MONITORING THE WEAR OF CUTTING TOOLS IN CNC-LATHES WITH ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

One of the most important tasks of automatic tool monitoring systems for CNC-lathes is the supervision of a tool's wear. Considering the state of wear and the actual working process (e.g. rough or finish turning) it is possible to exchange a tool (or only the insert) just in time, which offers significant economic advantages. This paper presents a new method to estimate two wear parameters by means of artificial neural networks (multilayer perceptrons or time-delay neural networks). The input parameters of the networks are process-specific parameters (like the feed rate or the depth of cut) and characteristic coefficients extracted from signals measured with a multi-sensor system in the tool holder.

1. INTRODUCTION

The determination of a tool's wear is one of the most important tasks in the area of monitoring chipping processes [1]. The importance of this task is implied by the expected economic advantages. On the one hand, it is possible to replace worn cutting tools in time (considering the actual working process, e.g. rough or finish turning). This measure guarantees products of higher quality with a certain maximum roughness of the workpiece surface. On the other hand, a precise exploitation of the tool's lifetime (usually in the range of some minutes) causes a significant reduction of tool costs.

Modern CNC-lathes provide several tools with throw-away inserts attached on a rotatable turret (see fig. 1). An extensive description of metal cutting processes can be found in [2].

If no monitoring systems are used, tools are mostly exchanged precautionary, e.g. after the first half of the average operational lifetime of a tool (corresponding to the operator's know-how). Presently used commercial tool monitoring systems have some serious disadvantages like causing false alarms and many reactions being not transparent and understandable to the operator [1]. Results of surveys show that many of these systems are disconnected. Actual approaches use fuzzy systems, neural networks or combinations of both for a classification of wear (e.g. in 'new', 'half worn' and 'worn') or a continuous estimate of characteristic parameters (see e.g. [3, 4, 5]). However, these methods are not marketable up to now due to unsufficient generalization capabilities (mostly the use is restricted to a small range of process-specific parameters).

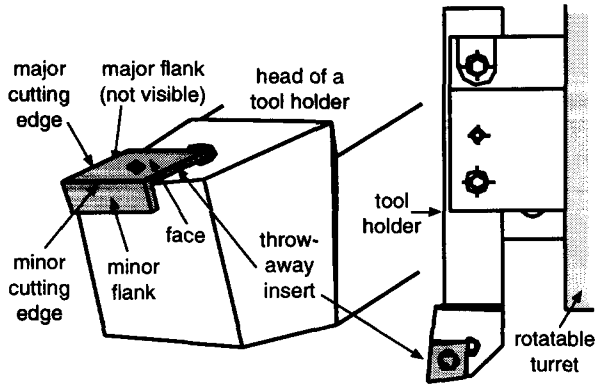

Figure 1: Tool holder with insert

This paper presents a new method using neural networks for an estimate of two continuous parameters describing the wear on the major and the minor flank of an insert. For that estimate the cutting process needs not to be intercepted. The method differs from others mainly in the variation possibilities for the process-specific parameters and in a dedicated pre-processing of the input parameters of the neural networks thus leading to improved results. Furthermore, one of the parameters has not been estimated so far. Results are shown for cylindrical turning processes, the most frequently used process type.

2. INPUT AND OUTPUT PARAMETERS

A tool's state of wear is influenced e.g. by abrasion

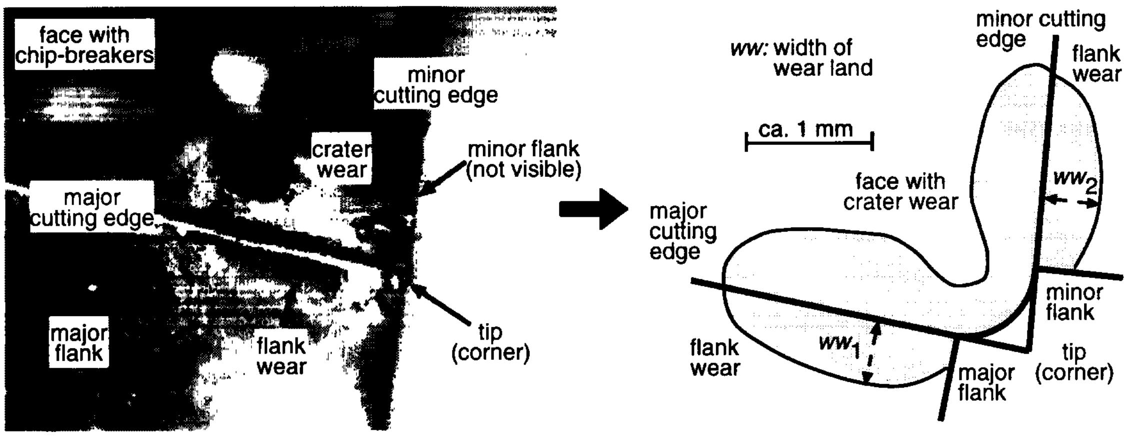

Figure 2: Wear of an insert: photographic and schematic representation (flattened)

or erosion on different faces of the insert or by tiny outbreaks at brittle cutting edges. Two parameters were defined, which describe the width of wear land at the major and the minor flank of an insert (see fig. 2); in our series of experiments they have reached values up to 1.5 *mm*. Each parameter has been estimated continuously by a separate neural network.

Signals from sensors in machine tools (even if direct parameters like forces are measured close to the cutting process) are disturbed for many reasons, e.g. noise, outbreaks at cutting edges, chatter (self-exited vibrations). Therefore only a multi-sensor approach provides sufficient information for an estimate of wear. Four sensors (piezo-electric elements) for the measurement of forces in the orthogonal cutting, feed and passive directions (up to 5 kHz) and vibrations (up to 20 kHz) were integrated into the tool holder. With this sensor system, a large number of experimental cylindrical turning processes with more than 30 inserts has been carried out. Wear parameters have been determined periodically by means of a microscope and a laser-triangulation system.

The variation of static and dynamic process parameters in these experiments is given in tab. 1. Work material has been steel Ck45; other parameters, particularly those which describe the tool geometry (e.g. corner radius, clearence and cutting angle or tool cutting edge inclination), have been identical in all experiments. Fig. 3 gives an example for the development of forces during a tool's lifetime. One insert has been used in this cylindrical turning process to cut several workpieces. At the end of the tool's lifetime outbreaks had occured at the cutting edges.

The input parameters of the neural networks can be divided into two categories. The first consists of a great number of characteristic coefficients extracted from the different sensor signals. The second category is composed of the process-specific parameters mentioned in tab. 1.

static parameter	
type of the insert (substrate and coating)	CPX: aluminium oxide on hard metal CL4: titanium nitride on hard metal PS5: titanium nitride on cermet
dynamic parameters	
depth of cut	0.8 – 4.0 mm
feed rate	0.15 – 0.5 $mm/revolution$
cutting speed	200 – 340 m/min
workpiece diameter	22 – 101 mm

Table 1: Variation of process-specific parameters

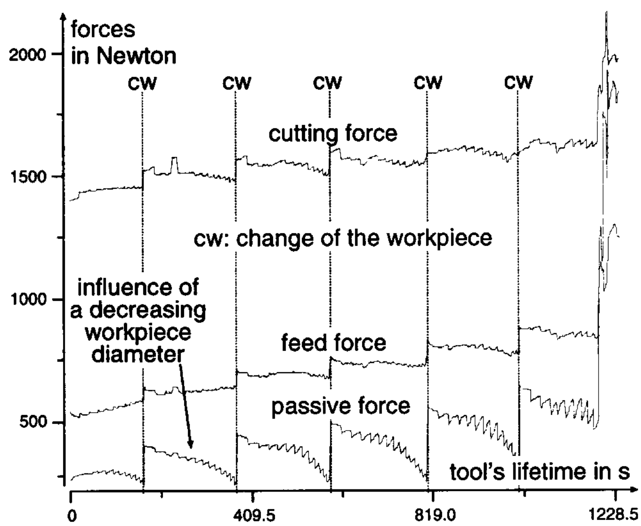

Figure 3: Development of forces during a tool's lifetime

The coefficients were selected in account of a thorough analysis of the experimental data. Coefficients in the time domain of these signals for example are the actual average of the forces, the increase of forces during the tool's life and the actual lifetime itself. In the frequency domain of the four signals, accumulated energy coefficients for the frequency band from 0 to 300 kHz have been computed. With increasing wear, vibrations have been found in a frequency band from 3.9 to 4.8 kHz; in addition, frequency shifts and enlarged amplitudes of the oscillations have been observed. Therefore actual and accumulated energy parameters in different small frequency bands have been used as coefficients.

3. NEURAL NETWORK TRAINING

The non-linear dependencies between the coefficients and the process-specific parameters on the one and the wear parameters on the other hand cannot be described by an exact mathematical model. However, based on a sufficient number of training patterns, neural networks are able to ignore disturbed or noisy information, detect fundamental interdependencies and approximate the sought non-linear function (see e.g. [6, 7, 8]). After the training, the network is able to adapt itself on changing process parameters. Especially multilayer perceptrons are suitable for the processing of continuous input values and the estimate of continuous output parameters [8].

By means of the experimental data, more than 130 training patterns have been obtained for a supervised training of the neural networks. Additional 30 patterns are available for testing the trained networks.

Perceptrons with one hidden layer have been trained in 50000 steps with the standard backpropagation learning algorithm. The activation function used has been the non-linear *tanh*; learning rate and momentum have been decreased from 0.3 to 0.0375 and from 0.4 to 0.05 respectively.

In order to consider the temporal development of wear and the position of a single pattern in a pattern sequence (corresponding to the lifetime of a single tool), a sliding window technique with a receptive window of length four has been used [7]. The training has been started with 209 neurons in the input and 100 neurons in the hidden layer (21000 programmable weights). With node and weight pruning methods, e.g. an analysis of the impact of input parameters on the result of the estimate, the number of neurons in the input layer has been reduced to 27 for ww_1 and 28 for ww_2 [9].

4. RESULTS

To assess the training result and to demonstrate the generalization capabilities of a trained network, the network should be tested with patterns which had not been used for learning purposes before (extrapolation). Fig. 4 and fig. 5 give examples for the estimate of the width of wear land on the major and the minor flank during the lifetime of two different inserts (the examples in fig. 3 and fig. 5 refer to the same insert).

An other assessment criterion is the identification rate of test patterns with a given acceptable maximum error. The estimate of wear at an advanced stage, where small outbreaks at the cutting edge had already occured, is a difficult task. However, such a worn insert wouldn't be used any more in a 'normal' chipping process. Therefore a wear criterion of 0.5 mm (i.e. $ww_1 \leq 0.5\ mm$ and $ww_2 \leq 0.5\ mm$) is usually considered meaningful. Tab. 2 shows the identification rates with and without this criterion. Applying this criterion, it is possible to estimate the parameter ww_1 with an average error of 33 μm.

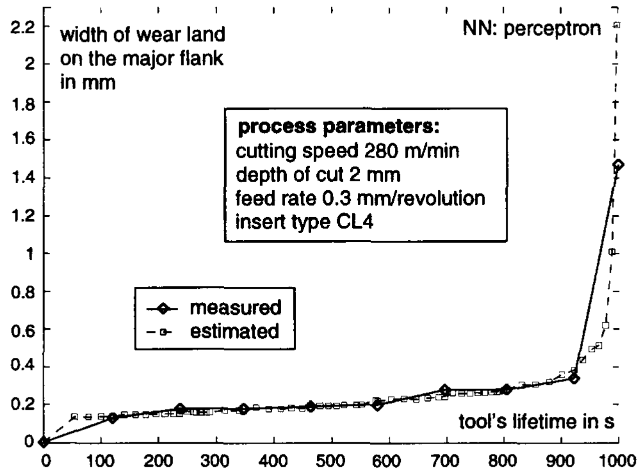

Figure 4: Width of wear land on the major flank I

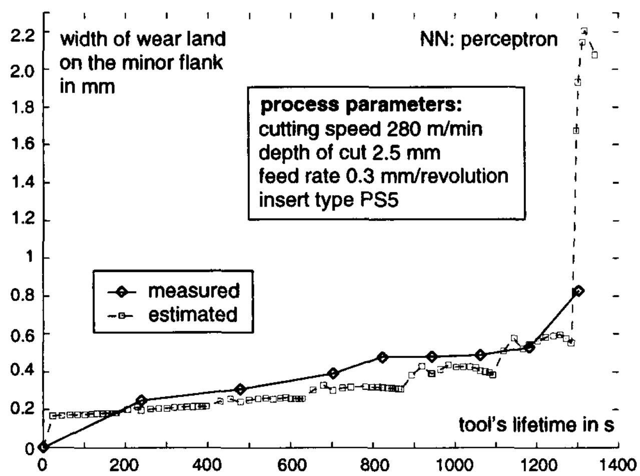

Figure 5: Width of wear land on the minor flank

Additionally used analysis methods have been correlation measures or confusion matrices [6, 7]. The coefficients extracted from feed and passive forces as well as the actual lifetime of a tool have a great influence on the estimate of ww_1. For ww_2 the coefficients extracted from the passive forces are of the greatest importance. Comparing fig. 3 and fig. 5, it can be stated that the influence of a decreasing workpiece diameter had been eliminated to a great extent [9].

The comparison of these results with related work is not easy. A promising and comparable approach is described in [3], where an interpolating (and therefore easier) estimate of the parameter ww_1 with a maximum error of 30 μm had been reached. A result for the parameter ww_2 is not published yet.

maximum error	without wear criterion		with 0.5 mm wear criterion	
	ww_1	ww_2	ww_1	ww_2
$\leq$ 25 μm	n.a.	n.a.	50%	n.a.
$\leq$ 50 μm	74%	7%	88%	10%
$\leq$ 100 μm	83%	48%	92%	65%
$\leq$ 150 μm	93%	59%	100%	80%
$\leq$ 200 μm	97%	74%	100%	90%
$\leq$ 250 μm	100%	81%	100%	95%
$\leq$ 300 μm	100%	85%	100%	100%
$\leq$ 400 μm	100%	89%	100%	100%
$\leq$ 500 μm	100%	93%	100%	100%
$\leq$ 750 μm	100%	96%	100%	100%
$\leq$ 1000 μm	100%	96%	100%	100%

Table 2: Identification rate for ww_1 and ww_2

5. CONCLUSIONS AND OUTLOOK

As a general result, it can be stated that neural networks are an outstanding method for monitoring a tool's wear in CNC-lathes. The approach could be transfered from turning to other chipping processes with geometric tools (e.g. milling or drilling).

The continuous estimate of two parameters allows to consider the state of wear in mathematical models describing the influences of static and dynamic process-specific parameters (incl. wear) on the three mentioned forces. Using these models, it is possible to compute dynamic thresholds, which may be compared with measured forces in order to fulfill two other important tasks of tool monitoring systems: the detection of collisions (unintended contacts between the tool and parts of the machine or workpiece causing rapidly increasing forces) and the identification of small outbreaks at the cutting edges of a tool (or complete breaks) [10].

Our actual and future research deals mainly with tests of other neural network paradigms (e.g. Elman- or Jordan-networks, ART (Adaptive Resonance Theory) architectures or time-delay neural networks) and learning methods. First attempts with time-delay neural networks (TDNN, see e.g. [7, 11]) showed promising results: again, it was possible to reduce the number of input parameters significantly. Fig. 6 gives an example for an estimate where a TDNN with only three input neurons has been used (compare to fig. 4 which refers to the same insert).

Furthermore, we investigate additional improvements of the pre-processing of the input parameters, e.g. by aligning the input values with respect to the afore mentioned force models.

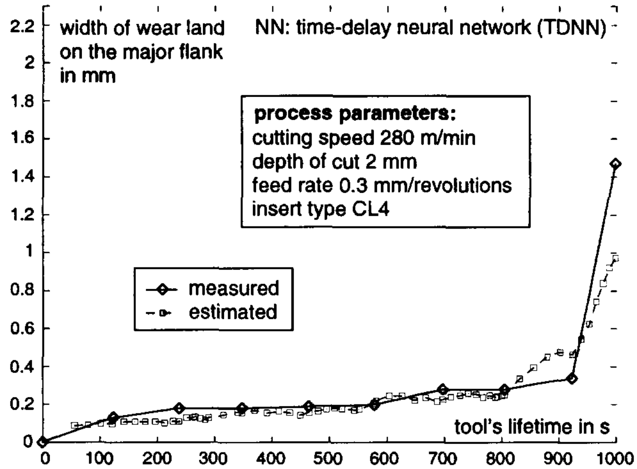

Figure 6: Width of wear land on the major flank II

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