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Multi-objective Optimization of Machining Parameters for Railway Wheel Re-profiling using LNUX 301940 Tool by using a Taguchi and ANOVA-based Empirical Study

M. Reddeiah , S .Vani, T . Ebesu , K. Vijaya Lakshmi
Academic consultant department of mechanical Engineering, S.V. University.

Abstract - This research investigates the optimization of machining parameters-cutting speed, feed rate, and depth of cut—to enhance the Material Removal Rate and Tool Life of the LNUX 301940 cutting tool. Experimental trials were structured using a Taguchi L8 orthogonal array, and the resulting data were analysed through Signal-to-Noise (S/N) ratios and Analysis of Variance. The S/N ratio analysis identified depth of cut as the most influential parameter for both MRR and Tool Life. The ANOVA results further quantified these influences, demonstrating that the depth of cut is the primary contributor to process variance, accounting for 83.13% of the impact on MRR and 60.80% on Tool Life. Secondary factors included cutting speed and feed rate, which contributed 9.92% and 6.18% to MRR, and 18.09% and 15.20% to Tool Life, respectively. Based on these findings, linear regression equations were developed for both responses to provide a mathematical model for predicting performance within the investigated design space. The study concludes that for the LNUX 301940 tool, prioritizing the depth of cut is the most effective strategy for maximizing material removal efficiency while maintaining tool longevity in turning operations.

Keywords: LNUX 301940 Tool, Taguchi Method, ANOVA, Material Removal Rate, Tool Life, Regression Equation, Machining Optimization.

1. INTRODUCTION

In the modern competitive manufacturing landscape, achieving a balance between high productivity and cost-effective production is a global challenge. The efficiency of a turning operation is typically measured by two vital yet conflicting parameters: the Material Removal Rate, which defines productivity, and Tool Life, which directly influences the overall production cost and downtime [1-2]. Recent literature suggests that multi-objective optimization using integrated statistical techniques is essential for handling these conflicting responses simultaneously [3]. Optimization of these parameters is particularly critical when using specialized tooling such as the LNUX 301940 insert, which is designed for high-performance machining requiring significant structural stability and material removal [4].

The selection of cutting parameters—cutting speed, feed rate, and depth of cut—plays a decisive role in determining the thermal and mechanical stresses at the tool-chip interface [5]. While high cutting speeds may increase the MRR, they often accelerate tool wear due to elevated temperatures, thereby drastically reducing tool life [6]. Research into the efficiency of experimental designs has shown that Taguchi-based approaches provide a more practical and robust framework for turning processes compared to complex dynamic programming methods [7]. Furthermore, the depth of cut is frequently identified as a dominant factor in determining the volumetric removal of material, though its impact varies significantly depending on the tool geometry and workpiece material [8].

To navigate these complex interdependencies, statistical tools such as the Taguchi Method and Analysis of Variance have become industry standards for process optimization. The Taguchi approach, utilizing signal-to-noise (S/N) ratios, allows for the identification of optimal parameter levels that are robust against environmental noise, while ANOVA quantifies the percentage contribution of each factor to the desired response [9-10]. Scientific studies have confirmed that ANOVA is critical for verifying the statistical significance of variables, ensuring that observed improvements in MRR or TL are not due to random chance. In many high-speed turning applications, the depth of cut can account for over 50% of the variance in performance characteristics [11].

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Despite the established literature on standard carbide inserts, there is limited data specifically addressing the optimization of the LNUX 301940 tool geometry using an L8 orthogonal array for simultaneous MRR and TL maximization. This study aims to fill that gap by analysing the influence of cutting speed 40–45 m/min, feed rate 1.2–1.4 mm/rev, and depth of cut 1–2 mm. Through the application of S/N ratio analysis and general linear models, this study provides empirical regression equations and identifies that the depth of cut is the primary driver of performance, contributing 83.13% to MRR and 60.80% to Tool Life. The findings presented here offer a mathematical framework for industrial applications to maximize productivity while ensuring the longevity of high-efficiency cutting tools.

2. MATERIALS AND METHODOLOGY

2.1 Workpiece Material: Railway Wheel

The experimental study was conducted on a heavy-duty railway wheel as shown in Fig. 1. These wheels are typically manufactured from high-strength forged steel, designed to withstand extreme mechanical loads and thermal stresses during service. The material is characterized by high hardness and toughness, making the re-profiling process a challenging machining task that requires robust tooling and optimized cutting parameters.

2.2 Cutting Tool: LNUX 301940

The turning operation, a high-performance LNUX 301940 index able insert was employed. This specific tool geometry is engineered for heavy-duty roughing and re-profiling operations. Its robust design allows for significant depths of cut and high feed rates, which are essential for removing the flat spots and thermal cracks typically found on worn railway wheels. The tool holder was secured on the tool post of the wheel lathe to ensure maximum rigidity during the cutting process.

2.3 Experimental Setup: Wheel Lathe

The machining trials were performed on a specialized Wheel Lathe as shown in Fig.1. This machine is specifically designed for the simultaneous re-profiling of a pair of wheels mounted on a common axle. The lathe provides the high torque and stability required to maintain precision while removing large volumes of material from the hardened wheel treads

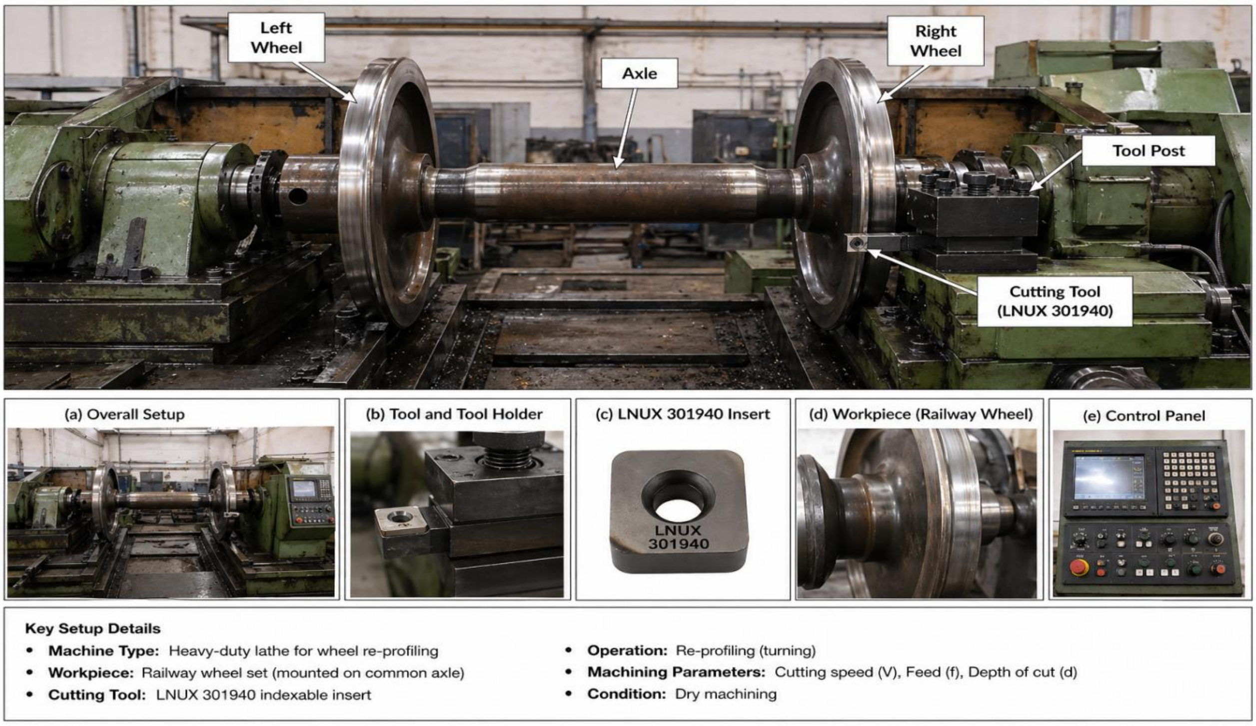

Fig.1 Experimental set up for wheel lathe

3. EXPERIMENTAL DESIGN

A Taguchi L8 orthogonal array was selected to evaluate the influence of three primary machining parameters at two levels each. This design allows for a comprehensive analysis of the process with a limited number of experimental runs.

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Table 1: Machining Parameters and their Levels

Factor	Level 1	Level 2
Cutting Speed (m/min)	40	45
Feed Rate (mm/rev)	1.2	1.4
Depth of Cut (mm)	1	2

Table.2 Experimental Results Cutting tool – LNUX 301940

S.NO	Speed(m/min)	Feed (mm/rev)	Depth of cut (mm)	MRR(mm)	Tool life (min)
1	40	1.2	1	0.1	111
2	40	1.2	2	0.24	104
3	40	1.4	1	0.08	108
4	40	1.4	2	0.2	99
5	45	1.2	1	0.06	110
6	45	1.2	2	0.2	96
7	45	1.4	1	0.01	103
8	45	1.4	2	0.16	89

3.1 Measurement of Responses

The performance of the machining process was evaluated based on two primary responses:

- .Material Removal Rate: The MRR was calculated as the volume of material removed per unit of time (mm^3/min). It is mathematically expressed based on the cutting speed, feed rate, and depth of cut to quantify productivity.
- Tool Life: Tool life was determined by the actual cutting time (minutes) until the tool reached a predetermined wear criterion or failed to maintain the required surface profile. Maximizing tool life is critical for reducing the high costs associated with specialized railway tooling.

3.2 Statistical Analysis

The experimental data were analysed using Signal-to-Noise (S/N) ratios and Means with the Larger is Better characteristic to determine the optimal settings for both MRR and Tool Life. Furthermore, Analysis of Variance was implemented to determine the percentage contribution and statistical significance of each cutting parameter at a 95% confidence level.

4. RESULTS AND DISCUSSION

4.1 Taguchi Analysis for Material Removal Rate

The Material Removal Rate is a critical indicator of productivity in the re-profiling of railway wheels. The experimental results were analysed using the Signal-to-Noise (S/N) ratio with the "Larger is Better" characteristic to identify the parameters that maximize material removal. As shown in Table 3, the Depth of Cut is the most influential factor affecting MRR, with the highest Delta value of 12.53, followed by Cutting Speed and Feed Rate. This ranking confirms that for the LNUX 301940 tool, increasing the depth of cut provides the most significant gain in productivity

Table 3: S/N Response Table for MRR

Level	Speed	Feed	Depth of Cut
1	-17.08	-17.70	-26.59
2	-23.58	-22.96	-14.07
Delta	6.51	5.26	12.53
Rank	2	3	1

International Journal of Engineering Research & Technology (IJERT)
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Vol. 15 Issue 04 , April - 2026

Table 4: Mean Response Table for MRR

Level	Speed	Feed	Depth of Cut
1	0.15500	0.15000	0.06250
2	0.10750	0.11250	0.20000
Delta	0.04750	0.03750	0.13750
Rank	2	3	1

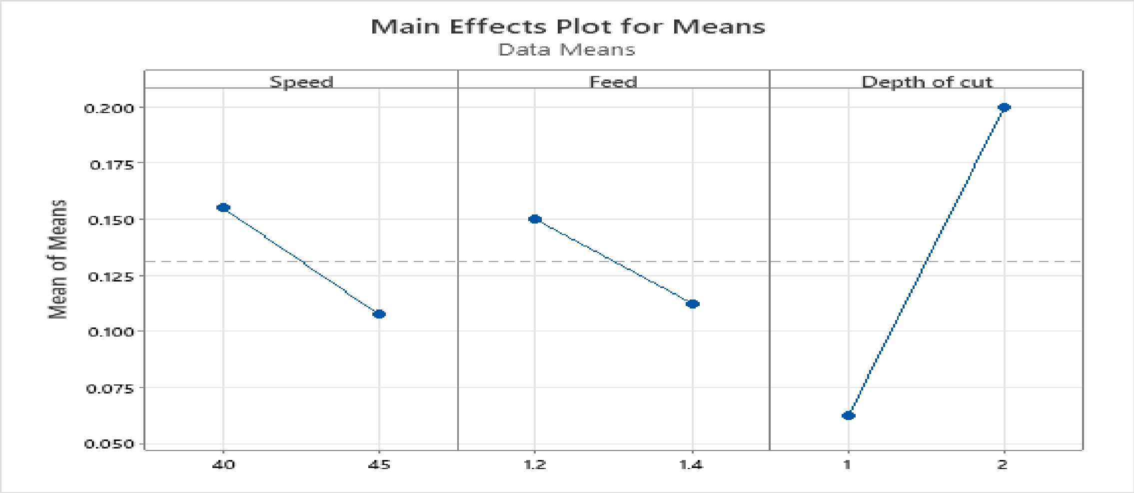

Fig.2 Graph of Means for MRR

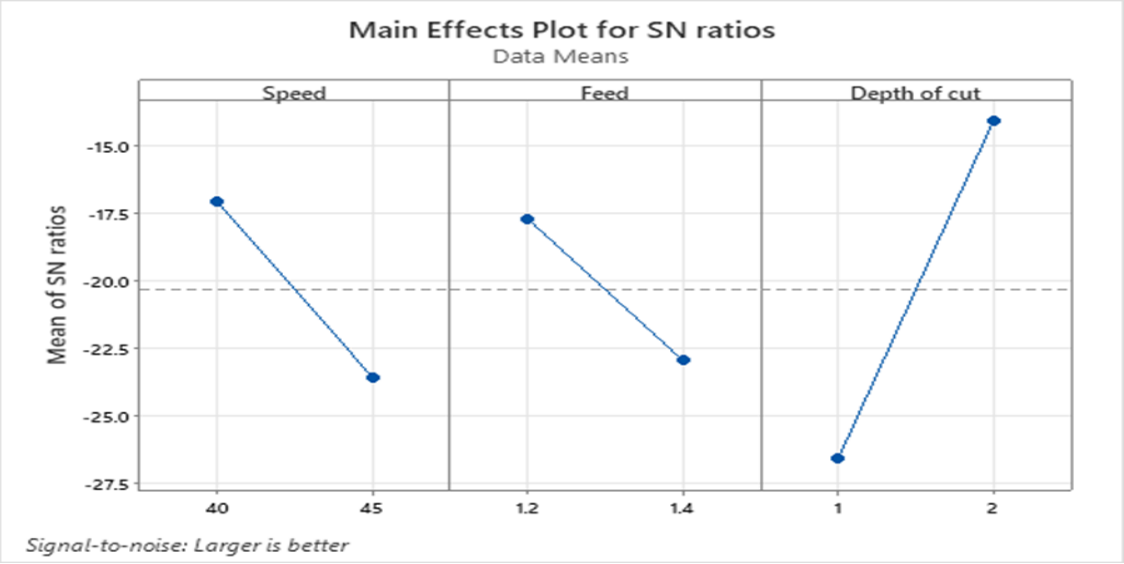

Fig.3 Graph of S/N Ratio for MRR

4.3 Analysis of Variance for MRR

To quantify the statistical significance and percentage contribution of each factor, ANOVA was performed at a 95% confidence level.

Table.5: ANOVA Results for MRR

Source	DF	Seq SS	Contribution (%)	Adj SS	Adj MS	F-Value	P-Value
Cutting Speed	1	0.004513	9.92%	0.004513	0.004513	51.57	0.002
Feed Rate	1	0.002813	6.18%	0.002812	0.002812	32.14	0.005
Depth of Cut	1	0.037813	83.13%	0.037813	0.037813	432.14	0.000
Error	4	0.000350	0.77%	0.000350	0.000088		
Total	7	0.045488	100.00%				

International Journal of Engineering Research & Technology (IJERT)
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The ANOVA results reveal that the Depth of Cut accounts for 83.13% of the total variance in MRR. The P-value of 0.000 indicates that the depth of cut is highly significant as shown in table 5. This dominance is attributed to the heavy-duty design of the LNUX tool, which is optimized to handle large chip loads during wheel re-conditioning.

4.4 Taguchi Analysis for Tool Life

The longevity of the LNUX 301940 tool is essential for cost management in railway workshops. The S/N ratio analysis for Tool Life was conducted using the "Larger is Better" criterion as shown in table 6.

Table 6: S/N Response Table for Tool Life

Level	Speed	Feed	Depth of Cut
1	40.46	40.43	40.66
2	39.93	39.96	39.72
Delta	0.53	0.47	0.94
Rank	2	3	1

Table 7: Mean Response Table for Tool Life

Level	**Speed**	**Feed**	**Depth of Cut**
1	105.50	105.25	108.00
2	99.50	99.75	97.00
Delta	6.00	5.50	11.00
Rank	2	3	1

For Tool Life, the Depth of Cut again holds Rank 1 (Delta 0.94). The S/N ratio analysis suggests that the optimal levels for maximizing tool life are Level 1 for Speed (40 m/min), Level 1 for Feed (1.2 mm/rev), and Level 1 for Depth of Cut (1 mm). This indicates that while higher parameters increase MRR, they simultaneously accelerate tool wear due to increased thermal and mechanical loading at the cutting edge.

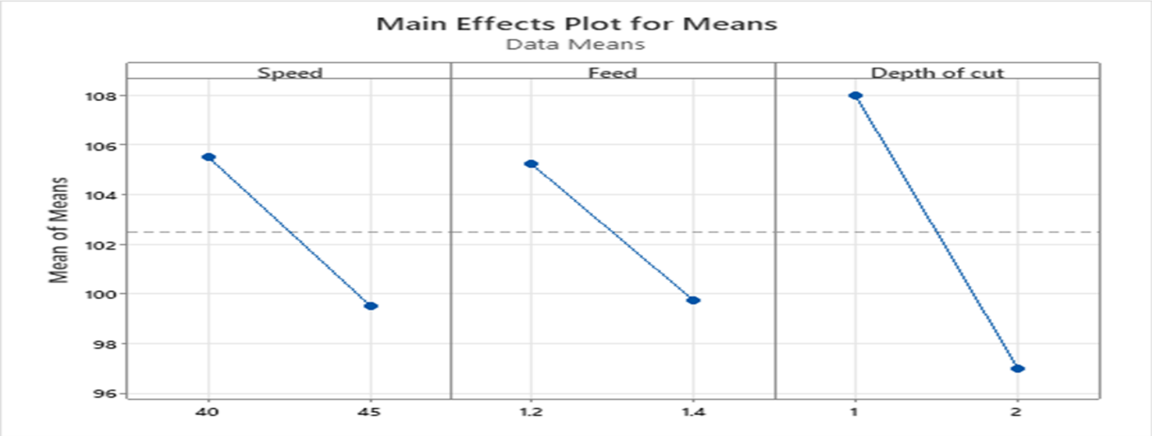

Fig.4 Graph of Means for Tool Life

International Journal of Engineering Research & Technology (IJERT)
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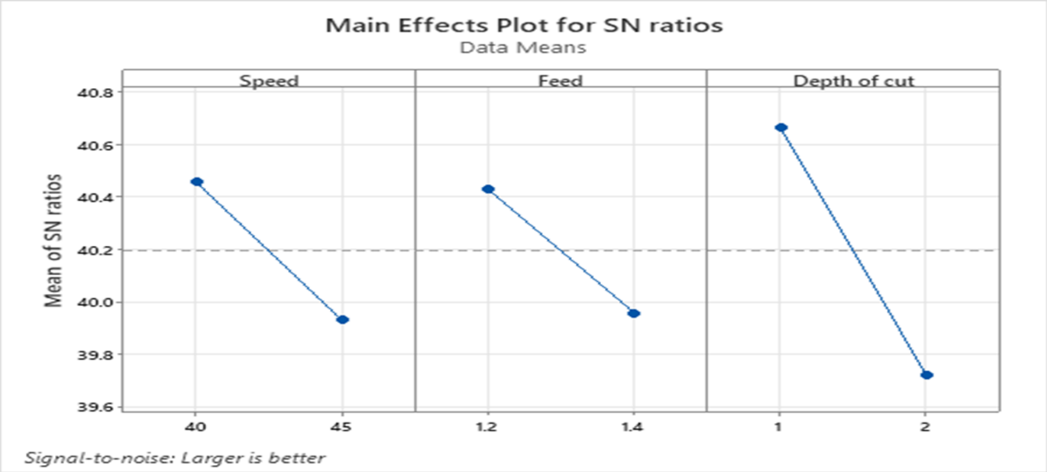

Fig.5 Graph of S/N Ratio for Tool Life

4.4 Analysis of Variance for Tool Life

Table.8: ANOVA Results for MRR

Source	**DF**	**Seq SS**	**Contribution (%)**	Adj SS	**Adj MS**	**F-Value**	**P-Value**
Cutting Speed	1	1	72.00	18.09%	72.00	72.000	12.26
Feed Rate	1	1	60.50	15.20%	60.50	60.500	10.30
Depth of Cut	1	1	242.00	60.80%	242.00	242.000	41.19
Error	4	4	23.50	5.90%	23.50	5.875	
Total	7	7	398.00	100.00%			

The depth of cut remains the most significant factor, contributing 60.80% to the variance in tool life. Interestingly, the combined contribution of speed and feed (33.29%) is more significant for tool life than it was for MRR, suggesting that the abrasive wear on the LNUX tool is highly sensitive to the sliding velocity and chip thickness.

4.5 Mathematical Modelling

Based on the experimental data, the following linear regression equations were developed to predict performance:

MRR = 0.13125+0.02375 speed 40 - 0.02375 speed 45+0.01875 feed 1.2 -0.01875 feed 1.4 – 0.06875 depth of cut 1 +0.06875 depth of cut 2.

- **The Intercept (0.13125):** This represents the global mean value of the MRR across all experimental runs in the L8 array. It serves as the baseline from which the influence of individual parameter levels is measured.
- **Coefficient Magnitude:** The coefficients indicate the sensitivity of the MRR to changes in each factor. The coefficient for Depth of Cut (0.06875) is significantly higher than those for Speed (0.02375) and Feed (0.01875). This mathematically confirms the ANOVA results, demonstrating that the Depth of Cut has the most profound impact on productivity.
- **Level Influence:** The positive sign for (+0.06875) indicates that increasing the depth of cut is (2 mm) significantly enhances the volume of material removed. Conversely, the negative sign for (-0.06875) reflects a reduction in MRR at a lower depth of cut.

Tool Life = 102.500 +3.000 speed 40 – 3.000 speed 45 +2.750 feed 1.2 -2.750 feed 1.4 +5.500depth of cut 1 -5.5000depth of cut.

- **The Intercept (102.500)**: This value represents the average tool life (in minutes) observed during the trials.
- **Significance of Coefficients**: Similar to the MRR model, the Depth of Cut dominates the equation with a coefficient of 5.500, which is nearly double the impact of Cutting Speed (3.000). This suggests that Tool Life is highly sensitive to the mechanical load and heat generated by a larger depth of cut.

International Journal of Engineering Research & Technology (IJERT)
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- **Directional Impact**: The positive coefficients for Speed (40) Feed (1.2), and indicate that the tool survives longest when the machining intensity is at its lowest levels. The negative coefficient for (-5.500) quantifies the "penalty" to tool life when the depth of cut is increased, reflecting the accelerated wear on the LNUX insert due to increased contact area and thermal stress at the cutting edge.

5. CONCLUSIONS

This study successfully investigated and optimized the machining parameters for the re-profiling of railway wheels using the LNUX 301940 cutting tool on a specialized wheel lathe. Based on the Taguchi analysis, ANOVA, and regression modelling, the following conclusions are drawn:

1. The Taguchi S/N ratio analysis identified Depth of Cut as the most influential parameter for both Material Removal Rate (Delta 12.53) and Tool Life (Delta 0.94). This confirms that for heavy-duty re-profiling operations, level is the primary driver of process performance.

2. To maximize the Material Removal Rate, higher levels of depth of cut are required. Conversely, the optimal settings for maximizing Tool Life were found at the lower levels of the tested range: Cutting Speed of 40 m/min, Feed Rate of 1.2 mm/rev, and Depth of Cut of 1 mm.

3. ANOVA results quantified the impact of each parameter, revealing that the Depth of Cut contributes an overwhelming 83.13% to the variance in MRR and 60.80% to Tool Life. The low P-values for all factors confirm their high statistical significance in the turning process.

4. The developed linear regression equations provide a robust mathematical framework for predicting machining outputs. The model possesses a strong signal-to-noise ratio and can be reliably used to navigate the design space for industrial wheel reconditioning.

5. Industrial Application: The findings suggest that railway workshops can significantly enhance productivity by prioritizing the depth of cut when using the LNUX 301940 tool, provided that the speed and feed are maintained at optimal levels to prevent premature tool failure.

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