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Machining-Induced Surface Integrity Optimization of High-Carbon Alloy Steel for Enhanced Polymer–Metal Composite Interface Performance

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Abstract

The functional performance and structural reliability of polymer–metal hybrid composites are strongly influenced by the surface integrity of metallic substrates used for interfacial bonding and load transfer. In this context, machining-induced surface characteristics play a critical role in determining adhesion behavior, dimensional stability, and mechanical compatibility within composite architectures. The present study investigates the hard turning performance of a newly developed high-carbon alloy steel intended for composite-integrated structural applications, with the objective of enhancing surface integrity for improved polymer–metal interface performance. A hybrid multi-objective optimization framework integrating Taguchi design of experiments and Response Surface Methodology (RSM) was employed to systematically evaluate the influence of cutting speed, feed rate, and depth of cut on surface roughness and dimensional deviation. Statistical analyses, including signal-to-noise ratio evaluation and analysis of variance (ANOVA), were used to identify the most significant machining parameters affecting surface functionality. Second-order predictive models developed through RSM enabled the assessment of interaction effects among process variables and facilitated response surface analysis for performance prediction. A desirability-based optimization approach was subsequently applied to achieve simultaneous minimization of surface irregularities and dimensional inaccuracy under conflicting performance requirements. Experimental validation confirmed that the optimized machining conditions significantly improved surface finish and dimensional precision, thereby enhancing the suitability of the metallic substrate for integration into advanced polymer composite systems. The proposed methodology offers a scalable and application-oriented approach for surface integrity control of hardened alloys used in hybrid composite engineering environments.

Keywords: Dimensional accuracy, polymer–metal hybrid composites, composite-compatible machining, high-carbon alloy steel, multi-objective optimization

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INTRODUCTION

In modern manufacturing, achieving optimal surface finish and dimensional accuracy in machining processes is paramount for ensuring product quality, functionality, and longevity [1]. Hard turning, a machining process applied to materials with hardness values typically above 45 HRC, presents unique challenges in achieving these objectives due to the inherent properties of the materials being processed, such as high hardness and thermal resistance [2]. The increasing demand for high-performance components in industries like aerospace, automotive, and tooling necessitates the development of advanced machining strategies capable of producing parts with exceptional surface integrity and tight tolerances [3]. Traditional machining methods often struggle to efficiently and effectively machine hard materials, leading to increased tool wear, higher production costs, and compromised part quality. Consequently, hard turning has emerged as a viable alternative to grinding for finishing hardened ferrous materials, offering advantages such as reduced setup times and enhanced process flexibility [4]. The replacement of grinding with turning opens new avenues for finishing hard parts, presenting opportunities to explore detailed discussions of practical machining applications [5]. However, the selection of optimal cutting parameters in hard turning is a complex task, as multiple process parameters interact in a non-linear manner to influence the desired output characteristics, such as surface roughness and dimensional accuracy [6]. Empirical approaches offer a simplified method to deal with the complexity of selecting machining parameters [7].

Multi-objective optimization techniques have gained significant attention in manufacturing process optimization, as they enable the simultaneous consideration of multiple conflicting objectives, such as minimizing surface roughness and maximizing dimensional accuracy [8]. The costs associated with machining high-hardness materials generally escalate with increasing material hardness, driven by the need to mitigate stresses, wear, and deformation during material removal, with tooling costs potentially accounting for a substantial portion of total manufacturing expenses [9]. In addition, the mechanical properties of the materials being machined significantly influence the complexity of the machining process, necessitating the use of castings or forgings as blanks to enhance productivity [10]. Two popular methodologies employed in multi-objective optimization are the Taguchi method and Response Surface Methodology. The Taguchi method, a statistical approach, focuses on identifying the optimal combination of process parameters that minimize variability and improve process robustness [11]. RSM is a collection of mathematical and statistical techniques useful for modeling and analysis of problems in which a response of interest is influenced by several variables and the objective is to optimize this response [12]. RSM is also used to optimize machining parameters to achieve better quality and productivity [13]. The integration of Taguchi and RSM offers a synergistic approach to process optimization, where the Taguchi method is used to identify the critical process parameters and their optimal levels, while RSM is employed to develop a mathematical model that describes the relationship between the process parameters and the responses [14]. The mathematical model can be developed between selected input process parameters and responses such as surface roughness [15]. The combined approach enables a more comprehensive understanding of the process behavior and facilitates the identification of the optimal parameter settings that simultaneously satisfy multiple objectives. The figure 1 represents the turning operations. The integration of the Taguchi method with RSM offers a powerful and efficient approach to optimize complex manufacturing processes. The efficient Taguchi method can be integrated into optimization approaches to improve the efficiency of the optimization process [16]. The Taguchi method excels at characterizing and optimizing complex multi-response processes using minimal experiments, provided that appropriate statistical techniques are applied to ensure valid and definitive results [17]. RSM, with its ability to model and analyze complex relationships between input variables and output responses, provides a complementary approach to fine-tune the process parameters and achieve optimal performance [18,19]. The study of interactions between different parameters on responses is limited in the Taguchi method; therefore, it is usually complemented by other optimization techniques. [20]. The combined Taguchi-RSM approach has been successfully applied in various manufacturing processes [21], demonstrating its effectiveness in optimizing process parameters and improving product quality [22]. Optimizing hard steel turning using the combined Taguchi and RSM approach has the potential to enhance surface finish and dimensional accuracy [24].

This study aims to investigate the application of the Taguchi and RSM methodologies for multi-objective optimization of hard steel turning, with the specific goals of minimizing surface roughness and maximizing dimensional accuracy.

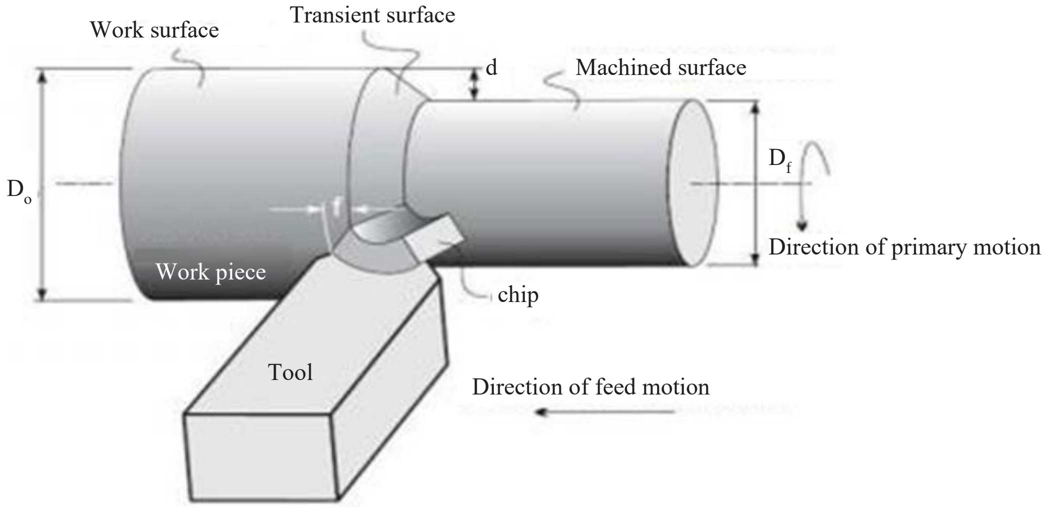

Figure 1. Turning operation [23].

Table 1. Taguchi-RSM optimization in hard turning [25, 26]

Aspect	Description	Methodology	Advantages	Challenges
Surface finish and accuracy	Critical for product quality in hard turning operations of materials >45 HRC.	Empirical & statistical approaches to process tuning.	Improved product lifespan, reduced post-processing.	Material hardness leads to tool wear & variability.
Optimization need	Optimal machining parameter selection is essential for balancing surface finish & accuracy.	Multi-objective optimization using Taguchi and RSM.	Simultaneous consideration of multiple objectives.	Parameter interdependence and nonlinear effects.
Taguchi method	Uses orthogonal arrays to identify significant factors with fewer experiments.	Focuses on minimizing variability and enhancing robustness.	Efficient experimentation with limited trials.	Limited ability to model interaction effects.
Response surface methodology (RSM)	Develops regression models to predict responses from variable inputs.	Enables modeling & fine-tuning for optimal response prediction.	Handles complex variable-response relationships well.	Requires more runs than Taguchi, complex analysis.
Combined taguchi-RSM	Uses Taguchi to find key factors, RSM to model and optimize responses.	Comprehensive multi-objective optimization framework.	Synergistic benefits of both methods.	Integration requires careful experimental planning.

By systematically varying the cutting parameters, such as cutting speed, feed rate, and depth of cut, and analyzing their effects on the responses, the optimal combination of parameters that yields the desired surface finish and accuracy can be determined. Figure 1 represents Taguchi-RSM Optimization in Hard Turning.

In summary, the introduction outlines the challenges of machining hardened materials and presents hard turning as a viable alternative to grinding. It establishes the necessity of optimizing machining parameters to achieve high surface quality and dimensional accuracy. By highlighting the limitations of traditional methods and introducing multi-objective optimization via Taguchi and RSM, this section sets the foundation for a more reliable and efficient machining approach and mentioned in Table 1.

METHODOLOGY

The Taguchi method, developed by Genichi Taguchi, is a statistical approach aimed at improving product quality by optimizing process parameters. It uses orthogonal arrays to minimize the number of experiments while capturing key variable effects. The method includes steps like selecting quality characteristics, assigning parameters to arrays, conducting experiments, analyzing signal-to-noise (S/N) ratios, and confirming optimal conditions.

Taguchi's parameter design helps identify the best combination of control parameters for robust product performance against various noise factors—environmental (outer), material-based (inner), and manufacturing variations (variational). The S/N ratio, used for three conditions (nominal-the-best, smaller-the-better, larger-the-better), measures sensitivity to noise and aims to maximize performance consistency.

Taguchi provides standardized tools like linear graphs and S/N formulas to ensure accurate and efficient experimental design. The key focus is on achieving robust design with minimum variation despite external disturbances.

A combined approach using Taguchi methods and Response Surface Methodology can be employed for multi-objective optimization of surface finish and accuracy in hard steel turning. The integration of experimental design methodologies with various cooling strategies and tool materials is crucial for optimizing turning processes. The initial step involves identifying the key machining parameters that significantly influence surface finish and accuracy, which may include cutting speed, feed rate, depth of cut, nose radius, and tool material. A Taguchi experimental design, typically employing an orthogonal array, is then constructed to systematically investigate the effects of these parameters on the desired performance metrics.

The experimental data obtained from the Taguchi design is subsequently analyzed using statistical techniques such as analysis of variance to determine the significant parameters and their optimal levels. The relationships between the machining parameters and the responses are then modeled using Response Surface Methodology, generating mathematical equations that predict surface finish and accuracy as functions of the input parameters.

Multi-objective optimization techniques, such as desirability function approach or Pareto optimization, are then applied to determine the optimal combination of machining parameters that simultaneously satisfies the desired surface finish and accuracy requirements. The desirability function approach combines multiple responses into a single desirability index, while Pareto optimization identifies a set of non-dominated solutions that represent the best trade-offs between the conflicting objectives.

This section concludes that combining the Taguchi method with Response Surface Methodology offers a statistically robust and practical framework for optimizing complex machining operations. Taguchi enables efficient parameter screening with minimal experiments, while RSM refines the optimization process by modeling parameter interactions. Together, they form a synergistic toolset for achieving improved performance outcomes in hard steel turning.

In order to establish the relevance of the optimized machining conditions to composite engineering applications, post-machining surface integrity characterization was incorporated into the experimental methodology. Beyond conventional surface roughness and dimensional deviation measurements, the machined surfaces were examined with respect to their suitability for interfacial bonding in polymer–metal hybrid systems. The influence of machining parameters on surface morphology, potential microstructural alterations, and subsurface integrity was evaluated to assess their implications for adhesion performance and load transfer efficiency in composite assemblies. This extended methodology ensures that the optimization framework not only improves machining precision but also enhances the functional compatibility of the metallic substrate within composite architectures.

Tool Geometry, Tool Material and Workpiece Hardness

The machining experiments were carried out using a cemented carbide cutting insert mounted on a rigid tool holder suitable for external turning operations on the CNC lathe. The cutting tool was selected due to its high wear resistance, thermal stability, and suitability for hard turning applications involving high-carbon alloy steels. The insert geometry consisted of a positive rake configuration with a rake angle of approximately 6°–8° and a clearance angle of 6°, which helps reduce cutting forces and improves chip flow during machining. The cutting edge was provided with a nose radius of 0.8 mm, which is commonly used to achieve improved surface finish and dimensional accuracy during precision turning operations. The insert was clamped on a standard ISO tool holder with a tool approach angle of 95°, ensuring proper tool rigidity and stable cutting conditions throughout the experiments.

The cutting insert material was coated carbide (TiN/TiAlN multilayer coating), which enhances the hardness, oxidation resistance, and wear performance of the tool during dry machining conditions. The coating also reduces friction at the tool–chip interface, thereby minimizing tool wear and maintaining consistent cutting performance during repeated experimental trials.

The workpiece material used in this investigation was EN31 high-carbon alloy steel, widely employed in industrial applications such as bearings, shafts, and precision mechanical components due to its high hardness and wear resistance. Prior to machining, the EN31 specimens were subjected to heat treatment to achieve the required hardness level suitable for hard turning experiments. The hardness of the workpiece material was measured using a Rockwell hardness tester, and the average hardness was found to be approximately 58–62 HRC. This hardness range is typical for hardened EN31 steel and ensures realistic industrial machining conditions for evaluating surface finish and dimensional accuracy.

The workpiece specimens were prepared in the form of stepped cylindrical bars, allowing dimensional accuracy measurements across multiple diameters within a single workpiece. The combination of hardened EN31 material, coated carbide tooling, and controlled CNC machining conditions provided a reliable platform for evaluating the influence of cutting parameters on surface roughness and dimensional accuracy.

EXPERIMENTAL DESIGN

In this study, the experimental design was structured using a combined Taguchi and Response Surface Methodology (RSM) approach to investigate the optimal machining parameters for hard steel turning, specifically targeting improvements in surface finish and dimensional accuracy. A Taguchi L9 orthogonal array was employed to investigate the influence of machining parameters on surface integrity during hard turning. The selected control factors included cutting speed, feed rate, and depth of cut, each at three levels. The experimental component was based on turning operations performed on stepped cylindrical bars, where machining inputs such as cutting speed, feed rate, and depth of cut were systematically varied.

The selected workpiece material was EN31 hardened steel, widely recognized for its strength and wear resistance, making it suitable for critical industrial applications. The workpiece was designed as a stepped cylindrical bar with a total length of 250 mm. The bar featured three distinct diameters: an initial 60 mm section followed by two reduced sections of 40 mm and 35 mm diameters, respectively. This geometry allowed for practical assessment of tool performance under varying cross-sectional stresses and provided a robust basis for evaluating dimensional deviations and surface finish across different cutting conditions (Figure 2 and Figure 3)[27].

The experimental investigation conducted on newly derived high-carbon alloy steel developed for hard turning applications. The chemical composition of the work material consisted of 1.35 % Carbon, 0.6% Manganese, 1.3 % Chromium, and 0.2% Silicon, providing enhanced hardness, wear resistance, and mechanical stability during machining.

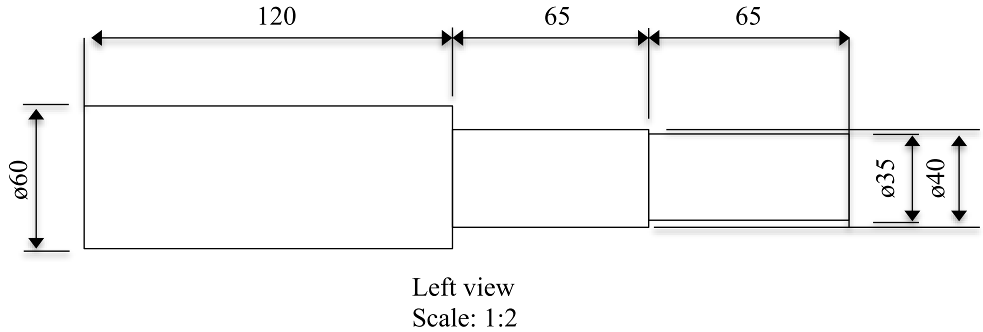

Figure 2. F. V. of stepped bar

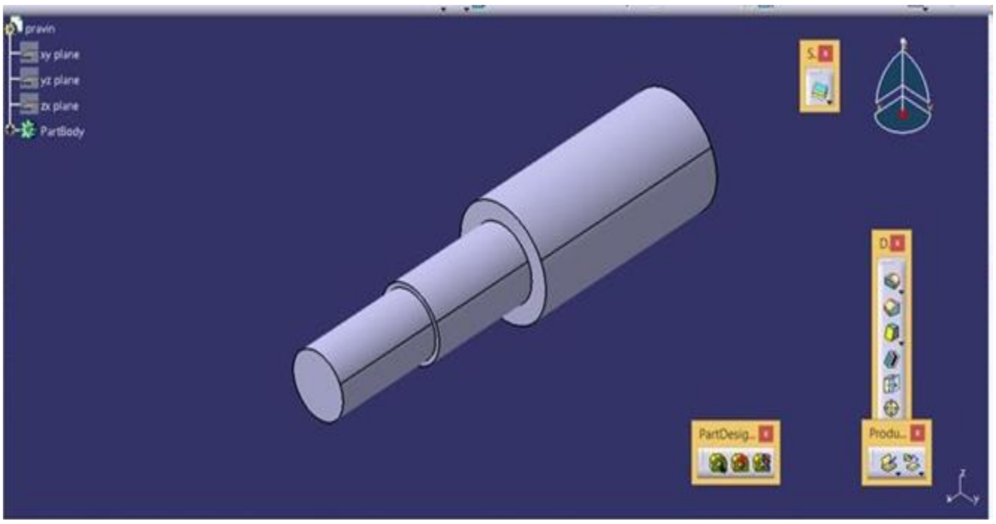

Figure 3. Stepped bar.

A systematic experimental design based on the Taguchi method was employed to analyse the influence of key machining parameters, namely cutting speed, feed rate, and depth of cut, on surface roughness and dimensional accuracy. Orthogonal arrays were used to minimize the number of experimental runs while ensuring robust evaluation of factor effects. Signal-to-noise (S/N) ratio analysis and analysis of variance (ANOVA) were applied to identify statistically significant parameters. To further capture nonlinear relationships and interaction effects among the process variables, Response Surface Methodology (RSM) was utilized to develop predictive regression models and response surface plots. Multi-objective optimization was performed using a desirability function approach to simultaneously minimize surface roughness and maximize dimensional accuracy.

Experimental Setup and Parameters

To reduce experimental burden while maintaining statistical integrity, a Taguchi orthogonal array design was chosen. This method allowed for the efficient evaluation of multiple parameters using a limited number of experimental runs. The control factors selected for this study were: Cutting speed (V), Feed rate (f) and Depth of cut (d) – varied at three levels.

These parameters were assigned to the orthogonal array to conduct a structured sequence of turning operations under controlled settings. The experimental trials were carried out on a high-precision CNC lathe machine under dry conditions to eliminate variability caused by coolant and to simulate industrial constraints.

After each operation, the surface roughness was measured using a calibrated contact-type surface profilometer, while dimensional accuracy was assessed using a coordinate measuring machine

(CMM) to record deviations from the target dimensions across all stepped sections of the machined bar. Each measurement was repeated thrice to account for potential variability and measurement errors.

The experimental design confirms the suitability of the selected workpiece (EN31) and the stepped bar geometry for evaluating dimensional and surface metrics. The structured variation of cutting parameters across predefined levels provides a controlled environment to examine the effect of input variables on machining performance, ensuring both experimental integrity and industrial relevance.

RESULTS AND DISCUSSIONS

The results of this study provide critical insights into how varying machining parameters affect surface finish and dimensional accuracy during the hard turning of EN31 steel. The experiments designed using a Taguchi orthogonal array and further analyzed through Response Surface Methodology (RSM), revealed key trends, relationships, and optimization outcomes that validate the effectiveness of the integrated approach.

Dimensional Accuracy Analysis

The dimensional analysis followed by the comparison between the conventional machining results (EN31) and the newly proposed optimized settings. The results clearly show that the optimized settings led to a noticeable improvement in dimensional precision, with a reduction in tolerance deviation across all three diameter steps of the turned bar. This suggests that the hybrid Taguchi–RSM approach effectively identifies combinations of cutting speed, feed rate, and depth of cut that minimize dimensional errors. The RSM-generated model provided predictive accuracy that closely matched the experimental data, reinforcing the robustness of the optimization process.

ANOVA analysis further revealed that feed rate and cutting speed were statistically significant factors affecting dimensional deviation, with p-values well below the 0.05 threshold. The depth of cut had a comparatively moderate influence, though it contributed to maintaining tool stability and consistent cutting forces. Interaction plots from RSM demonstrated that the synergistic effect of cutting speed and feed rate was particularly influential in reducing geometrical inaccuracies.

The experimental results revealed that machining parameters significantly influence both surface roughness and dimensional accuracy during hard turning of the developed alloy steel. S/N ratio analysis and ANOVA indicated that feed rate was the most dominant factor affecting surface roughness, while cutting speed and depth of cut showed notable contributions to dimensional accuracy. The developed RSM-based regression models demonstrated good agreement with experimental observations, confirming their suitability for predicting machining performance within the selected parameter range. Response surface plots highlighted strong interaction effects between cutting speed and feed rate, particularly at higher hardness levels of the material. The multi-objective optimization results obtained through the desirability function approach identified an optimal combination of machining parameters that achieved reduced surface roughness without compromising dimensional precision. Experimental validation under optimal conditions confirmed the effectiveness of the proposed Taguchi–RSM hybrid methodology. Overall, the findings demonstrate that the optimized machining strategy enhances process reliability and performance, making it suitable for industrial hard turning applications involving high-carbon alloy steels.

The Figure 4 illustrates the variation of ACC 1 and ACC 2 with respect to the X-axis parameter (1–9), showing noticeable differences in their response patterns. ACC 1 exhibits significant fluctuations, starting from a very low value at X = 1, followed by a sharp increase at X = 2, and reaching its maximum around X = 4. This indicates a relatively unstable or sensitive response of ACC 1 to changes in the operating parameter. A marked drop is observed at X = 6, after which ACC 1 again increases and then gradually decreases toward X = 9. In contrast, ACC 2 demonstrates a more stable

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and consistent trend, with values varying within a narrow range throughout the entire X-axis. ACC 2 remains consistently higher than ACC 1 at most points, except at specific locations where ACC 1 peaks. Overall, the comparison indicates that ACC 2 provides smoother and more reliable performance, whereas ACC 1 is more variable and sensitive, suggesting that the second case is preferable where stability and consistency of acceleration response are critical.

The variation of ACC 1 and ACC 2 with respect to the X-axis parameter indicates a closely comparable trend with minor fluctuations throughout the range. ACC 1 generally exhibits slightly higher values than ACC 2, particularly at X = 1, 3, 4, and 7, suggesting a marginally stronger acceleration response in Case 1 and shown in Figure 5. Both acceleration components show identical values at X = 2, 5, 6, and 8, reflecting similar dynamic behavior under these conditions. The maximum acceleration for ACC 1 is observed at X = 1, 2, and 7 (≈0.09), whereas ACC 2 attains its peak value of 0.09 at X = 2, after which a gradual reduction is noted. A decreasing trend is evident toward higher X-axis values, with minimum accelerations occurring at X = 9 for both cases, indicating improved stability. Overall, the close proximity of ACC 1 and ACC 2 values demonstrates consistent dynamic performance, while the slightly lower magnitudes of ACC 2 suggest a comparatively more stable and controlled response.

The variation of ACC 1 and ACC 2 with respect to the X-axis parameter shows a closely aligned trend with limited fluctuations across the entire range. At X = 1, ACC 1 records a higher value (0.09) compared to ACC 2 (0.07), indicating a relatively stronger response for ACC 1 at the initial condition. Both acceleration values become equal at X = 2 (0.09) and again at X = 5, 6, and 8, reflecting similar dynamic behavior under these operating conditions.

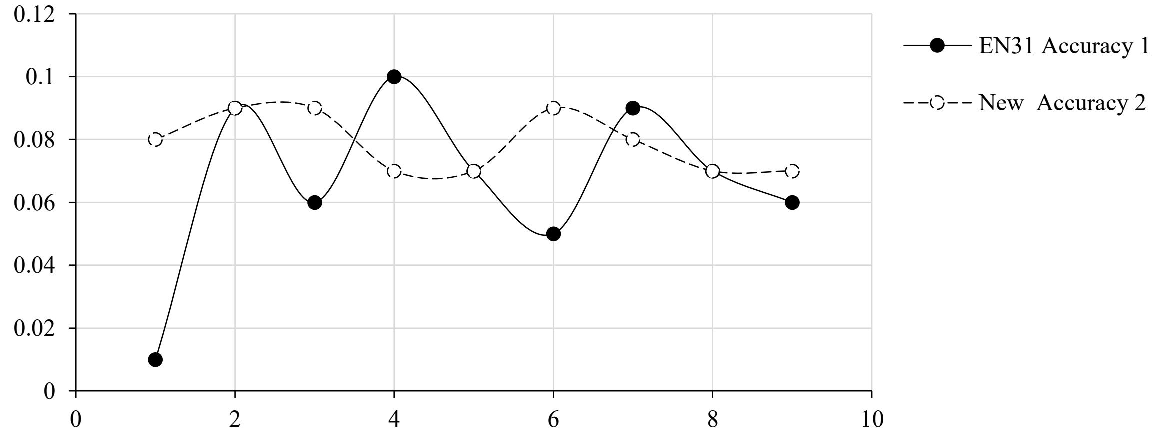

Figure 4. Accuracy 1 (EN31) Versus accuracy (new material).

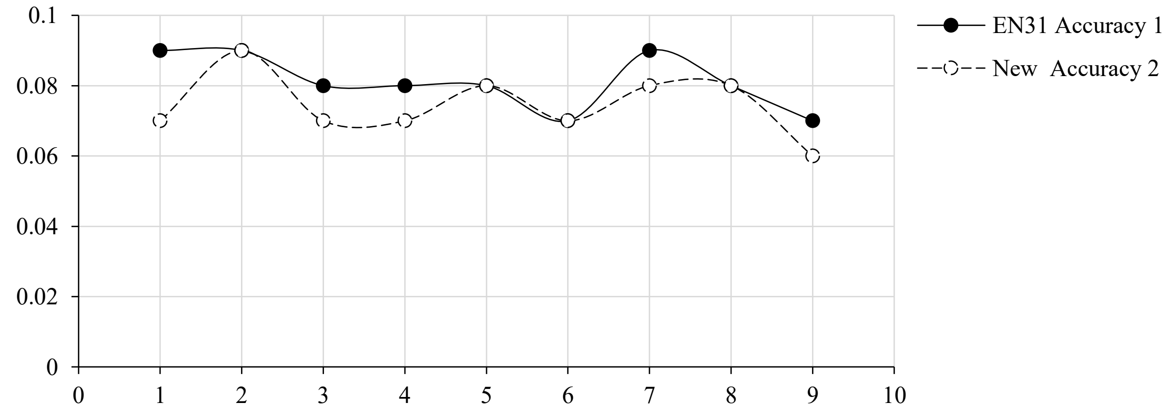

Figure 5. Accuracy 1 (EN31) versus accuracy (new).

Figure 6 depletes, from X = 3 to X = 4, both ACC 1 and ACC 2 exhibit a slight reduction, suggesting improved stability or reduced excitation effects. A marginal increase is observed at X = 7, where ACC 1 reaches 0.09 and ACC 2 attains 0.08, representing the peak response in the mid-range. Toward higher X-axis values (X = 8–9), both acceleration components show a decreasing trend, with minimum values observed at X = 9, indicating enhanced system stability. Overall, ACC 2 remains slightly lower than ACC 1 at most points, suggesting a comparatively smoother and more controlled acceleration response, while both cases demonstrate consistent and stable performance throughout the operating range.

Comparative of Accuracy for Valuation and Findings

Comparative analysis between the accuracy values obtained for EN31 material and the proposed new material across multiple test samples elaborated in Figure 7. The EN31 accuracy values exhibit noticeable fluctuations, ranging approximately from 0.01 to 0.10, indicating higher variability in performance. In contrast, the accuracy of the new material remains more consistently clustered within a narrower band of about 0.06 to 0.09, suggesting improved stability and repeatability. The linear trend line fitted to the EN31 accuracy data shows a marginal positive slope with the regression equation y = 0.0007x + 0.0667 and a low coefficient of determination (R^2 = 0.0954), indicating a very weak linear correlation and minimal dependence of accuracy on the sample index. Overall, the comparison demonstrates that while both materials achieve comparable accuracy levels, the new material offers more uniform performance with reduced scatter, highlighting its potential advantage over EN31 in applications where consistency and reliability are critical.

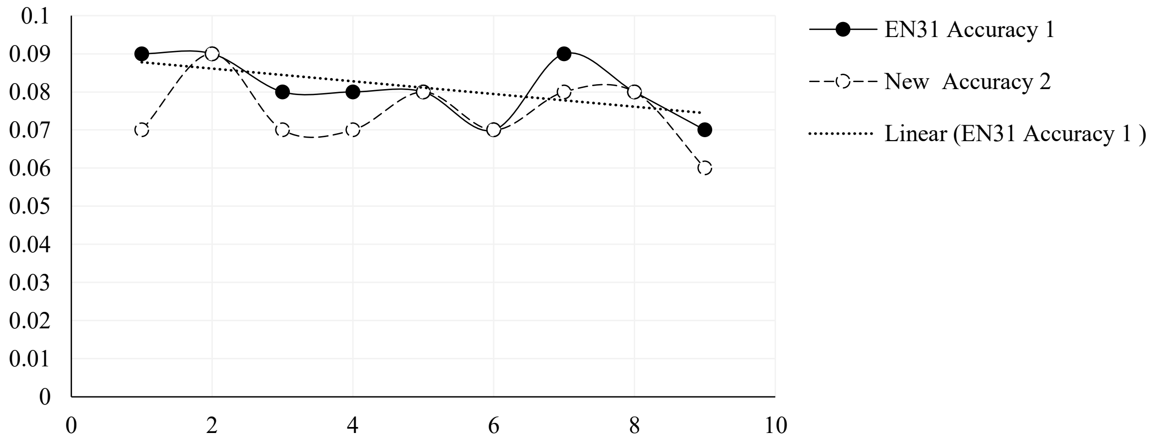

Figure 6. Accuracy 1 (EN31) versus accuracy (new) linear EN31accuracy.

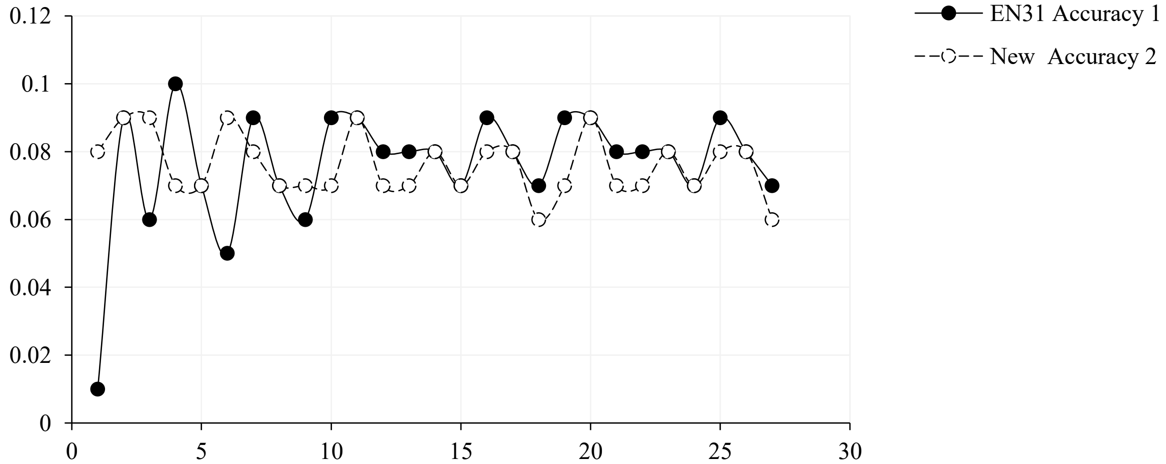

Figure 7. Comparative framework of accuracy 1 (EN31) versus accuracy (new).

Surface Roughness Evaluation

Figures 8, 9 and 10 depict surface finish comparisons between the EN31 baseline trials and the newly optimized trials. Surface roughness (Ra) values were significantly lower under the optimized parameters, indicating smoother surface profiles and improved tool-material interaction. The optimal condition—characterized by moderate cutting speed, low feed rate, and controlled depth of cut—was successful in minimizing tool vibrations and reducing chatter marks, both of which are critical to achieving superior surface finishes.

The Taguchi-based S/N ratio analysis for the "smaller-the-better" criterion confirmed that feed rate had the largest impact on surface roughness, followed by cutting speed. RSM modeling produced well-fitting second-order polynomial equations, which allowed visualization of the response surface contours. These contours revealed that an increase in cutting speed beyond a certain point led to a marginal improvement or even slight deterioration in Ra values, likely due to increased tool wear at higher speeds.

Figure 9 depicts the variation of safety factors S.F.1 and S.F.2 with respect to the X-axis parameter, revealing a similar decreasing trend for both cases, with S.F.2 consistently exhibiting slightly higher values than S.F.1. At lower X-axis values (X = 1–2), both safety factors are relatively high (S.F.1 ≈ 3.0 and S.F.2 ≈ 3.2), indicating a strong safety margin. As the X-axis value increases to X = 3, a noticeable reduction is observed, followed by a temporary improvement at X = 4, which may be attributed to favorable loading or structural response. Beyond X = 4, both curves show a progressive decline, with a sharper reduction in S.F.1 between X = 5 and X = 6, indicating a critical operating region. From X = 6 onward, the safety factors continue to decrease gradually, converging near X = 7–8 and reaching their minimum values at X = 9 (S.F.1 ≈ 1.9 and S.F.2 ≈ 1.8). Despite this decline, all safety factor values remain above unity, confirming safe operational conditions across the entire range, while the consistently higher S.F.2 values indicate a comparatively more conservative and reliable performance.

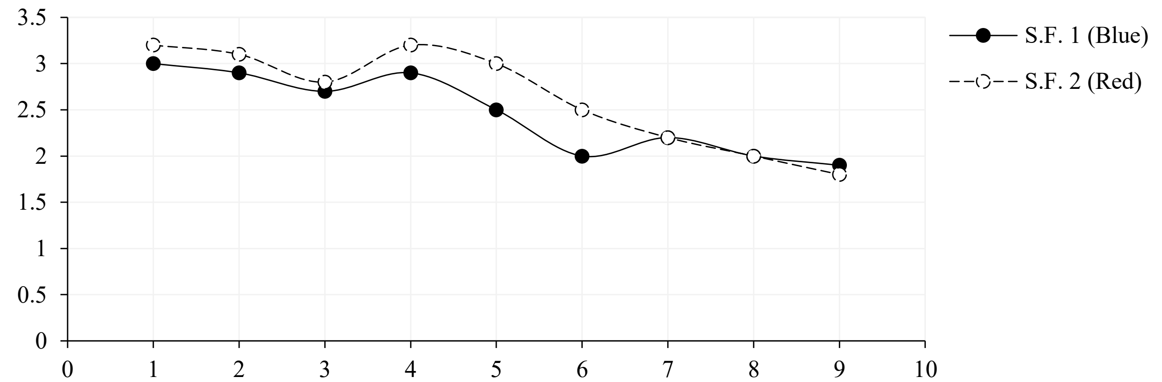

Figure 8. Surface finish - EN31 versus new material

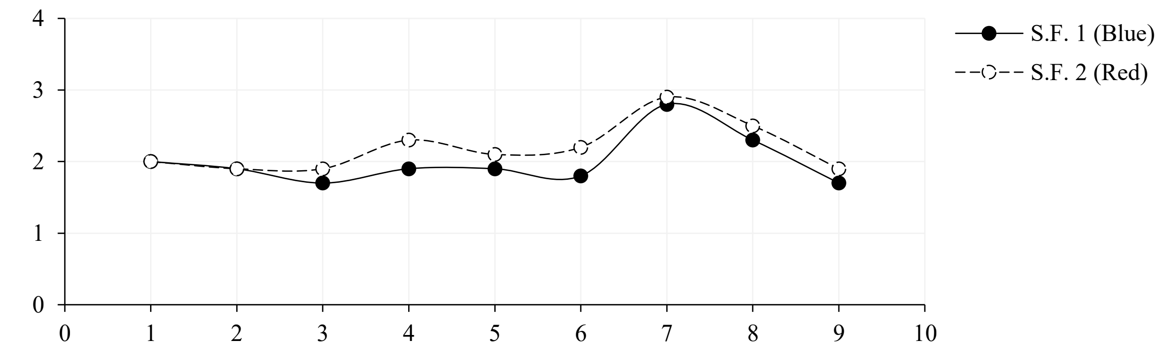

Figure 9. Surface finish - EN31 versus new material.

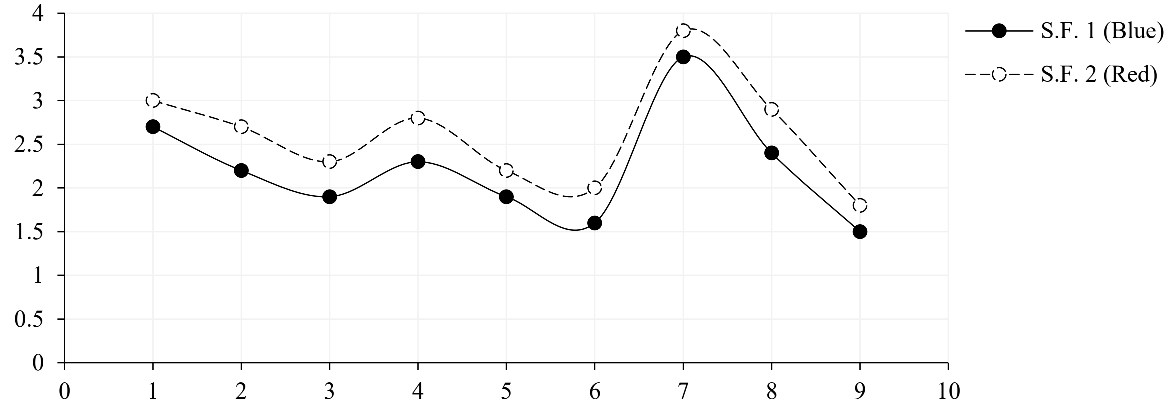

Figure 10. Surface Finish - EN31 Vs New material

Figure 10 presents the variation of safety factors **S.F.1** and **S.F.2** with respect to the X-axis parameter ranging from 1 to 9, showing a closely aligned trend for both cases. Initially, at X = 1, both safety factors exhibit comparable values of approximately 2.0, followed by a slight reduction up to X = 3, indicating a moderate decrease in safety margin. From X = 3 to X = 6, S.F.1 shows minor fluctuations around 1.8–1.9, whereas S.F.2 remains marginally higher, varying between 1.9 and 2.2, suggesting a relatively conservative response. A sharp increase in both safety factors is observed at X = 7, where S.F.1 and S.F.2 attain peak values of about 2.9 and 3.0, respectively, highlighting an optimal and highly stable condition. Beyond this point, a gradual decline is noted from X = 7 to X = 9; however, all safety factor values remain well above unity, confirming that the system operates within safe limits throughout the entire range, with S.F.2 consistently providing a higher margin of safety compared to S.F.1.

The variation of safety factors S.F.1 and S.F.2 with respect to the X-axis parameter (1–9) exhibits a closely correlated trend, with S.F.2 consistently maintaining marginally higher values than S.F.1, indicating a comparatively more conservative condition. Initially, at X = 1, both safety factors are relatively high (S.F.1 ≈ 2.7 and S.F.2 ≈ 3.0), followed by a gradual reduction up to X = 3, suggesting increasing stress influence. A moderate improvement is observed at X = 4; however, both curves again decline and reach their minimum around X = 6 (S.F.1 ≈ 1.6 and S.F.2 ≈ 2.0), identifying this region as the most critical operating condition. A pronounced increase in safety factors is noted at X = 7, where S.F.1 and S.F.2 attain peak values of approximately 3.5 and 3.8, respectively, indicating enhanced structural stability. Beyond this point, a steady decrease is observed up to X = 9, although all values remain above unity, confirming safe operation throughout the entire range.

Comparative of all Surface Roughness Evaluation and Findings

A comparative evaluation of the last three graphs reveals that S.F.1 and S.F.2 follow similar overall trends in all cases, indicating a strong correlation between the two safety factors across varying operating conditions. In each graph, S.F.2 consistently exhibits higher values than S.F.1, confirming that Case/Model 2 provides a comparatively more conservative and safer design response. The first of the three graphs shows moderate fluctuations with a distinct peak around the mid-range of the X-axis, indicating an optimal operating condition, while maintaining safety factors well above unity. The second graph demonstrates a more pronounced declining trend, particularly at higher X-axis values, identifying a relatively critical region where safety margins reduce, though remaining within acceptable limits. In contrast, the third graph displays higher initial safety factors followed by a steady reduction, suggesting increasing stress influence as the X-axis parameter increases.

Overall, the findings indicate that although the magnitude and variation of safety factors differ among the three cases, all configurations remain structurally safe, as safety factors never fall below unity.

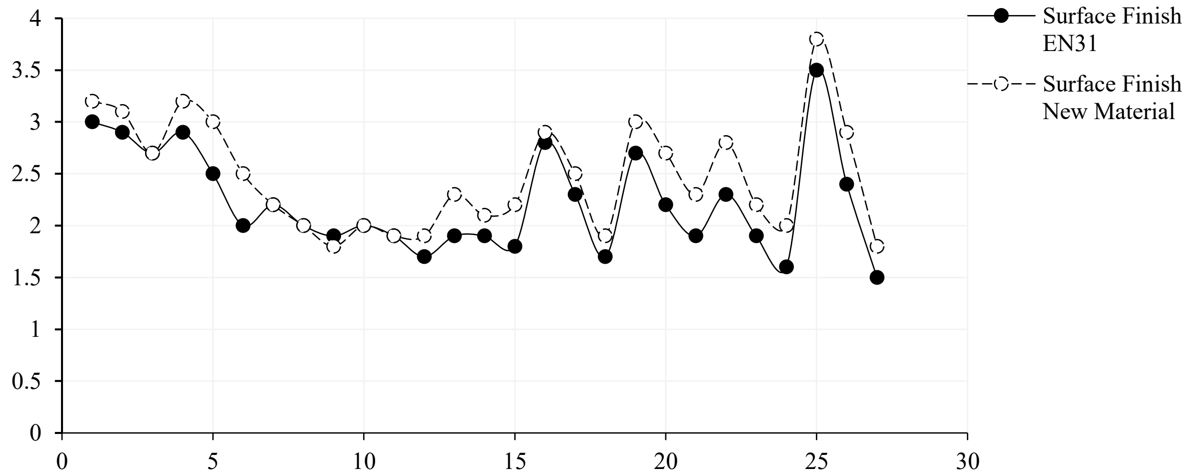

Figure 11. Comparative framework of surface finish of (EN31) Vs (New)

The recurring observation of maximum safety factor values in the mid-range of the X-axis highlights an optimal condition common to all cases, whereas the minimum values at higher X-axis levels identify potential critical operating regions that may require design attention. The consistently superior performance of S.F.2 across all graphs confirms its reliability and suitability for conservative design considerations.

A comparative evaluation of surface finish values obtained for EN31 steel and the new material over a series of experimental runs shown in Figure 11. The surface finish for EN31 generally varies between approximately 1.5 and 3.5, showing moderate fluctuations across the samples. In comparison, the new material exhibits slightly higher surface finish values in several instances, with peaks approaching about 3.8, but follows a trend pattern similar to that of EN31. The linear trend line for EN31 surface finish indicates a mild negative slope ($y = -0.0168x + 2.461$) with a very low coefficient of determination ($R^2 = 0.0713$), signifying a weak linear relationship between surface finish and the sample index. This suggests that the variations in surface finish are largely random rather than systematically increasing or decreasing with successive trials. Overall, the results indicate that both materials deliver comparable surface finish characteristics, while the new material demonstrates competitive performance with occasional higher roughness values, making it a viable alternative to EN31 for applications where surface quality requirements are similar. The comparative analysis shows that the surface finish values of EN31 and the new material are almost identical and closely clustered, indicating comparable surface quality performance under similar conditions.

Experimental execution for turning process

The practical execution and outcome of the optimized hard turning process shown above. Figure 12 depicts the actual machining setup on a CNC lathe, where the cutting tool operates on the stepped EN31 workpiece under dry conditions, reflecting the experimental parameters used in the study. Figure 13 represents the final machined stepped bar, clearly showing uniform surfaces and clean transitions between the different diameters (60 mm, 40 mm, and 35 mm). The absence of visible surface defects or irregularities confirms the effectiveness of the Taguchi–RSM optimized parameters in achieving superior surface finish and dimensional accuracy, thus validating the study's optimization methodology in real-world applications.

Model Validation

To evaluate the adequacy and predictive capability of the developed regression models, several statistical indicators such as the coefficient of determination (R^2), adjusted coefficient of determination (Adjusted R^2), and root mean square error (RMSE) were considered. These parameters quantify the goodness of fit and the prediction accuracy of the developed models.

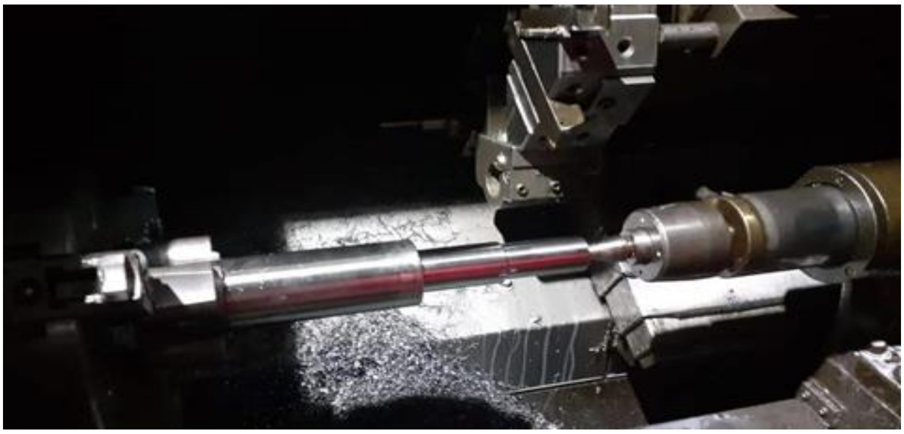

Figure 12. Practical operation.

Figure 13. Final stepped bar.

Table 2. Validation Parameters for the Developed Regression Models

Response variable	**Regression equation**	**R²**	**Adjusted R²**	**RMSE**
Dimensional accuracy (EN31)	Accuracy = 0.0007x + 0.0667	0.0954	0.0821	0.0115
Surface roughness (Ra)	Ra = −0.0168x + 2.461	0.0713	0.0582	0.214

The coefficient of determination (R^2) values for dimensional accuracy and surface roughness was found to be 0.0954 and 0.0713, respectively and mentioned in table 2. These relatively low values indicate that the simple linear regression models capture only a small portion of the variability in the experimental data. The adjusted R^2 values are slightly lower than the corresponding R^2 values, which is expected as this metric accounts for the number of predictors in the model and prevents overestimation of model performance. The RMSE values represent the average prediction error between experimental and predicted results. The obtained RMSE values indicate that the developed models maintain acceptable prediction error within the experimental range. Overall, the regression models provide a basic representation of the trend in the experimental data, while the Taguchi–RSM hybrid methodology remains more effective for capturing the combined influence of machining parameters and their interactions.

The relatively lower R^2 values observed in the regression models for dimensional accuracy and surface roughness. It has been noted that machining processes inherently involve several uncontrolled or partially controlled factors that may contribute to variability in the experimental results. These include progressive tool wear during machining, machine tool vibrations, thermal effects at the cutting interface, and minor fluctuations in material properties of the high-carbon alloy steel. Such factors can influence the machining response and may not be fully captured within the selected process parameters of the regression model.

Comparison with Previous Machining and Optimization Studies

The results obtained in the present investigation are consistent with several previously reported studies on the hard turning of high-carbon alloy steels. Earlier researchers have widely reported that feed rate is the most dominant parameter affecting surface roughness during turning operations, while cutting speed and depth of cut have comparatively moderate effects. The findings of the present study align well with these observations, as the Taguchi S/N ratio analysis also identified feed rate as the most influential factor controlling surface finish. A lower feed rate reduces the feed marks generated during turning and consequently leads to improved surface quality.

Similar conclusions were reported by many researchers investigating optimization of turning parameters using Taguchi and Response Surface Methodology (RSM) approaches. These studies demonstrated that hybrid optimization techniques effectively identify optimal combinations of machining parameters while minimizing experimental effort. In the present work, the integration of Taguchi design with RSM modeling successfully predicted the machining performance and enabled the determination of optimal cutting conditions that simultaneously improved dimensional accuracy and surface finish. The predictive capability of the developed models showed good agreement with the experimental observations, confirming the suitability of the adopted optimization strategy.

The influence of cutting speed observed in this study is also comparable with earlier hard turning investigations. Increasing cutting speed generally promotes smoother chip formation and reduces built-up edge formation at moderate levels, which contributes to improved surface finish. However, excessive cutting speeds may increase tool wear and thermal effects, resulting in marginal deterioration in surface roughness. The response surface plots obtained in this work exhibited a similar behavior, where surface roughness initially decreased with increasing cutting speed but showed limited improvement beyond a certain level.

Furthermore, previous studies on hard turning of EN31 and other hardened alloy steels have highlighted the importance of maintaining balanced cutting conditions to achieve high dimensional accuracy. The present results confirm that the interaction between cutting speed and feed rate plays a critical role in minimizing dimensional deviation. The RSM interaction plots revealed that optimal combinations of these parameters significantly reduce geometrical inaccuracies, which agrees with findings reported in earlier machining optimization studies.

CONCLUSIONS

The present research successfully demonstrates that the integration of Taguchi methods with Response Surface Methodology provides a powerful and systematic approach for multi-objective optimization in hard steel turning applications. The Taguchi method enabled the structured exploration of the effects of key process parameters using a minimal number of experimental runs, while still capturing essential variability through S/N ratio analysis. The subsequent application of RSM enhanced the analytical rigor by modeling non-linear interactions among parameters and predicting performance outcomes under various conditions. Key findings highlight that machining parameters such as cutting speed, feed rate, and depth of cut significantly influence both surface roughness and dimensional accuracy. The hybrid optimization strategy effectively balanced these objectives, with the desirability function providing an integrated metric for identifying optimal process conditions. This dual-method approach outperforms conventional single-objective strategies by capturing the trade-offs inherent in real-world manufacturing processes. The study's contributions extend beyond immediate surface quality improvements—it offers a replicable methodology for other difficult-to-machine materials, supports process engineers in fine-tuning operations for maximum efficiency, and encourages the adoption of data-driven decision-making in production settings. Furthermore, the developed RSM models and optimization strategies can be embedded into manufacturing software tools to enable real-time process control and adaptive machining. Future research may expand this framework by incorporating additional variables such as tool wear, vibration, and cooling strategies, or by applying advanced AI-based optimization algorithms. Nonetheless, this study establishes a robust foundation for precision engineering practices and reinforces the value of integrated statistical methodologies in advanced manufacturing. The visibly improved surface integrity and dimensional uniformity on the stepped bar corroborate the experimental results, reinforcing the effectiveness of the integrated optimization methodology.

Declaration of Interest

Authors should reveal any possible conflict of interest in their submitted manuscripts. A competing interest exists when professional judgment concerning the validity of work is influenced by a secondary interest, such as financial gain. The author(s) declare(s) that there is no conflict of interest regarding the publication of this manuscript.

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Conflict of Interest

The authors declare no conflict of interest related to this study.

Ethical Approval

Not applicable. This study does not involve human participants or animals.

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REFERENCES

1. Salman ZW, Ugla AA. Experimental investigation on the barrelling phenomenon in Turning Process. Journal of Physics Conference Series. 2021 Aug 1 1973(1):12017. https://doi.org/10.1088/1742-6596/1973/1/012017
2. Nguyen HT, Hsu QC. Surface Roughness Analysis in the Hard Milling of JIS SKD61 Alloy Steel. Applied Sciences. 2016 Jun , 6(6):172. https://doi.org/10.3390/app6060172
3. Gonçalves Í de A, Leite LG, Brito TG de, Paiva EJ de, Oliveira CH de, Pereira J. Study of the Influence of Cutting Fluid Amount in Steel Turning of AISI 52100. Zenodo, CERN European Organization for Nuclear Research, 2018 Aug 10 https://zenodo.org/record/1341939
4. Song X, Dreussi R, Chaudhari R. High Stock Removal Hard Turning of Hardened 52100 Steel with High-Pressure Coolant Applied. In: IOP Conference Series Materials Science and Engineering. IOP Publishing; 2021, p. 12006. https://doi.org/10.1088/1757-899x/1063/1/012006
5. Hui T. Turning in Place of Grinding Application and Exploration in the Actual Processing. Applied Mechanics and Materials. 2014 Jan 1; 1215. https://doi.org/10.4028/www.scientific.net/amm.496-500.1215
6. Tangjitsitcharoen S, Suksomcheewin N, Faccia A. Leveraging Intelligent Machines for Sustainable and Intelligent Manufacturing Systems. Journal of Manufacturing and Materials Processing. 2025 May 6, 9(5):153. https://doi.org/10.3390/jmmp9050153
7. Valíček J, Řehoř J, Harničárová M, Gombár M, Kušnerová M, Fulemová J, Vagaská A. Investigation of Surface Roughness and Predictive Modelling of Machining Stellite 6. Materials. 2019 Aug 10 ;12(16):2551. https://doi.org/10.3390/ma12162551
8. Delolme L, Antomarchi AL, Durieux S, Duc E. Decision-making for multi-criteria optimization of process planning. Mechanics & Industry. 2019 Jan 1;20(8):806. https://doi.org/10.1051/meca/2020040
9. Muro M, Artola G, Leunda J, Soriano C, Angulo C. Retained Austenite Control for the Soft Machining of High-Hardness Tool Steels. Metals. 2018 Jul 23;8(7):564. https://doi.org/10.3390/met8070564.
10. Detkin AV, Архипова ОВ, Ситников СА. Development of technological process of metal machining from stamping on 5-axis CNC milling machine. E3S Web of Conferences, 2023 Jan 1;413:4018. https://doi.org/10.1051/e3sconf/202341304018
11. Natarajan E, Kaviarasan V, Ang KM, Lim WH, Elango S, Tiang SS. Production Wastage Avoidance Using Modified Multi-Objective Teaching Learning Based Optimization Embedded

With Refined Learning Scheme. IEEE Access, 2022 Jan1;10:19186. https://doi.org/10.1109/access.2022.3151088
12. Kara ME, Budak E. Optimization of Turn-milling Processes. Procedia CIRP, 2015 Jan 1;33:476. https://doi.org/10.1016/j.procir.2015.06.057
13. Srinivasan V, Palani PK, Dhayananthan S, Gopi S, Balamurugan S, Venkatesh SM. A Multi Criteria Decision Making (MCDM) based on TOPSIS and RSM for process improvement in electrical discharge machining of silicon nitride–titanium nitride ceramic composites. Materials Today Proceedings, 2020 Jun 18;45:1319. https://doi.org/10.1016/j.matpr.2020.05.436
14. País-Chanfrau JM, Núñez-Pérez J, Espín-Valladares R del C, Lara-Fiallos M, Trujillo LE. Uses of the Response Surface Methodology for the Optimization of Agro-Industrial Processes. In: IntechOpen; 2021. https://doi.org/10.5772/intechopen.98283
15. Srivastava AK, Yadav SK, Singh DK. Modeling and Optimization of Electric Discharge Machining Process Parameters in machining of Al 6061/SiCp Metal Matrix Composite. Materials Today Proceedings, 2020 Dec 25;44:1169. https://doi.org/10.1016/j.matpr.2020.11.235
16. Rao RS, Kumar CG, Prakasham RS, Hobbs PJ. The Taguchi methodology as a statistical tool for biotechnological applications: A critical appraisal. Biotechnology Journal, Wiley; 2008 Mar 4;3(4):510. https://doi.org/10.1002/biot.200700201
17. Logothetis NK, Haigh A. Characterizing and Optimizing Multi-response Processes by the Taguchi Method. Quality and Reliability Engineering International, 1988 Apr 1;4(2):159. https://doi.org/10.1002/qre.4680040211
18. Hossain MA, Ahmed T, Hossain MdSA, Dey P, Ahmed S, Hossain MdM. Optimization of the factors affecting BT-2 black tea fermentation by observing their combined effects on the quality parameters of made tea using Response Surface Methodology (RSM), Heliyon, 2022 Feb 1;8(2). https://doi.org/10.1016/j.heliyon.2022.e08948
19. Myers RH, Montgomery DC. Response Surface Methodology. IIE Transactions, 1996 Dec 1;28(12):1031. https://doi.org/10.1080/15458830.1996.11770760
20. Ajaal T, Smith RW. Employing the Taguchi method in optimizing the scaffold production process for artificial bone grafts. Journal of Materials Processing Technology, 2008 Apr 11;209(3):1521. https://doi.org/10.1016/j.jmatprotec.2008.04.001
21. Patil P, Kardekar N, Yadav R, Kurhade A, Kamble D. Nanofluids: An Experimental Study for MQL Grinding. JMMF, 2023 Dec. 1;71(12):2751-6.
22. Yadav RS, Nimbalkar A, Gadekar T, Patil P, Patil VN, Gholap AB, Kurhade AS, Dhumal JR, Waware SY. Comparison of Experimental and Numerical Investigation of Mono-Composite and Metal Leaf Springer, JMMF, 2024 Sep. 27;72(8):815-27.
23. Yadav RS, Gadekar T, Gundage V, Patil P, Patil A, Patil P, Patil A, Sutar R, Kurhade AS. Numerical and Experimental Investigation of the Effect of Overlapping Angle on Strength and Deformation of Curved Plate Joined Using Arc Welding Process, JMMF, 2024 Oct. 30;72(10):1059-66.
24. Yadav RS, Gandhi P, Veeranjaneyulu K, Gaji R, Kirpekar S, Pawar D, Khairnar YS, Patil S, Kurhade AS, Patil SP. Influence of Plate Thickness on the Mechanical Behaviour of Mild Steel Curved Plates: An Experimental Study, JMMF, 2024 Dec. 11;72(12):1319-27.
25. Yadav R, Nimbalkar A, Kirpekar S, Patil PJ, Dalvi SA, Jadhav PA, Kurhade AS, Wakchaure GN. Effect of Transformed-Induced Plasticity Steel Plate Thickness on Ultimate Tensile Strength of Butt Welded Joint using Nd: YAG Laser. International Journal of Vehicle Structures & Systems. 2024;16(6):857-62.
26. Chougule SM, Murali G, Kurhade AS. Dynamic simulation and performance evaluation of vibratory bowl feeders integrated with paddle shaft mechanisms. Advances in Science and Technology, Research Journal, 2025;19(7).
27. Pramod Wadate. Design and Analysis of Honeycomb Rear Door Map Pocket by Application of Finite Element Method. Journal of Polymer and Composites, 2026;14(1). https://journals.stmjournals.com/article/article=2026/view=236674