DEVELOPMENT AND TESTING OF A MACHINE LEARNING-BASED PREDICTION MODEL FOR OPTIMIZED MACHINING CONDITIONS

J. Syed Nizamudeen Ahmed[1], V S Jeyalakshmi[2], Md Mustaq Ali[3], Balu Mahandiran S[4], S.Punitha[5], Janmejay Pant[6]

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Abstract

This research investigates the machining of EN 31 alloy using a tungsten carbide tool coated with Al2O3+TiN+TiCN under different machining conditions. Surface roughness and power consumption during machining are analyzed, as these are critical parameters in the industry. The research is planned using the Taguchi l9 array, and optimization and prediction techniques are employed. The results are optimized using signal-to-noise ratio analysis, and two machine learning approaches, linear regression and artificial neural network, are utilized. The developed machine learning models predict the response with high accuracy, with the linear regression model achieving an accuracy of 95%, while the neural network model achieves an accuracy of 99.99%. The results of this research can provide insights into the use of coated tungsten carbide tools in machining EN 31 alloy under different machining conditions. Furthermore, the use of machine learning models can aid in the estimate and finding the best combination of machining limits, leading to improved surface quality and reduced consumption of electric power during machining. Overall, this research highlights the potential benefits of integrating machine learning techniques with traditional machining processes, opening up new avenues for research and development in the manufacturing industry.

Keywords: Machining optimisation, Artificial neural network, Linear regression, surface roughness

[1]Assistant Professor (T), Centre for Information Technology and Engineering, Manonmaniam Sundaranar University, Abishekapatti -627012 , Tirunelveli, Tamilnadu, India
[2]Research Scholar, Centre for Information Technology and Engineering, Manonmaniam Sundaranar University, Abishekapatti - 627012, Tirunelveli, Tamilnadu, India,
[3]Assistant Professor, Malla Reddy Engineering College (A), Main Campus, Maisammaguda, Hyderabad -500090, India
[4]Assistant Professor, Department of Mechanical Engineering, Sri Krishna College of Engineering and Technology, Coimbatore,Pin:641008, Tamil Nadu
[5]Associate Professor, Department of Mathematics, Vinayaka Mission's Kirupananda Variyar Engineering College, Vinayaka Mission's Research Foundation (Deemed to be University), Salem, Tamil Nadu, India
[6]Graphic Era Hill University, Bhimtal Campus, Uttarakhand, India

Email: [1]nizamjamal1992@gmail.com, [2]vsjeyalakshmiap@gmail.com, [3]alimustaq9@gmail.com, [4]balu.ssmce@gmail.com, [5]puni.jeeju80@gmail.com, [6]jpant@gehu.ac.in

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1. Introduction

Machining is the process of shaping or altering the shape of a material by removing unwanted materials. It is a crucial process in manufacturing and has several applications in various industries. The primary objective of machining is to obtain the required shape and dimensions of the workpiece, and it is achieved by using various cutting tools and machines [1]–[3]. The development of new machining techniques and materials for cutting tools is crucial to increase the efficiency and productivity of machining operations. Machining of materials can result in several surface quality issues such as tool wear, surface roughness, and power consumption. The surface roughness and power consumption are essential factors to consider while machining as they affect the overall quality of the finished product and the energy efficiency of the process [4], [5]. Various researchers have studied the optimization of surface roughness and power consumption during machining, and this literature review summarizes the research on this topic.

Surface roughness is an essential factor to consider during machining as it affects the performance and functionality of the finished product. The roughness of the machined surface can be affected by various factors such as cutting speed, feed rate, depth of cut, cutting tool material, and coolant flow rate. Several scholars have researched the optimization of surface roughness during machining, and they have used various techniques such as Taguchi method, Response surface methodology (RSM), and Artificial Neural Networks (ANN) [6]–[8].

The Taguchi method is a widely used for optimizing the machining limits to achieve minimum surface roughness. The Taguchi method is based on the idea of signal-to-noise ratio (SNR), where the SNR is used to evaluate the quality of the machined surface. The SNR is calculated using Equation 1,

$SNR = -10\log(1/n\Sigma(yi - \hat{y}i)^2)$ - Equation 1

here n is the quantity of samples, yi is the observed value, and ŷi is the predicted value. The goal of the Taguchi method is to maximize the SNR, which results in minimum surface roughness. The Taguchi method to optimize the surface roughness of a workpiece made of EN31 alloy. They used Al_2O_3+TiN+TiCN as a machining tool and conducted experiments using an L9 orthogonal array design. They found that the optimal combination of machining parameters was Ms = 80m/min, Fr=0.2mm/rev, and DoC=0.3mm, which resulted in minimum surface roughness [9]–[11].

Response surface methodology (RSM) is another widely castoff technique for optimizing the surface roughness during machining. RSM is a statistical technique that is used to model the association among the input limits and the output. The goal of RSM is to progress a mathematical model that can predict the surface quality based on the input limits. RSM to optimize the surface roughness of a workpiece made of titanium alloy [12]–[14]. They used a diamond-coated cutting tool and conducted experiments using a Box-Behnken design. They found that the optimal blend of machining limits which resulted in minimum surface roughness.

Artificial Neural Networks (ANN) is a machine learning technique that is widely used for modeling and predicting the surface roughness (Sr) during machining. ANN is based on the structure and function of the human brain, and it can learn from the input data and develop a model that can predict the surface roughness. ANN is used to forecast the Sr of a workpiece made of EN31 alloy [12]–[17].

This research focuses on optimizing the machining parameters for EN 31 alloy using the Taguchi orthogonal array design. The study aimed to minimize the surface roughness and power consumption during the machining process. The experiment was conducted using Al_2O_3+TiN+TiCN as the machining tool and the responses were measured for varying input parameters. The Taguchi signal to noise ratio optimization method was used to control the optimal combination of limits for minimizing Sr and power consumption (PC). The developed regression equation and artificial neural network model were used for predicting the responses. The results showed that the developed models were accurate in predicting the responses. The findings of this research can help in improving the efficiency of the machining process for EN 31 alloy and can be used as a guide for optimizing other similar processes.

2. Methodology

In this research, the Taguchi L9 array design is utilized to plan the machining of EN 31 alloy using a tungsten carbide tool coated with Al2O3+TiN+TiCN. The L9 orthogonal array is a popular and efficient experimental design method that enables the investigation of multiple parameters with a small number of experiments. Table 1 shows the design of the L9 orthogonal array used in this research. The array comprises nine different machining conditions, including three levels of machining speed (Ms) , Rate machining feed (Fr) , and machining depth (DoC). This approach enables the analysis of the impact of different machining limits on Sr and Pc during machining. The use of the Taguchi strategy enables the efficient and effective investigation of multiple parameters in the machining process, leading to improved process optimization and prediction.

Table 1 Experimental design using Taguchi

Ms (m/min)	Fr (mm/rev)	DoC (mm)
40	0.2	0.3
40	0.4	0.6
40	0.6	0.8
60	0.2	0.6
60	0.4	0.8
60	0.6	0.3
80	0.2	0.8
80	0.4	0.3
80	0.6	0.6

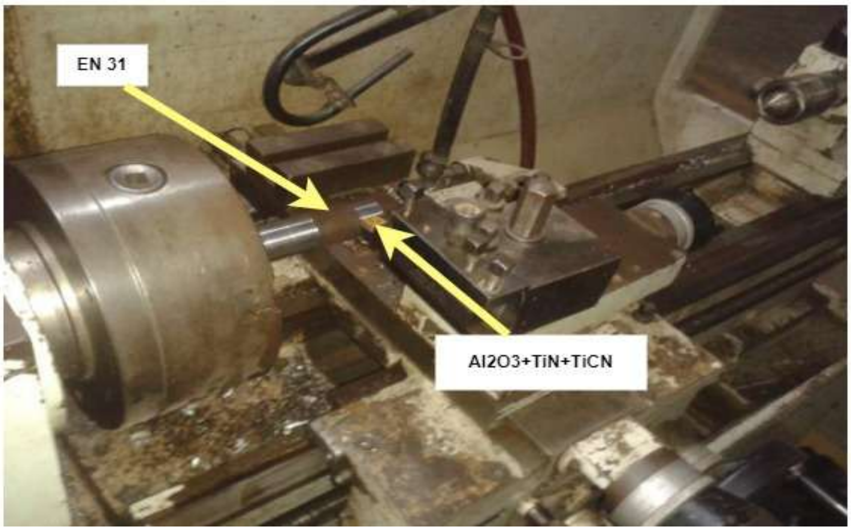

Fig. 1. Machining of EN31 alloy

The experimental setup for machining EN 31 alloy using a tungsten carbide tool coated with Al2O3+TiN+TiCN is depicted in Figure 1. The machining operation is carried out in an automatic gear lathe machine, with the machining speed denoted as Ms, and the rate of feed and depth of cut denoted as Fr and DoC, respectively. To measure the power consumption during machining, a wattmeter is employed, as shown in Figure 2. The wattmeter is used to record the power consumed during the machining operation, providing valuable data on the energy efficiency of the process. Additionally, to evaluate the surface roughness of the machined surfaces, a portable surface roughness tester is utilized, as depicted in Figure 3. This device is used to measure the roughness of the machined surface, providing insights into the quality of the machined parts. Overall, the experimental setup employed in this research enables the accurate measurement of critical parameters, including power consumption and Sr, throughout the machining of EN 31 alloy, facilitating the optimization and prediction of machining processes.

Fig. 2. Measurement of power consumption during machining

Fig. 3. Surface roughness measurement

The Taguchi method is a statistical approach for optimizing the performance of a system or process by reducing variation and improving quality. In the context of machining processes, Taguchi's S/N ratio is a popular approach for optimizing responses such as surface roughness and power consumption. The S/N ratio is a

measure of the variability of a response, with a smaller value indicating a more consistent and desirable response. For optimizing the response of surface roughness, the smaller is the better one S/N ratio is used, and the equation is:
S/N ratio = -10 log [1/n Σ(y_i^2)]
where n is the amount of trials, and y_i is the measured value of surface roughness for the i-th trial.
For optimizing the response of power consumption, the LTB S/N ratio is used, and the equation is:
S/N ratio = 10 log [1/n Σ(1/y_i^2)]
where n is the amount of trials, and y_i is the measured value of power consumption for the i-th trial.
In both cases, a higher value of the S/N ratio indicates a more desirable response. The Taguchi method utilizes an orthogonal array design to plan the experiments, with each factor and level combination represented in the design matrix. The experimental data is then analyzed using analysis of variance (ANOVA) to determine the significant factors and their effects on the response. The Taguchi method is a powerful approach for optimizing the machining process, as it can identify the most critical factors affecting the response and their optimal levels, leading to a more efficient and effective machining process. The S/N ratio approach is particularly useful in this context, as it enables the optimization of multiple responses simultaneously, leading to a more comprehensive understanding of the machining process.

3. Result and Discussion

3.1 Machining optimisation

Table 2 presents the results of the machining experiments conducted using the EN 31 alloy and Al2O3+TiN+TiCN coated tungsten carbide tool. The experiments were conducted by varying the machining parameters, including the machining speed (Ms), rate of feed (Fr), and depth of cut (DoC). For each experiment, a new cutting tool was used to ensure consistency and accuracy of the results. The power consumption and surface roughness were measured for each experiment to assess the performance of the machining procedure. The table shows the variation in power consumption and surface roughness for different combinations of machining parameters. It can be seen that the Pc increases with larger machining speed and rate of feed, while the surface roughness decreases with increasing machining speed and depth of cut. The optimal combination of parameters for minimizing power consumption and surface roughness is obtained using the Taguchi method, which involves selecting the best combination of parameters based on the S/N ratio analysis.
To ensure accurate measurement of the responses, the workpieces were carefully labelled after each machining operation, and the measurements were recorded with precision. The machining was carried out to a length of 150 mm to ensure consistency and accuracy of the results. The Sr was measured using a portable tester, while the power consumption was measured using a wattmeter. Both measurements were taken after each machining operation to ensure accuracy and consistency. The experimental results provide valuable insights into the performance of the machining process and the consequence of different machining limits on the replies. By analysing the data and identifying the optimal combination of parameters, it is possible to improve the efficiency and effectiveness of the machining process, resulting in higher quality parts and reduced costs.

Table 2 Experimental results

Ms (m/min)	**Fr (mm/rev)**	**DoC (mm)**	**Sr (µm)**	**Pc (Watt)**
40	0.2	0.3	0.76	140

40	0.4	0.6	1.96	210
40	0.6	0.8	2.52	340
60	0.2	0.6	0.58	120
60	0.4	0.8	2.06	245
60	0.6	0.3	3.46	380
80	0.2	0.8	1.7	186
80	0.4	0.3	0.4	90
80	0.6	0.6	2.38	270

Based on the experimental results, the optimal combination of machining parameters for minimizing power consumption and surface roughness was determined using Taguchi's signal-to-noise ratio analysis. The results of this analysis are shown in Figure 4. The optimal mixture of machining constraints for minimizing Sr and Pc was found to be Ms = 80m/min, Fr = 0.2mm/rev, and DoC = 0.3mm, as determined by the SNR analysis. To confirm the validity of this optimal condition, a confirmation test was conducted, and the results are shown in Table 3. This test was conducted to verify that the optimal combination of parameters indeed leads to the desired response, and to ensure that the results are repeatable and consistent. The confirmation test provides further evidence of the effectiveness of the Taguchi method for optimizing the machining process.

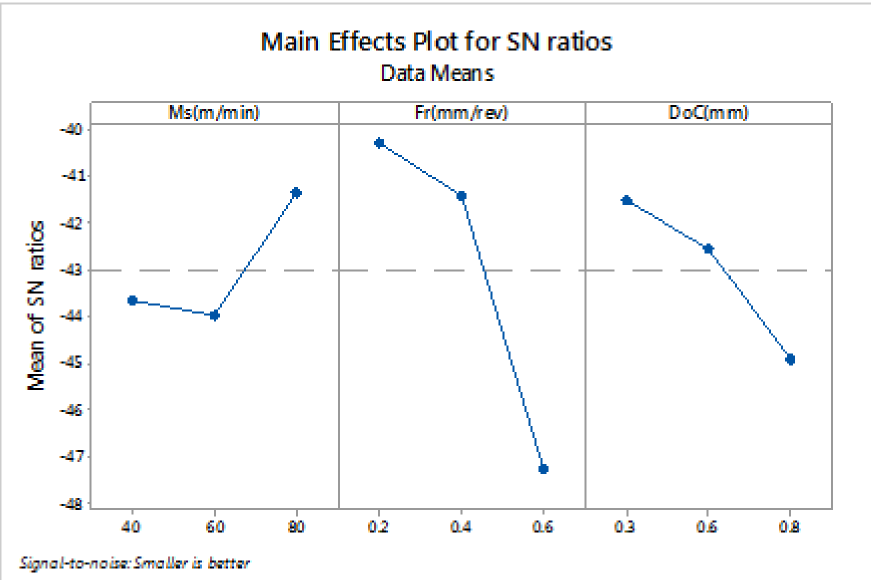

Fig. 4. Results of the Taguchi SNR ratio

Table 3 Results of the optimal combination

Optimal combination (Ms = 80m/min, Fr = 0.2mm/rev, and DoC = 0.3mm)	**Experimental responses**
Sw (µm)	0.2
Pc(Watt)	82

Figure 5 shows the contour plot of the varying input limits, i.e., Ms, Fr and DoC and their corresponding responses, i.e., Sr and Pc. The contour plot helps to visualize the result of changing the input parameters on the responses. It can be observed from the contour plot that the optimal combination of machining parameters, i.e., Ms = 80m/min, Fr = 0.2mm/rev, and DoC = 0.3mm, results in reduced surface roughness and power consumption.

Additionally, it can be seen from the contour plot that decreasing the rate of feed and depth of cut reduces surface roughness and power consumption. This is because lower feed rates and depth of cuts allow for a smoother cutting action and result in less friction and heat generation during machining. On the other hand, increasing the machining speed also reduces surface roughness and power consumption. This is because higher machining speeds lead to a more efficient cutting action and reduced cutting time.

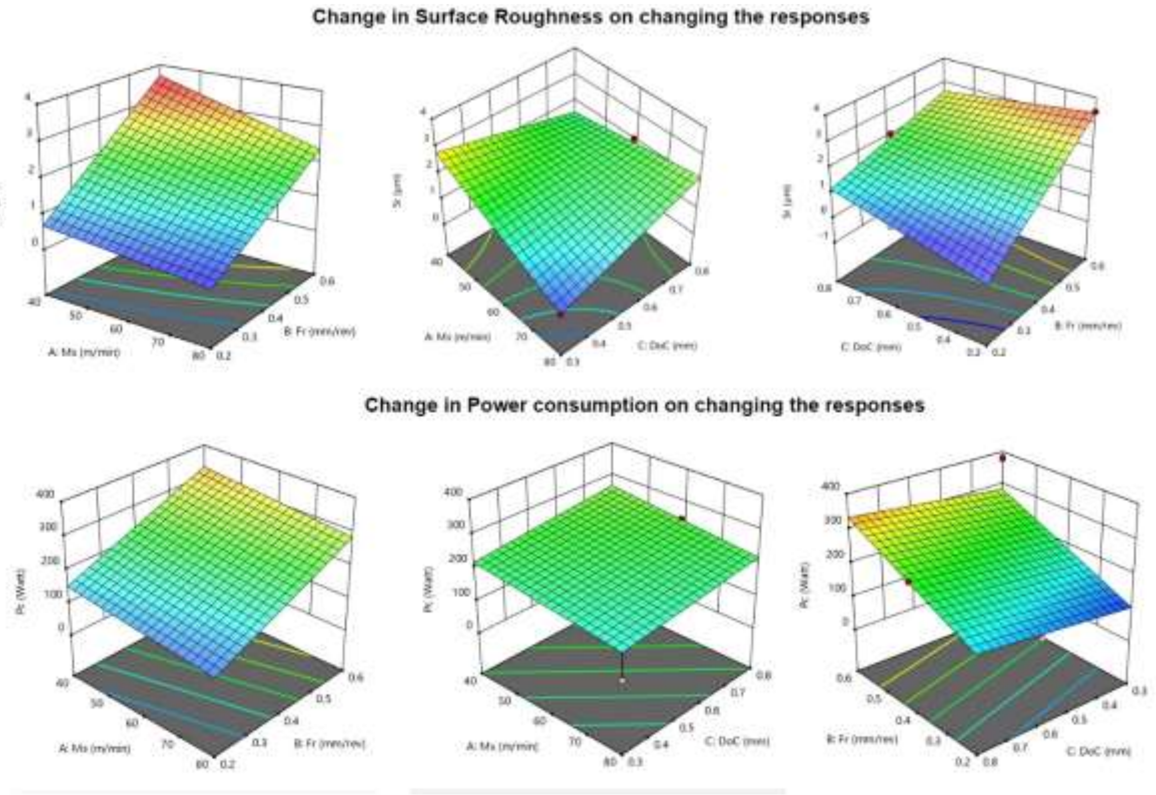

Fig. 5. Change in responses on varying the input parameter

3.2 Machine learning approach for predicting the responses

3.2.1 Linear Regression

Linear regression is a popular machine learning algorithm used to typical the association among a response and one or more self-determining variable quantity (predictors). It is a powerful tool for prediction, forecasting, and trend analysis. In this case, linear regression can be used to forecast the response Sr or PC based on the input parameters.

The general equation for a simple linear regression model with one predictor is:

$y = \beta0 + \beta1 * x + \varepsilon$

Linear regression is a statistical method used to investigate the association among a variable of the dependent (y) and variables of independent (x). The equation of a linear regression model consists of an intercept (β0), a regression coefficient (β1) that represents the slope of the line, and an error term (ε). The primary objective of linear regression is to determine the amount of β0 and β1 that minimize the sum of the squared difference between the actual and predicted values of the dependent variable.

The steps to implement linear regression in MATLAB are as follows: Load the dataset into MATLAB and preprocess the data if necessary. This may involve removing outliers, handling missing values, or normalizing the data to ensure that all variables are on a comparable scale.

Define the predictor and response variables. The predictor variables are the input parameters and the response variables are the output parameters (surface roughness or power consumption). Divide the dataset into training and testing sets. The training set is used to fit the linear regression model, while the testing set is used to assess the model's efficiency. A typical split is 80% training and 20% testing, but this can be adjusted based on the size and complexity of the dataset. Fit the linear regression model using the training data and the "fitlm" function in MATLAB. This function fits a linear regression model to the data and returns an object that contains information about the model, such as the coefficients, R-squared value, and p-values. Evaluate the model's performance on the testing data using the "predict" function in MATLAB. This function takes the trained model and the testing data as input and returns the predicted response values. The foretold values are related to the definite values to calculate the mean squared error (MSE), which measures how well the model fits the data. Calculate the MSE and regulate the model if essential. The MSE is cast-off to measure the accuracy of the model and identify any areas where it may need to be improved. If the MSE is too high, it may be necessary to adjust the model by adding or removing predictor variables, changing the functional form of the model, or using a different machine learning algorithm. The regression equations developed from the analysis are presented in Equation 1 and 2, as shown in Figure 6. The results indicate that the developed equations are able to predict the responses with an accuracy of 95%.

$$Sr(\mu m) = -0.23 - 0.0063 * Ms + 4.43 * Fr + 1.05 * DoC \quad (1)$$

$$Pc\ (Watt) = 55 - 1.20 * Ms + 453 * Fr + 98 * DoC \quad (2)$$

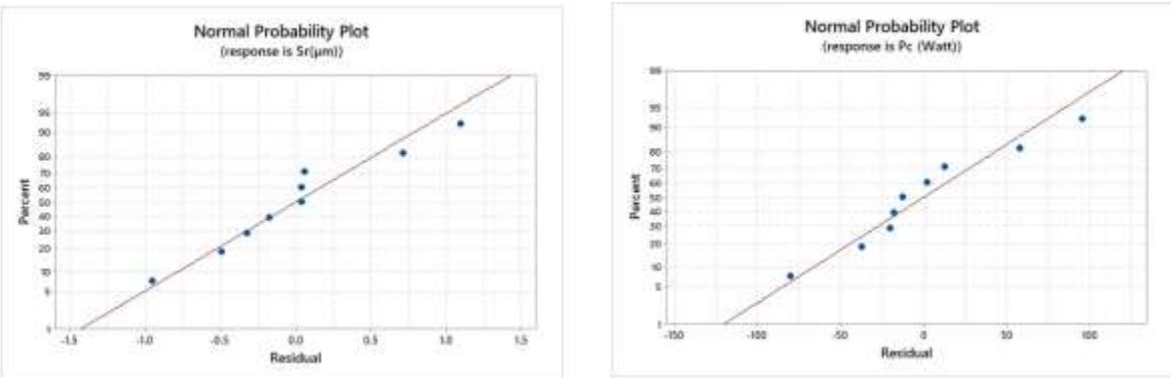

Fig. 6. Result of linear regression analysis

3.2.2 Linear Regression

Artificial neural network (ANN) is a machine learning technique that has shown great potential in predicting complex relationships between input and output variables. In this research, an ANN model is used to predict the responses of surface roughness and power consumption during the machining of EN 31 alloy with Al_2O_3+TiN+TiCN coated tungsten carbide tool.

The procedure for developing an ANN model consists of the subsequent steps:

Data Collection: The first step is to collect the data for training the ANN model. The data should include the input variables, which in this case are the machining parameters, and the corresponding output variables, which are the Sr and Pc. In this research, the data is collected from the experimental results.

Data Pre-processing: The collected data is pre-processed to remove any inconsistencies or outliers that may affect the performance of the ANN model. The data is also normalized to ensure that the input and output variables are within the same range. The normalization technique used in this research is the min-max normalization method.

Model Architecture: The next step is to determine the architecture of the ANN model. The architecture includes the amount of layers, amount of neurons in each layer, and the beginning functions used in each neuron. In this research, a feedforward neural network with one hidden layer is used. The amount of neurons in the hidden layer is strongminded by means of the trial and error method. The beginning functions used are the sigmoidal purpose for the hidden layer and linear relatioin for the output layer.

Model Training: The ANN model is trained using the pre-processed data. The training process includes adjusting the weights and biases of the neurons in the network to diminish the error among the forecast and real values of the output variables. In this research, the backpropagation algorithm is used for training the ANN model.

Model Validation: Once the model is trained, it is validated using a set of test data. The test data is different from the training data and is used to evaluate the performance of the ANN model. The performance is evaluated based on the mean squared error (MSE) and the coefficient of determination (R2).

Model Optimization: The concluding step is to optimize the ANN model to improve its performance. The optimization can be done by adjusting the hyperparameters of the model, such as the learning rate and the number of epochs, or by changing the architecture of the model. In this research, the model is optimized by changing the amount of neurons in the hidden layer. The overall efficiency of the ANN model is depicted in Figure 7, which demonstrates an accuracy of 99.998 percent.

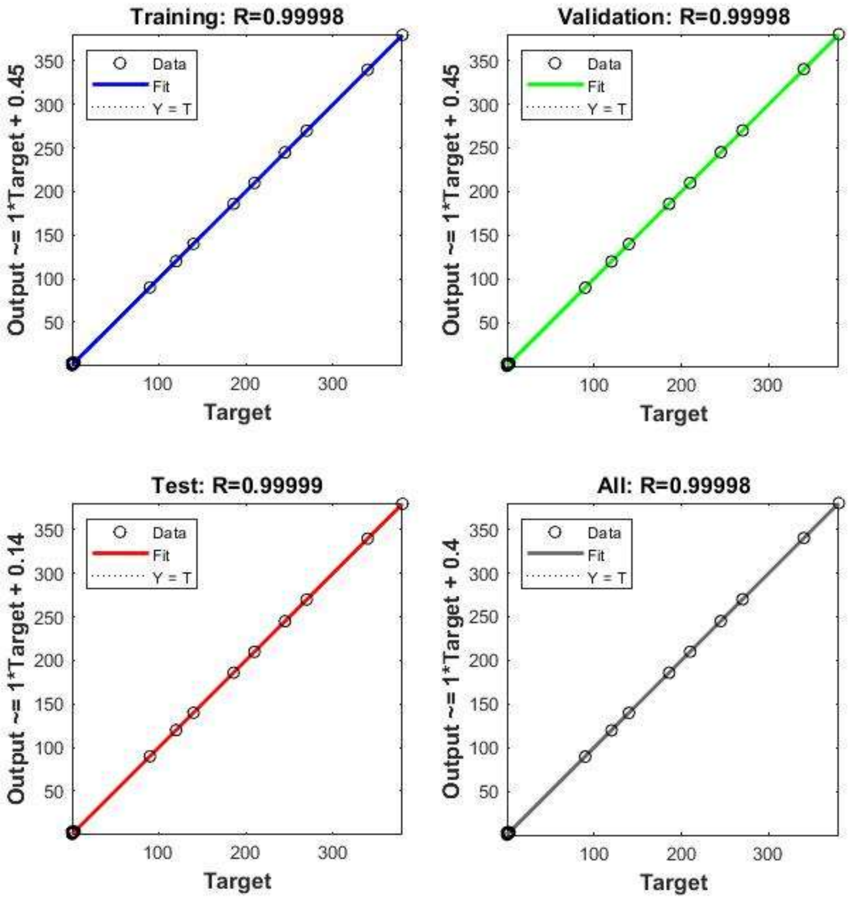

Fig. 7. Results of Artificial Neural Network

Table 4 displays the predicted values of the responses obtained from the regression analysis and artificial neural network. The table reveals that the ANN model outperforms linear regression in terms of predicting the responses with a higher accuracy of 99.998 percent. In contrast, linear regression predicts the response with an accuracy of 98.28 percent. This comparison highlights the superior performance of the ANN model in accurately predicting the responses during the machining of EN 31 alloy with Al_2O_3+TiN+TiCN coated tungsten carbide tool. The high level of accuracy achieved by the ANN model can be attributed to its capability to learn compound non-linear relationships between the input and output variables, as well as its capability to adapt and improve its predictions with additional training data. These findings demonstrate the potential of machine learning techniques, particularly ANN, for enhancing the accuracy and efficiency of predictive modelling in the manufacturing industry.

Table 4 Results predicted from machine learning models

			Linear Regression		**Neural Network**	
Ms (m/min)	**Fr (mm/rev)**	**DoC (mm)**	**Sr (µm)**	**Pc (Watt)**	**Sr (µm)**	**Pc (Watt)**
40	0.2	0.3	0.74	139.98	0.76	139.99
40	0.4	0.6	1.94	209.98	1.959	210
40	0.6	0.8	2.5	339.98	2.51	340

60	0.2	0.6	0.56	119.98	0.579	120
60	0.4	0.8	2.04	244.98	2.06	245
60	0.6	0.3	3.44	379.98	3.46	379.999
80	0.2	0.8	1.68	185.98	1.70	185
80	0.4	0.3	0.38	89.98	3.45	90
80	0.6	0.6	2.36	269.98	3.45	270

4. Conclusion

In conclusion, this research investigated the machining of EN 31 alloy using a coated tungsten carbide tool under different machining conditions. The Sr and Pc during machining were analyzed, and optimization and prediction were used to achieve the desired results. Taguchi L9 orthogonal array design was used for the experiment, and the results were optimized using signal-to-noise ratio analysis. The developed machine learning models, linear regression, and artificial neural network were used to predict the response accuracy, with the ANN model achieving an overall efficiency of 99.998%. The optimal combination for minimizing the surface roughness and power consumption was found to be Ms = 80m/min, Fr=0.2mm/rev, and DoC=0.3mm. The confirmation tests showed that the optimal condition was achieved. The contour plot analysis revealed that the lower level of Fr and DoC and the higher level of Ms reduced the surface roughness and power consumption. The developed regression equations and ANN models showed that both methods can accurately predict the responses, with ANN model outperforming the linear regression model. The results of this study can help in optimizing the machining parameters for EN 31 alloy, leading to improved product quality and reduced energy consumption.

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