Check for updates

Hybrid Taguchi- Machine Learning Based Optimization of Face Milling Parameters to Enhance Material Removal Rate of EN8 Steel

Kamaljeet Singh[1], Abhishek Pratap Singh Sachan[2], Jasjeevan Singh[3], Ajay Kumar[1],

[1]Department of Mechanical Engineering, Chandigarh University, Mohali-140413, Punjab, India
[2]Department of Academics, Pune Institute of Business Management, Pune, India
[3]Department of Mechanical Engineering, Khalsa College of Engineering & Technology, Amritsar, Punjab, India

*Corresponding Author E-mail: jasjeevansingh175@gmail.com

Abstract

In modern industrial manufacturing, minimizing machining time is essential to enhance productivity and reduce overall production costs. This study presents an artificial intelligence (AI) approach for optimizing face milling parameters to increase the material removal rate (MRR) of EN8 steel. Experiments were carried out on VMC named (HURCO-VM10) using a 75 mm diameter face milling cutter. The parameters considered include feed, cutting velocity and depth of cut (DOC). To enhance the capabilities of traditional statistical optimization, machine learning-based predictive modelling is used to capture the nonlinear relationship between machining parameters and MRR. The results show that the most prominent parameter is DOC, which contributes 72.67% of MRR variance, followed by feed rate (14.72%) and cutting velocity (8.58%). Regression-based learning models are used to assess experimental trends and forecast MRR outside of discrete experimental settings

Keywords: Artificial Intelligence, EN8 steel, face milling, Taguchi method, MRR, signal-to-noise ratio (S/N), ANOVA, optimization

1 Introduction

In current manufacturing sector there is huge competition between manufacturers to identify creative ways to boost output and product quality. The metal removal rate means volume of metal extracted from a specimen per unit time during the milling process [1]. In industrial engineering, MRR is a crucial factor for raising product quality and productivity. As the cutting parameters for various metals changes, MRR varies accordingly. The rate at which metal is removed has a significant effect on mechanical characteristics like chip formation, creep, fatigue etc. [2]. The researcher has main focus on improving surface quality in face milling operation of AISI 1040 steel by applying Taguchi approach. While experimenting with different cutting parameters, researchers identified the optimal settings for achieving a smoother finish DOC is 0.3 mm, cutting speed is 220.00 m/min and feed rate is 0.10 mm/tooth [3]. Among these factors, cutting speed is carried with most dominant influence (36.85%), followed by the type of cutting tool (21.38%). With these optimized settings, surface roughness (SR) improved dramatically from 2.90 µm to 1.42 µm with 51.03% enhancement, while reducing quality loss by 76.2%. The study confirmed that uncoated inserts contribute to better surface quality and Taguchi approach is a reliable method for reducing machining costs and

A. Agnihotri et al. (eds.), *Proceedings of the Conference on Bridging Engineering Disciplines with AI and Machine Learning (BEDAIML 2026)*, Advances in Intelligent Systems Research 209,
https://doi.org/10.2991/978-94-6239-697-5_25

time [4]. This study focused on milling of 1040 steel employing carbide insert [GC1030] to develop statistical models for MRR. Researcher have used multiple linear regression and RSM techniques to inspect the effects of feed per tooth, DOC and cutting speed on *MRR*. The findings show that cutting speed and feed per tooth had the most significant impact on MRR with contribution of 30.76% and 17.94% [5, 6]. The developed mathematical models demonstrated strong accuracy, with an R^2 value of 98.53% for MRR, confirming their reliability results in an MRR of [32,804.9 mm^3/min] [7]. Optimal cutting parameters are fz of 0.044 mm/tooth, Vc of 251 m/min and ap of 0.6 mm achieved an MRR of 8,396 mm^3/min. with a desirability score of 0.93 [8-11]. The study explores how different machining parameters affect MRR in machining using ANOVA. Among the tested factors Cv, Fr and Dc had the biggest impact on MRR (80.29%) [12], followed by coolant flow rate (2.32%), feed rate (10.84%) and spindle speed (5.55%). The ideal parameters for enhancing MRR were found during study are cutting speed of 500 m/min, *fz* of 0.14 mm/rev, *Dc* of 0.5 mm, and *CFR* of 150 ml/h [13, 14].

Researcher had conducted end milling experiment on EN8 steel using an L9 Array. The aim is to find the optimal settings for enhancing MRR. By analyzing response values and the *S/N* ratio, identified that "larger the better" approach is suitable. The results of ANOVA identified that spindle speed and feed rate were the most important factors for MRR [15]. The perfect parameters for achieving maximum MRR are, Dc of 1.5 mm, Fr of 30 mm/rev, and Ss of 450 rpm [16]. This study showed that how well Taguchi method is in optimizing process parameters. The C_V along with Feed makes the greatest impact on MRR with contribution of 39.84%. The reliability of the optimization process was confirmed, with a high confidence level of 99.14% for MRR [17, 18]. Researchers investigated different feed rates 60, 80, and 100 mm/min and how they affect machining performance. They discovered that increasing the feed rate enhances the (MRR) but results in a rougher surface finish. This study recorded the highest MRR of 2.40 mm^3/min using DOC of 0.6 mm, FR of 100 mm/min and SS of 1000 rpm [19]. For achieving a smoother surface with a roughness of 0.41 μm, the ideal parameters were *Fz* of 100 mm/min, spindle speed of 1000 rpm and reduced *Ap* of 0.2 mm [20, 21]. Researchers have observed that MRR increases with spindle speed up to 3100 rpm and after that it declines. Elevated feed rates and greater DOC significantly enhance MRR and playing an important role in the (S/N) ratio. This study reveals that optimizing these machining parameters lead to improved material removal during milling operation and enhanced overall efficiency [22, 23].

In order to increase work efficiency and minimize SR, the researcher optimizes the machining parameters for aluminum 7075 alloy employing the Taguchi method and ANOVA [24, 25]. Taguchi offered increased optimization to lower temperature and SR [26, 27]. Researcher examined the implementation of Grey Relational Analysis and Taguchi method. The primary aim of study is enhancing the CNC milling performance for stainless steel 304. The *AP* is determined to be a supreme factor for influencing SR and MRR [28]. While experimentation, they determined that DOC of 1.5 mm, FR of 0.150 mm/rev and CV of 75 m/min were the optimal machining parameters. These settings provided the best balance between efficiency and surface quality [29, 30].

In recent years, AI and machine learning (ML) techniques have developed as effective tools for modeling complicated, nonlinear machining phenomena. ML models may learn from experimental data, detect hidden parameter relationships, and make ongoing predictions about machining performance. Integrating ML with classical statistical approaches provides robust optimization and intelligent decision-making in line with Industry 4.0

The current study seeks to provide a hybrid Taguchi-machine learning framework for optimizing face milling parameters in EN8 steel. The goals are to (i) use Taguchi and ANOVA to discover the best machining parameters for maximizing MRR, and (ii) show how ML-based predictive modeling can be used to validate and extend experimental findings.

2. Methodology

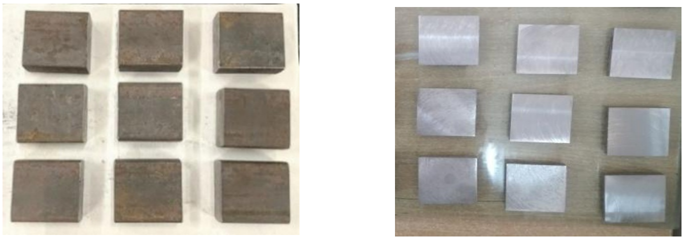
This flowchart illustrates the structured flow of research. It starts with fundamental work and existing knowledge through introduction and literature review. Then it informs the selection of appropriate optimization techniques and statistical tools which are crucial for robust design. The main part of study lies in methodology and material, specimen details. Design of experiment includes the precise selection of parameters and levels. Then study moves towards the experimentation and further planned study approaches.

Fig. 1. Flow chart of methodology

2.1 Material and Specimen

EN8 Steel is a versatile, cost-effective material for industries prioritizing strength, machinability, and heat treatability. The melting point of EN8 steel is 1425–1540°C (2597–2804°F) and its density is 7.85 g/cm³. The composition and physical properties of EN8 steel are illustrated in Table 1 [31]. HURCO VM10 CNC is employed with 75 mm diameter tool to perform the milling operation as presented in Fig. 2. The dimensions of specimen are 50mm x 50mm x 20mm. Figures 3(a) & 3(b) illustrate before and after machining.

Fig. 2. HURCO VM10 CNC



(a) (b)

Fig. 3. EN8 steel specimens (a) Before machining (b) After machining

Table 1 Alloying elements and properties of EN8 Steel [4]

Alloying Elements	Percentage (%age)	Physical Properties	
%Carbon	0.35 – 0.45	Density	7.785 g/cm^3
%Manganese	0.65 – 0.95	Creep Strength	292 MPa
%Phosphorus	0.65 – 0.95	Hardness (Rockwell)	149 BHN
%Sulfur	0.06	Tensile Strength	525 MPa
%Fe (iron)	98.6 – 99	Modulus of Elasticity	200 GPa

2.2 Design of Experiment

Taguchi method is a straightforward and reliable strategy for optimum process parameters by lowering process variation. Investigating why various process parameters impact the mean and variation of process performance characteristics, as well as which variable makes a substantial contribution, is the goal of the analysis. The Taguchi approach is widely used among many experimental design techniques that improve performance and machinability. Based to the Taguchi approach, the main goal of evaluating experiment responses is the S/N ratio [30]. ANOVA is utilized to determine the influence of each adjustable parameter. The quality loss function is divided into three categories by Taguchi higher the better, nominal the best and smaller the better [31]. For an input parameter, a level with the highest S/N ratio is identified as the optimal setting. To increase the MRR of EN8 steel, this study provides the most appropriate combination of DOC, feed and cutting speed [32, 33].

2.3 Process parameters and levels.

The machining experiment is done by taking three key parameters DOC, feed and cutting velocity [15]. The selection of parameters is based on experimental trials and an extensive preview of related literature. Table 2 outlines the machining parameters and levels, ensuring a systematic approach to analyzing their effects on the MRR. Taguchi technique is used for design of experiment by employing L9 orthogonal array facilitating an effective evaluation of parameter interactions. For precise results each trial was conducted under controlled conditions.

Table 2 Values of machining parameters at different levels [34]

Parameters	Units	Symbols	Level 1	Level 2	Level 3
Cutting velocity	m/min	*Cv*	100	150	200
Feed rate	mm/min	*Fz*	50	75	100
Depth of cut	mm	*Ap*	0.3	0.6	0.9

3. Experimentation

3.1 Material Removal Rate (MRR)

The MRR in milling operation refers to the volume of material removed/unit time measured in gm/min according to Eq. 1 [35]. The initial and final weights are measured using a digital weighing machine, as shown in Fig. 4. Evaluating this parameter is essential for attaining cost-efficient manufacturing, maintaining high product quality, and reducing production time [8].

MRR = Weight before milling (grams) –Weight after milling (grams) /Milling Time (min.) [Eq-1]

Fig. 4. Weighing machine

3.2 S/N Ratio

To achieve maximum MRR, the “larger-the-better” criterion is adopted for the calculations [33].

$$\frac{S}{N} for MRR = -10 \log\left[\frac{1}{n}\left(\sum_{i=1}^{n} \frac{1}{y_i}^2\right)\right] \text{- [Eq-2]}$$

In this context, y_i denotes the response value obtained from the i^{th} experiment, while n represents the total number of experiments conducted [33].

Table 3 Outputs of experimentation

Exp. No.	*Cv, m/min.*	*Fz, mm/min.*	*Ap, mm*	*Avg. MRR (gm/min.)*	*S/N ratio (db)*
1	100	50	0.3	7.717	17.748
2	100	75	0.6	7.513	17.516
3	100	100	0.9	10.013	20.011
4	150	50	0.6	9.367	19.431
5	150	75	0.9	10.917	20.761
6	150	100	0.3	7.017	16.922
7	200	50	0.9	11.783	21.425
8	200	75	0.3	7.957	18.014
9	200	100	0.6	8.523	18.610

To enhance measurement accuracy and minimize experimental errors, each specimen was tested three times, and the avg. readings were considered. The mean values of MRR along with their corresponding (S/N) ratios are presented in Table 3. The S/N ratio serves as a performance indicator for evaluating the response variable, as it accounts for data variability and ensures a more consistent and dependable interpretation of the experimental outcomes. An AI-based Random Forest regression (RFR) model was created as shown in Fig.5.

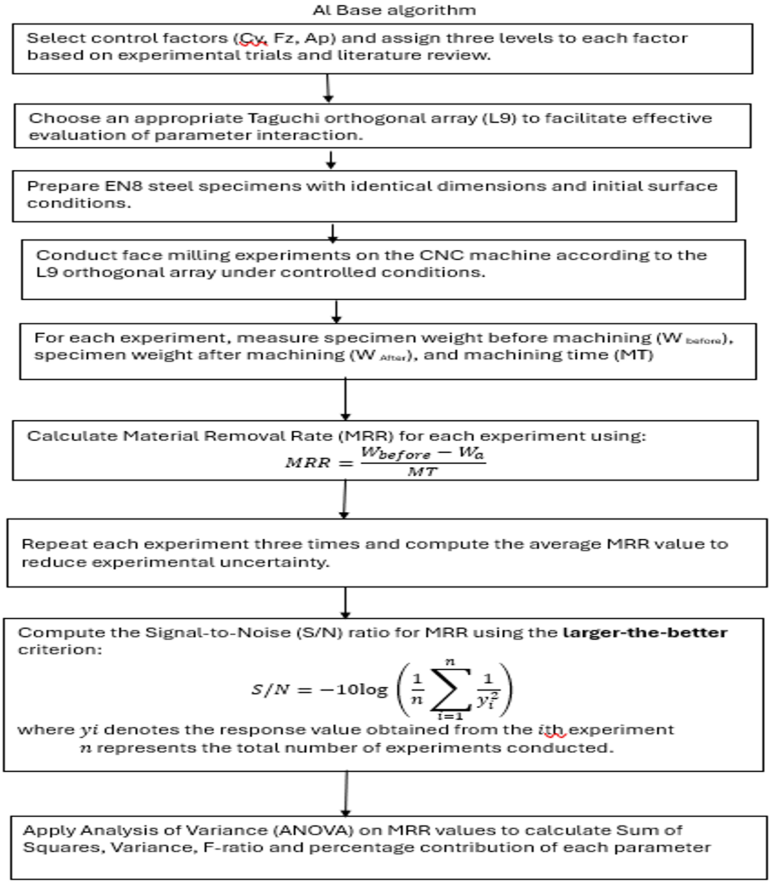


Fig 5. AI Base Algorithm of hybrid Taguchi- machine learning based optimization of face milling

4. Results and Discussion

The influence of the machining parameters on MRR, as evaluated through the (S/N) ratio, is illustrated in Fig. 6. The maximum S/N ratios, which indicate the most favorable conditions for achieving higher MRR, are observed at cutting speed (*Cv*) level 3, feed per tooth (*Fz*) level 1, and DOC (*Ap*) level 3. The main impact plot reveals that DOC exhibits the most significant variation between the maximum and minimum *S/N ratio* values, indicating its dominant influence on variance.

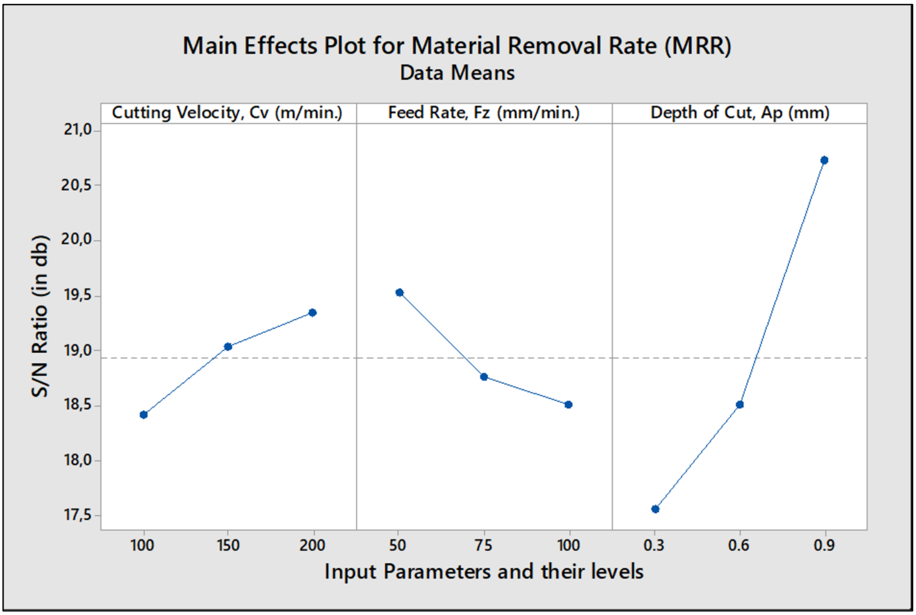


Fig. 6. Main impacts plot for MRR vs S/N Ratio

Table 4 ANOVA for MRR

S. No	*Input Machining parameters*	*Degree of freedom*	*Sum of square*	*Variance*	*F-ratio*	*Contribution (in %age)*
1	*Cv*, m/min.	1	1.363	1.363	11.676	8.58
2	*Fz*, mm/min.	1	2.101	2.101	19.680	14.72
3	*Ap*, mm	1	14.266	14.266	126.324	72.67
4	Error	5	0.194	0.0388		4.03
5	Total	8	17.924	2.2405		100.00

Among them, DOC stands out as the most prominent factor contributing 72.67% to the variation in MRR and having the highest F-ratio (126.324). This suggests that increasing the DOC has the biggest effect on material removal. Feed rate (14.72%) and cutting velocity (8.58%) also have a significant impact, though to a lesser extent. The error percentage is only 4.03%, meaning that almost all variations in MRR can be explained by these machining parameters. Since all the F-ratios exceed 6.39, we can confidently say that each factor is crucial in determining MRR. From this analysis DOC is the most essential parameter for MRR. The real vs predicted MRR plot in Figure 7 demonstrates good accordance between experimental and expected values, indicating that the AI model is effective at identifying the nonlinear relationship between machining parameters and MRR.

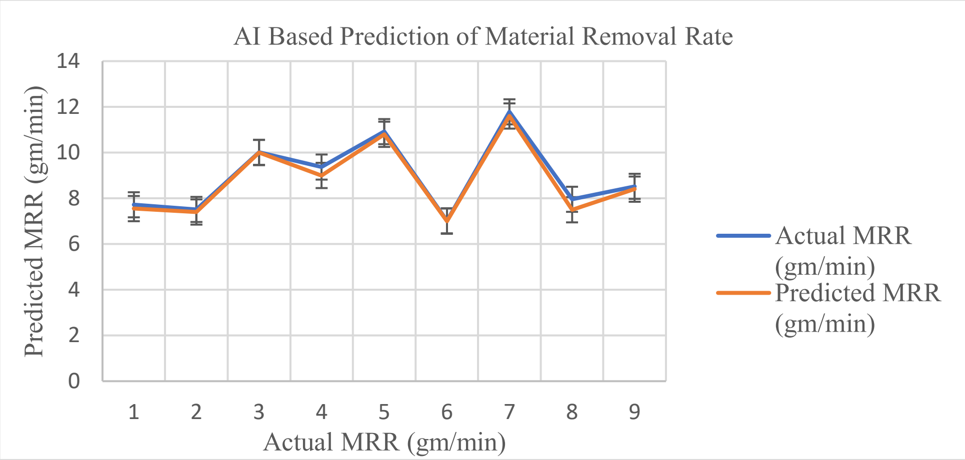


Figure 7. RFR model shows actual MRR vs predicted MRR

5. Conclusion

This study was carried out to analyze the face milling on EN8 steel by using Taguchi L9 Orthogonal array approach. The study's goal was to figure out the optimal machining parameters that maximize the MRR using the analysis of means. The optimal parameter settings were identified and the significance of each level was evaluated by using the ANOVA.

1.From the outcomes of ANOVA table, (*Ap)* contributes maximum to MRR with 72.67%, while, (*Fz)* with 14.72% and (*Cv)* with 8.58%.

2.The optimal parameters for achieving the highest MRR were identified as a (*Vc*) of 200 m/min, (*Fz*) of 50 mm/min., and (*Ap*) of 0.9 mm.

3.Since the F-ratio values of every parameter were higher than the critical threshold they all are determined to be statistically significant.

4.The measurement error is just 4.03%, indicating that the interactions between process parameters have a minimal impact on MRR.

5.The findings provide meaningful guidance for refining machining operations to achieve better performance and efficiency. Proper adjustment of process parameters can substantially improve the overall effectiveness of the milling process.

6.Overall, the implementation of Random Forest Regression provides a trustworthy and efficient decision-support tool for selecting machining parameters and optimizing processes.

References

1. Rizvi, S. A., & Ali, W. (2021). Analysis of surface roughness and material removal rate in machining of AISI 1040 steel using CNC turning process. *International Journal of Innovation in Engineering*, *1*(3), 8-19.

2. Pavani, P. N. L., Prasad, C. L. V. R. S. V., & Ramji, K. (2017). Experimental study and optimization of machining parameters in turning of AISI 1040 steel with micro-grooved WC cutting

tools. Engineering Journal, 21(4), 155-169.
3. Palanisamy, D., & Senthil, P. (2016). Optimization on turning parameters of 15-5PH stainless steel using Taguchi based grey approach and Topsis. Archive of Mechanical Engineering, 63(3).
4. Samtaş, G. (2016). Optimization of cutting parameters using Taguchi method during the face milling of AISI 1040 with coated and uncoated inserts. Duzce University Journal of Science and Technology, 4(1), 278-292.
5. Kuljanic, E., & Sortino, M. (2005). TWEM, a method based on cutting forces—monitoring tool wear in face milling. International Journal of Machine Tools and Manufacture, 45(1), 29-34.
6. da Silva, L. C., de Melo, A. C. A., Machado, Á. R., da Silva, M. B., & Júnior, A. M. S. (2006). Application of factorial design for studying the burr behaviour during face milling of motor engine blocks. Journal of materials processing technology, 179(1-3), 154-160.
7. Zhang, H., Qu, L., & Ding, C. (2023). Study of Surface integrity of SiCp/Al composites using high-speed milling under cryogenic liquid nitrogen conditions. Machines, 11(6), 608.
8. Fnides, M., Amroune, S., Mohamad, B., Fnides, B., & Toufik, B. (2024). OPTIMIZATION OF SURFACE ROUGHNESS AND MRR WHEN MILLING 25CRMO4-25 STEEL USING TAGUCHI DESIGN. Academic Journal of Manufacturing Engineering, 22(4).
9. Rana, M., Singh, T., Sharma, V. K., Singh, K., & Aggarwal, P. (2023). TGRA-Based Optimization of Face Milling of AISI 52100 Alloy Steel for Surface Microhardness and Tool Life. In Emerging Trends in Mechanical and Industrial Engineering: Select Proceedings of ICETMIE 2022 (pp. 663-675). Singapore: Springer Nature Singapore.
10. Rana, M., Singh, T., Sharma, V. K., Singh, K., & Aggarwal, P. (2023, September). Simultaneous optimization of multiple responses in face milling of AISI 52100 steel using MQL. In AIP Conference Proceedings (Vol. 2800, No. 1, p. 020284). AIP Publishing LLC.
11. Shi, K., Zhang, D., Ren, J., Yao, C., & Yuan, Y. (2014). Multiobjective optimization of surface integrity in milling TB6 alloy based on Taguchi-grey relational analysis. Advances in Mechanical Engineering, 6, 280313.
12. Singh, J., Mahajan, A., & Kumar, A. (2025). Sustainable machining of magnesium alloy (AZ31): investigating tool wear and surface roughness under various conditions. Physica Scripta, 100(5), 055977.
13. Joshi, A., Kothiyal, P., & Pant, R. (2012). Experimental investigation of machining parameters of CNC milling on MRR by taguchi method. International Journal of Applied Engineering Research, 7(11), 1796-1800.
14. Aydın, M., Gökcepınar, Ö. F., & Kalyoncu, M. (2024). Optimization of pre-turning parameters for diamond burnishing of AISI 4340 steel. Journal of Advances in Manufacturing Engineering, 5(2), 29-36.
15. Rao, R. V., & Pawar, P. J. (2010). Parameter optimization of a multi-pass milling process using non-traditional optimization algorithms. Applied soft computing, 10(2), 445-456.
16. Saif, M., Hasan, S., Rawat, R. K., & Jamal, M. (2025). Investigation of EN8 & EN31 steels in vertical milling machine for SR and MRR by adopting optimization approach. Advances in Materials Research, 14(2), 81-98.
17. Satyanarayana, K., Kumar, V. T., Rathod, R., Shafi, M. D., Chary, S., Alkhayyat, A., & Khanduja, M. (2023). Optimization of machining parameters of CNC milling operation for material removal rate and surface roughness on EN-24 steel using Taguchi method. In E3S Web of Conferences (Vol. 391, p. 01011). EDP Sciences.
18. Sharma, V. K., Singh, T., Rana, M., & Singh, K. (2022). Multi-output optimization during MQL based face milling of EN-31 steel employing Taguchi coupled grey relational analysis. Materials Today: Proceedings, 65, 3216-3223.
19. Daniyan, I. A., Mpofu, K., Adeodu, A. O., & Oyesola, M. (2023, May). Hard turning operation of Alloy Tool Steel (AISI D3) using cubic boron cutting tool. In 2023 14th International Conference on Mechanical and Intelligent Manufacturing Technologies (ICMIMT) (pp. 153-157). IEEE.
20. Abdulrazaq, M. M., Jaber, A. S., Hammood, A. S., & Abdulameer, A. G. (2019).

Optimization of machining parameters for MRR and surface roughness for 7024 Al-alloy in pocket milling process. Association of Arab Universities Journal of Engineering Sciences, 26(1), 10-16.
21. Sharma, V. K., Singh, T., Singh, K., Rana, M., & Kaur, G. (2023). Multi-response optimization in face milling of EN-31 steel using hybrid CRITIC and DFA technique. In Emerging Trends in Mechanical and Industrial Engineering: Select Proceedings of ICETMIE 2022 (pp. 723-738). Singapore: Springer Nature Singapore.
22. Tsegaw, A. A., Shiou, F. J., & Lin, S. P. (2015). Ultra-precision polishing of N-Bk7 using an innovative self-propelled abrasive fluid multi-jet polishing tool. Machining Science and Technology, 19(2), 262-285.
23. Singh, J., Gill, S. S., & Mahajan, A. (2024). Experimental investigation and optimizing of turning parameters for machining of al7075-t6 aerospace alloy for reducing the tool wear and surface roughness. Journal of materials engineering and performance, 33(17), 8745-8756.
24. Sathish, T. (2024). Taguchi and ANOVA-based Optimization of CNC Milling Parameters for Aluminium 7075 Alloy. J. Environ. Nanotechnol, 13(1), 72-77.
25. Singh, T., Sharma, V. K., Rana, M., Singh, K., & Saini, A. (2022). GRA based optimization of tool vibration and surface roughness in face milling of hardened steel alloy. Materials Today: Proceedings, 50, 2288-2293.
26. Nagamani, K., Venkatesh, B., & Keerthi, N. (2023). EXPERIMENTAL INVESTIGATION AND COMPARATIVE STUDY OF CNC MILLING PROCESS PARAMETER BY FACTORIAL METHODS WITH TAGUCHI METHOD ON ALUMINUM ALLOY. SHODHKOSH: JOURNAL OF VISUAL AND PERFORMING ARTS Учредители: Granthaalayah Publications and Printers, 4(2), 1552-1564.
27. Singh, T., Sharma, V. K., Rana, M., & Singh, K. (2023). Face milling of AISI 52100: evaluation of tool performance and surface integrity. In Emerging Trends in Mechanical and Industrial Engineering: Select Proceedings of ICETMIE 2022 (pp. 801-810). Singapore: Springer Nature Singapore.
28. Abbas, A. T., Sharma, N., Anwar, S., Hashmi, F. H., Jamil, M., & Hegab, H. (2019). Towards optimization of surface roughness and productivity aspects during high-speed machining of Ti–6Al–4V. Materials, 12(22), 3749.
29. Kumbhar, A., Bhosale, R., Modi, A., Jadhav, S., Nipanikar, S., & Kulkarni, A. (2015). Multi-objective optimization of machining parameters in CNC end milling of stainless steel 304. International Journal of Innovative Research in Science, Engineering and Technology, 4(9), 8419-8426.
30. Abebe, A. D., Jiru, M. G., & Kabeta, G. (2021). Comparative study on dry and wet machining during double tool turning of AISI 1045 steel. Int. J. Innov. Sci. Eng. Technol, 8(9), 71-101.
31. Malkiya Rasalin Prince, R., Selvakumar, N., Arulkirubakaran, D., Christopher Ezhil Singh, S., Ramkumar, T., & Kumar, R. M. (2020). Surface structural features and wear analysis of a multilayer Ti6Al4V-B4C thin film coated AISI 1040 steel. Materials Research Express, 7(1), 016436.
32. Singh, K., Singh, A. K., & Chattopadhyay, K. D. (2020). Selection of optimal cutting conditions and coolant flow rate (CFR) for enhancing surface finish in milling of aluminium alloy. Materials Today: Proceedings, 21, 1520-1524.
33. Pandey, P. M., Kumar, P., & Sharma, V. (2021). Advances in Production and Industrial Engineering. Springer.
34. Rao, R. V., & Taler, J. (2018). Advanced engineering optimization through intelligent techniques.
35. Yanda, H., Ghani, J. A., Rodzi, M. N. A. M., Othman, K., & Haron, C. C. (2010). Optimization of material removal rate, surface roughness and tool life on conventional dry turning of FCD700. International Journal of Mechanical and Materials Engineering, 5(2), 182-190.