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Research Article

Comparing the Regression Analysis and Artificial Neural Network in Modeling the Submerged Arc Welding (SAW) Process

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Abstract: Complexities of submerged arc welding variables on the one hand and its widespread use in producing the sensitive and expensive parts on the other hand have doubled the importance of precise control of its adjusting parameters. In general, in order to create high-quality joints in welding processes it is necessary to control three parameters of welding current, voltage and speed precisely from various variables. On this basis, the mentioned variables have been considered as the criteria for quality of the weld joints in this study as the adjusting parameters and weld bead geometry, which include the bead height, width and penetration. Thus, the accurate equations have been proposed for estimating the weld bead height, width and penetration based on the input parameters by the regression analysis and neural network. Based on the results, the designed neural network is markedly more accurate than the regression equations, but both models have high capabilities for optimizing the parameters of submerged arc welding and also predicting the weld bead geometry for a set of input values.

Keywords: Neural Network, regression, submerged arc welding

INTRODUCTION

Welding is one of the most useful methods for permanently joining of parts and is extremely important in the industry. Among a wide variety of welding processes, submerged arc welding is more taken into account based on the multiple benefits such as accepted quality and high deposition rate. Like other methods, the quality of welds in submerged arc welding is directly affected by weld bead geometry which includes the bead height, width and penetration. In this regard, the proper adjustment of input parameters is an unavoidable necessity in order to achieve the welding with desired geometric properties due to the vastness and variety of involved parameters. The experimental methods based on the trial and error were usually used in the past in order to determine the optimal levels of adjusting parameters, but in recent years, the theoretical approaches such as statistical methods, response levels, approaches for designing the experiments and neural network have been considered (Tarng *et al*., 2000; Rowlands and Antony, 2003). Since that compared with other methods, using the regression analysis and artificial neural network lead to the models, which generally resulted in more accurate findings, are more cost-effective and precise despite obtaining from a small number of experimental tests, predicting the weld bead geometry by the mentioned methods has become an active field for research. in this regard, Yang *et al.* (1993) have applied the regression equations in electric arc welding, Kim *et al*. (2003) have been attempted in establishing the relationship between the adjusting parameters and weld bead geometry in robotic CO_2 arc welding by using the linear and nonlinear regression equations, Lee and Um (2000) modeled the Gas Metal Arc Welding (GMAW) process by using the multiple regression analysis and neural network. Moreover, while some of the researchers have applied the neural network and fuzzy logic in order to control the arc welding processes (Di *et al*., 2004; Radovan and Yu, 1997). Kim *et al*. (2002) have predicted the weld bead geometry and bead penetration in Shielded Metal Arc Welding (SMAW) process by neural network. Ghosh *et al*. (2007) have applied the neural network for investigating the effects of adjusting parameters on submerged arc welding process, Serdar and Secgin (2008) have optimized the submerged arc welding based on the weld bead geometry by using the mathematical modeling and regression analysis. In this study, the weld bead geometry has been modeled by using the regression analysis and neural network and the obtained results have been compared.

RESEARCH METHOD

In submerged arc welding, the weld bead geometry is influenced by numerous variables including the welding current, type and polarity of electric current, welding voltage, speed of welding, chemical composition of workpiece and electrode and welding powder. According to the diversity of variables affecting the output of process, it is clear that

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Table 1: Input test

Voltage (V)	Speed (cm/min)	Welding current (A)	Level
26	17.40	490	0
32	18.50	640	1
37	19.70	720	2

Table 2: Experimental results

No	I	V	S	BP	BW	BH
1	490	26	17.40	3.12	14.44	1.00
2	490	26	18.50	3.60	14.26	1.30
3	480	26	19.70	3.78	13.76	1.88
4	490	32	17.40	2.16	13.34	1.38
5	490	32	18.50	2.76	14.92	1.56
6	490	32	19.70	3.22	15.64	1.88
7	490	37	17.40	4.16	16.32	1.48
8	490	37	18.50	4.79	17.60	1.40
9	490	37	19.70	5.72	14.92	1.80
10	720	26	17.40	6.10	14.69	2.00
11	720	27	18.50	5.57	14.20	1.79
12	720	26	19.70	2.89	15.05	1.58
13	720	32	17.40	8.62	12.50	2.35
14	720	32	18.50	6.97	13.44	2.33
15	720	32	19.70	5.28	15.54	1.24
16	720	37	17.40	9.82	15.94	2.02
17	720	37	18.50	9.62	16.10	2.11
18	720	37	19.70	9.42	16.22	2.29
19	640	26	17.40	5.95	13.14	2.34
20	640	26	18.50	7.34	14.95	1.52
21	640	26	19.70	4.52	14.28	2.12
22	640	32	17.40	4.29	13.12	2.48
23	640	3 2	18.50	5.49	13.77	2.84
24	640	32	19.70	4.55	12.17	2.72
25	640	37	17.40	8.59	11.69	2.16
26	640	37	18.50	6.70	16.41	2.78
27	640	37	19.70	7.18	15.54	2.32

investigating the effect of all parameters simultaneously requires the high cost and time. Although it is better to design the tests based on the investigation technique of all parameters in ideal state and in order to observe the effect of variables, all conducted research include a kind of designing the tests for systematic numerization of a small number of parameters. In this study, the variables of workpiece, electrode welding powder have been ignored in order to reduce the examined parameters. Moreover, the measures have been adopted for some of the parameters in order to ignore them by reducing the impact. This case clarifies the necessity for applying the advanced methods in designing the tests. Based on the conducted studies, 3^K factor method is a common method in designing the experiment for parameters with three variables each which are effective at three levels. Three impact levels as low (0), middle (1) and high level (2) are determined (Lee and Um, 2000). In this study, three parameters of welding current (I), speed (S) and welding voltage (V) have been considered as the input variables and thus the number of experiments has been obtained 27. Table 1 represents the values of input variables of experimental tests.

In terms of materials and equipment, the workpiece is made of steel CK40. The welding machine model KARA, which has the ability to regulate the range of welding current from 250 to 1250 A, voltage from 24 to 44 volts and welding speed from 14 to 22 centimeters per minute, has been used. After doing the welding, vernier caliper with resolution 0.02 mm has been used in order to evaluate the weld bead width and height. Moreover, the parts have been holed by drilling machine and then measured in order to measure the bead penetration. The results of these experiments are presented in the following Table 2.

MODELING TECHNIQUES

Regression model: Nowadays, the use of regression modeling in different fields of science is widely spread. In regression method, the objective is to predict one or several dependent variables from one or several independent variables. In general, this method is for solving issues which predict the dependent value of output variable compared to controlled value of input. If the independent coefficients of provided model are exponentially or logarithmically, the model is non-linear, otherwise it is linear. Linear correlation coefficient, as a criterion of linear relationship between two defined random input and output variables, is usually displayed with the symbol R. Furthermore, the coefficient of determination or R^2 refers to the covering rate of default function in changes of dependant variables. The more this value is closer to the number one, the more the_accuracy of equation is increased. In general, a random sample with n measured pairs is provided estimated in order to estimate the linear correlation coefficient and the possibility to extract the certain results are provided through creating a dispersion curve for input and output variables. If the points are located around a straight line with positive angle coefficient, a strong positive correlation will be expected between two variables. Moreover, if the points are located around a line with negative angle coefficient, a strong negative correlation will be expected between two variables. The more the distribution of points around the line is increased, the more the degree of their correlation is reduced. Naturally, if the points follow a random process, the null correlation, which refers to the lack of relationship between input and output, will be occurred. In this study, the software SPSS has been used for modeling and regression analysis. Moreover, the quadratic linear regression has been studied and selected from the models of first and quadratic linear regression due to higher accuracy.

Neural network model: Artificial Neural Network has been created inspired by the function of human brain and neural biological cells. Ability of neural network in modeling the nonlinear and complex systems has been caused that this technique to be applied in various branches of engineering. In general, the function of these systems includes gaining the input vector and creating the output vector by using the functions of weight and also the operator functions of each layer. In general, there are four main stages including preparing the training data, creating the network, network training and network simulation with new data in order to apply

Table 3: Table diffraction analysis model

Model		SS	Degrees of freedom	Mean square	Ratio
Bead penetration	Regression	116.004	9	12.889	17.147
	Remained	12.779	17	0.0752	
	Final	128.782	26		
Bead width	Regression	31.455	9	3.495	2.742
	Remained	21.671	17	1.275	
	Final	53.125	26		
Bead Height	Regression	4.712	9	0.673	7.672
	Remained	1.667	17	0.088	
	Final	6.379	26		

this tool. The basis of network training is to use an iterative method. In this way, first the input and target values are applied to the network and the network calculates an output by using the input vector and weighted functions. At the next stage, the output of network is compared with target values and the weight ratios are changed based on the obtained error in order to reach the lower errors and finally the minimum achievable error. After training (regulating) the neural network, applying a particular input to it leads to a specific response. Now, the weight ratios are not changed and the network is ready for simulation (test). At this stage, the new input and output variables are applied to the network, so that the network can predict the target outputs with accepted accuracy by using new inputs and weight obtained ratios then its is fully trained and can be used as a tool for other predictions. In this study, the software Matlab has been used in order to create and train the neural network. It should be noted that according to the common rule, nearly 80 percent of data have been used for training and the rest as the test. Moreover, in spite of different training algorithms, Levenberg-Marqurdt (LM) algorithm has been selected for educating the back-propagation neural network after the trial and error and Reviews. Designed network includes three neurons in the first layer and a neuron in the second layer (output), the transfer function of first layer is tansig and the transfer function of second layer is purelin.

RESULTS AND DISCUSSION

Bead penetration equations: Based on the regression model, the form of quadratic linear function is as the Eq. (1).

$$BP = -1.744 + 0.006I - 0.199V + 0.289S + 0.0001I^2 + 0.002V^2 - 0.009S^2 + 0.0001IVS + 0.006VS + 0.0001I^2V \quad (1)$$

In this fitting, the value of coefficient of determination is obtained 0.901 which shows the high accuracy of this model.

Bead width equations: Based on the results obtained from the regression modeling, the quadratic linear equation is presented in Eq. (2). It should be noted that the very small terms have been ignored in this model.

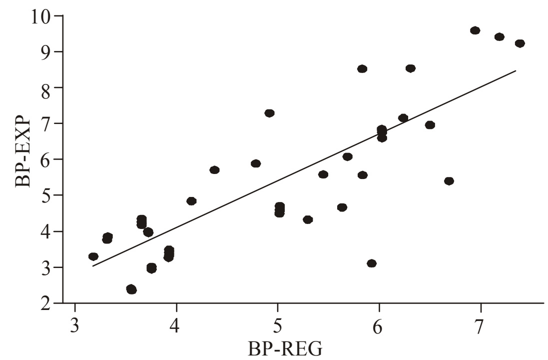

Fig. 1: Correlation diagram for the bead penetration

$$BW = -31.571 - 0.084I - 1.386V + 8.518S + 0.001VI + 0.002IS + 0.026VS - 0.0001V^3 - 0.01S^3 \quad (2)$$

Gaining the coefficient of determination 0.6 in this fitting confirms the acceptable accuracy of modeling.

Bead height equations: According to the performed modeling, the form of quadratic linear function is as the Eq. (3). For easy calculation, too small terms are ignored.

$$BH = 22.061 - 0.033I + 0.278V + 0.006V^2 - 0.001IS - 0.007VS \quad (3)$$

In linear fitting of quadratic function, the coefficient of determination was obtained 0.739 which indicates the appropriate accuracy of this model.

Discussion about the accuracy of regression equations: In Table 3 which is called the diffraction analysis table, the statistical data of quadratic models is presented.

The correlation diagrams between the experimental values and the regression model for all three models in Fig. 1, 2 and 3 refer to the low amount and frequency of remains by using the quadratic model. Distribution of points around the straight line suggests that the fitting has been acceptable and the remains are small enough.

Results of modeling for the bead penetration: The responses of regression and neural network models to the application of the 5 test inputs have been presented in Table 4.

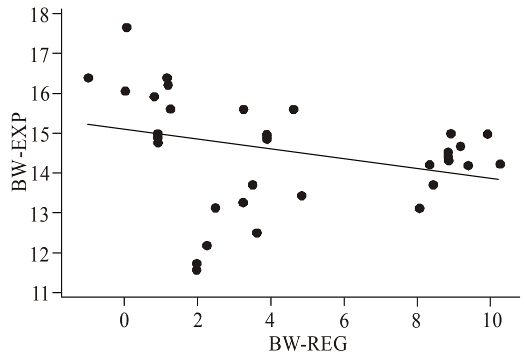

Fig. 2: Correlation diagram for the bead width

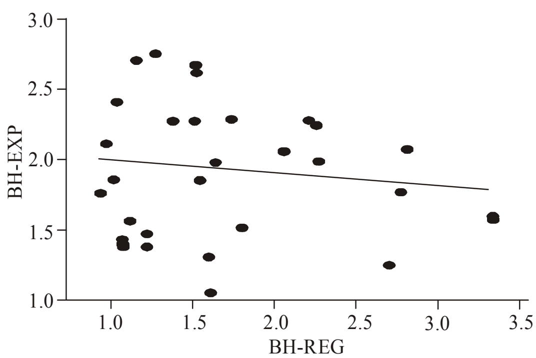

Fig. 3: Correlation diagram for the bead height

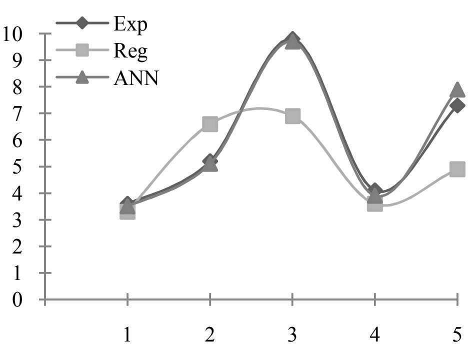

Fig. 4: Comparing the actual values of bead penetration and values of provided models

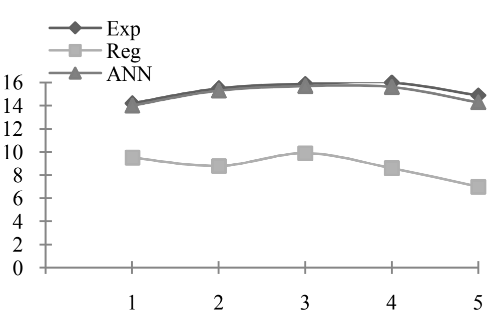

Fig. 5: Comparing the actual values of bead width and values of provided models

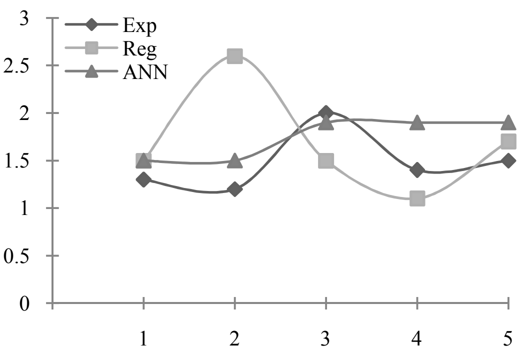

Fig. 6: Comparison of actual values of weld bead height and values of provided models

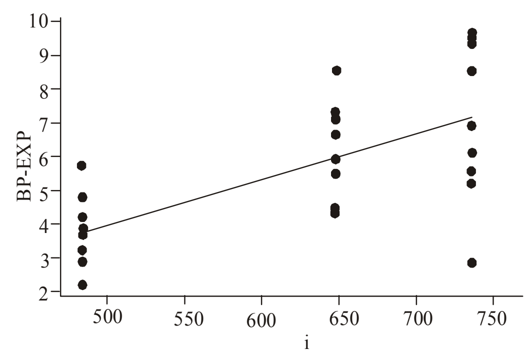

Fig. 7: Effect of welding current on the bead penetration

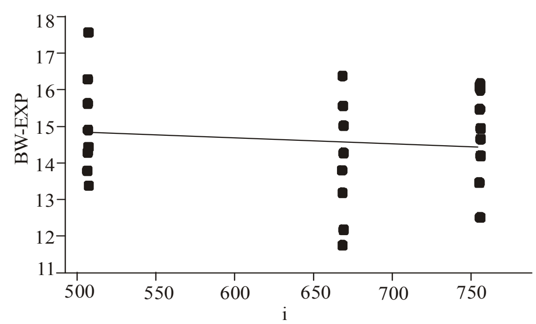

Fig. 8: Effect of welding current on the bead width

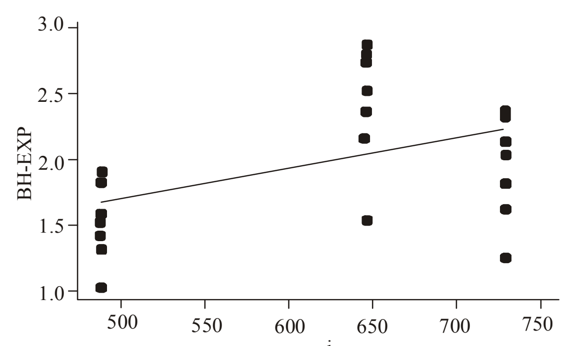

Fig. 9: Effect of welding current on bead height

According to the Table 4, although the regression model meets an acceptable level of reliability, the neural

Table 4: Comparison the results of test for the bead penetration

Test	I	V	S	Exp	Reg	ANN	Error (Reg)	Error (ANN)
1	490	26	16.50	3.60	3.342	3.598	0.071%	0.001%
2	720	32	19.70	5.28	6.654	5.156	0.259%	0.023%
3	720	37	17.40	9.82	6.935	9.712	0.293%	0.010%
4	490	37	17.40	4.16	3.690	3.904	0.112%	0.061%
5	640	37	18.50	7.34	4.909	7.954	0.331%	0.083%

Table 5: Comparing the results of test for bead width

Test	I	V	S	Exp	Reg	ANN	Error (Reg)	Error (ANN)
1	490	26	16.50	14.26	9.517	14.029	0.332%	0.016%
2	720	32	19.70	15.54	8.895	15.349	0.427%	0.012%
3	720	37	17.40	15.94	9.962	15.793	0.968%	0.001%
4	490	37	17.40	16.32	8.690	15.638	0.467%	0.041%
5	640	37	18.50	14.95	7.082	14.319	0.528%	0.042%

Table 6: Comparing the results of test for the weld bead heigh

Test	I	V	S	Exp	Reg	ANN	Error (Reg)	Error (ANN)
1	490	26	16.50	1.30	1.533	1.552	0.179%	0.193%
2	720	32	19.70	1.24	2.635	1.595	1.116%	0.286%
3	720	37	17.40	2.02	1.573	1.996	0.221%	0.011%
4	490	37	17.40	1.48	1.158	1.974	0.217%	0.333%
5	640	37	18.50	1.52	1.735	1.974	0.141%	0.298%

network model has been markedly closer to the actual values, the relative error less and the accuracy has been more. This issue is totally obvious in Fig. 4.

Results of modeling for the bead width: Output of the obtained models have been presented and compared in Table 5 for five inputs of test.

According to the Table 5, the neural network model has had a better match with the experimental results; the obtained regression model is not very precise in estimating the results. In Fig. 5, the actual value of bead width has been compared with the values obtained from modeling. Based on the figure, although all three diagrams almost follow the same way, the diagram related to the neural network closely matches the experimental results.

Results of modeling for the bead height: The responses of regression and neural network models to the application of the 5 test inputs have been presented in Table 6.

According to the Table 6, the output of both models is close to the experimental results with a good estimation. In Fig. 6, the comparison between the values obtained from the simulation and experimental results has been presented.

Investigating the effect of current intensity: Based on the obtained results and according to the Fig. 7, 8 and 9, the increased the welding current intensity leads to the increased bead penetration, reduced bead width and increased bead height.

Evaluating the effect of welding voltage: According to the results and based on the Fig. 10, 11 and 12, the increased welding voltage leads to the increases bead penetration, increased bead width and height.

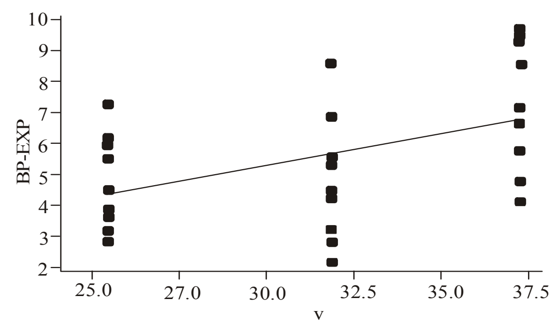

Fig. 10: Effect of voltage on the bead penetration

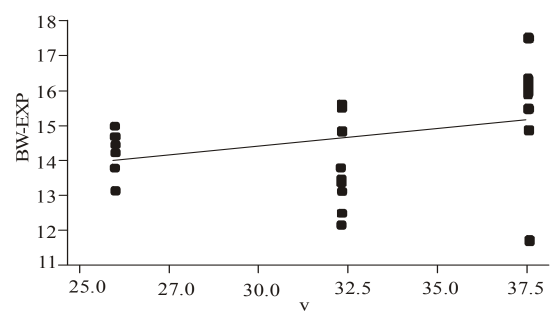

Fig. 11: Effect of voltage on the bead width

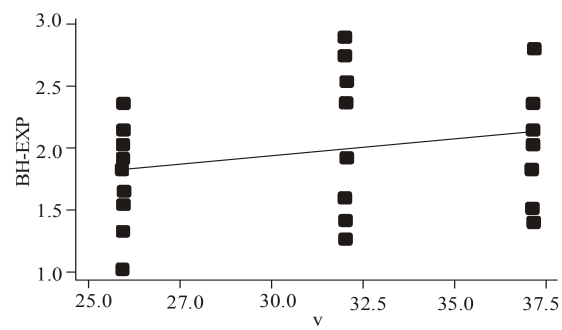

Fig. 12: Effect of voltage on the bead height

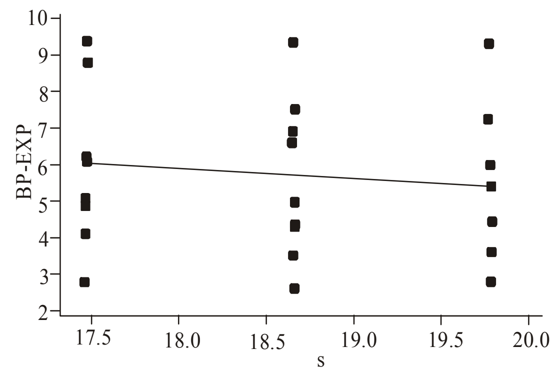

Fig. 13: Effect of speed on the bead penetration

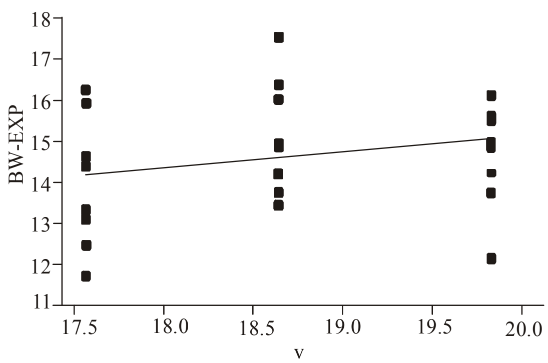

Fig. 14: Effect of speed on the bead width

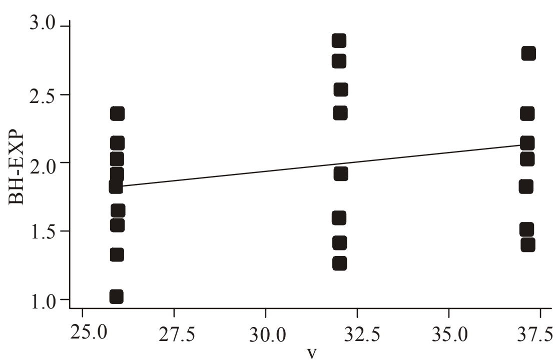

Fig. 15: Effect of speed on the bead height

Evaluating the effect of welding speed: Based on the obtained results and according to the Fig. 13, 14 and 15, increased welding speed will lead to the reduced weld bead penetration, increased bead width and height.

CONCLUSION

In this study, three parameters including the current, speed and welding voltage were selected as the input variables and the weld bead penetration, width and height were modeled by the regression and neural network methods. Obtained results show that:

- Obtained quadratic regression equations for bead weld penetration, width and height have the coefficients of determination 0.901, 0.6 and 0.739, respectively and they imply the accurate modeling, acceptable fitting and proper accuracy of quadratic model.
- Despite the accuracy of regression equations, designed neural network is significantly more accurate in predicting the weld bead geometry, so that the difference in relative error of two methods reaches 83%.
- By increasing the welding current, the weld bead penetration and height will be increased and the weld width will be reduced.
- By increasing the welding voltage, the weld bead penetration, height and width will be increased.
- By increasing the welding speed, the bead penetration will be decreased, while the bead width and height will be increased.

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