

Prediction of Weld Bead Geometry and Penetration in Electric Arc Welding using Artificial Neural Networks

Abdullah Al-Faruk, Md. Abdul Hasib, Naseem Ahmed, and Utpal Kumar Das

Abstract— Weldment characteristics like penetration, bead geometry and depth of heat affected zone are extremely important characteristics for structural integrity. Electric arc welding process is used throughout the world for its simplicity and versatility. Electrode diameter, current, voltage, arc travel speed, electrode feed rate, arc length and arc spread are influential factors in deciding the weldment characteristics. In this present works the effects of these process parameters on weldment characteristics in case of electric arc welding process was studied. Bead on plate experiments was conducted using a manual feed based metal arc welding machine. Weldment characteristics like depth of penetration, depth of heat affected zone and bead geometry were examined. An artificial neural network based modeling of the experiments was successfully done to predict the patterns of results obtained from the experiments.

Index Term— Arc Welding, Weldment Characteristics, Artificial Neural Network, and Back-Propagation Approach.

I. INTRODUCTION

THE weldment characteristics include bead geometry, depth of penetration, depth of heat affected zone, undercutting and thermal cracks. The parameters like arc length, arc spread, current, electrode diameter and rate of energy input influence the weldment characteristics. As the length of arc increases, the bead width also increases. Depth of penetration on the other hand decreases with either too long or too shorts an arc length. A long arc length may also cause oxidation and embitterment of the bead and heat affected zone. The electrode diameter has also considerable effect on the weldment

characteristics. With the increase in electrode diameter the area of arc increases, thus the energy density decreases. The depth of penetration decreases with the increasing electrode diameter. The contour of the weldment geometry gets effected by the electrode feed rate and the arc travel rate (table speed). With the increase in arc travel length the bead width decreases with consequent possibility of occurrence of defects like undercutting. With higher arc travel rate, the depth of penetration decreases to reach a steady level.

It is very important to consider all the welding parameters while studying the weldment characteristics. With different welding conditions the resulting characteristics of weldment differs significantly. It is generally difficult and time consuming to model the process numerically. Artificial neural networks (ANN) based approaches can be utilized to model and predict the patterns obtained from the experiments. In this work ANN with supervised learning has been utilized successfully for predicting bead geometry, depth of penetration and depth of heat affected zone for different welding conditions. The result obtained from the experiment and ANN closely matched thus proving the suitability of using ANN for predicting the weldment characteristics.

Artificial neural network modeling has been chosen for this work due to its capability to solve difficult and complex problems and recently welding related many researchers have been using ANN model to understand and predict their targeted information [9], [12-14].

II. MODEL FORMULATION

A. Artificial Neural Network

A neural network is a massively parallel distributed processor made up of simple processing units, which has a natural propensity for storing experimental knowledge and making its available for use. A neural network is a powerful data modeling tool that is able to capture and represent complex input/output relationships. The motivation for the development of neural network technology stemmed from the desire to develop an artificial system that could perform "intelligent" tasks similar to those performed by the human brain. Neural networks resemble the human brain in the following two ways:

- 1) Knowledge is acquired by the network from its environment through a learning process.
- 2) Inter neuron connection strengths, known as synaptic weights are used to store the acquired knowledge.

This work was done in partial fulfillment of the requirement for the B Sc. Engineering degree in Khulna University of Engineering & Technology.

A. Al-Faruk is with the Khulna University of Engineering & Technology, Khulna, Bangladesh. He is serving as a Lecturer in the Department of Mechanical Engineering till October 2008. His cell phone no: 880-1710352141; e-mail: alfaruk.bd@gmail.com.

M. A. Hasib, is with the Khulna University of Engineering & Technology, Khulna, Bangladesh as Lecturer in the Mechanical Engineering Department.

N. Ahmed is with the Mechanical Engineering Department as Professor, Khulna University of Engineering & Technology, Bangladesh.

U. K. Das, was the undergraduate student of Mechanical Engineering Department, Khulna University of Engineering & Technology, Bangladesh. He is now serving in a private company.

The procedure used to perform the learning process is called learning algorithm, the function of which is to modify the synaptic weights of the network in an orderly fashion to attain a desired design objectives.

The Multi-Layer Perception Neural Network is perhaps the most popular network architecture in use today. The units each perform a biased weighted sum of their inputs and pass this activation level through an activation function to produce their output, and the units are arranged in a layered feed forward topology. The network thus has a simple interpretation as a form of input-output model, with the weights and thresholds (biases) the free parameters of the model. Such networks can model functions of almost arbitrary complexity, with the number of layers, and the number of units in each layer, determining the function complexity. Important issues in Multilayer Perceptions (MLP) design include specification of the number of hidden layers and the number of units in each layer.

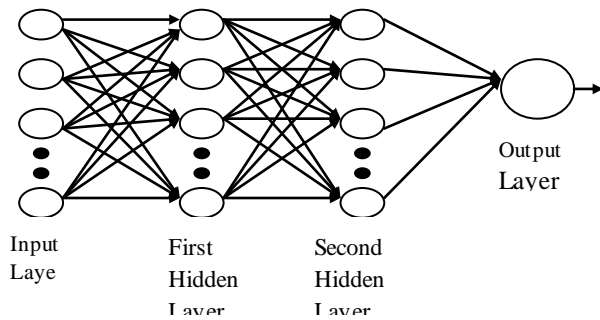


Fig. 1. Graphical representation of MLP.

Block diagram of a two hidden layer multi-layer perception (MLP). The inputs are fed into the input layer and get multiplied by interconnection weights as they are passed from the input layer to the first hidden layer. Within the first hidden layer, they get summed then processed by a nonlinear function (usually the hyperbolic tangent). As the processed data leaves the first hidden layer, again it gets multiplied by interconnection weights, then summed and processed by the second hidden layer. Finally the data is multiplied by interconnection weights then processed one last time within the output layer to produce the neural network output.

The MLP and many other neural networks learn using an algorithm called backpropagation. With backpropagation, the input data is repeatedly presented to the neural network. With each presentation the output of the neural network is compared to the desired output and an error is computed. This error is then fed back (back-propagated) to the neural network and used to adjust the weights such that the error decreases with each iteration and the neural model gets closer and closer to producing the desired output. This process is known as "training".

B. Back Propagation Approach

The back propagation networks are probably the most well known and widely used among the current types of neural

network systems available. In contrast to earlier work on perception, the back propagation network is a multilayer feed forward network with a different transfer function in the artificial neuron and more powerful learning rule. The learning rule is known as back propagation, which is a kind of gradient descent technique with backward error propagation. The training instance set for the network must be presented many times in order for the interconnection weights between the neurons to settle into a state for correct classification of input patterns. While the network can recognize patterns similar to these they have learned, they do not have the ability to recognize new patterns. This is true for all supervised learning networks. In order to recognize new patterns, the network needs to be retrained with these patterns along with previously known patterns. If only new patterns are provided for retraining, then old patterns may be forgotten. In this way, learning is not incremental over time. This is a major limitation of supervised learning networks.

The back propagation network in essence learns a mapping from set of input patterns to a set of output patterns. This network can be designed and trained to accomplish a wide variety of mappings. This ability comes from the nodes in the hidden layer or layers of the network which learn to respond to features found in the input patterns. The features recognized or extracted by the hidden units corresponding to the correlation of activities among different input units. As the network is trained with different examples, the network has the ability to generalize over similar features found in different patterns. The key issue is that the hidden units must be trained to extract a sufficient set of general features applicable to both seen and unseen instances. To achieve this goal, at first, the network must not be over trained. Over training the network will make it memorize the individual input output training pairs rather than settling in the mapping for all cases. The bottleneck will force the network to learn in a more general manner. This issue is explored later.

The back propagation network is capable of approximating arbitrary mapping given a set of examples. Furthermore, it can learn to estimate posterior probabilities for classification. The sigmoid function guarantees that the outputs are bounded between 0 to 1. In the multi class, it is not difficult to train the network so that the outputs sum up to 1. With accurate estimation of posterior probabilities, the network can act as a Bayesian classifier.

The back propagation network consists of one input layer, one output layer, and one or more hidden layers. If the input pattern is described by n bits or n values, then there should be n input units to accommodate it. The number of output units likewise determined how many bits or values involved in the output pattern. Theoretical guidance exists for determining the number of hidden layers and hidden units. They can be recruited or pruned as indicated by the network performance. Typically, the network is fully connected between and only between adjacent layers [1].

C. Backpropagation Algorithm

Weight Initialization

Set all weights and nodes threshold to small random numbers. Note that the node threshold is the weight from the bias unit whose activation level is fixed at 1.

Calculation of Activation

- 1) The activation level of an input unit is determined by the instance presented to the network.
- 2) The activation level O_j of a hidden and output unit is determined by

$$O_j = F\left(\sum W_{ji} O_i - \theta_j\right)$$

where, W_{ji} is the weight from an input O_i , θ_j is the node threshold, and F is sigmoid function:

$$F(a) = \frac{1}{1 + e^{-a}}$$

Weight Training

- 1) Start at the output units and work backward to the hidden layers recursively. Adjust weight by

$$W_{ji}(t+1) = W_{ji}(t) + \Delta W_{ji}$$

where, $W_{ji}(t)$ is the weight from unit i to unit j at time t (or t th iteration) and ΔW_{ji} is the weight adjustment.

- 2) The weight change is computed by

$$\Delta W_{ji} = \eta \delta_j O_i$$

where, η is a trial independent learning rate ($0 < \eta < 1$ e.g. 0.3) and δ_j is the error gradient at unit j . Convergence is sometimes faster by adding a momentum term:

$$W_{ji}(t+1) = W_{ji}(t) + \eta \delta_j O_i + \alpha [W_{ji}(t) - W_{ji}(t-1)]$$

where, $0 < \alpha < 1$.

- 3) The error gradient is given by:
For the output units:

$$\delta_j = O_j(1 - O_j)(T_j - O_j)$$

where, T_j is the desired (target) output activation and O_j is the actual output activation at output unit j .

For hidden units:

$$\delta_j = O_j(1 - O_j) \sum_k \delta_k W_{kj}$$

where, δ_k is the error gradient at unit k to which a connection points from hidden unit j .

- 4) Repeat iterations until convergence in terms in the selected error criterion. Iteration includes presenting an instance, calculating activations and modifying weights [1].

III. EXPERIMENTAL METHOD

To investigate the weldment characteristics beads were deposited on mild steel flat plates using mild steel electrodes.

A manual welding machine was used to deposit beads on plates. Since the weldment characteristics depend on the electrode diameter, three electrode diameters were used for experiments values namely 2.5 mm and 3.2 mm. Since manual welding machine was used for this experiment electrode feed rate and table speed were varied in several observations.

To study the bead geometry, each bead was sectioned transversely at two points one near the start (leaving 2 cm from the start) and the other near the end (leaving 2 cm from the end). To get the microstructure, these sectioned beads were then grinded and polished with 0, 2, 3 grade emery papers and then etched with 2% Nital solution. To measure the bead height and bead width of each sample a digital slide caliper was used. The average values of bead height, bead width and depth of penetration were measured. The values obtained were used further for training a network based on back propagation algorithm.

IV. NEURAL NETWORK MARKETING

Welding process might result into such characteristics which may not be indicating a trend as observed in the present work, in this situation the conventional forecasting techniques like regression analysis may be useful to show the current trend but future prediction is difficult and less accurate. Neural networks are generally used for pattern recognition. A neural network is an adaptive system that can learn relationships through repeated presentation of data and is capable of generalizing to new, previously unseen data. A supervised learning system can be used suitably train a network based on input process parameters and outputs to form a basis for further prediction.

Neurons are arranged in a distinct layered topology, the input layer is not really the neuron at all. The input units simply serve to introduce the values of the input variables. The input variables used in the present investigation are: current, voltage, electrode diameter, electrode travel speed & electrode feed rate. The output layer forming the variables which are to be predicted consist of bead height, bead width and depth of penetration. The hidden and output layer neurons are each connected to all of the units in the preceding layer. When the network is executed (used), the input variable values are placed in the input, and then the hidden and output layer units are progressively executed. Each of them calculates their activation value by taking the layer, and subtracting the threshold. The activation value is passed through the activation function to produce the output of the neuron. When the entire network has been executed, the output layer acts as the outputs of the entire network.

V. RESULTS AND DISCUSSION

The performance of the neural network depends on the number of hidden layers and number of neurons in the hidden neurons in the hidden layers. Therefore, many trials may be needed in choosing the optimal structure for the neural network by changing the number of hidden layers as well as the number of neurons in each of the hidden layers. The

appropriate neural network structure for predicting bead height, bead width and depth of penetration was chosen by trial and error method [9, 10]. In this back propagation algorithm based neural networks architecture was used. In this study the structure of neural network was 5-9-6-3 (5 neuron in the input layer, 9 neuron in the first hidden layer, 6 neuron in the second hidden layer and 3 in output layer). The network is trained for 40 samples and trained outputs were obtained. The network was trained for more than 1000 iterations. Further training did not improve the modeling performance of the network. A schematic diagram of the neural network in the present work is shown in figure-1

The results of the investigation conducted on the weldment characteristics of mild steel work pieces welded with mild steel electrodes for are shown in fig. 2 to 7. It was stated by Datta [11] that arc spread increases almost linearly with the arc length and the area of the arc is more with larger diameter of the electrodes.

From fig. 2, it can be observed that with 2.5 mm electrode diameter as the current increases the bead height decreases then slightly increases. In the case of 3.2 mm electrode diameter the bead height also decreases with the increase in the current as shown in the fig. 3.

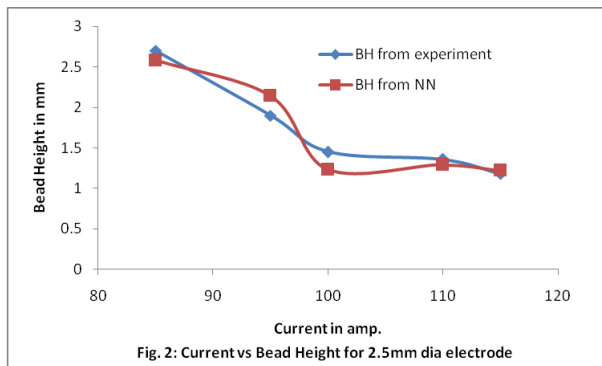


Fig. 2: Current vs Bead Height for 2.5mm dia electrode

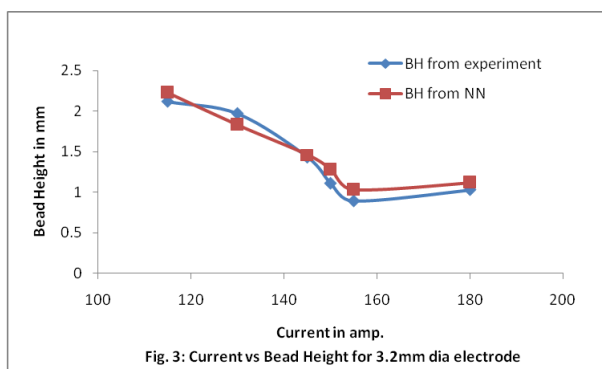


Fig. 3: Current vs Bead Height for 3.2mm dia electrode

Values of bead heights obtained from experiments and neural networks are given in the table I. It can be observed that maximum error percentage is -7.51 in case of 3.2 mm diameter electrodes. The minimum percentage error of 0.19 was obtained for 2.5 mm diameter electrodes. As observed in fig. 2 and 3 the neural network modeling closely matched with that of experimental result.

TABLE I
COMPARISON OF BEAD HEIGHT VALUES OBTAINED FROM EXPERIMENTS
AND NEURAL NETWORK

Sample No.	Electrode Diameter in mm	BH from experiments in mm	BH from NN in mm	Percentage of Error (%)
1a	3.2	1.32	1.42	-7.51
2a	3.2	1.18	1.21	-2.33
3a	3.2	1.41	1.43	-1.27
5a	3.2	1.60	1.61	-0.71
6a	3.2	1.77	1.76	-3.20
13a	2.5	1.45	1.48	-2.08
17a	2.5	1.18	1.23	-4.30
11a	2.5	1.52	1.54	-1.17
12a	2.5	1.36	1.39	-1.99
14a	2.5	2.19	2.19	0.19

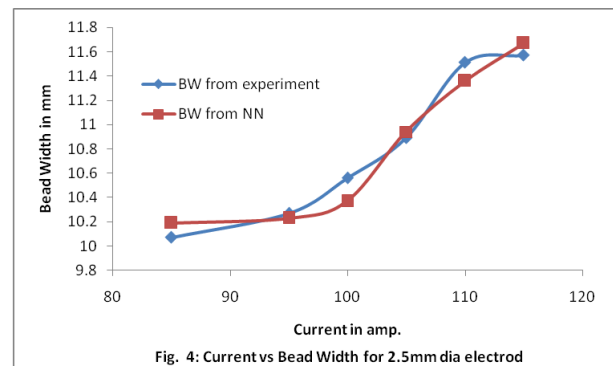


Fig. 4: Current vs Bead Width for 2.5mm dia electrode

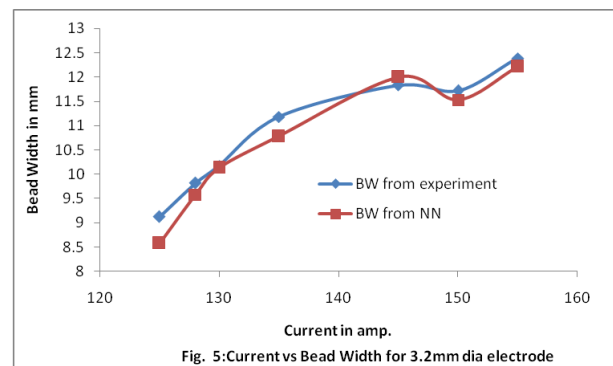


Fig. 5: Current vs Bead Width for 3.2mm dia electrode

It can be observed from fig. 4 and 5 that in case of 2.5 mm and 3.2 mm diameter electrodes initially the bead width increases as the current increases then attains almost a constant value for a certain current range. Beyond this current range welding is not possible with the said electrode diameter. The neural network prediction of bead widths also closely indicated the same trend as it can be observed from table II, which the maximum and minimum percentage error obtained for bead width is -13.21 and 0.49 respectively both for 3.2mm diameter electrodes.

TABLE II
COMPARISON OF BEAD WIDTH VALUES OBTAINED FROM EXPERIMENTS
AND NEURAL NETWORK

Sample No.	Electrode Diameter in mm	BW from experiments in mm	BW from NN in mm	Percentage of Error (%)
1a	3.2	9.100	10.30	-13.21
2a	3.2	8.810	9.270	-5.29
3a	3.2	14.90	14.83	0.49
5a	3.2	11.22	11.41	-1.66
6a	3.2	11.36	11.59	-2.04
13a	2.5	10.82	11.19	-3.38
17a	2.5	8.040	8.930	-11.07
11a	2.5	10.50	10.84	-3.28
12a	2.5	9.210	9.780	-6.14
14a	2.5	8.685	9.720	-11.97

In case of 2.5 mm diameter electrode, as the current increases the depth of penetration increases initially then decreases. This trend can be observed from fig. 6. The same trend is obtained for 3.2 mm diameter electrode also. Table III shows the values obtained for depth of penetration from neural networks and experiments. In this case it has been observed that the maximum error is -2.83 for 2.5 mm electrode diameter. The values of depth of penetration obtained from experiments and modeling are 2.4 mm and 2.5 mm respectively. The values in other cases matched closely.

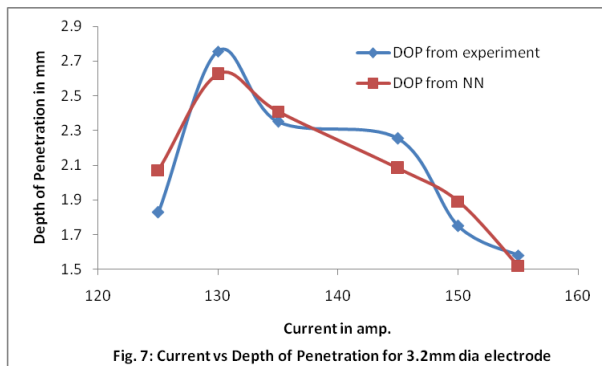
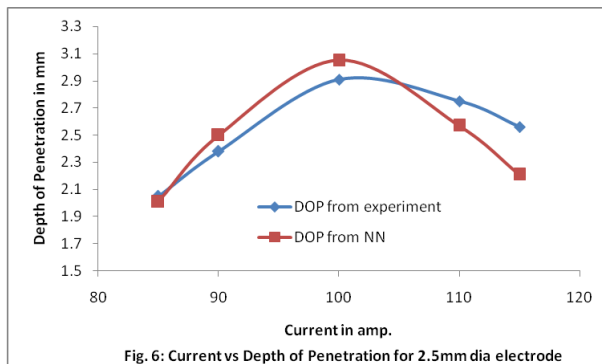


TABLE III
COMPARISON OF DEPTH OF PENETRATION VALUES OBTAINED FROM
EXPERIMENTS AND NEURAL NETWORK

Sample No.	Electrode Diameter in mm	DOP from experiments in mm	DOP from NN in mm	Percentage of Error (%)
1a	3.2	2.18	2.19	-0.42
2a	3.2	2.31	2.31	0.14
3a	3.2	2.56	2.56	0.02
5a	3.2	1.45	1.48	-2.40
6a	3.2	1.75	1.76	0.81
13a	2.5	2.75	2.75	0.095
17a	2.5	1.48	1.50	-1.45
11a	2.5	1.66	1.68	-0.96
12a	2.5	1.36	1.40	-2.83
14a	2.5	1.62	3.20	0.08

It has been seen from the literature that the penetration and HAZ are controlled by the rate of heat input, which is a function of current, arc length and polarity. When the energy density is low then the depth of penetration and bead height decreases and bead width increases.

VI. CONCLUSIONS

Based on the experimental work and the neural network modeling work done the following conclusions can be drawn:

- 1) With increase in the current the bead height decrease in case of 2.5 and 3.2 diameter electrodes. This trend can be observed from figures-2 and 3.
- 2) Penetration increases initially with increase in current then decreases. The rate of decrease of penetration with increasing current is more in case of 3.2mm diameter electrode. This trend can be observed in figures-4 and 5.
- 3) It can also be observed that the output trends for bead height, bead width and depth of penetration may not be predicted accurately by linear curve fitting.
- 4) Figures-6 and 7 show that for 2.5 and 3.2 mm diameter electrodes the trends obtained for bead height are similar but the trends obtained for bead width significantly different as observed from figures-4 and 5 for 2.5 and 3.2mm diameter electrodes. Similar type of trends for depth of penetration showing significant differences for different diameters of electrodes are observed as shown in figures-6 and 7. It is concluded that results of this type may not be easily predicted by conventional forecasting techniques.
- 5) Artificial neural networks based approaches can be used successfully for predicting the output parameters like bead width, bead height and depth of penetration as shown in tables-1, 2 and 3. However the error is rather high as some cases like predicting bead width as observed in table-2. Increasing the number of hidden layers and iterations can minimize this error.

REFERENCES

- [1] Limin Fu, "Neural Networks in computer intelligence", McGraw-HILL International Editions; 1994, computer science series.
- [2] S. Haykin, "Neural Networks A Comprehensive Foundation", Second Edition; Pearson Prentice Hall, 2005.
- [3] M. H. Hassoun, "Fundamentals of artificial neural networks", Prentice-Hall of India private limited, New Delhi- 110001, 2002.
- [4] J.A. Freeman, & D.M. Skapura, "Neural Networks Algorithms, Applications, and Programming Techniques", International student edition, computer and neural systems series, Addison-Wesley Limited.
- [5] R.K. Jain, "Production Technology", khanna publisher's 2-B, Nath market, Nai sarak, Delhi-110006(India).
- [6] O.P. Khanna, "A text book of welding technology", Dhanpat Rai & Sons, 1682, Nai sarak, Delhi-110006.
- [7] Kent's, "Mechanical Engineering Handbook", Design and Production volume; Twelfth Edition, Wiley Engineering handbook series.
- [8] R.S. Khurmi & J.K. Gupta, "Mechanical Engineering (conventional and objective type)", Eurasia publishing house (pvt) Ltd; Ram sagar, New Delhi-110056.
- [9] G.E. Cook, K. Andersen, G. Karasai and K. Ramaswamy, "Artificial neural network applied to arc welding process modeling and control", IEEE Trans.Ind. App., 26 (5) (1990), pp. 824-830 .
- [10] E.T. Gill, and E.N. Simons, "Sir Issac Pitman and sons Ltd, London, 1950, P.120
- [11] G.L. Datta, "Metal-Arc weld penetration capability-studies and analysis", proceedings of natural Seminar on Weld integrity, Jadavpur University, December 5-7, 2003, pp. 8-11.
- [12] G.E. Cook, R.J. Barnet K. Andersen and A.M. Strauss, "Weld modeling and control using artificial neural network", IEEE Trans.Ind. App.31 (6), (1995), pp. 1484-1491.
- [13] M.M. Mahapatra, M. Sadat Ali, G.L. Datta and B. Pradhan, "Modelling and predicting the effects of process parameters on weldment characteristics in shielded metal arc welding" Indian Welding Journal, 38(2), 2005, pp.22-29.
- [14] A. Ghosh, S. Mukherje, S. Chattopadhyaya and P.K. Sarker, "Weld bead parametric estimation of SAW process through neural network, Indian Welding Journal, 40(4), 2007, pp.33-43.

Abdullah Al-Faruk was born in Holidhani of Jhenidah Sadar in Bangladesh on June 10, 1986. He obtained the degree of Bachelor of Science in Mechanical Engineering from Khulna University of Engineering & Technology in the year 2008 and secured First Class with First Position out of about hundred Students. He is selected for the University Gold Medal for the best overall performance in the final year of Bachelor of Science in Mechanical Engineering Degree. His major field is Mechanical Engineering. Just after getting his B.Sc. Degree, he joined as a Lecturer in the Department of Mechanical Engineering, Khulna University of Engineering & Technology, Khulna, Bangladesh.