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Development of Predictive Model for Surface Roughness in End Milling of Al-SiCp Metal Matrix Composites using Fuzzy Logic

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Abstract**—**Metal matrix composites have been increasingly used as materials for components in automotive and aerospace industries because of their improved properties compared with non-reinforced alloys. During machining the selection of appropriate machining parameters to produce job for desired surface roughness is of great concern considering the economy of manufacturing process. In this study, a surface roughness prediction model using fuzzy logic is developed for end milling of Al-SiC$_p$ metal matrix composite component using carbide end mill cutter. The surface roughness is modeled as a function of spindle speed (N), feed rate (f), depth of cut (d) and the SiC$_p$ percentage (S). The predicted values surface roughness is compared with experimental result. The model predicts average percentage error as 4.56% and mean square error as 0.0729. It is observed that surface roughness is most influenced by feed rate, spindle speed and SiC percentage. Depth of cut has least influence.

Keywords**—** End milling, fuzzy logic, metal matrix composites, surface roughness

I. Introduction

INCREASING productivity and manufacturing high quality job at cheaper price are challenging tasks for manufacturing industries. While using new work and tool material the selection of appropriate machining parameters is an important step towards meeting above goals and thus gaining a competitive advantage in the world market [1]. The metal matrix composites (MMC) exhibit poor machinability due to hard and abrasive reinforcement used. It results in faster tool wear leading to increased manufacturing cost and production of poor surface. The higher machining cost has been one of the main reasons hindering the wide spread applications of MMC components [2], [3].

Turning and milling are common machining process to produce MMC components for obtaining desired shape and size. Surface roughness (R_a) in one the main attributes of machined component and it is influenced by cutting conditions, work material, tool geometry and statistical variation during machining. Reasonable surface finish is always desirable to improve tri-biological aspects and aesthetic appearance where as excessive surface finish involves higher machining cost.

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Researchers have attempted to model the surface roughness prediction using multiple regression, mathematical modeling based on physics of process, fuzzy logic, and artificial neural network [4]. Machining operation being highly non liner in nature, soft computing techniques have been found to be very effective for modeling. In this work the development of surface roughness prediction model in end milling of Al-SiC$_p$ MMC components using fuzzy logic is attempted. Brief literature survey is presented in section II. The problem considered for modeling is explained in section III. Section IV demonstrates the development of surface roughness prediction model using fuzzy logic. The result is discussed in section V and conclusions drawn from the present work are summarized in section VI.

II. Literature Review

Among various methods available fuzzy logic and neural network are the two popular soft computing methodologies found effective and applied by many researchers for modeling and optimization of machining process. Fuzzy logic technique based on fuzzy set theory was first introduced by Lotfi Zadeh [5] in the year 1965 and it is used as a tool for computing with language. Since then the number and variety of applications of fuzzy set theory in engineering field have grown significantly in the recent years including the area of artificial intelligence (AI)

Chandrasekaran *et al.* [4] have reviewed research work spanning over two decades on the application of soft computing techniques in modeling and optimization of various machining processes. In the area of machining, fuzzy logic modeling technique has been widely used for the prediction of surface roughness, cutting forces, tool wear, tool life and dimensional deviation. Abburi and Dixit [6] used fuzzy logic to develop a knowledge based system for prediction of surface roughness in turning process. The knowledge based system consists of a neural network module which generates data set to form if-then rules of the fuzzy model. Rajasekaran *et al.* [7] have modeled surface roughness prediction using fuzzy logic in turning of carbon fiber reinforced polymer (CFRP) composites using cubic boron nitride (CBN) cutting tool. The average percentage error is reported as 6.62% with a maximum and minimum percentage error as 18.30% and 0.32% respectively.

Harun Akkus *et al*. [8] suggested that fuzzy logic surface roughness prediction model found better than regression and neural network model in hard turning of AISI 4140 steel.

Pradhan and Biswas [9] used neural network and fuzzy logic to predict various responses (material removal rate, tool rate wear and radial over cut) in electrical discharge machining of AISI D2 steel. With average prediction errors in the range of 4.94% to 16.22% in all the three types of prediction, the models are considered to predict with agreeable accuracy. Davim and Antonio [10] proposed numerical approach for optimization of cutting conditions in drilling and turning of A356/20/SiC$_p$ MMC component. Variation of surface roughness in drilling [11] and end milling [12] of metal matrix composites is studied using response surface method. Tsao and Hocheng [13] have applied Taguchi and neural network methods to evaluate thrust force and surface roughness in drilling CFRP composite materials. It is concluded that radial basis function network (RBFN) is found to be more effective than the multi variable regression analysis in the evaluation of both thrust force and surface roughness. Optimization of machining parameters using ANN is found to be most effective compared with ANOVA by Muthukrishan and Davim [14] in turning of Al-SiC$_p$ MMC. Davim [15] has carried out evaluation of tool wear, power consumed and surface roughness in turning of MMC using multiple linear regression. The confirmation tests carried out reveal that maximum error in tool wear prediction is 10%. The maximum error in power consumed and surface roughness prediction is reported to be 3.2 % and 10.3% respectively. The neural network is used to model surface roughness and dimensional deviation in wet turning of steel with a high speed steel (HSS) tool. [16]. Similar attempt is made by Sonar et al [17] using radial basis function (RBF) neural network that predicts almost with same accuracy in a shorter computational time. Ali and Zhang [18] applied fuzzy logic approach to predict surface roughness of ground components using the data available in the literature.

III. Description of The Problem

In the present work, a surface roughness prediction model using fuzzy logic methodology is developed for end milling of MMC having LM25 Aluminum alloy matrix reinforced with Silicon Carbide (SiC) using carbide tool. The predicted values of Ra are compared with experimental results and response surface model (RSM) available in the literature. Also the effect of various parameters is studied. In addition to the three basic machining parameters viz. spindle speed, N (rpm), feed rate, f (rev/mm) and depth of cut, d (mm) another variable SiC percentage, S (% wt) is considered in the study. The level of the parameters considered is given in the Table I. The experimental data set of Arokiadass et al. [12] is used to develop surface roughness prediction model.

IV. Development of Fuzzy Logic Model

The surface roughness in end milling of Al-SiCp MMC is assumed as a function of four input variables viz. Spindle speed (*N*), feed rate (*f*), depth of cut (*d*) and SiC content (*S*). Recently Devarasiddappa *et al*. [19] developed artificial neural network (ANN) modeling for predicting the surface roughness in end milling of Al-SiC$_p$ MMC. They used small set of experimental data sets [12] to develop prediction model.

The trained networks predict surface roughness for large number of interpolated data sets which is used to develop fuzzy rule base. The methodology for generation of fuzzy rules from the given input and output data pairs is presented in [20]. The fuzzy logic prediction model is developed using Fuzzy Logic toolbox available in MATLAB version 7.8. (R2009a). In this work Mamdani type Fuzzy Inference Systems (FIS) is used for modeling. The steps followed in developing the fuzzy logic model are described below.

TABLE I
FACTOR LEVELS CONSIDERED

Factors	Coding of levels				
	-2	-1	0	1	2
X_1	2000	2500	3000	3500	4000
X_2	0.02	0.03	0.04	0.05	0.06
X_3	0.5	1.0	1.5	2.0	2.5
X_4	5	10	15	20	25

X_1: Spindle speed, *N* (rpm), X_2: Feed rate, *f* (mm/rev),
X_3: Depth of cut, *d* (mm), X_4: SiC content, *S* (%wt).

A. Fuzzification of I/O Variables

The input and output variables are fuzzified into different fuzzy sets. The triangular membership function is used for simplicity yet computationally efficient. It is easy to use and requires only three parameters to define. It is defined as a triangular shape which is a function of vector x that depends on three parameters a, b and c and is mathematically expressed as given in (1). Fig.1 shows graphical representation of the triangular membership function.

$$f(x;a,b,c) = \begin{Bmatrix} 0, x \le a \\ \dfrac{x-a}{b-a}, a \le x \le b \\ \dfrac{c-x}{c-b}, b \le x \le c \\ 0, c \le x \end{Bmatrix} \quad (1)$$

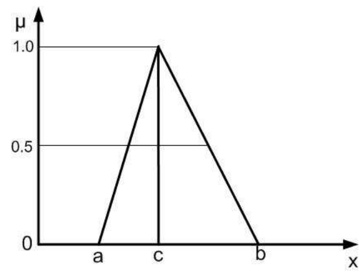

Fig. 1 Triangular membership function

The input variables spindle speed [2000 –4000 rpm] and feed rate [0.02–0.06 mm/rev] are fuzzified into four fuzzy sets viz. Very Low (L2), Low (L1), Medium (MD) and High (H) as shown in the Fig.2 and Fig.3 respectively. The other two input variables i.e. depth of cut [0.5–2.5 mm] and the SiC percentage [5–25] are fuzzified into three fuzzy sets as Low (L), Medium (M) and High (H). Fig.4 and Fig.5 depict the fuzzification of depth of cut and SiC percentage respectively.

The output variable i.e., the surface roughness is divided into eight fuzzy sets as Very Very Low (L3), Very Low (L2), Low (L1), Medium 1(MD1), Medium 2 (MD2), High (H1), Very High (H2) and Very Very High (H3) to increase the resolution and accuracy of prediction. Fuzzification of response variable is depicted in Fig.6.

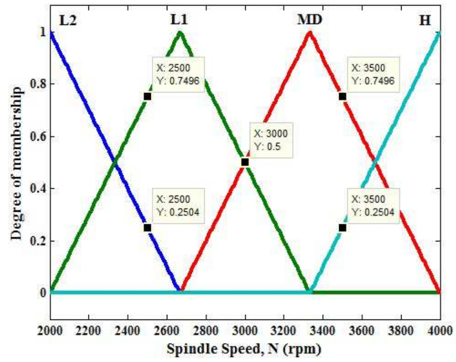

Fig. 2 Fuzzification of spindle speed

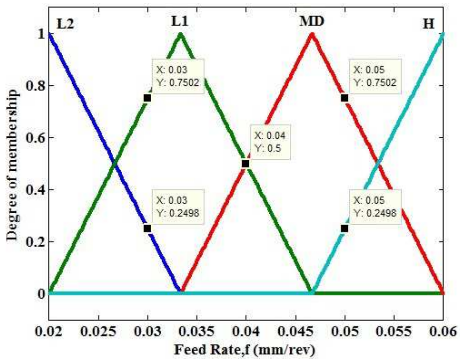

Fig. 3 Fuzzification of feed rate

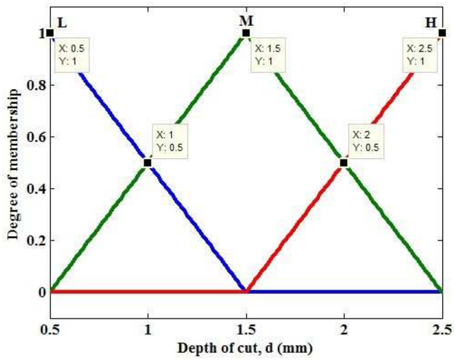

Fig. 4 Fuzzification of depth of cut

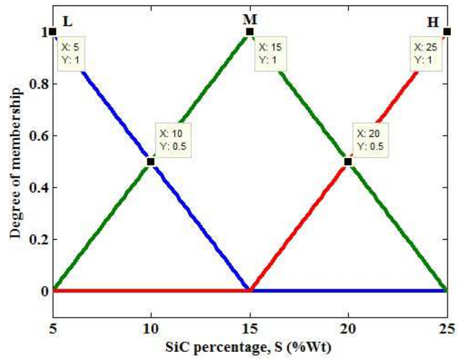

Fig. 5 Fuzzification of SiC percentage

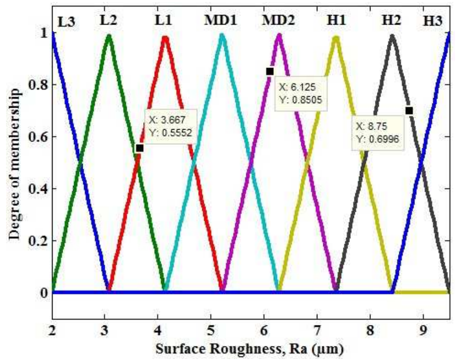

Fig. 6 Fuzzification of surface roughness

B. Evaluation of 'if –then' Rules

With two input variables fuzzified into four fuzzy sets each and other two variables fuzzified into three fuzzy sets each, the size of rule base becomes 144 (4x4x3x3). For generating the fuzzy rules, the level of the variable having more membership grade on a particular fuzzy set is considered. For example, in the case of spindle speed, the value of 2500 and 3000 rpm has membership grade of 0.7496 and 0.5 on fuzzy set L1. The other three values of spindle speed viz. 2000, 3500 and 4000 are non-members of the set L1. The spindle speed of 2500 is taken to represent the set L1 in rule forming. Similarly spindle speed 3000 and 3500 rpm are the only two members of the fuzzy set MD having respective membership grade of 0.5 and 0.7496. Therefore, the spindle speed 3500 rpm is used to represent the fuzzy set MD. The fuzzy sets L2 and H are represented by spindle speed 2000 and 4000 rpm respectively, as they are the only members of the said fuzzy sets. Thus in the entire process, the spindle speed 3000 rpm is not used in rule generation as it does not win over the other levels of spindle speed.

The same method is adapted to decide the fuzzy set member for rule generation in the case of feed rate also. However, in case of depth of cut and the SiC percentage, this is not an issue as the all the three fuzzy sets viz. L, M and H have distinct member with membership grade 1. With appropriate level of all the input variables representing the corresponding fuzzy set, ANN predicted surface roughness values are used for 144 data sets of fuzzy rule base. Since all the parts in the antecedent are compulsory for getting the response value, the AND (min) operator is used to combine antecedent parts of each rule.

The implication method min is used to correlate the rule consequent with its antecedent. The first rule of the FIS can be written as

Rule 1: if X_1 is L2 and X_2 is L2 and X_3 is L and X_4 is L then R_a is L1

In terms of the actual variable names, the above rule can be expressed as below.

Rule 1: if spindle speed is *Very Low* and feed rate is *Very Low* and depth of cut is *Low* and SiC percentage is *Low* then surface roughness is *Low*

In Rule 1, all the four input variables have membership grade equal to 1 and hence weight of the first rule equal to 1. Therefore the truth value of the statement R_a is Low is 1 for Rule 1. The weight of the second rule is evaluated in the same manner and was found to be equal to 0.7496. This means the truth value of the statement R_a is Very Low is 0.7496 for Rule 2.

C. Aggregation of Rules

The aggregation of all the rule outputs is implemented using max method, the commonly used method for combining the effect of all the rules. In this method the output of each rule is combined into single fuzzy set whose membership function value is used to clip the output membership function. It returns the highest value of the membership function of all the rules.

D. Defuzzification

The aggregate output of all the rules which is in the form of fuzzy set is converted into a numerical value (crisp number) that represents the response variable for the given data sets. In the present work, the centroid defuzzification method is used for this purpose. It is the most popular method used in most of the fuzzy logic applications. It is based on the centroid calculation and returns center of area under the curve.

V. RESULTS AND DISCUSSION

The predicted values of surface roughness are compared with the experimental result and response surface model. The response surface model developed by Arokiadass et al. [12] using second order polynomial equation found that the model is statistically significant with 95% confidence level. It is also reported that the feed rate has more influence on the surface roughness followed by spindle speed, SiC_p percentage and depth of cut. The comparison of prediction performance fuzzy logic and response surface models with the experimental result is given in Table II. The average percentage error and mean square error (mse) were calculated using the (2) and (3) respectively.

$$Avg\ Percentage\ \ Error = \frac{1}{n}\sum_{i=1}^{n}\left[\frac{abs\left(t_i - y_i\right)}{t_i}\times 100\right] \tag{2}$$

$$mse = \frac{1}{n}\sum_{i=1}^{n}\left(t_i - y_i\right)^2 \tag{3}$$

where t_i is the target, y_i is the output and n is the number of data sets. The fuzzy logic model predicts R_a values with an average percentage error of 4.56 where it is 0.51 for the response surface model [12]. The mean square error is 0.0729.

The maximum and minimum percentage error is 12.61 and 0.26 respectively. The prediction performance of the model is compared with experimental results. Fig.7 shows comparison of result in which the predicted values of R_a exhibit high correlation with experimental result.

TABLE II
COMPARISON OF R_A FOR FLM AND RSM WITH EXPERIMENTAL RESULT

Expt. No.	Surface roughness (R_a), µm			Percentage Error	
	Expt.	RSM	FLM	RSM	FLM
1	4.406	4.418	4.273	0.272	3.019
2	3.812	3.768	3.501	1.154	8.158
3	6.034	6.035	6.156	0.017	2.022
4	5.229	5.234	5.565	0.096	6.426
5	4.472	4.468	4.273	0.089	4.450
6	3.802	3.823	3.501	0.552	7.917
7	6.032	6.098	6.157	1.094	2.072
8	5.312	5.301	5.626	0.207	5.911
9	4.978	4.998	5.133	0.402	3.114
10	4.395	4.334	4.678	1.388	6.439
11	6.789	6.773	6.822	0.236	0.486
12	5.945	5.958	6.383	0.219	7.368
13	5.071	5.07	5.133	0.020	1.223
14	4.402	4.41	4.678	0.182	6.270
15	6.804	6.857	6.822	0.779	0.265
16	6.054	6.046	6.286	0.132	3.832
17	6.202	6.143	6.285	0.951	1.338
18	4.638	4.682	4.678	0.949	0.862
19	3.679	3.709	4.143	0.815	12.612
20	7.008	6.962	7.357	0.656	4.980
21	5.062	5.103	5.343	0.810	5.551
22	5.299	5.242	5.343	1.076	0.830
23	4.334	4.316	4.143	0.415	4.407
24	5.639	5.641	6.285	0.035	11.456
25	5.183	5.189	5.343	0.116	3.087

Expt.- Experimental, FLM- Fuzzy logic model RSM- Response surface model

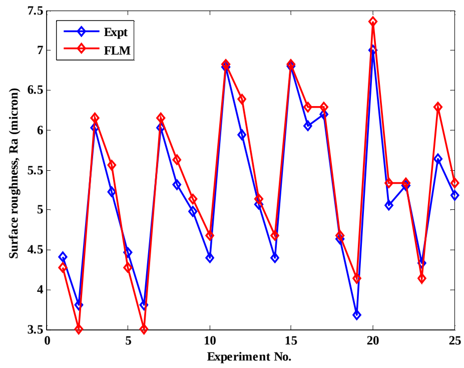

Fig. 7 Correlation between predicted R_a values and experimental result

The variation of surface roughness with different combinations of input variables is studied using the output surface of FIS. Fig.8 shows the functional dependence of R_a with spindle speed and feed rate. It can be observed that the surface roughness increases with feed rate. At lower feed rate of 0.02 to 0.03 mm/rev, the increase in spindle speed from 2000 to 2800 rpm has no significant reduction in R_a value. However, feed rate above 0.03 mm/rev the increase in spindle speed improves the R_a value. It is also observed that depth of cut variation has least influence on surface roughness value.

The higher value of depth of cut (2.0 to 2.5 mm) decreases surface roughness in the narrow range of spindle speed from 2000 to 2500 rpm. This is due to increased tooth load at higher depth of cut. Fig.9 shows the surface plot of R_a with depth of cut and SiC percentage. The surface roughness varies linearly with SiC percentage reinforcement whereas depth of cut has least influence in the range from 1 to 2 mm. The increase in depth of cut from 0.5 to 1.0 mm decreases surface roughness, but increasing depth of cut from 2 to 2.5 mm increases R_a value. The variation of R_a with feed and SiC percentage is shown in Fig.12. The increase in SiC percentage increases R_a values. From the above discussion, it can be inferred that to obtain good surface finish the MMCs should be machined at lower feed rate and higher spindle speed.

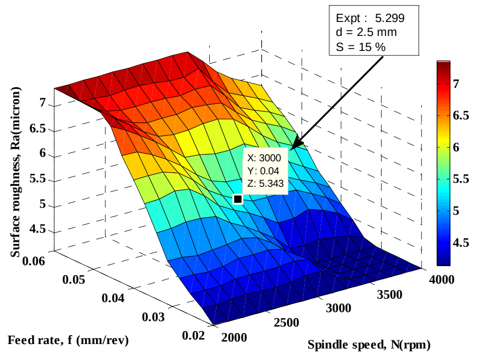

Fig. 8 Variation of R_a with spindle speed and feed rate

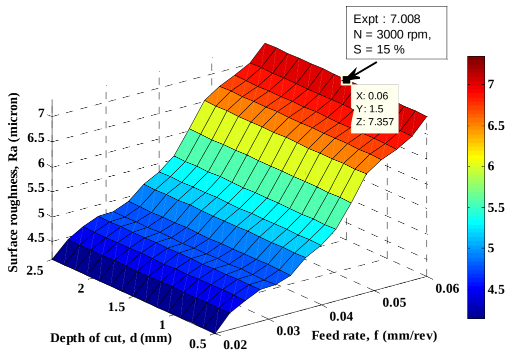

Fig. 9 Variation of R_a with feed rate and depth of cut

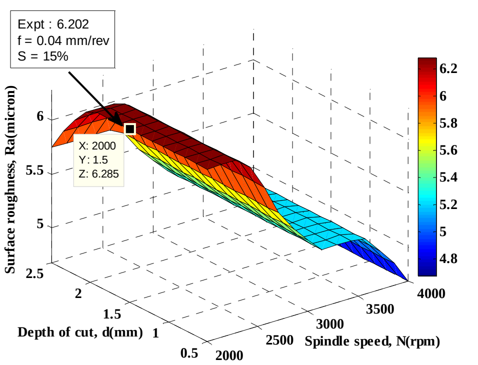

Fig. 10 Variation of R_a with spindle speed and depth of cut

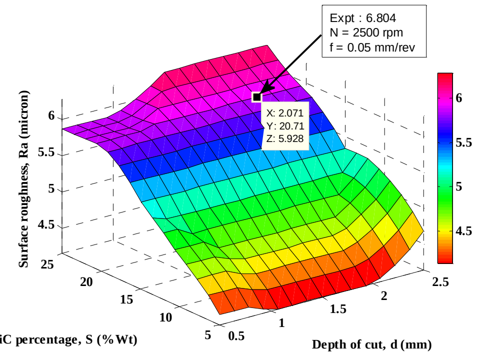

Fig. 11 Variation of R_a with depth of cut and SiC percentage

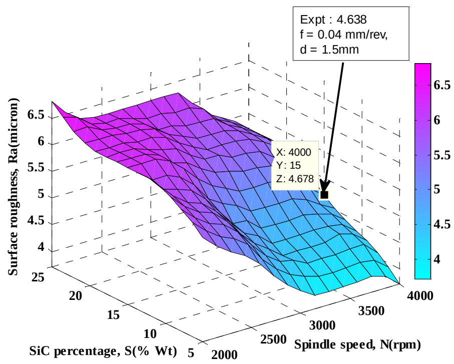

Fig. 12 Variation of R_a with spindle speed and SiC percentage

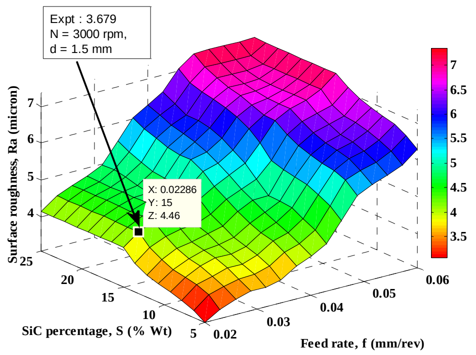

Fig. 13 Variation of R_a with feed rate and SiC percentage

VI. Conclusions

In the present work fuzzy logic model for surface roughness prediction in end milling of Al-SiCp MMC was developed. The influence of various cutting parameters on the surface roughness is studied. The effect of SiC reinforcement on response variable is also analyzed with the help of various surface plots. The model predicts with an average percentage error of 4.56. The following conclusions were drawn.

- The surface roughness depends mainly on feed rate followed by spindle speed whereas depth of cut has least influence.
- The R_a value varies linearly with the feed rate and inversely with the spindle speed.

- The SiC percentage bears linear relationship with surface roughness.
- Suitable cutting conditions for desired surface roughness can be obtained using the prediction model.
- To obtain good surface finish Al-SiC$_p$ MMCs should be machined at lower feed rate and higher spindle speed.

Since economy of machining plays an important role in the competitive global market, cutting conditions giving maximum tool life should be aimed.

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