An exTS based Neuro-Fuzzy Algorithm for Prognostics and Tool Condition Monitoring

O. Massol[1], X. Li[2], R. Gouriveau[1], J.H. Zhou[2], O. P. Gan[2]

[1] FEMTO-ST Institute, UMR CNRS 6174 - UFC / ENSMM / UTBM,
Automatic Control and Micro-Mechatronic Systems Department
24, rue Alain Savary, 25000 Besançon, France

[2] Singapore Institute of Manufacturing Technology,
71 Nanyang Drive, Singapore

Abstract— **The growing interest in predictive maintenance makes industrials and researchers turning themselves to artificial intelligence methods for fulfilling the tasks of condition monitoring and prognostics. Within this frame, the general purpose of this paper is to investigate the capabilities of an Evolving eXtended Takagi Sugeno (exTS) based neuro-fuzzy algorithm to predict the tool condition in high-speed machining conditions. The performance of evolving Neuro-Fuzzy model is compared with an Adaptive Neuro-Fuzzy Inference System (ANFIS) and a Multiple Regression Model (MRM) in term of accuracy and reliability through a case study of tool condition monitoring. The reliability of exTS also investigated.**

Keywords—**Tool wear estimation, Evolving eXtended Takagi Sugeno Neuro-Fuzzy algorithm, Prognostics, Tool condition monitoring**

I. INTRODUCTION

Monitoring of tool wear to prevent surface damage is one of the difficult tasks in the context of tool condition monitoring [1]. Currently, a general common approach is to measure several process parameters that are indirectly correlated to the tool performance, such as cutting force, tool vibration and acoustics emissions, transform the measured data into useful reference models for condition and performance monitoring. Numerous condition monitoring methodologies have been proposed and evaluated during the past two decades. Among them, Yamaguchi [2] investigated the cutting force and acoustic emission (AE) signals to gauge tool life of diamond cutting tool; Vallejo Jr [3] presented online monitoring of the cutting tool condition based on Hidden Markov Models.

Fuzzy-logic, neural-network and their combinations like Neuro-Fuzzy (NF) networks are widely used in modeling and prediction in precision engineering. Haber [4] applied intelligent process supervision for predicting tool wear in machining processes; and Li et al [5] applied the adaptive neuro-fuzzy inference system (ANFIS) [6] and wavelet transforms to tool condition monitoring. Similar cases are also discussed by [1]. A fuzzy-neuro adaptive surface roughness control is proposed for the prediction of the surface roughness and adaptive feed-rate control [7]. A hybrid Taguchi-genetic learning algorithm is used to set up a nonlinear model to correlate the surface roughness values with distinct spindle-speed, feed-rate and depth-of-cut [8]. It is shown that Gaussian membership functions are suitable choices for fuzzy layer of the network for predicting the surface-roughness in [8][9].

Although fuzzy neural networks are widely used in modeling and prediction in milling machining processes, even the most promising methods are not easily adoptable in real industrial operations [10][11] particularly due to insufficient generalisation capabilities (e.g. the use is restricted to a specific machine tool, only a small range of cutting conditions is allowed, or time-consuming 'teach-in' cycles are needed) or lack of precision. As such, there has been limited report on the development of a generic toolkit that provides reference models for on-line tool condition monitoring and remain useful life prediction. It is therefore desirable to develop an intelligent predictive monitoring system (IPMS) [12][13] with capabilities in feature extraction, feature selection, correlation modelling, and data clustering for tool condition monitoring, non-destructive characterization and tool life span prediction.

It is not easy to correlate sensory signals with tool conditions as each cutter will perform differently in a milling process. The technical challenge is to establish a model with acceptable repeatability and reliability for correlating signal data and the real performance from different cutters and use such model to predict cutter health condition and prevent the damage on work piece surface. Neuro-fuzzy (NF) systems are a very promising type of machine learning method for being used as prediction tools because of their ability to learn from examples and to capture unapparent relationships among the data.

This paper focuses on applying Neural-Fuzzy (NF) algorithms to tool wear estimation, which is part of an approach for monitoring the cutter health condition in a high speed milling process. We compared two NF algorithms, exTS and ANFIS, on their model accuracy, repeatability and reliability when dealing with signal data from 5 ball-nose tungsten carbide cutters on a hard to cut material in a machining process. The case study allows us to observe the predictions capabilities of the NF algorithms in a meaningful industrial application.

II. NEURO-FUZZY ALGORITHMS

Two commonly used neuro-fuzzy algorithms, ANFIS and exTS, are investigated on their model accuracy, repeatability and reliability for tool condition monitoring.

A. Adaptative Neuro-Fuzzy Inference System (ANFIS)

First introduced by [14], ANFIS is a straightforward way to implement the Takagi-Sugeno fuzzy inference system in a neural network structure.

The ANFIS architecture shown in Fig. 1 comports a neuron layer for each of the component needed by the fuzzy inference system. The first layer will be dedicated to the membership values of the inputs, the second layer will have the firing strength value associated to each rule, the third layer compute the weight of each rule (normalized firing strengths), the fourth layer determine the rule's value based on the inputs and the last layer does the weighted sum to deliver the system's output.
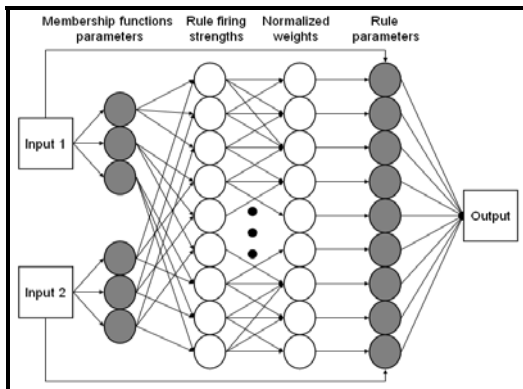

Fig. 1: ANFIS architecture with two inputs and three membership functions per input.

B. Evolving eXtended Takagi Sugeno (exTS) algorithm

First presented in [15], The exTS structure as shown in Fig. 2 is modular and it adapts itself to the process without needing a priori knowledge.
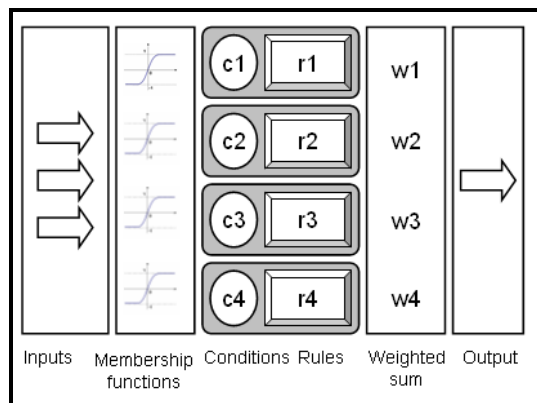

Fig. 2: The exTS with Condition-Rule modules.

During its learning phase, the system has to determine the rules and update the polynomial coefficients corresponding to each rule. For each new training value, the algorithm does two update operations:

The first one is a clustering operation with an aim to determine if the new inputs correspond to an existing condition, if they are close from an existing condition or if they are far from any existing condition. In the first case, no change is done in the model structure; the inputs are in a known configuration. In the second case – the inputs are close to an existing condition – the membership functions associated with this condition are modified. Finally, in the last case, a new condition of the process has been discovered, so we have to add a new condition - rule module to the structure.

The second operation consists in adjusting the rules parameters. Here again, similarly to the ANFIS algorithm we can use a supervised recursive least square method to determine them.

III. CASE STUDY

A case study of tool wear prediction in high speed milling machining process is carried out to evaluate neuro-fuzzy modeling accuracy, repeatability and reliability.

A. Experimental set-up and data acquisition

A high speed CNC machine (Röders Tech RFM760) was selected as a test-bed for the case study. The workpiece material used in the machining test is Inconel 718. The workpiece was cut off from original stock and its surfaces were prepared through face milling to get rid of the original skin layer containing hard particles. The surface was then machined to have a slope with 60˚ to accommodate the 3-flute ball nose cutter. A Kistler quartz 3-component platform dynamometer was mounted between the workpiece and machining table to measure the cutting forces in the form of Newton, and converted them to voltages by the Kistler charge amplifier. A Kistler piezo accelerometer were mounted on the workpiece to measure the machine tool vibration during the cutting process in X, Y, Z direction, respectively. The cutting tools are 5 tungsten carbide ball-nose end mills with the operation at a spindle speed of 10,360 rpm, a feed rate of 1.555mm/min. The cuts generated are 0.125mm wide and 0.2mm deep. Fig. 3 illustrates the experimental setup.

A Kistler acoustic emission (AE) sensor was mounted on the workpiece to monitor the high frequency stress wave generated by the cutting process.
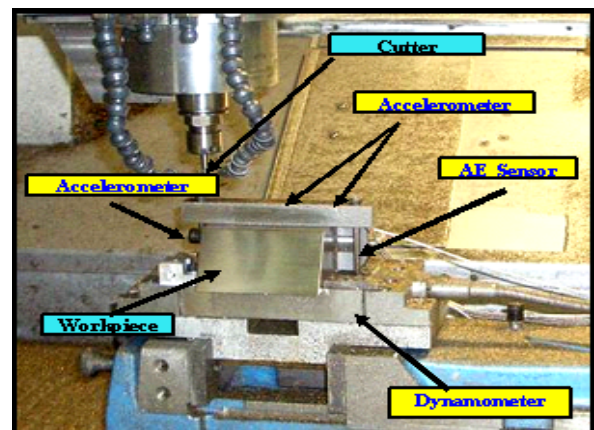

Fig. 3: The experimental set-up in a high speed milling machine

The outputs of these sensors were conditioned through corresponding signal conditioning accessories such as charge amplifiers or couplers and eventually converted into coltage signals. The voltage signals were captured by a NI DAQ PCI 9239 board with 50KHz frequency. The DAQ board generates 16-bit digitized data and directly streams the data to a hard disk of an Intel Core 2 Quad 2.66GHz based industrial PC with 8GB RAM.

Seven channels of signals (*force_x*, *force_y*, *force_z*, *acce_x*, *acce_y*, *acce_z*, AE_RMS) were captured by the DAQ card with an accumulated sampling rate of $50\text{kHz} \times 7 = 350\text{kHz}$.

B. Data pre-processing

The experimental data are used to built up the NF models. Input and output data sets for training and testing the models are extracted as described below.

1) Data as model inputs

Sensor signals are continuously received through data acquisition system in .txt files as model inputs. A data segmentation and pre-processing are carried out to filter noise and capture useful information. The signal stream is segmented to obtain data sets corresponding to each revolution [16]. The data length of one revolution, L is calculated with the sampling frequency and spindle speed that are known a priori. Assume sampling frequency is N Hz and the spindle speed S RPM (revolutions per minute). The data length of on revolution, L can be calculated with Equation 1.

$$L = \frac{N \times 60}{S} \qquad (1)$$

Hence, a data set for each revolution can be obtained by taking every L consecutive data points. Fig. 4 shows an example of force signal revolutions.
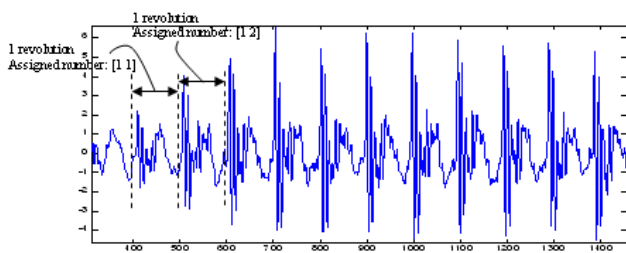

Fig. 4: Force signal revolutions

The segmented data sets are used as raw data, which were further processed to extract distinguished features for model set up.

2) Data as model output

During the experiment, the cutting process is stopped and the flank tool-wear value is measured with an Olympic microscope as model output.

Fig. 5: Flank tool wear after 320 cuts

The tool was dismounted and the wear-out taken in picture after the cut 4, 8, 16, 20, 32, 64, 96, 128, 160, 192, 224, 256, 288 and 320 Fig 5 shows the flank tool wear after 320 cuts. The total of 320 tool wear values is calculated according to a nonlinear interpolation as shown in Fig. 6. All captured tool wear values are used for training NF models and testing model prediction accuracy, repeatability and reliability.
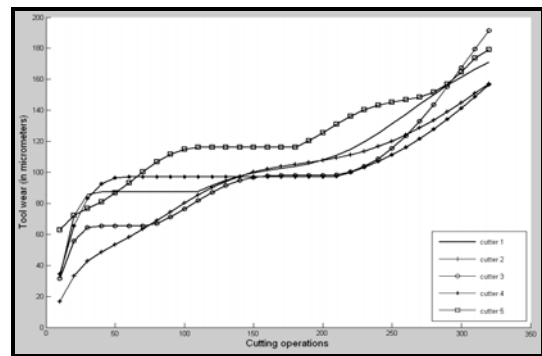

Fig. 6: Measured tool wear values

C. Feature extraction and selection

In this case study, 16 main features are extracted from force signals and 16 main features from acoustic emission signals as summarized in Table 1. The details of the feature extraction method are described elsewhere [17]. The 32 features have been shown to be effective.

Table 1: Extracted Features for Force and Acoustic Emission

No	Force Feature	AE Features
1	Residual Error	Standard deviation of band power
2	First Order Differencing	Peak
3	Second Order Differencing	Skewness
4	Maximum Force Level	Kurtosis
5	Total Amplitude of Cutting Force	Peak to peak
6	Combined Incremental Force Changes	Count
7	Amplitude Ratio	Rise time

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8	Standard Deviation of the Force Components in Tool Breakage Zone	Delta (change in signal)
9	Sum of the Squares of Residual Errors	Mean
10	Peak Rate of Cutting Forces	Standard deviation
11	Total Harmonic Power	Absolute deviation
12	Average Force	Mean of band power
13	Variable Force	Mean of RMS
14	Standard Deviation	Crest-factor
15	Skew	Duration
16	Kurtosis	Area under curve

Further feature subset selection is worked out with the extracted 32 features. The main goal of feature subset selection is to reduce the number of features used in classification without compromising on accuracy. The feature subset selection is necessary as it has been observed that, beyond a certain point, the inclusion of additional features leads to a worse performance. Moreover, the choice of features affects several aspects of the recognition process such as accuracy, learning time and the necessary number of samples. Most importantly, this leads to an increase in time and computational space complexity of the recognition process. Using Ant Colony Optimization to perform the feature subset selection, the selected features are summarized in Table 2. The details of the feature subset selection has been presented elsewhere [18].

Table 2: Selection of features for Force and Acoustic Emission

No	Force Feature	AE Features
1	Maximum Force Level	Peak to peak
2	Total Amplitude of Cutting Force	Skewness
3	Amplitude Ratio	Kurtosis
4	Average Force	Mean of band power

D. Correlation modeling through exTS and ANFIS models

The selected feature data and measured tool wear are then stored into a database. A total of 320 data sets of feature data were generated from raw signals matched with the interpolated tool wear data, half of which are used for rule training and the remaining for testing. The exTS modelling and tool wear prediction are realized by MATLab 2009.

The exTS model establishment starts from feeding the training data sets, one at a time, to the network from layer 1. The input data are fuzzified in layer 2. The exTS then goes to its self learning of fuzzy membership parameters (mean and variance). After the membership functions have been constructed, the next stage is to generate the fuzzy rules. Once the clustering and rule generation are completed, the exTS continues on correlation modeling with supervised leaning algorithm as to fine tune the rule values till mean squared error reaches an accepted level. Tool wear prediction is then conducted using established exTS correlation models. Similar

procedure was adopted for setting up the ANFIS model with the same data sets.

IV. RESULTS DISCUSSION

A. Prediction test on a single cutter

The first test aims to evaluate the prediction accuracy of two NF algorithms, exTS and ANFIS with a single cutter in order to benchmark their accuracy performance and repeatability.

A training set for a cutter is created by selecting randomly a half of the data set of this cutter. The remaining samples are used to test the accuracy of the generated model (for a more convenient display, they are presented in chronological order).
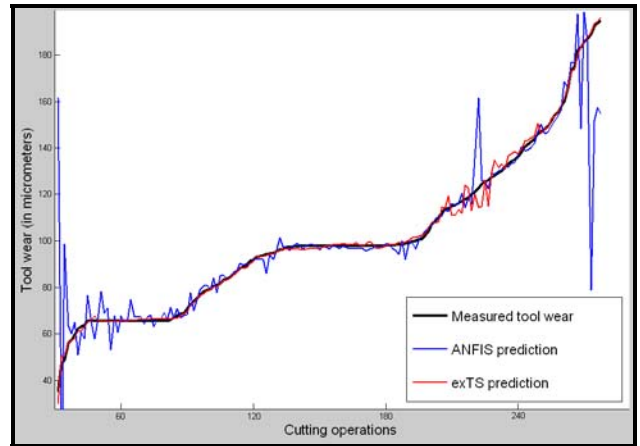

Fig. 7: Prediction performance comparison between ANFIS and exTS

(Tool wear prediction of cutter 3, with a training set of 150 samples. The ANFIS structure uses 2 membership functions per input. The input data are acoustic emission signal features.)

The tool wear prediction performance of exTS model has been compared with an ANFIS model with single cutter as shown in Fig. 7. A total of five cutters are tested with force features and acoustic emission features. The table 3 gives the accuracy indicators for this test, averaged between the five cutters.

Table 3: Prediction performance comparison between exTS and ANFIS

Modeling algorithm	Features from signal	Training set size	Accuracy indicators		
			RMSE	MAPE	R2
ANFIS (2mf)	Force	50	28.12	0.15	0.59
ANFIS (2mf)	AE	50	30.83	0.17	0.54
ANFIS (3mf)	Force	50	23.34	0.14	0.66
ANFIS (3mf)	AE	50	27.55	0.17	0.62
exTS	Force	50	5.96	0.04	0.95
exTS	AE	50	6.34	0.04	0.94
ANFIS (2mf)	Force	100	14.22	0.09	0.82
ANFIS (2mf)	AE	100	15.45	0.09	0.8
ANFIS (3mf)	Force	100	13.15	0.08	0.84
ANFIS (3mf)	AE	100	15.62	0.11	0.81
exTS	Force	100	4.07	0.02	0.96
exTS	AE	100	5.12	0.03	0.96

ANFIS (2mf)	Force	150	10.19	0.05	0.97
ANFIS (2mf)	AE	150	11.26	0.06	0.89
ANFIS (3mf)	Force	150	9.64	0.05	0.95
ANFIS (3mf)	AE	150	11.92	0.07	0.91
exTS	Force	150	2.97	0.02	0.99
exTS	AE	150	3.21	0.02	0.97
ANFIS (2mf)	Force	200	5.17	0.04	0.97
ANFIS (2mf)	AE	200	8.27	0.04	0.94
ANFIS (3mf)	Force	200	4.13	0.03	0.98
ANFIS (3mf)	AE	200	6.06	0.04	0.95
exTS	Force	200	2.38	0.02	0.99
exTS	AE	200	2.75	0.02	0.98

From the results we can conclude that the exTS produces better results in terms of accuracy and repeatability than ANFIS, especially when the model is generated by acoustic emission features. As such, further investigation on model reliability was done with the exTS only.

B. exTS prediction test with a multi-tool model

In the second test, the training data sets are generated by taking samples randomly from different cutters and test data from a single cutter to evaluate exTS reliability. The purpose is to observe how severely the prediction capabilities are affected in the case when the same model has to be used with multiple cutters.

The exTS model is evaluated with two cutters (cutters 3 and 5) and three cutters (cutter 3, 4 and 5). The results are shown in Fig. 8 and Table 4.
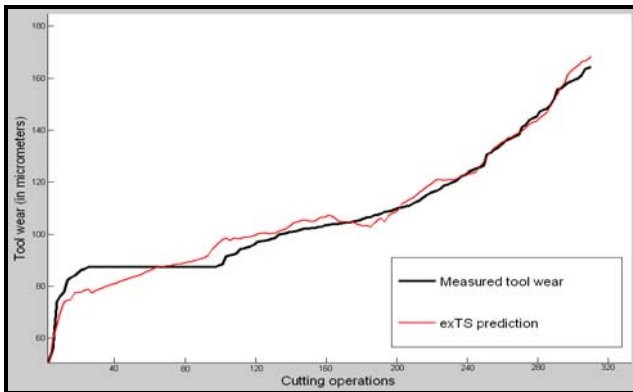

Fig. 8: Reliability performance with 3 cutters

(Prediction results of cutter 5, with a training set of 450 samples from cutter 3,4 and 5. The input data are force signal features.)

Table 4: The exST reliability performance with a multi-tool model

Number of cutters used to build the model	Features used	Accuracy indicators		
		RMSE	MAPE	R2
2	Force	7.07	0.07	0.93
2	AE	10.7	0.10	0.91
3	Force	12.2	0.13	0.90
3	AE	14.1	0.17	0.87

As expected, the accuracy indicator decreases. However, the prediction accuracy is still more than 85% which is within an acceptable level. So as we can conclude that the exTS model can be applied the case when the same model has to be used with multiple cutters.

C. exTS prediction test on an unknown tool

In this test we want to see if a reference model built by learning from two cutters can be used to predict the tool wear of a third, unknown cutter.

The training set is composed by all the samples of two cutters, put in random order. The generated model is then tested on a third cutter. We used the cutter 1, 3 and 5 for this test. For example, when cutter 1 is used for prediction, the cutters 3 and 5 are used to build the model. The results show in Table 5 and Fig. 9.

Table 5: The exST reliability performance with an unknown tool

Cutter used for prediction	Features used	Accuracy indicators		
		RMSE	MAPE	R2
cutter 1	Force	21.4	0.17	0.42
cutter 1	AE	22.1	0.16	0.40
cutter 3	Force	19.7	0.21	0.67
cutter 3	AE	21.5	0.19	0.65
cutter 5	Force	11.6	0.06	0.86
cutter 5	AE	17.0	0.09	0.71

The accuracy is poor when we try to predict the tool wear of cutter 1 and 3, and is acceptable for the cutter 5 if requested accuracy is more than 70%. This is mostly because the model predicts values located only between the boundaries of the cutters used for training.
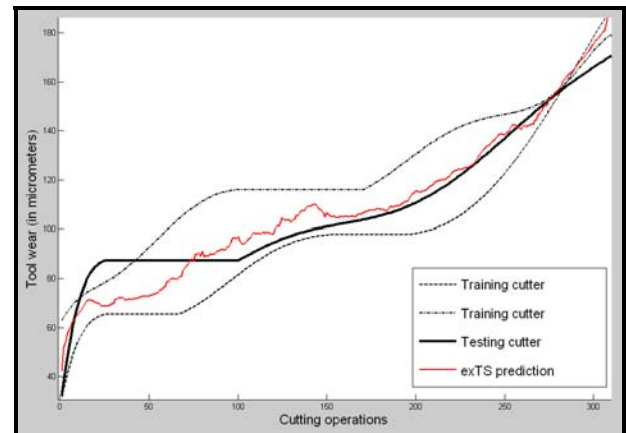

Fig. 9: Reliability performance on an unknown cutter.

(Prediction results of the cutter 1. The training set is composed from cutter 3 and 5 -630 samples-. The input data are acoustic emissions signal features.)

V. CONCLUSION

A method for predicting the tool wear using correlation models built by the exTS and ANFIS algorithms is presented. The exTF model performs better than a standard ANFIS algorithm

in accuracy, and is able to predict the tool wear based on both force and acoustic emission signals. The learning ability of the exTF algorithm allows building a reference model for multiple tools. However the accuracy of the model concerning an unknown tool is still insufficient. Improving the model reliability is still a future target.

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