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PREDICTION OF ROUGHNESS AND TOOL WEAR IN TURNING OF METAL MATRIX NANOCOMPOSITES

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ABSTRACT

The selection of suitable machining parameters is an important task to obtain a suitable surface finish at the least possible tool wear when machining metal matrix nanocomposites. The aim of this work is to predict the appropriate cutting parameters for machining of metal matrix nanocomposites through dry turning operations using uncoated carbide inserts to produce the desired surface roughness at minimum tool wear. Al/SiC metal matrix nanocomposites are employed in experimentation, utilizing five different volume percent of SiC nanoparticulates. Practical investigation is performed through dry turning operations that are conducted at different values of cutting speed, feed and depth of cut. A fuzzy logic control system is developed to predict both surface roughness and tool wear result as a function of the cutting parameters and the different volume percent of nanoparticulates under experimental consideration. The results of the fuzzy logic control system are compared with the obtained experimental results. The predicted values have an average accuracy of 90% in case of surface finish and 80% in case of flank tool wear. Thus, a fuzzy logic control system can be used to predict both surface roughness and tool wear in turning of such materials under the considered range of conditions.

KEYWORDS: Nano-composites, Machinability, Roughness, Tool wear, Fuzzy logic.

1. INTRODUCTION

Metal matrix nanocomposites (MMNCs) are hard to machine due to the presence of hard abrasive reinforcement particulates that grind the tool flank face in a similar way to a grinding wheel during machining of Al/SiC-MMNCs which results in faster tool wear [1, 2]. Turning operations are among the most common machining operations employed in automotive, aerospace and other industrial applications. Tool

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wear and surface roughness are considered as the two main attributes in any machining processes, which are affected by several factors including cutting conditions (feed rate, cutting speed, depth of cut, etc.). Tool material and properties of the machined components are also considered as important factors that affect the surface quality. The prediction of both surface roughness and tool wear during different machining processes is an important task as it gives the manufacturing engineers the ability to test a product before moving on to final production. Drilling of metal matrix composites based on Taguchi techniques to reveal the effect of cutting conditions on tool wear and surface roughness as well as the interaction between these factors [3]. An elaborative experimentation using the Taguchi technique of Al/SiC composites utilizing different size and volume fraction of SiC was performed to study the effect of reinforcements in composites, machined surface finish and cutting forces [4].

Several studies stated that Taguchi had shown some defects when dealing with multiple performance characteristics problems [5, 6]. Mathematical modeling for surface roughness based on fuzzy logic and artificial neural network was employed in studying machinability [7]. Fuzzy logic was utilized in developing a knowledge-based system for predicting the surface roughness in the turning process [8].

The knowledge-based system consists of a neural network model which generates a data set to form If-Then rules of the fuzzy model [9]. The effect of feed rate, cutting speed, depth of cut, rake angle and cutting fluid on both tool wear and surface finish was investigated [10]. The effect of volume percent of reinforcement, feed rate and cutting speed of MMCs were studied [11]. Fuzzy logic for machining of Al/SiC composites was employed in classifying the tool wear states to facilitate a defective tool replacement at the proper time [12]. Optimum machining characteristics in turning of Al- 15% SiC metal matrix composites for minimizing the surface roughness and power consumption using desirability function approach was investigated [13]. The neural network was utilized in modeling the surface roughness and dimensional deviation in the wet turning of steel with a high-speed tool [14]. A similar study was presented using a radial basis function neural network, which predicted approximately with the same accuracy in a shorter computational time [15].

Moreover, the fuzzy logic approach was utilized in predicting the surface finish of ground parts [16]. Optimum input parameters were determined to develop an aluminum metal matrix composites with respect to mechanical properties employing grey relation analysis [17]. A surface roughness prediction model using fuzzy logic was developed for end milling of Al/SiC metal matrix composites components using an end milling cutter. The surface roughness was modelled as a function of spindle speed, feed, rate, depth of cut and SiC percent [18]. The application of a traditional Taguchi method with fuzzy logic for multi objective optimization of the turning process of Al-5 Cu alloy in CNC Lathe machine was investigated and the cutting parameters were optimized with considerations of the multiple surface characteristics (Ra, Rz, Rt and Sa). The parameters utilized in the study were cutting speed, depth of cut and feed rate. Other parameters such as tool materials, work piece material and its diameter were fixed during experimentation. Thus, the study was recommended for undergoing continuous improvement of quality [19]. The investigation focused on finding the optimum turning parameters for multiple performance characteristics. The grey output was fuzzified into eight membership functions and 27 rules were developed. The proposed grey fuzzy logic approach was found to be more effective in evaluating the multiple performance characteristics and simplifies the optimization procedure in optimizing complicated process responses. A fuzzy logic artificial intelligence technique was utilized in predicting the machining performance of Al-Si-Cu-Fe die casting alloy treated with different additives, including strontium, bismuth and antimony to improve the surface roughness. The Pareto-ANOVA optimization method was used to obtain the optimum parameter conditions for the machining process. A confirmation experimentation was performed to check the validity of the model developed [21]. The predicted surface roughness had an error rate of only 5.4 %. Recently, a surface roughness prediction model was built using the acoustic emission (AE) single and fuzzy neural network in the grinding process. The experimental results proved that the proposed fuzzy neural networks prediction model based on AE was feasible and possessed higher prediction accuracy [22].

This paper aims to develop a fuzzy logic methodology for predicting surface roughness and tool wear resulting from the turning of Al/SiC metal matrix nanocomposites under suitable ranges of feed rate, cutting speed and depth of cut.

2. EXPERIMENTAL SET UP

The various sets of experiments are carried out on a Centre lathe utilizing uncoated carbide tips.

2.1 Work Material

A bar of 40 mm diameter and 120 mm long of Al/SiC metal-matrix nanocomposites are employed in experimentation. Table 1 shows the chemical composition and average particle size of Nano-composites. A tool room microscope is utilized in measuring tool flank wear resulting from machining.

Table 1. Chemical Composition of Al/SiC Nano-Composites Metal Utilized in Experiments.

Average Size of Particle (nm)	100
SiC	11.23
Fe	0.58
Cu	0.045
Mn	0.01
Mg	0.029
Zn	0.021
Ti	0.028
Ni	0.026
Sn	0.008
Al	Bal.

2.2 Cutting Tool

Uncoated carbide inserts of rhombic geometrical shape are employed in cutting operations, Table 2 shows the details of the cutting tool.

Table 2. Details of Cutting Tool Utilized in Experimentation.

CCGT09T304 – AK	
Tool material	Tungsten Carbide
Rake angle (˚)	5
Nose radius (mm)	0.4
Cutting edge angle (˚)	80
Clarence angle (˚)	7

2.3 Machining Parameters

The machining parameters are feed rate, cutting speed, depth of cut and SiC volume %. The selected range for each parameter is as follows:

Feed rate range: 0.08-0.2 mm/rev, cutting speed range: 50-275 m/min, depth of cut range: 0.25-2.0 mm, and SiC volume percent range is 1% - 5%.

Processes response parameters:

Surface roughness Rz (µm) and tool flank wear (mm) are selected as response parameters for describing the quality of the machining process.

2.4 Measurement Devices

The surface roughness measurement is carried out utilizing a Talysurf of commercial name (Taylor – Hobson), while a tool room microscope is used in measuring tool flank wear.

3. FUZZY LOGIC CONTROL SYSTEMS

Fuzzy control system starts with determining a set of fuzzy rules followed by fuzzifying the inputs (by mapping inputs with different values) utilizing the input membership functions. Rule evaluation, is next step in which inputs are applied to a set of If-Then rules. The results of different rules are summed together to generate a set of fuzzy outputs. Defuzzification is the final step in which outputs are combined into discrete values needed to drive the control mechanism.

The objective of this study is to check the quality of using fuzzy logic control system for predicting surface roughness and flank tool wear during machining similar classes of materials employing the given input parameters. Thus, in this system, the predicated values of surface roughness and flank tool are presented. The values of surface roughness and tool wear are assumed as a function of four input variables, which are feed rate, depth of cut, cutting speed, and the volume percent of SiC. The input variables employed in the study are as follows; Feed Rate: 0.08 – 0.2 (mm/rev.), Depth of Cut: 0.25 – 2.02 (mm), Cutting Speed: 50 – 280 (m/min) and SiC Volume: 1 – 5 (%). The given input variables, for simplification, are fuzzified into three fuzzy sets: low, medium, and high. The range of each set is shown in Table 3 for the fuzzy system input variables.

Table 3. Fuzzy Sets for Input Variables

		Fuzzy Sets		
		Low	Medium	High
Input Variables	Feed Rate	0.08 – 0.12	0.13 – 0.16	0.17 – 0.2
	Depth of Cut	0.25 – 0.85	0.95 – 1.45	1.55 – 2.02
	Cutting Speed	50 – 120	130 - 200	210 – 280
	SiC %	1 – 2	2.5 – 3.5	4 – 5

3.1 Fuzzy System For Surface Roughness

Figure 1 illustrates the fuzzy system used for predicting the resulting surface roughness as a function of different input variables, while Fig. 2a, b shows the membership function for input and output variables respectively.

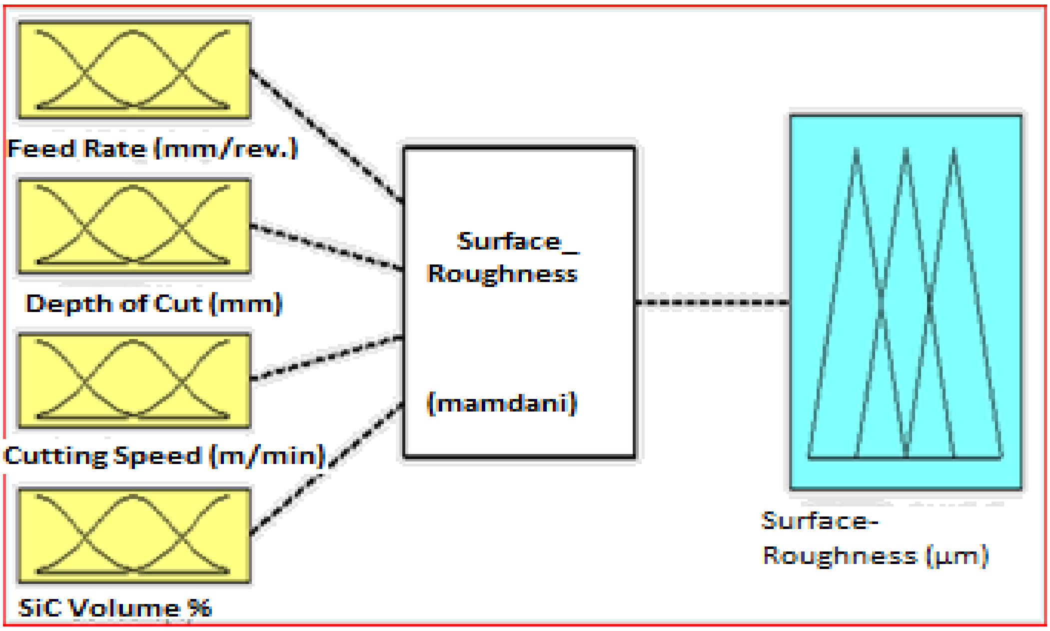
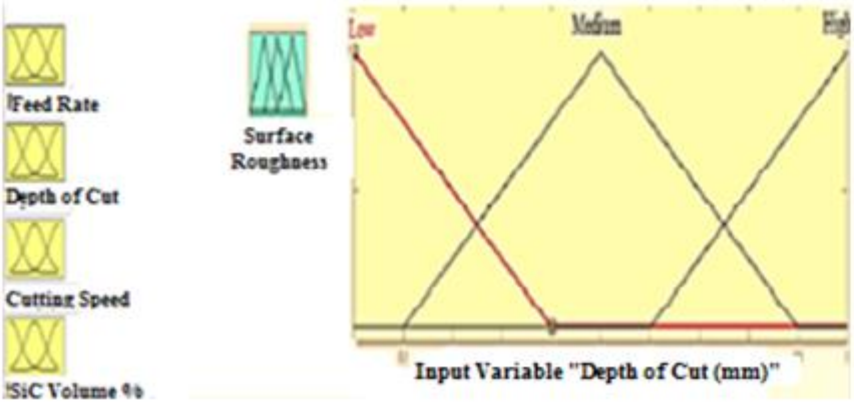
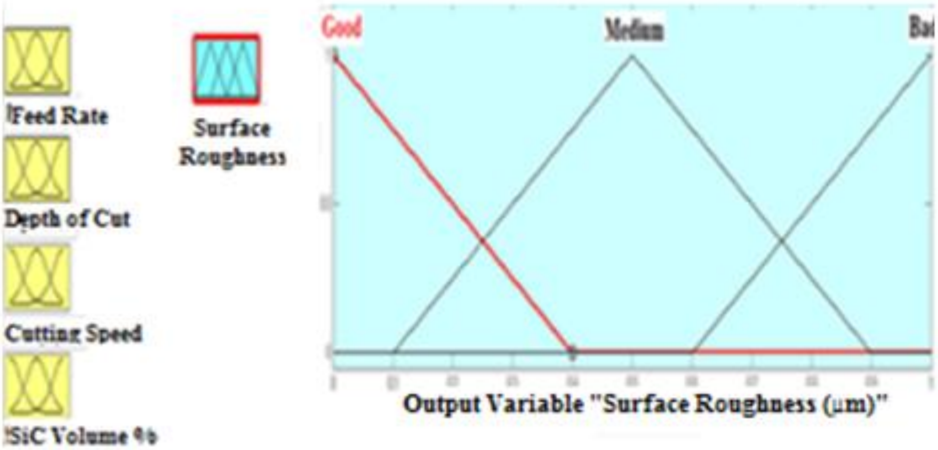


Fig 1. Fuzzy System for surface roughness predication.



a) Membership Function for Input Variables.



b) Membership Function for Output Variables.

Fig. 2. Membership Functions for Roughness.

3.2 If –Then Rule

Figure 3 illustrates If-Then rules; for example, if feed rate is low, depth of cut is low, cutting speed is high and SiC volume % is high, then the output Rz is good. The prediction of surface roughness values for different input variables is indicated in Fig. 4 in which changes in machining conditioning input values such as feed rate, depth of cut, cutting speed and SiC % (in yellow as inputs) through 12 If-Then rules influence surface roughness (in blue as output) that can be recognized depending on fuzzy logic model system as shown in the Figure. The effect of input variables sets on surface roughness are presented graphically in Fig. 5a-e.

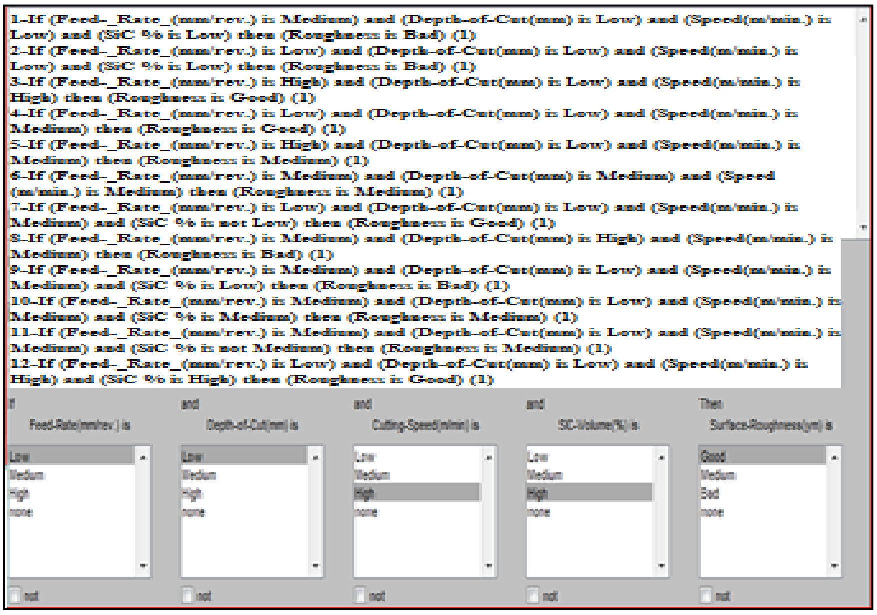


Fig. 3. Fuzzy system if-then rules.

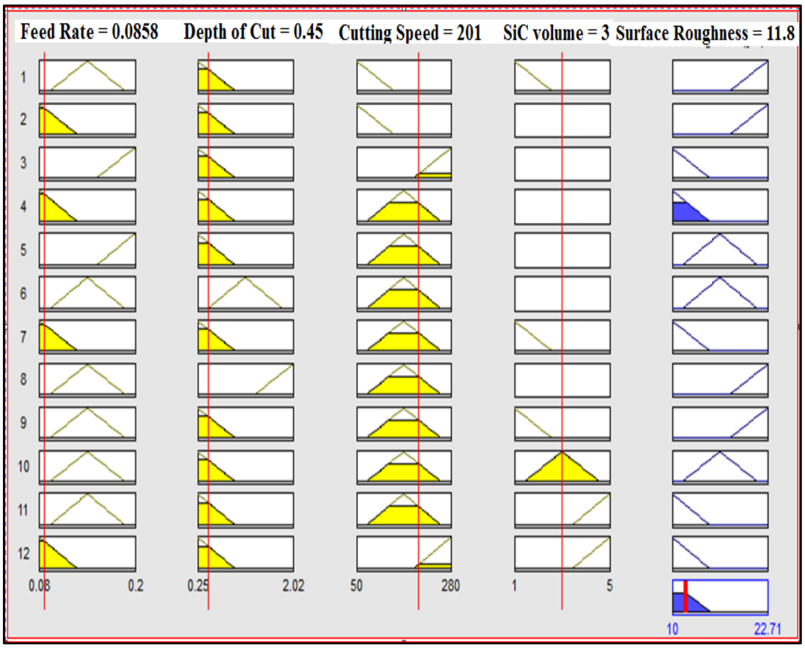
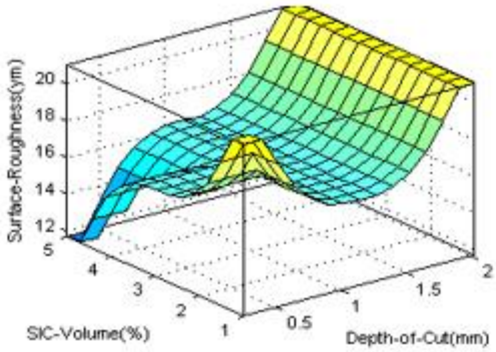
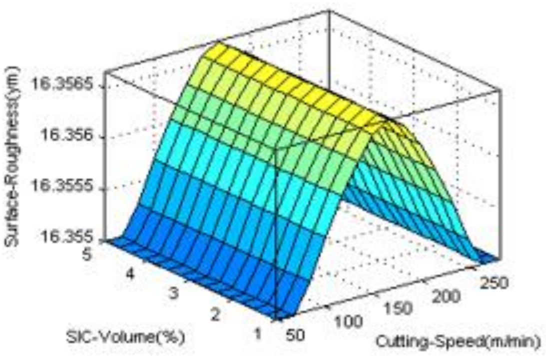


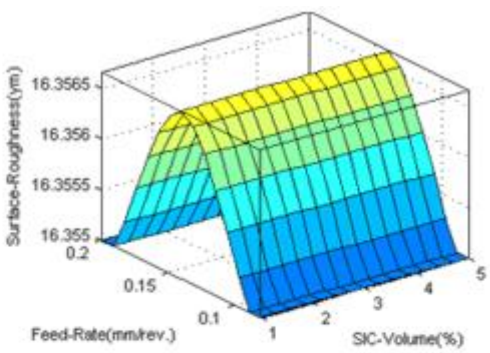
Fig. 4. Prediction of surface roughness values for different input variables.



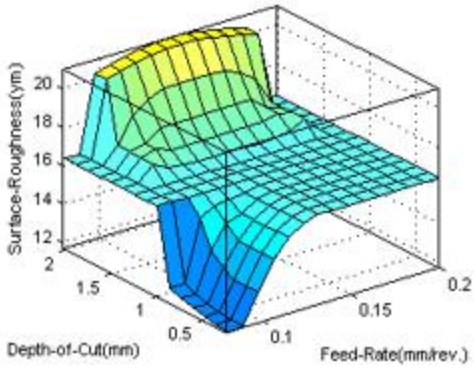
(a) Effect of Depth of Cut and SiC% on Surface Roughness



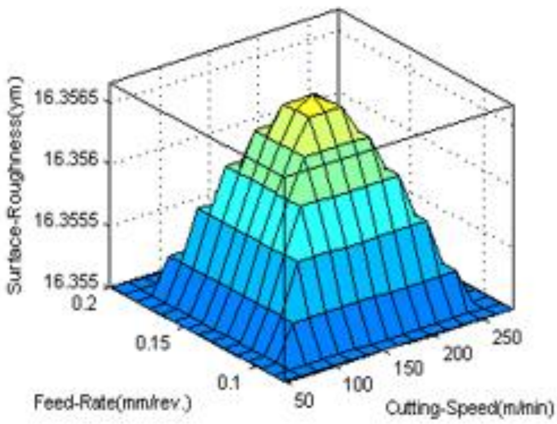
(b) Effect of Cutting Speed and SiC% on Surface Roughness



(c) Effect of Feed and SiC% on Surface Roughness



(d) Effect of Depth of Cut and Feed on Surface Roughness



(e) Effect of Cutting Speed and Feed on Surface Roughness

Fig. 5. the effect of input variables on Surface Roughness

4. FUZZY SYSTEM FOR FLANK WEAR

Figure 6 illustrates the fuzzy system used for predicting the resulting flank wear as a function of different input variables, while Fig. 7a, b shows the membership function for input and output variables respectively.

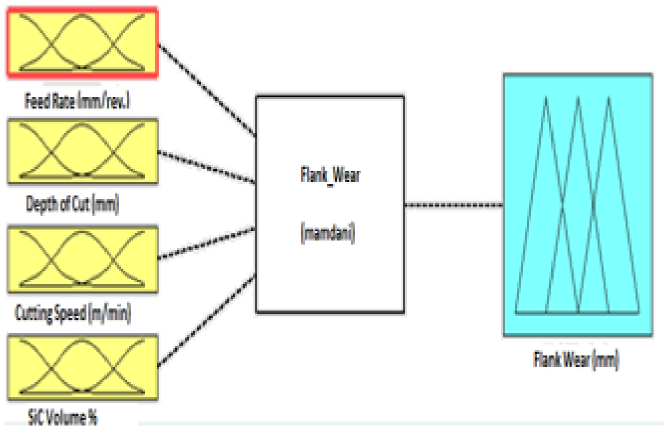
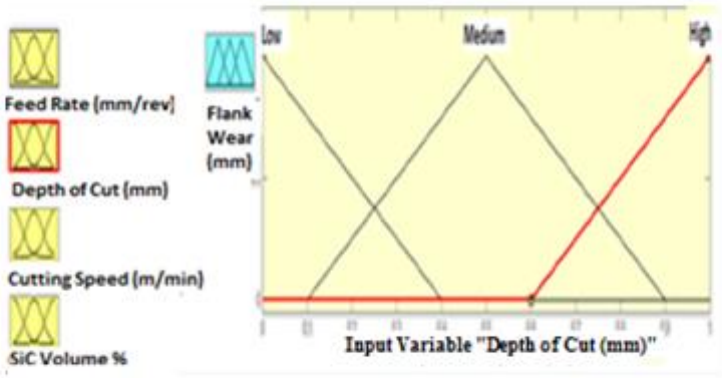
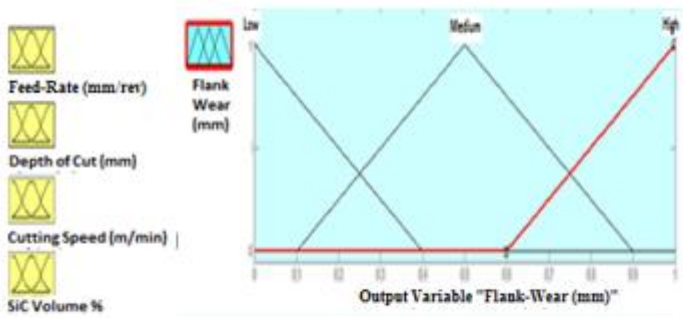


Fig. 6 Fuzzy System for Wear Prediction



(a) Membership Function for Input Variables



(b) Membership Function for Output Variables

Fig. 7 Membership Function for Flank Wear

4.1 If-Then Rules

Figure 8 illustrates If-Then rules; for example, if feed rate is low, depth of cut is low, cutting speed is high and SiC volume % is high then the flank wear is good. The prediction of flank wear values for different input variables is indicated in Fig. 9 in which changes in machining conditioning input values such as feed rate, depth of cut, cutting speed and SiC % (in yellow as inputs) through 12 If-Then rules influence tool wear (in blue as output) that can be recognized depending on fuzzy logic model system as shown in the Figure. The effect of input variables sets on flank wear are presented graphically in Fig. 10a-c.

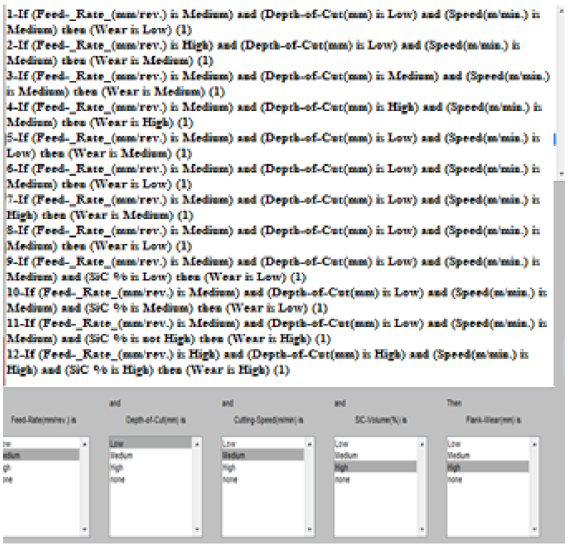


Fig. 8 Fuzzy System IF-Then rule

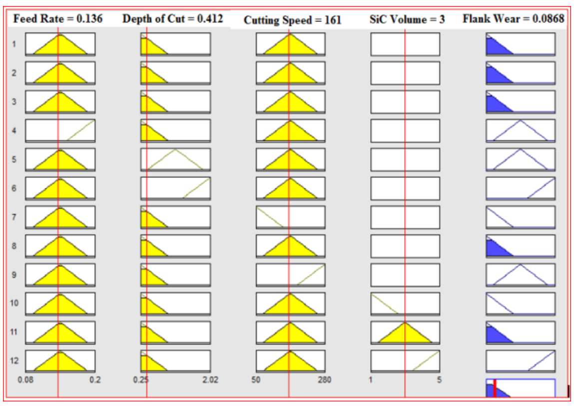
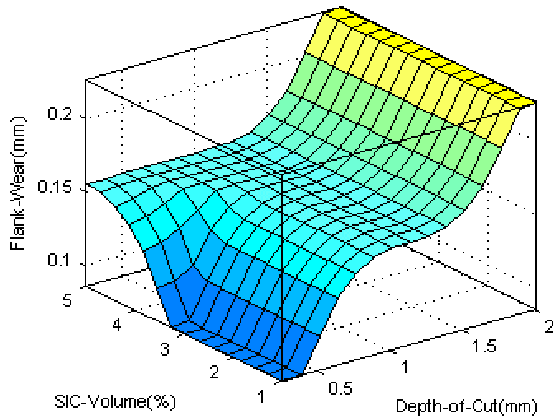
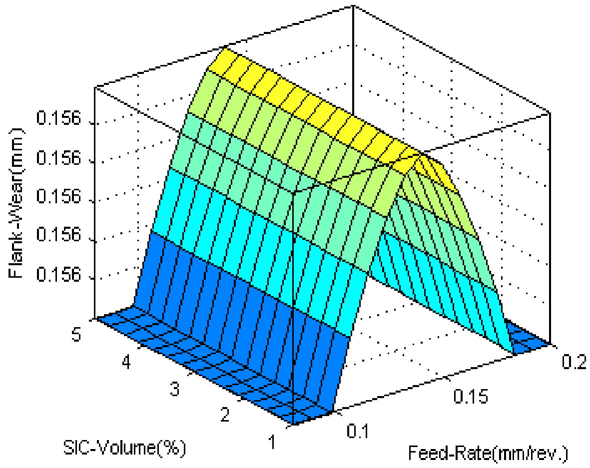


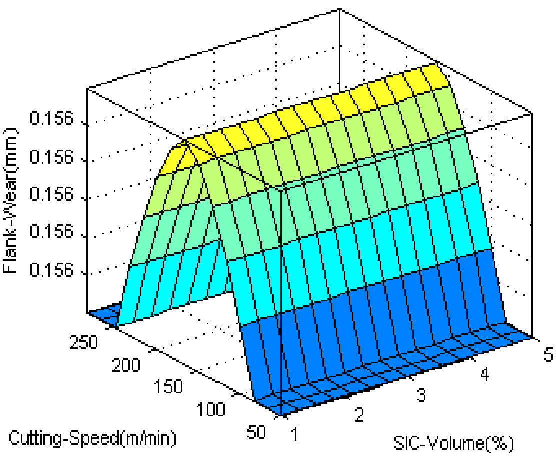
Fig. 9. Prediction of flank wear values for different input variables.



(a) Effect of Depth of Cut and SiC Volume % on Flank Wear.



(b) Effect of SiC Volume % and Feed Rate on Flank Wear.



(c) Effect of Cutting Speed and SiC Volume on Flank wear.

Fig. 10. The effect of input variables sets on flank wear.

5. DISCUSSION AND ANALYSIS OF FUZZY CONTROL SYSTEM RESULTS

A set of experimental tests are carried out under the chosen different input parameters as stated in the experimental section. On the other hand, a fuzzy control system is used to predict the results of both surface roughness and flank tool wear. Both the experimental and fuzzy control system results are tabulated. Table 4 shows the surface roughness results and Table 5 indicates the flank tool wear results so as to investigate and analyze the accuracy of the results under the same conditions.

Table 4. Effect of different variables on surface roughness.

Feed Rate (mm/rev)	Depth of Cut (mm)	Cutting Speed (m/min)	SiC Volume (%)	Surface roughness (μm)	Fuzzy Results
0.14	0.75	50	1	22.6	20.6
0.14	0.75	60	1	20.7	20.6
0.14	0.75	100	1	17.9	17.4
0.14	0.75	139	1	16.1	17.1
0.14	0.75	180	1	13.4	17.1
0.14	0.75	225	1	12.4	16.4
0.14	0.75	275	1	10.1	12.2
0.08	0.75	139	1	13.9	12.2
0.1	0.75	139	1	14.5	15.5
0.12	0.75	139	1	15.5	16.7
0.14	0.75	139	1	16.2	17.1
0.16	0.75	139	1	17.5	17.1
0.18	0.75	139	1	18.7	18
0.2	0.75	139	1	20.2	20.6
0.14	0.25	139	1	14.1	17.7
0.14	0.5	139	1	15.3	17.7
0.14	0.75	139	1	16.05	17.1
0.14	1	139	1	17.2	16.4
0.14	1.25	139	1	18.95	16.4
0.14	1.5	139	1	20.8	17
0.14	2	139	1	23.5	20.9
0.14	0.75	139	1	20.8	17.1
0.14	0.75	139	2	18.85	16.4
0.14	0.75	139	3	16.15	15.6
0.14	0.75	139	4	14.2	15.6
0.14	0.75	139	5	13.7	16.5

Table 5. Effect of different variables on flank wear.

Feed Rate (mm/rev)	Depth of Cut (mm)	Cutting Speed (m/min)	SIC Volume (%)	Flank wear (mm)	Fuzzy Results
0.14	0.75	50	1	0.065	0.0932
0.14	0.75	60	1	0.08	0.0932
0.14	0.75	100	1	0.094	0.141
0.14	0.75	139	1	0.103	0.144
0.14	0.75	180	1	0.115	0.144
0.14	0.75	225	1	0.136	0.142
0.14	0.75	275	1	0.158	0.156
0.08	0.75	139	1	0.086	0.112
0.1	0.75	139	1	0.096	0.143
0.12	0.75	139	1	0.098	0.144
0.14	0.75	139	1	0.103	0.144
0.16	0.75	139	1	0.125	0.144
0.18	0.75	139	1	0.146	0.147
0.2	0.75	139	1	0.148	0.156
0.14	0.25	139	1	0.061	0.0874
0.14	0.5	139	1	0.075	0.111
0.14	0.75	139	1	0.103	0.145
0.14	1	139	1	0.125	0.156
0.14	1.25	139	1	0.145	0.156
0.14	1.5	139	1	0.171	0.168
0.14	2	139	1	0.235	0.225
0.14	0.75	139	1	0.103	0.145
0.14	0.75	139	2	0.107	0.145
0.14	0.75	139	3	0.118	0.145
0.14	0.75	139	4	0.126	0.156
0.14	0.75	139	5	0.136	0.156

The individual deviation (error); ei between the measured (experimental value) and the predicted value is calculated by the following formula;

$$\mathbf{e_i} = (|V_m - V_p|) / V_m \quad (1)$$

Where; Vm is the measured value and Vp is the predicted value, Accuracy (A) can be calculated by the following equation;

$$A = 1/ N \sum_{i=1}^{i=N} (1- (|V_m - V_p|) / V_m \quad (2)$$

Where; N is number of data sets tested.

The average error and accuracy are 11% and 89% for surface roughness respectively; whereas in flank tool wear, the average error and accuracy are 20% and 80% respectively. It can be noticed that the maximum predicted accuracy in surfaces roughness is 94.2%, when studying the effect of feed rate. Meanwhile, in the case of flank tool wear the maximum predicted accuracy recorded is 90.2%, when predicting the effect of SiC volume percent. These results indicate that the surface finish is more sensitive to feed rate, while, the flank tool wear is more sensitive to SiC volume percent. Also, the optimal predicted values for both surfaces' roughness and flank tool wear at different machining parameters are listed in Table 6. These results can be illustrated from the experimental results showed in Figs. 11, 12, the Figures reveal the influence of cutting speed on both surface roughness and flank tool wear respectively. With further increasing of the cutting speed the surface finish value Rz is improved, while the value of flank tool wear is increased; these results may be due to the continuous reduction in built-up edge formation. Figures 13, 14 show the effect of feed rate on surface roughness and flank tool wear where increasing the feed rate increases the value of surface finish value Rz and flank tool wear; this trend also occurred in the case of increasing depth of cut Figs. 15, 16, which can be attributed to the aroused cutting resistance and amplitude of vibration values. Figure 17 reveals that increasing the SiC volume percent improves the surface finish, which can be attributed to the improved surface properties of workpiece material [23]. Figure 18 shows that on increasing the SiC volume percent the flank tool wear increases; this is due to the increase of workpiece hardness, which in turn increase the cutting resistance, friction and cutting temperature between the workpiece and the tool.

Table 6. Predicted acceptance ranges and optimal values.

Machining Parameters		Surface Roughness	Flank Wear
Acceptance Range		11.5 - 12	0.0868 - 0.118
Optimal Value		11.8	0.0868
Optimal Values of Inputs Variables	Feed Rate	0.0863	0.0845
	Depth of Cut	0.474	0.412
	Cutting Speed	200	161
	SiC Volume	3%	3%

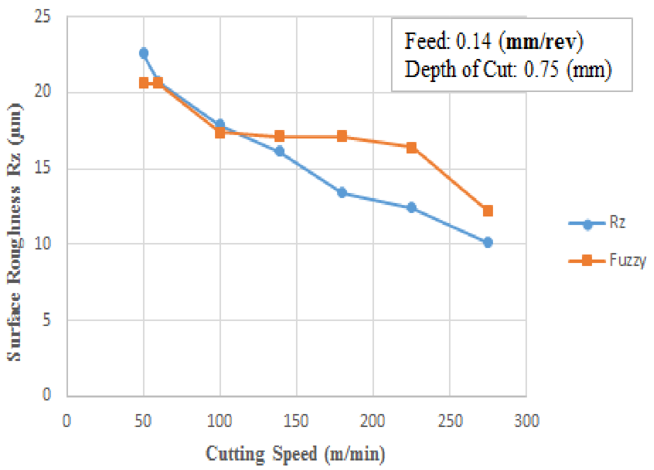


Fig. 11. The Effect of Cutting Speed on Roughness.

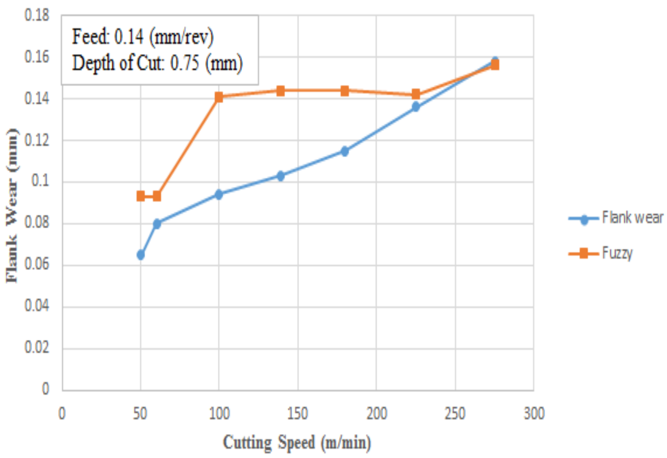


Fig. 12. The effect of cutting speed on flank wear.

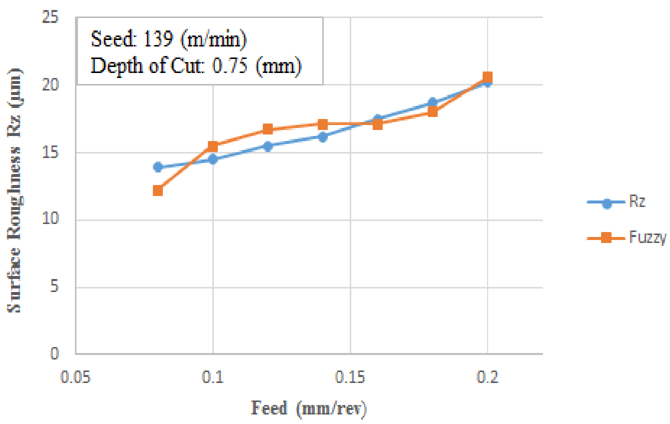


Fig. 13. The effect of feed on roughness.

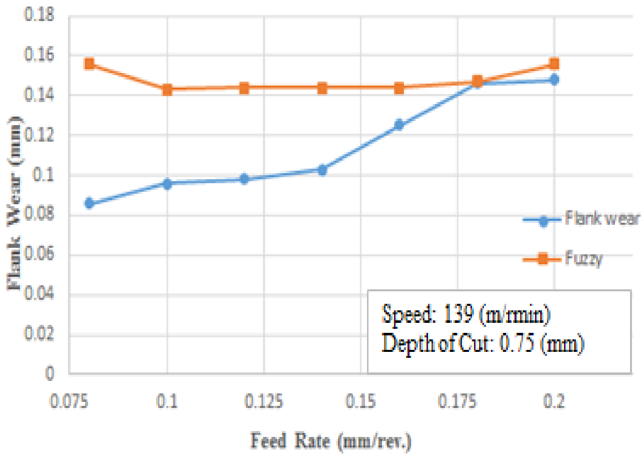


Fig. 14. The effect of feed on flank wear.

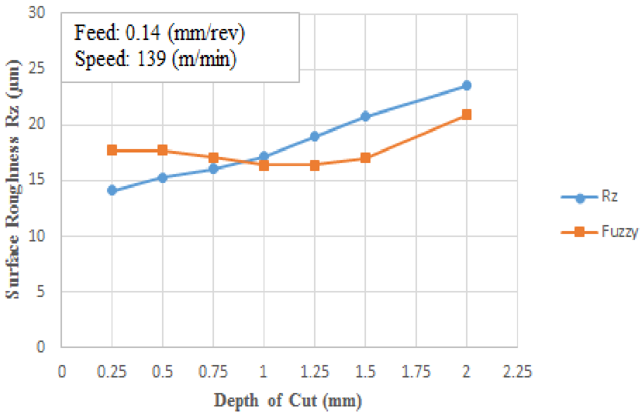


Fig. 15. The effect of depth of cut on roughness.

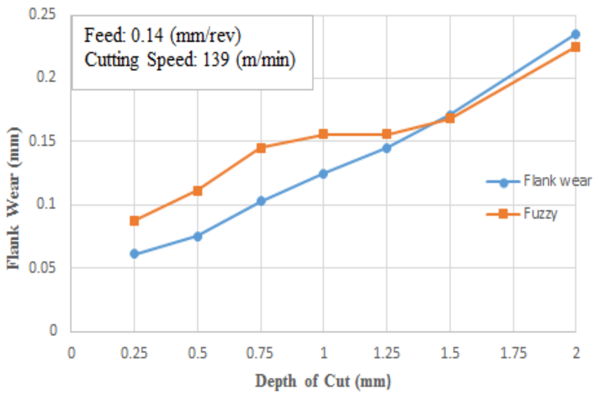


Fig. 16. The effect of depth of cut on flank wear.

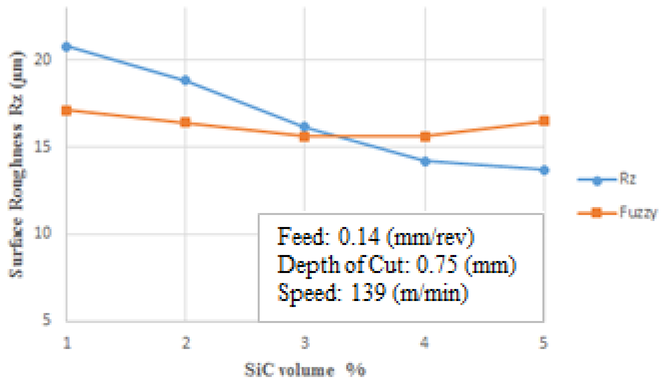


Fig. 17. The effect of SiC-volume % on roughness.

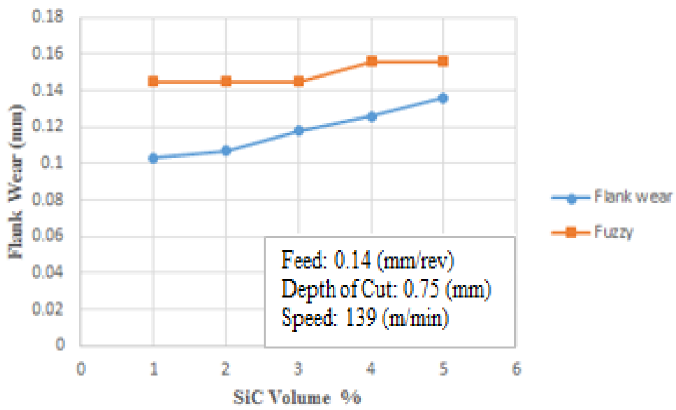


Fig. 18. The effect of SiC-volume % flank wear.

6. CONCLUSION

In this work, the influence of machining parameters such as feed rate, cutting speed and depth of cut, in addition to the volume percent of SiC on surface roughness and flank tool wear in turning of Al/SiC nanocomposites, is studied experimentally and predicted using fuzzy logic control as well. The main conclusions of the results can be summarized in the following points:

1. The surface finish Rz value increases on increasing feed rate and depth of cut, while it is improved on increasing the cutting speed.
2. The surface finish Rz value is improved on increasing the SiC content.
3. Flank tool wear increases on increasing cutting speed, feed rate and depth of cut.
4. Flank tool wear increases upon increasing the SiC content.

5. The predicted results possess an average accuracy of 90% in the case of surface finish and 80% in the case of flank tool wear.
6. The optimal predicted value of surface finish Rz is 11.8 um at feed rate = 0.0863 mm/rev, depth of cut = 0.474 mm, cutting speed = 200 m/ min and SiC content=3%.
7. The optimal predicted value of flank tool wear is 0.0868 m at feed rate = 0.0868 mm/rev, depth of cut= 0.412 mm, cutting speed= 161 m/ min and SiC content = 3%.
8. The fuzzy control system utilized in predicting the surface roughness and flank wear for Al/SiC nanocomposites can be used regardless of the type material. The fuzzy prediction system is affected with inputs parameters.
9. The predicted trend values are acceptable within the range of experimental conditions used in this work. The deviation between predicted and experimental values may be due to the fact that, the study neglected some factors, such the effect of vibrations, cooling and its levels during the cutting process.

7. FUTURE WORK

This research investigates the effect of machining parameters and SiC volume percent on surface roughness and tool flank wear, neglecting the effect of other related parameters such as vibrations that arise during the cutting process, geometry of cutting tool and etc. Thus, it will be useful to study the effect of those parameters on the whole process.

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التنبؤ بخشونة السطح وتاكل اداة القطع فى عملية الخراطة لسبيكة الالومنيوم المقواة بحبيبات النانو باستخدام نظام التحكم المنطقى الترجيحى

يدرس البحث تاثير عوامل القطع فى الخراطة الجافة على كل من خشونة السطح ومعدل تاكل اداة القطع لخراطة سبيكة الالومنيوم والمقواة بحبيبات النانو حيث تم اختيار عوامل القطع الاساسية مثل سرعة القطع ومعدل التغذية وعمق القطع ودراسة تغيير نسب النانو المضافة للسبيكة الاساسية واستخدم البحث طريقة نظام التحكم الترجيحى فى خشونة السطح ومعدل تاكل اداة القطع فى مستويات المتغيرات وعوامل القطع سالفة الذكر وتمت مقارنة النتائج العملية بنتائج التنبوء بنظام التحكم المنطقى الترجيحى واظهرت النتائج تحسن نعومة السطح لسبيكة الالومنيوم بزيادة سرعة القطع ونسبة النانو المضافة مع تقليل معدل التغذية وعمق القطع، وأن معدل تاكل اداة القطع يقل بزيادة سرعة القطع وتقليل معدل التغذية وعمق القطع، وأن هناك تقارب مقبول بين النتائج العملية ونتائج التنبوء بنظام التحكم المنطقى الترجيحى حيث كانت دقة التنبوء فى حالة خشونة السطح ٩٠ % وفى حالة معدل تاكل اداة القطع بلغت ٨٠%.