Intelligent Sensorless Monitoring Dual System to Detect the Tool Condition in CNC Milling Machines

G. Mota-Valtierra[1], **L.A. Franco-Gasca**[1]**, H. Aguirre-Becerra**[1] and **F. Ruiz-Vazquez**[2]
, [1]Facultad de Ingeniería, Universidad Autónoma de Querétaro, Querétaro, México
[2]Departamento de Mantenimiento, Instituto Tecnológico de Celaya, Celaya, Guanajuato, México

Abstract: *Tool state in the CNC milling machines will determine the product quality. An efficient tool state monitoring system will protect machinery from severe damages. For determining the state of the cutting tools in a milling machine there is a great variety of models in the industrial market, however those systems are not available for all companies because of their high costs and requirements of modifying the machining tool in order to attach the system sensors in the machine. This paper presents a sensorless intelligent dual system which classifies the cutters status in a CNC milling machine. The tool state is mainly determined through the analysis of the cutting forces drawn from the spindle motors currents. The tool classification is made by a Supervised SOM (Self Organized Maps), a MLP (Multilayer Perceptron) or both, achieving a reliability of 98%.*

Keywords: tool ware, wavelet transform, supervised SOM, Multilayer Perceptron, tool monitoring system.

1 Introduction

One of the main objectives of any company is to satisfy the customer needs by producing high quality products, optimizing costs by improving the manufacturing processes. In order to achieve the quality specifications it is important to eliminate variations during the production processes. For manufacturing companies the use of on line tool condition monitoring systems is essential in order to detect either breakage or tools ware to avoid poor quality production pieces due to the state of cutting tools and even preventing damage of machines.

Neural Networks (ANN) is one of the most common and reported methods used in monitoring systems that classifies tool state, it is widely used because of its adaptive learning, self-organization, fault tolerance and real-time operation, providing good solutions for classification or decision making problems. Examples of ANNs applied to tool condition classification are found in [1], [2], [3] and [4].

Literature suggests that exists a correlation between cutting forces (static and dynamic) and tool wear [5], and those parameters may be studied in several forms, such as the based on changes of friction force between cutting tools and workpieces [6]. In several works it has been decided to analyze the cutting forces in order to determine the level of tool wear [7], [8], [2] and [3]. In order to evaluate cutting forces [9] and [10] developed simulation models that determine cutting forces with more precision than analytical models due to the application of Multi Layer Perceptron (MLP).

The use of sensors is common, however, their application is limited because of the narrow operating range defined by the manufacturer, and usually system designs are made considering specific work conditions, which do not allow adjustments of manufacturing operations. In many occasions it is necessary to make machine modifications to place sensors. All those negative aspects are not presented in the proposed system because of its sensorless operation. It is presented the proposal of an intelligent system, with low cost and easy incorporation to the original process to classify physical condition of the cutting tool in a milling machine, helping to prevent defects in the working pieces and avoiding severe damage on the machine tool.

This paper is organized as follows: Section 1 introduction, Section 2 is related to the monitoring system, and finally in Section 3 conclusions are presented.

2. Development

2.1. Monitoring System.

A retrofitted CNC milling machine, model FNK25, with a head tool of two carbide inserts was used for testing the intelligent classifier. The correct set up of cutting parameters is an important step in the milling process. Parameters selection depends on the material hardness, type of cutter and work piece finish, among others. This choice will determine whether or not the final product meets the quality specifications (dimensions, finish, etc.). The stages that compose a milling process are shown in figure 1.

The milling parameters are shown in Table 1. The milling process was made on ASTM-4130 steel, and using cutters of different states such as new (good conditions), worn (with several degrees of wear) and broken.

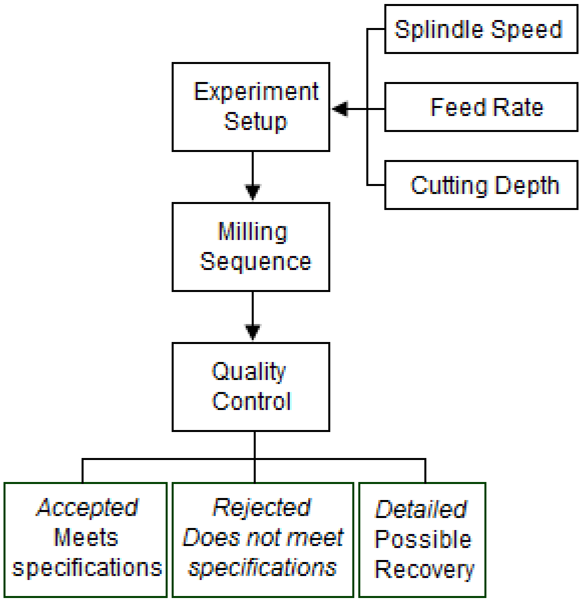

Figure 1. Stages of a milling process

Table 1. Milling parameters

Parameter	Value	
Spindle speed	300 – 450	rpm
Cutting depth	1 – 1.5	mm
Feed rate	100 - 120	mm / min

Values of spindle speed, depth of cut and feed rate were varied between the ranges shown in table 1 for each case. Signals from the motor spindle driver were acquired to determine the cutter status; these signals are a direct representation of the cutting forces. A Tektronik MSO4000 oscilloscope was the instrument used to acquire the signals. Finally, to obtain the neural networks inputs, a features extraction from the acquired data was made by digital signal processing techniques. Figure 2 represents the general system stages.

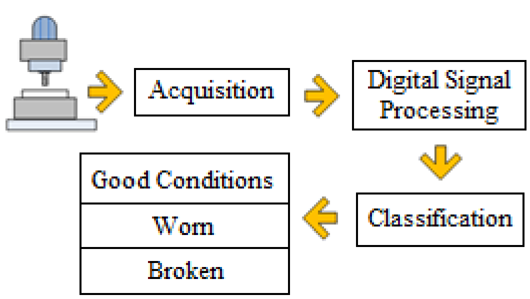

Figure 2. Monitoring system stages

2.2. Data Acquisition.

As mentioned before, the cutting forces will be the main parameter to be analyzed [11]; one of the points where is possible to acquire these signals is the spindle motor. Thus for avoiding the use of sensors, in this research the motor driver is proposed as the data source. The original signal presents the cutting force as its main component; however, it is important to mention that signals from the servo driver have severe noise interference by the ball-screw and the switching noise due to the associated digital systems [12]. Because of this, previously to the digital processing is necessary to filter the spindle current signals. Figure 3 shows the signal processing system, which was used to obtain the cutting forces.

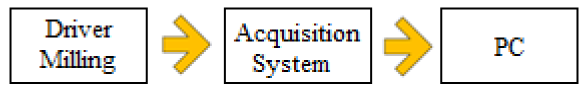

Figure 3. Experiment setup

For noise elimination, the original signal was filtered using a band-pass filter. A Finite Impulse Response (FIR) digital filter was chosen because it has a linear phase response. Table 2 presents the parameters of the applied filter; this was designed using the filter design and analysis tool from MatLab.

Table 2. Filter parameters

Filter characteristics	
Filter type	Bandpass
Design method	Kaiser window
Sampling frequency	6250 Hz
Order Filter	20
Cutoff frequencies	fc1 20 Hz
	fc2 138 Hz

Figure 4 displays an unfiltered signal (a) and its corresponding filtered signal (b). The filtering process removes noisy components and preserves the embedded cutting force.

To consolidate the classification process a data compression procedure was performed. This was done by the Wavelet Transform (WT), which implements a mapping of the time-domain to a time-scale representation, preserving the temporal aspect. The figure 5 shows a signal with different compression levels by applying a Daubechies-5 Wavelet function, it can be seen that those levels have the same pattern but a different resolution. The maximum transformation level is determined by the desired resolution, for this study the fifth level was selected, this allows to achieve a data reduction from 1024 to only 32 points per sample.

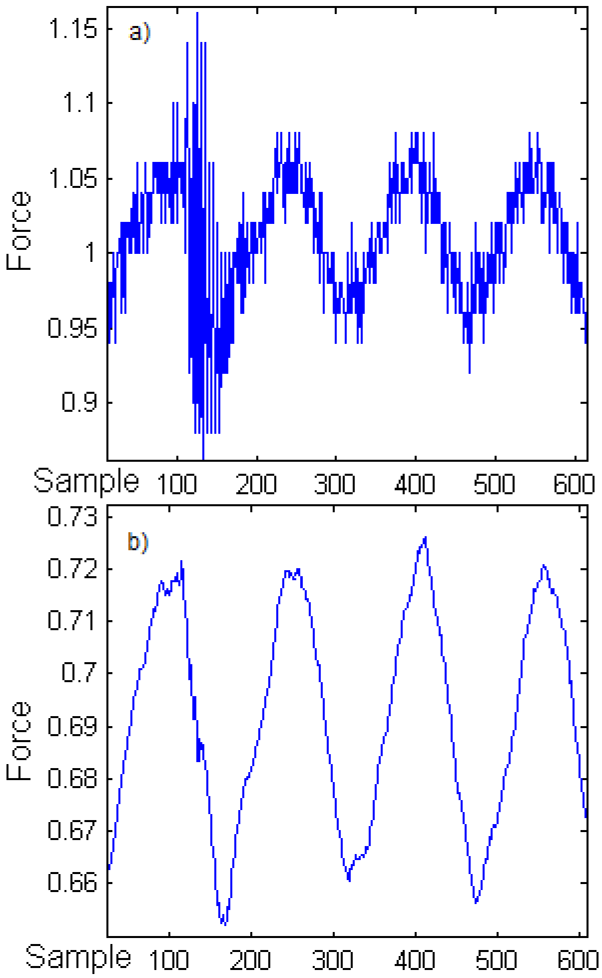

Figure 4. (a) Unfiltered signal. (b) Filtered signal.

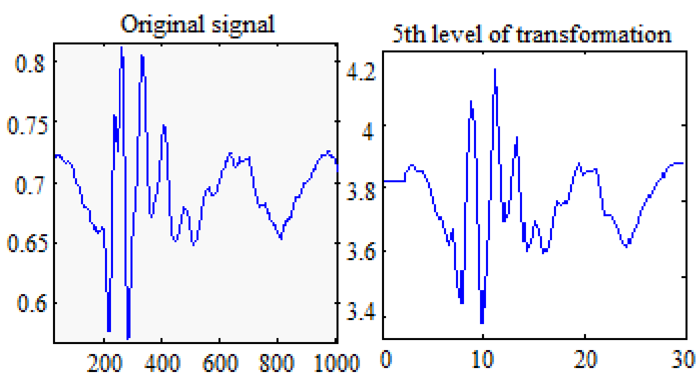

Figure 5. Data compression levels. The Y-axis represents the cutting force and the X-axis is the sample number

2.3. Intelligent Classification.

In order to select the optimal networks for tool state classification, several Multi Layer Perceptron (MLP) type networks with supervised training were tested. Self-Organizing Maps (SOM) with supervised and unsupervised training were supervised, this represents a significant variation because SOM networks are usually unsupervised trained. Some of the tested MLP networks included [3, 10, 10, 3], [3, 8, 8, 3], [3, 8, 12, 3] and [3, 8, 10, 3] structures. Figure 6 shows one of the MLP tested. The activation function is a sigmoid function and learning rate of 0.2.

It was decided to test a SOM network as classifier, due to its low sensitivity to noise, it is an appropriate tool to classify this kind of signals. Some of the analyzed structures were [4, 4], [4, 8] and [8 8], these were trained using both supervised and unsupervised learning. The supervised training was made adding a supervisor agent, which is an array of [*N* 1], where *N* is the number of existing classes. Figure 7 shows a [4, 4] SOM network with a neighborhood of 1.

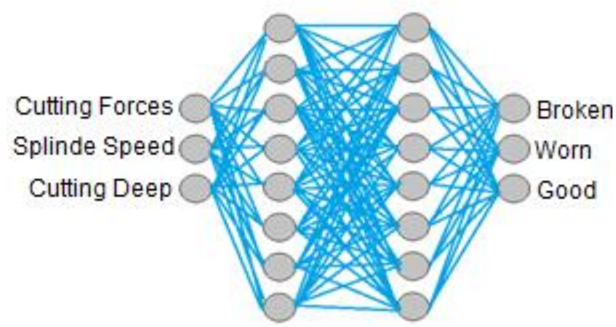

Figure 6. Multilayer Perceptron [4 8 8 3].

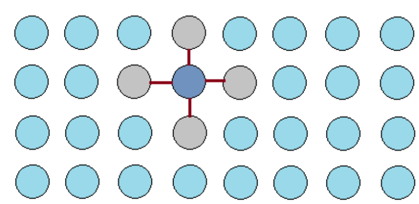

Figure 7 SOM-type artificial neural network [4,8], with neighborhood 1

The classifier was tested using two different kinds of ANNs with different size and training types. There are differences in the networks performance, but they are not significant. As summary, the Table 3 shows the achieved error during the training of the MLP networks and Table 4 shows the error using ANN SOM supervised.

Table 3. Error of MLP networks

Cutting depth (mm)	**Feed rate (mm/min)**	**Spindle speed (rpm)**	**Epoch**	**Neuron in hidden layers**	**Error**
1	100	300	1000	[8,8]	0.001397
1	100	450	1000	[8,8]	0.001298
1	120	300	1000	[10,10]	0.00099
1	120	450	1000	[10,10]	0.00099
1.5	100	300	1000	[8,10]	0.00099
1.5	100	450	1000	[8,10]	0.00099
1.5	120	300	1000	[8,12]	0.00099
1.5	120	450	1000	[8,12]	0.00099

Table 4. Error of MLP networks

Cutting depth (mm)	**Feed rate (mm/min)**	**Spindle speed (rpm)**	**Epoch**	**Structure**	**Error**
1	100	300	1000	[4,4]	0.001197
1	100	300	1000	[4,8]	0.001318
1	100	300	1000	[8,8]	0.00099
1.5	120	450	1000	[4,4]	0.00199
1.5	120	450	1000	[4,8]	0.00099
1.5	120	450	1000	[8,8]	0.00099

Figure 8 shows the way as the error decreases, there is not an important difference among the obtained errors when the number of neurons in the hidden layers is bigger than 8. The neural network that is considered as suitable for using in the proposed intelligent classifier should have at less eight neurons in the hidden layers. For validating the network performance two types of inputs were tested, signals previously used during the training and signals not used for the training process. Figure 9 shows the convergence of the ANN SOM supervised and unsupervised.

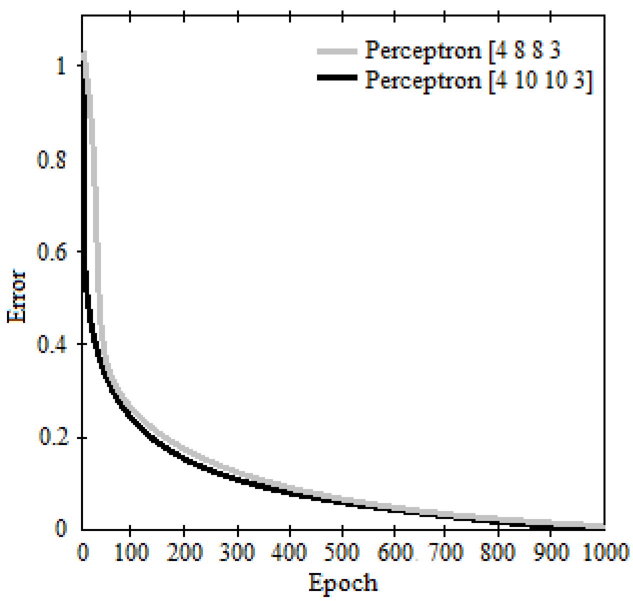

Figure 8. Error during neural networks training

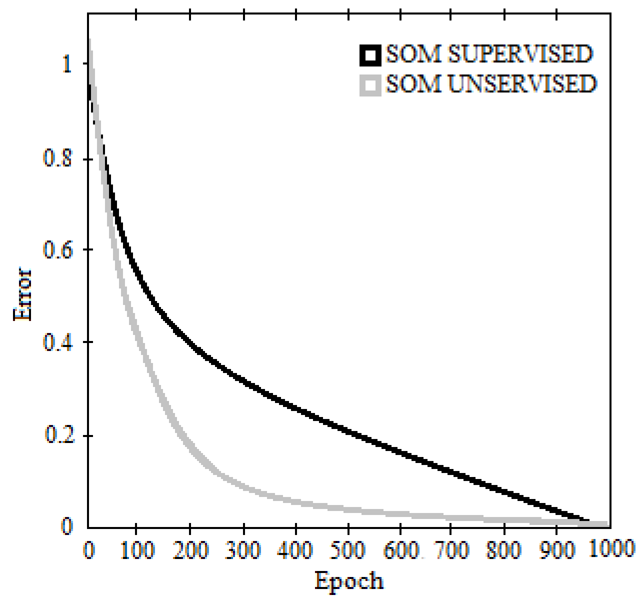

Figure 9. Error during neural networks training

For testing the monitoring system we can use one, two or both ANNs (MLP and SOM supervised). Some of the worn cutters were used during the training. To guarantee a good classification system it must identify either a broken or worn cutter. Figure 10 shows some results of correct identifications.

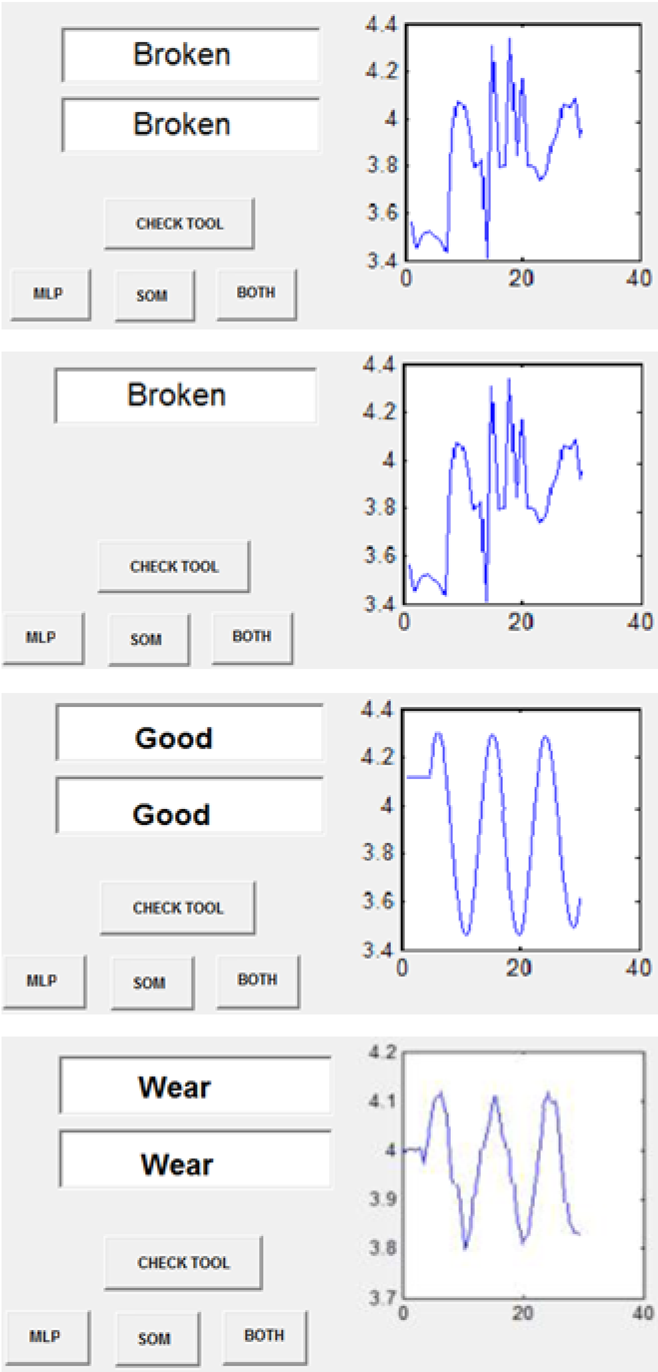

Figure 10. Status classification of tool using two and one ANN.

3. Conclusions

Cutting force variations have been correlated to the tool wear by using one or two Artificial Neural Network, as a consequence the correct classification of the cutting tool condition is achieved. The ANNs approach had made possible the online and fault tolerant monitoring of the tool, besides the system presents the advantage of not having to stop the machine for knowing the tool condition. From test using both training types, the SOM supervised obtained a faster convergence than SOM unsupervised. The presented tool condition monitoring system is sensorless, thus the machinery will not be modified if the system is attached to its structure.

There is not a significant difference in the achieved error when the MLP networks have a size more than [8, 8] neurons in the hidden layer, or when del SOM has an structure [8,8]; however, computationally it represents a considerable difference in resources consumption, for that reason is not appropriate to comprise more neurons. So this is the suitable size for a network which is going to be considered as classifier in the proposed system.

The proposed neural network is able to classify breakage levels greater than 0.3 mm with a confidence level of 98%, with the same confidence level it also determines the good condition of the tool. The wear tool can be resolved with an efficiency of 94% when the wear is greater than 0.25 mm. Its reliable confidence level avoids the damage to the machinery, the tool and the piece, which is the main objective of a tool condition monitoring system. In the worst case if the monitoring system fails the workpiece will need to be re-worked with a new cutting tool, since the damage will be just a piece of a lower quality finish. Future work will try to identify two levels of wear tool, in addition to the breakage and the good working conditions.

The maximum compression level of the signal was achieved with five levels of data processing. To verify that the original signal may be recovered, an inverse wavelet transformation was made, verifying that the signal is completely recoverable.

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