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Research paper

Enhancing surface quality of en31 steel using Taguchi robust design

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Abstract

This study employs Taguchi's robust design and regression to investigate how milling process parameters affect EN31 steel machin-ability. Three parameters—cutting speed, feed per tooth, and depth of cut—underwent nine experiments using Taguchi's L9 or-thogonal plan on a CNC milling center. Optimal settings were determined through mean analysis (ANOM), while analysis of vari-ance (ANOVA) with 95% confidence assessed parameter impact on surface roughness. Notably, feed per tooth displayed substantial influence (75.351%) on surface roughness. Regression analysis effectively aligned predictions with experimental outcomes, and a confirmation test validated successful Taguchi optimization.

Keywords: *EN31 Steel; Taguchi Robust Design; Optimization; Surface Roughness.*

1. Introduction

This EN31 steel is extensively used in a variety of industrial applications for its attractive characteristics in terms of machinability, hardness, compressive strength, and its high degree of abrasion and wear resistance[1]. By its character and appealing properties, this type of steel is widely used in diverse industrial applications and finds a place for components susceptible to severe abrasion, wear, and heavy surface loading [2]–[4]. EN31 steel is widely preferred for the manufacturing of bearings, bedding rolls, punches, and dies[5]–[7]Roughness is significant in determining the efficiency of machinery components since cracks lead to unwanted effects such as corrosion and failure, thereby playing a vital role in estimating manufacturing costs. Surface roughness, a measure of smoothness, greatly impacts the fit of mating components, the capability to survive corrosion, the flow along pipelines, and the aesthetics of the components. A measure of the smoothness of surfaces, surface roughness defines the cost of components, as it has a high influence on the manufacturing cost. Thus, to achieve a superior surface finish, it is now pivotal to offer optimal cutting conditions.
Various researchers [5]–[13] studied the influence of various process parameters on the surface quality of a product and found the output has been significantly affected by these input variables. Caro et al.[13] reported cutting speed and rack angle significantly affected the output response surface roughness of AA6061 during turning operation. Bolar et al[14]studied the parametric effect on the surface quality of a thin-walled component while performing milling operations and found various parameters showed a significant effect on output re-sponse. Vijay and Krishnaraj[15]revealed that the depth of cut highly influences the cutting force compared to other cutting variables and the feed rate has the highest contribution to surface roughness as compared to other process variables. Sathyamoorthy et al.[16] investigated the optimization of surface roughness during the milling of AM60 alloy. They reported that feed rate comes as the most significant param-eter which is followed by the depth of cut and spindle speed. Khurshid et al.[17] conducted a study to explore the influence of different input parameters on EN9 steel's surface roughness, employing Taguchi's robust design methodology. The findings underscored the sub-stantial impact of feed rate on surface roughness. The study's literature review revealed a widespread focus on investigating diverse input variables to establish optimal parameter ranges, enhancing surface quality, tool life, and cost-effectiveness while bolstering productivity.
In the current research, an analysis was performed on the effects of cutting speed, feed per tooth, and depth of cut on EN31 steel's surface roughness. Taguchi's robust design was employed to optimize the output response. The utilization of analysis of variance enabled the identification of significant relationships among control factors within the experimental design. These research findings offer valuable insights for process guidance, contributing to the enhancement of workpiece quality.

2. Materials and research methodology

2.1. Materials

In the current study, the workpiece used was EN-31 steel with dimensions 200mm x 200mm × 40 mm. The chemical composition of EN31 steel as assessed by spectroscopy is given in Table 1. A three-axis vertical milling centre using a 12mm diameter carbide end mill was used to conduct the present experimentation (see Fig. 1a). To measure the surface roughness, an SR-tester Mitutoyo Surftest SV-2100 (see Fig. 1b) was used to measure the surface roughness.

Table 1: Chemical Composition of EN-31 Steels (Wt.%)

Element	Fe	C	Si	Mn	S	P	Cr
Com.(%)	95-96	0.70-1.20	0.10-0.35	0.30-0.35	0.05	0.05	1.0-1.6

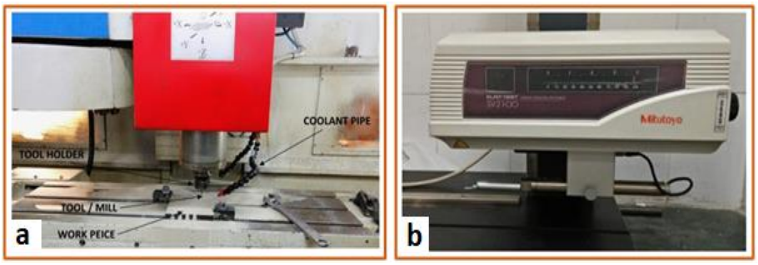

Fig. 1: (A) Milling Setup (B) Surface Roughness Tester.

3. Experimental design

3.1. Design of experiments (DOE)

Experimentation is one of the very important parts of the engineering method and they are conducted to evaluate the performance of the process and the system. A complete process is a combination of several input variables and output variables. The input variables are usually controllable and may contain some un-controllable variables as well. A general approach to experimenting is known as the strategy or design of the experiment. There are several strategies that an experimenter may adopt while planning experimentation.The various approaches of experimentation may include:

- Best guess approach.
- One factor at a time (OFAT).
- All factors at a time (AFAT).
- Factorial design (Full/Fractional).

Among the above, the best and correct approach for experimentation based on multiple factors is the factorial design where variables are varied together instead of one at a time. In full factorial design all combinations are studied and can be used when we have a limited number of variables each with multiple levels, however, if the number of factors and their levels increases it may become difficult to evaluate the design under the full factorial approach. In that case, a fractional factorial design can be adopted where a fraction of total runs can be used. The design of the experiment helps to conduct the experimentation more scientifically and helps to improve the process and the output.

3.2. Taguchi technique

Numerous variables influence the surface roughness produced by machining techniques. Several of these variables are changeable during machining and thus are referred to as "control variables." While un-controllable variables are referred to as “noise factors”. Robust optimization seeks to identify the combination of control factor settings that minimizes process output variance owing to the presence of noise sources. Taguchi approach is a method for designing robust parameters that combine orthogonal tests and signal-to-noise ratio technology [18], [19].The approach makes use of conventional orthogonal arrays, which streamlines the process to minimize the total number of experimental runs. This method provides an easy and precise approach to specifying optimum factors in a machining process. Taguchi's approach is based on the philosophy of robust design, where the loss function is utilized to determine the difference in values between the desired and calculated values [20]–[22].

For each experimental run, the S/N ratio is evaluated using SN analysis. In the present study, the smaller value of surface roughness is expected; thus, the smaller- the-better-quality characteristic is used as given in Eq.1.

$$S/N = -10\log\left[1/n \sum_{i=1}^{n} {y_i}^2\right] \quad (1)$$

Where ‘y’ represents an observed data at ith run ‘n’ represents total number of runs.

3.3. Selection of control parameters

In the present study three parameters, each at level three were selected to investigate their effect on response output (surface roughness), see Table 2

Table 2: Process Parameters with Levels

Parameter	Symbol	Unit	Level-1	Level-2	Level-3
Cutting speed (CS)	A	m/min	100	120	140
Feed per tooth (FT)	B	mm/rev	0.05	0.10	0.15
Depth of cut (DOC)	C	mm	0.5	1.0	1.5

4. Results and discussion

4.1. Evaluationof s/n ratio

Using the L_9 orthogonal array nine experimental runs were conducted. The workpiece with nine experimental runs is shown in Fig. 2. The evaluation of the signal-to-noise (S/N) ratio is found to be very effective in obtaining the optimal combination of various parameters. After conducting all nine experiments as per L_9 – orthogonal plan the surface roughness (Ra) for each combination was measured. In the present study, to improve the quality of the product and lower the production costs the lowest value of surface roughness is very significant. Thus, we choose the "smaller-the-better' 'quality characteristics approach to calculate the SN ratio (Eq. (1)). Also, Table 3. shows values of surface roughness and SN ratio for each combination. At the end of the experimentation, the calculated average surface roughness was 2.955 µm.
Similarly, the average value for the S/N ratio was -9.125 dB. The effect of each factor on surface roughness was analyzed from the S/N ratio response table given in Table 4. This table shows the optimal levels of each factor which tends to minimize the surface roughness. The adequate level for each factor was obtained according to the highest level of SN ratio in the SN response table, and according to which, the optimal combination of factors so generated is $A_1B_1C_1$, factor A (level= 1, SN = -8.502), factor B (level1, SN = -6.403) and factor C (level 1, SN = -8.325). In other words, the carbide tool helps to achieve an optimum value of surface roughness at CS (A_1) 100 m/min, FT (B_1) 0.05 mm/rev, and at a DOC (C_1) 0.5 mm.

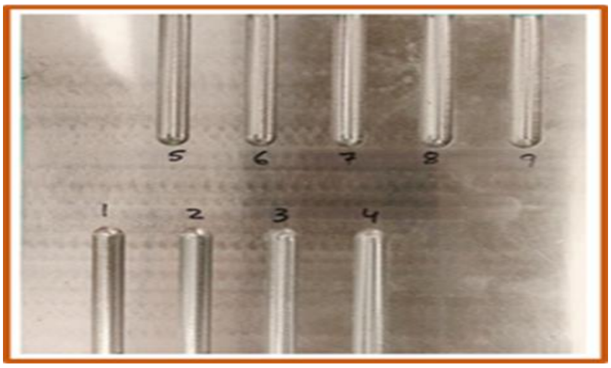

Fig. 2: Workpiece with Nine Milling Runs.

Table 3: Experimental Results and SN Ratio

Exp. No	A	B	C	Ra(µm)	R-ratio (dB)
1	100	0.05	0.5	0.17	-4.725
2	100	0.10	1.0	2.828	-9.029
3	100	0.15	1.5	3.869	-11.751
4	120	0.05	1.5	2.750	-8.786
5	120	0.10	0.5	2.905	-9.262
6	120	0.15	1.0	3.486	-10.846
7	140	0.05	1.0	1.927	-5.697
8	140	0.10	1.5	3.566	-11.043
9	140	0.15	0.5	3.543	-10.987

Here, $M_{Ra=}$ 2.955µm, and M_{Ra}- SN= -9.125 dB

Table 4: SN Ratio Response Table for Ra

S. No.	Symbol	Level 1	Level 2	Level 3	Delta (Range)
1	A	-8.502	-9.632	-9.243	1.130
2	B	-6.403	-9.779	-11.195	4.792
3	C	-8.325	-8.525	-10.527	2.202

4.2. Experimental results and their evaluation

The changes in the average S/N ratio with the variation of factors are shown in Fig. 3. Surface roughness offers a decreasing approach with increasing spindle speed [23]. The tool-chip contact area is decreased with increment in cutting speed and the friction is also decreased thus, results in an improvement in surface quality. Also, an increment in cutting speed raises the temperature in the cutting area, which results in the increment of thermal and mechanical loads, and this increases the deformation of the cutting tools. Also, feed per tooth was found the most significant factor. Since output response is a function of feed per tooth, an increment in the feed per tooth resulted in a large increase in output, which is the surface roughness[24]. Also, tool wear increases with increment infeed per tooth and cutting speed. Fig 5 depicts the parametric effect on surface roughness.

4.3. Variance analysis (ANOVA)

ANOVA is a statistical tool used to analyze the relationships between different factors in an experimental design, aiding in making informed decisions based on the collected data[25]. In essence, ANOVA assists in uncovering the significant connections among control factors within a test design[26].The outcomes of the ANOVA analysis are summarized in Table 5. For each factor, the calculated F-values are juxtaposed with the critical F-value derived from the F-table. This comparison helps determine whether a factor's effect is statistically significant. The analysis was conducted with a confidence interval of 95% and a significance level of 5%. The findings unveiled that among the factors, feed per tooth has the most pronounced impact on surface roughness[27]–[29]. This effect was substantiated by a substantial percentage contribution of 75.351%. In comparison, the depth of cut and cutting speed exhibited contributions of 18.442% and 4.094%, respectively, as visually depicted in Figure 5. These percentage contributions play a crucial role in elucidating the degree of influence that each process parameter holds over the overall process performance.

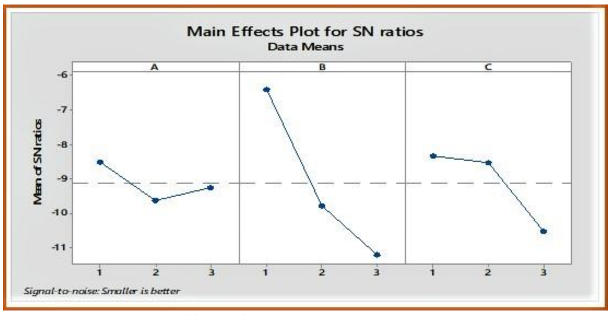

Fig. 3: Effect of Factors on Average SN Ratio.

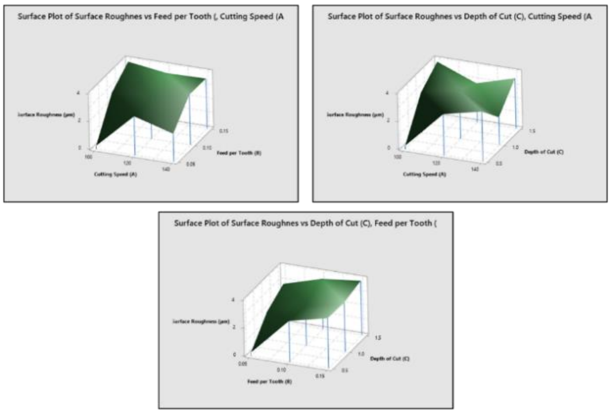

Fig. 4: Effect of Factors on Average SN Ratio.

Table 5: Results of Analysis of Variance for Surface Roughness

SOV	SS	DOF	MS	F-value	%cont.
A	1.97	2	0.9879	1.940	4.094
B	36.36	2	18.1815	35.690	75.351
C	8.90	2	4.4501	8.740	18.442
Error	1.019	2	0.5094	-	2.111
Total	48.25	8	-	-	100

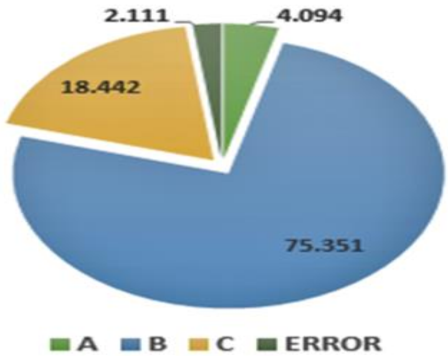

Fig. 5: Effect of Factors on Average SN Ratio.

4.4. Regression analysis of surface roughness

Whenever there is a connection between a dependent variable (output) and an independent variable (input), the analyses of these variables can be done through a regression model28–30). In the present study, the dependent variable is the surface roughness, while as, cutting speed, feed per tooth, and depth of cut are the independent variables. Regression analysis was used to obtain a predictive equation. The predictive equation, which was obtained through a linear regression model for surface roughness is as

$$\mathrm{Ra_l} = -0.609 + 0.000205\,\mathrm{A} + 0.002999\,\mathrm{B} + 6.71\,\mathrm{C}$$

$$\mathrm{R-Sq} = 91.94\%\ \mathrm{R-Sq(adj)} = 87.10\% \quad (2)$$

Where $\mathrm{Ra_l}$ represents the predictive equation of surface roughness. The comparison between experimental and predicted values generated by the linear regression model is given in Fig. 6. Also, the R2 value, generated by linear regression for surface roughness is 91.94 %.
The predictive equation which was generated through quadratic regression model for surface roughness is given

$$\mathrm{Ra_q} = -0.96 + 0.00186\,\mathrm{A} - 0.000001\,\mathrm{A}^2 + 0.00820\,\mathrm{B} - 0.000003\,\mathrm{B}^2 - 30.8\,\mathrm{C} + 124.9\,\mathrm{C}^2$$
$$\mathrm{R-Sq} = 99.25\%\ \mathrm{R-Sq(adj)} = 97\% \quad (3)$$

Where Ra_q represents the predictive equation for surface roughness. The comparison between test values and the predictive values, generated by the quadratic regression model is given in Fig. 7. Quadratic regression shows a good relationship between predicted and actual values. Also, the R2 value generated by quadratic regression for surface roughness is 99.25 %. Thus, the quadratic analysis gave more intensive results as compared to the linear method.

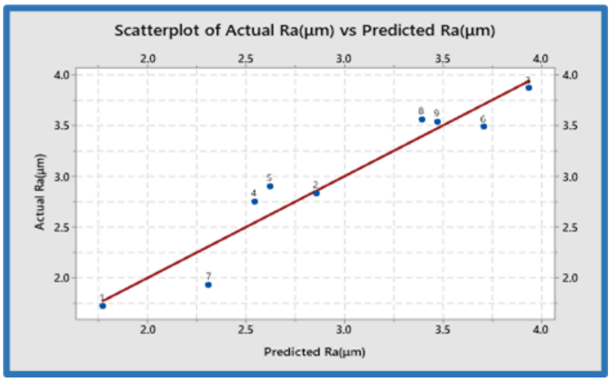

Fig. 6: Predicted and Actual Values Comparison for Ra Using Linear Regression.

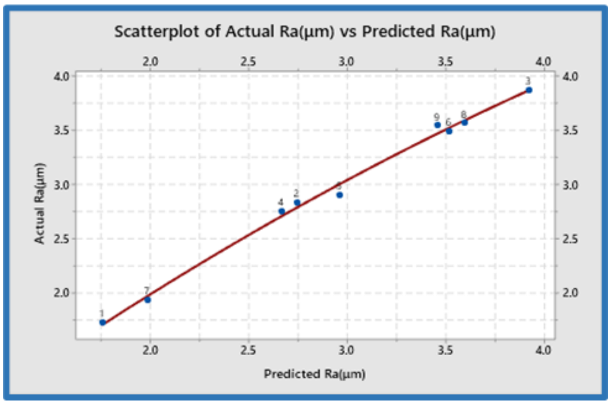

Fig. 4: Predicted and Actual Values Comparison for Ra Using Quadratic Regression.

Table 6: Mean Response Table for Surface Roughness

Levels	Factors		
	A	B	C
1	2.806	2.133	2.723
2	3.047	3.099	2.747
3	3.012	3.632	3.395
Delta	0.543	1.499	0.672

4.5. Estimation of optimum surface roughness

A confirmation test is required to validate the optimized setting. Thus, to estimate, optimum surface roughness, (Eq. (4)) given below were used.

$$Ra_{opt.} = (A_1 - T_{Ra}) + (B_1 - T_{Ra}) + (C_1 - T_{Ra}) + T_{Ra} \quad (4)$$

Where, A_1, B_1, and C_1 represent the optimum level of average surface roughness. Also, T_{Ra} denotes the average of all surface roughness values which were obtained from the experimental test as given in Table 6.
here A_1=2.806, B_1=2.133, C_1=2.723, and T_{Ra}=2.954
Using (Eq. (4)), we have:

$$Ra_{Opt.} = [(2.806 - 2.954) + (2.133 - 2.954) + (2.723 - 2.954) + 2.954] = 1.754\ \mu m \quad (5)$$

Similarly, we have;

$$Ra_{Random.} = [(2.806 - 2.954) + (3.632 - 2.954) + (3.395 - 2.954) + 2.954] = 3.925\ \mu m \quad (6)$$

Confidence interval (CI) for estimated Ra, the given below equation were used:

$$CI_{Ra} = \sqrt{F_{\propto,1,f_e,} V_e [\frac{1}{n_{eff}} + \frac{1}{R}]} \quad (7)$$

Also,

$$n_{eff} = \frac{N}{1 + T_{dof}} \quad (8)$$

Where, $F_{\propto,2,f_e,}$ is the F- ratio at 95 % CI and $\propto$ represents significance level, f_e represents error DOF, $V_e$denotes error variance, n_{eff} represents effective replication number, whereas, R represents replication number for confirmation experiments (Eq. (7)), N represents the total number of experimental runs. T_o represents a total degree of freedom of main factors (Eq. (8)).
$F_{0.05,1,2}$ =18.512 (F test - table), V_e= 0.509 (Table 7), R= 3, N= 9, T_{dof}= 6.
From (Eq. (8)), we have;

$$n_{eff} = \frac{N}{1+T_{dof}} = \frac{9}{1+6} = 1.285 \quad (9)$$

Putting values in (Eq. (7)), we have;
The confidence interval calculated is ± 3.237
The estimated optimal surface roughness at 95 % CI is:

$[Ra_{opt} – CI_{Ra}] < Ra_{exp} < [Ra_{opt} + CI_{Ra}]$

i.e., [1.754-3.237] < 1.723 < [1.754+ 3.237] = -1.483 < 1.723 < 4.991

Since the Ra obtained from the test falls within confidence interval limits. Thus, we can say the Taguchi method successfully helps to achieve optimization for surface roughness at a significance level of 5%.

4.6. Confirmation test

At optimum and random levels, confirmation tests of factors were conducted for the Taguchi method and regression equations. The comparison between results obtained from experimental tests and the values predicted by Taguchi and regression equations (Eqns. (2) - (3)) is given in Table 7. It was found that the experimental values and the predicted values fall close to each other. The error values calculated for surface roughness were found within acceptable limits. Thus, we can say the output obtained from the confirmation tests reveals a successful optimization.

Table 7: Predicted and Confirmed Test Values by Taguchi Andregression Model

Level	Taguchi technique			Regression (linear)			Regression (quadratic)		
	Exp	Pr	Er%	Exp	Pr	Er%	Exp	Pr	Er %
$A_1B_1C_1$ (Optimum)	1.72	1.75	1.79	1.72	1.76	2.55	1.72	1.75	1.74
$A_1B_3C_3$ (Random)	3.86	3.92	1.86	3.86	3.93	1.78	3.86	3.92	1.39

5. Conclusions

In the present study, Taguchi's robust design was used to generate an optimal combination of various process variables in the milling of EN31 steel. Also, to evaluate the experimental results ANOVA was used.

1) The optimum levels of independent process variables to minimize dependent process variable (surface roughness (Ra)) were successfully developed using SN values. The optimal combination obtained at $A_1B_1C_1$ (i.e., cutting speed (A) = 100 m/min, feed per tooth(B) = 0.05mm/rev, depth of cut C) =0.5 mm) respectively.
2) Statistical analysis revealed that the feed per tooth (B) significantly affects the surface roughness (Ra) at 75.351% contribution, whereas cutting speed (A) and depth of cut (C) were found insignificant.
3) Quadratic regression models so developed demonstrated a strong relationship with a high correlation coefficient (Ra = 0.97) between predicted and the calculated values for surface roughness.
4) Also, the confirmation test revealed the surface roughness (Ra) values fall within a 95% confidence interval.

The above results revealed Taguchi technique is a reliable technique to lower the manufacturing costs and machining time in the milling of EN-31 steel. This study can be utilized for further academic research and industrial application. Additional research may be undertaken on the other parameters such as cutting tool material, tool shape, various coating materials, lubricants, and chip breaker.

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Conflict of interest

There is no any known conflict of interest among the authors

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Abbreviations used

L1=Leve 1st
L2=Level 2nd
L3=Leve 3rd

SOV= Sources of variation
SS= Sum of squares
DOF= Degree of freedom
MS= Mean square
% cont.= percentage contribution
Exp.= Experimented
Pr. =Predicted
Er. = Error

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