

Investigation of GMAW Parameters and Plate Thickness Effects on Weld Bead Geometry and Development of Prediction Model Using RSM and ANN

Authors:

Seyed Amirreza Jamalian^{1,*}, Mostafa Habibnia², Majid Khodadadi³

¹M.Sc of Mechanical Engineering, Department of Mechanical Engineering, K.N.Toosi University of Technology (KNTU)

²Assistant Professor of Mechanical Engineering, Department of Mechanical Engineering, Islamic Azad university, Juybar Branch

³Phd of Mechanical Engineering, Department of Mechanical Engineering, University of Birjand

Corresponding Author:

Seyed Amirreza Jamalian

M.Sc of Mechanical Engineering, Department of Mechanical Engineering, K.N.Toosi University of Technology (KNTU)

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ABSTRACT:

The influence of gas metal arc welding (GMAW) parameters such as current, voltage, electrode extension, and welding speed on weld bead geometry (bead width, bead height, penetration) has been investigated using Response Surface Methodology (RSM). Through a designed experiment matrix generated by RSM, comprehensive experimentation has been conducted. The effects and effectiveness of these factors have been analyzed across three workpieces of varying thicknesses for quality control testing. For each geometric or physical characteristic mentioned above, a corresponding regression model has been developed. Furthermore, the impact of workpiece thickness on physical characteristics has been assessed using analysis of variance (ANOVA) techniques to construct regression models with varying thickness variables. Subsequently, an Artificial Neural Network (ANN) has been employed to predict the aforementioned physical characteristics or quality control metrics. Finally, the output of the network has been compared and analyzed against the output of the regression models and actual data.

Keywords: Weld bead geometry, RSM, ANN.

INTRODUCTION:

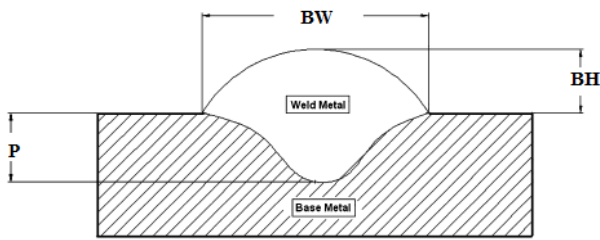
Nowadays, gas metal arc welding (GMAW) is widely utilized across various industries for metal manufacturing and joining processes. Originating in the 1920s, this method has seen extensive use in numerous industrial applications, initially with aluminum and later expanding to include steel. In GMAW, a continuous electrode is used to create an arc between the electrode and the base metal during welding. One of its primary advantages is the ability to protect the weld pool from atmospheric contamination by surrounding it with inert or active gas, such as CO₂, as employed in this research. Its automated welding capabilities have further enhanced its value in industrial settings. The quality of welding is evaluated based on various characteristics, with weld bead geometry comprising bead width, bead height, and penetration playing a crucial role in determining mechanical properties. These physical parameters are illustrated in Figure 1

Previous studies by Kumanan et al. utilized the Taguchi Method and Regression Analysis to optimize the Submerged Arc Welding (SAW) process, resulting in both optimized models and a mathematical framework for predicting weld bead geometry. Bingul and Cook developed a mathematical model for

electrode extension based on arc voltage in GMAW, derived from careful measurements and voltage control experiments. Kolahan and Heidary focused on identifying the most significant parameters in the GMAW process, presenting an optimized model for weld bead geometry using Regression Analysis (RA) and simulated annealing (SA). Thao et al. employed statistical analysis to predict weld bead geometry in lap joint welding and developed empirical models for predicting and controlling the welding process. Additionally, Mostafa and Khajavi investigated the effect of Flux-Cored Arc Welding (FCAW) parameters on weld penetration, evaluating parameters such as current, voltage, welding speed, nozzle-to-workpiece distance, and electrode angle to maximize weld penetration. Throughout these studies, the plate thickness remained constant and was not considered a variable. The researcher aims to investigate physical parameters and quality control testing deemed significant compared to other variables. These geometric parameters, influenced by factors such as current, voltage, welding speed, and electrode extension, necessitate numerous and targeted experiments for a refined and reliable predictive model of weld bead geometry and penetration. The Response Surface Method (RSM) proves to be an appropriate

approach, allowing for efficient targeted experiments, process optimization, and the development of an optimized model (Eq. 1 & 2) for quality control purposes.

Figure 1: Weld bead dimension



$$Y = F(x_1, x_2, x_3, \dots, x_n) + e_r \quad (\text{Eq.1})$$

$$Y = b_0 + \sum b_i x_i + \sum b_{ii} x_i^2 + \sum b_{ij} x_{ij} \quad (\text{Eq.2})$$

Data obtained through this method can be instrumental in developing an artificial neural network (ANN). An ANN is a data processing system comprising numerous interconnected processors that function in parallel or continuously to address a problem. The fundamental unit of an artificial neural network is the neuron. The structure of an ANN is relatively simple, consisting of layers including input layers, hidden layers, and output layers each composed of neurons, or nodes. These nodes are interconnected to form a network, which is then trained using a training algorithm. ANN finds wide application, including in the analysis of welding quality for industrial control processes.

Yangjoon and Rhee developed an ANN model for estimating and predicting spot resistance welding

quality. Iqbal et al. also employed ANN to predict the quality of front and back beads in the Tungsten Inert Gas (TIG) welding process. Al-Faruk et al. utilized ANN to predict weld bead geometry in electrical arc welding. Their model included parameters such as arc length, arc spread, and electrode diameter, which were identified as highly influential in predicting weld bead geometry.

Design of Experiment:

The experimental design utilized in this study is the Central Composite Design. The research was conducted using Response Surface Methodology (RSM) with the aid of Minitab 15 software. RSM comprises a set of mathematical and statistical techniques employed for process development, improvement, and optimization. Four factors, each with defined limits, were included in the experiment, with one replicate and an alpha value of 1.5 considered. The welding parameters consist of current, $180 \leq I(\text{A}) \leq 260$, voltage, $26 \leq V(\text{v}) \leq 30$, speed, $4 \leq S(\text{mm/s}) \leq 6$, and electrode extension, $20 \leq L(\text{mm}) \leq 28$. With an axial point included these variables were varied ± 1.5 times above and below their respective limits. Table 1 illustrates the high level (+1), middle level (0), and low level (-1) of the matrix design, as well as the axial points with $\alpha = \pm 1.5$. The experimental data obtained from this matrix informed the execution of 31 experiments. Additionally, the regression model statement for a simple 2 x 2 Factorial Design is provided. This design entails two main effects and one interaction.

Table 1: Matrix Design of RSM and weld bead geometry for each series of plate

Expt. NO.	Welding Variable Level RSM				Welding Variable Value				Bead Geometry Characteristic 6 mm			Bead Geometry Characteristic 10 mm			Bead Geometry Characteristic 14 mm		
	I (A)	V (v)	S (mm/s)	L (mm)	I (A)	V (v)	S (mm/s)	L (mm)	BW	BH	BP	BW	BH	BP	BW	BH	BP
1	-1	-1	-1	-1	180	26	4	20	12.0	2.8	2.7	12.2	2.4	2.1	13.0	2.0	2.8
2	1	-1	-1	-1	260	26	4	20	12.3	4.5	4.5	12.8	4.0	4.7	12.9	3.3	4.2
3	-1	1	-1	-1	180	30	4	20	12.3	2.4	3	12.6	2.5	2.2	13.4	1.9	2.5
4	1	1	-1	-1	260	30	4	20	12.8	3.8	4.2	13.6	3.6	4.6	14.0	3.0	4.8
5	-1	-1	1	-1	180	26	6	20	8.5	2.3	1.9	9.0	2.0	1.5	9.9	1.8	2.0
6	1	-1	1	-1	260	26	6	20	8.7	3.6	4	9.3	3.5	3.6	10.0	2.9	4.1
7	-1	1	1	-1	180	30	6	20	9.6	2.0	1.9	9.8	2.0	1.7	10.3	1.8	2.0
8	1	1	1	-1	260	30	6	20	11.0	3.1	3.8	11.3	2.7	3.0	12.0	3.0	3.7
9	-1	-1	-1	1	180	26	4	28	10.5	3.0	2.9	11.5	3.2	2.3	11.0	2.7	2.0
10	1	-1	-1	1	260	26	4	28	11.6	4.8	4.7	12.4	4.6	4.3	12.0	3.8	4.2
11	-1	1	-1	1	180	30	4	28	12.3	2.9	2.5	12.8	2.4	2.0	13.4	2.9	2.5
12	1	1	-1	1	260	30	4	28	13.0	4.4	4.6	13.7	4.6	4.5	14.6	3.6	4.1
13	-1	-1	1	1	180	26	6	28	9.2	2.5	1.9	9.3	2.8	1.8	9.0	2.0	2.2
14	1	-1	1	1	260	26	6	28	9.3	4.0	3.9	9.7	4.3	3.5	9.5	3.6	3.8
15	-1	1	1	1	180	30	6	28	10.1	2.4	2	10.3	2.9	1.8	10.8	1.8	2.1
16	1	1	1	1	260	30	6	28	11.2	3.5	3.8	11.0	3.8	3.6	11.8	3.4	3.4
17	-	0	0	0	160	28	5	24	9.7	2.0	1.8	10.5	2.4	1.5	10.0	1.9	1.8
	1.5																
18	1.5	0	0	0	280	28	5	24	10.8	4.3	4.2	11.5	4.0	4.6	12.3	4.2	5.0
19	0	-	0	0	220	25	5	24	9.7	3.5	2.5	10.0	3.3	2.8	10.4	3.0	3.0

		1.5															
20	0	1.5	0	0	220	31	5	24	10.8	3.0	3.4	12.1	2.9	2.9	12.3	2.6	2.6
21	0	0	-1.5	0	220	28	3.5	24	12.4	3.7	3.2	13.5	3.9	3.4	14.0	3.2	3.9
22	0	0	1.5	0	220	28	6.5	24	9.0	2.8	2.6	9.7	2.8	2.5	9.2	2.3	3.0
23	0	0	0	-1.5	220	28	5	18	11.0	2.8	3.2	11.2	2.7	2.9	11.4	2.3	3.1
24	0	0	0	1.5	220	28	5	30	10.8	3.4	3.4	11.0	3.0	2.8	10.6	3.0	2.6
25	0	0	0	0	220	28	5	24	10.5	3.0	3	10.0	3.5	3.2	12.2	2.6	3.0
26	0	0	0	0	220	28	5	24	11.1	3.4	2.8	11.4	2.8	3.0	12.0	2.5	3.4
27	0	0	0	0	220	28	5	24	10.7	3.2	3.2	10.3	3.3	3.3	11.0	3.0	2.6
28	0	0	0	0	220	28	5	24	10.2	3.0	3	10.7	3.2	2.9	11.4	2.7	2.8
29	0	0	0	0	220	28	5	24	11.2	2.9	3.4	11.2	3.1	2.7	11.6	2.0	2.4
30	0	0	0	0	220	28	5	24	9.9	3.2	2.9	10.3	3.0	3.1	11.3	2.8	3.3
31	0	0	0	0	220	28	5	24	10.0	3.0	2.6	11.8	2.8	3.0	11.5	2.7	2.8

dimensions (BW, BH and P) of each sample were measured and recorded which was indicated in table 1.

Procedure:

According to RSM matrix design, three different experiments, each of which consisting of 31 experiments, were done by means of a MAG welding machine, and ST 37-2 steels, the thicknesses of which are 6 mm, 10 mm, and 14 mm. CO2 was used as a shielding gas in all experiments which were done with a direct current and positive electrode polarity. Wire electrode was of ER70S-4 type and 1.2 mm in diameter. In this research, the wire electrode and the surface of work piece made a 90o. In all experiments, the welding torch stood still and the plate moved with definite steady speed. There was not a groove or a gap in the joint. After doing all the experiments, by splitting the weld joint down the middle the bead

ANOVA analysis of the developed models without the thickness variable:

ANOVA analysis was conducted on the developed models, excluding the thickness variable. The accuracy of the developed models was assessed, with significant and insignificant effects evaluated for their impact on each physical characteristic. Following the elimination of insignificant effects, the developed regression models were reexamined and presented. Specifically, only 2 x 2 interaction effects were evaluated in this investigation. The resulting models are detailed in Table 2.

Table 2: Regression coefficients of weld bead geometry for each series of plate

N0.	Term	Regression Coefficients								
		for 6 mm			for 10 mm			for 14 mm		
		BW	BH	P	BW	BH	P	BW	BH	P
1	Constant	24.8448	9.05087	7.2373	16.0358	0.922266	-2.76173	33.7388	-1.27943	9.01135
2	I	0.00859756	0.0552973	0.0223171	0.0095122	0.0162195	0.0459832	0.0115244	0.0160366	-0.0200650
3	V	0.289024	-0.841109	0	0.293902	-0.0707317	0	-0.588415	-0.207317	0
4	S	-2.68537	-0.521045	-0.331707	-4.81763	-0.241463	0.000457317	-1.37561	0.0628049	-2.04565
5	L	-1.21587	0.047561	-0.630989	0	0.077439	-0.106326	-1.1936	0	-0.0310976
6	I ²	0	0	0	0	0	0	0	0	9.82630E-05
7	V ²	0	0.0170696	0	0	0	0	0	0	0
8	S ²	0	0.0682783	0	0.347129	0	0	0	0	0.179443
9	L ²	0.018744	0	0.0132980	0	0	0	0	0	0
10	IV	0	-0.0009375	0	0	0	0	0	0	0
11	IS	0	-0.0021875	0	0	0	-0.0040625	0	0	0
12	IL	0	0	0	0	0	0	0	0	0
13	VS	0	0	0	0	0	0	0	0	0
14	VL	0	0	0	0	0	0	0.040625	0	0
15	SL	0.0625	0	0	0	0	0.021875	0	0	0

ANOVA analysis of the developed models including thickness variable:

ANOVA analysis was conducted on the developed models, incorporating the thickness variable. The accuracy of the developed models was assessed, with significant and insignificant effects evaluated for their impact on each physical characteristic. Following the elimination of insignificant effects, the developed regression models were reexamined and presented. The results from variance analysis before and after eliminating insignificant effects are provided.

Specifically, only 2 x 2 interaction effects were evaluated in this investigation. The following regression model represents the final iteration for predicting and estimating weld bead geometry after eliminating insignificant parameters and optimizing the model (Eq.3-5).

Y= f (I, V, S, L, T)

Y: Bead Geometry or bead physic (Bead Width, Bead Height, Penetration)

Bead Width = 41.3782 - 0.0404345 I - 0.565892 V - 4.75375 S - 0.776461 L + 0.107258 T + 0.258881 S²

$$+ 0.00179687 \text{ IV} + 0.0205729 \text{ VL} + 0.0359375 \text{ SL} \quad (\text{Eq.3})$$

$$\text{Bead Height} = 2.70874 - 0.00470320 \text{ I} - 0.0646341 \text{ V} - 0.256098 \text{ S} + 0.0626016 \text{ L} + 0.191935 \text{ T} + 0.000048845 \text{ I}^2 - 0.0126008 \text{ T}^2 \quad (\text{Eq.4})$$

$$\text{Penetration} = 3.47406 - 0.00524211 \text{ I} - 0.317073 \text{ S} - 0.200806 \text{ T} - 0.0000655 \text{ I}^2 + 0.00967742 \text{ T}^2 \quad (\text{Eq.5})$$

The validity and reliability of the optimized models incorporating the thickness variable were investigated. Figures 2, 3, and 4 depict the normal distribution of the observed and predicted values. Additionally, Table 3 presents the correlation coefficient between the variables, serving as an indicator of the models' reliability and validity.

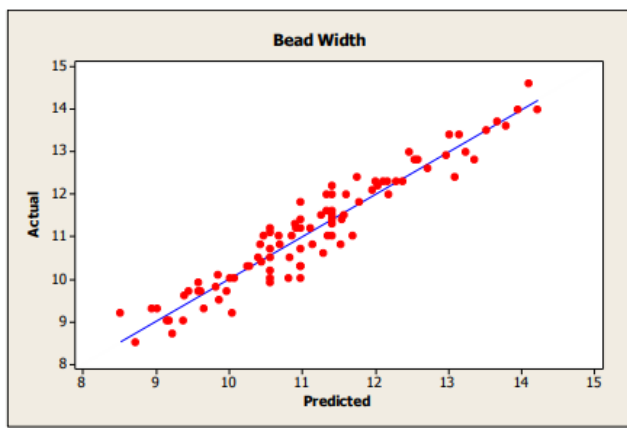


Figure 2: Actual values vs. predicted values for BW

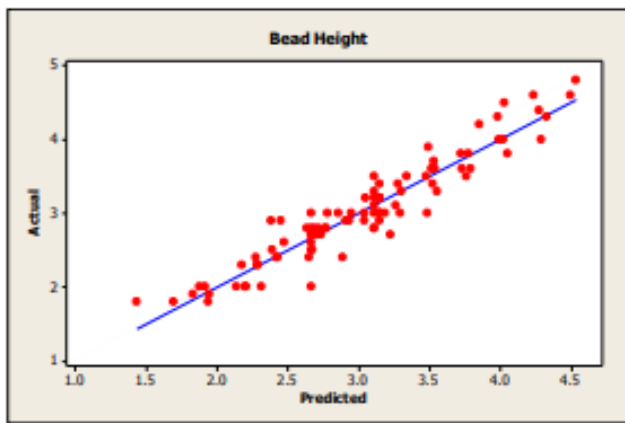


Figure 3: Actual values vs. predicted values for BH

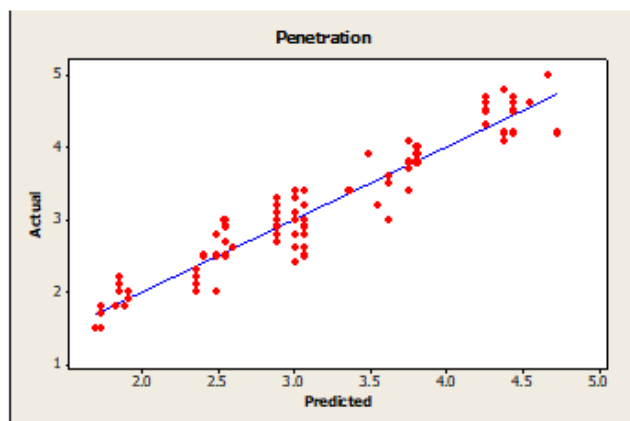


Figure 4: Actual values vs. predicted values for P

Table 3: Actual values vs. predicted values for BW, BH and P

Model	R-Sq	R-Sq (predict)	R-Sq (adjust)
BW	91.44%	89.50%	90.51%
BH	90.06%	88.08%	89.24%
P	90.78%	89.47%	90.25%

Artificial Neural Network (ANN):

The ANN modeling process was conducted in three steps. Firstly, networks were trained using available data, obtained from experiments conducted using RSM. Secondly, the developed networks were tested using independent test data, which comprised 30 percent of the total dataset and had not been used during training. The networks developed in this research consisted of 4 neurons in the input layer and 1 neuron in the output layer. Additionally, to determine the optimal structure of the hidden layer, hidden layers with 2 to 15 neurons and 2 hidden layers with 2 to 10 neurons were investigated. During the evaluation of network structures, the Mean Square Error (MSE) of the networks was calculated and compared to select the structure with the minimum MSE, deemed the most optimal. Thirdly, with the selected network structure, simulation was performed, and the predicted values were compared to the observed values to assess model accuracy. MATLAB R2010a software was utilized for developing the ANN models. The feedforward backpropagation network was built using a tansig transfer function in the hidden layer and a purelin transfer function in the output layer.

Table 4: Network structure with 1 hidden layers and their MSE

1 Hidden Layer				
Network Structure				
NO.	Input Layer	Hidden Layer	Output Layer	MSE
1	5	2	3	0.23
2	5	3	3	0.24
3	5	4	3	0.20
4	5	5	3	0.19
5	5	6	3	0.17
6	5	7	3	0.19
7	5	8	3	0.19
8	5	9	3	0.23
9	5	10	3	0.20
10	5	11	3	0.20
11	5	12	3	0.20
12	5	13	3	0.25
13	5	14	3	0.22
14	5	15	3	0.16

Table 5: Network structure with 2 hidden layers and their MSE

2 Hidden Layer																			
NO.	Network Structure				MSE		NO.	Network Structure				MSE		NO.	Network Structure				MSE
1	5	2	2	3	0.23		28	5	5	2	3	0.23		55	5	8	2	3	0.42
2	5	2	3	3	0.28		29	5	5	3	3	0.61		56	5	8	3	3	0.28
3	5	2	4	3	0.28		30	5	5	4	3	0.26		57	5	8	4	3	0.29
4	5	2	5	3	0.27		31	5	5	5	3	0.36		58	5	8	5	3	0.34
5	5	2	6	3	0.26		32	5	5	6	3	0.3		59	5	8	6	3	0.24
6	5	2	7	3	0.26		33	5	5	7	3	0.41		60	5	8	7	3	0.63
7	5	2	8	3	0.28		34	5	5	8	3	0.29		61	5	8	8	3	0.24
8	5	2	9	3	0.28		35	5	5	9	3	0.39		62	5	8	9	3	0.33
9	5	2	10	3	0.27		36	5	5	10	3	0.23		63	5	8	10	3	0.36
10	5	3	2	3	0.23		37	5	6	2	3	0.32		64	5	9	2	3	0.31
11	5	3	3	3	0.24		38	5	6	3	3	0.29		65	5	9	3	3	0.29
12	5	3	4	3	0.28		39	5	6	4	3	0.33		66	5	9	4	3	0.46
13	5	3	5	3	0.3		40	5	6	5	3	0.46		67	5	9	5	3	0.43
14	5	3	6	3	0.26		41	5	6	6	3	0.18		68	5	9	6	3	0.22
15	5	3	7	3	0.27		42	5	6	7	3	0.23		69	5	9	7	3	0.26
16	5	3	8	3	0.27		43	5	6	8	3	0.28		70	5	9	8	3	0.51
17	5	3	9	3	0.33		44	5	6	9	3	0.56		71	5	9	9	3	0.31
18	5	3	10	3	0.27		45	5	6	10	3	0.25		72	5	9	10	3	0.47
19	5	4	2	3	0.19		46	5	7	2	3	0.62		73	5	10	2	3	0.37
20	5	4	3	3	0.23		47	5	7	3	3	0.38		74	5	10	3	3	0.4
21	5	4	4	3	0.24		48	5	7	4	3	0.58		75	5	10	4	3	0.19
22	5	4	5	3	0.3		49	5	7	5	3	0.29		76	5	10	5	3	0.24
23	5	4	6	3	0.29		50	5	7	6	3	0.32		77	5	10	6	3	0.28
24	5	4	7	3	0.14		51	5	7	7	3	0.26		78	5	10	7	3	0.37
25	5	4	8	3	0.28		52	5	7	8	3	0.39		79	5	10	8	3	0.38
26	5	4	9	3	0.33		53	5	7	9	3	0.22		80	5	10	9	3	0.45
27	5	4	10	3	0.23		54	5	7	10	3	0.32		81	5	10	10	3	0.42

Table 6: Actual values vs. predicted values for BW, BH and P

NO.	Bead Width		Bead Height		Penetration	
	Actual_Test	Prediction	Actual_Test	Prediction	Actual_Test	Prediction
1	12.2	13.2	2.4	2.3	2.1	2.8
2	11.5	10.8	3.2	2.7	2.3	2.4
3	9	9.0	2.8	2.9	2.6	2.6
4	12.6	14.2	2.5	2.2	2.2	2.6
5	11.3	11.4	2.8	2.9	3.3	2.9
6	11.6	11.4	2	2.9	2.4	2.9
7	13.6	14.8	3.6	3.9	4.6	4.5
8	8.7	10.8	3.6	3.0	4	3.4
9	11	11.0	3	3.2	2.8	3.1
10	12.3	13.2	2.4	2.4	3	2.5
11	10	10.9	2.9	3.2	4.1	3.5
12	11.2	9.6	3.5	4.1	3.8	3.8
13	10.3	10.8	1.8	1.9	2	1.9
14	12.3	12.6	2.9	2.8	2.5	2.3
15	11.2	13.2	2.7	2.6	2.9	3.3
16	9.9	10.3	3.2	3.2	2.9	3.0
17	9.7	9.7	4.3	3.9	3.5	3.7
18	10.8	10.5	1.8	2.4	2.1	1.7
19	11.2	10.7	3.1	3.0	2.7	2.9
20	14.6	13.6	3.6	4.2	4.1	4.5
21	11.8	10.9	3.4	3.7	3.4	3.6
22	12	12.5	3.8	4.4	4.2	4.6
23	11.8	10.7	2.8	3.0	3	2.9
24	12	12.4	3	3.3	3.7	3.6

25	12.1	11.6	2.9	2.9	2.9	2.8
26	12.8	13.6	4	3.9	4.7	4.5
27	9.6	9.3	2	2.2	1.9	1.7
28	10.6	11.0	3	3.1	2.6	3.0

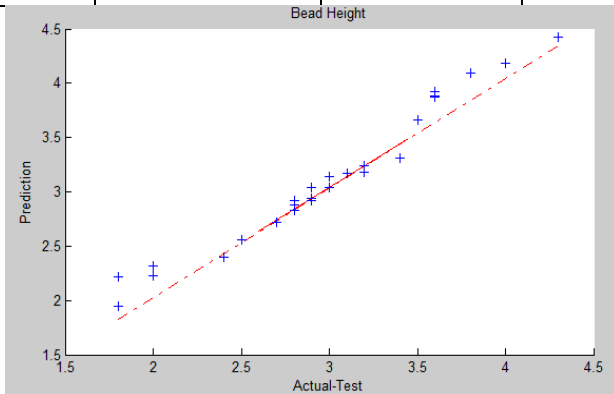


Figure 5: Actual values vs. predicted values for BW

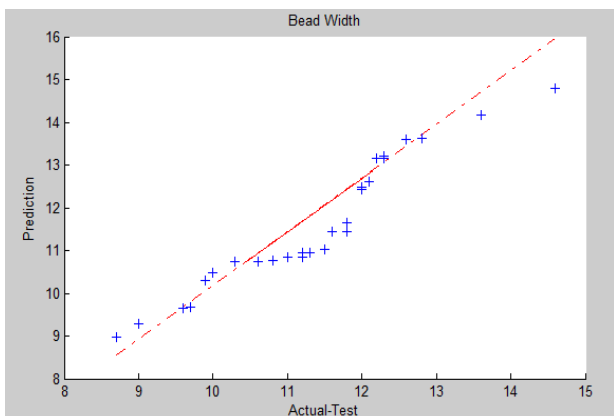


Figure 6: Actual values vs. predicted values for BH

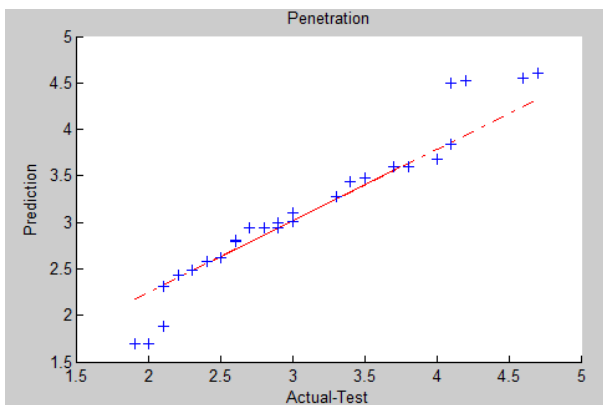


Figure 7: Actual values vs. predicted values for P

CONCLUSION:

In summary, the results of this study are as follows:

1. Mathematical models incorporating MAG welding parameters have been developed to estimate and predict weld bead geometry or physical characteristics using RSM.
2. An ANN model incorporating MAG welding parameters has been developed to estimate weld bead geometry or physical characteristics.
3. Given the complexity of the welding process, the ANN model offers enhanced efficiency and flexibility compared to mathematical

models. Therefore, the ANN model is deemed more reliable than mathematical models.

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