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PREDICTING SURFACE EXCELLENCE USING PARAMETRIC DESIGN CONCEPT: A PRACTICAL APPROACH WITH MATHEMATICAL MODEL

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ABSTRACT

This paper discusses empirical model development to predict surface roughness of components machined in CNC turning centre via parametric design concept. Process variables selected in parametric design are spindle speed, feed rate, cutter nose radius and depth of cut. Non linear regression analysis with logarithmic data transformation is used for the model development. The near optimum combination of machining parameters for the best surface roughness is achieved using Design of Experiments. Confirmation trial runs are conducted to get foolproof results. The regression model is validated with a case study.

Keywords: *Regression Model, OA, DoE, Surface Roughness, CNC Machining, Parametric Design.*

1. Introduction

Mankind had sensed the importance of surface quality in manufacturing field over centuries. In spite of its age, even today the quality has not attained saturation stage. In fact, predicting the surface finish compatible to manufacturing environment had been a major challenge to researchers. The quality of a surface is significantly an important factor in evaluating the productivity of machine tools and machined parts. Particularly, researchers along with engineers had been striving to develop the prediction model with the specific attention to determine the precise value of surface quality. Onwubolu [1] has developed surface roughness model for turning AISI 1040 carbon steel by PVD coated cutting tools. It assumes the non-linear relationship between the surface roughness and machining independent variables namely spindle speed, feed rate and depth of cut. A systematic procedure is formulated to identify the optimum surface roughness in the process control of individual end milling machines [2].

The impact of the turning parameters namely hardness, feed, point angle, depth of cut and spindle speed on surface roughness have been investigated by Feng [3]. Lou et al. have presented a multiple regression model technique to make certain the surface roughness in CNC end-milling process [4]. Huang and Chen suggested a predictable multiple regression model which forecast the in-process surface roughness in turning operation [5]. Savage and Chen studied the effects of tool diameter variations with the help of on-line surface roughness recognition system in end milling cutting [6]. Mounayri et al. used Particle Swarm Optimization and neural network, a computational intelligence technique for estimating dimensional accuracy in CNC milling [7]. An empirical model based on Meyer's index is developed to recognize the effect of machining parameters and cutting edge geometry on surface integrity of high speed turned Inconel 718 which enables to understand the characteristics of machining affected layers by Pawade et al. [8]. Designers bring out different design concepts that will do away with customized design; Process design meets both the functional and non functional requirements [9-13]. Due to variability in surface coating, a large number of experiments are usually required as to decide a suitable operating environment for obtaining the desired parameter setting in electroplating process [14].

Taguchi's Orthogonal Array (OA) based Design of Experiments (DoE) has been recognized as a powerful tool to optimize product / process variables of complex process in industry for quality and reliability [9, 15-19]. The intention of this research study is to examine the influence of key cutting parameters on surface finish. Therefore, the desired objective function is to improve the quality of surface finish. The experimental investigation is done to get hold of a better understanding how the variation in cutting parameters have an effect on the quality of surface finish in CNC machining processes. The cutting condition is planned for the obligatory surface finish and standards by allowing variability in machining processes and declining tool life while machining.

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1.1 Taguchi quality concept

Classical methods for design of experiments which include a full variety of statistical design techniques have discussed for some time [20]. However, engineers have generally avoided these techniques because they were too cumbersome to implement due to the high level of statistical sophistication required to use them. Bendell [21] and Taguchi [22] have formulated multivariate experimental techniques using orthogonal design arrays, which allow one to isolate the effect of a single parameter on a particular response characteristic. Evaluate the effects of all factors using conventional "one - factor - at - a- time" methods would require a large number of experiments which would be very time consuming and costly. As an alternative, the Taguchi method combines experimentation with statistical analysis to study several factors simultaneously and requires only a few experiments to evaluate the factors [12-19, 21, 23]. Hence, the time required to run the experiments is considerably less and costs are substantially reduced. Taguchi method can also be used to investigate the effects of interactions between the various factors, which can be easily missed when using conventional methods.

Though Taguchi method has been most extensively used in industrial and manufacturing sectors, their application to investigate surface quality has been very limited. Fig. 1 shows a flow chart of the Taguchi method implemented in this research work. The method consists of mainly eight steps:

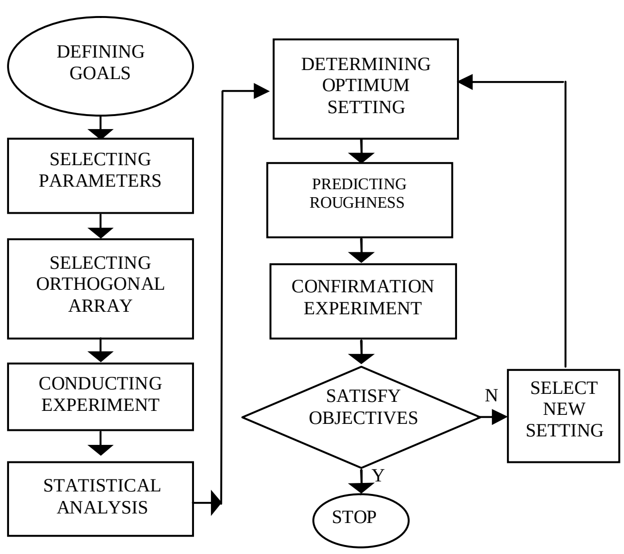

Fig. 1 Flow Chart of the Taguchi Method

1. Defining the goal
2. Selecting the parameters
3. Selecting the Orthogonal Array
4. Conducting the Experiment
5. Statistical Analysis
6. Finding optimum settings
7. Predicting roughness at optimum settings
8. Running confirmation Experiments

1.2 Taguchi techniques for quality improvement

Taguchi simplified the statistical design efforts by using orthogonal arrays and statistical analyses to evaluate experimental data. Orthogonal Array (OA) allows the researcher to make evaluations on parameter or system design settings with respect to their optimum values. Taguchi designs of experiments are most extensively used to determine the parameter values or setting required to achieve the desired function. Taguchi defined a "figure of merit" called the signal-to-noise (S/N) ratio which takes both the average and variation into account [22]. The S/N ratio is an evaluation of the stability of performance of an output characteristic such as quality of finishes or tool life.

1.3 Orthogonal arrays

Taguchi's orthogonal arrays provide a method for selecting an intelligent subset of the parameter space. In this array, the columns are mutually orthogonal. That is, for any pair of columns, all combinations of factor level occurs an equal number of times. The number of configurations or prototypes to be tested is decided by the row of the Table. The number of columns in an orthogonal array indicates the maximum number of factors that can be studied. For an example, L9 Orthogonal Array means that nine experiments are carried out in search of the 81 control factor combinations, which give the near-optimal mean and the near minimum variation away from this mean.

1.4 Background and organization of the paper

In recent past no one has included the cutter nose radius in model development. This paper illustrates the regression model development for improving the surface roughness by introducing the cutter nose radius in the machining process. This research study investigates the influence of spindle speed, feed rate, cutter nose radius and depth of cut in surface roughness using OA based DoE. The surface roughness is measured for each specimens using Taylor Hobson Talyround Profilometer. The near optimum combinations of machining parameters are arrived for the best surface roughness from Design of Experiments. Confirmation experiment is carried out to validate the regression model so developed. The experimental results infer that theoretical model predicts the exact surface quality if and when the optimal parameters are substituted. This paper is organized as follows. Section

2 is discussing problem identification phase which details the need for this investigations; Section 3 is briefing the experimental plan and also analyzing the experimental data. Section 4 presents the model development for predicting surface roughness. Section 5 illustrates Taguchi parametric design application to validate the effectiveness of the regression in the research study model. Sections 6 wrap up the crucial revelation of the experimental investigation and scope for further research.

2. Problem Identification

In CNC turning operations, achieving dimensional accuracy, minimizing tool wear rate and maintaining quality of surface finish are the main factors that any manufactures have to keep in control for customer delight. To obtain better surface smoothness, the proper setting of cutting parameters is crucial before the process takes place. As a starting point for determining cutting parameters, technologists could use the hands on data Tables that are furnished in machining data handbooks. Identifying the optimum cutting condition for a particular operation is a time consuming practice. DoE approach is the best way to address the above needs.

M/s. Q Plus Technologies, Coimbatore; a south Indian based industry had quality problem in CNC machined components. The sponsoring industry has arranged a brain-storming sitting to make a decision on the inestimable rejection of machined components in CNC turning centre. The brainstorm comprises representatives from quality control, material division and expert from manufacturing section. They have conclude that the negligence of cutter nose radius and the improper parametric combination in cutting variables during machining operation may by be the reasons for inferior quality resulting rejection of machined components. The technical crews have asked to investigate the effect and influence of cutting variables in CNC turning process. Hence this research study is undertaken how best the parameter design concept could be used in identifying and optimizing the significant cutting parameters for achieving best surface finish in CNC Turning Centre.

3. Experimental Plan and Execution

An experimental set up is established to demonstrate the use of Taguchi parameter design for identifying the optimum surface roughness with a particular combination of cutting parameters in turning centre. Jobber XL, ACE-CNC turning centre is used for conducting DoE trial (see Fig. 2). The maximum spindle speed of the machine is 4000 rpm. The tool used for the machining operation is carbide tip. EN8 Carbon Steel material having 50mm diameter and 30mm length is chosen for the experimentation. L 9 (3^4) OA is selected for Experiments plan. Table 1 gives the machining variables and its levels.

Table 1: Parameters and its Levels

Machining Parameters	Level 1	Level 2	Level 3
A - Depth of cut (mm)	0.25	0.50	0.75
B - Spindle speed (rpm)	1000	2000	3000
C - Feed rate (mm/rev)	0.05	0.15	0.25
D - Cutter nose radius (mm)	0.4	0.8	1.2

Fig. 2 CNC Turning Centre
(Courtesy – Q Plus Technologies, Coimbatore)

Table 2: Experimental Data value from L 9 (34) Orthogonal Array

Ex pt. No	Process Variable				Surface roughness (R_a) µm		
	A	B	C	D	1	2	3
1	0.25	1000	0.05	0.4	2.17	2.15	2.17
2	0.25	2000	0.15	0.8	1.78	1.77	1.76
3	0.25	3000	0.25	1.2	1.09	1.08	1.08
4	0.50	1000	0.15	1.2	2.43	2.44	2.44
5	0.50	2000	0.25	0.4	2.53	2.52	2.53
6	0.50	3000	0.05	0.8	0.57	0.54	0.58
7	0.75	1000	0.25	0.8	3.20	3.22	3.22
8	0.75	2000	0.05	1.2	0.41	0.42	0.40
9	0.75	3000	0.15	0.4	1.10	1.13	1.13

The data derived from the execution of the experiments are given in Table 2 and the results are analyzed using MINITAB 14 software. Taylor Hobson Talyrond Profilometer is used for examining the surface quality of the specimens.

4. Model development [20]

The correlation between surface roughness and process variables is defined in Eq. (1)

$$R_a = C\, d^{a1} s^{a2} f^{a3} r^{a4} \quad (1)$$

4.1 Data transformation for linearity

The mathematical model is expressed in the form of non-linear relationship in terms of process variables. Non-linear regression analysis is to be done by converting the non-linear form in to linear form and hence logarithmic transformation is performed. Table 3 represents the transformed logarithmic data values from the experimental data available in Table 2. The non-linear form is changed into linear additive through Eq. (2)

$$\ln R_a = \ln C + a_1 \ln d + a_2 \ln s + a_3 \ln f + a_4 \ln r \quad (2)$$

For simplicity, Eq. (2) is modified to Eq. (3)

$$Y = a_0 + a_1x_1 + a_2x_2 + a_3x_3 + a_4x_4 \quad (3)$$

Where, Y is the estimated response of surface roughness value on a logarithmic scale.a_0, a_1, a_2, a_3, a_4 are the estimates of the model parameters obtained from statistical software package (SSP).x_1, x_2, x_3, x_4 are the logarithmic transformation of d, s, f, r respectively.

Table 3: Transformed Logarithmic Data value

Y ($\ln R_a$)	x_1 (ln d)	x_2 (ln s)	x_3 (ln f)	x_4 (ln r)
0.7670	-1.3862	6.907	-2.995	-0.916
0.5709	-1.3862	7.600	-1.897	-0.223
0.0738	-1.3862	8.006	-1.386	0.182
0.8096	-0.6931	6.907	-1.897	0.182
0.9242	-0.6931	7.600	-1.386	-0.916
-0.5744	-0.6931	8.006	-2.995	-0.223
1.1662	-0.2876	6.907	-1.386	-0.223
-0.8915	-0.2876	7.600	-2.995	0.182
0.1133	-0.2876	8.006	-1.897	-0.916

4.2 Regression analysis

In this study MINITAB 14 software package is used to formulate the prediction model. The logarithmic transformed data value available in the Table-3 is the input to MINITAB software to perform the regression analysis. The regression analysis specified in Table 4 considers all process variables namely spindle speed, feed rate, cutter nose radius and depth of cut in CNC turning centre to investigate the influence of these machining parameters on surface roughness.

Table 4: Regression Analysis

The regression equation is
$Y = 8.39 - 0.293\, x_1 - 0.957\, x_2 + 0.605\, x_3 - 0.524\, x_4$

Predictor	Coefficient	SE Coefficient	T	P
Constant	8.3816	0.9285	9.03	0.001
X1	-0.2932	0.1207	-2.43	0.072
X2	-0.9572	0.1206	-7.94	0.001
X3	0.6052	0.0185	7.42	0.002
X4	- 0.5235	0.1207	-4.34	0.012

S = 0.163196 R-Sq = 97.3% R-Sq (adj) = 94.6%
Analysis of Variance

Source	d o f	SS	MS	F	P
Regression	4	3.8500	0.9625	35.7	0.002
Residual Error	4	0.1078	0.0269		
Total	8	3.9578			

Table 4 summarizes the results of regression analysis and ANOVA. As the Adj R^2 value comes to 94.6% in the regression analysis and the p-value comes to 0.002 in the ANOVA, the model developed for predicting the surface quality has a satisfactory goodness of fit [20].

4.3 Linear to non-linear transformation

The linear model in Equation (4) is transformed to non-linear model in Equation (5) as follows:

$$Y = 8.39 - 0.293x_1 - 0.958x_2 + 0.605x_3 - 0.524x_4 \quad (4)$$

Substituting the expressions of Y, x1, x2 , x3 and x4 in the linear model, we get,

$\ln R_a = 8.39 - 0.293 \ln d - 0.958 \ln s + 0.605 \ln f - 0.524 \ln r$

Taking exponential on both sides, we get

$$R_a = \frac{4402\ f^{0.605}}{D^{0.293}\, s^{0.958}\, r^{0.524}} \quad (5)$$

The prediction model in Equation (5) shows feed rate and spindle speed and cutter nose radius are the important parameters that have considerable effect on the surface roughness during the machining process. The **A**bsolute **P**ercent **E**rror (APE) is computed and presented in Table 5. Exponential on both sides, we get

$$\text{APE (\%)} = \frac{\text{(Model Predicted value – Observed value)}}{\text{Observed value}} \times 100$$

Table 5: Absolute Percent Error (APE)

Expt. No	Model predicted value (R_a) µm	Observed value (R_a) µm	Percentage error (%)
1	2.32	2.15	7.90
2	1.61	1.78	9.55
3	1.20	1.08	11.11
4	2.07	2.43	14.81
5	2.58	2.52	1.98
6	0.46	0.54	14.81
7	3.10	3.20	3.125
8	0.48	0.42	14.28
9	1.14	1.10	3.636

5. Data Analysis

Table 6 gives the Signal to Noise (S/N) ratios calculated using Taguchi off line design equation. As the surface roughness has to be minimized for superior quality, Taguchi's Smaller the Better quality characteristic is chosen for the analysis purposes.

$$SNLTB = -10 \log (1/n\ \Sigma\ y_i^2)$$

Where n is the number of responses and
Y_i is the response characteristics at level i.

Table 6: Summary Table for SN Ratio Calculation

Expt. No	Process Variable				S/N Ratio (dB)
	Depth of cut (A)	Speed (B)	Feed (C)	Cutter nose radius (D)	
1	0.25	1000	0.05	0.4	-6.663
2	0.25	2000	0.15	0.8	-4.959
3	0.25	3000	0.25	1.2	-0.695
4	0.50	1000	0.15	1.2	-7.735
5	0.50	2000	0.25	0.4	-8.059
6	0.50	3000	0.05	0.8	4.980
7	0.75	1000	0.25	0.8	-10.22
8	0.75	2000	0.05	1.2	7.742
9	0.75	3000	0.15	0.4	-0.985

Using the DOE based OA, the parametric level having the highest S/N ratio decides the optimum combination of settings. The response is calculated for each variable and is tabulated in Table 7. Response graph in Fig. 3 is drawn for each process variables at different levels to predict what would be the effect of process variables on surface quality, if the parametric levels are varied.

Table 7: Response Table

Levels	Depth of cut (A)	Spindle Speed (B)	Feed rate (C)	Cutter nose radius (D)
1	-4.08	-8.17	2.02	-5.20
2	-3.60	-1.75	-4.56	-3.36
3	-3.35	1.10	-6.28	-0.30
Max-Min	0.73	9.27	8.30	4.90
Rank	4	1	2	3

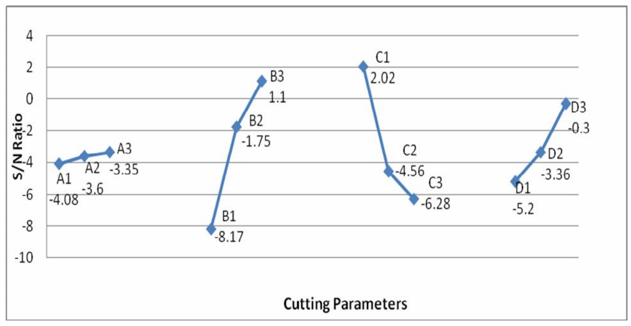

Fig. 3 Response Graph

5.1 Optimal solution

Pareto ANOVA is done to determine the near optimal combination of machining parameters and their Contribution ratios in terms of percentage (%). Table 8 shows the Pareto ANOVA results.
Table 8

Table 8: Pareto ANOVA Calculations

Process variables		A	B	C	D	Total
Sum at factor levels	1	-12.24	-24.50	6.06	-15.60	-26.68
	2	-10.80	-5.25	-13.68	-10.08	
	3	-10.05	-3.30	-18.84	-1.00	
Sum of squares of differences		7.43	1217.44	1036.30	326.07	2587.24
Contribution ratio (%)		0.30	47.05	40.05	12.60	100
Overall optimum conditions for all variables		A_3=0.75mm, B_3=3000rpm, C_1=0.05 mm/rev, D_3= 1.2 mm				

ANOVA is carried out to determine the significant factors which mostly have an effect on the surface roughness. All factors namely spindle speed, feed rate, cutter nose radius and depth of cut given in Table 9 are significant.

Table 9: Analysis of Variance

Square of variation	Sum of square	d o f	Mean of square	Fcal
Depth of cut	30.50	2	15.26	227.61
Spindle speed	134.90	2	67.45	1006.71
Feed rate	115.01	2	57.50	858.20
Cutter nose radius	25.61	2	12.80	190.29
Error	1.21	18	0.067	
Total	385.01	26		

Predicted S/N ratio for overall optimum condition
Predicted optimal S/N ratio

$$= \overline{A_2} + \overline{B_3} + \overline{C_1} + \overline{D_2} - 3(\overline{n})$$

= (-3.35) + (1.10) + (2.02) + (-0.30) - (3) (-2.97)

= 8.50dB

Confidence interval

$$\mathrm{C.I.} = \sqrt{F_{\propto(2,f_e)} \times V_e \times \frac{1}{n_{eff}}}$$

$$\mathrm{C.I.} = \sqrt{3.55 \times 0.067 \times \frac{1}{3}} = \pm 0.30$$

The predicted mean of S/N Ratio = ±0.30

Therefore, 99% confidence interval of the predicted optimal surface roughness is: 8.20 ≤ η ≤8.80 dB.

Table 10: Conformation Test Reports from the Profilometer

Sample	Trial 1	Trial 2	Trial 3	R_a (μm)	S/N Ratio (dB)
1	0.39	0.40	0.40	0.396	8.03
2	0.37	0.38	0.38	0.376	8.50
Average				0.386	8.26

5.2 Confirmation experiment

Conformation experiment was conducted at the optimum condition. The values obtained in the confirmation experiments are given in Table 10 fall within the predicted limits. The predicted optimal surface roughness falls between 8.20≤ Ra ≤8.80dB. The Confidence Interval (C.I) for confirmation runs lies within ± 0.30. The S/N Ratio value of surface roughness for confirmation runs at the optimal setting of turning process parameters is found to be 8.26dB which is within the predicted optimal S/N Ratio and hence the surface roughness is certainly optimum for the chosen machining environment.

6. Results and Discussion

The prediction model developed in the study shows that surface roughness value is directly proportional to the feed rate and inversely proportional to depth of cut, spindle speed and cutter nose radius. The percent contributions of parameters in surface roughness for turning of EN8 Steel material is spindle speed (47.05%), feed rate (40.05%), cutter nose radius (12.60%) and depth of cut (0.30%). Using the model it is easy to predict the machining response from a wide range of machining independent variables such as spindle speed, feed rate, cutter nose radius and depth of cut outside the range for experimentation resulting in more cost saving machining operations. Through experimentation the model so developed proved capable of predicting the surface roughness with about 94.6% accuracy. The important conclusion drawn from the experimental investigations of this research study are spindle speed being the most significant parameter followed by feed rate, cutter nose radius and depth of cut subject to stipulation that this particular influences of cutting conditions is applicable for the Jobber XL CNC turning centre alone and the parametric influence may vary with other turning centers. The optimized parameter combination derived from the parametric design concept is validated by confirmation trial runs for the best surface quality. L_9 (3^4) OA amounts to conducting 81 DoE for optimizing the parameters, which consumes ludicrous time. Instead of going for 81 trial runs, 9 trials were conducted to find the optimized parameter settings which saves considerable quantity of material, machine and man hours before arriving valid inference. Scope for further research includes consideration of material property say hardness and tool geometry like cutting tool angle etc. Second Order Regression Model could be formed for investigating the effects of parameters on surface quality.

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Nomenclature

Symbol	Meaning	Unit
C	Constant	
d	Depth of cut	mm
dB	Decibel	dB
DoE	Design of Experiments	
f	Feed rate	mm/rev
$F_{\alpha\ (2,fe)}$	Tabulated F ratio	
n	Number of responses	
OA	Orthogonal Array	
r	Tool nose radius	mm
Ra	Surface roughness	mm
s	Spindle speed	rpm
S/N	Signal to noise	
V_e	Pooled Error Variance	
Y_i	Response characteristics	

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