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ANN Based Estimation of Geometry of Bead-on-Plate in Pulsed Gas Tungsten Arc Welding

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Abstract - Artificial Neural Networks (ANN) has been constructed for estimating the geometrical parameters of bead-on plate obtained through Pulse TIG (Tungsten Inert Gas) welding, also known as Gas Tungsten Arc Welding (GTAW). For this, the dataset have been taken from the experimental work. Welding voltage, welding current, torch travel speed and pulse frequency have been considered to be the input parameters to predict weld bead width, height of reinforcement and depth of penetration. Hidden layers are varied. 6 numbers of nodes in the hidden layer has been found to give the best results in this work. Estimated values of bead width, depth of penetration and height of reinforcement have been found to be quite close to the experimental observation.

Keywords - **welding, bead-on plate, Pulse TIG, pulse frequency, GTAW, back propagation, ANN.**

INTRODUCTION

Determination of optimum set of welding parameters requires a large amount of data which can be made available with a lot of time-consuming and costly experiments. In the past, many investigations were carried out using various welding processes to explore the influence of welding process variables on the weld characteristics during welding of different steels and other non-ferrous alloys [1-3]. Desired weld bead geometry can be achieved by adjusting welding current and voltage, welding speed, flow rate of shielding gas and diameter of the filler wire in Gas Metal Arc Welding [4-6]. Hardness and strength of the welded joint is also influenced by these welding parameters [7-9]. The above parameters also influence on the amount of welding defects and occurrence of spatter. Welding defects can be reduced by adjusting the parameters suitably [10]. The microstructure of the welded joint is also affected by the selection of welding parameters [11]. In addition to the choice of welding parameters, use of various types of flux material influences the characteristics of welded joint [12].

Many simulation and optimization works in arc welding were investigated by the researchers to reduce the costly trials on welding [13-15]. Various mathematical models were employed for prediction of optimum weld bead geometry corresponding to a set of parametric conditions employed during welding [16-18]. This suitable set of process parameters would then be used for making welded joint. The Artificial Neural Networks (ANN) is a popularly used mathematical tool for prediction or estimation of and it is applied in a wide variety of fields including welding. It is mainly used to predict the welded joint characteristics from varying welding parameters [19-22].

In this work, Artificial Neural Networks (ANN) is applied for the estimation of weld bead geometry made with Gas Tungsten Arc Welding process. For the development of the model, data were taken from the experimental work [23] done by the 2nd and 3rd authors of this article. Results obtained are discussed and applicability of the method is explored.

Measurements are also carried out to observe the influence of operating parameters on the system performance. The obtained results show that the proposed system has ensured a substantial reduction in process air humidity at the dehumidifier exit while maintaining the conditioned room indoor thermal comfort.

ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (ANN) is an important paradigm of soft computing method. It is evolved from the biological neural network just like a basic neuron structure of a human body. The artificial neuron is called perceptron. Just like a biological neuron, ANN takes in data, recognize the pattern present in this data and predict output(s) with new set of data [24, 25]. ANN can be preferred because of its ability to update itself at any point with new types of data. Also ANN can rapidly operate enormous amount of input data. Application of neural networks is in a wide range of areas, such as, areas of finance like in stock market, medical field, engineering, etc. where prediction and estimation are needed.

Fig. 1 represents relationship between artificial neural networks and biological neuron. From the diagram, a neuron gets the input information from the connected neurons just like axons of a biological neuron, with xi as the i^{th} element of x vector. The weights w_i are related to the synapses of a biological neuron which are to be applied to the inputs. All the elements from the inputs are fed into the cell body where summation is done. Also a bias is added. At the final stage, the weighted sum is

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passed to filter called activation function to get the output. Activation function is also called threshold function.

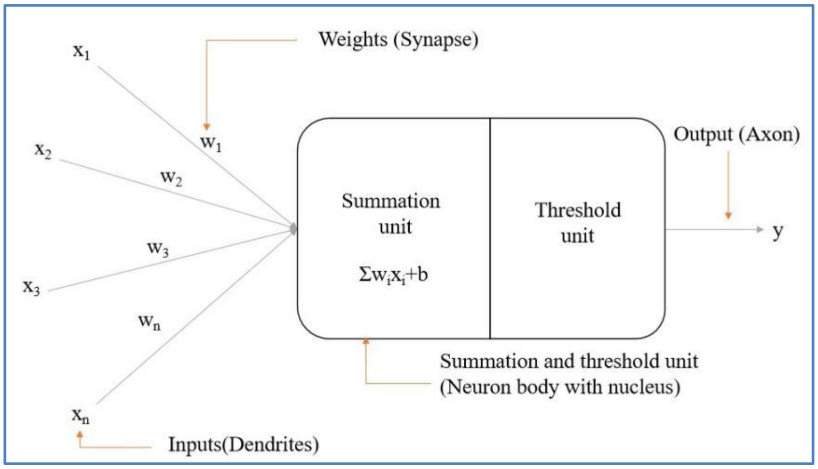

Fig. 1. Representation of a structure of artificial neural networks (ANN) mimicked from a biological neuron.

Learning is required for both human brain and artificial neural networks, so it can work more efficiently. Learning of ANN is done by updating the weights, bias and other elements. Learning can be either supervised learning or unsupervised learning. Some of the important supervised learning techniques for ANN are:

i) Back propagation neural network
ii) Radial basis function neural network
iii) Time delay neural network
iv) Regulatory feedback neural network
v) Probabilistic neural network

BACK PROPAGATION TYPE NEURAL NETWORKS FOR TRAINING

Back propagation algorithm is type of supervised learning where inputs and outputs were to be known in advance. Basic architecture in this type of network consists of three layers- input layer depicting input parameters, hidden layer which represents the unknown relationship between the input layer and the output layer and the output layer. At the time of designing the neural networks, some random weights are assigned. After that, neural networks output is compared with the desired output. And it is obvious that some error may be obtained. These errors are reduced by propagating backwards and changing the weights. This process is a type of iterative process and the training will continue until the error is reduced to a acceptable value. A typical back propagation neural network is shown in Fig. 2.

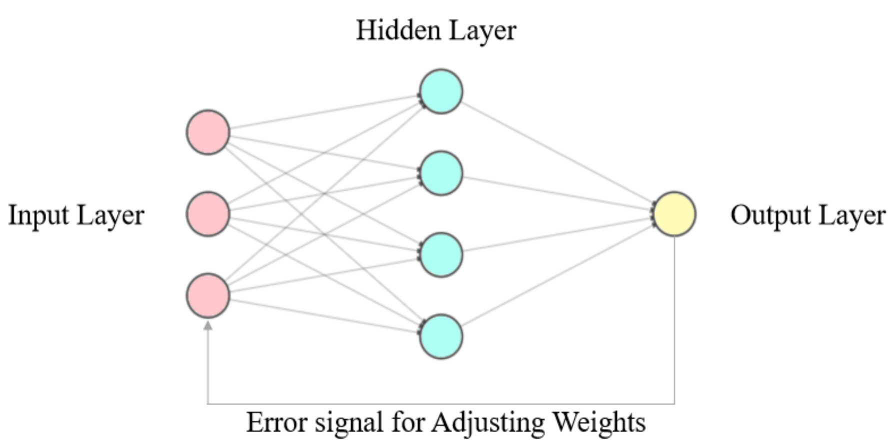

Fig. 2. A Typical Back Propagation Neural Network Model.

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The input parameters are fed into the input layer of the neural network. In the hidden layer, all the input signals, a_i are multiplied with the assigned weights, w_i. The summation of the product of input signals and weights is done followed by adding a bias, θ_1

$$x = \Sigma(a_i w_i) + \theta_1 \quad (1)$$

This x is used to formulate the activation function. Activation function is used as a filter to generate the final output. It works on simple Boolean theory.

$$f(x) = 1 \text{ if } X \geq \theta_1 \quad (2)$$
$$= 0 \text{ if } X < \theta_1 \quad (3)$$

In this work sigmoid function is used as activation function. The sigmoid function can be written as

$$F(x) = \frac{1}{1+e^{-x}} \quad (4)$$

The difference between targeted output and calculated output is the error. The computed error is then back propagated to update the weight values. This process is continuously done until acceptable value of error is reached. The weights are updated using Levenberg-Marquardt algorithm this study.

Levenberg-Marquardt algorithm is least square method which is used to solve non-linear problems fitting problem. It is a combination of gradient descent method and Gauss-Newton Method.

PREDICTION OF BEAD GEOMETRY OF TIG WELDED WORKPIECE USING ANN

In this study, experimental data are collected from the work of Bose and Das [23]. They worked on bead-on-plate welding using Pulsed Gas Tungsten Arc Welding (P-GTAW), or pulse-TIG, and determined weld bead geometry of 316-grade austenitic stainless steel deposited on low carbon steel plates. Effects of varying process parameters on the weld bead geometry of 316 austenitic stainless steel filler wire cladded on low carbon steel plates were investigated by them. Cladding was later done using Pulsed Gas Tungsten Arc Welding process. This experiment was done for the study corrosion resistance technique by cladding process.

The Experimental data taken from the work of Bose and Das [23] are given in Table 1. 15 sets of experiments were carried out by selecting welding current, Frequency, Travel speed, Weld Voltage, which are given in Table 1. And these 15 sets of experiment resulted in 15 combinations of weld bead geometry (Depth of Penetration, Height of Reinforcement and Weld Bead Depth) which are also given in Table 1.

Table 1. Experimental Data.

Sl. No	Welding Current, (A)	Frequency (F) (Hz)	Travel Speed (S) (mm/min)	Weld Voltage (V)	Average depth of Penetration (mm)	Average Height of Reinforcement (mm)	Average Weld Bead Width (mm)
1	150	33	90	9.7	2.54	2.46	9.99
2	130	60	90	10.4	2.36	2.66	8.93
3	130	6	150	14.9	1.54	2.51	5.84
4	110	60	120	13.9	1.02	2.85	4.72
5	150	60	120	11.6	1.07	2.36	7.59
6	130	33	120	12.3	0.96	2.44	6.06
7	150	33	150	13.2	1.16	1.6	7.53
8	110	6	120	14.2	1.09	2.43	4.27
9	110	33	90	13.3	1.57	2.28	7.49
10	150	6	120	14.1	1.63	2.22	5.31
11	130	60	150	16.8	0.95	2.43	6.42
12	130	33	120	12.9	1.4	2.47	4.09
13	110	33	150	15.1	0.94	2.6	5.76
14	130	6	90	15.9	2.45	2.26	11.05
15	130	33	120	12.5	0.92	2.44	5.21

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In this work, a neural networks model is constructed for the prediction of weld bead geometry of bead-on plate GTAW welding. For the development of the model, the set of data was taken from the experimental work of Bose and Das [23]. Four input parameters, i.e. welding voltage, welding current, travel speed and pulse frequency, were considered to predict output parameters, i.e. weld bead width, height of reinforcement and depth of penetration. Trial runs were attempted with a hidden layer with 4, 5 and 6 numbers of hidden nodes. Using 6 numbers of hidden nodes gives the best results for the neural networks model. Development of the neural networks and training is done using the application tool, MATLAB 2020a.

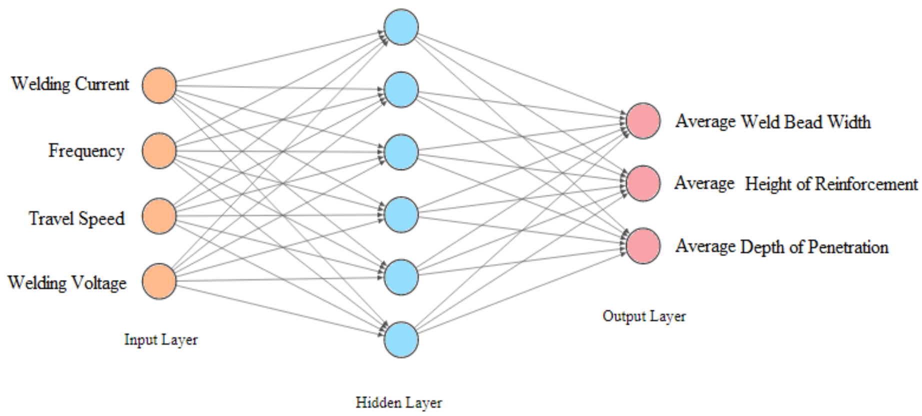

Fig. 3. Schematic Diagram of ANN Model for predicting Bead Geometry.

For the development of the model, fourteen sets of data were taken out of which 10 sets of data were used for training, two sets of data were used for validation and two sets of data for testing. Fig. 3. represents the artificial neural networks (ANN) model in which 6 hidden nodes are there in the single hidden layer chosen with four input nodes (for each parameter) and 3 output nodes (for each response). Selection of number of hidden layers is done by some trials. Trial was done with 3, 4, 5, 6 and 10 hidden nodes in the hidden layer. Training with 6 hidden nodes in a single layer gives the best results with minimum error.

In Fig. 4 through Fig. 7, regression analysis is done which determines the relationship between target data and predicted data. In Fig. 4, regression plot for training data is established. In Fig. 5, plot for validation of the model is shown. In Fig. 6, regression plot of testing data is shown. And Fig. 7 shows overall regression analysis.

In Fig. 8, the graph of comparison between experimental data and predicted data of average depth of penetration is given. The experimental data are very similar to predicted data with minor deviation in some sets.

In Fig. 9, the graph of comparison between experimental data and predicted data of average height of reinforcement is given. It can easily be observed that the predicted value is very much similar to the experimental data.

In Fig. 10, the comparison between experimental data and predicted data of average bead width is depicted. It can be seen that the predicted value is much similar to the experimental data as that of the other two bead geometry parameters.

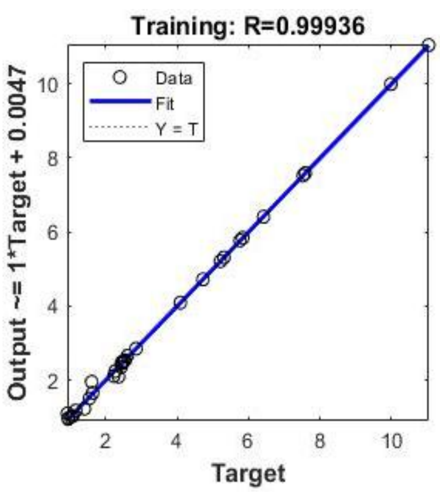

Fig. 4. Regression plot of predicted and target data for training samples.

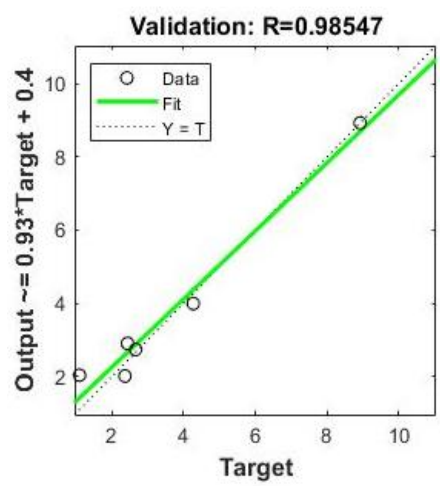

Fig. 5. Regression plot of predicted and target data for validation.

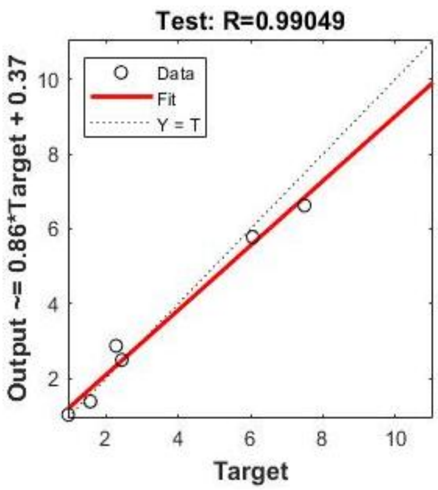

Fig. 6. Regression plot of predicted and target data for testing samples.

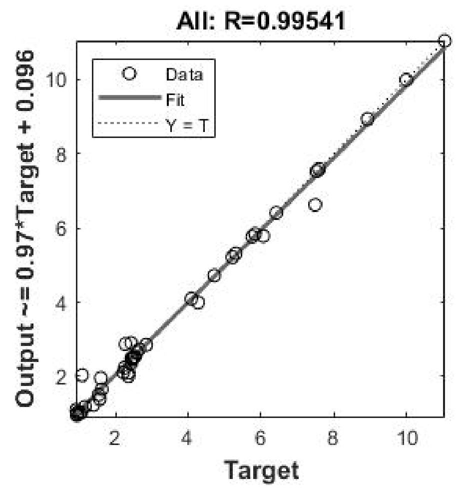

Fig. 7. Regression plot of predicted data and target data for all sample.

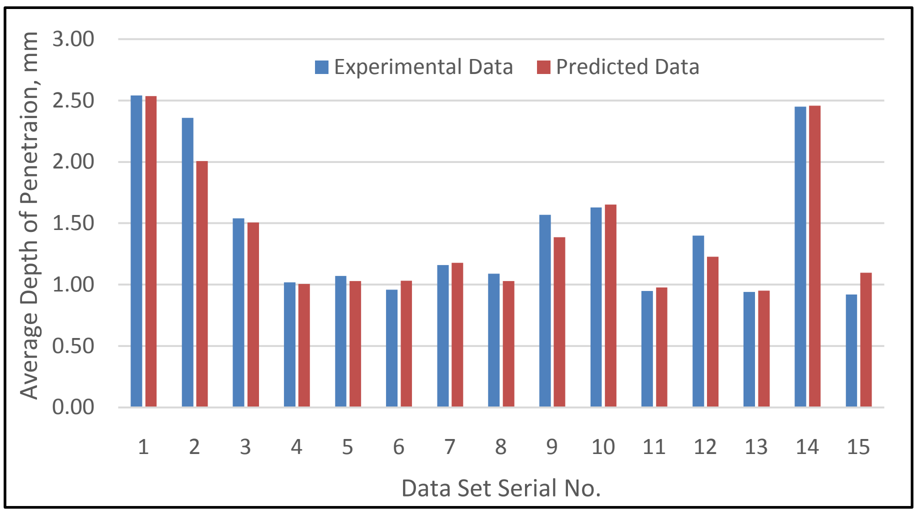

Fig. 8. Comparison between experimental and predicted data of depth of penetration.

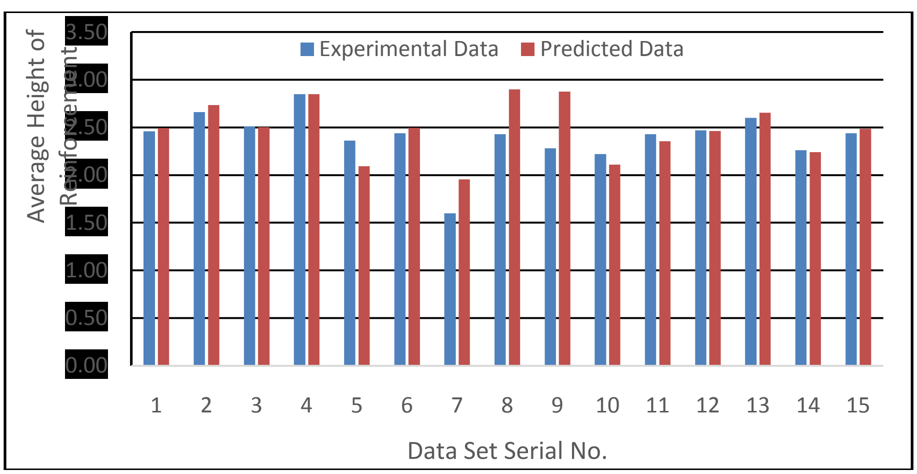

Fig. 9. Comparison between experimental and predicted data of height of reinforcement.

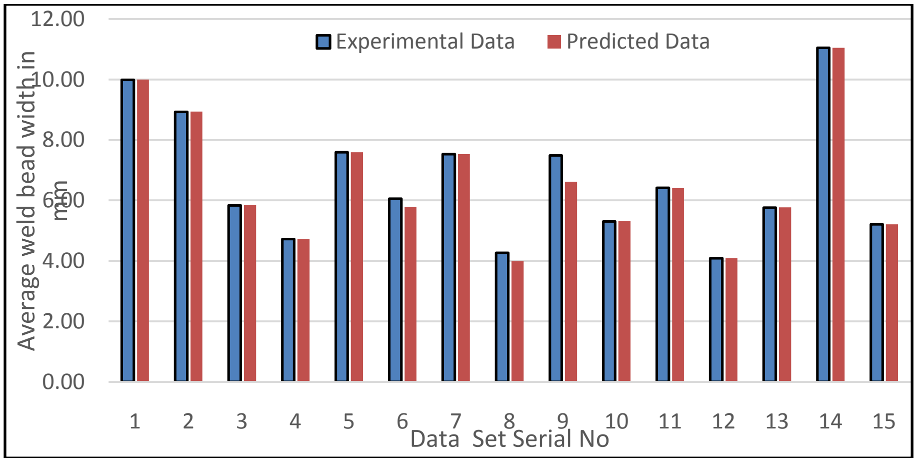

Fig. 10. Comparison between experimental and predicted data of weld bead width.

In Fig. 11 through Fig. 13, error percentages of weld beat geometry of predicted values are shown. From the Figures, it can be observed that most of the estimated values are close to be of zero error. Estimated values have a maximum of 20% error only at a few points.

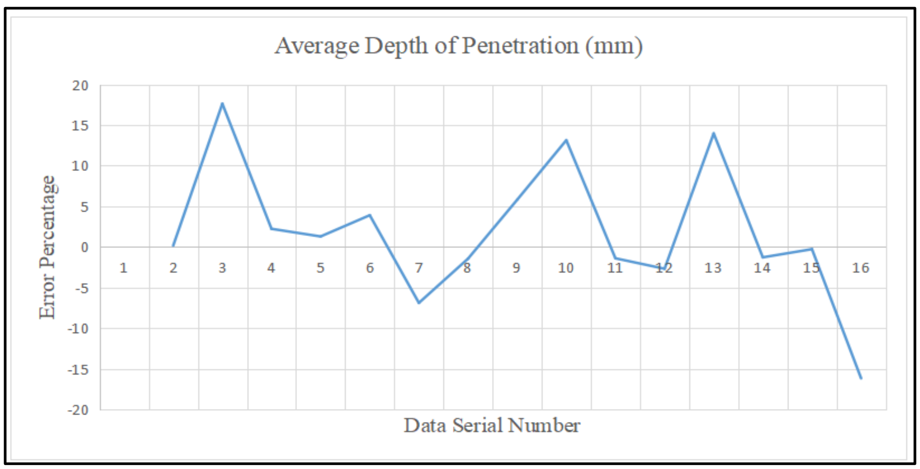

Fig. 11. Percentage of Errors in Estimated Values of Depth of Penetration.

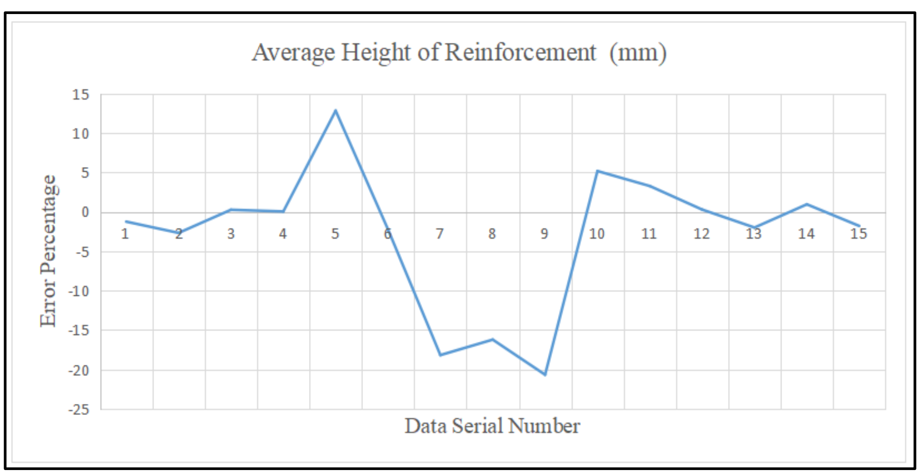

Fig. 12. Percentage of Errors in Estimated Values of Height of Reinforcement.

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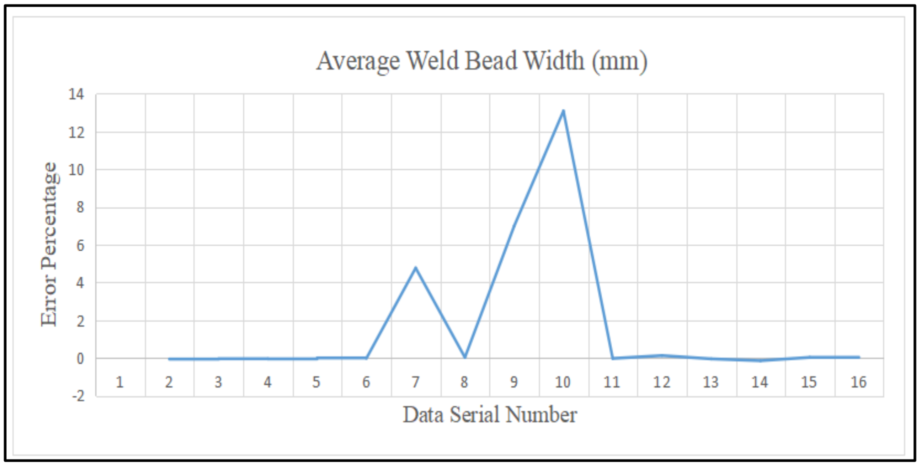

Fig. 13. Percentage of Errors in Estimated Values of Weld Bead Width.

CONCLUSION

In this work, the investigation has been conducted for the estimation of weld bead geometry from input parameters in the bead on plate pulsed GTAW process. From the investigation, it can be concluded that bead geometry of welded joint can be estimated without performing time-consuming and expensive experiments with the help of machine learning tool, an artificial neural networks (ANN) with perfection as predicted results from ANN are much close to the experimental data, and hence, its applicability.

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