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Studying the Effect of Cutting Conditions in Turning Process on Surface Roughness for Different Materials

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Abstract — **Surfaces quality is one of the most specified customer requirements for machine parts. The major indication of surfaces quality on machined parts is surface roughness. The research aim is to study the cutting conditions and their effects on the surface roughness. This research will use regression models and neuro-fuzzy to predict surface roughness over the machining time for variety of cutting conditions in turning. In the experimental part for turning, different types of materials (Aluminum alloy, brass alloy, and low carbon steel) were considered with different cutting speed, and feed rate. A linear regression and neuro-fuzzy model depending on statistical-mathematical method between surface roughness, R_a, and cutting condition will be derived, for the three materials. The effect of cutting parameters on surface roughness is evaluated and the optimum cutting condition for minimizing the surface roughness will be determined. The model will be established between the cutting conditions and surface roughness using regression and neuro-fuzzy model. As the results of this work, the linear regression and neuro-fuzzy model will be used in predicting surface roughness, can be used in manufacturing systems, this modeling helps engineer to reduce the efforts and improve the quality.**

I. INTRODUCTION

The surface quality is quite important for the efficient working of machine parts. The structure of a machined surface is one of the most important criteria in terms of quality, and tribological properties of the machined surface are considerably affected from the surface tissue. Generally, the surface quality is characterized with surface roughness. Surface roughness is an important factor which must be considered not only in the conventional subjects of tribology such as abrasion, friction and lubrication but also in different fields such as sealing, hydrodynamics, electrical and heat conductivity. Surface roughness is mainly affected during the machining process by cutting parameters such as cutting speed, feed rate and constant depth of cut. If these parameters are not chosen convenient, the surface roughness increases. This situation creates a notch effect and results in crack initiation, decrease in fatigue strength and corrosion resistance. So, the characterization and measurement of surface roughness has a great important in the sense of the optimization of machining process [4, 5]. Average roughness (R_a) is defined as the average roughness of the profile about the mean line (usually the least squares mean line or that generated by a standard filter). It represents the average absolute deviation of the profile points from a mean line and is perhaps the most widely used "quoted" parameter. If $z = f(x)$ is the profile measured from the reference mean line and L is the length of the profile measured from the reference mean line L is the length of the profile being assessed, then R_a is defined by

$$R_a = \frac{1}{L}\int_0^L |z|\,dx$$

An equally spaced digitised 3D surface can be denoted by a function $z(x_i, y_i)$ with $x_i = i\Delta x$ and $y_j = j\Delta y$, whereby $i = 1, 2, 3, ..., M$ and $j = 1, 2, 3, ..., N$. Δx and Δy are sampling intervals. M and N represent the number of sampling data points in the x and y directions, respectively. The 3D parameters are passed on the residual surface $\eta(x, y)$, which is the difference between the original surface $z(x_i, y_i)$ and the reference datum $f(x_i, y_i)$. The average amplitude of the surface S_a is defined in 3D as

$$S_a = \left[\frac{1}{l_x l_y}\int_0^{l_x}\int_0^{l_y} |\eta(x,y)|\,dxdy\right]^{1/2} \approx \left[\frac{1}{MN}\sum_{j=1}^{N}\sum_{i=1}^{M}|\eta(x_i,y_j)|\right]^{1/2}$$

This is an arithmetic average parameter. It insensitive to changes in the sampling interval. Many experiments have been made in order to investigate surface roughness in turning machining. Therefore, this research will focus on the

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effect of feed rate, spindle speed with three different material hardness on surface roughness, R_a.

II. METHODOLOGY

Neuro-Fuzzy Modeling

The adaptive network based fuzzy inference system (ANFIS) architecture and learning is based on a fuzzy inference system [6] implemented in a framework of an adaptive network. Using a hybrid learning procedure, ANFIS can learn an input-output mapping based on human knowledge (in the form of if-then fuzzy rules). The ANFIS architecture has been employed to model non-linear functions, identify non-linear components on-line in a control system, and predict a chaotic time series. ANFIS performs the identification of an input-output mapping, available in the form of a set of N input-output examples, with a fuzzy architecture, inspired by the Takagi-Sugeno modeling approach [7]. The fuzzy architecture is characterized by a set of rules, which are properly initialized and tuned by a learning algorithm. The rules are in the form:

- ***if speed1 is A11 and feed1 is A12 and size1 is A13 then output =f1(speed1,feed1,size1)***
- ***if speed2 is A21 and feed2 is A22 and size2 is A23 then output =f2(speed2,feed2,size2)***

Where, A_{ij} are parametric membership functions.

The model topology was based on TSK type, 2 input variables, 3 Gaussian membership functions for each variable, 9 rules; training was performed to 30 epochs. Three models were generated, for carbon, brass and aluminum. Results of the models response surface are shown in the following sections. Linear regression equation is given by:

$$\text{Roughness, } R_a = a \times \text{feed rate} + b \times \text{speed} + c$$

III. EXPERIMENTAL PROCEDURE

A. MATERIALS SELECTION

More than 36 samples (a rod bar, from Saline Water Conversion Corporation, Al Shuaiba, KSA) were used in this study with identical dimensions of length of 80 mm (length) × 38 mm (diameter). A saw machine was used to cut the rod bar into identical dimensions. Figure 1 shows the image of the samples (rod bars) to be tested and Table 1 shows the data sheet of the material specifications.

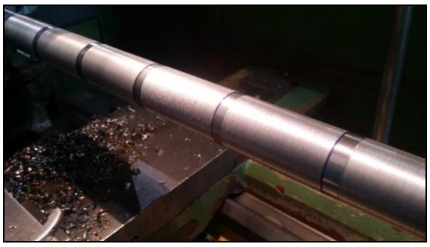


Figure 1: low steel rod while machining

Table 1: material specifications

Materials	Low Alloy Steel	Aluminum Alloy	Brass
Specification	ASTM A 193 GR B7	ASTM B 211-AL 5052	ASTM B 16-AL C36000
Finish		Hot Rolled	
Certificate	CL 2.1 OF ISO 10474	CL 2.2 OF ISO 10474	LC 2.2 OF ISO 10474

The chemical compositions and mechanical properties of work materials are shown in Tables 2, 3 and 4, respectively. The effectiveness of turning process can be determined by the effects of surface layer and depend upon three parameters of cutting conditions have been chosen which are cutting speed, feed rate and three different materials (different hardness):

1) Cutting speed, v = 132, 260, 320 and 500 m/min.
2) Feed rate, f = 0.18, 0.31, 0.71 mm/rev.
3) Depth of cut, DOC = 0.5 mm.

Table 2: Chemical compositions of Aluminum 5052

Al	Mn	Mg	Si	Cu	Ti	Zn	Fe	Cr
96.1	0.1	2.3	0.25	0.1	0.1	0.1	0.4	0.15

Table 3: Chemical compositions of Brass

Cu	Fe	Pb	Zn	Sn	Ni	Ti	Al	Fe
60.4	0.35	2.7	34.7	-	0.30	0.25	0.05	0.34

Table 4: Chemical compositions of low alloy steel

Fe	Mn	Cu	Si	Zn	Ti	C	Al	Fe
96.8	0.801	0.253	0.250	0.001	0.002	0.383	0.021	96.8

B. EXPERIMENTAL SETUP

The experiments for testing are carried out on turning machine using various solid carbide cutting tool at different cutting machining parameter combination. Figure 2 shows the image of the samples (rod/round bars) to be tested.

Aluminum Alloy

Brass

Low Alloy Steel

Figure 2: image of the samples (rod/round bars) to be tested

C. CLEANING PROCEDURE

It is of the utmost significant before starting the experiments to clean the samples of any sur`face contaminations, such as dust, grease, or any other soluble organic particles so that there will be no adverse effect on the results. Prior to measurement, samples (rod bar) were cleaned ultrasonically in three five-minute steps using: (i) water with detergent to remove dust and oils; (ii) distilled water to remove detergent; (iii) methanol to remove the distilled water. After cleaning, all samples were stored for 24 hours in the same metrology laboratory that was used for testing, to allow them to equilibrate with their environment (normally 20±1˚C and 40±5% relative humidity). The procedure that is described above was judge to be adequate at this stage of investigation.

D. TESTING PROCEDURE

The surface profile of all samples were quantitatively analyzed in order to determine the statistical standard parameter of average roughness, R_a, by using Taly-surf® (from Taylor Hobson Precision, Inc.) which delivers 0.8 nm resolution over 12.5 mm seamless measuring range and includes 0.125 µm horizontal data spacing. A nominal 2 µm stylus was used with a normal load of 0.7 mN and selectable traverse speed down to 0.5 mm s^{-1} and which conforms to British Standards, see Figure 3. Surface roughness errors were calculated from the standard deviation of the absolute values of height deviation (absolute values). The traces were auto-leveled to a linear least-squares straight line and then filtered with a standard 0.8 mm cut-off. The surface parameters were selected according to the recommendations in the literature and also with respect to the data processing facilities available [8-12].

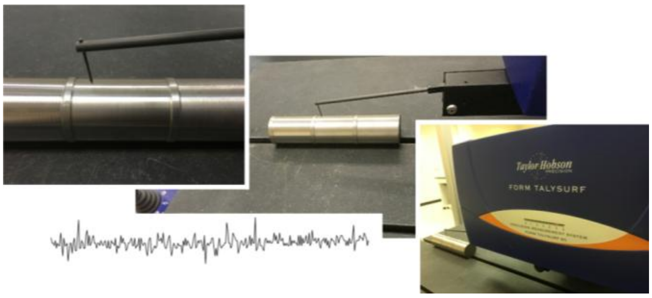
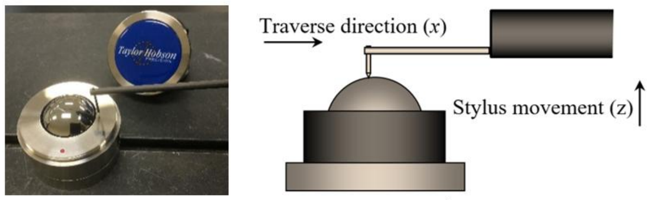


Figure 3: image of Taly-surf® and specimen

Every test condition was repeated at least three times at different "new" locations on a rod bar surface in order to ensure the repeatability and reproducibility of the results. The "new" location was at least ±100 µm from the previous one. This approach should have avoided any alteration of the counterbody surface, e.g., due to wear, which might occur during the test and affect the measurements in the following tests. All experiments were performed with a typical "*ball-on-flat*" arrangement applying a linear sliding contact at constant velocity over a specific distance. Tests were performed by using single scan mode (forwards motion). The profiler had a scan length of 10 mm, which is close to the size of a human fingertip.

E. CALIBRATION PROCEDURE

Standard calibration ball radius D = 22.0161 mm, 112/1844, Serial No. 639-506-B (from Taylor Hobson Precision, Ltd.) was used to calibrate the test-rig. For convenience, ten calibration trials have been carried out. This is adequate as these trials are predominantly about relative behavior; design interpretation to other systems is always vulnerable to variations in terms of materials and dimensions. Calibration showed the cantilever was a linear spring (R^2 > 0.99), under operating and environmental conditions typical for this type of device, with absolute uncertainties of <1% of reading and realizable measurement resolution down to at worst 50 nm. Figure 4 shows the set-up of the standard calibration ball and the systematic diagram of the ball and a nominal 2 µm stylus with a normal load of 0.7 mN and selectable traverse speed down to 0.5 mm s^{-1}. This method of calibration ensures that the gauge travels through (and therefore, is calibrated over) most of its range, see [13].



(a) (b)

Figure 4: (a) image of standard calibration ball radius D = 22.0161 mm, 112/1844, Serial No. 639-506-B (b) ball with nominal 2 µm stylus

IV. RESULTS AND DISCUSSION

The measured values of surface roughness for the machined surfaces corresponding to all the experimental runs are given in Tables 4, 5 and 6.

Table 4: repeatability performance of Aluminum

Aluminum					Surface Roughness, R_a, (µm)			
Cutting No.	Feed Rate (mm/rev)	Cutting Speed (m/min)	Length (mm)	Diameter (mm)	Trail No.1	Trail No.2	Trail No.3	Average
1	0.18	132	80	38	4.2661	4.2373	4.2984	4.27
2	0.31	132			17.5879	16.179	16.3689	16.71
3	0.71	132			141.848	142.034	141.794	141.89
4	0.18	260			4.5598	4.4821	4.4496	4.50
5	0.31	260			22.2715	25.0405	25.0482	24.12
6	0.71	260			151.07	153.497	153.409	152.66
7	0.18	320			3.2054	3.1754	3.0799	3.15
8	0.31	320			14.9875	14.7761	15.7622	15.18
9	0.71	320			98.7804	97.1942	91.2627	95.75
10	0.18	500			3.7238	3.675	3.7211	3.71
11	0.31	500			14.9578	15.3767	15.3325	15.22
12	0.71	500			116.143	126.155	115.111	119.14

Table 5: repeatability performance of Brass

Brass					Surface Roughness, R_a, (μm)			
Cutting No.	Feed Rate (mm/rev)	Cutting Speed (m/min)	Length (mm)	Diameter (mm)	Trail No.1	Trail No.2	Trail No.3	Average
1	0.18	132	80	38	5.6294	5.3204	5.3383	5.43
2	0.31	132			22.4361	20.6543	22.4829	21.86
3	0.71	132			90.4682	90.1949	88.8665	89.84
4	0.18	260			5.8919	5.8646	5.7449	5.83
5	0.31	260			21.4614	22.6225	23.132	22.41
6	0.71	260			89.3569	89.8432	91.846	90.35
7	0.18	320			5.4822	5.4509	5.661	5.53
8	0.31	320			23.3578	23.5526	21.929	22.95
9	0.71	320			89.052	88.4315	86.244	87.91
10	0.18	500			4.4503	4.33263	4.2679	4.35
11	0.31	500			21.555	22.0424	20.7043	21.43
12	0.71	500			82.7338	81.7665	79.4545	81.32

Table 6: repeatability performance of low carbon steel

Carbon Steel					Surface Roughness, R_a, (μm)			
Cutting No.	Feed Rate (mm/rev)	Cutting Speed (m/min)	Length (mm)	Diameter (mm)	Trail No.1	Trail No.2	Trail No.3	Average
1	0.18	132	80	38	6.6597	8.1768	8.1345	7.66
2	0.31	132			12.0783	12.4256	13.877	12.79
3	0.71	132			19.4475	18.3176	19.1891	18.98
4	0.18	260			5.2099	6.9874	7.1914	6.46
5	0.31	260			7.2849	7.9978	7.7982	7.69
6	0.71	260			18.6287	18.125	17.8566	18.20
7	0.18	320			2.868	3.4254	3.2185	3.17
8	0.31	320			4.3151	4.4497	3.977	4.25
9	0.71	320			19.0189	18.2117	18.7516	18.66
10	0.18	500			3.0107	3.2029	2.7492	2.99
11	0.31	500			3.3443	3.3228	3.1917	3.29
12	0.71	500			18.1182	18.7612	18.881	18.59

A. Repeatability Performance of Aluminum

Figure 5 shows the Aluminum roughness prediction model with linear regression. The linear regression equation is given by:

$$\text{Roughness, } R_a = a \times \text{feed rate} + b \times \text{speed} + c$$

Where,

$$a = 242.5899,\ b = -\ 0.0309 \text{ and } c = -37.9813$$

Figure 6 illustrates the neuro-fuzzy model of aluminum including the roughness, feed rate and speed. Figure 7 shows the repeatability performance of aluminum with different cutting speed and feed rate.

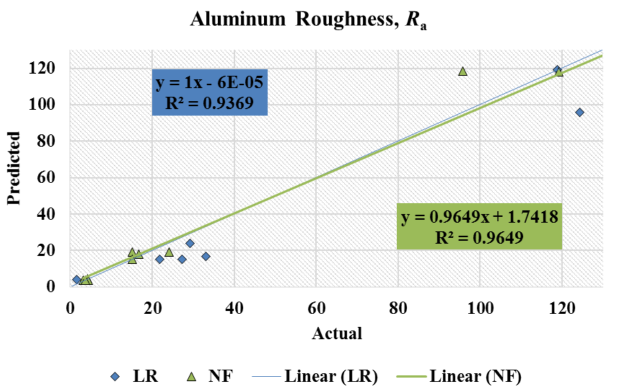


Figure 5: Aluminum roughness prediction model with linear regression

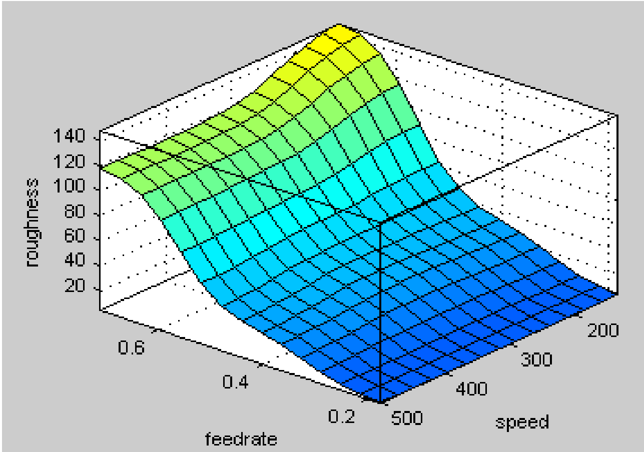


Figure 6: neuro-fuzzy model of aluminum

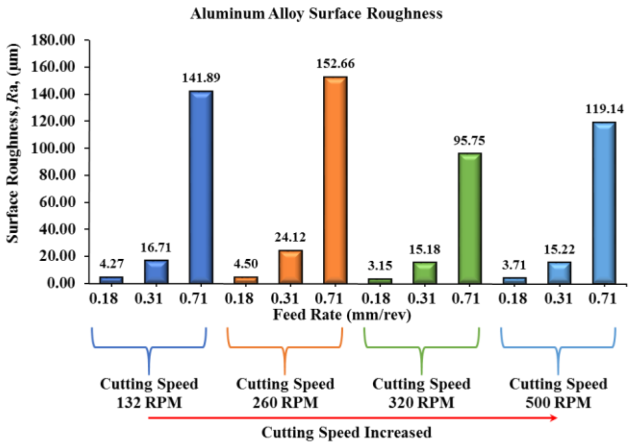


Figure 7: repeatability performance of Aluminum surface roughness

B. Repeatability Performance of Brass

Figure 8 shows the Brass roughness prediction model with linear regression. The linear regression equation is given by:

$$\text{Roughness, } R_a = a \times \text{feed rate} + b \times \text{speed} + c$$

Where,

$$a = 156.7675,\ b = -\ 0.00974 \text{ and } c = -21.4877$$

Figure 9 illustrates the neuro-fuzzy model of Brass including the roughness, feed rate and speed. Figure 10 shows the repeatability performance of Brass with different cutting speed and feed rate.

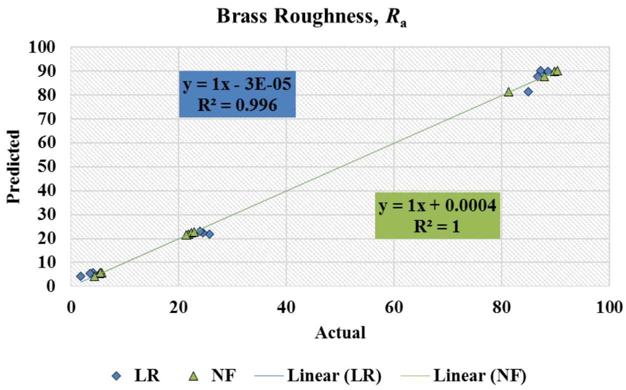


Figure 8: Brass roughness prediction model with linear regression

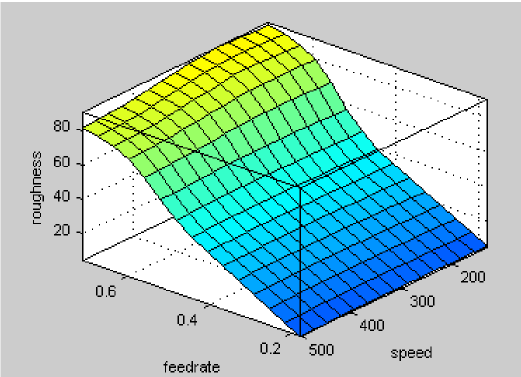


Figure 9: neuro-fuzzy model of brass steel

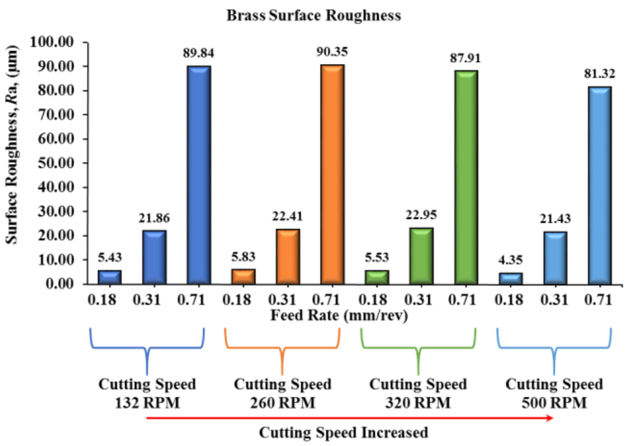


Figure 10: repeatability performance of Brass surface roughness

C. Repeatability Performance of Carbon Steel

Figure 11 shows the Carbon Steel roughness prediction model with linear regression. The linear regression equation is given by:

$$\text{Roughness, } R_a = a \times \text{feed rate} + b \times \text{speed} + c$$

Where,

$$a = 26.36,\ b = -\,0.01325 \text{ and } c = 3.699$$

Figure 12 illustrates the neuro-fuzzy model of Carbon Steel including the roughness, feed rate and speed. Figure 13 shows the repeatability performance of Carbon Steel with different cutting speed and feed rate.

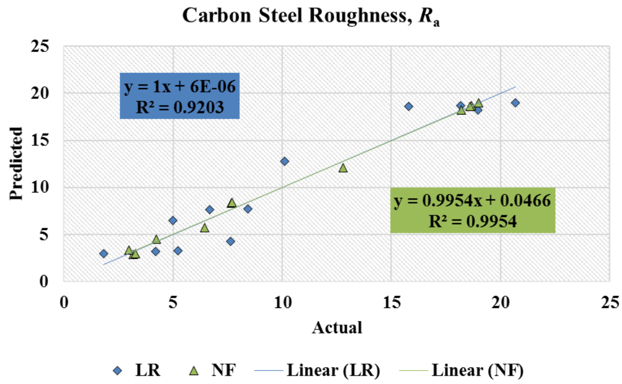


Figure 11: Carbon Steel roughness prediction model with linear regression

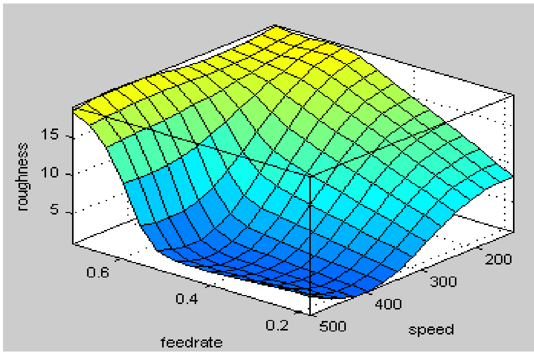


Figure 12: neuro-fuzzy model of carbon steel

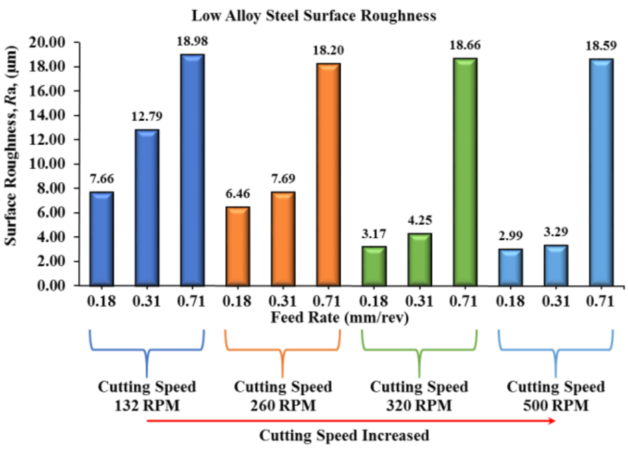


Figure 13: Carbon steel surface roughness

V. CONCLUSIONS

The effect of cutting speed and feed rate on the surface roughness shows that a low hardness material ductile material gives (R_a) more than the high hardness brittle materials at high cutting speed, at the low feed rate. The experiment shows that the change of cutting speed (v) at different cutting feed gives the same relationship, in general. Indeed, at 0.18 mm/rev federate and high speed 500 RPM, we got the best surface roughness, the effect of feed rate is the most important factor were we have to keep it low with high cutting speed to get the optimum surface roughness. The results of experiments allow considering the establishing cutting condition on the quality of surface, and then obtain linear regression and neuro-fuzzy models to ensure the quality. The analysis of the effects of various parameters shows that the feed rate has significant effect in the reducing roughness and cutting speed have second effects in reducing the surface roughness, while the working materials has the least effect. The models generated, which includes the effect of cutting speed, feed rate, and working materials. Finally, the most important points are:

- In general, the study shows that the cutting speed is by far the most dominant factor for surface roughness then the feed rate, while the working materials has less effect.
- The effect of cutting condition on the quality has been established with the help of mathematical models, the optimal conditions to minimize the surface roughness has been determined.

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