Estimation of Weld Bead Geometry of Gas Metal Arc Welding Process Using Artificial Neural Network

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ABSTRACT

A single weld bead geometry has significant effects on the mechanical properties of the bead, layer thickness, quality of surface bead and dimensional accuracy of the metallic parts of the welding. This research presents the application of an artificial intelligence approach using artificial neural network (ANN) and conventional multiple regression analysis for predicting the weld bead geometry in gas metal arc welding (GMAW) in which galvanized steel was the material used for the experiment. The developed models for the study were based on the experimental data. The welding voltage, welding current, welding speed and wire feed rate have been considered as the input parameters and the bead width (W) and height (H) are the output parameters in developing the models. In order to demonstrate which method performs better in terms of higher accuracy and prediction, three performance measures related to the coefficient of determination (R^2), root mean square error (RMSE) and mean absolute percentage error (MAPE) were applied to the models and later compared. The results from the analysis show that the ANN models are more accurate compared to multiple regression approach in predicting the weld bead geometry due to its great capacity in approximating the non-linear process of the system.

Keywords: *Artificial neural network, multiple regression, metal arc welding, weld bead geometry*

1.0 INTRODUCTION

Gas metal arc welding (GMAW) is one of the important manufacturing processes in many industries that requires the metal joining operations. GMAW is a process of molten metal and the heat affected zone are protected from contamination of the inert gas. The research on controlling the GMAW metal transfer modes is essential to highlight the high quality welding procedure. The GMAW welding input parameters are deemed the most significant factors affecting the cost, productivity and quality of the welded joint. Weld bead size and shape are regarded as the crucial factors to be considered for the design and manufacturing engineers involved in the fabrication industry.

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The GMAW, also known as metal inert gas (MIG) welding is one of the most widely used techniques for joining processes in various industries since it produces high quality welded joints, welds metal quickly, is highly economical and covers a wide variety of weldable metals. GMAW process uses a consumable wire electrode and the shielding is accomplished by flooding the arc with gases such as carbon dioxide and argon. The process can be done manually or automatically depending on the production process. Manufacturing engineers are often faced with the problems of process optimization, particularly the typical multiple response optimization in the GMAW process [1]. It is very hard to control the input process parameters to obtain a good welded joint with the required weld quality [2]. The quality of the joint in GMAW is mainly determined by the weld bead geometry and the presence of various welding defects. The single weld bead geometry plays a major role in the determination of the surface smoothness, layer thickness and dimensional accuracy of the deposited parts [3].

Bead geometry consists of several variables, for this study, only two significant variables were used for the analysis with reference to the bead width (*W*) and height (*H*) [4]. These two variables are greatly influenced by the welding process parameters such as welding voltage, welding current, welding speed, and wire feed rate. Weld bead shape and size are represented by *W* and *H* as shown in Figure 1.

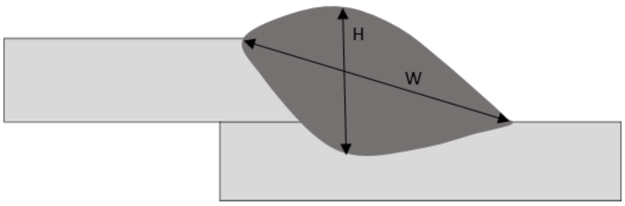

Figure 1: Weld bead geometry

Weld predictive modeling and optimization are essential for acquiring the knowledge on the mechanics of the weld processes and how they can be best controlled and used [5, 6]. However, the welding processes are found to be non-linear and created a highly coupled multivariable system. The problems of determining the weld quality are difficult because the welding process itself is a complex stochastic phenomenon characterized by a lack of analytic mathematical description, non-stationary, intolerance to control and irreproducibility of the measurements [7]. In recent years, many methods can be used to relate the relationship between the process variables and responses, such as factorial design, linear regression, second-order regression, *Taguchi* method, and artificial neural network. However, the accuracy of the linear regression method for predicting responses is not adequate [8]. *Taguchi* method cannot lead to an optimal solution while the factorial design method needs a large set of experiments. Thus, a more efficient method is needed for the analysis to determine the optimum welding process parameters. In this study, artificial neural network (ANN) and multiple regression methods, were proposed with the former in particular, is expected to provide an effective means or as a powerful tool in developing the models of the welding process. The ANN exhibits a great capacity to perform non-linear and multivariable mappings [9]. Furthermore, ANN approach can accurately represent complicated relationships for a multiple input and multiple output (MIMO) system that in turn can help resolving the prediction problems.

2.0 MATERIALS AND EXPERIMENTAL PROCEDURE

Firstly, during the experiments, a *Fronius* make welding machine (TPS4000) was used as a power source to execute the welding process. A powerful computer (PC) with a good monitoring display has been used in this experiment to control the process of welding in good condition. The electrode that was used in this experiment is made from carbon steel solid wire with a diameter of 1.2 mm. The shielding gas setting is a mixture containing 20% carbon dioxide and 80% argon. The material used for the base metal specimen is galvanized steel sheet or plate with a dimension of 130 mm × 100 mm × 2.3 mm. A lap joint method for the sample is used in this experiment with the dimension of the sample shown in Figure 2.

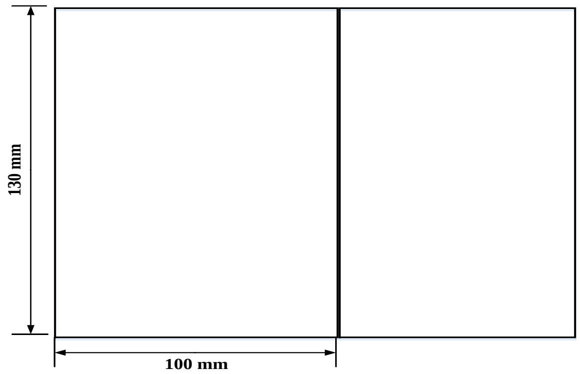

Figure 2: Dimension of the sample specimen

Four independently input process parameters were used for the experiment, namely, the welding voltage, welding current, welding speed and wire feed rate. Meanwhile, the chosen output responses are the bead width (*W*) and height (*H*). In order to run the analysis for determining the optimum welding process in this experiment, it is imperative to select a good welding setting condition for the independent variables. The welding condition for each input significant parameter is shown in Table 1. From the table, it is presumed that the proposed setting of the welding conditions to ensure the optimum condition of welding process can be achieved.

Table 1: Welding conditions for the input parameters

Parameters	Symbol	Welding Condition
Welding current (A)	X_1	88 – 168
Welding voltage (V)	X_2	12 – 18
Wire feed rate (m/min)	X_3	2/2.5/3/3.5
Welding speed (cm/min)	X_4	80/100 /120

3.0 RESULTS AND DISCUSSION

3.1 Data Collection

All the specimens have undergone several processes such as cutting, grinding, polishing, etching and the desired weld bead geometry was measured by using a microscope. Each specimen shows different values of measurement. The results from the experiment were recorded as shown in Table 2. The data set was selected based on 70% of the total observation for the training data, 15% for testing and another 15% for validation. These three data were used in the analysis in which the training data has been utilized to develop the mathematical modeling equation. The data was processed through a standard process by subtracting the mean and dividing it by the standard deviation. The purpose is to reduce multi-collinearity issues for the model. Regression with multiple explanatory variables in different units need to be standardized to ensure that each welding parameter has identical effect on the network [10]. By standardizing the data, the analysis is expected to produce better result.

Table 2: Welding condition input parameters

Run	Welding current, X_1 (A)	Welding voltage X_2 (V)	Wire feed rate, X_3 (m/min)	Welding speed, X_4 (cm/min)	Bead width, W (mm)	Bead height, H (mm)
1	94.19	15.80	2.0	80	4.26	1.82
2	119.21	16.51	2.5	80	5.20	2.10
3	133.61	17.02	3.0	80	5.70	2.62
4	157.55	17.54	3.5	80	6.45	2.99
5	91.81	16.22	2.0	100	4.13	1.61
6	123.92	16.37	2.5	100	4.90	1.71
7	149.08	16.48	3.0	100	5.03	1.95
8	166.57	17.13	3.5	100	5.63	2.54
9	88.37	16.04	2.0	120	3.43	1.34
10	118.22	16.61	2.5	120	4.11	1.49
11	140.25	16.82	3.0	120	4.67	1.68
12	164.81	17.21	3.5	120	5.17	1.8
13	97.02	15.73	2.0	80	3.92	1.85
14	124.12	15.96	2.5	80	4.76	1.81
15	144.01	16.23	3.0	80	5.31	2.99
16	162.70	16.94	3.5	80	5.99	3.13
17	95.54	15.83	2.0	100	3.65	1.59
18	125.67	15.97	2.5	100	4.53	1.85
19	148.36	16.47	3.0	100	5.08	2.61
20	162.90	16.91	3.5	100	5.58	2.79
21	91.63	16.15	2.0	120	3.36	1.53
22	122.09	16.11	2.5	120	4.09	1.66
23	145.68	16.62	3.0	120	4.71	1.74
24	167.42	16.64	3.5	120	4.98	1.89
25	121.0	12.54	2.0	80	2.93	2.02
26	129.59	13.86	2.5	80	3.84	2.06
27	142.14	15.13	3.0	80	4.16	2.52
28	160.31	15.21	3.5	80	4.34	2.48
29	110.67	15.10	2.0	100	2.40	1.95
30	127.43	13.73	2.5	100	3.42	1.83
31	142.61	14.90	3.0	100	3.31	1.65
32	158.31	15.42	3.5	100	4.18	1.78
33	118.20	12.75	2.0	120	3.08	1.74
34	134.46	13.60	2.5	120	3.44	1.58
35	143.56	14.78	3.0	120	4.37	1.89
36	151.78	15.54	3.5	120	4.55	2.20

3.2 Multiple Regression Analysis

Generally, conventional regression models can be divided into linear and non-linear regression. In this study, multiple regression model was applied to establish the relationship between the process variables and bead geometry [11]. The purpose of linear regression was to find a value for the slope and intercept of the line. The response function representing any of the controllable process parameters can be expressed as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3, \ldots, + \beta_k X_k \tag{1}$$

where Y is the response related to the bead width (W) and height (H), X_1 is the welding current [A], X_2 is the welding voltage [V], X_3 is the wire feed rate [m/min] and X_4 is the welding speed [cm/min].

A full entry selection method has been used for the analysis by using the SPSS software. By using this method, all independent variables were entered in a single step without removing any variables in the developed equations. The values of the regression coefficients were calculated using the experimental data. Table 3 shows the model summary for both responses.

Table 3: Model summary of multiple regression

Response	**Unstandardized**					**R^2**	**Standard error of the estimate**
	Constant	X_1	X_2	X_3	X_4		
Bead width, W	-5.414	0.029	0.560	-0.560	-0.014	0.905	0.4596
Bead height, H	0.929	0.020	0.088	-0.406	-0.018	0.843	0.2868

Thus, the full enter regression approach resulted in the following predictive equation:

$$W = -5.414 + 0.029(X_1) + 0.560(X_2) - 0.560(X_3) - 0.014(X_4) \tag{2}$$

$$H = 0.929 + 0.020(X_1) + 0.088(X_2) - 0.406(X_3) - 0.018(X_4) \tag{3}$$

3.3 Neural Network Analysis

In this study, the development and the training of the network is performed by using MATLAB software. There are two ANN models that were used in the study to predict the performance, i.e., the feedforward backpropagation NN and cascade backpropagation NN. The former moves in only one direction, forward, from the input nodes, through the hidden nodes and to output nodes as shown in the Figure 3. No cycles or loops in the network. Meanwhile, for the latter, it’s architecture is basically similar to the feedforward type but it also includes a connection from the input and every previous layer to the following layers as shown in the Figure 4.

The performance of a NN has an important bearing based on the number of hidden layers and neurons in every layer. In general, a network with one hidden layer can approximate any non-linear mappings. Thus, determining the number of neurons in the hidden layer is an important tuning process. Excessive hidden neurons result in overfitting and increasing the computational costs. On the contrary, too few hidden neurons can degrade the learning ability of the network and its approximation performance since it is regarded as undertrained.

In this analysis, the transfer function used for the hidden neurons for both methods was a logistic sigmoid function while a linear function was used for the output neurons. The number of neurons in the hidden layer was varied from 4 to 15. Different structures of the NN are trained until a minimum error margin was achieved. The performance function is the root mean square error (RMSE) minimization by updating the weights through the gradient descent approach. The best architecture based on the input layer-hidden layer-output layer (x-y-z) configuration was determined in the analysis considering the minimum RMSE. For the feedforward backpropagation NN; it was 4-9-2 while for the cascade backpropagation NN, it was 4-11-2.

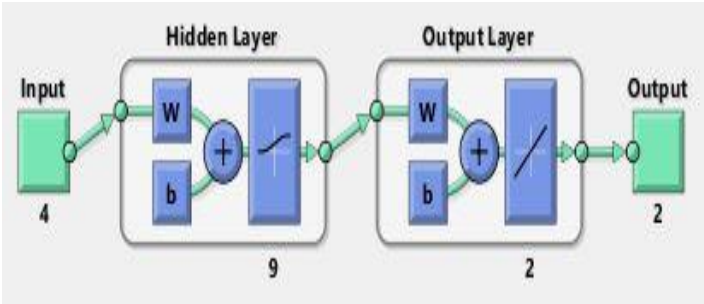

Figure 3: A schematic diagram of a feedforward backpropagation neural network

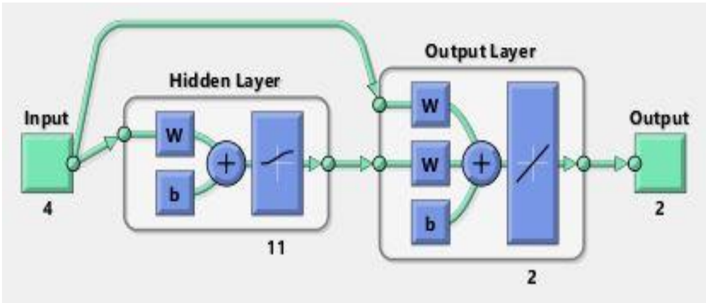

Figure 4: A schematic diagram of a cascade backpropagation neural network

3.4 Data Collection

The model prediction performance is evaluated by using the, coefficient of determination, R^2, root mean square error (RMSE) of the maximum residual error and mean absolute percentage error (MAPE) as shown in Table 4. For R^2, it is found that the closer it is to 1, the better the fit of the regression line. For RMSE, it is frequently used to measure the differences between the predicted and actual values. It measures the error between the data sets. Next, for the MAPE, it is explained as a measure of the prediction accuracy of a forecasting method in statistics. It usually expresses the accuracy in percentage. The performance of the suggested models is formulated from each of the regression model and NN experimental data.

Table 4: Model prediction performance

Model	Bead Width (*W*)			Bead Height (*H*)		
	R^2	RMSE	MAPE (%)	R^2	RMSE	MAPE (%)
Multiple Regression	0.8194	0.4596	7.78	0.7113	0.2868	10.89
Feedforward NN	0.9887	0.1076	1.93	0.9422	0.1206	3.92
Cascade forward NN	0.9918	0.0764	1.22	0.9537	0.0850	1.96

From the results, the analysis and comparison were made on the performance of the three developed models, i.e., the multiple regression, feedforward backpropagation NN and cascade forward backpropagation NN. Table 4 shows that both the NN models show better performance compared to the multiple regression due to its great capacity in approximating the non-linear process. The feedforward and cascade forward backpropagation NNs show a small difference for predicting both responses. The cascade forward backpropagation NN is deemed the best performance prediction model with a very low standard error of estimation, namely, 0.0764 and 0.0850 for the *W* and *H*, respectively. Further, the model also exhibits the best results - R^2 value of 0.9918 and MAPE of 1.22% for the bead width and 0.9537 (for R^2) and 1.96% (MAPE) for bead height compared to the multiple regression and feedforward backpropagation neural network approaches. Note that apart from the lower errors in RMSE and MAPE achieved by the cascade forward backpropagation model, it presents the highest R^2 (closer to 1) which is deemed better than its two counterparts.

Thus, the cascade forward backpropagation NN model was subsequently chosen and benchmarked with the multiple regression technique. In Figures 5 and 6, it can be clearly seen from the graphs that the distribution range of the evaluated data is quite comparable and located close to the actual values of the welded *W* (with a range of 2.3 to 6.3 mm) and *H* (with a range of 1.1 to 3.2 mm) for both models.

Figure 5: Comparison of measured and calculated bead width

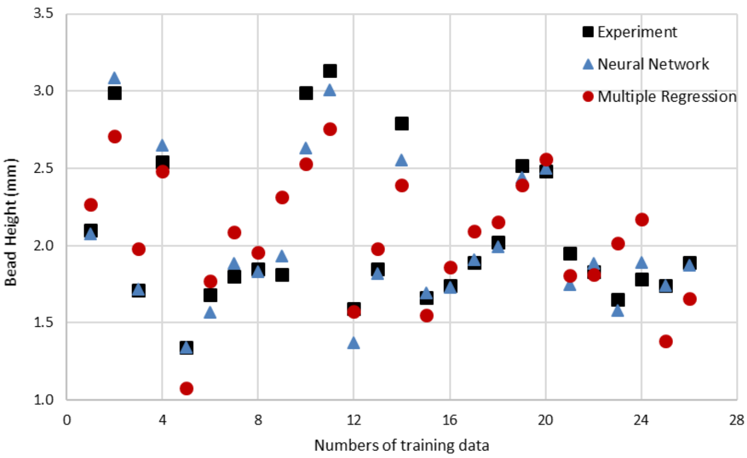

Figure 6: Comparison of measured and calculated bead height

4.0 CONCLUSION

The prediction model of the galvanized steel based gas metal arc welding (GMAW) process was successfully modeled and optimized by using multiple regression and artificial neural network (ANN) approach based on the four selected parameters to predict the weld bead geometry. The results demonstrate that not only the proposed models can predict the bead width (*W*) and height (*H*) with reasonable accuracy, but also the ANN model show better performance than the multiple regression counterpart due to its excellent capability in approximating the non-linear process. The ANN model has also been developed to resolve the prediction problems as it has the capability for learning and adaptation by adjusting the interconnections between the layers. Thus, it can be concluded that for the ANN developed models, the cascade backpropagation model is deemed better than the feedforward type in predicting the estimated *W* and *H*. Thus, the NN approach has been demonstrated to be effective in predicting the welding strength as a measured quality, thereby confirming its suitability as an alternative predictive method in the GMAW process.

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