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Real-Time Cutting Tool Condition Monitoring in Milling

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Reliable tool wear monitoring system is one of the important aspects for achieving a self-adjusting manufacturing system. The original contribution of the research is the developed monitoring system that can detect tool breakage in real time by using a combination of neural decision system and ANFIS tool wear estimator. The principal presumption was that force signals contain the most useful information for determining the tool condition. Therefore, the ANFIS method is used to extract the features of tool states from cutting force signals. ANFIS method seeks to provide a linguistic model for the estimation of tool wear from the knowledge embedded in the artificial neural network. The ANFIS method uses the relationship between flank wear and the resultant cutting force to estimate tool wear. A series of experiments were conducted to determine the relationship between flank wear and cutting force as well as cutting parameters. Speed, feed, depth of cutting, time and cutting forces were used as input parameters and flank wear width and tool state were output parameters. The forces were measured using a piezoelectric dynamometer and data acquisition system. Simultaneously flank wear at the cutting edge was monitored by using a tool maker's microscope. The experimental force and wear data were utilized to train the developed simulation environment based on ANFIS modelling. The artificial neural network, was also used to discriminate different malfunction states from measured signals. By developed tool monitoring system (TCM) the machining process can be on-line monitored and stopped for tool change based on a pre-set tool-wear limit. The fundamental limitation of research was to develop a singlesensor monitoring system, reliable as commercially available system, but 80% cheaper than multisensor approach.

Keywords: end-milling, tool condition monitoring (TCM), wear estimation, ANFIS

0 INTRODUCTION

The demand to reduce production costs has driven manufacturers to automate most operations previously controlled by skilled operators. Therefore, the Unmanned Flexible Manufacturing Systems (UFMS) have been developed. In such 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. A tool condition monitoring system (TCM) is a fundamental requirement for the control of the machining process.

The main goal of developing TCM systems is to increase productivity and hence competitiveness by maximizing tool life, minimising down time, reducing scrappage and preventing damage. The traditional ability of the operator to determine the condition of the tool based on their 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 and unloading parts for several machines in a manufacturing cell, meaning that their reaction time to a problem with any one machine will not be sufficient for the speed at which machining operations take place on modern machine tools.

Each TCM system consists of: sensors, signal conditioners/amplifiers and a monitor [1]. The monitor uses a strategy to analyse the signals from the sensors and to provide reliable detection of tool and process failures. It can be equipped with some signal visualisation system and is connected to the machine control.

Many studies have been conducted on 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. Current research in TCM is oriented towards the development of online TCM techniques.

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There are two techniques for tool wear sensing: direct and indirect. The direct technique includes measuring the actual wear, using radioactive analyses of the chip. Generally direct measurements are avoided because of difficulty of online measurements. For indirect methods of TCM, the following steps are followed: use of single or multiple sensors [3] to capture process information; use of signal processing methods to extract features from the sensor information; use of decision-making strategy to utilise extracted featured for prediction of tool failure. 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 spindle or feed motors and roughness of the machined surface [4]. Recent trend in TCM is a multisensory approach which is termed as 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 the 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 contain 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 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] developed an approach based on the least-squares regression for estimating tool wear in machining while 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 for 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 research 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 process. This model offers an ability to estimate tool wear as its neural network based counterpart but provides an additional level of transparency that neural networks fails 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 an indicator of the tool flank wear variation.

1 MONITORING SYSTEM COST AND SENSORS JUSTIFICATION

The ability of a TCM system relies on two basic elements: first, the number and type of sensors used and second, the associated signal processing and simplification methods utilised to extract the necessary important information from machining signals [3]. The first element involves expensive hardware which influences the cost of the system, whereas the second element affects the efficiency and the speed of the system. The main issue here is to design a condition monitoring system with high efficiency, short development time, and with a reduced number of sensors. This basically includes a selection of sensors and associated signal processing methods which provide the minimum classification error of process faults.

Most commonly used, in TCM systems, are sensors measuring cutting force components or quantities related to cutting force (power, torque, distance/displacement and strain). They are relatively easy to install in existing or new machines, and do not influence machine integrity and stiffness. Piezoelectric force sensors are well adjusted to harsh machine tool environment.

Monitoring systems developed in laboratories, are often multisensor systems embodying complex AI-based strategies to integrate information, extract features and make more reliable decisions on the state of the tool. In commercially available systems, the one sensor–one tool approach dominates. Multisensor here means providing the best sensor for each application. Only one manufacturer “wear estimator” uses more than one signal for monitoring the wear of one tool (exclusively for turning).

The goal of developing the TCM is not only to produce a reliable monitoring system, but also to keep the system as cheap as possible. In order to do this, the utilisation of sensors in the system should be kept relatively low (i.e. there is no need to maximise the number of sensory characteristic features used from an implemented sensor). The sensor utilisation factor (SUF) [3] is a function of: the number of sensory features used from the sensor (NSF), the total number of sensory features in the system (TNSF) and the number of signals which can be physically produced by the sensor (NS). It is found out that SUF factor is very useful in reducing the cost of the TCM by removing sensors which do not produce sufficient useful signals. The cost analysis is calculated using the variable cost of the system (costs of sensors). The fixed costs such as the PC, data acquisition card, and the software cost should be added to the nominal variable cost to acquire the total cost of the system. If a cheaper TCM with good performance is needed it is essential to make a compromise between cost and systems performance.

From our calculation it is obvious that the force dynamometer is the most utilised sensor. It has been found that the proposed sensor system has the lowest cost of 4,612 € but has an error of 20.21%. On the other hand the multisensor approach has an error of 9.01% but it has a high nominal cost of 23,524 €. Comparing both systems it can be seen that an improvement of 11.20% has caused an increase in the system cost of 18,912 €. Therefore, it is essential to compromise between cost and performance of the systems if a cheaper system with good performance is needed. The new system is 18,912 € cheaper than the cheapest multisensor monitoring approach.

2 PROBLEM DEFINITION

End-milling is 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 (Fig. 1).

Cutting parameters and tool conditions affect the magnitude of resultant force. Therefore, the resultant force F_R, generated from X and Y directions, is used in this experiment for detecting 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 cutter. 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 differ between good and broken tools [10]. Maximum peak force of a broken tool must be larger than that of a good tool.

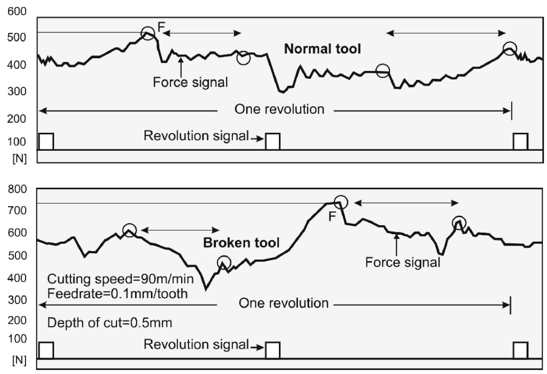

Fig. 1. *Cutting force signal of a good and damaged cutter (cutter diameter = 16 mm)*

Fig. 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 machining parameters were selected as input factors.

3 METHODOLOGY AND SYSTEM COMPONENTS

The proposed approach consists of two main steps: First, 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 subsequently merged with a neural network for estimating tool wear condition (fresh, worn). Fig. 2 shows the basic architecture of the proposed system.

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 estimator. The main purpose of the decision system and 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 backpropagation algorithm is used in TCM as a decision system due to its ability of learning, noise suppression and parallel processing. A random pattern classifier module divides the data into training and testing set. The training set is used for learning the purpose while the testing set is used for testing the decision system performance.

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, 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.

In this model, we adopted two different types of membership functions for analysis in ANFIS training and compared their differences regarding the accuracy rate of the flank wear prediction. After training the estimator, its performance was tested under various cutting conditions. The performance of this method turned out to be satisfactory for evaluating flank wear, within a 5% mean percentage error. 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.

3.1.1 ANFIS Arhitecture and Learning Method

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

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

ANFIS applies Hybrid Learning method for updating parameters. For premise parameters

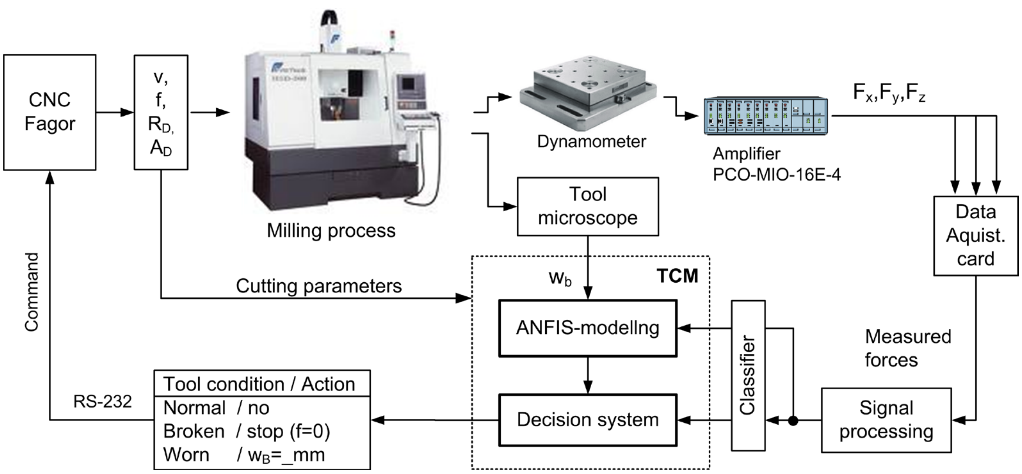

Fig. 2. *Architecture of tool condition monitoring system*

that define membership functions, ANFIS employs gradient descent to fine-tune them. For consequent parameters that define the coefficients of each output equations, ANFIS uses the least-squares method to identify them.

This approach is thus called Hybrid Learning.

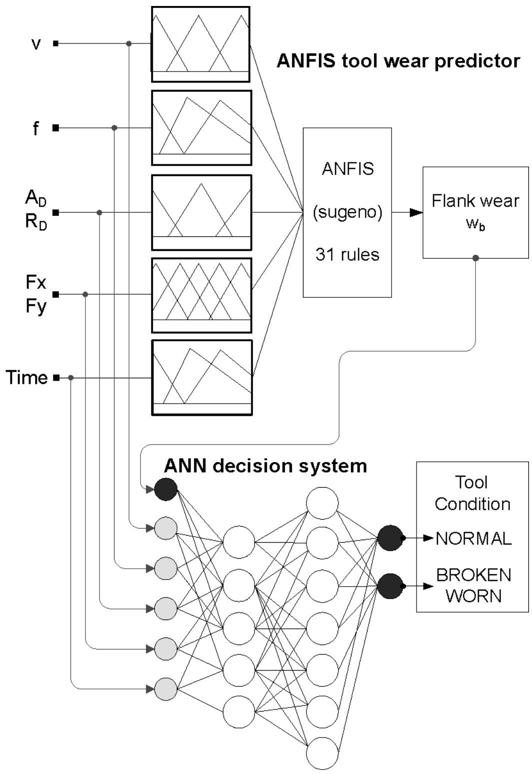

Fig. 3. *Components of TCM (in-process ANFIS predictor and ANN decision system)*

3.1.2 ANFIS Modeling Algorithm

Modeling process starts by selecting a data set (input-output data pairs) and dividing it into training and testing data sets. The training data set is used to find the initial premise parameters for the membership functions by equally spacing each of the membership functions. A threshold value for the error between the actual and desired output is determined. The consequent parameters are found 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 decent method as the following (Q_{next}=Q_{nov}+η_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 actual system.

During training in ANFIS, 150 sets of experimental data were used to conduct 500 cycles of learning.

The findings are analyzed and discussed in the fourth chapter.

3.2 Neural Decision System Development

A neural decision-making system was developed in Matlab software. The neural network used to predict the cutting tool condition is shown in Fig. 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, cutting force suddenly rises for a while, and then drops to zero. The system continuously monitors the signal for the break pattern. If a pattern is identified, a break is declared within 10 ms of the breakage.

Four steps are required to develop a neural decision system. In step one, network architecture and prediction factors were selected. The network has two hidden layers and uses 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. Output layer consist 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 training and testing set. 200 data points were used in this research. Good tools collected half of these and broken tools collected the rest. All the data were scaled.

In step 4 the training and testing faze 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.

4 EXPERIMENTAL DESIGN

Monitoring experiments were performed on a HELLER machine tool (type BEA1) with FAGOR CNC controller. It involved an end-milling process of steel parts using two end-mill cutters [11]: normal and on tooth broken. 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 featuring 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 × 70 × 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. Force dynamometer was mounted on the machining table and connected to a 3-channel charge amplifier. The signals were monitored using a fast data acquisition card (National Instruments PC-MIO-16E-4) and software written with The National Instruments CVI programming package.

The force measurements were sampled at 15000 points/second, then digitally low-pass filtered at a cut-off frequency of 400 Hz to eliminate the high-frequency components resulting from the machine tool dynamics.

The measured force signals were digitized using an A/D converting board at 1 kHz sampling rate for each channel. The experimental set-up is shown in Fig. 2.

The 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 experiments were carried out for all combinations of the chosen cutting parameters and tool wear.

In the experiments the cutting parameters were set as [12]: four level of feed rate (f_1 = 0.05, f_2 = 0.25, f_3 = 0.35, f_4 = 0.45 mm/tooth), four level of spindle speed (n_1 = 200, n_2 = 360, n_3 = 340 and n_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). Parameters such as tool diameter, rake angle, etc. are kept constant.

The sampling frequency was 400 Hz and total numbers of 83 data points were used for signal processing at the spindle speed of 360 min^{-1}, and 45 data points at 580 min^{-1}. The number of data points is the total sampled during one revolution of a spindle with a 0.0025 s sampling interval.

5 RESULTS AND DISCUSSION

In-process sensing technique in connection with decision-making system is essential for

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

the successful operation of TCM. The neural network was capable of detecting tool conditions accurately in real time. The accuracy of training data was 98.1%, and the accuracy of testing data was 94.9%. The results of neural network testing are shown in Table 1. The output node value of a back-propagation 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), it sends the signal "Tool broken" to the PC. When both the neural network outputs are below 0.9, it sends the signal "Tool condition Normal".

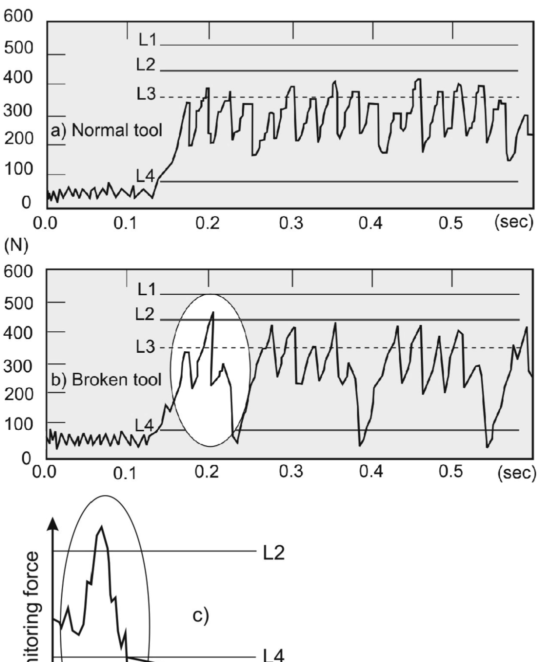

Fig. 4. *Thrust force of a) normal and b) broken tool in real time monitoring, c) indicative tool breakage force pattern with limits*

Figs. 4a and b represent the cutting force signals for the normal and broken cutter. Cutting conditions used in the experiments are: spindle speeds of 360 min^{-1}, and feed rates of 187 mm/min. Neural network takes 0.1575 s to accumulate 83 data points in one buffer using the sampling time of 0.0025 s under the cutter rotation of 360 min^{-1}. Total processing time is 0.143 s for processing data points in a buffer, identifying the states in neural networks and sending/presenting a result to a computer.

The developed decision system incorporates simple fixed limits for tool breakage detection. Limits are: L1 (collision), L2 (tool fracture), L3 (worn tool) and L4 (missing tool limit).

In the future it will be appropriate to replace fixed limits with self-adjusting limits. The detection system demonstrated a very short response-time to tool conditions. Since tool conditions could be monitored in real-time, the worn tool could be replaced immediately to prevent damage to the product and machine. In this research ANFIS system is used to predict the flank wear of the cutter 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 small computational time. The following conclusions can be drawn from the analysis:

1. The flank wear could efficiently be predicted by using cutting conditions and forces as the fuzzy input variables in ANFIS system.
2. The error of the tool wear values predicted by ANFIS with the triangular membership function is only 4%, reaching accuracy as high as 94%. When the trapezoidal membership function is adopted the average error is around 5.4%, with an accuracy of 92%.
3. The ANFIS system could predict flank wear for different cutting conditions with an average percentage deviation of 4.72%, or an accuracy of 93.64%.
4. The predicted flank wear was found to be significantly sensitive to the measured maximum cutting forces (radial), especially the thrust cutting component (*Fx*).

Fig. 5 shows the scatter diagram of the predicted values and measurement values of the flank wear of 150 sets of testing data when triangular membership functions are used in ANFIS.

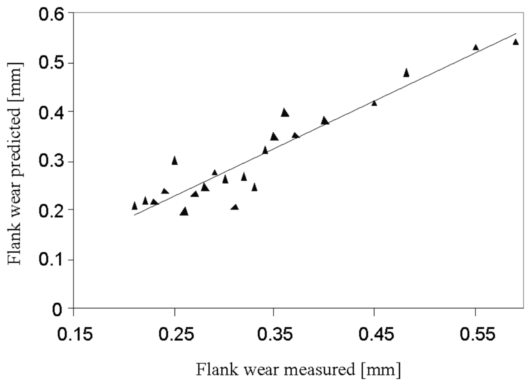

Fig. 5. *Scatter diagram of measured W_B and predicted for the testing data using the triangular membership function*

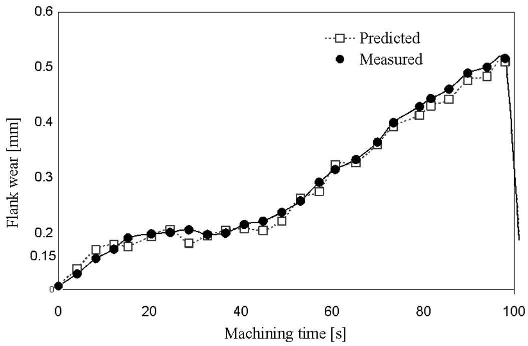

Fig. 6. *Comparison of measured and predicted flank wear (v=180 m/min, AD=2 mm, f = 0.1 mm/tooth)*

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. Fig. 6 compares the predicted values and measurement values after training by ANFIS with triangular membership functions.

6 CONCLUSION

We developed a system for monitoring tool condition in real time and obtained the following results through verification experiments: (1) The proposed monitoring system of cutting process may be very useful because of its parallel processing capability; (2) It enables the monitoring of the cutting process with high reliability; ANFIS component can estimate flank wear progress very quickly and accurately, once the maximum cutting forces are known. A monitoring system using a neural network is able to classify the various cutting states such as tool breakage, and tool wear. In the future different decision making tools, such as fuzzy logic should be applied to see which one could obtain a smaller error of detection.

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