International Journal of Applied Engineering Research ISSN 0973-4562 Volume 12, Number 13 (2017) pp. 3631-3638
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A Study on Modeling and Controlling Bead Height in the Robotic GMA Welding

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Abstract

Welding, one of the most common joining processes in the metal industries was applied for facilities from job shop outfits to highly-automated computer-controlled factories. More recently, products of piles and columns to support wind turbines has grown significantly in importance. However, an intelligent algorithm that predicts bead geometry and accomplishes the desired mechanical properties of the weldment in the automated 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, one of AI (Artificial Intelligence) technologies has been developed to study the effects of welding parameters on bead height and predict bead height for lab joint in the robotic GMA welding process. BP (Back Propagation) and LM (Levenberg-Marquardt) neural network algorithm have been used to develop the intelligent model. Not only the fitting of these models have been checked and compared by using variance test, but also the prediction on bead height using the developed models have been verified.

Keywords: GMA(Gas Metal Arc) welding process, BP(Back Propagation)neural network, LM(Levenberg-Marquardt) algorithm, Lab joint, Bead height

INTRODUCTION

The GMA welding process, sometimes called Metal Inert Gas (MIG) welding, is a welding process that yields coalescence of metals by heating with a welding arc between a continuous filler metal (consumable) electrode and the workpiece. One of the important tasks in the robotic GMA welding process is to understand how process parameters affect the bead geometry and subsequently develop the suitable models for predicting the desired outputs as welding quality. High quality welds by carefully choosing and closely controlling welding parameters may be made in all circumstances for arc welding process [1].

Many attempts have been made to understand and estimate the effect of process parameters on the optimal bead geometry. These include theoretical studies, numerical analysis, empirical models and AI (Artificial Intelligence) technology for actual welding application [2-3]. 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 appear 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] has proposed a neural network for on-line prediction of quality in 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 are the yield and ultimate tensile strengths, elongation and reduction of area has been 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 identification rates for normal and abnormal welding conditions are 100% and 95%, respectively.

Bead geometry depends on the amount and distribution of the input energy on the workpiece surface and the dissipation of input energy in the workpiece[13]. In GMA welding process, heat and mass inputs are coupled and transferred by 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 in order to accomplish the optimal bead geometry and the desired mechanical properties of the weldment[14]. To make effective use of the automated and robotic GMA welding, it is imperative that the mathematical models are used 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 for predicting top-bead width through 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 robotic GMA welding, additional multi-pass butt welds were carried out in order 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 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 bead height for lab joint welding using neural network is not carried out. Consequently, the objective of this paper is to propose intelligent models for the lab joint in the robotic GMA welding process by neural network algorithm. Two neural network models which based on BP and LM neural networks have been developed for studying the effects of process parameters on bead height as welding quality. Not only the fitting of these models has been checked and compared by using variance test, but also the prediction on bead height with the additional experiments using the developed models has been carried out.

EXPERIMENTAL WORKS

Experiments were designed for developing the intelligent models to correlate independently controllable welding parameters. The experiment provides the smallest number of treatment combinations with which the main effect of a factor and the interaction between the factors can be defined. Since the robotic GMA welding process is considered as a multi-parameter process, it's hard to find optimal parameters for good welding. According to previous studies, 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 height 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.

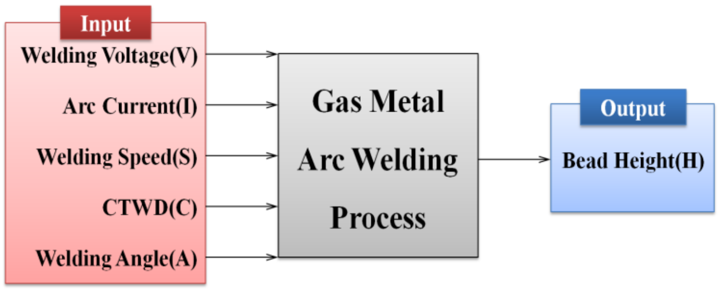

Figure 1: A schematic diagram for relationship between input and output parameters

The concept of design of experiment to establish quantitative relationship between welding parameters and bead height was utilized. Therefore, welding parameters with two levels were employed, as shown in Table 1. Generally, the bead height, an important role in determining the optimal welding conditions, is employed to study the welding quality. A schematic view of bead height on a lap joint in the robotic GMA welding process was presented in Fig. 2. In this study, the bead height 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*	º	55, 65

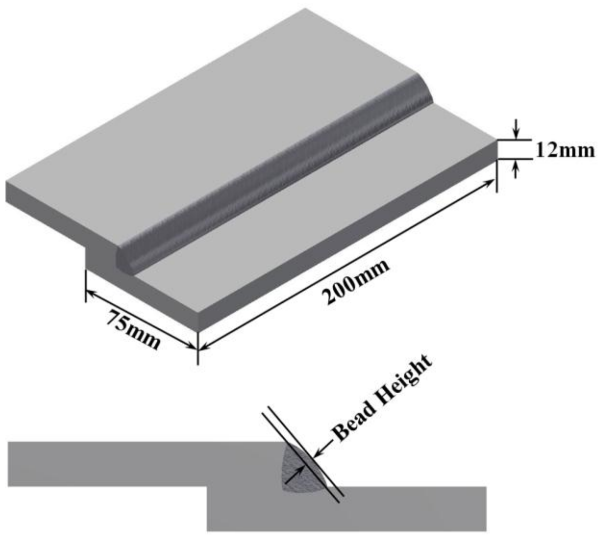

Figure 2: A schematic diagram for measurement of bead height

Statistically designed experiments that are based upon full factorial techniques, reduce costs and provide the required information about the main and interaction effects on the response factors. All other parameters except these were fixed. The experimental data that included five process parameters on bead height were obtained by using a welding robot. The design matrix that has 72 experimental welding runs was employed where each row corresponds to one experimental run with two replications. 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.

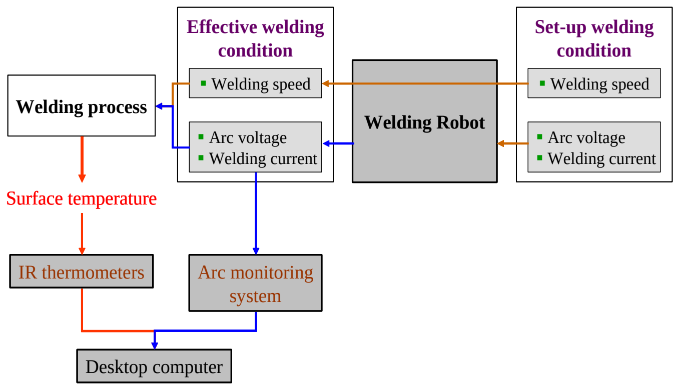

Figure 3: Block diagram in the robotic GMA welding process for this study

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 has been 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 height were machined. Specimen end faces were polished and etched using a 2.5% nital solution to reveal grain boundaries and to display the bead height. An image analysis package called Image Analyst, manufactured in the United States by Automatix Inc., was employed to accurately measure bead height. 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.

RESULTS AND DISCUSSION

Development of BP neural network model :

GMA welding is complex and of multiple interactions so that a mathematical and/or theoretical for welding parameters on bead height has not been achieved. Therefore, the neural network to overcome this difficulty was employed in this research because it has been noted as being particularly advantageous for modeling systems which contain noisy, fuzzy and uncertain elements while a sufficient algorithm is employed.

BP learning algorithm is the most widely applied neural network model. Since the welding parameters of the robotic GMA welding process are inter-dependent and constantly in conflict in a complex way, a structure of feed-forward neural network is adapted to this work. A one-layer feed-forward network is constructed with five input neurons in the input layer and one neurons in the output layer to map the output parameters of bead height to five input parameters of welding voltage, arc current, welding speed, CTWD, and welding angle. The tangential sigmoid function is employed as non-linear function of neuron, and BP neural network algorithm is employed as this algorithm could generally provide a faster convergence than the gradient descent algorithm used in the other neural network.

The effectiveness and convergence of the BP learning algorithm depends significantly on the value of the learning constant which is strongly related to the class of the learning problem and the network architecture. In general, the optimal value of the learning constant will be decided only for the given problem, and there is no single learning-constant value suitable for the different training cases. Therefore, the value of the learning constant has to be chosen experimentally by the trial and error approach. The choice of the hidden layer size is one of the most important considerations for the neural network design. The exact analysis of this issue is 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 is determined by the trial and error approach. Several attempts have been made to study the network performance with different numbers of neurons. The number of neurons within the hidden layer is selected based on the accuracy of the prediction.

Modeling of the GMA welding process with BP neural network algorithm is composed of two phases: training and testing of the neural networks with experimental welding data. A total of 72 data from the experimental results for the purpose of training were collected, and 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 has been employed to train the developed BP neural network model, and the development architecture of the network is carried out on a Pentium PC using MATLAB.

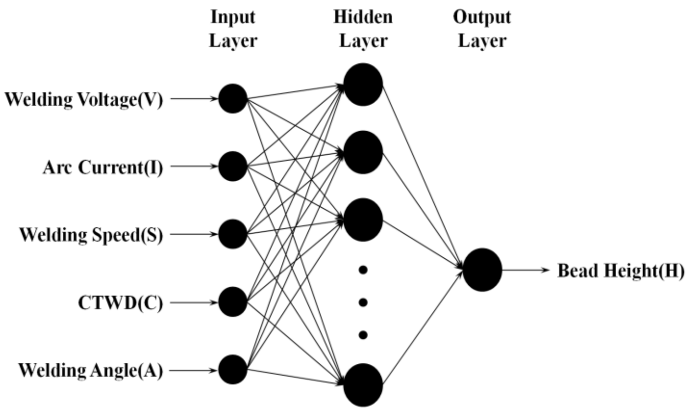

Figure 4: Optimal BP neural network architecture for this study

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.

Table 2: Experimental data to verify the developed model

Trial No.	V (Volt)	I (Amp)	S (mm/min)	C (mm)	A (°)	H (mm)
1	17	110	46	15	65	1.59
2	17	110	48	18	55	1.23
3	17	120	46	18	55	1.54
4	17	120	48	15	65	1.49
5	19	110	46	18	55	1.31
6	19	110	48	15	65	1.26
7	19	120	46	15	65	1.57
8	19	120	48	18	65	1.25

The measured and predicted bead heights 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 height 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 height is indicated in Fig 6. The maximum error was limited within 0.26mm 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

$$\text{Error} = y_i' - y_i \qquad (1)$$

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

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

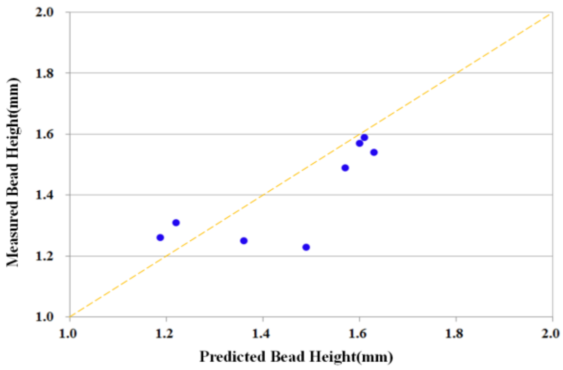

Figure 5: Comparison between measured and predicted bead height

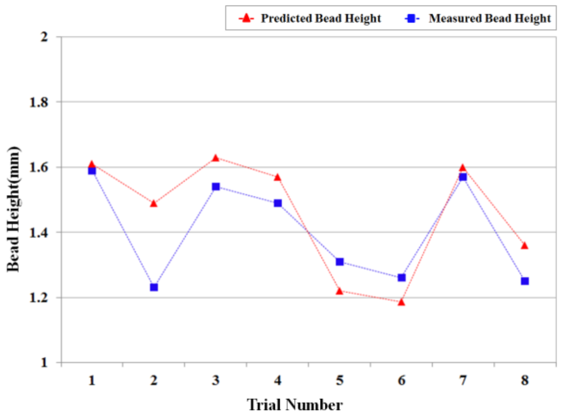

Figure 6: Performance of the developed BP neural network model for predicting bead height

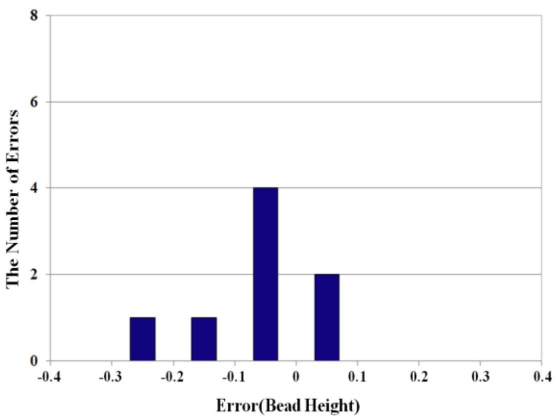

Figure 7: The error of the predicted bead height using the developed BP neural network model

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:

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

Where $\boldsymbol{J}$ is Jacobian matrix of derivation of each error, μ is a scalar and e is error function. The training process was continued until either the maximum number of epochs was completed or μ reaches a maximum value. The variable μ 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-8
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

Fig 8 showed comparisons between measured and predicted bead height using the developed LM neural network model. It was observed that the calculated values obtained using the developed LM neural network model was approximately equal to those obtained by the experiment. Performance of the developed LM neural network model for predicting bead height is represented in Fig. 9. According to Fig. 9, the maximum error was limited within 0.07mm. In the case of trail number 4, 8 the predicted values were the same as the experimental results. . 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. It can be indicated that 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 height with the developed LM neural network model. According to Fig. 10, the error of the predicted bead height with the developed LM neural network model increased along with the error increasing when the error was lower than 0. It can also be observed that distributions of predicted bead height were quite close to the best fit line, indicated that the predicted results from the developed LM neural network model were reasonable reliable. Therefore, it can be concluded that the use of the developed LM neural network model was able to predict bead height for lab joint for a given welding conditions.

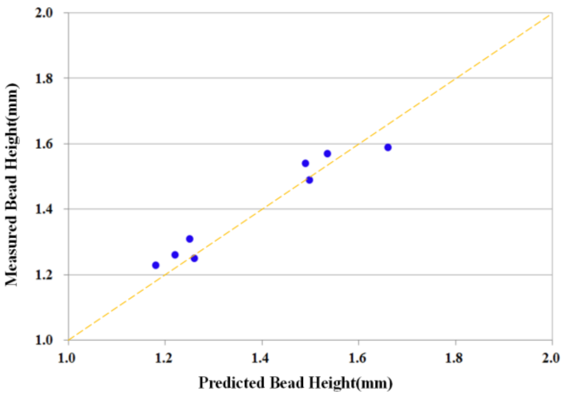

Figure 8: Comparison between measured and predicted bead height using developed LM neural network model

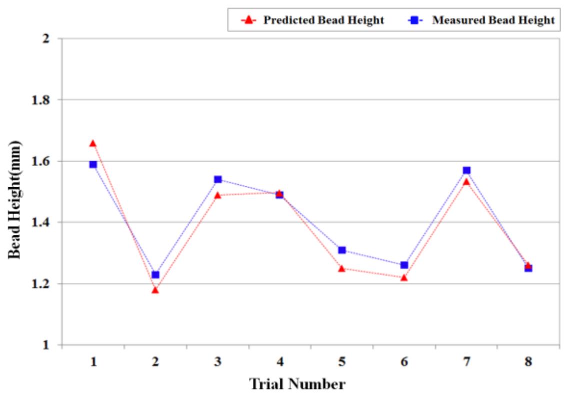

Figure 9: Performance of the developed LM neural network model for predicting bead height

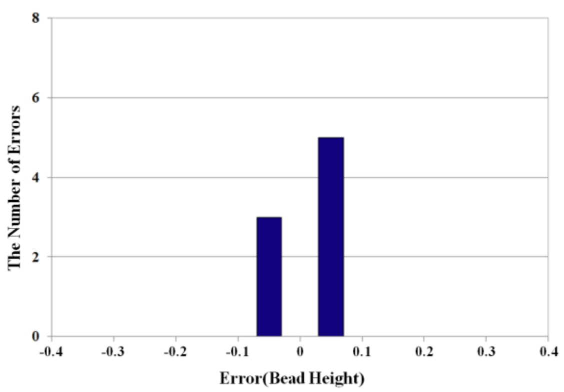

Figure 10: The error of the predicted bead height with developed LM neural network model

Selection of the best neural network model :

To select the most accurate neural network model for prediction of bead height 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.:

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

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.

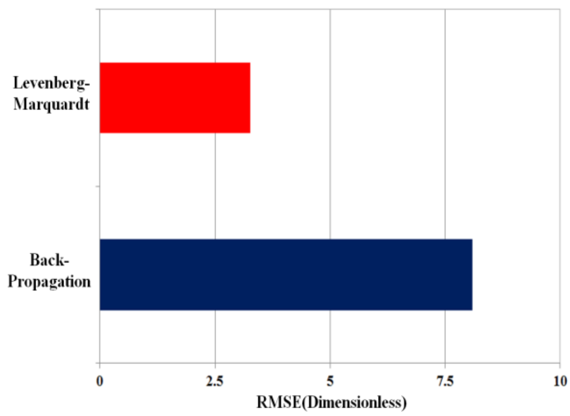

Figure 11: Comparison between the developed BP and he developed LM neural network models

To compare the precision of two developed neural network models, PAM(Predictive Ability of Model)[18], standard deviation and average error for bead height 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 height, 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 height 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 height for given welding conditions and was capable of modeling of non-linear problem such as welding process.

Table 4: Performance of the two developed neural network models

	The developed LM model	The developed BP model
PAM(%)	100	25
Standard deviation	3.26	8.09
Average error	0.040	0.094

CONCLUSIONS

The neural network models to predict optimal welding parameters on the required weld height in lab joint in the robotic GMA welding process has been developed. To establish the relationships between the welding process parameters and bead height as welding quality, experiments were carried out to gather the data (as per full-factorial design) related to bead height. Experimental results have been employed to find the optimal algorithm to predict bead height by BP and LM neural networks in lab joint in the robotic GMA welding. 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 predict bead height 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 height within an acceptable range of error. However the developed LM neural network model can provide 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 height and weld criteria, help the development of automatic control system and expert system and establish guidelines and criteria for the most effective joint design.

ACKNOWLEDGMENT

This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (No.2015R1D1A 3A01020246).

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