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Predictive modeling of shearing power in turning operations using Response Surface Methodology (RSM) and Artificial Neural Networks (ANN)

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Abstract

Machining parameter optimization is a major issue in modern manufacturing, owing to its direct impact on efficiency, stability, and product quality. Predictive modeling and optimization of shearing power in turning operations under constraints was the aim of this study, where a comparative evaluation of the usefulness of Response Surface Methodology (RSM) and Artificial Neural Networks (ANN) methods is provided. Three major factors affecting shearing power and machining behaviour are the concern of this study: depth of cut, cutting speed, and feed rate. Using well-planned and executed experiments, the data necessary to construct predictive models was gathered. Using Response Surface Methodology (RSM), equations that describe the intricate interaction of these variables were obtained. Artificial Neural Networks (ANN) was a very effective means of modeling the intricate patterns in the data, giving a more detailed image of the machining process. When the two techniques were compared against each other, Artificial Neural Networks (ANN) emerged as the better predictive model, delivering spot-on predictions of shearing power with impressively low error margins and robust regression performance. While both models showed statistical effectiveness, ANN's capability for capturing the intricate relationships between machining variables was unparalleled. This implies that ANN could revolutionize process optimization, unlocking new levels of machining efficiency. By tapping into the potential of data-driven decision-making, this work fosters smart manufacturing, enabling machine processes that are more agile, responsive, and self-tuning than ever before.

Keywords: *Shearing Power, Turning, Machining, RSM, ANN.*

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1. INTRODUCTION

In today's manufacturing landscape, the demand for greater precision, efficiency, and adaptability has led to increased attention on machining processes operating under constrained conditions (Imad, 2022). Among these, turning remains a key operation for producing high-accuracy components used in critical industries such as aerospace, automotive, and biomedical engineering (Singh & Singh, 2023). However, turning is highly sensitive to adjustments in process variables like depth of cut, cutting speed, and feed rate (Bazaz et al., 2023; Ragai et al., 2022). These factors have a direct influence on important outcomes such as thrust force, shearing power, tool wear, and surface finish (Kuang et al., 2022). The challenging nature of constrained machining which is often shaped by limitations in allowable cutting forces, heat dissipation, material properties, and dynamic interactions between the tool and workpiece, has driven the development of more advanced predictive and optimization tools (Mativenga et al., 2024). Traditional modeling approaches, such as empirical regression and analytical methods, while widely applied, often lack the flexibility to handle nonlinear behavior or the complex interplay among multiple variables (Khan et al., 2020; Bhowmik et al., 2019).

Response Surface Methodology (RSM) has proven to be a very effective statistical method in machining optimization, offering deep insights into the interaction of input variables and their impact on system behavior. Founded on second-order polynomial models, RSM is effective at capturing main effects, along with very subtle interactions. In addressing systems of relatively linear or slightly nonlinear trends it has been able to show its strength, and it has become the first choice in an overwhelming majority of machining applications (Asiltürk et al., 2021). Response Surface Methodology (RSM) has been successfully used to optimize machining responses like surface roughness, material removal rate, and cutting force. Artificial Neural Networks (ANN), by contrast, take a more generalized method, learning from examples without being limited by known equations. This makes ANN extremely powerful at revealing intricate, nonlinear relationships in large data sets, a hugely desirable attribute for modeling a wide variety of machining conditions. Applications of ANN have been amply documented in a wide variety of machining contexts, from foreseeing bead geometry in TIG welding (Kesse et al., 2020), predicting weld penetration (Chandrasekhar et al., 2025), and equating tensile strain in welded joints (Igbinake, 2025). Perhaps the greatest advantage of ANN is the way it deals with nonlinear, real-world process conditions where variables are all interrelated. And experiments prove that it surpasses RSM in precise prediction and generalization to new data. For instance, Kshirsagar et al. (2020) reported that the integration of ANN and evolutionary algorithms led to phenomenal performance improvement in the optimization of TIG welding parameters, particularly in predicting bead features and mechanical properties. Similarly, Costa et al. (2023) found that ANN models were extremely effective in revealing complex interactions in machining data and surpassed RSM in the experiment.

Despite significant advancements, there is one critical knowledge gap in the field of constrained turning operations; shearing power prediction and maximization. Previous research was largely focused on individual response outcomes, thrust force or surface finish, and failed to consider the complex interaction between different responses against constrained situations. The current work bridges this gap directly by developing a predictive model based on the complementary strengths of RSM and ANN. By combining RSM's strength for uncovering early trends and ANN's strength for non-linear dynamics, an enhanced and robust model can be developed. Together, they provide an integrated complementary approach to constrained turning conditions. The double-model approach is in line with changing trends towards smart manufacturing and Industry 4.0, where intelligent, knowledge-based technologies are increasingly crucial for process optimization, design for minimal waste, and maximization of resources in real-time manufacturing systems.

2. METHODOLOGY

2.1 Research Design

The research design of this study is developed to deal systematically with the prediction and optimization challenge of machining parameters in constrained situations in turning operations. The study design is quantitative in nature, and experimental data collection and high-level predictive modeling are being undertaken. The general aim is to examine the influence of machining parameters (cutting depth, cutting velocity, and feed rate) on the main machining response (shearing power) that in turn will lead to the establishment of predictive models through Response Surface Methodology (RSM) and Artificial Neural Networks (ANN).

2.2 Data Collection

The data is collected for each experimental run, and machining parameters are varied systematically based on experimental design. The data are used to construct the basis of the modeling effort, including precise measurements of shearing force. For accuracy and reliability, instruments are of high quality and each trial is replicated to include any variability. The experiment was designed carefully to create consistency and accuracy. Order trials was repeated and randomized systematically to minimize environmental influences and measurement error. Randomizing order and repeating every combination of level of factors multiple times permits the verification that the results are unbiased and reliable. By such means, precise and reproducible data collection is obtained under well established and controlled machining conditions, constituting the appropriate basis for predictive modeling and optimization phases of this work.

2.3 Design of Experiments (DOE)

In this work, the intricacies of machine work were studied. A structured approach known as Design of Experiments (DOE) was employed to investigate the relationship between critical machining parameters (depth of cut, cutting speed, and feed rate) and the power consumed during cutting operations. This methodology enabled a systematic examination of how these variables interact, allowing the identification of significant effects that might otherwise remain undetected. By utilizing the well-defined framework provided by DOE, it became possible to analyze seemingly disordered data and isolate the fundamental forces that influence machining performance outcomes.

2.4 Response Surface Methodology (RSM)

The study commenced with the application of Response Surface Methodology (RSM), which facilitated the development of mathematical models to evaluate the individual effects of key process variables. RSM also made it possible to observe how these variables interact and influence one another. Its strength lies in its ability to uncover complex interdependencies that may not be immediately apparent. By examining how operational changes affect outcomes, RSM serves as a powerful tool for identifying trends, critical points, and providing actionable insights. It is particularly effective for interpreting underlying patterns within noisy or complex datasets. In this investigation, RSM functioned as the primary modeling framework. Predictive equations were constructed to accurately represent the contribution of each factor and their interactions. Based on the experimental data, a mathematical model was formulated to estimate shearing power as a function of three machining parameters: depth of cut (A), cutting speed (B), and feed rate (C). The model, expressed in Equation 1, includes linear, quadratic, and interaction terms. To assess the statistical relevance of each term, Analysis of Variance (ANOVA) was performed, allowing the model to remain both concise and statistically valid. Diagnostic evaluations, including residual analysis and goodness-of-fit tests, were conducted to ensure model accuracy and reliability. With the validated model in place, RSM was then employed to optimize the machining conditions, ultimately identifying the parameter settings that yield the most efficient performance.

$$Y = \beta_0 + \beta_1 A + \beta_2 B + \beta_3 C + \beta_{11} A^2 + \beta_{22} B^2 + \beta_{33} C^2 + \beta_{12} AB + \beta_{13} AC + \beta_{23} BC + \epsilon \qquad \ldots\ldots\ldots\ldots\ldots 1$$

where:

- β_0 is the intercept,
- β_1, β_2, β_3 represent the main effects,
- β_{11}, β_{22}, β_{33} represent the squared terms, and
- β_{12}, β_{13}, β_{23} represent interaction effects.

2.5 Artificial Neural Networks (ANN)

Artificial Neural Network (ANN) models were developed to complement the Response Surface Methodology (RSM) by capturing complex, nonlinear relationships that RSM might not fully detect. These models learned from experimental data and were structured using a typical feedforward architecture consisting of an input layer, one or more hidden layers, and an output layer. The input layer received machining parameters—depth of cut, cutting speed, and feed rate—while the hidden layers processed nonlinear interactions, and the output layer predicted shearing power. To train the network and mitigate overfitting, the dataset was divided into training and validation subsets. During training, backpropagation was employed to iteratively adjust weights and biases, minimizing the mean squared error (MSE) between predicted and actual values. Key hyperparameters, such as the number of hidden layers, neurons per layer, learning rate, and activation functions, . were fine-tuned using grid search and cross-validation techniques to improve the model's generalization capability. Once trained, the ANN's performance was evaluated using Root Mean Square Error (RMSE) and the coefficient of determination (R^2) on the test data. The results demonstrated that the ANN effectively mapped input conditions to machining responses with high accuracy, confirming its advantage over traditional linear or polynomial-based modeling approaches.

2.6 Model Comparison and Validation

Both RSM and ANN was put to series of experiments to ensure their efficiency. R^2 values were calculated to assess the predictive validity of the models and to compare the performance of the two modeling approach, highlighting their respective strengths and limitations. To further validate the models, cross-validation techniques were applied, ensuring consistency and reliability across the datasets. These validation steps confirmed the robustness of the findings under varying data conditions. This study effectively integrates the strengths of both empirical experimentation and advanced modeling to address complex challenges in metal cutting operations. By combining the statistical rigor of Response Surface Methodology (RSM) with the adaptive learning capabilities of Artificial Neural Networks (ANN), a comprehensive modeling framework was established that leverages both numerical precision and pattern recognition. This hybrid approach not only fulfills the objectives of the study but also provides practical insights that can be applied to a wide range of machining scenarios.

3. RESULTS

3.1 Experimental Results

The experimental findings so obtained for this investigation offer an overall picture of interrelationships among the principal machining variables, i.e., depth of cut, cutting speed, and feed rate, and their influence on the response variable, i.e., shearing power. This kind of information is essential for building predictive models, optimizing machining conditions, and realizing the subtle interactions involved during the turning process. The results, summarized in Table 1, form the foundation for subsequent model building and analysis in this study

Table 1: Experimental Data of Shearing Power Based on Varying Parameters

Std	Run	Factor 1	Factor 2	Factor 3	Response
		A:Depth of cut	B:Cutting Speed	C:Feed Rate	Shearing power
		mm	m/min	mm/rev	W
14	1	0.63	225	0.17	532.7
10	2	0.63	225	0.17	599.33
5	3	0.63	225	0.17	532.7
9	4	0.63	225	0.17	695.33
18	5	0.25	300	0.25	1216.2
6	6	0.63	225	0.17	695.33
15	7	0.63	225	0.17	532.7
11	8	0.25	150	0.1	521
12	9	0.63	351.13	0.17	908.6
17	10	1	300	0.25	403.05
20	11	0.63	98.87	0.17	589
2	12	0.01	225	0.17	695.33
19	13	1	300	0.1	724.8
3	14	0.63	225	0.3	695.33
8	15	1	150	0.25	620.48
16	16	1	150	0.1	1129
1	17	0.63	225	0.05	1216.2
13	18	0.25	150	0.25	332
7	19	1.26	225	0.17	488
4	20	0.25	300	0.1	1321

Table 1 illustrates the variations in machining responses obtained by systematically adjusting the machining parameters. These data serve as the baseline for predictive modeling and optimization processes.

Table 2 presents the Sequential Model Sum of Squares for Shearing Power, revealing how each set of model terms contributes to explaining variation in the response. The Mean vs. Total term has the largest sum of squares (1.044E+07), establishing the baseline variation in shearing power. Adding linear terms for individual factors (such as depth of cut, cutting speed, and feed rate) explains additional variation, with a sum of squares of 5.171E+05, an F-value of 2.67, and a p-value of 0.0827, suggesting limited significance for linear terms alone. The addition of two-factor interaction (2FI) terms significantly improves the model, with a sum of squares of 7.112E+05, an F-value of 9.58, and a p-value of 0.0013, indicating meaningful interaction effects among the machining parameters. Quadratic terms further enhance the model's fit, with a sum of squares of 2.843E+05, a high F-value of 25.26, and a very significant p-value of < 0.0001, justifying the inclusion of quadratic effects. In contrast, cubic terms add minimal explanatory power, with a sum of squares of only 5772.96, an F-value of 0.1819, and a p-value of 0.9576, indicating that further terms would not meaningfully improve the model. The residual variance remains relatively small (31740.30), supporting the adequacy of the quadratic model for capturing significant effects on shearing power.

Table 2: Sequential Model Sum of Squares for Shearing Power

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Mean vs Total	1.044E+07	1	1.044E+07			
Linear vs Mean	5.171E+05	3	1.724E+05	2.67	0.0827	
2FI vs Linear	7.112E+05	3	2.371E+05	9.58	0.0013	
Quadratic vs 2FI	**2.843E+05**	**3**	**94774.48**	**25.26**	**< 0.0001**	**Suggested**
Cubic vs Quadratic	5772.96	5	1154.59	0.1819	0.9576	Aliased
Residual	31740.30	5	6348.06			
Total	1.199E+07	20	5.994E+05			

By employing sequential SS, the analysis provides a clearer understanding of the individual and combined contributions of each factor and interaction. This method also highlights which terms contribute significantly to the model and informs further model refinement for optimal predictive accuracy.

Table 3 presents the ANOVA for the quadratic model used to predict shearing power. The model itself is highly significant ($F = 44.80$, $p < 0.0001$), which means it does a good job of explaining the variations in shearing power. The machining parameters can be thought of as interacting components in a mechanical system were each contributes differently to the final outcome. Among these, Feed Rate (C) emerges as the most influential factor, comparable to the engine driving a vehicle, with a highly significant effect indicated by a p-value < 0.0001. Cutting Speed (B) also plays a vital role, similar to adjusting gears to achieve optimal performance, as reflected by its p-value of 0.0043. In contrast, Depth of Cut (A), while contributing to the overall process much like the mass of the vehicle influences dynamics, exhibits a weaker individual effect in this study, with a p-value of 0.0860. Additionally, interaction terms such as Depth of Cut × Feed Rate (AC) and Cutting Speed × Feed Rate (BC) demonstrate significant or near-significant contributions, suggesting that the combined influence of these parameters further shapes the shearing power observed. Interestingly, the squared terms like A^2 don't make much of a difference ($p = 0.9813$), indicating that the relationship between Depth of Cut and shearing power isn't more complex than initially assumed. Lastly, the lack of fit isn't significant ($p = 0.9576$), so the model fits well and captures the important factors that affect shearing power.

Table 3: ANOVA for Quadratic model for Shearing power

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	1.513E+06	9	1.681E+05	44.80	< 0.0001	significant
A-Depth of cut	13605.22	1	13605.22	3.63	0.0860	
B-Cutting Speed	50555.09	1	50555.09	13.48	0.0043	
C-Feed Rate	2.895E+05	1	2.895E+05	77.17	< 0.0001	
AB	6.655E+05	1	6.655E+05	177.39	< 0.0001	
AC	36053.78	1	36053.78	9.61	0.0112	
BC	9675.44	1	9675.44	2.58	0.1394	
A^2	2.16	1	2.16	0.0006	0.9813	
B^2	44679.30	1	44679.30	11.91	0.0062	
C^2	2.539E+05	1	2.539E+05	67.68	< 0.0001	
Residual	37513.25	10	3751.33			
Lack of Fit	5772.96	5	1154.59	0.1819	0.9576	not significant
Pure Error	31740.30	5	6348.06			
Cor Total	1.550E+06	19				

Equations 2 represent the quadratic models for various machining parameters, showing how factors like depth of cut (A), cutting speed (B), and feed rate (C) influence the shearing power. The equation includes linear, interaction, and squared terms for the factors. For instance, in Equation 2, the response is influenced by linear terms (e.g., A, B, C), interaction terms (e.g., AB, AC, BC), and quadratic terms (e.g., A^2, B^2, C^2), indicating that the relationship between the factors and the response is nonlinear. These models provide insight into how each factor and their interactions impact the outcomes, which is useful for optimizing the machining process.

$$Shearing\ power = 456.446 + 2{,}547.15A + 2.47241B - 10{,}249.6C - 10.2543AB - 2{,}384.66AC + 6.17687BC + 2.79296A^2 + 0.00989295B^2 + 23{,}991.7C^2 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 2$$

Table 4 provides fit statistics for the quadratic model predicting shearing power, showing high accuracy and reliability. The standard deviation of 61.25 around a mean shearing power of 722.40 suggests controlled variability in the model predictions. An R^2 of 0.9758 indicates that the model explains 97.58% of the variability in shearing power, with an adjusted R^2 of 0.9540 confirming model robustness after adjusting for predictor count. The predicted R^2 of 0.9405 highlights strong predictive performance on new data. An adequate precision of 22.5145 indicates a high signal-to-noise ratio, validating the model's capability to provide dependable predictions, and the coefficient of variation (C.V.) of 8.48% demonstrates moderate consistency.

Table 4: Fit Statistics for Shearing power

Std. Dev.	61.25	**R^2**	0.9758
Mean	722.40	**Adjusted R^2**	0.9540
C.V. %	8.48	**Predicted R^2**	0.9405
		Adeq Precision	22.5145

Figure 1 illustrates the normal plot of residuals for shearing power. This plot is used to assess whether the residuals from the regression model for shearing power follow a normal distribution, which is an assumption for validating the model's adequacy. If the residuals closely follow the reference line in the plot, it indicates that the model fits the data well, and the assumption of normality holds. Any major deviations from the line would suggest non-normality, indicating potential issues such as outliers or model mis-specification. A well-aligned plot supports the use of the model for reliable shearing power predictions.

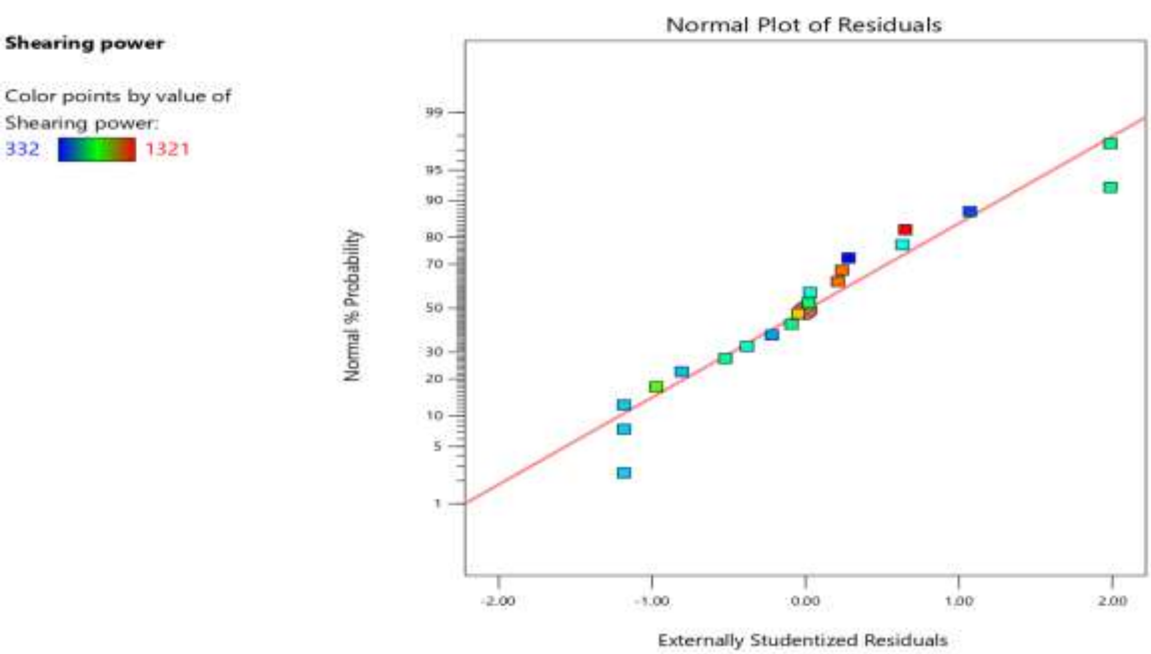

Figure 1: Normal plot of residuals for Shearing Power

Figure 2 presents the predicted versus actual plot for shearing power. This plot is a diagnostic tool used to evaluate the accuracy of the model's predictions by comparing the predicted values of shearing power against the actual observed values. Ideally, the data points are to indicate high model accuracy through lying in close proximity to the diagonal line. Any deviations from this line highlight discrepancies between predicted to actual values, so this suggests areas where the model may need improvement. Smaller deviations are indicative of better model performance. Larger deviations might point to factors the model missed or errors in data or model design.

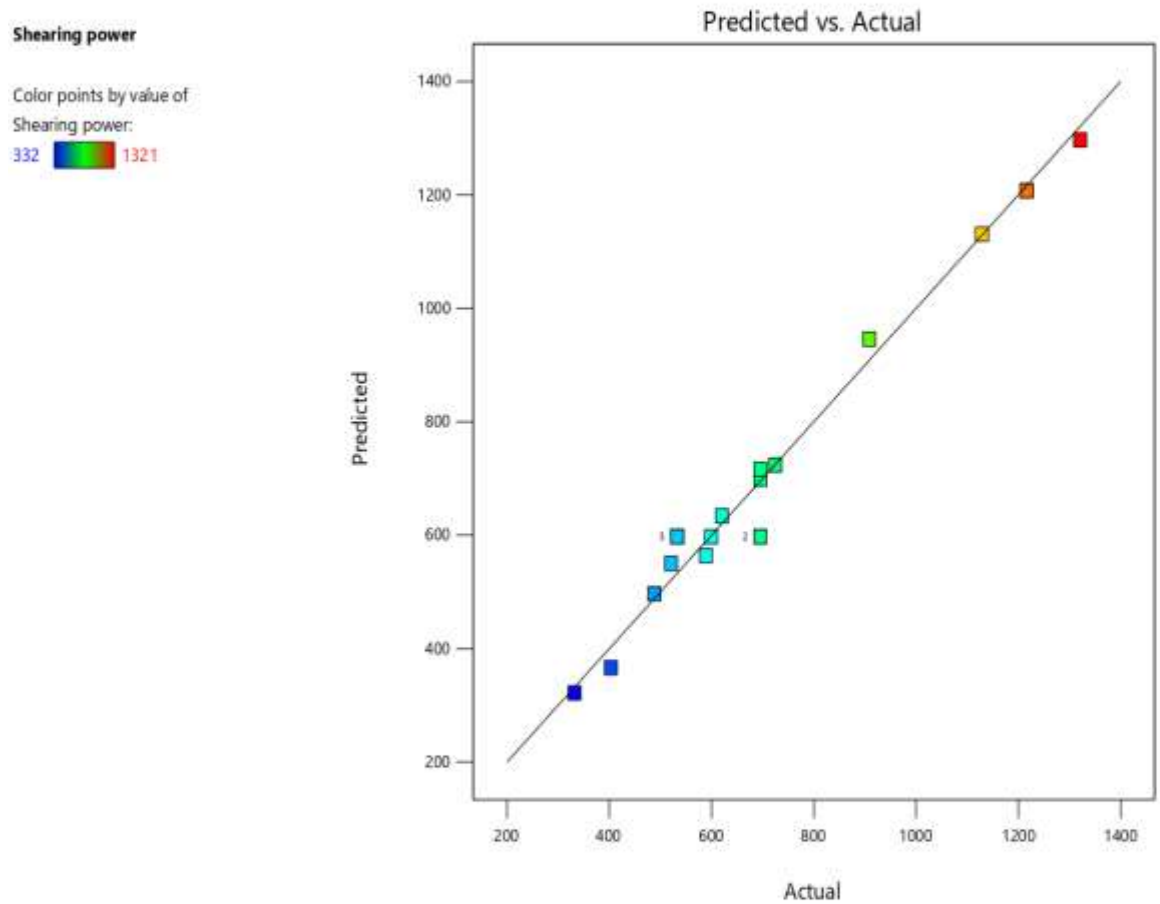

Figure 2: Predicted vs. Actual Plots for Shearing power

3.1.1 Report summary

Table 5 summarizes the diagnostic statistics for "Shearing power," detailing the residuals, leverage, studentized residuals, Cook's Distance, and DFFITS for each run. Residuals are differences between actual and predicted values. Large residuals in certain observations indicate that the model does not fit those specific data points well, signaling potential issues with accuracy. Leverage measures how much an observation influences the predicted values. High-leverage points have the potential to substantially alter the model if their values were different, whereas low-leverage points exert minimal influence. When an observation exhibits both high residual and high leverage, it becomes a point of concern, as it may disproportionately distort the model’s fit. To quantify such influence, metrics like Cook’s Distance and DFFITS are employed; although they differ in formulation, both serve to identify observations that may have an undue impact on the model's overall behavior.

Table 5: Report summary of diagnostic statistics for Shearing power

Run Order	Actual Value	Predicted Value	Residual	Leverage	Internally Studentized Residuals	Externally Studentized Residuals	Cook's Distance	Influence on Fitted Value DFFITS	Standard Order
1	532.70	597.62	-64.92	0.166	-1.161	-1.184	0.027	-0.528	14
2	599.33	597.62	1.71	0.166	0.031	0.029	0.000	0.013	10
3	532.70	597.62	-64.92	0.166	-1.161	-1.184	0.027	-0.528	5
4	695.33	597.62	97.71	0.166	1.747	1.988	0.061	0.888	9
5	1216.20	1207.72	8.48	0.692	0.250	0.238	0.014	0.356	18
6	695.33	597.62	97.71	0.166	1.747	1.988	0.061	0.888	6
7	532.70	597.62	-64.92	0.166	-1.161	-1.184	0.027	-0.528	15
8	521.00	550.31	-29.31	0.660	-0.821	-0.807	0.131	-1.125	11
9	908.60	945.97	-37.37	0.609	-0.976	-0.974	0.149	-1.216	12
10	403.05	366.34	36.71	0.683	1.064	1.072	0.244	1.572	17
11	589.00	564.03	24.97	0.609	0.652	0.632	0.066	0.790	20
12	695.33	699.10	-3.77	0.586	-0.096	-0.091	0.001	-0.108	2
13	724.80	723.97	0.8337	0.650	0.023	0.022	0.000	0.030	19
14	695.33	716.43	-21.10	0.598	-0.543	-0.523	0.044	-0.637	3
15	620.48	634.23	-13.75	0.683	-0.398	-0.381	0.034	-0.559	8
16	1129.00	1130.83	-1.83	0.650	-0.050	-0.048	0.000	-0.065	16
17	1216.20	1207.70	8.50	0.609	0.222	0.211	0.008	0.264	1
18	332.00	321.99	10.01	0.692	0.295	0.281	0.020	0.421	13
19	488.00	496.70	-8.70	0.621	-0.231	-0.219	0.009	-0.281	7
20	1321.00	1297.06	23.94	0.660	0.671	0.651	0.087	0.908	4

Figure 3 Contour plots for shearing power display the interaction between the two independent variables and the corresponding shearing power. Contours plot the different shearing power values, indicating the interaction between the power for shearing and the change in independent variable. Closely spaced contours indicate a steep transition for shearing power, while widely spaced contours indicate a gentle transition. Identification of the optimal settings for shearing power maximization or optimization based on the independent variables is achievable by means of the plots. The plots optimize the energy usage and efficiency of the machining process. The optimum operating conditions for the attainment of the desired shearing power with minimal waste can be determined by means of interpretation of the contour plots

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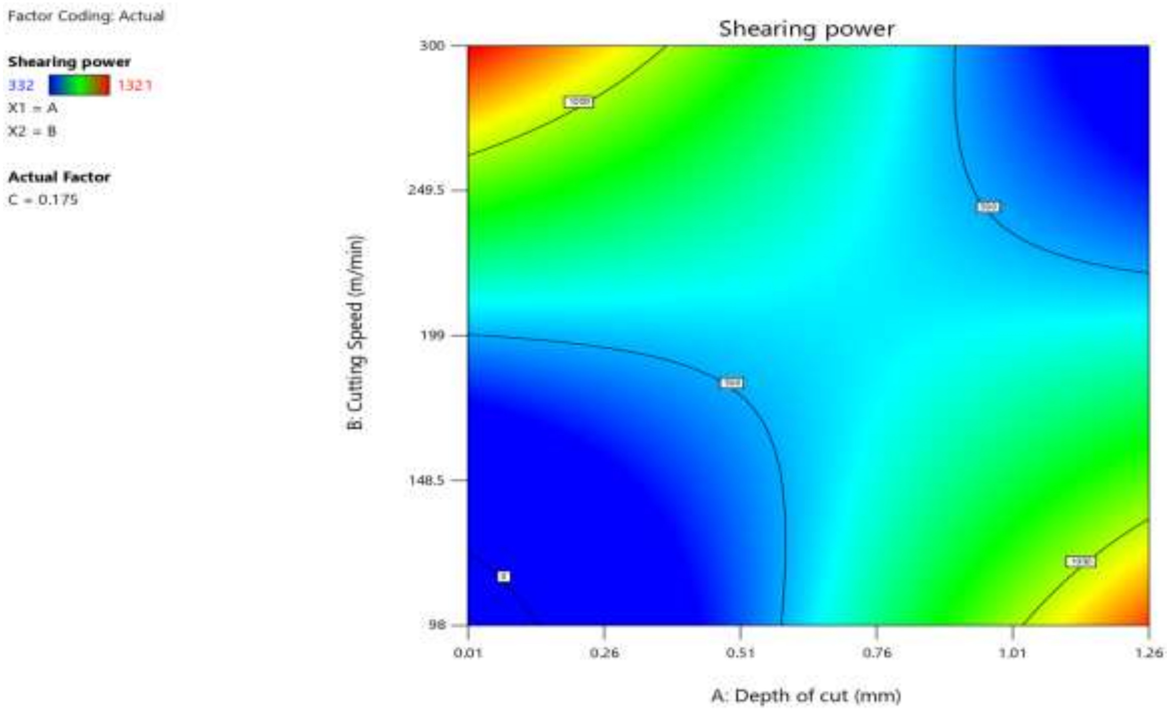

Figure 3: Contour plots for Shearing Power

Figure 4 Surface plots for Shearing Power show the relationship between shearing power required during machining and two independent process parameters, such as cutting speed, feed rate, or depth of cut. The surface plot shows the influence of these parameters on the shearing power, with the surface height representing the quantity of power required to cut. The color gradient typically highlights areas of higher or lower shearing power requirements. By displaying this information in three dimensions, the plot allows the optimal process parameters for power minimization or power optimization to be observed at a glance, making machining more energy-efficient and cost-effective.

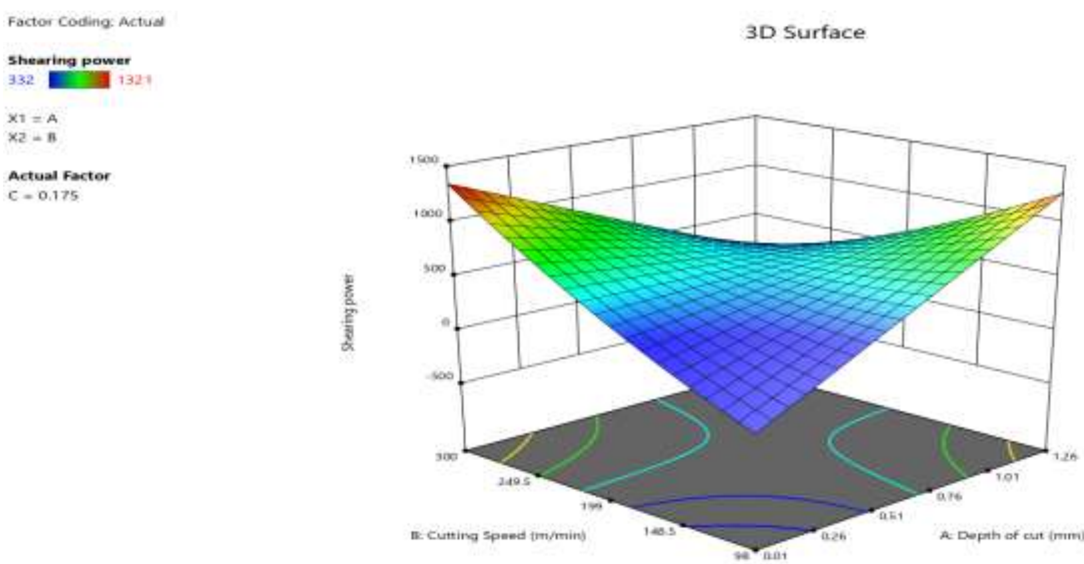

Figure 4: Surface plots for Shearing Power

3.2 Artificial Neural Network (ANN) Model Development

Here, Artificial Neural Networks (ANNs) have been employed to simulate the complex, nonlinear interactions between machining parameters (depth of cut, cutting speed, and feed rate) and the shearing power developed. ANNs have been employed as they have a greater ability to simulate interactions that generally go unaddressed by typical regression models. The data were normalized prior to preprocessing and 80/20 training-testing splitting, and later trained through backpropagation to minimize mean squared error (MSE). Model performance was evaluated using MSE, correlation coefficient (R^2), k-fold cross-validation, and predicted vs. actual value plots. These metrics collectively demonstrated the ANN's accuracy, generalizability, and robustness in predicting machining outcomes.

Figure 5 displays the network training diagram for predicting Shearing Power. In this figure, the training process involves using 8 epochs out of a maximum of 1000, with validation checks being conducted at intervals, in this case, 6 times during the training process. The diagram typically shows how the model is being trained, with the error decreasing across the epochs, indicating improvement in the model's ability to predict Shearing Power. The validation checks ensure that the model is not overfitting by evaluating its performance on a separate validation set during the training process.

Figure 5: Network training diagram for predicting Shearing power

Figure 6 shows the performance curve of the trained neural network for predicting Shearing Power. The curve tracks the model's performance over epochs, showing how the error (or performance metric) evolves during training. The best validation performance of 8389.874 was achieved at epoch 2, indicating that the model's predictions were most accurate at that point. After epoch 2, the performance may have either plateaued or slightly worsened, suggesting the model had already reached its optimal performance on the validation set. The curve helps to visually assess how well the network learned and generalized from the data.

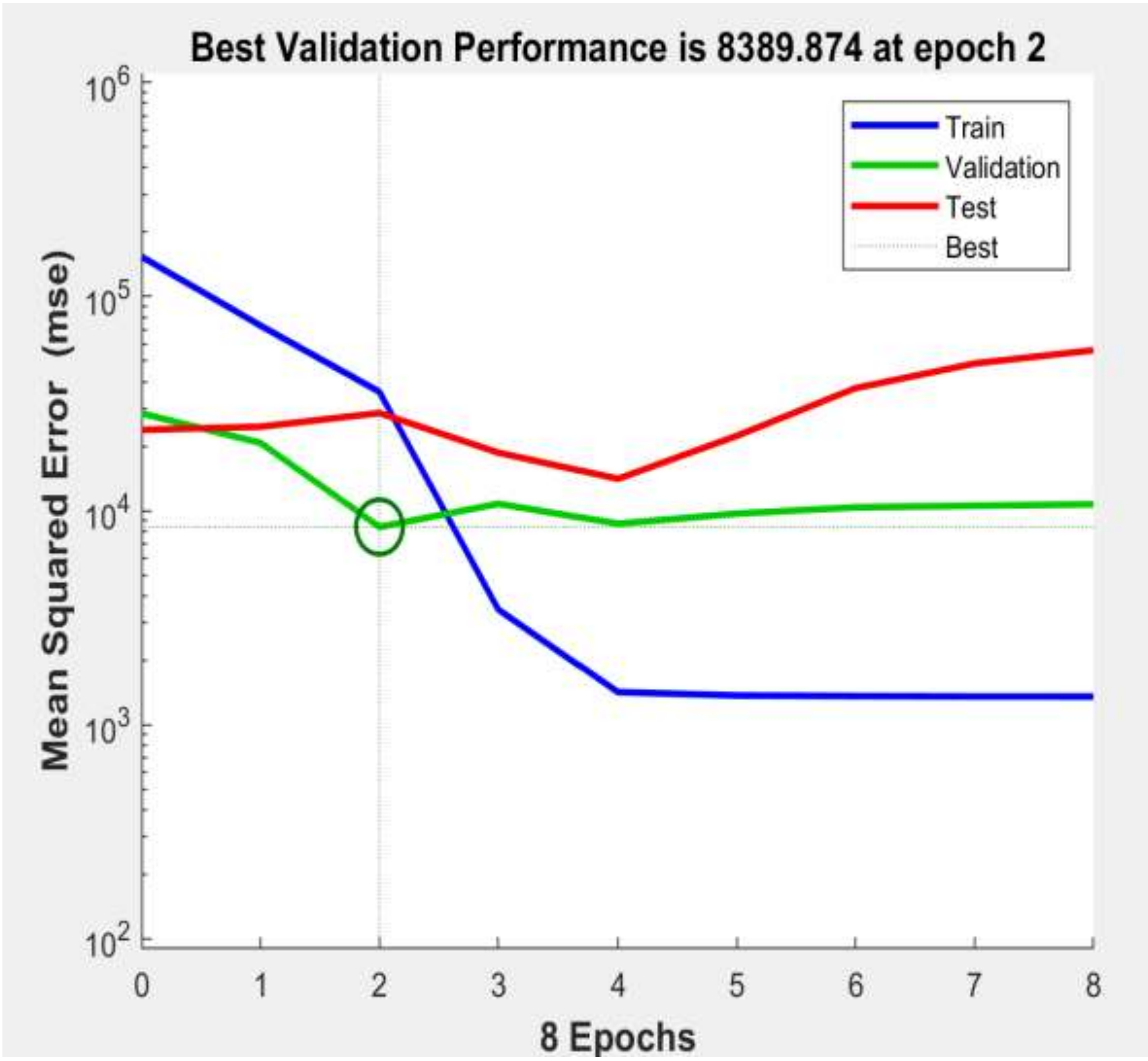

Figure 6: Performance curve of trained network for predicting Shearing power

Figure 7 shows the neural network training state for predicting Shearing Power at epoch 8. The gradient value of 516.8665 indicates the rate of change of the error with respect to the model's parameters, which suggests the magnitude of the adjustments being made to the weights during training. The value of Mu (1) represents the step size or learning rate used in the training process, affecting how much the weights are adjusted with each update. The validation checks (6) refer to the number of times the model's performance was evaluated on a separate validation set to ensure it was not overfitting to the training data. This training state snapshot provides insights into how the model was converging at this particular epoch, indicating the learning dynamics and progress during training.

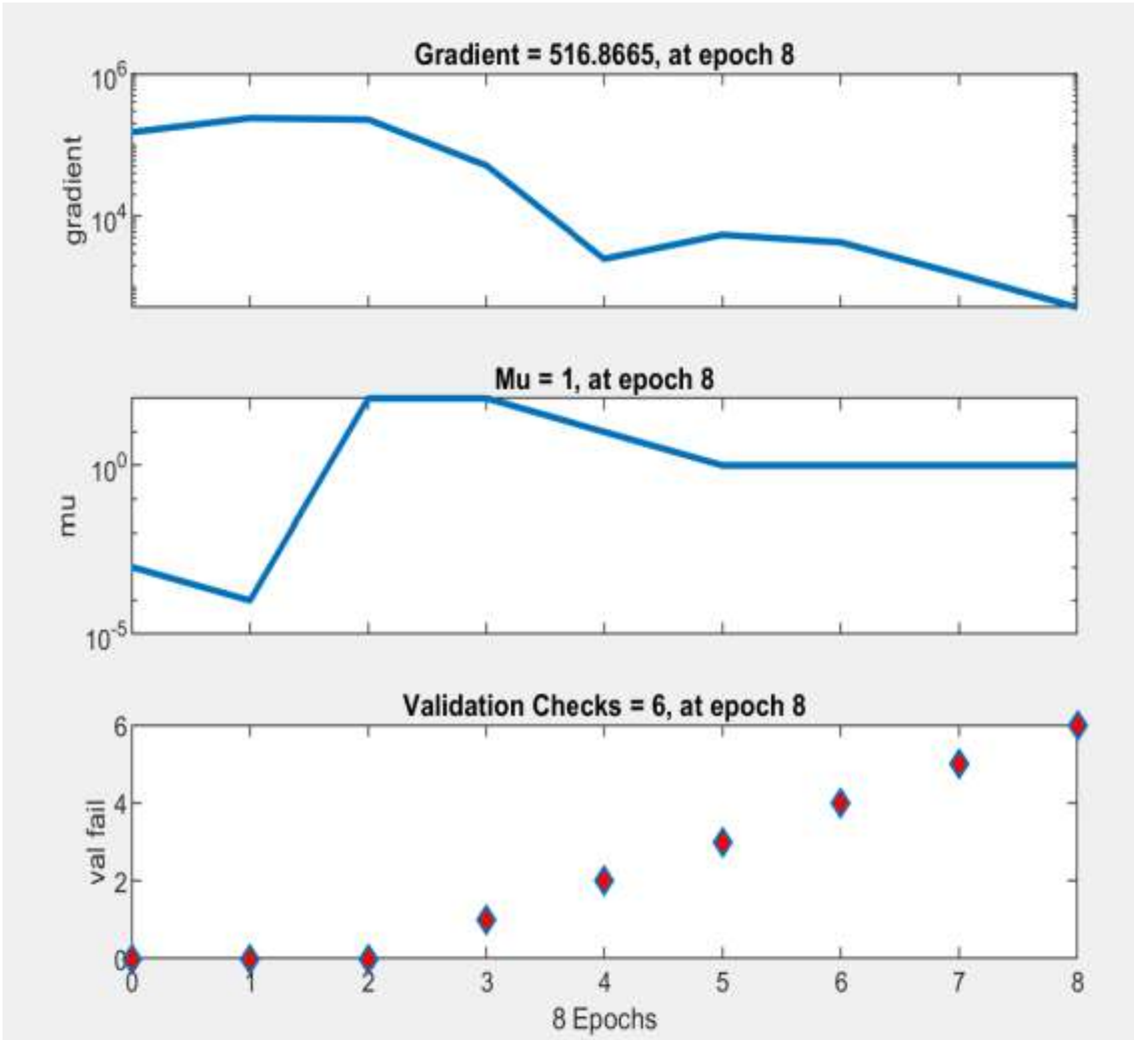

Figure 7: Neural network training state for predicting Shearing power

Figure 8 displays the regression plots for predicting Shearing Power, showing the relationship between the predicted and actual values across different data sets: training, validation, testing, and all data combined. The training R-value of 0.95573 indicates a strong correlation between the predicted and actual values for the training data. The validation R-value of 0.93697 suggests a good fit for the model when evaluated on the validation set, although it is slightly lower than the training set, implying some potential overfitting. The test R-value of 0.99344 is very high, indicating excellent performance on the unseen test data. The overall R-value of 0.94605, combining all the data, suggests that the model generalizes well across all data sets, with a strong predictive capability for Shearing Power. These regression plots show how well the neural network model performs in predicting Shearing Power for different subsets of the data.

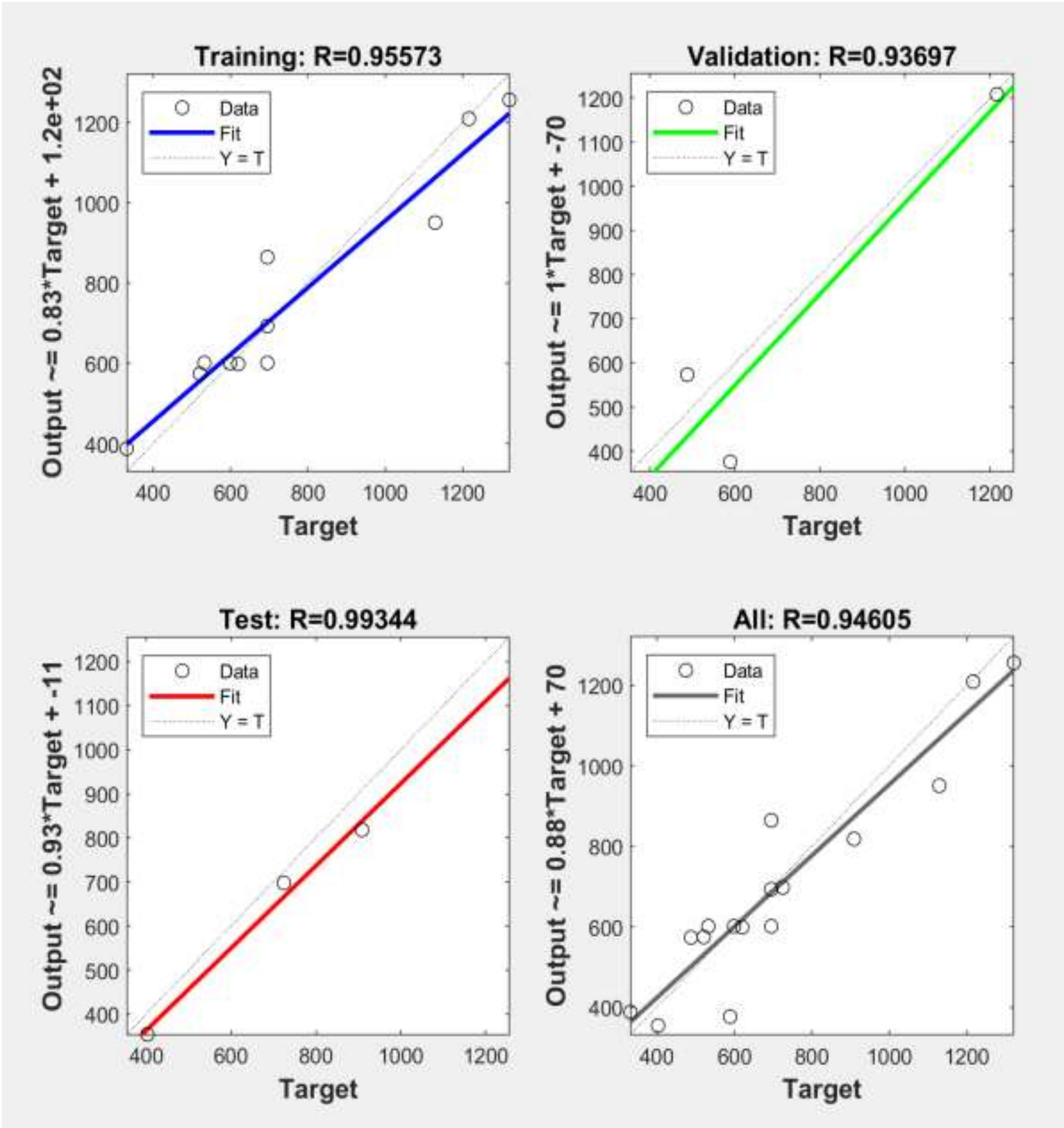

Figure 8: Regression, training, validation and testing plots for Shearing power

Table 6 presents the prediction of Shearing Power using an Artificial Neural Network (ANN). The table includes experimental data and predicted values for Shearing Power based on three factors: Depth of Cut (Factor 1), Cutting Speed (Factor 2), and Feed Rate (Factor 3). For each run, the experimental values of Shearing Power and the ANN-predicted values are compared and the corresponding prediction error computed. In most cases, the errors are extremely small, like for runs 1, 2, 5, and 13, where the predicted values are very close to the experimental values. In some cases, larger errors are observed, like for runs 7, 8, 9, and 19, where the predicted values are quite far from the experimental values. The range of the accuracy of the prediction shows that although the ANN model is mostly correct, there could be experimental conditions where the prediction error could be larger, which can indicate where the refinement or the fine-tuning could be done in the model.

Table 6: Prediction of Shearing power using ANN

Run	Factor 1	Factor 2	Factor 3	**Shearing power**		
	A:Depth of cut	B:Cutting Speed	C:Feed Rate	Experiment	ANN	Error
	mm	m/min	mm/rev			
1	0.63	225	0.17	532.7	531.19	1.51
2	0.63	225	0.17	599.33	601.19	-1.86
3	0.63	225	0.17	532.7	531.19	1.51
4	0.63	225	0.17	695.33	654.19	41.14
5	0.25	300	0.25	1216.2	1214.02	2.18
6	0.63	225	0.17	695.33	691.19	4.14
7	0.63	225	0.17	532.7	601.19	-68.49
8	0.25	150	0.1	521	574.46	-53.46
9	0.63	351.13	0.17	908.6	818.12	90.48
10	1	300	0.25	403.05	354.36	48.69
11	0.63	98.87	0.17	589	576.31	12.69
12	0.01	225	0.17	695.33	694.43	0.9
13	1	300	0.1	724.8	724.78	0.02
14	0.63	225	0.3	695.33	693.32	2.01
15	1	150	0.25	620.48	598.78	21.7
16	1	150	0.1	1129	1130.71	-1.71
17	0.63	225	0.05	1216.2	1216.91	-0.71
18	0.25	150	0.25	332	388	-56
19	1.26	225	0.17	488	573.5	-85.5
20	0.25	300	0.1	1321	1256.12	64.88

3.3 Comparative Analysis of RSM and ANN Models

Table 7 provides RSM and ANN model predictions of shearing power and experimental measurements. The table provides the input factors (Depth of cut, Cutting Speed, and Feed Rate) for each run, experimental values of shearing power, and RSM and ANN predictions. Experimental values of shearing power differ based on the input factors' combinations. The RSM and ANN models also predict values close to the experiment but with variations. The ANN model predicts more closely, as can be seen from its values compared to the RSM model, where variations with experiment are higher. This signifies that the ANN model better learns the highly nonlinear relationships between the machining parameters and shearing power compared to the RSM model.

Table 7: RSM vs ANN Prediction for Shearing power

Run	A:Depth of cut	B:Cutting Speed	C:Feed Rate	Experiment	RSM	ANN
	Mm	m/min	mm/rev			
1	0.63	225	0.17	532.7	597.62	531.19
2	0.63	225	0.17	599.33	597.62	601.19
3	0.63	225	0.17	532.7	597.62	531.19
4	0.63	225	0.17	695.33	597.62	654.19
5	0.25	300	0.25	1216.2	1207.72	1214.02
6	0.63	225	0.17	695.33	597.62	691.19
7	0.63	225	0.17	532.7	597.62	601.19
8	0.25	150	0.1	521	550.31	574.46
9	0.63	351.13	0.17	908.6	945.97	818.12
10	1	300	0.25	403.05	366.34	354.36
11	0.63	98.87	0.17	589	564.03	576.31
12	0.01	225	0.17	695.33	699.1	694.43
13	1	300	0.1	724.8	723.97	724.78
14	0.63	225	0.3	695.33	716.43	693.32
15	1	150	0.25	620.48	634.23	598.78
16	1	150	0.1	1129	1130.83	1130.71
17	0.63	225	0.05	1216.2	1207.7	1216.91
18	0.25	150	0.25	332	321.99	388
19	1.26	225	0.17	488	496.7	573.5
20	0.25	300	0.1	1321	1297.06	1256.12

Figure 9 plots the experimental results and predictions of the RSM and ANN models for the 20 experimental runs. The figure shows the experimental values of the shearing power and the corresponding RSM and ANN model predictions. While the two models capture the general trend in the experimental data, the ANN model closely mimics the fluctuations in the actual shearing power, proving its better ability in capturing the nonlinearities and complexities of the process. The RSM is, however, observed to make a more linear prediction that does not capture all the fluctuations in the experimental data, proving the better fit of the ANN model.

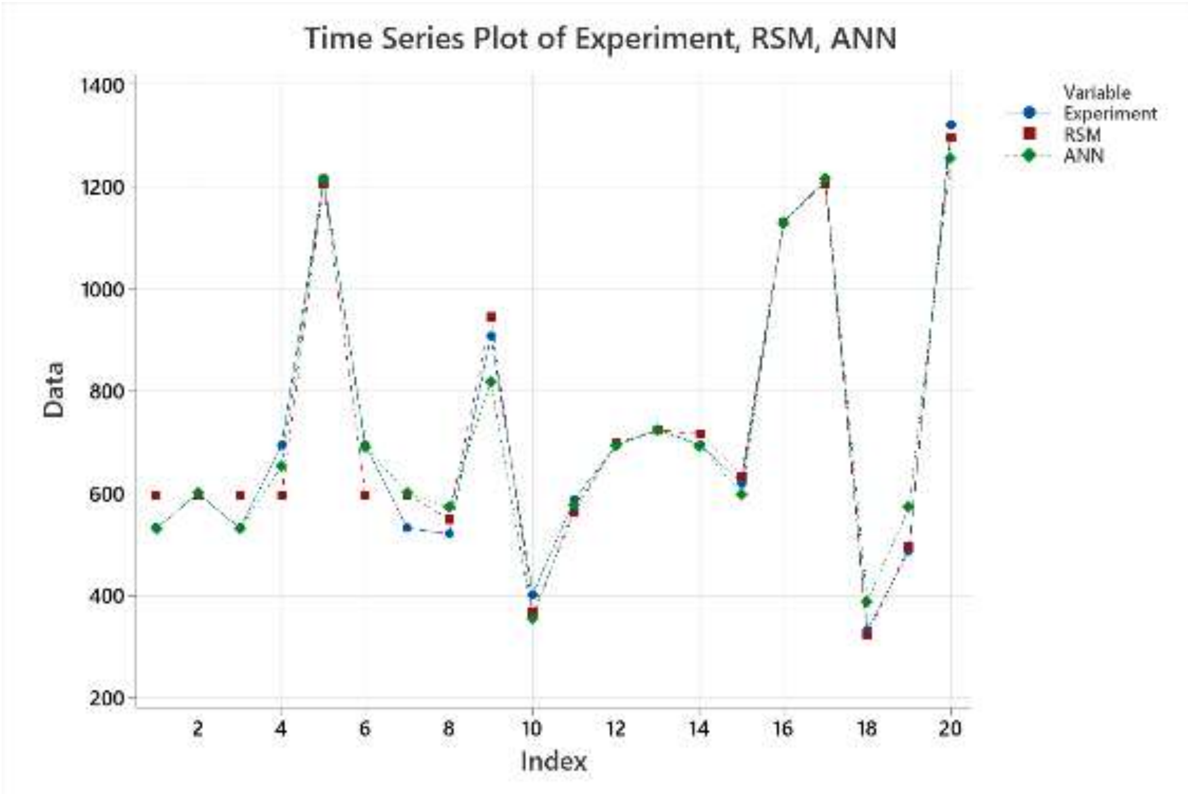

Figure 9: Time Series Plot of Experiment, RSM, ANN for Shearing power

The regression equation 3 indicates that there is a perfect linear relationship between the experimental shearing power values and those predicted by the RSM model. The coefficient of 1.000 suggests that for every unit change in the RSM prediction, the experimental value changes by an equal amount. The term "- 0.00" implies that there is no significant offset between the experimental and predicted values, indicating that the RSM model accurately predicts the shearing power with minimal error. This perfect linearity further suggests a high degree of correlation and an effective RSM model in this case.

Experiment = - 0.00 + 1.000 RSM ………………..3

Table 8 presents the RSM Model Summary for Shearing power, where the standard deviation (S) is 45.6519, and the R-squared (R-sq) value is 97.58%, with an adjusted R-squared (R-sq(adj)) of 97.45%. This indicates that the RSM model explains approximately 97.58% of the variability in shearing power, with only a small reduction in explanatory power when adjusted for the number of predictors. Furthermore, Table 9 shows the RSM Analysis of Variance (ANOVA) for Shearing power, with a regression sum of squares (SS) of 1,512,606 and a mean square (MS) of 1,512,606. The corresponding F-value of 725.79 and a p-value of 0.000 indicate that the regression model is statistically significant, meaning that the model effectively captures the relationship between the input variables and the shearing power. The error sum of squares (SS) of 37,514 and the associated mean square (MS) of 2,084 suggest that the residuals (or error) are relatively small compared to the regression sum, reinforcing the model's predictive accuracy.

Table 8: RSM Model Summary for Shearing power

S	R-sq	R-sq(adj)
45.6519	97.58%	97.45%

Table 9: RSM Analysis of Variance for Shearing power

Source	DF	SS	MS	F	P
Regression	1	1512606	1512606	725.79	0.000
Error	18	37514	2084		
Total	19	1550119			

Shearing power regression equation, as provided in Equation 4, shows the agreement of experimental shearing power values with the ANN model predictions. The equation suggests that one would obtain a rise in the experimental shearing power by approximately 1.047 units with an intercept of -32.74 when there is a one unit rise in the ANN-predicted value. The regression suggests that the ANN model is extremely close to the experimental data with a slightly higher sensitivity (1.047) than the perfect 1:1 relationship. The negative intercept suggests that, when the predicted shearing power is zero, the experimental value would deviate by -32.74 units, highlighting the model's accuracy and the close match between the predicted and experimental results.

$$\text{Experiment} = -32.74 + 1.047\ \text{ANN} \quad (4)$$

In Table 10, the ANN Model Summary for Shearing power shows that the ANN model has a high coefficient of determination (R-squared) of 97.93%, and the adjusted R-squared value is 97.82%. These values indicate that the ANN model explains nearly 98% of the variance in the experimental shearing power data, suggesting that it is a highly effective model for predicting the shearing power. While in Table 11, the ANN Analysis of Variance (ANOVA) for Shearing power reveals that the regression model is statistically significant, with a very high F-value of 853.20 and a p-value of 0.000. This indicates that the ANN model provides a significantly better fit to the data compared to the error (residuals). The regression explains the majority of the variance in the data, as indicated by the very low error sum of squares (SS = 32,027) relative to the regression sum of squares (SS = 1,518,092). These results underscore the effectiveness of the ANN model in accurately predicting shearing power.

Table 10: ANN Model Summary for Shearing power

S	R-sq	R-sq(adj)
42.1816	97.93%	97.82%

Table 11: ANN Analysis of Variance for Shearing power

Source	DF	SS	MS	F	P
Regression	1	1518092	1518092	853.20	0.000
Error	18	32027	1779		
Total	19	1550119			

4. CONCLUSION

This study presents a comprehensive assessment of the effectiveness of Response Surface Methodology (RSM) and Artificial Neural Networks (ANN) in optimizing machining processes, specifically for predicting shearing power. Both approaches demonstrated the ability to forecast machining outcomes based on key parameters (depth of cut, cutting speed, and feed rate). However, clear differences emerged between the two, particularly when dealing with complex or non-linear patterns in the data. The RSM model, with its relatively simple and interpretable structure, delivered reliable predictions under conditions where the relationships among variables were predominantly linear. In such cases, it offered reasonable approximations of machining responses. The RSM model showed strong results in the prediction of shearing power, due mainly to the input parameters connected with the output in a fairly simple way. Since RSM relies upon linear assumptions, its benefit also suggests a problem it often faces with more detailed connections among input variables.

RSM and ANN both offer methods valuable for optimization and prediction in machining processes. However, the results from this study clearly indicate the ANN model's accuracy. Adaptability is superior also in the ANN model in comparison to RSM. Due to the fact that it is able to capture complex and nonlinear relationships between machining parameters, it generates predictions. The predictions are more precise over a broad range of conditions. ANN suits applications well because they need optimization that is accurate and flexible. The ANN model identifies optimal process settings to machine more efficiently, and it operates at lower costs while relying less on trial-and-error methods. ANN thus offers a stronger as well as dependable predictive tool to aid future research including practical implementation for machining optimization.

REFERENCES

Asiltürk, İ., Tuğrul, A., & Akkuş, H. (2021). Optimization of surface roughness and cutting force in CNC turning using RSM and genetic algorithm. *Measurement*, *173*, 108626. https://doi.org/10.1016/j.measurement.2020.108626

Bazaz, S. M., Ratava, J., Lohtander, M., & Varis, J. (2023). An investigation of factors influencing tool life in the metal cutting turning process by dimensional analysis. *Machines*, *11*(3), 393.

Bhowmik, S., Pal, S. K., & Paul, S. (2019). Estimation of tool wear in turning using unscented Kalman filter. *Measurement*, *146*, 470–480. https://doi.org/10.1016/j.measurement.2019.06.011

Chandrasekhar, B., Natarajan, U., & Satpathy, A. (2025). Deep learning-based classification of weld penetration in A-TIG welding using CNN. *Journal of Intelligent Manufacturing*, *36*(1), 112–124.

Costa, J. A., Ribeiro, A. F., & Pereira, A. I. (2023). Performance comparison between statistical and machine learning models for machining process prediction. *Journal of Manufacturing Processes*, *88*, 578–590. https://doi.org/10.1016/j.jmapro.2023.06.013

Igbinake, R. (2025). Application of artificial neural networks to predict tensile strain in TIG-welded mild steel joints. *Materials Today: Proceedings*, *72*, 334–340.

Imad, M., Hopkins, C., Hosseini, A., Yussefian, N. Z., & Kishawy, H. A. (2022). Intelligent machining: a review of trends, achievements and current progress. *International Journal of Computer Integrated Manufacturing*, *35*(4-5), 359-387.

Kesse, C., Mensah, P., & Addy, F. (2020). Artificial intelligence-based prediction of bead geometry in TIG welding using hybrid deep learning models. *Journal of Manufacturing Science and Engineering*, *142*(12), 121005. https://doi.org/10.1115/1.4048605

Khan, M. A., Haider, A., & Raza, M. R. (2020). Experimental analysis of turning process parameters under machining constraints. *Journal of Manufacturing Processes*, *53*, 263–273. https://doi.org/10.1016/j.jmapro.2020.02.027

Kshirsagar, R., Kulkarni, S. G., & Patil, M. A. (2020). Optimization of TIG welding process using hybrid evolutionary algorithms. *Procedia Manufacturing*, *48*, 370–375. https://doi.org/10.1016/j.promfg.2020.05.055

Kuang, W., Miao, Q., Ding, W., & Li, H. (2022). A short review on the influence of mechanical machining on tribological and wear behavior of components. *The International Journal of Advanced Manufacturing Technology*, *120*(3), 1401-1413.

Maneesh, R., Basha, K. M., & Prasad, B. (2023). Multi-response optimization of machining parameters in turning under constrained environments using machine learning. *Engineering Science and Technology, an International Journal*, *38*, 101095.

Mativenga, P., Schoop, J., Jawahir, I.S., Biermann, D., Kipp, M., Kilic, Z.M., Özel, T., Wertheim, R., Arrazola, P. and Boing, D. (2024). Engineered design of cutting tool material, geometry, and coating for optimal performance and customized applications: A review. *CIRP Journal of Manufacturing Science and Technology*, *52*, pp.212-228.

Mehta, D., & Patel, S. (2024). Optimization strategies for TIG welding of dissimilar metal joints: A comprehensive review. *Materials Today: Proceedings*, *76*, 1081–1090.

Nwulu, N. I., Oke, A. O., & Akinlabi, E. T. (2024). Real-time adaptive control in machining using predictive machine learning techniques. *Procedia CIRP*, *113*, 423–428.

Pimenov, D. Y., Giasin, K., & Mikolajczyk, T. (2022). Integration of machine learning into manufacturing: A review of challenges and outlook. *Journal of Manufacturing Systems*, *62*, 731–752. https://doi.org/10.1016/j.jmsy.2022.07.006

Ragai, I., Abdalla, A. S., Abdeltawab, H., Qian, F., & Ma, J. (2022). Toward smart manufacturing: Analysis and classification of cutting parameters and energy consumption patterns in turning processes. *Journal of Manufacturing Systems*, *64*, 626-635.

Singh, J., & Singh Gill, S. (2023). Turning of Al 7075-T6 aerospace alloy under different sustainable metalworking fluid strategies by coated carbide tools. *Surface Engineering*, *39*(3), 275-294.