THE USE OF NEURAL NETWORK TECHNOLOGIES TO DETERMINE WELDING PARAMETERS IN GMA WELDING PROCESS

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ABSTRACT

This paper presents the use of the neural network technology to establish a mathematical model for predicting bead geometry (top-bead width, top-bead height, back-bead width and back-bead height) for multi-pass welding, and understand relationships between process parameters and bead geometry for robotic GMA welding process. Using a series of robotic arc welding, additional multi-pass butt welds were carried out in order to verify the performance of the developed neural network model. The results show that not only the proposed model can predict the bead geometry with reasonable accuracy and guarantee the uniform weld quality, but also the neural network model could be better than the linear and curvilinear equations developed from Lee [8].

KEYWORDS

Neural network, GMA welding, Bead geometry, Multi-pass welding, Butt weld

1. Introduction

Process parameters for the GMA welding should be well established and categorized for the robotic welding system. With the increase of automation in arc welding, the selection of welding procedure must be more specific to ensure that adequate bead quality is obtained. Further, to get the desired quality welds, it is essential to have a complete control over the relevant process parameters to obtain the required bead geometry and shape which is based on capacity of a weldment [1].

In recent years, the neural network architecture has become more and more important as an effective learning technique in pattern recognition areas. The neural networks have strong abilities to learn self-organized information, and need only a few specific requirements and prior assumptions for modeling. Juang et al. [2] explored BP and counter-propagation neural networks to associate the process parameters with the features of bead geometry, and concluded that the counter-propagation network has better learning ability for the TIG (Tungsten Inert Gas) welding process than BP network. Tarng et al. [3] studied relationships between the process parameters and the features on the bead geometry for TIG welding process, and applied a global optimization algorithm called simulated annealing for solving the process parameters with optimal bead geometry based on an objective function using BP neural network. Jeng et al. [4] predicted the laser butt welding parameters using BP and LVQ (Learning Vector Quantization) neural network. The input parameters of the neural network include workpiece thickness and welding gab, whilst the output parameters include optimal focused position, acceptable welding parameters of laser power and welding speed. They also insisted that both neural networks are very useful in selecting suitable welding parameters and help in avoiding inappropriate welding design. However, there are few published documents that discuss the modeling of GMA welding using a neural network. Srikanthan and Chandel [5] proposed the steps adopted to construct the neural network model for GMA welding and evaluated the proposed neural network model.

The objectives of this study are to develop the intelligent model to predict bead geometry by applying BP neural network. The experimental data are employed in the training of BP neural network. The simulation results are compared with the experimental results and those of Lee's empirical models [6]. The developed BP neural network model can be suitable model that predicted the process parameters on bead geometry for multi-pass welding in butt GMA welding process and provided the weld final configuration and properties as output, and employed the process parameters as input.

2. Description of GMA Welding for BV-AH 32 Steel Plates

Statistically designed experiments that are based upon factorial techniques, reduce costs and provide the required information about the main and interaction effects on the response factors. The process parameters included in this study were three levels of pass number (2, 3 and 4), sometimes called layer, three levels of arc current (170, 220 and 270 A), three levels of welding voltage (23, 26 and 28 V) and 12 to 50 cm/min of welding speed that depends on weld quality. All other parameters except these parameters under consideration were fixed. The welding facility was chosen as the basis for the data collection and evaluation. The base material used for this study was the BV-AH32 steel with 12 mm in thickness for multi-pass butt-welding process. Chemical compositions and mechanical properties of BV-AH 32 steel are shown in Tables 1 and 2.

Table 1 Chemical compositions of BV-AH 32 steel

C	Si	Mn	P	S	Cr	Ni	Cu	Nb	V	Mo
0.16	0.42	1.5	0.018	0.005	0.03	0.03	0.02	0.003	0.005	0.03

Table 2 Mechanical properties of BV-AH 32 steel

Yield strength (kgf/mm2)	Tensile strength (kgf/mm2)	Elongation (%)	Young's modulus (kgf/mm^2)
41.02	57.35	20	21,740

This plate was cut into 300×200mm pieces, and both surfaces were blasted to remove dirt and oxides by using the sand papers. GMA/CO2 welding system and an automatic traveling unit were combined to make an automatic process system. The shielding gas composition was Ar 80%, CO2 20%. Experimental test plates were located in the fixture jig by the robot and the required weld conditions were fed for the particular weld steps in the robot path. With power supply and argon shield gas turned on, the robot was initialized and welding was executed. This continued until experimental runs were completed. To measure the bead geometry, the transverse sections of each weld were cut using a power hacksaw from the mid-length position of welds, and the end faces were machined. Specimen end faces were polished and etched using a 2.5% nital solution to display bead geometry. The schematic diagrams of bead geometry employed were made using a metallurgical microscope interfaced with an image analysis system. Images are represented by a 256 level gray scale, and the program [7] can be employed to identify bead geometry. The fractional factorial matrix was assumed to link the mean values of the measured results with changes in the four process parameters for determining bead geometry associated with the quality characteristics of a GMA welding process.

3. Model of BP neural network for GMA welding process

Neural network is composed of many interconnected identical simple processing units called neurons. Each connection to a neuron has an adjustable weight factor associated with it. The experiment data is used here as learning examples. We adopt a total of 54 examples for training the neural network and 9 examples for testing and predicting the network. Four input parameters used are pass number, welding speed, welding current and arc voltage, but bead geometry such as top-bead width, top-bead height, back-bead width and back-bead height is the output. In order to establish the process model, it is very important to decide how many layers and how many neurons per layer of the network are utilized to describe the behavior of the GMA welding process. As mentioned in the above, the number of neurons in the input and output layers can be set at 4 and 1 respectively. Generally, one hidden layer is enough to form the mapping between inputs and outputs [8]. The designed $4\times 4\times 1$ network structure shown in Figure 1 is used here to perform the learning scheme. In this study the development and the training of the network is carried out on a Pentium PC using MATLAB application tool. With a learning rate of 0.6 and a momentum term of 0.9, the network was trained for 200,000 iterations. The error between the desired and actual outputs is less than 0.001 at the end of the training process.

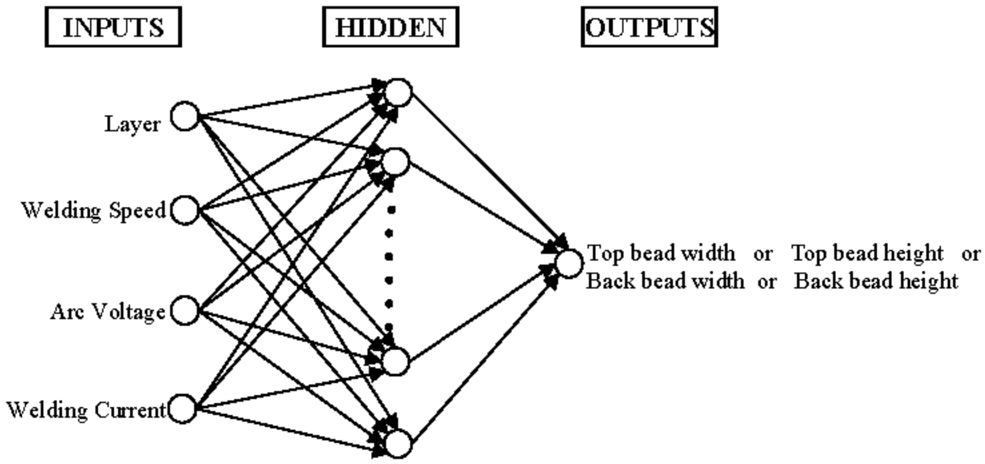

Fig. 1 Optimal BP neural network architecture for predicting bead geometry

4. Results and Discussion

To ensure the accuracy of the developed and survey the spread of the values, additional experiments were carried out. Table 3 showed process parameters for the additional experiment. BP neural network developed and Lee's empirical equations have been compared with their corresponding experimental results. The experimental results and welding conditions including number of pass, welding speed, arc current and welding voltage are employed as the input parameter. Output parameter is the bead geometry (top-bead width, top-bead height, back-bead width and back-bead height) calculated by each model and the corresponding errors of prediction. To verify the developed BP model for top-bead width, top-bead height, back-bead width and back-bead height, the predicted results from BP neural network model and Lee's empirical models are plotted in Figures 2-5 together with the process parameters as listed in Table 3. Figure 2 shows a plot of the measured top-bead width versus the calculated values, whereas Figure 3 presents a plot of the measured top-bead height versus the calculated values obtained using the developed BP model and Lee's models. Figure 4 shows a plot of the measured back-bead width versus the calculated values, whereas Figure 5 presents a plot of the measured back-bead height versus the calculated values obtained using the developed BP model and Lee's empirical models. According to Table 3 and Figures 2-5, BP neural network model gives the best fit to the experimental results and produce better prediction of the bead geometry than the Lee's empirical equations [6].

Table 3 Process parameters for the additional experiment

Trial. No.	No. of pass	Welding current(A)	Welding speed 1(cm/min)	Welding speed 2(cm/min)	Welding speed 3(cm/min)	Welding speed 4(cm/min)	Arc voltage(V)
1	2	250	26	26	-	-	27
2	2	200	22	18	-	-	25
3	3	250	34	34	34	-	27
4	3	200	27	27	22	-	25
5	4	250	37	37	45	45	27
6	4	200	28	28	33	33	25

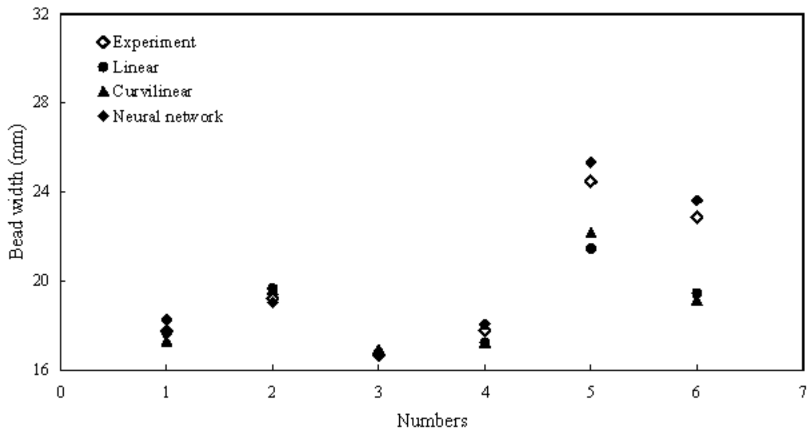

Fig. 2 Comparison of measured and calculated top-bead width using BP neural network and Lee's multiple regressions

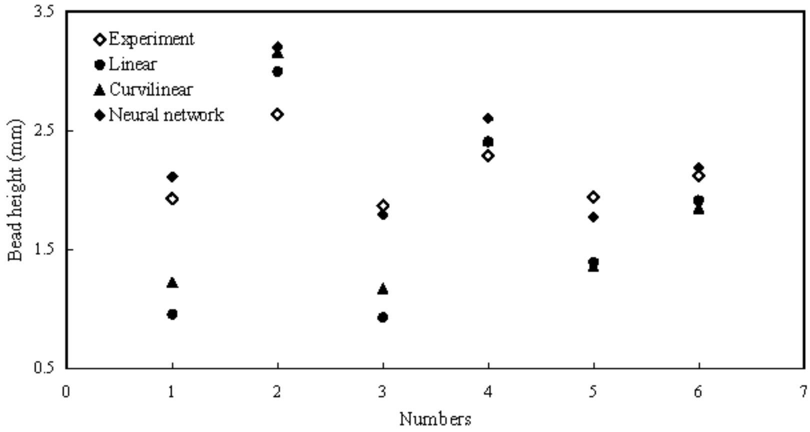

Fig. 3 Comparison of measured and calculated top-bead height using BP neural network and Lee's multiple regressions

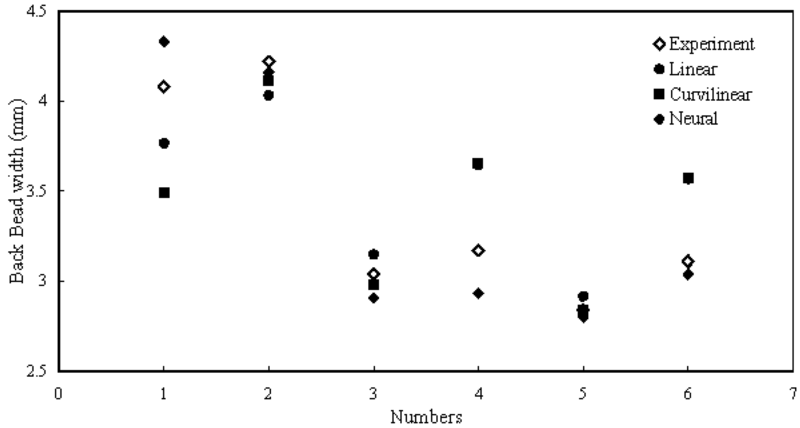

Fig. 4 Comparison of measured and calculated back-bead width using BP neural network and Lee's multiple regressions

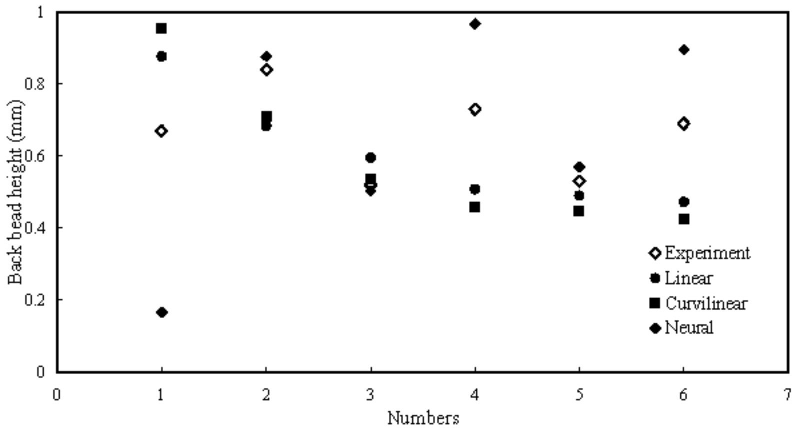

Fig. 5 Comparison of measured and calculated back-bead height using BP neural network and Lee's multiple regressions

5. Conclusions

In this paper, BP neural network is introduced to study the effects of process parameters on bead geometry such as top-bead width, top-bead height, back-bead width and back-bead height and model GMA welding process. The learning results for GMA welding process reveal that the developed model can be employed to conduct a systematic study on the efficient algorithm and control the process parameters in order to achieve the desired bead geometry. Also, the developed BP neural network is able to predict process parameters required to achieve desired bead geometry, and to establish guidelines and criteria for the most effective joint design. It is proposed that the developed BP neural network model is extended to shielding gas composition, weld joint position, polarity and many other parameters which are not included in this research.

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