

ANN Assisted Prediction of Weld Bead Geometry in Gas Tungsten Arc Welding of HSLA Steels

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Abstract— Weld bead geometry (front bead width and height, and back bead width and height) is a significant physical characteristic of a weldment. Several welding parameters such as welding speed, weld current, voltage, and shielding gas flow rate affect the weld bead geometry. Traditionally, an expert welder from his experience of trial and error selects a set of parameters that may yield fairly good results. However, the trial and error can be avoided, if a suitable automation tool can be developed, which could forecast the output from a set of desired parameters. Artificial neural net (ANN) was applied to predict the weld bead geometry in gas tungsten arc (GTA) welding of high strength low alloy (HSLA) steel. Back-propagation neural network algorithm has been followed to associate the welding process parameters with the weld bead geometry.

Index Terms— neural nets, learning, back propagation, welding parameters

I. INTRODUCTION

GAS tungsten arc (GTA) welding is an arc-welding process that produces coalescence of metals by heating them with an arc between a non-consumable tungsten electrode and the base metal [1]. GTA welding is a highly nonlinear, strongly coupled, multivariable process [2]. The weld pool geometry and, hence, the quality of GTA welded joints are greatly dependent on the selection of input control variables such as Welding Speed, Current, Voltage, and Shielding Gas Flow Rate [3]. The profile of the bead has significant influence on the welding [4].

Traditionally it has been necessary to determine the weld input parameters for every new weld product to obtain a welded joint with the required specifications. An expert welder from his experience of trial and error selects a set of parameters that may yield fairly good results. However, the obtained results may not be the optimal one. The welder, usually, has to adjust the aforementioned input parameters using past experience or hit-and-trial in order to achieve

acceptable values of bead geometry parameters (front bead width and height, and back bead width and height), which becomes costly and time consuming. The trial and error of the welder can be avoided, if a suitable automation tool can be developed, which could forecast the output from a set of desired parameters.

The profile of the bead has significant influence on the welding. From the cross-sectional area of the bead, the cooling rate of the weldment can be judged [4]. Bead cross-sectional area along with the bead height and width determines the residual stresses and thus, distortion of the welded structure. Weld cracking is also related to the profile of the bead. Moreover, a considerable amount of micro-structural change occurs in the welded zone. The size of the grains in the welded zone is generally found to be larger than that of the base metal. Due to these reasons, the mechanical properties of a welded structure are dependent on the size and shape of the weld bead.

Different methods and approaches have been used to achieve excellent mechanical properties. In the last two decades, designs of experiment (DOE) techniques have been used to carry out parameter optimization. Evolutionary algorithms and computational network have also grown rapidly and been adapted for many applications in different areas [5].

The paper presents an automation rich tool consisting of feed-forward back-propagation artificial neural network, which gets trained from past experimental data and then predicts the GTA weld bead parameters with acceptable accuracy. Not much work has been done related to application of ANN towards optimizing welding process, in general, and weld bead, in particular. Following literature survey is noteworthy.

The field of neural networks has a history of some five decades but has found solid application only in the past fifteen to twenty years, and the field is still developing rapidly [6]. Cook *et al.* have explained some concepts related to neural networks and how they can be used to model weld-bead geometry, in terms of equipment parameters [7]. Vitek *et al.* have developed a model to predict the weld pool shape parameters (penetration, width, width at half-penetration and cross-section area) in pulsed Nd YAG laser welds of Al-alloy 5754 using neural network [8]. They have considered the following process parameters: travel speed, average power, pulse energy and pulse duration. D.S. Nagesh and G.L. Datta used ANN for prediction of weld bead geometry and penetration in shielded metal-arc welding (SMAW) [3]. G.E. Cook *et al.* have used ANN for monitoring and control of variable

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polarity plasma arc welding process. The following areas of welding were investigated: weld process modeling, weld process control, and weld bead profile analysis for quality control [9]. G. Kim *et al.* used fuzzy logic and neural networks to determine the difficult and unique relationship between the weld bead geometry and the combination of various welding parameters especially arc voltage, current and welding speed [10]. K. Ramaswamy *et al.* in their work on new techniques for modeling and control of GTA welding presented solutions to modeling the process. They concluded that ANN application is a viable approach towards reliable weld modeling [11].

II. EXPERIMENTAL DATA FOR TRAINING ANN

A total of 17 experimental runs – following a 4 factor, 2 level, 1 center point Design of Experiments – were performed in order to establish the effects of four GTA weld parameters (Welding Current – I [Amp], Voltage – V [Volts], Speed – S [cm/min], and Shielding Gas Flow Rate – F [lit/min]) on four weld bead related performance measures (front bead width – FW [mm], front bead height – FH [mm], back bead width – BW [mm], and back bead height – BH [mm]) in linear plate welding of AISI 4340 (an HSLA steel). These four measures have been presented in Fig.1. The size of each plate was $300 \times 150 \times 3$ mm, thus achieving after weld size of $300 \times 300 \times 3$ mm. The edge for weld was prepared for 30° bevel with root-face and root-gap of 1mm each. Filler wire (having the same composition as that of the parent alloy) of diameter 1.6mm was used at a consumption length rate of 90cm/pass and weld process was completed in one pass only. To measure the bead geometry 25mm portion of the bead at start and end was excluded. Table 1 presents the experimental results.

III. ANN MODEL DEVELOPMENT

The neural network performance depends on the number of hidden layers and number of neurons in the hidden layers.

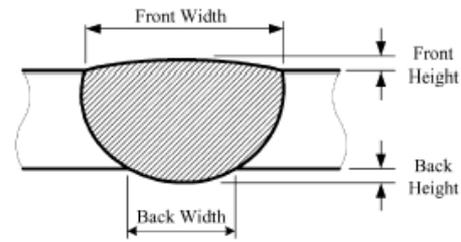


Fig.1. Schematic of Weld Bead Geometry [1]

In this work, exhaustive search was done for number of hidden layers (2 to 3) and number of neurons per hidden layer (12 to 14) for optimal prediction of weld bead geometry. The papers [7, 9] have also put forward trial-and-error approaches for determining number of hidden layers and neurons per hidden layer. For the current work, the best structure for the ANN was found to be 4-14-12-4 (4 neurons in the input layer; 14 in the first hidden layer; 12 in the second; and 4 in the output layer). The topology of the feed-forward back-propagation network has been shown in Fig. 2. The four neurons of the input layer take in-feed for the four predictor variables (I , V , S , and F). The four neurons in the output layer present the computed results related to the four response variables (FW , FH , BW , and BH). When the network is run all the neurons of any layer process in parallel and they provide their outputs to all the neurons of the successive layer. The processing continues in the same way until the results are obtained from the neurons of the output layer. The ANN was modeled using Neural Network Toolbox of Matlab 7.10. Fig. 3 presents the Matlab model of the ANN. The algorithm used for training of network was resilient back propagation (trainrp). This algorithm is generally faster than the standard steepest descent algorithm. The transfer functions used in all hidden layers were logarithmic sigmoidal and in output layer were pure linear.

TABLE I.
EXPERIMENTAL WELDING PARAMETERS AND METROLOGY RESULTS OF WELD BEAD GEOMETRY

S/No.	I (Amp)	V (Volts)	S (cm/min)	F (Lit/min)	FW (mm)	FH (mm)	BW (mm)	BH (mm)
1	190	13.5	20	15	8.72	0.5	6.1	0.88
2	180	13.5	20	15	8.03	0.55	4.49	0.63
3	180	12.5	20	15	8.83	0.33	5.98	0.83
4	190	12.5	20	20	8.83	0.23	6.45	0.78
5	180	13.5	18	20	9.31	0.38	6.16	0.8
6	190	12.5	18	20	9.2	0.3	6.03	0.83
7	190	13.5	18	20	8.58	0.53	6.09	0.93
8	180	12.5	18	15	9.12	0.6	4.49	0.83
9	190	12.5	20	15	9.02	0.73	5.1	0.68
10	180	12.5	20	20	8.18	0.6	4.21	0.5
11	180	13.5	20	20	8.46	0.6	4.48	0.53
12	190	13.5	20	20	7.11	0.85	4.29	0.55
13	190	12.5	18	15	9.43	0.65	5.81	1.05
14	185	13	19	17	8.49	0.9	4.93	0.45
15	180	12.5	18	20	8.87	1.1	4.93	0.45
16	180	13.5	18	15	7.7	0.83	5.03	0.88
17	190	13.5	18	15	8.43	0.75	5	0.88

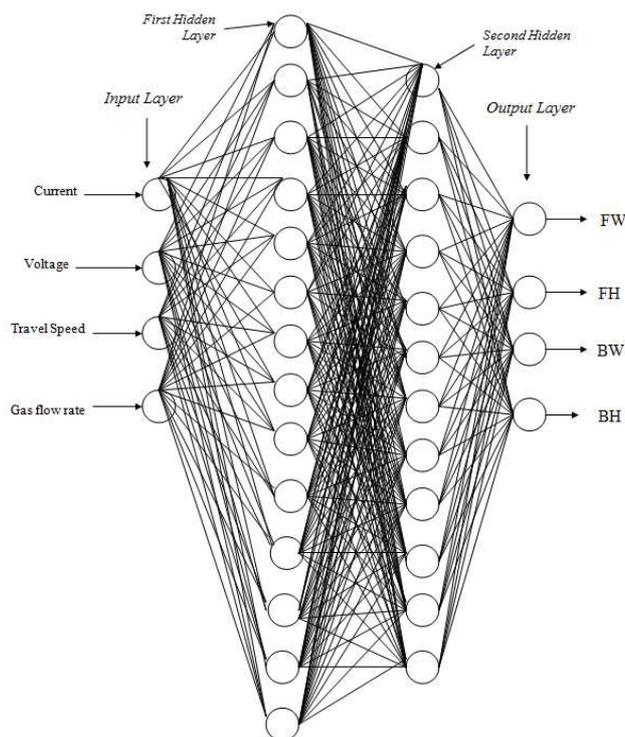


Fig. 2. Topology of ANN used for prediction of weld bead geometry

The network was planned to perform up to 11000 iterations, which are necessary to obtain minimized mean standard error, but the minimum mean square error (MMSE) of 5.74449e-13 was obtained after 6722 iterations. Fig. 4 describes the gradual reduction of minimum mean square error with respect to number of iterations.

A. Simulation of the Trained Network

To evaluate the prediction accuracy of the trained ANN developed for Gas Tungsten Arc Weld modeling, it was presented with previously unseen randomly selected welding data. The testing data consisted of following welding parameter: current, voltage, travel speed, and gas flow rate. The model simulated the process with reasonable accuracy. Tables 2 and 3 present the comparison of the testing experiments results and the prediction values of the network model. It can be observed from the results that simulation results rarely exceeded 20% error; hence the network was able to predict the weld bead geometry with fair deal of accuracy. Therefore, it can be concluded from the presented work that ANN constitute a practical model for predicting

the weld bead geometry under given set of welding input parameters.

IV. ANALYSIS AND DISCUSSION

The data presented in Table 1 was subjected to Analysis of Variance (ANOVA). Highly significant effects of welding current and speed were ascertained on bead heights. It was observed that high welding speed or low welding current normally produces poor fusion, since both the conditions produce lesser heat input per unit length run of weld bead. It was observed that front bead width and height and back bead width and height increase in magnitude with decreasing travel speed.

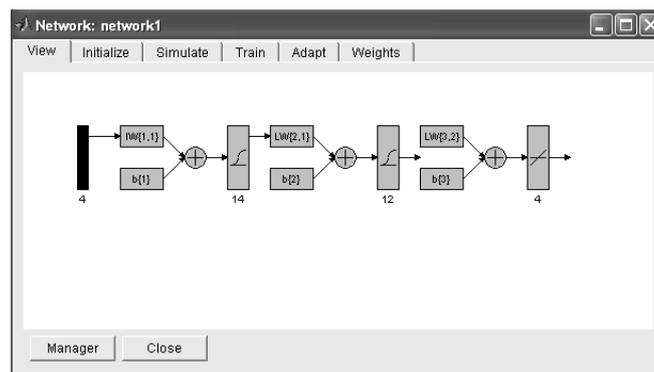


Fig.3. Matlab model of the ANN

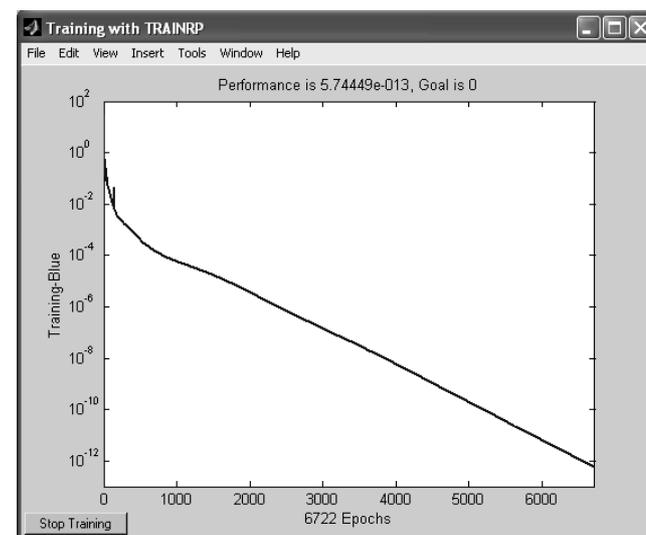


Fig. 4. Gradual drop in prediction error

TABLE II
COMPARISON OF SIMULATION (PREDICTION) RESULTS [FRONT BEAD WIDTH AND FRONT BEAD HEIGHT] WITH EXPERIMENTAL RESULTS

S/ No.	Parameters				Experimental Results		Simulation Results		Percentage Error (%)	
	I (Amp)	V (V)	S (cm/min)	F (lit/min)	FW (mm)	FH (mm)	FW (mm)	FH (mm)	FW (mm)	FH (mm)
1	185	12.5	19	15	8.7	0.76	9.56	0.61	9.9	-20.3
2	190	13.5	20	15	7.81	0.59	8.72	0.5	11.6	-15.3
3	180	13.5	20	20	7.88	0.68	8.46	0.6	7.4	-11.8
4	190	13	18	20	8.98	0.51	8.61	0.56	-4.1	8.3
5	185	12.5	18	20	9.04	0.45	9.26	0.35	2.4	-21.3
6	190	12.5	20	18	9.41	1.09	7.09	1.29	-24.6	18.6

TABLE III.
COMPARISON OF SIMULATION (PREDICTION) RESULTS [BACK BEAD WIDTH AND BACK BEAD HEIGHT] WITH EXPERIMENTAL RESULTS

S/ No.	Parameters				Experimental Results		Simulation Results		Percentage Error (%)	
	I (Amp)	V (V)	S (cm/min)	F (lit/min)	BW (mm)	BH (mm)	BW (mm)	BH (mm)	BW (mm)	BH (mm)
1	185	12.5	19	15	4.82	0.53	5.78	0.59	19.9	11.9
2	190	13.5	20	15	5.23	0.74	6.1	0.88	16.5	18.2
3	180	13.5	20	20	3.96	0.46	4.48	0.53	13.2	14.1
4	190	13	18	20	6.04	0.63	5.89	0.76	-2.5	19.8
5	185	12.5	18	20	6.35	0.56	6.01	0.66	-5.3	17.0
6	190	12.5	20	18	4.26	0.43	3.6	0.36	-15.4	-15.6

It was observed that welding voltage also affected the weld bead geometry; increasing the arc voltage increased arc length, thereby, producing wider, flatter bead with less penetration. It was further observed by ANOVA that shielding gas flow rate doesn't significantly affect any of the weld bead geometry parameters.

V. CONCLUSION

The experimental work and subsequent analysis of ANN model developed and used for prediction of weld bead geometry in gas tungsten arc (GTA) welding confirm that ANN tool can be fruitfully applied in modeling and predicting complex and nonlinear manufacturing processes with fair deal of accuracy. It is a beauty of neural nets that although they consume some processing time during training phase, but once trained provide the simulation/prediction results with a single feed-forward process, thereby, saving considerable processing time, especially when applied on number of different situations falling within their scope of application.

The effects of weld current and weld speed are highly significant on bead geometry parameters. The effect of welding voltage is moderately significant, while that of gas flow rate is insignificant.

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