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Tool wear estimation in micro-machining. Part II: neural-network-based periodic inspector for non-metals

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Abstract

Cutting forces are small, and in many cases insignificant, compared with noise during the micro-machining of many non-metals. The Neural-Network-based Periodic Tool Inspector (N^2PTI) is introduced to evaluate tool condition periodically on a test piece during the machining of non-metal workpieces. The cutting forces are measured when a slot is being cut on the test piece and the neural network estimates the tool life from the variation of the feed- and thrust-direction cutting forces. The performances of three encoding methods (force variation, segmental averaging and wavelet transformations) and two neural networks [back-propagation (BP) and probabilistic neural network (PNN)] are compared. The advantages of N^2PTI are simplicity, low cost, reliability and simple computational requirements. © 1999 Elsevier Science Ltd. All rights reserved.

Keywords: Micro-tool; End-mill; Milling; Monitoring; Neural network; Wear; Micro-machining; Wavelet transformation; Non-metal

1. Introduction

Micro-end-mills with less than 1 mm diameter have a very short and unpredictable tool life when they are used to cut metals. However, it is possible to obtain a long tool life (a few hours)

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from these types of tool when non-metallic materials such as graphite electrodes and plastics are machined at conservative cutting conditions. After a long machining operation, the micro-tools wear out, lose material and their dimensions change. When the tool is rounded the quality of the surface finish deteriorates, burrs are created, and the dimensional accuracy of the manufactured parts is ruined. The Neural-Network-based Periodic Tool Inspector (N^2PTI) is introduced to evaluate tool condition during the machining of soft materials with very small cutting forces. The N^2PTI requires the tool to cut a test piece, which is attached to a dynamometer. When the test piece is machined the variation of the feed- and thrust-direction cutting force is measured. Neural networks estimate the tool wear depending on the information about the cutting forces. In this paper, the performances of three encoding and two neural networks are discussed.

To estimate tool wear in conventional machining operations, cutting forces have been monitored for turning [1–3], drilling [4,5] and milling [6] operations. Neural networks [4–8] and various approaches including wavelet transformation [1] and fuzzy logic were used to estimate tool wear [9] from the collected data. To improve the accuracy, the synthesis of multiple sensors has been proposed [4,8,9]; however, their cost and fine-tuning of the system restrict the practical implementation of these approaches.

The N^2PTI is developed with the following goals.

- To obtain the cutting force signal of micro-machining with an acceptable signal-to-noise (S/N) ratio: typically the cutting forces are very small when electrodes and plastic materials are micro-machined. The inertia forces and other sources create noise which has an amplitude almost equal to or larger than that of the cutting force signals. The S/N ratio of the cutting force is too low to evaluate the tool condition accurately. The material of the test piece and the cutting conditions can be selected to have desired S/N ratios.
- To have a low-cost, reliable system convenient for industrial applications: the characteristics of the cutting forces change continuously during the machining of a workpiece, if the metal removal rate and machining parameters change. The N^2PTI uses a test piece and cuts the material at exactly the same cutting conditions. In this test, the characteristics of the cutting forces are only affected by the tool wear. The encoding and interpretation of the signal become much simpler and the cost of the system is reduced.

In the following sections, neural networks, the operation of the N^2PTI, the experimental set-up, results and conclusions are presented.

2. Theoretical background

In this study wavelet transformation [10–13] was used to encode the cutting force signals. For classification, backpropagation (BP) [14–16] and a probabilistic neural network (PNN) [17] were used. In this section, wavelet transformation and PNN will be outlined briefly. The backpropagation method can be reviewed in the first paper in this series [18].

2.1. Wavelet transformation

Wavelet transformations [10,11] are used to represent a signal with a family of functions derived from a single function. The relationship between a signal and its wavelet transformation can be represented with the following relationship:

$$f(t)=\sum_{n=-\infty}^{\infty} c(n)\Phi_n(t)+\sum_{i=0}^{\infty}\sum_{j=-\infty}^{\infty} d(i,j)\Psi_{i,j}(t), \tag{1}$$

where

$$c(n)=\int f(t)\Phi_n(t)\,\mathrm{d}t,$$

$$d(i,j)=\int f(t)\Psi_{i,j}(t)\,\mathrm{d}t$$

and $f(t)$ is the original function. The coefficients of the wavelet transform are $c(n)$ and $d(i,j)$. $\Phi(t)$ and $\psi(t)$ are named the scaling function and the primary wave, respectively. It is possible to calculate the wavelet coefficients in a computationally very efficient manner by using digital filters [13].

2.2. Probabilistic neural network

The PNN has four layers [17]. These layers are the input, pattern, summation and output layers. One neuron is assigned to the pattern layer for each training case. After training, pattern and summation layer neurons create the output. For each class there is one summation neuron. Training is very fast; however, the size of the network depends on the number of training cases. If there are many training cases, a large network will be established. In this paper the basic version of the PNN with a single scaling parameter is used.

3. The proposed Neural-Network-based Periodic Tool Inspector (N^2PTI)

The operation of the N^2PTI is outlined in Fig. 1. The N^2PTI evaluates the tool wear at periodic intervals. The workpiece is attached to the table of the milling machine. A test piece is installed on a dynamometer, which is attached to the table next to the workpiece. The user prepares the part program to cut the workpiece and periodically move the tool to the test piece to cut a slot on it. The feed- and thrust-direction cutting forces are measured while the test piece is being cut.

To estimate the tool usage (wear), the raw data are processed in two stages: encoding and classification (Fig. 2). In the first stage, hundreds of cutting force measurements are reduced to a few representative parameters. The encoded parameters are given to the neural network in the second stage for estimation. The system is first trained on the experimental data with known usage. The performance of the system is evaluated from the estimation accuracy of the system

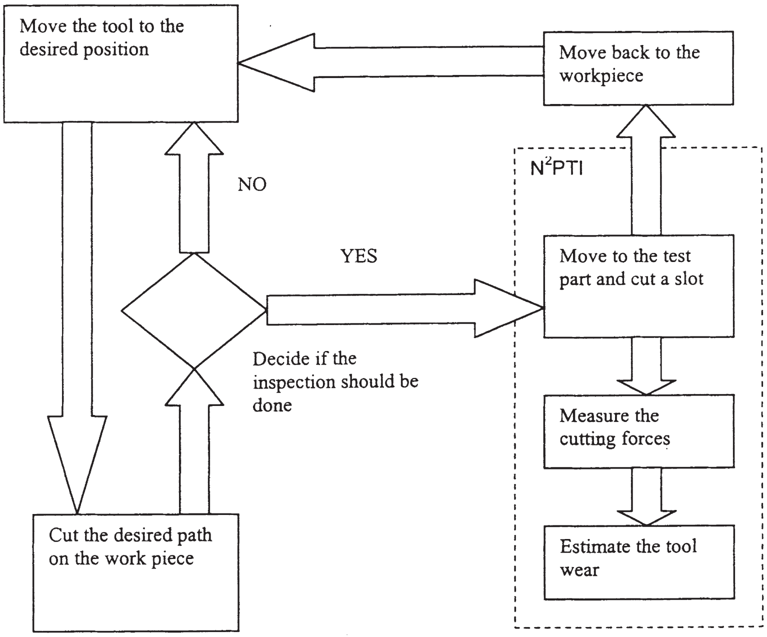

Fig. 1. Operation of the N^2PTI.

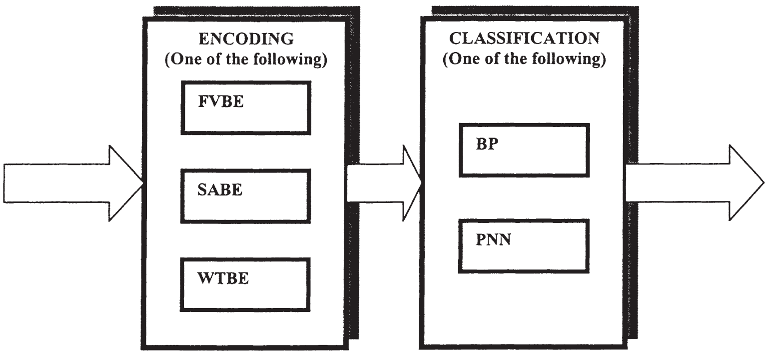

Fig. 2. Tool wear estimation from the cutting force variations.

on data it has never used before. Three different encoding methods and two neural networks were used.

In this study, the primary goal was to investigate the tool life estimation accuracy of the neural networks. In practical applications the N^2PTI should be designed by considering the requirements of the application. The system might be trained for a different size and type of tool ahead of time or a simple threshold might be assigned.

In the following sections these three encoding methods are presented.

3.1. Force-variation-based encoding (FVBE)

The encoded parameters are calculated for each cutting force separately from the difference of the measured maximum and minimum values in each period. Two parameters (feed- and thrust-direction force variations) are given to the neural network. The neural network is first made to run in the training and later in the testing mode. During the training mode two inputs (feed- and thrust-direction cutting force variation) and one output (the tool life) are given to the network. The network establishes a model between the inputs and the outputs. In the testing mode only the two inputs are given to the network. The network estimates the tool life (output) by inspecting the feed- and thrust-direction cutting force variations.

The FVBE-based encoding and neural-network (NN)-based classification process is presented in Fig. 3.

3.2. Segmental-average-based encoding (SABE)

Feed- and thrust-direction forces are sampled and normalized. Starting from the maximum data point of one complete rotation period, the data of one revolution are divided into 10 segments with equal lengths (data points) and the averages of each segment are calculated. In total 20 parameters (10 for each cutting force) are presented to the NN. This encoding and classification process is presented in Fig. 4.

3.3. Wavelet-transformation-based encoding (WTBE)

In the first step, wavelet transformation of the data of each cutting force is performed five times to compress the data to the desired level. The approximation coefficients of each force component after the last transformation are normalized to minimize the influence of the depth of cut. These 16 normalized parameters (eight for each cutting force) are presented to the NN. Fig. 5 presents the proposed processing of the data.

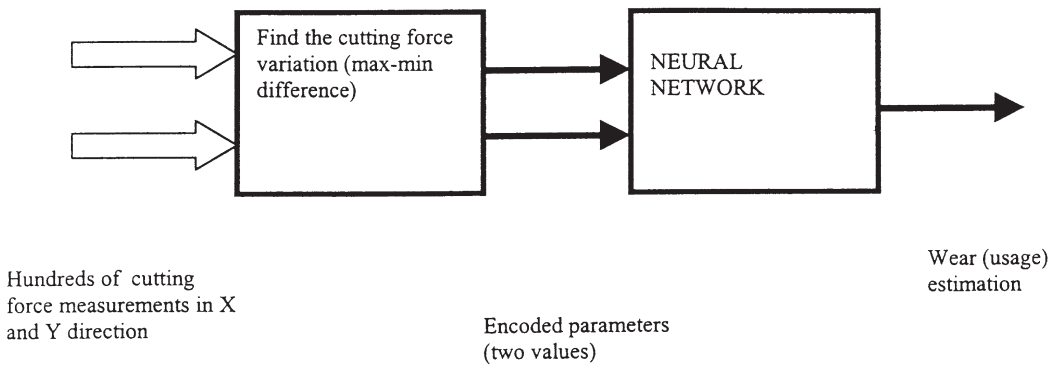

Fig. 3. Tool wear estimation by using FVBE.

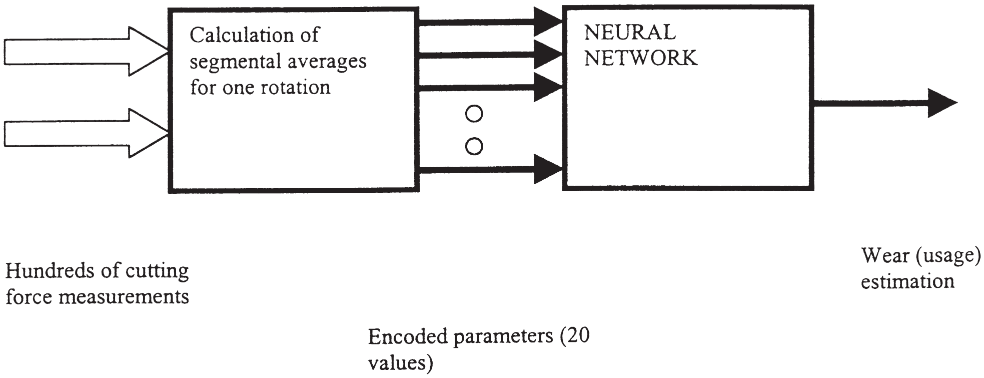

Fig. 4. Tool wear estimation by using SABE.

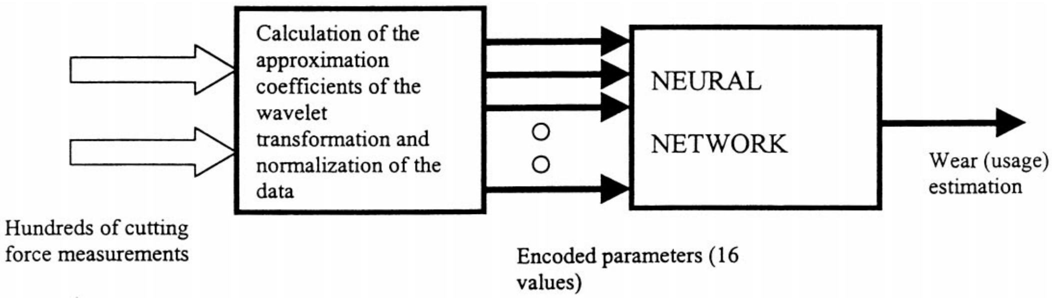

Fig. 5. Tool wear estimation by using WTBE.

4. Experimental set-up

The experimental set-up is presented in Fig. 6. The main workpiece, a POCO-EDM-C3 electrode, and an aluminum test piece were held with the help of screws on a 9257B three-component Kistler dynamometer. The dynamometer was connected to a charge amplifier. The feed- and thrust-direction forces were digitized by using a Nicolet 310 digital oscilloscope. The cutting forces were recorded while the aluminum test piece was cut. A 1/16 in. carbide tool was used to collect the experimental data. The spindle speed was 15,000 rev/min. The tool was worn by cutting POCO EDM-C3 electrode material with a feed rate of 20 in./min and 0.030 in. depth of cut. To test the tool condition, an aluminum test piece was cut at 15,000 rev/min with a feed rate of 5 in./min and a 0.015 in. depth of cut (Table 1).

5. Results and discussion

The performances of three encoding and two classification methods were studied on the experimental data. The cutting forces during machining of the electrode with a new tool were almost smaller than the inertia-related false force measurements. When the tool wears out the cutting forces increase and the S/N ratio become acceptable. The cutting forces were always significant

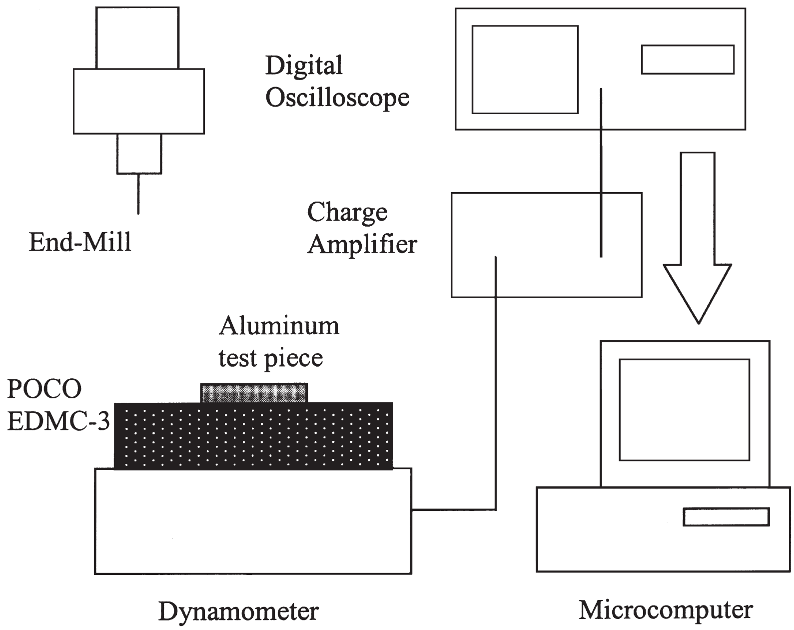

Fig. 6. The diagram of the experimental set-up for tool wear on POCO EDMC-3.

Table 1
Test conditions for POCO EDMC-3 and aluminum test workpiece

Tool type	Carbide two-flutes end-mill
Tool diameter (in.)	0.0625
Spindle speed (rev/min)	15,000
Feed rate (in./min)	5 (electrode)
	2.5 (aluminum)
Depth of cut (in.)	0.015
	(both same)
Workpiece	POCO EDMC-3
	Aluminum

when the aluminum test piece was cut. For encoding, the signals from machining of the test piece were used. The machined slots of the aluminum test piece are presented in Fig. 7 (see Section 5.3 for a typical cutting force signal).

In this section, the performances of each encoding and classification method will be outlined.

5.1. Force-variation-based encoding

Experimentally observed cutting force variation readings are presented in Fig. 8 by means bubble diagrams. The size of the bubble corresponds to the tool life. The observed thrust- and feed-direction force variations are shown on the X and Y axes, respectively. It can be inferred from the diagram that both of the cutting force variations increased while the tool wore out.

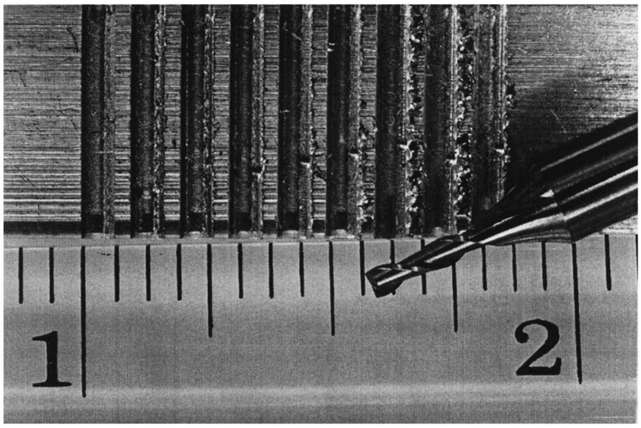

Fig. 7. The machined slots of the test piece.

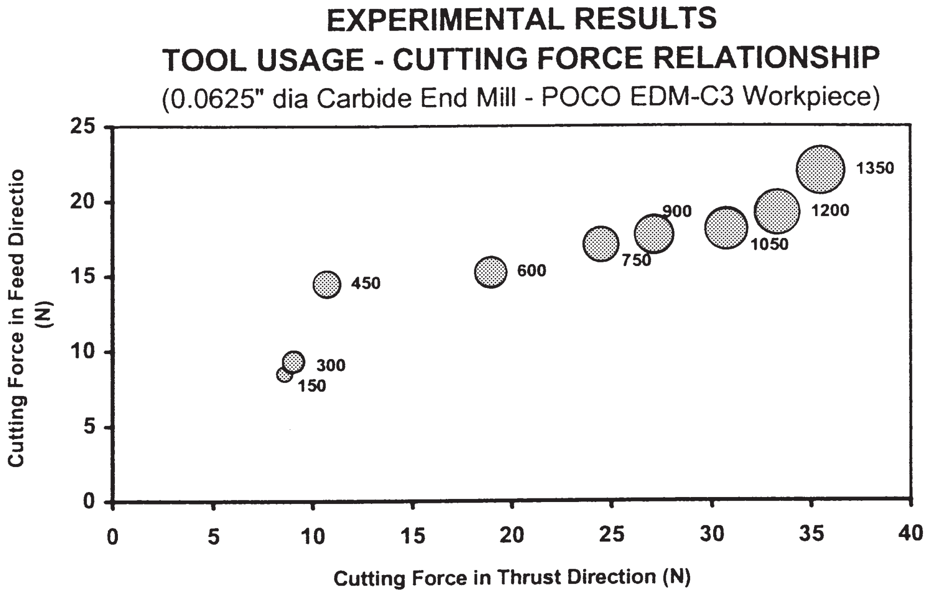

Fig. 8. The variation of the feed- and thrust-direction cutting forces with tool usage (wear). The usage of the tool is written for each circle. The areas of the circles are proportional to the usage.

The cutting force variations were obtained at five different stages of tool life and used to train BP and PNN (basic) neural networks. BP had two hidden nodes. The training of the BP and PNN took 11 s and 1.54 s, respectively. After the training, the neural networks estimated the tool life of four other cases they had never seen before. The estimation accuracy of both neural networks is presented and compared with the other methods in Section 5.4.

5.2. Segmental averaging-based encoding

For segmental averaging, 40 cases at four different wear levels were used to train the BP and PNN neural networks. Both neural networks had 20 inputs and one output. The BP-type neural network had 10 hidden nodes. Training of the BP and PNN took 121.5 s and 12.3 s, respectively. The estimation accuracy of the networks was tested on the training cases and 30 test cases collected at three different wear levels. The estimation accuracy of the approach is outlined in Section 5.4 and compared with the other approaches.

5.3. Wavelet-transformation-based encoding

The wavelet transformation represented the original signal very accurately by only eliminating the high-frequency components. The original signal and recomposed signal (using only eight approximation parameters) are presented in Fig. 9.

The BP and PNN were trained on the encoded parameters of 32 cases obtained at four different wear levels. Both neural networks had 16 inputs and one output. Eight hidden nodes were used for the BP networks. Training of the BP took 156.2 s while the PNN finished the same task in

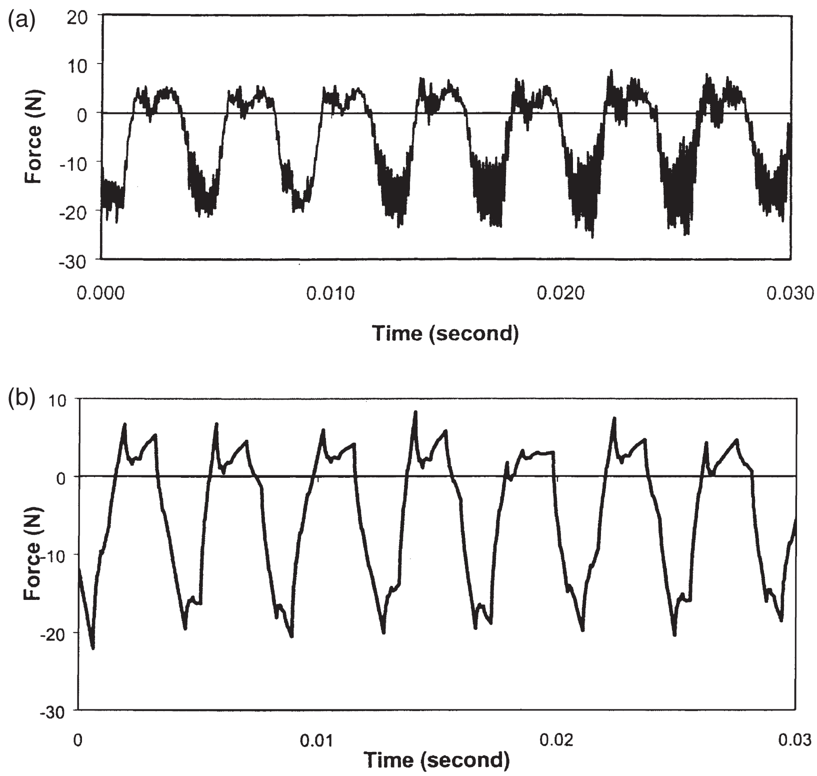

Fig. 9. Comparison of the original and recomposed signal after wavelet transformation: (a) original signal; (b) recomposed signal by using eight approximation parameters.

15.3 s. The performance of the networks was tested on 24 cases at three different wear levels. The estimation accuracy of the networks is presented in Section 5.4.

5.4. Comparison of the performances of the proposed encoding and classification methods

The estimation accuracy of the proposed encoding approach and neural networks is outlined in Table 2. The performances of the six proposed methods were acceptable. According to the selected components of the monitoring hardware and allowable user involvement, one of the proposed six approaches can be used.

The best results were obtained when wavelet-transformation-based encoding (WTBE) was used. The recomposed signals after the wavelet transformation, using only eight approximation coefficients, were very well represented by the original signal with 200 data points. The only missing information was the noise. Segmental-averaging-based encoding (SABE) was the second best. Compared with preparation of the wavelet transformation program, this approach can be implemented in a very short time. Force-variation-based encoding (FVBE) gave the worst estimates; however, it was very simple and can be easily implemented with very low-cost hardware.

Training of the BP was almost 10 times longer than that of the PNN but the average estimation error was two to five times better. The speed and automatic selection of the internal structure make the PNN very attractive. However, when the training set does not distribute in the parameter space with very small resolution, the performance of the PNN is limited since it tries to remember the training data and declines drastically. The training times of the BP reported in the paper were for the selected hidden layer structure (number of nodes in the hidden layer). Since the user has to try different numbers of nodes until he finds the best size, the training process should be repeated. The actual time spent on training of the BP-type network is much longer than the time spent in training the PNN.

6. Conclusion

An off-line tool wear estimation method is proposed primarily for the micro-machining of non-metals. Although the proposed approach is almost inevitable for non-metals, which create very

Table 2
Estimation accuracy of the proposed encoding approaches and neural networks

Material: POCOEDMC-3 machined, tested on aluminum		Force-variation-based encoding		Segmental average network (40 training–30 testing)		Wavelet transformation network (32 training–24 testing)	
		Analog	PNN (basic)	Analog	PNN (basic)	Analog	PNN (basic)
Training	Average	6.60	21.00	4.78	12.54	3.49	19.62
	Maximum	13.73	30.08	10.71	18.50	9.24	31.53
	Minimum	1.47	13.46	0.47	7.72	0.85	14.09
Testing	Average	12.28	25.64	10.46	23.53	7.07	28.65
	Maximum	21.16	34.21	12.88	25.96	8.84	37.04
	Minimum	4.48	15.09	8.14	16.72	5.09	23.99

small cutting forces during micro-machining operations, it might be used for conventional machining operations to evaluate tool wear with a reliable low-cost system. The N^2PTI evaluates the cutting force signals recorded at identical cutting conditions. In such conditions, only changes related to usage (wear) affect the characteristics of the cutting force. Since this relationship can be easily represented, many encoding and mapping techniques can be used. The disadvantage of the N^2PTI is the inability to monitor tool wear continuously during the machining of a workpiece when the cutting conditions change continuously.

Three different encoding methods were proposed in the study. The wavelet-transformation-based encoding (WTBE) was the most sophisticated approach and the smallest estimation errors were observed when this approach was used. Especially if wavelet transformation hardware becomes commercially available at affordable prices, this approach can be easily implemented. The accuracy of the segmental-averaging-based encoding (SABE) was also very good but not on a par with WTBE. Even the performance of the force-variation-based encoding (FVBE) was satisfactory for many applications.

To estimate the usage (wear) from the encoded signal, backpropagation and probabilistic neural networks were used. Both approaches were found acceptable but BP gave the most accurate estimations.

On the basis of the results, WTBE and a BP neural network was the best combination for N^2PTI. This combination had an excellent average usage (wear) estimation error of 7.07% relative to the whole range on test data that were never before seen. The maximum and minimum errors were 8.84% and 5.09%, respectively. On the training data the error was better than half of these values.

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