Experimental and ANN-Based Multi-Response Milling Parameter Optimization for Ti-6Al-4V Tire Mold Surface Quality Enhancement

Arul Raja R A[1], Sankar E[2], Anilkumar S[3]

[1]Department of Mechanical Engineering, SRM Institute of Science and Technology, Chennai, 600025, India
Email: *arulrajar[at]srmist.edu.in*

[2]Department of Mechanical Engineering, T. S. Srinivasan Centre for Polytechnic College and Advanced Training, Chennai, 600095, India
Email: *sankar.e[at]cpat.co.in*

[3]Department of Mechanical Engineering, T. S. Srinivasan Centre for Polytechnic College and Advanced Training, Chennai, 600095, India
Email: *anilkumar.s[at]cpat.co.in*

Abstract: ***Titanium alloy Ti-6Al-4V is widely utilized in high-performance engineering applications because of its excellent strength-to-weight ratio, corrosion resistance, and thermal stability. To improve surface finish and functional performance, its use in the production of tyre molds necessitates exact control over machining settings. Nevertheless, systematic milling optimization of Ti-6Al-4V for this particular application is the subject of few investigations. This study examines how surface roughness, material removal rate (MRR), and surface hardness are affected by spindle speed, feed rate, and depth of cut. Grey Relational Analysis (GRA) was used for multi-response optimization, while the Taguchi approach was used for experimental design. To forecast surface roughness from machining parameters and identify ideal circumstances for a particular surface finish, an Artificial Neural Network (ANN) model was created in Python. Surface integrity was greatly enhanced while manufacturing efficiency was maintained by the combined experimental, statistical, and artificial intelligence framework. The suggested method offers a dependable and clever way to maximize Ti-6Al-4V milling in tire mold production applications.***

Keywords: Milling optimisation, Surface roughness, Artificial Neural Network, Grey Relational Analysis, Tyre moulds

1. Introduction

One of the most popular material removal techniques in contemporary manufacturing is milling, which makes it possible to produce parts with excellent surface integrity and great dimensional precision. The method is appropriate for complicated geometries and precision applications because it uses spinning multi-point cutting instruments to remove material from a workpiece. Surface roughness (Ra) is a crucial quality characteristic among the many performance indicators as it has a direct impact on the mechanical performance, fatigue life, wear resistance, and visual appeal of machined components. Surface finish, material removal rate (MRR), tool life, and overall productivity are all greatly impacted by machining parameters including spindle speed, feed rate, and depth of cut. The remarkable strength-to-weight ratio, corrosion resistance, thermal stability, and biocompatibility of titanium alloys, especially Ti-6Al-4V, have made them extremely important. These characteristics make them ideal for applications in the automotive, biomedical, aerospace, and mold production industries. However, because to its strong chemical reactivity, low thermal conductivity, and propensity for quick tool wear, Ti-6Al-4V is categorized as a difficult-to-machine material. These features frequently lead to higher cutting temperatures, shorter tool life, and difficulties obtaining the required surface quality. In order to balance productivity and surface integrity, it is crucial to optimize the milling settings for Ti-6Al-4V. Conventional trial-and-error methods are costly and time-consuming, especially when many performance responses like hardness, MRR, and surface roughness need to be taken into account at the same time. While Grey Relational Analysis (GRA) provides multi-response optimization by combining several performance criteria into a single relational grade, statistical approaches like the Taguchi method offer a methodical framework for experimental design employing orthogonal arrays.

Artificial Neural Networks (ANNs) have become a potent tool for modelling intricate nonlinear interactions in industrial processes in recent years. Adaptability, resilience, and the capacity to generalize from small datasets are all provided by ANN-based models. They can reduce the need for significant physical experimentation by accurately predicting machining outcomes like surface roughness, MRR, and tool wear. The use of ANN models for multi-objective optimization of Ti-6Al-4V milling is still largely unexplored, despite its potential, especially when combined with statistical optimization methods. Ti-6Al-4V. In order to improve the milling parameters of Ti-6Al-4V manufacturing applications, this study suggests an integrated experimental, statistical, and artificial intelligence framework that combines the Taguchi technique, Grey Relational Analysis, and ANN modelling. In order to improve surface performance and machining efficiency for advanced manufacturing applications, the goal is to increase material removal rate while reducing surface roughness and increasing hardness.

In order to optimize the reaming process parameters of Ti-6Al-4V alloy under wet and cryogenic LN2 conditions, Shakeel Ahmed L [1] used Taguchi-Grey relational analysis. He discovered that wet coolant performed better than cryogenic cooling in terms of minimizing cutting temperature, thrust force, torque, surface roughness, and hole

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quality. In order to predict surface roughness in machining AA7075 aluminum alloy, Aleksandar Kosarac [2] created ANN models using backpropagation multilayer feedforward neural networks, proving that ANNs can be effectively trained with small datasets produced by Taguchi's 27-run orthogonal design. Kuram E [3] examined the effects of commercial and vegetable-based cutting fluids on thrust force and surface roughness when drilling AISI 304 austenitic stainless steel at different spindle speeds, feed rates, and drilling depths. Using carbide inserts and Taguchi's L9 orthogonal array, Pratyusha J [4] investigated the effects of spindle speed, feed rate, and depth of cut on surface roughness during milling of AISI 304 stainless steel. She used analysis of mean and variance to determine the significance of each machining parameter. The 3–1–1 network structure with a coated cutting tool produced the best prediction accuracy, with high speed and low feed rate advised for optimal surface quality, according to Zain AM's review and evaluation of ANN-based modeling's ability to predict surface roughness in the milling of Ti-6Al-4V [5].

When compared to traditional milling, the longitudinal ultrasonic-assisted milling system for Ti-6Al-4V developed by Lü et al. [6] lowered milling forces by 17.66% and surface roughness by 36.36% thanks to the optimization of ultrasonic amplitude, milling depth, and feed per tooth. Siregar et al. [7] adjusted the milling parameters of SLM-manufactured Ti6Al4V using the Taguchi L9 orthogonal array and discovered that spindle speed was the main factor, contributing over 83.67% to surface roughness variance. Sumesh et al. [8] established an integrated RSM-ANFIS-GA framework for dry turning of Ti-6Al-4V, attaining a minimal anticipated surface roughness of 0.3392 µm under optimal circumstances of SS = 660.10 rpm, FR = 30 mm/min, and DoC = 0.3 mm. In the micro-milling of SLM Ti6Al4V, Rehan et al. [9] used ANN modeling and NSGA-II multi-objective optimization, obtaining improvements in surface roughness and cutting force of 335.61% and 592.61%, respectively, at optimum settings. When MQL and cryogenic cooling were compared in ball-end milling of Ti-6Al-4V, Cica et al. [10] found that cryogenic cooling performed better than MQL in terms of machining performance and environmental sustainability, with feed per tooth accounting for 39.4% of surface roughness variance.

2. Materials

The material used for this study is Ti-6Al-4V (Titanium Grade 5), an α+β titanium alloy that is often utilized in high-performance tooling, biomedical, and aerospace applications because of its exceptional strength-to-weight ratio, corrosion resistance, and thermal stability [11][12]. With trace elements like Fe (≤0.25%), O (≤0.20%), C (≤0.08%), N (≤0.05%), and H (≤0.015%), the alloy is composed of 6 weight percent aluminum (α-phase stabilizer) and 4 weight percent vanadium (β-phase stabilizer), with titanium making up the remaining percentage. With a tensile strength of 900–950 MPa, a minimum yield strength of 880 MPa, elongation of 10–15%, an elastic modulus of around 110 GPa, and a hardness of about 36 HRC, Ti-6Al-4V has exceptional mechanical strength. Its density is 4.43 g/cm³, its specific heat capacity is 0.526 J/g·K, its melting point is around 1660°C, and its thermal conductivity is 6.7 W/m·K. Because of these qualities, the alloy may be used in precision milling applications where dimensional stability, surface integrity, and endurance under cyclic thermal loading are crucial, such as the production of tire molds.

3. Experimental Setup and Procedure

In order to guarantee sufficient machining allowance and precise measurement of surface roughness and material removal rate (MRR), milling tests were conducted on rectangular specimens of Ti-6Al-4V fabricated to appropriate dimensions. A precise vice was used to firmly grip the workpieces while they were being machined. A DMC 65 V CNC Vertical Machining Center was used for all of the tests. The machine features an 850 x 600 mm table, a maximum spindle speed of 30,000 rpm, and axis travels of 650 mm (X), 500 mm (Y), and 500 mm (Z). To improve tool life and regulate cutting temperature, flood coolant was used. Every milling operation was performed using a 0.5-inch, four-flute solid carbide end mill. A Rockwell Hardness Tester (C-scale, 150 kgf load, diamond indenter) was used to test the surface hardness. A Taylor Hobson Surface Roughness Tester with a 5 µm stylus tip and 0.001 µm precision was used to measure surface roughness (Ra).

3.1 Input Process Parameters

Spindle speed (N), feed rate (F), and depth of cut (a_p) were the three main cutting parameters taken into consideration as control elements in the milling studies on Ti-6Al-4V. These factors were chosen because they have a significant impact on machining productivity and surface integrity. To make statistical analysis easier, each component was examined at three levels using the Taguchi orthogonal array design. In order to provide stable cutting conditions, the chosen parameter ranges were established based on machine tool capacity, tool manufacturer recommendations, and first experimental trials.

- Spindle speed (N): 1000, 1500, 2000 rpm
- Feed rate (F): 100, 150, 200 mm/min
- Depth of cut (a_p): 0.5, 1.0, 1.5 mm

3.2 Output Performance Measures

Three response variables—surface quality, productivity, and mechanical integrity—were used to assess the machining performance:

- Surface Roughness (Ra, µm): Indicator of surface finish and functional performance.
- Material Removal Rate (MRR, mm³/min): Measure of machining efficiency and productivity.
- Surface Hardness (HV): Indicator of surface integrity and work hardening effects.

3.2.1 Material Removal Rate (MRR)

In milling operations, the material removal rate was calculated using the relationship:

MRR = F X ap x w

where: F = feed rate (mm/min), a_p = depth of cut (mm), w = width of cut (mm)

Since the width of cut was maintained constant throughout the experiments, variations in MRR were primarily governed by changes in feed rate and depth of cut.

For end milling operations, MRR can also be expressed as:
MRR = vf x ap x ae
where:
vf = table feed (mm/min)
a_p = axial depth of cut (mm)
a_e = radial depth of cut (mm)

4. Results and Analysis

4.1 Material Removal Rate (MRR)

The Material Removal Rate (MRR), a crucial measure of machining productivity, is shown in Table 1. The quantity of material extracted from the workpiece per unit of milling time is known as MRR. It is computed by dividing the difference between the workpiece's starting weight before to machining and its final weight following machining by the machining time. The Material Removal Rate is expressed using the following equation:

MRR = (Wb−Wat) /t

Where, Wb = Weight of the workpiece before machining (g)
Wa = Weight of the workpiece after machining (g)
t = Machining time recorded (sec)

Table 1: Material Removal Rate (MRR)

E. No.	*Feed (mm/min)*	*Spindle Speed (rpm)*	*Depth of Cut (mm)*	*Weight Before (g)*	*Weight After (g)*	*Time (min)*	*MRR (g/min)*
1	500	1500	0.1	30.08	30.00	4.72	0.016
2	500	2000	0.2	32.20	32.04	4.84	0.032
3	500	2500	0.3	29.82	29.52	4.97	0.060
4	1000	1500	0.2	28.14	27.98	2.81	0.056
5	1000	2000	0.3	28.16	28.01	2.54	0.059
6	1000	2500	0.1	29.19	29.13	2.90	0.020
7	1500	1500	0.3	30.35	30.13	1.69	0.130
8	1500	2000	0.1	32.45	32.36	1.90	0.047
9	1500	2500	0.2	32.40	32.31	1.83	0.049

Material Removal Rate (MRR), Surface Roughness (Ra), and Surface Hardness acquired during the milling of Ti-6Al-4V are the experimental results of the output responses that are shown in Table 2. When assessing machining performance, these response values are crucial indications. Surface Hardness displays the mechanical properties and surface integrity following machining, Surface Roughness (Ra) shows the quality of the machined surface, and MRR depicts the machining process productivity. Table 2 summarizes the measured values of these reactions under various machining conditions.

Table 2: Material Removal Rate (MRR), Surface Roughness (Ra) and Surface Hardness

S. No.	*Feed (mm/min)*	*Spindle Speed (rpm)*	*Depth of Cut (mm)*	*MRR (g/min)*	*Ra (µm)*	*Hardness (HRC)*
1	500	1500	0.1	0.016	0.9	39
2	500	2000	0.2	0.032	1.1	38
3	500	2500	0.3	0.060	1.3	37
4	1000	1500	0.2	0.056	1.7	37
5	1000	2000	0.3	0.059	1.6	36
6	1000	2500	0.1	0.020	1.3	37
7	1500	1500	0.3	0.130	2.4	35
8	1500	2000	0.1	0.047	1.9	35
9	1500	2500	0.2	0.049	1.6	36

5. Multi Response Optimisation (Taguchi Analysis)

Taguchi analysis is used in multi-response optimization to find the best set of machining settings that concurrently enhance several performance attributes. The impacts of feed rate, spindle speed, and depth of cut on responses like Material Removal Rate (MRR), Surface Roughness (Ra), and Surface Hardness are examined in this study using the Taguchi technique. The best parameter settings that offer better machining performance and surface quality are found by analyzing the Signal-to-Noise (S/N) ratios and response tables.

4.1 Material Removal Rate (MRR)

A greater Material Removal Rate (MRR) denotes more effective machining, which shortens processing times and boosts output. Thus, it is preferable to maximize MRR. The Material Removal Rate (MRR) Signal-to-Noise (S/N) ratios at various levels of the machining parameters feed rate, spindle speed, and depth of cut are shown in Table 3. The S/N ratios are used to determine the ideal parameter levels for optimum machining productivity and to assess how these parameters affect the material removal rate.

Table 3: Response Table for MRR (Larger-the-Better)

Level	*Feed*	*Spindle Speed*	*Depth of Cut*
1	-30.08	-26.22	-32.15
2	-27.87	-27.01	-27.04
3	-23.49	-28.20	-22.25
Delta	6.59	1.98	9.90
Rank	2	3	1

Table 3 shows that Depth of Cut is the most important factor affecting MRR, with the greatest Delta value of 9.90. With a

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Delta of 6.59, feed ranks second, and spindle speed, which has the lowest Delta of 1.98, has the least impact on MRR. These results indicate that while adjustments in feed and spindle speed have less of an effect, increasing the depth of cut will result in a significant rise in material removal rate.

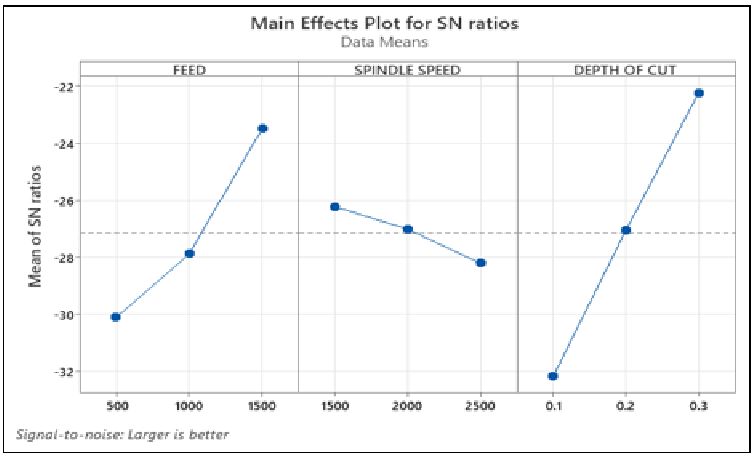

Figure 1: Main Effects Plot for MRR

The major effects plot for the Material Removal Rate (MRR) in Figure 1 depicts how the machining parameters- such as feed rate, spindle speed, and depth of cut- affect the material removal performance. The graphic shows how each process parameter's levels affect the mean signal-to-noise (S/N) ratio. Each line in the plot highlights the relative impact of each machining variable on MRR by showing the response's trend as the parameter level rises. The plot confirms that while Feed has a discernible effect, increasing the Depth of Cut leads to a considerable rise in MRR. In contrast to the other two characteristics, spindle speed has little impact.

5.2 Surface Roughness (Ra)

When assessing the machined component's surface finish, Surface Roughness (Ra) is crucial. For improved surface quality, particularly in precision and mold-making applications, a lower Ra value is preferred. The Signal-to-Noise (S/N) ratios for Surface Roughness (Ra) at various levels of the machining parameters feed rate, spindle speed, and depth of cut are shown in Table 4. The S/N ratios are used to determine the best combination of machining conditions for obtaining better surface quality and to assess the impact of each parameter on surface roughness.

Table 4: Response Table for Ra (Smaller-the-Better)

Level	*Feed*	*Spindle Speed*	*Depth of Cut*
1	-0.7305	-3.7660	-2.3129
2	-3.6567	-3.4951	-3.1731
3	-5.7539	-2.8800	-4.6552
Delta	5.0234	0.8860	2.3422
Rank	1	3	2

According to the Delta values, Feed has the biggest effect on Surface Roughness (Delta = 5.0234), followed by Depth of Cut (Delta = 2.3422), and Spindle Speed (Delta = 0.8860). This suggests that a smoother surface is produced by a reduced feed rate, and spindle speed has little effect when compared to the other factors.

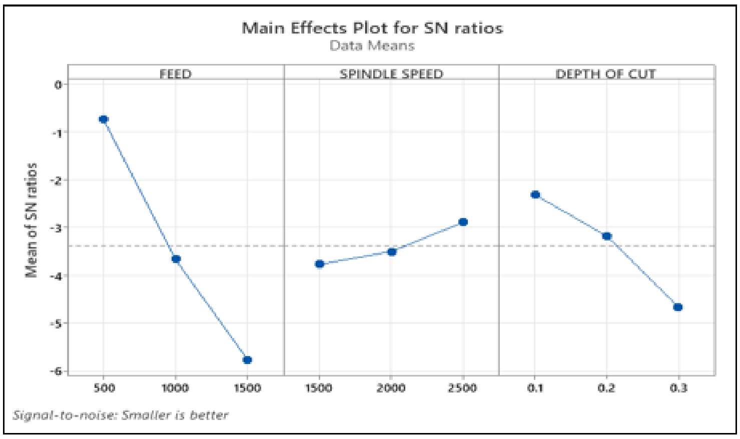

Figure 2: Main Effect Plots for Surface Roughness (Ra)

The major effects plot for Surface Roughness (Ra) is shown in Figure 2, which shows how the mean Signal-to-Noise (S/N) ratio varies with various levels of the machining parameters, including feed rate, spindle speed, and depth of cut. The graphic aids in determining the ideal parameter settings that reduce surface roughness throughout the milling process and clarifies how each parameter affects surface roughness. The plot demonstrates that while increasing Spindle Speed enhances surface smoothness, increasing Feed deteriorates surface finish (increasing Ra). Therefore, the best way to achieve minimal surface roughness is to use lower feed rates and moderate spindle speeds.

5.3. Hardness (HRC)

The material's resistance to deterioration and wear is indicated by its hardness (HRC). For parts that encounter impact or friction during operation, a higher hardness is preferred. The Signal-to-Noise (S/N) ratios for surface hardness at various machining parameter levels feed rate, spindle speed, and depth of cut are shown in Table 5. The S/N ratios are used to assess how these factors affect the machined surface's hardness and to identify the best machining parameters for increasing surface hardness.

Table 5: Response Table for Hardness (Larger-the-Better)

Level	Feed	Spindle Speed	Depth of Cut
1	31.59	31.36	31.36
2	31.28	31.20	31.36
3	30.96	31.28	31.12
Delta	0.63	0.15	0.24
Rank	1	3	2

According to the Delta values, feed has the biggest impact on hardness (Delta = 0.63), followed by depth of cut (Delta = 0.24). The least impact is caused by spindle speed (Delta = 0.15). Thus, maximizing Hardness requires optimizing Feed. The major effects plot for surface hardness is shown in Figure 3, which shows how feed rate, spindle speed, and depth of cut affect the machined surface's hardness. The findings reveal that while spindle speed has little effect on the material's hardness, an increase in feed rate resulted in an increase in surface hardness.

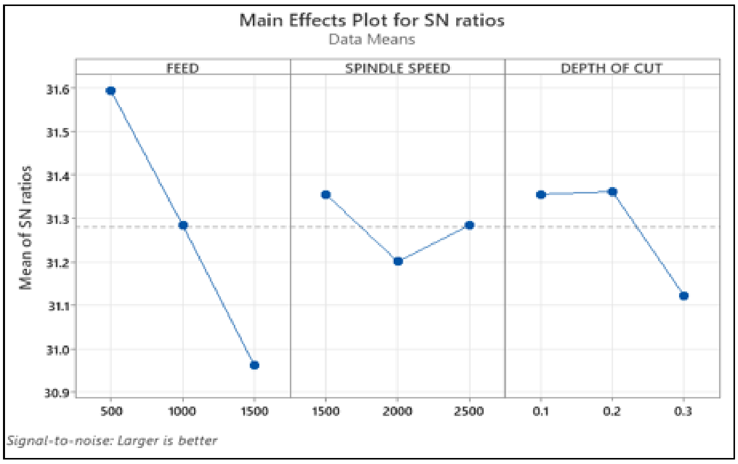

Figure 3: Main Effects Plot for Hardness (HRC)

5.4 Summary of Taguchi Analysis of individual parameters

The Taguchi technique was effectively used to optimize the milling parameters influencing the Ti-6Al-4V alloy's performance. The ideal parameter combinations for maximizing MRR, decreasing Ra, and maximizing Hardness were found using a L9 orthogonal array. Efficient optimization with fewer experiments was made possible by the Signal-to-Noise (S/N) ratio analysis, which offered clear insights into the impact of each machining parameter. The major effects plots clearly verified the relative relevance of the parameter levels, while the response tables emphasized their quantitative consequences. Each plot demonstrated how Speed, Feed, and Depth of Cut affected the output responses in terms of both direction and intensity. In order to create mathematical models that explain the connection between input factors and output performance, regression analysis will be performed for each output parameter in the following chapter. This will allow the process parameters to be further refined for better performance.

5.5 Taguchi Analysis of GRG

In this section, the ideal machining parameters for Ti-6Al-4V alloys are determined by applying the Taguchi method to Grey Relational Analysis (GRG). The Grey Relational Grade (GRG) is a composite metric that indicates the overall machining quality by combining several performance indicators, including Material Removal Rate (MRR), Surface Roughness (Ra), and Hardness (HRC). We can methodically assess how input factors like Feed, Spindle Speed, and Depth of Cut affect the GRG and determine the best parameter combinations by utilizing Taguchi's orthogonal array and S/N ratio methodology. Each experimental trial's GRG is calculated as part of the analysis, and then the S/N ratio is determined. To see and understand how each machining parameter affects the overall milling performances, the GRG response table and main effects graphic are then created. The Grey Relational Grades (GRG) for every set of machining parameter values are shown in Table 6. The overall performance of several replies taken into account in the study is represented by the GRG values. It is possible to determine the parameter combination that offers the optimum overall machining performance by comparing these grades.

Table 6: Response of table for GRG (Larger always better)

Level	Feed	Spindle Speed	Depth of Cut
1	0.8134	0.8473	0.8115
2	0.8543	0.8347	0.8365
3	0.8915	0.8569	0.8703
Delta	4.705	1.948	1.994
Ranks	1st	3rd	2nd

The Grey Relational Grade (GRG) answer table is shown in Table 6. Feed at Level 3, Spindle Speed at Level 3, and Depth of Cut at Level 3 produce the maximum GRG value, according to the data. Thus, it is determined that this set of machining settings is the greatest for obtaining the best overall machining performance.

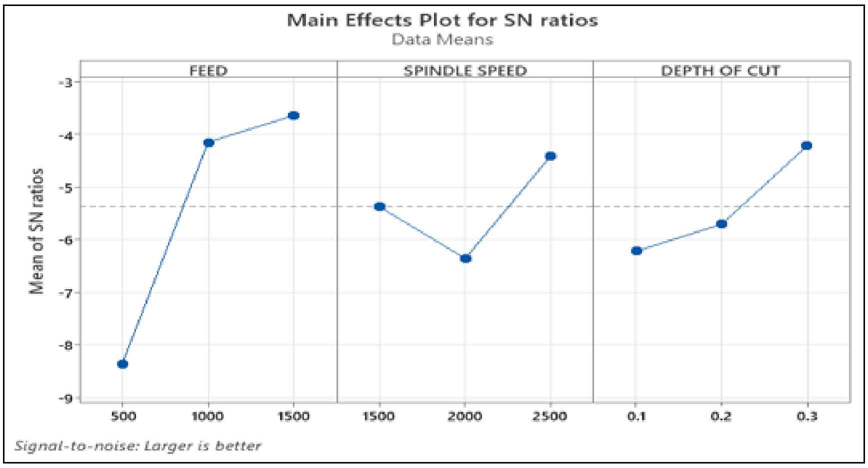

Figure 4: Main effects plot for grey relational grade (GRG)

The major effects plot for the Grey Relational Grade (GRG) is shown in Figure 4, which shows how feed rate, spindle speed, and depth of cut affect total machining performance. The plot shows that, at Level 3, feed rate and spindle speed have the biggest beneficial effects on raising the GRG, followed by depth of cut. While depth of cut has a somewhat smaller but still beneficial impact, higher feed rate and spindle speed levels help to increase overall performance.

5.6 Summary of Grey Relational Analysis (GRG)

In this part, the milling process of Ti-6Al-4V alloy was optimized using Grey Relational Analysis (GRG) by concurrently taking into account the performance metrics of Material Removal Rate (MRR), Surface Roughness (Ra), and Hardness (HRC). Important conclusions include:

1) Since feed and spindle speed produced the highest Grey Relational Grades, they have the greatest impact on enhancing total machine performance.
2) Although to a lesser degree, Depth of Cut also makes a favourable contribution.
3) Important information about the ideal parameter choices for increasing MRR, decreasing Ra, and optimizing HRC was revealed by the response table and main effects plot.

We successfully determined the ideal set of input parameters for improved machining performance by applying Taguchi Analysis on GRG, guaranteeing a fair trade-off across all performance metrics.

6. Regression Analysis

6.1 Material Removal Rate (MRR)

The amount of material removed during the milling process and the cutting parameters have a linear relationship according to the regression equation for MRR. Estimating productivity and modifying parameters to improve efficiency are made possible by this methodology.

Regression equation:
MRR = 0.0061 + 0.000039 × Feed − 0.000024 × Spindle Speed + 0.2767 × Depth of Cut

6.1.1. Interpretation

1) MRR is favorably impacted by feed and depth of cut, meaning that greater values of these inputs result in more material removal.
2) Spindle speed has a somewhat detrimental effect, indicating that higher speeds may eventually decrease removal efficiency.
3) This model can be used to optimize productivity and forecast MRR.

6.2 Surface Roughness (Ra)

The quality of the machined surface can be predicted using the surface roughness (Ra) regression model. In crucial applications, it enables proactive management of machining conditions to produce smoother finishes.

Regression equation:
Surface Roughness = 0.800 + 0.000867 × Feed − 0.000267 × Spindle Speed + 2.000 × Depth of cut

6.2.1. Interpretation

1) A rougher surface finish (higher Ra) is produced by increasing feed and depth of cut.
2) By lowering Ra, increasing spindle speed enhances surface quality.
3) The model guides balanced parameter selection by highlighting the trade-offs between roughness and other machining objectives.

6.3 Hardness (HRC)

The impact of machining factors on the workpiece's surface hardness is explained by this regression model. It is crucial to comprehend how cutting conditions affect the finished product's mechanical integrity.
Regression equation:

Hardness = 41.00 − 0.002667 × Feed − 0.000333 × Spindle Speed − 5.00 × Depth of Cut

6.3.1. Interpretation

1) Hardness is negatively impacted by all machining parameters, with depth of cut being the most important.
2) Heat production and surface changes during vigorous cutting could be the cause of this.
3) The formula allows for modifications to maintain surface integrity when milling.

6.4 Grey Relational Grade (GRG)

The GRG regression model allows for overall process optimization by combining MRR, Ra, and HRC into a single performance measure. It assists in determining parameter configurations that produce excellent and balanced results for every goal.

Regression equation:

GRG = 0.066 + 0.000284 × Feed + 0.000043 × Spindle Speed + 0.620 × Depth of Cut

6.4.1 Interpretation

1) GRG is positively impacted by all three criteria, with depth of cut having the most impact.
2) By combining MRR, Ra, and HRC, this model represents the entire machining performance.
3) It acts as a comprehensive manual for choosing the best process parameters.

6.5 Summary of Regression Analysis

Regression models for MRR, Ra, HRC, and GRG were created in this chapter using feed, spindle speed, and depth of cut as input parameters. The study's key conclusions show that regression analysis greatly improves knowledge of the connection between response variables and machining process parameters. Feed rate and depth of cut were found to be the most significant factors influencing most of the output responses among the parameters taken into consideration. Spindle speed had a mixed effect on the responses; it improved surface smoothness while marginally lowering material removal rate (MRR) and hardness (HRC). Additionally, the Grey Relational Grade (GRG) regression model offers a thorough and efficient method for multi-objective machining process optimization. To obtain balanced and effective machining performance of Ti-6Al-4V alloy, these regression equations can be used successfully in simulations, experimental design, and process planning.

7. Artificial Neural Network (ANN) Model Implementation

Using deep learning tools like TensorFlow and Keras, an Artificial Neural Network (ANN) model was created in Python to forecast milling performance characteristics. The model creates a nonlinear relationship between the output responses, such as Material Removal Rate (MRR), Surface Roughness (Ra), and Hardness (HRC), and the machining input parameters, such as Feed (mm/min), Spindle Speed (rpm), and Depth of Cut (mm). The developed program lets the user enter a target Surface Roughness (Ra) value for optimization. The algorithm uses experimentally derived regression equations to anticipate output responses while methodically searching within predetermined parameter ranges (Feed: 50–1000 mm/min, Speed: 1000–3000 rpm, Depth of Cut: 0.1–1.5 mm). For every combination, the absolute error between predicted and target Ra is calculated, and the parameter set that produces the lowest error is chosen as the best option. Next, corresponding values for MRR, Hardness, and Grey Relational Grade (GRG) are computed. In machining applications, this method improves decision-making precision and guarantees systematic parameter optimization.

7.1 ANN Architecture

For regression analysis, the ANN architecture was created as a feed-forward multilayer perceptron (MLP) model. An input layer, two hidden layers, and an output layer make up the network. The input, hidden, and output layers make up the three primary layers of the artificial neural network (ANN) model utilized in this investigation. Three neurons in the input layer represent the three machining parameters: depth of cut (mm), spindle speed (rpm), and feed rate (mm/min). The machining performance is influenced by these independent variables. Two completely linked hidden layers were used in order to efficiently capture the nonlinear interactions between the input parameters and output responses. The ReLU (Rectified Linear Unit) activation function is used by 12 neurons in the first hidden layer and 8 neurons in the second hidden layer. During training, the ReLU activation function increases the model's capacity to capture nonlinear patterns and speeds up convergence. Material Removal Rate (MRR), Surface Roughness (Ra), and Hardness (HRC) are the three neurons in the output layer that correlate to the machining reactions. These neurons indicate the anticipated performance results of the machining process. The output layer employed a linear activation function because the challenge involves continuous output prediction.

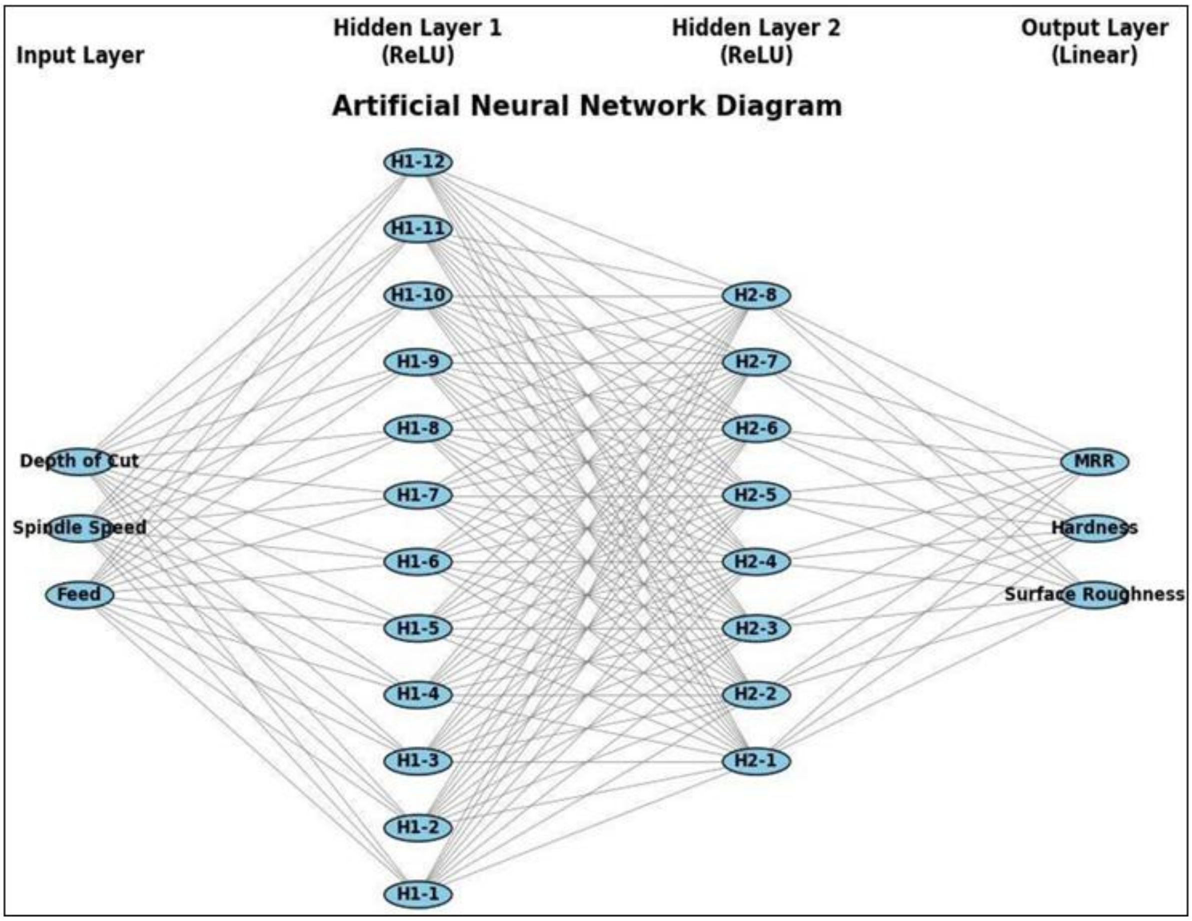

Figure 5: ANN model

7.2 Architecture Summary

The overall ANN configuration is summarized as follows:

Layer Type	Number of Neurons	Activation Function	Description
Input Layer	3	–	Feed, Speed, Depth of Cut
Hidden Layer 1	12	ReLU	Feature extraction
Hidden Layer 2	8	ReLU	Nonlinear mapping
Output Layer	3	Linear	MRR, Ra, HRC prediction

The model training employed supervised learning with the backpropagation algorithm, while Mean Squared Error (MSE) served as the loss function to evaluate prediction accuracy. An optimization algorithm such as Adam enabled iterative updating of network weights during the training process. This optimizer minimizes prediction error and enhances convergence stability, thereby improving the overall learning efficiency and predictive performance of the model.

7.3 Model Performance and Output

For a given goal Surface Roughness (Ra), the trained ANN model forecasts the best machining parameters. The model determines the optimal combination of feed, spindle speed, and depth of cut for a given Ra value. It also gives the expected MRR and Hardness values for the optimized parameters. The model's performance was assessed using three criteria: agreement with experimental data, error minimization, and prediction accuracy. The findings show that the ANN model is a dependable tool for machining process optimization and intelligent manufacturing applications because it successfully captures the nonlinear correlations between machining inputs and performance outputs.

8. Discussion

The generated ANN model's prediction capacity for Ti-6Al-4V alloy machining optimization is validated by the confirmation experiments. The measured value in Experiment 1 was 1.035 µm for a target Surface Roughness (Ra) of 0.9 µm, which represents a variation of around 15%. Experiment 2 yielded a result of 2.712 µm for a target Ra of 2.4 µm, indicating a variation of around 13%. The prediction accuracy was more than 85% in both situations, indicating a high degree of agreement between the model's output and the experimental findings. Practical machining uncertainties including tool wear, Ti-6Al-4V microstructural inhomogeneity, heat effects during cutting, and machine tool vibration can all be blamed for the observed variations. The ANN model effectively captured the nonlinear interactions between feed rate, spindle speed, and depth of cut with regard to surface finish in spite of these intrinsic process fluctuations. All things considered, the findings show that the ANN-based predictive framework is reliable enough for industrial machining applications. The model can greatly reduce trial-and-error experimentation, increasing productivity and process efficiency in sophisticated manufacturing environments. It also offers accurate parameter estimation for reaching target surface quality.

9. Conclusion

An Artificial Neural Network (ANN)-based predictive framework for maximizing the milling performance of Ti-6Al-4V alloy was effectively created and verified in this study. The model successfully developed nonlinear correlations between the output responses, such as Surface Roughness (Ra), Material Removal Rate (MRR), Hardness (HRC), and Grey Relational Grade (GRG), and the machining input parameters, such as feed rate, spindle speed, and depth of cut. During confirmation trials, the trained ANN showed remarkable predictive performance, attaining more than 85% agreement between anticipated and experimental values. Taking into account realistic machining uncertainties such tool wear, vibration, and heat impacts, the reported variance (about 13–15%) is within acceptable industrial tolerance. The suggested method offers a dependable data-driven tool for parameter selection in precision machining applications and greatly lessens reliance on trial-and-error experimentation. Additionally, the study validates Ti-6Al-4V's applicability for high-precision manufacturing settings like tire mold fabrication, where temperature resistance, surface integrity, and dimensional stability are crucial. A route toward intelligent and automated manufacturing techniques is provided by the integration of ANN-based optimization with CNC machining systems.

10. Future Scope

Even though the generated ANN model performed satisfactorily, there are a few improvements that could strengthen its industrial usability. In order to facilitate adaptive parameter control and dynamic process optimization, future research may concentrate on incorporating real-time machining data with IoT-enabled sensors. A more thorough prediction framework would be produced by adding more response variables including tool wear, cutting temperature, vibration amplitude, and residual stress. To improve generalization accuracy, larger experimental datasets, hyperparameter optimization strategies, and sophisticated deep learning architectures can all be investigated. Prediction accuracy may be further increased through comparative research employing hybrid optimization techniques, such as ANN combined with genetic algorithms. Lastly, real-time implementation in smart manufacturing environments would be made easier by integrating the trained ANN model into CNC-based decision-support systems with user-friendly interfaces. These advancements will greatly advance Industry 4.0 projects and increase the practical use of AI-driven machining optimization in the advanced tooling, automotive, and aerospace sectors.