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Modelling of Cutting Parameters in Turning Operation to Enhance Surface Quality

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Abstract

In order to obtain the desired surface quality by machining, proper machining parameter selection is essential. This research paper presents an experimental study of roughness characteristics of the surface profile generated in turning of AISI 1040 mild steel using a NAGMATI-175 lathe machine. Machining was done using high-speed steel, and a dry turning process was used. The study aims at the modeling of machining parameters in turning operations to enhance surface quality. The objective was to develop a multiple regression model for the prediction of surface roughness parameter, $R_{a.}$ and to avoid "trial and error" approaches in setting up machining conditions in order to achieve the desire surface quality. The Taguchi method was used for the experimental design, in which the L27 orthogonal array was selected. The multiple regression model was developed using the Regression Analysis technique in the program software, MatLab 7.5 and the average error rate of the model developed with the experimental data is within 2.8%. Besides, the developed response surface model for $R_a$was checked by using residual analysis. Analysis using S/N and ANOVA were performed to find the optimum level and percentage of contribution of each parameter. Analysis of Variance (ANOVA) technique in the program software Minitab 16 was used to examine the impact of cutting parameters on surface roughness. The result reveals that the combination that gives the optimum condition of better surface finish is feed rate of level 1 (0.10mm/rev), spindle speed of level 3 (900rpm), depth of cut at level 1 (0.5mm), and nose radius at level 1 (0.6mm).

Keywords - *Machining, Surface roughness, Dry turning, Taguchi method, Regression analysis (RA).*

I. INTRODUCTION

Due to the increasing demand for superior quality components for its functional properties, the surface roughness of a machined part plays a significant role in modern manufacturing process [1]. In any machining process, apart from obtaining accurate dimensions, achieving a good surface quality and maximized metal removal is also of utmost importance. Regardless of the manufacturing process, a fine and smooth surface cannot be obtained. The machined part or workpiece retains the surface irregularities left after machining [2]. In manufacturing industries, there are various manufacturing processes used to remove material from a workpiece. Of all these methods, turning is the most popular method because of its ability to remove materials faster and achieve a reasonably good surface quality [3].

Turning can be described as a process whereby a single-point cutting tool removes unwanted material from the cylindrical workpiece, which is rotating. In turning operation, the tool is fed parallel to the axis of rotation. It can be done manually in a traditional form of lathe, which requires continuous supervision by the operator, or by using a computer-controlled and automated lathe, which does not require constant supervision. In turning operations, it is important to select the cutting parameters properly to achieve high-quality performance. Turning is used to reduce the diameter of the workpiece, usually to a specified dimension. Mathematically, each surface machined on a lathe is a surface of revolution. A turning operation is shown in Fig. 1.1.

Figure 1.1: Turning Operation

The surface finish of turned components has a massive influence on the quality of the finished product. Surface roughness is one of the most important parameters in the machining process to determine the quality of a finished product. Surface roughness plays an important role in many areas, and it is a factor of great importance in evaluating machining accuracy [4]. Surface roughness is a quantitative measure of the process marks produced during the creation of the surface and other factors such as the structure of the material.

In actual practice, many factors affect surface roughness, such as; cutting conditions, workpiece variables, and tool variables. Cutting conditions include feed, speed, and depth of cut. At the same time, tool variables include tool material, rake angle, nose radius, cutting edge geometry, tool overhang, tool vibration, tool point angle, the coolant used. Moreover, workpiece variables include work hardness and other mechanical properties [3]. The desired cutting parameter of material is selected by using a handbook or based on the experience of the operator. Nevertheless, a better result is achieved by modeling the surface roughness and optimizing the cutting parameters [3].

There are many ways to define surface roughness depending on its applications like R_a, R_t, R_q, R_k, but roughness average R_a is widely used in industry for the mechanical components to indicate surface roughness. It is also known as arithmetic aver-age (AA) or centre line average [5]. Each of the roughness parameters is calculated using a formula for describing the surface. R_a is used for this present work and it is given by:

$$\boldsymbol{R_a = \frac{1}{L}\int_0^L |Y(x)|dx} \qquad (\mathbf{1.1})$$

Since these parameters reduce all of the information in a profile to a single number, great care must be taken in applying and interpreting them. Small changes in how the raw profile data is filtered, how the mean line is calculated, and the physics of the measurement can greatly affect the calculated parameter [6].

Inspecting and assessing surface roughness of machined workpieces can be carried out employing different measurement techniques.
These methods can be classified into the following:

- Direct measurement methods
- Non-contact methods
- Comparison based techniques
- On-process measurement

Based on the parameters affecting surface roughness, a review of previous related researches is presented as follows.

Kumar and others [5] carried out the optimization of surface roughness in face turning operation in the machining of EN – 8. They investigated the effect of cutting parameters like spindle speed, feed, and depth of cut on the surface finish on EN-8 using multiple regression analysis. Feed rate has a greater influence on surface roughness parameter (R_a), followed by cutting speed and percentage volume fraction of SiC in the machining of Al/SiC particulate composites [20].

Srikanth and Kamala [8] developed a real coded Genetic Algorithm (RCGA) to locate optimum cutting parameters and explained its advantages over the existed approach of binary-coded Genetic Algorithm (BCGA).

Nalbant and others [9] optimized the cutting parameters for turning AISI 1030 steel bars using the Taguchi method. They considered the centerline average (R_a) only. They recommended using a low feed rate, greater insert radius, and low depth of cut to obtain a better surface finish for a specific test range.

Al-Ahmari [10] proposed empirical models for tool life, cutting force, and surface roughness for turning operation. The two powerful techniques used were; Neural networks and response surface methodology. Singh and Rao [11] developed a mathematical model for R_a and optimized the cutting parameters and tool geometry for hard turning using a genetic algorithm.

Noordin and others [22] described the performance of coated carbide tools using response surface methodology when turning AISI 1040 mild steel. They found out that feed rate is the most significant parameter influencing the surface roughness R_a and tangential force. Grey relational analysis was used by Lin [13] to optimized turning operations with multiple performance characteristics such as; cutting force and surface roughness Ra in turning operation.

Groover [14] focuses on developing an empirical model to predict surface roughness in finish turning. The model considers the following working parameters: workpiece hardness (material), feed, cutting tool point angle, depth of cut; spindle speed; and cutting time. One of the most important data mining techniques, nonlinear regression analysis with logarithmic data transformation, was applied in developing the empirical model. A popularly used model for estimating the surface roughness value is given according to Groover [14] as:

$$\boldsymbol{R_i = \frac{f^2}{32r}} \qquad (\mathbf{1.2})$$

Where:

R_i	=	ideal arithmetic average (AA) Surface roughness (in or mm), and
f	=	feed (in rev^{-1} or mm rev^{-1})

II. MATERIALS AND METHOD

The turning was done using a Nagmati 175 lathe machine, having the following specifications:

Height of center	: 175 mm,
Swing over bed	: 350mm,
Spindle speed NO. 8	: 54 To 1200 RPM,
Cross slide travel	: 215mm,
Top slide travel	: 125mm,
Power required	: 2.25KW/3H.P.

The surface roughness of the turned samples was measured with a portable Mitutoyo make Surface dial test indicator, model 513-404E, having the following specifications;

Graduation	: 0.01mm,
Dial reading	: 0-40-0,
Accuracy	: 8μm.

The cutting tool used was the High-Speed Steel (HSS) cutting tool. It has a typical cutting speed range from 10—60m/min. AISI designation of the tool is Grade M—7 (1%C, 3.8%Cr, 9.5%Mo, 1.6%W, and 2%V). The tool signature is:

Rake angle	(back—100, side—120),
Cutting edge angle	(150),
Relief angle	(50), and
Nose radii	(0.6mm, 0.8mm, and 1.0mm).

Table 2.1: chemical composition of HSS (M series grade)

Elements	Mo	W	V	Cr	Co	Fe
Weight Percentage	5—10%	1.5—10%	1—4%	4%	5—10%	Balance

Table 2.2: Chemical composition of mild steel (AISI 1040)

C	Mn	Si	P	S	Cu	Ni	Cr	Fe
0.42%	0.48%	0.17%	0.02%	0.018%	0.1%	0.09%	0.07%	98.6%

Table 2.3: Domain of Experiments

VARIABLES	SYMBOL	LEVEL 1	LEVEL 2	LEVEL 3
Feed rate (mm/rev)	**P1**	**0.10**	**0.15**	**0.20**
Spindle speed (rpm)	**P2**	**400**	**650**	**900**
Depth of cut (mm)	**P3**	**0.5**	**1.0**	**1.5**
Tool nose radius (mm)	**P4**	**0.6**	**0.8**	**1.0**

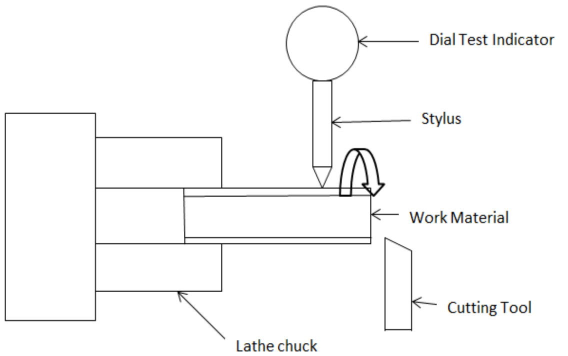

Figure 2.1: Schematic diagram of the experimental setup.

The present study is carried out using AISI 1040 mild steel as the workpiece material. All the specimens are of bars with a diameter of 20mm and a length of 60mm. The chemical composition of mild steel (AISI 1040) is shown in Table 2.2.

The mechanical properties of the workpiece material are Hardness – 201BHN, density - 7.85g/cc, and Tensile strength – 620MPA [3].

A. Experimental Details/Procedure

The experiment was conducted on one workpiece material: AISI 1040 mild steel using a High-speed steel tool. Firstly the mild steel workpiece was clamped with the three-jaw chuck, and the HSS cutting tool is clamped to the tool post of the NAGMATI-175 lathe machine. Each test was carried out for a bar of ϕ20 x 60mm dimension. The turning tests were carried out to determine the surface roughness under various cutting parameters. The Taguchi experimental design, which helps in reducing the number of experiments, was used. The L27 orthogonal array with three levels for each factor was used, and three levels of spindle speed, depth of cut and feed rate, and tool nose radius were employed, as shown in Table 2.3. A dry turning process was used. That is, the experiments were conducted without the application of cutting fluids. The different units used here are; spindle speed (rpm), Feed-(mm/rev), depth of cut (DOC) – mm, nose radius – mm, the surface roughness Ra - µm.

B. Regression Analysis (RA)

In statistics, regression analysis is any technique for modeling and analyzing several variables Surinder and others, [15]. The regression model was developed for surface roughness by applying the regression analysis tool in the program software MatLab 7.5. The purpose of developing a mathematical model is to relate the machining response to the process parameters to facilitate the optimization of the machining process. That is, it focuses on the relationship between a dependent variable and one or more independent variables. Regression analysis enables us to understand how the typical value of the dependent variable changes when any one of the independent variables is varied, while the other independent variables are held constant. Regression analysis is widely used for prediction and forecasting Surinder and others, [15]. It is used to investigate and model the relationship between a response variable and one or more predictors [5].

C. Taguchi Method

Taguchi methods are statistical methods developed by Genichi Taguchi to improve the quality of manufactured goods, and more recently, also applied to biotechnology, advertising, marketing, and engineering [16]. The Taguchi method involves reducing the variation in a process through a robust design of experimentation. The overall objective of the method is to produce a high-quality product at a low cost.

Taguchi's work includes three principal contributions to statistics:

- Innovations in the design of experiments.
- A specific loss function, Taguchi loss function; and
- The philosophy of off-line quality control.

The beauty of the Taguchi method lies in the fact that it integrates statistical methods into the powerful engineering process. Taguchi philosophy was mostly used for engineering optimization processes. According to Nalbant and others [9], Taguchi also defined a performance measure known as the signal to noise ratio

(S/N) and aims to maximize it by properly selecting the parameter levels.

Nominal is the best:

$$\frac{S}{N_T} = 10\log\left(\frac{\bar{y}}{s^2}\right) \quad \ldots\ldots\ldots\ldots\ldots\ldots. \quad (2.1)$$

Larger is the better (maximize):

$$\frac{S}{N_L} = -10log\frac{1}{y}\sum_{i=1}^{n}\frac{1}{y^{i2}} \quad \ldots\ldots\ldots\ldots\ldots \quad (2.2)$$

Smaller is better (minimize):

$$\frac{S}{N_S} = -10log\frac{1}{y}\sum_{i=1}^{n} y^{i2} \ldots\ldots\ldots\ldots\ldots (2.3)$$

Where: $\bar{y}$is the average of observed data, Sy^2 is the variance of y, n the number of observations, and Y is the observed data.

III. RESULTS AND DISCUSSION

Surface roughness data were collected according to the Taguchi analysis method of the Minitab 16 software. The result of the surface roughness obtained for each experiment is shown in Table 3.1.

Table 3.1: Design of experiment and collected data.

Expt. Run	Feed (mm/rev) P1	Speed (rpm) P2	DOC (mm) P3	Nose Radius (mm) P4	Surface Roughness, Ra (μm)
1	0.1	400	0.5	0.6	0.36
2	0.1	400	1	0.8	0.76
3	0.1	400	1.5	1	1.17
4	0.1	650	0.5	0.6	0.32
5	0.1	650	1	0.8	0.68
6	0.1	650	1.5	1	1.05
7	0.1	900	0.5	0.6	0.30
8	0.1	900	1	0.8	0.63
9	0.1	900	1.5	1	0.97
10	0.15	400	0.5	0.8	0.57
11	0.15	400	1	1	1.18
12	0.15	400	1.5	0.6	1.65
13	0.15	650	0.5	0.8	0.51
14	0.15	650	1	1	1.05
15	0.15	650	1.5	0.6	1.47
16	0.15	900	0.5	0.8	0.47
17	0.15	900	1	1	0.98
18	0.15	900	1.5	0.6	1.37
19	0.2	400	0.5	1	0.79
20	0.2	400	1	0.6	1.47
21	0.2	400	1.5	0.8	2.29
22	0.2	650	0.5	1	0.71
23	0.2	650	1	0.6	1.32
24	0.2	650	1.5	0.8	2.06
25	0.2	900	0.5	1	0.66
26	0.2	900	1	0.6	1.22
27	0.2	900	1.5	0.8	1.91

A. Building the Multiple Regression Model

A multiple regression model has been developed from stepwise regression in Matlab, which includes Feeds, Speeds, Depth of Cut, and Nose Radius. The result of the regression analysis is shown in Fig. 3.1.

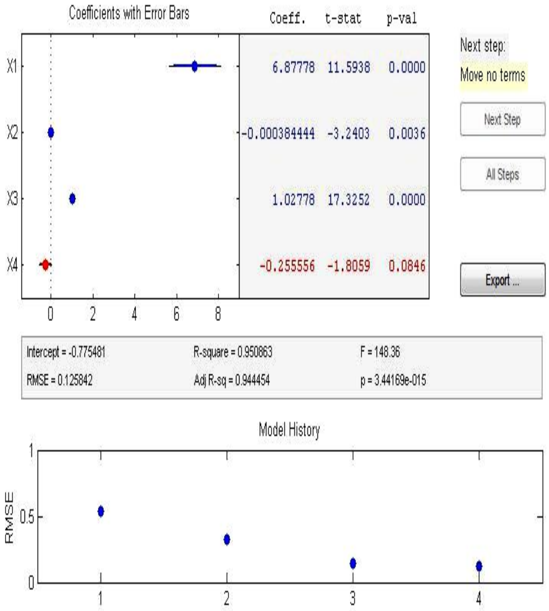

Figure 3.1: Regression Analysis result.

The model obtained from the Stepwise Multiple Regression analysis is as follows:

R_a = – 0.775481+6.87778*Feed–0.000384444*Speed + 1.02778*DOC–0.255556*Nose Radius--- (3.1)

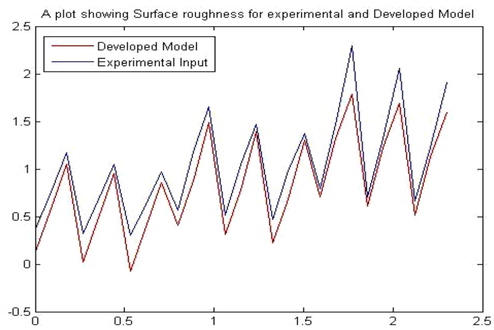

Figure 3.2a: A plot showing surface roughness for experimental and developed model.

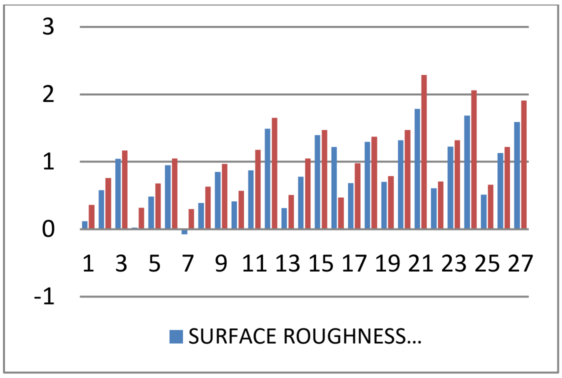

Figure 3.2b: A plot showing surface roughness for the experimental and predicted model.

Table 3.2: Experimental and Calculated R_a.

Exp. Run	Feed (mm/rev) P1	Speed (rpm) P2	DOC (mm) P3	Nose Radius (mm) P4	Surface Roughness, Ra (µm)Exptal.	Surface Roughness, Ra (µm) Calculated
1	0.1	400	0.5	0.6	0.36	0.1191
2	0.1	400	1	0.8	0.76	0.5819
3	0.1	400	1.5	1	1.17	1.0446
4	0.1	650	0.5	0.6	0.32	0.0230
5	0.1	650	1	0.8	0.68	0.4857
6	0.1	650	1.5	1	1.05	0.9485
7	0.1	900	0.5	0.6	0.30	-0.0731
8	0.1	900	1	0.8	0.63	0.3896
9	0.1	900	1.5	1	0.97	0.8524
10	0.15	400	0.5	0.8	0.57	0.4119
11	0.15	400	1	1	1.18	0.8746
12	0.15	400	1.5	0.6	1.65	1.4907
13	0.15	650	0.5	0.8	0.51	0.3157
14	0.15	650	1	1	1.05	0.7785
15	0.15	650	1.5	0.6	1.47	1.3946
16	0.15	900	0.5	0.8	0.47	1.2196
17	0.15	900	1	1	0.98	0.6824
18	0.15	900	1.5	0.6	1.37	1.2985
19	0.2	400	0.5	1	0.79	0.7046
20	0.2	400	1	0.6	1.47	1.3207
21	0.2	400	1.5	0.8	2.29	1.7835
22	0.2	650	0.5	1	0.71	0.6085
23	0.2	650	1	0.6	1.32	1.2246
24	0.2	650	1.5	0.8	2.06	1.6874
25	0.2	900	0.5	1	0.66	0.5124
26	0.2	900	1	0.6	1.22	1.1285
27	0.2	900	1.5	0.8	1.91	1.5913

Figures 3.2a and 3.2b shows a comparison between experimental surface roughness and predicted surface roughness using the developed model. The graph gives a good prediction ability of the model.

B. Determining the Model Accuracy

The model accuracy percentage for all data sets can be found by Paulo and others [23].

$$\Delta = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_{i,expt} - y_{i,pred}}{y_{i,pred}}\right| \ldots \ldots . \ldots (3.3)$$

Where $y_{i,expt}$ is the measured response corresponding to the data set i, $y_{i,pred}$ is the predicted response corresponding to the data set i and n is the number of data set, in this case, n = 27. Therefore,

$$\Delta = \frac{100}{27} \times \frac{26.244}{1}\%$$

$$\Delta = 97.2\%$$

Therefore, the model accuracy is 97.2%, and the average error rate of this model (equation 3.1) with the experimental data is within 2.8%.

C. Analysis of Variance (ANOVA) for Surface Roughness

The analysis was done using uncoded units, and the result shows that the factors were all significant, with probability factors less than 0.05 except the nose radius that has a probability factor greater than 0.05, as shown in Table 3.4.

Table 3.4: Analysis of Variance for Ra (µm)

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	4	7.09544	7.09544	1.77386	123.02	0.000
Linear	4	7.09544	7.09544	1.77386	123.02	0.000
P1	1	2.12867	2.12867	2.12867	147.63	0.000
P2	1	0.16627	0.16627	0.16627	11.53	0.003
P3	1	4.75347	4.75347	4.75347	329.67	0.000
P4	1	0.04702	0.04702	0.04702	3.26	0.085
Residual Error	22	0.31721	0.31721	0.01442		
Total	26	7.41265				

D. Computation of (Signal-to-Noise Ratio) S/N ratio

Computation of (Signal-to-Noise Ratio) S/N ratio of experimental data has been done, as shown in Table 3.5. For calculating the S/N ratio of Ra, a Lower-the Better (LB) criterion has been selected.

Table 3.5: Response Table for Signal to Noise Ratios. Smaller is better.

	Feed	Speed	DOC	Nose Radius
Level	(mm/rev) P1	(rpm) P2	(mm) P3	(mm) P4
1	4.16137	0.05484	6.12768	1.25701
2	0.57475	1.02083	0.06397	0.88235
3	-1.99426	1.66619	-3.44979	0.60250
Delta	6.15563	1.61135	9.57746	0.65450
Rank	2	3	1	4

The ranks indicate the relative importance of each factor to the response. The ranks and the delta values for the various parameters show that depth of cut has the greatest effect on surface roughness, and it is followed by feed, spindle speed, and tool nose radius in that order. This is also observed in the main effects plot, Fig. 3.3.

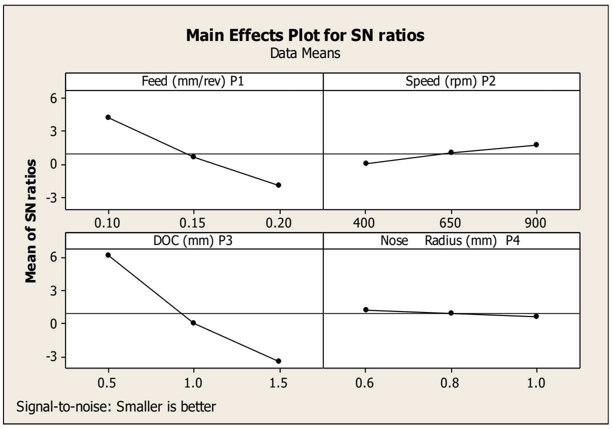

Figure 3.3: Main effects plot for SN ratios.

From Fig. 3.3, it is concluded that the optimum condition for the better surface finish is meeting at feed rate (L1), cutting speed (L3), depth of cut (L1), and nose radius (L1).

The following deductions are made from the ANOVA and Regression table:

I. The F-value of 148.36 implies the model is significant with an appreciably high correlation of ($R^2 = 0.95086$).
II. Since$P - value = 3.44 \times 10^{-15} < 0.05 = \alpha$, hence null hypothesis is rejected and is significantly a good fit.
III. The output R-square value (0.95086) indicates the accuracy of the model, and the coefficient of determination Adjusted R-square (0.94445) for the model is quite close.
IV. When the coefficient of determination, R^2 approaches unity (0.9508), it indicates a good correlation between the experimental and the predicted values.

E. Residual Analysis

The individual deviations of the observations Y_i from their fitted values are known as residuals. Residual plots can also help to examine the assumptions about the regression model [18]. Besides, the developed response surface model for $R_a$has been checked by using residual analysis. In a normal probability plot, Fig. 3.4, the data are spread approximately in a straight line, which shows a good correlation between experimental and predicted values for the response Suleiman and others [19].

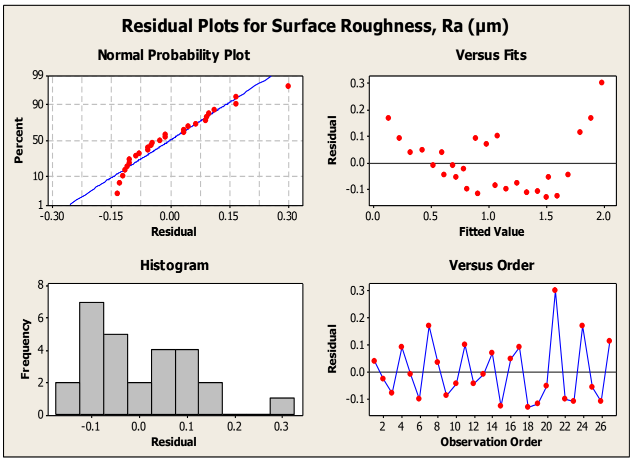

Figure 3.4: Residual Plot

IV. CONCLUSION

The significant conclusions drawn from this research are recapitulated as follows:

1.) The experiment was conducted in the dry turning process using Taguchi design.
2.) A multiple regression model was developed to study the effect of cutting parameters on surface quality/roughness.
3.) The prediction ability of the model was tested and analyzed using ANOVA.
4.) "Trial and error" approach to setup machining condition in order to achieve the desire surface quality can be avoided by applying the combination that gives the optimum condition of better surface finish, which is feed rate of level 1 (0.10mm/rev), spindle speed of level 3 (900rpm), depth of cut at level 1 (0.5mm) and nose radius at level 1 (0.6mm). Besides, further study can be possible considering other factors such as cutting fluid, the effect of coolant systems on turning operation may be considered for the better quality of the machined surface.

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