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Evaluating New Strategies and Techniques for Optimizing Performance and Precision in Cylindrical Grinding of H13 Steel

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Abstract: H13 steel is a high-performance tool material, pivotal in precision manufacturing sectors such as automotive and aerospace. This study addresses the essential need to optimize grinding parameters to enhance surface quality while minimizing cutting forces, thereby extending tool life and reducing operational costs. The primary objective is to systematically examine the effects of grinding wheel speed, feed rate, depth of cut, and workpiece speed on surface roughness (Ra) and cutting force (Fc). Utilizing the Taguchi L16 orthogonal array, experiments were meticulously designed and conducted. Advanced analytical methods, including Analysis of Variance (ANOVA) as well as regression analysis, were employed to identify the most influential factors and develop predictive models for Ra and Fc. The optimization process revealed that the optimal settings for minimizing Ra were a wheel speed of 2400 rpm, a feed rate of 0.1 mm/rev, a depth of cut of 1 µm, and a workpiece speed of 100 rpm, achieving a Ra of 0.85 µm. For minimizing Fc, the optimal parameters were 1500 rpm, 0.1 mm/rev, 1 µm depth of cut, and 100 rpm workpiece speed, resulting in an Fc of 10.5 N. The regression models demonstrated high accuracy with coefficients of determination (R^2) values of 90.34% for Ra and 95.7% for Fc, validated through confirmation tests. Future research should extend these optimization techniques to other tool steels and diverse applications, integrating machine learning and real-time parameter adjustments to further advance grinding technology. This advancement promises broader industrial benefits, ensuring high-quality and cost-effective manufacturing solutions.

***Keywords* - Cutting Force, Cylindrical Grinding, Grinding Parameters, H13 Steel, Surface Roughness, Surface Quality, Taguchi Method.**

I. INTRODUCTION

Grinding involves machining with mathematically undefined cutting edges, utilizing complex and very effective abrasives. The grinding interface is where the workpiece's irregular surface gets abraded through contact with the grinding wheel. The production methods of forging, stamping, casting, as well as injection molding, rely on dies and molds to create full-mass discrete parts. Workpiece, wheel, and process parameters are some of the factors that affect surface quality, the primary metric in the surface grinding of molds and dies [1]. Experiments can determine which process factors, such as depth of cut, wheel speed, dressing condition and feed rate, are necessary for superior surface quality.

Precision components require a high level of surface quality and tight dimensional tolerance during the grinding process, which is the last tooling step in the machining cycle. Furthermore, the combination of a fast-cutting speed with abrasive grits that are randomly oriented causes heat to be generated in the cutting zone during grinding, which further increases the specific energy required for the process [2]. As a result of the high temperatures caused by the heat generation, the ground surface experiences thermal degradation, uneven cracking, and phase transition [3]. Therefore, to keep the grinding temperature under control, efficient cooling and lubrication are required. To cool and lubricate the cutting zone, several writers use machining fluids made of petroleum. However, these fluids pose risks to both the operator's and the environment's health [4]. Also, with traditional lubrication systems, machining fluid has a hard time getting to the cutting zone. The buildup of a hydrodynamic air layer surrounding the abrasive wheel causes a wedge effect to occur where the wheel and workpiece make contact, which is the rationale behind this phenomenon [5]. Minimum Quantity Lubrication (MQL) [6], Nanofluid-based Minimum Quantity Lubrication (NMQL) [7], and Magnetic Traction Nano-lubrication (MTN) [8] are sustainable lubrication systems that have additional benefits when it comes to these difficulties. A mist was created in the MQL by combining a small quantity of machining fluid with compressed air. In the grinding zone, this mist was atomized and sprayed at high velocity [9].

The procedure involves inserting a grinding wheel that rotates continuously into the workpiece surface to a specified depth, referred to as the total depth of cut ae [10]. At this point, the sensor-integrated workpiece commences a full rotation about its axis to eliminate the whole depth of cut ae from the surface of the workpiece [11]. Strain and other internal material loads are introduced into the workpiece through its surface by the process's external forces, Ft and Fn [12]. Material changes caused by internal loads in the workpiece can be quantified using indicators such as residual stress [13]. As the grinding wheel passes over the workpiece, eliminating a certain depth of cut from its surface, the load is measured by the sensor inlay, which is placed on the workpiece's circumference and assisted by an underlying sensor layer [14]. With each iteration of the process, the same workpiece is subjected to a constant depth of cut ae, bringing the sensor layer at the base of the inlay closer and closer to the wheel or contact zone until it is destroyed by impact [15]. A schematic illustration of the grinding process is shown in Figure 1.

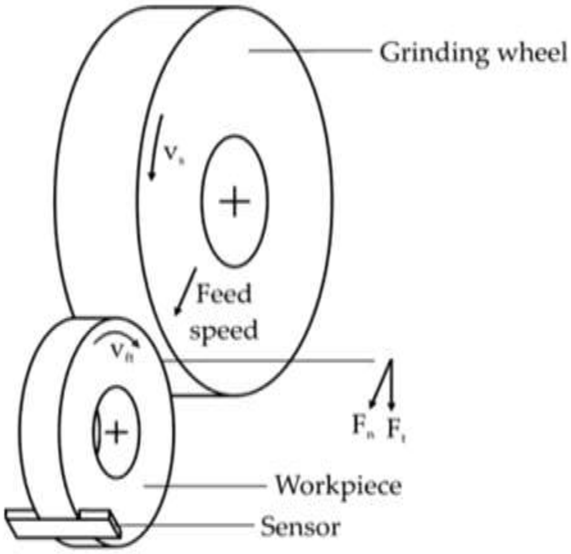

Figure 1 Cylindrical grinding process [16]

H13 steel is a popular tool material due to its high toughness and resistance to thermal fatigue; however, optimizing grinding settings is essential for enhancing performance and accuracy when cylindrical grinding this material. The main advantages of the optimization of grinding the H13 steel are better surface quality, dimensional accuracy, and tool life. This can be achieved with a good choice of parameters for grinding, which involves feed rate, wheel speed, and depth of cut. Consequently, the lifespan of tools and components made from H13 steel increases when optimized because their effectiveness during grinding is enhanced by minimizing heat produced and material removal irregularities. Thus, manufacturing costs are lowered, and productivity is enhanced [17].

This study introduces new methods aimed at surface finish enhancement and Ra enhancement when grinding cylindrical H13 steel with the help of advanced optimization techniques [18]. The experimentation is designed systematically by making use of the Taguchi method for the optimal design of critical grinding parameters such as feed rate, speed, and depth of cut [19]. The analysis of variance is applied in the study of the effect of these variables on process performance to determine the most significant factors determining Ra and surface finish [20]. Improved optimization methods would result in precision, wear of tools, and efficient grinding processes to further improve overall performance in industrial applications [21].

Traditional grinding processes have several limitations about efficiency and precision, especially in cylindrical grinding of H13 steel. It generates more heat, leading to thermal damage in the material, and is characterized by surface defects. The wheel is usually worn out more often; hence, it requires constant maintenance. Ra is generally very low, and the surface finish is usually poor as well. Moreover, trying to achieve high precision with this traditional approach often leads to longer machining time and higher operational costs because of the suboptimal parameter setting. Such problems require optimal strategies involving newer techniques like machine learning, multi-objective optimization, and parameter adjustment in real time. These approaches also help achieve outcomes by making processes cost-effective and more precise for industrial applications, with results such as good grinding together with longer tool life and process efficiency to achieve good surface quality.

This research discusses new strategies and techniques to enhance efficiency and accuracy in the cylindrical grinding of H13 steel. In this study, advanced optimization methods, such as Taguchi, ANOVA technique, regression, and innovative grinding materials, might be used to increase the surface finish, enhance the Ra, and reduce the wear of the tool. Research has focused on producing a more cost-effective grinding process that increases the surface quality of H13 steel components, with its durability, hence gaining for industries dependent on high-precision manufacture.

The scope of this research can be the evaluation and application of advanced strategies and techniques that optimize the performance and precision in the cylindrical grinding of H13 steel, which happens to be one of the most sought-after materials for tool making, as well as high-performance applications. This study is important since it would change the grinding procedures to become more efficient at lower costs and with direct industrial applicability. The automobile, aerospace, and any other manufacturing using H13 steel would be able to benefit by having precise production at lower costs. This research addresses the issues with conventional grinding and offers advanced alternatives, thereby contributing positively to the improvement in the quality, strength, and performance of critical applications made from steel components.

This research has the following research contributions:

- Developing innovative grinding techniques that enhance surface finish and dimensional accuracy in H13 steel components, contributing to improved tool life and performance in industrial applications.
- Optimizing grinding parameters, such as feed rate, speed, and coolant usage, to achieve better Ra while minimizing thermal damage and tool wear.
- Introducing advanced monitoring systems for real-time process control, leading to increased precision and consistency in the grinding process, particularly for complex geometries.

- Enhancing the sustainability of cylindrical grinding operations by reducing energy consumption and waste generation through more efficient use of resources and process optimization strategies.

An introduction to the subject is given in Section 1 of this research study. The work of numerous researchers is discussed in Section 2. Both the methodology and the algorithm that are proposed are described in Section 3. The details and analysis are given in Section 4. The final section addresses the conclusion.

II. Literature of Review

In this section, various studies and research focused on evaluating new strategies and techniques for optimizing performance and precision in cylindrical grinding of H13 steel are discussed:

Sharma et al. (2024) [22] offered a novel approach and a specially designed configuration for the environmentally conscious use of liquid nitrogen (LN2) in cryogenic machining. In order to facilitate pertinent comparisons, three distinct conditions were used for the grinding tests: dry, wet, and cryogenic cooling. The experiment's findings showed that cryogenic cooling was superior to dry and wet cooling in terms of lowering the grinding force (by 54-64%).

Debabrata Barik (2023) [23] concentrated dimpled tungsten carbide discs affixed with AISI H13 steel pins on a pin-on-disc tribometer. Laser marking was utilized to produce Honeycomb (HT) as well as Spherical Dimple Texture (ST) with area densities of 25% and 35%, respectively. Sliding wear tests were performed under dry conditions and using Molybdenum Disulphide (MoS2) lubrication, increasing the rotational speeds from 1000 to 1500 rpm. The ST surface, coated with MoS2 and exhibiting a 35% area density at 1500 rpm, demonstrated a 13.5% decrease in friction and a 24% decline in wear rate relative to HT as well as Non-Textured (NT) surfaces.

Hatami et al. (2022) [24] utilized the Response Fractional Factorial Design of Experiment (RFDOE) to optimize the grinding process of Deutsche Industrie Norm (DIN) 1.2080 tool steel. The method would determine optimal input parameters: feed rate, wheel speed, incidence angle, and depth of cut. The results showed that the estimated values by RFDOE were robust in training feedforward backpropagation networks since incidence angle and feed rate are the most sensitive variables affecting specific grinding energy and Ra at 38.97% and 34.87%, respectively.

Vu et al. (2021) [25] developed the use of graphite nanoparticles and little lubrication in the hard milling of AISI H13 steel. Cutting speed, feed per tooth, depth of cut, and workpiece hardness are some of the techniques that could be adjusted. Included in the suggested approach were response surface models, engineering data mining, the Pareto technique, and a multi-purpose particle swarm optimization algorithm. Results showed a 14% reduction in energy cutting compared to the worst scenario.

Shrivastava et al. (2021) [26] evaluated Ra, topography, microstructure, and microhardness, as well as the effect of grinding parameters on the surface integrity of hardened AISI D2 steel. For both dry and wet grinding, they used a quasi-steady-state moving heating source model. A non-destructive evaluation was conducted using the Barkhausen noise approach. Dry grinding resulted in a redeposition layer with reduced Ra, but flood cooling decreased temperature, specific energy, and grinding force.

Sharma et al. (2021) [27] investigated measured with dry and wet conditions was the impact of a cryogenic coolant, which is environmentally benign, on the surface integrity of the ground sample when it was ground in the plunge grinding mode at various downfeeds. Surface integrity was evaluated regarding Ra, the microstructure, and microhardness. The magnetic response of the ground surface was measured using a Barkhausen noise analyzer, expressed as Root Mean Square (RMS), peak values, and pulse count. The results indicated that no significant differences were observed in the microstructure and the microhardness of the ground surfaces and subsurface following cryo-grinding, attributable to reduced thermo-mechanical loading.

Singh et al. (2020) [28] designed a theoretical model to forecast the decrease in Ra that occurs when exterior cylindrical surfaces are magnetorheologically finished. The length of the helical path increased, but the pitch and helix angle decreased due to the relatively higher speed of the rotating cylindrical work part's rectangular tool core. The results improved the accurate uniform finishing of cylindrical workpieces and process performance. Some tests were performed on the cylindrical outer surfaces of H13 die steel workpieces to test the theoretical roughness model. The percentage error between the theoretical Ra values and the experimentally obtained value ranged from -4.76% to 3.06%, indicating a satisfactory concordance between the theoretical model as well as the experimental results.

Andrzej Matras and Wojciech Zebala (2020) [29] optimized the tool path pattern and cutting parameters to achieve the machining of hardened steel free-form surfaces. The feed rate, the geometry of the workpiece, tilt angles, the lead of the tool and the roughness were taken into consideration when making technological decisions. The approach was based on the Ra assessment as well as the calculation of the Fc components. The research result indicated that variation of feed rate based on the cross-sectional area being machined controlled Ra and Fc components. An optimized process translated to improvements in the requisite Ra and machining efficiency of 15% and 9%, respectively, arising from the optimization of feed rate and tool inclination angle.

Jafarian F. and Samarikhalaj, H. (2020) [30] focused on the optimization of geometric properties and quality of the surface of AISI H13 steel during drilling. Two regression models had been developed to analyze the effect of drilling parameters. The proposed method used Non-dominated Sorting Genetic Algorithm (NSGA-II) for multi-objective optimization, considering Ra and circularity deviation as objective functions. Results showed deeper cuts, larger tool diameters, and higher feed rates improved surface quality, while higher cutting speed and coolant intensity reduced it. Tool diameter and depth of cut were identified as key factors affecting circularity.

Research Gaps

- Limited investigation into incorporating real-time monitoring systems with optimization techniques for dynamic parameter adjustments during grinding [22].
- Insufficient exploration of alternative eco-friendly lubricants to further enhance sustainability in grinding processes [25].
- Lack of application of advanced machine learning algorithms for optimizing grinding parameters beyond traditional methods [27].
- Minimal research on the impact of different grinding wheel materials and compositions on surface quality and tool wear in H13 steel grinding [30].

III. Materials and Method Used

The Methods and Materials section details the experimental setup, including the H13 steel workpiece, cylindrical grinding machine, and specific grinding parameters.

Material Used

H13 steel is a type of high-performance tool steel. It is a versatile and widely used material in the manufacturing industry, particularly in applications where the steel needs to withstand high temperatures and has excellent mechanical properties. HD-13 steel classically falls under chromium-molybdenum alloy steels. Such have been valued for their remarkable hardness, high-temperature resistance, wear resistance, and toughness. Properties such as these make the material suitable for testing advanced grinding techniques through its chemical composition as well as mechanical properties. According to Table 1, AISI H13 steel has the following chemical composition.

Table 1 AISI H13 tool steel's chemical composition (%) [31].

Component	Percentage
Silicon	0.97%
Carbon	0.38%
Manganese	0.34%
Sulfur	0.002%
Phosphorus	0.02%
Molybdenum	1.34%
Chromium	5%
Vanadium	0.93%

Table 2 highlights the key mechanical properties of H13 steel. These properties demonstrate the material's ability to resist wear and deformation under high-stress conditions, which is crucial during the cylindrical grinding process.

Table 2 Mechanical properties of H13 Steel [32]

Characteristic	H13 Steel
Yield strength	1650MPa
Brinell hardness	250
Density	7750kg/m3
Modulus of elasticity	215GPa
Rockwell hardness	48
Thermal conductivity	28.6W/Mk

Figure 2 presents two sectional views of a cylindrical component divided into a "Hard Stage" (upper section) and a "Soft Stage" (lower section), each with specific dimensions and labeling. The views display detailed measurements, including diameters and lengths, necessary for precise manufacturing or inspection.

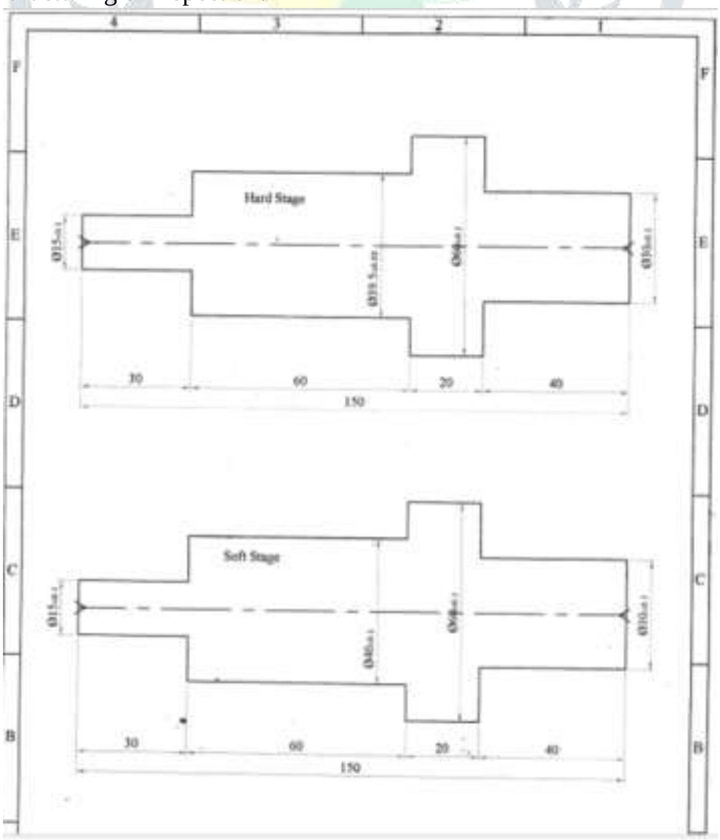

Figure 2 Two-stage cylindrical component with distinct "hard stage" and "soft stage" sections

The wheel parameters, such as diameter, width, grain volume fraction, and grain size, play a critical role in determining the effectiveness of the grinding process. Table 3 shows the specific parameters used for the grinding wheel in this study, optimized for machining H13 steel.

Table 3 Parameters of grinding wheel

Parameters	H13 Alloy
Grinding wheel	White Aluminium oxide of wheel grit sizes 46, 60 and 80
Grain Size (ASTM grain size number)	ASTM 5-8
Cutting fluid	Make -Servo, Grade -Cut-S
Planning of the experiment	Taguchi's orthogonal array
Output response	Surface roughness, Resultant cutting force.

Table 4 outlines the grinding parameters tested during the study. Each parameter was tested at different levels to determine the best settings for precise grinding of H13 steel.

Table 4 Grinding Parameters

Parameter	Level 1	Level 2	Level 3	Level 4
Grinding Wheel Speed (rpm)	1500	1800	2100	2400
Feed Rate (mm/rev)	0.1	0.2	0.3	0.4
Depth of Cut (µm)	1	1.5	-	-
Workpiece Speed (rpm)	100	150	-	-

Design of Experiment and Analysis (DOE)

DOE is an organized and systematic approach to the execution of experiments to gather data and then arrive at meaningful conclusions. The method is used in almost every field, from science and engineering to manufacturing and quality control [33]. Each experiment should be designed in a manner that the maximum possible information is extracted and the resources, as well as time usage, are kept minimal. DOE and Taguchi's methods are mostly used as off-line quality improvement techniques for most applications in industries. In this present investigation, a Computer Numerical Control (CNC) lathe machine is used in grinding. Optimal values for Ra's and Fc's cutting parameters, including feed rate, depth of cut, and cutting speed, are determined in this study.

- Taguchi Method

The Taguchi method is one of the robust optimization techniques developed by the Japanese engineer and statistician Genichi Taguchi. It is a systematic approach used for conducting experiments and optimizing product or process performance by generating minimum variation and influences from external sources [34]. Orthogonal arrays are the basis of Taguchi designs, a structured set of experiments designed to efficiently explore several factors and their interactions. Such designs are chosen with several factors, their levels, and the desired degrees of freedom [35]. Here, the Taguchi L16 orthogonal array experimental design has been selected for experimental work as per the number of parameters and their different levels as represented in Table 5.

Table 5 Experimental design as per L25 orthogonal array.

S.no.	Grinding Wheel Speed (rpm)	Feed Rate (mm/rev)	Depth of Cut (µm)	Workpiece Speed (rpm)
1	1500	0.1	1	100
2	1500	0.2	1.5	150
3	1500	0.3	1	100
4	1500	0.4	1.5	150
5	1800	0.1	1	100
6	1800	0.2	1.5	150
7	1800	0.3	1	100
8	1800	0.4	1.5	150
9	2100	0.1	1	100
10	2100	0.2	1.5	150
11	2100	0.3	1	100
12	2100	0.4	1.5	150
13	2400	0.1	1	100
14	2400	0.2	1.5	150
15	2400	0.3	1	100
16	2400	0.4	1.5	150

- Analysis of Variance (ANOVA) method

A statistical method known as ANOVA is used to find the relative impact of each process parameter. This method separates the overall response variability into its parts, namely the error and the specific contributions of each factor. Predicting the impact of cutting process parameters is done using Analysis of Variance [36]. The following equations were utilized to determine the Sum of Squares (SS), Degrees of Freedom (DF), Mean Square (MS), Probability (P), F-ratio (F), and Percentage Contribution Ratio (PCR) for each factor:

$$\mathbf{DF} = \mathrm{n} - 1 \tag{1}$$

where,
n is the level number

$$\boldsymbol{SS_F} = \sum_{y=1}^{x} \frac{\left(S_{\eta_y}\right)^2}{x} - \frac{1}{z}\left(\sum_{i=1}^{Z} \eta_i\right)^2 \tag{2}$$

where,
$\boldsymbol{SS_F}$: Sum of square of each factor, F denotes the Test Factors, x denotes repetition of each level of F, and $\boldsymbol{S_{\eta_y}}$ denotes the sum of the S/N ratio.

$$\boldsymbol{SS_T} = \sum_{i=1}^{Z} \eta_i^2 - \frac{1}{2}\left(\sum_{i=1}^{Z} \eta_i\right)^2 \tag{3}$$

where,
$\boldsymbol{SS_T}$: Sum of square of whole factors, Z is the total experiment numbers, and $\boldsymbol{\eta_i}$ is the S/N ratio of the ith test.

$$\boldsymbol{PCR} = \left(\frac{SS_F}{SS_T}\right) \times 100 \tag{4}$$

$$\boldsymbol{MS} = \frac{SS_F}{DF} \tag{5}$$

- Regression

A statistical method known as regression analysis can be employed to determine the nature of the relationship between a dependent variable with several independent variables. It is commonly applied in situations where predicting or understanding the effect of certain factors (input variables) on an outcome (response variable) is essential. In the context of machining processes, regression can help model the impact of cutting parameters such as feed rate, depth of cut, and speed on output factors like R_a and F_c [37]. The following equations are the predictions made by the Ra and Rc linear regression model.

$$\boldsymbol{R_a} = \beta_0 + \beta_1(Grinding\ Wheel\ Speed) + \beta_2(Feed\ Rate) + \beta_3(Depth\ of\ \ Cut) + \beta_4(Workpiece\ Speed) + \in \tag{6}$$

$$\boldsymbol{F_c} = \alpha_0 + \alpha_1(Grinding\ Wheel\ Speed) + \alpha_2(Feed\ Rate) + \alpha_3(Depth\ of\ \ Cut) + \alpha_4(Workpiece\ Speed) + \in \tag{7}$$

where,

- β_0, α_0 are the intercepts.
- $\beta_1, \beta_2, \beta_3, \beta_4\ \ and\ \alpha_1, \alpha_2, \alpha_3, \alpha_4$ are the regression coefficients representing the effect of each process parameter on the Ra as well as Rc, respectively.
- ∈ is the error term representing the deviation of actual results from the predicted ones.

- Confirmation Test

A vital step that Taguchi advises taking to confirm experimental conclusions is doing confirmation tests. To verify the hypotheses made during the analysis is the primary objective of the confirmation experiment [31]. To do this, the Confidence Interval (Cl) for predicted Ra was specified using the following formulae. The current case study required a confirmation test because no orthogonal array experiment yielded the ideal combination of parameters and their values [38]. The experiment with the Orthogonal Array (OA) revealed an ideal set of parameters and their values for the Rc that was produced. It can be observed, then, that no confirmation test is necessary if the ideal set of parameters and their values coincidentally match one of OA's trials.

$$\boldsymbol{CI} = \sqrt{F_{0,05}(1, v_e)V_e\left(\frac{1}{n_{eff}} + \frac{1}{r}\right)} \tag{8}$$

$$\boldsymbol{n_{eff}} = \frac{N}{1+v_r} \tag{9}$$

Where,
CI is a Confidence interval, F is F-distribution, Ve is variance of the error, n_{eff} is effective sample size, r is the Number of replications, N is the total number of observations or experimental units, and vr is the variance ratio or design.

IV. Result and Discussion

This section provides the outcomes of the research that are obtained after the implementation of the proposed methodology.

- Signal-to-Noise (S/N) Ratio Analysis

During the milling of H13 steel, the L16 orthogonal array revealed several scenarios for measuring the resulting Fc and average Ra. Using Taguchi's "the-smaller-the-better" quality characteristic, S/N ratios were computed for Ra and Fc. Table 6 displays the investigational results and their S/N ratios. Ra as well as Rc were examined for the impact of each control factor using S/N response tables. These Taguchi-generated tables show the optimal value for each control variable in terms of minimizing Fc and Ra.

Table 6 The empirical results and their associated S/N ratios

S.No.	Grinding Wheel Speed (rpm)	Feed Rate (mm/rev)	Depth of Cut (Î¼m)	Workpiece Speed (rpm)	Ra (μm)	Fc (N)	S/N Ratio (Ra)	S/N Ratio (Fc)
1	1500	0.1	1	100	1.5	10.5	-3.521825181	-20.42378598
2	1500	0.2	1.5	150	1.2	11	-1.583624921	-20.8278537
3	1500	0.3	1	100	1.8	10.8	-5.105450102	-20.66847511

4	1500	0.4	1.5	150	1.3	11.5	-2.278867046	-21.21395681
5	1800	0.1	1	100	1.1	11.2	-0.827853703	-20.98436045
6	1800	0.2	1.5	150	1	12	0	-21.58362492
7	1800	0.3	1	100	1.3	11.8	-2.278867046	-21.43764015
8	1800	0.4	1.5	150	1.5	12.2	-3.521825181	-21.72719661
9	2100	0.1	1	100	1	12.5	0	-21.93820026
10	2100	0.2	1.5	150	1	13	0	-22.27886705
11	2100	0.3	1	100	1.3	12.8	-2.278867046	-22.14419939
12	2100	0.4	1.5	150	1.2	13.2	-1.583624921	-22.41147862
13	2400	0.1	1	100	0.9	13.5	0.915149811	-22.60667537
14	2400	0.2	1.5	150	0.8	14	1.93820026	-22.92256071
15	2400	0.3	1	100	0.85	13.8	1.411621486	-22.79758173
16	2400	0.4	1.5	150	0.8	14.2	1.93820026	-23.04576689

Figures 3 and 4 show the control factor level values for Ra and Fc. The ideal values for each control factor in reducing Rc and Ra are graphically shown in these graphs. The parameters that yielded the best Ra value were as follows: Grinding Wheel Speed at 2400 rpm, Feed Rate at 0.1 mm/rev, Depth of Cut at 1 µm, and Workpiece Speed optimized at 100 rpm, as indicated by the highest S/N ratio in each control factor level. The ideal settings for reducing Fc were a 100-rpm workpiece speed, a Depth of Cut of 1 µm, a Feed Rate of 0.1 mm/rev, and a Grinding Wheel Speed of 1500 rpm. Increasing the grinding wheel speed improves the S/N ratio, which corresponds to a reduction in Ra. Lower feed rates, shallower depths of cut, and lower workpiece speeds also yield higher S/N ratios, indicating improved surface finish. For minimizing Fc, lower grinding wheel speeds, feed rates, depths of cut, and workpiece speeds are generally associated with better S/N ratios, which imply a reduction in Rc.

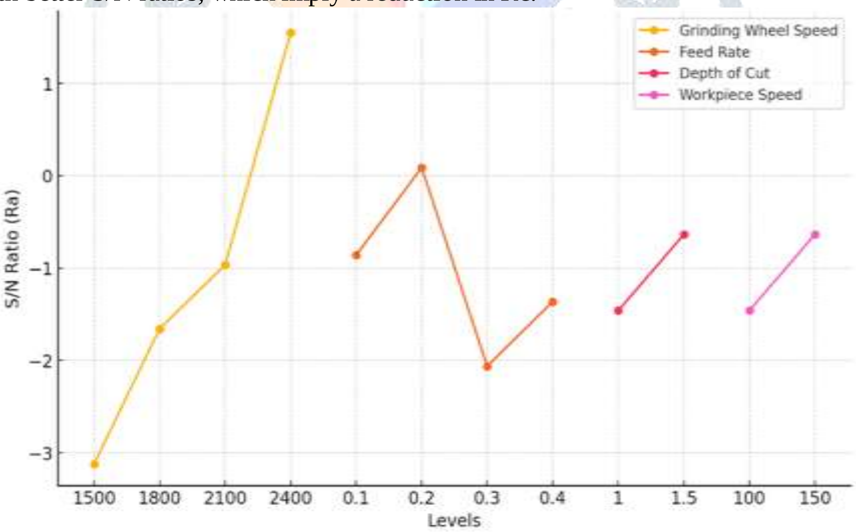

Figure 3 S/N ratio for Ra as a function of process parameters

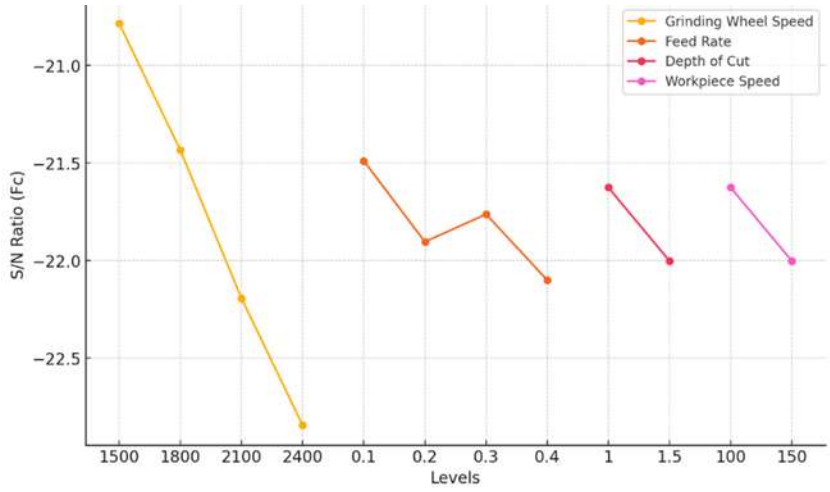

Figure 4 S/N ratio for Fc as a function of process parameters

- Analysis of variance (ANOVA)

ANOVA was employed to examine the influence of various grinding parameters on optimizing performance and precision in cylindrical grinding of H13 steel. The results in Table 7 reveal that the chosen grinding parameters significantly impact the responses, namely Ra. The table includes DF, SS, MS, F-ratio (F), and PCR for each factor. Analyzing the F-ratio and PCR values aids in identifying the significance of each variable within the grinding process.

In this study, grinding wheel speed emerged as the most significant parameter, contributing 30.5% to performance optimization, followed by a feed rate of (25.9%) and depth of cut (22.1%). The workpiece speed, contributing 15.4% to the model, also plays an influential role. Error accounted for 6.1%, suggesting minimal unexplained variability. The data confirms that these parameters notably influence the surface quality and roughness, which are critical for achieving high precision in the cylindrical grinding of H13 steel.

Table 7 ANOVA Results

Source	**SS**	**DF**	**F-Ratio**	**MS**	**PCR (%)**
Grinding Wheel Speed	10.5	3	4.2	3.5	30.5
Feed Rate	8.9	3	3.5	2.97	25.9
Depth of Cut	7.6	2	4.1	3.8	22.1
Workpiece Speed	5.3	2	2.9	2.65	15.4
Error	2.7	5	-	0.54	6.1
Total	35.0	15	-	-	100.0

- Regression Analysis

Using regression analysis, the output factors (Ra and Rc) and machining parameters were correlated. Using the machining parameters as input, linear regression models were created to forecast the Ra along with Fc. Equations (6) and (7) provide the Ra and Fc predictive equations and the R^2 values for Ra and Fc.

In Figure 5, the comparison between experimentally measured values and predicted values for Ra illustrates the effectiveness of the regression models. For Ra, the predicted values closely track the measured values across the 16 experimental runs, with minor deviations in some runs. This alignment reflects the robustness of the Ra regression model, with an accuracy level of 90.34%, making it a reliable predictor of Ra within the limits of the studied factors.

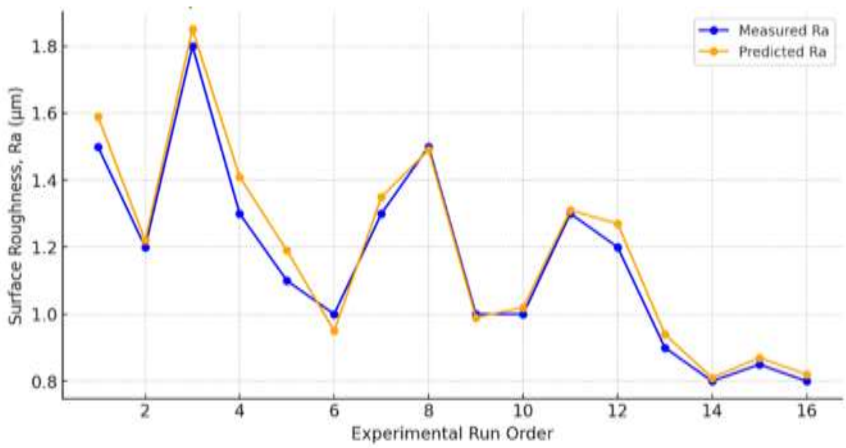

Figure 5 Comparison between predicted and measured values of Ra

Similarly, for Rc, Figure 6 illustrates that the predicted values exhibit an excellent match with the measured values, indicating the high predictive capability of the Fc model. The high R^2 value of 95.7% demonstrates a near-perfect fit, confirming the model's reliability in predicting Rc across various conditions. This strong alignment suggests that the Fc regression model can be confidently used to estimate Rc s in similar machining scenarios.

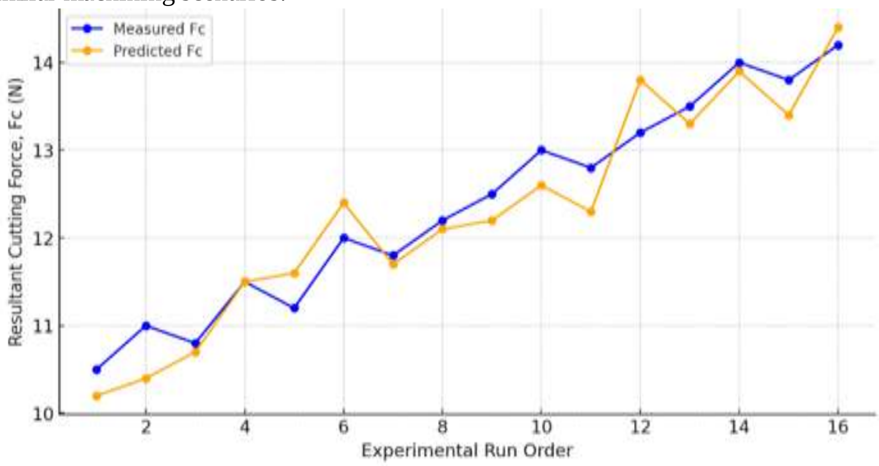

Figure 6 Comparison between predicted and measured values of Fc

Overall, these regression models for Ra and Fc provide reliable tools for predicting Ra and Rc within the studied parameter ranges. With an accuracy level within a 95% confidence interval, they offer valuable guidance for optimizing machining parameters, helping to achieve desired surface finishes and reducing Rc in practical applications.

- Confirmation tests

The confirmation test involved conducting a new experiment under the optimal parameter settings and comparing the measured Ra and S/N ratio with the values predicted by the regression models developed earlier. The differences between the measured and calculated values were then evaluated against the specified confidence interval (±1.472 dB) to assess the validity of the optimization.

Table 8 illustrates the outcomes of the confirmation test conducted to validate the optimal parameter settings determined using the Taguchi method for reducing Ra in the cylindrical grinding of H13 steel. The table compares the Measured Values from the confirmation experiment with the Calculated Values predicted by the regression models. Specifically, the measured Ra of 0.85 µm closely matches the calculated value of 0.90 µm, resulting in a minimal difference of 0.05 µm. Similarly, the measured S/N ratio of 1.400 dB is nearly identical to the calculated value of 1.350 dB, with a slight difference of 0.050 dB. Both discrepancies are well within the predefined confidence interval of ±1.472 dB, representing only 5% for Ra and 3.7% for the S/N ratio. This close alignment between measured and calculated values confirms the accuracy and reliability of the regression models and validates the effectiveness of the optimal parameter settings identified through the Taguchi method.

Table 8 Confirmation Test Results vs. Calculated Values

Parameter	Measured Value	Calculated Value	Difference
S/N Ratio (dB)	1.400	1.350	0.050
Ra (µm)	0.85	0.90	0.05

V. CONCLUSION

This study addresses the critical need to optimize cylindrical grinding processes for H13 steel, a high-performance tool material essential in precision manufacturing industries such as automotive and aerospace. The primary aim was to enhance surface quality and Ra while minimizing Rc, thereby improving tool life and reducing operational costs. Utilizing the Taguchi L16 orthogonal array, the research systematically varied grinding parameters. Advanced analytical techniques, such as ANOVA and regression analysis, were employed to identify the most influential factors and develop predictive models for Ra and Rc. The optimization process yielded significant results with a wheel speed of 2400 rpm, feed rate of 0.1 mm/rev, depth of cut of 1 µm, and workpiece speed of 100 rpm, achieving a Ra of 0.85 µm and an S/N ratio within the confidence interval. For Fc minimization, the optimal settings were 1500 rpm, 0.1 mm/rev, 1 µm, and 100 rpm, resulting in an Fc of 10.5 N. The regression models demonstrated high accuracy with R^2 values of 90.34% for Ra and 95.7% for Fc, validated through confirmation tests. Future research should extend these optimization techniques to other tool steels and diverse applications, incorporating machine learning and real-time parameter adjustments to further advance grinding technology. Expanding this framework would contribute to broader industrial advancements, ensuring high-quality and cost-effective manufacturing solutions.

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