 doi:10.20944/preprints201807.0447.v1

Article

A Neuro-Fuzzy Approach based Tool Condition Monitoring in AISI H13 Milling

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Abstract: In the manufacturing industry, cutting tool failure is a probable fault which causes damage to the cutting tools, workpiece quality and unscheduled downtime. It is very important to develop a reliable and inexpensive intelligent tool wear monitoring system for use in cutting processes. A successful monitoring system can effectively maintain machine tools, cutting tool and workpiece. In the present study, the tool condition monitoring system has been developed for Die steel (H13) milling process. Effective design of experiment and robust data acquisition system ensured the machining forces impact in the milling operation. Also, ANFIS based model has been developed based on cutting force-tool wear relationship in this research which has been implemented in the tool wear monitoring system. Prediction model shows that the developed system is accurate enough to perform an online tool wear monitoring system in the milling process.

Keywords: TCM; Cutting Force; Flank wear; ANFIS; Fuzzy; LabVIEW

1. Introduction

In recent years, research on the monitoring of machining operations has been intensively conducted as it significantly contributes to the automation of the manufacturing process and minimizes human factor. However, studies on TCM systems considering 3- to 5-axis end-milling have rarely been conducted as it is complicated due to the complex cutting paths and the varying cutting conditions. Previous research shows that there are four parameters, including cutting force, acoustic emission, motor power/current and vibration, which could be used to monitor tool wear condition in real time during turning [1]. Cutting force is one important characteristic variable to be monitored during the Cutting processes. Research results show that tool breakage, tool wear and workpiece deflection are strongly related to cutting force [2][3]. Turchetta [4] measured the forces to analyze the influence of different conditions of tool wear in the milling operation using a diamond tool. TCM systems have two main goals: accurate evaluation of the tool's cutting condition and right-on-time tool breakage or tool chipping detection. The occurrence of tool wear during machining is a natural effect of the material removal process and it is very difficult to estimate its level. Tool breakage, on the other hand, is the most crucial phenomenon in end-milling as it can cause irreversible damage to the product's surface and it should be prevented. Researchers who attempt to develop TCM systems by applying Artificial Neural Networks (ANN) have often failed to consider that ANNs are inefficient in terms of time series due to issues related to over-fitting and ANN local minima [5]. For this reason, a Fuzzy Inference System (FIS) was developed offline which can map online sensor values to their related cutting tool condition.

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The conditions that were taken into consideration include tool wear, tool breakage and variations in cutting condition [6] [7]. In the present study, tool condition monitoring system has been developed for die tool steel (H13) milling process. Adaptive Neuro Fuzzy Interface System (ANFIS) based approach has been introduced in the article to develop the tool wear monitoring system.

2. Experimental Methodology

2.1. Experimental Setup

The experimental data for Tool Condition Monitoring (TCM) were acquired through a series of experiment conducted on a MAKINO M56, 5-axis CNC milling center. For the experimental part of the research, end-milling operation have been conducted repeatedly along the 265 mm length of the hardened Die tool steel H13 (47HRC) workpiece under dry condition (with air pressure) with square end multi-flute uncoated carbide cutting tools (12.7 mm diameter and 75 mm cutting length) until it was severely worn or broken. During machining, the feed force (Fx), cutting forces (Fy) and radial force (Fz) were continuously monitored using a Kistler® 9255B, 3-component piezoelectric force dynamometer, max capacity of 20KN with sampling rate of 10,000Hz. Also, at every predetermined machining intervals tool flank wear was measured using a Keyance digital microscope VHX-6000 Series. The details of machining conditions are shown in Table 1. Experiments were replicated under the identical machining parameters to ensure the repeatability as well as to verify and validate the developed tool wear prediction model were used in the present study.

Table 1. Machining Parameters

Parameters	Level 1	Level 2
Cutting Speed, Vc (m/min)	90	105
Feed, f (mm/min)	1375	1600
Feed/tooth (mm/tooth) = 0.076		
Axial & Radial Depth of Cut (mm) = 5.00 & 3.00		

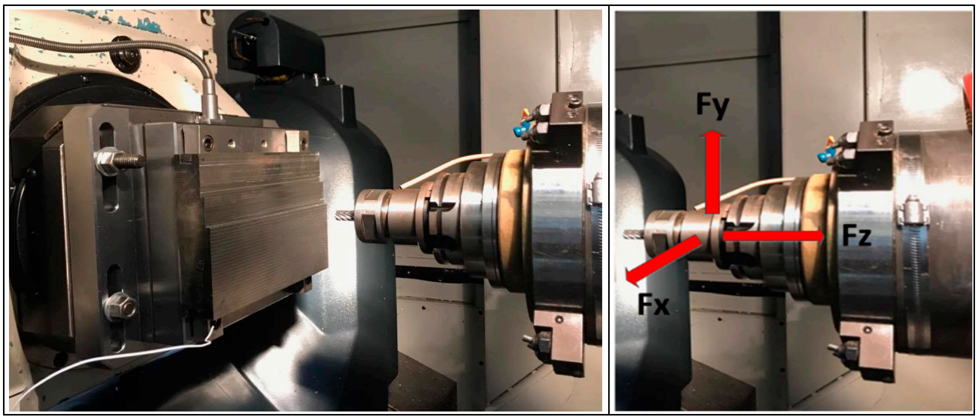


Figure 1. Experimental setup in MAKINO-M56, 5-axis CNC milling center

2.2. Monitoring System & Sensor Data Acquisition

The main objective of the monitoring system is to extract the important features of the machining process and categorized them by their relevant features. The monitoring system consists of sensor data acquisition and the data classification process. Kistler®9255B, 3-component piezoelectric force dynamometer was used to collect forces during machining. This device was connected to a Kistler® 5001 charge amplifier, DAQ (HI-speed NI USB 9162) and a PC with LabVIEW data acquisition software. The raw data from each machining passes was sampled and filtered at 10 kHz. The purpose of this is to reduce the possible noise in the raw data by attenuating the force signals. Figure 2 the generalized steps for the realization of an on-line tool condition monitoring system

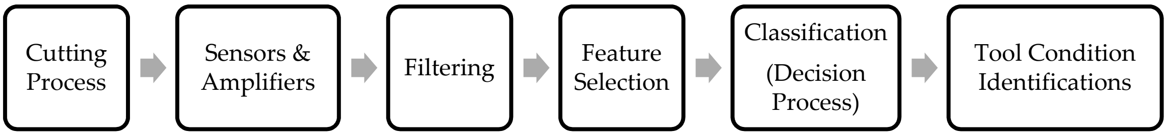
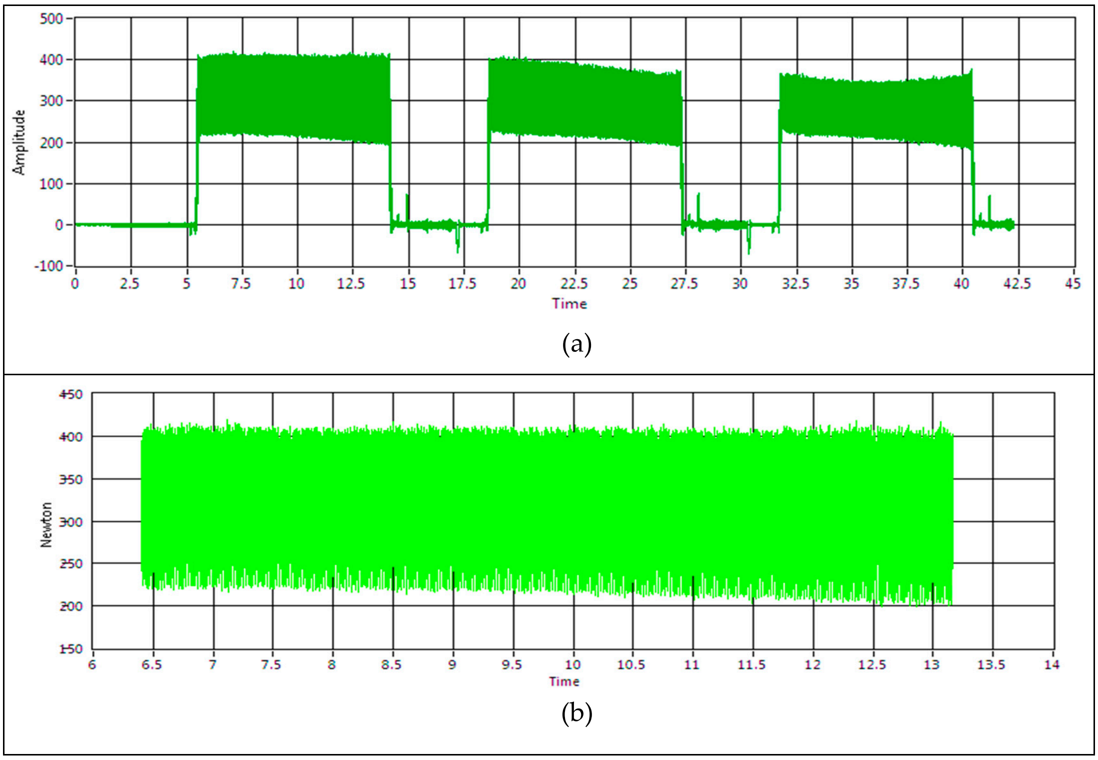


Figure 2. Monitoring System for Tool Condition Identification

2.3. Signal Processing

In the present study, the data collected from the sensor was processed and classified to extract the main features of machining operations from the enormous amount of data's. Beside data acquisition system, application of signal processing is the other important steps of Tool Condition Monitoring system. The signal from the machining operation is generally categorized either in the time domain or in the frequency domain. To learn about the machining operation variable changes with time, time domain analysis is performed. Signal Conditioning, filtering & RMS (root mean square) computations are the commonly used procedure. On the other hand, frequency domain signal processing enhances the differences between normal and irregular behaviour of the machine. To receive the significant information from the signal of cutting process, sensors should undergo certain processing.

The air-cut signals were extracted easily from the raw signals as it could be differentiated easily by the magnitude (Figure 3(a)). Also, the features from the signals were extracted from the entry cut and the exit cut of the raw signals in the next step. Generally, noise is the main obstacle to obtain signals through sensor data acquisition. Also, FFT (Faster Fourier Transformed) has been used to plot the frequency response graph of the featured signals (Figure 3(c)) with TPF's (tooth passing frequency) signal for each machining condition. The magnitude elevation of the specific TPF's in each machining condition was observed with the deterioration of the cutting tool.



(a)

(b)

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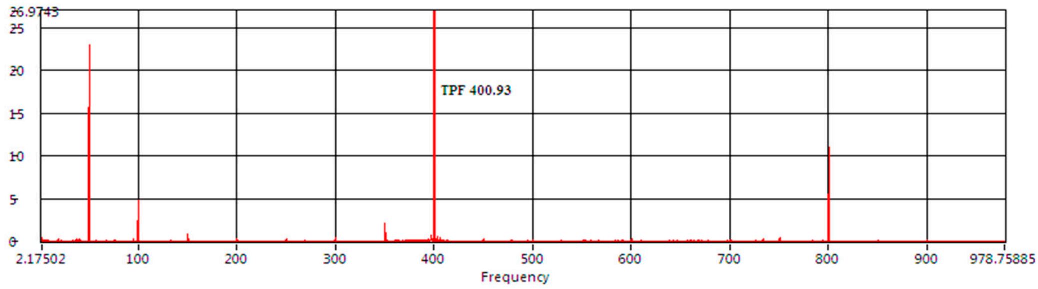

(c)

Figure 3. (a) Raw Signal (b) Signals after feature extraction (c) FFT's of signals with significant Frequency

3. Development of ANFIS System for Tool Wear Monitoring

ANFIS (Adaptive neuro-fuzzy interface system) is an artificial neural network based Takagi-Sugeno fuzzy interface system which integrates both ANN (artificial neural network) and fuzzy logic principals in a single frame. The objective of ANFIS is to find a model, which will correctly simulate the input to the outputs. In FIS modelling, the output signals from each layer are processed by the node functions. The signal processing by the node functions in each layer of the ANFIS architecture is explained by Rizal et al. (2013) [8]

In the present study, MATLAB software was used for ANFIS Model development. Following Figure 4 represents the flowchart of ANFIS Modelling architecture.

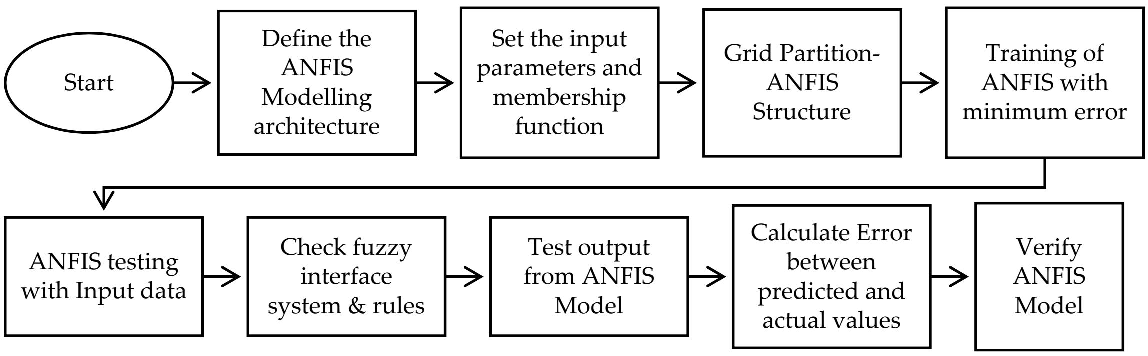

Figure 4. Flowchart of ANFIS Modelling architecture

Table 2. ANFIS modelling learning structure

Number of nodes	193
Number of linear parameters	81
Number of nonlinear parameters	24
Total number of parameters	105
Number of training data pairs	74
Number of fuzzy rules	81

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4. Results & Discussion

In the present study, different conditions of the end mill cutter were observed during the present study (Figure 5). Tool breakage was identified by the chipping of the cutting tool. Tool wear was categorized in low-level wear (average flank wear was below 100µm); medium-level wear (average flank wear was between 100 to 300µm) and severe tool wear (average flank wear more than 300µm). Machining forces were collected during the machining process & also quantitative tool wear evaluation had been made with optical microscope to find out the machining forces effect on tool wear during the end milling process.

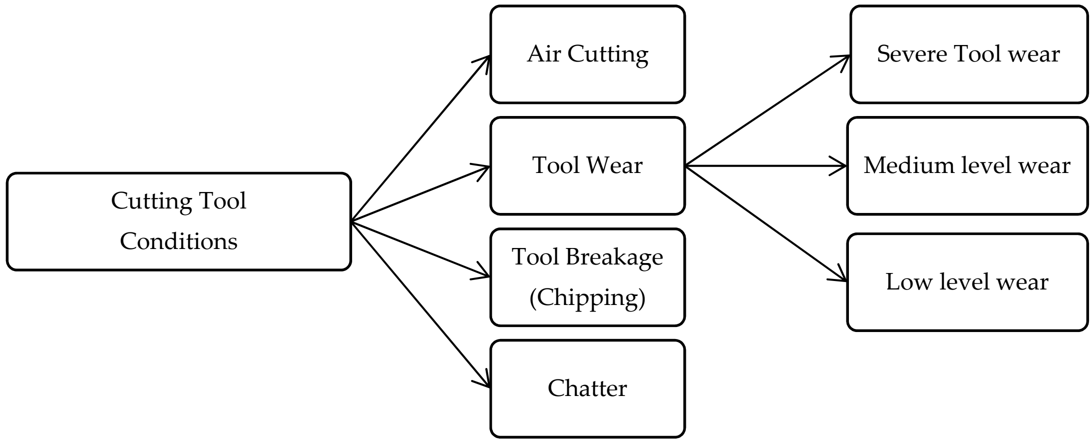

Figure 5. Classification of Tool Conditions

- Experiment result shows that each machining force, such as Feed Forces (Fx), Cutting Forces (Fy) and Radial Forces (Fz) curve has different trend from each other over the different tool conditions (Figure 6). But it's to be noted that in all machining condition, cutting force (Fx) is always higher than other components of machining forces. Also cutting forces increases with the increase of tool wear during machining.
- In the present study, the developed ANFIS model yields to achieve the best results for tool wear monitoring. After developing the fuzzy logic system for the tool wear prediction, the system has undergone with training the input data. The output data changes correspondingly with the change of the input data.
- The error of the wear rate prediction rarely exceeds 4% and thus the developed ANFIS system can predict the tool wear prediction accurately. Figure 7 represents the ANFIS modelling result for tool wear prediction. The lowest ANFIS model MAPE (mean average percentage error) has been achieved as 1.58% in compare with the actual machining data.
- To develop a robust tool wear monitoring system, ANFIS modelling can be used first to predict the tool wear condition for the previously developed libraries based on cutting force. It can also be used to detect tool wear monitoring online. LabVIEW based data acquisition software can be used to develop a program in this purpose. This program can act as a feedback control interface while collecting the sensors data simultaneously during machining to enhance the accuracy for tool condition monitoring.
- Once, the measured input values from the sensors reached the threshold values it'll classify the tool wear condition in accordance with the established model. To assure the part quality, this online monitoring system will give the feedback response about the worn-out tool so that it can be pulled out from the machining process.

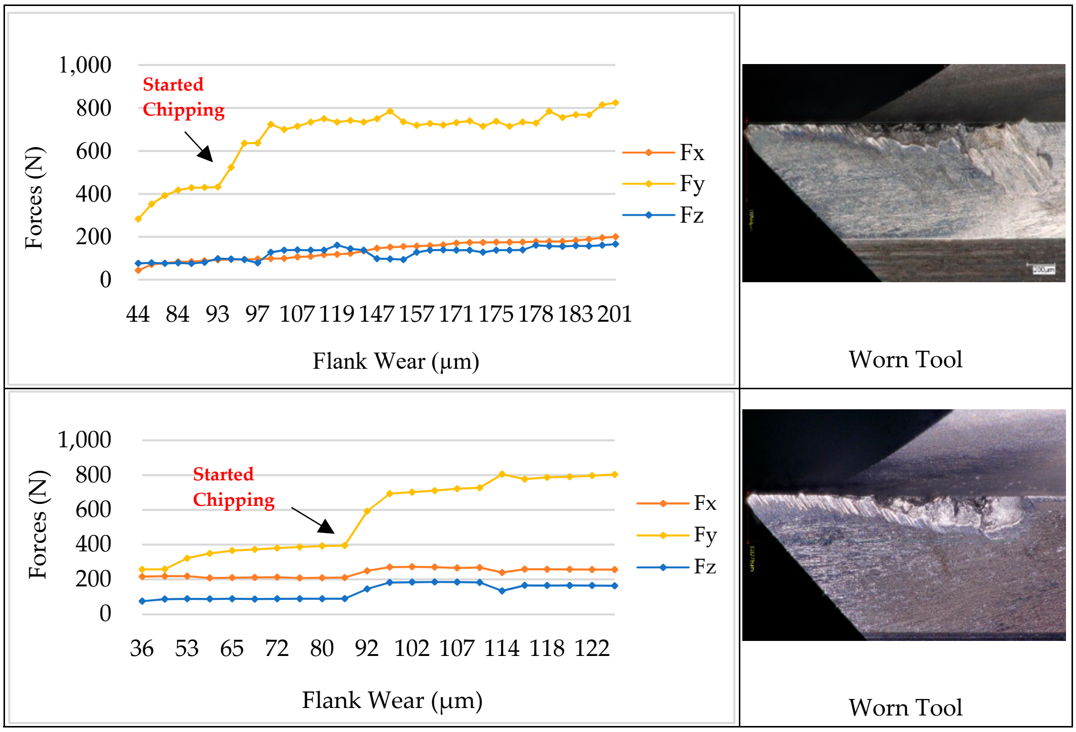

Figure 6. Machining Forces vs. Flank wear in different cutting condition (a) Vc=90m/min (b) Vc=105m/min

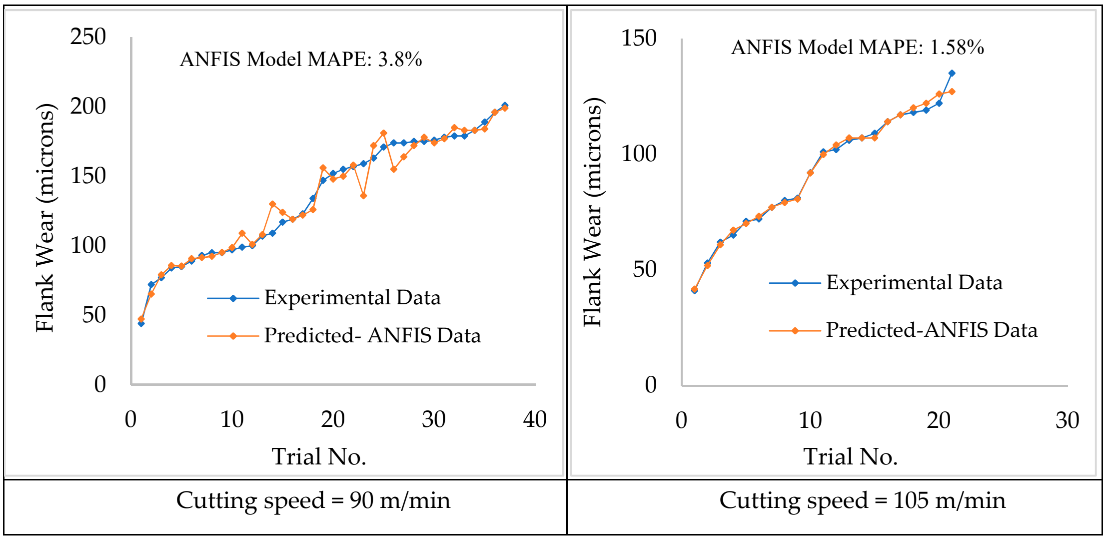

Figure 7. Comparison analysis of ANFIS data with experimental data

4. Conclusion

Online monitoring of the milling tool wear can be developed successfully based on this ANFIS model for the present study and precision milling of Die tool steel (H13) can be ensured to enhance the part quality and machining cycle time. Prediction of tool wear and the tool wear monitoring method can be applied to develop a condition monitoring interface in industrial application where tooling cost and part quality is as much important as cycle time in the production. This research introduced the Artificial Intelligence (AI) technique for online tool condition monitoring. It proposed a recommendation about the sensorial data's effect on tool wear monitoring. Sensor fusion, more advanced machine learning algorithm can be introduced in this field to make the tool condition monitoring interface more robust.

Acknowledgements: The authors acknowledge the financial support from the Natural Sciences and Engineering Research Council of Canada (NSERC) and the Canadian Network for Research and Innovation in Machining Technology (CANRIMT). The author also acknowledges the McMaster Manufacturing Research Institute (MMRI) for its state of the art research facilities.

Conflicts of Interest: The authors declare no conflict of interest.

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