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Optimization of surface roughness parameters in dry turning

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Analysis and modelling

ABSTRACT

Purpose: The precision of machine tools on one hand and the input setup parameters on the other hand, are strongly influenced in main output machining parameters such as stock removal, toll wear ratio and surface roughnes.
Design/methodology/approach: There are a lot of input parameters which are effective in the variations of these output parameters. In CNC machines, the optimization of machining process in order to predict surface roughness is very important.
Findings: From this point of view, the combination of adaptive neural fuzzy intelligent system is used to predict the roughness of dried surface machined in turning process.
Research limitations/implications: There are some limitations in the properties of various kinds of lubricants. The influence of some undesirable factors in experiments is Another limitation in this research.
Practical implications: From this point of view, some samples are machined with various input parameters and then the experimental data is used to create fuzzy rules and their processing via neural networks. So that, the prediction model is created with some experimental data first. Then the results of this model are compared with the real surface roughness.
Originality/value: When the cutting speed is increased the machined surface quality is improved.The quality of machined surface is decreased with the feeding rates and the depth of cut.The error of the model is more less than the error of using ordinary equations. The comparison results show that this model is more effective than theoretical calculation methods.
Keywords: Adaptive neural fuzzy intelligent system; Roughness; Fuzzy logic; Dependent function

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1. Introduction

Nowadays a lot of works have been done to improve the capability of machine tools. The continuing development and trends in manufacturing and operations engineering can not be sustained using current methods and processes [1]. Some set up parameters or machining processes are affected on main parameters such as tool life. One way to reduce work hardening effect on tool life is to conduct end-milling operations at high speed rates [2]. The study of criteria for evaluating the surface roughness represents, today, one of the most important problem for the production of some specific and functional characteristics. For this reason many authors consider the roughness as the fourth dimension of the design [3]. Incraesing productivity, decreasing costs, and mantaining high product quality at the same time are the main challenges manufacturing face today[4]. Due to the widespread use of high automated machine tools in industry, manufacturing requires reliable monitoring and optimization models and methods [5]. The selection of optimal cutting parameters is a very important issue for every machining process in order to enhance the quality of machining products, to reduce the machining costs and to increase the production rate [6]. CNC machines play a very important rule in manufacturing centers. In recent years, trying is carried out in order to produce a kind of machine tool with artificial intelligent. The aim of these systems as the next offspring of machine tools will be self-working operating with computers without any roles of hands or minds of operators. In these machine tools the computers should have some capabilities such as follows [7]:

1. Learning capability with primary data and their processing via system.
2. To be able to recognize the process conditions via data processing of the feedback of the sensors and then choosing the suitable action based on the experience resulted from the learning process.
3. Connection capability with the human so that the decisions and operations will be visible.

Some software calculation techniques are used to create these capabilities. Fuzzy theories and neural networks are two more useful techniques in this area. Recently and from this point of view, there have been a lot of researches to predict the roughness of machined surfaces [8-10]. Generally, these researching can be categorized according to the results based on the machining theories [11], lab tests [12], designed tests [13] and neural network [14]. Totally the researches in this field can be divided in four groups:

1. The trends based on machining theories [12-14].
2. The trends based on experimental tests [15,16].
3. The trends based on designed tests [17,18].
4. The trends based on intelligent neural networks [19,20].

Intelligent researches can be divided into some subgroups such as; intelligent neural networks, genetic algorithms, fuzzy logic and expert systems [21]. A combination of artificial neural networks and fuzzy logic methods is used in this research.

2. Real and ideal surface roughness

The ideal surface roughness is defined as the best finishing surface which can be obtained with the best machining feed rate and required tool geometry. This is possible if there are not any built up edge and self-existed vibrations together with precise set up of machining movement elements[20]. For example the ideal surface finishing in turning with a sharp tool's tip and required feed rate can be calculated as follows:

$$R_{\max} = \frac{f}{ctgk_{re} + ctgk'_{re}} \tag{1}$$

where k_{re}, k'_{re} and f are ; main set up angle, primary angle and feed rate respectively. For the tool with rounded tip, the following applicable equation is used[21]:

$$R_a = \frac{0.0321 \cdot f^2}{r_\varepsilon} \tag{2}$$

where R_a (μm) and r_ε (mm) are the surface roughness and the radius of tool,s tip respectively.

Since the ideal as a theoretical surface roughness can be obtained only with ideal conditions, there is usually difference between ideal and real surface roughness so that, the real surface roughness is something more. Totally, the main affected factors in real surface roughness are as follows:

- Machining parameters such as; feed rate, cutting speed, tool angle, depth of cut, lubricant.
- Machining process conditions such as; vibrations, cheap formation, friction on the cutting zone,variations in cutting forces.
- Workpiece material properties such as; hardness, length, diameter.
- Cutting tool properties such as; material, tool tip sharpness.

Table 1 shows some main parameters which are influenced on machined surface roughness.

Table1.
Main parameters infuence on surface roughness

Machining Parameters	Kinematics of process, Lubricant, Step over Depth of cut, Cutting speed, Feed rate.
Cutting tool Specifications	Tool material, Shape of tool, Tool's cutting angle Tool tip radii, Run out errors.
Workpiece Specifications	Hardness, Diameter of workpiece, length of workpiece
Cutting Process	Accelerations, Vibrations, Chip form.

3. Surface roughness prediction via adaptive neural fuzzy intelligent system

It can be predicted that the next decade machine tools will be intelligent machines with various capabilities such as prediction of self set up required parameters to reach to the best surface finishing qualities. From this point of view, the work of Shutting Lei et .al can be pointed out [21]. They used adaptive fuzzy-neural networks to model machining process especially surface roughness. So that, cutting force, depth of cut and cutting feed as three effective input parameters in surface roughness are used. In our research, the radius of tool tip as one of cutting tool's property which is effective parameter is considered as another input parameter. Totally the prediction of surface roughness can be categorized in four methods (See Fig. 1).

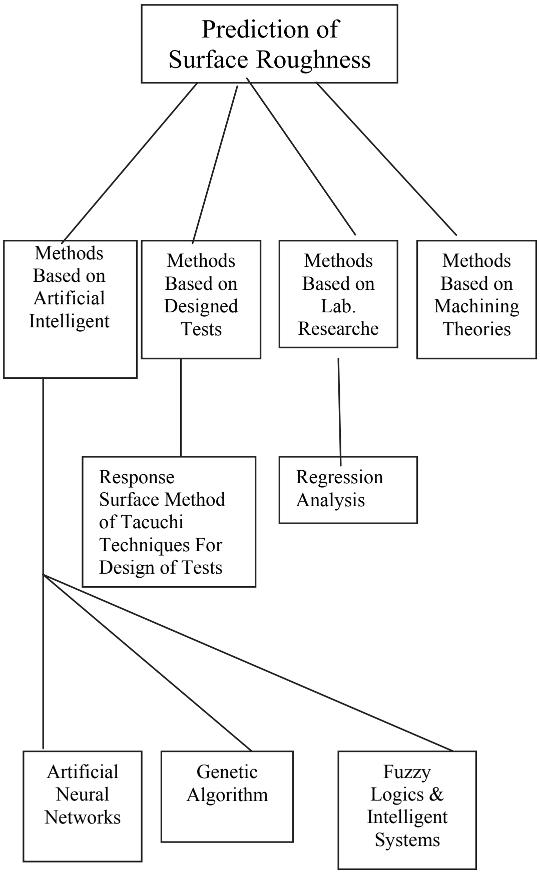


Fig. 1. Various methods for prediction of surface roughness

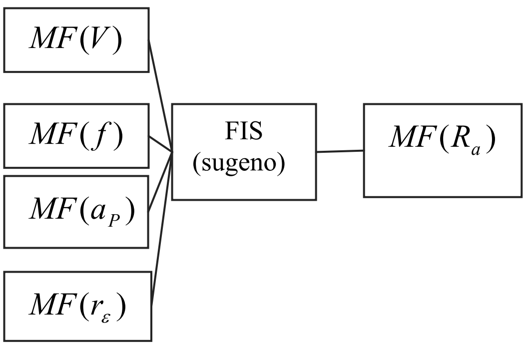


Fig. 2. Schematic of Sugeno system

4. Primary model

The primary predicting fuzzy inference system (FIS) is created via fuzzy logic toolbox of MATLAB. This system is constructed according to the perception of machining process and the influence of machining parameters on the machined surface roughness. Cutting speed (v), feed rate (f), depth of cut (a_p) and the angle of tool bit (r_e) as input parameters and the value of predicted surface roughness as output parameters are considered in this system. The schematic of this Sugeno system is shown in Figure 2.

In this model, two membership functions are respected to each input data. One of this function is related to the low value and the other for the high value of input data. The kind of the input membership function is Gaussian MF form as follows:

$$f(x;\sigma,c) = e^{\frac{-(x-c)^2}{2\cdot\sigma^2}} \tag{3}$$

where c, σ are two parameters of membership function which should be corrected during training. In the fuzzy-logic Sugeno system one output membership function is related to each rule. These functions are linear or constant. In recent work, the output membership function used is constant.

Fuzzy rules in this system is based on the assumption that according to the reduction in feeding rates, cutting depths and the radius of tool bit and also increasing in cutting speed, then the surface finishing will be improved. For example, a fuzzy rule is considered as follows:

If (v is high) and (f is low) and (a_p is low) and (r_ε is high) then (R_a is Ll).

Since, there are two membership functions four input parameters are related to each function, then there will be $2^4 = 16$ conditions in which for each condition there is a rule and an output membership function.

After creation rules and training, fuzy-neural network will be as shown in Figure 3.

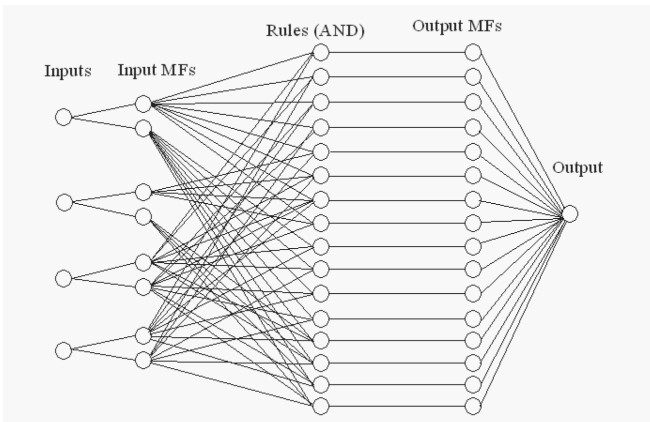


Fig. 3. Structure of Fuzzy-Neural network

5. Testing conditions

Ninety tests are carried out. The conditions are as follows:

- Machine Tool: WEILER T07/LZ330 turning machine.
- Workpiece: Two steel blocks 75 mm length with 19 mm and 23 mm diameters.

- Tool: SN MGO 90204, SNMGO 90208 and SNMGO 90212 inserts.
- Perthometer: M_2 from Mahr Company, Germany.

Figure 4 shows Perthometer M2 which is used for surface roughness measuring. The limitations and the levels of input variables is shown in Table 2.

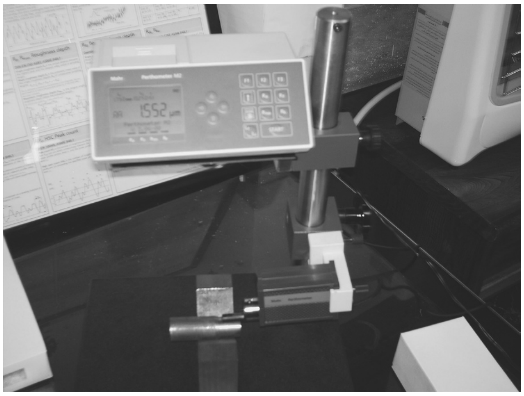


Fig.4. Schematic view of testing perthometer

Table 2.
Limitation and the number of input level variables

Input variables	Limitations	No. Of Levels
Cutting Speed (m/min)	125 -28	3
Feed (mm/rev)	0.2-0.37	2
Cutting Depth (mm)	0.3-0.4	2
Tool Radius Bit (mm)	0.4-1.2	2

In this table the range column indicates the working limitation of the system and also the number of layers determines the possibility combinations of various input parameters.

Experimental data Blaine for network training is shown in Table 3.

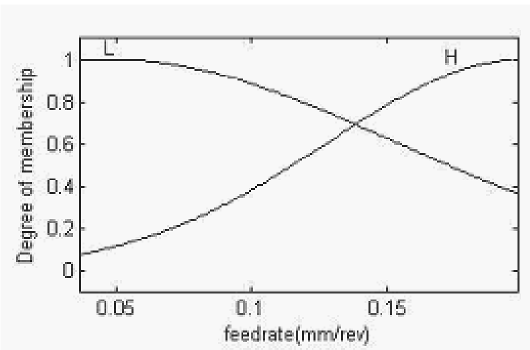


Fig. 5. A relationship function for feed rate training

Table 3.
Experimental data for network training

No.	Cutting speed (m/min)	Feed rate (mm/rev)	Cutting depth (mm)	Tool nose radius (mm)	Surface roughness (µm)
1	28.9	0.037	0.3	0.4	4.45
2	58.4	0.037	0.3	0.4	3.5
3	127.1	0.037	0.3	0.4	1.11
4	29.3	0.037	0.7	0.4	4.93
5	88.5	0.037	0.7	0.4	3.8
6	117.5	0.037	0.7	0.4	1.62
7	29.4	0.198	0.3	0.4	5.71
8	65	0.198	0.3	0.4	4.3
9	132.5	0.198	0.3	0.4	2.5
10	30.2	0.198	0.7	0.4	6.2
11	87	0.198	0.7	0.4	4
12	133.7	0.198	0.7	0.4	3.3
13	30.4	0.037	0.3	1.2	3
14	50	0.037	0.3	1.2	3
15	121.7	0.037	0.3	1.2	1.1
16	28.7	0.037	0.7	1.2	3.8
17	71.5	0.037	0.7	1.2	3.3
18	121.1	0.037	0.7	1.2	2.5
19	28.8	0.198	0.3	1.2	6.5
20	45.6	0.198	0.3	1.2	4.1
21	122.9	0.198	0.3	1.2	3.4
22	28.7	0.198	0.7	1.2	4.5
23	62.3	0.198	0.7	1.2	4.3
24	122.3	0.198	0.7	1.2	4.4

5.1. Network training

In these tests, the hybrid back propagation method is used for network training in which 0.01 bound of error is considered as the index of the error of training. This bound of error is choosed because of the least of error with enough flexibility of the network to be obtained. The relationship functions are proceed at the end of training. Figure 5 shows one of these functions.

5.2. Network testing

To evaluate simulation capability of surface roughness, some tests are modeled and compaired. Table 4 shows the testing data, the values of actual and predicted surface roughness and the error percentages.

Table 4.
Actual and predicted surface roughness from data testing

No.	C.S. m/min	F. Rate mm/rev	C.D. (mm)	Tool nose radius (mm)	Actual S.R. (μm)	Model S.R. (μm)	Error (%)
1	136.9	0.049	0.4	0.4	2.67	1.52	43
2	138.1	0.099	0.4	0.4	3	1.32	29
3	129.5	0.099	0.7	0.4	3.98	2.79	30
4	69.2	0.15	0.7	0.4	4.37	4.67	6.7
5	70.7	0.15	0.4	0.4	4.54	5.15	13.4
6	68.9	0.099	0.4	0.4	4.15	5.08	22.4
7	68.8	0.099	0.7	0.4	4.25	5.61	32
8	31.8	0.15	0.7	0.4	3.52	4.57	30
9	32.2	0.049	0.4	0.4	5.79	5.42	6.5
10	31.5	0.099	0.4	0.4	4.79	4.94	3.3
11	31.5	0.099	0.7	0.4	5.86	5.32	9
12	29.6	0.15	0.7	0.4	6.22	5.86	5.8
13	125.9	0.049	0.4	1.2	2.47	2.06	16.6
14	131.9	0.099	0.4	1.2	3.85	2.79	27.5
15	128.9	0.099	0.7	1.2	3.45	3.04	11.5
16	125.3	0.15	0.7	1.2	3.37	3.81	13
17	63.9	0.15	0.4	1.2	4.87	5.06	4
18	31.1	0.099	0.4	1.2	3.16	3.43	40
19	30.8	0.099	0.7	1.2	3.12	3.91	25
20	28.9	0.15	0.7	1.2	3.12	4.14	32.7
21	83	0.1	0.5	0.8	3.38	3.37	0.3
22	57.8	0.15	0.5	0.8	5.3	4.95	6.6
23	27.7	0.198	0.5	0.8	3.67	6.01	63.7
24	119.4	0.03	0.5	0.8	1.91	1.67	12.5

6. Discussion

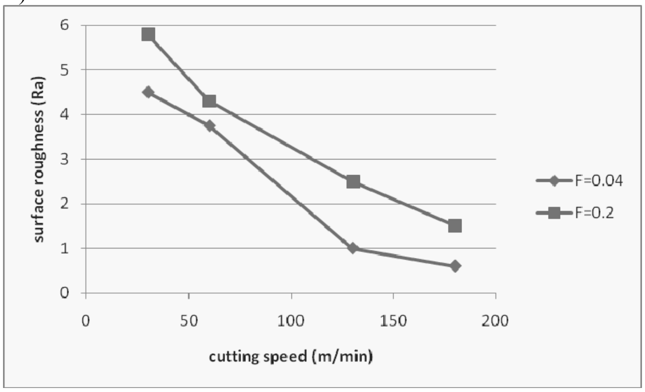
Variations of surface roughness with cutting speed are shown in Figure 6.

According to this figure increasing in cutting speed improves the surface quality. It is also shown that this surface quality decreases with the feeding rate. With the variations of feed rate in low value of cutting speed, the surface roughness in more high (Fig. 6). Since, in machining without any coolant, the plastic deformation of chips takes place so that, the friction between tool and chip surfaces will be decreased according to increasing of temperature zone.

The variations of surface roughness with cutting speed in two feeding rates and with 1.2 mm radius of tool bit is shown in Figure7.

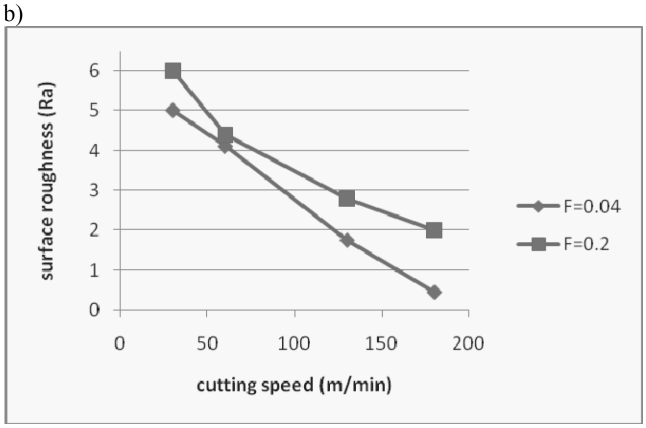
The variations trend in the same as the previous one. According to this figure, in high feeding rate and increasing in cutting speed to V= 50 m/min, the surface roughness decreases rapidly. The surface roughness also increases with feed rate (Fig.7). This is probably because of the creation of built-up edge in low cutting speed due to the high friction between tool and chip in this manner.

a)



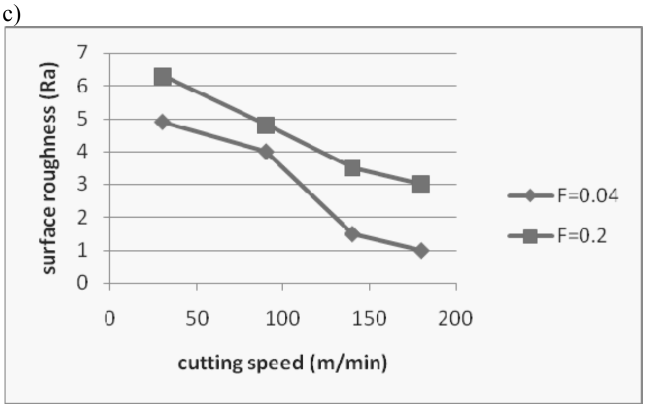
(a_p=0.3mm , r_e=0.4mm)

b)



(a_p=0.5mm , r_e=0.4mm)

c)

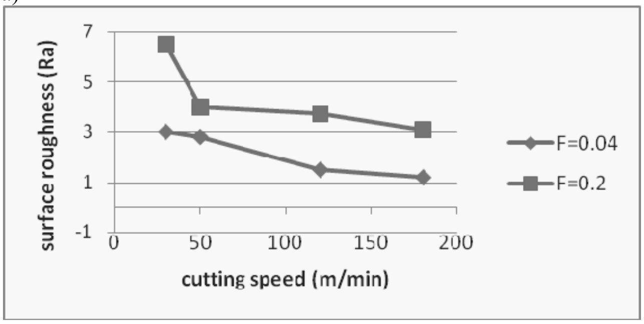


(a_p=0.7mm , r_e=0.4mm)

Fig. 6. Variations of surface roughness with cutting speed

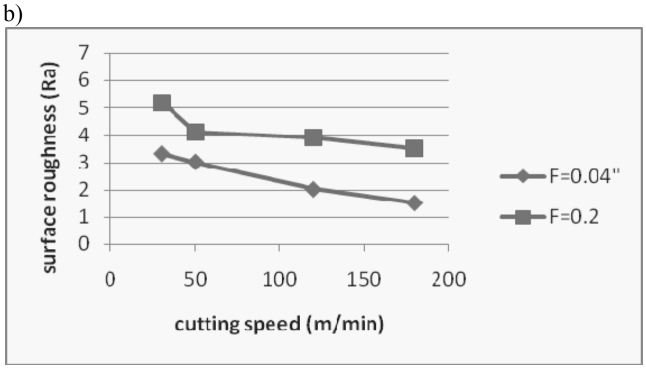
Figure 8 shows a comparison between the errors of surface roughness prediction resulted from processing of dry machining via fuzzy-logic network and ordinary theoretical methods.

a)



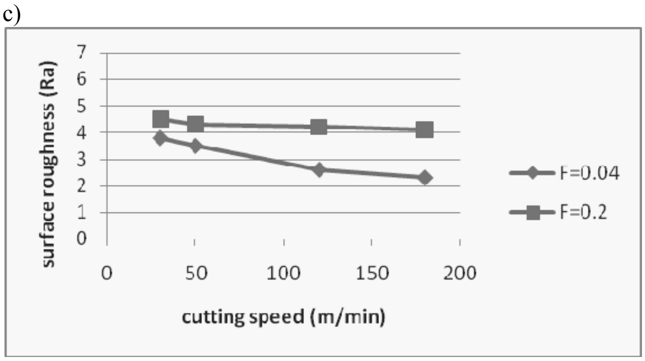
(a_p=0.3mm , r_e=1.2mm)

b)



(a_p=0.5mm , r_e=1.2mm)

c)



(a_p=0.7mm , r_e=1.2mm)

Fig. 7. Variations of surface roughness with cutting speed

The difference errors between these two methods are very high. The reason is that in the theoretical calculation methods, the feeding speed and the radius of tool bit are considered as the main factors whereas, in our model, cutting speed plays as a main factor in this case. Besides, according to this figure, the error of the model is very low in comparison with the calculation error.

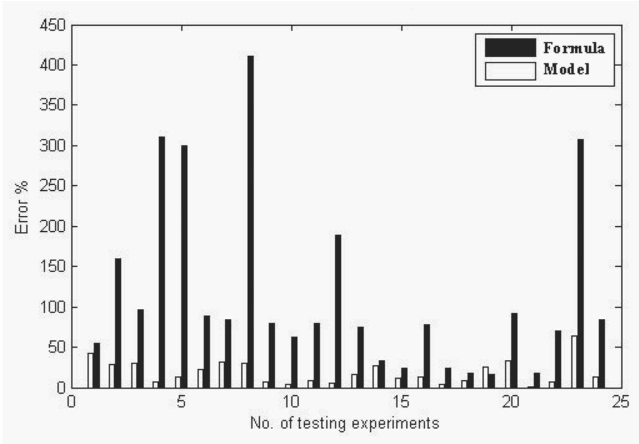


Fig. 8. Comparison between theoretical and model resulted errors

7. Conclusions

In this research, an adaptive neural fuzzy inteligent system is used to predict the surface roughness in dry turning. From this point of view, after the creation of the prediction model with some data and its processing via neural networks, some tests are carried out to evaluate the capability of this model. Then, some experimental tests are carried out and the results of them are compaired with the results of the model. The results are as follows:

- The creation method of chips from discrit to continiuos is changed when the cutting speed is increased. In this manner, the machine chatter is decreased and the machined surface quality is improved.
- The quality of machined surface is decreased with the feeding rates.
- Generally, the surface quality is decreased with the depth of cut.
- The error of the model is more less than the error of using ordinary equations.
- The out put surface roughness from fomula dos,t show any action against the variations of cutting speeds whereas, the model do completly response against these kinds of variations.

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