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TOOL WEAR CONDITION MONITORING IN TAPPING PROCESS BY FUZZY LOGIC

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ABSTRACT

The objective of this research is to study tool wear condition monitoring in tapping process on CNC machining center machine by using fuzzy logic, to determine the status of cutting tool and the suitable time of changing tool before the tool failure or damage on work piece. The input data that were used in fuzzy logic system obtained from three sensors signal include a spindle current, force and vibration sensor. Fuzzy C-mean clustering and neural network were used to guide in the development of membership function. The status of tool was identified by crisp output values from fuzzy logic system. The results showed fuzzy logic can be used to monitor the tool wear. The performance of fuzzy system based on the number of input data sets and validation of expert in fuzzy rules.

Keywords: Tapping Process, Fuzzy Logic, Tool Wear, Fuzzy C-mean Clustering, Neural Network

INTRODUCTION

Tool wear condition monitoring is important for all metal cutting, such as in tapping process, tool wear or tool breaking has affect to quality of thread and it is difficult or unable to fix it. Then early replacement of tool before tool wear or tool breaking may be safe production loss. There are many techniques are used in monitoring of tool wear. It can be categorized into direct methods and indirect methods. Direct methods require direct measurements from the tool, while the indirect methods utilize cutting parameters such as force, vibration, sound, temperature and power measured during the cutting process. Although the direct methods are likely to be more accurate but it is not feasible in automated machining processes. So the indirect methods are preferred over the direct methods in this field (Aliustaoglu *et al*., 2009).

For indirect methods, fuzzy logics is used extensively to analysis about tool wear and tool condition such as in turning process (Ren *et al.*, 2011), in milling process (Kim and Jeon, 2011; Huang and Chen, 1998) and drilling process (Biglari and Fang, 1995). Other than tool wear and tool condition fuzzy logic can use in applications of data selection for machining parameters with different material and tools type (Hashmi *et al*., 1998; Hashmi *et al*., 2000). These studies showed that fuzzy logic is successful to use in many field of metal machining.

This paper proposes a fuzzy logic model for tool wear condition monitoring in tapping process. In this work has two main stages, the first stage is data collection from sensor signal and adjustment to input to fuzzy system, the membership function and rule base of fuzzy system are designed as show in the second stage.

EXPERIMENTAL SETUP AND DATA ACQUIREMENTS

The first stage, Makino Model BMC60 3-axis CNC milling machine was used in tapping process. A force transducer was mounted on mounting plate under work piece to measured force, accelerometer was mounted on a mounting clip near work piece to measured vibration and current of spindle motor was measured by power logger. The experimental setup as shown in Figure 1. Tap size M6x1 was used in experiment. Machining parameters were set as spindle speed at 200 rpm, feed rate at 200 mm/min and tapping dept 15 mm. The signal of each sensor as shown in Figure 2. The data from each sensor were analyzed to statistical parameters such as mean, maximum, minimum and root mean square (RMS) etc. These statistical parameters were input in to fuzzy modeling.

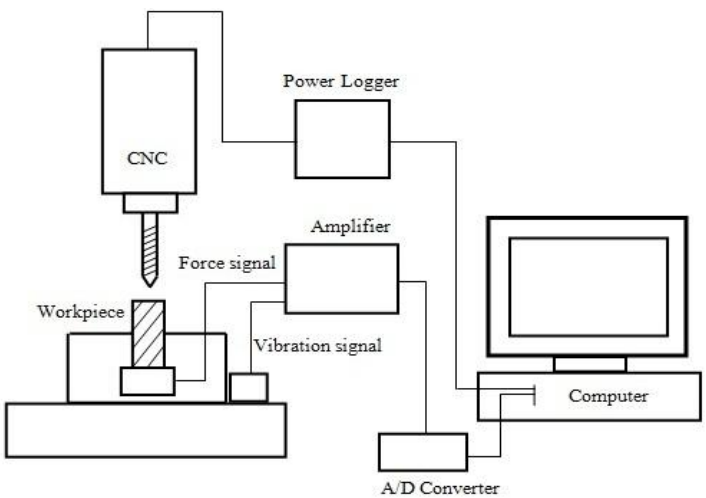


Figure 1. Experimental setup.

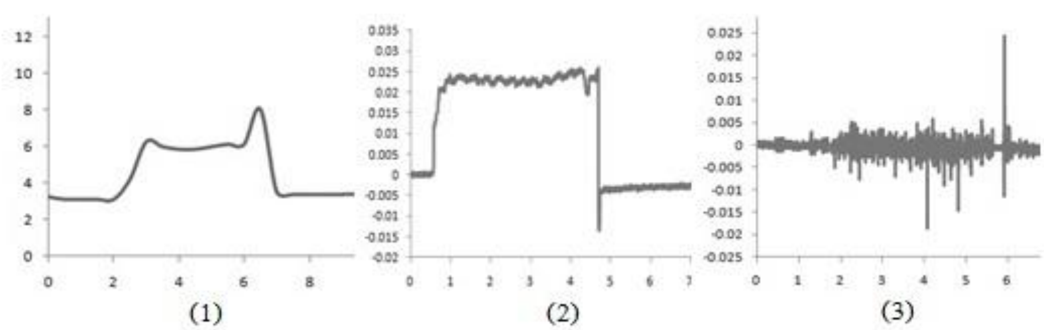


Figure 2. Current (1), Force (2), and Vibration (3) signal.

FUZZY MODELING

In second stage is the development of fuzzy logic system. There are two models of fuzzy system, the first model is the fuzzy system for each sensor that refer to mamdani fuzzy system, and the second model is the fuzzy system for sensors fusion that uses refer to fuzzy system. The output of each sensor was weighted by decision about the important of each sensor before sent to sensor fusion model. Figure 3 shows fuzzy modeling. The statistical parameters of each sensor were sent to input of mamdani fuzzy system and output of mamdani system were sent to input of sugeno fuzzy system. For final output from sugeno fuzzy system is the decision about status of tool.

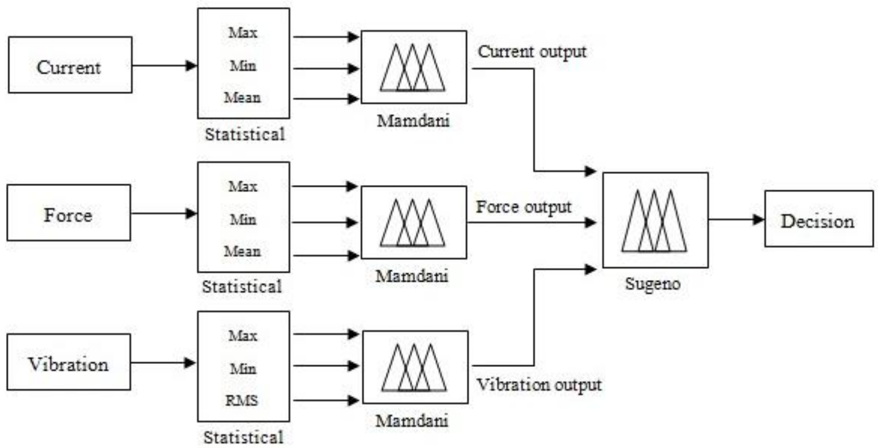


Figure 3. Fuzzy modeling.

1. Fuzzy variable

In mamdani fuzzy system, the inputs and outputs of fuzzy system are explained in fuzzy sets that defined by linguistic terms such as LOW, MEDIUM and HIGH etc. For sugeno fuzzy model the inputs of fuzzy system are explained as same as mamdani fuzzy system, but the output of sugeno fuzzy system is explained with function or constant output (Meesad, 2009). Input and output of fuzzy systems as shown in Table 1.

Table 1. Fuzzy sets for input and output of fuzzy system

Mamdani		Sugeno	
Input (Statistical parameter)	Output (Tool Condition Decision)	Input (Mamdani output)	Output (Wear rate)
LOW MEDIUM HIHG	Normal Tool Warning Tool Failure Tool	LOW MEDIUM HIHG	0.2 0.4 0.6 0.8 1.0

2. Membership functions of fuzzy sets

The structure of fuzzy set and membership function was done manually based on human knowledge or using data-driven technique (Ren *et al*., 2011) such as rank ordering, data clustering, neural networks and genetic algorithms etc. (Meesad, 2009: Ross, 2010). In this work, fuzzy c-mean clustering method was used to calculate center of data in fuzzy sets and calculate membership value for data in fuzzy sets. For development of membership function, the shape of membership function was defined by human expert or use curve fitting technique such as neural network. In this work, neural network fitting tool was used to fit curve between data and membership value from fuzzy c-mean clustering, the result of curve was compared with standard membership function because standard it is easy to calculate output. For example of membership function development can see in Figure 4. The results of comparing were chosen Z S and Gaussian membership function.

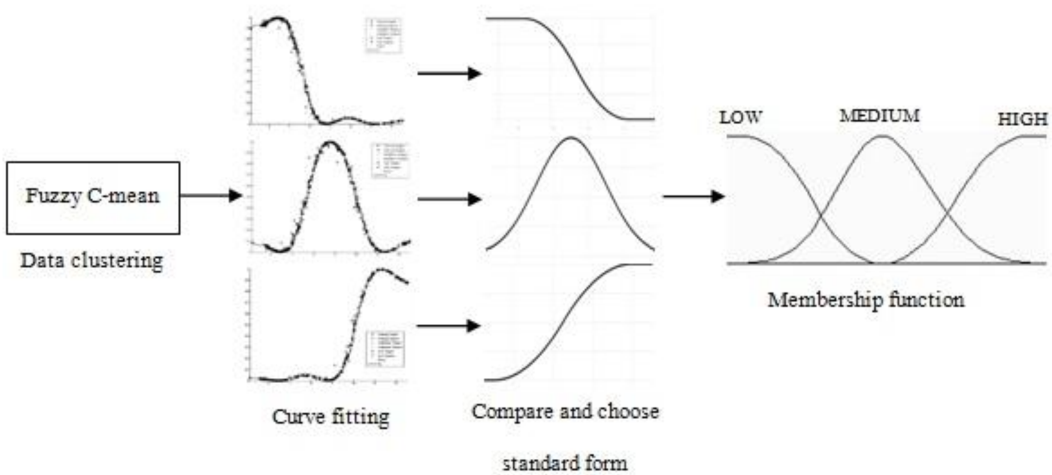


Figure 4. Membership function development.

3. Fuzzy rule-based

The fuzzy rules were defined by if-then rule. They were constructed in the form as:

> If (Input1) is … and (Input2) is … and (Input3) is … Then (Output) is …

For example, the rule of mamdani fuzzy system was followed:

> If (Min) is LOW and (Max) is LOW and (Mean) is LOW Then (Tool Condition Decision) is Normal Tool.

The rule of sugeno fuzzy systems was followed:

> If (Current) is HIGH and (Force) is HIGH and (Vibration) is HIGH Then (Wear rate) is 1.0.

The relationship between inputs and outputs in fuzzy systems was defined based on human expert and engineering knowledge. The number of fuzzy rules in a fuzzy system was related to number of inputs and number of fuzzy variable (Biglari and Fang, 1995). The maximum number of ruled can calculated by the follow equation (Aliustaoglu *et al*., 2009):

$$Z = M^P \tag{1}$$

In this equation, Z is number of fuzzy rules, M is number of input of fuzzy systems and P is number of fuzzy. In this work, there are three inputs of each sensor fuzzy model and three fuzzy variables. Therefore, the maximum number of rules is 27 rules. However, in any cases that have many rules, it is reasonable and efficient to use fewer rules by screening out of impossible rules (Biglari and Fang, 1995). Fuzzy rules of each sensor and sensor fusion model as shown in table 2 and 3 respectively.

Table 2. Fuzzy rules for each sensor model (mamdani)

Min	Max	Mean/RMS		
		LOW	MEDIUM	HIGH
LOW	LOW	Normal Tool	Normal Tool	Warning Tool
	MEDIUM	Normal Tool	Warning Tool	Warning Tool
	HIGH	Warning Tool	Warning Tool	Warning Tool
MEDIUM	LOW	Normal Tool	Warning Tool	Warning Tool
	MEDIUM	Warning Tool	Warning Tool	Warning Tool
	HIGH	Warning Tool	Warning Tool	Failure Tool
HIGH	LOW	Warning Tool	Warning Tool	Warning Tool
	MEDIUM	Warning Tool	Warning Tool	Failure Tool
	HIGH	Warning Tool	Failure Tool	Failure Tool

Table 3. Fuzzy rules for sensor fusion model (sugeno)

Current	Force	Vibration		
		LOW	MEDIUM	HIGH
LOW	LOW	0.2	0.2	0.4
	MEDIUM	0.2	0.4	0.6
	HIGH	0.4	0.6	0.6
MEDIUM	LOW	0.4	0.4	0.6
	MEDIUM	0.4	0.6	0.8
	HIGH	0.6	0.8	0.8
HIGH	LOW	0.6	0.6	0.8
	MEDIUM	0.6	0.8	1.0
	HIGH	0.8	1.0	1.0

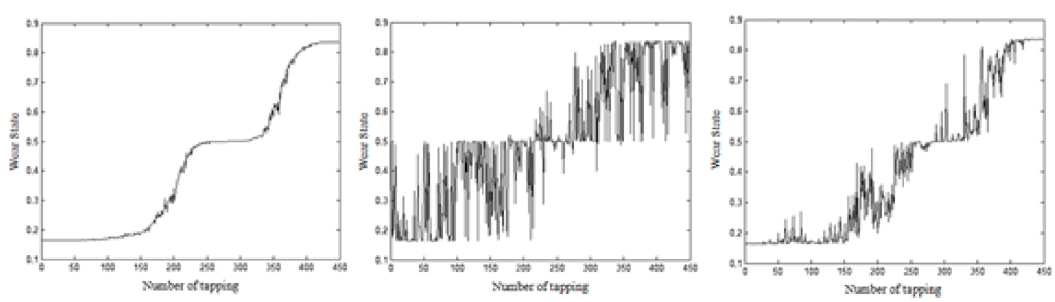
4. Fuzzification and defuzzification

Fuzzification is the process of making input data (crisp input) to be the input of fuzzy system (Ross, 2010). Next the input of fuzzy were sent to fuzzy rules and analyzed to fuzzy output. Output of fuzzy system were calculated to output data (crisp output) that used to control systems or decision in any systems by defuzzification method. There are many types of defuzzification in fuzzy system such as centroid, bisector, mean-of-max, weighted-average and weighted-sum etc. In this work, centroid was used in mamdadi fuzzy system and weighted-average was used in sugeno fuzzy system.

RESULTS AND DISCUSSION

The outputs from each sensor fuzzy model and sensor fusion model are showed in Figure 5-6 respectively, it should be a monotonically increasing function which not realizable because of the measurement noise and uncontrolled variable. However, the sensor fusion model with weighting the importance of input data can improve results. For example, in tapping process spindle speed and feed must be related. So spindle current and tapping force are important to monitoring tool wear while vibration is supported to detect about the smooth of cutting. But when looking about quality of signals, high quality signals should be important than low quality signals.

For example in model testing, while in tapping process, the data that measured and analyzed from instruments will sent to calculate in fuzzy model. There are six cases of data in tapping were used to test in this work. The results of model testing as shown in table 4.



(1) (2) (3)

Figure 5. Current (1), Force (2), and Vibration (3) crisp output of mamdani fuzzy.

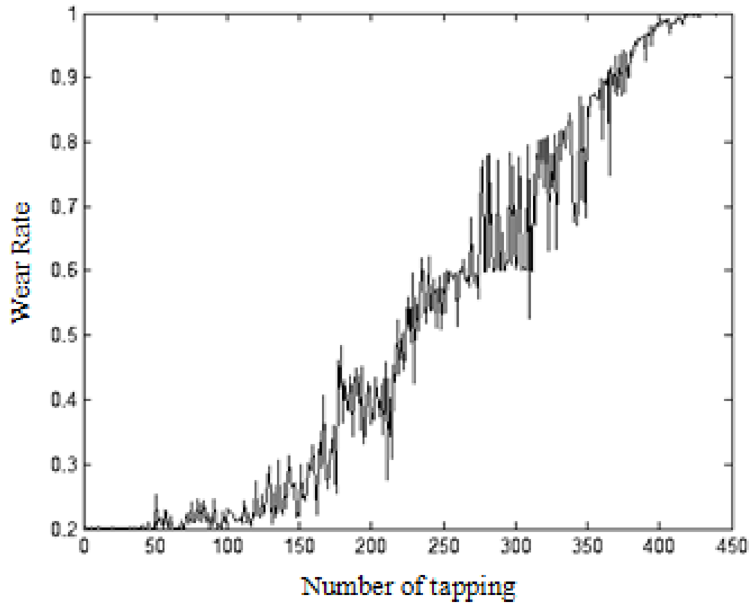


Figure 6. Crisp output of sugeno fuzzy.

Table 4. Results from model testing

Case No.	Sensor	Measurement Data Input			Fuzzy Decision Output	Tool Condition Decision
		Min	Max	Mean/RMS		
1	Current Force Vibration	6.7389 0.0329 -0.0083	7.8299 0.0359 0.0074	7.0766 0.0345 0.0012	0.2325	Normal Tool
2	Current Force Vibration	7.3570 0.0281 -0.0120	8.4408 0.0314 0.0118	7.6170 0.0294 0.0018	0.3313	Normal Tool
3	Current Force Vibration	9.7284 0.0458 -0.0273	10.6798 0.0535 0.0270	9.9719 0.0504 0.0038	0.7708	Warning Tool
4	Current Force Vibration	9.7441 0.0525 -0.0404	10.5621 0.0558 0.0368	9.9521 0.0546 0.0048	0.8169	Warning Tool
5	Current Force Vibration	12.4969 0.0482 -0.0476	13.1789 0.0502 0.0493	12.7049 0.0492 0.0071	0.9998	Failure Tool
6	Current Force Vibration	12.5242 0.0644 -0.0525	13.4792 0.0670 0.0482	12.8891 0.0658 0.0063	1.0000	Failure Tool

The results of fuzzy model explain the status of tool such as, the value closed to zero explains the status of tool is workable, whereas the value closed to one that explains the status of tool is nearly to failure. This value is applied to use in decision-making programs. From results table, tool conditions are set by fuzzy decision output as shown Table 5. For a suitable point of tool changing, operator should be sets a fuzzy decision value of tool changing as one.

Table 5. Tool condition decision setting by fuzzy decision output

No.	Fuzzy Decision Output	Tool Condition Decision
1	0-0.6	Normal Tool
2	0.6-0.85	Warning Tool
3	0.85-1.0	Failure Tool

CONCLUSION

Fuzzy logic can be used to monitoring tool wear in tapping process. The model of fuzzy logic is not complicate and easy to understand. Output from fuzzy logic can apply to use in automatic control or real-time monitoring tool. Fuzzy c-mean clustering and neural network can help expert to develop fuzzy sets and membership function. The matching of expert and data-driven technique can make credibility of fuzzy model more than using only expert opinion. The performance of fuzzy model could be improved by using more data sets of tapping and more input parameters such as feed motor current, machine sound, or tapping torque etc.

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