Forecasting Cutting Force by Using Artificial Neural Networks Based on Experiments of Turning Aluminum

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***Abstract*—The cutting force of the aluminum workpiece was forecasted using the Artificial Neural Networks (ANNs) methodology in this study. Two ANN structures, one with a single hidden layer and the other with a double hidden layer, were constructed using MATLAB codes. The Levenberg-Marquardt back-propagation technique served as the training algorithm, employing a sigmoidal transfer function in the hidden layer and a purline transfer function in the output layer. The performance of the ANN models was assessed using Mean Squared Error (MSE) and coefficient of determination (R^2). The experimental findings revealed that the cutting speed, feed rate, and depth of cut significantly influenced the cutting force. The optimal number of neurons in both single and double hidden layers was determined to be 6. The validation stage achieved the best performance with an MSE of approximately 0.002747 for a single layer and 0.00144 for double hidden layers, both at epoch 5. In conclusion, both ANN structures demonstrated the capability to predict cutting force, with a preference for the double hidden layer structure.**

***Keywords*—depth of cut, feed, cutting force, artificial neural network**

I. Introduction

The cutting force that is generated in manufacturing methods is an important parameter for evaluating the machining power and for dimensioning the components of the machine tool and the tool body [1, 2]. Many factors affect the cutting force and play a major role in determining it, for example, cutting speed, depth of cut, and feed [3, 4]. Therefore, it is necessary to control these factors to obtain a suitable cutting force that acts on the worked specimens. Controlling and reducing cutting force are very important to avoid several adverse effects like decreased tool life, high energy usage, and increased surface roughness that cause bad finishing surfaces [5].

Nowadays, artificial intelligence methodology is a modern method used to predict the cutting force in the machining process [6, 7]. Among these methodologies, artificial neural networks (ANNs) are a good technique for solving the nonlinear relationship between the input and output variables in all the sectors of engineering, especially the industrial applications (turning, milling, grinding, *etc*.). Additionally, it has the ability to estimate the complex interactions between these variables [8, 9]. A few researchers were able to use this technique under different conditions and techniques at the level of the turning process. For example, Ibraheem M. Q. *et al.* [10] used an ANN structure consisting of four parameters as input to predict the cutting force in the turning process. These input parameters are named as: feed rate, depth of cut, work piece hardness, and cutting speed. The results showed that the ANN model recorded perfect agreement between the predicted and measured cutting forces for all the components (feed and radial). In the same manner, AL-Khafaji *et al.* [11] built ANN models to predict the cutting force that was generated during the turning process of the high-strength aluminum alloy 7075-T6. The input parameters of the ANN models were cutting speed, depth of cut, and feed rate. All the results showed that the predicted cutting force was in good agreement with the measured force, with a correlation coefficient (R^2) equal to 1.

An Adaptive Neuron-based Fuzzy Inference System (ANFIS) was used by Naresh *et al.* [12] to predict the cutting force during the Laser-Assisted Turning (LAT) process of AISI 304 stainless steel. The fuzzy ANFIS model was dependent on four input factors: cutting speeds, feed rates, depth of cut, and laser powers. Besides, these factors varied within the ranges of (25, 50, and 75) m/min, (0.025, 0.05, and 0.075) mm/rev, (0.5, 0.75, and 1) mm, and (0, 150, 300, and 450) W, respectively. The results achieved satisfactory accuracy between the predicted and measured cutting forces. Luis W. *et al.* [13] used polynomial regression and artificial neural networks to estimate the cutting force and Specific Energy Consumption (SEC) during dry high-speed turning of AISI 1045 steel under the influence of the materials of the cutting tool and cutting speed. The indications that were used for analyzing the prediction results depended on two metrics: R^2 and Root Mean Square Error (RMSE). The results of the polynomial indicated that the models did not reach 70% in their representation of the variability of the data. In addition, the specific energy consumption

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of the GC4225 tool was found to be higher than that of the CT5015 tool.

Irgolic *et al.* [14] predicted the cutting force for milling functionally graded material using neural network methodology. The findings of the ANN model show that it is very reliable in predicting the cutting force with an error smaller than 10% under the effects of cutting speed, feed rate, and cutting depth. Kadirgama and Abou-El-Hossein *et al.* [8] described the methodology of neural network methods to predict the cutting force in milling 618 stainless steel under the influence of cutting speed, feed rate, axial depth, and radial depth. Firstly, the software of the design of experiments was used to provide the optimum experimental conditions. The predictive results between the experimental result and the neural network were compared. According to the comparison between the predicted and measured values of cutting force, the percentage of error showed that the ANN was acceptable for achieving its purpose. Kland *et al.* [15] developed a MATLAB code using interface and ANN to estimate the cutting force under the effect of cutting parameters such as speed, feed rate, and depth of cut. The results showed that all the cutting parameters have a significant effect on the cutting force. It can be concluded that the ANN gives precise results.

Rastorguev and Sevastyanov *et al*. [16] used a feed-forward ANN with a Bayesian regularization algorithm and an adaptive neuro-fuzzy inference system to predict the value of cutting force during hard turning of 105WCr6 steel. In general, the results showed that the ANN model can predict the cutting force with high accuracy. Hanafi *et al.* [1] applied ANN methodology to predict the cutting force components in turning operations of PEEK CF30 using TiN-coated cutting tools under dry conditions. The machining parameters were cutting speed ranges, feed rate, and depth of cut. The results indicated that the ANN model has the ability to predict the cutting force components in the turning of carbon fiber reinforced polymer (CFRP) composites. Alajmi and Almeshal *et al*. [5] developed three models to predict the cutting force for turning AISI 4340 alloy steel. These models were the Gaussian Process Regression (GPR), Support Vector Machines (SVM), and ANN methodologies. The GPR model demonstrated a reliable prediction of surface roughness for the dry turning method with $R^2 = 0.9843$, MAPE = 5.12%, and RMSE = 1.86%. The comparison between the three models showed that the GPR is an effective method that can ensure high predictive accuracy of the cutting force in the turning of AISI 4340.

The main objective of this study is to forecast the cutting force in the turning process using Artificial Neural networks (ANNs) based on experimental investigation under the influence of cutting parameters like depth of cut, cutting speed, and feed. The novelty of this research lies in the compelling comparison between the predictive accuracy achieved by a single hidden layer and a double hidden layer, employing the Levenberg-Marquardt back-propagation technique for estimating cutting force in aluminum workpieces. By systematically evaluating and contrasting the performance of these two architectures, this study provides valuable insights into the optimal network configuration for enhancing the precision of cutting force prediction in aluminum machining processes.

II. Experimental Part

An aluminum workpiece with a diameter of 30 mm and a length of 500 mm was selected and installed on lathe machine Type FI-1000AG/ZJ to achieve the cutting process under various cutting parameters, as shown in Fig. 1. A High-Speed Steel (HSS) cutting tool with dimensions of 120 mm overall length, 16 mm shank diameter, 20 mm cutting edge length, 60° cutting edge angle, and 5 mm width was utilized. Under lubricated conditions, the turning process of aluminum involved the utilization of soluble oil coolant. The cutting force (F_c) was measured by using a force dynamometer (9265B) connected to a signal amplifier (5019B), both of which are branded Kistler. In addition, a data acquisition system was utilized for recording the data and transferring it to a computer.

The cutting parameters included the cutting speed, feed rate, and depth of cut. Generally, the cutting speed ranged between 65 and 2000 meters per minute (m/min), the feed ranged between 0.2 and 0.45 millimeters per revolution (mm/rev), and the depth of cut ranged between 0.1 and 0.3 mm. These ranges were determined based on the characteristics of the workpiece and the desired range of experimental conditions. Totally, 133 different conditions were tested during the experiment, and the measured data were collected. This number of tests was performed to cover a wide range of operating conditions, capture relevant variations, and ensure statistical significance. By addressing these points, a comprehensive understanding of the experimental design and its relevance to the research objectives is aimed at being provided. Almost half of these data are represented in Table I. It is noteworthy that the other machining force components (feed force F_f and passive force F_p) were not included because this study is focused on investigating only the main cutting force F_c.

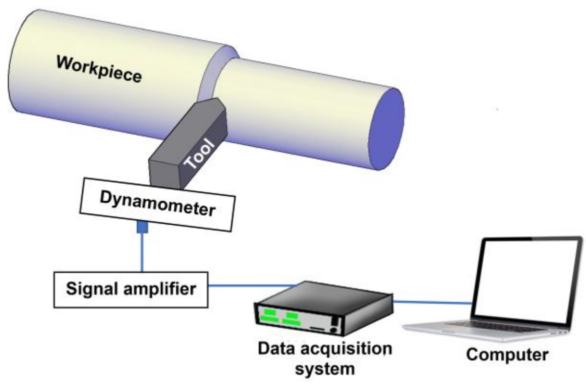

Figure 1. Schematic diagram of the experimental set-up for force measurement.

TABLE I. SAMPLES OF COLLECTED DATA

No.	Cutting speed (m/min)	Feed (mm/rev)	Depth of cut (mm)	Cutting force (N)
1	65	0.2	0.1	16.02
2	65	0.2	0.2	31.99
3	65	0.2	0.3	48.07
4	100	0.3	0.1	24.12
5	100	0.3	0.2	47.84
6	100	0.3	0.3	72.21
7	115	0.35	0.1	27.78
8	115	0.35	0.2	56.32
9	115	0.35	0.3	83.94
10	190	0.4	0.1	32.05
11	190	0.4	0.2	64.18
12	190	0.4	0.3	95.99
13	200	0.45	0.1	35.84
14	200	0.45	0.2	72.09
15	200	0.45	0.3	108.01
16	240	0.4	0.1	127.87
17	240	0.4	0.2	160.17
18	240	0.4	0.3	192.32
19	290	0.3	0.1	96.03
20	290	0.3	0.2	119.88
21	290	0.3	0.3	144.31
22	300	0.3	0.1	143.98
23	300	0.3	0.2	168.06
24	300	0.3	0.3	191.79
25	320	0.2	0.1	96.15
26	320	0.2	0.2	112.03
27	320	0.2	0.3	128.00
28	380	0.35	0.1	167.91
29	380	0.35	0.2	196.07
30	380	0.35	0.3	224.20
31	460	0.25	0.1	160.09
32	460	0.25	0.2	180.24
33	460	0.25	0.3	199.95
34	500	0.3	0.1	192.04
35	500	0.3	0.2	216.32
36	500	0.3	0.3	240.18
37	560	0.2	0.1	160.13
38	560	0.2	0.2	191.89
39	560	0.2	0.3	208.07
40	730	0.25	0.1	200.14
41	730	0.25	0.2	280.03
42	730	0.25	0.3	299.86
43	755	0.275	0.1	330.12
44	755	0.275	0.2	374.03
45	755	0.275	0.3	396.41
46	860	0.3	0.1	431.78
47	860	0.3	0.2	456.28
48	860	0.3	0.3	480.15
49	920	0.4	0.1	576.09
50	920	0.4	0.2	608.03
51	920	0.4	0.3	639.89
52	1100	0.2	0.1	288.19
53	1100	0.2	0.2	304.01
54	1100	0.2	0.3	320.27
55	1150	0.3	0.1	479.78
56	1150	0.3	0.2	504.04
57	1150	0.3	0.3	528.18
58	1255	0.2	0.1	319.99
59	1255	0.2	0.2	352.03
60	1255	0.2	0.3	368.00
61	1400	0.3	0.1	456.27
62	1400	0.3	0.2	480.03
63	1400	0.3	0.3	503.87
64	1800	0.2	0.1	335.79
65	1800	0.2	0.2	352.00
66	1800	0.2	0.3	399.91
67	2000	0.4	0.1	672.06
68	2000	0.4	0.2	736.17

III. THEORY OF ARTIFICIAL NEURAL NETWORKS

Basically, the main function of artificial neural networks is to predict a linear or nonlinear relationship between input and output parameters [17]. In general, it consists of three layers named input, hidden, and output [18]. These layers are connected between them by nodes [19], as shown in Fig. 2. These nodes, connected by links, have weights and biases [20], whereas, the function of weight values is to interconnect the neurons, while the bias is used to specify the freedom degree of the system. Mathematically, the output parameters can be represented as a function of input parameters and weights as follows [19, 21]:

$$y_i = f\left(\sum_{i=1}^{n} w_{ji} x_i\right) \tag{1}$$

where y_i is the output, w_{ji} is the synaptic weights, and x_i is the input parameter.

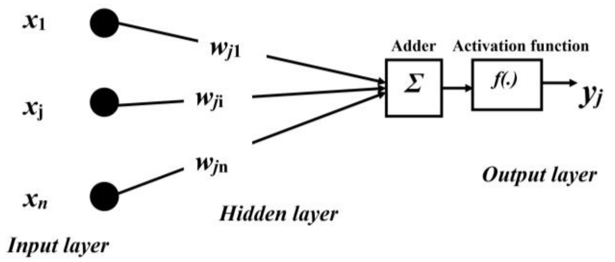

Figure 2. Design of the neural network and connections between layers.

The purpose of the transfer function is to transfer and translate the obtained signals from the hidden layer to the output layer, and then from the output layer as a final output. Three kinds of transfer functions are used in ANNs: linear, sigmoid, and hyperbolic tangent. The mathematical models of three types of transfer functions can be defined as [20]:

$$f(S) = \left\{ \begin{array}{ll} S & linear\ function \\ \dfrac{1}{1+e^{-s}} & sigmoid\ function \\ \dfrac{e^{+s}-e^{-s}}{e^{+s}+e^{-s}} & hyperbolic\ tangent\ function \end{array} \right\} \tag{2}$$

IV. RESULTS AND DISCUSSION

To achieve the main objective of this study, an experimental investigation was carried out to analyze the influence of cutting parameters on the cutting force. The experimental results showed that the cutting parameters have a significant effect on cutting force. As the cutting speed increases the cutting force increases. As shown in Fig. 3, the cutting force increases linearly with the depth of cut. However, the cutting force changed from 8 to 64 N when the depth of cut varied from 0.05 to 0.4 mm at a constant cutting speed of 65 m/min and feed rate of 0.2 mm/rev. The regression analysis of this relation is fitted by the equation ($y = 160\times x + 2\times10^{-14}$) with $R^2 = 1$. In addition, the cutting force increases with increasing cutting speed in linear behavior. Nevertheless, it was changed from 16 to 320 N when the cutting speed varied from 65 to 1255 m/min at a constant depth of cut of 0.1 mm and a feed rate of 0.2 mm/rev. The fitting equation that represents this relation can be expressed as ($y = 0.256 \times x + 5.593$) corresponding to $R^2 = 0.9961$ (see Fig. 4). Furthermore, the cutting force will increase with an increase in feed rate and depth of cut.

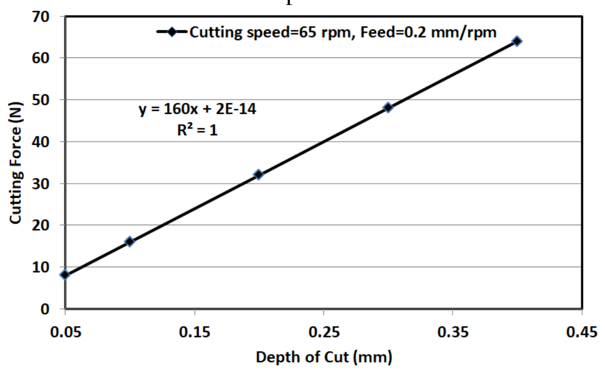

Figure 3. Variation of cutting force with depth of cut.

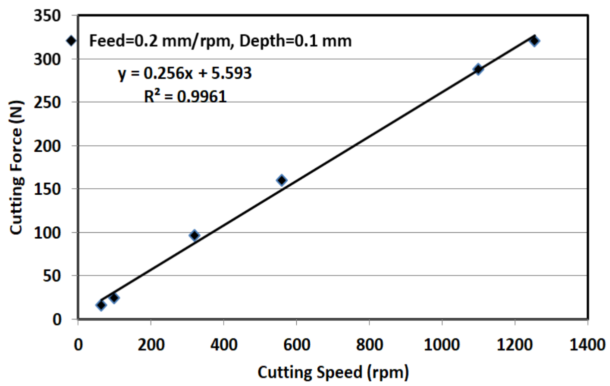

Figure 4. Variation of cutting force with cutting speed.

On the other side, a total of 133 measured datasets were used as input data to run MATLAB code for predicting the cutting force using the AAN methodology. These data were divided as follows: 70% for the training stage and 15% for each of the testing and validating stages. The Levenberg-Marquardt back-propagation technique was proposed as an algorithm to achieve the training stage. Two ANN structures were used: the first structure used a single hidden layer, while the second structure used a double hidden layer. Mean squared error (MSE) and coefficient of determination (R^2) were considered the main indicators to evaluate the performance of ANN models. Firstly, the trial-and-error method was used to control the best neuron number in hidden layers. Mean Squared Error (MSE) served as the performance function for the network, quantifying the average squared difference between outputs and targets. Smaller MSE values indicated better performance, with zero denoting no error. During the training phase, the number of neurons in the hidden layer was systematically altered to identify the smallest MSE values for validation. By employing a trial-and-error method, the study identified the smallest MSE value of 0.0014 for validation when 6 neurons were present in the hidden layer. This trial-and-error approach enabled the determination of the optimal number of hidden layer neurons and the optimization of the network's performance for accurate cutting force estimation. As shown in Fig. 5, the best neuron number in the hidden layer was 6 in each single and double layer. Therefore, the final structure of ANN was (3-6-1) and (3-6-6-1) for single and double hidden layers, respectively. Additionally, the neurons were activated by the sigmoidal transfer function in the hidden layer and the purline transfer function in the output layer. The sigmoid function is used in the hidden layer mainly due to its range of existence between 0 and 1. This range makes it particularly suitable for models aimed at predicting probabilities as output. Given that probabilities lie within the range of 0 and 1, the choice of the sigmoid function is considered appropriate. Also, the sigmoidal function was selected for the hidden layer because it allows for non-linear transformations, enabling the network to capture complex relationships between input and hidden neurons. On the other hand, the purline function was chosen for the output layer as it provides a continuous output range suitable for regression tasks, such as predicting cutting force values. Including these reasons in the article will enhance the clarity of our methodology.

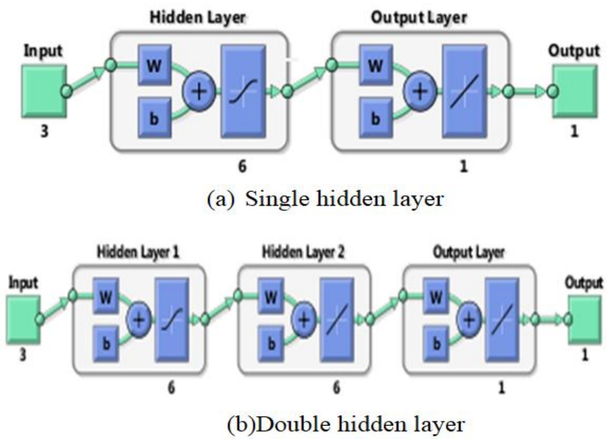

Figure 5. Structure of ANN models.

A. Performance of ANN Model with Single Hidden Layer

Fig. 6 shows the best validation of the ANN model with a single hidden layer (3–6–1). As shown in the figure, the best performance in the validation stage was achieved with a mean squared error of 0.002747 at epoch 5. The performance of the ANN model in a single layer is represented in Fig. 7. It was clear that the coefficient determination (R^2) was recorded (0.931, 0.976, 0.891, and 0.932) for training, testing, validation, and all stages. The value of R^2 gave an indication that the database was well trained. Therefore, the best performance of the validation stage was recorded at a good R^2 of about 0.891. This means that the ANN model with a single layer has good ability for predicting the cutting force under the mentioned cutting parameters.

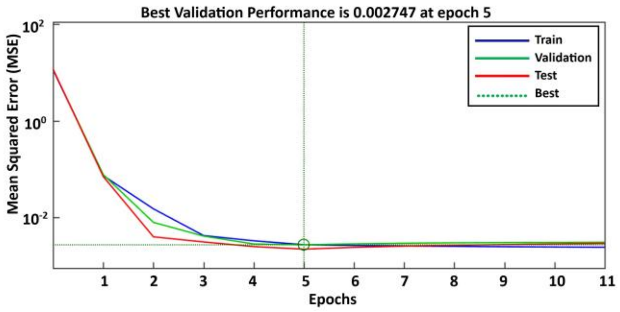

Figure 6. Best validation of the ANN model with a single hidden layer.

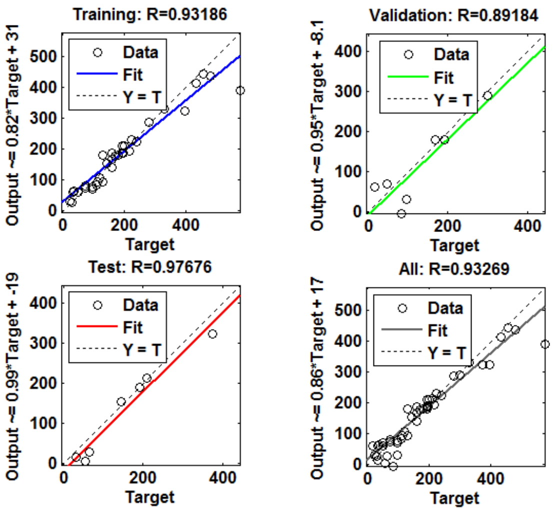

Figure 7. Performance of the ANN model in four stages.

B. Performance of ANN Model with Double Hidden Layer

The best performance in the validation stage was achieved at about 0.00144 at epoch 5, as shown in Fig. 8. Although the R^2 in the training stage with a double hidden layer was recorded at about 0.978, the R^2 in the validation stage was recorded at 0.988. Fig. 9 shows the values of R^2 for training, testing, validation, and all the stages of the ANN model. According to the value of R^2, the ANN with a double hidden layer is a very accurate model for predicting the cutting force.

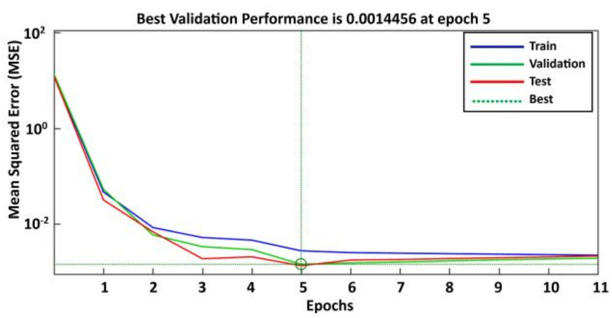

Figure 8. Best validation of the ANN model with a double hidden layer.

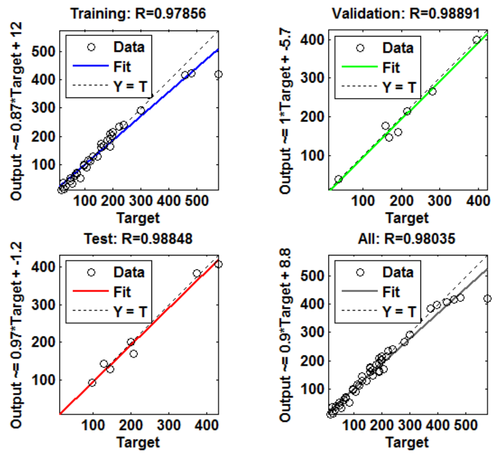

Figure 9. Performance of the ANN model in four stages.

C. Comparison of Results

The predicted results from the ANN model were compared with the measured results for the validation stage only. The number of data points for validation was considered to be 20 (15% of the data set). As shown in Fig. 10, the convergence is clear and precise between the predicted and measured cutting forces in the case of ANN with a double hidden layer. While the convergence between the graphs of predicted cutting force with a single layer and measured force is good. The absolute error between the predicted and measured cutting force is represnted in Fig. 11 and Table II. Whereas, it was recorded from a minimum value of about 1.97% to a maximum value of about 8.33% in AAN with a double hidden layer and was recorded from 1.19 to 13.04. This gives a great indication that the two structures of ANN have achieved the required accuracy. But the structure with the double hidden layer system is more accurate.

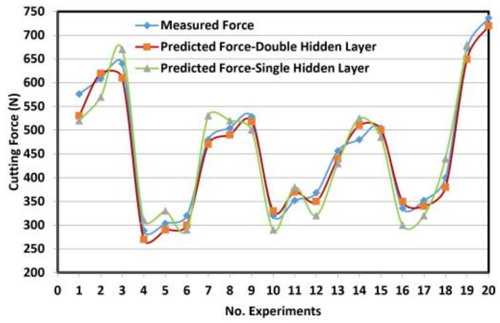

Figure 10. Comparison between predicted and measured cutting forces.

Figure 11. Absolute errors for experiment data in the validation stage.

TABLE II. COMPARISON BETWEEN THE PREDICTED AND MEASURED CUTTING FORCE IN THE VALIDATION STAGE FOR SOME OF THE TESTED PARAMETERS

No.	Cutting speed (m/min)	Depth of cut (mm)	Feed (mm/rev)	Measured force (N)	Predicted Force-ANN (N)		Error of Multi ANN (%)	
					Double	Single	Double	Single
1	920	1.8	0.4	576.13	530	520	7.98	9.72
2	920	1.9	0.4	608.08	620	570	1.97	6.25
3	920	2	0.4	639.86	610	670	4.68	4.68
4	1100	1.8	0.2	288.01	270	310	6.25	7.63
5	1100	1.9	0.2	304.00	290	330	4.60	8.55
6	1100	2	0.2	319.92	300	290	6.25	9.37
7	1150	2	0.3	480.19	470	530	2.08	10.41
8	1150	2.1	0.3	504.04	490	520	2.77	3.17
9	1150	2.2	0.3	528.21	518	500	1.89	5.30
10	1255	2	0.2	319.89	330	290	3.12	9.37
11	1255	2.2	0.2	352.40	370	380	5.11	7.95
12	1255	2.3	0.2	368.03	350	320	4.89	13.04
13	1400	1.9	0.3	456.00	440	430	3.50	5.70
14	1400	2	0.3	479.98	510	525	8.33	9.37
15	1400	2.1	0.3	504.16	500	485	0.79	3.76
16	1800	2.1	0.2	336.22	350	300	4.16	10.71
17	1800	2.2	0.2	351.87	340	320	3.40	9.09
18	1800	2.5	0.2	400.05	380	440	5.00	10.00
19	2000	2.1	0.4	672.00	650	680	3.27	1.19
20	2000	2.3	0.4	736.17	720	700	2.17	4.89

V. CONCLUSION

In this work, the prediction of the cutting force of the turning process for an aluminum workpiece under the influence of cutting parameters (cutting speed, depth of cut, and feed) using the ANN methodology was achieved. The prediction process was conducted based on measured data from the experimental part. According to the analysis of the results, the following conclusions can be drawn:

- From the experimental results, it can be observed that the cutting parameters (cutting speed, depth of cut, and feed) significantly affect cutting force; as cutting speed increases, the cutting force will increase. However, the cutting force has the same behavior with the depth of cut and feed.
- The ANN models with single and double hidden layers can predict the cutting force with acceptable accuracy.
- The ANNs with a double hidden layer are more accurate than a single hidden layer model. For example, the best performance in the validation stage was recorded at about a MSE equal to 0.00144, while in the single layer it was recorded at about 0.002747.

A comparison between different models based on artificial intelligence would be a valuable extension to our study in the future. A deeper understanding of their strengths, weaknesses, and performance in the context of the current research domain can be gained by exploring and evaluating alternative models.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Conceptualization, D.S.M. and M.M.H.; methodology, D.S.M.; software, M.M.H.; validation, D.S.M.; formal analysis, D.S.M.; investigation, D.S.M.; resources, M.M.H.; data curation, D.S.M.; writing—original draft preparation, D.S.M.; writing—review and editing, M.M.H. and A.A.K.; visualization, D.S.M.; supervision, M.M.H. All authors had approved the final version.

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