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Neural network based model for estimating cutting force during machining of Ti6Al4V alloy

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A B S T R A C T

The evolving technology has pushed machine learning techniques to replace human smartness. A machine learning model is capable of learning and replicating like our brain. This approach of data-driven model is implemented to predict the cutting force in machining of Ti6Al4V. Titanium alloys are commonly used in high strength applications due to their excellent properties. These same properties make the machining of the titanium alloy complicated. An attempt has been made for finding the cutting force under minimum quantity lubrication (MQL). MQL is a sustainable manufacturing-based lubrication system. Taguchi's approach was used to attain a full factorial design for combination of different parameters. Accordingly, a neural network (NN) model was developed which was capable of predicting cutting forces based on the trained model. The proposed model could be implemented to find optimal parameters in shortest duration, thereby eliminating the need for experimental computations.

1. Introduction

With the development of technology, automated and adaptable manufacturing techniques have been implemented in manufacturing. To remove the material from the workpiece, different procedures are being used in the industries. The most common method for removing metal in machining is by turning operation. It involves the reduction of diameter of a cylindrical workpiece. The mechanical device required for this kind of operation is called a CNC-lathe. Turning is one of the widely used machining processes to trim the excess material and achieve an excellent surface finish. Good machining output can be achieved if the parameters are tweaked to optimal performance. Certain parameters can help increase productivity and save both cost and time. The input parameters such as cutting speed, feed rate, depth of cut, tool angles and cooling conditions can be controlled by the operator. For controlling these parameters and getting the desired output, the manufacturer intends to know the optimal conditions in machining processes.

Artificial intelligence has been implemented into a number of technological advancements that have influenced and made our lives better. Through advanced analytics, automation, and networked systems, machine learning offers huge opportunities to transform industries. These technologies have already enabled enormous developments across a lot of sectors. The arrival of futuristic applications like facial recognition in smartphones, virtual personal assistants, product recommendations in online shopping and self-driving cars are real-world examples of machine learning. Machine learning algorithms are produced by data-driven predictions and judgments. The algorithm learns and adjusts itself based on a connection to a data source. There are many different types of machine learning algorithms that perform a variety of tasks and functions. Deep learning is one such type that focuses on extracting sophisticated feature representations from complex data. Artificial neural network (ANN) is a way of accomplishing deep learning, using evolved data processing and decision-making processes.

The use of artificial neural networks can be used to train systems to analyze data like the human brains. The human brain is

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made up of something like a neural network composed of neurons, which are the nerve cells that are connected with each other. The computation happens at the nucleus, or cell body, of the neuron. From one neuron to another, the axon transmits the electrical signal of the activity (Graupe, 2013). This is how the biological neural network functions.

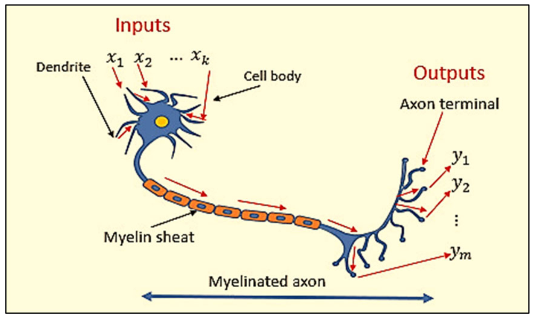

Fig. 1. Biological Neural Cell

ANN uses a connectionist model of computation to interpret data and it consists of a network of artificial neurons that are connected to each other thoroughly. In a number of situations, an ANN is an adaptive system that modifies its structure in response to input coming from the outside or within the network during the learning period. Usually, layers are used to set up a neural network model. The 'activation function' is found in each of the highly interconnected 'nodes' that make up a layer. The 'input layer' communicates with one or more 'hidden layers', where the real processing is performed using a system of weighted 'connections', to present patterns to the network. The response is then delivered in an 'output layer' that is connected to the hidden layers and can predict values (Wu & Feng, 2018).

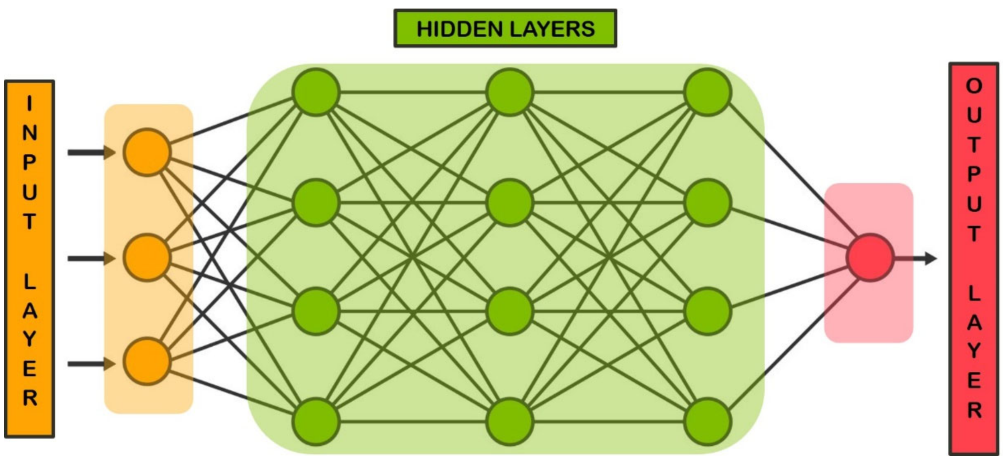

Fig. 2. Neural Network Model

Titanium Grade 5 alloy commonly referred to as Ti6Al4V, has outstanding qualities which includes its high strength-to-weight ratio, exceptional resistance to corrosion, low coefficient of thermal expansion and high toughness (Caggiano, 2018). This makes the alloy very appealing for cutting-edge applications in a multitude of sectors, including the aerospace, automotive and medical domains. According to reports, titanium alloys make up 15% of the Boeing 787 and 14% of the Airbus A350-900 aero frames (Shokrani & Newman, 2019). The qualities of titanium alloys that make them desirable for many engineering applications are also the factors that make them challenging for machining. Due to the inherent material characteristics, titanium alloys typically have poor machinability. The factors such as high cutting temperature, strong adhesion at the interface between the tool and workpiece, and low thermal conductivity and high chemical reactivity of titanium alloys, makes the machining difficult due to rapid tool wear and short tool life. Workpiece bending is caused by the low elastic modulus and high strength that is retained at high temperatures.

Hard turning of titanium alloys generates high cutting forces, which causes poor surface finish and increased mechanical vibrations. The use of cutting fluid in metal cutting processes consequently appears to be an efficient technique of controlling the cutting temperatures, which are related to the optimum cutting parameters. Cutting fluids have the tendency to produce a thin film on the tool-chip interface, reducing friction on the cutting tool edges (Salur et al., 2021). However, conventional flood cooling unfortunately poses serious threats to both the environment and public health. The benefit of dry cutting is that it doesn't require any fluid, which also eliminates the need for additional equipment to deliver the coolant. However, some drawbacks of dry machining include inadequate chip evacuation, premature tool wear, unexpected tool breakage, and poor surface quality. To enhance the characteristics during the machining process, a near-dry machining method called minimum quantity lubrication (MQL) is implemented. By applying a pressured fine coolant spray and reducing the lubrication cost by 40–60%, MQL was capable of effectively reducing temperatures in the cutting zone (Jamil et al., 2021). The fluid used in MQL is usually an environmentally friendly oil such as palm oil or soybean oil.

2. Related Works

The work done in (Wang et al., 2020) predicted the degree of tool wear using physics-based and data-driven modelling. The model proposed a cross physics-data fusion scheme to fuse the hidden information explored from both the models. A loss function was derived based on the physics knowledge that tool wear increases with the number of cuts. The developed method would provide sufficient information from both physics and machine learning domains to eliminate the inconsistency of conventional methods. Online tool condition monitoring systems were used to prevent downtime and get high quality production in (Kaya et al., 2011). Cutting force components in all three axes and torque data was collected using MATLAB data acquisition toolbox. Based on this data an ANN model was developed to predict the flank wear on the tool. The cutting forces and torque signals were observed to be sensitive to cutting conditions. These parameters would decrease with the effect of crater wear.

The ball end milling process was analyzed for change in cutting forces with respect to varied cutting parameters in (Balasubramanian et al., 2021). The milling operation was simulated using CutPro software and cutting force data of all three mutually perpendicular directions was obtained. The neural network model was trained using python scripting with PyTorch optimizer to decrease rates of error during training. A linear surface was observed to be fitting over the data with 5% deviation in the predicted values. The neural network based on increment learning scheme was suggested for predicting fatigue growth by (Ma et al., 2021). The specimens were made of 7B04 T6 aluminum and TA15 titanium alloy, placed under constant amplitude stress. Since the back propagation algorithm is not effective for small datasets, inputs were employed with multiple increment information to improve quality and quantity of the dataset. The developed NN model showed superiority to conventional curve fitting models with high accuracy.

ANN model of high performance has numerous advantages as noted in (Madić & Radovanović, 2011). If the training data and architectural parameters are chosen correctly then the model can be used for optimising machining processes. A L18 orthogonal array was developed using Taguchi method with four factors to estimate the resultant cutting force. The Levenberg-Marquardt algorithm is used as it is faster and finds better optima than other methods. Around eight different models were developed and a trial-and-error method was implemented to determine the best NN model. It was observed that the transfer function in the hidden layer is most influential on ANN prediction performance. Prediction of cutting force using fuzzy logic was done (Malagi et al., 2018), for titanium alloy Ti-6Al-4V under minimum quantity lubrication. To calculate and improve the experimental cutting conditions, response surface methodology and fuzzy logic model were used. Cutting the titanium alloy at a speed of 45 m/min, a feed rate of 0.11 mm/rev, and a depth of cut of 0.25 mm was found to be the ideal conditions. The cutting force could be predicted using fuzzy logic during turning of the alloy.

The study for prediction of cutting forces in milling of 618 stainless steel was undertaken in (Kadirgama & Abou-El-Hossein, 2006). Cutting force was used as a response, and the variables taken into account were cutting speed, feed rate, axial depth, and radial depth. Using design of experiments, the optimal experimental circumstances were attained. For the neural network, the Levenberg-Marquardt training algorithm was combined with Bayesian regularisation. The created model was capable of successfully predicting the data for the trained range. The simulation model for predicting mechanical properties of Ti6Al4V using NN is described in (Detak et al., 2010). Tensile strength, elongation, and Rockwell Hardness were the predicted mechanical properties. The alloy's chemical composition at ambient temperature was used as the input. Gradient Descent and Levenberg-Marquardt learning algorithms were used for the training. The results indicated that Gradient Descent is more suitable to achieve a high performance of output criterion and even that the Levenberg-Marquardt algorithm demonstrated great ability for training.

The researchers have suggested that the NN training model gives higher accuracy based on the architecture of the model. This model can be used to predict values that can reduce the time for experimental estimation and conventional calculations. An ANN model can be suited for accurate prediction of cutting force based on the varying input parameters such as cutting speed, depth of cut and feed rate.

3. Research Methodology

Artificial neural networks require data for training and prediction of models. This data has to be obtained from true experiments and fed to the system. The larger the dataset, the accuracy of predicted values increases in the neural network. The experiments were performed to obtain the cutting force data.

3.1 Experimental Setup

The cutting forces were measured by an experiment conducted using a combination of different input parameters. The Ti6Al4V workpiece used was of a cylindrical-shaped, with dimensions of 30 mm in diameter and 250 mm in length. Cubic

Boron Nitride (CBN) was used as the cutting tool because of its capacity for turning off hard materials. After diamond, it is the second-hardest material available on earth. CBN's key advantage is that it retains its mechanical stability even when it is subjected to air temperatures higher than 1000 °C. The workpiece and the cutting tool are the same throughout the experiment, regardless of their composition or dimensions.

Fig. 3. (a) CBN Cutting Tool (b) Ti6Al4V Workpiece

Design of Experiment (DOE) is a powerful technique to gain insights of the process and optimize them for high performance. It helps researchers to plan the experimentation appropriately. Taguchi method is widely used for planning of experiments to acquire data in a controlled manner. It is an orthogonal array-based experiment. The full factorial technique takes into account all possible interactions between factors and their varying levels. A full-factorial Taguchi design of L27 orthogonal array was used with three factors and three levels. The cutting speed, feed rate and depth of cut was varied to obtain different values of cutting forces. There were three different cutting speeds: 45, 73, and 101 m/min. While the depth of cut was set as 0.25, 0.5, and 0.75 mm, the feed rate varied between 0.11, 0.18, and 0.25 mm/rev.

Table 1
Machining Parameter Factors and Levels

Factors	Level 1	Level 2	Level 3
Cutting Speed (m/min)	45	73	101
Feed Rate (mm/rev)	0.11	0.18	0.25
Depth of Cut (mm)	0.25	0.5	0.75

The turning operation is conducted on a PSG conventional lathe model A141. The tool-workpiece interface was lubricated using the MQL technique. The MQL arrangement included an oil reservoir, air filter, pressure gauge, jet nozzle, variable-speed control motor, and oil injection pump. Through the tip of the system, coconut oil was sprayed to the tool-workpiece interface. The cutting force data was captured using the Kistler 9257BA Dynamometer. Data obtained from the Kistler amplifier was monitored closely by a laptop.

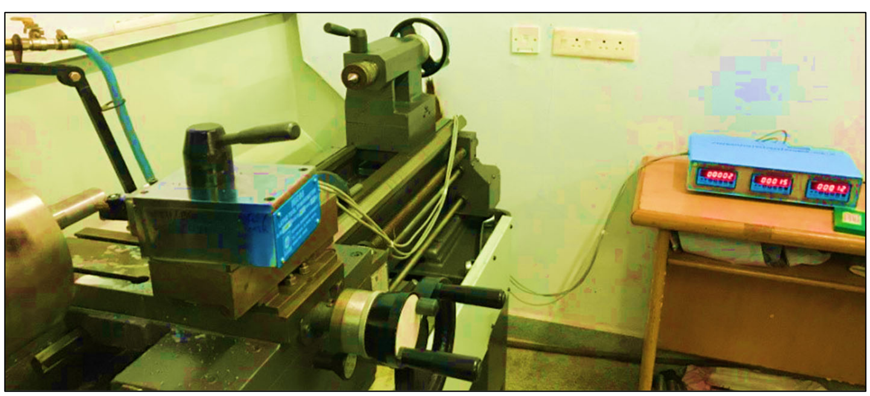

Fig. 4. Machining Setup

3.2 Dataset for Artificial Neural Network Training

MATLAB, which stands for 'MATrix LABoratory', is a powerful programming language used in scientific computing. When it pertains to data analysis, algorithm development, and model creation, MATLAB has significant advantages over other programming languages. The Neural Network toolbox in MATLAB R2021a was used to build and train the ANN model. The NN toolbox in MATLAB offers algorithms, trained models, and a graphical user interface to construct, train, test, and simulate shallow neural networks (one hidden layer) or deep neural networks (several hidden layers). The performance factor is taken into consideration when designing neural networks, which streamlines complicated issues. For ANN training, the data collected using experimental cutting force with MQL was considered. Since the data was an L27 orthogonal array, it was adequate to train a neural network model. The.csv (comma separated values) file format is being used by MATLAB to smoothly import external data into matrix format.

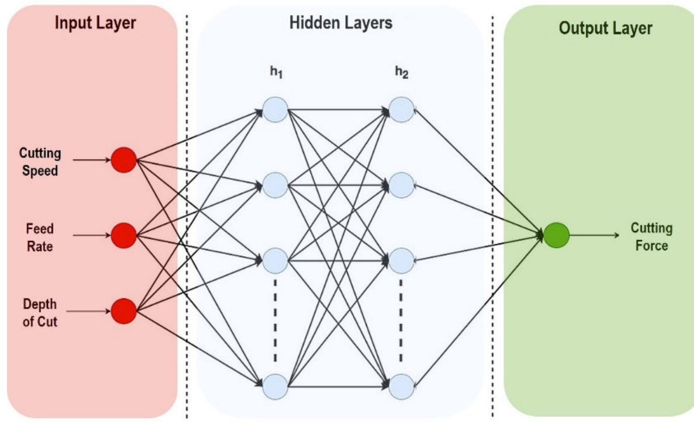

Fig. 5. Structure of Cutting Force Prediction Model based on ANN

3.3 Hidden Layers and Number of Neurons

The input layer and the output layer are separated by layers that are termed as 'hidden layers'. The hidden layer establishes a relationship with the input and output layer using a combination of weights and biases. They serve as the basis for the trained data but are inaccessible to users. More data is needed for more hidden layers as the number of weights associated with each node grows consequently. Because of this, there are more calculations to be performed, which takes longer time. A two-layered neural network was subsequently suggested for ANN training. The method suggested by Master based on the geometric pyramid rule was used to calculate the number of neurons for an ANN with two hidden layers (Rachmatullah et al., 2020). The number of neurons can be calculated as follows:

$$r = \sqrt[3]{(n/m)} \tag{1}$$

here,

n is the number of input features
m is the number of outputs

Also,

$$Nh_1 = mr^2 \tag{2}$$
$$Nh_2 = mr \tag{3}$$

here,

Nh_1 is the number of neurons in hidden layer 1
Nh_2 is the number of neurons in hidden layer 2

Using the dataset for training ANN model, we get

$r = \sqrt[3]{(3/27)} = 0.48074$
$Nh_1 = 27*(0.48074)^2 = 6.24 \approx 6$ neurons
$Nh_2 = 27*(0.48704) = 12.98 \approx 12$ neurons

To approximate the number of neurons, values have been truncated. Six and twelve neurons will constitute the first and second layers of the two-layer neural network respectively.

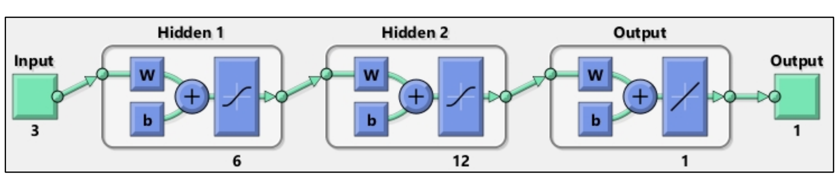

Fig. 6. NN Training Model

3.4 Neural Network Architecture

The Levenberg-Marquardt algorithm entails nonlinear least squares programming with an unconstrained or unbounded constrained problem for locating minima. Due to the storage of specific matrices, this technique takes more memory, but it converges faster than other algorithms. It works effectively for handling nonlinear regression problems (Alaneme George & Mbadike Elvis, 2019). Because of their ability to self-learn from examples rather than using a user-defined algorithm, feedforward artificial neural networks are employed in a wide range of applications. They are capable of recognizing and responding to patterns that are similar but not identical to the trained data. The only issue with this approach is that there is no certainty that it would work successfully for the specific subject at hand (Benardos & Vosniakos, 2007). The feedforward network consists of sigmoid neurons in one or more layers, followed by a layer of linear neurons on the output. The prior layer provides inputs to the subsequent layers. Levenberg-Marquardt backpropagation technique was used as the training function in MATLAB programming to create an ANN based on a feedforward neural network.

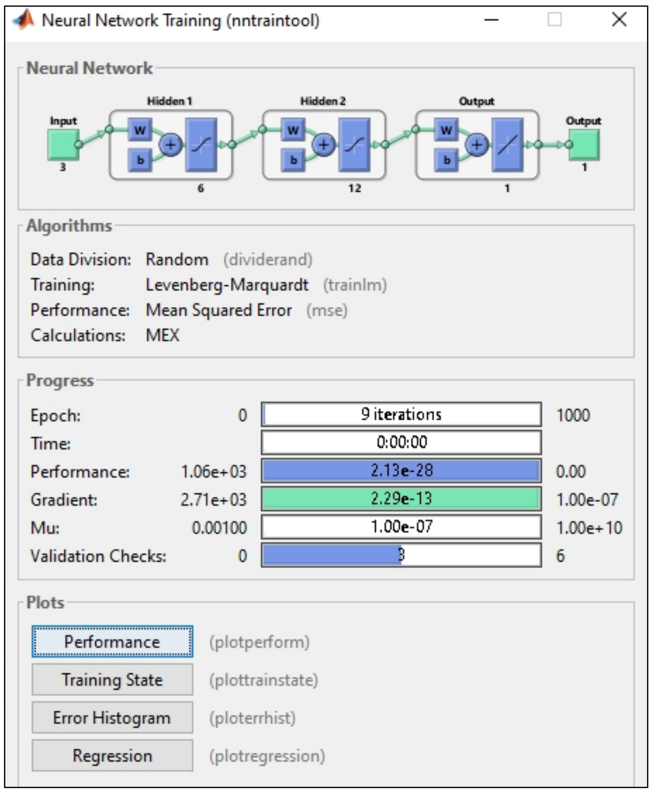

Fig. 7. NN developed in MATLAB

The data was divided into a training set, validation, and testing clusters in the ratio 7:1.6:1.4. The training set refers to the real dataset that we utilize to train the model. A trained model is evaluated using the validation set, which offers a true reflection of the model fit. This dataset has no effect on how the model trains. Once the model has been fully trained, the test set is used to assess the model and provide its fitting based on the selected samples. A neural network's behavior can be graded using performance functions. The performance measurement for the network is the mean squared error (MSE). By determining the MSE with the lowest value, the trained NN performance is measured.

4. Results and Discussion

The two-layer feed-forward neural network's results were analyzed. Fig. 7 illustrates the effectiveness of the network used to train the samples for the cutting force prediction model. The validation performance value of 0.44871 was attained at epoch 6 and these values were obtained after 9 epochs. The linear fit of the actual data to the predicted data is depicted in Fig. 8. The MSE and Pearson's R-value for the trained model were 0.27907 and 0.99826, respectively. The MSE measurement indicates the deviation in statistical models. It considers the average squared difference between the values that were predicted and those that were found experimentally. Its value increases in proportion to the model error. A measurement of how strongly two variables are correlated linearly is determined by Pearson's correlation coefficient (R value). A perfect linear relationship between the variables is indicated by an R-value of 1, while an R-value of 0 denotes the lack of any linear relationship.

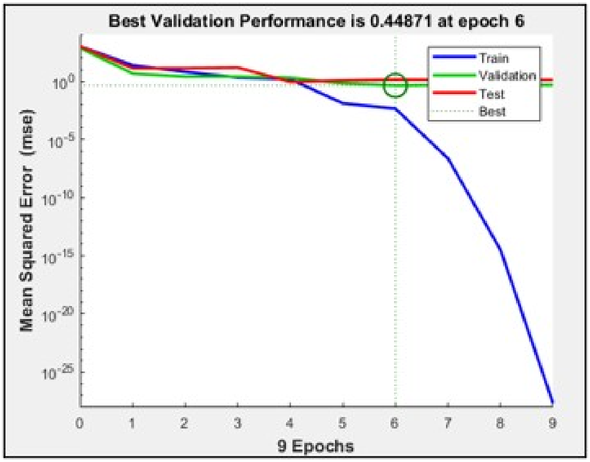

Fig. 8 Validation Performance using ANN

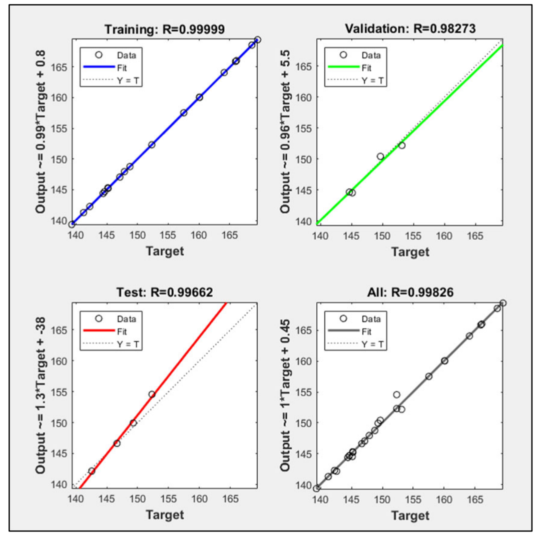

Fig. 9. Regression Plots for NN Model

Table 2
Errors obtained in NN Model

	Cutting Force (N)					Cutting Force (N)			
Sr. No	Experimental	ANN Model	Error	Percentage Error	Sr. No	Experimental	ANN Model	Error	Percentage Error
1	160.083	160.076	-0.0074	-0.00462	15	152.326	152.3181	-0.0079	-0.00519
2	164.123	164.087	-0.0359	-0.02187	16	145.178	145.3195	0.1415	0.09747
3	168.635	168.553	-0.0819	-0.04857	17	149.655	150.4151	0.7601	0.5079
4	152.321	154.569	2.2478	1.4757	18	153.123	152.1814	-0.9416	-0.61493
5	157.539	157.533	-0.0058	-0.00368	19	139.298	139.3326	0.0346	0.02484
6	160.121	160.039	-0.082	-0.05121	20	144.654	144.701	0.047	0.03249
7	165.964	165.888	-0.0766	-0.04615	21	147.872	147.9478	0.0758	0.05126
8	166.121	166.888	-0.0957	-0.05761	22	141.221	141.2818	0.0608	0.04305
9	169.567	169.431	-0.1363	-0.08038	23	144.651	144.6672	0.0162	0.0112
10	142.234	142.277	0.0425	0.02988	24	146.656	146.6263	-0.0297	-0.02025
11	144.387	144.387	0	0	25	142.567	142.1463	-0.4207	-0.29509
12	147.126	147.065	-0.0611	-0.04153	26	145.221	145.2289	0.0079	0.00544
13	145.124	144.550	-0.5746	-0.39594	27	148.765	148.7645	-0.0005	-0.00034
14	149.293	149.943	0.6501	0.043545					

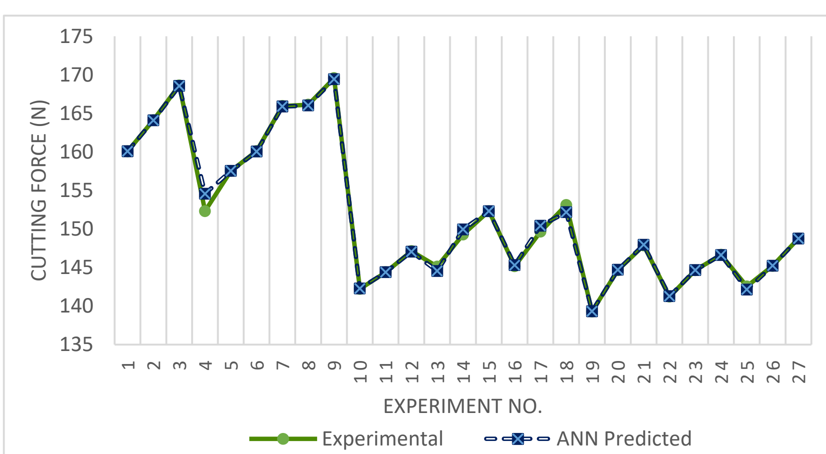

Fig. 10. Comparison Plot between Experimental and NN Predicted Cutting Force

A detailed representation of predicted values and their associated errors is depicted in Table 2. The minimum error was found to be 0 suggesting a perfect fit of actual and predicted result at cutting speed of 73 m/min, feed rate of 0.11 mm/rev and depth of cut of 0.5 mm. The maximum error is observed to be 2.2478 with a percentage error of 1.4757 %. The mean absolute error (MAE) was calculated as 0.246. It evaluates accuracy for continuous variables. The average of the absolute errors is known as MAE. The absolute difference between the experimental value and the value that was predicted using NN is known as the absolute error. Without taking the direction of error into account, the MAE alerts us about the average size of the forecast inaccuracy. Figure (9) shows the graph of prediction using NN model against the experimental cutting force. A negligible difference is observed between both the models.

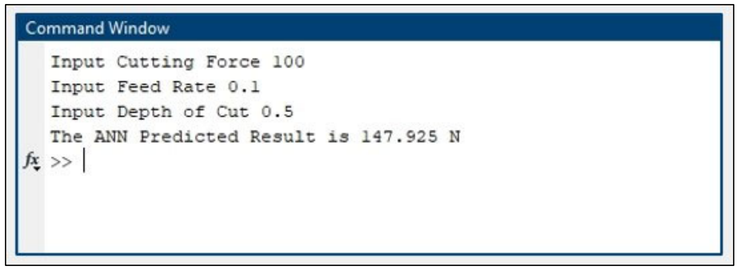

Fig. 10 Cutting Force Prediction Model based on ANN

Based on the trained dataset, a cutting force prediction model is developed. The model was generated in the command window of MATLAB. Cutting force, feed rate, and depth of cut are all inputs that the user will be required to enter. The trained neural network would then be used to calculate the cutting force. During MQL machining, this model can be used to estimate the cutting forces. Optimal cutting conditions can be retrieved using the NN prediction model. Increasing the input dataset's row count will improve the model's predictive capabilities. Consequently, a large amount of manufacturing data trained using NN can be used to provide a superior prediction model.

5. Conclusion

A machine learning-based model to predict cutting forces during turning operation was presented in this research. The findings can be summarized as:

i. Artificial neural network model was developed successfully for minimum quantity lubrication. Data obtained using the Taguchi method was used for training the model.
ii. It can be observed from the results that the cutting parameters have a significant effect on cutting force. The cutting force decreases with increase in either cutting speed or feed rate, but increases with increase in depth of cut.
iii. Most of the errors were observed around the range of 0.06452 with close to 15 occurrences. The trained model was able to predict cutting forces with high accuracy.
iv. Overfitting of the curve is the occurrence of error when the training set is reduced to a very tiny amount, but it increases when the network is exposed to newer inputs. The overfitting was avoided by training the model in minimal time.
v. The developed prediction model would save the time and expenses incurred in performing experimental calculations.

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