Efficacy of Applying Expert System in Monitoring of Milling Process

Asif Iqbal, Iqbal Khan, Naeem Ullah Dar, and Ning He

Abstract— **Precise monitoring of any manufacturing process is vital for guaranteeing high standards of productivity and product quality. In this article the application of fuzzy rule-based expert system will be provided for estimation of condition of tool used in a milling process. Two methodologies involving different major parameters will be compared for accuracy. For accomplishment, milling experiments were performed to generate necessary data. The data were analyzed in order to develop fuzzy rule-bases for both methodologies. The rule-bases were tested and compared against new experimental data. The estimations provided were extremely accurate, especially for the methodology utilizing real time process parameter.**

Index Terms— **Fuzzy reasoning, Intelligent manufacturing, Process monitoring, Rule-base, Tool damage**

I. Introduction

For any manufacturing process the productivity and the product quality are extremely important performance measures. In order to ensure peak values of these measures it is utmost important that the key areas of the process be monitored with high level of precision. For milling process, the critical most area is the portion of the tool that removes the material from the workpiece. Gradual, but unsteady, damage of the cutting edge deteriorates surface quality of the workpiece and at some specific stage of damage the quality of the generated surface becomes unacceptable. Moreover, the sudden tool damage, like severe chipping or plastic deformation, leads to failure of tool and discontinuation in process, thus causing loss in productivity; and it may also cause loss of the workpiece and damage to the machine tool as well [1]. For this reason it becomes very important to know condition of the tool during the in-progress milling process.

It is almost impossible to measure the tool damage when milling process is in progress. The only answer to this problem is to have estimations of the damage using different techniques. AI tools have been used in the past for this purpose, with most of them utilizing the automation of Artificial Neural Networks (ANN). Comprehensive literature survey, in this regard, will suggest that knowledge-based systems have remained at back end in this domain, despite the immense potentials they possess.

In [2], the authors used ANN based multi-sensor integration technique to determine tool wear states in turning process. Again ANN was used in [3] to estimate tool wear states, onset of chatter, and chip tangling in turning process by utilizing force signals as input parameter. Fang in [4] developed knowledge-intensive fuzzy feature-state relationship matrices for the diagnosis of tool wear states in finish turning process. In [5] the researchers interpreted input parameters: cutting speed, feed, etc., using transition fuzzy probability to estimate wear conditions of tool in a boring process. In [6] Gaussian Wavelet Algorithm was utilized to transform the spindle vibration signals for estimation of tool wear states in machining of fiber-board.

It is observable from the survey that monitoring of tool's condition is rarely applied to the milling process, especially utilizing the expert system technique. In the following article fuzzy rule-based expert system will be used for estimation of tool damage by employing two methodologies. The methodology A will make use of area of material removed (A) {= length of cut × radial depth of cut} as major input parameter, while the methodology B will employ cutting force (F) as the major parameter. See [7] for further details of the parameter "area of material removed".

II. Experimental Data Generation

Besides area of material removed, there are lots of influential parameters that significantly affect the tool damage state, but for the purpose of simplicity the effects of only two of the most influential parameters – cutting speed (V_c) and radial depth of cut (a_e) – will be put into calculations here. Table 1 shows the design of experiments for the purpose of development of rule bases. 2 levels for radial depth of cut, 3 levels for cutting speed, and 6 levels each for A and F were tested for average width of tool's damaged portion (VB). This technique gives 36 (= 2 × 3 × 6) data points for each methodology.

The experiments were performed on Micron UCP 710, 5-axis, vertical milling center having maximum power of 16 kW. The workpiece material used was AISI 4340, hardened to value of 50HRc. The cutting tools used were flat end solid K30 carbide cutters coated with TiAlN, having diameter (D) of 10mm, corner radius (R) of 1.5mm, helix angle (λ) of 45°, rake angle (γ) of 5°, flank angle (α) of 6°, and number of flutes (z) equal to 4.

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A. Iqbal is with the Department of Mechanical Engineering, University of Engineering & Technology, Taxila, Pakistan (Phone: +92-302-8548307; fax: +92-51-4830532; e-mail: asif.asifiqbal@gmail.com).

I. Khan is with the Department of Mechanical Engineering, University of Engineering & Technology, Taxila, Pakistan (Phone: +92-300-8540976; fax: +92-51-4830532; e-mail: iqbalkhan1950@yahoo.com).

N.U. Dar is with the Department of Mechanical Engineering, University of Engineering & Technology, Taxila, Pakistan (Phone: +92-300-8544016; fax: +92-51-4830532; e-mail: nudar@hotmail.com).

N. He is with the College of Mechanical & Electrical Engineering, Nanjing University of Aeronautics & Astronautics, Nanjing, China (Phone: +86-25-84892551; fax: +86-25-84892551; e-mail: drnhe@nuaa.edu.cn).

Table 1 Levels of input parameters tested in the experiments

Level	a_e(mm)	V_c(m/min)	A(mm^2)	F(N)
1	0.15	150	1000	400
2	0.4	225	2500	600
3	-	300	4000	800
4	-	-	5500	1000
5	-	-	7000	1200
6	-	-	8500	1400

The measurement of forces were performed using Kistler piezoelectric dynamometer 9265B, utilizing force plate 9443B, having measuring range of 0 – 15kN in x- and y-directions and range of 0 – 30kN in z- direction. The dynamometer was connected to four channel Gould Classic oscilloscope using charge amplifiers. The cutting force (F) is the resultant of instantaneous peak values of two force components F_x and F_y, measured by the dynamometer. Tool's edge damage was measured using 10x tool maker's microscope.

For all the experiments the feed rate was fixed to 0.1mm/tooth and axial depth of cut (a_p) was maintained as 5mm. Down-milling was employed as milling orientation and no coolant was used. Milling was performed in straight line with length of cut for a single pass equal to 100mm.

For the purpose of testing of expert systems of both of methodologies, further milling experiments were performed with different values of input parameters and resulting *VB* values were measured. Detail has been provided in upcoming sections.

A. Experimental Results

Experimental results are shown in graphical form in Figs. 1 – 4. It can be observed that the progress of tool damage is related almost linearly with area of material removed and cutting force, especially with the latter one.

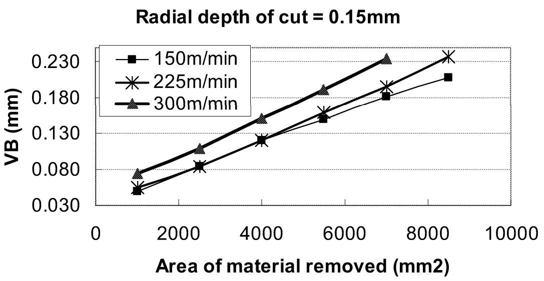

Fig. 1 Progress of tool damage along area of material removed for a_e = 0.15mm.

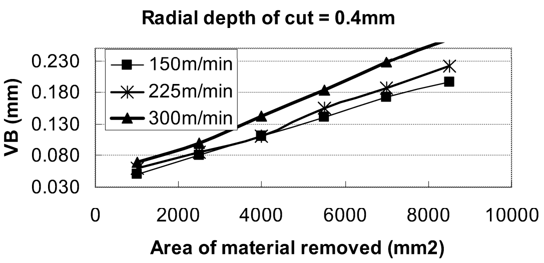

Fig. 2 Progress of tool damage along area of material removed for a_e = 0.4mm.

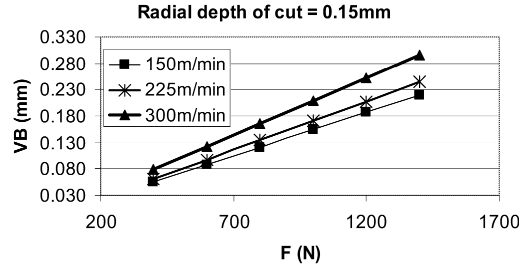

Fig. 3 Progress of tool damage along area versus that of cutting force for a_e = 0.15mm.

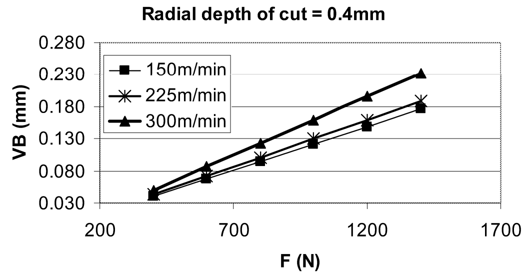

Fig. 4 Progress of tool damage along area versus that of cutting force for a_e = 0.4mm.

The experimental results were analyzed using analysis of variance (ANOVA). It was found that the major parameters: area of material removed and cutting force are more influential, upon magnitude of tool damage, as compared to cutting speed and radial depth of cut. Moreover, cutting speed was found more influential than radial depth of cut. The fuzzy sets of the parameters were designed based upon this information.

III. The Development of Expert System

After analyzing the experimental results, the next step is to divide the experimented range of input and output variables (parameters) into fuzzy sets. Fuzzy sets and logic is a discipline that has proved itself successful in automated reasoning of expert systems [8]. It deals with the theory of vague reasoning in order to model human-like reasoning problems of real life. In recent past, fuzzy logic has found high degree of applicability in development of expert systems and the same has been selected as the reasoning mechanism in development of presented rule bases.

The experimented range of more influential parameters is divided into more number of fuzzy sets as compared to less influential parameters. Ten fuzzy sets were designed for the output parameter (*VB*) applicable to both of the methodologies. For all of the parameters, equally distributed triangular shaped fuzzy sets were utilized. Figs. 5 – 9 show the detail, while tables 2 – 3 provide the abbreviation details of these fuzzy sets.

A. The Rule-Bases

The relationship between inputs and output in a fuzzy system is characterized by set of linguistic statements which are called fuzzy rules [9]. The number of fuzzy rules in a fuzzy system is related to the number of fuzzy sets for each input variable.

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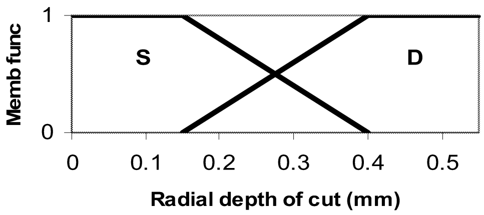

Fig. 5 Fuzzy sets for a_e.

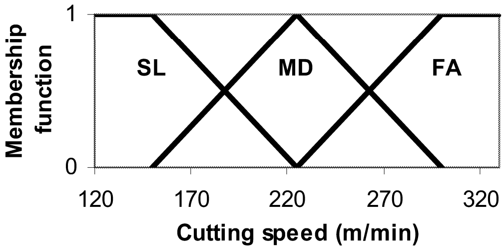

Fig. 6 Fuzzy sets for V_c.

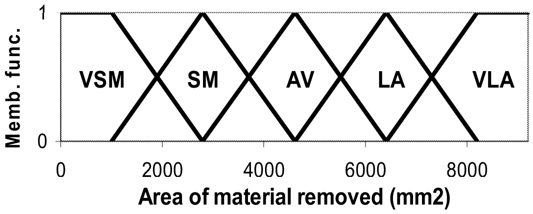

Fig. 7 Fuzzy sets for A.

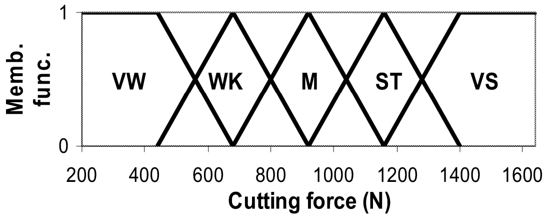

Fig. 8 Fuzzy sets for F.

Table 2 Expressions used in fuzzy sets of a_e, V_c, and A

a_e		V_c		A	
Abbr.	Expr.	Abbr.	Expr.	Abbr.	Expr.
S	Shallow	SL	Slow	VSM	V. Small
D	Deep	MD	Medium	SM	Small
		FA	Fast	AV	Average
				LA	Large
				VLA	V. Large

Table 3 Expressions used in fuzzy sets of F and VB

F		VB	
Abbr.	Expression	Abbr.	Expression
VW	Very Weak	VEL	Very Extremely Low
WK	Weak	EL	Extremely Low
M	Mean	VL	Very Low
ST	Strong	LO	Low
VS	Very Strong	SL	Slightly Low
		SH	Slightly High
		HI	High
		VH	Very High
		EH	Extremely High
		VEH	Very Extremely High

Table 4 Rule-bases for methodologies A and B (VB represents the consequent parameter)

			Methodol. A		Methodol. B	
Rule No.	a_e	V_c	A	VB	A	VB
1, 31	S	SL	VSM	EL	VW	VL
2, 32	S	SL	SM	LO	WK	SL
3, 33	S	SL	AV	SH	M	HI
4, 34	S	SL	LA	VH	ST	VH
5, 35	S	SL	VLA	VEH	VS	VEH
6, 36	S	MD	VSM	EL	VW	VL
7, 37	S	MD	SM	LO	WK	SL
8, 38	S	MD	AV	SH	M	HI
9, 39	S	MD	LA	EH	ST	VEH
10, 40	S	MD	VLA	VEH	VS	VEH
11, 41	S	FA	VSM	VL	VW	LO
12, 42	S	FA	SM	SL	WK	SH
13, 43	S	FA	AV	VH	M	EH
14, 44	S	FA	LA	VEH	ST	VEH
15, 45	S	FA	VLA	VEH	VS	VEH
16, 46	D	SL	VSM	EL	VW	VEL
17, 47	D	SL	SM	LO	WK	VL
18, 48	D	SL	AV	SH	M	SL
19, 49	D	SL	LA	HI	ST	SH
20, 50	D	SL	VLA	EH	VS	VH
21, 51	D	MD	VSM	VL	VW	EL
22, 52	D	MD	SM	LO	WK	LO
23, 53	D	MD	AV	SH	M	SL
24, 54	D	MD	LA	VH	ST	VH
25, 55	D	MD	VLA	VEH	VS	EH
26, 56	D	FA	VSM	VL	VW	EL
27, 57	D	FA	SM	SL	WK	SL
28, 58	D	FA	AV	HI	M	HI
29, 59	D	FA	LA	VEH	ST	EH
30, 60	D	FA	VLA	VEH	VS	VEH

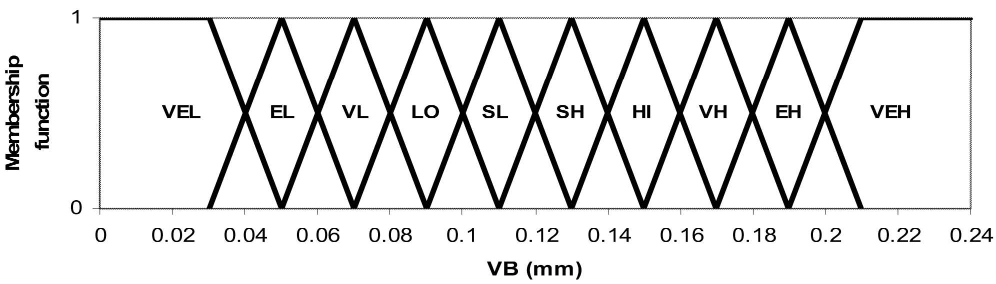

Fig. 9 Fuzzy sets for width of tool damage

Table 5 Testing of expert system following methodologies A and B (*VB* represented in mm)

			Methodology A			Methodology B		
S/No.	a_e(mm)	V_c(m/min)	*A*(mm2)	*VB*(actual)	*VB*(expert)	*F* (N)	*VB*(actual)	*VB*(expert)
1	0.2	200	1000	0.055	0.055	450	0.065	0.065
2	0.2	200	2200	0.081	0.075	621	0.09	0.086
3	0.2	200	3800	0.117	0.112	784	0.116	0.116
4	0.2	200	5300	0.153	0.157	943	0.143	0.146
5	0.2	200	7900	0.207	0.187	1122	0.176	0.168
6	0.2	280	1000	0.069	0.064	460	0.091	0.083
7	0.2	280	2200	0.091	0.087	615	0.113	0.102
8	0.2	280	3800	0.139	0.134	776	0.139	0.143
9	0.2	280	5300	0.175	0.169	951	0.169	0.166
10	0.2	280	7900	0.223	0.195	1101	0.189	0.171
11	0.3	200	1000	0.054	0.062	448	0.079	0.079
13	0.3	200	3800	0.116	0.111	780	0.107	0.108
14	0.3	200	5300	0.152	0.157	938	0.134	0.133
15	0.3	200	7900	0.211	0.186	1130	0.168	0.162
16	0.3	280	1000	0.076	0.064	433	0.078	0.067
17	0.3	280	2200	0.102	0.086	606	0.103	0.095
18	0.3	280	3800	0.138	0.134	792	0.133	0.139
19	0.3	280	5300	0.174	0.166	953	0.16	0.157
20	0.3	280	7900	0.221	0.194	1114	0.184	0.17
			Estimation error (methodology A)		0.0099		(methodology B)	0.0054

In this work, there are 30 (= 2 × 3 × 5) possible rules for each of two methodologies. A question arises, "which *VB* fuzzy sets to be assigned to 30 possible combinations of input fuzzy sets, for each of two methodologies"? For a simple 2-inputs 1-output fuzzy model, the designer has to select the most optimum set of fuzzy rules from more than 10,000 combinations [10]. For each methodology, there are 30 fuzzy rules with 10 possibilities each. Thus the total number of possible fuzzy rules combination will be 10^{30}.

For the most optimal formation of rule-bases, simulated annealing algorithm was utilized and the best possible combination of rules for both methodologies, giving minimum values of estimation error, are provided in table 4. The term "estimation error" can be defined as follows:

$$\textit{estimation error} = \frac{1}{l \times m \times n}\left[\sum_{i=1}^{l}\sum_{j=1}^{m}\sum_{k=1}^{n}\left|(VB_{actual} - VB_{expert})\right|\right] \quad (1)$$

In above equation *l*, *m*, and *n* stand for number of levels of input parameters used.

The max-min inference was employed for aggregation of the rules. The detail of this methodology can be read from [11].

IV. Testing

For the purpose of testing and comparison of expert systems related to methodologies A and B, further milling experiments were performed, utilizing following levels of input parameters: (1) a_e = 0.2mm and 0.3mm; and (2) V_c = 200m/min and 280m/min. For this case, the values of variables *l*, *m*, and *n* (related to Eq.1) would be 2, 2, and 5, respectively, thus giving 20 data points for each methodology.

The magnitude of tool damage (*VB*) was measured at different levels of area of material removed and cutting force, as shown in table 5. For each and every combination of input parameters, the values of *VB* were estimated from the rule-bases presented in table 4 and compared with the actual *VB* values obtained from the experiments. Table 5 shows the detail.

Table 5 shows that estimation capability of both of methodologies is very good but still the methodology B outperforms the methodology A, as the former gives 45.5% better estimation of *VB* as compared to the latter one.

The reason for the better performance of methodology B is that it deals with real time input data (cutting force), which possesses better information of condition of in-progress process. On the other hand, methodology B makes use of area of material removed as major input parameter, which has not the ability to account for real process uncertainties. For instance, if the tool, unluckily, undergoes some rapid wear due to possible local hardening of workpiece or due to tool unbalance, such abnormal increase in damage would be reported by increase in cutting force, while, on the other hand, the input parameter *A* remains indifferent to this. This proves that fuzzy expert system technique incorporating cutting force as major input can successfully monitor the tool damage states.

V. Conclusion

This paper describes the effectiveness of applying expert system technology in condition monitoring of any manufacturing process. The description was provided with regard to its application in monitoring the damage state of tool used in milling process. Following conclusions can be drawn from the discussion provided:

1. Expert system approach, utilizing fuzzy reasoning mechanism, can be used for accurate estimation of damage state of tool.
2. Cutting force gives better real time information about condition of in-progress machining process as compared to area of material removed and, thus, it can be used as major input parameter for condition monitoring process.

This research work will help to reduce the strong dependence of process monitoring activities upon utilization of artificial neural networks.

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