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Research article

Evaluation of ANN and ANFIS modeling ability in the prediction of AISI 1050 steel machining performance

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A R T I C L E I N F O

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A B S T R A C T

In the development of an accurate modeling technique for the design of an efficient machining process, manufacturers must be able to identify the most suitable technique capable of producing a fast and accurate performance. This study evaluates the performance of the Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) models in predicting the machining responses (metal removal rate and tool wear) in an AIS steel turning operation. With data generated from carefully designed machining experimentation, the adequacies of the ANN and ANFIS techniques in modeling and predicting the responses were carefully analyzed and compared. Both techniques displayed excellent abilities in predicting the responses of the machining process. However, a comparison of both techniques indicates that ANN is relatively superior to the ANFIS techniques, considering the accuracy of its results in terms of the prediction errors obtained for the ANN and ANFIS of 6.1% and 11.5% for the MRR and 4.1% and 7.2% for the Tool wear respectively. The coefficient of correlation (R^2) obtained from the analysis further confirms the preference of the ANN with a maximum value of 92.1% recorded using the ANN compared to that of the ANFIS of 73%. The experiment further reveals that the performance of the ANN technique can yield the most ideal results when the right parameters are employed.

1. Introduction

Advances in engineering design witnessed in recent times has become a major driving force behind technological developments in almost all fields of engineering. As it's been witnessed in the metal cutting industry, the development of suitable machining techniques capable of guaranteeing highly-accurate parts at a minimized cost is continuously being looked into by manufacturers to accelerate and automate the different machining processes. According to Struzikiewicz and Sioma [1], the development of a suitable machining technique is necessary to meet the engineering design requirements of shape and dimension accuracy, surface quality, and optimal cost and/or rate of production. However, relating the process parameters amongst which are; the number of passes, depth of cut for each pass, feed rate, and cutting speed, to the performance measure of machinability; metal removal rate (MRR), surface finish, chip flow pattern, specific energy consumption, and tool life [2], are often very challenging and complex for manufacturers, thus preventing the attainment of an acceptable process performance [3].

According to Koenigsburger [4] and Melkote [5], manufacturers in the past depended solely on the use of large empirical databases compiled from previous machining operations in carrying designs. Groover [6] illustrates that two types of variations are recorded in manufacturing; random and assignable variations. Random variations can be attributable to factors such as machine cycle, the vibration of the machine, etc. but assignable variation is caused by poor control of the machining process. He stated further that many defective machined parts are a result of the lack of expertise in the application of machining parameters in batch manufacturing of components. Moreover, it has been observed that 50% of machining operations are performed using incorrect cutting tools and process parameters [7]. Nevertheless achieving an effective and efficient machining process can be made possible with the application of scientifically developed techniques such as the different artificial intelligence techniques.

According to Rao and Mukherjee [8], artificial intelligence (Al) tools such as artificial neural networks (ANNs), particle swarm optimization (PSO), fuzzy logic, neural-based fuzzy interference system (ANFIS), genetic algorithm (GA), and geometric programming (GP) have proven very useful in the areas of simulation/modeling of input and output machining parameters. Different studies ranging from determining the optimal process parameters [9], finding the optimal Hyperparameters in

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Table 1. Experimental results of the machining process.

Exp. No.	Cutting Speed (m/min)	Depth of Cut (mm)	Feed Rate mm/rev.	MRR mm^3/min	Tool Wear (mm)
1	210.00	1.10	0.20	2.29	1.21
2	210.00	1.10	0.20	1.31	2.32
3	83.87	1.10	0.20	2.16	4.19
4	210.00	1.10	0.40	2.27	2.58
5	135.00	0.60	0.32	3.12	3.12
6	210.00	1.10	0.20	1.23	1.06
7	336.13	1.10	0.20	2.19	2.76
8	285.00	1.60	0.32	1.89	3.72
9	210.00	1.10	0.20	2.43	3.25
10	285.00	0.60	0.32	2.42	1.72
11	210.00	1.10	0.20	2.32	3.21
12	135.00	0.60	0.08	3.21	4.25
13	210.00	1.10	0.20	1.32	2.31
14	285.00	1.60	0.08	3.20	3.45
15	210.00	0.26	0.20	2.12	3.43
16	285.00	0.60	0.08	3.37	3.14
17	210.00	1.10	0.20	2.74	2.12
18	135.00	1.60	0.32	1.74	4.47
19	135.00	1.60	0.08	2.93	1.16
20	210.00	1.94	0.20	2.15	2.83
21	210.00	1.10	0.20	2.29	1.21
22	210.00	1.10	0.10	1.31	2.32
23	83.87	1.10	0.20	2.16	4.19
24	210.00	1.10	0.40	2.27	2.58
25	135.00	0.60	0.32	3.12	3.12
26	210.00	1.10	0.20	1.23	1.06
27	336.13	1.10	0.20	2.19	2.76
28	285.00	1.60	0.32	1.89	3.72
29	210.00	1.10	0.20	2.43	3.25
30	285.00	0.60	0.32	2.42	1.72
31	210.00	1.10	0.20	2.32	3.21
32	135.00	0.60	0.08	3.21	4.25
33	210.00	1.10	0.20	1.32	2.31
34	285.00	1.60	0.08	3.20	3.45
35	210.00	0.26	0.20	2.12	3.43
36	285.00	0.60	0.08	3.37	3.14
37	210.00	1.10	0.20	2.74	2.12
38	135.00	1.60	0.32	1.74	4.47
39	135.00	1.60	0.08	2.93	1.16
40	210.00	1.94	0.20	2.15	2.83

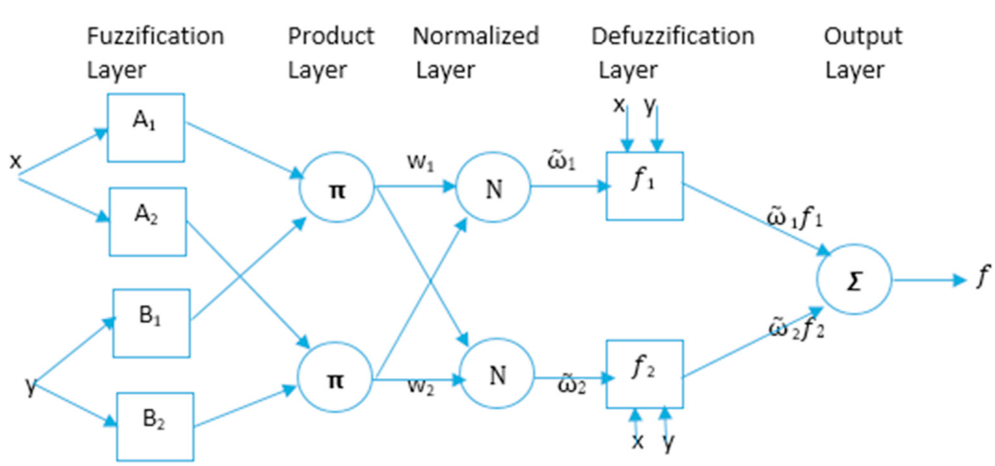

Figure 1. General ANFIS architecture.

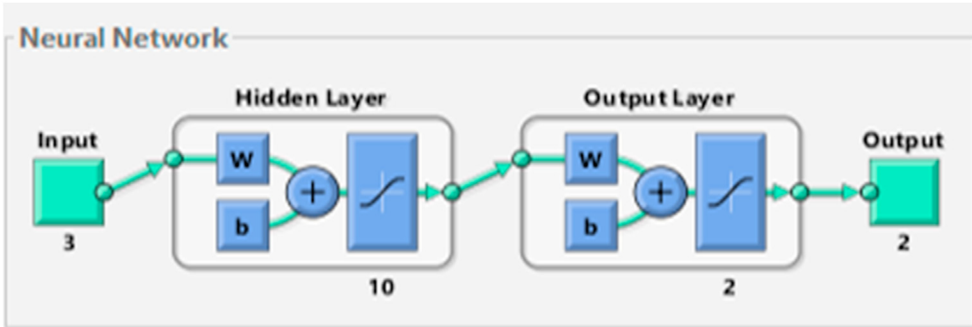

Figure 2. Two layer MLP neural network structure.

ANN applications for modeling the machining process [10] have been performed, all aimed at improving the machining process. However, it is paramount that the adequacies of these techniques be investigated by comparing their performance ability in predicting the process parameters and responses of the machining operation. Bakinde et al. [11], states that among the different AL techniques, artificial neural networks (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) have been effectively applied to rule-based process controls, classification tasks, function approximation, and pattern recognition problems. The ANN and ANFIS represent very effective modeling techniques capable of producing outputs with high accuracy irrespective of the presence of variation in the process parameters [12, 13]. The ANN derives its ideology from the biological nervous system, as they can represent a process just by having similar examples related to the given process. The adaptive neuro-fuzzy inference system (ANFIS) however is an attractive soft computing modeling technique that brings together the strength of the artificial neural network (ANN) and fuzzy logic theory techniques [14]. Just like the ANN, it can learn from training data with any complex mathematical model, after which it maps out the solutions onto a fuzzy inference system (FIS) [15]. With the fuzzy inference system (FIS) in the ANFIS network, it can determine the hidden layers as well as improve its prediction ability thereby eliminating the rigor of determining hidden layers often associated with ANN [16]. Their ability in overcoming the setback associated with empirical and deterministic models makes it very ideal for the machining processes [17]. However, the ineffective application of these ANN parameters remains a major challenge in obtaining a very accurate model for the process. For this reason, Hosoz et al. [18], argue that the adaptive neuro-fuzzy inference system (ANFIS), can perform accurately better than the ANN given recent successes recorded in its application in other fields of engineering and comparison to other numerical methods. But Gill et al. [19], in their study report that the accuracy of these techniques is subject to their application.

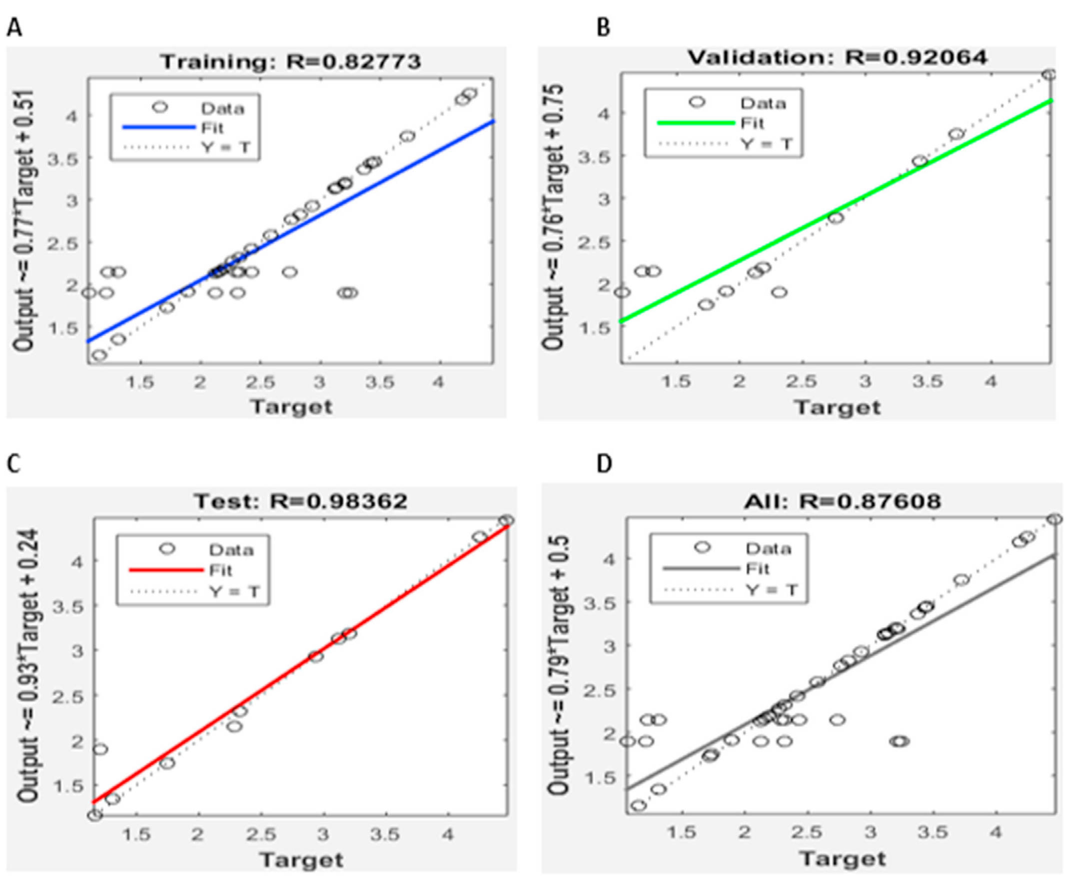

Figure 3. Network Model Regression Analysis for a. training dataset, b. validation dataset, c. testing dataset and d. the combined datasets.

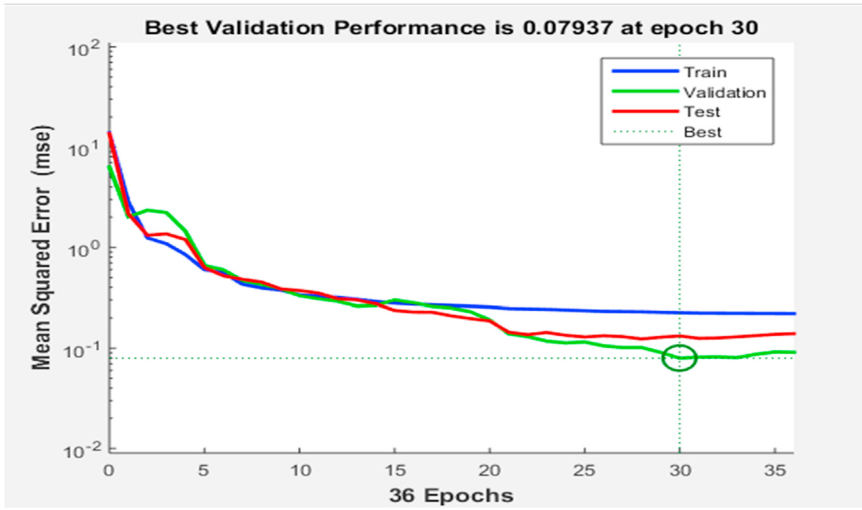

Figure 4. Comparison of the neural network training performance.

Table 2. Statistical evaluation of different training algorithm, transfer functions, and neurons.

Learning algorithm	No of Neuron	Activation fn (layer)		Training			Testing		
		hidden	output	R^2	MAE	RMSE	R^2	MAE	RMSE
LM	**4-10-2**	**Tansig**	**logsig**	**0.938**	**0.074**	**0.122**	**0.938**	**0.094**	**0.142**
SCG	4-20-2	Tansig	logsig	0.989	0.072	0.141	0.989	0.087	0.113
RP	4-16-2	tansig	Logsig	0.964	0.044	0.204	0.964	0.044	0.210

While manufacturers seem to be in dare desire of the most suitable technique, several studies comparing these different approaches within the diverse context in several engineering disciplines [20, 21], and non-science related applications have been performed with varying results recorded [15, 22, 23]. For the machining operation, most studies have either been based on the single application of the individual techniques or a comparism of either the ANN or ANFIS to techniques such as the meta-heuristics [22, 24, 25] or complementary application to other techniques. To determine the most suitable technique for predicting the machining process, it important that the performance of the Neural Network (NN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) models be evaluated. This is the basis for which this study has been performed.

2. Methodology

2.1. Experimentation

The study was performed using AISI 1050 cylindrical steel of 32 cm diameter and 140 cm in length as specimen along with an AISI T-42, CT, S-400, 3/8″ x 4″ single point HSS tool with hardness value 67HRC as cutting material on an NH22e lathe machining powered with an 11 KW capacity spindle power and 3000 rpm maximum speed. During the turning operation, a tool holder of ISO coding SVJCR steel EN47 was used.

Using the central composite design (CCD) to the experiment, with the aid of design expert software three-level experimental matrix comprising

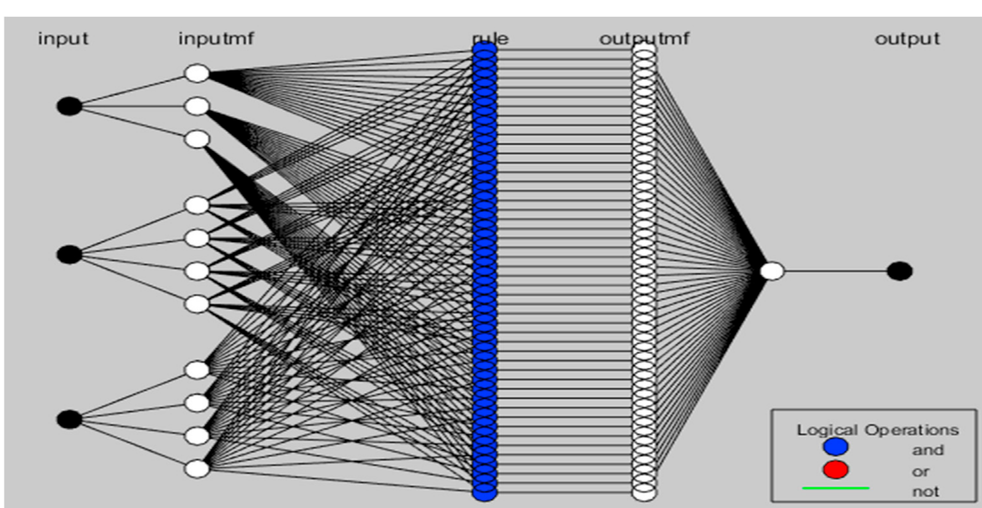

Figure 5. Proposed ANFIS architecture.

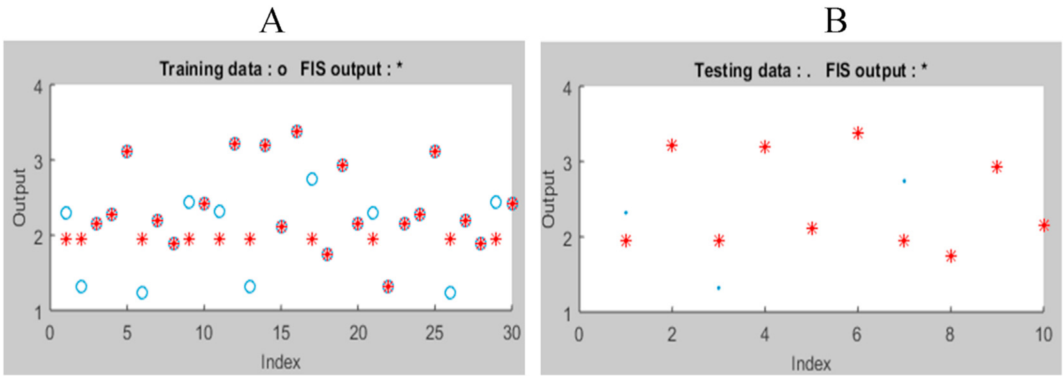

Figure 6. ANFIS Editor showing the (a) checking dataset and (b) test dataset for the MRR Model.

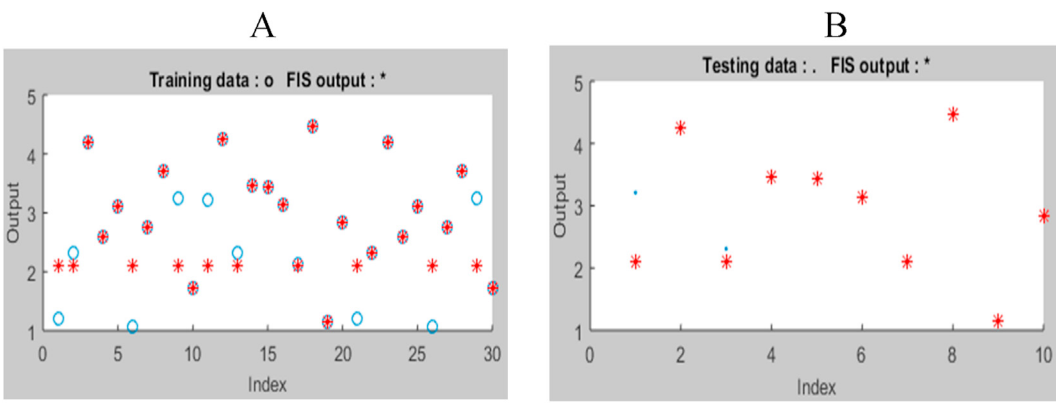

Figure 7. ANFIS Editor showing the (a) checking dataset and (b) test dataset for the Tool Wear Model.

forty (40) experimental runs were developed for this experiments based on the following input parameters and their ranges; cutting speed (135–380), depth of cut (3.89–6.26), and feed rate (0.2–0.4). The experiment focused on the following responses; metal removal rate (MRR) and tool wear with results obtained tabulated as shown in Table 1.

2.1.1. Material removal rate

The material removal rate (MRR) in turning operation is the volume of material/metal that is removed per unit time in mm^3/s, with each revolution of the workpiece, extracting a ring-shaped layer of material [23]. Eq. (1) gives an expression of the material removal rate, in mm^3/s.

$$\mathrm{MRR} = \frac{\frac{\pi}{4} D_o^2 L - \frac{\pi}{4} D_i^2 L}{L/CN} \tag{1}$$

Where, L length of the workpiece to be turned in mm, D_0 denotes initial diameter in mm, Di final diameter in mm, C- feed rate in mm/rev and N spindle speed in rpm.

2.2. Artificial neural network theory

ANNs are computer programs very useful for prediction and categorization issues related to data processing. They are inspired by the at-

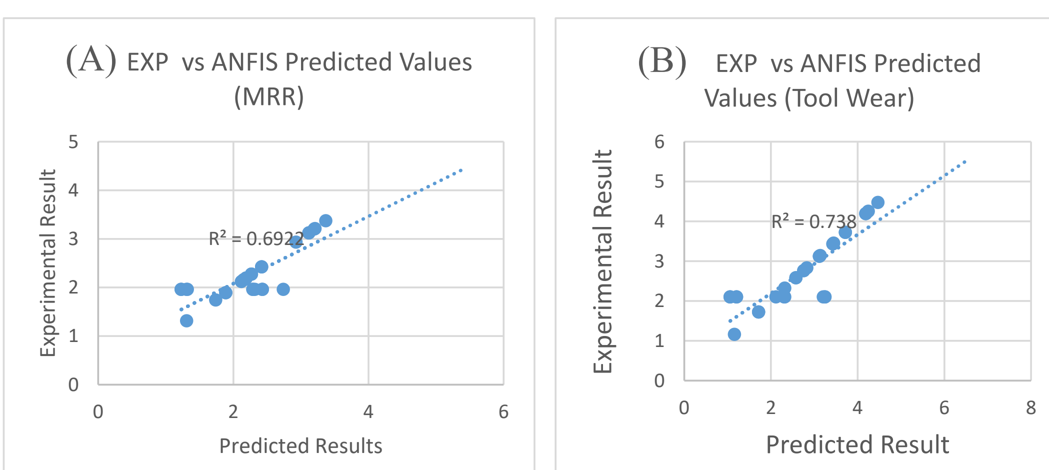

Figure 8. Plot of experimental and predicted values for (a) the MRR and (b) tool wear model.

tributes of biological neuron systems similar to the human brain that learn by experience to develop information, used for prediction and categorization in data processing [22]. ANN's predictive ability is executed by adjusting the weights and biases (learning) in a network to capture the linear and non-linear structure of the data while maintaining an acceptable error limit. The weights are iteratively adjusted until the network presents a minimum error for each of the input x(k) and output y(k) data. This is made possible by the selection of a suitable network design, training algorithms, and Hyperparameters [26]. The neuron network performance is evaluated using statistical measures such as the coefficient of correlation (R^2), and the root mean squared error (RMSE) [27, 28] as given in Eqs. (2) and (3).

$$R^2 = 1 - \left(\frac{\sum_j (Opre_i - Oexp_i)^2}{\sum_j (Opre_i)^2}\right) \tag{2}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_i^n (Opre_i - Oexp_i)^2}{n}} \tag{3}$$

$Opre_i$ and $Oexp_i$ represent the predicted and experimental output, while n is the number of paired input/output.

For this study, the experimental data generated were divided into three sets; 70% for training, 15% for validation, and 15% for testing of the ANN model. Three different training algorithms, activation functions, and a no of neurons varied from 2-20 were selected [29] for performing the training, validation, and testing of the network to identify the most ideal for the machining process. By following Haykin [30], the network error was checked periodically for validation as the training process continued to effect an early stopping technique. This process was implemented with the aid of the MATLAB 2016b software.

Table 3. Predicted ANN and ANFIS Values for the Metal Removal Rate (MRR) and Tool wear.

Exp. No.	Cutting Speed (m/min)	Depth of Cut (mm)	Feed Rate (mm/rev)	MRR (mm3/min)			Tool Wear (mm)		
				EXP	ANN	ANFIS	EXP	ANN	ANFIS
1	210.00	1.10	0.20	2.29	2.19	1.96	1.21	1.18	2.10
2	210.00	1.10	0.20	1.31	1.30	1.96	2.32	2.30	2.10
3	83.00	1.10	0.20	2.16	2.16	2.16	4.19	4.16	4.19
4	210.00	1.10	0.40	2.27	2.25	2.27	2.58	2.58	2.58
5	135.00	0.60	0.32	3.12	3.10	3.12	3.12	3.12	3.12
6	210.00	1.10	0.20	1.23	1.13	1.96	1.06	1.06	2.10
7	336.00	1.10	0.20	2.19	2.11	2.19	2.76	2.75	2.76
8	285.00	1.60	0.32	1.89	1.81	1.89	3.72	3.72	3.72
9	210.00	1.10	0.20	2.43	2.43	1.96	3.25	3.25	2.10
10	285.00	0.60	0.32	2.42	2.42	2.42	1.72	1.72	1.72
11	210.00	1.10	0.20	2.32	2.32	1.96	3.21	3.20	2.10
12	135.00	0.60	0.08	3.21	3.21	3.21	4.25	4.24	4.25
13	210.00	1.10	0.20	1.32	1.30	1.96	2.31	2.30	2.10
14	285.00	1.60	0.08	3.20	3.21	3.20	3.45	3.45	3.45
15	210.00	0.26	0.20	2.12	2.12	2.12	3.43	3.43	3.43
16	285.00	0.60	0.08	3.37	3.35	3.37	3.14	3.14	3.14
17	210.00	1.10	0.20	2.74	2.74	1.96	2.12	2.11	2.10
18	135.00	1.60	0.32	1.74	1.72	1.74	4.47	4.46	4.47
19	135.00	1.60	0.08	2.93	2.93	2.93	1.16	1.16	1.16
20	210.00	1.94	0.20	2.15	2.15	2.15	2.83	2.83	2.83
21	210.00	1.10	0.20	2.29	2.29	1.96	1.21	1.21	2.10
22	210.00	1.10	0.10	1.31	1.31	1.31	2.32	2.32	2.32
23	83.00	1.10	0.20	2.16	2.16	2.16	4.19	4.19	4.19
24	210.00	1.10	0.40	2.27	2.27	2.27	2.58	2.58	2.58
25	135.00	0.60	0.32	3.12	3.12	3.12	3.12	3.12	3.12
26	210.00	1.10	0.20	1.23	1.23	1.96	1.06	1.06	2.10
27	336.00	1.10	0.20	2.19	2.19	2.19	2.76	2.76	2.76
28	285.00	1.60	0.32	1.89	1.89	1.89	3.72	3.72	3.72
29	210.00	1.10	0.20	2.43	2.43	1.96	3.25	3.25	2.10
30	285.00	0.60	0.32	2.42	2.42	2.42	1.72	1.72	1.72
31	210.00	1.10	0.20	2.32	2.32	1.96	3.21	3.21	2.10
32	135.00	0.60	0.08	3.21	3.21	3.21	4.25	4.25	4.25
33	210.00	1.10	0.20	1.32	1.32	1.96	2.31	2.31	2.10
34	285.00	1.60	0.08	3.20	3.20	3.20	3.45	3.45	3.45
35	210.00	0.26	0.20	2.12	2.12	2.12	3.43	3.43	3.43
36	285.00	0.60	0.08	3.37	3.37	3.37	3.14	3.14	3.14
37	210.00	1.10	0.20	2.74	2.74	1.96	2.12	2.12	2.10
38	135.00	1.60	0.32	1.74	1.74	1.74	4.47	4.47	4.47
39	135.00	1.60	0.08	2.93	2.90	2.93	1.16	1.16	1.16
40	210.00	1.94	0.20	2.15	2.14	2.15	2.83	2.83	2.83
	Prediction error %				6.1	11.5		4.3	7.2
	Coefficient of correlation (R^2)				0.9206	0.693		0.9206	0.738

2.3. Adaptive neuro-fuzzy inference system (ANFIS)

The ANFIS is a machine learning technique that integrates the adaptive neural network (ANN) rules and fuzzy logic (FL) theories inside an adaptive network framework to form a logical relationship between inputs and outputs [31]. The toolbox feature of the ANFIS forms a fuzzy inference system (FIS) whose membership structure or parameters can be calibrated either by using a backpropagation method alone or combining with the least-squares-type method. However, with ANN procedure the FIS model of the ANFIS is developed through which data are learned or trained. A well-utilized demonstration of the ANFIS procedure is given in Figure 1, showing two inputs (a; b) and one output (Si) in this system [32].

To create an inference system, five different layers namely fuzzy layer, product layer, normalized layer, de-fuzzy layer, and the total output layer are used, with each consisting of different nodes (adaptive nodes) represented by squares which allow factors to be changed and circles for fixed factors.

The first layer contains several membership functions (MF) with which numerical input data are converted into fuzzy inputs. With Eqs. (4) and (5), the output of each node is determined, with O_{ij} representing the output, and μ_{xi} and μ_{Yi-2} representing the membership functions of the first layer [31].

$$O_{1i} = \mu_{x_i}(x), \quad i = 1, \ 2 \tag{4}$$

$$O_{1i} = \mu_{x_i}(y), \quad i = 3, \ 4 \tag{5}$$

The network's second layer is formed when the fuzzy rules are established. The set of fuzzy inference rules that apply to the structure given in Figure 2 contains fuzzy if-then rules of Sugeno type [33]. The two rules for a first-order Sugeno fuzzy inference system can be expressed as shown in Eqs. (6) and (7) [34, 35].

$$\text{IF x is } A_1 \text{ AND y is } B_1, \text{ THEN } f_1 = p_1x + q_1y + r_1 \tag{6}$$

$$\text{IF x is } A_2 \text{ AND y is } B_2, \text{ THEN } f_2 = p_2x + q_2y + r_2 \tag{7}$$

where x and y represent the ANFIS inputs, A and B the fuzzy sets, fi the first-order polynomial, and p_i, q_i, and r_i are the parameters set, referred to as the consequent parameters.

Taking the fuzzy subset as an algebraic multiplication, the fuzzy rules are formed by multiplying output signals of the first layer as expressed by Eq. (8) [36]:

$$O_{2i} = \mu A(x)\mu_B(x), \ i = 1, \ldots, 4, \ \ j,k = 1,2 \tag{8}$$

At the third layer, the effectiveness of the second layer outputs $\tilde{\omega}$ is determined by normalizing it, to obtain a suitable weight coefficient given by Eq. (9).

$$O_{3i} = \tilde{\omega}_i = \frac{w_i}{\sum_i wj}, \quad i = 1, \ldots., 4 \tag{9}$$

At the fourth layer, haven obtained the weight coefficients from the third layer, the effect of each of the parts of the system's output is determined using fuzzy rules using Eq. (10).

$$O_i^4 = \tilde{\omega}_i f_i = \tilde{\omega}(p_i x + q_i y + r_i), \quad i = 1, \ldots., 4 \tag{10}$$

The last layer which is the fifth utilizes the sum of the weighted values obtained in the fourth to generate the system output as a numerical variable equal to the non-fuzzy part in the fuzzy systems as given in Eq. (11).

$$O_5 = \sum_i \tilde{\omega} f_i \tag{11}$$

For this study, the Neuro Fuzzy design tool of MATLAB Mathwork along with a graphical user interface (GUI) was used in constructing and evaluating a fuzzy system. With the ANFIS editor, loading of data, generation of the Fuzzy Inference System (FIS), and the training and testing of the FIS were enabled with 150 epochs along with the hybrid learning algorithm choose for the analysis. Prior to this, a training data set is used to search the constant of the membership function, and thereafter the dataset is verified for error. Generally, the performance of the ANFIS is evaluated by the root mean square error between the data and system output [37].

3. Results and discussion

Results from the experiment conducted have been tabulated as shown in Table 1 and the analysis performed have been discussed in this section.

3.1. Training of the neural network model for the AISI steel turning data

The experimental data generated were divided into three sets; 70% for training, 15% for validation, and 15% for testing of the ANN model. Different training algorithms (Levenberg-Marquardt (LM), Scalar conjugate gradient (SCG), and Resilient backpropagation (RP)), activation functions (logsig, tangsig and purelin) along with a range of neurons (2–20) were evaluated in order to determine the most suitable for performing the training, validation, and testing of the network. As revealed by Haykin [30], the number of neurons most adequate in the hidden layer is dependent upon how complex the system being approximated is.

In trying to determine the optimal Hyperparameters of the ANN model, different parameters were evaluated and tested. The LM training algorithm with 10 no of neurons and tansig activation function at the hidden layer and logsig function at the output layer recorded the lowest statistical performance with a coefficient of correlation (R^2) value of 0.938, MAE value of 0.074, and RMSE value of 0.122 for the training. Based on the above, an ANN architecture as displayed in Figure 2, comprising 10 hidden neurons is selected for the optimal ANN model design. Figure 3a, b, c and d displays machining values predicted for the different data sets, revealing the correlation between the target (experimental data) and the ANN model output values in the three sub-datasets.

The dots and solid lines as shown in Figure 3a, b, c and d, represents the data and best-fit linear regression with R-values of 0.8277, 0.9206, and 0.9836 recorded for the training in Figure 3a, validation in Figure 3b and testing sub-dataset in Figure 3c respectively, while the overall R value of 0.876 as displayed in Figure 3d was obtained for the overall training process. The regression coefficient of the ANN models is approximately equal to one, which is satisfactory and a confirmation of the predictive ability of the model. Further analysis to confirm the optimal ANN model is made by studying the network architecture based on the average performance of the validation dataset errors and the number of training epochs. The plot as shown in Figure 4 shows a decrease in the large network values as the weights were improved during the network training which was terminated at 36 epochs based on adaptive weight minimization [38].

The plot shows that the model possesses a good generalization ability, an indication that the size of the input parameters is ideal enough for the training of the network.

3.2. Development of ANFIS model for the AISI steel turning prediction

In developing the ANFIS model, the experimental data tabulated in Table 2 were divided into two sets: 70% for the training and 30% for testing data sets and then employed in constructing a fuzzy inference system, whose membership function parameters were adjusted, using the back-propagation algorithm in combination with the least-squares method. The ANFIS analysis only considers one output value for each model hence the models for each of the responses are considered separately. The proposed architecture of the ANFIS model is composed of three input parameters and one output value as displayed in Figure 5 below. Figures 6a, b and 7a, b reveals the performance of the training and testing for the two responses by comparing the predicted and experimental values for the 30 sets of trained data as shown in Figures 6a and 7a for the MRR and tool wear and 10 sets of test data as shown in Figures 6b and 7b for the MRR and tool wear, using the ANFIS editor.

The dots and asterisks points as shown in Figures 6a, b and 7a, b represents the predicted and experimental values. The graph reveals that the predicted responses values are relatively close to the experimental measured values. An indication of the adequacy of the ANFIS in the modeling of the experimental data.

Figure 8a and b shows a plot of the Experimental measured values and ANFIS predicted values for the MRR and tool wear values. The plot with the solid line representing the best fit of the data, reveals that the error is uniformly distributed.

The analysis is further analyzed by comparing the predicted responses from both techniques as shown in Table 3.

The predicted and the experimental values of the MRR and Tool wear as tabulated for the different modeling techniques reveals that the average error of the ANN and ANFIS prediction is 6.1% and 11.5% for the MRR and 4.3% and 7.2% for the tool wear. The prediction accuracy of the ANN as can be observed is higher than that of the ANFIS.

4. Conclusion

The prediction of machining parameters has become necessary considering the increasing need for increased production rate, reduced cost of production, and sustainability of quality. However, with the nonlinear nature of the machining process, applying and identifying a suitable and adequate technique is very crucial to achieving success. For this reason, machine learning approaches such as an artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS) have been applied in this study to predict the metal removal rate and tool wear in the turning operation of AIS cylindrical steel. Based on the literature, the following process parameters: cutting speed, feed rate, and depth of cut, was selected as the input parameters for the study. The performance of the ML algorithms were comprehensively and successfully evaluated by determining the optimal training parameters for the ANN and ANFIS models to ascertain their accuracy and suitability in the prediction of the responses.

The results show that the ANN and ANFIS techniques are very suitable for predicting the machining process. However, a comparison of both techniques indicates that ANN is relatively superior to the ANFIS techniques, considering the accuracy of its results in terms of prediction errors for the ANN and ANFIS of 6.1% and 11.5% for the MRR and 4.1% and 7.2% for the Tool wear respectively. Furthermore, the Coefficient of correlation (R^2) for the ANN 92.1% recorded the maximum values compared to that of the ANFIS of 60% and 73%. The result of this study confirms the argument by Sada and Enyi [39] attributing the efficiency of the ANN over other approaches to the ability of designers to determine the optimal hyper-parameters for training the ANN model. It is concluded that with the successful application of the AL techniques, the machining process can be accurately predicted for planning purposes as well as the improvement of production/manufacturing processes.

Furthermore, the accuracy of the developed models can be further evaluated by increasing the experiment data and increasing the input variables as researchers [20] have often argued that the performance of the ANN and ANFIS model can be affected by the size of experimental data considered.

Declarations

Author contribution statement

Sada, S. O.: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Wrote the paper.

Ikpeseni, S. C.: Performed the experiments; Contributed reagents, materials, analysis tools or data.

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Additional information

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