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A Study on New Method for Control to Bead Width using Infrared Sensors

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Abstract— **Generally automatic welding process is applied for many manufacturing areas which included pressure vessel fabrication, production of offshore structures and the nuclear industry. More recently, products of piles and columns to support wind turbines have significantly been grown in importance. However, an intelligent algorithm that predicted the optimal bead geometry and accomplishes the desired mechanical properties of the weldment in the robotic GMA(Gas Metal Arc) welding should be developed. The algorithm should also cover a wide range of material thicknesses and be applicable for all welding position. In addition, the proposed model for the automatic welding system must be available in the form of mathematical equations. In this study, an intelligent model which employed the neural network algorithm, one of AI (Artificial Intelligence) technologies were developed to study the effects of welding parameters on bead width and predict the optimal bead width for lap joint in the robotic GMA welding. BP(Back-Propagation) and LM(Levenberg-Marquardt) neural network algorithm were used to develop the intelligent model. Not only the fitting of these models were checked and compared by using variance test, but also the prediction on bead width using the developed models were verified.**

Key Words—**GMA(Gas Metal Arc) Welding, BP(Back-Propagation) Neural Network, LM(Levenberg-Marquardt) Neural Network, Lap Joint Welding, Bead Geometry**

I. INTRODUCTION

The GMA welding process in which the welding electrode is melted and molten metals is transferred to the workpiece, is the technology for assembling metal structures included ships, cars, trains, pipelines and bridges. One of the important tasks in the robotic GMA welding process is to understand how welding parameters affect the bead geometry and subsequently develop the suitable models for predicting the desired outputs as welding quality. High weld quality by carefully choosing and closely controlling welding parameters may be made in all circumstances for arc welding process[1]. Many attempts[2-3] were made to understand and estimate the effect of welding parameters on the optimal bead geometry. These included theoretical studies, numerical analysis, empirical models and AI(Artificial Intelligence) technology for actual welding application.

In recent years, neural networks have become a very useful tool in the modeling of interrelationships between input and output variables of many complicated systems. With the development of computational technology, the neural networks appeared to constitute a workable model for predicting the bead geometry under given set of welding conditions according to the work done by Nagesh and Datta[4]. Vitek et al.[5] described the use of the neural network to predict weld pool shape as a function of welding parameters for a welding process and showed that a neural network model is a viable technique for predicting weld pool shape. Eguchi et al.[6] employed a neural network not only to achieve the good back-bead geometry, but also to estimate the wire extension and the arc length by using measurements of both welding voltage and arc current. Jeng et al.[7] predicted the laser butt welding parameters using a BP and a Learning Vector Quantization(LVQ) neural networks. They also insisted that both networks are very useful in selecting suitable welding parameters and help in avoiding inappropriate welding design. Srikanthan and Chandel[8] proposed the steps adopted to construct the neural network model in the GMA welding and evaluated the proposed neural network model. Kim and Jun[9] have used for a BP neural network to predict bead geometry in the GMA welding process and concluded that the proposed neural network estimator can predict bead geometry with reasonable accuracy. Li et al.[10] proposed a neural network for on-line prediction of quality in the GMA welding process. A neural network for shipbuilding in which the input parameters were the chemical elements and the weld cooling rate, while the responses were the yield and ultimate tensile strengths, elongation and reduction of area, were constructed[11]. Wu et al.[12] developed a real-time monitoring system for detecting abnormal conditions in robotic GMA welding on the butt weld. Through the statistical processing, it was found that the correct identify-cation rates for normal and abnormal welding conditions are 100% and 95%, respectively. In addition, bead geometry depended on the amount and distribution of the input energy on the workpiece surface and the dissipation of input energy in the workpiece[13]. In the GMA welding process, heat and mass inputs are coupled and transferred by

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the weld arc to the molten weld pool and by the molten metal which is being transferred to the weld pool. The amount and distribution of the input energy are basically controlled by the obvious and careful choices of welding parameters to accomplish the optimal bead geometry and the desired mechanical properties of the weldment[14]. To make effective use of the robotic GMA welding, it is imperative that the mathematical models are employed to predict bead geometry, applicable to all welding positions and covering a wide range of material thicknesses. Kim et al.[15] represented a new algorithm to establish a mathematical model with a neural network to understand relationships between welding parameters and top-bead width, and to predict welding parameters on top-bead width in the robotic GMA welding process. Using a series of the robotic GMA welding process, additional multi-pass butt welds were carried out to verify the performance of the neural network models as well as to select the most suitable model. Generally joint configurations for GMA welding process have classified square butt, edge butt, V-butt, T-butt, lap, multiple lap, T-lap, etc. Several researchers [16-17] done in joining of thick plates have mainly focused on the butt joint configurations. However, lap-joint welds are one of the most commonly used types of weld joints in the automotive industry and are often joined using continuous seam welds or resistance spot welds. Buffa et al.[16] investigated the welding parameters on the metallurgical and mechanical properties of friction stir welded lap joints for T4 aluminum alloy. More recently, Salari et al.[17] conducted the investigation of influence of tool geometry on the structural and mechanical properties of the lap joint of 5456 aluminum alloy and the result indicated that the stepped conical thread pin improved the joint mechanical properties by improving the material flow during FSW(Friction Stir Welding).

However, the study of prediction of welding parameters on the optimal bead width for lap joint welding in the robotic GMA welding process using neural network is not carried out. Consequently, the objective of this paper is to propose intelligent models for the lap joint in the robotic GMA welding process by neural network algorithm. Based on the experimental results, two neural network models which based on BP and LM neural networks have been developed for studying the effects of welding parameters on bead width as welding quality. These two neural network models are verified by data obtained from additional lap joint welds, and compared. Finally predictive behaviors and advantages of each model are discussed.

II. Experimental Works

Experiments were designed for developing the intelligent models to correlate independently controllable welding parameters. The experimental design provided the smallest number of treatment combinations with which the main effect of a factor and the interaction between the factors could be defined. Since the robotic GMA welding process was considered as a multi-parameter process, it's hard to find optimal parameters for good welding. According to previous studies[15], five welding parameters included welding voltage, arc current, welding speed, CTWD (Contact Tip to Work Distance) and welding angle were selected as the input parameters and the response was bead width to control welding quality in this research. Fig. 1 shows a schematic diagram for relationship between input and output parameters in the robotic GMA welding process.

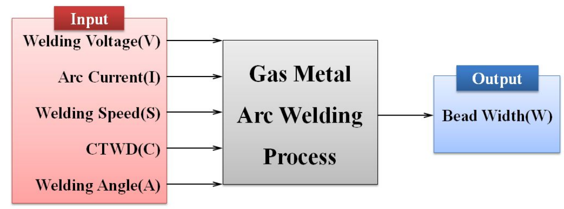

Fig. 1 A schematic diagram for relationship between input and output parameters

The concept of design of experiment to establish quantitative relationship between welding parameters and bead width was utilized. Therefore, welding parameters with two or three levels were employed, as shown in Table 1. Generally, the bead width, an important role in determining the optimal welding conditions, was employed to study the welding quality. A schematic view of bead width on a lap joint in the robotic GMA welding process was presented in Fig. 2. In this study, the bead width as welding quality was mainly considered.

Table 1 Welding parameters and their levels for study

Parameter	Symbol	Unit	Values
Welding Voltage	V	Volt	17, 19, 21
Arc Current	I	Amp	100, 130, 160
Welding Speed	S	mm/min	45, 50
CTWD	C	mm	12, 20
Welding Angle	A	°	55, 65

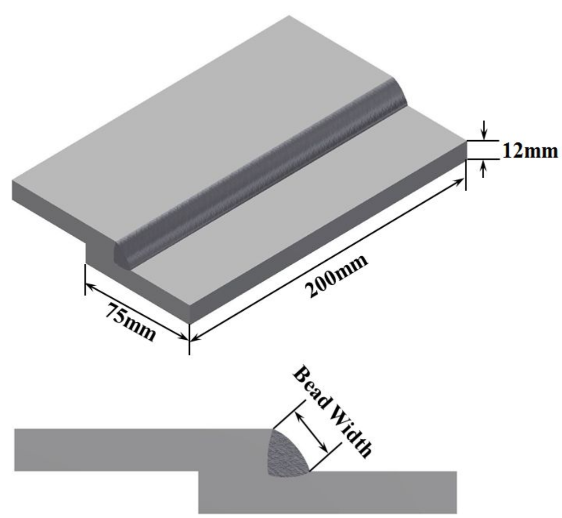

Fig. 2 A schematic diagram for measurement of bead width

Statistically designed experiments which were based upon full factorial techniques reduced costs and provided the required information about the main and interaction effects on the response factors [18]. All other parameters except these were fixed. The design matrix that had 72 experimental welding runs was employed where each row corresponds to one experimental run with two replications. The experimental data that included five process parameters on bead width were obtained by using a welding robot. In this study, the mean of these replications was considered output parameters to utilize the development of intelligent models. Fig. 3 shows a block diagram in the robotic GMA welding process for this study.

The 200x75x12mm AS 1204 mild steel and steel wire with a diameter of 1.2mm was employed for the experiment. In order to quantify the welding quality in the robotic GMA welding process, series of experiments were performed using different welding parameter. Data collection and evaluation were carried out using the robot welding facility. After 72 welds, the plates were cut using a power hacksaw and the end faces to measure the bead width were machined. Specimen end faces were polished and etched using a 2.5% nital solution to reveal grain boundaries and to display the bead width. An image analysis package called Image Analyst, manufactured in the United States by Automatix Inc., was employed to accurately measure bead width. The results of the experiment were employed on the basis of development of an intelligent model using two neural network algorithms in the robotic GMA welding process.

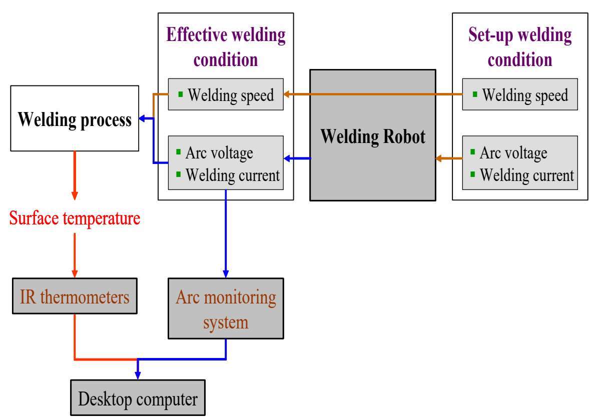

Fig. 3 Block diagram in the robotic GMA welding process for this study

III. RESULTS AND DISCUSSION

A. Development of BP Neural Network Model

GMA welding is a complex and of multiple interactions so that a mathematical and/or theoretical model for welding parameters on bead width has not been achieved. Therefore, the neural network to overcome this difficulty was employed in this research because it was noted as being particularly advantageous for modeling systems which contain noisy, fuzzy and uncertain elements while a sufficient algorithm was employed. The BP learning algorithm has been widely applied neural network model. Since the welding parameters of the robotic GMA welding process were inter-dependent and constantly in conflict in a complex way, a structure of feed-forward neural network was adapted to this work. A one-layer feed-forward network was constructed with five input neurons in the input layer and one neurons in the output layer to map the output parameters of bead width to five input parameters such as welding voltage, arc current, welding speed, CTWD and welding angle. The tangential sigmoid function was used as non-linear function of neuron, and BP neural network algorithm was used for this study as this algorithm could be provided a faster convergence than the gradient descent algorithm used in the other neural network.

The effectiveness and convergence of the BP learning algorithm depended significantly on the value of the learning constant which was strongly related to the class of the learning problem and the network architecture. In general, the optimal value of the learning constant would be decided only for the given problem, and there was no single learning-constant value suitable for the different training cases. Therefore, the value of the learning constant should be chosen experimentally by the trial and error approach. The choice of the hidden layer size was one of the most important considerations for the neural network design and this area of study was still under intensive research with no conclusive solutions available yet. The exact analysis of this issue was quite difficult due to the complexity of the network mapping and the non-deterministic nature of the many successfully completed training procedures. In this work, the number of neurons in the hidden layer was determined by the trial and error approach. Several attempts have been made to study the network performance with different numbers of neurons [7, 15]. The number of neurons within the hidden layer was selected based on the accuracy of the prediction. Modeling of the robotic GMA welding process with BP neural network algorithm was composed of two phases: training and testing of the neural networks with experimental results. A total of 72 data from the experimental results for the purpose of training were collected, and the chosen 8 data from the experimental results for the purpose of testing were taken. The schematic representation of the multi-layer neural network architecture employed in this research is shown in Fig. 4. In this research, a specific training algorithm was employed to train the developed BP neural network model, and the development architecture of the network was carried out on a PC using MATLAB. The effectiveness and convergence of the BP learning algorithm depended significantly on the value of the learning constant which was strongly related to the class of the learning problem and the network architecture. In general, the optimal value of the learning constant would be decided only for the given problem, and there was no single learning-constant value suitable for the different training cases. Therefore, the value of the learning constant should be chosen experimentally by the trial and error approach. The choice of the hidden layer size was one of the most important considerations for the neural network design and this area of study was still under intensive research with no conclusive solutions available yet. To get an effective neural network, a large amount of training examples were employed. By simulations of trails and errors, an optimal network configuration was found to have the best performance to predict bead geometry under given conditions. Results of the prediction by the optimal BP network configuration were listed on Table 2.

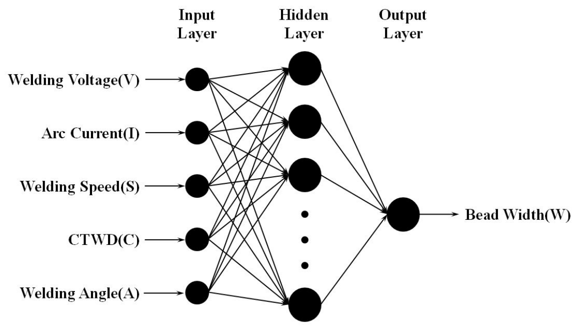

Fig. 4 Optimal BP neural network architecture for this study

Table 2 Experimental data to verify the developed model

Trial No.	V (Volt)	I (Amp)	S (mm/min)	C (mm)	A (°)	W (mm)
1	17	110	46	15	65	4.908
2	17	110	48	18	55	4.587
3	17	120	46	18	55	4.897
4	17	120	48	15	65	4.918
5	19	110	46	18	55	5.081
6	19	110	48	15	65	5.102
7	19	120	46	15	65	5.412
8	19	120	48	18	65	5.181

The measured and predicted bead widths with the optimal network configuration using the developed BP neural network model were calculated and represented in Fig. 5. According to Fig. 5, the dotted line represented the predicted bead width using the developed BP neural network model, and the solid line indicated the actual data obtained from robotic welding operation. It was observed that the calculated values obtained using the developed BP neural network model was approximately equal to those obtained by experimental results. The performance of the developed BP neural network model for predicting bead width is indicated in Fig 6. The maximum error was limited within 0.3mm as shown in Fig. 6. In the case of trail number 2, the predicted value was the most similar as the experimental one. In other words, these errors generated from the developed BP neural network model were reasonably small to be accepted in most cases of practical applications.

In order to statistically analysis the accuracy of the developed BP neural network, errors of the predicted results was calculated by

$$Error = y_i' - y_i \qquad (1)$$

Where y_i' are the predicted values of bead width, y_i represent the experimental ones and i is the serial number of testing data.

Fig. 7 presents the error of the predicted bead width using the developed BP neural network model. As shown in Fig. 7, it can also be observed that distributions of the predicted bead width were quite close to the best fit line so that the predicted results were reasonable reliable.

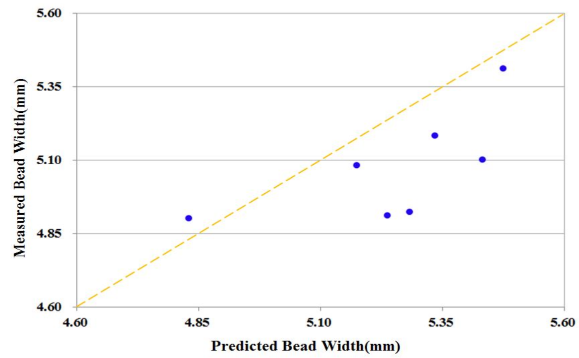

Fig. 5 Comparison between the measured and predicted bead width(BP)

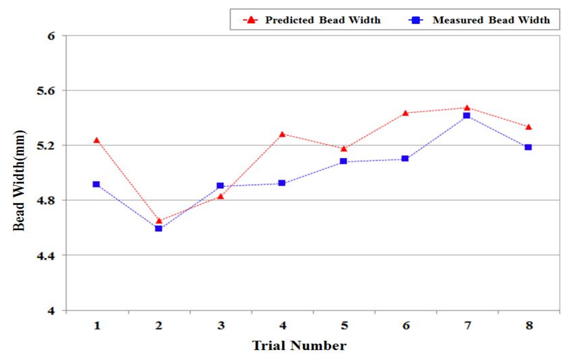

Fig. 6 Performance of the developed BP neural network model for predicting bead width

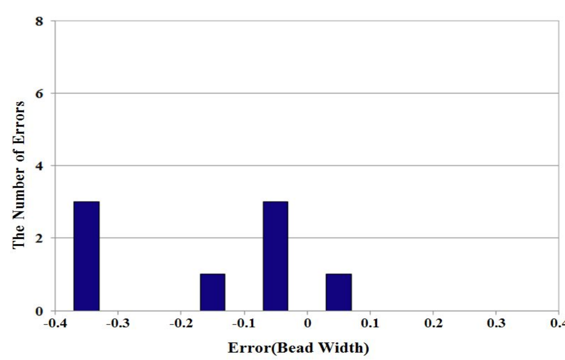

Fig. 7 The error of the predicted bead width using the developed BP neural network model

B. *Development of LM Neural Network Model*

The authors of the accepted manuscripts would be given a copyright form and the form should accompany your final submission. While the BP neural network algorithm was a steepest descent algorithm, the LM neural network algorithm was generally an approximation to Newton's method. The LM neural network algorithm was employed in this research to further improve the overall accuracy of the neural network because this algorithm could generally be provided a faster convergence than the gradient descent algorithm used in the BP neural network algorithm. The adjustment of weights and biases for the LM neural network algorithm were done according to transfer function:

$$\Delta W = (J^T J + \mu I)^{-1} J^T e \qquad (2)$$

Where $\boldsymbol{J}$ is Jacobian matrix of derivation of each error, $\boldsymbol{\mu}$ is a scalar and e is error function. The training process was continued until either the maximum number of epochs was completed or $\boldsymbol{\mu}$ reaches a maximum value. The variable $\boldsymbol{\mu}$ determined whether learning processes was according to Newton's method or by gradient descent. The parameters and their values of LM neural network for configuration setup are shown in Table 3.

Table 3 The parameters and their values of LM neural network

Parameters	Values
Goal Error	1e-08
Epochs	200
Transfer Function of Hidden Layer	Tan-Sigmoid Transfer Function
Transfer Function of Output Layer	Tan-Sigmoid Transfer Function
Number of Input Nodes	6
Number of Hidden Nodes	13
Number of Input Nodes	1

Comparison between the measured and predicted bead width using the developed LM neural network model is indicated in Fig 8. According to Fig. 8, the developed LM neural network model was similarly good performance as the developed BP neural network model. Performance of the developed LM neural network model for predicting bead width is represented in Fig. 9. Performance of the developed model was excellent at the prediction for the bead width as plotted in Fig. 9. It was observed that the calculated values obtained using developed LM neural network model was approximately coincided with the measured ones, and the maximum error was limited within 0.3mm. In the cases of trail number 2, 6, 7 and 8, the predicted value was almost the same as the experimental ones.

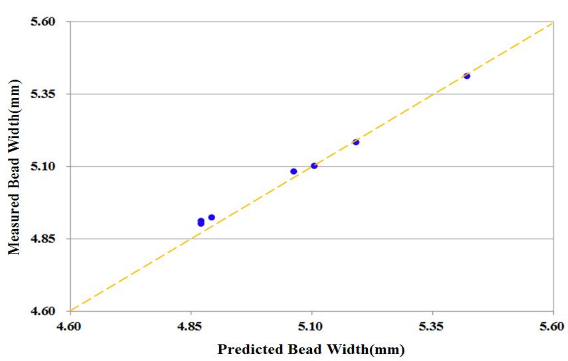

Fig. 8 Comparison between the measured and predicted bead width(LM)

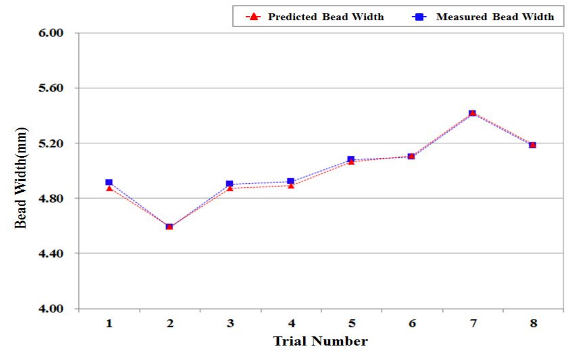

Fig. 9 Performance of the developed LM neural network model for predicting bead width

In other words, these errors generated from the developed LM neural network model were reasonably small to be accepted in most cases of practical applications. Fig. 10 presents the error of the predicted bead width with the developed LM neural network model. It can be seen that the error of the predicted bead width with the developed LM neural network model were closed into 3%.

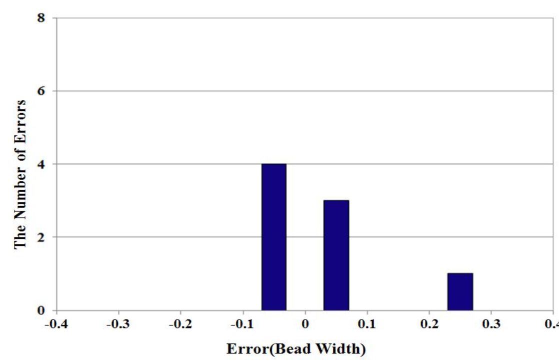

Fig. 10 The error of the predicted bead width with the developed LM neural network model

C. *Selection of Best Neural Network Model*

To select the most accurate neural network model for prediction of bead width in the robotic GMA welding process, the 8 additional experimental data for testing were employed. The convergence criterion for the developed neural network models was determined by the average RMS error between the desired output value y_i and predicted output value y_i' for the prediction, i.e.:

$$E_{RMS} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_i')^2} \qquad (3)$$

The results of the performance between the developed BP and the developed LM neural network models were plotted in Fig. 11. According to Fig. 11, the calculated values obtained using the developed LM neural network model was universally lower than those by the developed BP neural network model. However, it was shown that the amount of the errors generated from the developed BP neural network model was still reasonably small to be accepted in most cases of practical applications.

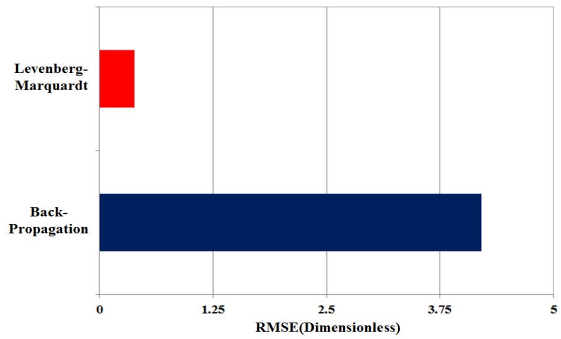

Fig. 11 Comparison between the developed BP and the developed LM neural network models

To compare the precision of two developed neural network models, PAM(Predictive Ability of Model) [20], standard deviation and average error for bead width using the two developed neural network model were performed and presented in Table 4. The two developed neural network models were predicted very accurately. In the bead width, the developed LM neural network model did achieve 100% in PAM. Compared with the developed BP neural network model the developed LM neural network was significantly improved accuracy. In the comparison of standard deviation and average error, the predicted bead width showed the most concentrated distribution. As shown in Table 4, the developed LM neural network had a predictive ability that was superior to the developed BP neural network. Therefore, it can be concluded that the use of LM neural network algorithm was able to predict bead width for given welding conditions and was capable of modeling of non-linear problem such as welding process.

Table 4 Performance of the developed neural network models

	The Developed LM Model	The Developed BP Model
PAM(%)	100	62.5
Standard Deviation	0.385	4.204
Average Error	0.184	0.017

IV. Conclusions

The two neural network models to predict optimal welding parameters on the required weld width in lap joint for the robotic GMA welding process was developed. To establish the relationships between the welding process parameters and bead width as welding quality, experiments were carried out to gather the data (as per full-factorial design) on bead width. Experimental results were employed to find the optimal algorithm to predict the optimal bead width by BP and LM neural networks in lap joint in the robotic GMA welding process. The developed neural network models by BP and LM algorithms were trained with data collected from the experiment. After cycles of a training process, optimal algorithms that predicted bead width in the robotic GMA welding process were proposed. Analyses on the predicted results were made comparing to the target value generated from additional experiment. Both of them were proved to be capable to predict bead width within an acceptable range of error. However the developed LM neural network model could be provided better accuracy of predictions and was more effective than the developed BP neural network model.

The developed neural network models are able to predict the optimal welding parameters on the desired bead width and weld criteria, help the development of automatic control system and expert system and establish guidelines and criteria for the most effective joint design.

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