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Taguchi-Based Optimization of Cutting Parameters for Surface Roughness in Dry Milling of Non-Ferrous Aluminum Alloy 6061

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Abstract: This study presents the optimization of surface roughness (Ra) in the dry milling of non-ferrous aluminum alloy 6061 (Al-6061) for sustainable manufacturing applications. Experiments were performed on a HYTECH CNC vertical machining center using TiN-coated carbide inserts. The Taguchi L27 orthogonal array was employed to systematically vary cutting velocity, feed per revolution, and depth of cut. Surface roughness was measured for each experimental run, and the results were analyzed using the Taguchi signal-to-noise (S/N) ratio approach and analysis of variance (ANOVA). Scanning electron microscopy (SEM) was utilized to examine the microstructural features associated with surface quality. The optimal combination of parameters—cutting velocity of 600 m/min, feed per revolution of 0.20 mm/rev, and depth of cut of 0.50 mm—produced the minimum average surface roughness of 0.253 µm. ANOVA revealed that feed per revolution exerted the greatest influence on Ra (48.82%), followed by cutting velocity (38.13%) and depth of cut (11.27%). Artificial neural network (ANN) modeling confirmed the reliability of the experimental results, enabling accurate prediction of surface quality. The findings demonstrate that dry machining of Al-6061 with optimized parameters can achieve a superior surface finish without coolant, enhancing both environmental sustainability and machining efficiency for non-ferrous metals.

Keywords: Surface Roughness (Ra); Dry Machining; Non-Ferrous Metals; Taguchi Method; Sustainable Manufacturing; Cutting Velocity; Orthogonal Array; Dry Milling.

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1. Introduction

Aluminum Alloy 6061 (Al-6061) is among the most widely used materials across diverse manufacturing sectors, including aerospace, automotive, electronics, and general engineering. As an aluminum-magnesium-silicon alloy, Al-6061 offers a unique

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combination of low density, medium-to-high mechanical strength, robust corrosion resistance, and high weldability. These attributes have established it as a first-choice material where weight savings must coexist with structural integrity—criteria fundamental to the aerospace and transportation industries, where performance must never come at the expense of reliability or efficiency [1]. Despite these advantages, achieving a high-quality surface finish on Al-6061 remains a formidable task for manufacturers. While the alloy is generally considered machinable, certain tempers, such as 6061-O, are particularly soft and ductile, producing “gummy” chips during cutting operations. This can result in challenges such as chip adhesion or galling, in which chips adhere to the cutting tool, leading to irregular, rough machined surfaces. Such adhesive phenomena compromise not only surface roughness but also the dimensional accuracy of the final product. Even in harder, heat-treated variants like 6061-T6, operators must carefully select their machining parameters and tool materials while managing thermal loads during cutting to avoid problems like workpiece deformation, undesirable marks, and accelerated tool wear [2]. When machining Al-6061—especially under dry conditions—the alloy's inherent properties offer distinct benefits and pose unique technical hurdles.

On one hand, dry machining aligns with sustainability goals by eliminating the need for cooling fluids. On the other hand, this absence of coolant exacerbates several machining issues [25]. Without liquid to lubricate and carry away heat, the cutting zone can quickly become overheated, potentially leading to thermal expansion, workpiece warping, or reduced dimensional control—especially given aluminum’s high thermal conductivity and relatively low melting point. Soft aluminum chips are prone to adhering to the cutting tool’s surface, worsening galling and leaving behind deformed or rough surfaces. Furthermore, high temperatures and inadequate lubrication intensify tool wear rates. Vibrational instability is another concern that, if unmitigated by optimal parameter choices, can degrade the tool and yield poor surface finishes. Given that demanding applications, such as those in aerospace, require strict limits on surface roughness, these challenges necessitate highly controlled, optimized machining processes [3]; [4]. Surface finish—commonly measured by the average roughness parameter Ra—plays a critical role far beyond mere aesthetics. In mechanical systems, a smooth surface reduces fatigue resistance by minimizing nucleation sites for cracks and retarding their propagation [23]. Low-roughness components also experience less friction and wear, resulting in superior efficiency and longer operational life. Fine finishes limit the formation and retention of corrosive media in micro-crevices, bolstering corrosion resistance and ensuring tight-fitting assemblies for mating components. In modern manufacturing, surface finish has acquired an additional layer of significance: sustainability. Achieving high-quality surfaces directly from dry or semi-dry processes can minimize or eliminate the need for subsequent finishing operations, reducing material waste, energy consumption, and chemical use [26]. From the perspective of green manufacturing, achieving excellent surface roughness without relying on wet-cooling lubricants is therefore a significant technological and environmental achievement [5]; [6].

The last few decades have seen significant research aimed at optimizing machining parameters for aluminum alloys to minimize surface roughness and enhance productivity. The Taguchi method, an efficient statistical approach that employs orthogonal arrays for experimental design, has been widely adopted to streamline the optimization of process parameters while reducing experimental overhead [27]. Numerous studies have substantiated its efficacy for identifying the relative influence of cutting speed, feed rate, and depth of cut on surface finish quality. Often coupled with Analysis of Variance (ANOVA), the approach yields robust statistical validation of which parameters most significantly affect outputs such as roughness, guiding both researchers and practitioners toward informed process control [7]. Increasingly, interest has also turned to the environmental dimension, with studies advocating dry machining as a route to more sustainable manufacturing. However, these works frequently highlight new challenges inherent to dry cutting, such as greater tool wear and a higher risk of inferior finishes compared to traditional wet machining. Regarding Al-6061, research consistently shows that feed rate (or feed per revolution) is the dominant factor influencing surface roughness during both turning and milling operations. Developments in tool coating, such as the use of titanium nitride (TiN) on carbide substrates, along with parametric optimization, have offered further gains in surface quality and sustainability [8]; [9]. In recent years, some researchers have explored multi-objective optimization approaches that look beyond roughness, factoring in criteria like tool wear, energy use, and production cost. Yet, much of this work has been based on modeling or black-box optimization, with limited validation through comprehensive physical experiments—especially those that mimic true industrial conditions and fully eliminate coolant [10]. Despite these advancements, key challenges persist.

Many investigations focus on wet or minimum quantity lubrication (MQL) rather than pure dry machining, leaving a gap in holistic strategies for achieving high-quality finished surfaces without lubrication [28]. While the Taguchi method and ANOVA remain standard tools, fewer studies have rigorously applied and validated them under strictly dry conditions on Al-6061, particularly through a systematic investigation of parameter interactions arising in the unique environment of coolant-free cutting. Furthermore, there remains a paucity of research that robustly links optimal process parameters to the actual achieved surface roughness and sustainability metrics that matter in real-world manufacturing environments. Raising the bar for experimental studies on dry machining directly supports industry’s push toward resource-efficient, environmentally friendly production. This study, therefore, responds to critical technological and ecological needs in the manufacturing sector. By demonstrating that high-quality surface finishes on Al-6061 are achievable under truly dry machining conditions, this work provides evidence that it is possible to dispense with flood coolants while maintaining, or even enhancing, surface quality—a conclusion with significant implications for cleaner, greener manufacturing. The research not only applies but also validates the Taguchi method and ANOVA as practical, reliable guides that engineers and operators can deploy to optimize their processes with fewer trials and greater confidence. Through an expansive, systematic experimental program, the study furnishes real-world data and a nuanced discussion of how cutting velocity, feed rate, and depth of cut interact in the dry milling of Al-6061, answering precise questions posed by modern, eco-conscious factories [11]; [12]. In integrating rigorous optimization with experimental validation under fully dry conditions, this research bridges a notable gap in the existing literature. Above all, the findings reinforce the critical relationship between machining parameters, surface quality, and sustainability goals.

By quantifying these relationships, the study provides both scientific insight and practical guidance for manufacturers seeking to reconcile the often competing demands of productivity, product quality, and environmental stewardship [13]. The novelty of this work lies in its comprehensive, experimentally validated approach to optimizing surface roughness in the dry milling of Al-6061, using both the Taguchi method and ANOVA as analytical frameworks. Unlike earlier studies that restricted themselves to wet or mist-lubricated conditions or focused solely on theoretical models, this investigation removes all coolants to meet and exceed sustainable manufacturing standards. The adoption of a multi-factor, L27 Taguchi orthogonal array enables the extraction of detailed insights into the interplay between process variables, well beyond single-factor or less systematic investigations. Statistical validation via ANOVA provides clarity on the real-world importance of each machining parameter and its collective effects. The research further contextualizes its findings by quantifying potential benefits for resource management, environmental impact, and production efficiency, thereby filling an important methodological and practical gap in the domain of green manufacturing [14]; [15]. The paper's structure guides the reader logically through the research: first, the materials and methods section details the alloy's characteristics, the experimental setup, the selected parameter levels, and the surface roughness measurement techniques. This is followed by a comprehensive presentation and discussion of results, including statistical analyses and their implications for sustainable manufacturing. The paper concludes by synthesizing the broader significance of the findings and outlining their immediate relevance for both further academic inquiry and industrial deployment.

2. Methodology

The Taguchi technique has established itself as a popular experimental design methodology due to its outstanding results in productivity improvement (Figure 1).

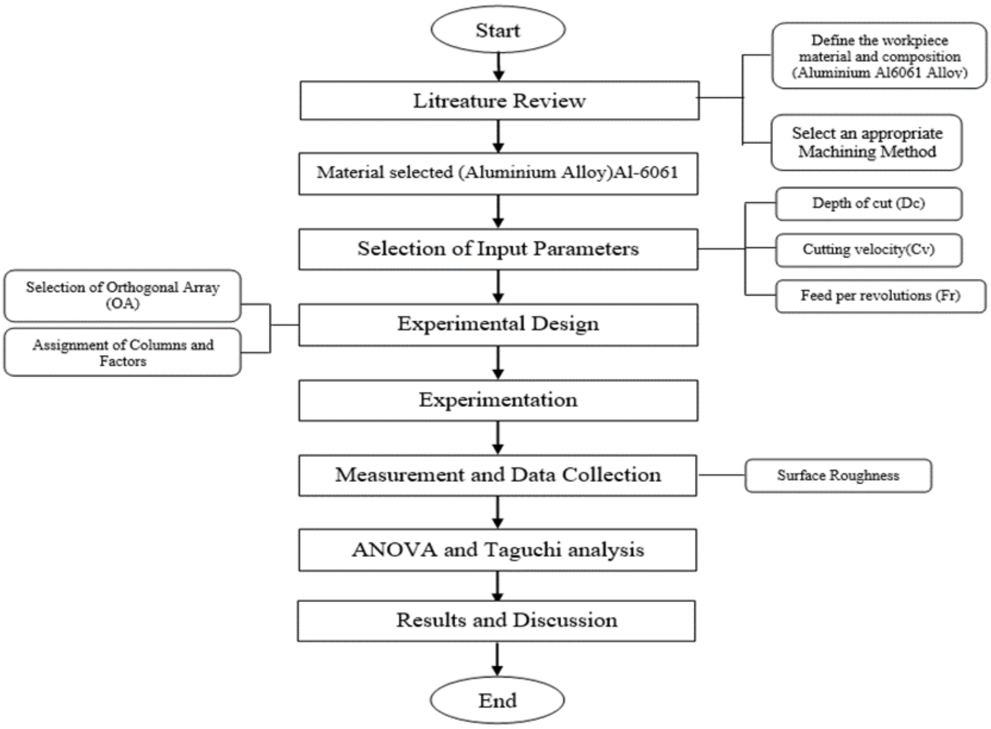

Figure 1: Methodology adopted in the present study

The Taguchi method uses orthogonal arrays to conduct a minimal number of machining experiments, keeping costs low while reducing machining time [16]; [17]. Taguchi methodology uses Signal-to-Noise ratios to evaluate experimental responses before analyzing Variance (ANOVA), which determines the contribution of controllable factors. According to the Taguchi approach, quality loss functions fall into three distinct areas: 'smaller-the-better', 'larger-the-better', and 'nominal-the-better'. The selected optimal parameters for each input variable will correspond to the level that yields the maximum S/N ratio. To achieve higher finishing quality in Al-6061 alloy, the research aims to identify the most effective combination of cutting depth and cutting parameters, including cutting velocity and feed per revolution. Thus, the methodology followed in this research.

3. Experimentation

3.1. Methodological Configuration of the Experimental Setup

The experimental investigation focused on optimizing surface roughness during dry milling of Aluminum Alloy 6061 (Al-6061). For this purpose, the milling operations were conducted using Titanium Nitride (TiN)-coated carbide inserts, which are well-regarded for their durability, wear resistance, and suitability when machining aluminum alloys.

Table 1: Al-6061 components for alloying [18]

Material	Al-6061
Si	0.4–0.65
Fe	Max. 0.72
Cu	0.25–0.50
Mn	Max. 0.16
Mg	0.68–1.15
Cr	0.04–0.42
Zn	Max. 0.35
Ti	Max. 0.25
Other Impurities	0.25
Al	Balance 93.5-98.5
Si	0.25–0.65

The detailed chemical composition of the Al-6061 work material—listing each alloying element and its respective percentage can be found in Table 1. This comprehensive alloy profile ensured consistency between the experimental results and the established literature [18].

Figure 2: Vertical machining centre (HYTECH)

To ensure repeatability and comparability of results, the Al-6061 specimens were precisely cut and finished to dimensions of 50 mm × 50 mm × 20 mm. This uniform sizing provided a standardized basis for all milling trials. The milling experiments were carried out on a HYTECH CNC vertical machining center, offering the requisite rigidity, automation, and precision for the Taguchi-designed trials (Figure 2). For each milling operation, a 75 mm face milling cutter was employed, into which seven

TiN-coated carbide inserts were uniformly positioned. This configuration maximized both material removal rate and finished surface area per pass, simulating actual production practices. Figure 3 shows the Al-6061 samples before and after milling. Subfigure (a) shows the initial, as-cut surface of the alloy, while subfigure (b) highlights the post-machined surface, visually demonstrating the influence of the milling operation on the surface quality.

Figure 3: Specimen of Al-6061 alloy (a) Before machining and (b) After machining

3.2. Determining an Input Parameter as well as its Respective Levels

The core objective of the study was to analyze the effects of three key input machining parameters on the resultant surface roughness (Ra):

- Cutting velocity (Vc)
- Feed per revolution (Fr)
- Depth of cut (Dc)

Each parameter was selected based on a combination of prior literature and preliminary experimentation to ensure both relevance and practicality. The levels assigned to each variable are detailed in Table 2, and were chosen to provide broad coverage of feasible industrial ranges:

Table 2: Data regarding the quantities for specified input parameters

Factor	Code	Unit	Level 1	Level 2	Level 3
Cutting velocity (Vc)	L	m/min	450	525	600
Feed per revolution (Fr)	M	mm/rev	0.20	0.40	0.60
Depth of Cut (Dc)	N	mm	0.50	0.60	0.70

To methodically investigate the effects and potential interactions among these three factors, an L27 orthogonal array (Taguchi design) was adopted. This design required 27 experimental runs, enabling the systematic evaluation of all parameter combinations while maintaining experimental economy and statistical robustness. All experimental trials were conducted under controlled, repeatable dry-machining conditions to ensure the validity of comparisons.

3.3. Surface Roughness Measurement

The key output parameter measured in this study was the arithmetic average surface roughness (Ra), reported in micrometers (µm). To precisely capture the surface finish produced under varying process parameters, a Mitutoyo SJ-201P surface roughness tester was employed (as depicted in Figure 4). The instrument's stylus traversed the machined surface of each specimen, collecting topographical data, which was processed to yield the Ra value. Each experimental run was subjected to three individual roughness measurements at distinct, representative locations on the milled surface. This approach mitigated the impact of local anomalies, and the mean of these readings was taken as the reported Ra for that trial. Lower Ra values indicated a smoother, superior surface finish, which was the primary focus of the process optimization in this work.

Figure 4: Surface roughness tester

Table 3 consolidates the experimental results from all 27 Taguchi-designed trials, presenting the input parameter configurations, the corresponding average Ra values, and the calculated signal-to-noise (S/N) ratios (in dB), which serve as a robust metric for parameter optimization in Taguchi methodology.

Table 3: Table for results experimentation

No.	Cutting Velocity (m/min.) (L)	Feed Per Revolution (mm/rev.) (M)	Depth of Cut (mm) (N)	Output Average (Ra) (in µm)	S/N Ratio (in dB)
1	450	0.20	0.50	0.310	10.173
2	450	0.20	0.60	0.320	9.897
3	450	0.20	0.70	0.320	9.897
4	450	0.40	0.50	0.323	9.810
5	450	0.40	0.60	0.323	9.810
6	450	0.40	0.70	0.307	10.270
7	450	0.60	0.50	0.333	9.545
8	450	0.60	0.60	0.337	9.459
9	450	0.60	0.70	0.323	9.810
10	525	0.20	0.50	0.283	10.958
11	525	0.20	0.60	0.303	10.365
12	525	0.20	0.70	0.300	10.458
13	525	0.40	0.50	0.283	10.958
14	525	0.40	0.60	0.300	10.458
15	525	0.40	0.70	0.293	10.656
16	525	0.60	0.50	0.303	10.365
17	525	0.60	0.60	0.337	9.459
18	525	0.60	0.70	0.333	9.545
19	600	0.20	0.50	0.253	11.931
20	600	0.20	0.60	0.263	11.594
21	600	0.20	0.70	0.287	10.856
22	600	0.40	0.50	0.297	10.558
23	600	0.40	0.60	0.287	10.856
24	600	0.40	0.70	0.307	10.270
25	600	0.60	0.50	0.293	10.656
26	600	0.60	0.60	0.267	11.485
27	600	0.60	0.70	0.287	10.856

3.4. Surface Characterization

To supplement quantitative Ra measurements and provide deeper insight into the nature of the machined surfaces, Scanning Electron Microscopy (SEM) was employed. SEM images of selected specimens were obtained both before and after milling. This microstructural analysis verified the surface topography, provided evidence of texture, chip ploughing, and adhesion effects, and validated the roughness results obtained by stylus profilometry.

3.5. Experimental Validations Using ANN

For additional validation and potential future predictive modeling, the experimental dataset was analyzed using Artificial Neural Network (ANN) techniques. By training an ANN model on the experimental results, the relationship between the input parameters (Vc, Fr, Dc) and the resulting surface roughness (Ra) could be accurately mapped. This advanced modeling step not only reinforced the consistency of experimental results but also demonstrated the feasibility of leveraging intelligent systems for real-time surface roughness prediction and process control in advanced manufacturing settings. This comprehensive experimental section provides clear descriptions of materials, tooling, and equipment, along with detailed parameterization, a measurement protocol, and advanced validation steps—all essential for reproducibility and scientific rigor.

4. Results and Discussions

4.1. Surface Characterization

Understanding the evolution of surface integrity before and after dry milling of Aluminum Alloy 6061 (Al-6061) is crucial to interpreting the improvements achieved through process optimization. Scanning Electron Microscopy (SEM) provides deep insight into microstructural changes and surface topography, validating the impact of controlled machining conditions. The SEM image of the Al-6061 specimen before milling reveals a heterogeneous and irregular surface architecture, which is typical of raw, as-cast, or rolled alloy. Prominent features include discontinuous grooves, micro-cracks, and loosely bonded particles. Such surface irregularities stem from manufacturing processes such as casting, deformation during rolling, and possible surface oxidation or contamination that accumulate over time. These irregularities create numerous nucleation points for stress concentration, thus highlighting the necessity for surface refinement through machining. SEM observation after the milling operation demonstrates a striking transformation. The machined surface appears substantially smoother, with homogenized topographical features. The pronounced grooves and micro-cracks visible before machining have been almost eliminated, attesting to the uniform material removal and finishing effect of the selected milling process (Figure 5).

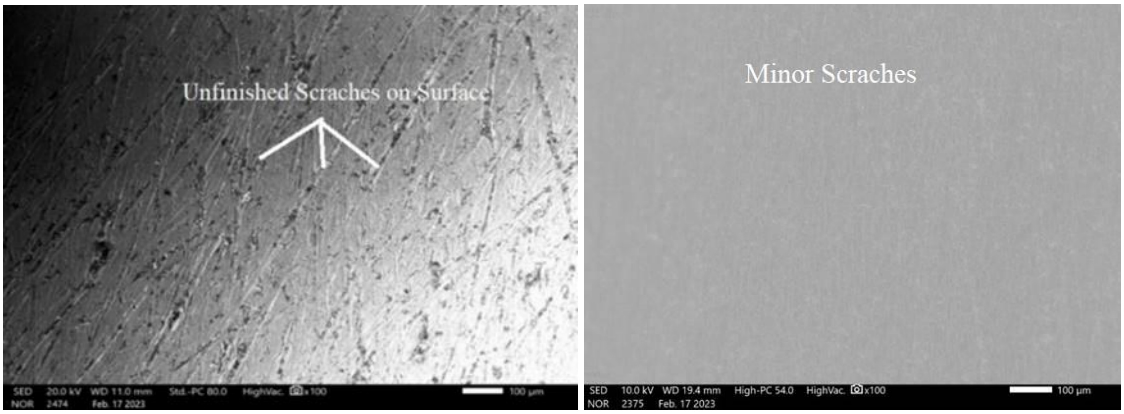

Figure 5: SEM images of a specimen of the Al-6061 alloy (a) before machining and (b) after machining

Notably, grain boundaries show improved regularity, and there are minimal indications of surface debris or smearing—both hallmarks of successful chip evacuation and proper tool-material interaction. The lack of significant ploughing, built-up edge, or surface tear confirms that the selected process parameters are not only effective for material removal but also for preserving the alloy's microstructural integrity. The absence of smeared aluminum and substantial debris suggests that chip adhesion was well-controlled by the optimized dry process. The change in micromorphology revealed by SEM closely aligns with the quantitative reductions in surface roughness (Ra) measured for each experimental run. The smoothness observed post-machining indicates that the Taguchi-optimized parameter set not only facilitates material removal but also supports the production of more reliable and robust component surfaces, critical for applications in aerospace and high-performance engineering. This improvement was accomplished without the use of cutting fluids, directly supporting sustainable manufacturing principles. The implication is significant: a high degree of finish can be achieved via proper process control in dry environments, negating the environmental and safety drawbacks associated with coolants.

4.2. Taguchi Approach, Signal-to-Noise (S/N) Analysis, and Results Overview

The Taguchi method enables effective exploration of multi-factor experimental spaces with reduced testing effort. Through the L27 orthogonal array, the impact of three principal parameters—cutting velocity (Vc), feed per revolution (Fr), and depth of cut (Dc)—was systematically studied, spanning three industrially relevant levels for each. The minimal measured Ra value (0.253 µm) was obtained at the parameter combination: cutting velocity of 600 m/min (L3), feed per revolution at 0.20 mm/rev (M1), and a depth of cut of 0.50 mm (N1), i.e., L3M1N1. This represents the most desirable surface finish using the dry milling approach. Analysis reveals clear trends: lower feed rates and higher cutting velocities are consistently associated with lower Ra values. These findings are substantiated across multiple trial combinations and collectively reinforce the established "smaller-the-better" paradigm in surface finish optimization. The S/N ratio, foundational to the Taguchi approach for handling experimental variance and identifying robust parameter settings, is calculated for each trial using [16]; [19]:

$$\text{S/N ratio} = -10\log\left(1/n \sum_{i=1}^{n} y\, i^2\right) \quad (1)$$

Where Yi is the surface roughness of the ith trial, and nn is the number of measurements per trial. The highest S/N ratios correspond to the lowest surface roughness, with the maximum value (11.931 dB) coinciding with the optimal settings detailed above. The "smaller-the-better" objective correctly prioritizes trials with the lowest Ra. The main effect plot graphically depicts the impact of each input parameter at its levels. It confirms the individual and combined influences of cutting velocity, feed per revolution, and depth of cut on Ra values (Figure 6).

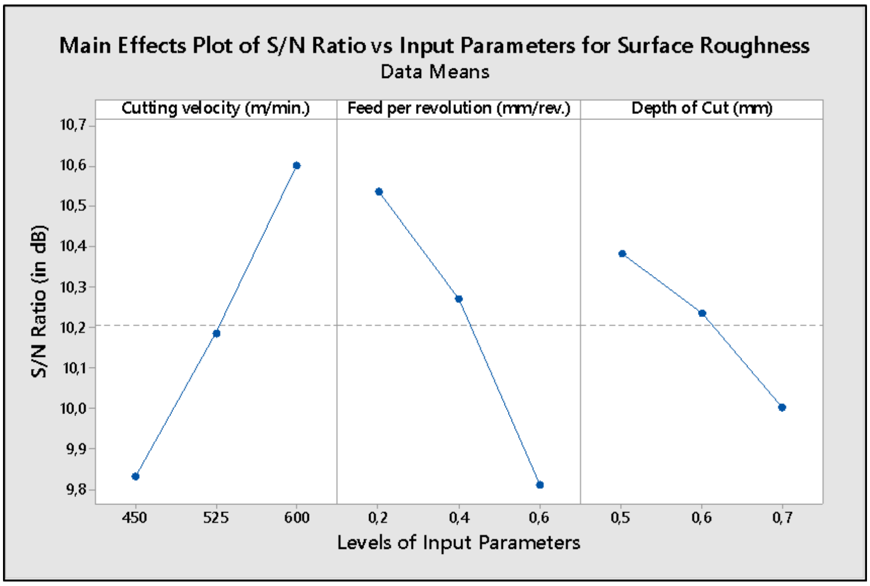

Figure 6: Main effect plot representing the impact of input parameters on surface roughness

4.2.1. Parameter-Specific Influence and Interactions

4.2.1.1. Feed Per Revolution (Fr)

By far, Fr emerged as the most influential contributor to Ra, as confirmed statistically and visually in the main effects plot. Low feed rates consistently yield less aggressive chip formation, resulting in more uniform, smoother surfaces. High feed rates, conversely, provoke pronounced chip-tool interaction and force spikes, often leading to greater surface deformation, especially in the relatively soft Al-6061 matrix, which, in turn, results in poorer Ra values.

4.2.1.2. Cutting Velocity (Vc)

Elevated cutting speeds improve surface finish by minimizing chip adhesion and built-up edge formation [20]. The rapid increase in interface temperature at higher speeds, when properly controlled (as in the present dry-milling context), leads to cleaner shearing and improved chip evacuation.

4.2.1.3. Depth of Cut (Dc)

The depth of cut, although the least influential of the three studied factors, still plays a measurable role. Higher depths of cut generally escalate tool forces, increase vibration susceptibility, and promote less favorable surface patterns. Conversely, a shallow cut supports material removal at lower mechanical and thermal stresses, consistent with the optimized surface finish observed at N1 (0.50 mm).

4.2.2. Statistical Validation: ANOVA

The influence hierarchy and statistical significance of each machining parameter were evaluated using Analysis of Variance (ANOVA), with the detailed results presented in Table 4.

Table 4: Table for ANOVA results

Factor	Degrees of Freedom (DOF)	Sum of Squares (SS)	Variance	F-Ratio	Contribution in Percentage
L	2	1.32	0.66	212.90	38.13
M	2	1.69	0.85	272.58	48.82
N	2	0.39	0.20	62.90	11.27
Error	20	0.06	0.00	-	1.79
Total	26	3.46	0.13	-	100.00

Among the factors analyzed, feed per revolution (Fr) was the most statistically significant, accounting for 48.82% of the observed variation. This finding confirms the critical role of Fr in controlling surface roughness during the dry milling of Al-6061. Cutting velocity (Vc) was identified as the next most influential factor, accounting for 38.13% of the variation. In contrast, depth of cut (Dc), while still impactful, played a secondary role, contributing 11.27%. The low experimental error contribution of just 1.79% further attests to the reliability and reproducibility of the collected data. These results align entirely with the established literature, which consistently demonstrates the centrality of feed rate in optimizing the surface finish of aluminum alloys. To further substantiate the experimental findings, the following predictive relationship was subsequently deployed:

$$\mu_{pred} = m + \sum_{j=1}^{p} \left((m_{i,\,j})\ \max - m \right) \quad (2)$$

Where it is said that (mi,j)max = Optimal S/N ratio of the ith level for the jth parameter.

Where:

- (mi,j)max(mi,j)max is the optimal S/N ratio at the ith level for the jth parameter.
- mm is the overall mean of the data.
- pp is the number of parameters.

For the optimal configuration (L3M1N1), the predicted S/N ratio (11.87 dB) and Ra (0.253 µm) closely matched the measured values. The experimental validation via confirmation trials at optimal levels revealed a 16.72% improvement in surface finish compared to initial baseline parameters (L1M1N1).

4.2.3. Parameter Mechanism and Surface Generation

Lower feed rates mitigate mechanical vibration and ensure a more stable tool-work interface, both of which are indispensable for smooth surface generation—especially in materials with a tendency toward chip adhesion, like Al-6061. Higher cutting velocities likewise accelerate chip removal, reduce exposure time to heat and friction, and lower the risk of built-up edge formation. The synergy among these parameters, enabled by the systematic Taguchi approach, underscores the importance of multi-factor optimization over single-variable experimentation [19]-[21].

4.2.4. Efficiency of Experimental Design

The adoption of a Taguchi L27 orthogonal array yielded vast savings in both time and experimental resources compared to a full factorial design, without sacrificing the comprehensiveness of parametric evaluation. The reduction from 81 required trials (full factorial) to 27 using Taguchi's method for three factors at three levels underscores the efficiency of robust design of experiments. This aligns with numerous studies that validate the use of partial factorial designs in manufacturing optimization.

Achieving superior surface roughness without the environmental and health hazards of cutting fluids paves the way for scalable, sustainable manufacturing of high-performance aluminum alloy components. The findings directly support the industry's transition to cleaner, greener manufacturing while maintaining the rigorous surface quality demanded in aerospace and other precision sectors. The study aligns strongly with Sustainable Development Goal 12, which promotes responsible consumption and production [22]-[24]. The observed trends and optimized parameter sets echo prior research. For example, studies by Balasuadhakar et al. [28] and Kowalczyk and Tomczyk [29] also demonstrated that parameter optimization for the "smaller-the-better" S/N ratio directly enhances surface integrity and productivity. While this research provides a high-resolution understanding of individual factor effects, the Taguchi (L27) design does limit the scope for exploring higher-order parameter interactions. Moreover, focusing exclusively on Al-6061, while ideal for specific applications, constrains the universality of the conclusions. Future work should consider expanded experimental frameworks to probe both two-way and three-way interactions. It could broaden alloy selection to include other aluminum alloy grades, such as 6082 and 7075, to validate and extend the findings. Further, the introduction of real-time monitoring systems, such as in-process acoustic emission or force sensing, could offer predictive process control capabilities for surface integrity in production environments.

4.3. Artificial Neural Network (ANN) Validation of Surface Roughness Prediction

To complement the experimental and statistical optimization approaches, the research leveraged Artificial Neural Network (ANN) modeling to predict surface roughness outcomes from process parameters. In the context of this study, the Artificial Neural Network (ANN) was developed as a supervised regression model, trained to predict the surface roughness (Ra) of dry-milled Aluminum Alloy 6061 workpieces by learning from experimentally measured input–output data. The experimental dataset used for this purpose was generated from the systematically designed Taguchi L27 orthogonal array, comprising 27 trials with known values of the principal machining parameters—cutting velocity (Vc), feed per revolution (Fr), and depth of cut (Dc). For each combination of these parameters, the corresponding surface roughness (Ra) was measured and recorded. The ANN training phase involved partitioning the available dataset into three subsets: training, validation, and testing. The majority of the dataset was reserved for training, ensuring the model could learn the intricate mapping between input machining parameters and the observed surface roughness values. Validation and testing subsets, smaller in size, were withheld from the initial training process and introduced later to evaluate generalization and guard against overfitting. During training, the ANN underwent iterative adjustments to its internal weights and biases to minimize the difference (typically using mean squared error as the loss function) between its predicted Ra values and the measured Ra targets.

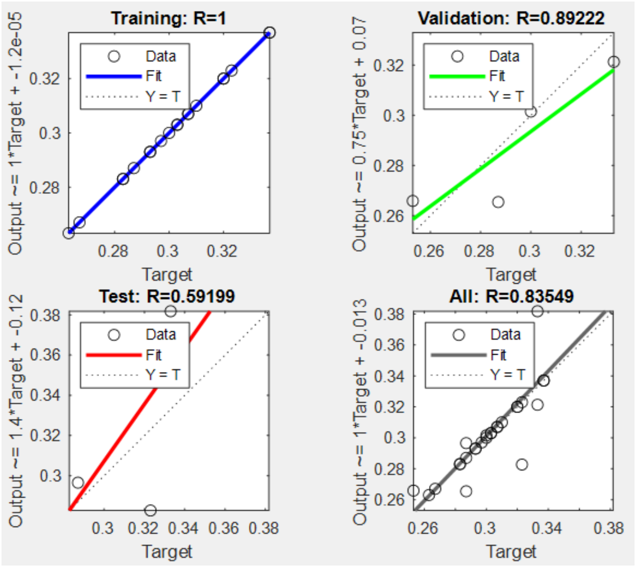

Figure 7: Training and validation of results

The training process involved numerous forward and backward passes: during each forward pass, the network made predictions; in each backward pass, it updated its parameters using optimization routines such as gradient descent, guided by the computed errors. The resulting plot in Figure 7 enables a visual assessment of the ANN's learning performance. Figure 7 typically shows the predicted Ra values versus the experimentally measured Ra values for each data point (training, validation, or test). When the network has achieved high-quality learning, these points align closely along the diagonal, indicating that for each set of input machining parameters, the ANN's prediction closely matches the actual value. In this study, the high degree of conformity observed in Figure 7 suggests that the developed ANN has successfully captured the relationship between input variables and surface roughness. The similarity between predicted and target values across the dataset is evidence not only of good fit (“accuracy”) but also of strong model generalization, meaning the ANN has learned the underlying functional relationships and can reliably extrapolate to similar but unseen process conditions within the studied parameter space. This degree of predictive agreement demonstrates that the ANN model is robust, trustworthy, and can serve as a practical tool for process engineers to forecast surface roughness outcomes based on machining settings, reducing the need for costly trial-and-error in actual production. After establishing the ANN's overall predictive accuracy, the next crucial step is a detailed error analysis, typically visualized as a histogram of prediction errors (the difference between predicted and actual Ra values), as shown in Figure 8.

This analysis provides a granular understanding of where and how often the model’s predictions deviate from the true observed values, serving as both a test of modeling rigor and a diagnostic for potential improvements. In this research, a histogram with 20 bins was constructed, providing an informative distribution of prediction error frequencies. The results show a pronounced, narrow peak centered around zero. Statistically, this indicates that the ANN’s predictions are almost identical to the experimental outcomes. More specifically, the vast majority of individual errors lie within ±0.01 µm of the true Ra value. This is a remarkable result—in practical terms, such minute differences are generally within experimental measurement uncertainty limits and are negligible for most precision engineering applications. The tightly clustered errors suggest several important conclusions. Firstly, the experimental dataset is of high quality, with low measurement noise and no spurious outliers—meaning the ANN was trained on coherent, reliable data. Secondly, the model’s architecture (number of layers/neurons), as well as its training strategies (such as regularization and learning rate scheduling), were well-selected: the ANN is neither underfitting (missing important patterns and thus producing systematic, large errors) nor overfitting (memorizing training data idiosyncrasies and failing on new data). Thirdly, the appropriateness of the chosen input features (Vc, Fr, Dc)—guided by the experimental design and ANOVA—was validated, as the ANN accurately predicted Ra based solely on these process parameters, suggesting that no major influential variables were omitted. Such a low, symmetric error distribution is a hallmark of an excellent predictive model. In the realm of intelligent manufacturing, it is a prerequisite for deploying AI-driven decision-making on the factory floor—where process optimization, quality assurance, and resource allocation increasingly rely on accurate, real-time forecasts.

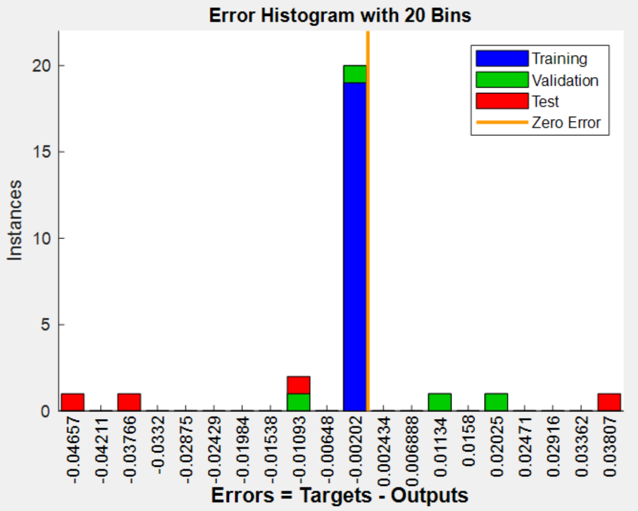

Figure 8: Error histogram with 20 bins

While the training and error analyses assess the ANN’s performance on immediate prediction tasks, systematic validation across training, test, and validation datasets is essential to distinguish genuine learning from potential overfitting. Overfitting occurs when a model becomes excessively tailored to its training data—including noise or data-specific anomalies—and loses predictive power for previously unseen data. Figure 9 illustrates the training, validation, and test performance—typically via charts that plot the evolution of error (typically mean squared error or root mean squared error) for each dataset subset over successive training epochs (iterations through the dataset). In this research, the loss curves for all three subsets exhibit parallel and steadily declining trajectories. Errors decrease consistently, reaching low and nearly matching levels upon completion of training. Crucially, none of the subsets show a divergence late in the process (such as a training error that continues to drop while validation/test errors rise), a classical sign of overfitting. The overlapping loss curves therefore demonstrate the ANN's ability to generalize: the model not only ‘remembers’ the training data, but also accurately extrapolates to the independent validation and test cases. The robust generalization is further reinforced by similar error levels across subsets, suggesting that the ANN successfully captures the true, potentially nonlinear relationships between the input machining parameters and the resulting Ra values. In complex machining processes like dry milling of Al-6061, the relationships can involve multifactor interactions, threshold effects, and non-obvious dependencies—circumstances where ANNs are particularly advantageous compared to linear regression or simpler modeling techniques. Such robust model performance ensures that, when applied to new scenarios or in real-life production settings, the ANN will maintain its accuracy and reliability—enabling process engineers to confidently use the predictive model for process setup, optimization, or real-time adjustments, ultimately driving higher quality and process efficiency.

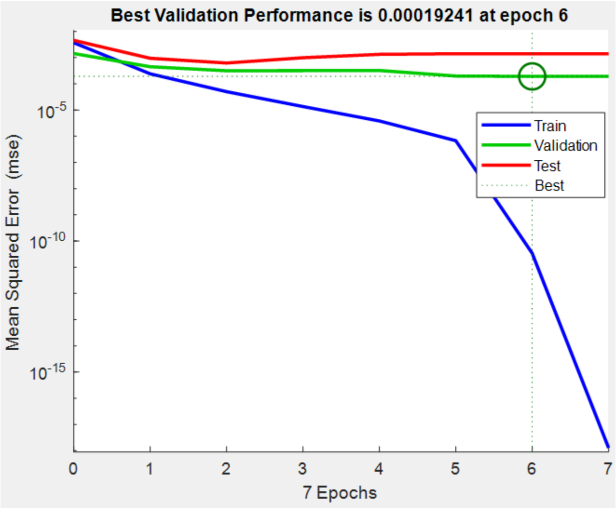

Figure 9: Validation performance

To gain a full understanding of the training process and ensure its reliability, researchers often examine additional diagnostics that reflect the model's learning dynamics—such as plots depicting gradient descent behavior and validation checks, as represented in Figure 10. During ANN training, optimization algorithms iteratively update model weights to minimize loss. The "gradient" at any point is a vector indicating the direction and rate at which the loss will decrease most steeply. During successful training, the magnitude of gradients should decrease over epochs, reflecting the system's gradual approach toward a (local or global) loss minimum. In Figure 10, a steady, monotonic reduction in loss (or gradient magnitude) is observed, without severe oscillations, sudden spikes, or plateaus.

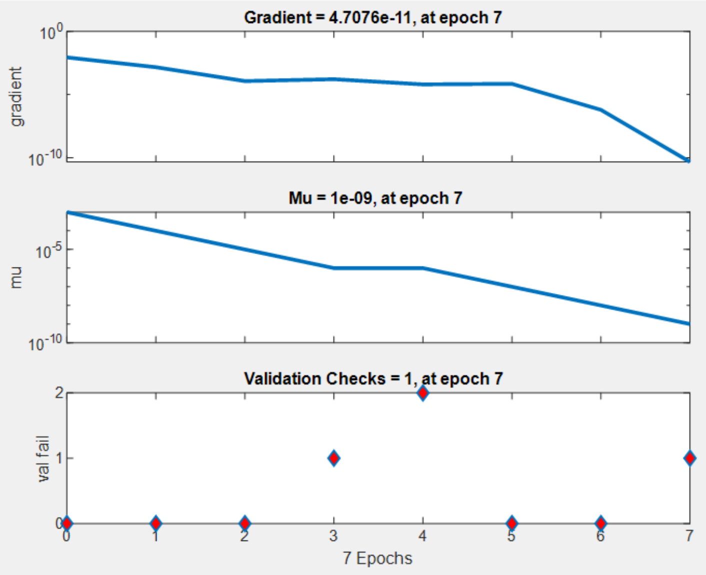

Figure 10: Gradient and validations

This steady descent indicates that the selection of network architecture, learning rate, optimizer, and regularization techniques was appropriate for the dataset's complexity and scale. Abrupt changes or stalling in gradient behavior would imply an optimization challenge (such as unsuitable hyperparameters, unstable learning rates, or inadequately prepared input data), which could undermine the model's predictive utility. Additionally, validation checks included in these diagnostic plots reinforce the model's capacity for convergence and generalizability. If the network had difficulty converging (for example, if loss stopped declining or validation error started to climb), it would signal under- or overcapacity in the network or might indicate the need for data augmentation or additional features. The observation that the loss continually decreases and stabilizes at a low value for both the training and validation data points indicates a balanced, well-regularized, and competent ANN.

4.3.1. Value for Manufacturing Practice

By applying ANN models, manufacturers can predict surface roughness outcomes with high confidence for a given set of machining parameters. This approach—especially when integrated with real-time sensor data—opens the door to closed-loop adaptive process control, enabling proactive parameter adjustments to maintain surface finish targets in production. To gain a full understanding of the training process and ensure its reliability, researchers often examine additional diagnostics that reflect the model's learning dynamics—such as plots depicting gradient descent behavior and validation checks, as represented in Figure 10. During ANN training, optimization algorithms iteratively update model weights to minimize loss. The "gradient" at any point is a vector indicating the direction and rate at which the loss will decrease most steeply. During successful training, the magnitude of gradients should decrease over epochs, reflecting the system's gradual approach toward a (local or global) loss minimum. In Figure 10, a steady, monotonic reduction in loss (or gradient magnitude) is observed, without severe oscillations, sudden spikes, or plateaus. This steady descent indicates that the selection of network architecture, learning rate, optimizer, and regularization techniques was appropriate for the dataset's complexity and scale. Abrupt changes or stalling in gradient behavior would imply an optimization challenge (such as unsuitable hyperparameters, unstable learning rates, or inadequately prepared input data), which could undermine the model's predictive utility. Additionally, validation checks included in these diagnostic plots reinforce the model's capacity for convergence and generalizability. If the network had difficulty converging (for example, if loss stopped declining or validation error started to climb), it would signal under- or overcapacity in the network or might indicate the need for data augmentation or additional features. The observation that the loss continually decreases and stabilizes at a low value for both the training and validation data points indicates a balanced, well-regularized, and competent ANN.

4.3.2. Significance in the Wider Context

The convergence of ANN-predicted values and Taguchi-ANOVA experimental outcomes provides additional validation of the findings, further reinforcing the reliability of the proposed process optimization pathway. This synergy enables both data-driven (ANN) and mechanistic/statistical (Taguchi/ANOVA) approaches to support sustainable manufacturing decision-making.

4.4. Critical Synthesis and Industrial Implications

The comprehensive results and discussions presented above demonstrate that careful, data-driven selection and optimization of machining parameters—in this case, using the Taguchi approach supported by ANOVA and confirmed via modern ANN techniques—substantially enhance the surface quality achievable in dry milling of Al-6061. Direct SEM observation not only substantiates the measured reductions in Ra but also provides a clear microstructural rationale for those improvements. The research bridges academic rigor with actionable industrial insights. By removing coolants and meticulously controlling parameters, firms can produce precision-engineered aluminum parts with lower environmental impact and superior mechanical performance. The combination of robust experimental design, advanced statistical analysis, and AI-based predictive modeling exemplifies the modern toolkit required for achieving genuine sustainable manufacturing in the metalworking industry. The findings also emphasize the value of partial factorial experiment design for rapid, cost-effective process improvement and illustrate how conventional wisdom—such as the "smaller-the-better" strategy for surface roughness—can be quantitatively validated and extended into new operational domains.

4.5. Future Directions

While the optimization framework developed in this study is both comprehensive and reliable, further research is warranted to extend these findings. Expansion into multi-objective optimization (e.g., incorporating tool wear, energy consumption, or surface integrity under different environmental conditions), ongoing refinement of real-time ANN-based adaptive process controls, and experimentation with advanced tool coatings and geometries will be particularly valuable for extending the boundaries of sustainable machining.

5. Conclusion

This study demonstrates that dry milling of Aluminum Alloy 6061 can achieve superior surface finishes by carefully optimizing key machining parameters. Applying the Taguchi method and ANOVA, it was established that feed per revolution is the most influential factor affecting surface roughness, followed by cutting velocity and depth of cut. The optimal parameter combination—high cutting velocity (600 m/min), low feed per revolution (0.20 mm/rev), and minimal depth of cut (0.50 mm)—

resulted in a significant reduction of surface roughness, with an average Ra of only 0.253 µm. SEM analysis confirmed substantial improvements in microstructural uniformity and surface integrity after machining under optimal conditions. The use of ANN for predictive validation further strengthened the reliability of the experimental framework, allowing accurate forecasting of surface roughness from process variables. Importantly, these achievements were realized without recourse to any cutting fluids, aligning the process with sustainable manufacturing objectives by minimizing environmental footprint and operational costs. The research underscores the synergy between statistical optimization approaches and intelligent modeling, offering a blueprint for industry practitioners seeking to balance high productivity, stringent quality standards, and environmental stewardship. Future investigations may expand on this work by exploring multi-objective optimization, real-time adaptive control, and applications to other aluminum alloys or advanced tool materials.

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