Advances in Materials Research, *Vol. 14, No. 2 (2025) 81-98*
https://doi.org/10.12989/amr.2025.14.2.081

Investigation of EN8 & EN31 steels in vertical milling machine for SR and MRR by adopting optimization approach

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(*Received October 26, 2022, Revised March 14, 2024, Accepted February 4, 2025*)

Abstract. The optimum machining parameters of milling operations are of great concern with manufacturing environment. The aim of the work is to observe the impact of variables on outcomes like surface roughness and material removal rate for EN8 and EN31steels. In these, EN8 are used for moderately stressed parts of motor vehicles while EN31 are used for components that are subjected to severe abrasion, wear or high surface loading due to its high resisting nature against wear. The experiments have conducted on a vertical milling machine using a carbide tool. This investigation deals with the optimization of the milling parameters, as spindle speed, feed rate and depth of cut by using Taguchi's optimization and GRA techniques to select the best combination of input parameters towards maximum material removal rate and minimum surface roughness for these materials. These milling parameters were optimized by utilizing Taguchi's L9 orthogonal array, signal-to-noise ratios and analysis of variance. The analysis reveals that the spindle speed is the dominant factor affecting surface roughness and MRR. Spindle speed contributes 97.38% and 72.39% for SR and 51.37% and 14.45% for MRR towards EN8 and EN31 respectively. The response table of S/N ratios for GRG ranked spindle speed at1 for EN8 and EN31 individually. Further, the optimum level of process parameters for attaining optimal values of outcomes by employing GRA. The gray relational analysis reveals that the spindle speed at 228 rpm is the dominant factor affecting the consequences.

Keywords: EN8 and EN31 steel alloy; GRA; MRR; surface roughness; Taguchi method

1. Introduction

The various machining techniques are used in the manufacturing sector to produce better productsby extracting material from the workpiece. Similar to this, the end milling machining is one of the most essential and popular metal removing process utilized for producing the components because it can remove materials more quickly while maintaining a passable surface quality. Since numerical controlled machine tools offer greater productivity improvements, improve the precision of machined parts, and demand less operational inputs therefore they have recently implemented to for achieving automation in milling processes. (Rawangwonga *et al*. 2014). The machining process known as milling, involves advancing (or feeding) rotary cutters in a direction that forms an angle

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http://www.techno-press.org/?journal=amr&subpage=5 ISSN: 2234-0912 (Print), 2234-179X (Online)

with the tool's axis in order to extract material from a job. It widely covers a range of various machines and operations, on a scale ranging from tiny individual parts to sizable, powerful gang milling operations. To machine parts in exact sizes and shapes, it is currently one of the procedures that are most frequently used in industry and machine shops. (Chauhan *et al*. 2017). Nevertheless, the performance of milling operations are influenced by several input parameters to enhance the outcomes such as surface roughness (SR) and material removal rate (MRR) etc.

In last few decades, several optimization methods are now being adopted to minimize the experimental trails keeping in mind to enhance the productivity of the operation. The most widely employed are the fuzzy logic, the genetic algorithms (GA), artificial neural network (ANN) and the Taguchi's method (Ribeiro *et al*. 2017). Since, SR is one of the highly significant parameters to evaluate the quality of product. So, several factors which influence the SR and MRR in a milling process are categorized as controllable variables like; spindle speed (N), feed rate (f), depth of cut (DOC) and nose radius and uncontrollable variables (tool geometry and material properties of both tool and work piece). Most of the researcher evaluated that as the spindle speed increases the surface finish also improves whereas the surface roughness decrease as machinability improved (Singh *et al*. 2016). In addition to this, for attaining high productivity means, minimum SR and maximum MRR, many design methodology such as factorial design, response surface methodology (RSM), gray relational analysis (GRA), ANN and Taguchi's methods are now widely implemented in place of one factor at a time experimental approach for avoiding undesirable factors. The Taguchi's design experiments are a quick, systematic, and effective way to find settings for machining parameters that are optimal or nearly so. (Parashar *et al*. 2015).

2. Literature review

Many authors have studied steel and its alloys in milling operation to optimize the parameters for improving the output responses. The input responses like N, f, and DOC have been considered by adding other variables as well. Similarly, authors have also studied other output responses besides SR and MRR. Some of them has covered in this article. A report by, Siva *et al*. (2017) investigated the EN19 steel by considering N, f and DOC to optimize the multi-response objectives by utilizing Taguchi's method and Grey relational analysis (GRA). Further, Vishnu *et al*. (2017) optimized the variables like N, f, nose radius, axial depth of cut, and radial depth of cut in CNC milling for P20 steel by using Taguchi L50 OA, ANOVA and RSM techniques to achieve lower SR and higher MRR. Furthermore, Vu *et al*. (2018) analyzed the multi-objective optimization for SR and resultant cutting force in a milling of SKD61 steel by adopting Taguchi's method, RSM and Cutpro software. Similarly, Vignesh *et al*. (2018) adopted Taguchi and RSM based optimization for predicting the end milling process of OHNS by anticipating carbide tools coated and uncoated in both dry and wet conditions to minimize SR along with better cutting conditions. In addition to this, Sarikaya *et al*. (2015) investigate the milling of AISI 1050 steel during milling for output responses such as vibration signals, cutting force and SR by optimizing input variables like DOC, N, f and number of inserts with Taguchi-based GRA method. The feed rate is the most important factors for the minimizing to responses as per ANOVA and GRA.A study done by Gupta and Sood (2016) studied the input parameters like N, f and different cooling conditions while machining AISI 4340 steel by adopting the Taguchi and utility approach to minimize the outcomes as specific cutting force and SR. In addition, Myers *et al*. (2016) examined the milling operation to lessen the surface roughness by implementing the Taguchi's technique. In the same manner authors like, Shankar *et al*. (2016)

optimized the machining variables in milling for mild steel over SR, cutting force and tool wear rate by adopting Taguchi method, GRA and ANOVA. From ANOVA, spindle speed is highly affecting variables. Ramesh *et al*. (2016) observed the machining of alloy steels and predicted that feed rate is the highly important factor affecting SR. Ribeiro *et al*. (2017) optimized the most significant variables like, N, f and DOC to minimize SR by applying the Taguchi's methodology to elect the machining parameters that contribute significantly to surface quality. The coolant flow was the highly effective parameter on SR. Nevertheless, Kumar *et al*. (2020) implemented the Taguchi techniques for optimizing input variables of face milling operation in case of AISI 1005 steel for SR and MRR. Kumar *et al*. (2021) investigated SS-304 in end milling machining to optimize the variables like N, f and DOC for attaining better surface finish and quality by implementing Taguchi L18 OA. A report by, Tlhabadira *et al*. (2019) investigated the AISI P20 by taking several parameters of a CNC vertical milling operation by adopting Taguchi L9 OA method to observe the impact on surface irregularities on machined surface. Further, Azim *et al*. (2020) optimized the input parameter of CNC milling for Mild Steel Grade 60 to enhance the SR through Taguchi's method with ANOVA. The analysis reveals that spindle speed highly affect the SR of the workpieces. Similarly, Rooprai *et al*. (2021) evaluated the Taguchi's technique combining with GRA to enhance the SR for EN 31 milling operations and to determine the proper set of process variables. The analysis reveals that feed rate highly affects the SR. In a review study, Patel *et al*. (2021) evaluated the different machining processes for their respective parameters like cutting speed, feed, and DOC along with different materials to observe the impact particularly on SR by adopting the Taguchi's method, ANOVA, RSM etc.

In a different approach, Mauz and Choudhury (2019) analyzed different cutting fluids through the MQL method for nano-finishing of AISI 4340 steel in flat end milling by implementing the hybrid TGRA approach for optimizing the input variables for optimum results. When applying MQL, low viscosity fluids have shown to yield superior outcomes. Similarly, Singh *et al*. (2023) optimized the several input variables during face milling of AISI 52100-alloy steel under MQL environment by adopting Taguchi with GRA for observing the impact on SR and tool wear. The DOC has the most influencing factors on responses. Singh *et al*. (2020) modified the input variables such as N, f and DOC along with rolling direction, cutter offset, soaking time in a face milling of AISI1040 steel to achieve a superior surface quality by implementing Taguchi's L27 OA, S/N ratio and ANOVA. Further, Sharma *et al*. (2022) examined the functioning of tungsten carbide tool for EN31 steel in face milling under different machining conditions incorporate with cutting parameters (N, f and DOC) to observe the effect on tool flank wear. Taguchi L18 OA, ANOM and ANOVA were utilized for getting optimum values. Moreover, a novel approach by, MacThi-bich *et al*. (2018) investigated the efficacy of the heating process in a milling operation for SKD 11 tool steel on cutting forces, chip morphology during the thermal-assisted machining, and compared with traditional machining. The impact of cutting parameters and elevated temperature on the cutting force where analyzed by adopting Taguchi's OA and ANOVA. In a similar manner, Sivaranjan *et al*. (2022) studied the EN31 steel in hard machining with TiAlN coated cutting tool by considering nine experimental setup with three levels of factors to estimate the surface finish by utilizing Fuzzy logic. The fuzzy logic model can predict surface roughness with a respectable degree of accuracy.

In addition, other processes have also been utilized in alloy steels to examine their effects on various output responses. In turning, a study by, Ozbek *et al*. (2020) examined the outcomes for flank wear and SR of AISI 304 steel by considering the parameters during wet turning of coated cutting tool, N and f by adopting Taguchi (L18) OA, S/N ratio and ANOVA. In another approach, Ozbek *et al*. (2021) observed the impact of parameters like N, f and DOC with two types of coated cutting tools on outcomes like cutting temperature, vibrations, SR and noise by utilizing Taguchi L18 design and ANOVA for AISI P20 die steel in turning. Further, Ozbek (2023) investigated superalloy UDIMET 720 in turning by adding graphene and multi-walled carbon nano tubes in vegetable oil with MQL technique by considering different N and f in distinct machining for improved tool wear, cutting zone temperature and SR. Additionally, Chauhan and Kumar (2020) compared the execution of plain carbide and coated carbide tools with parameters in CNC turning for EN9 steel to observe their effects on responses like surface roughness, flank wear and crater wear by implementing optimization practices like ANOVA and RSM. Likewise, Maurya and Niranjan (2024) experimented EN-36C alloy steel in turning, using a tungsten carbide cutting tool in a dry environment, in order to maximize material removal rate and minimize tool wear as well as residual stresses. The process parameters (N, f and DOC) were optimized by applying ANOVA and RSM. Moreover, in EDM, authors like Ubaid *et al*. (2017), Patel *et al*. (2021) and Ganapathy *et al*. (2023) conducted experiments on Electro discharge machining (EDM) for SS304, AISI304 steel and EN 31 alloy steel by considering EDM parameters regarding the responses like SR, MRR and tool wear by implementing optimization techniques (Taguchi, ANOVA and GRA).

Additionally, some authors adopted two materials for their studies with both traditional and non-traditional machining. A research by Akkurt (2014) examined the aluminum and AA6061 for their shaped surfaces with distinct conventional and non-conventional processes. Tilekar *et al*. (2014) evaluated aluminum and mild steel for their outcomes like SR and kerf width in WEDM by adopting single objective technique. Similarly, Saif and Tiwari (2021) considered AA 5083 and AA 6061to compare the results particular SR and MRR in WEDM by adopting Taguchi's optimization method. Moreover, Liao *et al*. 2014) compared the optimum values of machining parameters in WEDM for AA6061 and tool steel with unique SDE values. Furthermore, Singh and Kumar (2018) studied EN31 and EN19 alloy steels by considering WEDM parameters by utilizing optimization techniques Taguchi L18 OA and ANOVA for enhancing SR. Servo voltage is the most effecting factors followed by other parameters. In addition, Mian *et al*. (2022) analyzed the responses SR and cutting zone temperature of NDT for EN8 and EN31 steels in CNC turning with input variables as, N, f, nano-fluid and compressed air by using Taguchi and GRA method. The study reveals that, Nano fluids played important role in minimizing SR and cutting zone temperature.

From the above mentioned manuscripts overviews, steel and its alloys are widely used in milling machines and other conventional/CNC machines by employing different optimization techniques for the evaluation of outcomes especially surface quality and MRR. Consequently, two material EN8 and EN31 have selected to expand the scope of the investigation in the vertical milling machine with coated carbide tool by implementing optimization techniques (Taguchi's method and GRA) to predict the optimum combination of input variables towards the consequences i.e. SR and MRR for the both the materials.

3. Materials and method

This section of the manuscript provides the details regarding the machine and materials opted for examination along with their specifications like physical, mechanical, chemical properties, tool detail and input parameters with their levels. The experiment has designed based on Taguchi's L9 OA and GRA to evaluate the suitable parameters for the outcome responses like SR and MRR. The following points about job material and apparatus are mentioned below

- The job materials elected for this investigation are EN8 and EN31steels.

(a) The vertical milling machine (b) The cutting tool (c) After machined workpieces

Fig. 1 Shows the setup of milling machine along with tool and workpiece

Table 1 Shows physical and mechanical properties of materials

Material	Density (Kg/m^3)	Poisson's ratio	Tensile strength (GPa)	Hardness (Brinell/HRC)	Yield strength (GPa)
EN8	7.48 to 8.00	0.27 to 0.30	0.70 to 0.85	201 to 255	0.465
EN31	7.70 to 8.03	0.27 to 0.30	2.24	60 to 67	2.03

Table 2 Shows chemical properties of materials (wt %)

Material	C	Si	Mn	S	P	Mo
EN8	0.44	1.0	0.05	0.015	0.5	-
EN31	1.08	0.25	0.53	0.015	0.02	0.02

Table 3 Shows process parameters of EN 8 and EN31 steels

Process parameters	Units	Level 1	Level 2	Level 3
Spindle speed (N)	rpm	228	317	450
Feed rate (f)	mm/rev	30	48	75
Depth of cut (DOC)	mm	1	1.5	2.0

• The characteristic feature of the alloy includes high tensile strength with good ductility, surface hardened by induction which results in improved wear resistance, formability and corrosion resistance, which made them suitable for specially automotive components and other general engineering applications.

• The physical, mechanical and chemical properties of work pieces EN8 and EN31 steels are shown in Table1-2.

• The selected process parameters, units and their levels are depicted in Table 3.

• The water-soluble fluid has utilized as the coolant during the process.

• The tests have performed in a vertical milling machine with carbide-inserted tool having diameter 10 mm, number of flutes 4 and length 100 mm as depicted in Figs. 1(a)-(b).

• The measurements of workpiece are 150×150×10 mm and the workpieces are depicted in Fig. 1(c).

3.1 The methodology

3.1.1 The Taguchi's approach

The Taguchi's technique is a statistical technique based on orthogonal array (OA) experiments and significantly reduces deviation for experiments with optimal control configurations to enhance the quality of produced items. The maximum possible signal-to-noise ratios (S/N ratios) are the best level of control factors for this method. The desired result characteristics are a log function of the signal-to-noise ratios. The three S/N ratios smaller is better, larger is better, and nominal is best are used to optimize the system. Hence, for SR, smaller is better and for MRR, larger is better is implied for the process.

3.1.2 The design of experiments (DOE)

The orthogonal array accommodates multiple factors that affect the performance of operations for optimization. The L9 OA table was selected which shows that spindle speed, feed rate and depth of cut were varied for three (3) factors and three (3) levels. The MINITAB analysis software has applied for interpreting the investigated results. The DOE of L9 OA has represented in Table 4. The SR and MRR are the measured output responses.

3.1.3 The surface roughness (SR)

The surface finish refers to the process of altering metal surface that involves removing, reshaping and adding, because of surface imperfections could create corrosion or cracking initiation sites. The values of SR have calculated by applying a portable surface roughness tester Taylor–Hobson (SURTRON-2S).

3.1.4 The material removal rate (MRR)

The difference between the workpiece weight before and after the process, as well as the product of procedure's duration and density has used to calculate the material removal rate. For this specified research, Eq. 1 has utilized for evaluating the MRR.

$$MRR = (wt.\,before\ machining - wt.\,after\ machining)/\ (time\ \times density) \tag{1}$$

3.1.5 The grey relational analysis (GRA)

The GRA is a tool for evaluating how closely sequences approximate each other using the Grey relational grade (GRG). In this method, the data are normalized in between 0 and 1. The SR considering the lower the better has expressed by Eq. 2.

$$xi = \frac{\max yi - yi}{\max yi - \min yi} \tag{2}$$

Similarly, the normalized the data processing for MRR are considering the higher the better has expressed by Eq. 3.

$$xi = \frac{yi - \min yi}{\max yi - \min yi} \tag{3}$$

where,

Table 5 Shows surface roughness of EN8 steel with L9 OA

Sr. No.	Spindle speed (rpm)	Feed rate (mm/rev)	Depth of cut (mm)	Surface roughness (μm)	Material removal rate (mm^3/min)
1	228	30	1.0	2.31	115.955
2	228	48	1.5	2.30	54.047
3	228	75	2.0	1.93	274.894
4	317	30	1.5	2.33	340.136
5	317	48	2.0	2.37	334.190
6	317	75	1.0	2.40	231.910
7	450	30	2.0	3.65	175.520
8	450	48	1.0	3.58	838.360
9	450	75	1.5	3.68	911.070

xi(k) = normalized value.
yi(k) = individual value in the column for the response k.
min yi (k) = smallest value in the column for the response k.
max yi (k) = largest value in the column for the response k.

After the normalized value, Grey relational coefficient (GRC) and Grey relational Grade (GRG) calculated that can be deliberate expressed by Eqs. (4)-(5) respectively

$$\mathcal{E}i = \frac{\min yi(k) + (0.5 * \max yi(k)}{yi(k) + (0.5 * \max yi(k)} \tag{4}$$

$$\gamma i = \frac{1}{n}\sum_{k=1}^{n} \mathcal{E}i \tag{5}$$

where, $\mathcal{E}i$ is the Grey relational coefficientγi is the grey relational grade and where n is the number of output response. Higher the value of grey relational grade indicates the better quality. By allocating equal weight for machine outcome, grey relational grade is calculated.

3.2 The evaluation of experimental results by utilizing Taguchi's L9 OA method

The experimental results evaluated by applying Taguchi's L9 OA of EN8 and EN31 steel alloys for SR and MRR are represented in Table 5-6.

4. The results and discussion

4.1 The analysis for EN8 Steel

4.1.1 The analysis of response table for S/N ratio

The response table contains the rows and each row includes the mean of S/N ratio for each level of factor followed by two rows named delta and rank. The factor having highly significant in a response table is shown by its rank. Those factors with the maximum S/N ratio has considered as

Table 6 Shows surface roughness of EN31 steel with L9 OA

Sr. No.	Spindle speed (rpm)	Feed rate (mm/rev)	Depth of cut (mm)	Surface roughness (μm)	Material removal rate (mm^3/min)
1	228	30	1.0	2.81	57.72
2	228	48	1.5	2.66	383.58
3	228	75	2.0	2.87	346.32
4	317	30	1.5	3.09	166.50
5	317	48	2.0	3.21	673.85
6	317	75	1.0	3.43	321.46
7	450	30	2.0	3.12	309.21
8	450	48	1.0	3.56	302.02
9	450	75	1.5	3.23	739.76

Table 7 Shows the main factors that influence the SR

Level	Spindle speed	Feed rate	Depth of cut
1	-6.739	-8.622	-8.651
2	-7.482	-8.602	-8.633
3	-11.213	-8.211	-8.151
Delta	4.474	0.411	0.501
Rank	1	3	2

Table 8 Shows the main factors that influence the MRR

Level	Spindle speed	Feed rate	Depth of cut
1	41.57	45.60	49.02
2	49.47	47.87	48.16
3	54.18	51.76	48.05
Delta	12.61	6.16	0.97
Rank	1	2	3

the best combination for executing results. The analysis for response tables has carried out by MINITAB software. Therefore, from response Table 7, the best combination for attaining minimum surface roughness are spindle speed at level 1, depth of cut at level 2 and feed rate at level 3. Therefore, spindle speed is the main affecting factor and second most affecting factor is depth of cut.

From Table 8, the best combination for attaining maximum MRR are spindle speed at level 1, fed rate at level 2 and depth of cut at level 3. Therefore, spindle speed is the main affecting factor and second most affecting factor is feed rate.

4.2 The analysis of main effects for S/N ratios

4.2.1 The main effects plot for S/N ratios

Based on the machining execution condition “smaller is better” for SR have attained, spindle speed at 228 rpm, feed rate at 75 mm/rev and DOC at 2 mm as depicted in Fig. 2. The variation in

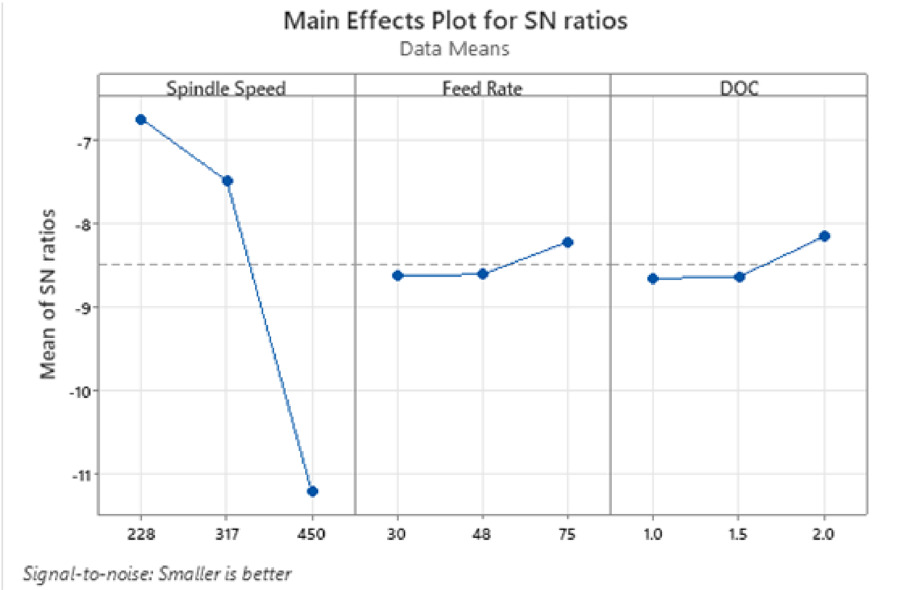

Fig. 2 Shows variation of surface roughness with other parameters

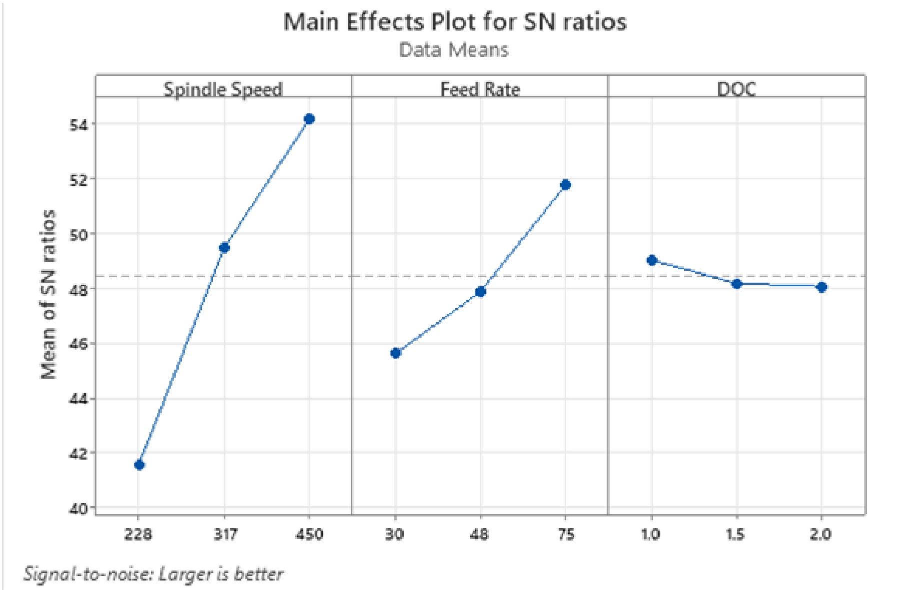

Fig. 3 Shows variation of MRR with other parameters

spindle speed from 228 to 450 rpm decreases the SR. Because higher spindle speeds in the milling process lead to improved SR due to the creation of built-up edges (BUE) that has decreased on cutting tools at high spindle speeds, therefore, lowering BUE has a favourable effect on SR. Further at higher speed, due to the generation of higher magnitude cutting forces, resulting in improved quality cuts and smoother surfaces. However, the opposite trend has observed in case of feed rate and DOC for SR as the values of these factors raises the value of SR enhanced.

Table 9 Shows the ANOVA for SR

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Spindle speed	2	3.76962	97.38%	3.76962	1.88481	63.94	0.015
Feed rate	2	0.01529	0.39%	0.01529	0.00764	0.26	0.794
DOC	2	0.02729	0.70%	0.02729	0.01364	0.46	0.684
Error	2	0.05896	1.52%	0.05896	0.02948		
Total	8	3.87116	100.00%				

Table 10 Shows the ANOVA for MRR

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Spindle speed	2	382353	51.37%	382353	191176	1.91	0.344
Feed rate	2	112089	15.06%	112089	56045	0.56	0.641
DOC	2	49616	6.67%	49616	24808	0.25	0.801
Error	2	200213	26.90%	200213	100106		
Total	8	744271	100.00%				

Moreover, based on the machining execution condition “large is better” for MRR have attained, spindle speed at 450 rpm, feed rate at 75 mm /rev and DOC at 1 mm as depicted in Fig. 3. The same trend has observed in case of spindle speed and feed rate for MRR as the values of these factors raises the value of MRR enhanced. Because, higher spindle speed means the tool moves faster relative to the workpiece, resulting in enhanced relative interactions, which increases the material removal rate. Further, it has seen that MRR increases as feed rate increases, because the tool is moving faster in the direction of the workpiece and removing extra material from the workpiece’s exterior at higher feed rates.

4.3 The analysis of variance

The objective of ANOVA is to quantify the effects of different parameters on a performance factors. The relative importance of the machining parameter with respect to the SR and MRR have been examined by ANOVA was to more precisely identify the ideal machining parameter combination. In terms of statistics, the F-test helps determine whether these estimates are significantly different at a certain degree of confidence. A higher F-value suggests that there is a significant impact of the process parameter variation on the performance attributes and if the related P- value is less than 0.05, which indicate that, the model are statistically significant.

The results of ANOVA for surface roughness are presented in Table 9. It was identified that spindle speed contributes a maximum role towards SR that is 97.38% and its P and F-value are 0.015 and 63.94 respectively. The contribution of DOC and feed rate are 0.70% and 0.39% respectively.

Further, the result of analysis of variance for MRR has illustrated in Table10. It has marked that spindle speed contribute a maximum role towards MRR that is 51.37% and its P and F-value are 0.344 and 1.91 respectively. The contribution of feed rate and DOC are 15.06% and 6.67% respectively.

Table 11 Shows the main factors that influence the SR

Level	Spindle speed	Feed rate	Depth of cut
1	-8.876	-9.552	-10.236
2	-10.212	-9.886	-9.494
3	-10.365	-10.016	-9.724
Delta	1.489	0.464	0.743
Rank	1	3	2

Table 12 Shows the main factors that influence the MRR

Level	Spindle speed	Feed rate	Depth of cut
1	45.90	43.15	44.99
2	50.38	52.62	51.16
3	52.26	52.77	52.39
Delta	6.36	9.62	7.40
Rank	3	1	2

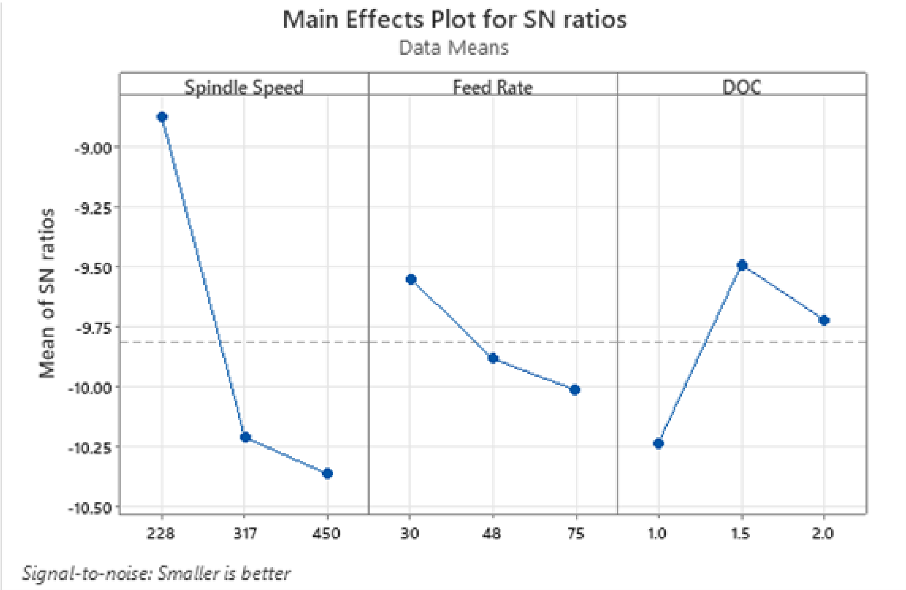

Fig. 4 Shows the variation of surface roughness with other parameters

4.4 The analysis for EN31 steel

As discussed earlier about response table, Table 11 shows the best combination for attaining minimum surface roughness are N at level 1, DOC at level 2 and f at level 3. Therefore, spindle speed is the main affecting factor for SR and second most affecting factor is depth of cut.

Moreover, from Table 12, the best combination for attaining maximum MRR are feed rate at level 1, depth of cut at level 2 and spindle speed at level 3. Therefore, feed rate is the main affecting factor for MRR and second most affecting factor is DOC.

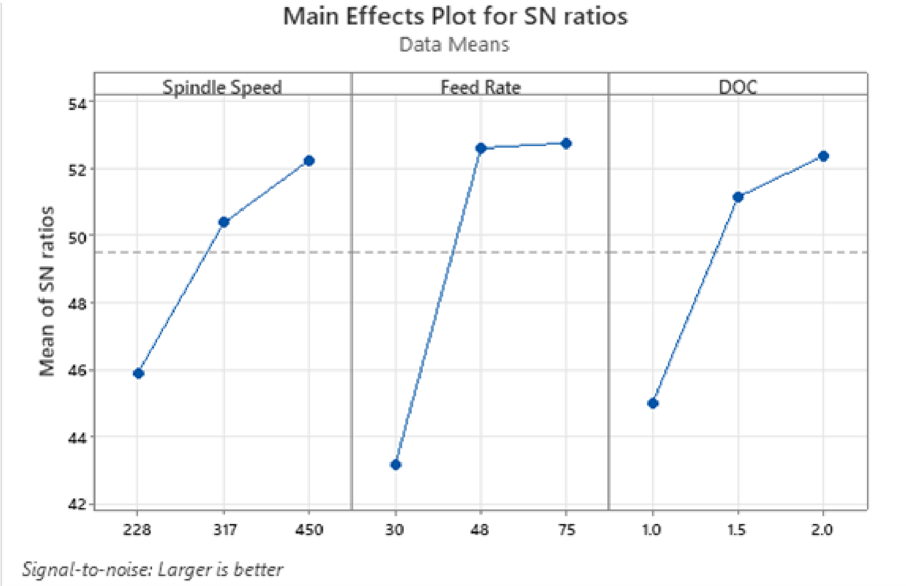

Fig. 5 Shows the variation of MRR with other parameters

Table 13 Shows the ANOVA for SR

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Spindle speed	2	0.49216	72.39%	0.49216	0.246078	25.96	0.037
Feed rate	2	0.04869	7.16%	0.04869	0.024344	2.57	0.280
DOC	2	0.12009	17.66%	0.12009	0.060044	6.34	0.136
Error	2	0.01896	2.79%	0.01896	0.009478		
Total	8	0.67989	100.00%				

4.4.1 The analysis of main effects for S/N ratios

Based on the machining execution condition "smaller is better" for SR have attained N at 228 rpm, f at 30 mm /rev and DOC at 1.5 mm as depicted in Fig. 4. The same trend has observed in case of spindle speed and feed rate for SR as the values of these factors raises the value of SR decreases but in case of DOC, a reverse trend has noticed that initially the value of SR enhances and then decreases.

Moreover, based on the process execution condition "large is better" for MRR have attained, N at 450 rpm, and f at 75 mm /rev and DOC at 2 mm as depicted in Fig. 5. The same trend has noted in case of spindle speed, feed rate and DOC for MRR as the values of these factors raises the MRR enhances. With increasing depth of cut, the tool and workpiece interaction enhances, resulting in maximal bulk material removal and a larger MRR.

The results of ANOVA for surface roughness are presented in Table 13. It was identified that spindle speed contribute a maximum role towards SR that is 72.39% and its P and F-value are 0.037 and 25.96 respectively. The contribution of DOC and feed rate are 17.66% and 7.16% respectively.

The result of analysis of variance for MRR has illustrated in Table14. It has marked that feed rate contribute a maximum role towards MRR that is 42.44% and its P and F-value are 0.579 and 0.73 respectively. The contributions of DOC and spindle speed are 23.20% and 14.45% respectively.

Table 14 Shows the ANOVA for MRR

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Spindle speed	2	54799	14.45%	54799	27400	0.73	0.579
Feed rate	2	160966	42.44%	160966	80483	2.13	0.319
DOC	2	88016	23.20%	88016	44008	1.17	0.462
Error	2	75518	19.91%	75518	37759		
Total	8	379299	100.00%				

Table 15 The output values from GRA analysis for EN8

Expt. No.	Process parameters			Output parameters		Normalized		GRC		GRG	RANK
	N (rev)	f (mm/rev)	DOC (mm)	SR	MRR	SR	MRR	SR	MRR		
1	228	30	1.0	2.31	115.955	0.782857	0.927764	0.697211	0.873765	0.785488	3
2	228	48	1.5	2.3	54.047	0.788571	1	0.702811	1	0.851406	1
3	228	75	2.0	1.93	274.894	1	0.742309	1	0.6599	0.82995	2
4	317	30	1.0	2.33	340.136	0.771429	0.666183	0.686275	0.599652	0.642963	5
5	317	48	1.5	2.37	334.19	0.748571	0.673121	0.665399	0.604683	0.635041	6
6	317	75	2.0	2.4	231.91	0.731429	0.792464	0.650558	0.706678	0.678618	4
7	450	30	1.0	3.65	175.52	0.017143	0.858262	0.337187	0.779134	0.55816	7
8	450	48	1.5	3.58	838.36	0.057143	0.08484	0.346535	0.353317	0.349926	8
9	450	75	2.0	3.68	911.07	0	0	0.333333	0.333333	0.333333	9

Table 16 Shows the main factors that influence the GRG

Level	Spindle speed	Feed rate	Depth of cut
1	-1.704	-3.666	-4.862
2	-3.716	-4.821	-4.925
3	-7.909	-4.843	-3.543
Delta	6.205	1.177	1.383
Rank	1	3	2

4.5 The results of Grey Relational Analysis

This section of analysis specified the yield reactions of GRA for EN8& EN31 steels. Therefore, the normalized value, GRC, GRG, and Rank values obtained by combining with the L9 OA values have illustrated in Table 15 for EN8 steel.

In addition, according to the response table of S/N ratios for GRG, the status of parameters such as, Spindle Speed at level 1, Feed rate at level 3 and DOC at level 2. The outcomes reveals that, spindle speed is highly valuable factor followed by DOC to obtain the greatest value of GRG as depicted in Table 16.

Moreover, the normalized value, GRC, GRG, and Rank values obtained by combining with the L9 OA values have illustrated in Table 17 for EN31 steel.

Table 17 The output values from GRA analysis For EN31

Expt. No.	Process parameters			Output parameters		Normalized		GRC		GRG	RANK
	N (rev)	f (mm/rev)	DOC (mm)	SR	MRR	SR	MRR	SR	MRR		
1	228	30	1.0	9.3060	12.4560	0.833333	1	0.75	1	0.875	1
2	228	48	1.5	9.5340	11.3703	1	0.520701	1	0.510569	0.755285	2
3	228	75	2.0	8.1716	11.4193	0.766667	0.575171	0.681818	0.540641	0.611229	4
4	317	30	1.0	8.5713	11.6264	0.522222	0.83805	0.511364	0.755345	0.633354	3
5	317	48	1.5	8.6290	11.6666	0.388889	0.096354	0.45	0.356215	0.403108	8
6	317	75	2.0	9.7310	10.9262	0.144444	0.611514	0.368852	0.562755	0.465804	6
7	450	30	1.0	9.2220	11.8826	0.488889	0.629422	0.494505	0.574331	0.534418	5
8	450	48	1.5	9.6200	12.3679	0	0.639933	0.333333	0.58135	0.457342	7
9	450	75	2.0	8.7153	13.4735	0.366667	0	0.441176	0.333333	0.387255	9

Table 18 Shows the main factors that influence the GRG

Level	Spindle speed	Feed rate	Depth of cut
1	-2.625	-3.523	-4.864
2	-6.165	-5.708	-4.882
3	-6.826	-6.384	-5.870
Delta	4.201	2.861	1.006
Rank	1	2	3

Table 19 The optimized values of parameters by adopting Taguchi and GRA techniques (EN8)

S. No.	Process parameters	Units	Taguchi method				GRA	
			SR		MRR		GRG	
			Best Level	Value	Best Level	Value	Best Level	Value
1	Spindle speed	rpm	1	228	3	450	1	228
2	Feed Rate	mm/rev	3	75	3	75	1	30
3	DOC	mm	3	2.0	1	1.0	3	2.0

Table 20 The optimized values of parameters by adopting Taguchi and GRA techniques (EN31)

S. No.	Process parameters	Units	Taguchi method				GRA	
			SR		MRR		GRG	
			Best Level	Value	Best Level	Value	Best Level	Value
1	Spindle speed	rpm	1	228	3	450	1	228
2	Feed Rate	mm/rev	1	30	3	75	1	30
3	DOC	mm	2	1.5	3	2.0	1	1.0

Also, according to the response table of S/N ratios for GRG, the status of parameters such as, Spindle Speed at level 1, Feed rate at level 2 and DOC at level 3. The outcomes reveals that, Spindle Speed is highly valuable factor followed by feed rate to obtain the greatest value of GRG as depicted in Table 18.

Furthermore, the Tables 19-20 for EN8 and EN31steels respectively exhibits the information about the optimum level of initial parameters according to Taguchi's method along with GRA for obtaining the optimized results of outcomes for SR and MRR. The results reveal that spindle speed at 228 rpm has the utmost influencing factors for both steels.

5. Conclusions

The current experimental study of end milling operations for EN8 and EN31steels have been performed for input factors like, spindle speed, feed rate and depth of cut to optimize the outcomes for minimum SR and maximum MRR. The optimization of responses has accomplished by considering Taguchi's approach, GRA along with Minitab software. The following conclusions are listed below

• The spindle speed has a dominating factor affecting the surface roughness, which contributes 97.38% and 72.39% for EN8 and EN31steels, as per ANOVA Tables 9 and 13.

• The average values of SR for EN8 and EN31 are 2.72 and 3.11 µm, respectively, as per Tables 5 and 6. Therefore, EN8 steel has a good surface finish as compared with EN31 steel.

• The spindle speed is the dominating factor affecting the material removal rate, with a contribution of 51.37% for EN8 and the feed rate with 42.44% in case of EN31steels, as per ANOVA Tables 10 and 14.

• The average values of MRR for EN8 and EN31 are 364.009 and 366.71mm^3/min respectively, as per Tables 5 and 6. Therefore, EN31 steel has a better MRR as compared with EN8 steel.

• The GRA of EN8 exhibits the most significant input factors, which are spindle speed 228 rpm, feed rate30 mm/rev and depth of cut 2.0 mm for SR and MRR.

• The GRA of EN31 exhibits the most significant input factors, which are spindle speed 228 rpm, feed rate30 mm/rev and depth of cut 1.0 mm for SR and MRR.

Acknowledgments

The authors would like to acknowledge the support of Motilal Nehru National Institute of Technology Allahabad (MNNIT), Prayagraj, India as well as for providing the resources used in the conducting this researchwork.

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