Predicting the Influence of Process Parameters on Depth of HAZ Using Artificial Neural Network on Shielded Metal Arc Welded AISI 1018 Low Carbon Steel Joints

R P Singh¹, D Pathak²
¹Associate Professor, Department of Mechanical Engineering, GLA University, Mathura-281406, INDIA
²Research Scholar, School of Engineering & Information Technology, Sanskriti University, Mathura-281401, INDIA

Email:d.pathak1610@gmail.com

Abstract. An artificial neural network model was executed after being developed by training a program in C++ by utilizing welding variables including input parameters like electrode angle, welding current, welding speed and welding voltage and output parameters like depth of HAZ. Experimental data were utilized to model neural network based on back propagation algorithm to predict the effects of welding parameters on weld bead geometry factors. It has been noticed that an accurately trained artificial neural network model can be easily and efficiently utilized for predicting the optimum values of depth of heat affected zone.

Keywords: Welding, Welding Parameters, Bead geometry, Artificial Neural Network, Prediction

1. Introduction
In the recent times, welding processes are monitored and controlled by implementing artificial intelligence techniques like fuzzy logic, artificial neural network (ANN) and expert system [1]. Weld bead geometry factors like weld width, reinforcement height, penetration depth and heat affected zone (HAZ) depth are considered to be most important responsible for achieving sound weldments. The weldment characteristics might be strengthened by improving the microstructures of the HAZ [2]. Datta et al. found that the various characteristics of weldments are highly influenced by several process parameters. [3]. Ahmed et al. performed experiments to analyse the relation between SMAW parameters such as current, arc length, speed, electrode diameter and welding gap with weld bead geometry as responses. They predicted the results by using ANN models [4]. Influence of welding polarity was studied on the depth of penetration, reinforcement height and weld bead width of shielded metal arc welded AISI 1020 steel joints [5]. An experimental investigation was conducted using SMAW process to fabricate the mild steel joints considering input process parameters like welding current, speed, voltage under the effects of external magnetic field. [6]. The effects of groove angle were investigated on the reinforcement height and hardness of the welded joint for low carbon steel by carrying out SMAW process [7]. A study was conducted to investigate the influence of SMAW process variables and on weld bead geometry for AISI 1016 steel [8]. In the present work, a model connected with ANN has been developed for the purpose of predicting the depth of heat affected zone (HAZ) for several input process parameters like welding current, welding voltage, welding speed and electrode angle in shielded metal arc welded joints for low carbon steel plates. Back propagation algorithm was used to train the ANN model.
2. Experimentation

In this experimental work, two low carbon AISI 1018 steel plates of dimensions 150 mm x 50 mm x 10 mm were joined in V-groove butt position by carrying out SMAW to achieve weld beads for investigating the structural characteristics at macro level of the weldments. Tables 1 and 2 show the chemical compositions of low carbon steel and filler material respectively. Total 25 sets of values were achieved out of which 18 sets of values were utilized for training ANN model and remaining 7 values for prediction purposes. Tables 3 and 4 show the data achieved for training and prediction purposes by conducting the experiments. A backpropagation algorithm in neural network in C++ was implemented to train the network model and predict the output values. In this algorithm one input layer consisting of four neurons, two hidden layers, both containing five neurons and one output layer having one neuron, were used, depicted in figure-1.

| Table1 - Chemical analysis of AISI 1018 |
|----------------------------------------|
| C  | Mn  | Cr  | Ni  | Mo  |
| 0.166 | 0.63 | 0.04 | 0.03 | 0.005 |

| Table2 - Chemical analysis of Electrode E-6013 |
|---------------------------------------------|
| C  | Si  | Mn  | P  |
| ≤0.11 | ≤0.36 | ≤0.31-0.61 | ≤0.05 |

| Table3 - Factors and their Levels |
|----------------------------------|
| Levels | Welding Current(I) | Welding Voltage(V) | Welding Speed(S) | Electrode Angle(β) |
|-------|--------------------|--------------------|------------------|--------------------|
| 1     | 90                 | 21                 | 40               | 0                  |
| 2     | 95                 | 22                 | 60               | 5                  |
| 3     | 100                | 23                 | 80               | 10                 |
| 4     | 105                | 24                 | -                | 15                 |
| 5     | 110                | 25                 | -                | 20                 |

| Table 3 - Data for training |
|-----------------------------|
| Sample No. | I (A) | V (v) | S (mm/min) | β (*) | Depth of HAZ (mm) |
|--------------|------|------|------------|------|------------------|
| 1            | 90  | 25   | 40         | 0    | 1.36             |
| 2            | 90  | 25   | 40         | 5    | 1.36             |
| 3            | 90  | 25   | 40         | 10   | 1.37             |
| 4            | 90  | 25   | 40         | 15   | 1.34             |
| 5            | 90  | 25   | 40         | 20   | 1.33             |
| 6            | 95  | 21   | 60         | 15   | 1.63             |
### Table 4 - Data for prediction

| Sample No. | I (A) | V (v) | S (mm/min) | β (°) | Depth of HAZ (mm) |
|------------|-------|-------|------------|-------|-------------------|
| 1          | 90    | 24    | 40         | 0     | 1.39              |
| 2          | 95    | 23    | 60         | 10    | 1.62              |
| 3          | 95    | 22    | 80         | 15    | 1.64              |
| 4          | 100   | 25    | 40         | 10    | 1.90              |
| 5          | 105   | 22    | 60         | 10    | 2.01              |
| 6          | 105   | 23    | 60         | 5     | 1.99              |
| 7          | 110   | 22    | 60         | 5     | 2.02              |

### Table 5 - Normalized data for training

| Sample No. | I (A) | V (v) | S (mm/min) | β (°) | Depth of HAZ (mm) |
|------------|-------|-------|------------|-------|-------------------|
| 1          | 0.8182 | 1.0000 | 0.5000 | 0.0000 | 0.4658           |
| 2          | 0.8182 | 1.0000 | 0.5000 | 0.2500 | 0.4658           |
| 3          | 0.8182 | 1.0000 | 0.5000 | 0.5000 | 0.4692           |
| 4          | 0.8182 | 1.0000 | 0.5000 | 0.7500 | 0.4589           |
| 5          | 0.8182 | 1.0000 | 0.5000 | 1.0000 | 0.4555           |
| 6          | 0.8636 | 0.8400 | 0.7500 | 0.7500 | 0.5582           |
| 7          | 0.8636 | 0.8800 | 0.7500 | 0.7500 | 0.5514           |
| 8          | 0.8636 | 0.9200 | 0.7500 | 0.7500 | 0.5479           |
| 9          | 0.8636 | 0.9600 | 0.7500 | 0.7500 | 0.5411           |
| 10         | 0.8636 | 1.0000 | 0.7500 | 0.7500 | 0.5308           |
| 11         | 0.9091 | 0.9200 | 0.5000 | 0.5000 | 0.6575           |
| 12         | 0.9091 | 0.9200 | 0.7500 | 0.5000 | 0.6644           |
| 13         | 0.9091 | 0.9200 | 1.0000 | 0.5000 | 0.6781           |
| 14         | 0.8182 | 0.8400 | 1.0000 | 0.2500 | 0.4349           |
| 15         | 0.8636 | 0.8400 | 1.0000 | 0.2500 | 0.5342           |
Table 6 - Normalized Data for prediction

| Sample No. | I (A) | V (v) | S (mm/min) | β (°) | Depth of HAZ (mm) |
|------------|-------|-------|------------|-------|------------------|
| 1          | 0.8182| 0.9600| 0.5000     | 0.0000| 0.6881           |
| 2          | 0.8636| 0.9200| 0.7500     | 0.6667| 0.8020           |
| 3          | 0.8636| 0.8800| 1.0000     | 1.0000| 0.8119           |
| 4          | 0.9091| 1.0000| 0.5000     | 0.6667| 0.9406           |
| 5          | 0.9545| 0.8800| 0.7500     | 0.6667| 0.9950           |
| 6          | 0.9545| 0.9200| 0.7500     | 0.3333| 0.9851           |
| 7          | 1.0000| 0.8800| 0.7500     | 0.3333| 1.0000           |

Table 7 - Prediction made by ANN model in normalized form

| Sample No. | I (A) | V (v) | S (mm/min) | β (°) | Depth of HAZ (mm) |
|------------|-------|-------|------------|-------|------------------|
| 1          | 0.9545| 0.8800| 0.7500     | 0.0000| 0.7186           |
| 2          | 0.9545| 0.9200| 0.7500     | 0.6667| 0.8079           |
| 3          | 0.9545| 0.8800| 1.0000     | 1.0000| 0.8229           |
| 4          | 1.0000| 0.8400| 1.0000     | 0.6667| 0.9683           |
| 5          | 1.0000| 0.8400| 0.5000     | 0.6667| 0.9869           |
| 6          | 1.0000| 0.8800| 1.0000     | 0.3333| 0.9992           |
| 7          | 1.0000| 0.8800| 0.7500     | 0.3333| 0.9928           |

Table 8 - Prediction made by ANN model in Actual form

| Sample No. | I (A) | V (v) | S (mm/min) | β (°) | Depth of HAZ (mm) |
|------------|-------|-------|------------|-------|------------------|
| 1          | 105   | 24    | 60         | 0     | 1.52             |
| 2          | 105   | 23    | 60         | 10    | 1.71             |
| 3          | 105   | 22    | 80         | 15    | 1.74             |
| 4          | 110   | 25    | 80         | 10    | 2.05             |
| 5          | 110   | 22    | 40         | 10    | 2.09             |
| 6          | 110   | 23    | 80         | 5     | 2.12             |
| 7          | 110   | 22    | 60         | 5     | 2.07             |
Table 9-Percentage Error in Predicted Output Values by ANN

| Sample No. | I (A) | V (v) | S (mm/min) | β (°) | Depth of HAZ (mm) |
|------------|-------|-------|------------|-------|------------------|
| 1          | 105   | 24    | 60         | 0     | -9.35            |
| 2          | 105   | 23    | 60         | 10    | -5.55            |
| 3          | 105   | 22    | 80         | 15    | -6.09            |
| 4          | 110   | 25    | 80         | 10    | -7.89            |
| 5          | 110   | 22    | 40         | 10    | -3.98            |
| 6          | 110   | 23    | 80         | 5     | -6.53            |
| 7          | 110   | 22    | 60         | 5     | -2.47            |

Figure 1 Feed-forward neural network (4-5-5-1) architecture

3. Approach of Neural Network Modelling

A trial-and-error method can be utilized to select the suitable neural network model. Feed forward ANN model was set up by placing four neurons in the input layer, two hidden layers each having five neurons and one neuron in the output layer using C++. feed forward back propagation (BP) algorithm was used to train the ANN model. The configured neural network model was 4-5-5-4(4 neurons in input layer, 5 neurons in both hidden layers and 4 neurons in output layer). Figure 1 shows the suggested feed forward neural network model.

4. Results

4.1 Depth of HAZ

There occurs no change in depth of penetration and depth of HAZ when the electrode angle is increased from 0° to 10°. However depth of penetration and depth of HAZ decrease from 1.05 mm to 1.01 mm and from 1.37 mm to 1.33 mm respectively with the increase in electrode angle from 10° to 20°. If welding current is increased from 90 to 110 amp. then depth of penetration and depth of HAZ increase from 0.95 mm to 1.04 mm and 1.27 mm to 2.92 mm respectively. Depth of penetration and depth of HAZ also increase from 1.01 mm to 1.08 mm and 1.92 mm to 1.98 mm respectively when the welding speed is increased from 40 mm/min to 80 mm/min. On the other hand, depth of penetration and depth of HAZ
decrease from 1.03 mm to 0.97 mm and 1.63 mm to 1.55 mm respectively if the welding voltage is increased from 21 v to 25 v. Figures 2, 3, 4 and 5 depict the change of depth of HAZ with welding current, welding voltage, welding speed and electrode angle respectively.

![Figure 2](image1.png)  
**Figure 2** Variation of Current with depth of HAZ

![Figure 3](image2.png)  
**Figure 3** Variation of Voltage with depth of HAZ

![Figure 4](image3.png)  
**Figure 4** Variation of speed depth of HAZ

![Figure 5](image4.png)  
**Figure 5** Variation of Electrode angle depth of HAZ

4.2 Prediction of Depth of HAZ using ANN model

Back propagation algorithm is used to train the developed neural network model by utilizing 18 data sets. Testing of the developed neural network model was done with the help of 7 additional data sets. Table 3 gives the training data and table 4 provides the testing data for prediction. Tables 5 and 6 provides the normalized values of the data sets given for training and prediction purposes. Tables 7, 8 and 9 show normalized, actual and percentage error in predicted values by ANN. The range of percentage error is from -9.35 to -2.47. All the predicted parameters come in the above range and are very near to the experimental values indicating the high predicting capability of ANN model.
5. Discussion

In this research work, there have been attempts made to discover the optimum set of values of electrode angle, welding current, welding speed and welding voltage so that a high-quality weldment can be achieved with respect to weld quality. An accurate mathematical model representing the relationship between several input process parameters is very difficult to develop due to the complex nature of the welding process. In the present study, ANN based on back propagation algorithm is implemented effectively.

6. Conclusion

Following points are concluded based on the experimentation and artificial neural network modelling:

1. When electrode angle, welding current and welding speed is increased, depth of HAZ increases.
2. When welding voltage is increased, depth of HAZ decreases.
3. Artificial neural network model can be implemented successfully to predict the output parameters like depth of HAZ.

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