Prediction of Weld Width of Shielded Metal Arc Weld under Magnetic Field using Artificial Neural Networks

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I. Abstract:

The prediction of the optimal weld bead width is an important aspect in shielded metal arc welding (SMAW) process as it is related to the strength of the weld. This paper focuses on investigation of the development of the simple and accurate model for prediction of weld bead width of butt joint of SMAW process. Artificial neural networks technique was used to train a program in C++ with the help of sufficient number of welding data sets having input variables current, voltage, speed of welding and external magnetic field and output variable weld bead width. These variables were obtained after welding mild steel plates using SMAW process. The welding set-up was mounted on a lathe machine. In this paper, the effect of a longitudinal magnetic field generated by bar magnets on the weld bead width was experimentally investigated. Using the experimental data a multi-layer feed forward artificial neural network with back propagation algorithm was modeled to predict the effects of welding input process parameters on weld width accurately. It was found that welding voltage, arc current, welding speed and external magnetic field have the large significant effects on weld bead width. It has been realized that with the use of the properly trained program, the prediction of optimal weld bead width becomes much simpler to even a novice user who has no prior knowledge of the SMAW process and optimization techniques.

Keywords: Artificial Neural Network, Back Propagation, External Magnetic Field, Hidden Layer, Input Process Parameters, Shielded Metal Arc Welding, Weld Bead Width.

II. Introduction:

Welding is a process of joining different materials. It is more economical and is a much faster process compared to both casting and riveting [1]. The weld bead width is the maximum width of the weld metal deposited. It influences the flux consumption rate and chemistry of the weld metal and hence determines the mechanical properties of the weld [2]. SMAW input process parameters like welding current, welding speed; open circuit voltage and external magnetic field are highly influencing the quality of weld joints. The applications of magnetic field in welding processes have drawn much attention of researchers [3]. However, the effect of external magnetic field on quality of weld is still lack of understanding. Selection of process parameters has great influence on the quality of a welded connection. 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. The weld bead width is an important factor of the shape of the weld. The weld quality can be achieved by meeting 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 [4]. Among all the welding processes, SMAW is very important. The advantages of this method are that it is the simplest of the all arc welding processes. The equipment is often small in size and can be easily shifted from one place to the other. Cost of the equipment is very less. This process finds a number of applications because of the availability of a wide variety of electrodes which makes it possible to weld a number of metals and their alloys. The welding of the joints may be carried out in any position with highest weld quality and therefore the joints which are difficult to be welded because of their position by automatic welding machines can be easily welded by shielded metal arc welding. Both alternating and direct current power sources could be used effectively. Power sources for this type of welding could be plugged into domestic single phase electric supply, which makes it popular with fabrications of smaller sizes [5]. However, non equilibrium heating and cooling of the weld pool can produce micro-structural changes which may greatly affect mechanical properties of weld metal. To get the desired weld quality in SMAW process, it is essential to know interrelationships between process parameters and bead geometry as a welding quality. Many efforts have been done to develop the analytical and numerical models to study these relationships, but it was not an easy task because there were some unknown, nonlinear process parameters. For this reason, it is good for solving this problem by the experimental models. One of the experimental models is artificial neural networks technique that can be utilized to establish the empirical models for various arc welding processes. Investigation into the relationship between the welding process parameters and bead geometry began in the mid 1900's and regression analysis was applied to welding geometry research [6]. Many efforts have been carried out for the development of various algorithms in the modeling of arc welding process. In the early days, arc welding was carried out manually and the weld quality was totally controlled by the welder ability. Mc Glone and Chadwick have reported a mathematical analysis correlating process variables and bead geometry for the submerged arc welding of square edge close butts. Chandel first applied this technique to the GMA welding process and investigated relationship between process variables and bead geometry [7]. These results showed that arc current has the greatest influence on bead geometry, and that mathematical models derived from experimental results can be used to predict bead width accurately. Nearly 90% of welding in world is carried out by one or the other arc welding process; therefore it is imperative to discuss the effects of welding parameters on the weldability of the materials during the arc welding. Mild steel was selected for work-pieces to be welded because it is the most common form of steel as its price is relatively low while it provides material properties which are acceptable for many applications.

III. Experiment 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 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, we select different set of values of these inputs [8]. 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, 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 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. 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 [9]. In this program one input layer having four neurons, two hidden layers, both having five neurons and one output layer having three neurons, were used.

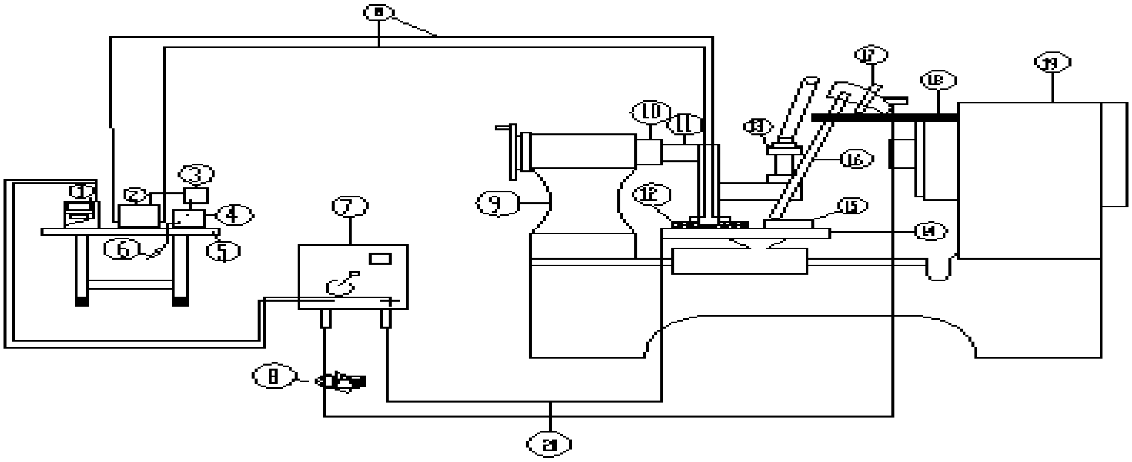
Table 1 Data for training and prediction

	Serial Number	Current (A)	Voltage (V)	Welding Speed (mm/min)	Magnetic Field (Gauss)	Weld idth(mm)
Data for Training	1	90	24	40	0	6.95
	2	90	24	40	20	6.94
	3	90	24	40	40	6.96
	4	90	24	40	60	6.99
	5	90	24	40	80	7.03
	6	95	20	60	60	6.01
	7	95	21	60	60	6.08
	8	95	22	60	60	6.10
	9	95	23	60	60	6.15
	10	95	24	60	60	6.25
	11	100	22	40	40	5.94
	12	100	22	60	40	5.90
	13	100	22	80	40	5.86
	14	90	20	80	20	5.91
	15	95	20	80	20	5.92
	16	100	20	80	20	5.94
	17	105	20	80	20	5.95
	18	110	20	80	20	5.97
Data for Prediction	1	90	23	40	0	6.92
	2	95	22	60	40	6.05
	3	95	21	80	60	6.04
	4	100	24	40	40	6.99
	5	105	21	60	40	5.98
	6	105	22	60	20	5.96
	7	110	21	60	20	5.97

Table 2 Measured and predicted values with percentage error

S.N.	Current (A)	Voltage (V)	Welding Speed (mm/min)	Magnetic Field (Gauss)	Weld Width (mm) Measured	Weld Width (mm) Predicted	Error in Weld Width % age
1	90	23	40	0	6.92	6.54	-5.49
2	95	22	60	40	6.05	6.42	+6.12
3	95	21	80	60	6.04	6.44	+6.62
4	100	24	40	40	6.99	6.58	-5.87
5	105	21	60	40	5.98	6.41	+7.20
6	105	22	60	20	5.96	6.40	+7.38
7	110	21	60	20	5.97	6.39	+7.04

Figure 1 Real experimental set-up on a lathe machine



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 2 Experimental set-up (Line Diagram)

IV. 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. ANN model has been developed for general application consisting of the following steps: (i) Database collection, (ii) pre-processing of input/output data, (iii) design and training of neural network, (iv) testing of trained network, (v) post processing and (vi) use trained network for prediction [10]. 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: (i) Input layer receives the welding parameters, (ii) Hidden layers considered as black boxes and (iii) 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. 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 one 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 were used BP to model welding processes and predict welding parameters using Neural network. The designed neural networks structure was 4-5-5-1 (3 neurons in input layer, 5 neurons in both hidden layers and 1 neuron 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.

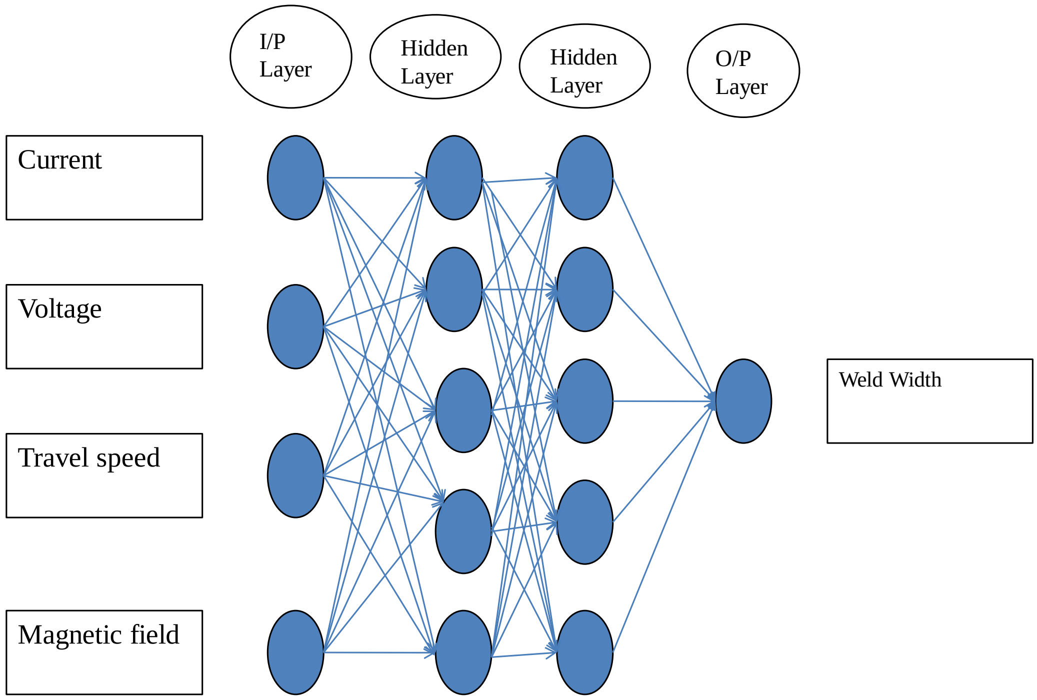


Figure 3 Feed-forward neural network (4-5-5-1) architecture

V. Results and Discussion

Table-2 depicted, the measured weld bead width, 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 weld width accurately.

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 4, 5, 6 and 7 respectively.

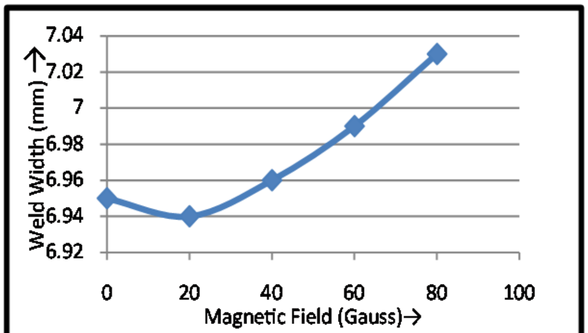
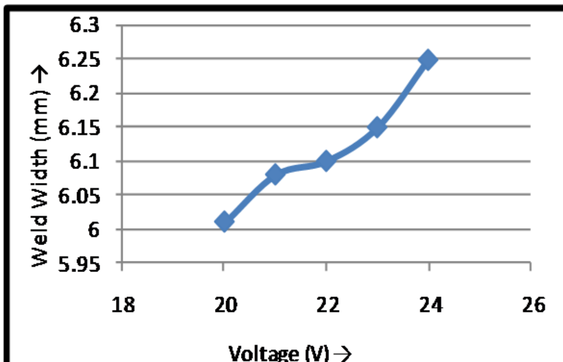


Fig. 4, Magnetic field vs weld width
At 90 A, 24 V and 40 mm/min



Fig, 5, Voltage vs weld width
At 95 A, 60 mm/min and 60Gauss

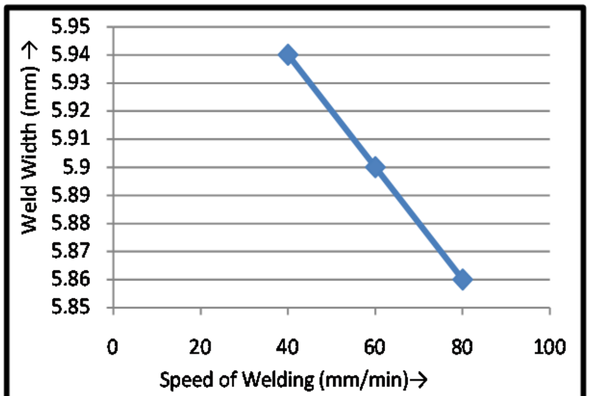


Fig. 6, Speed of welding vs weld width
At 100 A, 22 V and 40 Gauss

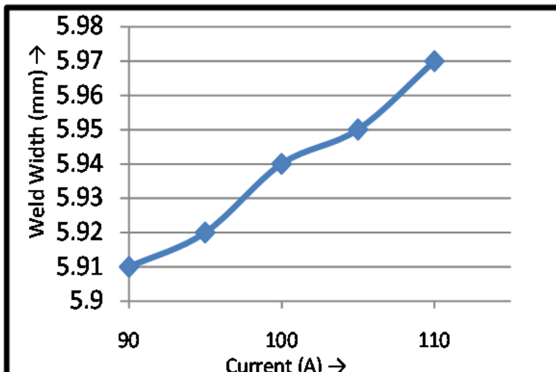


Fig. 7, Current vs weld width
At 20 V, 80 mm/min and 20 Gauss

Prediction of Weld Width 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 figure-2. The %age error is ranging between -5.87 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.

VI. 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 weld width. 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.

VII. 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 the alternatives methods to predict the weld width. 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, weld width generally increases.
(3) If voltage of the arc is increased, weld width generally increases.
(4) If travel speed is increased weld width generally decreases.
(5) If magnetic field is increased weld width, generally increases.
(6) Artificial neural networks based approaches can be used successfully for predicting the output parameters like weld width of weld as shown in table 2. However the error is rather high as in some cases in predicting weld width it is more than 7 percent. Increasing the number of hidden layers and iterations can minimize this error.

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