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Tool wear estimation in micro-machining. Part I: tool usage–cutting force relationship

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Abstract

The relationship between the cutting force characteristics and tool usage (wear) in a micro-end-milling operation was studied for two different metals. Neural-network-based usage estimation methods are proposed that use force-variation- and segmental-averaging-based encoding techniques.

Keywords: Micro-tool; End-mill; Milling; Monitoring; Neural network; Wear; Micro-machining

1. Introduction

A successful on-line monitoring system for conventional machining operations has the potential to reduce cost, guarantee consistency of product quality, improve productivity and provide a safer environment for the operator. In micro-machining, typical signs of tool problems such as vibration, noise, chip flow characteristics and visual signs are almost unnoticeable without the use of special equipment. These characteristics increase the importance of automatic monitoring in micro-machining; however, sensing and interpretation of signals are more complex. In addition, the shafts of the micro-tools break before the typical extensive cutting edge of the tool gets damaged. In this study, the existence of a relationship between the characteristics of the cutting force and tool

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usage was investigated, and the usage (wear) estimation capability of the two encoding methods and backpropagation-type neural networks was evaluated.

In conventional machining operations the operator mainly monitors vibration, noise and visual indicators to estimate the tool condition. Similarly, wear monitoring techniques have been developed to encode and interpret the cutting force signals [1–5], vibrations [6,7], sound [8], acoustic emission [9–11] and multiple signals [12]. Most of the time the cutting force is the most reliable information source; however, its characteristics, in addition to tool wear, vary with change in cutting conditions and machining direction. Monitoring of micro-machining operations is generally more critical and complicated than conventional cutting. This is due to the fact that the magnitude of the signals is low and the tiny shafts of tools break suddenly when wear reaches a certain level. Acoustic-emission-based wear monitoring [13], cutting-force-based breakage [14] and pre-failure stage detection [15] systems were developed in micro-end-milling by the author and co-workers.

In this study, instead of detecting the pre-failure stage, the aim was the estimation of exact usage (wear). Typically, cutting force signals have more information than acoustic emission signals; however, estimation of wear is more difficult if the cutting conditions vary.

In this study, backpropagation-type neural networks were used for the estimation of tool usage. In the following sections, the theoretical background of neural networks, the proposed wear estimation method, the experimental procedure, results and conclusions are presented.

2. Theoretical backgound

Neural networks were developed to perform classification tasks efficiently after a training session without programming. Backpropagation (BP) [16] is the most well known and commonly used neural network. This feedforward-type neural network has connections between the nodes of the input, hidden and output layers. Each connection between the neurons represents a weight and a simple threshold (most commonly a sigmoid) function. The user selects the number of hidden layers and hidden neurons. BP can be used for mapping or characterization. Optimization of the network parameters during the training process is extremely inefficient; however, many repetitions of the weight calculations may create a very compact and representative model.

3. Proposed wear estimation methods

In this study two different encoding methods were used to estimate the tool usage (life or wear) from the cutting forces by using backpropagation-type neural networks. The accuracy of the proposed methods was tested on experimental data that were collected at different wear levels than the levels used in training. The two following encoding methods were used to represent the characteristics of the cutting force signal.

3.1. Force-variation-based encoding (FVBE)

The encoder calculated the variations of feed- and thrust-direction cutting forces. These two variations were the inputs to the neural network. A diagram of the encoding process is presented in Fig. 1.

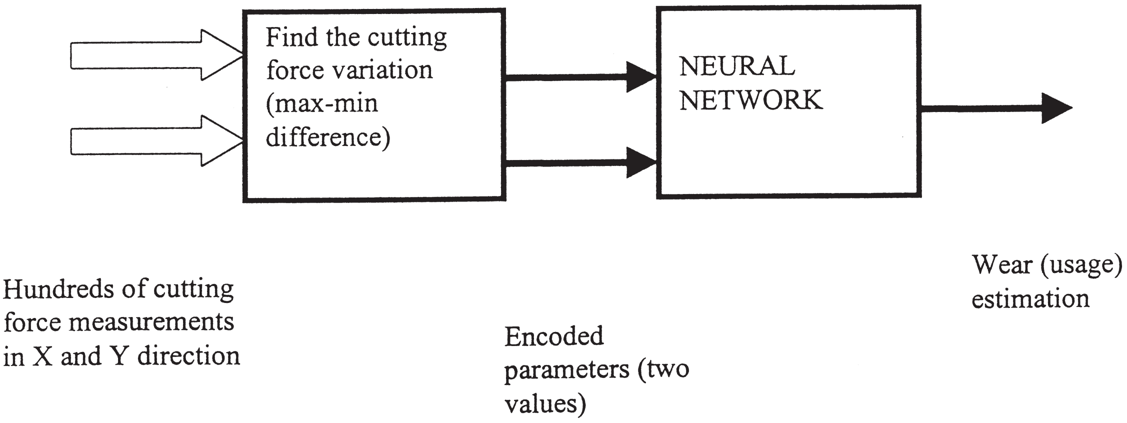


Fig. 1. Tool wear estimation by using FVBE.

3.2. Segmental-average-based encoding (SABE)

Feed- and thrust-direction forces were sampled and normalized. Starting from the maximum data point, the data of one revolution were divided into 10 segments with equal lengths and the averages of each segment were calculated. In total 20 parameters (10 for each cutting force) were presented to the neural network. This encoding and classification process is presented in Fig. 2.

4. Experimental procedure

The experiments were conducted on a Fadal three-axis CNC Machining Center with carbide tools (Fig. 3). A 1/32 in. carbide tool was used to collect the experimental data. Spindle speeds of 45,000 rev/min and 15,000 rev/min were used to cut aluminum and steel workpieces, respectively. The tool dimensions and cutting conditions are outlined in Table 1. 50% overlapping cuts

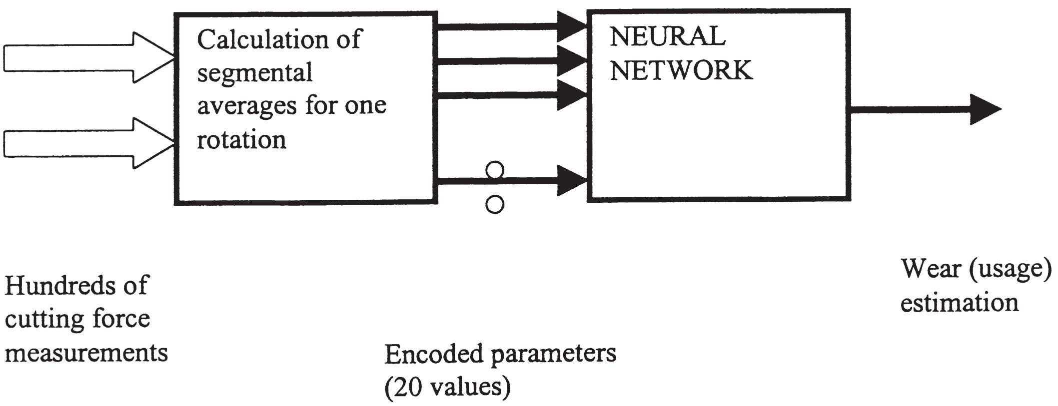


Fig. 2. Tool wear estimation by using SABE.

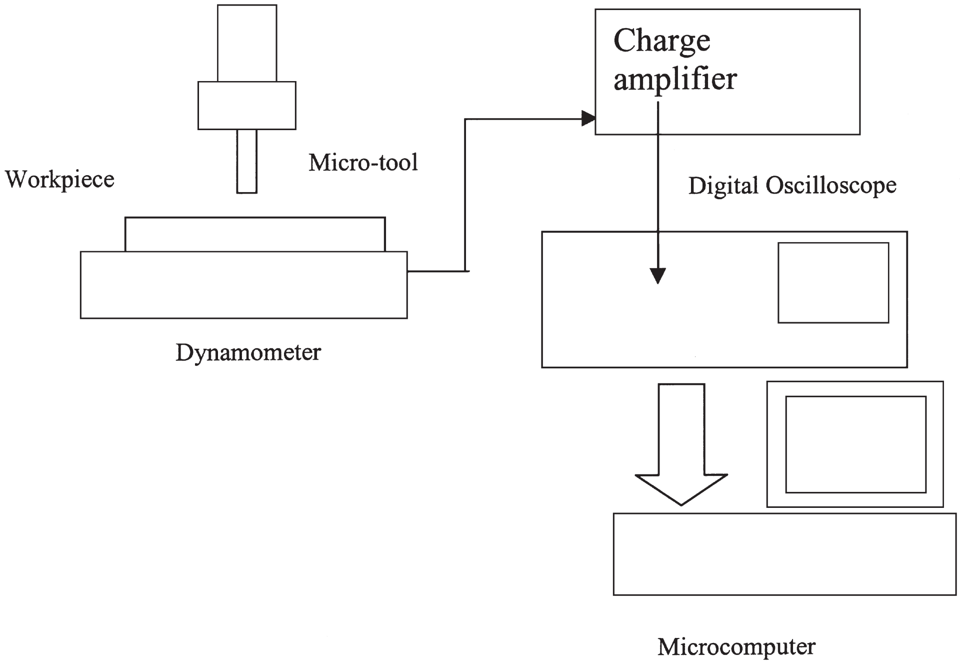


Fig. 3. Experimental set-up.

Table 1
Experimental conditions

	Aluminum	Steel
Tool	1/32 in. carbide end-mill	1/16 in. carbide end-mill
Depth of cut (in.)	0.015	$3d/4$[a]
Spindle speed (rev/min)	45,000	15,000
Feed rate (in./min)	5	2.5

[a] d=Tool diameter.

were made in all the experiments. The workpiece was attached to a Kistler 9257B dynamometer. Cutting force signals were digitized and stored simultaneously by using two digital oscilloscopes at different sampling rates (Nicolet Integra with four channels and a Nicolet 310 with two channels). SmartCAM was used to generate the tool path program (Production Milling Version10).

5. Results and discussion

In this section, we discuss the relationship between tool usage and cutting force, and the performance of the proposed wear estimation methods.

5.1. Tool usage–cutting force characteristics relationship

The relationship between tool usage and characteristics of the cutting force was studied during the machining of soft and very hard materials (aluminum and steel).

5.1.1. Aluminum

The typical relationship between tool usage and variation of the two force components on the horizontal plane [thrust- and feed-direction cutting force variation (difference between the maximum and minimum force)] is presented in Figs. 4 and 5. Both the graphs show that cutting force variation increases with usage.

5.1.2. Steel (NAK 55)

The tool usage–cutting force relationship of the steel (NAK 55) was very different from that of aluminum. Cutting forces remained at almost the same level as at the first stage of tool life. When the tool reached half of its life, the cutting force variation started to increase inconsistently. After four-fifths of the tool life, the slope changed and the cutting force increased very quickly until the tool broke. The relationship is presented in Figs. 6 and 7. This result shows that the pre-failure stage could be identified; however, it would be difficult to estimate usage.

5.1.3. Tool usage–cutting force relationship

The study suggested that the distinctiveness of the linear cutting force–usage relationship depends on the hardness of the material and cutting conditions. It is easier to estimate tool usage (wear) from the characteristics of the cutting force if the workpiece is made of a soft material and the feed rate is selected conservatively. This relationship is very complex for hard materials.

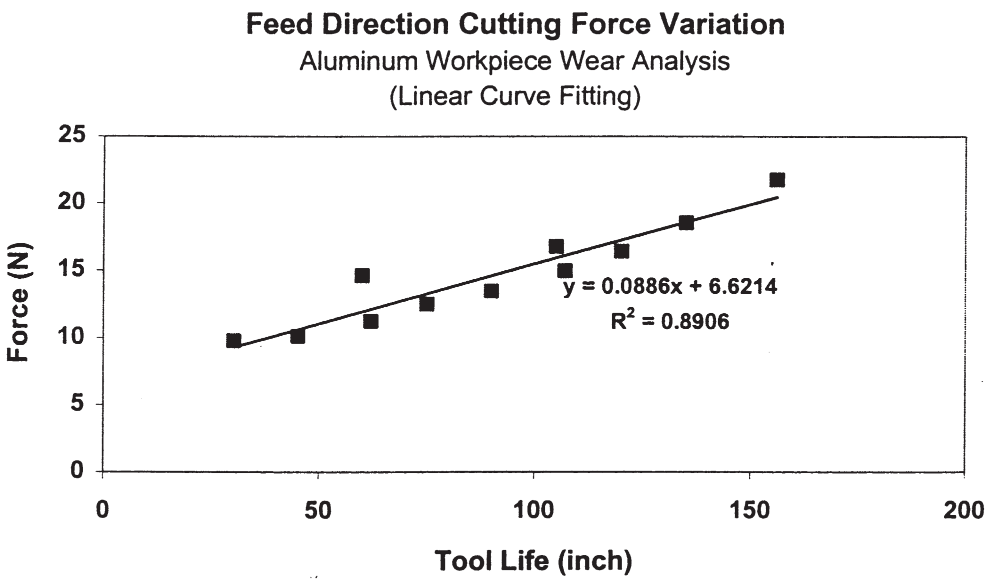


Fig. 4. Representation of the usage–thrust-direction cutting force variation relationship with a linear model.

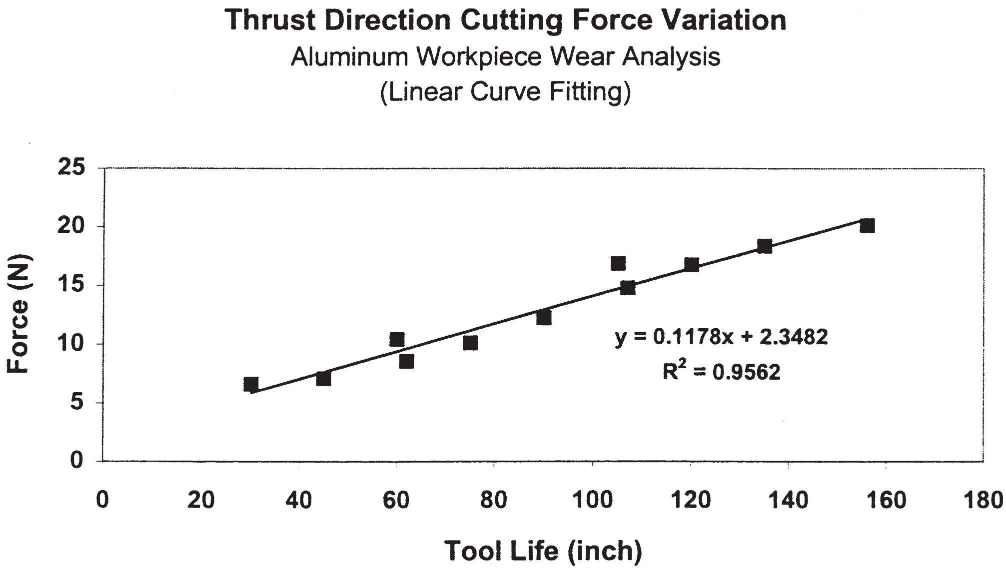


Fig. 5. Representation of the usage–feed-direction cutting force variation relationship with a linear model.

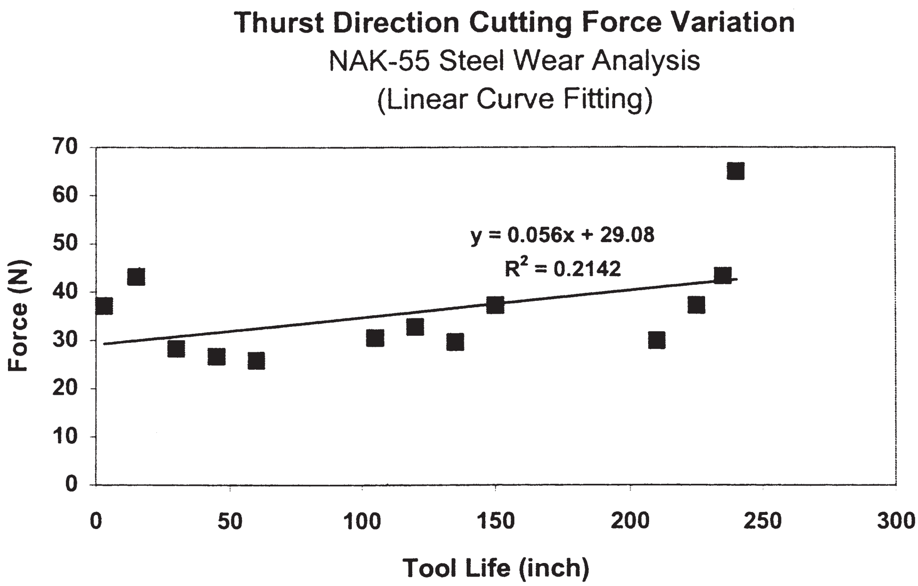


Fig. 6. Thrust-direction cutting force variation with tool usage on NAK 55 steel.

Since the cutting forces are very high during the machining of hard materials, small defects at the cutting edges of the tool increase the cutting forces drastically and the tiny shaft of the micro-tool is broken in a very short time. These results indicate that the wear could be easily monitored for soft materials compared with the hard materials. For hard materials, detection of the pre-failure stage is easier.

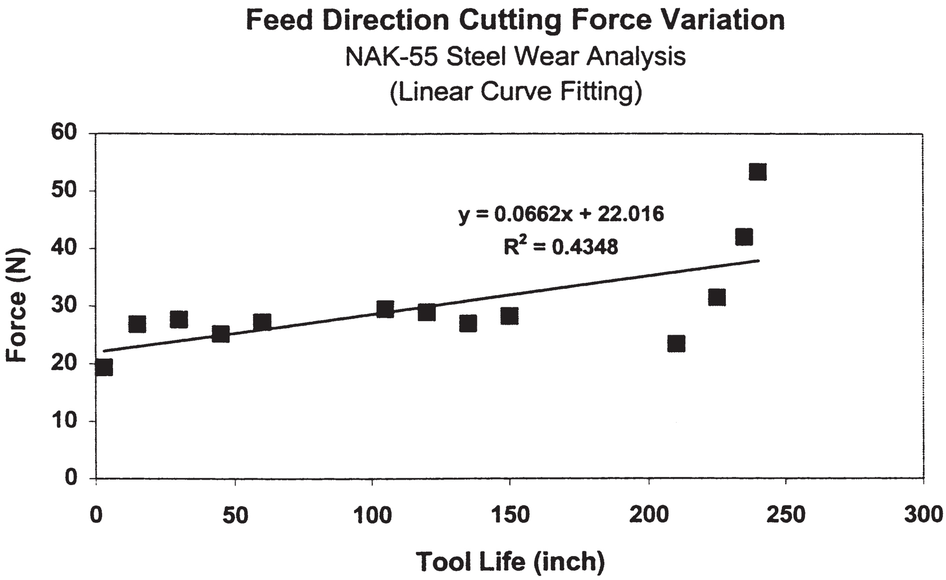


Fig. 7. Feed-direction cutting force variation with tool usage on NAK 55 steel.

In this study, tool wear estimation methods were tested only for machining of aluminum workpieces.

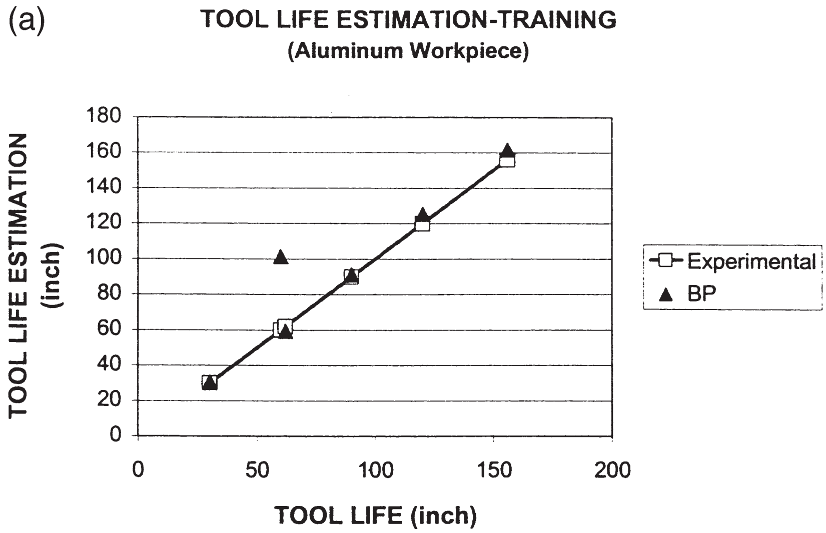
5.2. Estimation of tool usage (wear) during the machining of aluminum workpieces

Two different approaches [FVBE (Fig. 1) and SABE (Fig. 2)] were used to encode the experimental data and BP-type neural networks were used to estimate tool wear. Characteristics of these approaches are the following:

1. FVBE is a simple approach. The BP network estimates the wear from feed- and thrust-direction cutting force variation data. The network was trained with experimental data collected at six different wear levels. Two neurons were satisfactory at the hidden layer. Training took about 13 s. After training the network was used to estimate wear at five different levels that were not used during the training. The estimations and the actual wear levels are presented in Fig. 8.
2. SABE is a more complicated approach. The characteristics of the cutting forces in the feed and thrust directions were represented with 10 segmental averages for each component. For each case 20 inputs were used. Fifty cases were used during the training and the performance of the network was tested for 40 cases at different wear levels. The network had 10 neurons at the hidden layer and training took about 151 s. The performance of the method is presented in Fig. 9.

6. Conclusion

The applications of micro-machining have increased drastically in the last 10 years. In this study, the characteristics of cutting forces were studied at different wear levels by using aluminum



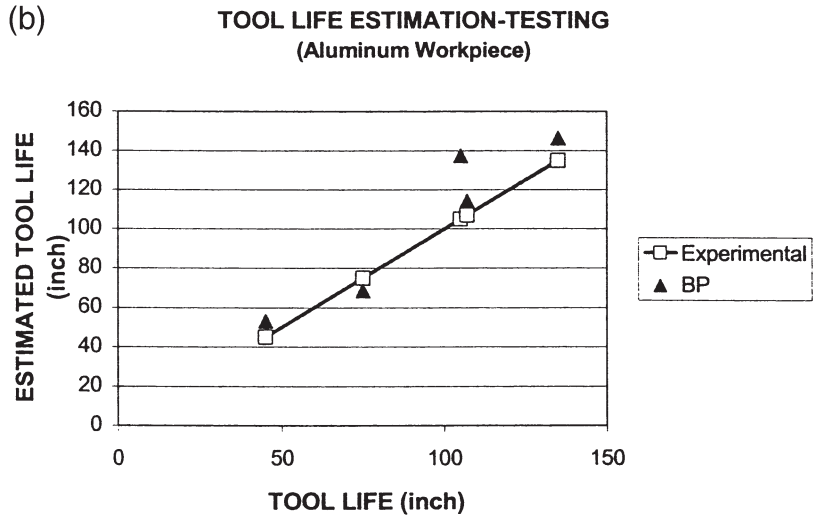


Fig. 8. Estimation accuracy of the FVBE: (a) accuracy of the proposed approach on the training cases; (b) accuracy of the proposed approach on the test cases.

and steel workpieces. Two different encoding methods were proposed to estimate wear during the machining of soft materials such as aluminum.

Cutting force variations increased constantly during the machining of aluminum or any soft material. These results demonstrated that the cutting edges gradually lost their effectiveness and became dull. The results also indicated that it was easier to estimate the tool condition from the characteristics of the cutting forces during the machining of soft materials. It is possible to estimate the tool condition pretty accurately if the feed and thrust cutting forces are measured at identical cutting conditions.

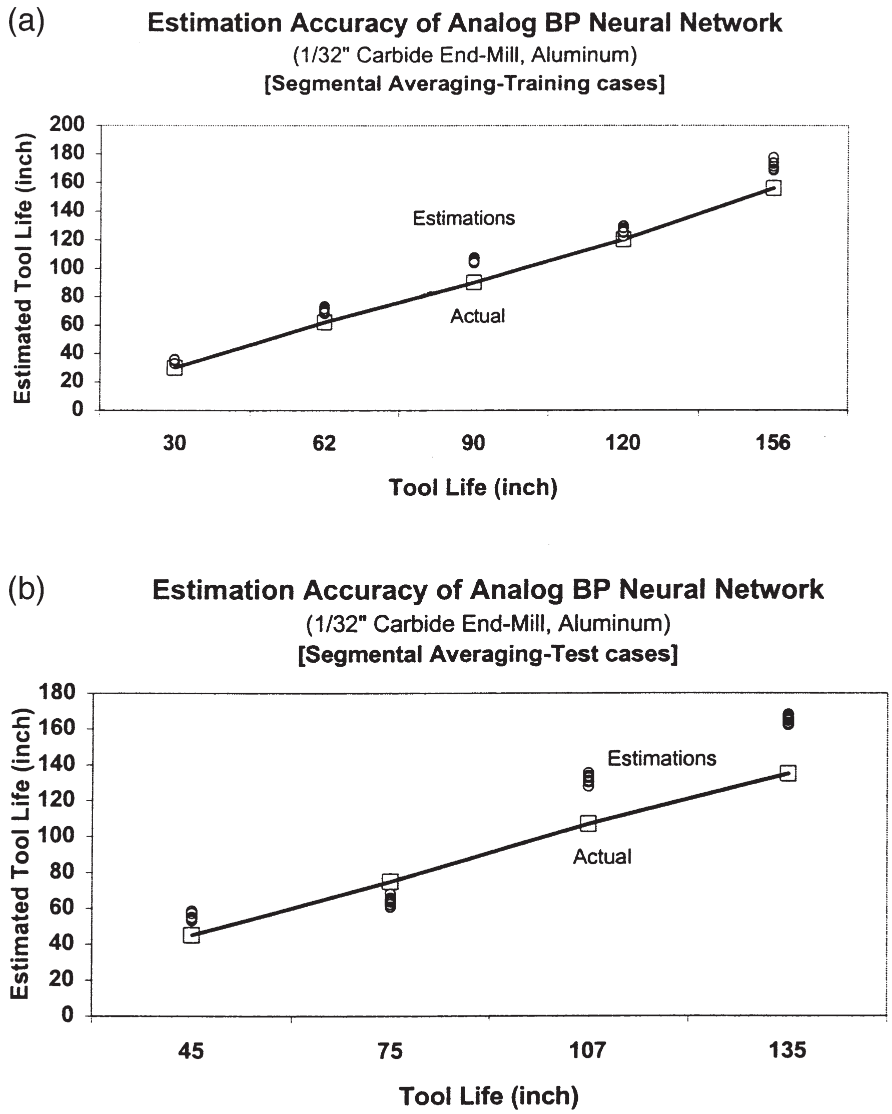


Fig. 9. Estimation accuracy of the SABE: (a) accuracy of the proposed approach on the training data; (b) accuracy of the proposed approach on the test data.

There was no regularly changing, distinctive pattern when the steel workpiece was cut. Before breakage, the cutting force variation suddenly started to increase. It was very difficult to estimate tool wear when hard materials were cut. Identification of the pre-failure phase is easier in this case.

Two encoding methods were proposed for use with BP-type neural networks to estimate wear. Both encoding techniques and BP-type neural networks made excellent usage (wear) estimations.

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