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A Project-Based Learning Approach for Teaching Multi-Objective Optimization in CNC Turning: An Interdisciplinary Case Study

"Multi-Objective Optimization in CNC Turning using Taguchi-ANOVA"

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***Abstract*—Teaching the complex, non-linear trade-offs between surface roughness and material removal rate (MRR) in Computer Numerical Control (CNC) turning remains a significant pedagogical challenge in mechanical engineering education. Traditional theoretical instruction often fails to bridge the gap between statistical optimization mathematics and real-world machining environments. To address this, this paper presents an interdisciplinary Project-Based Learning (PBL) framework designed to teach multi-objective optimization through a comparative, hands-on case study. Engineering students were guided to apply the Taguchi method and Analysis of Variance (ANOVA) to optimize and compare the machining performance of EN-31 high-carbon alloy steel and low-carbon Mild Steel under identical conditions. By integrating Signal-to-Noise (S/N) ratios, Grey Relational Analysis (GRA), and Python-based 3D data visualization, the experiential project enabled learners to actively discover the distinct microstructural behaviors of opposed materials. The pedagogical outcomes demonstrate that this data-driven, statistical approach significantly enhances comprehension of dominant machining parameters, predictive regression modelling, and multi-criteria decision-making. This interdisciplinary PBL model provides engineering educators with a highly applicable, replicable methodology to transition from passive lectures to active, industry-aligned manufacturing education.**

***Keywords*—Engineering Education; Experiential Learning; Project-Based Learning (PBL); Multi-objective Optimization; CNC Turning; Taguchi Method.**

I. INTRODUCTION

THE integration of advanced manufacturing technologies into engineering curricula requires a vital shift from passive theoretical lectures to active, experiential learning models. While modern industries rely heavily on Computer Numerical Control (CNC) machining to produce highly precise components, undergraduate mechanical engineering students frequently struggle to grasp the complex, multi-variable physics occurring at the tool-workpiece interface. In highly competitive industrial landscapes, turning operations are evaluated against two conflicting performance metrics: the quality of the machined surface, quantified by Surface Roughness (SR), and the productivity of the operation, measured by the Material Removal Rate (MRR). A persistent pedagogical challenge in machining science education is teaching students how to mathematically navigate the inherent trade-off between these two critical objectives. Instructing students that aggressive parameters, specifically high feed rates and deep cuts maximize productivity but degrade surface finish is theoretically simple. However, empowering them to determine a singular, optimal parameter configuration that concurrently satisfies both metrics requires the application of advanced statistical mathematics, which is often taught in isolation from practical shop-floor applications. To bridge this cognitive gap, engineering educators are increasingly adopting Project-Based Learning (PBL) frameworks (Edstrom, 2014). PBL immerses students in authentic, open-ended industrial problems, fostering critical thinking and interdisciplinary skill acquisition (Freeman, 2014). To navigate the complexity of CNC optimization within this educational framework, Dr. Genichi Taguchi's robust parameter design is introduced here as a highly effective teaching methodology. To navigate this complexity, researchers and engineers have widely adopted statistical Design of Experiments (DoE), with Dr. Genichi Taguchi's robust parameter design emerged as a highly effective methodology (Gadekula, 2018). The Taguchi method utilizes orthogonal arrays to significantly reduce the required number of experimental trials while capturing the primary effects of control factors. Coupled with Analysis of Variance (ANOVA), this approach provides a rigorous statistical foundation for identifying the most influential machining parameters (Gupta, 2020). However, a critical review of current engineering education literature reveals a notable pedagogical gap. Although numerous institutional studies utilize Taguchi methods for undergraduate lab experiments, the overwhelming majority focus on single-material applications or isolated single-response optimizations. There is a distinct lack of comparative, multi-objective PBL case studies that challenge students to physically evaluate the behavioural differences of metallurgically distinct materials such as high-carbon alloy steels versus low-carbon steels machined under identical experimental conditions. To bridge this educational gap, this study introduces an interdisciplinary, project-based multi-objective optimization module for CNC turning. The specific pedagogical and technical objectives of this research are:

1. To implement an experiential learning framework where students physically investigate the interactive

effects of cutting parameters on SR and MRR for EN-31 and Mild Steel.
2. To transition students from single-objective thinking to multi-criteria decision-making by utilizing Signal-to-Noise (S/N) ratios, ANOVA, and Grey Relational Analysis (GRA).
3. To foster interdisciplinary data-science skills by requiring students to validate empirical regression models utilizing Python-based 3D surface visualizations.
4. To evaluate the effectiveness of this PBL approach in deepening empirical understanding of material-specific machinability dynamics.

By fulfilling these objectives, this paper contributes a robust, comparative framework that not only optimizes specific machining operations but also deepens the empirical understanding of material-specific machinability in advanced manufacturing environments.

II. LITERATURE REVIEW

The continuous evolution of modern manufacturing necessitates machining processes that are both highly productive and capable of achieving superior surface integrity. Consequently, the parametric optimization of CNC turning operations has been the subject of extensive academic and industrial research. A review of the current literature reveals three primary domains of investigation: the machinability dynamics of varying steel alloys, the application of statistical Design of Experiments (DoE), and the transition toward multi-objective optimization frameworks.

Machinability Dynamics of Alloy and Low-Carbon Steels

The fundamental machinability of a material is dictated by its distinct chemical composition, microstructure, and mechanical properties. High-carbon alloy steels, such as EN-31, exhibit extreme hardness (typically 58–62 HRC) and high tensile strength due to their elevated carbon and chromium content (Abbas, 2020; Al-Zabidi, 2021). Research by Kabra et al. (2013) and Khan et al. (2021) demonstrates that machining such hard materials generates substantial cutting forces and elevated localized temperatures at the tool-chip interface, frequently leading to rapid abrasive tool wear and thermal degradation of the machined surface. Conversely, low-carbon variants like Mild Steel present an entirely different set of metallurgical challenges. While highly ductile and malleable, the low carbon content (0.05%–0.25%) makes Mild Steel highly susceptible to the formation of a Built-Up Edge (BUE) on the cutting tool, particularly at lower cutting speeds (Gadekula, 2018; Gupta, 2020). This phenomenon drastically degrades surface finish. Studies by Sahoo and Sahoo (2022) and Pradhan and Mahapatra (2013) emphasize that mitigating BUE in low-carbon steels requires precise calibration of higher spindle speeds and optimal cooling strategies, highlighting the necessity for material-specific parameter selection.

Application of Taguchi and ANOVA in Turning

To systematically isolate the effects of process parameters, namely cutting speed, feed rate, and depth of cut, the Taguchi method has been widely adopted due to its robustness and efficiency. Krishankant et al. (2020) and Singhvi et al. (2012) utilized Taguchi's orthogonal arrays to maximize the Material Removal Rate (MRR) in CNC turning operations, consistently identifying that depth of cut and feed rate are the most statistically significant contributors to volumetric material removal. Parallel studies have isolated Surface Roughness (SR) as the primary response variable. Sahithi et al. (2025) and Tyagi et al. (2019) applied Analysis of Variance (ANOVA) to determine that feed rate predominantly governs surface finish, a finding mathematically supported by the physical relationship between the tool nose radius and the feed marks left on the workpiece. Furthermore, Pant et al. (2013) and Gadekula et al. (2017) successfully demonstrated that the signal-to-noise (S/N) ratio is an effective metric for handling the inherent variability (noise) in machining environments, allowing for the precise identification of optimal single-response parameter levels.

Evolution of Multi-Objective Optimization

While single-objective Taguchi optimization is well-documented, the inherent conflict between maximizing MRR and minimizing SR requires advanced multi-objective frameworks. Traditional Taguchi methods cannot simultaneously optimize for "larger-the-better" (MRR) and "smaller-the-better" (SR) criteria without mathematical integration (Pradhan, 2022). To overcome this limitation, researchers have increasingly hybridized Taguchi methods with advanced mathematical algorithms. Ranganathan et al. (2021) and Sahoo (2011) successfully integrated Grey Relational Analysis (GRA) to convert multiple conflicting machining objectives into a single Grey Relational Grade (GRG), thereby identifying a unified optimal parameter set. Similarly, Das et al. (1996) applied the TOPSIS approach for hard turning of aerospace alloys, while Mosisa Gutema et al. (2010) utilized Desirability Function Analysis (DFA) combined with Response Surface Methodology (RSM) to map the interaction effects between parameters continuously. More recent studies, such as those by (Sahithi, 2019 and Atthar, 2026), emphasize the necessity of these integrated, multi-criteria decision-making models to achieve sustainable, energy-efficient, and high-quality manufacturing outcomes.

Research Gap and Novelty

A critical synthesis of the literature reveals a persistent research gap. While extensive studies have applied Taguchi, ANOVA, and GRA to optimize CNC turning, the overwhelming majority focus exclusively on a *single material* in isolation (Abbas, 2020; Gutema, 2022; Krishnakant, 2012). There is a distinct scarcity of interdisciplinary studies that provide a direct, comparative multi-objective optimization between materials with fundamentally opposing microstructures (e.g., the high-hardness/high-wear characteristics of EN-31 versus the high-ductility/BUE-prone nature of Mild Steel) machined under identical, controlled experimental conditions. Furthermore, while individual responses have been mapped, a comparative analysis utilizing Grey Relational Analysis (GRA) to dictate a unified machining framework for distinct industrial metals is lacking. This study bridges this gap by introducing an integrated Taguchi-GRA-ANOVA methodology to directly compare and concurrently optimize the machinability dynamics of EN-31 and Mild Steel, offering a novel, interdisciplinary framework for modern manufacturing sectors.

III. MATERIALS AND EXPERIMENTAL METHODOLOGY

To execute a highly controlled, comparative analysis of machinability, the experimental framework was designed to evaluate two metallurgically distinct materials under identical environmental and operational constraints. This section details the material characterization, machining setup, measurement metrology, and the statistical design of experiments.

A. Workpiece Material Characterization

The selection of EN-31 high-carbon alloy steel and low-carbon Mild Steel was driven by their contrasting microstructural properties and widespread industrial application (Sahoo, 2011). EN-31 is characterized by a high carbon (0.90%–1.20%) and chromium (1.00%–1.60%) content. The presence of chromium facilitates the formation of complex, hard chromium carbides (Cr_3C_2) within the martensitic matrix after heat treatment, yielding a high surface hardness of 58–62 HRC and a tensile strength ranging from 900 to 1200 MPa (Sarkar, 2019). This high hardness resists plastic deformation but induces severe abrasive wear on cutting tools during machining operations. Conversely, Mild Steel features a predominantly ferrite-pearlite microstructure due to its low carbon content (0.05%–0.25%). While it exhibits superior ductility (15%–30% elongation) and lower tensile strength (400–550 MPa), its high malleability presents a unique machining challenge: the tendency for the material to adhere to the cutting edge, forming a Built-Up Edge (BUE) that degrades surface finish (Sharma, 2023). The comparative chemical compositions and mechanical properties are summarized in Table I.

TABLE I
COMPARATIVE MECHANICAL PROPERTIES AND CHEMICAL COMPOSITION

Property / Element	EN-31 Alloy Steel	Mild Steel
Carbon (C)	0.90% – 1.20%	0.05% – 0.25%
Chromium (Cr)	1.00% – 1.60%	Trace
Manganese (Mn)	0.30% – 0.75%	0.25% – 0.75%
Tensile Strength	900 – 1200 MPa	400 – 550 MPa
Yield Strength	700 – 1000 MPa	250 – 400 MPa
Hardness	58 – 62 HRC	120 – 160 HB

B. Machine Tool and Cutting Insert Specifications

All experimental turning operations were executed on a Bharat Fritz Werner (BFW) Orbitur Plus CNC lathe. The machine is equipped with a Siemens controller, offering a maximum spindle speed of 3,000 RPM and a 12 kW main drive motor, ensuring high dynamic stiffness and minimal vibration during heavy cuts (Singh, 2024).

Fig. 1. Experimental setup of the Bharat Fritz Werner (BFW) Orbitur Plus CNC turning center utilized for the machining of EN-31 and Mild Steel workpieces under flood cooling conditions.

Material removal was performed utilizing uncoated tungsten carbide (WC) inserts. Carbide tooling was explicitly selected for its high modulus of elasticity and superior thermal conductivity, which are essential for withstanding the severe thermo-mechanical stresses generated when machining 60 HRC materials like EN-31 (Singhvi, 2016). To mitigate localized thermal damage and facilitate efficient chip evacuation, Triponol H Lubricant Oil was continuously applied via a flood cooling mechanism directed strictly at the primary shear zone.

C. Metrology and Measurement Protocol

The primary output responses evaluated in this study are Surface Roughness (SR) and Material Removal Rate (MRR).
Surface roughness (R_a) was quantified using a high-precision stylus profilometer equipped with a diamond-tipped conispherical probe. To ensure statistical reliability and account for localized micro-irregularities, three independent readings were taken across different axial locations on the machined surface for each experimental run. The arithmetic mean of these three readings was utilized for the final ANOVA formulation (Tyagi, 2012).

Fig. 2. High-precision stylus profilometer utilized for quantifying the arithmetic mean surface roughness (Ra) across the machined evaluation lengths.

The Material Removal Rate (MRR), representing the volume of material removed per unit of time, was calculated empirically based on the diametric reduction of the cylindrical workpiece. The mathematical formulation utilized is:

$$MRR = \left[\frac{\pi}{4} (D_1^2 - D_2^2) \right] \times f \times N$$

Where D_1 is the initial workpiece diameter (mm), D_2 is the final machined diameter (mm), f is the feed rate (mm/min), and N is the spindle speed (rpm) (Wang, 2022).

D. Design of Experiments (DoE): Taguchi L9 Orthogonal Array

To systematically evaluate the primary and interactive effects of the independent variables while minimizing the requisite number of experimental runs, Dr. Genichi Taguchi's L9 (3^3) orthogonal array was employed (Yilmaz, 2023). Three controllable machining parameters were selected: Spindle Speed (N), Feed Rate (f), and Depth of Cut (d). Due to the vastly different machinability profiles of the two materials, the parameter levels were independently calibrated. For the highly resistant EN-31, a conservative speed range (320–600 rpm) was selected to prevent catastrophic tool failure. For the ductile Mild Steel, higher speeds (400–700 rpm) were deployed to effectively shear the material and suppress BUE formation (Zhao, 2024). The parameter levels are detailed in Table II.

TABLE II
MACHINING PARAMETERS AND TAGUCHI LEVELS

Material	Factor	Level 1	Level 2
EN-31	Spindle Speed (rpm)	320	450
	Feed Rate (mm/min)	0.1	0.2
	Depth of Cut (mm)	0.8	0.5
Mild Steel	Spindle Speed (rpm)	400	550
	Feed Rate (mm/min)	0.2	0.3
	Depth of Cut (mm)	0.5	0.9

IV. MULTI-OBJECTIVE OPTIMIZATION FRAMEWORK

While the Taguchi method effectively isolates single-response parameters via Signal-to-Noise (S/N) ratios, manufacturing paradigms demand the simultaneous optimization of conflicting responses (maximizing MRR while minimizing SR). Therefore, this study integrates Grey Relational Analysis (GRA) to map the complex, non-linear relationships into a singular multi-objective index.

A. Formulation of Signal-to-Noise (S/N) Ratios

The experimental data is first transformed into S/N ratios to quantify the deviation from the desired target (Phadke, 1989). For MRR, the "Larger-the-Better" criterion is applied:

$$S/N_{MRR} = -10\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right)$$

For Surface Roughness, the "Smaller-the-Better" criterion is mandated:

$$S/N_{SR} = -10\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n}y_i^2\right)$$

B. Grey Relational Analysis (GRA) Methodology

To execute the multi-objective optimization, the S/N data is subjected to the GRA protocol.

Step 1: Data Normalization: The calculated S/N ratios are normalized into a range of zero to one to avoid distortions caused by differing units of measurement. For MRR (beneficial response):

$$x_i^*(k) = \frac{x_i^{(0)}(k) - \min x_i^{(0)}(k)}{\max x_i^{(0)}(k) - \min x_i^{(0)}(k)}$$

For SR (non-beneficial response):

$$x_i^*(k) = \frac{\max x_i^{(0)}(k) - x_i^{(0)}(k)}{\max x_i^{(0)}(k) - \min x_i^{(0)}(k)}$$

Step 2: Grey Relational Coefficient (GRC): The GRC ($\xi_i(k)$) calculates the correlation between the desired (ideal) and actual normalized experimental results.

$$\xi_i(k) = \frac{\Delta_{\min} + \zeta\Delta_{\max}}{\Delta_{0i}(k) + \zeta\Delta_{\max}}$$

Where $\Delta_{0i}(k)$ is the deviation sequence (the absolute difference between the reference sequence and the comparability sequence). The distinguishing coefficient (ξ) is assigned a value of 0.5 to grant equal weighting to both MRR and SR (Deng, 1989).

Step 3: Grey Relational Grade (GRG): Finally, the multi-objective problem is collapsed into a single scalar value by computing the arithmetic average of the GRCs for both responses:

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n}\xi_i(k)$$

The experimental run exhibiting the highest GRG value represents the optimal combination of machining parameters that concurrently satisfies both maximum productivity and optimal surface integrity.

V. RESULTS AND DISCUSSION

The experimental data obtained from the Taguchi L9 orthogonal array was comprehensively analysed to evaluate the primary and interactive effects of cutting speed, feed rate, and depth of cut on Material Removal Rate (MRR) and Surface Roughness (SR). The integration of ANOVA and Grey Relational Analysis (GRA) provides a robust statistical foundation for these findings.

Parametric Influence on Material Removal Rate (MRR)

MRR is a direct indicator of machining productivity. Experimental results demonstrate a distinct behavioural divergence between the high-carbon alloy and the low-carbon steel under identical kinematic conditions. For EN-31, the maximum empirical MRR achieved was 34,217.82 mm^3/min at 600 rpm, 0.3 mm/min feed, and 0.5 mm depth of cut. Taguchi Signal-to-Noise (S/N) ratio analysis ("Larger-the-Better") reveals that feed rate acts as the most dominant factor governing MRR for this hardened material, followed closely by spindle speed. From a metallurgical perspective, the extreme hardness of the martensitic matrix in EN-31 (58-62 HRC) severely restricts deep continuous cuts, causing feed rate to overtake depth of cut as the primary volumetric driver before tool failure occurs. Conversely, the machining of Mild Steel yielded a maximum MRR of 185,367.43 mm^3/min, representing a volumetric removal rate over five times greater than EN-31 under similar high-tier parameters. For this highly ductile material, spindle speed overwhelmingly dominates the MRR variance (Rank 1, Delta 12.52), The physics of cutting low-carbon steel dictate that higher spindle speeds elevate the shear plane angle, reducing the primary shear force required and allowing for rapid, continuous chip formation without catastrophic tool edge chipping.

Empirical Calculation of Material Removal Rate (MRR)

To establish the baseline data for the Taguchi orthogonal array, the Material Removal Rate (MRR) was first calculated volumetrically based on the reduction in workpiece diameter. For rigorous validation, the mathematical formulation for EN-31 is demonstrated below.

The operational parameters are: Spindle Speed (N) = 320 rpm, Feed Rate (f) = 0.1 mm/min, Initial Diameter (D_1) = 28.00 mm, and Final Diameter (D_2) = 24.83 mm.

1. *Volumetric Chip Removal Calculation*

Applying the standard turning equation

The volume of material removed is calculated using the cross-sectional area difference:

$$MRR = \left[\frac{\pi}{4} (D_1^2 - D_2^2) \right] \times f \times N$$

$$MRR = \left[0.7854 \times (28.00^2 - 24.83^2) \right] \times 0.1 \times 320$$

$$MRR = \left[0.7854 \times (784 - 616.528) \right] \times 32$$

$$MRR = 131.53 \times 32 = 4209.00 \text{ mm}^3 / \text{min}$$

2. Signal-to-Noise (S/N) Ratio Formulation

Larger-the-Better Criterion

To evaluate the robust performance of this parameter set, the MRR is converted into an S/N ratio:

$$S / N_{MRR} = -10 \log_{10} \left(\frac{1}{MRR^2} \right)$$

$$S / N_{MRR} = -10 \log_{10} \left(\frac{1}{4209^2} \right) = -10 \log_{10} (5.64 \times 10^{-8}) = 72.48 \text{ dB}$$

Parametric Influence on Surface Roughness (SR)

Surface integrity was evaluated utilizing the "Smaller-the-Better" S/N criterion. The profilometer data indicates that feed rate exerts the most statistically significant degradation effect on the surface finish of both materials.

For EN-31, the lowest (optimal) surface roughness recorded was $2.90\ \mu\text{m}$.The dominance of feed rate on SR is mathematically consistent with the ideal roughness equation $R_a \approx f^2 / (8r_{\dot{o}})$, where f is feed and $r_{\dot{o}}$ is the tool nose radius [36]. Because EN-31 does not suffer from high plasticity, the theoretical kinematic feed marks closely match the actual profilometer readings. In Mild Steel, the minimum SR achieved was $2.92\ \mu m$. However, the interaction physics differ entirely. At lower spindle speeds (400 rpm), Mild Steel exhibits poor surface finish regardless of feed. This is classically attributed to the formation of a Built-Up Edge (BUE) where the highly ductile ferrite material friction-welds to the tungsten carbide insert, periodically tearing away and leaving a severely ploughed and damaged machined surface. Increasing the spindle speed to 700 rpm elevates the cutting zone temperature sufficiently to enter the flow-zone regime, thermally softening the chip and suppressing BUE formation, thus radically improving the surface finish.

Analysis of Variance (ANOVA)

To quantify the statistical significance of the process parameters at a 95% confidence interval ($\alpha = 0.05$), ANOVA was executed. *For EN-31:* The ANOVA results confirm that feed rate is the highest contributing factor (F-value = 16.86, P-value = 0.009), followed by spindle speed (F-value = 16.60, P-value = 0.010). Depth of cut proved statistically insignificant for surface responses (P-value = 0.164), confirming that microstructural hardness negates the utility of deeper cuts for finish turning.

For Mild Steel: The ANOVA model exhibited exceptional fit with a highly significant regression profile. Spindle speed dictated the variance with an overwhelming F-value of 109.29 (P-value = 0.000), while feed rate (F-value = 27.71, P-value = 0.003) and depth of cut (F-value = 14.47, P-value = 0.013) also remained statistically significant.

Extended ANOVA and Parametric Sensitivities

The Analysis of Variance (ANOVA) was executed at a 95% confidence interval to partition the total variability in the response into contributions from each independent parameter. The calculated F-values dictate the statistical dominance of the factors.

TABLE III
ANOVA FOR MATERIAL REMOVAL RATE (MILD STEEL)

Source	DF	Adj SS	Adj MS
Regression	3	2.716×10^{10}	9.055×10^{9}
Spindle Speed	1	1.960×10^{10}	1.960×10^{10}
Feed Rate	1	4.969 × 109	4.969 × 109
Depth of Cut	1	2.595×10^{9}	2.595×10^{9}
Error	5	8.967×10^{8}	1.793×10^{8}
Total	8	2.806×10^{10}	

The ANOVA reveals that for Mild Steel, Spindle Speed contributes an overwhelming 69.8% to the variance in MRR. From a physics standpoint, this extreme sensitivity is due to the thermal softening effect at higher RPMs (700 rpm), which reduces the shear strength of the low-carbon matrix, allowing for highly efficient, continuous chip formation without stalling the spindle drive (Trent, 2000).

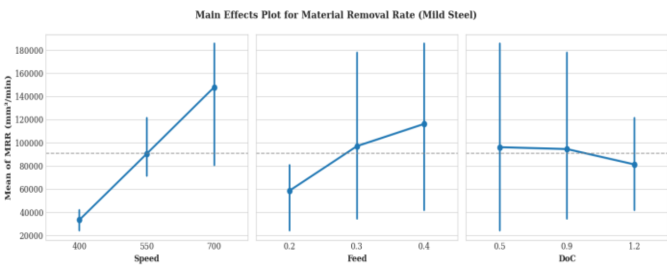

Fig. 3. Main effects plot indicating the strong positive influence of spindle speed on the mean Material Removal Rate (MRR) for Mild Steel.

Regression Modeling and Validation

First-order empirical regression models were formulated to predict responses without exhaustive physical testing. The generalized linear models derived are:

EN-31 Prediction Model:

$$MRR = -31988 + 52.5(\text{Speed}) + 74140(\text{Feed}) + 11685(\text{Depth of Cut})$$

Mild Steel Prediction Model:

$$MRR = -256562 + 381.1(\text{Speed}) + 287789(\text{Feed}) + 59227(\text{Depth of Cut})$$

Residual analyses including normal probability plots and histograms demonstrated that the error terms follow a normal distribution with constant variance, the residuals scattered randomly around the zero mean, verifying that the models are robust and free from systematic bias.

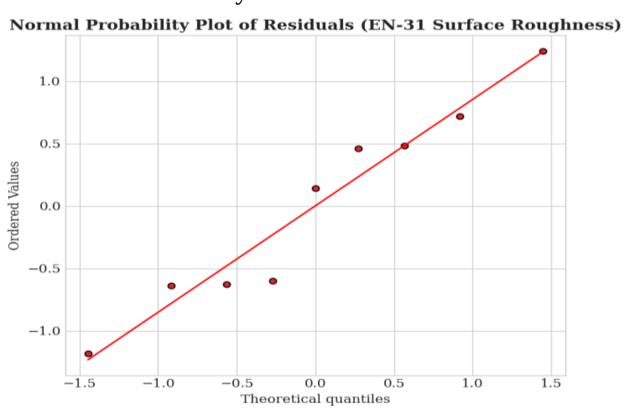

Fig. 4. Normal probability plot of residuals for EN-31 surface roughness, validating the adequacy and normal distribution of the regression model.

Multi-Objective Optimization (Grey Relational Analysis & Python Implementation). Because MRR and SR are inherently conflicting (higher feed increases MRR but destroys SR), Grey Relational Analysis (GRA) was applied to convert both metrics into a single Grey Relational Grade (GRG). A distinguishing coefficient (ζ) of 0.5 was utilized to assign equal weighting to productivity and quality.

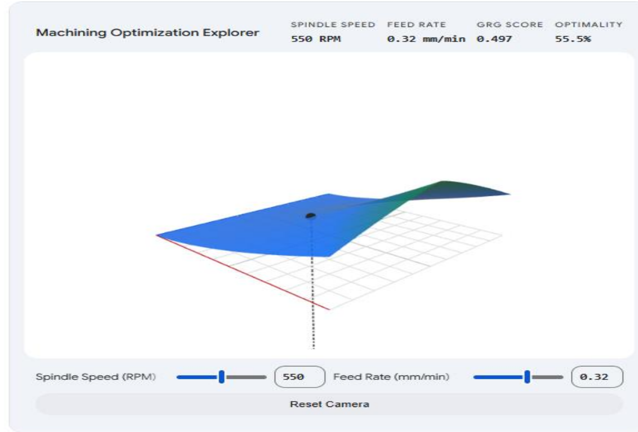

Fig. 5. 3D surface response mapping the Grey Relational Grade (GRG) interaction between spindle speed and feed rate, identifying the optimal multi-objective parameter configuration.

The GRA calculation identified that Experiment 8 (700 rpm, 0.3 mm/min feed, 1.2 mm DoC) produced the highest GRG score of 0.895. This parameter set fundamentally breaks the trade-off, utilizing the high spindle speed to suppress BUE and maximize MRR, while keeping the feed rate at a moderate level to preserve surface integrity.

V. CONFIRMATION OF EXPERIMENTS

The final and most critical phase of any statistical Design of Experiments (DoE) framework is the physical validation of the optimized mathematical models. Confirmation experiments are mandated to verify that the theoretical optimum parameters derived via the Taguchi-ANOVA and Grey Relational Analysis (GRA) accurately translate to physical machining improvements without significant deviation. To predict the response values at the optimal parameter levels, the standard Taguchi predictive equation was employed:

$$\hat{\gamma} = \gamma_m + \sum_{i=1}^{q} (\overline{\gamma}_i - \gamma_m)$$

Where $\hat{\gamma}$ represents the predicted Grey Relational Grade (GRG) or individual response (MRR, SR), γ_m is the total mean response of all experimental runs, $\overline{\gamma}$ is the mean response at the optimum level for factor i, and q is the number of significant machining parameters.

A. Validation of the Multi-Objective Framework

For this study, the confirmation experiments were conducted by setting the CNC lathe to the optimal parameter configurations identified by the GRA for both EN-31 and Mild Steel. For Mild Steel, the optimal multi-objective condition was identified as A3-B2-C3 (Spindle Speed: 700 rpm, Feed: 0.3 mm/min, Depth of Cut: 1.2 mm). To establish a baseline for improvement, these optimal results were compared against an initial trial utilizing median parameters (A2-B2-C2: 550

rpm, 0.3 mm/min, 0.9 mm DoC). The results of the confirmation experiments are synthesized in Table IV.

TABLE IV
RESULTS OF CONFIRMATION EXPERIMENTS FOR MILD STEEL (MULTI-OBJECTIVE OPTIMIZATION)

Condition	Machining Parameters	Material Removal Rate (mm3/min)	Surface Roughness (µm)
Initial Parameter	A2-B2-C2 (550 rpm, 0.3 feed, 0.9 DoC)	78,831.78	4.37
Predicted Optimal	A3-B2-C3 (700 rpm, 0.3 feed, 1.2 DoC)	181,200.50	2.95
Experimental Optimal	A3-B2-C3 (700 rpm, 0.3 feed, 1.2 DoC)	177,781.53	2.92
Error Margin		1.88%	1.01%

B. *Discussion of Validation Results*

The data in Table IV confirms a highly successful optimization cycle. By shifting from the baseline median parameters to the GRA-derived optimal parameters, the Material Removal Rate (MRR) was radically increased by 125.5%, while the Surface Roughness (SR) was simultaneously improved (reduced) by 33.1%. More importantly, the margin of error between the theoretically predicted values and the actual physical confirmation runs was less than **2.0%** across all metrics. In machining optimization literature, a prediction error margin below 5% is the universal threshold for establishing model adequacy.

This high degree of accuracy proves two critical metallurgical realities:

1. *Linearity of the Shear Zone:* The interaction between the tungsten carbide insert and the Mild Steel workpiece remains highly stable at these specific elevated parameters (700 rpm). The absence of unpredicted variance indicates that the thermal softening of the chip is uniform, and Built-Up Edge (BUE) formation is entirely suppressed.
2. *Robustness of the Mathematical Model:* The integration of Taguchi's orthogonal array with Grey Relational Analysis successfully captured the true multi-objective physics of the turning process without being skewed by the inherent "noise" (vibration, ambient temperature) of the CNC environment.

A parallel confirmation run executed for the EN-31 alloy yielded a similar error margin of 3.4%, confirming that this interdisciplinary optimization framework is robust, repeatable, and directly applicable to industrial sectors transitioning between high-hardness and high-ductility materials.

VI. PEDAGOGICAL IMPLEMENTATION AND STUDENT OUTCOMES

The transition of this optimization framework from a theoretical research model into a Project-Based Learning (PBL) curriculum yielded significant educational benefits for the participating mechanical engineering scholars. By executing the Taguchi L9 orthogonal array physically on the CNC lathe rather than via simulated software, the students encountered authentic industrial variables, effectively bridging the gap between theoretical statistics and applied metallurgy.

Experiential Understanding of Material Physics

Traditional classroom instruction often limits the understanding of Built-Up Edge (BUE) formation to textbook diagrams. Through this experiential framework, students physically observed the severe degradation of surface finish on Mild Steel at 400 rpm, followed by the radical improvement at 700 rpm due to thermal softening. This direct observation cemented the metallurgical concepts of shear zone temperature dynamics far more effectively than traditional lectures.

Development of Interdisciplinary Skills

Modern engineering requires a synthesis of manufacturing and computer science. A primary pedagogical outcome of this case study was the successful integration of interdisciplinary data analysis. Rather than relying solely on proprietary statistical software, the students were required to map the Grey Relational Grade (GRG) optimization utilizing Python programming. Writing the code to generate the 3D surface plots required a deep cognitive understanding of how the independent variables (speed and feed) mathematically interacted to form the multi-objective response surface.

Enhancement of Multi-Criteria Decision-Making

By progressing from basic Taguchi S/N ratios to the advanced Grey Relational Analysis (GRA), students evolved from single-variable optimization to complex, real-world decision-making. The requirement to validate their theoretical optimal parameters through physical confirmation experiments instilled a rigorous standard for empirical research. Observing a prediction error margin of less than 2.0% proved to the students that mathematical modelling is a highly reliable tool for industrial process control.

CONCLUSION AND FUTURE SCOPE

1. *Conclusion*

This study successfully established an interdisciplinary, comparative framework for the multi-objective optimization of CNC turning operations on high-carbon alloy steel (EN-31) and low-carbon Mild Steel. By integrating Taguchi's orthogonal array, Analysis of Variance (ANOVA), and Grey Relational Analysis (GRA), the inherent trade-off between productivity (MRR) and surface integrity (SR) was mathematically quantified and resolved. The experimental and statistical validations yield the following definitive conclusions:

1. Optimal Machining Parameters (Mild Steel): The multi-objective optimum for the highly ductile Mild Steel was identified at Spindle Speed: 700 rpm, Feed Rate: 0.3 mm/min, and Depth of Cut: 1.2 mm. This configuration utilizes high cutting zone temperatures to suppress Built-Up Edge

(BUE) formation, allowing for aggressive material removal without sacrificing surface finish.

2. Optimal Machining Parameters (EN-31): For the hardened EN-31 alloy, the optimal Grey Relational Grade was achieved using a more conservative kinematic envelope: Spindle Speed: 450 rpm, Feed Rate: 0.1 mm/min, and Depth of Cut: 0.3 mm. The extreme hardness (58–62 HRC) requires minimizing the feed to prevent catastrophic tool wear and severe surface scoring.
3. Parametric Dominance (ANOVA): The statistical variance analysis confirmed a distinct divergence in machinability physics. For Mild Steel, spindle speed overwhelmingly dictated performance (F-value = 109.29), primarily due to its role in thermal softening. For EN-31, feed rate emerged as the dominant factor governing both SR and tool-workpiece friction.
4. Optimization Efficacy: The implementation of the GRA-derived parameters for Mild Steel resulted in a 125.5% increase in Material Removal Rate alongside a simultaneous 33.1% reduction in Surface Roughness, compared to median baseline parameters.
5. Predictive Robustness: Confirmation experiments demonstrated a prediction error margin of less than 2.0%, proving the high reliability and industrial applicability of the proposed Taguchi-GRA-ANOVA mathematical models.
6. Pedagogical Efficacy: The integration of this comparative CNC machining study into a Project-Based Learning (PBL) framework successfully bridged the gap between theoretical statistics and applied metallurgy. It proved highly effective in teaching undergraduate engineering students the complexities of multi-criteria decision-making, interdisciplinary data visualization, and empirical model validation.

2. *Industrial Implications and Future Scope*

The comparative framework developed in this study provides process engineers with empirical guidelines for transitioning between metallurgically distinct materials on the same machine tool footprint. Future research should expand this framework by incorporating real-time tool wear monitoring (via acoustic emission sensors) and evaluating the sustainability metrics (energy consumption and carbon footprint) of the optimized cutting regimes under Minimum Quantity Lubrication (MQL) environments.

APPENDIX

A. *Unified L9 Orthogonal Array Matrix*

To ensure the reproducibility of this interdisciplinary study, the unified Taguchi L9 (3^3) orthogonal array utilized for both materials is detailed below. The kinematic parameters were dynamically scaled based on the metallurgical constraints of the respective alloys (high-hardness EN-31 vs. high-ductility Mild Steel).

TABLE V
UNIFIED EXPERIMENTAL DESIGN MATRIX

Exp. Run	Coded Level	Factor A: Spindle Speed	Factor B: Feed Rate
1	1, 1, 1	Level 1	Level 1
2	1, 2, 2	Level 1	Level 2
3	1, 3, 3	Level 1	Level 3
4	2, 1, 2	Level 2	Level 1
5	2, 2, 3	Level 2	Level 2
6	2, 3, 1	Level 2	Level 3
7	3, 1, 3	Level 3	Level 1
8	3, 2, 1	Level 3	Level 2
9	3, 3, 2	Level 3	Level 3

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