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Parametric Optimization of Cutting Parameters for High-Speed Machining of EN8 Alloy Steel using PROMETHEE - II

N. Nagesha[1]* and B. S. Praveen Kumar[2]

[1]Department of Mechanical Engineering, RRC, Visvesvaraya Technological University, Belagavi - 590018, Karnataka, India; nnageshmuni@gmail.com

[2]Department of Mechanical Engineering, K.R Pet Krishna Government Engineering College, Krishnarajpet - 571426, Karnataka, India

Abstract

This study examines the process of optimising machining parameters in the turning of EN8 steel. The PROMETHEE-II multi-criteria decision-making technique is utilised for this purpose. The analysed machining variables consist of Material Removal Rate (MRR), Surface Roughness (SR), Acceleration (Ac), and Tool Wear (TW). These variables are influenced by the cutting speed (Vc), Feed Rate (FR), and Depth of Cut (DoC) which serve as input parameters. The experimental trials were performed utilizing Taguchi's L27 orthogonal array on a CNC lathe. The ANOVA analysis showed that Vc had the most substantial effect on MRR, SR, and Ac, whereas FR had the greatest influence on TW. The PROMETHEE-II approach determined that the most favourable machining settings are a cutting speed (Vc) of 200 m/min, an FR of 0.08 mm/rev, and a DoC of 0.2 mm. Given these circumstances, the MRR achieved a value of 2.887 cubic millimetres per second, the SR was minimized to 0.744 micrometres, the Ac was decreased to 0.026 meters per second squared, and the TW was restricted to 0.026 millimetres. The study finds that PROMETHEE-II is a highly successful method for optimizing multiple machining reactions, resulting in substantial enhancements in machining performance.

Keywords: *EN8 Alloy Steel, Carbide Tool, High-Speed Machining, MRR, Surface Roughness, Tool Vibration, Tool Wear*

1.0 Introduction

The unique properties of steel coupled with a wide range of manufacturing flexibility have embarked steel family in various engineering applications. Several grades of ferrous alloys are comprised under the category of steel. Among them, EN8 steel takes a special place owing to its better mechanical properties and is appreciated widely in engineering applications demanding mild steel[1]. Further, the improved surface hardness of EN8 steel through heat treatment enabled design engineers to employ it for automotive parts, fasteners, shafts and other engineering components[2]. Machining of steel is challenging for manufacturing engineers to achieve better accuracy, optimization of cutting parameters and selection of cutting tool[3]. Thus, the machining of various grades of steel has garnered worldwide researchers' attention in recent years.

In conventional machining, the machinability of materials is studied as a function of material removal rate, Fc, SR and TW. Nayak *et al.*[4] investigated the effect of machining conditions on SR and TW in AISI D6 steel machining. Sonawane and Sargade[5] studied the machining performance through the evaluation

*Author for correspondence

of cutting force, TW and surface quality during dry cutting of Duplex Stainless Steel (DSS) 2205 alloy. The impact of variation of cutting parameters on machining performance was investigated. Das *et al.*[6] studied the machinability characteristics in dry turning of AISI D6 steel using different types of tool coating materials. The effect of cutting parameters and cutting tool materials on machining performance was investigated. In addition to the above machining characteristics, feed acceleration was also studied as a machining response in the available literature on machining[7]. Kaplan *et al.*[8] Depicted the machining factors that influence acceleration amplitude during the drilling of cold work steels. Ambhore *et al.*[9] Developed the model to correlate the tool vibration with TW using regression and ANN modelling approach. The adequacy of established models was satisfactory.

The optimization of machining parameters is the focused area of machining of steels in the past few years to achieve better machinability characteristics. Mutyalu *et al.*[10] optimized cutting parameters to yield minimum cutting force during the machining of EN8, EN36 and mild steel with the help of the Taguchi approach. The experiments were conducted with L9 Taguchi's orthogonal array and optimal points were obtained from the analysis. Gugulothu *et al.*[11] conducted the experiments as per Taguchi's design of experiments to yield a better surface finish and higher MRR. The authors concluded that Vc and DoC contribute significantly to the variation of MRR and SR during the machining of EN8 steel. Gurugubelli *et al.*[12] attempted to optimize parameters for turning of EN8 steel through Taguchi's technique for minimum SR. Kalyon *et al.*[13] employed ANOVA analysis for machinability studies. The grey relation grade approach was used for machining parameter optimization to achieve minimum cutting force and better surface quality.

The intelligent soft computing and modelling approach were employed for the prediction of machinability characteristics. Caydas and Ekici[14] developed a Support Vector Machine (SVM) model and an Artificial Neural Network (ANN) model to predict machinability performance in dry cutting of AISI 304 steel. The prediction feasibility of the SVM model was found to be better than the ANN model. Xu *et al.*[15] established the ANFIS model to estimate TW and optimize machining parameters for minimum TW using the Vibration Communication Particle Swarm Optimization (VCPSO) technique. The ANFIS-VCPSO approach was successfully implemented in the study for real-time TW monitoring and improved machining efficiency, subsequently enhancing tool life. Burande *et al.*[16] developed Bat inspired optimization algorithm for process optimization to yield minimum SR in turning EN8 steel. The modelling and analysis of machinability studies have shown that FR and Vc are the most influencing parameters on machining characteristics.

The optimization of machining parameters with a multi-objective optimization approach has been successfully implemented by various researchers. Bhirud *et al.*[17] Have shown that the response surface methodology approach is capable of analyzing the effect of parameters and optimization of multiple machining responses for milling of EN8 steel. The statistical approaches have been utilized widely for machining response optimization. Besides, recent literature has paid attention to the successful implementation of multi-criteria decision-making approaches for multi-response optimization of machining responses. Karnan *et al.*[18] Have reported that TOPSIS and Taguchi's GRA approach help find optimal process parameter levels during the turning of EN8 steel using cryo-treated carbide inserts. Shaikh *et al.*[19] utilized MEREC integrated with PIV multi-criteria decision-making approach was multi-objective optimization during the machining of EN8 steel. Bag *et al.*[20] showed that the MCDM approaches such as TOPSIS, GRA and ARAS possess the capability to optimize multiple responses simultaneously and can suggest corresponding parameter levels in the machining of EN8 steel. In addition, ARAS was found to have better adequacy compared to TOPSIS and GRA techniques. Sristi *et al.*[21] have compared the performance of COPRAS, TOPSIS and GRA multi-optimization techniques. The authors concluded that COPRAS and TOPSIS approaches are relatively easy to compute compared to GRA and are feasible. MCDM methodologies have been extensively employed to improve machining parameters by effectively managing several objectives, including MRR, SR, TW, and Ac. The PROMETHEE-II technique, a Multicriteria Decision Making (MCDM) methodology, is highly efficient in generating a comprehensive ranking of options by considering the net flow values. This makes it well-suited for intricate decision-making

situations in machining. Gupta and Bhardwaj[22] utilized the PROMETHEE-II technique to improve machining parameters in turning operations. They highlighted the method's capacity to manage many competing criteria and its resilience in producing optimal solutions. Rao and Patel[23] utilized the PROMETHEE-II technique to determine the most favourable machining settings for milling hardened steel in a separate research investigation. The study showcased the efficacy of the strategy in multi-objective optimization, exhibiting substantial enhancements in both surface quality and material removal efficiency.

Karthik *et al.*[24] used an ANOVA study to investigate the impact of cutting speed, feed rate, and depth of cut on surface roughness and tool wear when machining AISI 1045 steel. The study found that the cutting speed had the greatest influence on the reactions, which is consistent with the results of the current investigation on EN8 steel. Similarly, Senthil Kumar and Ramesh[25] used ANOVA to examine the machinability of titanium alloys. Their study emphasized the significance of the feed rate in impacting the surface roughness and tool life, offering valuable insights that may be used in the machining of EN8 steel.

The summarization of the available literature indicates that MCDM approaches are feasible to predict the optimal parameter levels. Also, multi-objective optimization can be adequately accomplished with different MCDM techniques. Among various MCDM techniques, TOPSIS is a widely adopted technique in the available literature. The current study aimed to utilize the based PROMETHEE technique for multi-response optimization. The Fc, SR, TW and acceleration were considered as responses to optimize machinability characteristics. Whereas Vc, FR and DOC were considered as machining input parameters in the present investigation. The machining was performed on EN8 steel using a carbide tool insert. Experimentation was conducted as per Taguchi's L27 orthogonal array. The obtained results were analyzed and the machining responses using the PROMETHEE approach.

2.0 Materials and Methods

2.1 Workpiece Material

The workpiece material employed in the current study was medium carbon alloy, EN8 steel with 32HRC hardness. The composition of the workpiece materials is illustrated in Table 1. Initially, the workpiece material was turned about 1 mm to eliminate the possible errors due to surface alterations and surface characteristics influencing machinability characteristics. The workpiece for experimentation was considered with dimensions of 50mm diameter and 100 mm length. Experimental trials were conducted on a CNC lathe, which is connected to a tool vibration analyzer to capture Ac signals. The complete system is connected to data acquisition software available in the computer to capture experimental responses such as tool vibration signals as a function of Ac. Figure 1a shows the schematic illustration of the experimental setup employed in the current investigation. Figure 1b shows

Table 1. Chemical composition of EN8 alloy steel

Elements	C	Si	P	Mn	Mo	Ni	S	Fe
Wt.%	0.40	0.3	0.05	0.74	0.001	0.005	0.05	Balance

Table 2. Cutting parameters and their levels

Sl. No.	Process Parameters	L1	L2	L3
1	Vc (m/min)	100	150	200
2	Feed (mm/rev)	0.08	0.16	0.24
3	DOC (mm)	0.2	0.4	0.6

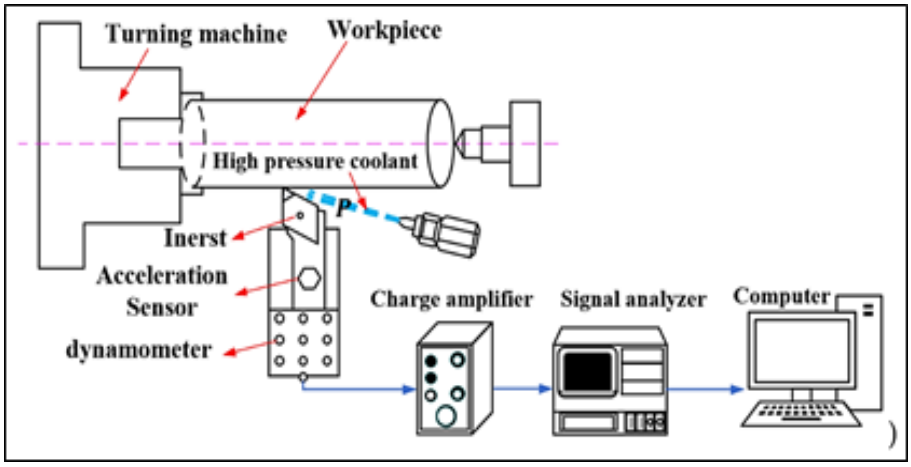


Figure 1. **(a).** Schematic diagram of the experimental setup of turning operation with tool vibration and force measurement system.

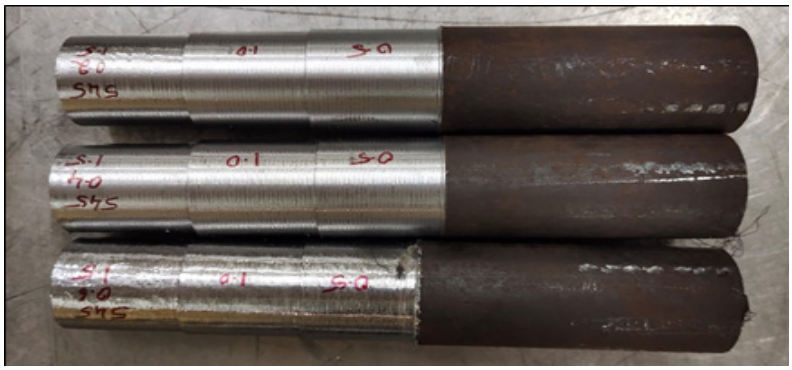


Figure 1. **(b).** Photograph of test samples utilized for experimental trials.

the photograph of samples utilized in the experimental trials.

The CNC lathe used in this study was equipped with a high-precision spindle and sophisticated control mechanisms, guaranteeing consistent machining performance. The tool vibration analyzer, in conjunction with accelerometers, yielded precise data on tool vibrations, which was essential for evaluating the stability of the cutting process. The data-gathering procedure entailed the real-time capture and processing of vibration signals, enabling prompt analysis and change of machining settings to enhance performance.

The SR was recorded for each machined surface using Talysurf®, a probe-based surface measuring instrument. SR measurement was done with a 0.8 mm cut-off length and five trials. The average SR (Ra) was considered for the study. Tool wear was measured using a toolmaker microscope. The cutting parameters *viz.* Vc, FR and DOC were accounted as input parameters with each at 3 levels as illustrated in Table 2. Whereas MRR, SR, Ac and tool wear were studied as machining responses. The experimentation was planned as per Taguchi's technique. Experiment trials were performed as per Taguchi's L27 orthogonal array. The captured results were analyzed using the ANOVA technique to study the influence of parameters on responses. Also, responses to the study were optimized using the PROMETHEE approach. The detailed procedure adopted for the computation of optimal points is discussed in the following section.

2.2 PROMETHEE II Method

The PROMETHEE II was developed by Bran in 1982. It is one of the well-established MCDM approaches for

optimization problems. The advantage of PROMETHEE II is its capability to yield a complete ranking of candidate alternatives. Consequently, it is reasonably successful in finding the optimal solutions for problems in management, engineering, operations research, healthcare industries, electronic industries, and so on[26,27].

PROMETHEE-II is an MCDM method that provides a comprehensive ranking of alternatives by calculating net outranking flows. It is based on the concept of outranking, where one alternative is preferred if it performs better on all criteria and strictly better on at least one. The method involves defining alternatives and criteria, assigning weights, constructing an evaluation matrix, calculating preference functions, and determining positive, negative, and net flows to rank alternatives. PROMETHEE-II was chosen for its simplicity, flexibility, ability to handle incomplete information, and effectiveness across various decision-making scenarios.

The detailed step-by-step procedure adopted for the computation of optimal points and ranking of alternative solutions is described in the following points.

Step 1: Considering the values of machining responses *viz.* material removal rate, SR, Ac and TW, captured for each experimental trail as possible alternatives. Construct the decision matrix with *m* number of alternatives (x_i, i=1,2, 3,…m) and n number of criteria (C_j, *j=1,2,3,…n*) which is represented as Equation (1).

$$X_{m\times n}=\begin{array}{c} \\ x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_m \end{array}\begin{array}{c} \begin{array}{ccccc} C_1 & C_2 & C_3 & \cdots & C_n \end{array} \\ \begin{bmatrix} X_{11} & X_{12} & X_{13} & \cdots & X_{1n} \\ X_{21} & X_{22} & X_{23} & \cdots & X_{2n} \\ X_{31} & X_{32} & X_{33} & \cdots & X_{3n} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ X_{m1} & X_{m2} & X_{m3} & \cdots & X_{mn} \end{bmatrix} \end{array} \qquad \text{Equation (1)}$$

Step 2: The weight w_j of each response was considered equally about 0.25, such that the sum of weights is equal to 1. i.e.,

$$\sum_{j=1}^{n} w_j = 1 \qquad \text{Equation (2)}$$

Step 3: Normalization of the decision matrix using equation (3)

$$X_{ij}=\frac{x_{ij}-\min.(x_{ij})}{\max.(x_{ij})-\min.(x_{ij})} \quad \text{for maximization criteria}$$

$$X_{ij}=\frac{\max.(x_{ij})-x_{ij}}{\max.(x_{ij})-\min.(x_{ij})} \quad \text{for minimization criteria}$$

Equation (3)

where, x_{ij} is the recorded experimental values provided by decision makers i=1,2,….n and numbers of criteria j=1,2,….m, which are considered as alternatives in the calculation.

Step 4: Computation of deviation of each alternative concerning other alternatives, which is performed through comparing pairwise manner as illustrated in Equation (4)

$$\Delta_j(a,b)=g_j(a)-g_j(b) \qquad \text{Equation (4)}$$

$\Delta_j(a,b)$ represents the deviation between the computed values of a and b on each criterion

Step 5: Computing the preference function using the Equation (5)

$$P_j(a,b)=F_j\left[\Delta_j(a,b)\right] \qquad \text{Equation (5)}$$

$P_j(a,b)$ denotes the function of the deviation on comparing alternative *a* with alternative *b* for each criterion with values ranging from 0 to 1.

Step 6: Computation of multi-criteria preference index value using Equation (6)

$$\pi(a,b)=\sum_{j=1}^{n} P(a,b)w_j \qquad \text{Equation (6)}$$

Step 7: Computation of positive and negative outranking flows using Equations (7) and (8) respectively.

$$\phi^{+}(a)=\frac{1}{n-1}\sum_{x\in A}\pi(a,x) \qquad \text{Equation (7)}$$

$$\phi^{-}(a)=\frac{1}{n-1}\sum_{x\in A}\pi(x,a) \qquad \text{Equation (8)}$$

Step 8: Computation of net flow using Equation (9) and rank them correspondingly

$$\phi(a)=\phi^{+}(a)-\phi^{-}(a)=\frac{1}{n-1}\sum_{j=1}^{n}\sum_{x\in A}\left[P_j(a,x)-P_j(x,a)\right]w_j$$

Equation (9)

The least ranked alternative is considered the best and optimal value of responses of experiments. The optimum response values and corresponding optimum input parameter levels are deduced from the discussed PROMETHEE – II method.

3.0 Results and Discussion

The captured experimentation results as per Taguchi's L27 orthogonal array are illustrated in Table 3. Columns 5th, 6th, 7th and 8th correspondingly represent the results for MRR, SR, Ac and TW. Results in each row

Table 3. Taguchi's L27 Orthogonal Array with experimental results

Sl. No.	Vc (m/min)	DOC (mm)	FR (mm/rev)	MRR (mm^3)	SR (µm)	Ac (m/s^2)	TW (mm)
1	100	0.20	0.08	2.250	2.784	0.196	0.045
2	100	0.20	0.16	2.497	3.432	0.426	0.067
3	100	0.20	0.24	2.609	3.672	0.518	0.081
4	100	0.40	0.08	2.223	2.88	0.306	0.051
5	100	0.40	0.16	2.314	3.576	0.514	0.073
6	100	0.40	0.24	2.404	4.248	0.629	0.085
7	100	0.60	0.08	1.885	3.06	0.442	0.056
8	100	0.60	0.16	2.105	3.792	0.628	0.079
9	100	0.60	0.24	2.239	3.96	0.762	0.091
10	150	0.20	0.08	2.356	1.164	0.052	0.031
11	150	0.20	0.16	2.641	0.984	0.158	0.051
12	150	0.20	0.24	2.712	1.536	0.206	0.064
13	150	0.40	0.08	1.710	1.236	0.058	0.037
14	150	0.40	0.16	2.179	1.656	0.202	0.058
15	150	0.40	0.24	2.671	1.764	0.255	0.071
16	150	0.60	0.08	2.110	0.732	0.121	0.044
17	150	0.60	0.16	2.221	1.572	0.245	0.066
18	150	0.60	0.24	2.337	1.836	0.315	0.086
19	200	0.20	0.08	2.887	0.744	0.026	0.026
20	200	0.20	0.16	3.022	0.876	0.066	0.046
21	200	0.20	0.24	2.973	1.02	0.088	0.053
22	200	0.40	0.08	2.567	0.636	0.040	0.035
23	200	0.40	0.16	2.671	0.948	0.078	0.056
24	200	0.40	0.24	2.887	1.032	0.090	0.068
25	200	0.60	0.08	2.852	0.816	0.054	0.042
26	200	0.60	0.16	2.952	1.092	0.078	0.053
27	200	0.60	0.24	3.015	1.188	0.102	0.062

of the table illustrate the experimental results for the corresponding combination of machining parameter levels.

3.1 ANOVA and Main Effect Plot Analysis

The ANOVA analysis of MRR indicates that Vc, FR and DOC yielded p-values less than 0.5, whereas the interaction effect of parameters yielded >0.05 p-values. Consequently, individual parameters have a significant influence on the MRR, SR, Ac and TW whereas the interaction effect of parameters for different combinations was not statistically significant. Further, the percentage of contribution suggests that Vc was found to have the highest influence on MRR, followed by FR and DOC. Furthermore, Table 5 suggests that Vc has greater influence on SR which is followed by FR and DOC. The ANOVA analysis (Table 6) of Ac indicated the speed was considerably affected by Vc followed by FR and least by DOC. Whereas, ANOVA of TW (Table 7) depicted that FR exhibited the highest influence on TW followed by Vc, DOC effect on TW was minimal. In addition, the effect of DOC on MRR and TW was slightly considerable, whereas its effect on SR and Ac was negligible.

The main effect plots of MRR (Figure 2) indicated that an increase in the cutting parameter viz. speed, FR and DoC led to the increase in MRR. Further, the variation of MRR due to change in speed was considerably greater compared to DOC and FR. Besides, the change in MRR due to changes in FR and DOC is relatively significant. It is attributed to the increased interaction of the tool with the workpiece in the unit time due to an increase

Table 4. ANOVA of MRR

Parameters	DF	SS	Variance	F	P	% of Cont.
Vc	2	1.705	0.853	131.43	0	63.76
DOC	2	0.293	0.147	22.58	0.001	10.55
FR	2	0.288	0.144	22.21	0.001	10.37
Vc × DOC	4	0.231	0.058	8.89	0.005	7.71
Vc × FR	4	0.027	0.007	1.05	0.438	0.00
FR × DOC	4	0.058	0.014	2.23	0.155	1.20
Residual Error	8	0.052	0.006			6.41
Total	26	2.654				100.00

Table 5. ANOVA of SR

Parameters	DF	SS	Variance	F	P	% of Cont.
Vc	2	33.576	16.788	496.51	0	90.69
DOC	2	0.2403	0.1201	3.55	0.079	0.47
FR	2	2.1827	1.0913	32.28	0	5.72
Vc × DOC	4	0.1363	0.0341	1.01	0.458	0.00
Vc × FR	4	0.3935	0.0984	2.91	0.093	0.00
FR × DOC	4	0.1477	0.0369	1.09	0.422	0.03
Residual Error	8	0.2705	0.0338			3.08
Total	26	36.947				100.00

in speed, FR and DOC. Furthermore, an increase in FR raises the tool movement and an increased DOC raises the substantiated amount of material removed[28]. Thus, the amount of material removed within the unit time increases leading to higher MRR.

The increase in speed, FR and DOC have increased by SR (Figure 3) and Ac (Figure 4). In addition, speed and FR influence on SR was considerably higher compared to the influence of DOC. The higher SR is attributed to an increase in speed and FR increases the tool vibration, perhaps owing to the increased cutting forces. Consequently, higher cutting forces coupled with greater chip generation at higher speed and feed leads to the enhanced tendency of BUE formation[7]. Also, the higher hardness of EN8 workpiece material employed in the study has contributed to the caused tool vibration. Whereas, increased DOC has resulted in the augmentation of the volume of material removed owing to amplified interaction of the volume of material with the tool surface. Furthermore, the machined surface of hard work material employed in the study was characterized by the material side flow at a higher level of FR and DOC combination as noticed in Figure 5. Perhaps, it has contributed to the increase of SR of machined surfaces at higher FR and DOC. Hence, higher values of Ac due to vibration and SR were observed at greater levels of cutting parameters during the machining of EN8 steel.

Among the four responses (MRR, SR, Ac, and TW), Vc regularly stands out as a crucial element that affects the results. It makes considerable contributions and has P-values far below the 0.05 level. The FR is a critical aspect that significantly affects tool wear and is considered the

Table 6. ANOVA of Ac

Parameters	DF	SS	Variance	F	P	% of Cont.
Vc	2	0.863	0.432	3671.500	0.000	73.56
DOC	2	0.057	0.029	243.080	0.000	4.85
FR	2	0.160	0.080	681.240	0.000	13.63
Vc × DOC	4	0.035	0.009	75.320	0.000	0.00
Vc × FR	4	0.056	0.014	118.430	0.000	0.00
FR × DOC	4	0.001	0.000	1.080	0.426	0.00
Residual Error	8	0.001	0.000			7.95
Total	26	1.173				100.00

Table 7. ANOVA of TW

Parameters	DF	SS	Variance	F	P	% of Cont.
Vc	2	1994.74	997.37	107.72	0.000	25.01
DOC	2	746.3	373.15	40.3	0.000	9.21
FR	2	4892.74	2446.37	264.21	0.000	61.68
Vc × DOC	4	100.15	25.04	2.7	0.108	0.00
Vc × FR	4	86.37	21.59	2.33	0.143	0.00
FR × DOC	4	8.15	2.04	0.22	0.92	0.00
Residual Error	8	74.07	9.26			4.10
Total	26	7902.52				100.00

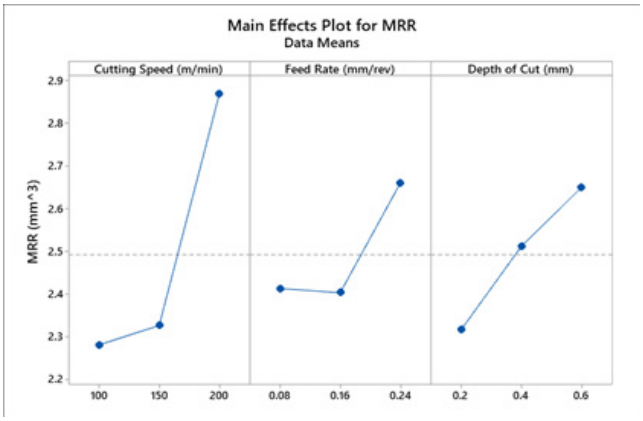


Figure 2. Main effect plot analysis of MRR.

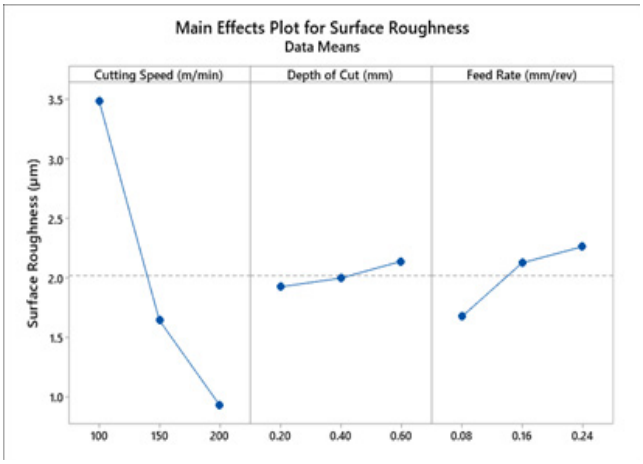


Figure 3. Main effect plot analysis of surface roughness.

most influencing factor in this regard. The DoC has a moderate impact on all responses, but its influence is often lower compared to Vc and FR. The interactions between the components are typically not significant, except for the interaction between Vc and DoC in MRR, which has a considerable impact. In general, the residual errors of the model are minimal, suggesting that the primary influences of Vc, FR, and DoC adequately account for most of the observed variability in the machining responses under investigation.

Tool wear was studied as a function of flank wear in the current investigation. The increase in speed, FR and DOC have increased tool flank wear. Perhaps, an increase in cutting parameter levels leads to tool-work interaction. Thus, progressive TW has occurred, which is revealed as an adhesive TW surface (Figure 6). The SEM photos clearly showed notable alterations in the tool's flank wear region, such as the existence of microcracks

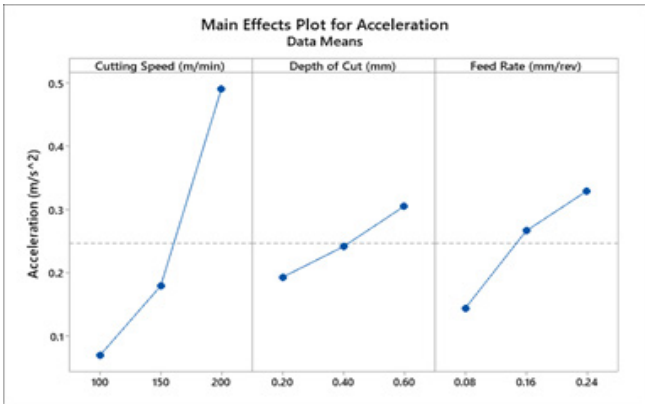


Figure 4. Main effect plot analysis of acceleration.

and surface deformations. These observations indicate the occurrence of elevated stress concentration due to higher cutting speeds and feed rates. The examination of the tool's crater wear surface revealed indications of ploughing and micro-grooving, which are in line with the abrasive impact of serrated chips during the machining process. In addition, the Scanning Electron Microscope (SEM) studies revealed the presence of thin oxidation layers on the surface of the tool. These layers are believed to have grown because of high cutting temperatures. The oxidation layers are responsible for the softening and increased wear of the tool material. Ultimately, the text emphasizes the occurrence of localized chipping, which is caused by brittle fracture processes that are worsened by both high cutting pressures and heat stresses resulting from the raised machining parameters.

Furthermore, tool crater surface wear was characterized by the ploughing and rubbing action. It may be because sharp irregular adjacent edges of serrated chips formed during machining (Figure 7) have rubbed over the crater surface[29]. In addition, cutting tool temperature has elevated to rise in the interaction between tool work and tool chip[30]. It has resulted in the tool temperature softening, leading to tool material weakening. Thus, TW was accelerated with increment of machining parameter levels aided with chipping of tool edge as illustrated in Figure 7. Therefore, diminished tool life with greater TW at higher levels of parameters was recorded during the machining of EN8 steel. Similar observations were reported by Prabhakara[31] during the machining of hardened steel.

The study of tool wear during the machining of EN8 steel uncovered an intricate interaction between

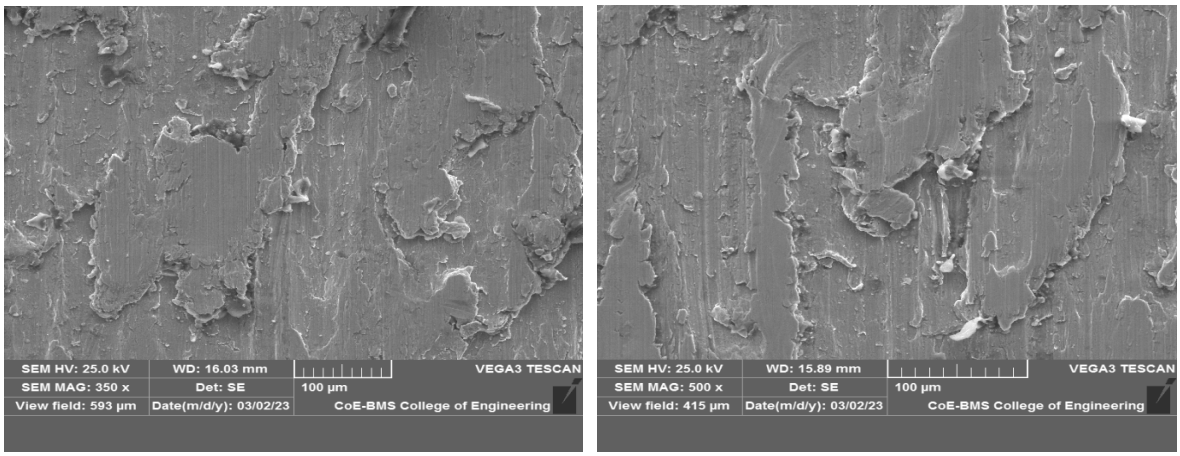


Figure 5. SEM images of the machined surface indicated material side flow at **(a)** DOC of 0.6 mm FR of 0.24 mm/rev, Vc of 100 m/min **(b)** DOC of 0.2 mm, FR of 0.08 mm/min, and Vc of 100 m/min.

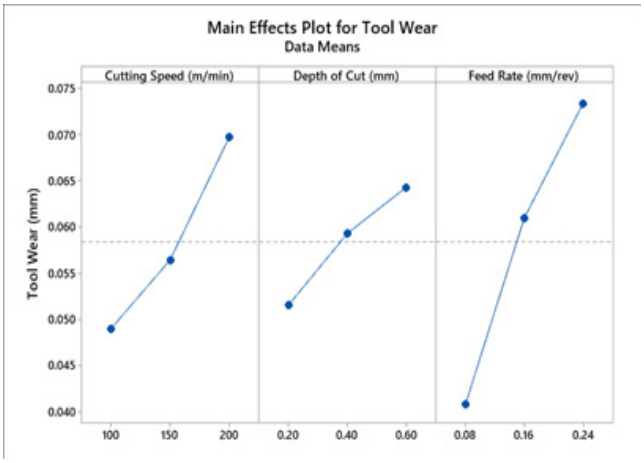


Figure 6. Main effect plot analysis of tool wear.

adhesive wear, abrasive wear, oxidation wear, thermal softening, and chipping. The augmentation of machining parameters, such as cutting speed, feed rate, and depth of cut, further expedited these wear mechanisms, resulting in reduced tool longevity. Adhesive wear was the main kind of wear occurring at the interface between the tool and the workpiece, whereas abrasive wear was more noticeable on the surface of the crater because of the serrated chips. The combined impact of these processes led to gradual tool deterioration, marked by heightened flank wear, surface distortions, microcracks, and localized chipping.

3.2 Optimization of Machinability Characteristics

In the current investigation, the PROMETHEE – II method, an MCDM approach was adopted for the optimization of machinability characteristics such as MRR, SR, Ac and TW, subsequently to determine the optimal process parameter levels. Further, maximization of MRR and minimization of SR, Ac and TW were considered as objectives of the study. The decision matrix for the optimization of machining responses is considered with the response values of different machining characteristics considered in the study for 27 process parameter level combinations. Hence, the decision matrix considered has 27 rows with 4 columns viz. column no. 2, 3, 4 and 5 of Table 8. Each column correspondingly represents each machine response studied. As mentioned in the earlier section, each response was considered with an equal weightage of about 0.25. Later, the response values were normalized using Equation (3), such that values of responses exist in the range of 0 to 1. The normalized values of different responses are illustrated in columns 6, 7, 8 and 9 of Table 8. The preference function values were computed using Equation 5. The computed deviated values and preference function values are shown in Table S1 (supplementary file). Utilizing the preference function values, multi-criteria preference index values were computed with the help of equation 6, which is also illustrated in Table S2. Further, positive outranking flow and negative outranking flows are also shown in Table S3. Based on the net outranking flow values order, the ranking was done with the highest value being ranked least and the least value being ranked as highest. The net outranking flow values and rank were shown in columns 10 and 11 respectively of Table 8. The least ranked value net outranking value obtained was 0.3709 with the

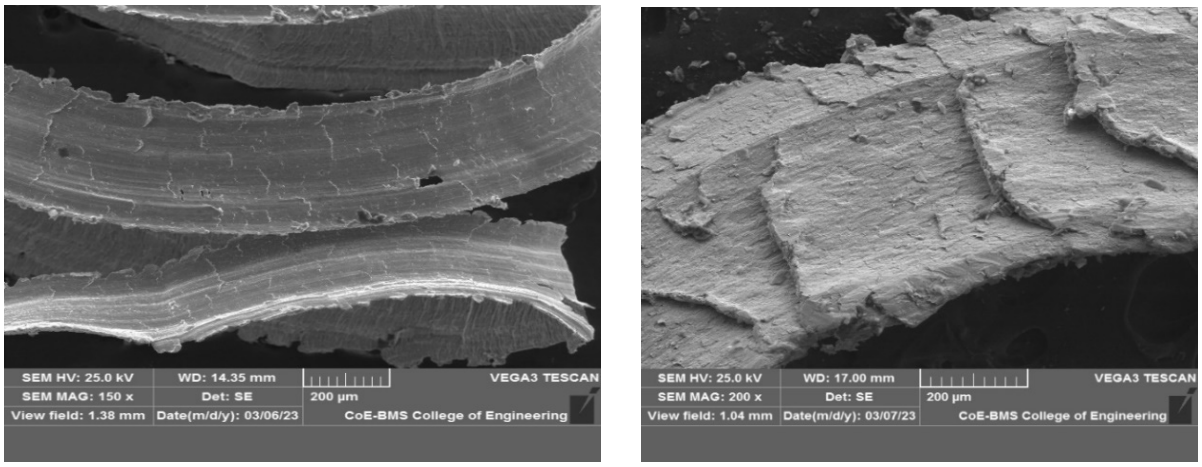


Figure 7. Chips produced at **(a)** DOC of 0.6 mm FR of 0.24 mm/rev, and Vc of 200 m/min **(b)** DOC of 0.2 mm, FR of 0.08 mm/min, and Vc of 200 m/min.

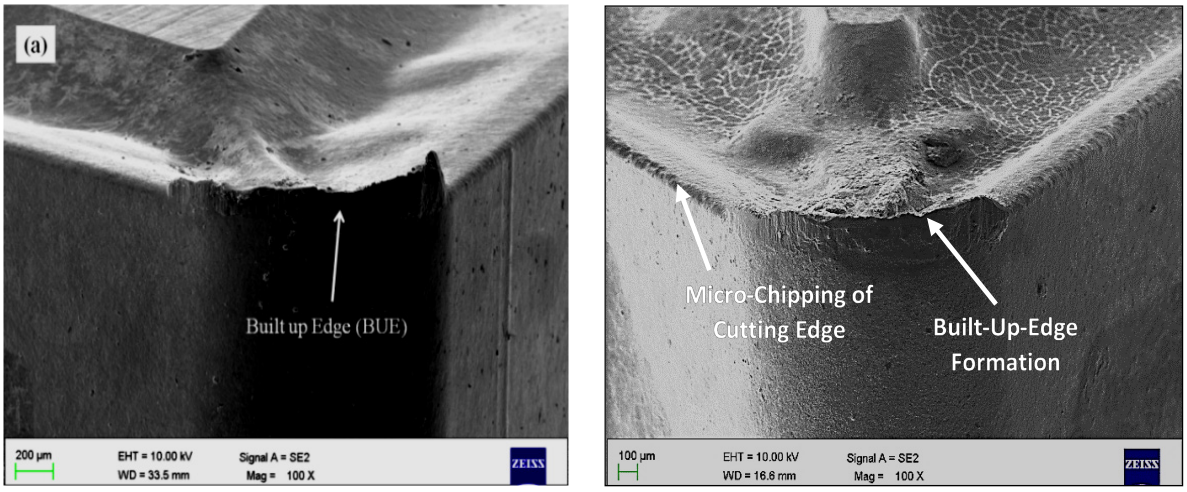


Figure 8. Built-Up-Edge (BUE) formation at **(a)** DOC of 0.6 mm FR of 0.24 mm/rev, and Vc of 100 m/min **(b)** microchipping of cutting edge at FR of 0.08 mm/min, DOC of 0.2 mm and Vc of 200 m/min.

corresponding values of MRR, SR, Ac and TW are 2.887 mm^3, 0.744 µm, 0.026 m/s^2 and 0.026 mm. Therefore, the optimal process parameter level combination obtained for desired objectives is Vc of 200 m/min, FR of 0.08 mm/rev and DOC of 0.2 mm. The yielded optimum values of responses evidence that, the obtained MRR values are relatively higher and other response values are relatively least among the captured values of experimental results. Thus, validates the optimal combination of parameter levels achieved from the PROMETHEE–II approach. Hence, it can be concluded that the PROMETHEE–II approach can be successfully implemented for parametric optimization in machining. Also, the employed method is feasible to obtain optimal parameter combination levels in the machining of EN8 steel.

4.0 Conclusion

In the current study, PROMETHEE – II, an MCDM approach was implemented for the optimization of parameters in the machining of EN8 steel. The considered machining parameters were Vc, FR and DOC, whereas responses are material removal rate, surface roughness, acceleration and tool wear. Based on the investigation

Table 8. Taguchi's L27 orthogonal array with optimization results

Trial No.	MRR (mm^3/min)	SR (µm)	Ac (m/s^2)	TW (mm)	Normalized Response Values				Net outranking flow	Rank
					MRR	SR	Acc	TW		
1	2.250	2.784	0.196	0.045	0.412	0.405	0.769	0.708	-0.0376	17
2	2.497	3.432	0.426	0.067	0.600	0.226	0.457	0.369	-0.2043	21
3	2.609	3.672	0.518	0.081	0.685	0.159	0.332	0.154	-0.2878	23
4	2.223	2.88	0.306	0.051	0.391	0.379	0.620	0.615	-0.1126	19
5	2.314	3.576	0.514	0.073	0.460	0.186	0.337	0.277	-0.3059	24
6	2.404	4.248	0.629	0.085	0.529	0.000	0.181	0.092	-0.4249	25
7	1.885	3.06	0.442	0.056	0.133	0.329	0.435	0.538	-0.2604	22
8	2.105	3.792	0.628	0.079	0.301	0.126	0.182	0.185	-0.4269	26
9	2.239	3.96	0.762	0.091	0.403	0.080	0.000	0.000	-0.5077	27
10	2.356	1.164	0.052	0.031	0.492	0.854	0.965	0.923	0.2065	7
11	2.641	0.984	0.158	0.051	0.710	0.904	0.821	0.615	0.1586	11
12	2.712	1.536	0.206	0.064	0.764	0.751	0.755	0.415	0.0641	13
13	1.710	1.236	0.058	0.037	0.000	0.834	0.957	0.831	0.0474	14
14	2.179	1.656	0.202	0.058	0.357	0.718	0.761	0.508	-0.0246	16
15	2.671	1.764	0.255	0.071	0.732	0.688	0.689	0.308	-0.0057	15
16	2.110	0.732	0.121	0.044	0.305	0.973	0.871	0.723	0.1126	12
17	2.221	1.572	0.245	0.066	0.389	0.741	0.702	0.385	-0.0574	18
18	2.337	1.836	0.315	0.086	0.478	0.668	0.607	0.077	-0.1580	20
19	2.887	0.744	0.026	0.026	0.897	0.970	1.000	1.000	0.3709	1
20	3.022	0.876	0.066	0.046	1.000	0.934	0.946	0.692	0.2941	2
21	2.973	1.02	0.088	0.053	0.963	0.894	0.916	0.585	0.2384	5
22	2.567	0.636	0.040	0.035	0.653	1.000	0.981	0.862	0.2745	4
23	2.671	0.948	0.078	0.056	0.732	0.914	0.929	0.538	0.1753	9
24	2.887	1.032	0.090	0.068	0.897	0.890	0.913	0.354	0.1599	10
25	2.852	0.816	0.054	0.042	0.870	0.950	0.962	0.754	0.2850	3
26	2.952	1.092	0.078	0.053	0.947	0.874	0.929	0.585	0.2326	6
27	3.015	1.188	0.102	0.062	0.995	0.847	0.897	0.446	0.1937	8

carried out and obtained experimental results, the following conclusions were drawn.

1. The PROMETHEE-II approach determined that the ideal machining parameters are a cutting speed (Vc) of 200 m/min, an FR of 0.08 mm/rev, and a DoC of 0.2 mm. These settings resulted in enhanced machinability characteristics.
2. The process parameters were improved, resulting in a Material Removal Rate (MRR) of 2.887 mm^3/s. This indicates a substantial increase in the efficiency of removing material.
3. Under the best machining circumstances, the surface roughness was reduced to 0.744 µm, suggesting an improvement in surface quality.
4. The acceleration resulting from tool vibration was decreased to 0.026 m/s^2, indicating improved stability and reduced vibration throughout the machining process.
5. The tool wear was decreased to 0.026 mm, suggesting that the adjusted settings led to a longer tool lifespan and less tool deterioration.
6. The study confirmed the efficacy of the PROMETHEE-II approach in multi-response optimization, showcasing its practicality in reaching the most favourable machining conditions for turning EN8 steel.

5.0 Author Designation

N. Nagesha- Research scholar
B. S. Praveen Kumar- Associate professor

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