

Research Article

Hybrid ANN-GA Optimization of Burnishing Parameters for Improving Surface Finish and Hardness in 6061-T6 Aluminum Alloy

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Abstract:

Improving surface finish and hardness in 6061-T6 aluminum is crucial for aerospace and automotive applications. This study presents a hybrid Artificial Neural Network–Genetic Algorithm (ANN-GA) model to optimize burnishing parameters—spindle speed, feed rate, and pressure. A full factorial design was used to analyze their effects on surface roughness and hardness. Experiments identified optimal conditions: 500 rpm, 0.3 m/min, and 2.0 GPa, achieving 0.372 μm roughness and 140.30 HV hardness. The ANN-GA model exhibited high predictive accuracy ($R^2 = 0.9513$, RMSE = 0.22), and proposed an alternative optimum at 799.02 rpm, 0.31 m/min, and 1.48 GPa. The findings confirm the effectiveness of the ANN-GA in capturing nonlinear interactions and reducing experimental trials. This integrated approach offers a robust tool for optimizing burnishing processes, particularly for high-performance components requiring superior surface integrity.

Keywords: Artificial Neural Network, Genetic Algorithm, Hybrid optimization, Burnishing process, Surface roughness, 6061-T6 aluminum alloy

1. Introduction

In precision manufacturing, surface integrity is a critical performance criterion that directly impacts fatigue strength, wear resistance, and functional reliability of machined components, particularly in aerospace, biomedical, and automotive sectors [1–3]. Among various post-machining enhancement methods, the burnishing process has emerged as an efficient, non-material-removal technique capable of significantly improving surface roughness and inducing beneficial surface hardening through plastic deformation [4–6]. However, achieving optimal surface quality using burnishing is nontrivial due to the complex, nonlinear interactions among key process parameters—spindle speed, feed rate, and contact pressure [7,8]. Traditional optimization methods, while effective to an extent, often fall short in fully capturing these interdependencies and their influence on the final surface characteristics of advanced alloys like 6061-T6 aluminum, a material widely used for its strength-to-weight ratio and corrosion resistance [9–11]. Previous research on welding and surface enhancement has increasingly turned to intelligent modeling techniques to better understand and optimize such multivariable systems. Notably, in welding applications, Artificial Neural Networks (ANN) and Response Surface Methodology (RSM) have been extensively applied to predict output variables such as tensile strength and hardness based on input conditions [12]. While RSM offers a statistically sound framework using

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polynomial regression to model parameter relationships, its predictive capabilities are limited when nonlinearities are due to its learning-based structure and ability to generalize from empirical data. In burnishing and welding contexts alike, ANN models have successfully predicted outcomes like weld bead geometry and surface roughness [13–15], particularly when combined with powerful optimization tools such as Genetic Algorithms (GA).

Friction Stir Spot Welding (FSSW), a solid-state joining technique suitable for aluminum alloys, has also benefited from data-driven optimization frameworks. Unlike conventional fusion welding, FSSW generates joints through frictional heat and mechanical stirring, offering superior mechanical properties and lower defect rates [16]. However, welding aluminum 5083, especially in its semi-solid state, poses additional challenges due to complex material flow and microstructural evolution. Prior studies have investigated how rotational speed, dwell time, and tool geometry influence weld quality, including tensile shear strength and hardness [17–18]. FSSW has found successful applications in high-load sectors, yet its process optimization remains sensitive to parameter tuning, prompting the integration of ANN and RSM for predictive and control purposes [19].

Artificial Neural Networks have been employed across various welding and surface processing domains to capture intricate, nonlinear relationships among variables. Feedforward architectures with hidden layers and Levenberg–Marquardt learning algorithms have been particularly successful in accelerating convergence and reducing prediction errors in welding parameter studies [20]. Furthermore, Genetic Algorithms, inspired by biological evolution, provide a robust search mechanism for identifying global optima in large and nonlinear solution spaces. GA has been widely used in conjunction with ANN to refine model weights and optimize multi-parameter systems, often outperforming traditional methods like Taguchi and RSM when dealing with high-dimensional input spaces [21]. While both ANN and GA independently offer significant modeling and optimization capabilities, recent studies advocate hybrid ANN-GA frameworks as a more powerful tool for process prediction and control. In welding applications, ANN-GA models have been applied to resistance spot welding, friction stir welding, and gas metal arc welding, delivering improvements in prediction accuracy and optimization efficiency over standalone methods [22]. Despite their success in joining processes, the use of hybrid ANN-GA models in post-machining surface treatment, especially in burnishing, remains relatively underexplored. Moreover, integrating ANN-GA with experimental factorial designs has the potential to not only identify parameter interdependencies but also reduce reliance on trial-and-error strategies, which are time-consuming and cost-intensive in high-precision environments.

In light of this, the present study focuses on optimizing the burnishing parameters of 6061-T6 aluminum alloy using a hybrid ANN-GA framework, aiming to improve both surface roughness and hardness simultaneously. In this study, hardness was experimentally validated and statistically analyzed, while the ANN-GA framework was specifically applied to surface roughness optimization as a proof-of-concept. Future work will extend the framework toward a true multi-objective formulation to optimize both roughness and hardness simultaneously. The research problem lies in the difficulty of tuning spindle speed, feed rate, and pressure to achieve optimal surface conditions, given their complex and often non-intuitive interactions. Thus, the objectives of this study are: (1) to evaluate the individual and interaction effects of burnishing parameters through a full factorial experimental design; (2) to develop an accurate ANN model for predicting surface roughness; and (3) to implement a GA-based search strategy to identify the optimal parameter combination. The hypothesis is that the ANN-GA model will outperform traditional statistical methods in both predictive accuracy and optimization robustness, particularly when validated against experimental results. In addition to statistical validation through ANOVA and RSM, this study incorporates an ANN-GA framework to capture complex parameter interactions and to explore intermediate conditions beyond the factorial grid, thereby extending the robustness and practical applicability of the findings.

To achieve these aims, a structured methodology is employed. First, burnishing experiments are conducted on 6061-T6 aluminum using a CNC lathe and SKD 11 tool under various combinations of spindle speed, feed rate, and pressure. The surface roughness and hardness are measured using a JEDTO SRT-6100 roughness tester and a Micro Vickers hardness machine. The collected data are then statistically analyzed using ANOVA, and the results are used to train an ANN. GA is subsequently applied to fine-tune the model and search for optimal parameter settings within defined bounds. The hybrid ANN-GA model's performance is assessed using metrics such as RMSE, MAE, and R^2 [23].

The novelty of this research lies in applying a hybrid AI-driven optimization framework to a non-removal surface treatment process, burnishing, which has traditionally relied on empirical or semi-statistical tuning. By extending hybrid ANN-GA methods beyond welding into surface enhancement of semi-solid metals like aluminum 6061-T6,

the study contributes both a new methodology and new insights into parameter interactivity, modeling accuracy, and practical optimization. It also provides a robust basis for expanding hybrid intelligent systems into multi-objective process optimization, particularly in applications demanding high surface integrity. The remainder of this paper is organized as follows. Section 2 presents the experimental setup and materials. Section 3 details the results, including statistical analysis, optimization findings, and model validation. Section 4 discusses implications, practical applications, and the ANN-GA model’s performance. Section 5 concludes the paper with a summary of key contributions and suggestions for future research directions.

2. Materials and methods

2.1 Experimental Procedure and Materials

Burnishing experiments were conducted using a CNC lathe machine (UL-1 5 Flat Bed) to ensure high precision and repeatability of machining conditions. The burnishing tool employed in this study was a roller fabricated from hardened SKD 11 tool steel, chosen for its exceptional wear resistance and structural stability during high-load contact applications. The tool geometry consisted of an inner diameter of 18 mm, an outer diameter of 28 mm, and a thickness of 10 mm, as illustrated in Fig.1 (a). The workpieces were cylindrical bars made of 6061-T6 aluminum alloy, a material widely used in aerospace and automotive engineering due to its high strength-to-weight ratio, corrosion resistance, and favorable machinability. Each specimen measured 25 mm in diameter and 100 mm in length, as shown in Fig. 1 (b). Before testing, the specimens were prepared to uniform dimensions and surface conditions to ensure consistent burnishing effects. To comprehensively evaluate the influence of process parameters on surface characteristics, three levels were defined for each factor: spindle speed (200, 500, and 800 rpm), feed rate (0.1, 0.3, and 0.5 m/min), and contact pressure (1.0, 1.5, and 2.0 GPa). These values, presented in Table 1, were selected based on preliminary trials and existing literature, ensuring coverage of both low and high deformation conditions [24,25]. Surface roughness measurements were performed using a JEDTO SRT-6 100 surface roughness tester with a resolution of 0.01 μm , while hardness evaluation was carried out using Micro Vickers hardness testing (HV 10) with an applied load of 500 gf and an accuracy of $\pm 1\%$ [26]. All measurements were taken in a controlled environment at $22 \pm 2^\circ\text{C}$ and $50 \pm 5\%$ relative humidity to minimize external influences and ensure data consistency [27].

Table 1: Burnishing process parameters and their corresponding levels used in the factorial design.

Parameter	Values
Spindle Speed (rpm)	200, 500, 800
Burnishing Feed Rate (m/min)	0.1, 0.3, 0.5
Contact Pressure (GPa)	1, 1.5, 2
Workpiece Material	Aluminum 6061-T6
Burnishing Tool Material	Hardened SKD 11 Steel

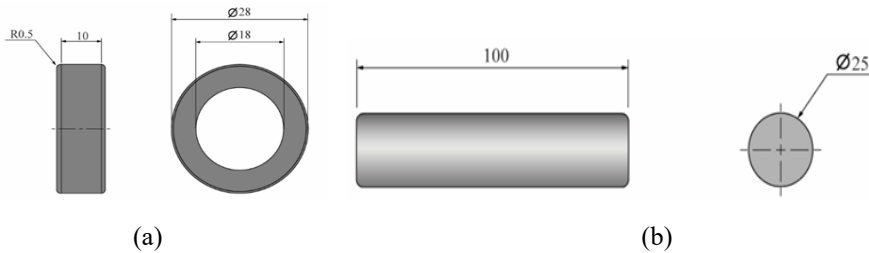


Fig. 1. Geometry of the experimental components: (a) Burnishing tool made of hardened SKD 11 steel and (b) 6061-T6 aluminum alloy workpiece.

2.2 Experimental Design and Parameter Optimization

A General Full Factorial Design was employed to systematically investigate the effects of key burnishing parameters—spindle speed, feed rate, contact pressure, surface roughness, and hardness. Each experimental condition was repeated three times to ensure statistical reliability and minimize experimental variability. Minitab V.19 software was used for both experimental design and statistical analysis. Before performing Analysis of Variance (ANOVA), data normality was assessed to validate the use of parametric inference methods. This approach ensured that the relationships among

process parameters and their effects on surface characteristics were accurately captured. The selection of parameter levels was based on a combination of literature review and preliminary experiments to ensure adequate coverage of the process window. Specifically, spindle speeds of 200, 500, and 800 rpm were chosen to balance plastic deformation and thermal effects, which are crucial for achieving high-quality surface finish and hardness [28]. Feed rates of 0.1, 0.3, and 0.5 m/min were selected to span a range of material deformation rates, from minimal to excessive [29]. Contact pressures of 1.0, 1.5, and 2.0 GPa were applied to evaluate the role of compressive stress in enhancing surface integrity through plastic flow and strain hardening [30]. Measurement precision was a key priority throughout the experimental campaign. Surface roughness was measured using a JEDTO SRT-6100 tester with a resolution of 0.01 μm , while hardness was evaluated using a Micro Vickers hardness tester (HV 10), which offered a force application accuracy within $\pm 1\%$. All tests were performed in a climate-controlled laboratory with ambient temperature maintained at $22 \pm 2^\circ\text{C}$ and relative humidity at $50 \pm 5\%$ to eliminate environmental variability from influencing the results [31].

2.3 Hardness and Surface Roughness Testing

To evaluate the mechanical properties of the burnished specimens, hardness and surface roughness measurements were conducted under controlled laboratory conditions. For hardness testing, each specimen was sectioned to a length of 20 mm and surface-ground using silicon carbide abrasive papers ranging from grit sizes 300 to 600 to eliminate contaminants and achieve a uniform surface finish. The Micro Vickers hardness test was performed by applying a 10 kgf indentation load with a dwell time of 10 seconds. The contact pressures (1.0–2.0 GPa) used in this study were calculated from the applied burnishing force and the Hertzian contact area between the SKD11 roller and the aluminum surface, representing nominal stresses applied during the burnishing process. Indentations were made horizontally along the centerline of the specimen at 1 mm spacing intervals to maintain measurement consistency. The precision of the hardness tester was maintained within ± 0.5 HV to reduce instrumental error and improve reliability [32]. Surface roughness measurements were taken at three axial positions along each specimen—head, middle, and tail—as shown in Fig. 2. A JEDTO SRT-6100 surface roughness tester, with a resolution of 0.01 μm , was used for all measurements. Each location was measured three times to ensure statistical reliability. The data were processed using Microsoft Excel, and average values were computed for analysis. All measurements were conducted at a constant ambient temperature of $22 \pm 2^\circ\text{C}$ and a relative humidity of $50 \pm 5\%$ to minimize the influence of environmental fluctuations on the experimental results [33]. The measurement methods and test parameters are summarized in Table 2.

Table 2: Parameters used for hardness and surface roughness testing.

Parameter	Description
Hardness Testing Method	Micro Vickers Hardness Test
Indentation Force (kgf)	10
Dwell Time (s)	10
Surface Roughness Measurement	JEDTO SRT-6100 Tester
Roughness Measurement Locations	Head, Middle, Tail

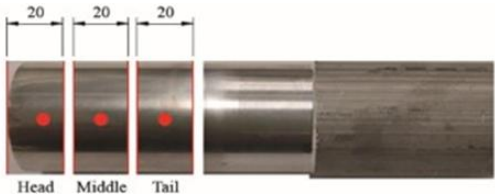


Fig. 2. Specimen Preparation for Hardness and Surface Roughness Measurement.

3. Results and Discussion

3.1Effect of Burnishing Feed Rate on Surface Roughness

The influence of burnishing feed rate on surface roughness was investigated under three spindle speed conditions: 200 rpm, 500 rpm, and 800 rpm, as illustrated in Fig. 3(a), Fig. 3(b), and Fig. 3(c). Each combination was tested at three contact pressures (1.0, 1.5, and 2.0 GPa), enabling evaluation of the interaction between feed rate and pressure.

At 200 rpm (Fig. 3(a)), surface roughness exhibited a consistent decline with increasing feed rate across all pressure levels. The lowest roughness, falling below 1.0 μm , was recorded at 2.0 GPa and 0.5 m/min feed rate. This trend suggests that at lower spindle speeds, prolonged contact duration promotes uniform plastic deformation, allowing smoother material flow and more effective asperity reduction. At 500 rpm (Fig. 3(b)), surface roughness demonstrated a nonlinear response. A minimum roughness was observed at a feed rate of 0.3 m/min, especially under higher pressures. However, further increasing the feed rate to 0.5 m/min resulted in a notable rise in roughness, particularly at 1.0 GPa. These findings indicate that moderate feed rates can enhance surface finish under intermediate speeds, but excessive feed rates reduce tool-workpiece interaction time, leading to incomplete surface modification. At 800 rpm (Fig. 3(c)), surface roughness increased with feed rate under all pressure conditions. The highest roughness was observed at 1.0 GPa and 0.5 m/min, exceeding 4.0 μm . This behavior is attributed to reduced contact time and increased frictional heat, which limit effective plastic flow and may introduce thermal softening or surface irregularities.

Analysis of Variance (ANOVA) confirmed the statistical significance of feed rate on surface roughness ($P = 0.032$). The model yielded a coefficient of determination of $R^2 = 81.41\%$, indicating a strong correlation between the process parameters and the resulting surface quality. In summary, low feed rates are preferable at high spindle speeds to maintain surface integrity, while moderate feed rates (0.3 m/min) are optimal at intermediate speeds. At low speeds, surface roughness remains acceptably low even as feed rate increases, provided that sufficient contact pressure is applied. These insights reinforce the importance of multi-variable optimization to achieve a superior surface finish in precision burnishing operations

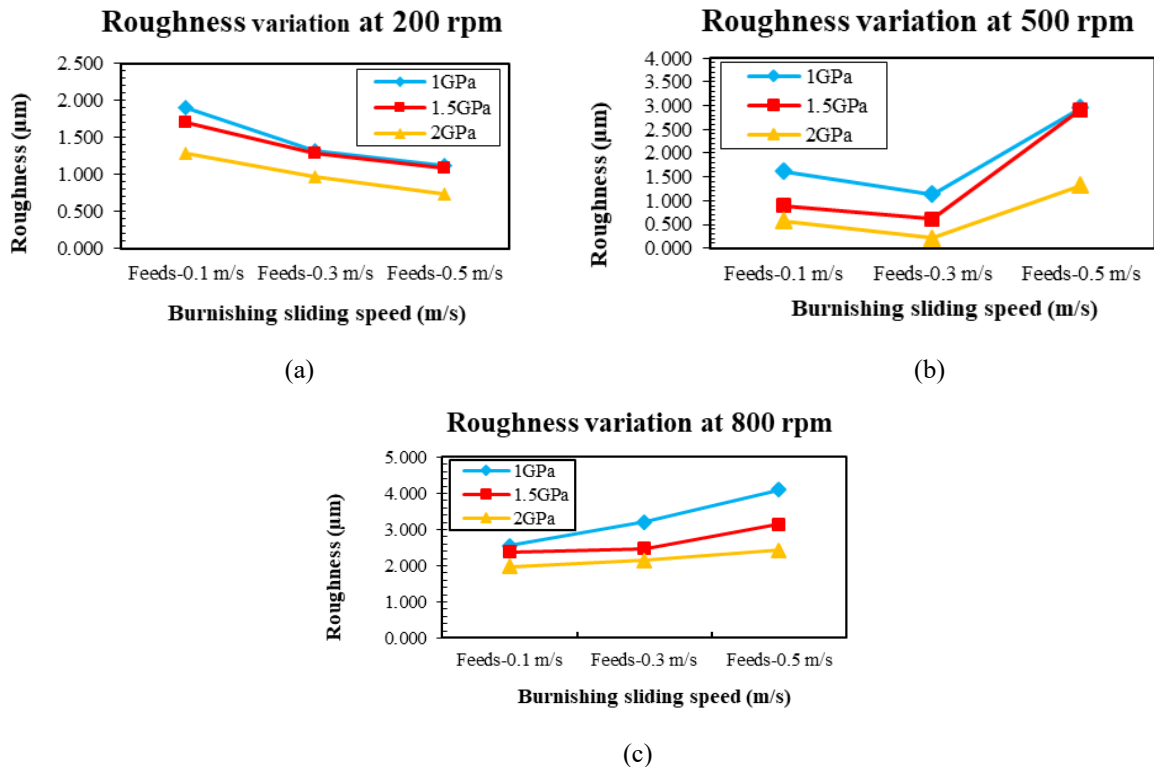


Fig. 3. Variation in Surface Roughness with Burnishing Feed Rate at Different Spindle Speeds: (a) 200 rpm, (b) 500 rpm and (c) 800 rpm.

3.2 Influence of Burnishing Feed Rate on Hardness

Building upon the analysis of surface roughness in this section explores the corresponding influence of burnishing feed rate on surface hardness under identical process conditions. The relationship between feed rate and hardness was examined at spindle speeds of 200 rpm, 500 rpm, and 800 rpm, with each test conducted under three levels of contact pressure (1.0, 1.5, and 2.0 GPa) and feed rates (0.1, 0.3, and 0.5 m/min). The resulting trends are presented in Fig.

4(a), Fig. 4(b), and Fig. 4(c). At 200 rpm (Fig. 4(a)), surface hardness increased with feed rate up to 0.3 m/min and then plateaued or slightly decreased at higher feed rates. The maximum hardness of 137.74 HV was recorded at 1.5 GPa and 0.3 m/min, indicating that moderate feed rates and pressure levels promote effective strain hardening without excessive heat generation. The longer contact duration at low spindle speeds enhances subsurface plastic deformation, leading to improved hardness. At 500 rpm (Fig. 4(b)), the combination of a 2.0 GPa pressure and 0.3 m/min feed rate resulted in the highest recorded hardness of 140.30 HV. This suggests that mid-range spindle speeds, coupled with high contact pressure, create optimal conditions for compressive plastic deformation and material densification. The improvement over lower-speed results demonstrates the beneficial interaction between increased dynamic force and plastic flow behavior. In contrast, at 800 rpm (Fig. 4(c)), a diminishing trend in hardness was observed across all pressure levels. The maximum hardness achieved was 128.02 HV at 2.0 GPa and 0.3 m/min. The decline is likely due to the reduced tool–workpiece interaction time and elevated frictional heat at high spindle speeds, which can soften the material surface and limit strain hardening. The thermal effect appears to counteract the benefits of higher pressure, resulting in diminished hardening performance.

Analysis of Variance (ANOVA) confirmed the statistical significance of the burnishing feed rate and its interaction with spindle speed and pressure ($P = 0.027$). The model yielded a high coefficient of determination ($R^2 = 84.52\%$), validating the strong correlation between the process parameters and measured hardness values. In summary, the results demonstrate that moderate spindle speeds (e.g., 500 rpm) and high burnishing pressures (2.0 GPa) provide the most favorable conditions for achieving superior surface hardness. Excessively high speeds reduce the effectiveness of the burnishing process due to reduced deformation time and potential thermal softening. These findings reinforce the importance of optimizing process parameters holistically to enhance both surface geometry and mechanical performance.

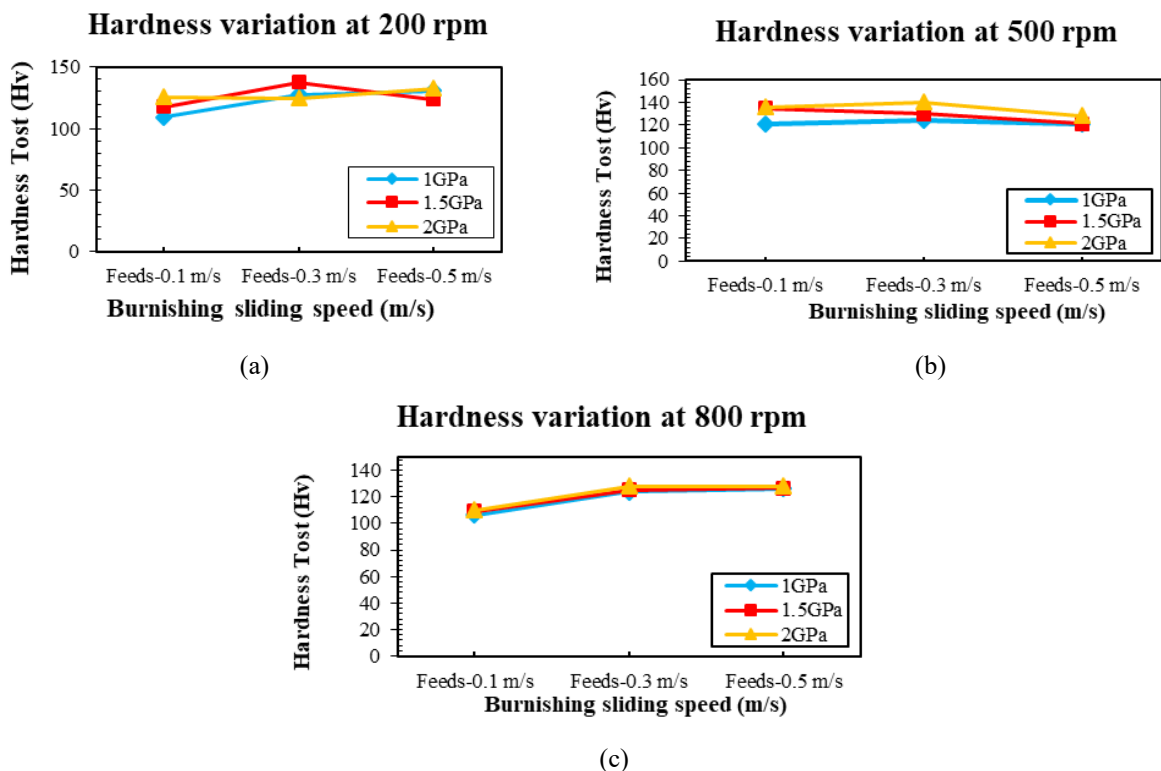


Fig. 4. Effect of Burnishing Parameters on Surface Hardness at Different Spindle Speeds: (a) 200 rpm, (b) 500 rpm, (c) 800 rpm.

3.3 Analysis of Variance for Surface Roughness

A comprehensive Analysis of Variance (ANOVA) was conducted to assess the effects of spindle speed, burnishing feed rate, and contact pressure, including their interactions, on surface roughness. The model demonstrated strong

explanatory power, with a coefficient of determination ($R^2 = 81.41\%$), indicating that the majority of the variation in surface roughness could be attributed to the selected process parameters. The linear effects revealed that spindle speed and contact pressure significantly influenced surface roughness, both yielding P-values of 0.000, while the effect of feed rate was not statistically significant ($P = 0.132$) within the examined range. This finding suggests that under controlled conditions, surface roughness is more sensitive to changes in spindle speed and pressure than to feed rate alone. Nonetheless, the importance of feed rate becomes evident when considering its interaction with other parameters. The two-way interaction between spindle speed and feed rate was highly significant ($P = 0.000$), indicating a synergistic relationship that influences surface finish outcomes. Additionally, the interaction between spindle speed and contact pressure also demonstrated significance ($P = 0.049$), suggesting that the combined influence of these two variables must be considered in optimization strategies. In contrast, the interaction between feed rate and pressure was not statistically significant ($P = 0.552$), implying a relatively weaker combined effect on surface quality.

Furthermore, the three-way interaction among spindle speed, feed rate, and pressure was found to be statistically significant ($P = 0.045$). This result reinforces the importance of adopting a multivariate approach in process optimization, as the combined effects of multiple parameters can substantially influence surface integrity. Such interactions, though sometimes subtle, can alter the material response and are particularly relevant in precision finishing processes. The statistical significance of the main and interaction effects underscores the need for integrated parameter tuning in burnishing applications. These results are consistent with previous studies, which have highlighted the dominant roles of spindle speed and applied pressure, while also acknowledging the context-dependent influence of feed rate when interacting with other process variables. In modern manufacturing environments, such multivariate interactions are increasingly addressed through advanced data-driven techniques, including Response Surface Methodology (RSM) and Artificial Intelligence-based optimization. A detailed summary of the ANOVA results is provided in Table 3, offering quantitative evidence for the relative contributions of each factor and their combinations in influencing surface roughness.

Table 3: ANOVA for Surface Roughness.

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	28	58.4124	2.0862	8.23	0.000
Blocks	2	0.0518	0.0259	0.10	0.903
Linear	6	38.2471	6.3745	25.14	0.000
Speeds (rpm)	2	25.3857	12.6928	50.07	0.000
Feeds (m/min)	2	1.0695	0.5347	2.11	0.132
Pressure (GPa)	2	11.7920	5.8960	23.26	0.000
2-Way Interactions	12	15.7021	1.3085	5.16	0.000
Speeds (rpm)*Feeds (m/min)	4	12.3183	3.0796	12.15	0.000
Speeds (rpm)*Pressure (GPa)	4	2.6061	0.6515	2.57	0.049
Feeds (m/min)*Pressure (GPa)	4	0.7777	0.1944	0.77	0.552
3-Way Interactions	8	4.4114	0.5514	2.18	0.045
Speeds (rpm)*Feeds (m/min)*Pressure (GPa)	8	4.4114	0.5514	2.18	0.045
Error	52	13.1828	0.2535		
Total	80	71.5952			

3.4 Optimal Burnishing Parameters

To determine the most effective combination of burnishing parameters for enhancing both surface finish and mechanical performance, a multi-variable optimization analysis was conducted. The goal was to identify process conditions that simultaneously minimize surface roughness and maximize surface hardness—two critical indicators of surface integrity and wear resistance. The optimal parameter combination was found to be a spindle speed of 500 rpm, a feed rate of 0.3 m/min, and a contact pressure of 2.0 GPa. Under these conditions, the lowest surface roughness ($0.372 \mu\text{m}$) and the highest hardness (140.30 HV) were obtained. It should be noted that although some runs (e.g., $R_a = 0.22 \mu\text{m}$) exhibited lower roughness individually, they did not correspond to maximum hardness. Therefore, the condition at 500 rpm, 0.3 m/min, and 2.0 GPa was selected as the practical optimum, since it achieved the best combined outcome of very low R_a ($0.372 \mu\text{m}$) and the highest hardness (140.30 HV). These results confirm that moderate spindle speeds, when paired with high compressive forces, enhance plastic deformation without generating excessive heat, thereby achieving a favorable balance between material densification and thermal stability. Statistical

validation was performed using ANOVA, where both spindle speed and contact pressure exhibited statistically significant influences ($P < 0.05$) on surface quality. The model also demonstrated high predictive capability, with a coefficient of determination ($R^2 = 86.74\%$), indicating that the selected parameters reliably explain the observed variations in roughness and hardness. Further insights were gained through Response Surface Methodology (RSM), which revealed nonlinear interactions among the process parameters. While RSM was referenced for statistical validation, the analysis in this study was primarily focused on factorial-based ANOVA and graphical evaluations. Nonlinear interactions among burnishing parameters were interpreted through ANOVA outcomes and response trends illustrated in Figs. 3–5, providing equivalent insight without constructing a separate polynomial RSM model. This underscores the inadequacy of one-factor-at-a-time approaches and highlights the necessity of simultaneous multi-factor optimization. The graphical summary in Fig. 5 visually illustrates the optimal parameter combination and its corresponding effect on minimizing surface roughness. To enhance interpretability and guide practical implementation, the relative influence of burnishing parameters was qualitatively evaluated based on ANN and factorial analysis results. Contact pressure was identified as the most dominant factor affecting surface roughness, followed by feed rate and spindle speed. Based on ANN-GA optimization and experimental validation, the recommended parameter ranges of 400–600 rpm spindle speed, 0.2–0.3 m/min feed rate, and 1.5–2.0 GPa pressure provide a practical balance between surface finish and hardness improvement.

These findings are consistent with prior studies that reported improvements in surface integrity under moderate spindle speeds and elevated burnishing pressures. However, the present study advances the existing literature by integrating factorial experimental design with robust statistical and RSM-based optimization, thus improving both the reliability and industrial applicability of the outcomes. In conclusion, the results reinforce the importance of precise process parameter tuning in achieving optimal burnishing outcomes. Such optimization contributes not only to superior surface finish but also to enhanced fatigue strength, load-bearing capacity, and tribological behavior. These improvements are particularly critical for high-precision industries such as aerospace, automotive, and biomedical engineering, where surface integrity directly impacts product performance and durability.

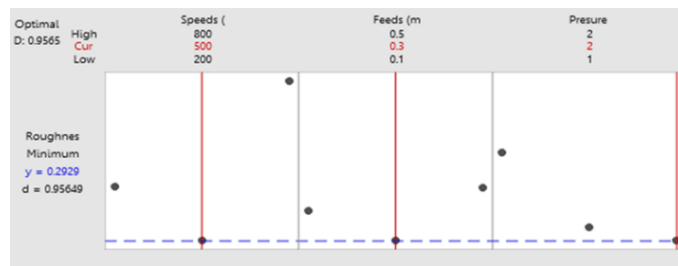


Fig. 5. Optimized Burnishing Parameters for Enhanced Surface Quality and Hardness.

3.5 Artificial Neural Network (ANN) Optimization

An Artificial Neural Network (ANN) was employed to model the relationship between the three primary burnishing parameters- spindle speed, feed rate, and burnishing force-and the resulting surface roughness. As shown in Fig. 6, the network is a feedforward architecture composed of an input layer, a hidden layer, and an output layer. Each neuron in the hidden layer computes a weighted sum of its inputs plus a bias term, then applies an activation function to capture the nonlinear interaction among variables. Mathematically, the output of each neuron in the hidden layer can be expressed as

$$p_j = f\left(\sum_{i=1}^n \beta_{ij} x_i + b_j\right), \quad (1)$$

where x_i represents the input parameters, β_{ij} denotes the weight from the i -th input to the j -th neuron, b_j is the bias term, and $f(\cdot)$ is the activation function. The final network output $\hat{y}$, corresponding to the predicted surface roughness, is then computed by summing the weighted outputs of all hidden neurons plus an output-layer bias, typically given by

$$\hat{y} = \sum_{j=1}^m \beta_j^{(out)} p_j + b^{(out)}, \quad (2)$$

where m is the number of neurons in the hidden layer, $\beta_j^{(out)}$ denotes the weight connecting the j -th hidden neuron to the output neuron, and $b^{(out)}$ is the output-layer bias. Through an iterative training process, these weights and biases are adjusted to minimize the prediction error, enabling the ANN to accurately map the input parameters to the corresponding surface roughness values.

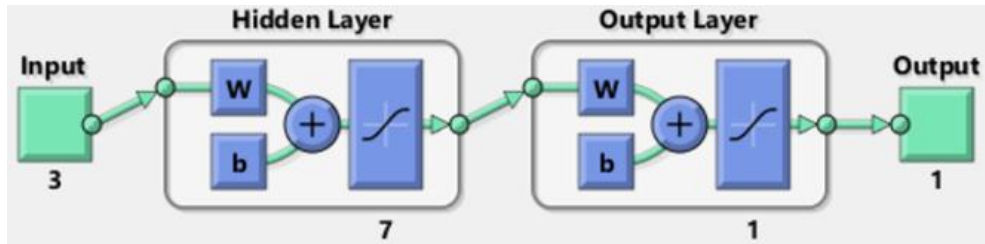


Fig. 6. Schematic Representation of the Artificial Neural Network (ANN) Model.

A hybrid optimization approach combining an Artificial Neural Network (ANN) with a Genetic Algorithm (GA) is implemented to further refine the prediction and optimization of burnishing parameters for surface quality improvement. In this approach, a feedforward neural network with a single hidden layer of 7 neurons is developed to model the nonlinear relationship between the input process parameters- spindle speed, feed rate, and burnishing pressure- and the resulting surface roughness. To ensure robustness in training, the dataset is split into 80% for training, 10% for validation, and 10% for testing.

The GA is then applied to search for the optimal combination of process parameters, with the specific parameter bounds and GA settings summarized in Table 4. As shown, the input space is constrained by lower bounds [200, 0.1, 1] and upper bounds [800, 0.5, 2] for spindle speed (rpm), feed rate (m/min), and pressure (GPa), respectively. The population size is set to 50, with a maximum of 50 generations, a Gaussian mutation function (mutation rate = 0.01), a crossover fraction of 90%, and a 1% mutation probability. Additionally, the GA displays iterative progress and uses a plotting function to monitor the best fitness value. The integration of ANN and GA allows the model not only to predict surface roughness accurately, as demonstrated by performance metrics such as RMSE, MAE, and R^2 , but also to effectively optimize the process parameters for an enhanced surface finish.

Table 4: Genetic Algorithm (GA) Optimization Parameters.

Parameter	Value
The range of bounds	Lower [200, 0.1, 1] Upper [800, 0.5, 2]
GA Population Size	50
GA Maximum Generations	50
Mutation Function	Gaussian (0.01)
Crossover Fraction	90 %
Mutation probability	1%

Summarizes the experimental results from the burnishing process, providing both the measured surface roughness values and the corresponding predictions from the ANN model. Each experimental trial is identified by a standard order and run order, with the input parameters- spindle speed (rpm), feed rate (m/min), and burnishing pressure (GPa)- specified for each run. The "Output" column presents the actual measured surface roughness in micrometers, while the "ANN model" column displays the predicted values obtained from the feedforward neural network. The strong concordance between the measured and predicted values is quantitatively demonstrated by the performance metrics: a root mean square error (RMSE) of 0.22, a mean absolute error (MAE) of 0.15, and a coefficient of determination (R^2) of 0.9513. These results indicate that the ANN model effectively captures the complex, nonlinear relationships between the input parameters and surface roughness, thus validating its high predictive accuracy. Overall, the data in Table 5 confirm the efficacy of the ANN model as a robust tool for process optimization in burnishing applications.

Table 5: Experimental results.

Std Order	Run Order	Input			Output Surface roughness (μm)	ANN model Surface roughness (μm)
		speeds (rpm)	Feed (m/min)	Pressure (GPa)		
48	1	800	0.10	2.0	1.97	1.924
42	2	400	0.25	2.0	0.22	0.680
51	3	800	0.25	2.0	2.43	2.348
20	4	800	0.10	1.5	2.38	2.127
28	5	200	0.10	1.0	1.91	1.290
27	6	800	0.50	2.0	2.15	2.246
24	7	800	0.25	2.0	2.43	2.348
2	8	200	0.10	1.5	1.71	1.524
43	9	400	0.50	1.0	2.95	2.996
40	10	400	0.25	1.0	1.32	1.335
29	11	200	0.10	1.5	1.68	1.524
14	12	400	0.25	1.5	0.61	0.862
31	13	200	0.25	1.0	1.31	1.371
13	14	400	0.25	1.0	1.14	1.335
36	15	200	0.50	2.0	0.97	0.403
54	16	800	0.50	2.0	2.16	2.246
39	17	400	0.10	2.0	0.57	0.621
18	18	400	0.50	2.0	1.32	1.196
19	19	800	0.10	1.0	2.55	2.541
10	20	400	0.10	1.0	1.62	1.564
22	21	800	0.25	1.0	4.09	4.101
6	22	200	0.25	2.0	0.98	0.613
53	23	800	0.50	1.5	2.47	2.526
46	24	800	0.10	1.0	2.55	2.541
26	25	800	0.50	1.5	2.47	2.526
25	26	800	0.50	1.0	3.71	3.709
50	27	800	0.25	1.5	3.64	3.588
38	28	400	0.10	1.5	0.9	0.941
9	29	200	0.50	2.0	0.97	0.403
21	30	800	0.10	2.0	1.97	1.924
35	31	200	0.50	1.5	1.09	1.148
3	32	200	0.10	2.0	0.73	0.633
15	33	400	0.25	2.0	0.22	0.680
17	34	400	0.50	1.5	2.92	2.823
12	35	400	0.10	2.0	0.57	0.621
52	36	800	0.50	1.0	3.77	3.709
1	37	200	0.10	1.0	1.93	1.290
33	38	200	0.25	2.0	0.93	0.613
49	39	800	0.25	1.0	4.00	4.101
4	40	200	0.25	1.0	1.30	1.371
16	41	400	0.50	1.0	2.95	2.996
45	42	400	0.50	2.0	1.33	1.196
34	43	200	0.50	1.0	1.14	1.276
44	44	400	0.50	1.5	3.02	2.823
23	45	800	0.25	1.5	3.65	3.588
11	46	400	0.10	1.5	0.91	0.941
5	47	200	0.25	1.5	1.26	1.264
41	48	400	0.25	1.5	0.58	0.862
8	49	200	0.50	1.5	1.10	1.148
37	50	400	0.10	1.0	1.60	1.564

Std Order	Run Order	Input			Output Surface roughness (μm)	ANN model Surface roughness (μm)
		speeds (rpm)	Feed (m/min)	Pressure (GPa)		
32	51	200	0.25	1.5	1.30	1264
30	52	200	0.10	2.0	0.71	0.633
47	53	800	0.10	1.5	2.36	2.127
7	54	200	0.50	1.0	1.08	1.276
RMSE						0.2200
MAE						0.1500
R^2						0.9513

The performance of the Artificial Neural Network (ANN) model in predicting surface roughness was evaluated using regression plots, as shown in Fig. 7, which illustrates the results for the training, validation, testing, and overall datasets. In each subplot, the horizontal axis represents the experimentally measured surface roughness (target), while the vertical axis shows the ANN-predicted output. The diagonal line denotes the ideal scenario in which predictions perfectly match the measured values. The model demonstrated high accuracy, with correlation coefficients (R) of 0.98444 for the training set, 0.95805 for the validation set, 0.65828 for the testing set, and 0.97641 for the combined dataset. These values confirm the ANN model's ability to capture the underlying nonlinear relationships between spindle speed, feed rate, and contact pressure. While the testing set exhibits a relatively lower R -value, it still indicates reasonable generalization performance, suggesting the model is neither over-fitted nor under-fitted. It should be noted that the dataset size (~ 81 points) is relatively modest for ANN training, which contributes to the lower correlation observed in the test set ($R^2 = 0.658$). Nevertheless, the ANN-GA framework demonstrates clear feasibility in modeling nonlinear parameter interactions in burnishing and is presented as a proof-of-concept study. Future research will focus on expanding the dataset and applying advanced validation techniques to further enhance robustness and generalization.

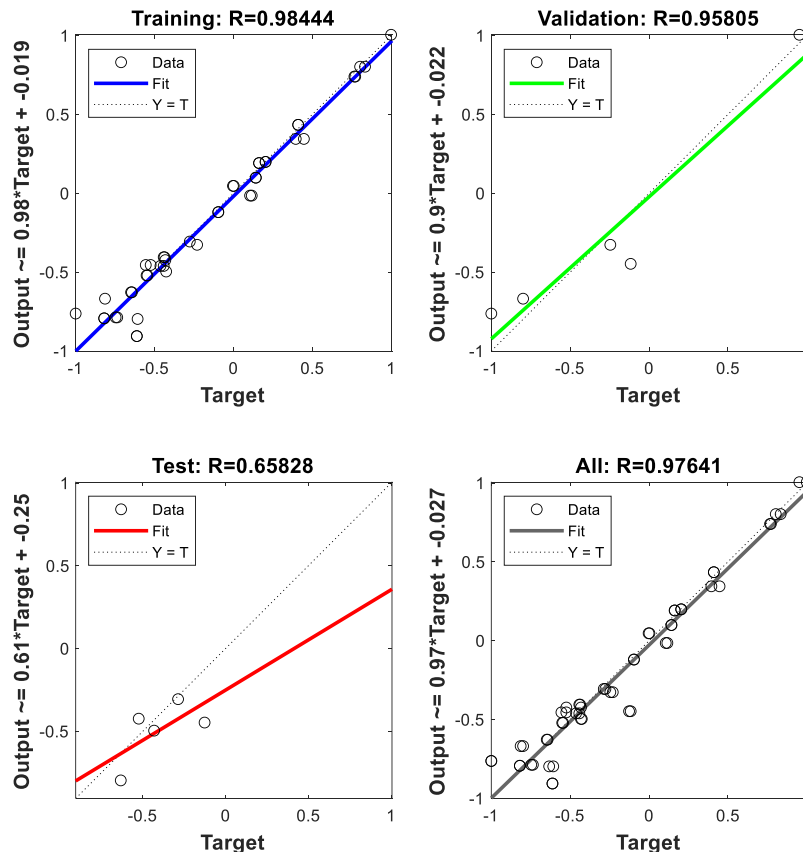


Fig. 7. Experimental and prediction (ANN) data regression plot.

In addition to regression performance, the convergence behavior of the Genetic Algorithm (GA) used for optimizing the ANN model was analyzed, as depicted in Fig. 8. The plot illustrates the fitness evolution over 50 generations, with the blue curve representing the best fitness in each generation and the orange curve representing the population's mean fitness. The rapid decline in the best fitness to 1.44279×10^{-9} , along with the stabilization of the mean fitness around 6.13319×10^{-7} , indicates that the GA efficiently searched the solution space and identified near-optimal parameter combinations at an early stage. Moreover, the narrow gap between the best and average fitness in the later generations confirms a strong convergence of the population toward high-quality solutions. This outcome underscores the robustness of the ANN-GA hybrid model in predicting surface roughness and highlights its potential for optimizing complex multi-parameter manufacturing processes such as burnishing.

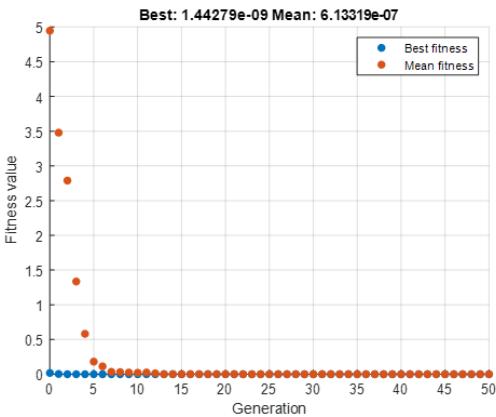


Fig. 8. ANN-GA Optimization Convergence.

3.6 Discussion of Results

The best parameter combination, as summarized in Table 6, consists of a spindle speed of 799.02 rpm, a feed rate of 0.31 m/min, and a burnishing pressure of 1.48 GPa, which together yield a predicted surface roughness of 4.00 μm . The ANN-GA predicted optimum (799.02 rpm, 0.31 m/min, 1.48 GPa) yielded $R_a = 4.00 \mu\text{m}$, which is higher than several measured values. This outcome reflects trade-off behavior at high spindle speeds rather than a global R_a minimum, underscoring the importance of extending the framework toward multi-objective optimization in future studies. The ANN-GA model in this study focused only on roughness optimization, with hardness considered as an experimental outcome. Incorporating hardness into a true multi-objective framework, such as Pareto-based optimization, is identified as an important future direction. This outcome illustrates how effectively the ANN-GA framework explores the burnishing parameter space to identify near-optimal conditions. Notably, operating close to the upper limit of spindle speed, combined with a moderate feed rate and an intermediate pressure, aligns with broader findings from earlier analyses. In particular, the interplay between spindle speed and pressure appears crucial for achieving a refined surface, while the feed rate helps modulate both contact time and deformation depth. Consequently, these results underscore the capability of the integrated ANN-GA method to handle the complex, nonlinear interactions among burnishing parameters and provide a robust data-driven basis for process optimization. It should be emphasized that RSM was employed for statistical validation of the factorial dataset, whereas ANN-GA provided predictive flexibility and optimization beyond the tested grid. This dual approach combined the transparency of RSM with the adaptability of ANN-GA, thereby reinforcing the reliability and novelty of the proposed framework in burnishing applications.

Table 6: The best outcomes were achieved through the ANN-GA approach.

Speed (RPM)	Feed (m/min)	Pressure (GPa)	Predicted Surface Roughness (μm)
799.02	0.31	1.48	4.00

Furthermore, the graphical comparison of the measured surface roughness with the ANN-predicted values, as illustrated in Fig.9, reinforces these findings. In this figure, the horizontal axis represents the sequence of experimental trials, and the vertical axis indicates the surface roughness in micrometers. The close alignment between the ANN’s predictions (red line) and the actual measurements (black circles) for most samples demonstrates that the model

effectively captures the underlying relationships among spindle speed, feed rate, and burnishing pressure. Although minor discrepancies are observed at a few points, these deviations are minimal and consistent with the previously reported performance metrics (RMSE, MAE, and R^2), thereby confirming the reliability of the ANN model as a predictive tool for guiding the selection of burnishing parameters to achieve the desired surface finish.

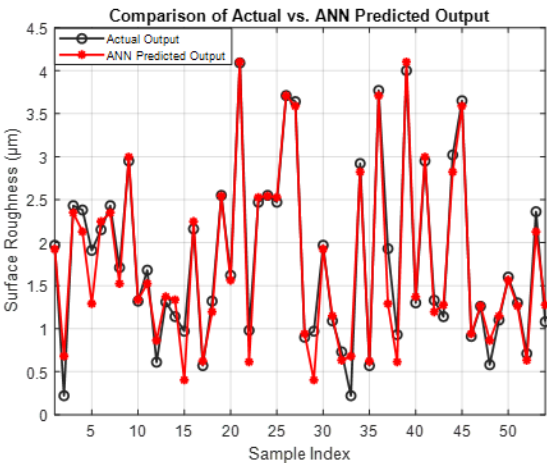


Fig. 9. Comparison of Actual vs. ANN-Predicted Surface Roughness.

4. Conclusions

This study presents a comprehensive investigation and hybrid optimization approach for enhancing the surface quality and hardness of 6061-T6 aluminum alloy through the burnishing process. A General Full Factorial Experimental Design was employed to examine the effects of spindle speed, feed rate, and contact pressure on surface roughness and hardness. Experimental results revealed that spindle speed and burnishing pressure significantly influence surface finish and mechanical properties, while feed rate plays a secondary yet interactive role, particularly in combination with other parameters. The optimal condition identified through experimental analysis-500 rpm, 0.3 m/min, and 2.0 GPa-yielded the best practical results, with a minimum surface roughness of 0.372 μm and a maximum surface hardness of 140.30 HV. Furthermore, the developed Artificial Neural Network–Genetic Algorithm (ANN-GA) framework successfully modeled the nonlinear interactions among parameters and predicted surface roughness with high accuracy ($R^2 = 0.9513$, RMSE = 0.22, MAE = 0.15).

The ANN-GA also proposed a theoretical optimum at 799.02 rpm, 0.31 m/min, and 1.48 GPa, predicting a surface roughness of 4.00 μm , thus illustrating the model's capability in exploring broader parametric conditions. The results confirmed that moderate spindle speeds and high pressures are critical to achieving superior surface integrity, while feed rate governs contact time and deformation characteristics. The integration of statistical analysis (ANOVA), RSM, and AI-based optimization provides a robust, data-driven pathway to eliminate trial-and-error approaches in industrial settings.

This research offers valuable insights for precision manufacturing, particularly in high-performance applications in aerospace, automotive, and biomedical sectors. Future work may focus on extending the optimization framework to include multi-objective optimization, multi-pass burnishing, real-time parameter control, and adaptive learning models to further refine the process and broaden its applicability across diverse materials and geometries.

Nomenclature

- P_j output of the j -th neuron in the hidden layer
- $\hat{y}$ The final network output
- x_i input parameters
- β_{ij} weight from the i -th input to the j -th neuron

b_j	bias term
$f(\cdot)$	activation function
$\hat{y}$	The final network output
$\beta_j^{(out)}$	weight connecting the j -th hidden neuron to the output neuron
$b^{(out)}$	output-layer bias

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