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PREDICTION AND ANALYSIS OF THE ROUGHNESS OF MILLED SURFACES BASED ON FUZZY LOGIC

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Abstract: The influence of the cutting conditions of machining process on the surface roughness has been the subject of several scientific works in order to optimize the milling process to get the best-finished surface machined by milling. During the last decades, many methods of artificial intelligence have been carried out to investigate the effect of milling conditions like the cutting speed, feed per tooth and depth of cut on surface integrity of machined surfaces by milling process. However, the progress on the use of Numerical Approaches to predict the surface integrity of machined surfaces like roughness, microhardness, residual stress and cutting temperature still lagging behind the other advances in the industry. The aim of this work is to use the fuzzy logic to predict the surface roughness of the milled surfaces and to study the effect of cutting parameters (cutting speed, feed per tooth and depth of cut) on the roughness of the surfaces machined by milling. a new model was created using fuzzy logic based on an experimental database. The database includes the variation of the surface roughness of machined surfaces of the Ti-6Al-4V by milling according to the cutting parameters (cutting speed, feed per tooth and depth of cut) on which the model was develop on MATLAB using fuzzy tool. The inputs of the fuzzy inference model were the three cutting parameters of milling: the cutting speed, feed per tooth and depth of cut, and the output of the fuzzy system was the roughness of the machined surfaces by milling of the Ti-6Al-4V. The predicted values of roughness obtained by the fuzzy model were compared to the experimental values and the result was very good, the average error rate was verry low that's mean that the prediction model based on fuzzy logic works correctly and with high accuracy and can be used as a solution to predict the surface roughness before starting milling provided to respect a very specific range of parameters (defined by the universe of discourse) when using this model. The approach based on fuzzy logic can be used also to predict other phenomena of milling process like cutting temperature and microhardness.

Key words: milling, roughness, cutting parameters, fuzzy logic, machined surfaces.

1. INTRODUCTION

In the last years, many experiments have been carried out to investigate the surface integrity (roughness, microhardness, residual stress and cutting temperature etc.) affected by the cutting conditions in the milling process, these experiments are extremely difficult and require a lot of time and material. This current study will focus on the roughness of surfaces machined by milling, and here is a small bibliographic search for some scientific works that have studied the roughness of milled surfaces:
(Yang et al., 2012) in their experimental study they found that and the surface roughness for higher cutting speed is lower and more stable than that for lower cutting speed and the surface roughness in the axial depth of cut direction is slightly lower than that in the feed direction.
(Sun and Guo, 2009) in their research they found that the sensitivity of surface roughness value to process parameters shows that the feed has the most significant influence, followed by the radial depth of cut, while cutting speed has the least influence.
(Oosthuizen et al., 2016) in their work the effect of cutting parameters they reported that when the cutting speed is increased the roughness value decreases. This is because of the reduced plastic deformation on the cutting zone incurred by a higher cutting speed, the surface defect is therefore smaller, leading to an overall lower roughness value. And also, when higher feed rates are implemented at constant cutting speeds a gradual increase in surface roughness is observed. the surface roughness becomes less sensitive to a change in the feed per tooth as the cutting speed increases. The higher roughness is also influenced by the increased tool wear recorded with the greater feeds.
(Mhamdi et al., 2012) noticed that tool position influences the surface roughness and the microhardness of the machined surface.
(Shokrani et al., 2016) in their Investigation of the

effects of cryogenic machining on surface integrity reported that Cryogenic cooling has drastically improved surface roughness and the samples machined in cryogenic cooling demonstrated lower surface defects when compared to flood and dry cooling. And also, from ANOVA test they found that the feed rate is the most significant parameter affecting surface roughness while the machining environment is the second most significant parameter.

(Liu et al., 2019) compared the effects of rotary ultrasonic elliptical machining and conventional machining for side milling on the surface integrity of Ti-6Al-4V, they reported that the application of rotary ultrasonic elliptical machining has a bad influence on the surface roughness. And the values of the surface roughness for both conventional machining for side milling and rotary ultrasonic elliptical machining decrease as cutting speed increases, and also with conventional machining, surface roughness increases with increasing feed rate per tooth while with rotary ultrasonic elliptical machining, as the feed rate per tooth increases, surface roughness initially decreases until it reaches a minimum value at a feed rate per tooth of 0.05 mm/z, and then it start to increase as the feed rate per tooth continues to increase.

(Outeiro, 2014) in his work to identify the optimum combination of cutting parameters to get the best surface integrity he used a procedure based on artificial neural network, response surface methodology and genetic algorithm approaches, he found also that the tool edge radius, tool nose radius, feed and depth of cut are the most influential parameters for surface roughness.

(Santhakumar and Mohammed Iqbal, 2019) in their study in order to identify the optimal process parameter combinations in end milling to get the best surface roughness they used centered central composite design of response surface methodology. The developed mathematical model was statistically significant and accuracy was very high.

(Okokpujie et al., 2018) they used least square approximation method and response surface methodology for modelling and the optimization of the surface roughness, the prediction of the surface roughness for both methods were very precise and from the analysis of variances they found that the most influential parameters were the feed rate.

This bibliographic research show that some prediction methods have been used to solve the problem of the changing in the roughness of milled surfaces and this for their ability to model different phenomena.

However, the progress on the use of Numerical Approaches to predict the roughness of milled surfaces still lagging behind the other advances in the industry.

This is the reason why in this article was used the fuzzy logic to predict the roughness and to study the effect of cutting conditions on the roughness of milled surfaces machined.

2. MATERIALS AND METHODS

2.1 Experimental database

The milling experiment was done using a FB4MB milling machine, the diameter of the cutter was 40 mm with six inserts (R390-1806 12M-PM manufactured by SANDVIK). The Ti-6Al-4V Titanium alloy was the material of the work-piece, the surface roughness value of the machined work piece was measured using Taylor Hobson Surftronic + 3 (Mahdavinejad et al., 2012).

The table 1 presents the experimental values of the variation of the roughness as a function of the cutting parameters (cutting speed, feed per tooth and depth of cut).

2.2 Fuzzy modelling

The main objective of this work is to make a smart prediction of the roughness of surfaces after milling, a new model will be created using one of the artificial intelligence methods which is fuzzy logic based on the experimental database, which includes the variation of the roughness according to the cutting parameters (cutting speed, feed per tooth and depth of cut) that will develop the model on MATLAB.

Table 1. Experimental data [2]

$a_p (mm)$		**0.3**	**0.6**	**0.9**	**1.2**	**1.5**
$f_z (mm/tooth)$	$V_c (m/\min)$	The Roughness (μm)				
0.05	**60**	1.96	1.86	1.78	1.72	1.76
	75	1.82	1.72	1.63	1.58	1.63
	90	1.39	1.24	1.11	1.05	1.12
	105	1.04	0.94	0.85	0.73	0.81
	120	0.93	0.89	0.86	0.75	0.81
0.15	**60**	2.4	2.3	2.23	2.17	2.22
	75	2.52	2.36	2.27	2.22	2.25
	90	1.71	1.61	1.52	1.46	1.5
	105	1.12	1.02	0.93	0.87	0.91

	120	1.14	1.04	0.93	0.9	0.95
0.25	**60**	2.46	2.4	2.31	2.27	2.3
	75	2.71	2.61	2.52	2.46	2.5
	90	1.85	1.75	1.68	1.62	1.65
	105	1.24	1.11	1.02	0.94	0.98
	120	1.53	1.36	1.27	1.24	1.29

2.2.1 Fuzzy variables

The table 2 represents the limit values of the input and output parameters, for the fuzzy model used, it is to define the universe (Domain) of discourse associated with this study.

Table 2. Limit values for the inputs and the outputs

Parameter	MIN value	MAX value
$a_p(mm)$	0.3	1.5
$f_z(mm/tooth)$	0.05	0.25
$V_c(m/\min)$	60	120
$Ra(\mu m)$	0.73	2.71

2.2.2 Fuzzy system

The input (cutting parameters) and output (roughness) variables of the fuzzy system used for the prediction of the roughness during milling of Ti-6Al-4V Titanium alloy are shown in the figure 1.

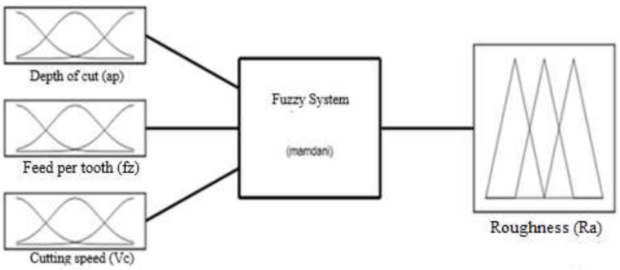

Fig. 1. Input and output of the fuzzy system

2.2.3 Definition of linguistic variables

In this part will be defined all the linguistic variables associated with each parameter used from the experimental basis used as shown in the figures 2, 3 and 4.

0.05	**P**		
0.15		**M**	
0.25			**G**

Fig. 2. Linguistic variables for feed per tooth

0.3	**TP**				
0.6		**P**			
0.9			**M**		
1.2				**G**	
1.5					**TG**

Fig. 3. Linguistic variables for depth of cut

60	**TP**				
75		**P**			
90			**M**		
105				**G**	
120					**TG**

Fig. 4. Linguistic variables for the cutting speed

Now the representation of the experimental values of the output parameter which is the roughness for all the experimental tests in the form of a scatter plot in order to define the linguistic variables associated with the roughness. This representation allows to divide the universe of discourse into a set of intervals, the purpose of which is to minimize the number of intervals as shown in the figures 5 and 6.

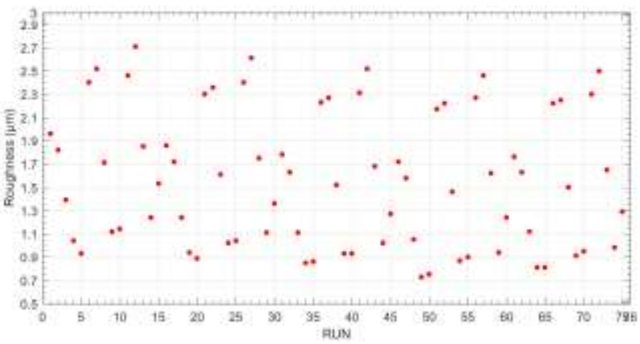

Fig. 5. Scatter plot of the roughness values for the 75 tests

Fig. 6. Linguistic variables for roughness

2.2.4 Membership functions

In this study three types of membership functions will be used, the Triangular, Trapezoidal and Gaussian function as shown in the figures 7, 8 and 9.

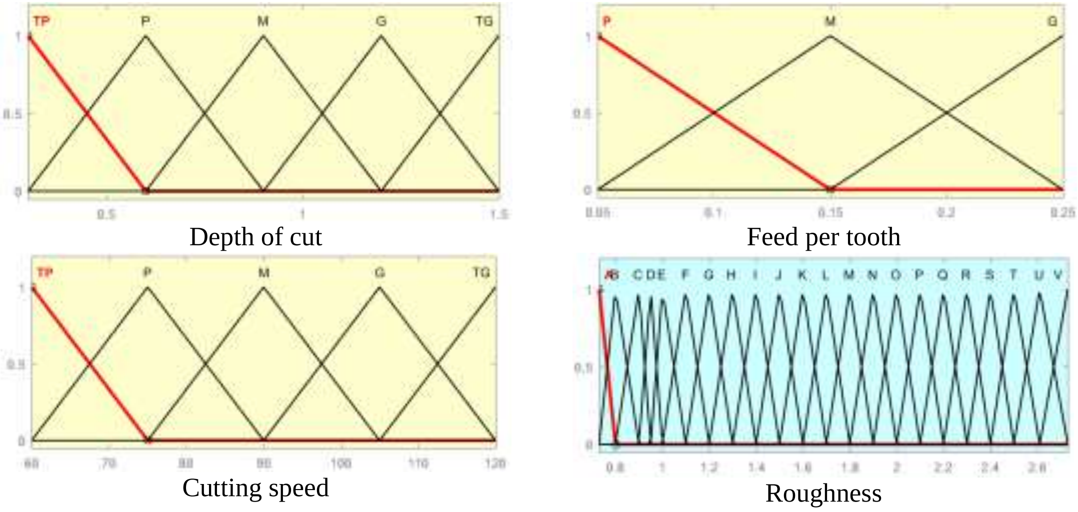

Fig. 7. Triangular membership functions

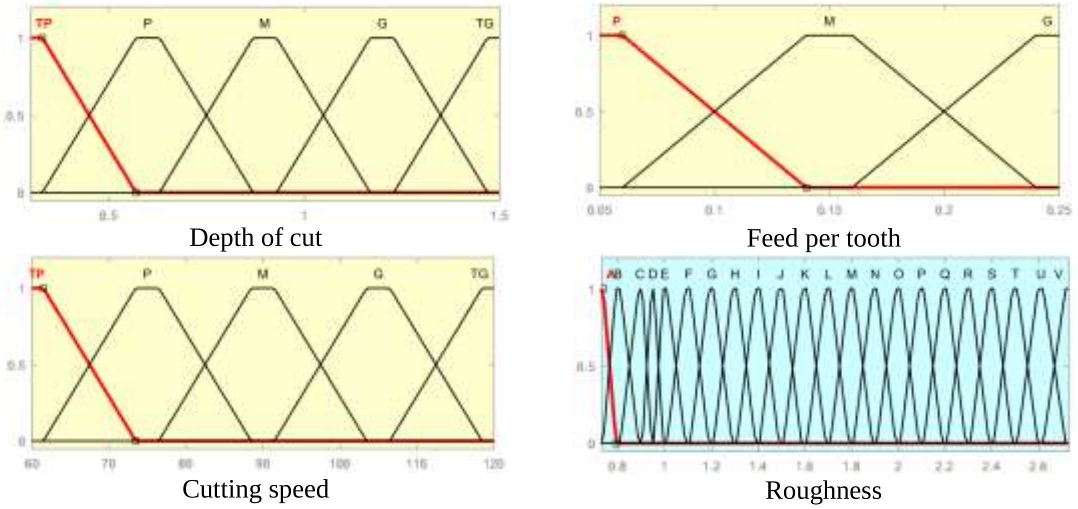

Fig. 8. Trapezoidal membership functions

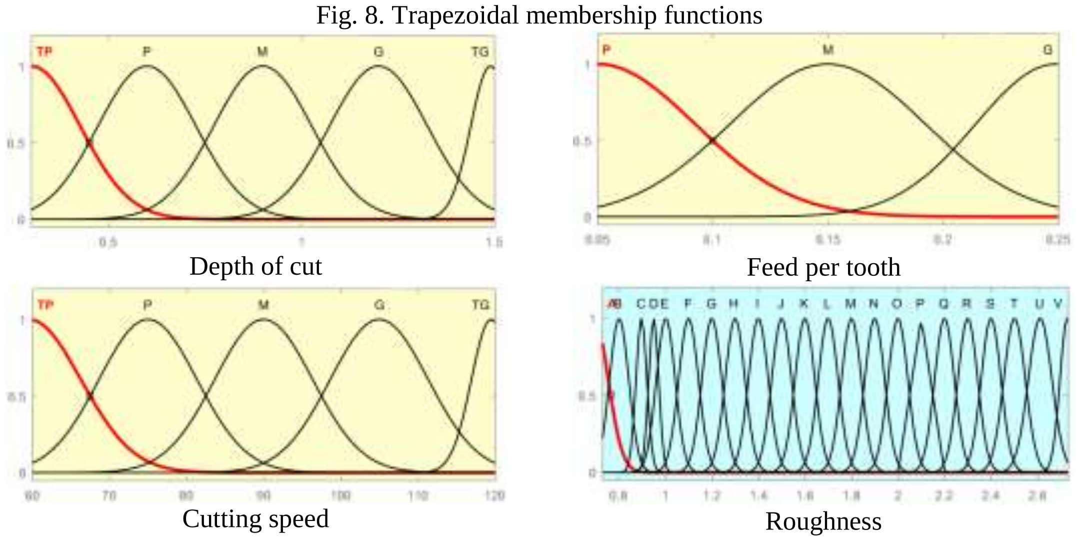

Fig. 9. Gaussian membership functions

2.2.5 The fuzzy rules

The seventy-five fuzzy rules, in table 3, were established according to the experimental conditions, each rule takes the following form: If a_p (linguistic variable) and f_z (linguistic variable) and V_c (linguistic variable) then Ra (linguistic variable).

The set of fuzzy rules developed are grouped together in the table 3.

Table 3. The fuzzy rules

a_p		TP	P	M	G	TG
f_z	V_c	The Roughness (Ra)				
P	**TP**	N	M	L	L	L
	P	M	L	K	J	K
	M	H	G	F	E	F
	G	E	C	B	A	B
	TG	C	B	B	A	B
M	**TP**	S	R	Q	P	Q
	P	T	R	Q	Q	Q
	M	L	K	J	I	J
	G	F	E	C	B	C
	TG	F	E	C	C	D
G	**TP**	S	S	R	Q	R
	P	V	U	T	S	T
	M	M	L	K	K	K
	G	G	F	E	C	D
	TG	J	H	G	G	G

3. RESULTS AND DISCUSSION

3.1 Results

Now the linguistic values of the fuzzy model will be transformed into numerical values, it is the defuzzification which represents the last step. The figure 10 represents the superposition of the values of the experimental roughness and the values of the roughness obtained with the three membership functions (Triangular, Trapezoidal and Gaussian):

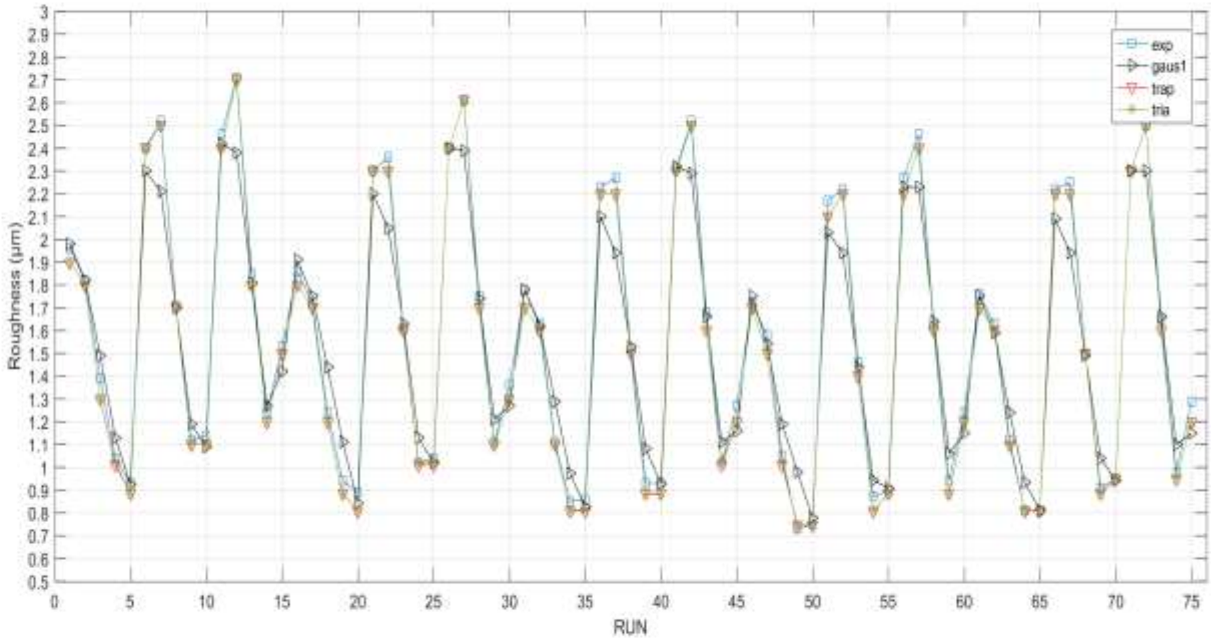

Fig. 10. Variation of roughness (Experimental, Trapezoidal, Triangular and Gaussian) according to the number of tests

A similarity between the roughness values using the three types of membership functions is noticed, and also, it is noticed that the Triangular and Trapezoidal membership functions are almost identical, so to make the choice between the three types of the membership functions: Triangular, Trapezoidal and Gaussian, the standard deviation is proposed in order to define the values closest to the experimental results.

To calculate the standard deviation, the formula 1 is used:

$$\sigma = \left(\frac{1}{N} \sum_{i=1}^{N} (Ra_{pred} - Ra_{\exp})^2 \right)^{1/2} \quad (1)$$

$Ra_{\exp}$: The experimental roughness in µm; Ra_{pred} : The predicted roughness in µm.

- The standard deviation for the Triangular-type membership function is 0.043219.
- The standard deviation for the Trapezoidal-type membership function is 0,04345.
- The standard deviation for the Gaussian-type

membership function is 0,131127.
The standard deviation shows that the results of the Triangular membership function are closest to the experimental results compared to the results of the Trapezoidal and Gaussian membership functions, so the Triangular-type membership function is the best one.

3.2 Validation of the developed model

For the verification of the system fifty experimental values are tested which are not used in the construction of the fuzzy model as shown in Table 5, and the accuracy and the error of the fuzzy system have been investigated.
To calculate the percentage error of the 50 tests, the formula 2 is used:

$$e_i = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{\left|Ra_{\exp} - Ra_{pred}\right|}{Ra_{\exp}}\right]\times 100 \qquad (2)$$

$Ra_{\exp}$: The experimental roughness in μm.

Ra_{pred} : The predicted roughness (Triangular) in μm.

In this case N = 50 Tests.

e_i : Error rate.

To calculate the percentage of the accuracy of the 50 tests, the formula 3 is used:

$$A = \frac{1}{N}\sum_{i=1}^{N}\left[1 - \frac{\left|Ra_{\exp} - Ra_{pred}\right|}{Ra_{\exp}}\right]\times 100 \qquad (3)$$

$Ra_{\exp}$: The experimental roughness in μm.

Ra_{pred} : The predicted roughness (Triangular) in μm.

In this case N = 50 Tests.

A : Accuracy.

All results are grouped together in the table 4.

Table 4. The fuzzy system results

Tests	**Cutting parameters**			**Roughness results**			
	V_c	f_z	a_p	$Ra_{\exp}$	Ra_{pred}	**Error %**	**Accuracy %**
1	60	0.1	0.3	2.03	2.15	5.91	94.09
2	75	0.1	0.3	2.02	2.16	6.93	93.07
3	90	0.1	0.3	1.46	1.5	2.74	97.26
4	105	0.1	0.3	1.09	1.07	1.83	98.17
5	120	0.1	0.3	0.99	1.01	2.02	97.98
6	60	0.2	0.3	2.15	2.4	11.63	88.37
7	75	0.2	0.3	2.19	2.58	17.81	82.19
8	90	0.2	0.3	1.78	1.75	1.69	98.31
9	105	0.2	0.3	1.17	1.15	1.71	98.29
10	120	0.2	0.3	1.43	1.3	9.09	90.91
11	60	0.1	0.6	1.95	2.05	5.13	94.87
12	75	0.1	0.6	1.92	2	4.17	95.83
13	90	0.1	0.6	1.36	1.4	2.94	97.06
14	105	0.1	0.6	0.93	0.95	2.15	97.85
15	120	0.1	0.6	0.94	0.91	3.19	96.81
16	60	0.2	0.6	2.05	2.35	14.63	85.37
17	75	0.2	0.6	2.12	2.47	16.51	83.49
18	90	0.2	0.6	1.68	1.65	1.79	98.21
19	105	0.2	0.6	1.07	1.07	0.00	100.00
20	120	0.2	0.6	1.33	1.18	11.28	88.72
21	60	0.1	0.9	1.89	1.95	3.17	96.83
22	75	0.1	0.9	1.83	1.9	3.83	96.17
23	90	0.1	0.9	1.27	1.3	2.36	97.64
24	105	0.1	0.9	0.9	0.842	6.44	93.56
25	120	0.1	0.9	0.91	0.842	7.47	92.53
26	60	0.2	0.9	1.96	2.25	14.80	85.20
27	75	0.2	0.9	2	2.35	17.50	82.50
28	90	0.2	0.9	1.59	1.55	2.52	97.48
29	105	0.2	0.9	0.98	0.95	3.06	96.94
30	120	0.2	0.9	1.22	1.06	13.11	86.89
31	60	0.1	1.2	1.83	1.9	3.83	96.17

32	75	0.1	1.2	1.77	1.85	4.52	95.48
33	90	0.1	1.2	1.19	1.24	4.20	95.80
34	105	0.1	1.2	0.85	0.799	6.00	94.00
35	120	0.1	1.2	0.87	0.834	4.14	95.86
36	60	0.2	1.2	1.91	2.15	12.57	87.43
37	75	0.2	1.2	1.94	2.3	18.56	81.44
38	90	0.2	1.2	1.51	1.5	0.66	99.34
39	105	0.2	1.2	0.92	0.842	8.48	91.52
40	120	0.2	1.2	1.16	1.06	8.62	91.38
41	60	0.1	1.5	1.86	1.95	4.84	95.16
42	75	0.1	1.5	1.8	1.9	5.56	94.44
43	90	0.1	1.5	1.24	1.3	4.84	95.16
44	105	0.1	1.5	0.87	0.842	3.22	96.78
45	120	0.1	1.5	0.88	0.864	1.82	98.18
46	60	0.2	1.5	1.95	2.25	15.38	84.62
47	75	0.2	1.5	1.98	2.35	18.69	81.31
48	90	0.2	1.5	1.53	1.55	1.31	98.69
49	105	0.2	1.5	0.95	0.906	4.63	95.37
50	120	0.2	1.5	1.2	1.2	0.00	100.00
The average						**6.59 %**	**93.41 %**

The average error rate is 6.59 % and the average accuracy is 93.41 %, that's mean that the prediction model based on fuzzy logic works correctly and with high accuracy and can be used as a solution to predict roughness before starting milling provided to respect a very specific range of parameters (defined by the universe of discourse) when using this model.

3.3 Graphical representation of results

Figure 11 shows the functions obtained using fuzzy logic simulation as follows:

- The surface (a) represents the variation of the surface roughness as a function of the cutting speed and the depth of cut for a feed per tooth 0.15 m / tooth.
- The surface (b) represents the variation of the surface roughness as a function of the cutting speed and the feed per tooth for a depth of cut 0.9 mm.
- The surface (c) represents the variation of the surface roughness as a function of the depth of cut and the feed per tooth for a cutting speed 75 mm / min.

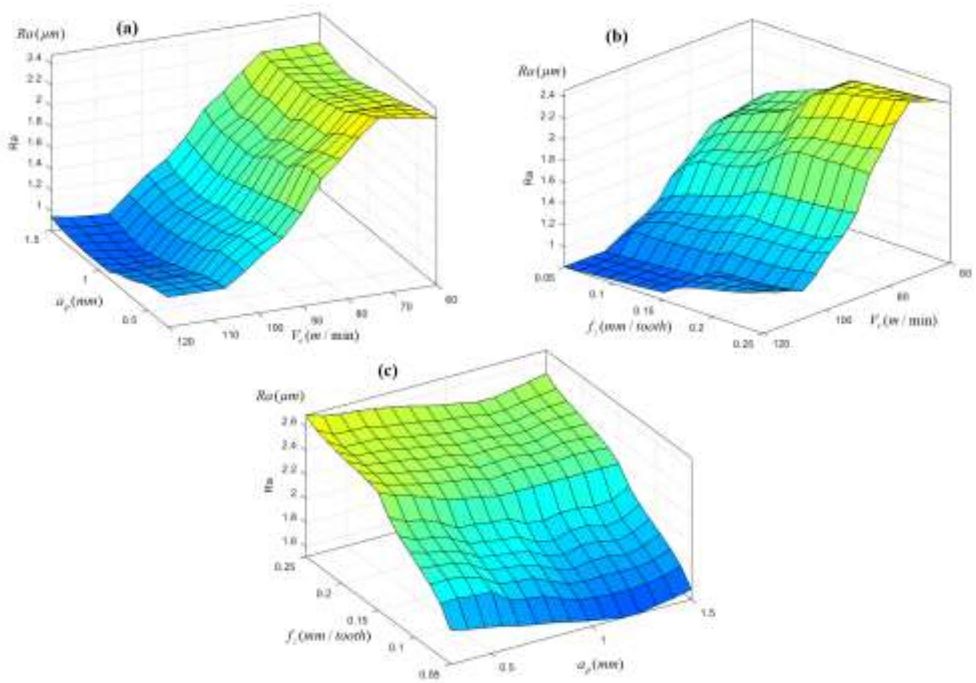

Fig. 11. Variation of the predicted roughness with the fuzzy logic model as a function of the cutting parameters

Figure 11 illustrates the influence of cutting parameters on the roughness of machined surfaces during milling operations.

From the figure 11 (a) it can be seen that the value of the roughness becomes maximum for minimum values of cutting speed. While the minimum values of roughness are obtained for maximum values of cutting speed and average values of depth of cut (1.2 mm).

On the other hand, a lower cutting speed leads to an increase on the roughness while the depth of cut doesn't have a big influence on the roughness of the machined surfaces.

From the figure 11 (b) it can be seen that the value of the roughness becomes maximum for minimum values of cutting speed and maximum values of feed per tooth. While the minimum values of roughness are obtained for maximum values of cutting speed and minimum values of feed per tooth.

On the other hand, a lower cutting speed leads to an increase on the roughness while a higher feed per tooth leads to an increase on the roughness of the machined surfaces.

From Figure 11 (c) it can be seen that the value of the roughness becomes maximum for maximum values of feed per tooth. While the minimum values of roughness are obtained for minimum values of feed per tooth and average values of depth of cut (1.2 mm).

On the other hand, a higher feed per tooth leads to an increase on the roughness while the depth of cut doesn't have a big influence on the roughness of the machined surfaces.

4. CONCLUSION

In this work an approach based on fuzzy logic was carried out in order to predict the effects of cutting parameters on the roughness of milled surfaces. The main results of this work can be summarized as follows: A lower cutting speed leads to an increase on the roughness of machined surface by milling, this is due to a reduced plastic deformation cutting zone incurred by a higher cutting speed. The surface defect is therefore smaller, leading to an overall lower roughness value; Also, a higher feed per tooth leads to an increase on the roughness of milled surface; The depth of cut doesn't have a big influence on the roughness of the machined surfaces; The most influential parameter affecting the roughness of the milled surface is the cutting speed; The fuzzy model, developed during this study, makes it possible to predict the roughness of surfaces machined by milling; The study of the fuzzy model efficiency was confirmed by the analysis of the error / accuracy ratio; The analysis of the error/accuracy ratio confirmed the fuzzy model efficiency; The predicted values are in good agreement with the experimental values, with an average percentage error of 6.59% for the roughness calculation of surfaces machined by milling; The approach based on fuzzy logic can be used also to predict other phenomena of milling process like cutting temperature and microhardness.

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