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Prediction and Optimization of Pipeline Welded Tool Life using Response Surface Methodology (RSM) and Artificial Neural Network (ANN)

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Abstract: Pipeline networks play a pivotal role in transporting an array of fluids and gases across various industrial domains. The study aims to fill this void by investigating the impact of a specific non-flexible component, namely the surface area of contact, on pipeline weldments and its interaction with elastic properties. To fulfil this objective, a comprehensive experimental inquiry is conducted, encompassing diverse welding methods, materials, and environmental conditions to authentically replicate real-world situations. The response surface methodology analysis yields optimal outcomes, suggesting a depth of cut of 0.400, cutting speed of 250.000, and feed rate of 0.500. These input parameters collectively yielded a machined structure with tool life of 149.958 and this was attained at a desirability value of 0.973. Additionally, the Artificial Neural Network model is utilized to forecast output parameters and compared against the Response Surface Methodology. The findings underscore the pivotal role of optimizing non-elastic performance factors in pipeline weldments. By accurately controlling the surface area of contact, weldments can be designed with capabilities of enduring harsh conditions, curbing the risk of failures, and significantly prolonging pipeline operational lifespans.

Keywords: Pipeline networks, tool life, response Surface methodology, artificial neural network

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1. INTRODUCTION

A primary factor that restricts machining productivity is the lifespan of the tool [1]. The state of the cutting tool, a pivotal component in the machining process that directly interacts with the workpiece, significantly influences the quality of the final product and production expenses. Ongoing wear leads to the degradation of the cutting tool's condition. Neglecting this aspect could lead to a decline in machining accuracy and potentially unexpected machine tool downtime [2]. A crucial aspect in the turning process is to forecast the tool's lifespan to avoid unnecessary material wastage and resource depletion [3]. The tool life in machining operations is a critical parameter influencing manufacturing efficiency and cost-effectiveness. Extending tool life is a primary objective in machining industries, as it directly impacts production downtime, tool replacement costs, and overall productivity. Tool life enhancement is pivotal in machining operations, as it contributes to reduced production costs, minimized downtime, improved surface quality, and enhanced overall machining efficiency. Prolonging tool life directly translates to economic and environmental benefits. Various materials are used in machining, each presenting unique challenges and opportunities for tool life enhancement. Ideally, in the implementation of machining processes, the optimal scenario is predicting tool performance without the need for real-world experimentation. Yet, given the variability in machine-tool configurations, materials being processed, cutting tools, and fixture systems within an industrial environment, every set of machining condition remains unique [4]. The generation of thermo-mechanical stresses during the chip formation process of machining operations can lead to a diminished lifespan of the cutting tool and the quality of machined components are impacted, therefore, analyzing cutting temperatures and the longevity of the cutting tool during milling can enhance manufacturing productivity by leveraging CNC machine tools [5]. Broadening the scope of automated turning processes consistently demands adherence to stringent standards for precise tool life predictions. Evaluating tool life is typically an expensive procedure that necessitates a significant investment of time and materials. Therefore, it is critical to estimate tool life and the cutting-edge replacement schedule precisely before faults or catastrophic wear interrupt the procedure. This is especially true because precise tool life is essential for maximizing cutting productivity and minimizing turning process costs. Tool cutting edge wear directly affects how long a tool will last [6]. Accurately predicting tool lifespan stands as a pivotal element in intelligent and automated machining processes. This practice also contributes towards the objective of producing top-notch products while lowering production costs [7]. Ensuring quality in the manufacturing process and enhancing production efficiency necessitates precise prediction of cutting tool lifespan [8]. In a recent publication, [9] investigated the feasibility of predicting tool lifespan in a side milling application by employing empirical models of tool life in medium carbon steel. Additionally, [10] developed an algorithm utilizing a genetic algorithm to accurately forecast the tool's lifespan in their research. The manufacturing industry required specific dimensional components or parts in diverse engineering applications, with machining serving as the essential method to achieve this. These industries faced continuous pressure to devise effective strategies employing various optimization methods to increase production, reduce costs, conserve energy, enhance product quality, and extend the life of tools. The primary goals centered around cost-effective operations, minimal energy consumption, and superior product quality, all rooted in production management concepts. The sustainable machining selection technique identified the crucial turning input factors influencing energy consumption and tool lifespan. Various dilemmas related to economic and environmental concerns were explored, focusing on innovative methods to reduce energy usage and improve tool life. The optimal input turning parameters and their limitations play a significant role in meeting the requirements for energy efficiency and tool longevity [11]. [12] Introduced an extended Taylor's functional correlation in their study by incorporating tool work temperature measurements. By utilizing thermocouple temperature readings at the tool's workplace, this system enabled the prediction of tool life, differing from traditional tool-wear studies. Conventional tool-life testing methods were then implemented to validate the reliability of the suggested temperature-based approach for estimating tool lifespan. These methods included employing standard experimental protocols to examine tool-to-surface interactions [13]. [14] found that at low "cutting speed conditions," A rise in the feed rate resulted in a decrease in tool life and the development of build-up edges because of escalating temperatures. Conversely, they observed that the depth of cut has a lesser impact on tool life concerning temperature elevation. Due to the minute-area plastic deformation occurring in the cutting tool during machining, a significant quantity of heat is produced. This elevated temperature significantly affects the mechanics of chip formation, tool wear, tool lifespan, and the surface integrity and quality of the workpiece. Hence, comprehending this temperature is crucial [14]. [15] noted that when utilizing a flank wear criterion of 0.3 mm, the coated carbide insert exhibited a lifespan 15 times longer than the uncoated carbide insert. [16] Applied a multi-objective optimization technique employing the NSGA-II algorithm and BP neural network to tackle concerns regarding high carbon emissions and shortened tool life in CNC milling. This study is focused on forecasting and enhancing the lifespan of specific tools, crucial in contemporary pipeline welding using expert systems. Prolonging tool life directly influences heightened productivity, reduced environmental effects, and cost efficiencies. This multidisciplinary realm integrates data analytics, machining technology, science of materials, and mathematics.

2. METHODOLOGY

According to the number of input parameters, an experimental plan was established for this research study. The matrix was generated using software specifically designed for experts in design. The design incorporated both the central composite design (CCD) and the 2k factorial design. The CCD was used for input parameters evaluated within a range of three to five levels, whereas the 2k factorial design was implemented for any number of input parameters considered at two levels. The central composite design for this study, encompassing 20 experimental runs, was developed using the 7.1 program for the layout. The test runs incorporated the findings of the selected material along with input and output parameters. This matrix was then subjected to analysis using Artificial Neural Network (ANN) and Response Surface Methodology (RSM) approaches.

2.1 Response Surface Methodology (RSM)

RSM are extensively used in situations where there are many input factors that may influence one or more response variables. Response Surface Methodology (RSM) integrates quantitative and statistics-based models to analyze processes where the central aim is to optimize a desired outcome affected by various variables. It plays a vital role in crafting, designing, and developing new products, as well as in refining existing designs. The core components of the response surface approach involve regression analysis, optimization algorithms, and experimental design, which are employed to explore the empirical connections between variables.

2.2 Artificial Neural Network

A neural network is a highly parallel distributed computer system capable of storing experimental data for multiple applications. It functions as a data mining tool and is primarily designed to uncover hidden patterns within datasets. Interestingly, there are two key similarities between neural networks and the human brain. First, during the learning process within the network, synaptic weights are employed to store knowledge. These weights indicate the strength of connections between internal neurons. Second, each basic neuron with R inputs receives appropriate weights (*w*), and the transfer function (*f*) calculates the total of these weighted inputs along with a bias term. The transfer function (f) utilized to compute neuron outputs can be any differentiable function.

3.0 RESULTS AND DISCUSSION

This study comprised 20 experimental trials, each involving variations in feed rate, spindle speed, and depth of cut. Responses were measured for each individual experiment.

3.1 RSM-Based Modelling and Optimization

This study endeavours to establish a quadratic mathematical association between chosen input variables - specifically, cutting speed, feed rate, and depth of cut - linked with four response variables, including tool life, using response surface methodology (RSM). The objective of the maximization model is to optimize tool life. Table 1 displays the sequential total of squares for tool life response as a means of evaluating system adequacy.

Table 1: Sequential Model Sum of Squares tool life

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Mean vs Total	2.439E+05	1	2.439E+05			
Linear vs Mean	7386.43	3	2462.14	20.76	< 0.0001	
2FI vs Linear	374.10	3	124.70	1.06	0.3980	
Quadratic vs 2FI	**1333.60**	**3**	**444.53**	**23.41**	**< 0.0001**	**Suggested**
Cubic vs Quadratic	51.32	4	12.83	0.5554	0.7038	Aliased
Residual	138.60	6	23.10			
Total	2.532E+05	20	12660.42			

To better determine the most suitable model for the Tool Life, a lack of fit test was conducted, and the model showing least significant lack of fit was chosen. The lack of fit table for the Tool Life is shown in Table 2.

Table 2: Lack of Fit Tests tool life

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Linear	1769.97	11	160.91	6.30	0.0273	
2FI	1395.87	8	174.48	6.83	0.0244	
Quadratic	**62.27**	**5**	**12.45**	**0.4878**	**0.7752**	**Suggested**
Cubic	10.95	1	10.95	0.4289	0.5414	Aliased
Pure Error	127.65	5	25.53			

To further evaluate the framework's applicability, the Tool Life summary statistics were looked at. The model with the highest coefficient of determination is preferable. The Table 3 displays the model overall statistics for the Tool Life.

Table 3: Model Summary Statistics tool life

Source	Std. Dev.	R^2	Adjusted R^2	Predicted R^2	PRESS	
Linear	10.89	0.7956	0.7573	0.6429	3315.08	
2FI	10.83	0.8359	0.7602	0.6688	3075.31	
Quadratic	**4.36**	**0.9795**	**0.9611**	**0.9284**	**665.15**	**Suggested**
Cubic	4.81	0.9851	0.9527	0.7202	2597.55	Aliased

The goodness of fit statistics test was conducted to evaluate robustness of the developed framework for tool life, illustrated in Table 4.

Table 4: Goodness of Fit Statistics for Tool life

Std. Dev.	4.36		**R^2**	0.9795
Mean	110.44		**Adjusted R^2**	0.9611
C.V. %	3.95		**Predicted R^2**	0.9284
			Adeq Precision	29.9599

There is a disparity of less than 0.2 between the Adjusted R^2 of 0.9611 and the Predicted R^2 value of 0.9284. **Adequate Precision** evaluates the ratio of signal to noise. A ratio higher than 4 is ideal.
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To demonstrate the frame work's suitability for the data concerning Tool Life, Figure 1 displays a normal plot of residuals for Chip Size

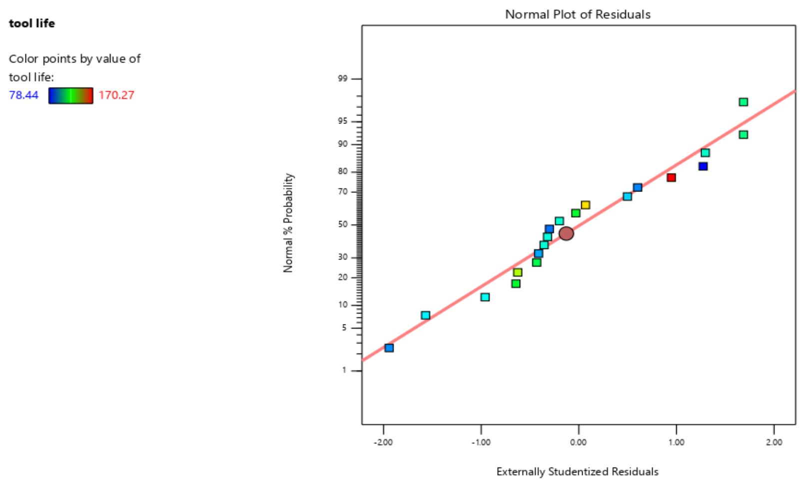

Figure 1: Normal Plot of Residuals for Tool Life

The normal probability plot serves to determine if the residuals conform to a normal distribution, with a straight-line indicating normality. Even a moderate scatter can be linked to normally distributed data. The normal plot of residuals Tool Life revealed a moderate scatter indicating that the data is normal.

To detect for the presence of mega patterns or expanding variance a plot of residuals and the predicted was produced for Tool Life which is shown in the Figure 2.

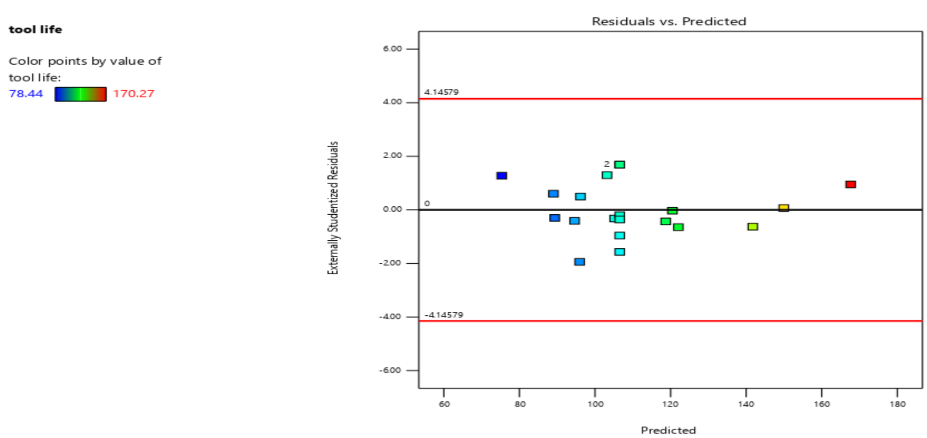

Figure 2: Plot of Residual Versus Predicted for Tool Life

A Cook's distance plot was made especially for Tool Life in order to find any possible outliers in the information collected during the experiment. Cook's distance calculates the change in regression that would occur if an outlier were taken out of the analysis. When a point shows a significantly higher distance value than the rest, it may be an anomaly and needs to be looked into. Figures 3 present the generated cook's distance for Tool Life.

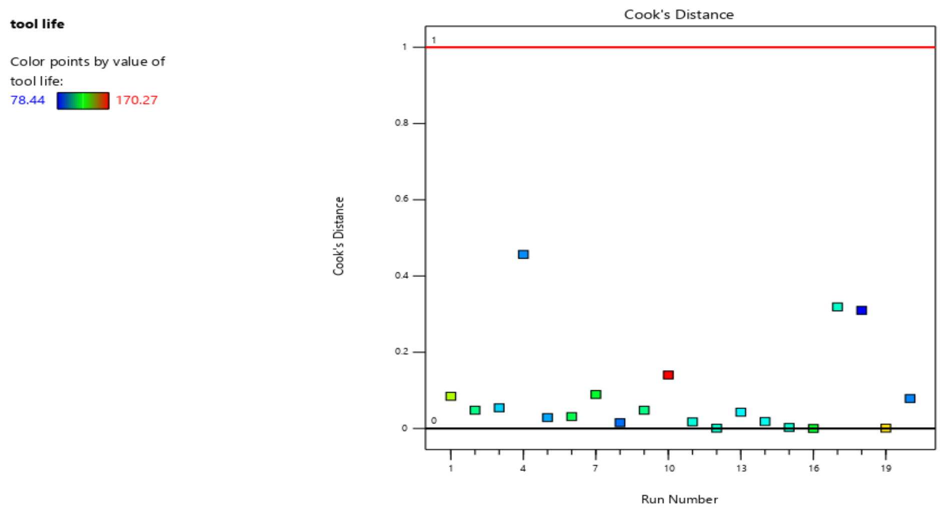

Figure 3: Cook Distance for Tool Life

To identify any values or groups that the model doesn't readily detect, a plot of predicted values against actual values for Tool Life is depicted in Figure 4.

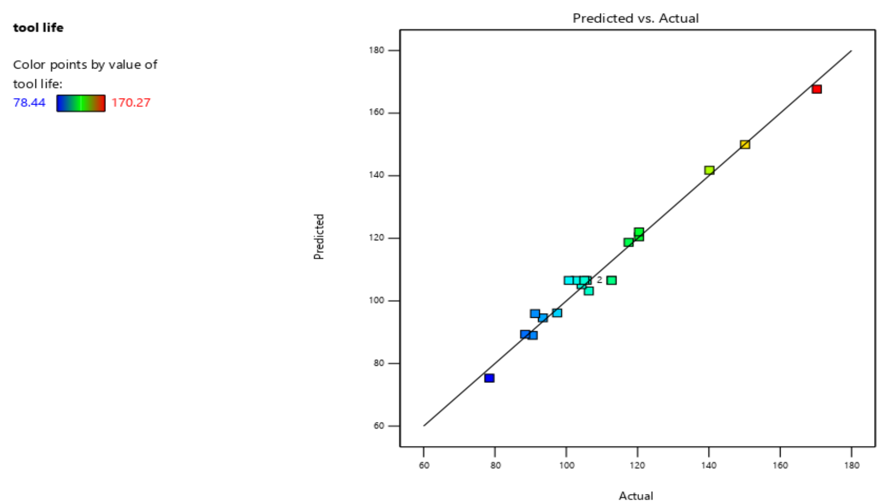

Figure 4: Plot of Predicted Vs Actual for Tool Life

Points that are closely aligned with the fitted line are displayed on the graph. Essentially, the model adequately predicts the majority of the data points.

The 3D surface plot, illustrating the impact of feed rate and cutting speed on the chip removal rate, demonstrates that an increase in both feed rate and cutting speed leads to a higher chip removal rate. nonetheless, the feed rate exhibits a more pronounced effect on the chip removal rate as shown in Figure 5.

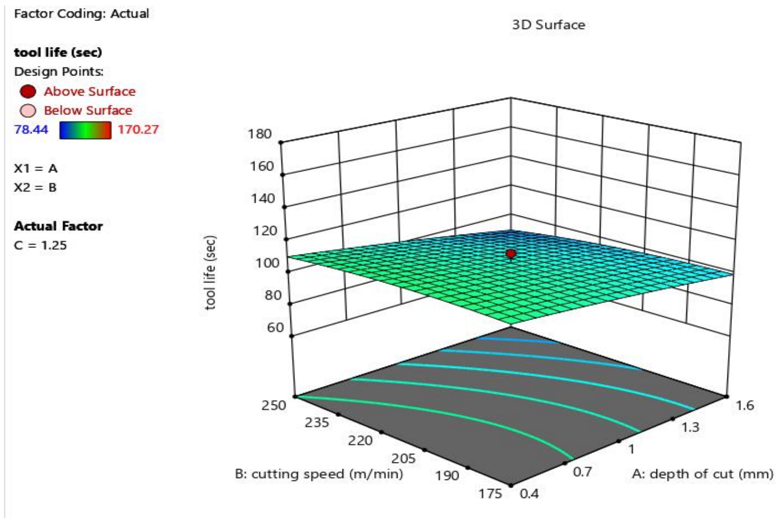

Figure 5: Effect of Cutting Speed and Depth of Cut on Cutting Force

Figure 6 shows a 3D surface plot, displaying the impact of cutting speed and depth of cut on tool life, demonstrates that greater cutting speed correlates with more tool life, while a decrease in depth of cut corresponds to a reduction in tool life.

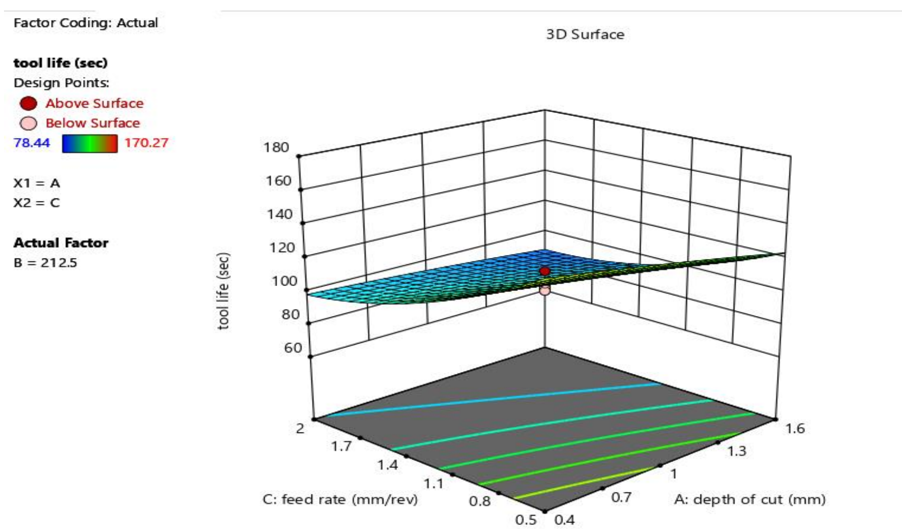

Figure 6: Effect of Feed Rate and Depth of Cut on Tool Life

Figure 7 depicts the 3D surface plot showing the impact of feed rate and depth of cut on tool life. tool life diminishes with a rise in feed rate, although it is not significantly affected by an improvement in depth of cut.

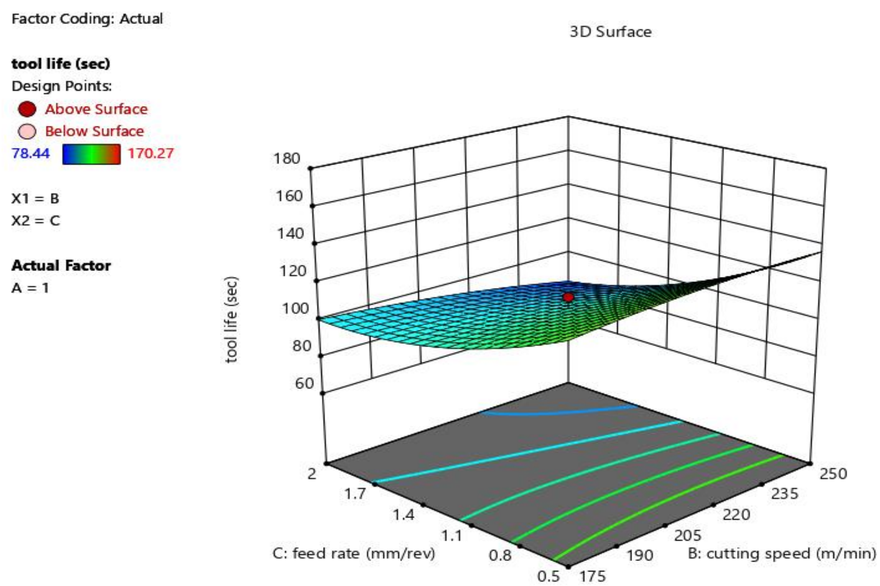

Figure 7: Effect of Feed Rate and Cutting Speed on Tool Life

The 3D surface plot in Figure 7 reveals that increase in feed rate leads to decrease in the tool life while increase in the cutting speed leads to increase in the tool life.

3.2 Prediction of the Tool Life using ANN

MATLAB R2022a is used in the analysis for the Artificial neural network. After being put into the MATLAB folder, the data is standardized by being put into a Numeric Matrix format. This will immediately select the range of the dataset, and import selection is used to load the data into MATLAB. The Levenberg-Marquardt Back Propagation, an enhanced second-order gradient method, was chosen as the most effective learning rule and subsequently employed in crafting the network architecture. In order to ascertain the optimal count of hidden neurons, various quantities of hidden neurons were chosen to establish a trained network utilizing the Levenberg-Marquardt Back Propagation training algorithm. The network performance was observed with 20 neurons set for each hidden layer using coefficient of determination (r2) and MSE. The network's input layer employs the hyperbolic tangent (tan-sigmoid) transfer function to compute the layer output based on the network input, while the output layer utilizes the linear (purelin) transfer function. During the network construction phase, the input data is divided into training, validation, and testing datasets. In this research work, 70% of the data was utilized for training the network, 15% for validating the network, and the remaining 15% to assess the network's performance, with a maximum of 1000 epochs in the training cycle. Trainlm is a network training function that adjusts weight and bias values using Levenberg-Marquardt optimization. With these parameters, an optimal neural network structure was created, as depicted in Figure 8. The identical network architecture was employed to predict tool life as a singular response variable, utilizing three input variables. The Artificial Neural Network architecture is structured as 3-20-1.

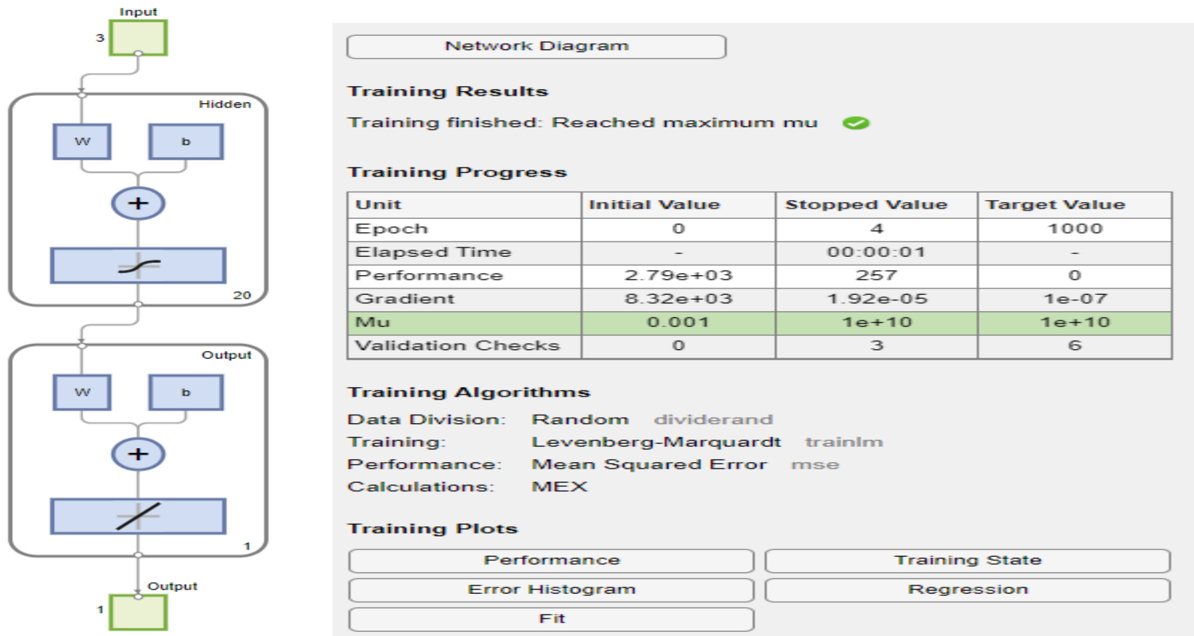

Figure 8: Artificial Neural Network Architecture

In the network training diagram displayed in Figure 8, the observed network performance stood at 2.79e+03. A validation check of three (3) was noted out of a total of six (6). Nonetheless, this outcome was anticipated as the concern regarding weight bias was rectified through the normalization of the raw data. Figure 9 displays a performance evaluation plot illustrating the progression of training, validation, and testing.

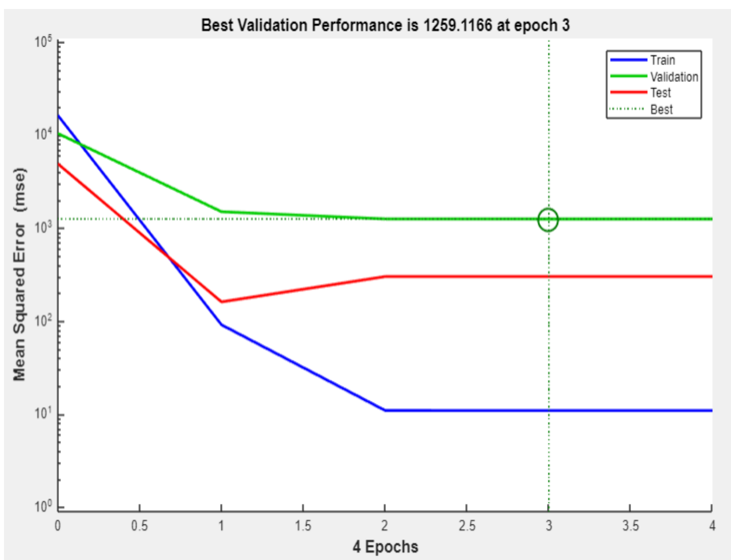

Figure 9: Trained Network's Performance Curve for Tool Life Prediction

The performance plot in Figure 15 didn't reveal signs of overfitting. Additionally, a consistent pattern was observed in the conduct of the training, validation, and testing curves, which was normal as the raw data had been standardized prior to use. A key indicator for evaluating a network's training accuracy is the lower mean square error. At epoch 3, an error value of 1259.1166 demonstrates a network's strong ability to predict tool life. Figure 10 showcases the training state featuring the gradient function, training gain (Mu), and, validation check.

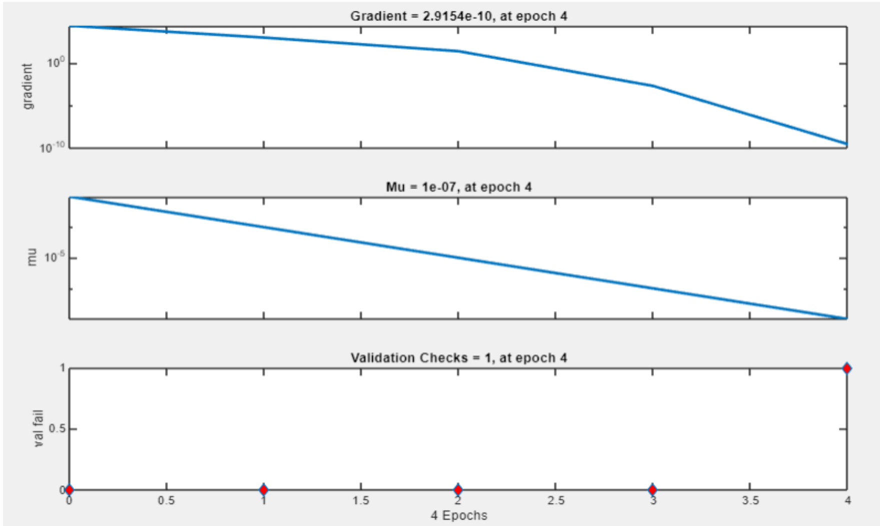

Figure 10: State of Neural Network Training for Tool Life Prediction

Within artificial neural networks, backpropagation is a method employed to ascertain the error input of the neurons, one by one, after processing a batch of training data. In more technical language, the network calculates the loss function's gradient to explain the error contribution of each chosen neuron. A smaller error is generally more desirable. Computed gradient value of 2.9154e-10 as observed in Figure 10 indicates that the error contributions of each selected neurons is insignificant. The control parameter governing the neural network training process is referred to as momentum gain, denoted as Mu. Its value should be below one since it represents the training gains. Momentum gains at 1e-07 signify a highly predictive network for tool life. Figure 11 portrays the regression graph, depicting the correlation between the input factors (DOC, cutting speed, and feed rate) and the target variable (tool life), along with the progression of training, validation, and testing.

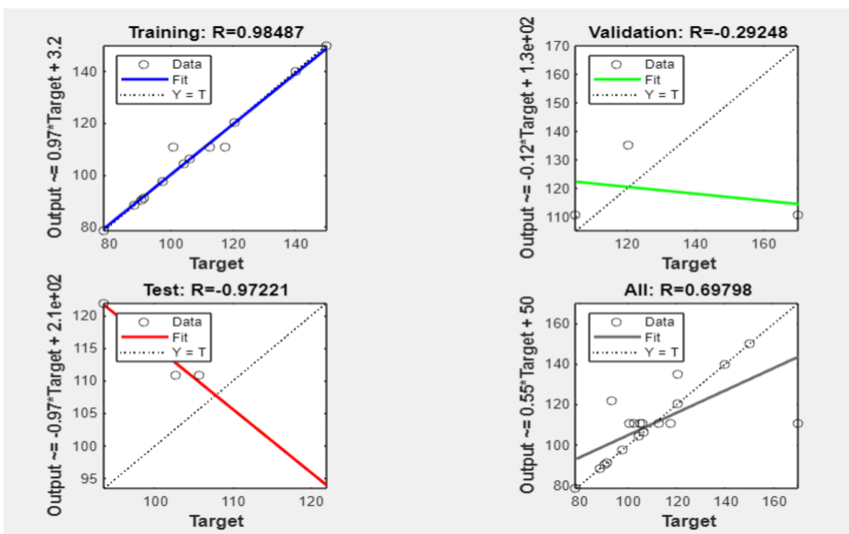

Figure 11: Regression Plot Demonstrating the Progression of Training, Validation, and Testing

Based on analyzing the computed correlation coefficient values as depicted in Figure 11, it was deduced that the network has been effectively trained and can be utilized for predicting tool life.

4. CONCLUSION

Chip size, chip removal rate, and cutting force all affect how long a machined engineered structure lasts in operation. To enhance and predict tool life, this research constructs numerical models incorporating feed rate, depth of cut, and cutting speed. These models are subsequently formulated using artificial neural networks and response surface methods. The Response Surface Method (RSM) analysis yielded the best solutions with a depth of cut of 0.400, cutting speed of 250.000, and feed rate of 0.500, resulting in a machined structure with a tool life of 149.958, achieved at a desirability value of 0.973. The experimental design employed was the central composite design, which was created using the Design 7.1 software. In addition to forecasting the output parameters, the artificial neural network model was utilized and compared with the RSM methodology. The Response Surface Methodology, having a higher coefficient of determination compared to the artificial neural network, is selected as the superior predictive model based on the obtained data.

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