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A robust parameter design study in turning bright mild steel based on taguchi method

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ABSTRACT: The aim of the robust design technique is to minimize the variance of the response and orthogonal arrays are an effective simulation aid to evaluate the relative effects of variation in different parameters on the response with the minimum number of experiments. Using this technique of robust design the quality of a product or process can be improved through minimizing the effect of the causes of variation without eliminating the causes. This study discusses an investigation into the use of Taguchi Parameter Design for optimizing surface roughness generated by a CNC turning operation. Controlled factors include spindle speed, feed rate, and depth of cut in straight turning of bright mild steel bar using HSS tool. It have been studied in review research that feed rate has got the most significant influence in controlling dimension characteristics, material specially observed in turning bright mild steel size possibility & emissions.

Keywords: Robust parameter design, Surface Roughness, Feed, Speed & Depth of cut.

I. INTRODUCTION

Surface roughness is an important parameter in manufacturing engineering with significant influence on the performance of mechanical parts. Owing to the need for improvement of machining parameters in order to obtain a prescribed surface roughness, new developments have been recently investigated. The present study applied extended Taguchi method for predicted optimal setting ensured minimization of surface roughness and designing high quality product ,processes at low cost is an economic and technological challenge. Therefore a systematic and efficient way to meet this challenge is a new method of design optimization for performance, quality & cost, called Robust Design, shown in Fig.1 which is capable of

1. Making product performance insensitive to raw material variation, thus allowing the use of lower grade alloys & components in most cases,
2. Making designs robust against manufacturing variation, thus reducing labor & material cost for rework & scrap,
3. Making the design least sensitive to the variation in operating environment, thus improving reliability and reducing operating cost, and
4. Using a new structured development process so that engineering time is used more productively.

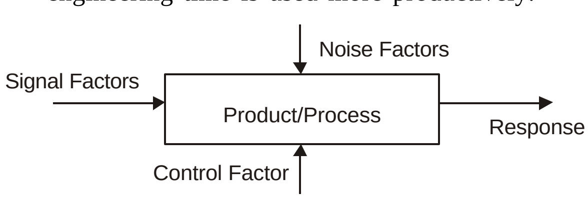

Fig. 1: Block diagram of robust design.

The Robust Design method uses a mathematical tool called Orthogonal Arrays to study a large number of decision variables with a small number of experiments. It also uses a new measure of quality called signal-to-noise (S/N) ratio to predict the quality from the customer's perspective. Thus, the most economical product & process design from both manufacturing & customers' viewpoint can be accomplished at the smallest, affordable development cost.

II. METHODOLGY

Taguchi suggested that one may summarize the observation in each outer array with a summary statistic that provides information about mean and variance. The summary statistic is computed across four observation is called a signal-to-noise ratio (SNR), and the statistical analysis is done using the SNR as the response variable. There are many different SNRs. However, there are four primary ones suggested by Taguchi. The choice depends on the goal of the experiment. As in case of response surface work, there are three specific goals:

- The smaller the better. The experimenter wishes to minimize the response.
- The large the better. The experimenter wishes to maximize the response.
- The target is best. The experimenter wishes to achieve a particular target value.

Taguchi design is a powerful method utilized to improve process performance, yield and productivity. This approach is focused on eliminating the sources of poor quality so products and processes are robust to the variability. Taguchi utilized the statistical design of experiment in the form of orthogonal array to determine the optimal settings of the process and achieve the operation on-target. These signal-to-noise ratios are determined from the quadratic loss function Eqn.1

$$L(y) = k(y - T)^2 \qquad ...(1)$$

Therefore smaller the better have chosen to minimize the surface roughness by controlling variable feed, speed and depth of cut.

A. The smaller the better

For quality characteristics which can never take negative values and their ideal value will be zero and as their value increases, performance becomes progressively worse as shown in Fig 2. The loss is minimized as the output value is minimized.

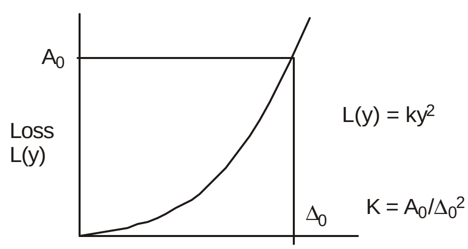

Fig. 2: Quality Loss for smaller the better type.

Thus, the quadratic lossfunction $E_z\ (y - 0)^2$ leads to the performance criterion

$$S/N_{small} = -10 \log \Sigma y^2/n \qquad ...(2)$$

Here y is the average observation. In the SNR calculation, Σ implies summation over n response values at the outer array points. Because the -log transformation is used, one seek to maximize SNRs. The signal-to-noise ratio SNRT will be utilized if the objective is to reduce the variability around a specific target. However, if the largest response is desired, the SNRL will be selected. The SNRS is appropriate when the response is desired to be as small as possible.

III. PLANNING AND SETUP

In order to meet purpose in terms of both efficiency and effectiveness, this study will utilize the Taguchi Parameter Design methodology. This includes selection of parameters, utilizing an orthogonal array, conducting experimental runs, data analysis, determining the optimum combination, and verification. The working ranges of the parameters for subsequent design of experiment, based on Taguchi's L9 Orthogonal Array (OA) design have been selected. The process variables with their units (notations) are listed in table 1.

Table 1 : Variable level used in experiment.

Level	Spindle speed/ Cutting speed	Feed rate	Depth of cut
Low	825 rpm/65 mm per min	0.06mm/rev	0.1 mm
Medium	1150 rpm/90 mm per min	0.12mm/rev	-
High	1475 rpm/115 mm per min	0.18mm/rev	-

Cutting tool used : Tool material-HSS, MIRANDA S-400 STS (5/8',*6") 15.88*152.80 mm

Work piece used- AISI 1040 bright mild steel bars (diameter 25mm and length 100mm).

A. Data collection

MS bars (of diameter 25 mm and length 100mm) required for conducting the experiment have been prepared first. Nine numbers of samples of same material and same dimensions have been made. Then, using different levels of the process parameters nine specimens have been turned in CNC lathe accordingly. Then surface roughness and surface profile have been measured precisely with the help of a portable stylus-type surfocoder-1200. The results of the experiments have been shown in Table 2. Confirmatory tests have also been conducted finally to validate optimal results. Considering that the literature suggested that feed rate has a much higher effect on surface roughness than the other two parameters, it was determined that a robust but efficient experiment would include feed rate with more levels than the other factors. The feed rate factor Spindle speed in this experiment therefore has three levels: 0.065, 0.130, and 0.195 mm per revolution and 825, 1150, 1475 rpm respectively. Depth of cut was then given only one levels; d = 0.10 mm. These ranges of feed rate would be expected to produce a good finish on the parts , and the spindle speed and depth of cut were selected to meet the hardware setup specifications while providing reasonable variability in the experiment.

Table 2 : Orthogonal array & observed Ra value.

Std Order	Run	Feed	Spindle speed	Depth of cut	Surfce roughness response1	SNR response2
4	1	0.065	1150	0.10	1.311	– 2.345
9	4	0.195	1475	0.10	1.365	– 2.702
1	8	0.065	825	0.10	1.372	– 2.751
6	9	.0195	1150	0.10	1.332	– 2.493
5	2	0.130	1150	0.10	1.287	– 2.194
7	3	0.065	1475	0.10	1.357	– 2.654
2	5	0.130	825	0.10	1.347	– 2.587
8	7	0.130	1475	0.10	1.342	– 2.588
3	6	0.195	825	0.10	1.352	– 2.622

It was also intended that this would allow the selection of an orthogonal array with as few runs as possible, while still allowing for a robust experiment. This is included as a separate outer array, which requires a replication of each run in the orthogonal array for each noise condition. A customized array, with all factors and noise conditions included, in Table 2. The average roughness (R_a) is the area between the roughness profile and its mean line, or the integral of the absolute value of the roughness profile height over the evaluation length. Values of surface roughness (R_a) were measured by Surfcorder SE-1200. Three measurements of surface roughness (R_a) were taken at different locations and the average values are shown in the below table 2.

In figure 3 shows matrix plot of run, feed, speed, depth of cut, response it can be observed that the mean surface roughness of 9 experiment various between1.287 to 1.372 um where the target value is 1.2 um. Now in order to evaluate the relative effect of variation in different parameters on performance the analysis of variance (ANOVA) is performed.

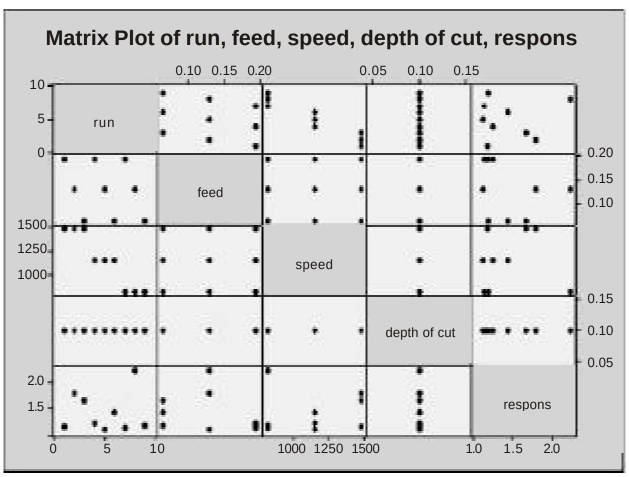

Fig. 3: Matrix plot of run, feed, speed, depth of cut, response.

B. Analysis of variance

The analysis was performed using a statistical package, Design Expert 7 version 7.6.1, to quantify the effect of the machining factors on the responses. A better feed or a relative feed incorporating the error variance for relative effect of different factor can be obtained by decomposition of variance, which is commonly called as analysis of variance. ANOVA will generate the variance ratio F for different factors. Large value of F means the effect of factor is large compared to error variance.

If F less than 1(one), factor is small and can be neglected. If F > 2 means factor is not quite small. If F > 4 factor effects is quite large.

Total sum of square = grand total sum of square -sum of square due to mean.

Error variance = sum of square due to error/ degree of freedom for error

The analysis of variance (ANOVA) in table 3 shows that depth of cut (C), spindle speed (B) and feed rate (A) have a significant effect on the surface roughness, since their p-values are very small (<0.5). Moreover, the interactions, depth of cut*spindle speed and spindle speed*feed rate, are also significant.

Table 3 : Analysis of variance
[Classical sum of squares -Type II]

Source	Sum of Squares	df	Mean Square	F-value	p-value	Prob
A-feed	*0.96*	*2*	*0.48*	*10.62*	*0.0107*	significant
Residual	0.27	6	0.045			
Cor Total	1.23	8				
Model	**0.96**	**2**	**0.48**	**10.62**	**0.0107**	**significant**

The Model F-value of 10.62 implies the model is significant. There is only a 1.07% chance that a "Model F-Value" this large could occur due to noise. Values of "Prob > F" less than 0.0500 indicate model terms are significant. In this case A are significant model terms. Values greater than 0.1000 indicate the model terms are not significant.If there are many insignificant model terms (not counting those required to support hierarchy),model reduction may improve our model.

C. Analysis signal-to-noise ratio

Signal-to-noise ratio (SNR) is utilized to measure the deviation of quality characteristic from the target. In this experiment, the response is the surface roughness which should be minimized, so the desired SNR characteristic is in the category of smaller the better. Table 4 shows the SNR of the surface roughness for each level of the factors. Since the experimental design is orthogonal, it is then possible to separate out the effect of each machining parameter at different level. The mean of S/N ratio for factor A (Feed) at level 1, 2, 3 can calculated by averaging the S/N ratios for experiment for level1 – 1, 4, 7, for level 2 – 2, 5, 8, and for level 3 – 3, 6, 9, respectively. The mean of S/N ratio for each level of others factors can e computed in similar manner.

Table 4 : SNR of the average surface roughness at different factor levels

Level	Depth of cut	Spindle speed	Feed rate
1	2.562	2.458	2.617
2	-	2.530	2.520
3	-	2.599	2.439
Δmax-min	0.054	0.141	0.176
Rank	3	2	1

The difference of SNR betwwen level 1 & 3 indicate that feed rate contributes the highest effect (Δmax-min = 0.176) on surface roughness followed by spindle speed (Δmax-min = 0.141) and depth cut (Δmax-min = 0.054).

Final Equation in Terms of Coded Factors:

SNR= –2.49–0.033 * A[1]–0.021 * A[2]+0.079 * B[1]+0.021 * B[2]+0.043 * C–0.058 * A[1]B[1]+0.050 * A[2]B[1]+0.069 * A[1]B[2]+5.333E–003 * A[2]B[2]–0.015 * A[1]C–0.071 * A[2]C+0.018 * B[1]C-0.029 * B[2]C–0.16 * A[1]B[1]C+0.15 * A[2]B[1]C+0.19 * A[1]B[2]C -0.086 * A[2]B[2]C (3)

D. Analysis average surface roughness

The data in Table 2 can then be analyzed using informal and statistical methods. This begins with determining the effects of each treatment level on the response and S/N ratio. The effects are merely the means of the response and S/N ratio at each level for each factor, which are shown in Table 5. The average of surface roughness for factor A (Feed) at level 1, 2, 3 can calculated by averaging the surface roughness for experiment for level1 – 1, 4, 7 for level 2 – 2, 5, 8 and for level 3 – 3, 6, 9 respectively. The average of surface roughness for each level of others factors can e computed in similar manner and confirm the results from the average surface roughness at different level.

Table 5 : Average surface roughness at different factor levels.

Level	Depth of cut	Spindle speed	Feed rate
1	1.234	1.331	1.337
2	–	1.335	1.336
3	–	1.347	1.344
Δmax-min	0.094	0.017	0.007
Rank	3	2	1

The difference of average surface roughness between level 1 and 3 indicates that feed rate contributes the highest effect (Δmax-min = 0.094) on the surface roughness followed by spindle speed (Δmax-min = 0.017) and depth of cut (Δmax-min = 0.007). As a result of the analysis, the regression equation is shown as follows.

Final Equation in Terms of Coded Factors:

Surface roughness = +1.33+0.016 * A[1]–4.056E–003 * A[2] –0.011 * B[1]–.556E–04* B[2]–6.611E–003 * C+8.889E –003 * A[1]B[1]–6.778E–003 * [2]B[1]

–1.111E–003 *A[1]B[2]–7.778E–003 * A[2]B[2]+5.778E –003 * A[1]C+7.944E–003 * A[2]C–8.222E–003 * B[1]C+9.778E–003 * B[2]C ...(4)

The formed equation was validated by test and the error between the theoretical and actual was very negligible.

E. Model adequacy checking

After the ANOVA was performed the model adequacy checking was conducted to verify the normality assumption of the residual. Normal probability plot in figure 4 shows that the residual follows a straight line pattern and there are no unusual patterns or outliers. As a result, the assumptions regarding the residual were not violated. The "Pred R-Squared" of 0.5043 is not as close to the "Adj R-Squared" of 0.7063 as one might normally expect. This may indicate a large block effect or a possible problem with your model and/or data.

Table 6 : Model adequacy checking.

Std. Dev.	0.21	R-Squared	0.7797
Mean	1.33	Adj R-Squared	0.7063
C.V. %	14.21	Pred R-Squared	0.5043
PRESS	0.61	Adeq Precision	6.437

Things to consider are model reduction, response tranformation, outliers, etc."Adeq Precision" measures the signal to noise ratio.A ratio greater than 0.7 is desirable. Our ratio of 6.437 indicates an adequate signal. This model can be used to navigate the design space.

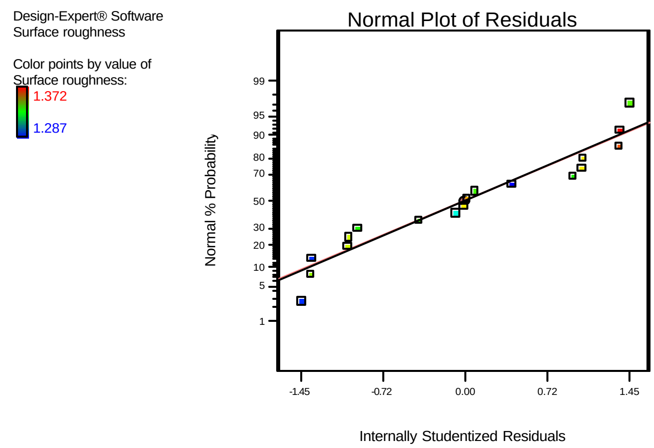

Fig. 4 : Normal plot residual.

The residual vs predicted value plot is shown in figure 5 and show a random pattern of residual both sides of 0. Thetre are not any recognizable pattern in residual plot and non of residual are too high.

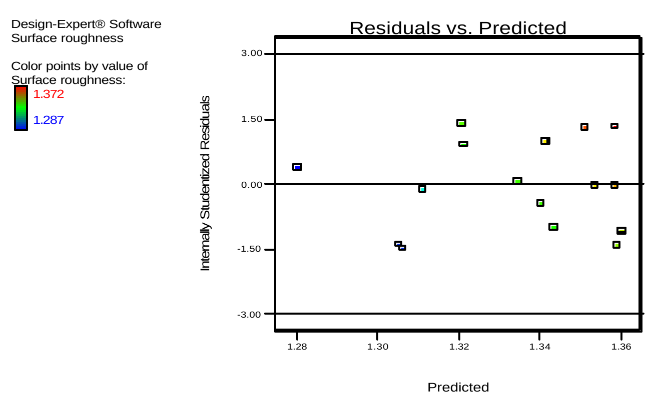

Fig. 5 : Residual vs. predicted surface roughness.

The main interaction plots points out that surface roughness should be minimized when depth of cut is set to level (0.0mm) while spindle speed and feed rate are set to medium level (1150 rpm and 0.130 mm/rev). All interaction plot in Fig. 6 & 7 also conclude in same manner as the main effect plots.

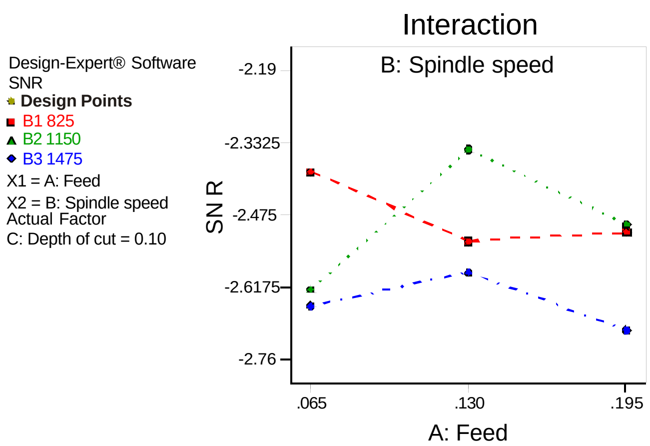

Fig. 6 : Main interaction between surface roughness, spindle speed and feed.

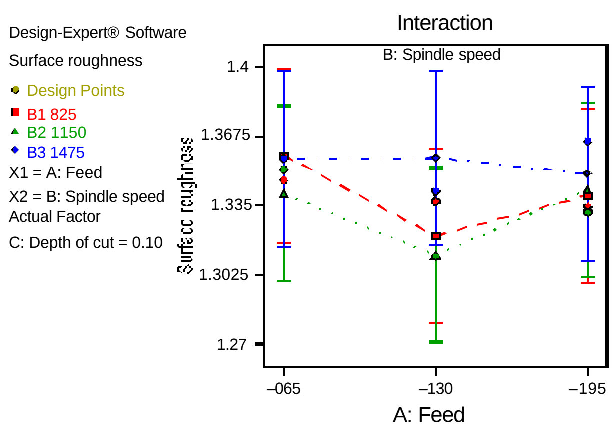

Fig. 7 : interaction between SNR, spindle speed and feed.

The graphical method was also employed to illustrate the range of controllable factors at which the minimization of surface roughness is achieved. Moreover, the regression model for the surface roughness was derived.

IV. RESULTS AND DISCUSSION

After the optimal conditions of machining factors were determined a confirmation test was conducted to verify the experimental results. The confirmation test is a repetition of the experiment at selected optimal levels of factors with the purpose of obtaining the predicted value of the quality characteristic. As a result, nine bright mild steel work pieces were sampled and tested by following the optimal conditions as follows: depth of cut 0.1 mm, feed rate 0.130 mm/rev and spindle speed 1150 rpm. According to table 7, since the 95% confidence interval of the predicted surface roughness (1.33 μm, 1.34μm) includes the observed average (Ra 1.3372 μm), there is no significant difference between these two values.

Table 7 : Results of the confirmation experiment.

Response	predicted average	Confidence interval of Predicted average		Observed average
		95% low	95% high	
Ra	1.33	1.32	134	1.3372

Industry Application: The most important contribution of this research is the determination of the best conditions for manufacturing the turning of bright mild steel parts in automobile industry, which lead to a significant reduction in the surface roughness. Before implementing the optimal conditions, each cutting parameter was set by manufacturers as shown in table 8. After the new conditions were introduced, the surface roughness was significantly reduced from 1.3372 μm to 1.33 μm. The optimal parameter combination for minimum surface roughness / SNR is found A2B2C1.

Table 8 : Results of the optimization.

Factors	Before optimization	After optimization
Depth of cut	0.1 mm	0..1 mm
Spindle speed	825	1150 rpm
Feed rate	0. 065 mm/rev	0.1.30 mm/rev
Ra	1.3372 μm	1.33μm

With model validation, the model developed proved to be accurate and has the capability to predict the value of the response within the limits of the factors investigated. After the model was implemented to optimize the cutting conditions, the result showed that there was an 11% reduction in the surface roughness.

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