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Research Paper

ANALYSIS OF BEAD WIDTH AND REINFORCEMENT HEIGHT DURING SHIELDED METAL ARC WELDING UNDER MAGNETIC FIELD USING ARTIFICIAL NEURAL NETWORKS

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The weld bead geometry influences the mechanical properties of the weld. The reinforcement height and bead width are important factors of the bead geometry. This study is concerned with the multi-response optimization of Shielded Metal Arc Welding (SMAW) process for an optimal parametric combination to yield favorable weld bead width and reinforcement height of welded joints produced on 5 mm thick mild steel plates using the Artificial Neural Networks (ANN). To disperse molten droplets of the electrode, a longitudinal external magnetic field was created by a bar magnet which was mounted on the tailstock side of a lathe machine with the help of a wooden structure. Speed of welding was made constant with the help of the cross slide of the lathe machine. Eighteen experimental data sets were used to train the ANN. Seven experiments were conducted to get other seven sets of data to compare the results obtained with the corresponding prediction made by ANN. It was found that the predictions made by the ANN were very close to the experimental values.

Keywords: Artificial Neural Networks (ANN), Back propagation, Bead geometry, Input process parameters, Reinforcement height

INTRODUCTION

The mechanical properties of a weldment depend largely upon the bead geometry parameters (Tarang and Yang, 1998) such as reinforcement height and bead width. The weld quality can be achieved by meeting the quality requirements such as bead geometry which is highly influenced by various process parameters involved in the process. Inadequate weld bead dimensions will contribute to failure of the welded structure. Since welding is now highly mechanized, the

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welding procedure must ensure that the weld bead is of good quality (Gridharan and Murugan, 2008) and is obtained at minimum cost. Perfect reinforcement height is required to provide the strength in the welding; the thickness code has defined the limit for the re-inforcement height. Excessive re-inforcement will develop the stress on that particular point because of high depth width ratio (based on thickness). It is very challenging to make any weld without any reinforcement, so the codes have dictated the extent by which reinforcement height is allowable without adversely affecting the strength of the weld in most applications. Removing excess reinforcement by means of grinding, machining, or any other is a costly and often dangerous. On the mechanical point of view, the reinforcement height does not affect the mechanical proprieties of the joint itself, and this is why no matter, whatever is the reinforcement height, it is always taken as the thickness of the base metal. But on the metallurgical point of view, it is very difficult just by welding to have a reinforcement height matching the thickness of the base metal. This is why the reinforcement height is to be a little higher than the base metal thickness. The reinforcement structure is made of much bigger grains than the base metal and to avoid a stress location on the toe, the reinforcement height is limited. The weld joint quality is determined by various welding input process parameters (Benyounis and Olabi, 2008) such as welding speed, arc current, voltage, and many others. Kang *et al.* (2003), explained that the selection of significant input process parameters is very important to obtain good bead geometry, which represents the strength of weld and its quality. As welding has strong effects not only on the quality but also on the safety of the structures, it should be performed under optimal conditions. To obtain the optimal welding conditions, the experiments should be repeated several times, as the welding quality may change according to the thickness and shape of the welded part. This requires a large number of experiments and a tool which can predict the conditions. Artificial neural network can be used for this purpose. Kim *et al.* (2003), comprehended that the back propagation neural network is considerably more accurate than multiple regression analysis. Longitudinal magnetic field disperses the molten droplets of the electrode and changes the dimensions of the weld bead. Electromagnetic stirring technique can be successfully applied in arc welding by affecting the shape of weld pool and refining crystal grains as described by Luo *et al.* (2003).

EXPERIMENTAL WORK

The experiments of welding were conducted in the workshop lab of the GLA University, Mathura. The experimental set-up is shown in Figure 1. To investigate the weldment characteristics weld beads were obtained by welding two mild steel flat plates of 150 mm $\times$ 50 mm $\times$ 5 mm dimensions in butt position using mild steel electrodes of 3.15 mm diameter. A manual welding machine was used to weld the plates. A lathe machine was used to provide uniform speed of welding to support electrode holder and bar magnet. The work piece was kept on cross slide with some arrangement. Work-piece moves with cross slide. Bar magnet was connected with tailstock with a wooden structure. Since the weldment characteristics depend on welding current, welding voltage, speed of welding and magnetic field (Khan, 2007) we select different set of values of these inputs. Welding currents were chosen as 90, 95,100, 105 and 110 A, arc voltages were chosen as 20, 21, 22,23 and 24 V, the welding speeds were chosen as 40, 60 and 80 mm/min and external magnetic field strengths were used as 0, 20,40, 60 and 80 Gauss for the experiments. Current was measured with a clamp meter, voltage was measured with a multi meter and magnetic field was measured with a Gauss meter. 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 ground with emery belt grinder having 0, 2, 3 grade emery papers then polished with a double disk polishing machine. Etching was done with a mixture of 2% nitric acid and 98% ethyl alcohol solution. To measure the reinforcement height and bead width of each sample a digital slide caliper was used. The average values of reinforcement height and bead width were measured. Eighteen sets of values out of twenty five such sets obtained were used for training a network based on back propagation algorithm. Remaining seven sets of the values were used for prediction. These data sets are shown in Table 1. A program of back propagation neural network in C++ was used for training and prediction. In this program one input layer having four neurons, two hidden layers, both having five neurons and one output layer having two neurons, were used.

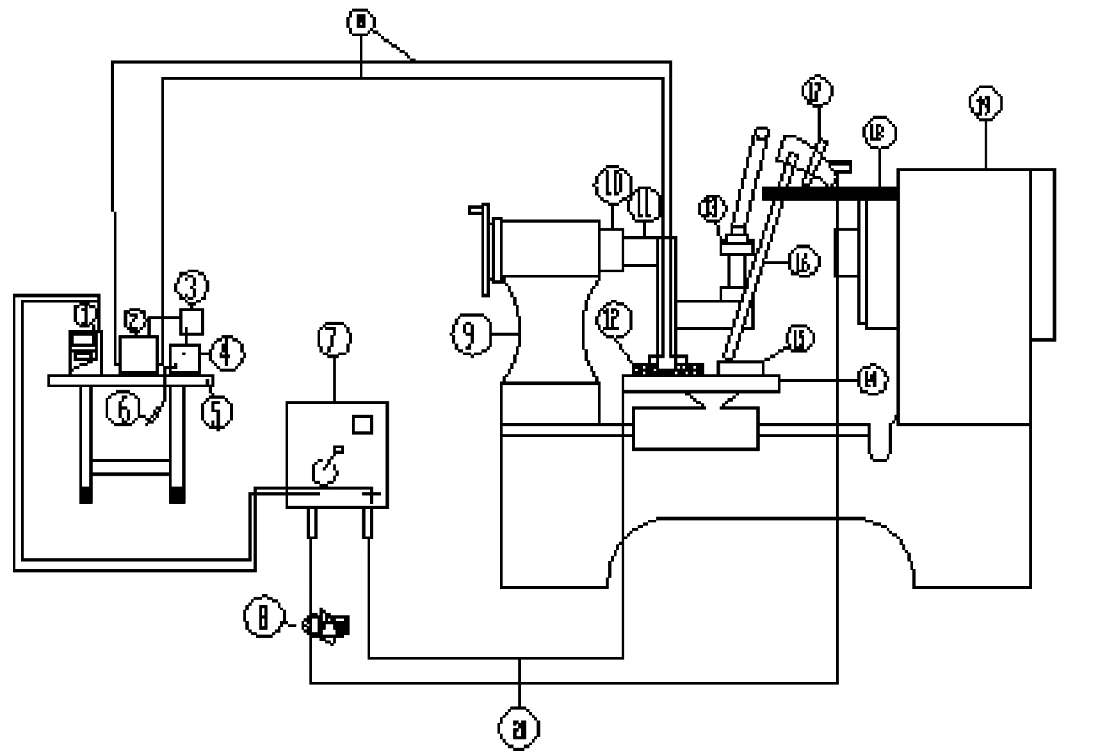
Table 1: Data for Training and Prediction

	Serial Number	Current (A)	Voltage (V)	Welding Speed (mm/min)	Magnetic Field (Gauss)	Weld Width (mm)	Reinforcement Height (mm)
Data for Training	1	90	24	40	0	6.95	1.13
	2	90	24	40	20	6.94	1.13
	3	90	24	40	40	6.96	1.14
	4	90	24	40	60	6.99	1.11
	5	90	24	40	80	7.03	1.09
	6	95	20	60	60	6.01	1.06
	7	95	21	60	60	6.08	1.07
	8	95	22	60	60	6.10	1.09
	9	95	23	60	60	6.15	1.11
	10	95	24	60	60	6.25	1.12
	11	100	22	40	40	5.94	1.17
	12	100	22	60	40	5.90	1.15
	13	100	22	80	40	5.86	1.11
	14	90	20	80	20	5.91	1.06
	15	95	20	80	20	5.92	1.09
	16	100	20	80	20	5.94	1.11

Table 1 (Cont.)

	Serial Number	Current (A)	Voltage (V)	Welding Speed (mm/min)	Magnetic Field (Gauss)	Weld Width (mm)	Reinforcement Height (mm)
	17	105	20	80	20	5.95	1.13
	18	110	20	80	20	5.97	1.08
Data for Prediction	1	90	23	40	0	6.92	1.14
	2	95	22	60	40	6.05	1.11
	3	95	21	80	60	6.04	1.04
	4	100	24	40	40	6.99	1.16
	5	105	21	60	40	5.98	1.14
	6	105	22	60	20	5.96	1.13
	7	110	21	60	20	5.97	1.10

Figure 1: Experimental Setup

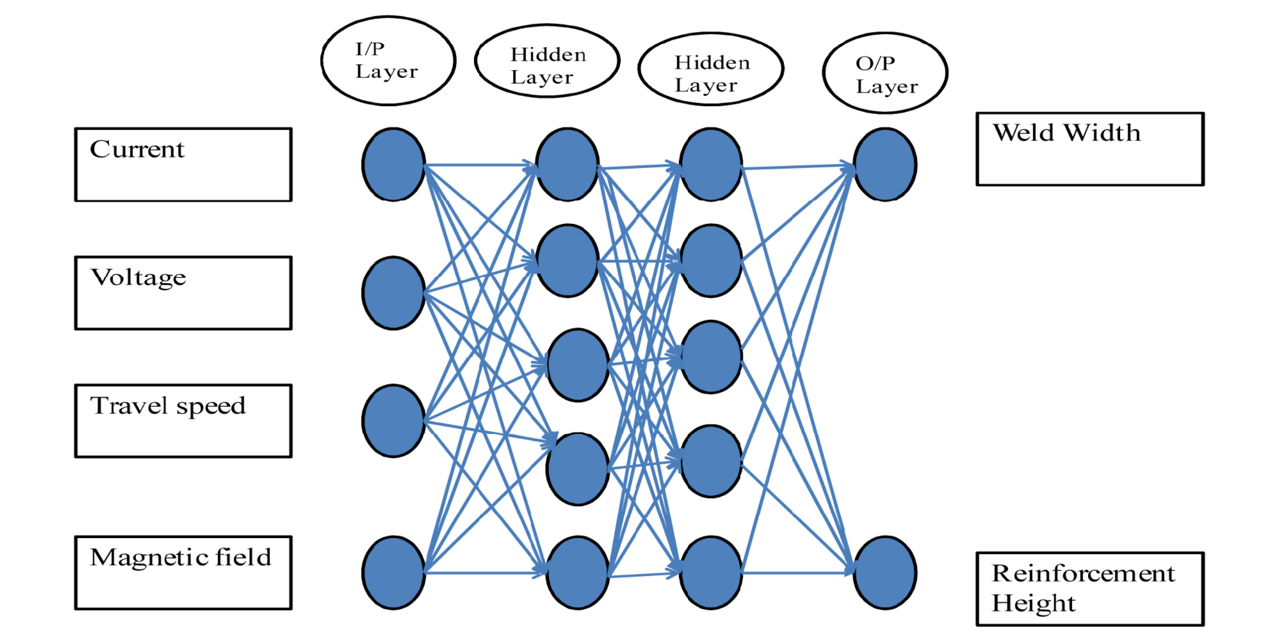


1. Multi-meter
2. Battery Eliminator
3. Electric Board
4. Gauss Meter
5. Table
6. Measuring Prob
7. Transformer Welding Set
8. Clamp meter
9. Tail Stock
10. Sleeve
11. Link (Wood)
12. Solenoid
13. Tool post
14. Iron sheet
15. Workpiece
16. Electrode
17. Electrode Holder
18. Metal Strip Connected with head stock
19. Head stock
20. Connecting Wires

METHODOLOGY OF ARTIFICIAL NEURAL NETWORK MODELING

An artificial 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 the artificial 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. Generally the industrial processes are non-linear, complex and more input variables are involved in the processes. The mathematical models are not giving closer approach to describe the behavior of the processes. ANNs are easy to understand, cost effective and have the capability to learn from examples. The arrangement of neurons into layer and the connection pattern within and between the layers are called as network architecture. The architecture is consisted of three parts, input layer receives the welding parameters, the hidden layers considered as black boxes and the output layer obtaining the values of bead geometry. The performance of the neural networks depends upon, the number of hidden layers and number of neurons in the hidden layers. Hence, optimum structure is obtained by changing number of hidden layers and neurons by making many attempts. The appropriate neural networks structure was chosen by the trial and error method by Yosuf *et al.* (2008). Feed forward artificial neural network structure was established by keeping four neurons in the input layer, two hidden layers having five neurons in each and two neurons in output layer using C++. It was trained with help of Back Propagation (BP) algorithm. In training (Rajasekaran and Vijayalakshmi, 2003) it is essential to balance the importance of each parameter; hence the data must be normalized. Since, neural networks works better in the range of 0 to 1.

Figure 2: Feed-Forward Neural Network (4-5-5-2) Architecture



The input and output vector values are converted in the range of 0 to 1. The designed neural networks structure was 4-5-5-2 (4 neurons in input layer, 5 neurons in both hidden layers and 2 neurons in output layer). Proposed feed forward neural network architecture was shown in Figure 2. Non-linearity and input-output mapping are the useful complement in neural networks. Hence, it has been adapted to model the input-output relation of non-linearity and interconnected system by Jeng *et al.* (2000).

RESULTS AND DISCUSSION

Table 2 provides the measured and predicted weld width and reinforcement height of the weld. The experimental output values were measured and the prediction for output values was made applying feed forward artificial neural network. The measured and predicted output values are close to each other. The aim of this paper was to show the possibility of the use of artificial neural network to predict the weld bead geometry in terms of weld bead width and reinforcement height.

Table 2: Measured and Predicted Values with Percentage Error

S. No.	Current (A)	Voltage (V)	Welding Speed (mm/min)	Magnetic Field (Gauss)	Weld Wedth (mm) Measured	Weld Wedth (mm) Predicted	Error in Weld Wedth %	Reinforcement Height (mm) Measured	Reinforcement Height (mm) Predicted	Error in Reinforcement Height (mm) %
1.	90	23	40	0	6.92	6.54	–5.49	1.14	1.10	–3.51
2.	95	22	60	40	6.05	6.42	+6.12	1.11	1.08	–2.70
3.	95	21	80	60	6.04	6.44	+6.62	1.04	1.06	+1.92
4.	100	24	40	40	6.99	6.58	–5.87	1.16	1.14	–1.72
5.	105	21	60	40	5.98	6.41	+7.20	1.14	1.11	–2.63
6.	105	22	60	20	5.96	6.40	+7.38	1.13	1.09	–3.54
7.	110	21	60	20	5.97	6.39	+7.04	1.10	1.08	–1.82

Weld Width

The weld width of the welded joints was almost unaffected if the magnetic field was changed from 0 to 20 gauss or from 20 to 40 gauss. If the field was increased from 40 gauss to 60 gauss, the weld width increased from 6.97 mm to 6.99 mm. and if it was increased from 60 gauss to 80 gauss, the weld width increased from 6.99 mm to 7.03 mm. If the speed of welding was increased from 40 mm/min to 60 mm/min, the weld width decreased from 5.94 mm to 5.90 mm, and if it was increased from 60 mm/min to 80 mm/min, the weld width of the weld decreased from 5.90 mm to 5.86 mm. The effect of voltage was positive for weld width, i.e., if voltage was increased from 20 V to 24 V, the weld width increased from 6.01 mm to 6.25 mm. The increment in current, increased the weld width for all the investigated values. If the current was increased from 90 A to 110 A the weld width increased from 5.91 mm to 5.97 mm. The variation of weld width with magnetic field, voltage, welding speed and current were shown in Figures 3, 4, 5 and 6 respectively.

Figure 3: Magnetic Field vs. Weld Width

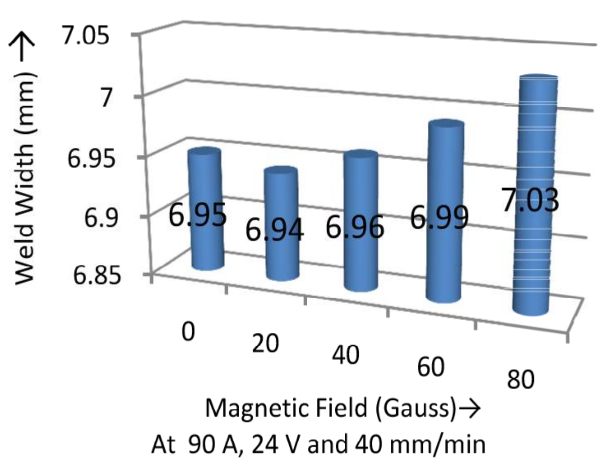


Figure 4: Voltage vs. Weld Width

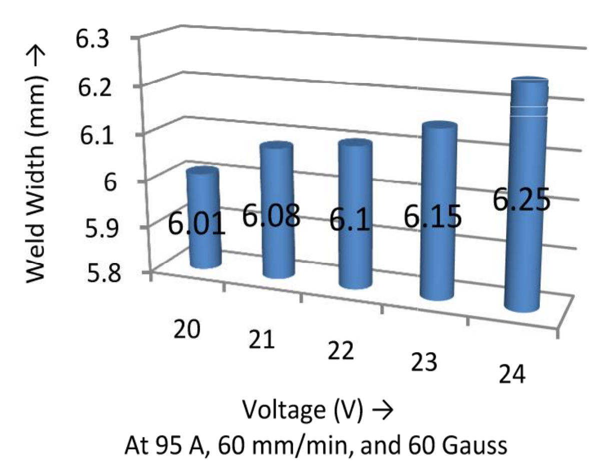


Figure 5: Speed of Welding vs. Weld Width

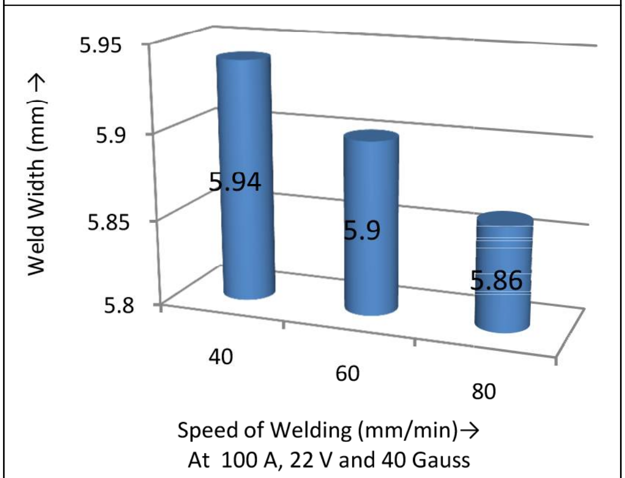
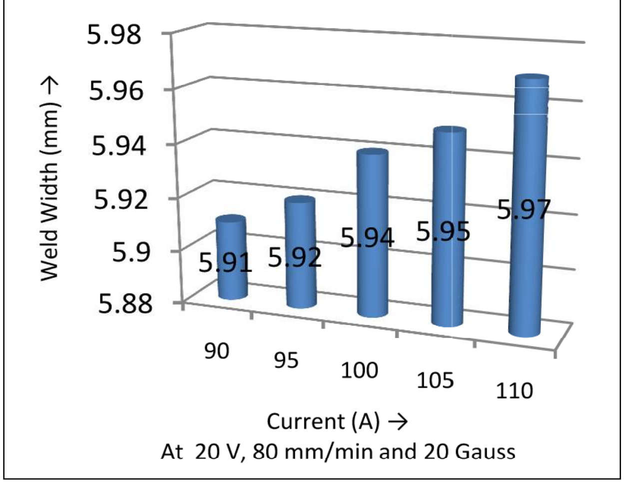


Figure 6: Current vs. Weld Width



Reinforcement Height

Reinforcement heights of all the joints were evaluated and they were presented in Table 1. The magnetic field had almost no effect on reinforcement height if it was changed in between 0 and 40 gauss, and after this the reinforcement height decreased if magnetic field was increased upto 80 gauss which was our investigation range. If the magnetic field was increased from 40 gauss to 60 gauss the reinforcement height decreased from 1.14 mm to 1.11 mm and if it was increased from 60 gauss to 80 gauss the reinforcement height decreased from 1.11 mm to 1.09 mm. If the speed of welding was increased from 40 mm/min to 80 mm/min the reinforcement height continuously decreased. Increment in voltage from 20 to 24 V, increased the reinforcement height from 1.06 mm to1.12 mm. If the increment in current was from 90 A to 110 A, the reinforcement height of weld generally increased. The variation of reinforcement height with magnetic field, voltage, welding speed and current were shown clearly in Figures 7, 8, 9 and 10 respectively.

Figure 7: Magnetic Field vs. Reinforcement Height

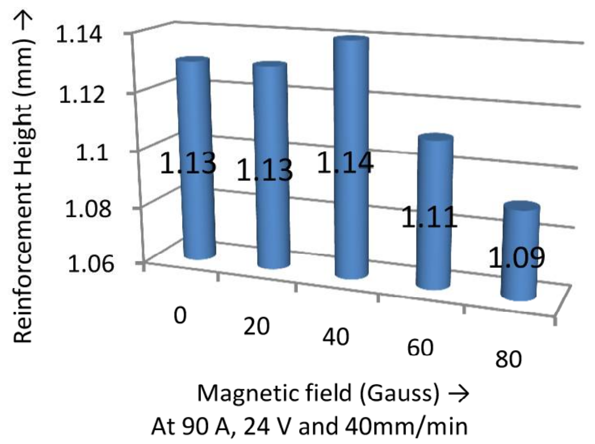


Figure 8: Voltage vs. Reinforcement Height

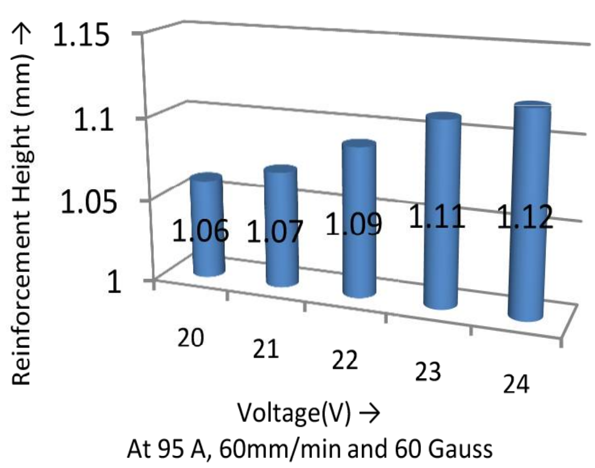


Figure 9: Speed of Welding vs. Reinforcement

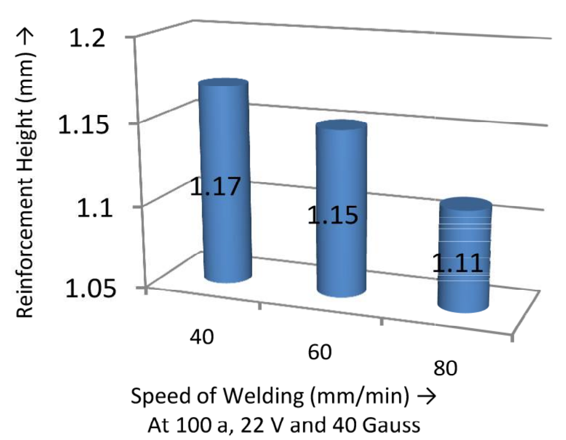
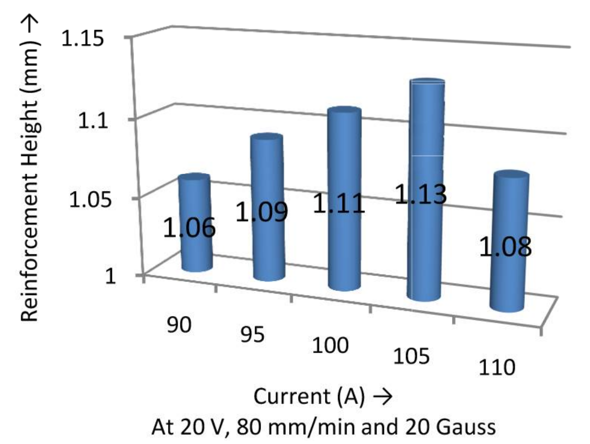


Figure 10: Current vs. Reinforcement Height



Prediction of Weld Bead Geometry Using Artificial Neural Networks

The developed neural network architecture was trained with help of back propagation algorithm using 18 data sets. The developed network was tested out of 7 datasets. The training data sets and testing data sets are shown in Table 1, the testing data were not used for training the network. The % error was calculated between the experimental and predicted values as shown in Figure 2. The % error is ranging between –6.41 to 7.38. The other predictions are in between the above ranges and hence are very close to the practical values, which indicate the super predicting capacity of the artificial neural network model.

DISCUSSION

In this investigation, an attempt was made to obtain the best set of values of current, voltage, speed of welding and external magnetic field to produce the best quality of weld in respect of weld width and reinforcement height. Shielded metal arc welding is a universally used process for joining several metals.

Generally in this process speed of welding and feed rate of electrode both are controlled manually but in the present work the speed of welding was controlled with the help of cross slide of a lathe machine hence only feed rate of electrode was controlled manually which ensures better weld quality. In the present work external magnetic field was utilized to distribute the electrode metal and heat produced to larger area of weld which improves several mechanical properties of the weld. The welding process is a very complicated process in which no mathematical accurate relationship among different parameters can be developed. In present work back propagation artificial neural network was used efficiently in which random weights were assigned to co-relate different parameters which were rectified during several iterations of training. Finally the improved weights were used for prediction which provided the results very near to the experimental values.

CONCLUSION

The experimental analysis confirms that, artificial neural networks are power tools for analysis and modeling. Results revealed that an artificial neural network is one of the alternatives methods to predict the bead width and reinforcement height of the weld. Hence it can be proposed for real time work environment. Based on the experimental work and the neural network modeling the following conclusions are drawn:

- A strong joint of mild steel is found to be produced in this work by using the SMAW technique.
- If amperage is increased, weld width and reinforcement height both generally increase.
- If voltage of the arc is increased, weld width and reinforcement height both generally increase.
- If travel speed is increased, weld width and reinforcement height both will decrease.
- If magnetic field is increased, weld width, increases but reinforcement height of weld generally decreases.
- Artificial neural networks based approaches can be used successfully for predicting the output parameters like weld bead width and reinforcement height of weld as shown in Table 2. However the error is rather high as in some cases in predicting reinforcement height it is more than 7%. Increasing the number of hidden layers and iterations can minimize this error.

REFERENCES

1. Benyounis K Y and Olabi A G (2008), "Optimization of Different Welding Processes Using Statistical and Numerical Approaches", *A reference Guide. Adva. Engg. Software*, Vol. 39, pp. 483-496.
2. Gridharan P K and Murugan N (2008), "Optimization of Pulsed Welding Process Parameters for the Welding of AISI 304 L Stainless Steel Sheets", *Int. J. Adv. Manuf. Technol.*, DOI 10.1.1007/ S00170-008-1373-0.
3. Jeng Y J, Mau T F and Leu S M (2000), "Prediction of Laser Butt Joint Welding Using Back Propagation and Learning Vector Quantization Networks", *J. Mater. Procs. Tech.*, pp. 207-218.

4. Kang M J, Kim Y S and Ahn Rhee S (2003), “Spatter Rate Estimation in the Short Circuit Transfer Region of GMAW”, *Weld. J.*, Vol. 82, No. 9, pp. 238-247.

5. Khan M I (2007), *Welding Science and Technology*, New Age International (P) Limited Publishers.

6. Kim L S, Lee S H and Yarlagadda P K D V (2003), “Comparison of Multiple Regression and Back Propagation Neural Network Approaches in Modeling Top Bead Height of Multipass Gas Metal Arc Welds”, *Sci. & Tech. of Welding and Joining*, Vol. 8, No. 5, pp. 347-352.

7. Luo J, Luo Q, Lin Y H and Xue J (2003), “A New Approach for Fluid Flow Model in Gas Tungsten Arc Weld Pool Using Longitudinal Electromagnetic Control”, *Weld. J.*, Vol. 82, pp. 202-206.

8. Rajasekaran S and Vijayalakshmi G A (2004), *Neural Networks, Fuzzy Logic and Genetic Algorithms Synthesis and Applications*, 4th Edition, Prentice Hall of India.

9. Tarang Y S and Yang W H (1998), “Optimization of Weld Bead Geometry in GTAW by Taguchi Method”, *Int. J. Adv. Manuf. Technol.*, Vol. 14, pp. 549-554.

10. Yousif Y K, Daws K M and Kazem B I (2008), “Prediction of Friction Stir Weldingm Characteristic Using Neural Network”, *Jourdan J. Mech & Indus. Engg.*, Vol. 2, pp. 151-155.