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SINGLE SENSOR TOOL WEAR MONITORING SYSTEM

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Abstract: *The aim of this study is to develop a reliable monitoring system for cutting tools in end milling. In this research, cutting force sensor and a vision system are used to monitor milling operations. The fundamental challenge to research is to develop a single-sensor monitoring system, reliable as a commercially available system, but much cheaper than the multi-sensor approaches. The cutting forces are measured with piezoelectric table dynamometer. Optical visual system is used to observe the actual tool conditions after the machining tests. The force sensor signals are then sent to the neuro-fuzzy algorithm, which is trained to determine the tool condition and the amount of tool wear. A neuro-fuzzy algorithm is investigated, to identify the parameters of membership functions, the set of rules and the output weights. The trained adaptive neuro-inference system is also used to discriminate different malfunction states from measured signals. By developed tool condition monitoring system, the machining process can be on-line monitored and stopped for tool change based on a pre-set tool-wear limit. The developed system is used to monitor milling operations and provide warnings to operator, to minimize tool breakage. The effectiveness of tool condition monitoring in ball end milling is investigated through several cutting experiments.*

Key words: *monitoring, wear, tool condition, single sensor, visual system, ANFIS.*

1. INTRODUCTION

In high speed end-milling it is very difficult to measure tool wear and detect tool breakage. Detection of cutting tool condition is essential for faultless machining in flexible manufacturing systems (FMS).

The main goal of the development of tool condition monitoring system (TCM) is to increase productivity and hence competitiveness by maximizing tool life, minimizing 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 analyze 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 researchers have proposed monitoring systems for milling processes with various sensors. Haber [2] has used motor current and power for detecting tool wear and breakage.

Achiche [3] investigated the feasibility of using acoustic emission (AE) and cutting force signals for the detection of tool breakages. Mulc [4] has used force signals to detect tool failure and breakage in milling.

Among all these methods, the accurate measurement of cutting forces provides the most effective method for monitoring tool conditions.

Despite many researches, there are no available methods for monitoring and controlling the process of high-speed milling. In this study, we attempt to solve this situation by using the Adaptive Neuro-Fuzzy Inference System (ANFIS) to predict the tool condition in end-milling processes.

This model offers the ability to estimate tool conditon as its neural network based counterpart providing also an additional level of transparency that neural networks fail to provide. Therefore, a neuro-fuzzy algorithm is investigated, for the purpose of end-milling processes monitoring.

The cutting forces were measured with piezoelectric table dynamometer. Optical visual system was used to observe the actual tool conditions during the machining tests. The force sensor signals were sent to the neuro-fuzzy algorithm, which had been trained to determine the tool condition and the amount of tool wear.

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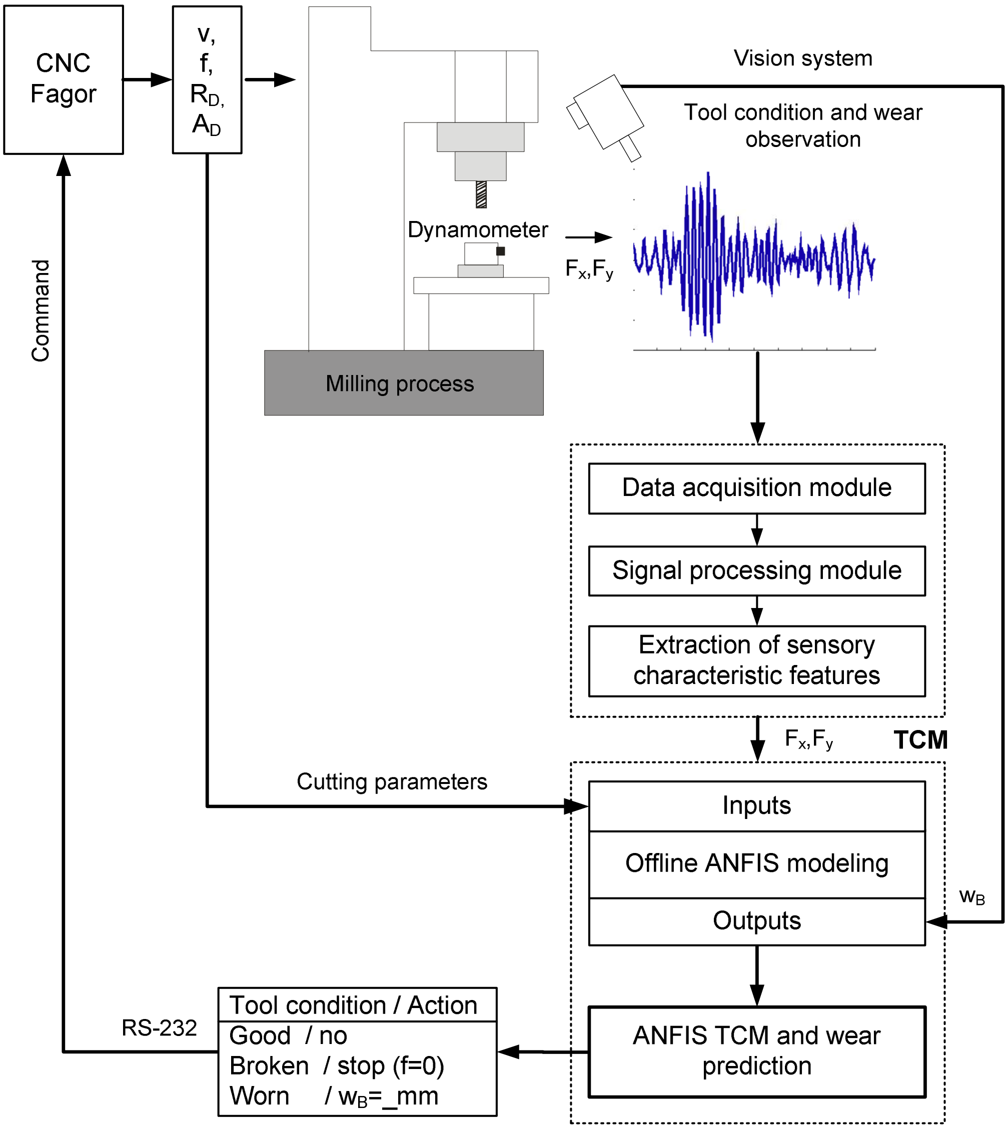

Fig. 1. Architecture of tool condition monitoring system.

2. ANFIS BASED MONITORING SYSTEM

The aim of this study was to develop the accurate and reliable monitoring of tool condition in end milling operations. Fig. 1 shows the basic architecture of the proposed TCM system.

An adaptive neuro-fuzzy inference system (ANFIS) was chosen to estimate the state of the tool under different cutting conditions based on single sensor.

The output of the sensor combined with cutting conditions is sent to fuzzy logic model to provide information to machine tool operator. ANFIS used to predict the cutting tool condition is shown in Fig. 2. It has tool-breakage detection capability and is based on pattern recognition.

The method 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 are required to develop an ANFIS system. In step 1, the fuzzy inference system FIS architecture and training parameters were selected. The process variables are force sensor readings (*Fx*, *Fy*), cutting speed (*v*), feed rate (*f*), depth of cutting (A_D/R_D), machining time, flank wear (w_B) and tool condition.

The domain of definition of these variables is normalized in the range (0,1), where 1 corresponds to the maximal value of that variable.

The fuzzy inference system under consideration has 6 inputs and one output.

In step 2, the optimization method, the tolerance error, the maximal number of epoch, the FIS architecture, the number of membership functions and the membership functions types are defined.

Finding the proper membership function and associated parameters is very difficult and time consuming task. The ANFIS architecture is explained in detail in [5].

In step 3, the data set is divided into the training and the testing set. 350 data points were used in this study.

Good tools collected half of these and broken tools collected the rest.

All the data were scaled. Neuro fuzzy algorithm needs to be trained with a set of training data to be able to estimate tool condition based on input- output data.

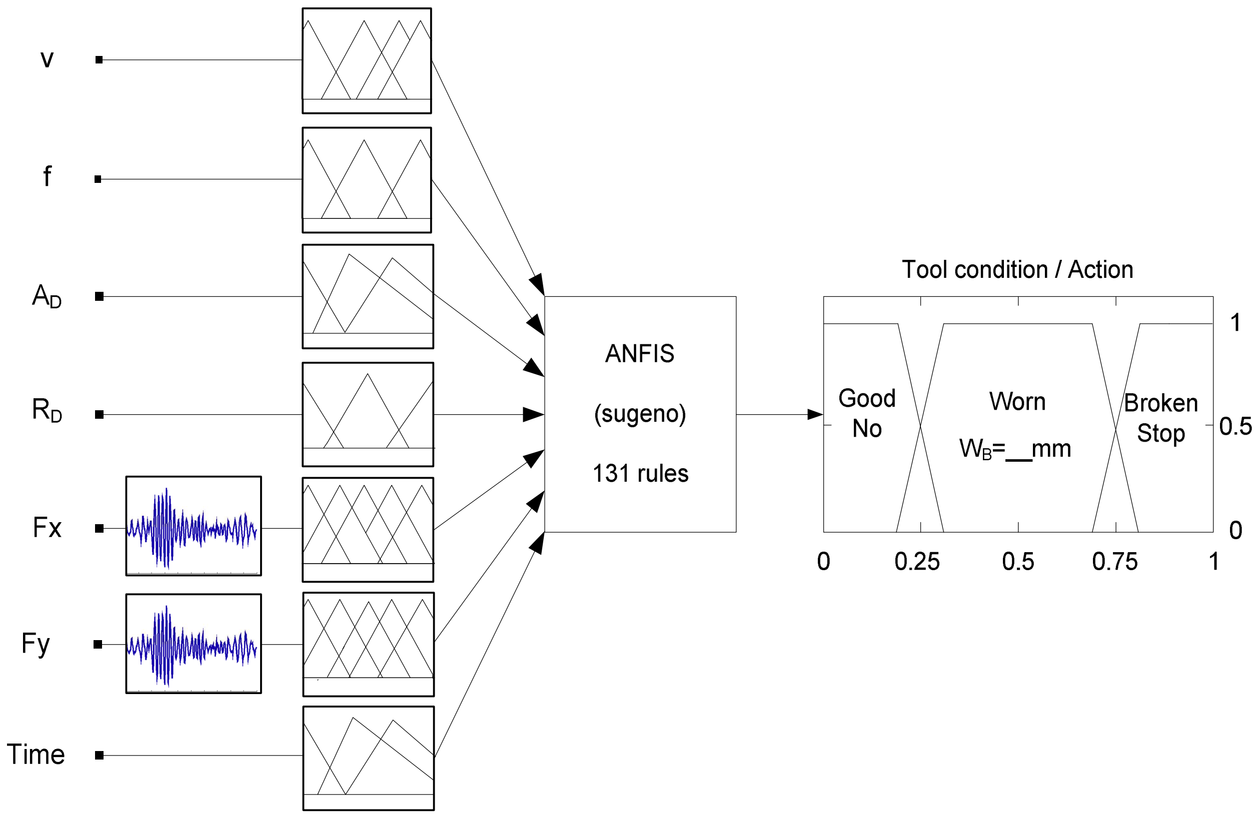

Fig. 2. ANFIS tool conditionand wear estimator.

In step 4, the training and testing phase is accomplished. Fig. 2 shows the flow chart of tool condition estimation via ANFIS. With the input–output data, the neuro-fuzzy algorithm is trained, and the unknown parameters are identified.

Fig. 2 shows the inputs, membership function, and the fuzzy inference system for tool condition monitoring. During the training stage, the ANFIS adjusts its internal structure to give correct output results according to the input features. 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. Fig. 2 shows the fuzzy rule architecture of ANFIS when the triangular membership function is adopted. The architectures shown in Fig. 2 consist of 131 fuzzy rules.

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 [5].

During training in ANFIS, 350 sets of experimental data are used to conduct 1 000 cycles of learning. Finally, in the last step the trained ANFIS is used to predict tool conditions. After the training, the inference system could estimate tool conditions from cutting force measurement and cutting conditions in real time. The developed ANFIS model can guide control system or operator in tool change decisions making.

3. EXPERIMENTAL DESIGN

Experiments were performed on a CNC machining platform Heller with FAGOR CNC controller. The monitoring involved an end milling process of steel parts using two end mill tools: 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 × 70 mm × 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

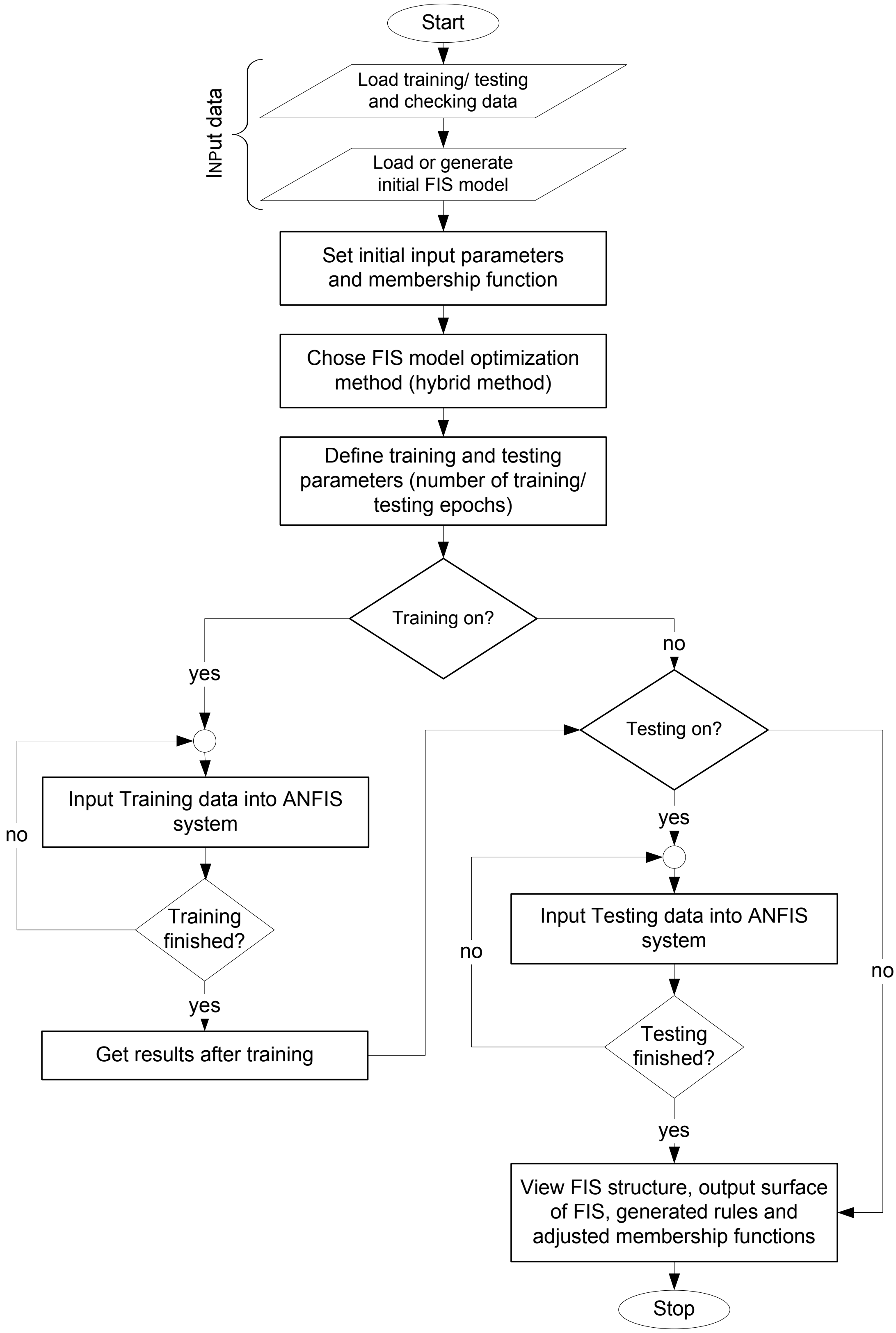

Fig. 2. ANFIS tool conditionand wear estimator.

dynamometer was mounted on the machining table and connected to a three channel charge amplifier.

Charge amplifier (Kistler 5001) converts the charge signals into voltage signals. The signals were monitored by using a fast data acquisition card (National Instruments NI 9215 A) and software written with the National Instruments CVI programming package.

Flank wear was observed during the experiments. The cutting tool condition after each cutting test was discontinuously observed with a vision system of 0.01 mm accuracy.

A vision system consists of a high speed smart camera NI 1772C which was used to detect flank wear without dismounting the tool from the tool holder.

Table 1

Partial results of ANFIS tool condition estimation

Tool conditions	Input factors					ANFIS outputs	ANFIS Prediction	ANFIS Prediction W_B [mm]
	F [N]	n [min^{-1}]	f [mm/rev]	A_D [mm]	R_D [mm]			
Normal	427.2	440	0.17	1.2	8	0.9	Normal	0.11
Broken	777.9	440	0.17	1.2	8	0.02	Broken	0.24
Normal	433.9	440	0.13	1.4	8	0.3	Broken	0.17
Broken	729.6	440	0.13	1.4	8	0	Broken	0.26
Normal	650.5	440	0.20	1.4	8	0.89	Normal	0.13
Broken	925.7	440	0.20	1.4	8	0	Broken	0.27
Normal	614.4	480	0.20	1.4	8	0.88	Normal	0.15
Broken	751.9	480	0.20	1.4	8	0.03	Broken	0.23
Normal	904.3	360	0.22	1.6	8	0.89	Normal	0.14
Broken	991.9	360	0.22	1.6	8	0	Broken	0.31

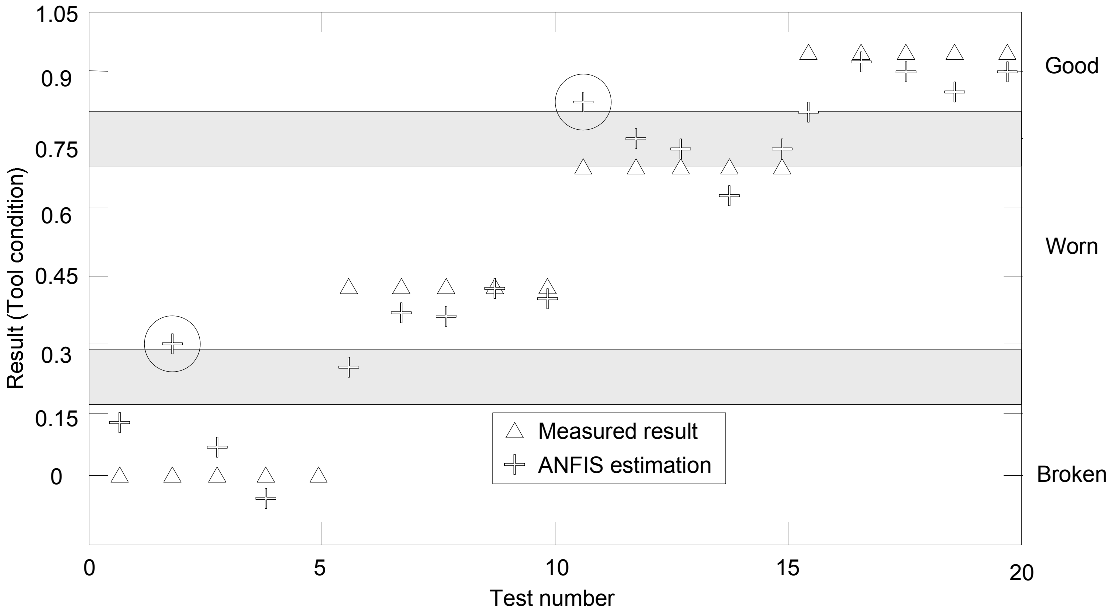

Fig. 3. ANFIS output of tool condition.

It was calibrated using a 10 µm resolution.

The main cutting edge and wear land depth was used to monitor the tool condition.

The flank wear was measured by counting pixels from the vision system and comparing the number with the measuring scale.

The output was assigned a 0–0.25 for good tool, 0.4–0.8 for worn tool and 0.9 for broken tool, based on amount of flank wear.

Cutter with more flutes has different wear on each insert. Therefore only one flute is selected for tool wear measurements. This insert is marked.

Trapezoidal membership functions were used to convert the output of ANFIS algorithm from numbers to linguistic values. This will result in greater accuracy and robustness of tool condition estimations.

The 3-axis machine tool with ball-end mills was used for executing cutting experiments to collect tool wear data.

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: four levels of feed rate (f_1 = 0.05, f_2 = 0.25, f_3 = 0.35, f_4 = 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.

4. RESULTS AND DISCUSSION

During training of the neuro-fuzzy algorithm the parameters of membership functions, the optimal rules and the output weights were determined.

The best results were obtained when triangular membership functions were chosen for the neuro-fuzzy model. By using trapezoidal membership functions higher error was reached. When the ANFIS model was trained, testing data were used for verification. The training was very fast, and the error reached a constant value after about 30 epochs. In this case, there were 131 rules in the fuzzy inference system. After the training, the testing data was applied to the algorithm to determine its validity.

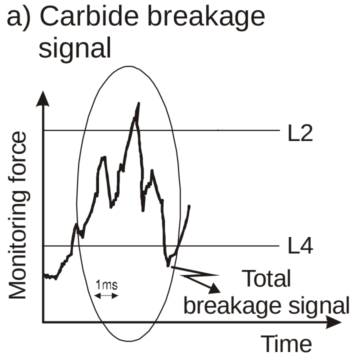

Fig. 4. *a* – Indicative tool breakage force pattern with limits; *b* – Dynamic limit strategy.

The system 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 ANFIS testing are shown in Table 1 and in Fig.3.

The output node value of ANFIS algorithm was mapped as 0.1 for the normal cutting state and 0.9 for the tool breakage. When the outputs are over 0.9 (bad tool), the ANFIS system sends the signal “Bad tool” to the PC.

When output is below 0.8, the ANFIS sends the signal “Tool worn”. 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 ANFIS may decide about the states incorrectly.

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

In our current study, we are trying to replace fixed limits (Fig. 4) with self-adjusting limits. The two dynamic limits above and below the monitoring signal follow the monitor signal continuously, for every load level at a limited adoption speed.

In the case of an extremely fast crossing of one of the two dynamic limits, the limits are frozen and total breakage is distinguished via the fuzzy decision system.

The detection system demonstrated a very short response time to tool conditions. Because tool conditions could be monitored in a real time, the worn tool could be replaced immediately to prevent damage to the product and the machine.

The developed algorithm correctly estimated tool wear condition for 18 out of 20 cases.

Wrong estimations accrued when the feed rate and rotational speed were low. This may have resulted due to effects of the built-up edge. This issue can change the cutting forces and affect the tool wear estimation via force signals. Fig. 3 shows the actual outputs (tool condition) versus the outputs obtained from the neuro-fuzzy algorithm. There are three different regions in the diagram: good, worn and broken. Shaded areas represent transition regions.

The force sensors give a good estimation of the tool condition.

The time of training increases with the increase of the number of inputs. This is not a problem since the training is done off-line.

After the off-line training, the neuro-fuzzy algorithm is able to predict tool wear on-line.

Tool wear measurements were very sensitive to the lighting of the vision system.

5. CONCLUSIONS

In this research, cutting force sensor and a vision system were used to monitor milling operations. A monitoring system using a neuro-fuzzy algorithm is able to classify various cutting states, such as tool breakage and tool wear.

Tool wear was monitored after each cutting test with a vision system that measured the flank wear of the tool. The cutting force signals signals and the measured tool wear were analyzed off-line and applied to a neuro-fuzzy method to 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. The trained model can be used to monitor milling operations and provide warnings to an operator, in order to minimize tool breakage.

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