Diagnosis of a Cutting Tool in a Machining Center

Antonio J. Vallejo, Rubén Morales-Menéndez, Ciro A. Rodríguez, and L. Enrique Sucar

Abstract—The successful performance of machining centers involves selection, control and monitoring of a large number of parameters. Cutting tool condition is one of the most important variables due to the strong influence on dimensional accuracy and surface finish of the product. However, the cutting tool condition is difficult to measure online. A new proposal for online monitoring of the cutting tool condition based on Hidden Markov Models is presented. The generated vibration signals between the cutting tool and the workpiece are used for classification of the tool condition in different states (new, half-new, half-worn, and worn cutting tool). Feature vectors were obtained from these vibration signals by applying a triangular filter bank and computing the Mel Frequency Cepstrum Coefficients. The proposal includes a training step using the Baum-Welch algorithm and a diagnosis step exploiting the Viterbi algorithm. A Monte Carlo simulation validates a successful performance using experimental data in a face milling process. A comparison with classical approaches such as Artificial Neural Network is discussed.

I. INTRODUCTION

Next-Generation Manufacturing refers to the application of new concepts, models, methodologies and information technologies, with the goal of preparing manufacturing companies to become more competitive in a global networked environment, [14]. An important characteristic of future manufacturing equipment will be its ability to adapt to changing environments and conditions, [12]. This implies to build intelligent machine to achieve a goal or keep the performance under these conditions. An intelligent system must possess: sensory perception, pattern recognition, learning, knowledge acquisition, inference from incomplete information, adaptation, etc. In this work, we are interested in the cutting tool monitoring system where some of the previous features are exploited.

In any typical metal-cutting process, key indexes that define the product quality are dimensional accuracy and surface finish, both are directly influence by the cutting tool condition. One of the main goals in a Computer Numerically Controlled (CNC) machining center is to find an appropriate trade-off among cutting tool condition, surface quality and productivity. This economical goal implies the cost of the tool, its replacement, the idle time cost, and so forth. It is very appreciated a cutting tool condition monitoring system that optimizes the operating cost with the same quality of the product, [17], [10].

Cutting tool failures represent about 20 % of machine tool down-time. Also, cutting tool wear negatively impacts the end product quality in the terms of dimensions, surface finishing, and surface integrity, [13]. However, cutting tool monitoring is not an easy task by several reasons. There is not a direct method for measuring the cutting tool wear, so indirect measurements are needed for estimation of the cutting tool wear. Additionally, signals coming from sensors in machine tools are disturbed for many other reasons such as outbreaks of cutting tool, chatter, variances of the tool geometry, properties of the workpiece material, noise of digitizers, sensor nonlinearity, etc. There is not a straightforward solution.

In this work, we review the main factors that influence the cutting tool condition during the face milling process, and a novel feature extraction is proposed. A methodology for monitoring the cutting tool condition based on continuous Hidden Markov Models (HMM) is presented. This paper is organized as follows. In section II, we review the state of the art. In section III, we define the cutting tool conditions used in the experiments. Also, we describe the experimentation. In section IV, we discuss the relationship among the cutting parameters, geometry of tool, and the tool-wear condition. In section V we describe a proposal for monitoring and diagnosis the cutting tool-wear condition. In section VI, experimental results are shown and compared with the classical approaches such as Artificial Neural Network. Finally, section VII concludes the paper.

II. STATE OF THE ART

There are important contributions for cutting tool monitoring systems based on Artificial Neural Networks (ANN), Bayesian Network (BN), multiple regression approaches and stochastic methods.

In [8], a monitoring and diagnosis approach based on a Bayesian Network (BN) is presented. This approach integrates multiple process metrics from sensor sources in sequential machining operations to identify the causes of process variations. It provides a probabilistic confidence level of the diagnosis. The BN was trained with a set of 16 experiments, and the obtained performance was evaluated with 18 new experiments. The BN diagnosed the correct state with 60 % confidence level in 16 of 18 cases. [18] proposed a new hybrid technique for cutting tool wear monitoring in turning which fuses a physical process model with an ANN model. The physical model describes the influence of cutting conditions on measure force signals and it is used to
normalize these force signals. The \( \text{ANN} \) model establishes a relationship between the normalized force signals and the wear state of the cutting tool. The performance for the best model was 99.4\% for the learning step, and 70.0\% for testing step.

Haber and Alique, [10], developed an intelligent supervisory system for cutting tool wear prediction using a model-based approach. The dynamic behavior of the cutting force is associated with the cutting tool and process conditions. First, an \( \text{ANN} \) model is trained considering the cutting force, the feed rate, and the radial depth of the cut. Second, the residual error obtained from the measure and predicted force was compared with an adaptive threshold in order to estimate the cutting tool condition. This condition is classified as new, half-worn, and worn cutting tool.

In [11], presented an investigation of cutting tool wear monitoring in a High Speed Machining process based on the analysis of different signals signatures in time and frequency domains. They used sensorial information coming from dynamometers, accelerometers, and acoustic emission sensors in order to obtain the deviation of representative variables. The tests were designed at different cutting speeds and feed rates to determine the effects of a new and worn cutting tool. Data were transformed from time to frequency domain using the Fast Fourier Transformer (\( \text{FFT} \)) algorithm. They concluded second harmonic of the tooth path excitation frequency in the vibration signal is the best indicator for cutting tool wear monitoring. A similar methodology based on the frequency domain is presented by [5] for on-line detection when cutting tool breaks. The frequency domain presents two important peaks at low frequencies, which are compared to compute a ratio that could be an indication for monitoring tool breakage. Also, [17] worked with multilayered \( \text{ANN} \) for monitoring and diagnosis of the cutting tool condition and surface roughness. The obtained success rates was of 77\% for tool wear and 80\% for surface roughness.

An interesting approach was presented by [15]. A feature extraction from vibrations during the drilling is generated by a Self-Organizing Feature Maps (\( \text{SOFM} \)). The preprocessing of the signals implies a spectral feature extraction to obtain the time-frequency representation. The features are the inputs of a \( \text{HMM} \) classifier. The authors demonstrated that \( \text{SOFM} \) are an appropriated algorithm for feature extraction of vibration signals. [3] also used \( \text{HMM} \) for evaluation of the tool wear in milling process. The feature extraction from vibrations signals were the root mean squared, energy and its derivative. The cutting tool conditions were worn and no-worn. The reported performance was around 93\%.

Table I summaries the approaches discussed in this section, where different sensors such as acoustic emission (AE), dynamometer (DY), accelerometers (AC) and spindle power (SP) were used.

The contribution of this work is the implementation of a new methodology for monitor and diagnosis the cutting tool condition considering:

- Exploit the \( \text{HMM} \) classifier to increase the recognition performance of cutting tool condition at different tool-wear states.
- Apply a new approach in the pattern recognition based on speech recognition framework (Mel frequency Cepstrum coefficients).
- Implement classical models of \( \text{ANN} \) for comparison with the \( \text{HMM} \) approach.

### Table I

**Comparison of different research efforts in cutting tool condition monitoring.**

<table>
<thead>
<tr>
<th>Process</th>
<th>Monitoring states</th>
<th>Sensor signals</th>
<th>Recognition methods</th>
<th>Refers.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Face Milling</td>
<td>Tool wear (Low-high)</td>
<td>AE, SP</td>
<td>BN</td>
<td>[8]</td>
</tr>
<tr>
<td>Turning</td>
<td>Tool wear (Wear value)</td>
<td>Process parameters</td>
<td>ANN</td>
<td>[18]</td>
</tr>
<tr>
<td>Milling</td>
<td>Tool wear (New/half worn, worn)</td>
<td>Process parameters</td>
<td>ANN</td>
<td>[10]</td>
</tr>
<tr>
<td>Milling</td>
<td>Tool wear (New/half worn, worn)</td>
<td>AE, DY, AC</td>
<td>FFT</td>
<td>[11]</td>
</tr>
<tr>
<td>End Milling</td>
<td>Tool Breakage (Normal/Broke)</td>
<td>AC</td>
<td>FFT</td>
<td>[5]</td>
</tr>
<tr>
<td>Face Milling</td>
<td>Tool wear Surface Rough.</td>
<td>DY</td>
<td>ANN</td>
<td>[17]</td>
</tr>
<tr>
<td>Drilling</td>
<td>Tool wear</td>
<td>AC</td>
<td>HMM</td>
<td>[15]</td>
</tr>
<tr>
<td>End milling</td>
<td>Tool wear (worn-no worn)</td>
<td>AC</td>
<td>HMM</td>
<td>[3]</td>
</tr>
<tr>
<td>Face milling</td>
<td>Tool wear (New, half-new, half-worn, worn)</td>
<td>AC</td>
<td>HMM</td>
<td>Current Study</td>
</tr>
</tbody>
</table>

### III. Experimental technique for evaluation of the cutting tool-wear condition

#### A. Design of experiments

The experiments were designed for the face milling process of AISI 1045 workpiece. The cutting parameters were defined according to manufacturer Table II, [1]. A full factorial design was used for the experimentation with factors cutting speed and feed per tooth. Based on this information, the spindle speed and feed rate were defined to obtain all required cutting parameters.

#### Table II

**Specification of the parameters for the design of experiments**

<table>
<thead>
<tr>
<th>Cutting parameters</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Cutting Speed</td>
<td>( f_c )</td>
<td>100, 200 m/min</td>
</tr>
<tr>
<td>Feed per tooth</td>
<td>( f_z )</td>
<td>0.12, 0.16, 0.24 mm per tooth</td>
</tr>
<tr>
<td>Depth of cut</td>
<td>( d )</td>
<td>0.5 mm</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Cutting tool inserts</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Type of inserts</td>
<td>Coated grade</td>
<td>BK-34 (APKT 1203PD-R)</td>
</tr>
<tr>
<td>Cutting tool diameter</td>
<td>( D )</td>
<td>TiC/TiN-PVD</td>
</tr>
<tr>
<td>Number of inserts</td>
<td>( z )</td>
<td>63 mm</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Workpiece parameters</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Material</td>
<td>Dimensions</td>
<td>AISI 1045 Steel</td>
</tr>
<tr>
<td>Hardness</td>
<td>8 ( \times ) 2.5 ( \times ) 2.5 inches</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Hardness</td>
<td>170 BHN</td>
</tr>
</tbody>
</table>
B. Machining center and cutting tool

The experimental tests were implemented in a KX-10 Huron machining center with a capacity of 20 KW, three axis, and equipped with a Siemens open Sinumerik 840D controller, Fig 1a. The cutting tool was a Komet face mill F511, with a diameter of 63 mm, and five inserts BK-84 (APKT 1203 PDR) with TiCN/TiN-PVD coated grade, which combines toughness with good resistance, Fig 1b.

![Fig. 1. a) KX-10 Huron CNC-milling center. b) Komet cutting tool and evolution of the wear in the cutting tool edge. Cutting conditions: \( V_c = 100 \) m/min, and \( f_z = 0.12 \) mm/tooth. Insert condition : New, Half-worn, and Worn (right to left).](image)

C. Multi-sensor system

We developed an integrated multi-sensor data acquisition system. The vibration signals were recorded using an industrial accelerometer, model number 621B41 with a 100 mV/g sensibility, which was localized in the y-axis workpiece. The signal conditioning was carried out by an ICP sensor signal conditioner 480C02 which was connected to a CompuScope data acquisition card, Fig 2. The spindle load, spindle speed, feed of rate, and depth of cut were read through the MPI card which talks directly to the open CNC, Fig 2.

![Fig. 2. Data Acquisition System. Two data acquisition cards allows us to get the appropriate signals.](image)

IV. CHARACTERIZATION OF THE CUTTING TOOL WEAR.

In the milling process, the cutting tool life can frequently be reduced because of chipping, cracks, and breakage of the cutting edge. This occurs because milling is an interrupted operation, where cutting tool edge enters and exits the workpiece several times. Additionally, chip thickness varies at the edge penetrates the workpiece. Regular tool wear mechanisms will be predominant only if the tool is tough enough to resist the mechanical and thermal shocks of the workpiece, [9]. The employed inserts in the cutting tool presented this last condition.

We need to define the dimension tool life, because we want to show the results in a general form (i.e. independent of the machined length). The proper assessment of cutting tool wear requires some quantitative characteristics. The selection of these characteristics depends upon a particular objective of a tool wear study. Dimension tool life can be characterized by the time within which the tool works without adjustment or replacement (\( T_{tool} \)). It is defined as,

\[
T_{tool} = n_p \frac{l \times a_e}{f_z \times V_c \times 1000}
\]

where:
- \( T_{tool} \) is the time (min) within which the tool works
- \( n_p \) defines the number of passes over the workpiece
- \( l \) is the length (mm) of the workpiece
- \( a_e \) is the width (mm) of workpiece

Cutting tool wear could be considered in different surfaces of the inserts: flank, nose and crater. We register the flank wear \( (V_b) \) because it is the most important. Its measures was carried out according to ISO 8688-2. Fig 1b depicts the evolution of the tool wear during the experiments.

Fig 3 shows the results of the cutting tool wear condition versus the dimension tool life. As we can see cutting speed has a great influence in the wear of the cutting tool. There is a clear separation among results based on \( V_c = 100 \) m/min (upper left lines) and \( V_c = 100 \) m/min (lower right lines). For each cutting speed there is linear relationship among cutting tool-wear and cutting tool time; however this linear regression has greater slope as cutting speed grows.

We can conclude that the influence of either feed per tooth or feed velocity (which in this case is proportional to the volume of chip removed per minute) is much lower than the influence of cutting speed in cutting tool wear and tool life.

Considering the above results, and in agreement with [2], we define the flank wear of cutting tool as the criterion to evaluate the tool life. Some values of the wear for carbide tools indicate that the average width of the flank wear land is \( V_b = 0.3 \) mm, and the maximum width of the flank wear land is \( V_b_{max} = 0.6 \) mm.

The cutting tool condition was discretized in four states according to Table III.

<table>
<thead>
<tr>
<th>Tool-wear condition</th>
<th>Allowed wear</th>
</tr>
</thead>
<tbody>
<tr>
<td>New</td>
<td>( 0 ) ( \mu )m ( \leq V_{b_{max}} &lt; 75 ) ( \mu )m</td>
</tr>
<tr>
<td>Half-new</td>
<td>( 75 ) ( \mu )m ( \leq V_{b_{max}} &lt; 150 ) ( \mu )m</td>
</tr>
<tr>
<td>Half-worn</td>
<td>( 150 ) ( \mu )m ( \leq V_{b_{max}} &lt; 250 ) ( \mu )m</td>
</tr>
<tr>
<td>Worn</td>
<td>( 250 ) ( \mu )m ( \leq V_{b_{max}} )</td>
</tr>
</tbody>
</table>

TABLE III

STATES OF THE CUTTING TOOL CONDITION.
V. Monitoring and Diagnosis Methodology

Fig 4 shows a conceptual flow diagram of monitoring and diagnosis system based on continuous HMMs. The vibration signal referring to the y-axis accelerometer in the milling process is considered the input signal. As we can see in Fig 4, the signal is preprocessed and then it is split into two: training and test branches. The training branch produces the HMM model. With the given HMM and test branches, the training branch produces the signal is preprocessed and then it is split into two: training and test branches. The testing branch uses the parameterized signal a decoder produces a transcript of a specific pattern as a result. In this training phase the system learns the patterns that have a higher probability is selected as result, [19]. We will review the steps and basic concepts of the proposed algorithm.

A. Hidden Markov Models

Hidden Markov Models (HMM) are an extensive of Markov chains and used to model process whose characteristics vary with the time. A HMM, as defined by [16], is a doubly embedded stochastic process, where one process is hidden, and it can only be observed through another set of stochastic processes that produce the sequence of observations, [4]. For completeness we will review some basic definitions.

- \( T \), length of observations sequence.
- \( N \), number of states in the model.
- \( M \), number of distinct observation symbols per state.
- \( A \), the state transition probability distribution.
- \( B \), the observation symbol probability distribution in state.
- \( O \), an observation sequence.
- \( \pi \), the initial state distribution.

Given appropriate values of \( N, M, A, B, \) and \( \pi \), the HMM can be used as a generator to give an observation sequence \( O \). Then, a complete specification of an HMM requires of two model parameters (\( N \), and \( M \)), specification of observation symbols, and also the specification of the three probability measures \( \lambda = (A, B, \pi) \). These parameters are learned in the training branch, Fig 4. Given this model and the observation we can compute \( P(O|\lambda) \).

B. Feature extraction

The vibration signals during the machining process contain abundant information of the tool status, such as, fundamental frequencies related with the spindle speed and number of inserts, wide frequency band, amplitude of vibration signal, and the sensitivity to detect the condition of the tool, the chatter, and so forth. The vibration signals are pre-processed calculating their Mel Frequency Cepstrum Coefficient MFCC representation, [7]. This common transformation has shown to be more robust and reliable than other techniques, [6]. There is a mapping between the real frequency scale \( (f_{Hz}) \) and the perceived frequency scale \( (f_{Mel}) \). The scale Mel is defined by equation (1).

\[
    f_{Mel} = 2,595 \times \log(1 + \frac{f_{Hz}}{700}) \tag{1}
\]

The process to calculate the MFCC is shown in Fig 5.

In this process, we must define the number of filters (20), sampling frequency (50,000Hz), amplitude of the filters, and the configuration of the filter banks (triangular or rectangular shape). At the end, the MFCC are computed using the Discrete Cosine Transform:

\[
    MFCC_i = \sqrt{\frac{2}{N} \sum_{j=1}^{N} m_j \cos\left(\frac{\pi}{N}(j - 0.5)\right)} \tag{2}
\]

where \( N \) is the number of bandpass filters, \( m_j \) is the log bandpass filter output amplitudes. The result is a 13-dimension vector, where each dimension corresponding to one parameter. Fig 6 presents the obtained coefficient for a specific vibration signal shown in the same figure.
C. Baum-Welch algorithm

The Baum-Welch algorithm, [16], is used to adjust the model parameters to maximize the probability of the observation sequence given the model. The observation sequence used to compute the model parameters is called a training sequence. The training problem is crucial in the applications of the HMMs, since it allows us to optimally adapt model parameters to observed training data. The Baum-Welch algorithm is an iterative process that uses the forward and backward probabilities to solve the problem. The goal is to obtain a new model \( \lambda = (\bar{A}, \bar{B}, \bar{\pi}) \) to maximize the function,

\[
Q(\lambda, \bar{\lambda}) = \sum_{Q} \frac{P(O, Q | \lambda)}{P(O | \lambda)} \log[P(O, Q | \bar{\lambda})]
\]

First, a current model is defined as \( \lambda(A, B, \pi) \), and used to estimate a new model as \( \bar{\lambda} = (\bar{A}, \bar{B}, \bar{\pi}) \). The new model must present a better likelihood than first model to reproduce the observation sequence. Based on this procedure, if we iteratively use \( \bar{\lambda} \) in place of \( \lambda \) and repeat the reestimation calculation, then we can improve the probability of \( O \) being observed from the model until some limiting point is reached. The result of the recalculation procedure is called a maximum likelihood estimate of the HMM. At the end, the new set of parameters (means, variance, and transitions) for each HMM are obtained.

D. Viterbi Algorithm

In pattern recognition applications, it is useful to associate an optimal sequence of states to a sequence of observations, given the parameters of model. In pattern recognition, the feature vector, representing the observations, is known, but the sequence of states that defines the model is unknown. An optimal criterion consists in choosing the state sequence (or path) that brings a maximum likelihood with respect to a given model. This sequence can be determined recursively via the Viterbi algorithm, [4]. This algorithm allows to find the single best state sequence, for the given observation sequence, and it makes use of two variables:

1) The highest likelihood \( \delta_t(i) \) along a single path among all the paths ending in state \( i \) at time \( t \).
2) A variable \( \psi_t(i) \) which allows to keep track of the best path ending in state \( j \) at time \( t \).

VI. Results

A database was built with 110 experiments for testing our proposal. Basically, we want to classify the cutting tool condition according Table III. Our experimental database has 23 experiments using new cutting tool, 35 using half-new cutting tool, 29 for half-worn, and 23 for worn cutting tool.

The configuration for the HMM was: 4 states, 4 Gaussian, and a feature vector of 13 dimensions (1 energy coefficient and 12 MFCC coefficients). We evaluated the HMM for different states, and with several number of Gaussians to determine the best configuration of the HMM with an optimal performance. Table IV shows the performance results where 4 Gaussians with 4 states is the best configuration.

<table>
<thead>
<tr>
<th>States Number</th>
<th>Number of Gaussians</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>1</td>
<td>82.83 %</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>86.87 %</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>86.87 %</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>86.87 %</td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>85.86 %</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>85.86 %</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>86.87 %</td>
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<tr>
<td></td>
<td>8</td>
<td>86.87 %</td>
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<tr>
<td>5</td>
<td>1</td>
<td>86.87 %</td>
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<tr>
<td></td>
<td>2</td>
<td>87.88 %</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>86.87 %</td>
</tr>
</tbody>
</table>

We applied a Monte Carlo simulation for training/testing the approach. Basically, we
1) Randomly define the training \((T_r)\) and testing \((T_s)\) experiments (70 % and 30 % respectively).
2) Train and test the model with both \(T_r\) and \(T_s\) experiments.
3) Repeat step 2 with different number of Gaussians.
4) Evaluate the classifier performance for different combination of \(T_r\) and \(T_s\).

Fig. 7 presents the results for 1, 2, and 4 Gaussians. To illustrate the variability of the diagnosis, we show the performance versus number of Gaussian for the algorithm as a box and whisker plot in Fig 7. The boxes have lines at the lower quartile, median, and upper quartile values. The whiskers are lines extending from each end of a box to show the extent of the rest of the data. The boxes are notched. Notches represent a robust estimate of the uncertainty about the medians for box-to-box comparison. Outliers are data values beyond the ends of the whiskers; outliers are shown as circles. Note an excellent performance when the algorithm was trained/tested with the same database. When the algorithm was trained/tested with different database, we observe that the \(HMM\) with 4 Gaussians presents the best results. The obtained result was of 99.87 % for \(T_r = T_s\), and 84.55 % for \(T_r \neq T_s\) condition.

Fig 8 shows the performance of the diagnosis system over time, when the \(HMM\) (with 4 Gaussians) was tested with different database. This figure depicts that almost all cutting tool conditions were detected. Also, low quality product can be generated. Fig 9 presents the obtained probability for the mentioned conditions. The \(HMM\) with 4 Gaussians presents the smallest probability for the FFR.

A. Artificial Neural Network

In order to compare our results with classical approaches, the cutting tool wear condition was modelled with an Artificial Neural Network \((ANN)\). An \(ANN\) is often defined as a computing system made up of a number of simple elements called neurons, which possesses information by its dynamic state response to external inputs. We proposed two architectures for the \(ANN\), Fig 10. First model \(ANN(4,4,1)\) implies 4 input neurons, 4 hidden neurons and 1 output neuron. We used a feedforward \(ANN\) model and \(tanh\) activation function. The trained algorithm was classical backpropagation.

For computing, input data were normalized and output data were mapped to \([-1, 1]\). Table V shows the mapped values being detected. Also, low quality product can be generated.
between the normalized tool-wear and tool-wear condition. The data set was randomly divided into two sets as training (70%), and testing (30%) sets in order to evaluate its generalization capacity. We obtained the performance of the models for different sets of data.

**TABLE V**

<table>
<thead>
<tr>
<th>Normalized tool condition</th>
<th>Cutting tool condition</th>
</tr>
</thead>
<tbody>
<tr>
<td>From +0.66 to +1.00</td>
<td>New</td>
</tr>
<tr>
<td>From 0.0 to +0.66</td>
<td>Half-new</td>
</tr>
<tr>
<td>From -0.66 to 0.0</td>
<td>Half-worn</td>
</tr>
<tr>
<td>From -1.00 to -0.66</td>
<td>Worn</td>
</tr>
</tbody>
</table>

The obtained results with the ANNs are depicted in Fig. 11. First, each model was trained/tested with the same data set ($T_r = T_s$). Then, the models were evaluated with different data set ($T_r \neq T_s$). The average performance for model 1 was of 71.43 % when the model was trained/tested with the same database. A lower performance was achieved, 52.72 % when training and testing step were implemented with different database. For model 2, the results were 97.53 % and 71.21 % respectively. The success rate with the second model is similar to the presented results in [17] with an ANN(5,10,2).

Figure 12 presents the obtained results of the diagnosis system over time, when the ANN models were tested to detect the cutting tool condition. The model two shows the better results.

**VII. CONCLUSIONS**

This paper describes an algorithm for monitoring and diagnosis a cutting tool wear condition in a machining center, based on continuous HMMs. After analysis of the main...
factors that influence the wear of the cutting tool, the cutting speed was found to have a predominant influence on tool life, regardless of whether there is variation in either feed rate or feed per tooth. A database was built with the vibration signals and cutting parameters during the machining process of 1045 steel workpiece. The HMMs were trained/tested by considering four states of the cutting tool: new, half-new, half-worn, and worn inserts. The obtained performance was of 99.87 % when the HMMs were trained/tested with the same database, and 84.55 % when HMMs were trained/tested with different databases (more realistic condition). The results were compared with an ANN(5,5,1) approaches, whose performance was of 71.43 % and 52.72 % for same condition of our proposal.

There are several advantages of our proposal based on HMM over ANN approaches. HMM uses only the vibration signal, while ANN demands more variables (which means more sensors). HMM detects the cutting tool condition with better results than ANN, considering large variations of spindle speed and feed rate. HMM approach is ideal for supervisory control systems having monitoring, control and diagnosis features. It is important to say that feedforward ANN classical models, and backpropagation algorithm were used. Therefore, the ANN model was not optimized in this study.

In the future, a Decision-Making block will be implemented, as integral part, to a monitoring and diagnosis system of a cutting tool condition. Decision theory techniques will be used to obtain the maximum utility in the machining process, considering the cutting tool wear and cutting parameters.

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