as 0.5 mm, compared with the width of flank wear of only 0.19-0.25 mm for the down milling cases after the same cutting pass.

In step 4, the training and testing phase is accomplished. During the training stage, the neural network adjusted its internal weight values to give correct output results according to the input features. Finally, in the last step the trained neural network was used to predict tool conditions.

3.2. Tool deflection module

The main objective of the deflection module is to determine the deflection of end mills under milling forces. For the deflection analysis of end mills, the tool holder is assumed to be rigid and the cantilever beam model is used. However, the holder and the clamping stiffness can also be included in the analysis if they are known.

End mill deflections can be approximated by using the beam model. The loading and the boundary conditions of the end mill used in the model are shown in Figure 4, where $D1$ is the mill diameter, $D2$ is the shank diameter, $L1$ is the flute length, $L2$ is the overall length, F is the point load. Modelling can be unpractical and time consuming for each tool configuration in a virtual machining environment. Therefore, simplified equations are generated to predict deflections of tools for given geometric parameters and density. The static characteristics of end mills can be shown as:

$$X_m = \text{deflection}_{\max} = C \frac{F}{E} \left[\frac{L1^3}{D1^4} + \frac{(L2^3 - L1^3)}{D2^4} \right]^N \quad (1)$$

where F is the applied force and E is the modulus of elasticity (MPa) of the tool material. The geometric properties of the end mill are in mm. The constant C is 9.05, 8.30 and 7.93 and constant N is 0.950, 0.965 and 0.974 for 4-flute, 3-flute and 2-flute tools, respectively [5].

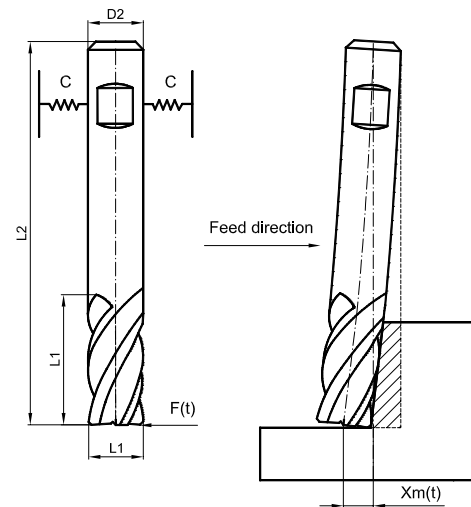


Fig. 4. Cutting force induced tool deflection

3.3. Error compensation module

The developed module (see Figure 2) aims at facilitating the compensation of surface errors in machining caused by tool deflection and tool wear [5]. The measured cutting forces are fed into a deflection model for the prediction of dynamic behaviour of the tool during cutting. An iterative procedure is used to determine the milling error through trial and error of the cutting force and deflection. The predicted deflected tool profile is used to identify the “real” material volume that is removed during machining. As soon as the milling error is obtained, the error compensation can be achieved by optimising the tool path or by feed rate adjustment.

Both modifications lead to changes of cutting conditions. Figure 5 shows an instance of the tool path with and without compensation. Due to cutting force-induced tool deflections, some amount of material will be left on the desired surface (surface error) as shown in Figure 5a. In this case, the resulted milled profile (actual profile) will be different from the desired profile and the error depends on many factors, such as cutting conditions, tool material, tool overhang, etc. In order to reduce the error between actual and desired profiles, one can offset the tool towards the machined surface by an amount which depends on the local surface error. It is necessary to compute the amount of offset or compensation along the entire path of cut.

The second way is to adjust (decrease) the feed rate in sections where the predicted tool deflection is the greatest thus avoiding surface error.

The compensation procedure steps can be formulated as an algorithm as shown below:

1. Measure the cutting forces;
2. predict the tool deflection;
3. compare the difference between ideal tool position and deflected tool position with the prescribed tolerance value; if the difference is within the tolerance value then go to step 1, or else reduce the feed rate or modify the tool position;
4. go to step 1.

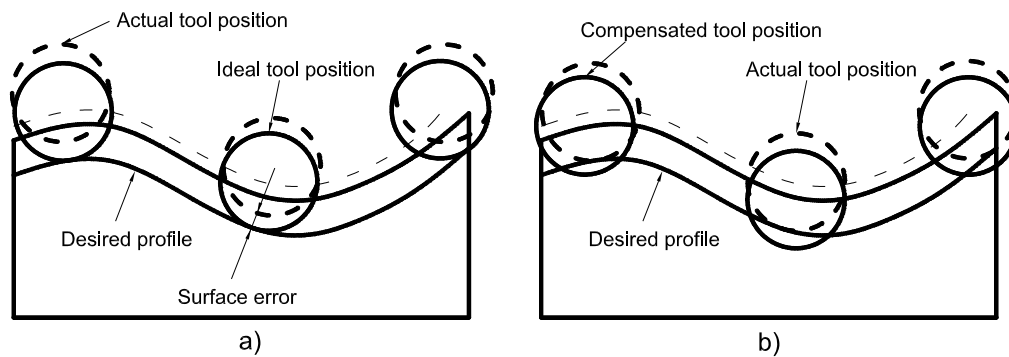


Fig. 5. Final surface profile before and after compensation; a) without compensation, b) with compensation

The machining experiments were conducted on a variety of variable curvature surfaces to assess the compensation module and also to know the extent of possible improvement in accuracy of machined parts. In carrying out machining experiments, it is necessary to distinguish between two types of curved geometries, namely convex and concave geometries. Here, the concave type of geometry is the one in which the local centre of curvature of a workpiece and the tool centre lie on the same side. Cutter deflections and surface error were estimated based on the methodology discussed earlier. The workpiece geometry was first machined without compensation. Subsequent to machining, surface error was measured along the entire path of cut. The measured surface error values were compared with the estimated values.

4. Experimental design

Experiments were performed on a HELLER machine tool (type BEA1) with FAGOR CNC controller.

The monitoring involved an end milling process of steel parts using two end mill tools [15]: a normal tool and a tool with a broken tooth. The cutting tool used in the machining test was a solid end milling cutter (R216.24-16050 IAK32P) with four cutting edges. The tool diameter was 16 mm. Its helix angle was 10° .

The corner radius of the cutter was 4 mm. The insert had an outer coated layer of TiN exhibiting low friction and welding resistance. The workpiece material used in the machining test was Ck 45 and Ck 45 (XM) with improved machining properties. Workpieces were cut off from a warm-rolled bar. The dimension of the workpiece was 200 mm \times 70 mm \times 70 mm. The workpiece was mounted in a 3 component piezoelectric dynamometer (Kistler 9255) to monitor the cutting forces in the X and Y directions. The force dynamometer was mounted on the machining table and connected to a 3-channel charge amplifier.

The signals were monitored by using a fast data acquisition card (National Instruments PC-MIO-16E-4) and software written with the National Instruments CVI programming package. The experimental set-up is shown in Figure 2. Flank wear was observed during the experiments. The cutting tool flank wear was discontinuously measured with a tool microscope of 0.01 mm accuracy. The machining tests were carried out in two types of end milling operations: down milling and up milling operations. The experiments were carried out for all combinations of the chosen

cutting parameters and tool wear. In the experiments the cutting parameters were set as [16-19]: 0.45 mm/tooth, four levels of cutting speed ($v_1=200$, $v_2=360$, $v_3=340$ and $v_4=480$ min^{-1}) and three levels of 0.45 mm/tooth, four levels of cutting speed ($v_1=200$, $v_2=360$, $v_3=340$ and $v_4=480$ min^{-1}) and three levels of radial/axial depth of cut ($R_{D1}=1d$, $R_{D2}=0.5d$, $R_{D3}=0.25d$; $A_{D1}=2$, $A_{D2}=4$, $A_{D3}=8$ mm; $d=16$ mm-cutting parameter).

The parameters such as tool diameter, rake angle, etc. were kept constant.

5. Results and discussion

The in-process sensing technique together with a decision-making system are essential for the successful operation of TCM. The neural network was capable of detecting tool conditions accurately in real time.

The accuracy of the training data was 98.1%, and the accuracy of the testing data was 94.9%.

The results of the neural network testing are shown in Table 1.

The output node value of a backpropagation neural network was mapped as 0.01 for the normal cutting state and 0.99 for the tool breakage.

When the neural network outputs are over 0.9 (tool breakage), the neural network sends the signal "Tool broken" to the PC. When both neural network outputs are below 0.9, the neural network sends the signal "Tool condition Normal".

The reason why values over 0.9 were recognized as the abnormal state is that the cutter with severe flank wear increases power at frequencies higher than tooth-passing frequency, so that the neural network may decide about the states incorrectly.

To evaluate the effects of the threshold value on the performance of the neural decision-making system, about 45 experimental tests were carried out. From the results the following conclusions can be drawn:

- The optimum threshold value ranges from 0.87 to 0.92,
- The decision system with a threshold value of 0.9 gives the smallest tool failure prediction errors. Experimental tests have confirmed that this method with the 0.9 threshold has monitored tool breakage very accurately. Figures 6a and 6b represent the cutting force signals for the normal and the broken tool. The developed decision system incorporates simple fixed limits for the tool breakage detection.

Table 1.
Partial results of TCM testing (ANFIS wear prediction and ANN tool condition estimation)

| Tool conditions | Input factors | | | | | ANN outputs | | ANN prediction | ANFIS prediction W_B , mm |
|-----------------|---------------|-------------------------|--------------|------------|------------|-------------|---------|----------------|-----------------------------|
| | F , N | n , min^{-1} | F , mm/rev | A_D , mm | R_D , mm | ANN_1 | ANN_2 | | |
| Normal | 427.2 | 440 | 0.17 | 1.2 | 8 | 0.9 | 0.1 | Normal | 0.11 |
| Broken | 777.9 | 440 | 0.17 | 1.2 | 8 | 0.02 | 0.98 | Broken | 0.24 |
| Normal | 433.9 | 440 | 0.13 | 1.4 | 8 | 0.3 | 0.7 | Broken | 0.17 |
| Broken | 729.6 | 440 | 0.13 | 1.4 | 8 | 0 | 1 | Broken | 0.26 |
| Normal | 650.5 | 440 | 0.20 | 1.4 | 8 | 0.89 | 0.11 | Normal | 0.13 |
| Broken | 925.7 | 440 | 0.20 | 1.4 | 8 | 0 | 1 | Broken | 0.27 |
| Normal | 614.4 | 480 | 0.20 | 1.4 | 8 | 0.88 | 0.12 | Normal | 0.15 |
| Broken | 751.9 | 480 | 0.20 | 1.4 | 8 | 0.03 | 0.97 | Broken | 0.23 |
| Normal | 904.3 | 360 | 0.22 | 1.6 | 8 | 0.89 | 0.11 | Normal | 0.14 |
| Broken | 991.9 | 360 | 0.22 | 1.6 | 8 | 0 | 1 | Broken | 0.31 |

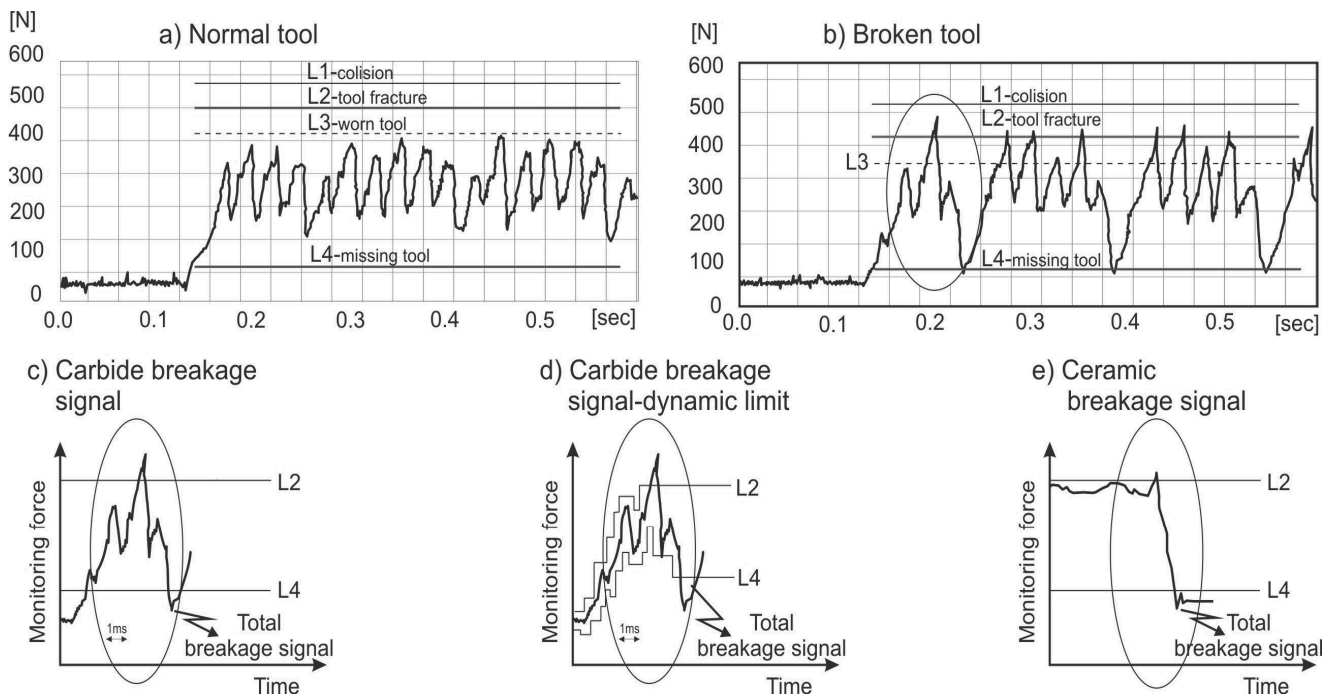


Fig. 6. Thrust force of normal (a) and broken (b) tool in real time monitoring; (c) Indicative tool breakage force pattern with limits; (d) Dynamic limit strategy; (e) Indicative tool breakage force pattern – ceramic

The limits are: L1 (collision), L2 (tool fracture), L3 (worn tool) and L4 (missing tool limit).

In this study, the ANFIS system is used to predict the flank wear of the tool in an end milling process.

A total of 150 sets of data were selected from the total of 300 sets obtained in the end milling experiments for the purpose of training in ANFIS. The other 150 sets were then used for testing after the training was completed to verify the accuracy of the predicted values of flank wear. The experimental results indicate that the proposed ANFIS model has a high accuracy for estimating flank wear with short computational time. Figure 7 shows the scatter diagram of the predicted values and the measurement values of flank wear of 150 sets of testing data when triangular membership functions are used in ANFIS.

It shows that the predicted values of flank wear between 0.15 and 0.4 all follow the 45° line very closely. In other words, the predicted values are not far from the experimental measurement values (Figure 8).

5.1. Quantitative effect of tool flank wear on the cutting forces

The study further evaluates the three dynamometer cutting force components in order to identify which component is the most sensitive to tool wear. The study also shows that tool flank wear results in a substantial increase in the force components and

that the maximal thrust force is more sensitive to tool flank wear. These findings are used as a primary basis for developing the tool condition monitoring strategy.

Figure 9 shows the evolution of cutting forces, F_x , F_y and F_z with the tool flank wear ($w_B = 0, 0.1, 0.2$ and 0.3 mm).

It can be noted that the cutting forces increase with the tool flank wear.

This result is in agreement with the experimental results found by [17]. It is believed that the increase in the force components with wear land size is a result of the secondary rubbing or ploughing process between the wear land and the workpiece.

Quantitative comparisons have been carried out based on the percentage increase in the “as measured” force components for cutting tools with a wear land with respect to those of “sharp” tools.

It is apparent that average deviations in the maximal cutting force component are noticeable with about 11.7 and 21.36% for 0.4 and 0.6 mm wear land sizes, respectively, as compared to the sharp tool cutting.

The corresponding thrust force component shows similar trends, but with increased average deviations for the two wear land sizes (18.2 and 32.6%, respectively).

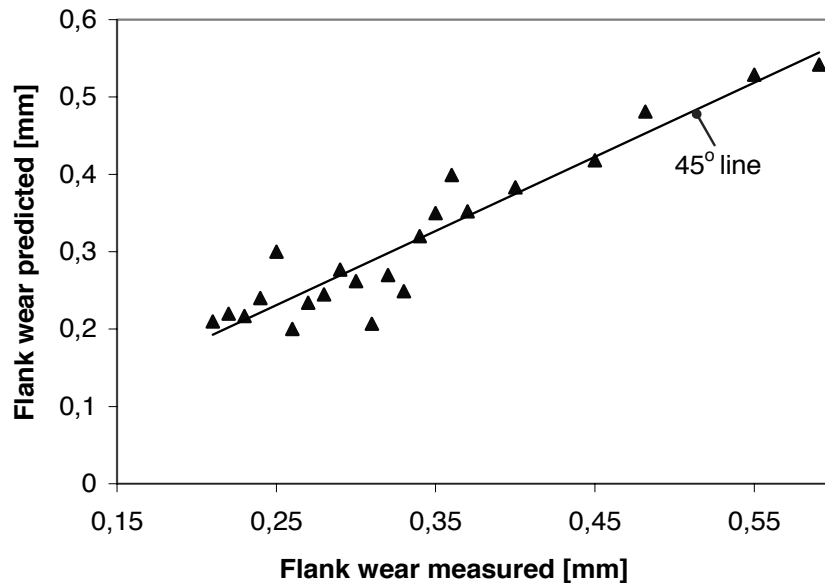


Fig. 7. Scatter diagram of measured w_B and predicted for testing data using triangular membership function

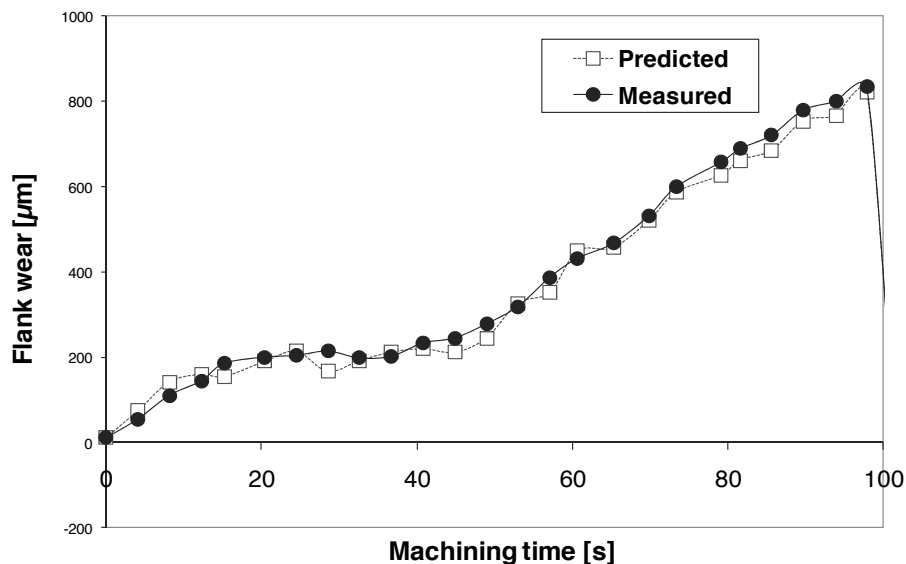


Fig. 8. Comparison of measured and predicted flank wear ($v=180$ m/min, $AD=2$ mm, $f=0.1$ mm/tooth)

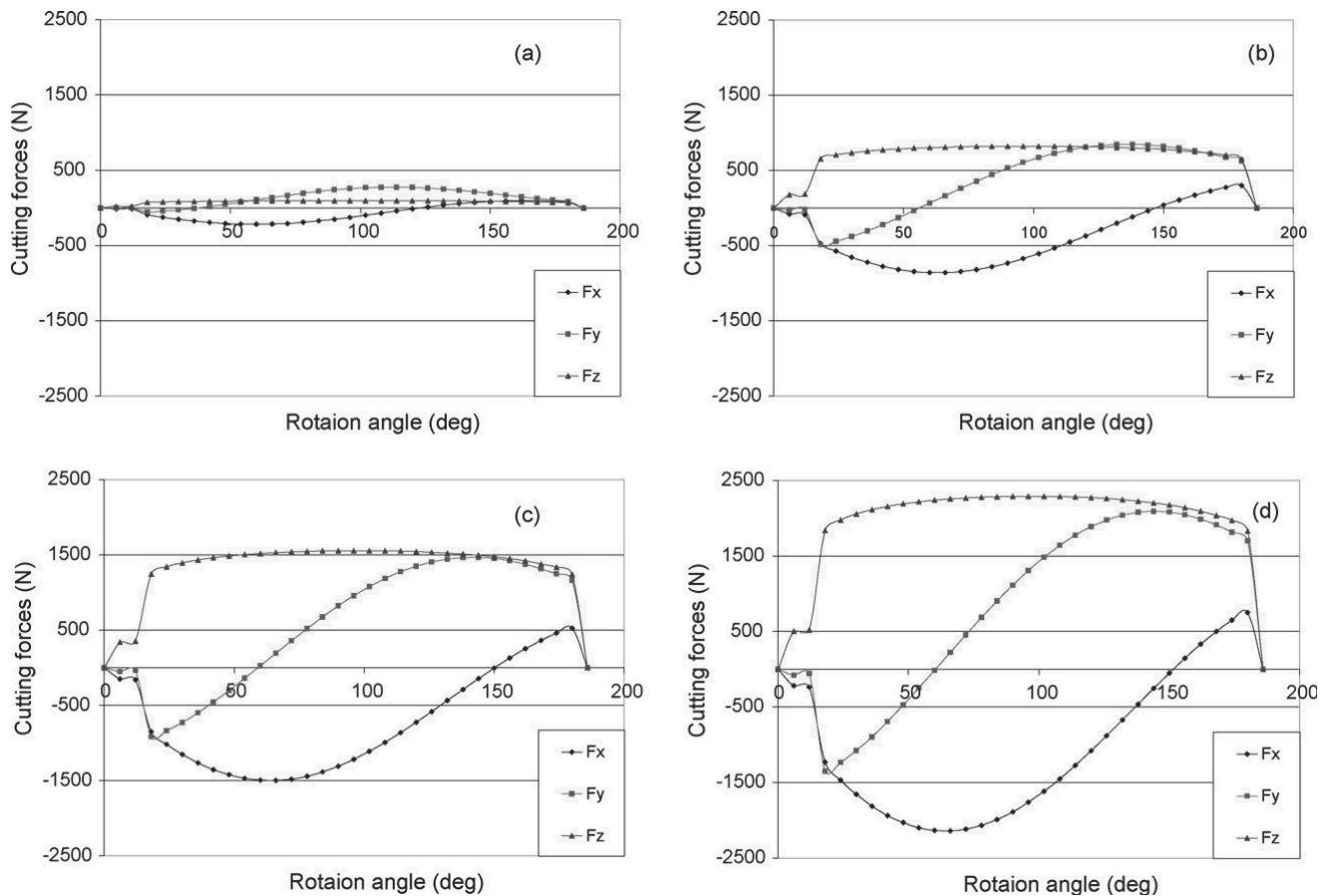


Fig. 9. Effect of tool flank wear on cutting forces (F_x , F_y and F_z) cutting parameters: (a) $w_B = 0$ mm, (b) $w_B = 0.1$ mm, (c) $w_B = 0.2$ mm and (d) $w_B = 0.3$ mm

6. Conclusions

A system for monitoring tool condition in real time was developed and the following results were obtained through verification experiments:

- (1) The proposed monitoring system of a cutting process may be very useful because of its parallel processing capability;
- (2) It enables monitoring of the cutting process with high reliability; the ANFIS component can estimate the flank wear progress very fast and accurately, once the maximum cutting forces are known.

A monitoring system using a neural network is able to classify various cutting states, such as tool breakage and tool wear. In future, different decision making tools, such as fuzzy logic, should be applied to see which one could obtain a smaller error of detection.

The following conclusions can be drawn from the analysis:

- Flank wear could efficiently be predicted by using cutting conditions and forces as the fuzzy input variables in the ANFIS system.
- The error of the tool wear values predicted by ANFIS with the triangular membership function is only 4%, reaching accuracy as high as 96%.

- When the trapezoidal membership function was adopted, the average error was around 5.4%, with an accuracy of 94.6%.
- The ANFIS system could predict flank wear for different cutting conditions with an average percentage deviation of 4.7%, or an accuracy of 95.3%.
- The predicted flank wear was found significantly sensitive to the measured maximum cutting forces (radial), especially the thrust cutting component (F_x).

This study also briefly presents a compensation method in milling in order to take into account tool deflection during cutting condition optimization or tool path generation.

The results indicate that surface errors due to tool deflections can be reduced by 65-78%.

The presented research will be useful in many industrial scenarios to achieve quality parts without sacrificing productivity.

References

- [1] P. Fu, A.D. Hope, Intelligent Classification of Cutting Tool Wear States, *Advances in Neural Networks* 39 (2008) 1611-3349.

- [2] T. Mulc, T. Udiljak, F. Cus, M. Milfelner, Monitoring cutting-tool wear using signals from the control system, *Strojniški vestnik – Journal of Mechanical Engineering* 12 (2004) 568-579.
- [3] R.J. Kuo, Multi-sensor integration for on-line tool wear estimation through artificial neural networks and fuzzy neural network, *Engineering Applications of Artificial Intelligence* 3 (2003) 49-261.
- [4] S. Achiche, M. Balazinski, L. Baron, K. Jemielniak, Tool wear monitoring using genetically-generated fuzzy knowledge bases, *Engineering Applications of Artificial Intelligence* 15 (2008) 303-314.
- [5] J. Kopac, Cutting forces and their influence on the economics of machining, *Strojniški vestnik – Journal of Mechanical Engineering* 3 (2002) 72-79.
- [6] A. Iqbal, N. He, N. Dar, L. Li, Comparison of fuzzy expert system based strategies of offline and online estimation of flank wear in hard milling process, *Expert Systems with Applications* 33 (2009) 61-66.
- [7] R.E. Haber, A. Alique, Intelligent process supervision for predicting tool wear in machining processes, *Mechatronics* 13 (2005) 825-849.
- [8] W.-T. Chien, Ch.-S. Tsai, The investigation on the prediction of tool wear and the determination of optimum cutting conditions in machining 17-4PH stainless steel, *Journal of Materials Processing Technology* 140/1-3 (2005) 340-345.
- [9] F. Čuš, U. Župerl, Adaptive self-learning controller design for feedrate maximization of machining process, *Advances in Production Engineering & Management* 2 (2007) 18-27.
- [10] M. Smaoui, Z. Bouaziz, A. Zghal, Simulation of cutting forces for complex surfaces in ball-end milling, *International Journal of Simulation Modelling* 7/2 (2008) 93-105.
- [11] U. Župerl, F. Čuš, Tool cutting force modelling in ball-end milling using multilevel perceptron, *Journal of Materials Processing Technology* 153/154 (2004) 268-275.
- [12] M. Norgaard, O. Ravn, N.K. Poulsen, L.K. Hansen, *Neural networks for modelling and control of dynamic systems*, Springer, London, 2000.
- [13] F. Dweiri, M. Al-Jarrah, H. Al-Wedyan, Fuzzy surface roughness modeling of CNC down milling of Aluminic-79, *Journal of Materials Processing Technology* 133 (2001) 266-275.
- [14] M.A. Shoorehdeli, M. Teshnehlab, A.K. Sedig, A. Khanesar, Identification using ANFIS with intelligent hybrid stable learning algorithm approaches and stability analysis of training methods, *Applied Soft Computing* 2 (2001) 833-850.
- [15] R. Sirkant, S. Subrahmanyam, K. Chen, V.P. Krishna, Experimental selection of special geometry cutting tool for minimal tool wear, *Advances in Production Engineering & Management* 5/1 (2010) 13-24.
- [16] M. Milfelner, U. Zuperl, F. Cus, Optimisation of cutting parameters in high speed milling process by GA, *International Journal of Simulation Modelling* 3/4 (2004) 121-131.
- [17] J. Wang, C.Z. Huang, W.G. Song, The effects of tool flank wear on the orthogonal cutting process and its practical implications, *Journal of Materials Processing Technology* 142 (2003) 338-346.
- [18] L.A. Dobrzański, K. Golombek, J. Kopac, M. Sokovic, Effect of depositing the hard surface coatings on properties of the selected cemented carbides and tool cermets, *Journal of Materials Processing Technology* 157-158 (2004) 304-311.
- [19] J. Kopac, Influence of high speed cutting on the structure of machined high speed steel material, *Proceedings of the 11th International Scientific Conference “Contemporary Achievements in Mechanics, Manufacturing and Materials Science” CAM3S’2005, Gliwice – Zakopane, 2005, 40-44.*