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ORIGINAL ARTICLE

Bead Geometry Prediction in Pulsed GMAW Welding: A Comparative Study on the Performance of Artificial Neural Network and Regression Models

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Abstract: Weld bead geometry is a critical factor for determining the quality of welded joints, for this the welding process input parameters play a key role. In this study, the relationships between welding process variables and the size of the weld bead produced by pulsed GMAW process were investigated by a neural network trained with Bayesian–Regulation Back Propagation algorithm and a second degree regression models. A series of experiments were carried out by applying a Box-Behnken design of experiment. The results showed that both models can predict well the bead geometry. However, the neural network model had a slightly better performance than the second-order regression model. Both models can be used for further analyses and using them may surmount or reduce the need of experimental procedures especially in thermal analysis validations of welding finite element modelling.

Key-words: Artificial neural network; Regression model; Pulsed GMAW.

1. Introduction

The quality of a welded joint is directly influenced by the input parameters during the welding process. Unfortunately, a common problem for manufacturers is the control of the process input parameters to obtain a welded joint with the required bead geometry and quality. For this, it has been necessary to determine the weld input parameters for almost every new welded product to obtain the required specifications, which requires the application of the trial and error method, where the weld input parameters are chosen by the skill of the engineer or machine operator [1]. Besides, fusion welding processes submit the materials to heating and cooling thermal cycles, which induce distortion and residual stresses and affects the joint mechanical properties. However, it is very difficult to quantify the thermal gradients and temperature fields by experimental tests. Thus, a numerical simulation becomes a powerful tool for the prediction of the workpiece temperature and residual stress in welding processes. However, one of the challenges in finite element modelling of welded structures is to define a heat source model which is accurately able to perform the heat input simulation. Usually, some of the input parameters of a selected heat source model, regarding the bead geometry, are estimated based on experimental measurements. Therefore, new methods to estimate the bead geometry and the heat source model are vital in order to reduce the amount of experimental work.

Statistical and numerical methods are used to correlate the relationship between process variables and responses and optimization of the processes, such as factorial design, linear regression, second-order regression, Taguchi method, and artificial network. Xiong et al. [2] observed that the linear regression method does not provide adequate accuracy for bead geometry prediction, Taguchi method can't lead to an optimal solution, and factorial design method needs a large number of experiments. However, it is known that these behaviors depend on the analyzed data set. Artificial neural network (ANN) and second order regression methods have been demonstrated to be powerful tools to establish welding process models. The ANNs exhibits a great capacity to perform nonlinear and multivariable mappings [2]. Kim et al. [3] compared the multiple regression and back propagation neural network approaches to study relationships between process parameters and top bead height for robotic multipass gas metal arc welding process. The back propagation neural network (BPNN) was considerably more accurate than multiple regressions. Towsyfyan et al. [4] compared the Regression Analysis and Artificial Neural Network for estimating the weld bead height, width and penetration based on the input parameters in the Submerged Arc Welding (SAW) process. Based on the results, they concluded that the designed neural network was markedly more accurate than the regression equations, but both models have high capabilities for SAW parameters optimization and also to predict the bead geometry for a set of input values. Xiong et al. [2] applied the neural network and a second-order regression analysis for predicting bead geometry in robotic gas metal arc welding for rapid manufacturing. A series of experiments were carried out by applying a central composite rotatable design, the results demonstrate that both the proposed models can predict the bead width and height with reasonable accuracy.

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Many researchers apply the back-propagation neural network (BPNN) with gradient descent momentum or BPNN with Levenberg–Marquardt (LM) algorithm for artificial neural network (ANN) modelling. BPNN with LM is faster [5] algorithm compared to traditional BPNN, but sometimes yield poor prediction capability for noisy datasets [6]. However, a network trained through BPNN with Bayesian regularisation (BR) [7] can perform exceptionally well during testing or prediction with small and noisy dataset. Few applications were found in literature for this training algorithm [6,8]. Chaki and Ghosal [8] optimized depth of penetration during CO_2 laser–MIG hybrid welding of 5005 Al–Mg alloy using a hybrid model with an ANN and Genetic Algorithm (GA). The network trained using BPNN with the BR method showed the best prediction capability. The results indicated that the GA–ANN model can predict the output with reasonably good accuracy. Chaki [6] have employed it to model relationship between CO_2 laser–MIG hybrid welding parameters. Input parameters for the study included laser power, welding speeds and wire feed rate while tensile strength of the joint was considered as output. Variants of BPNN and Radial Basis Function Networks have been used as training algorithm. ANN trained using BPNN with Bayesian regularization showed best prediction capability and was considered the best ANN for this case.

Sarkar et al. [9], performed a comparative study of multiple regression analysis and back propagation neural network approaches to predict weld bead geometry and HAZ width in SAW process on plain carbon steel. Design of experiments was based on Taguchi's L16 orthogonal array by varying wire feed rate, transverse speed and stick out. They found that the error related to the prediction of bead geometry and HAZ width is smaller in ANN than MRA. Tafarroj and Kolahan [10] employed artificial neural networks and regression modelling to establish the relationships between welding input variables and the parameters for the Goldak heat source model in GTA welding. The data needed for modelling has been gathered based on full factorial design. They showed that these approaches may be used to accurately specify heat source parameters for any given set of welding process variables. Both ANN and second order regression functions presented good agreements with the experiments. Zhao et al. [11] studied the performances of the regression model and artificial neural network in predicting the nugget diameter of TC2 titanium alloy spot welded joints by monitoring the dynamic power signature. The experimental results proved that, as compared with the quadratic regression model an artificial neural network, it can provide more accurate results of the nugget-diameter-prediction and a better target. Furthermore, the quadratic polynomial-stepwise-regression method may not provide precise values of certain points for some highly nonlinear equations.

In this work it was proposed a comparative study on the performance of artificial neural networks and a second degree regression models for prediction of the bead geometry in the pulsed gas metal arc welding (GMAW) process. The pulsed GMAW process has received increased attention in the welding industry, owing to its comparatively low heat input and precise control over the thermal cycles. This is because the pulsed current gas metal arc welding process spray transfer, or other precisely controlled droplet transfer mode, are obtained at a low average current [12]. A series of experiments were carried out by applying a Box-Behnken experiment design. The backpropagation ANN with the Bayesian–Regulation training algorithm was used to train the neural network models. The results obtained from these two models are then compared through a new set of validation data.

2. Experiments Description

The pulsed GMAW process was performed on a TransPlus Synergic 4000R power source, a MA1400 Robot was applied to control the welding path. Experimental setup used for the present work is shown Figure 1.

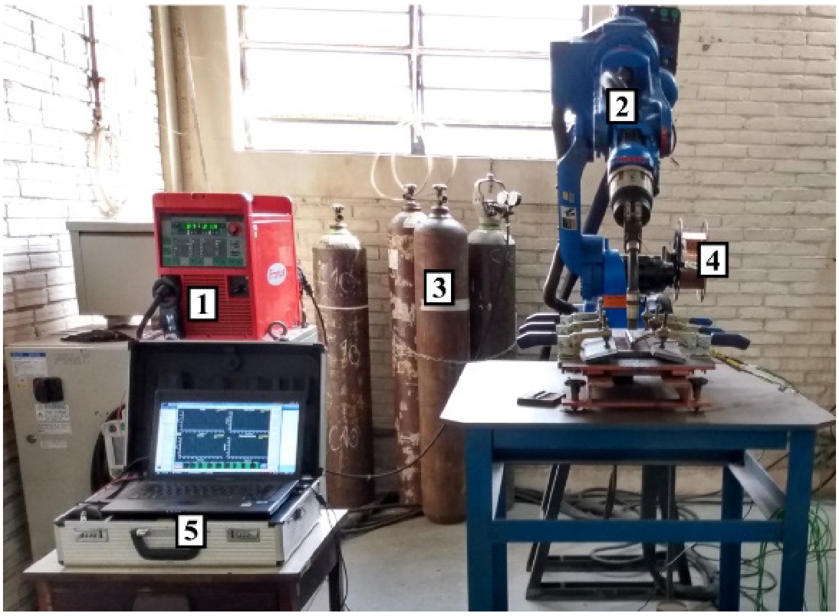

Figure 1. Experimental setup (1): welding power source (2), robot (3), shielding gas (4), solid wire (5), current and voltage acquisition system.

Deposition was implemented on a AISI 1010 mild steel substrate with 6.35 mm thick, 250 mm length and 150 mm width. The AWS ER70S-6 copper-coated solid wire of diameter 0.8 mm was selected as the filler material. The shielding gas was a mixture of 90% Ar and 10% CO_2. The weld beads were deposited side by side keeping a distance of 20 mm between them, a sufficient distance to avoid interference from their isotherms.

The three process parameters varied during the experiments were the wire feed speed (w), contact tip to work distance ($CTWD$) and welding speed (s). The current and voltage was automatically tuned by the welding machine, since this was a synergistic process. The other controllable parameters as torch angle and gas flow rate were kept fixed in this experiment, set to 0° and 15 L/min, respectively. Initial experiments have been conducted to determine the range of input process parameters, in order to obtain weld beads with smooth appearance and free of visual defects. In this way, the feasible operating regions for the process parameters were selected. The working limits of the input parameters were fixed as 6.0 – 7.5 m/min for wire feed speed, 16.0 – 20.0 mm for contact tip to work distance and 2.0 – 6.0 mm/s for the welding speed.

For this number of parameters the amount of experiments for a complete factorial design would be extensive and expensive to perform. Therefore, in order to reduce the cost of the experiments while maintaining the significance and sensitivity of the parameters, it was decided to use a Box-Behnken design of experiment (DOE) [13], which consists of a class of rotatable or nearly rotatable second-order (2k) designs based on three-level incomplete factorial designs. In this model, the number of experiments (N) required for your development is defined by $N = 2k(k-1) + C_0$, where k is number of factors and C_0 is the number of central points.

Due to the large range and the strong influence of this parameter, the welding speed was divided into two groups. Using the three proposed factors, the test was carried out with 15 experiments for each group, of which 12 are combinations of factors and 3 are the central points. A characteristic of this DOE is that it does not contain points in its vertices maximum and minimum values of the variables. Therefore, the three factors will not be at their lower or upper limits in the same experiment at same time, which could cause damage to the experiment. The process parameters and their levels are given in Table 1.

Table 1. Process parameters and their limits.

Parameters		**Factor levels**		
		Level 1	**Level 2**	**Level 3**
Wire feed speed [m/min]		6.0	6.7	7.5
Contact tip to-work distance [mm]		16.0	18.0	20.0
Welding speed [mm/s]	Group 1	2.0	3.0	4.0
	Group 2	4.0	5.0	6.0

After setting up the required equipment and designing the matrix for the experiments, the specimens were welded together. 30 experiments have been designed and conducted, 15 for each welding speed group. The experiments matrix and the outputs are shown in Table 2.

Table 2. Design matrix and responses.

	S. no[1]	**Design matrix**			**Response**		
		w **[m/min]**	**CTWD** ***[mm]***	s **[mm/s]**	l **[mm]**	h **[mm]**	p **[mm]**
Group 1	1	6.7	20.0	2.0	7.485	3.849	0.727
	2	6.7	18.0	3.0	6.456	3.338	0.721
	3	7.5	20.0	3.0	6.928	3.570	1.047
	4	7.5	16.0	3.0	7.648	3.272	1.040
	5	6.7	18.0	3.0	6.849	3.213	0.877
	6	6.7	20.0	4.0	5.666	2.708	0.850
	7	6.0	16.0	3.0	6.224	3.095	0.606
	8	6,7	18.0	3.0	6.644	3.296	0.879
	9	6.7	16.0	4.0	6.103	2.713	0.855
	10	7.5	18.0	2.0	9.016	3.935	0.821
	11	6.0	18.0	2.0	7.315	3.673	0.540
	12	7.5	18.0	4.0	6.481	2.927	1.074
	13	6.0	18.0	4.0	5.506	2.732	0.578
	14	6.0	20.0	3.0	5.777	3.156	0.518
	15	6.7	16.0	2.0	8.122	3.726	0.584

Table 2. Continued…

	S. no[1]	Design matrix			Response		
		w [m/min]	CTWD *[mm]*	s [mm/s]	l [mm]	h [mm]	p [mm]
Group 2	1	6.7	20.0	4.0	5.647	2.923	0.780
	2	6.7	18.0	5.0	5.660	2.541	0.663
	3	7.5	20.0	5.0	5.900	2.621	1.054
	4	7.5	16.0	5.0	6.170	2.550	0.970
	5	6.7	18.0	5.0	5.569	2.539	0.706
	6	6.7	20.0	6.0	4.783	2.308	0.808
	7	6.0	16.0	5.0	5.367	2.364	0.662
	8	6.7	18.0	5.0	5.636	2.544	0.773
	9	6.7	16.0	6.0	5.330	2.127	0.607
	10	7.5	18.0	4.0	6.491	2.855	1.018
	11	6.0	18.0	4.0	5.495	2.660	0.553
	12	7.5	18.0	6.0	5.508	2.359	0.812
	13	6.0	18.0	6.0	5.237	2.103	0.525
	14	6.0	20.0	5.0	4.958	2.511	0.520
	15	6.7	16.0	4.0	6.196	2.682	0.893

In this study, three dimensions of the weld bead were measured, width (l), height (h) and weld penetration depth (p). As an example, the image and the measured characteristics of a welded sample are shown in Figure 2. A EZ4 HD magnifying glass and the ImageJ® image processing software were implemented as the measuring tools. The bead geometries were measured using images of the cross sections of the beads, as shown in Figure 2, for this the samples were cut (transversal to the weld bead) and metallographic prepared (sanded, polished and chemically attacked).

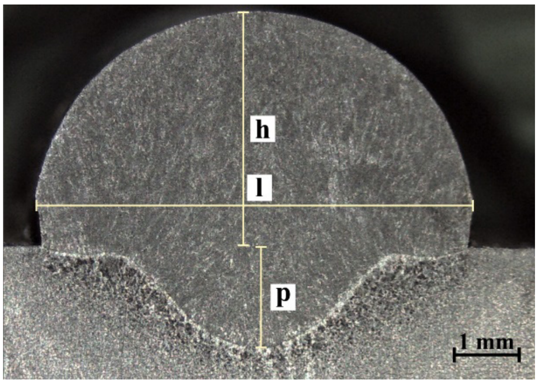

Figure 2. Cross section of the weld bead showing the geometry.

2.1. Neural network model

Initially, an artificial neural network (ANN) was adopted to characterize the complex relationship between input variables (welding parameters) and the bead geometry. The structure of the ANN was a multilayer feedforward trained with the back-propagation error algorithm. The development and training of the network were performed using Matlab® toolbox. A schematic representation of the structure of the multilayer feedforward network that performs the mapping between the three input process variables and the four output responses is shown in Figure 3. The training data of the neural network were the 30 input output pairs shown in Table 2.

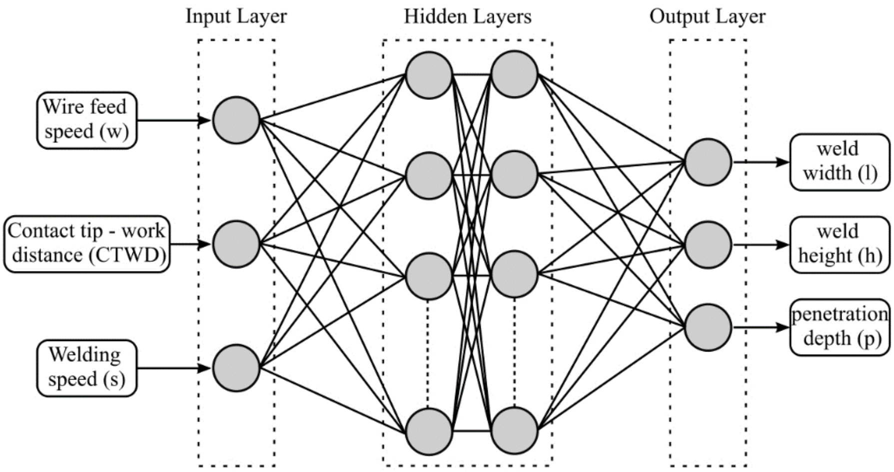

Figure 3. A schematic diagram of feedforward neural network.

To train the network accurately, all training data was normalized into the closed interval [−1, 1]. This ensures that each welding parameter has the identical effect on the network. The normalised value (X_i) for each input and output was calculated through Equation 1.

$$X_i = \frac{2}{R_{max} - R_{min}} (R_i - R_{min}) - 1 \quad (1)$$

Where R_i is the correspondent input or output value, R_{max} and R_{min} are the maximum and minimum values of the data set, respectively.

The number of neurons in the input and output layers are equal to the number of input and output variables, respectively. Neurons in the hidden layers are the computational elements accomplishing nonlinear mapping between process variables and output. The number of hidden layers and the number of neurons in each layer has a great influence in the performance of a neural network. Determining this number is an important step, excessive hidden neurons result in overfitting and increase computational costs. On the contrary, too few hidden neurons can degrade the learning ability of the network and its approximation performance [14]. The number of hidden layers and neurons in each layer was obtained numerically, in order to find the minimum error between the desired and actual outputs. For this, different feedforward neural networks with 1 and 2 hidden layers and 1 to 30 neurons in each layer were trained. The least error between the desired and actual outputs was obtained for the network with two hidden layers and 23 and 12 neurons in the first and second layers, respectively. Bayesian–Regulation Back Propagation algorithm was used as the training method. Tangent sigmoid and linear functions were respectively selected as the activation functions in neurons of hidden and output layers.

The Bayesian regularization neural network is an artificial neural network training algorithm which corrects the weight values based on the Levenberg-Marquardt optimization. This algorithm minimizes the combination of error squares and weights (introducing network weights into the objective function of training) and then determine the correct combination so as to produce a good network. Thus, the objective function of the training is noted as shown in Equation 2 [15,16].

$$F(\omega) = \alpha E\omega + \beta ED \quad (2)$$

where $E\omega$ is the sum of squares of the network weight, and ED the sum of squares of network errors. The values α and β are parameters of the objective function.

In the Bayesian process flow, network weights are seen as random variables, then the previous distribution of network weights and training is considered a Gaussian distribution follows [15,16]. The principle of Bayesian Regularization artificial neural network training algorithm is shown in Figure 4.

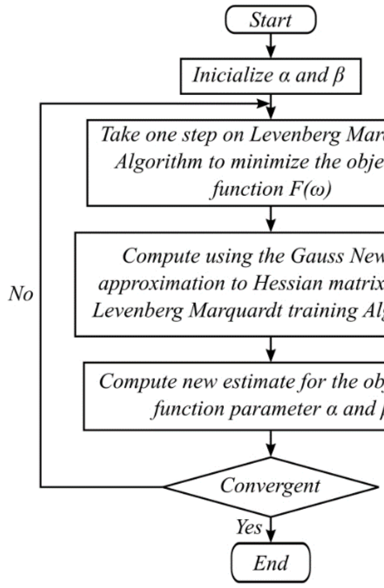

Figure 4. Principles of Bayesian regularization algorithm [15,16].

2.2. Regression model

For the problem at hand, a second degree regression model has been selected. The objective is to establish the relations between process variables (wire feed speed, contact tip to work distance and welding speed) and the bead geometry. The response function representing any of the controllable process parameters can be expressed by Equation 3 [17].

$$Y = f(x_1, x_2, \dots x_n) \tag{3}$$

where Y is the response, $(x_1, x_2, \dots x_n)$ the controllable process variables. A second-order (quadratic) polynomial for n factors is formulated as (Equation 4):

$$Y = a_0 + \sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n} a_{ii} x_i^2 + \sum_{i=1,i<j}^{n} a_{ij} x_i x_j \tag{4}$$

where, $\propto_0$ is the constant value; $\propto_i$, $\propto_{ii}$ and $\propto_{ij}$ are the coefficients to be calculated, which are usually obtained via the least square method.

The same datasets, as used in neural network model, were used to develop the regression models, showed in Table 2. The values of the regression coefficients were calculated using the MINITAB® statistical analysis software.

3. Results and Discussion

3.1. Investigating the parameters effect

The effects of the input parameters in the weld bead dimensions are detailed in Figure 5. It can be seen that for the welding conditions used in this work, increasing the wire feed speed lead to the increase of all dimensions, this effect is more significant in weld width and penetration depth and smoother in weld height. The contact tip to work distance, which is associated to arc length, showed lower influence on weld bead geometry.

An increase in welding speed caused a decrease in weld width and weld height. Regarding the bead penetration, it presented a low value for the minimum welding speed of 2 mm/s and started to increase reaching the maximum at 4 mm/s. Then, it decreased again for higher speeds. For high welding speeds, weld bead penetration reduces with the increases of welding speed due to low heat content of the weld pool [18].

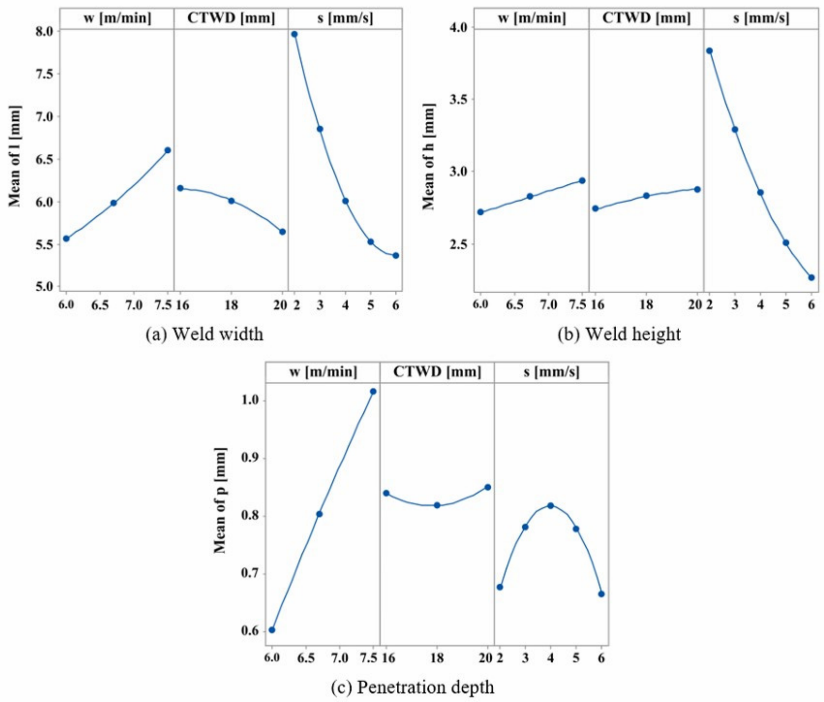

Figure 5. Effect of parameters in the bead geometry.

3.2. Neural network model

Figure 6 shows the scatter plots of the datasets, the three plots represent the training, testing, and overall dataset. The dashed line in each plot represents the perfect result – outputs = targets. The solid line represents the best fit linear regression line between outputs and targets. The R value is an indication of the relationship between the outputs and targets. If R = 1, there is an exact linear relationship between outputs and targets. If R is close to zero, then there is no linear relationship between outputs and targets.

The results shown in Figure 6 indicate a high efficiency of the neural network. All R's have high values, which demonstrates a good performance of the built model. Hence, it can be noted that the developed neural network is appropriate and can predict the weld bead geometry accurately. Besides, the results of the test data (Figure 5b) indicate a good generalization capability between input and output data.

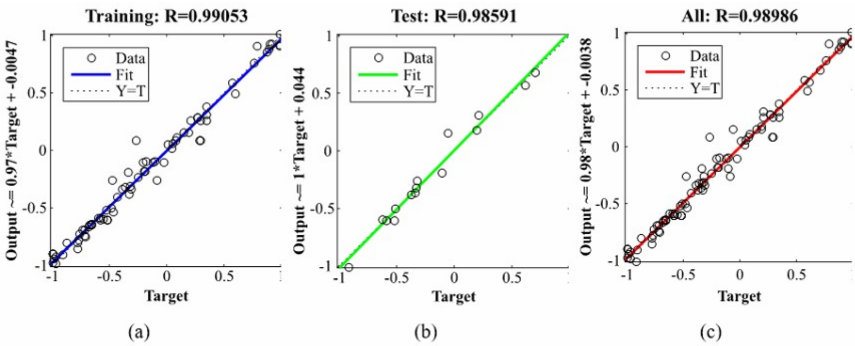

Figure 6. Regression plots of datasets: (a) training; (b) testing and (c) overall dataset.

The artificial neural network predicted versus actual values for the three outputs are plotted in Figure 7. In this figure, the dashed line represents the perfect fit between the experimental data (measured weld bead geometry) and those calculated by the ANN.

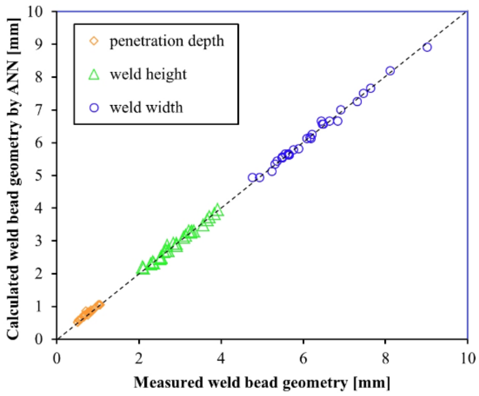

Figure 7. Comparison between calculated with ANN and measured weld bead geometry.

Based on the results shown in Figure 7, it can be observed that there is a good relationship between the actual and predicted values. The mean of the relative error between the measured values and the neural network predicted values was 0.031 for weld width, 0.052 for weld width and 0.196 for penetration depth.

3.3. Regression model

As mentioned previously, second order polynomial regression model was selected to determine the bead geometry parameters using MINITAB® software. In all regression models the α − level (significance level) was assumed to be 0.05. The constituted models for weld width, height and penetration depth are listed in the following (Equations 5-7).

- Weld width

$$\mathrm{l} = -\mathbf{0.68} + \mathbf{0.070}.\boldsymbol{w} + \mathbf{0.906}.\boldsymbol{CTWD} - \mathbf{0.803}.\boldsymbol{s} + \mathbf{0.12}.\boldsymbol{w}^{2} - \mathbf{0.028}.\boldsymbol{CTWD}^{2} + \mathbf{0.161}.\boldsymbol{s}^{2} - \mathbf{0.0101}.\boldsymbol{w}.\boldsymbol{DTWD} - \mathbf{0.204}.\boldsymbol{w}.\boldsymbol{s} + \mathbf{0.014}.\boldsymbol{CTWD}.\boldsymbol{s} \quad (5)$$

- Weld height

$$\boldsymbol{h} = \mathbf{3.28} - \mathbf{0.035}.\boldsymbol{w} + \mathbf{0.108}.\boldsymbol{CTWD} - \mathbf{0.675}.\boldsymbol{s} + \mathbf{0.0008}.\boldsymbol{w}^{2} - \mathbf{0.00447}.\boldsymbol{CTWD}^{2} + \mathbf{0.0517}.\boldsymbol{s}^{2} + \mathbf{0.0134}.\boldsymbol{w}.\boldsymbol{CTWD} - \mathbf{0.0173}.\boldsymbol{w}.\boldsymbol{s} - \mathbf{0.00053}.\boldsymbol{CTWD}.\boldsymbol{s} \quad (6)$$

- Penetration depth

$$\boldsymbol{p} = \mathbf{2.96} + \mathbf{0.063}.\boldsymbol{w} - \mathbf{0.43}.\boldsymbol{CTWD} + \mathbf{0.275}.\boldsymbol{s} - \mathbf{0.0166}.\boldsymbol{w}^{2} + \mathbf{0.0069}.\boldsymbol{CTWD}^{2} - \mathbf{0.0366}.\boldsymbol{s}^{2} + \mathbf{0.0257}.\boldsymbol{w}.\boldsymbol{CTWD} - \mathbf{0.0058}.\boldsymbol{w}.\boldsymbol{s} + \mathbf{0.0029}.\boldsymbol{CTWD}.\boldsymbol{s} \quad (7)$$

The statistical characteristics of the models are presented in Table 3. Regarding to the F-distribution tables, it can be seen that for the selected α − level, the F-values are greater than the critical values of F. Therefore, it can be concluded that all models are well suited. The high values of R^2, R^2_{adj}, and R^2_{pred} prove that in all cases the models fit very well with the data.

Table 3. The statistical characteristics of the constructed models.

Regression model	F-value	R^2 [%]	R^2_{adj} [%]	R^2_{pred} [%]
Weld width	111.90	98.05	97.18	94.56
Weld height	170.56	98.71	98.14	97.20
Penetration depth	15.96	87.78	82.28	67.01

The regression values versus actual values for the three outputs are plotted in Figure 8. In this figure, the dashed line in this plot represents the perfect fit between the experimental data (measured weld bead geometry) and those calculated by the regression model.

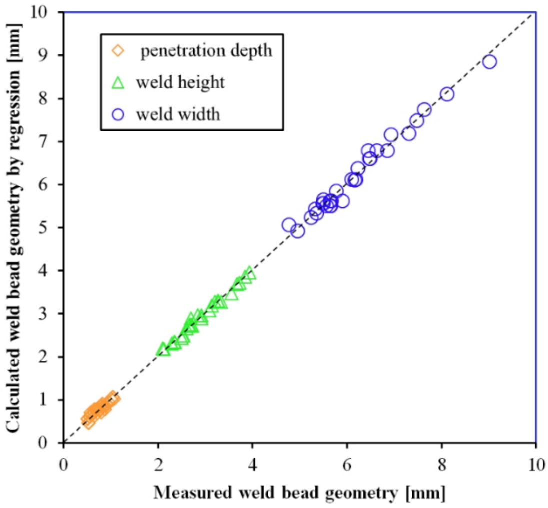

Figure 8. Comparison between calculated with regression models and measured weld bead geometry.

Based on the results shown in Figure 8, it can be observed that there is a good relationship between the actual and predicted values. The mean of the relative error between the measured values and the regression values is 0.055 for weld width, 0.060 for weld width and 0.204 for penetration depth.

3.4. Validation tests

To check the accuracy of the established models, the validation of developed models from the neural network and regression is presented. The model has been validated using three samples that were welded with different values of process variables within the limits that were performed in Table 2, as can be observed in Table 4.

Table 4. Dataset of input parameters and results for the validation model.

S. no	Parameter		
	w [m/min]	CTWD*[mm]*	s [mm/s]
#1	6.7	18.0	6.0
#2	7.5	20.0	6.0
#3	6.0	20.0	6.0

The performance of the designed ANN was evaluated via the test samples which were presented in Table 4. Also, are show the relative error between the numerical and experimental results. These values are calculated according to Equation 8.

$$Error = \left|\frac{x_{exp}-x_{out}}{x_{exp}}\right| \cdot 100 \quad (8)$$

Where x_{exp} represents the experimental value and x_{out} the corresponding outputs of ANN and regression models.

The results of the network validation tests are shown in Table 5. According to the results, the maximum number of relative errors is 31.734, 13.657 and 25.326 for the test numbers 1, 2 and 3, respectively. Furthermore, the average of all errors is 9.847, 7.191 and 15.490 for weld width, height and penetration depth, respectively. The average error of all tests and output parameters was 10.843.

Table 5. Validation of the neural network model.

S. no		l [mm]	h [mm]	p [mm]
1	Outputs of ANN model	5.283	2.242	0.642
	Experimental result	5.260	2.340	0.940
	Relative Error	0.437	4.176	31.734
2	Outputs of ANN model	5.324	2.392	0.997
	Experimental result	5.130	2.770	1.080
	Relative Error	3.777	13.657	7.646
3	Outputs of ANN model	4.742	2.243	0.576
	Experimental result	6.350	2.330	0.620

	Relative Error	25.326	3.737	7.091

Then, the corresponding geometry of test samples presented in Table 4 was obtained using Equations 5-7. The results of validation tests are presented in Table 6. According to the results, the maximum number of relative errors is 30.682, 13.016 and 25.439 for the test numbers 1, 2 and 3, respectively. Furthermore, the average of all errors is 9.293, 7.301 and 23.046 for weld width, height and penetration depth, respectively. The average error of all tests and output parameters was 13.213.

Table 6. Validation of the regression model.

S. no		l [mm]	h [mm]	p [mm]
1	Outputs of regression model	5.354	2.253	0.652
	Experimental result	5.260	2.340	0.940
	Relative Error	1.795	3.717	30.682
2	Outputs of regression model	5.323	2.415	0.939
	Experimental result	5.130	2.770	1.080
	Relative Error	3.754	12.812	13.016
3	Outputs of regression model	4.932	2.205	0.462
	Experimental result	6.350	2.330	0.620
	Relative Error	22.331	5.373	25.439

Figure 9 shows the scatter diagram of predicted versus actual bead geometry from the neural network and regression models. It can be seen that both models produce good fit to the experimental results and give accurate prediction of the width, height and penetration depth weld.

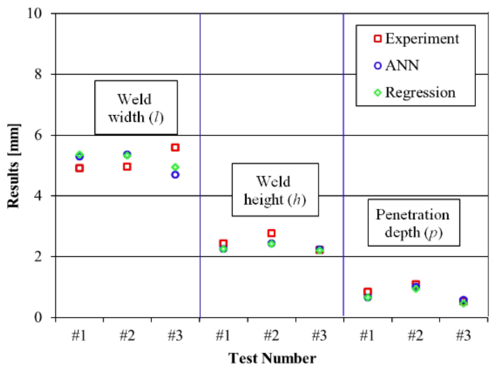

Figure 9. Comparison between the measured dimensions, estimated by the neural network and calculated with the regression models.

With regard to Table 5 and Table 6 and Figure 9, it can be concluded that both ANN and regression models are capable to predict the bead geometry very well. In general, the ANN model has lower error values. It can be concluded that owing to the lower mean value of the relative error, it performs slightly better than the second-order regression model. One of the principal reasons for the superior performance of the BP neural network model is that it displays a better predictive capability than the regression model in actual application, owing to its random non-linear mapping ability [19]. But, on the other hand, the construction and execution of regression models is easier than the neural networks. If the regression model is constructed well, it is recommended to use this method due to the simplicity. Otherwise, the ANN is highly recommended.

4. Conclusions

This article aimed to compare different methods to predict the weld bead geometry of Pulsed GMAW bead on a steel plate. The relationships between process variables and bead geometry were investigated by a neural network trained with Bayesian–Regulation Back Propagation algorithm and a second degree regression model. A series of experiments were carried out by applying a Box-Behnken experiment design.

After training different structures of neural networks, it was found that a four-layer feed-forward back propagation neural network model with two hidden layer and 23 and 12 neurons in these layers was more accurate. Then a second-order regression model was established to predict the bead geometry from the process variables. The significance and adequacy of the regression model were verified.

The results indicated that the geometry can be well predicted by both models. The overall mean error was 10.843 for the neural network and 13.213 for the regression model. In general, the neural network model presented an improved performance than the second-order regression model. But, on the other hand, the construction and execution of regression models is easier than the neural networks. If the regression model is constructed well, it is recommended to use this method due to its simplicity.

Authors' contributions

DFG: data curation, formal analysis, investigation, methodology, writing – original draft, writing review & editing. WH: project administration, data curation, writing – review & editing. CCPM: supervision, formal analysis, writing – review & editing. JAEM: supervision, formal analysis, writing – review & editing.

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