Prediction of Depth of Penetration and Reinforcement Height of Shielded Metal Arc Weld under Magnetic Field using Artificial Neural Networks

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Abstract -R**einforcement height and depth of penetration are significant physical characteristics of a weldment which determine the qualities of the weld. This paper highlights a study and analysis of various process control variables such as welding speed, welding current, voltage, and external magnetic field with reinforcement height and depth of penetration as important weld bead quality parameters in shielded metal arc welding of mild steel plates of 6 mm thickness using 3.15 mm diameter, E-6013 electrodes. The longitudinal external magnetic field was produced by a bar magnet. With the help of experimental data, a multilayered, back propagation, feed forward, artificial neural network model was trained to predict the reinforcement height and depth of penetration of weld. The welding speed was kept constant with the help of a lathe machine. Sensitivity analysis was also carried out to predict the direct and few interaction effects of important process parameters on reinforcement height and depth of penetration of the weld bead. The results were presented in graphical form. The results of the sensitivity analysis are very useful to understand the weld bead, to improve weld quality and to increase productivity with the available welding facilities and to minimize the total welding cost. The prediction made by the model closely matched with the experimental results which concludes that the artificial neural network models are capable to predict the values accurately.**

Keywords: Artificial neural networks; Back propagation; Depth of penetration; Input process parameters; Magnetic field; reinforcement height.

1. INTRODUCTION

Welding process is commonly used for fabrication and repairing damaged structures in industries. The thermal effect of the welding process sometimes produces hard and brittle microstructure which has very bad effect on the mechanical properties in the heat affected zone (HAZ) [1]. In shielded metal arc welding (SMAW) process, the heat required for welding is produced by an arc established between a consumable electrode which is covered with flux and the work-piece. The core wire of the electrode conducts the current to the arc and provides filler metal for the joint. The heat produced by the arc melts the core wire and the flux covering at the tip of the electrode to create metal droplets. Molten metal solidifies into the weld metal but the molten flux floats on the top surface and solidifies to form a slag layer. The weld portion is protected by a gaseous shield obtained from the combustion of the flux. The slag provides additional shielding [2]. The quality of SMAW can be affected by several welding parameters like arc-length, type of electrode, metal deposition, arc-travel rate and welding polarity [3]. These factors have control on the reinforcement height, depth of penetration and heat affected zone. Current, voltage, welding speed and polarity influence the bead shape and size [4]. The depth of penetration is influenced by polarity, current, voltage and arc-travel rate [5]. In shielded metal welding (SMAW) process, engineers generally face the problems of relating the process variables to the weld bead quality and optimization of the bead parameters. Generally the welding is done with the aim of achieving a sound joint at a low cost. But without optimization, it is impossible to achieve low-cost welding. The design and optimization process require the repeated use of the same set of calculations [6] and [7]. Since any welding process is a multi-objective problem like maximum depth of penetration, minimum reinforcement height, minimum heat input, minimum bead width, minimum dilution, low cost and maximum production rate, the optimum solution obviously is a compromise [8]. Selection of an appropriate weld bead parameter is also equally important because if the selected parameter is the one determined and controlled by most of the other important bead parameters, then the optimization of that parameter will obviously include all the other parameters. The cost of welding is less if the size of the weld is minimum but if the depth of penetration is reduced to minimize the size of the weld the quality of weld reduces. This indicates that there is a strong requirement of optimization of important bead parameters like depth of penetration and reinforcement height. To obtain a strong weld in any application, it is always desirable to have maximum depth of penetration with minimum reinforcement height, bead width and dilution without sacrificing other bead qualities [9]. Artificial neural networks are computational models used to address complex nonlinear relationships between input and output variables. It is one of the powerful modeling techniques, based on statistical approach, presently practiced in the field of engineering for modeling complex relationships which are difficult to be explained with physical models. The artificial neural network models developed are useful for selecting correct process parameters to achieve the desired weld bead quality and to predict weld bead quality

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for the given process parameters. Some researchers applied the back-propagation neural network to predict the bead geometry in shielded metal-arc welding process. They claimed that the neural network is a workable model to predict the bead geometry and penetration under a given set of welding conditions [10]. The need to achieve higher productivity and stringent safety requirement has put growing emphasis on the use of automated welding systems. In such automated applications, a precise means of selection of the process variables and control of weld bead shape has become essential because mechanical strength of weld is influenced not only by the composition of the metal, but also by the weld bead shape. ANN modeling has been chosen by its capability to solve complex and difficult problems. Kim et al. used multiple regression analysis and back propagation ANN in modeling bead height in metal arc welding [11] The applications of magnetic field in welding processes have drawn much attention of researchers. However, the effect of external magnetic field on quality of weld is still lack of understanding. In this paper, the effect of a longitudinal magnetic field generated by bar magnets on the weld was experimentally investigated considering the fact that the field applies a force on droplets of the melted electrode.

2. EXPERIMENTAL WORK

To investigate the weldment characteristics weld beads were obtained by welding two mild steel flat plates of 150 mm x 50 mm x 5 mm dimensions in butt position using AWS E 6013 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 and 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, 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 24V, 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, the welded mild steel plates were cut at the center of the bead to obtain 10-mm-wide test specimens. These specimens were prepared by the usual metallurgical polishing methods and etched with 2% nital. The weld bead profiles were traced using a reflective-type optical profile projector with 10X magnification. The depth of penetration and reinforcement height were measured with a digital planimeter with 1-µm accuracy. To measure the bead height of each sample a digital slide caliper was used. The average values of reinforcement height and depth of penetration 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)	Reinforcement eight (mm)	Depth of Penetration (mm)
Data for Training	1	90	24	40	0	1.13	0.79
	2	90	24	40	20	1.13	0.79
	3	90	24	40	40	1.14	0.80
	4	90	24	40	60	1.11	0.77
	5	90	24	40	80	1.09	0.76
	6	95	20	60	60	1.06	0.78
	7	95	21	60	60	1.07	0.76
	8	95	22	60	60	1.09	0.75
	9	95	23	60	60	1.11	0.74
	10	95	24	60	60	1.12	0.72
	11	100	22	40	40	1.17	0.83
	12	100	22	60	40	1.15	0.79
	13	100	22	80	40	1.11	0.76
	14	90	20	80	20	1.06	0.70
	15	95	20	80	20	1.09	0.71
	16	100	20	80	20	1.11	0.74
	17	105	20	80	20	1.13	0.77
	18	110	20	80	20	1.08	0.75
Data for Prediction	1	90	23	40	0	1.14	0.76
	2	95	22	60	40	1.11	0.72
	3	95	21	80	60	1.04	0.66
	4	100	24	40	40	1.16	0.78
	5	105	21	60	40	1.14	0.77
	6	105	22	60	20	1.13	073
	7	110	21	60	20	1.10	0.75

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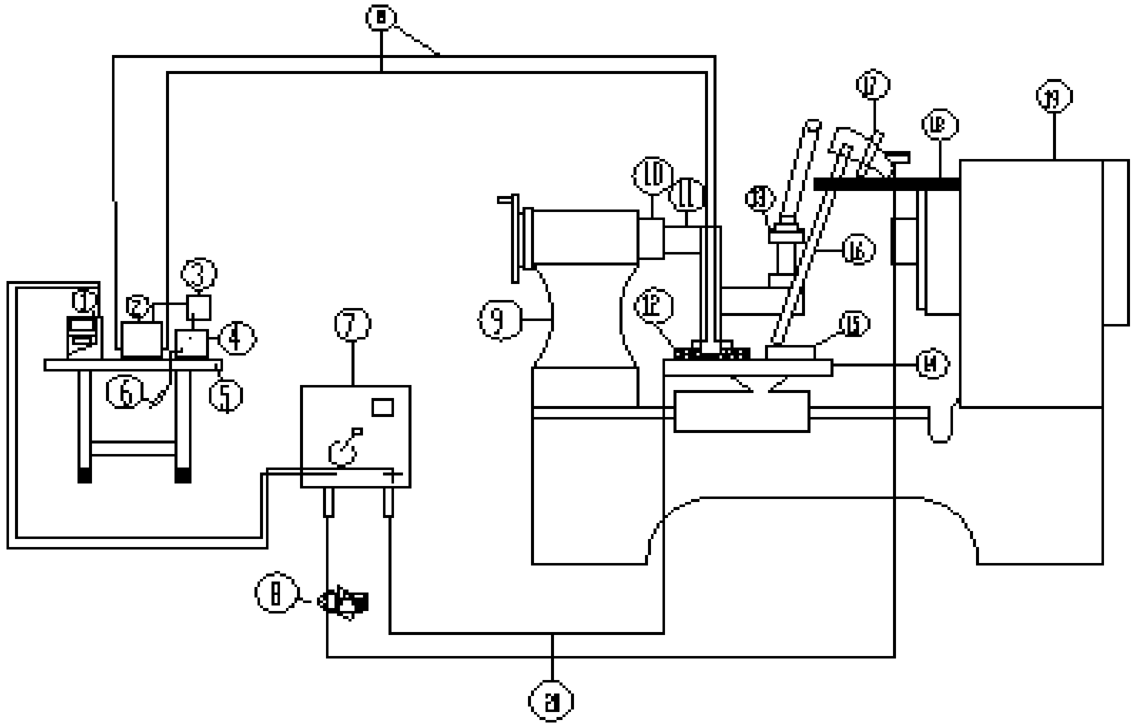
Table-2, Measured and Predicted Values with percentage Error

1	90	23	40	0	1.14	1.10	-3.51	0.76	0.74	-2.63
2	95	22	60	40	1.11	1.08	-2.70	0.72	0.71	-1.39
3	95	21	80	60	1.04	1.06	+1.92	0.66	0.70	+6.06
4	100	24	40	40	1.16	1.14	-1.72	0.78	0.73	-6.41
5	105	21	60	40	1.14	1.11	-2.63	0.77	0.74	-3.90
6	105	22	60	20	1.13	1.09	-3.54	0.73	0.72	-1.37
7	110	21	60	20	1.10	1.08	-1.82	0.75	0.74	-1.33



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

Figure-1, Experimental Setup

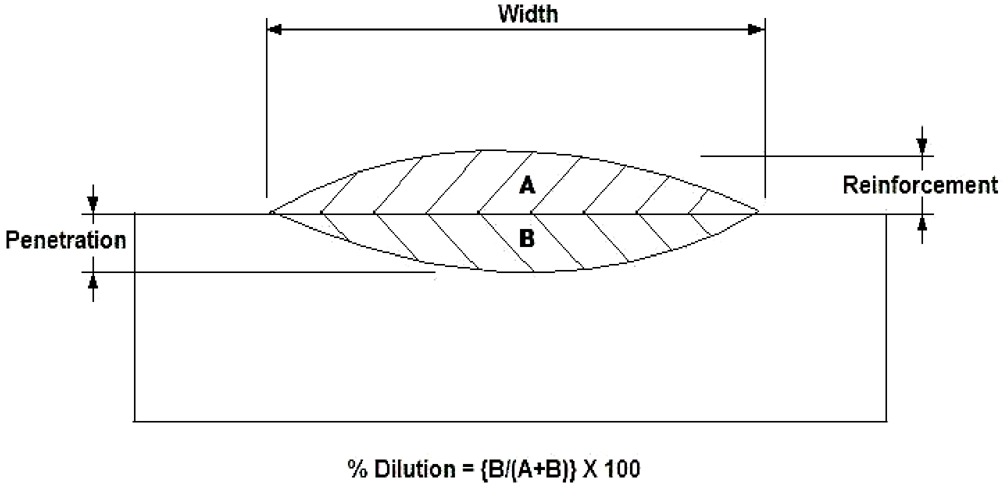


Figure 2: Diagrammatic Presentation of Weld Bead

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3. METHODOLOGY OF ARTIFICIAL NEURAL NETWORK MODELING

Most of the industrial processes are non-linear, complex and more input variables are involving in 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 and have found in many industrial application [12]. 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 work as black boxes and the output layer provides 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. 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. BP is essentially stochastic approximation to nonlinear regression. Several researchers used BP to model welding processes and predicted welding parameters using ANN. In training, 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 [13], 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 (3 neurons in input layer, 5 neurons in both hidden layers and 2 neurons in output layer). Proposed feed forward neural network architecture is shown in figure-3. 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.

4. RESULTS

Table-2 depicted, the measured reinforcement height and depth of penetration from the experiment and predicted output values using artificial neural feed forward network. The measured and predicted output values are close to each other. The aim of this paper shows the possibility of the use of neural network to predict the depth of penetration and reinforcement height of weld bead geometry.

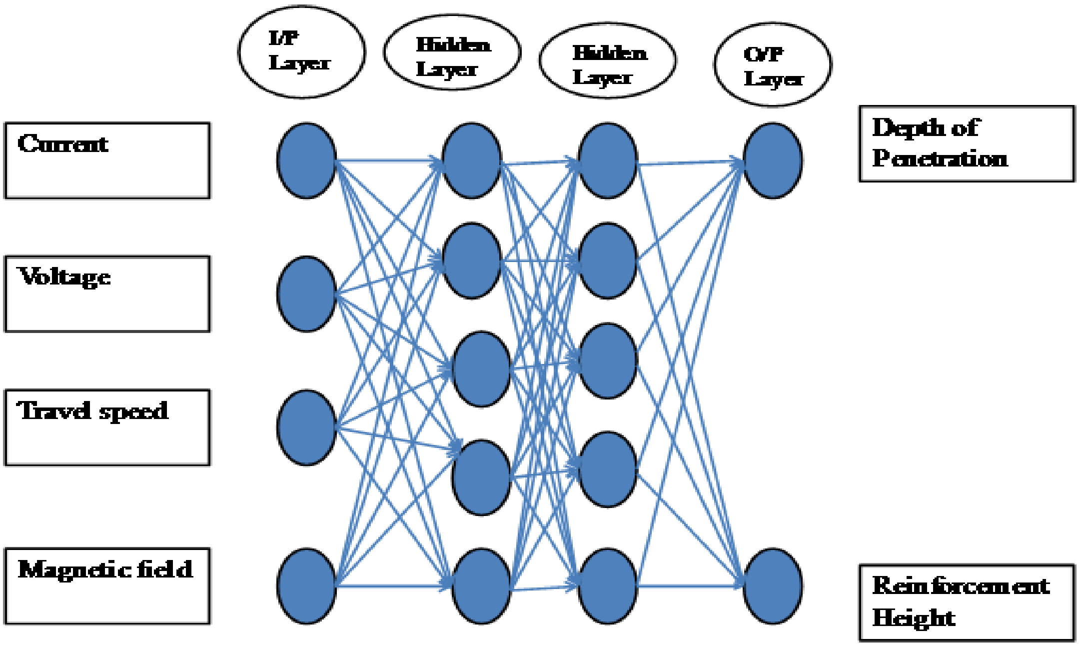

Figure-3, Feed-forward neural network (4-5-5-2) architecture

4.1 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 24V, 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. The variation of reinforcement height with magnetic field, voltage, welding speed and current were shown clearly in figures 7, 8, 9, and 10 respectively.

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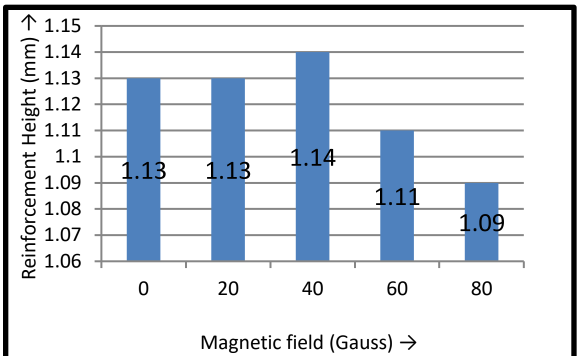

Fig. 4, Magnetic Field vs Reinforcement Height
At 90 A, 24 V and 40mm/min

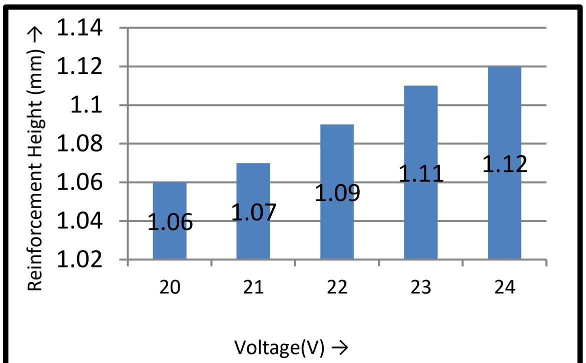

Figure 5, Voltage vs Reinforcement Height
At 95 A, 60mm/min and 60 Gauss

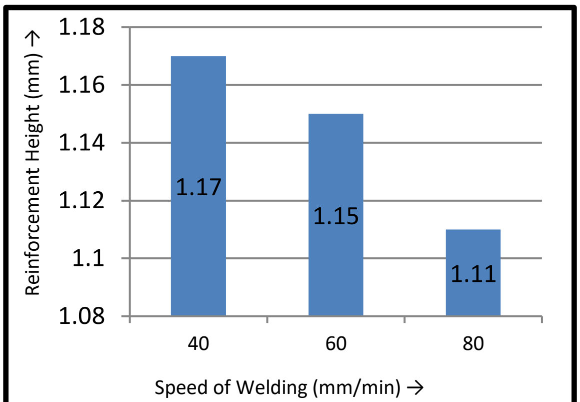

Fig. 6, Speed of welding vs Reinforcement Height →
At 100 a, 22 V and 40 Gauss

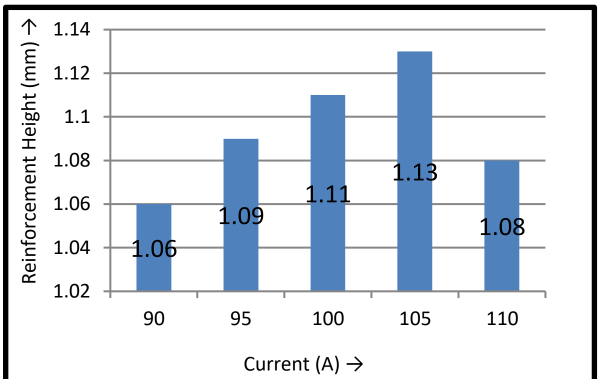

Fig. 7, Current vs Reinforcement Height
At 20 V, 80 mm/min and 20 Gauss

4.2 Depth of Penetration

The depth of penetration of the weld cross-section was measured and the results were displayed in table 1. There was generally no effect of magnetic field on depth of penetration if the strength of the field was less than 40 gauss and if it was increased from 40 gauss to 80 gauss the depth of penetration decreased from 0.80 mm to 0.76 mm. If the speed of welding was increased from 40 mm /min to 80 mm/ min the depth of penetration decreased from 0.83 mm to 0.76 mm. If the voltage was increased from 20 V to 24 V the depth of penetration decreased from 0.78 mm to 0.72 mm. If the current was increased from 90 V to 110 V, the depth of penetration increased from 0.70 mm to 0.75 mm. The variation of depth of penetration with magnetic field, voltage, welding speed and current were shown in figures 11, 12, 13 and 14 respectively.

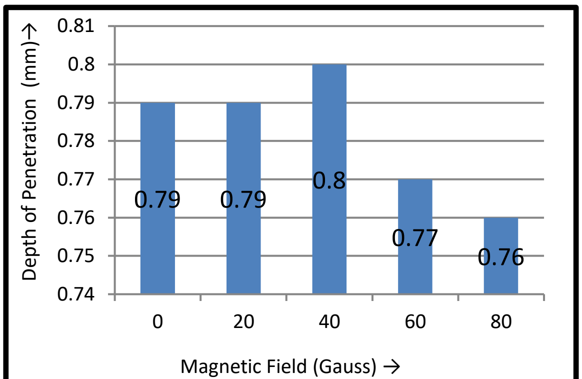

Fig. 8, Magnetic Field vs Depth of Penetration
At 90 A, 24 V and 40 mm/min.

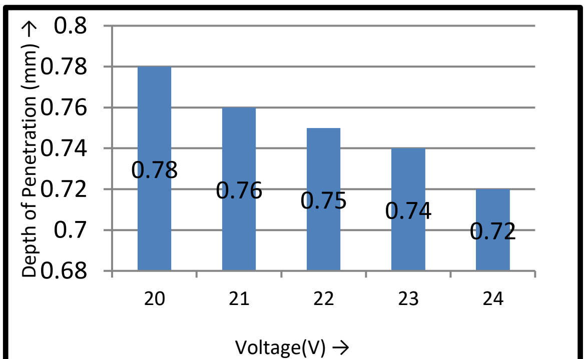

Fig. 9, Voltage vs Depth of Penetration
At 95 A, 60 mm/min and 60 Gauss

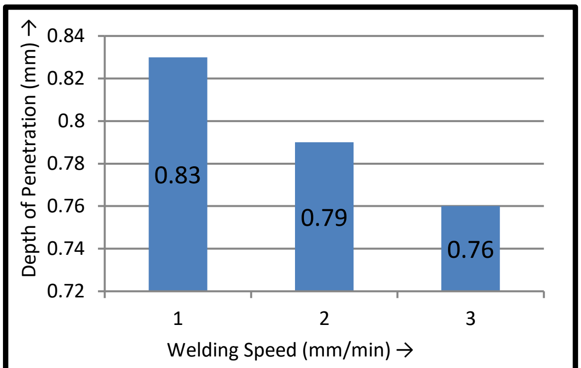

Fig.10, Welding Speed vs Depth of Penetration
At 100 A, 22 V and 40 Gauss

4.3 Prediction of Depth of Penetration and Reinforcement Height 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 % age error was calculated between the experimental and predicted values as shown in table-2. The % age error is ranging between 6.06 to -6.41. The other predictions are in between these ranges and hence are very close to the practical values, which indicate the super predicting capacity of the artificial neural network model.

5. DISCUSSION

In this investigation, an attempt was made to find out 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 reinforcement height and depth of penetration. 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.

6. 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

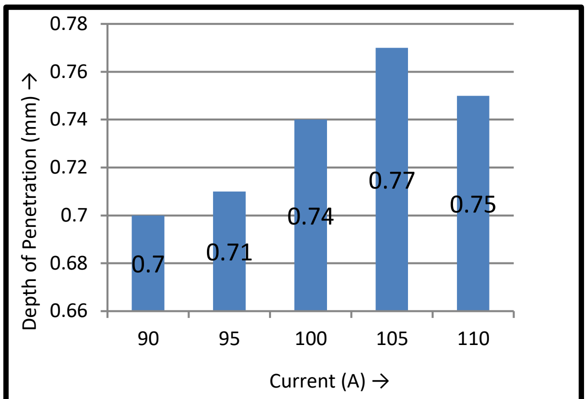

Fig. 11, Current vs Depth of Penetration
at 20 V, 80 mm/min and 20 Gauss

the alternatives methods to predict the weld bead geometry. 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:

(1) A strong joint of mild steel is found to be produced in this work by using the SMAW technique.

(2) If amperage is increased, depth of penetration and reinforcement height both generally increase.

(3) If voltage of the arc is increased, reinforcement height generally increases but depth of penetration decreases.

(4) If travel speed is increased, reinforcement height and depth of penetration of weld, both generally decrease.

(5) If magnetic field is increased, reinforcement height and depth of penetration of weld, both generally decrease.

(6) Artificial neural networks based approaches can be used successfully for predicting the output parameters like reinforcement height and depth of penetration of weld as shown in table 2. However the error is rather high as in some cases in predicting depth of penetration it is more than 6 percent. Increasing the number of hidden layers and iterations can minimize this error.

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