Prediction of Welding Penetration in Gas Metal Arc Welding Process using an Artificial Neural Network

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Abstract-- **Gas metal arc welding (GMAW) process is an important component in many industrial operations. The research on controlling GMAW metal transfer modes is essential to high quality welding procedures. The GMAW parameters are the most important factors affecting the quality, productivity and cost of welding joint. The present work describes the development of an ANN based on back propagation (BP) of error for prediction of the gas metal arc welding parameters. The input parameters of the model consist of arc current, voltage and welding speed whereas the output of the model is the depth of the penetration. The effect of network parameters on the mean square error (MSE) of prediction is studied. In present work an attempt has been made to use Neuro solution 4.3 for the ANN applying to gas metal arc welding process. The ANN was subsequently trained with experimental data. Testing of the ANN is carried out using experimental data not used during training. The results showed that the outcomes of the calculation were in good agreement with the experimental data; this indicates that the developed neural network can be used as an alternative way for calculating the process parameters.**

Index Terms-- **Gas metal arc welding, Artificial Neural Network, Welding parameters, Penetration.**

I. Introduction

GAS metal arc welding (GMAW) process is an important component in many industrial operations. The gas metal arc welding process is a welding method that gives coalescence of metals by heating with a welding arc between continuous filler metal (consumable) electrode and the workpiece. The continuous wire electrode, which is drawn from a reel by an automatic wire feeder, and then fed through the contact tip inside the welding torch, is melted by the internal resistive power and heat transferred from the welding arc. Molten weld pools and electrode wire are protected from contaminants in the atmosphere by a shielding gas obtained from various combinations. The research on controlling GMAW metal transfer modes is essential to high quality welding procedures. The GMA welding parameters are the most important factors affecting the quality, productivity and cost of welding joint [1,2]. Weld bead size and shape are important considerations for design and manufacturing engineers in the fabrication industry. In fact, weld geometry directly affects the complexity of weld schedules and thereby the construction and manufacturing costs of steel structures and mechanical devices [2]. Artificial neural networks (ANNs) are biologically inspired by intelligent techniques. Artificial neural networks have been very popular in many engineering fields because of their fascinating features such as learning, generalization, faster computation and ease of implementation. ANNs are generally made up of a number of simple and highly interconnected processing elements organized in layers. These processing elements or neurons process information by their dynamic state response to external inputs. ANNs are capable of learning patterns by training with a number of known patterns. The learning process automatically adjusts the weights and thresholds of the processing elements. Once adjusted with minimal difference between ANN output and targeted output, the neural network is said to be trained. Artificial neural networks have found extensive applications in diverse fields like manufacturing, signal processing, bio-electric signal classification, pattern recognition, speech recognition, image processing, communications, autonomous vehicle, navigation control of gantry crane to name a few. Even in manufacturing, ANN applications to cold forging, for predicting the flow stress in hot deformation, for tool wear monitoring, for prediction of machining behavior, and for optimization of manufacturing processes among many others, are well documented and only a few illustrative references are cited here[1,2,3,5].

II. Details Of Experiment On GMAW Welding Process

Erdal Karadeniz et al [2] study, the effects of various welding parameters on welding penetration in Erdemir 6842 steel having 2.5 mm thickness welded by robotic gas metal arc welding were investigated. The welding current, arc voltage and welding speed were chosen as variable parameters. The depths of penetration were measured for each specimen after the welding operations and the effects of these parameters on penetration were researched. The welding currents were chosen as 95, 105, 115 A, arc voltages were chosen as 22, 24, and 26 V and the welding speeds were chosen as 40, 60 and 80 cm/min for all experiments. The experimental data are taken from the experimental database of Erdal Karadeniz et al.[2] shown in Table 1.

TABLE I
EXPERIMENTAL DATA

Welding current	Arc voltage	Welding speed (cm/min)	Penetration(mm)
95	22	40	2.46
95	22	60	2.51
95	22	80	2.36
95	24	40	2.61
95	24	60	2.67
95	24	80	2.56
95	26	40	2.64
95	26	60	2.69
95	26	80	2.59
105	22	40	2.84
105	22	60	2.92
105	22	80	2.79
105	24	40	2.89
105	24	60	2.97
105	24	80	2.84
105	26	40	2.98
105	26	60	3.01
105	26	80	2.91
115	22	40	3.02
115	22	60	3.06
115	22	80	2.94
115	24	40	3.11
115	24	60	3.14
115	24	80	3.04
115	26	40	3.19
115	26	60	3.24
115	26	80	3.16

III. ANN MODELING FOR GAS METAL ARC WELDING PROCESS USING NERO SOLUTION S/W

1) Introduction

A multi layer perception was developed using neuro solution and used for the prediction of penetration. The BP was initially trained with experimental data and testing was performed with experimental data which was not used during training[4]. For the gas metal arc welding data was generated experimentally [2]. Out of 28 data 7% data had taken for cross validation and 15% data had taken for testing. Scaling has the advantages of mapping the desired range of a variable (with a range between the minimum and maximum values) to the full "working" range of the network input. All the Input output data was normalized between 0.1 and 0.9 using the following equation[6]. Sample data has been shown in the table2.

$$Y(nor) = (0.8/\Delta)Z + (0.9-(0.8\, Z_{max})/ \Delta)$$

TABLE II
SAMPLE NORMALIZED DATA

Nor Welding current	Nor Arc voltage	Nor Welding speed (cm/min)	Nor Penetration(mm)
0.1	0.1	0.1	0.190909
0.1	0.1	0.5	0.236364
0.5	0.1	0.1	0.536364
0.5	0.1	0.5	0.609091
0.9	0.9	0.5	0.9
0.9	0.9	0.9	0.827273

2) Inputs to ANN

The following three parameters were the input of ANN.
1. Arc voltage
2. Welding speed
3. Welding current

3) Outputs to ANN

1. Penetration

4) Back Propagation Neural Network

For many years there was no rule available for updating the weight of a multi layer network undergoing supervised learning. The weight adaptation rule is known as back propagation. Neural networks are mathematical models composed by several neurons arranged in different layers, linked through the variable weights. These weights are calculated by an iterative method during the training process when the network is fed with a large amount of training data, input and output pairs that represent the pattern attempting to be modeled [1].

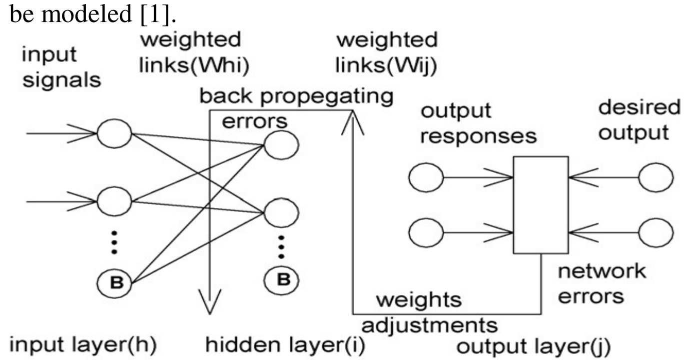

Fig. 1. A back propagation network [1]

The back propagation algorithm defined two aspects of the network: first a forward sweep from the input layer to the output layer, and then a backward sweep from output layer to input layer. The forward sweep propagates input vector through the network to provide output at the out put layer. The backward sweep is similar to the forward sweep, except that error values are propagated back through the network to determine how the weights are to be changed during the training. During the back ward sweep value pass along the weighted connection in the reverse direction to that which was taken during the forward sweep. Fig.1 shows a back propagation network a unit in the hidden layer will send the activation to the every unit in the out put layer during the forward sweep and so during the back ward sweep a unit in the hidden layer will receive an error signals from the every unit in the out put layer[1].

5) ANN Architecture

As mention above three different inputs(welding current, arc voltage and welding speed) and one outputs(penetration) are given to ANN. Consider the eight hidden nodes and single layer feed forward neural network, network architecture is become as follows (Refer fig.2).

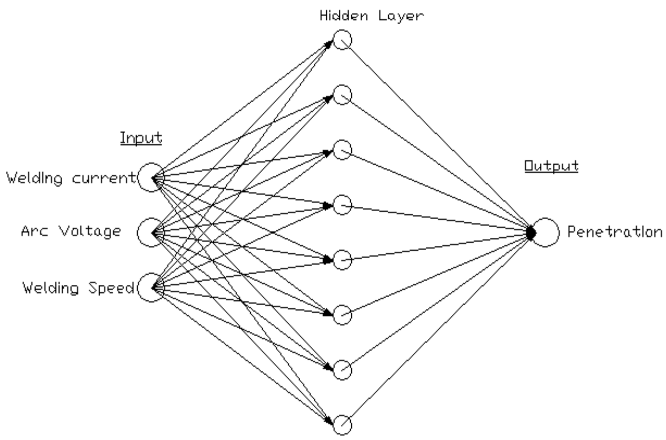

Fig.2. Network Architecture

6) Training of ANN

For this study will be broach under a supervised learning strategy, which means that for all the input patterns ,the objective out puts are known and batch pattern training style is chosen. The training set construction represents a key point of the network generalization property especially for avoiding the over fitting problem. For avoiding the over fitting problem, the early stopping technique is used considering the three data sets: training, cross validation and testing. The training set for training and weight adjustments. The validation set to refine the network by early stopping technique and finally the testing data set an unseeing set during the training that is used to determine the network performance by an error computation [12].Using this training technique the ANN was trained and same training set is shown in table3.

TABLE III
SAMPLE TRAINING DATA

Nor Welding current	Nor Arc voltage	Nor Welding seed (cm/min)	Nor Penetration (mm)
0.1	0.5	0.5	0.3818
0.5	0.1	0.9	0.4909
0.5	0.1	0.5	0.6090
0.9	0.5	0.1	0.7818
0.1	0.5	0.1	0.3272

IV. NETWORK EXPERIMENTATION

Here Neuro Solution version 4.3 is used which was found by Curt Lefebvre and Jose Principle. Neuro Solution based on the back propagation learning algorithm with momentum term is used. Network parameter such a Learning rate, Momentum, no of hidden nodes in hidden layer, no of hidden layers and activation functions were chosen based on the parametric study reported in the literatures [11] .The parametric study was intended to obtain the optimal parameters for faster convergence of data and minimum MSE.

For Gas metal arc welding three parameters were selected as an input to ANN based on the experimentation. ANN was trained with the experimental data up to 40000 epochs. While training, to arrive at optimal parameter, parametric variation was under taken, varying one parameter at once and keeping other parameter constant. The parametric variation was selected based on the effect of it on MSE of training as reported in literature [4,8,10]. Subsequently network was tested with that experimental data which was not used during training [4,10]. After testing, ANN results were compared with experimental results for the % of error of penetration in GMAW.

7) Effect of Network Parameters

The effects of the network parameters namely, momentum (a), learning rate (Z) and the number of nodes in the hidden layer (n) on the mean square error (MSE) were studied in the pattern mode of training for 40000 iterations using the training data from experimental. The effect of the learning rate on the MSE was studies using values of 0.1 to 0.9 with constant momentum rate 0.1 and a 3-8-1 ANN architecture. The results are plotted in Fig.3. The effect of the momentum on the MSE was studied using initial values of 0.1to 0.9 for a learning rate 0.6 for a 3-8-1 ANN architecture. The results are given in Fig. 4. The effect of the number of hidden layer nodes was studied for 6, 8, 10, 12 and 14 with momentum 0.7 and learning rate 0.6. The results are plotted in fig.5.

It may be concluded from Fig. 3 and Fig.4 that when momentum value was 0.7 and learning rate was 0.6, MSE value was minimum. Fig. 5 shows hidden layer nodes 8 was found to be marginally lower than the others after 40000 iterations. It is known that neither too few, nor too many nodes achieve a low MSE since too few nodes would lead to inadequate training while too many of them would cause poor generalization. Based on the above results the ANN architecture of 3-8-1 was chosen for training and testing using the experimental data.

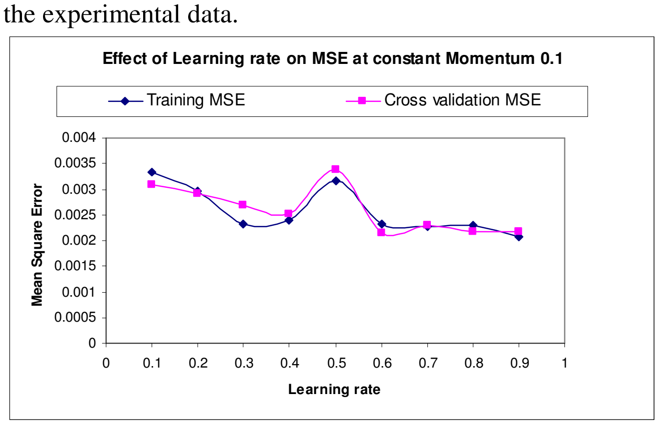

Fig.3. Effect of learning rate on MSE

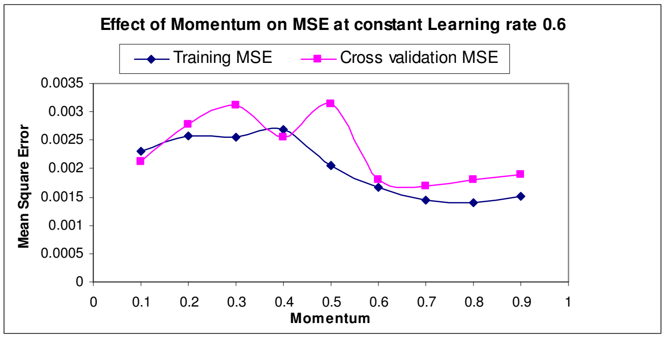

Fig.4. Effect of momentum on MSE

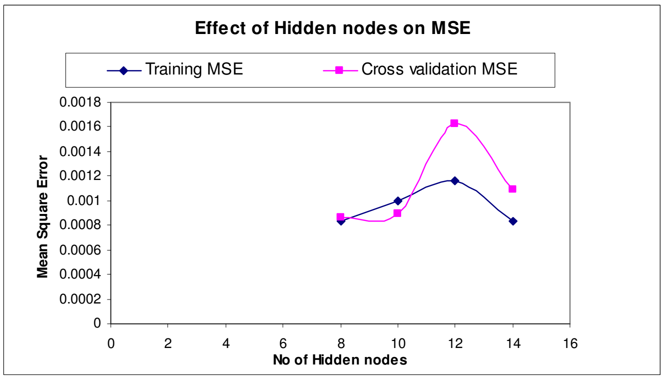

Fig. 5. Effect of hidden nodes on MSE

The optimum parameter values obtained for the ANN architecture are shown in table4.

TABLE IV
OPTIMAL PARAMETER VALUES FOR ANN ARCHITECTURE

Sr.No	Parameter	Data Normalized as a whole set
1	Number of Inputs	3
2	Number of out puts	1
3	Number of hidden nodes	8
4	Number of hidden layers	1
5	Momentum	0.7
6	Learning rate	0.6
7	Activation function	Sigmoidal
8	Normalized range	0.1 to 0.9

V. TESTING RESULT OF ANN

Testing result clearly shows Table 5 and Table 6. R value is nearly about to 1 which co-relate desired out put to the ANN predicted output. Also the graph shows desired out put and ANN out put result is coincide with each other as shown in fig.6.

TABLE.V COMPARISON OF PREDICTIONS OF THE ANN WITH EXPERIMENTAL OBSERVATIONS: TEST DATA

Welding current	Arc voltage	Welding speed (cm/min)	Penetration (mm)	Observed Penetration (mm)
115	24	60	3.14	3.1368
95	22	60	2.51	2.5076
115	22	60	3.06	3.0448

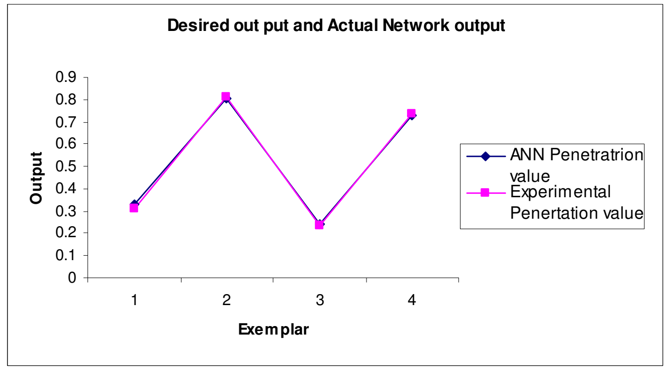

Fig.6 Desired out put and ANN predicted output.

TABLE VI
CO RELATION BETWEEN DESIRED OUTPUT AND ANN OUTPUT

Performance	Nor penetration
MSE	0.000142
NMSE	0.00223
Min Abs Error	0.00284
Max Abs Error	0.0219
R	0.9994

1) Sensitivity Analysis Result

The sensitivity analysis is carried out using artificial neural network. From the sensitivity result shown in fig.7, it can be clearly understand the effect of welding current approximately 2.5 times greater than that of arc voltage and welding speed on penetration which is matching with experimental result.

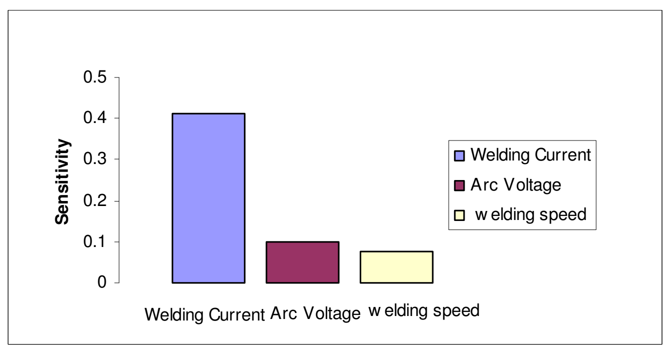

Fig.7. Effect of each input parameter on output (gas metal arc welding)

VI. CONCLUSION

Following conclusions are derived from the parametric study of gas metal arc welding process on penetration using the artificial neural network.

- MSE during the training and testing was found to be affected by normalization of data. Because of this, ANN can be used only for the range of the input variables for which it has been trained.
- Network parameter like momentum and learning rate were found to influence MSE, Larger initial values of learning rate leads to the faster decrease in MSE. Similar was the case with momentum parameter. Parametric

study indicates that there exists unique combination of network parameters like momentum and learning rate for MSE. Optimal parameter values are required to be finding out by trail and error.

- It is observed from the results that a correlation coefficient of 0.99 is obtained between the results obtained by the experimental and the BPN model developed. This shows that the developed neural network model is capable of making the prediction of the weld penetration with reasonable accuracy.
- As a result of this study, it was obvious that increasing welding current increased the depth of penetration. In addition, arc voltage is another parameter in incrimination of penetration. However, its effect is not as much as current's. The highest penetration was observed in 60 cm/min welding current.
- The aim of this study was to show the possibility of the use of neural networks for the calculation of the depth of penetration of GMA welded components. Results showed that, the neural networks can be used as an alternative way for calculating the process parameters (arc voltage, welding current and speed).

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