REVISTA MATÉRIA V.29 N.2
ISSN 1517-7076 articles e20240019, 2024

Green machinability studies on SAE 8822 alloy steel using RSM and taguchi method

Suresh Kumar Ramalingam[1], Aravinth Karuppusamy[1],
Balu Mahandiran Subramaniyam[2], Sathish Radhakrishnan[3]

[1]Sri Eshwar College of Engineering, Department of Mechanical Engineering, Centre for Advanced Materials & Testing. Coimbatore, Tamil Nadu, India.

[2]Sri Krishna College of Engineering and Technology, Department of Mechanical Engineering. Coimbatore, Tamil Nadu, India.

[3]Karpagam College of Engineering, Department of Mechanical Engineering. Coimbatore, Tamil Nadu, India.

e-mail: rsureshkumarsece@gmail.com, aravinth53n@gmail.com, balu.ssmce@gmail.com, sathishradha25@gmail.com

ABSTRACT

The study aims to optimize machining parameters for turning SAE 8822 Alloy steel under green machining (without coolant), using a CNC turning machine with a carbide tool. The controlled factors are spindle speed (*A*), feed rate (*B*), and depth of cut (*C*), with roughness (R_a) as the response variable. The experimental runs are conducted using an L_9 Orthogonal Array (*OA*). Orthogonal arrays are used to efficiently explore the parameter space with a relatively small number of experimental runs while maintaining statistical validity. The impact of the machining parameters on the roughness is interpreted using Analysis of Variance (ANOVA). ANOVA is a statistical technique that helps identify the significance of each parameter and their interactions on the response variable. The result indicated that variation of *A* between 1500 rpm to 2000 rpm resulted in a significant increase in R_a. Similarly, the effect of *B* and *C* contributed towards huge variations in R_a. The optimal values of 1500 rpm for *A*, 0.5 mm/rev for *B*, and 1 mm for *C* are identified as the most favorable combination for achieving the desired R_a. Achieving a minimum R_a of 0.04 microns indicate a very high-quality surface, which may be desirable in precision engineering applications. The analysis shows that the *C* and *B* have the highest influence followed by *A* on R_a.

Keywords: Optimization; CNC turning; ANOVA; RSM; Green machining.

1. INTRODUCTION

Green machining (*GM*), also known as sustainable machining or environmentally friendly machining, is an approach to manufacturing that prioritizes ecological sustainability and resource efficiency in machining processes. This concept addresses the environmental impact of traditional machining methods, aiming to reduce energy consumption, waste generation, and the overall carbon footprint associated with manufacturing. *GM* techniques includes high speed machining (*HSM*), dry machining (*DM*), minimum quantity lubrication (*MQL*), drop lubrication, cryogenics etc.

1.1. Impact of cutting fluids

While cutting fluids offer essential benefits in machining processes, it's important to manage their usage carefully, considering environmental, health, and safety factors. Cutting fluids contain chemicals that can be harmful to the environment. Disposal and management of used cutting fluids require careful consideration to prevent environmental pollution. Exposure to certain cutting fluid additives may pose health risks to machine operators. Inhalation or skin contact with some fluids may lead to respiratory or skin issues. The use of cutting fluids contributes to the generation of machining residues, which require appropriate handling and disposal methods to prevent environmental impact. Stringent environmental regulations and workplace safety standards may require manufacturers to implement proper measures for cutting fluid management, increasing compliance responsibilities. Addressing the environmental and health-related issues associated with cutting fluids in the production sector often requires a significant additional investment, both in terms of financial resources and commitment to adopting sustainable practices. To minimize these risks dry machining techniques plays a crucial role providing solution.

Corresponding Author: Suresh Kumar Ramalingam Received on 22/01/2024 Accepted on 13/03/2024

DOI: https://doi.org/10.1590/1517-7076-RMAT-2024-0019

1.2. Dry Machining (DM)

DM refers to a machining process in which cutting operations are performed without the use of traditional liquid cooling or lubricating agents, commonly known as cutting fluids or coolant. Instead of relying on a continuous flow of fluids to cool the cutting tool and workpiece, dry machining operates without any external liquid support. This approach has gained attention for its potential environmental, economic, and operational benefits. One of the primary motivations for adopting dry machining is the reduction of environmental impact. Traditional cutting fluids can contain chemicals that are hazardous to the environment. Eliminating the need for these fluids minimizes the potential for pollution and simplifies waste management. This technique also contribute to energy savings as the process eliminates the need for pumping, filtering, and treating cutting fluids. The energy required for the production, transportation, and disposal of cutting fluids is also reduced. By eliminating the need for cutting fluids, manufacturers can achieve cost savings associated with purchasing, maintaining, and disposing of these fluids. Additionally, the costs associated with the treatment and recycling of used cutting fluids are avoided.

Though *DM* offers several advantages, it may pose challenges in certain applications. Heat generated during machining can affect tool life and workpiece quality. Therefore, careful selection of cutting tools, machining parameters, and workpiece materials is crucial for successful implementation of DM technique. This article made an attempt towards application of dry machining technique while experimenting on SAE 8822 alloy steel.

2. LITERATURE REVIEW

The importance of machining parameters in optimization lies in their direct impact on surface finish, tool life, productivity, energy consumption, and overall cost-effectiveness of machining operations. By carefully selecting and fine-tuning these parameters, manufacturers can achieve the desired outcomes while maximizing efficiency and minimizing environmental impact. Well-optimized machining parameters contribute to process stability and consistency. This reduces the likelihood of unexpected variations in the machining results, leading to reliable and repeatable manufacturing processes. Optimal machining parameters contribute to reduced material wastage by achieving the desired outcomes with minimal excess material removal. This aligns with sustainable manufacturing practices and cost-effective resource utilization. The selection of suitable combination of parameters is a complex task and highly influenced by the skill of the person in judging the ideal level of parameter settings prior to machining. However, these time consuming process has been drastically reduced by the optimization tools and techniques resulting in significant reduction in the lead time involved with great accuracy and quality. On the other side, consistent changes in functionality module of CNC and high-speed machining tremendously increased the machining efficiency. The availability of such optimization techniques and sophisticated machines given a new dimension in machinability studies. Numerous research studies have been carried out and are on-going towards finding ways and means to improve the machining processes in manufacturing sectors.

For instance, the performance of the cyclone separator using design of experiments was studied by KUMAR *et al.* [1]. The study included application of multi-objective optimization and computational fluid dynamics (CFD) approach to arrive at the optimized values. GHOSH *et al.* [2] investigated the tribological performance of Al-7.5% SiC_p using taguchi and GRA methods. The entire study was based on L_{27} OA with load, time and speed as the controlling factors and responses as friction and wear characteristics. Another study investigated and studied the machining behaviour [3, 4] to arrive at the optimized machining parameter for attaining minimum R_a using taguchi robust design. The minimum R_a was attained while working on aluminium alloy and grey cast iron respectively using taguchi robust design. An extensive study was made by AZIZI *et al.* [5]. The study involved experimental mathematical modeling in determining optimized level for attaining minimum R_a. The work involved turning process on EN19 with carbide tool considering A, B, C and D as the machining parameters.

SURYARAJ *et al.* [6] worked on RSM tool to optimize the parameter for increasing the impact toughness of the boride steel (AISI 1015). Optimization of M_{rr} was performed in EN19 steel [7] using taguchi L_9 OA. Tin-coated carbide cutting tool with 4 flutes of 8 mm diameter was used for machining operation. The study involved factors A, B and C as the controlling factors and M_{rr} as the response. An optimization study was performed on EN31 steel [8] using hybrid optimization techniques involving application of taguchi design and GRA. The study involved factors A, B and C as controlling factors for governing R_a and vibration of tool. The entire study was performed under MQL technique. CNC end milling were performed based on Box Behnken Design (BBD) followed with ANOVA analysis. SAMTAS and BEKTAS [9] investigated TiN-TiCN-Al2O3 inserts (both the untreated and cryogenically treated) using L_{18} OA. The study involved optimization of tool insert wear and R_a using grey relation analysis (GRA). The result showed better performance for cryogenically treated insert.

MIA *et al.* [10] studied the optimization of machinability parameters on Al/SiC-MMC. The study involved optimization of R_a and M_{rr}. The study employed design of experiments (DoE) for conducting trial runs and ANOVA for analysis, followed by optimization using ANN.

Another study involved optimization of temperature and R_a and temperature while machining EN31 alloy [11]. The study involved taguchi based grey relational analysis involving face milling under minimum quantity lubrication environment. Parameters A, B, C and lubricant flow rate were taken as controlling factors and responses as temperature and R_a. ANAND *et al.* [12] investigated the process parameter for drilling polyamide 6 (PA6) hybrid nano composites through optimization technique.

DEVARAJ *et al.* [13] investigated the MQL assisted optimization for turning AISI 1060 steel using taguchi design. Coated cemented carbide tool was used for the experimental work. The entire study was performed to analyze the behaviour of roughness in terms of R_a, R_q and R_z tool wear, and M_{rr}. Significant factor affecting the responses were identified by ANOVA. SOUNDHAR *et al.* [14] investigated the effect of fly ash and egg shell on AA6082. The hybrid composite thus developed was investigated for its performance as a measure of R_a and tool flank wear. For single-objective, L_{16} OA was employed and for multi-objective taguchi based GRA was opted. The result showed significant improvement in terms of machinability, wear, and mechanical properties. RSM method was employed to optimize the welding (CO_2 laser) parameters for welding AISI 316 and nickel 201 [15]. SRIDHAR *et al.* [16] investigated the wear pattern of SiC tool inserts and tool inserts coated with titanium nitride. The study was carried on EN8 steel and involved parameters A, B, C and tool insert properties as machining parameters.

PREMNATH [17] optimized the machining parameters in EDM by working on titanium alloy. Voltage, current, pulse time (on and off) were the controlling factors and studied its impact on the responses R_a, M_{rr} and electrode wear rate. The entire study was performed based on central composite design. The study concluded with development of empirical model for predicting the responses. RAJESWARI *et al.* [18] employed hybrid Taguchi-artificial neural network approach while performing EDM for predicting R_a. The entire study was performed on titanium alloys. Eight parameters were considered and out of which two significantly contributing factors namely current and pulse on time were taken for prediction of R_a using hybrid model involving taguchi and neural networks. The result showed that higher discharge resulted in errors like cracks, micro pores, holes, residual stress and craters on the machined surfaces. KARABULUT *et al.* [19] studied the machining performance of Al_2O_3 micro composite by applying taguchi method in milling. The trials were based on L_9 OA with M_{rr} taken as the response. Another study aimed towards determining the optimized level of geometrical parameters resulting in minimum vibration while working on end milling. The machining was performed on Al356/SiC MMC using HSS end mill cutter using L_{27} OA [20]. Based on the experimental data an empirical model was developed and optimized using particle swarm optimization.

SAINI *et al.* [21] made an attempt towards parameter optimization in milling operation while machining Al6061/Al_2O_3/Gr. The work involved application of RSM for optimization of R_a, machining forces and tool wear. RSM was used to develop mathematical model followed by analysis for its significance by ANOVA. An investigation on the effect of reinforced particles of SiC was performed [22] using box behnken design compromising of 27 experimental runs. Optimized solution was identified leading to min R_a and machining force using genetic algorithm. The optimized settings were validated using ANOVA for its significance. PRANAV KUMAR *et al.* [23] studied the machinability optimization in milling for AA7039. The experimental runs were based on taguchi L_{18} mixed OA followed by application of RSM and ANN for optimization. The results showed that artificial network was associated with less deviation compared with RSM. Process parameter optimization in Al6063 T6 [24] was performed using L_{16} OA for optimizing M_{rr} and channel variation in micro milling. The result showed that parameter B contributed with 63.10% of influence, claiming as the primary significant factor followed by parameter C with 33% of contribution. Least significant factor was found to be parameter A with a contribution of 1.16%. GNANASEKARAN *et al.* [25] optimized laser hard facing process parameters using RSM with an objective of maximizing the wear resistance in Ni-Based hard-faced deposits. FUAT *et al.* [26] investigated the effect of machining parameters while machining 17-4 PH stainless steel in milling using taguchi-gray relational analysis. The study involved L_{18} experimental design with tree levels of speed and feed and constant level assigned for depth of cut. Another research by the author was made on mold steel in turning operation. It involved experimental and statistical investigation on the type of coating over roughness, temperature noise and vibration. The most effective parameter setting were identified using ANOVA analysis [27].

MAHIR *et al.* [28] studied the effect of PVD-TiN and CVD-Al_2O_3 coatings. The study involved the effect of coatings on the responses namely machining forces, roughness, power consumed and temperature. The study employed hard turning of AISI H13 steel. Another study performed by NURSEL *et al.* [29] investigated the statistical analysis of sustainable machining parameters involving coated cutting tools. Turning operation was performed on AISI P20 die steel with coated tungsten carbide tool. The experimental runs were conducted as per L_{18} orthogonal array. The analysis involved both chemical powder deposited coated tool and physical vapour deposited tool. The study involved controlling factors at 3 levels for spindle speed, feed rate and depth of cut respectively. Another study [30, 31] made a comparative investigation while working on AISI D6 steel. The study involved dry milling using AlTiN and AlTiSiN coated carbide tools.

2.1. Gap identified

There is a scarcity of studies specifically focusing on the dry machining of SAE 8822. Dry machining, as an eco-friendly alternative, has not been extensively investigated for this particular alloy. Exploring the sustainability aspects, such as no coolant, reduced coolant usage and energy savings, in the context of this specific alloy is one of the gap identified based on the literature review performed.

The literature survey carried out provides an overview on the extensive research carried and on-going for optimizing the responses. Green Machining is the process of machining that does not include the use of coolant in during the operation. Moreover, SAE 8822 is a low-alloy steel with specific mechanical and chemical properties, making it suitable for various applications in different industries. The specific applications can depend on factors such as the alloy's strength, toughness, and heat-treatability. SAE 8822, being a steel alloy, is commonly used in the automotive industry for manufacturing various components. It is employed in the production of parts such as gears, shafts, axles, and other structural components due to its strength and durability. For this research work SAE 8822 was used as a working sample, and the turning parameters were optimized using the RSM tool. In this instance, the turning of SAE 8822 was carried out without the utilization of coolant, and the process parameter was optimized, which is something that the research community has not done before.

3. TAGUCHI METHOD

Several tools and techniques were used in predicting the optimized level of machining parameters for better machinability and process. Taguchi design is one of the optimization tool, playing an important role in defining quality by eliminating the variations before they affect the process. This design is an off-line technique for ensuring better performance of a process. One of the best advantage of taguchi is that it provides the value in terms of performance characteristics close to the target defined ensuring quality improvement in the defined objective. Moreover, this technique requires few experimental runs based on OA opted, involving minimum cost and time to execute. Taguchi method [5, 6] refers to a set of concepts built to ensure quality into the process. It serves as a base for evaluating and providing means of improvement in process or product. So called improvements are aimed towards enhancing the favored characteristics and simultaneously decreasing the defects by optimizing strategies to propose the optimal solutions [7–10]. Taguchi proposed a trendy system for making use of his approach for optimizing any technique. The outcome of the study is to attain optimal solution for minimizing the responses influencing the process. To attain this objective, the controllable parameters are systematically iterated using orthogonal array [12, 15]. Once the experiments were conducted then the impact of response was interpreted using the signal-to-noise (S/N) ratio. Taguchi specializes in arriving at the best outcome using: a) Signal-to-noise ratio and b) Orthogonal arrays.

3.1. Orthogonal array

Degrees of freedom has its own importance in selection of orthogonal array for conducting initial trial runs. In this study, 3 factors were considered with 3 levels assigned to each factors as enlisted in Table 1. According to taguchi design, for 3 factors and 3 levels either L_9 or L_{27} orthogonal arrays (OA) can be opted for experimental runs, where 9 and 27 represents the total number of trial sequences involved. In this study, L_9 OA was finalized as shown in Table 2.

Table 1: Controlling parameters with assigned levels.

LEVELS	PARAMETERS		
	SPINDLE SPEED, rpm (A)	FEED RATE, mm/min (B)	DEPTH OF CUT, mm (C)
1	2500	0.05	0.5
2	2000	0.12	0.75
3	1500	1.20	1.0

Table 2: L_9 sequences with parameters.

S. No.	A	B	C
1.	2500	0.05	0.5
2.	2500	0.12	0.75
3.	2500	1.20	1.0
4.	2000	0.05	0.75
5.	2000	0.12	1.0
6.	2000	1.20	0.5
7.	1500	0.05	1.0
8.	1500	0.12	0.5
9.	1500	1.20	0.75

3.2. S/N ratio

S/N ratio eventually showcases the design reliability and based on the objective function, performance of the expected function is interpreted that covers both internal and external variations. S/N ratio is characterized in three patterns: Larger-is-better for maximizing the response and is represented by Equation (1). Nominal-is-best for responses relied on standard deviations alone and represented by Equation (2). Smaller-is-better for minimizing the response and is represented by Equation (3). This study involves the optimization using smaller-the-better function.

$$S/N = -10 * \log(\Sigma(1/Y^2)/n) \tag{1}$$

$$S/N = -10 * \log(\sigma^2) \tag{2}$$

$$S/N = -10 * \log(\Sigma(Y^2)/n)) \tag{3}$$

3.3. Analysis of variance

Analysis of Variance (ANOVA) is a statistical technique used to assess the differences among group means in a sample. It is used in manufacturing and engineering to analyze the effects of different factors (such as machining parameters or material variations) on the outcome of a process, such as surface roughness or tool wear. It helps identify which factors significantly influence the variability in the results. It helps in assessing variations in product quality attributing to factors such as machinery, operators, or raw materials. This information aids in optimizing processes and improving overall product quality. Following are the significance of ANOVA related to this study:

a) It helps identify which factors or variables have a statistically significant impact on the response variable.
b) Helps in evaluating the significance of each factor or parameter, aiding optimization of parameters.
c) It not only identifies main effects but also helps understand interactions between different factors.
d) It provides a quantitative measure of variability in the data, distinguishing between variation due to random factors and variation attributed to the manipulated variables.
e) It serves as a tool for validating the accuracy and effectiveness of the model. It helps researchers assess whether the model adequately represents the real-world system and whether the predicted outcomes align with the observed results.

3.4. Response surface methodology

It is a statistical tool effective in analyzing the data for construction of models, evaluating the data in arriving at the optimal solutions, interpretation the interactive effects between the factors considered for the study. It offers the investigator a cost effective platform for performing the evaluation on the effects of one or more factors simultaneously. Since the graphical presentation are in 3-dimensional form, it provides a lucid view on the factors taken for the study and its influence in various levels. Few highlights of this methodology are:

a) It allows for the design of experiments in a systematic and efficient manner. It helps researchers select a limited number of experimental runs while still capturing the essential information needed to model and optimize the process.
b) In situations where the relationships between variables are complex and nonlinear, RSM provides a powerful tool for building accurate mathematical models. These models can then be used to predict responses across a range of input variables.
c) RSM facilitates the exploration of interactions between multiple factors. It helps researchers understand how changes in one variable may affect the response, considering the influence of other variables.

3.5. Pareto analysis

Pareto Analysis is a decision-making tool used to prioritize and focus efforts on the most significant factors contributing to a particular problem or outcome. In optimization processes, Pareto Analysis can be applied in various ways to streamline efforts and enhance efficiency. It helps in identifying the critical factors that have the most significant impact on a particular outcome. By identifying and prioritizing the factors contributing the most to a problem or objective, Pareto Analysis aids in optimizing the allocation of resources. It allows for a targeted approach, ensuring that resources are directed toward addressing the most influential factors. It helps in distinguishing between major and minor contributors, guiding efforts toward addressing the root causes effectively. In the context of sustainability and energy efficiency, Pareto Analysis can be applied to identify the major energy-intensive aspects of the machining process. This information guides efforts toward optimizing energy consumption and minimizing environmental impact.

4. EXPERIMENTAL WORK

4.1. Materials

SAE 8822, an alloy steel mainly consisting of nickel-chromium-molybdenum exhibiting high hardenability. It finds its application in various heavy-duty purposes due to its superior core strength and heat treatability. Mostly its available in both carburized and non-carburized form based on its area of applications. These alloys are heat-treatable between 1168˚C to 1249˚C. The chemical and mechanical properties of SAE 8822 is listed in Table 3 and Table 4.

Table 3: Chemical composition SAE 8822.

ELEMENTS	CONTENT (%)
Carbon	0.25
Sulphur	0.04
Chromium	0.4
Manganese	0.85
Phosphorous	0.035
Molybdenum	0.35
Nickel	0.5
Silicon	0.30

Table 4: Mechanical properties-SAE8822.

PROPERTY	METRIC
Poisson's Ratio	0.30
Density	7.79 g/cm^3
Hardness	245 BHN
Modulus of Elasticity	207 GPa

4.2. Machine and tool

MTAB Flex turn was used for performing the experimental runs and cemented carbide (coated) tool is used for machining as shown in the Figure 1. Cemented carbide coatings are known for their exceptional hardness and wear resistance. These properties make them ideal for cutting, milling, drilling, and other machining processes where tools are subjected to high levels of abrasion and wear. The hardness and wear resistance of cemented carbide coatings contribute to extended tool life. Tools with these coatings can withstand prolonged use without experiencing significant wear, resulting in longer intervals between tool replacements. It exhibits excellent resistance to high temperatures, making them suitable for applications involving elevated cutting temperatures. This is particularly advantageous in cutting hard materials or performing high-speed machining operations. The enhanced hardness and wear resistance of cemented carbide coatings allow for increased cutting speeds and feeds. This leads to higher machining efficiency and productivity, as tools can maintain their performance even under demanding conditions. The low coefficient of friction of cemented carbide coatings contributes to reduced heat generation during machining making it suitable for dry machining. This is beneficial for minimizing tool wear, improving surface finish, and avoiding thermal damage to the workpiece. Table 5 describes the specifications of the MTAB Flex Turn CNC machine.

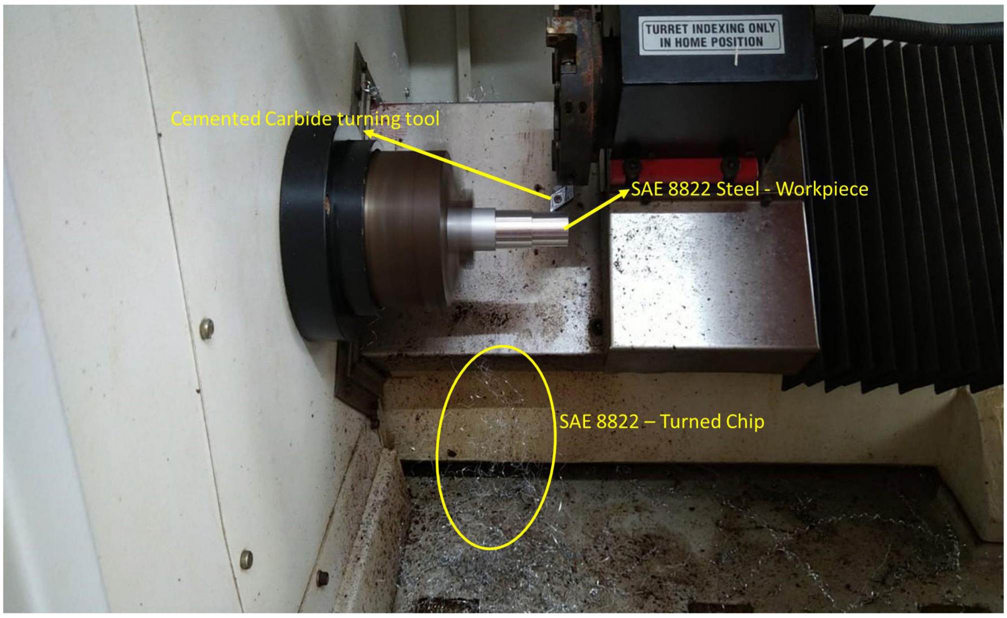

Figure 1: Experimental run - turning of SAE 8822 without coolant.

Table 5: Detailed specification of the MTAB flex turn CNC machine.

PARAMETERS	SPECIFICATION
Chuck size (mm)	100
X - Travel (mm)	95
Z - Travel (mm)	210
Swing over bed (mm)	245
Swing over cross slide (mm)	80
Distance between centers (mm)	345
Spindle bore (mm)	20
Spindle speed range (rpm)	150 – 4000
Spindle motor (KW)	3.73 AC spindle motor
Controller	FANUC
Machine overall dimensions (mm)	Length – 1710 Width – 1000 Height – 1650

4.3. Surface tester

The R_a was measured using MITUTOYO Surface Tester as shown in Figure 2. For each runs the R_a was measured thrice and the average value is taken for calculation. Table 6 shows the average R_a measured as per the sequence of experimental runs using MITUTOYO Surface Tester according to ASTM D7127.

5. RESULTS AND DISCUSSION

5.1. S/N ratio

The S/N ratio is performed based on smaller-the-better approach defined in taguchi design. Table 7 and Table 8 shows the responses of ratio and means. The stated tables provide a clear picture that the SAE8822 machining process is highly influenced by the parameter B (delta = 18.639) followed by C (delta = 9.237). Though the delta score of A 8.515 is nearest to C, its significance affecting the entire machining process is rated to the lowest rank. It implies that for optimizing the machining process, B and C must be given priority to attain the minimum R_a.

5.2. Analysis of variance (ANOVA)

ANOVA is performed to determine whether the means of two or more factors are unique or different. It provides a simple method to ensure the influence of factors on each other through comparison of the calculated means of the measured samples. The influencing trends can be interpreted by the main effect plots generated. Based on the trend of the factors the optimum result is predicted. Most importantly, understanding and interpreting the influence of individual factors plays the prominent role in providing the best solution for process under study. Statistical analysis, ANOVA determines the percentage contribution of the controlling factors. ANOVA analysis provides a lucid view on which factor needs significant attention.

Table 6: Measured values of R_a for the sequence of experimental runs.

S. No.	A	B	C	R_a	S/N RATIO
1.	2500	0.05	0.5	0.59	4.5830
2.	2500	0.12	0.75	1.87	–5.4368
3.	2500	1.20	1.0	2.09	–6.4029
4.	2000	0.05	0.75	0.63	4.0132
5.	2000	0.12	1.0	1.27	–2.0761
6.	2000	1.20	0.5	2.03	–6.1499
7.	1500	0.05	1.0	0.04	27.9588
8.	1500	0.12	0.5	1.39	–2.8603
9.	1500	1.20	0.75	2.19	–6.8089

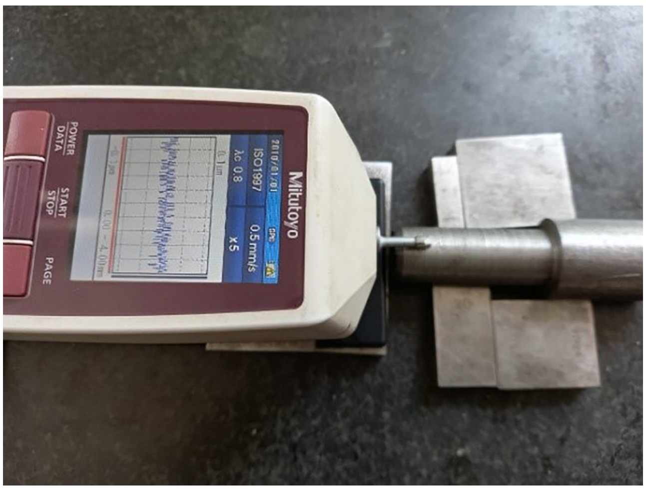

Figure 2: Surface roughness measurement of workpiece after turning.

The ANOVA analysis for the S/N ratios and Means are shown in Table 9 and Table 10. The relative importance of each parameter with the response can be easily interpreted by coefficients attained in ANOVA analysis. The interpretation is simple as the highest coefficients signifies the greatest impact on the machining process. The sum of squares (Sequential and adjusted) also provides the significance of the influence caused based on the attained values of coefficients. In this study, B shows highest influence on the process as claimed in the Table 7 and 8. The process found to be significant at 90% confidence level. For SN rations, A (p = 0.433), B (p = 0.086) is attained and for means A (p = 0.32), B (p = 0.001).

Table 7: S/N ratios responses for different levels versus input parameters.

FUNCTION: SMALLER IS BETTER			
LEVEL	**A**	**B**	**C**
1	6.097	12.185	–1.476
2	–1.404	–3.458	–2.744
3	–2.419	–6.454	6.493
Delta	8.515	18.639	9.237
Rank	3	1	2

Table 8: Response – means for different levels versus input parameters.

FUNCTION: SMALLER IS BETTER			
Level	**A**	**B**	**C**
1	1.2067	0.4200	1.3367
2	1.3100	1.5100	1.5633
3	1.5167	2.1033	1.1333
Delta	0.3100	1.6833	0.4300
Rank	3	1	2

Table 9: S/N ratios responses for different input parameters.

SOURCE	DF	SEQ (SS)	ADJ (SS)	ADJ (MS)	F	P	P (%)
A	2	129.8	129.8	64.90	1.04	0.433	43.3
B	2	601.1	601.1	300.54	4.81	0.086	8.6
C	2	150.44	150.4	75.22	1.51	0.398	39.8
Residual Error	2	99.54	99.54	49.77			
Total	8	980.9					

Table 10: Response – means for different input parameters.

Source	DF	SEQ (SS)	ADJ (SS)	ADJ (MS)	F	P	P (%)
A	2	0.149	0.149	0.074	30.17	0.032	3.2
B	2	4.373	4.373	2.187	82.60	0.001	0.1
C	2	0.277	0.277	0.139	56.02	0.018	1.8
Residual Error	4	0.005	0.005	0.003			
Total	8	4.806					

5.3. PARETO analysis

Figures 3, 4 and 5 shows the PARETO analysis of R_a with respect to parameters A, B and C based on the experimental runs and measured responses recorded. From Figure 3 for speed, one can predict that the min R_a is attainable in all levels spreading between 1500 rpm to 2500 rpm (R_a varying between 0.04 µm to 0.63 µm). The interpretation makes it clear that for machining SAE8822, factors B and C plays much vital role when compared to A. Consider exploring the interactions and synergies between factors B and C. It's possible that the combined effect of feed rate and depth of cut, rather than their individual effects, contributes significantly to achieving the desired surface finish. Interaction plots or response surface analysis provide more insights into these relationships. Adjustments in feed rate and depth of cut, rather than focusing on spindle speed alone, leads to more effective control over surface roughness. This information is valuable for process optimization and setting machining parameters in real-world applications.

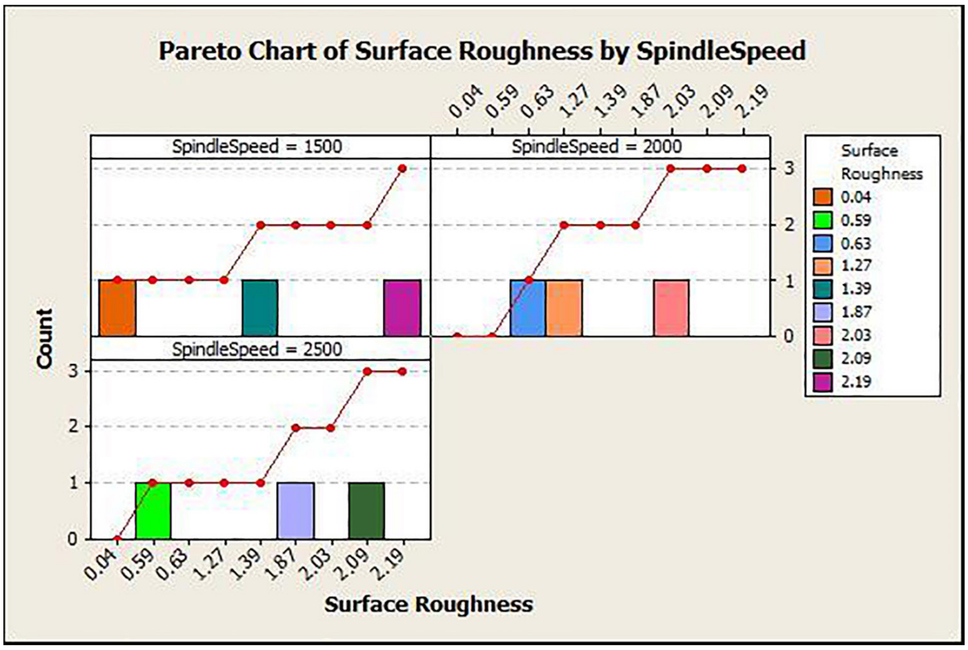

Figure 3: Pareto chart of surface roughness (R_a) by spindle speed (A).

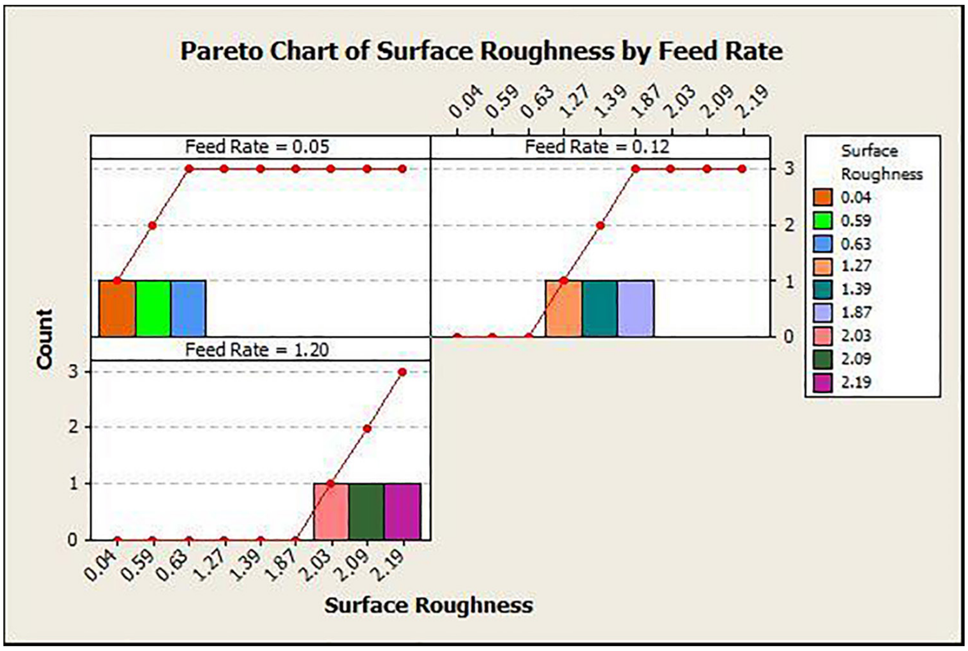

Figure 4: Pareto chart of surface roughness (R_a) by feed rate (B).

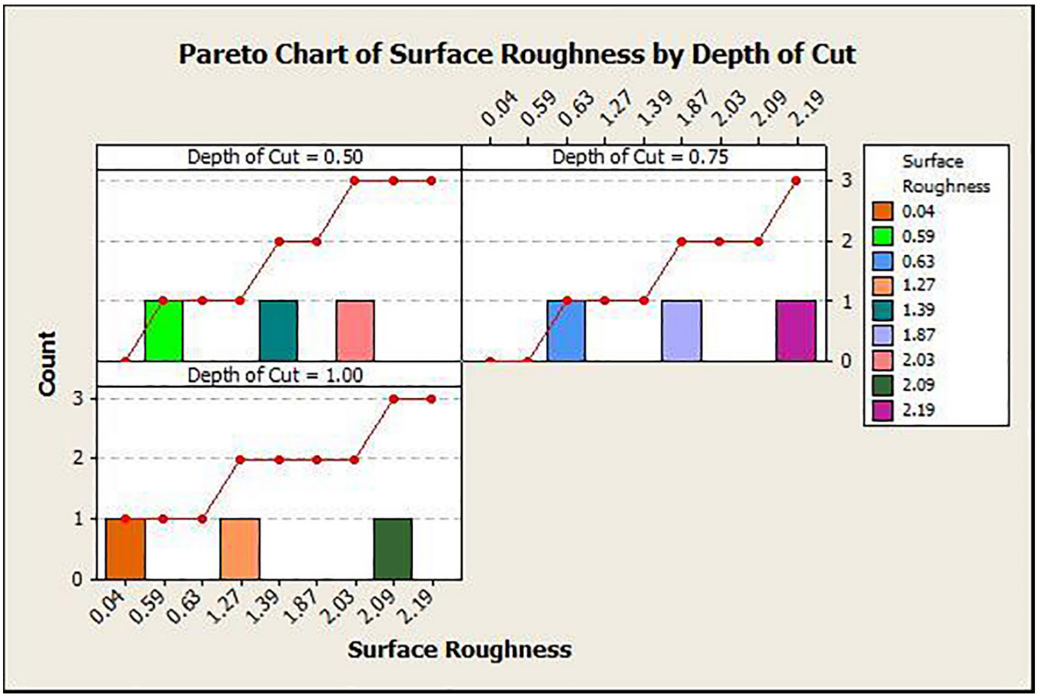

Figure 5: Pareto chart of surface roughness (R_a) by depth of cut (C).

From Figure 4, min R_a is achieved when B is maintained at lower level of 0.05 mm/rev as evident. Increase in R_a is witnessed as level of B increased from 0.12 mm/rev to 1.20 mm/rev). From Figure 5, one can interpret the behaviour of factor C. The graph shows the scattered display of min R_a across all levels. It is noteworthy to state that, R_a varies from minimum to higher value as C is increased from 0.50 mm to 0.75 mm. Whereas, when C is further increased from 0.75 mm to 1 mm one can witness a gradual decrease in R_a resulting in minimum R_a. This varying effect is induced due to the interaction effect of parameters B and A. As a whole, the most influencing factor is B followed by C and A. The varying effect of depth of cut (C) is attributed to the interaction effect with parameters B (feed rate) and A (spindle speed). This indicates that the influence of C on R_a is not isolated but is influenced by the levels of feed rate and spindle speed. Understanding these interactions is crucial for making informed decisions during process optimization. The overall conclusion is that the most influencing factor is B (feed rate), followed by C (depth of cut) and A (spindle speed). This hierarchy of influence is vital for prioritizing optimization efforts. Focusing on adjusting feed rate within optimal levels appears to have a more substantial impact on achieving the desired surface finish.

5.4. Response Surface Methodology (RSM)

RSM explores the relationship that exists between the parameters and the responses under examination. The advantage of such analysis is that more information can be collected with minimum experimental data. And it also helps in to study the interaction affect between the parameters in a better way. Figure 6 shows the contour plot for R_a influenced by A and B. Parameter B shows variations between 0.05 to 0.3 mm/rev providing variations in R_a. Beyond that higher R_a can be witnessed. The min R_a is figured when lowest level is assigned to B. Whereas, A shows significant change in R_a depending on the assigned level of B. However, min R_a is evidences when both are assigned with lowest levels.

The contour plot shows the optimized level is achieved when A is maintained between 1500 rpm to 1750 rpm with B at 0.05 mm/rev or less. Hence it is noteworthy to state that setting level for B is crucial for optimizing the process. The contour clearly shows that the C has higher influence in governing the R_a with respect to A. There is gradual increase in R_a as the C is improved followed by decrease as the A reaches its higher level. Figure 7 shows the contour plot for R_a influenced by A and C. The plot shows varied influence on R_a. The varied influence is due to the presence of another factor highly influential to these two. The graph shows that min R_a (R_a < 0.5 µm) is predicted when C is maintained at low level and A with higher level. R_a between 0.5 µm to 1 µm is predicted when A is maintained between 1750 rpm to 2250 rpm and C between 0.65 mm to 0.97 mm. It is evident from the plot that C provides very narrow flexibility towards minimum R_a.

The contour clearly shows unpredictable and unstable relationship. For the machining of SAE8822, the interaction effect of these two parameters are very much significant. Since there is uneven pattern of distribution, a small variation in level will lead to drastic change in R_a. The plot clearly shows the R_a attained in the experimental runs performed. As stated previously, to have optimum R_a, the C need to be maintained at higher level as far as SAE8822 is considered. Figure 8 shows the contour plot for R_a influenced by B and C. These two parameters are contradictory in behaviour. As a combination of both parameters, min R_a is achievable only when B is assigned with lower level and C assigned with higher level. The contour plot shows the optimized value is achieved when the B is maintained at a lower level of 0.05 mm/rev and C maintained between 0.97 to 1.0 mm. From the graph, it is clearly evident that B plays a dominant role over C. The interaction between these two parameters shows that, the optimum level for B can be assigned only between 0.1–0.2 mm/rev. However, due to the influence of A, the same is achieved at 0.5 mm/rev. This shows the concentration of influence individual parameter on the entire machining process.

5.5. SEM analysis

The following section explains on the SEM images taken for the experimental runs conducted. To have further interpretation on surface texture attained by the dry machining, SEM analysis was carried out as shown in the below sections. Figure 9(a to d) shows the SEM images for runs 1, 4, 5 and 7 at a magnification level of 500×. In all the images, one could find the presence of adhered material fragments developed during plastic deformation during machining. Smeared materials and presence of micro pores and grooves were the other features that could be visible in the image. These are formed during the material removal process and found be present throughout as the machining. The Figure 9(d) shows the SEM image that resulted in minimum R_a.

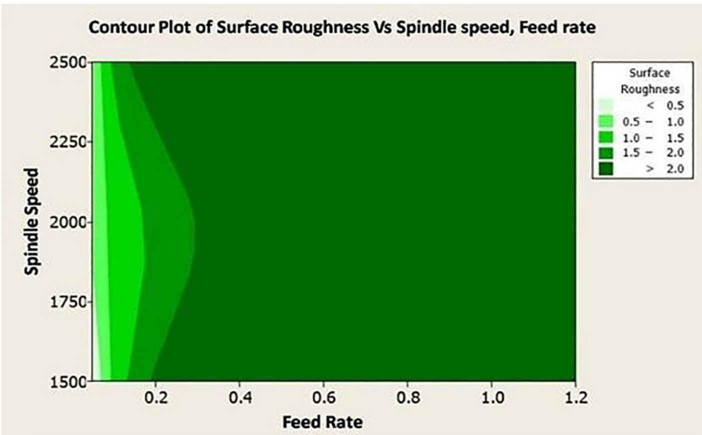

Figure 6: Contour plot for roughness (R_a) versus spindle speed (A) and feed rate (B).

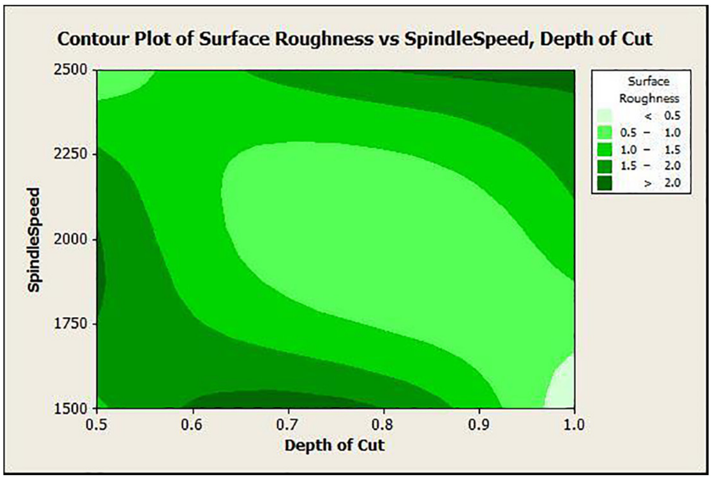

Figure 7: Contour plot for roughness (R_a) versus spindle speed (A) and depth of cut (C).

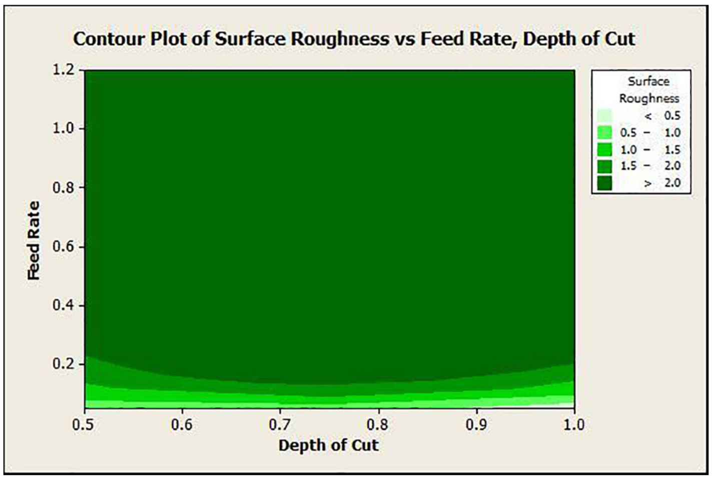

Figure 8: Contour plot for roughness (R_a) versus feed rate (B) and depth of cut (C).

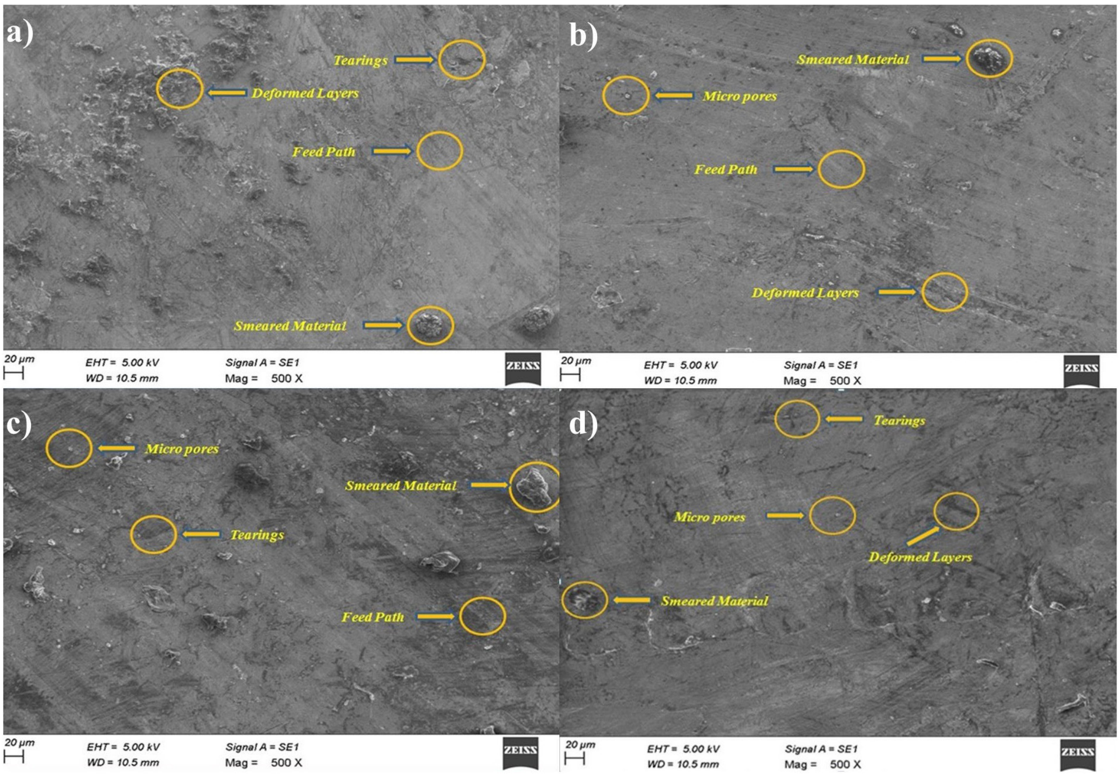

Figure 9: SEM images of experimental runs conducted (a) run 5 (b) run 4 (c) run 1 (d) run 7.

6. CONFIRMATORY RUNS AND SEM IMAGES

Confirmatory runs were conducted with the optimized values to validate the results and the following Table 10 shows the results recorded and the deviations registered. The deviation shows a minimal variations and confirms the validity of the optimized parameters. Figure 10(a) and (b) shows the SEM images recorded for the confirmatory runs conducted at the optimized parameter combination. The SEM images shown in Figure 10(a) and (b), reflects the surface morphology recorded resulting in minimum R_a as recorded in Table 11.

Moreover, the confirmatory SEM in Figure 10(a) and (b) also resembles the pattern shown in Figure 9(d) which also reflects the experimental run that resulted in minimum R_a. A finish machining study on AISI 1019 registered a deviation of 4.2% between the predicted value of 0.769 microns and experimental value of 0.738 microns [23, 24, 25]. Considering the above case, the result attained in the optimization of SAE8822 is appreciable with minimum deviation.

Table 11: Confirmatory runs – roughness predicted and experimental.

S. No.	A	B	C	R_a (Pred)	R_a (Exp)	DEVIATION
1.	1500	0.05	1.0	0.047	0.054	+0.007
2.	1500	0.05	1.0	0.055	0.078	+0.023
3.	1500	0.05	1.0	0.052	0.069	+0.017

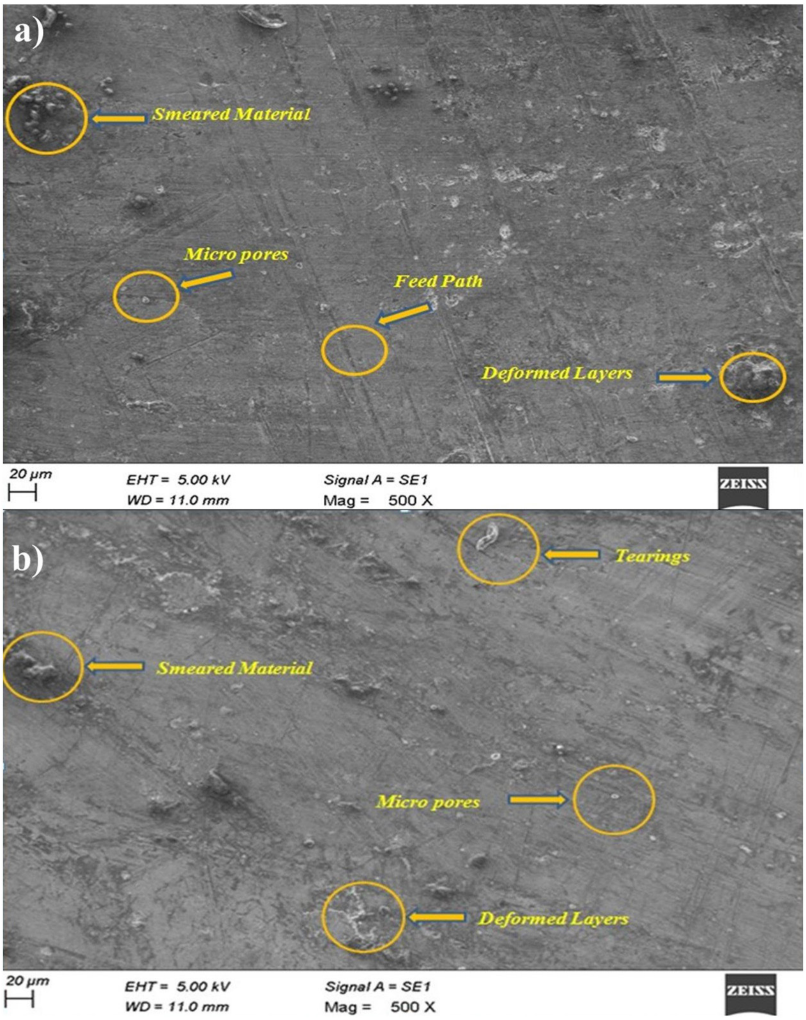

Figure 10: SEM images of confirmatory runs conducted.

7. CONCLUSION

The taguchi method, through its robust experimental design and S/N ratio analysis, provides valuable insights into the most influential factors affecting the response variable. The Signal-to-Noise (S/N) ratio analysis has identified the most influential factors in the machining process, with feed rate and depth of cut playing crucial roles.

a) The high delta score of 18.639 for the feed rate indicates its substantial influence on the machining process.
b) In Taguchi experimentation, a higher S/N ratio generally corresponds to better performance. Therefore, a positive delta score for feed rate suggests that increasing or optimizing this parameter can lead to improved machining outcomes, possibly in terms of surface finish, accuracy, or efficiency.
c) The S/N ratio's delta score of 9.237 for depth of cut also signifies its noteworthy impact on the machining process.

d) A positive delta score indicates that variations or adjustments in the depth of cut can significantly affect the machining performance. Optimizing the depth of cut according to the experimental conditions definitely lead to improved results.

ANOVA results provided the following valuable insights into the significance of different factors in affecting surface roughness (R_a) during machining.

a) The F values from ANOVA are indicators of the significance of each factor. In this study, feed rate has the highest F value (4.81), suggesting it as the most influential factor affecting surface roughness.
b) Depth of cut follows with an F value of 1.51, indicating a moderate level of influence. Spindle speed has the least impact, as reflected by its lower F value.
c) The minimum R_a was achieved under specific conditions: spindle speed at 1500 rpm, feed rate at 0.5 mm/rev, and depth of cut at 1 mm.
d) This configuration represents the optimal combination of machining parameters that result in the lowest surface roughness. It's noteworthy that finding the optimal conditions can lead to improved product quality and performance.
e) The observation of a drastic increase in R_a when spindle speed increased from 1500 rpm to 2000 rpm indicates that higher spindle speeds may negatively impact surface roughness. This insight is crucial for setting operational limits and avoiding conditions that lead to suboptimal outcomes.
f) The higher F value for feed rate reinforces its significance in affecting surface roughness, emphasizing the need for careful optimization of this parameter. Depth of cut, while not as influential as feed rate, still plays a substantial role in the machining process.

7.1. Future scope of work

a) Exploring the application of advanced tool coatings or treatments to further enhance the performance of cutting tools. Investigate how different coatings may affect tool life, wear resistance, and the overall machining process.
b) Analysis of the environmental impact of machining without coolant and explore eco-friendly alternatives. Evaluate the overall sustainability of the optimized machining process by considering factors such as energy consumption, waste generation, and emissions.
c) Performing a detailed analysis of the microstructure and material properties of SAE 8822 Alloy steel after machining. Investigate any changes in material integrity, hardness, or other mechanical properties that may result from the optimized machining process.
d) Development of mathematical models for predicting tool wear and estimating tool life under the optimized machining conditions. This can contribute to proactive maintenance strategies and further improvements in the efficiency of the machining process.
e) Multi-objective optimization by simultaneously optimizing for multiple performance criteria, such as surface roughness, tool life, and energy efficiency. This approach can lead to a more holistic optimization considering various aspects of the machining process.

8. ACKNOWLEDGMENTS

This project is funded by DST-FIST (2022), Government of India vide Ref. No: SR/FST/College-/2022/1300.

9. BIBLIOGRAPHY

[1] KUMAR, R.S., KUMAR, S.S., RAJENDRAN, C., *et al*., "Investigation on corrosion behaviour of LM25-SiC_p composite using taguchi method", *Advances in Materials Science and Engineering*, v. 2022, pp. 4341018, Mar. 2022.

[2] GHOSH, S., SAHOO, P., SUTRADHAR, G., "Tribological performance optimization of Al-7.5% SiCp composites using the Taguchi method and grey relational analysis", *Journal of Composites*, v. 2013, pp. 1–9, Sep. 2013. doi: http://dx.doi.org/10.1155/2013/274527.

[3] NADALE, H.C., SVOBODA, H.G., "Fatigue life of PAW welded joints of high strength microalloyed boron steels", *Matéria (Rio de Janeiro)*, v. 23, n. 2, pp. e11996, 2018.

[4] VENKATESH, S., KUMAR, R.S., SIVAPIRAKASAM, S.P., *et al*., "Multi-objective optimization, experimental and CFD approach for performance analysis in square cyclone separator", *Powder Technology*, v. 371, pp. 115–129, Jun. 2020. doi: http://dx.doi.org/10.1016/j.powtec.2020.05.080.

[5] AZIZI, M.W., KEBLOUTI, O., BOULANOUAR, L., *et al.*, "Design optimization in hard turning of E19 alloy steel by analysing surface roughness, tool vibration and productivity", *Structural Engineering and Mechanics*, v. 73, n. 5, pp. 501–513, Mar. 2020.

[6] SURYARAJ, G.K., PRINCE, M., MANIRAJ, J., "Optimization of boriding process on AISI 1015 steel using response surface methodology", *Matéria (Rio de Janeiro)*, v. 28, n. 2, pp. e20230086, Jun. 2023. doi: http://dx.doi.org/10.1590/1517-7076-rmat-2023-0086.

[7] AKHTAR, M.N., SATHISH, T., MOHANAVEL, V., *et al.*, "Optimization of process parameters in CNC turning of aluminum 7075 alloy using L27 array-based taguchi method", *Materials (Basel)*, v. 14, n. 16, pp. 4470, Aug. 2021. doi: http://dx.doi.org/10.3390/ma14164470. PubMed PMID: 34442992.

[8] SINGH, T., SHARMA, V.K., RANA, M., *et al.*, "GRA based optimization of tool vibration and surface roughness in face milling of hardened steel alloy", *Materials Today: Proceedings*, v. 50, pp. 2288–2293, Jan. 2022. doi: http://dx.doi.org/10.1016/j.matpr.2021.09.546.

[9] SAMTAS, G., BEKTAS, B.S., "Investigation of the effect of cutting parameters on the milling process of cryogenically treated aluminum alloy with cryogenically treated and untreated inserts, using the Taguchi and Gray Relational Analysis methods", *Surface Topography: Metrology and Properties*, v. 9, n. 4, pp. 045044, Dec. 2021. doi: http://dx.doi.org/10.1088/2051-672X/ac41fe.

[10] MIA, M., DEY, P.R., HOSSAIN, M.S., *et al.*, "Taguchi S/N based optimization of machining param-eters for surface roughness, tool wear and material removal rate in hard turning under MQL cutting condition", *Measurement*, v. 122, pp. 380–391, Dec. 2018. doi: http://dx.doi.org/10.1016/j.measurement.2018.02.016.

[11] ONONIWU, N.H., OZOEGWU, C.G., MADUSHELE, N., *et al.*, "Characterization, machinability studies, and multi-response optimization of AA 6082 hybrid metal matrix composite", *International Journal of Advanced Manufacturing Technology*, v. 116, n. 5–6, pp. 1555–1573, Sep. 2021. doi: http://dx.doi.org/10.1007/s00170-021-07549-7.

[12] ANAND, T., RAGUPATHY, K., RANGANATHAN, L., "Optimization of drilling parameters using GRA for polyamide 6 nanocomposites", *Matéria (Rio de Janeiro)*, v. 28, n. 2, pp. e20220337, May. 2023. doi: http://dx.doi.org/10.1590/1517-7076-rmat-2022-0337.

[13] DEVARAJ, S., MALKAPURAM, R., SINGARAVEL, B., "Performance analysis of micro textured cutting insert design parameters on machining of Al-MMC in turning process", *International Journal of Lightweight Materials and Manufacture*, v. 4, n. 2, pp. 210–217, Jun. 2021. doi: http://dx.doi.org/10.1016/j.ijlmm.2020.11.003.

[14] SOUNDHAR, A., ZUBAR, H.A., SULTAN, M., *et al.*, "Dataset on optimization of EDM machining parameters by using central composite design", *Data in Brief*, v. 23, pp. 103671, Apr. 2019. doi: http://dx.doi.org/10.1016/j.dib.2019.01.019. PubMed PMID: 30788395.

[15] KRISHNA KUMAR, G., VELMURUGAN, C., KANNAN, T., "Using the RSM method of improving process parameters of welding AISI 316 and nickel 201 using CO_2 laser", *Matéria (Rio de Janeiro)*, v. 27, n. 3, pp. e20220129, Aug. 2022. doi: http://dx.doi.org/10.1590/1517-7076-rmat-2022-0129.

[16] SRIDHAR, R., PERUMAL SUBRAMANIYAN, S., RAMESH, S., "Optimization of machining and geometrical parameters to reduce vibration while milling metal matrix composite", *Transactions of the Indian Institute of Metals*, v. 72, n. 12, pp. 3179–3189, Dec. 2019. doi: http://dx.doi.org/10.1007/s12666-019-01783-0.

[17] PREMNATH, A.A., "Studies on machining parameters while milling particle reinforced hybrid (Al6061/Al2O3/Gr) MMC", *Particulate Science and Technology*, v. 33, n. 6, pp. 682–692, Nov. 2015. doi: http://dx.doi.org/10.1080/02726351.2015.1025457.

[18] RAJESWARI, B., AMIRTHAGADESWARAN, K.S., "Study of machinability and parametric optimization of end milling on aluminium hybrid composites using multi-objective genetic algorithm", *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, v. 40, n. 8, pp. 1–15, Aug. 2018. doi: http://dx.doi.org/10.1007/s40430-018-1293-3.

[19] KARABULUT, S., GOKMEN, U., CINICI, H., "Optimization of machining conditions for surface quality in milling AA7039-based metal matrix composites", *Arabian Journal for Science and Engineering*, v. 43, n. 3, pp. 1071–1082, Mar. 2018. doi: http://dx.doi.org/10.1007/s13369-017-2691-z.

[20] KUMAR, R.S., SENTHIL, K.S., MURUGAN, K., *et al.*, "Green machining characteristics study of Al-6063 in CNC milling using Taguchi method and grey relational analysis", *Advances in Materials Science and Engineering*, n. Dec, pp. 1–12, 2021.

[21] SAINI, P., SINGH, P.K., KUMAR, D., "Effect of machining parameters for surface finish and material removal rate of Al-4032/SiC composite during end milling using TGRA and ANN", *Journal of Advanced Manufacturing Systems*, v. 21, n. 1, pp. 85–109, Mar. 2022. doi: http://dx.doi.org/10.1142/S0219686721500438.

[22] KUMAR, K., DABADE, B., WANKHADE, L., "Determination of prediction model and optimiza-tion of process parameters for fabrication of Al-SiC composite using response surface methodology", *Advances in Materials and Processing Technologies*, v. 8, n. 4, pp. 1983–1999, Nov. 2022. doi: http://dx.doi.org/10.1080/2374068X.2022.2033000.

[23] PRANAVKUMAR, G., SRUTHIKKUMAR, Y., RAMAKRISHNA, K., *et al*., "Optimization of process parameters for end milling operation on En-31 using taguchi-grey relation", *Advanced Materials Research*, v. 1178, pp. 3–14, Aug. 2023. doi: http://dx.doi.org/10.4028/p-Qt3NPv.

[24] SHINGE, A.R., DABADE, U.A., "The effect of process parameters on material removal rate and dimensional variation of channel width in micro-milling of aluminium alloy 6063 T6", *Procedia Manufacturing*, v. 20, pp. 168–173, Jan. 2018. doi: http://dx.doi.org/10.1016/j.promfg.2018.02.024.

[25] GNANASEKARAN, S., CHELLADURAI, S.J.S., RAMAKRISHNAN, T., *et al*., "Optimizing the characteristics of the laser hardfacing process parameters to maximize the wear resistance of ni-based hard-faced deposits using the RSM technique", *Advances in Materials Science and Engineering*, v. 2021, n. Nov, pp. 1–5, 2021. doi: http://dx.doi.org/10.1155/2021/3665631.

[26] FUAT, K., NURETTIN, B., MAHIR, A., *et al*., "Multi-objective optimization of process parameters in milling of 17-4 PH stainless steel using taguchi-based gray relational analysis", *Engineered Science*, n. Sep, pp. 861–868, 2023.

[27] FUAT, K., FURGAN, B., FURKAN, S., *et al*., "Experimental and statistical investigation of the effect of coating type on surface roughness, cutting temperature, vibration and noise in turning of mold steel", *Journal of Materials and Manufacturing*, n. June, pp. 31–34, 2023.

[28] MAHIR, A., BARIS, O., FUAT, K., "Effect of PVD-TiN and Al2O3 coatins on cutting force, surface roughness, cutting power, and temeprature in hard turning of AISI H13 steel", *Journal of Materials Engineering and Performance*, n. Aug, pp. 1390–1401, 2022.

[29] NURSEL, A.O., ONUR, O., FUAT, K., "Statistical analysis of the effect of the cutting tool coating type on sustainable machining parameters", *Journal of Materials Engineering and Performance*, n. Oct, pp. 7783–7795, 2021.

[30] DAS, A., KAMAL, M., DAS, S.R., *et al*. "Comparative assessment between AlTiN and AlTiSiN coated carbide tools towards machinability improvement of AISI D6 steel in dry hard turning", In: *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science,* pp. 3174–3197, March 2022. doi: http://dx.doi.org/10.1177/09544062211037373.

[31] DAS, A., MOHAPATRA, S., GAJRANI, K.K., *et al*. "Comparative performance evaluation between HSN-TiAlxN and TiCN coated carbide tools in hard turning of AISI D6 steel", In: *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture,* Jul 2022. doi: http://dx.doi.org/10.1177/09544054221111884.