

SURFACE ROUGHNESS MODELING IN FACE MILLING OF METAL MATRIX COMPOSITES BY FUZZY SUBTRACTIVE CLUSTERING METHOD

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Abstract: A fuzzy modeling approach is presented in this paper for the prediction of surface roughness (R_a) in face milling of Metal Matrix Composites (MMC). This study deals with the experimental results obtained during face milling of MMC Al/SiC, 15% volume fraction by using face milling cutter with K10 grade insert. The data used for the training and checking of the model performance were obtained from experiments conducted on a vertical milling machine. The model uses the cutting speed, depth of cut and the feed as input data and the surface roughness as the output data. The process of model building is carried out by using subtractive clustering in both the input and output spaces. A minimum error model is obtained through exhaustive search of the clustering parameters. The fuzzy model obtained is capable of predicting the surface quality for a given set of inputs (the cutting speed, depth of cut and the cutting feed). This model is verified experimentally using different sets of inputs.

Key words: Surface roughness, face milling, metal matrix composites, fuzzy subtractive clustering

1. INTRODUCTION

Metal matrix composites (MMCs) having high specific stiffness, strength, improved wear resistance and thermal properties have been used in some advanced structural, aerospace, automotive, electronics and other applications. The properties of MMCs are influenced by type and properties of matrix, reinforcement and interface directly. Matrix materials are usually lightweight materials especially, aluminum and its alloys to get high specific strength. Ceramic reinforcements have been used in the form of particulates, whiskers or continuous fibers. Particulate metal matrix composites (PMMCs) are more attractive than continuous fiber reinforced MMCs due to the fact that they show higher ductility and lower anisotropy. Moreover, they are much cheaper and need simpler processing methods (Koczak et al., 1993).

After production of PMMCs, they often need to be machined to get net shape and the specified tolerance. Nevertheless, their machining is difficult because of hard ceramic reinforcements causing serious abrasive tool wear and then poor machinability (El-Gallab & Sklad 1998). Though the most generally used machining operations are turning, milling is also needed in finishing operation during fabrication of components by composite materials. Even though there have been many studies on the modeling of surface roughness by using coated and uncoated tools in turning and drilling of MMCs, a very limited study is available on the modeling of surface roughness in milling of these materials.

Surface roughness is a measure of the technological quality of a product and a factor that greatly influences manufacturing cost. It describes the geometry of the machined surface and combined with the surface texture, which is process dependent, can play an important role

on the operational characteristics of the part (e.g. excessive friction and/or wear). The achievement of a desirable value is a repetitive and empirical process that can be very time consuming. The part must be machined more than once until an acceptable value is obtained. The mechanism behind the formation of surface roughness is process dependent and complicated, so it is very difficult to calculate its value through analytical formulae. Various theoretical models (Çolak 2007, Ozcelik & Bayramoglu 2006) that have been proposed are not accurate enough and apply only to a limited range of processes and cutting conditions or must be used in conjunction with obscure diagrams and statistical tables. Consequently, there is a need for a tool that will allow the evaluation of the surface roughness value before the machining of the part and which, at the same time, can be easily used in the production-floor environment contributing to the minimization of required time and cost. Moreover, it could be used for the determination of the appropriate cutting conditions to achieve specific surface roughness value.

The early research on machining of MMCs concentrated mainly on the study of cutting tool wear (Joshi 1999). Also the same authors studied chip formation during machining of Al/SiCp composites. Very limited researches have been carried out on quality of surfaces generated in machining of composites. In this context, Pendse & Joshi (2004) postulated a correlation between the size of reinforcement in the composite material and roughness of the machined surface on these composites. Basher (2007) developed surface roughness model for precision turning of metal matrix composites. So far no attempt has been made for developing surface roughness model in milling metal matrix composite. Hence, this article aims to develop a surface roughness

model by fuzzy subtractive clustering for face milling of Al/SiC metal matrix composites with minimum error.

2. SURFACE ROUGHNESS MODEL

2.1. Subtractive clustering

Subtractive clustering proposed by (Chiu 1994) is considered as an alternative to the mountain-clustering algorithm. In subtractive clustering, all data points are considered as candidates for cluster centers; this will solve the problem of computational complexity in mountain clustering when the dimension of the problem under consideration is increased. In subtractive clustering, the computational complexity is proportional to the number of data points and has nothing to do with the dimension of the problem. The density measure at any point x_i is equal to

$$P_i = \sum_{j=1}^N \exp\left(-\frac{\gamma \|x_i - x_j\|^2}{r_a^2}\right) \quad (1)$$

Where x_i is the i th data point and N is the total number of data points, γ is a positive constant and r_a is a constant that defines the neighborhood (data points outside this radius will contribute less to the density measure). The data point with the highest potential (density measure) is selected as the first cluster center. To find the next cluster center, we reduce the effect of the previously identified cluster center and the data points near this center by revising the density measure; this is done by subtraction as shown in the following equation:

$$P_i = P_i - P_k^* \exp\left(-\frac{\gamma \|x_i - c_k\|^2}{r_b^2}\right) \quad (2)$$

$$r_b = \eta \times r_a$$

Where P_k^* the potential of the k^{th} cluster center and c_k is the k^{th} cluster center; η is a positive constant called squash factor, which is greater than 1; and r_b is a positive constant greater than r_a , which helps to avoid closely spaced cluster centers. After subtractions, the second cluster center is selected based on its new potential in relation to an upper acceptance threshold $\bar{\varepsilon}$ called accept ratio, lower rejection threshold $\underline{\varepsilon}$ called reject ratio and a relative distance criterion. This process is repeated until a sufficient number of cluster centers is identified in the input and output space. Subtractive clustering has four significant parameters; accept ratio $\bar{\varepsilon}$, reject ratio $\underline{\varepsilon}$, cluster radius r_a , and squash factor η . These parameters have influence on the number of rules and the error performance measures. For example, a large value of r_a generally results in fewer clusters that lead to a coarse model. However, a small value of r_a can produce excessive number of rules that may result in an over defined system. The optimal parameters suggested by Chiu 1994 are $1.25 \leq \eta \leq 2.00$ and $0.15 \leq r_a \leq 0.3$. The membership functions of all data points in each input space are assigned exponentially as proposed by Chiu 1994 with respect to all cluster centers as follows:

$$\mu_{ij} = \exp\left(-\frac{\gamma \|x_i - c_k\|^2}{r_a^2}\right) \quad (3)$$

Where $\|x_i - c_k\|$ is the distance measure between the i th data point and k th cluster center.

2.2 The fuzzy model

The most common type of fuzzy models is Mamdani type (Mamdani, 1975) in which both antecedents and consequents of the IF-THEN rules consist only of fuzzy sets. Another major type of fuzzy models was proposed by (Takagi & Sugeno, 1985). The Sugeno model is associated with a rule base of a special format that is characterized with functional-type consequents instead of the fuzzy consequents used in Mamdani. In the Sugeno model, a multi-input single-output (MISO) system with m antecedents can be represented as a set of n rules of the following format:

$$R_i : IF x_1 \text{ is } A_1^i \text{ AND } x_2 \text{ is } A_2^i, \dots, x_m \text{ is } A_m^i \\ THEN y_i = a_{i0} + a_{i1}x_1 + \dots + a_{im}x_m$$

Where $(a_{i0}, a_{i1}, \dots, a_{im}; i = 1, 2, \dots, n)$ are regression parameters to be identified using the least-squares estimation (LSE) algorithm. These parameters can also be tuned using neural networks.

3. EXPERIMENTAL PROCEDURE

3.1. Cutting parameters for face milling during training

While designing the experiments for this work, the experimental parameters that influence the surface roughness were selected based on the literature review and the past experimentation (Quan & Ye, 2003) and (Pendse & Joshi, 2004). A 50 mm diameter face-milling cutter with single K 10 grade coated grade carbide insert was used in this experiment to machine Al/SiC MMC. cutting speed, feed rate and depth of cut were selected as the machining parameters to analyze their effect on surface roughness. A total of 27 training sets were used in the Fuzzy subtractive clustering method. The machining parameters used for training the model are given in Table 1. The value of surface roughness was measured after milling according to machining parameters and then used as the training data in fuzzy model, as listed in Table 2.

Table 1. Cutting parameters for face milling during training

Cutting speeds (m/min)	63, 100 and 157
Feed rate (mm/min)	25, 40 and 63
Depth of cut (mm)	0.25 0.50 and 1.0
Width of cut (mm)	25
Coolant	Dry

Table 2. Training data

S#	v m/min	f mm/min	D mm	R _a in μm
1.	63	25	0.25	2.25
2.	63	25	0.5	2.32
3.	63	25	1.0	2.52
4.	63	40	0.25	2.27
5.	63	40	0.5	2.41
6.	63	40	1.0	2.51
7.	63	63	0.25	2.41
8.	63	63	0.5	2.71
9.	63	63	1.0	2.79
10.	100	25	0.25	1.85
11.	100	25	0.5	2.02
12.	100	25	1.0	2.08
13.	100	40	0.25	2.13
14.	100	40	0.5	2.26
15.	100	40	1.0	2.33
16.	100	63	0.25	2.3
17.	100	63	0.5	2.42
18.	100	63	1.0	2.59
19.	157	25	0.25	0.98
20.	157	25	0.5	1.14
21.	157	25	1.0	1.26
22.	157	40	0.25	1.19
23.	157	40	0.5	1.32
24.	157	40	1.0	1.56
25.	157	63	0.25	1.33
26.	157	63	0.5	1.53
27.	157	63	1.0	1.91

4. EXPERIMENTAL RESULTS

4.1 Effect of cutting parameters on the surface roughness

Fig.1, 2 and 3 show the effect of depth of cut and feed rate on the surface roughness when the spindle speeds are 63, 100 and 157 m/min. As shown in fig. 1, for the cutting speed as 63 m/min, at the feed rate of 25 mm/min and the depth of cut of 0.25 mm the average roughness obtained is the lower of 2.25 μm. As the feed rate is increased from 25mm/min to 63 mm/min the surface roughness increases from 2.25 μm to 2.41 μm i.e 7.11% increase in value. Also from fig. 1, for feed rate 25,40 and 63mm/min, the increase in depth of cut from 0.25 mm to 1.0 mm the surface roughness value has increased from 2.25 μm to 2.52 μm, 2.27 μm to 2.51 μm and 2.41 μm to 2.75 μm, representing an increase of 12%, 10.5% and 14.1% respectively.

From fig.2, for the cutting speed 100 m/min at feed rate 25, 40 and 63 mm/min, the increase in depth of cut from 0.25 mm to 1.0 mm the surface roughness increased from 1.85 μm to 2.08 μm, 2.13 μm to 2.33 μm and 2.30 μm to 2.59 μm, representing an increase of 12.4%, 9.38% and 12.61% respectively.

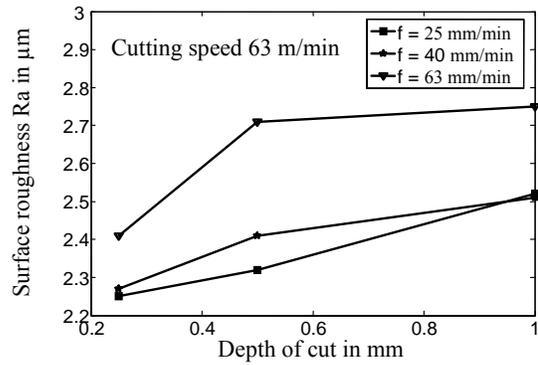


Fig.1. The effect of depth of cut and feed rate at spindle speed 63 m/min

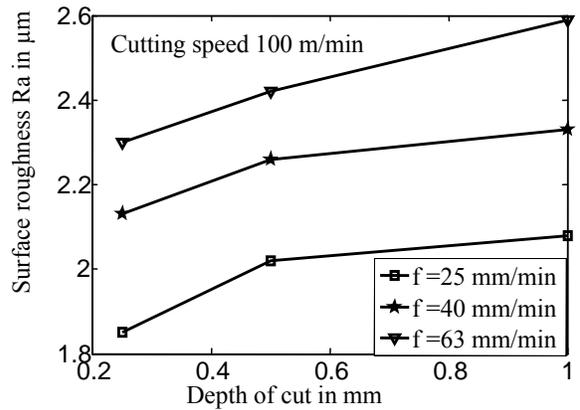


Fig.2. The effect of depth of cut and feed rate at spindle speed 100 m/min

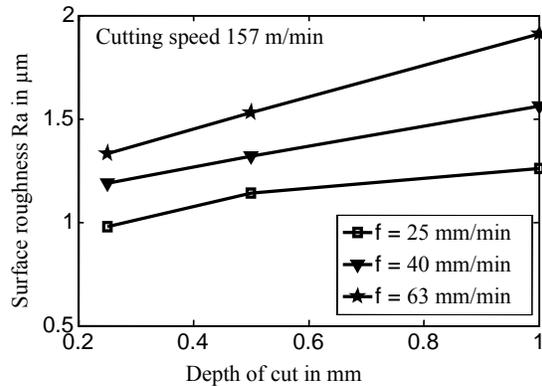


Fig.3. The effect of depth of cut and feed rate at spindle speed 157 m/min

From fig. 3, for the cutting speed 157 m/min at feed rate 25, 40 and 63mm/min, the increase in depth of cut from 0.25 mm to 1.0 mm the surface roughness increased from 0.98 μm to 1.26 μm , 1.19 μm to 1.56 μm and 1.33 μm to 1.91 μm , representing an increase of 28.57%, 31.09% and 43.6% respectively.

While comparing Fig.1, 2 and 3, a higher spindle speed achieves a smaller roughness value, i.e. superior milling quality. Given the machining condition of a smaller depth of cut at 0.25 mm as the spindle speed increases from 63 to 157 m/min for the feed rate of 25 mm/min, the average roughness value decreases from 2.25 μm to 0.98 μm ., representing a drop around 56.44%. The results indicate that the spindle speed has a greater impact on milling quality, i.e. surface roughness value, under a change in depth of cut from 0.25 mm to 1 mm. Besides, it also seen from fig.1,2 and 3, that given the depth of cut at 0.25mm, as the spindle speed increases from 100 to 157 m/min, the average surface roughness value decreases from 1.85 μm to 0.98 μm ., or only a 47% drop. In other words, under the milling condition of 0.25 mm depth of cut, the increase of spindle speed from 100 to 157 m/min has a limited improvement on the average surface roughness. From fig.1,2 and 3, for the depth of cuts 0.5 mm and 1 mm, the average roughness value decreases from 2.32 μm to 1.14 μm and 2.52 μm to 1.26, representing a drop of 50.86% and 50% respectively as the spindle speed increases from 63 to 157 m/min. That is, among the three cutting speeds, the speed of 157 m/min achieves the best surface quality.

The results suggest that the larger the feed rate at higher speed, the larger the percentage increase in roughness value for increase in depth of cut obtained after milling, indicating an inferior milling quality. Hence for the higher speed and feed rate, the change in depth of cut significantly influences surface roughness.

5. MODEL DEVELOPMENT

5.1. Fuzzy modeling process

The model developed by using the cutting speed, feed and depth of cut as input data and roughness as the output data. The model-building process is performed by using subtractive clustering in both input and output spaces. Each cluster represents certain parts of the system behavior. Then, the clusters are projected into each dimension in the input space; each projection forms an antecedent of a rule. Thus, the premise parameters of the model are identified. The model is completed by LSE method, which identifies the optimal consequent parameters in Sugeno system (Takagi & Sugeno 1985).

The optimization of the system modeling, however, depends mainly on clustering parameters that generate optimal models. Therefore, an enumerative search is carried out on parameters such as squash factor, cluster radius, accept ratio, and reject ratio which are given in Table 3.

Table 3. Value of clustering parameters

Parameter	Value
Squash factor(η)	2.0
Accept ratio (ε)	0.8
Reject ratio($\underline{\varepsilon}$)	0.7
Cluster radius(r_{cl})	0.5

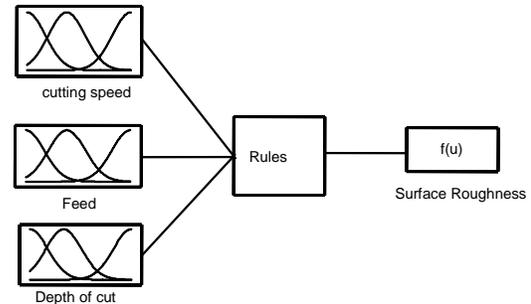


Fig.4. Fuzzy rule architecture of the membership function

The rule base of a model built by using subtractive clustering method with zero modeling error is shown in Fig. 4. There are 26 rules identified in this model. Once the rule base for the surface roughness is identified, the rule base for the surface obtained by a given input vector (x_1', x_2', x_3') can be predicted by computing

$$y^* = \frac{\sum_{k=1}^k w_k y_k}{\sum_{k=1}^k w_k} \quad (4)$$

Where $w_k = (A_1^k(x_1'), A_2^k(x_2'), A_3^k(x_3'))$, y_k is the rule output computed by substituting x_1', x_2' and x_3' in rule R^k . The fuzzy model obtained is capable of predicting the surface roughness for a given set of inputs (speed, feed and depth of cut). Therefore, the operator can predict the quality of the surface for a given set of working parameters and then will be able to set the machining parameters to achieve a specified surface quality.

5.2 Testing the model

A total of 20 testing sets were used in the model for testing. The machining parameters used for testing the model are given table 4. Experiments were conducted with the same condition as given in section 3.1. The value of surface roughness was measured after milling according to machining parameters and then used as the training data in fuzzy model.

Table 4. Cutting parameters for face milling during testing

Cutting speeds (m/min)	78,100,125 and 157
Feed rate (mm/min)	25, 31.5,40, 50 and 63
Depth of cut (mm)	0.4 and 0.8
Width of cut (mm)	25
Coolant	Dry

6. RESULTS AND DISCUSSIONS

6.1. Validation of model

The Fuzzy model was generated using the MATLAB program. The data for training was selected in such a way that all the results corresponding to the Al/SiC/23p/15%VF composite material.

A comparison of the experimental results with the predicted response is shown in figure 5. The proposed fuzzy model shows a good prediction accuracy with coefficient of correlation of $R = 0.9123$ and mean squared error of 0.0197 was observed between the actual and predicted value, see fig. 5.

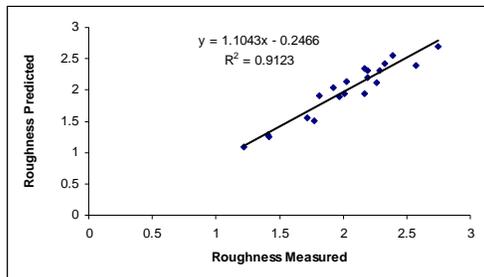


Fig.5 Experimental Results vs. Predicted by model

From the figure 6 it can be observed that the predicted surface roughness values using the fuzzy subtractive clustering method follows very closely the trend of the experimental data with less error.

In the test data, there is good correlation between functional data and experimental data. In face milling of AlSiC MMC with 15% volume fractions, the model will reduce the need of high cost experimental studies. This model is suitable for AlSiC MMC with 15% volume fractions. Hence, as a further work volume fraction also included in surface roughness measurement.

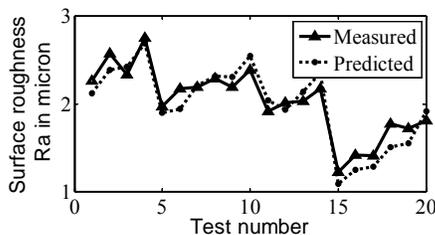


Fig.6 Comparison between desired outputs and predicted outputs

5. CONCLUSION

This article establishes the relationship between the basic input and output parameters in face milling of metal matrix composites using a fuzzy modeling approach. The model for the surface roughness is developed by using the cutting speed, feed and depth of cut as input data and roughness as the output data. Model is obtained through enumerative search of clustering parameters with good prediction accuracy with coefficient of correlation 0.9123 observed between the actual and predicted value.

In manufacturing environment prediction of surface roughness is important for product quality and production time. In this study, using Fuzzy subtractive clustering method, surface roughness prediction model has been done using a few experimental data.

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