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Estimation of Undercuts in Mild Steel Weldment using Artificial Neural Network

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ABSTRACT

Weld undercut is a common welding defect that occurs when the weld metal penetrates too deeply into the base metal, creating a groove or undercut along the base metal adjacent to the weld. To improve and predict this weld defect with respect to the weld current, voltage and gas flow rate factors, artificial neural network (ANN) was employed. 100 welded specimens of mild steel, measuring 60mm x 40mm x10mm were prepared and measured using the V-WAC gauge. The results were employed to train ANN. The research produced an R^2 of 93% in comparison to the experimental result on a fitted line plot using regression analysis, while correlation analysis obtained in the training and validation exercise from ANN were all above 80%. Result of the study have shown that ANN is a robust predictive tool in welding which could help reduce trial and error in welding processes.

1. INTRODUCTION

Metal welding is a process that joins two metal components by heating the surfaces to the point of melting and then fusing them together. The resulting bond is strong and durable, making it a common method for fabricating and repairing metal structures, machinery, and equipment (Dhobale and Mishra, (2015) and (Etin-osa and Achebo, 2017). Weld undercut is a common welding defect that occurs when the weld metal penetrates too deeply into the base metal, creating a groove or dent along the base metal adjacent to the weld (Etin-Osa and Ogbeide, 2021). Undercut can weaken the joint and reduce its load-carrying capacity, and can also provide a place for cracks to initiate and propagate. Undercut can be caused by several factors, including:

- Incorrect welding technique:Welding too fast or too slow,or using incorrect welding parameters.
- Improper joint preparation: Poor joint preparation, such as not removing all contaminants from the base metal before welding.
- Incorrect electrode selection: Using the wrong type of electrode can cause undercut if it does not provide adequate penetration into the base metal.
- Inadequate joint design: Joint design that does not provide adequate access to the root of the joint can result in undercut.
- Improper shielding: Improper shielding can cause undercut if it

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allows the base metal to become contaminated during welding.

It's important to detect and prevent undercut through proper welding techniques, joint preparation, electrode selection, joint design, and shielding, as well as through inspection and testing (Achebo, 2011) (Allen et al, 1985) and (Imhansoloeva et al, 2018). If undercut is detected, it can be corrected through grinding the undercut to remove it, and then rewelding. Undercut in welds can be measured using a variety of methods, including:

- Visual inspection& Measurement: Undercut can be identified by visual inspection using a magnifying lens, V-Wac gauge, digital depth gauge, or fluorescent penetrant inspection (FPI). This method is best suited for detecting undercut in relatively shallow welds.
- Ultrasonic testing (UT): UT uses high-frequency sound waves to inspect the weld and detect any discontinuities, including undercut. This method is best suited for detecting undercut in deeper welds.
- Radiographic testing (RT): RT uses X-rays or gamma rays to inspect the weld and detect any discontinuities, including undercut. This method is best suited for detecting undercut in deeply buried welds.
- Magnetic particle inspection (MPI): MPI uses a magnetic field and iron oxide or iron oxide-coated magnetic particles to inspect the weld and detect any discontinuities, including undercut.
- Eddy current testing (ET): ET uses a magnetic field and induced currents to inspect the weld and detect any discontinuities, including undercut. The method used to measure undercut will depend on the type of weld, the material being welded, the size of the undercut, and the level of accuracy required. In many cases, a combination of methods may be used to accurately measure and evaluate undercut in a weld (Achebo, 2012).

While it is important to detect and prevent weld undercutting through best practices such as outlined above, In this work, emphasis is placed on predicting weld undercut using artificial neural network (ANN) (Achebo 2012), (Achebo, 2011) and (Achebo and Omoregie, 2015). This technique offers a more precise way of predicting good quality weld, avoiding the trial and error approach.

2. MATERIALS AND METHODS

2.1. Materials

200 coupons measuring 60mm x 40mm x10mm were prepared for welding. The sample material is made from mild steel type. To weld these coupons, input parameters in Table 1 was fed into design expert 13.

2.2. Method of Data Collection and Analysis

The central composite design matrix using response surface methodology of design expert 13 was employed to create the design of experiment shown in Table 2. To perform the experiment, the prepared 200 coupons were divided into 20 groups with 10 coupons for each group. These groups corresponded to the numbers of run presented in Table 2. The tungsten inert gas (TIG) welding equipment presented in Figure 1, following the value of current, voltage and gas flow rate provided for each run was used to weld the coupons. A total of 100 samples were obtained with 5 samples per group.

Weld undercut is the unfilled part of a welded plate, this defective area usually occurs at the bottom part of the welded part as shown in Figure 2.Presented in Figure 3 is the Digital depthgaugeemployed for the measurement of weld undercut.

Table 1: Process parameters and their levels

Factors	Unit	Symbol	Low (-1)	High (+1)
Welding Current	Ampere	I	150	180
Welding Voltage	Volts	V	16	19
Gas Flow Rate	Lit/min	GFR	13	16

Table 2: Design of experiment (DOE) matrix

Run	Current (A)	Voltage (V)	Gas flow rate Lit/min
1	165.000	17.500	14.500
2	180.000	16.000	16.000
3	150.000	19.000	16.000
4	165.000	17.500	14.500
5	165.000	17.500	14.500
6	165.000	20.023	14.500
7	180.000	19.000	16.000
8	165.000	17.500	14.500
9	150.000	19.000	13.000
10	165.000	17.500	14.500
11	180.000	16.000	13.000
12	139.773	17.500	14.500
13	180.000	19.000	13.000
14	165.000	14.977	14.500
15	190.227	17.500	14.500
16	165.000	17.500	11.977
17	165.000	17.500	17.023
18	150.000	16.000	13.000
19	150.000	16.000	16.000
20	165.000	17.500	14.500

Figure 1: Tungsten Inert Gas welding equipment

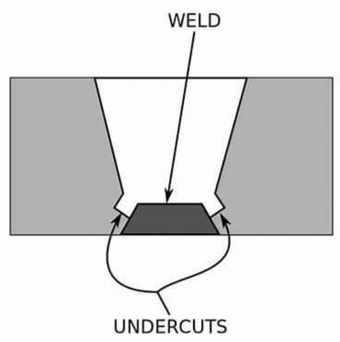

Figure 2: Weld samples

Figure 3: Digital depth guage

3. RESULTS AND DISCUSSION

To predict the weld undercut using ANN, the network has to be trained with actualexperimental response. The design matrix showing the real value of three input variables namely; current (Amp), voltage (volts) and gas flow rate (L/min) and the weld undercut response is presented in Table 3.

Table 3: Design matrix showing the real values and the experimental values

Run	Factor 1 A:Weld Current Ampere	Factor 2 B:Weld Voltage Volt	Factor 3 C:Gas flow rate Lit/min	Response 1 Weld undercut (mm)
1	165.000	17.500	14.500	0.080
2	180.000	16.000	16.000	0.060
3	150.000	19.000	16.000	0.060
4	165.000	17.500	14.500	0.070
5	165.000	17.500	14.500	0.080
6	165.000	20.023	14.500	0.050
7	180.000	19.000	16.000	0.050
8	165.000	17.500	14.500	0.080
9	150.000	19.000	13.000	0.070
10	165.000	17.500	14.500	0.080
11	180.000	16.000	13.000	0.080
12	139.773	17.500	14.500	0.090
13	180.000	19.000	13.000	0.040
14	165.000	14.977	14.500	0.070
15	190.227	17.500	14.500	0.070
16	165.000	17.500	11.977	0.070
17	165.000	17.500	17.023	0.050
18	150.000	16.000	13.000	0.090
19	150.000	16.000	16.000	0.060
20	165.000	17.500	14.500	0.080

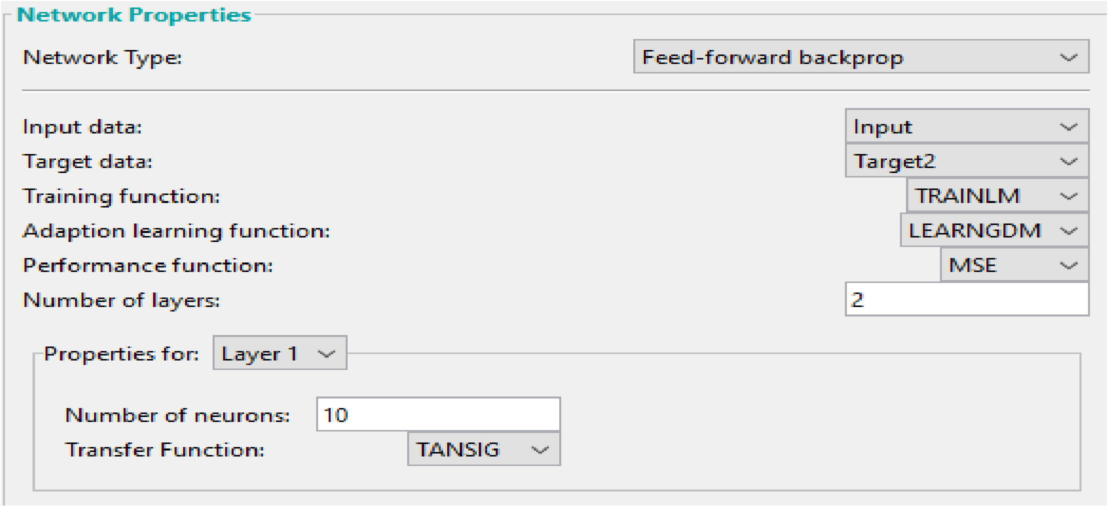

Figure 4: Network properties interphase for predicting weld undercut response

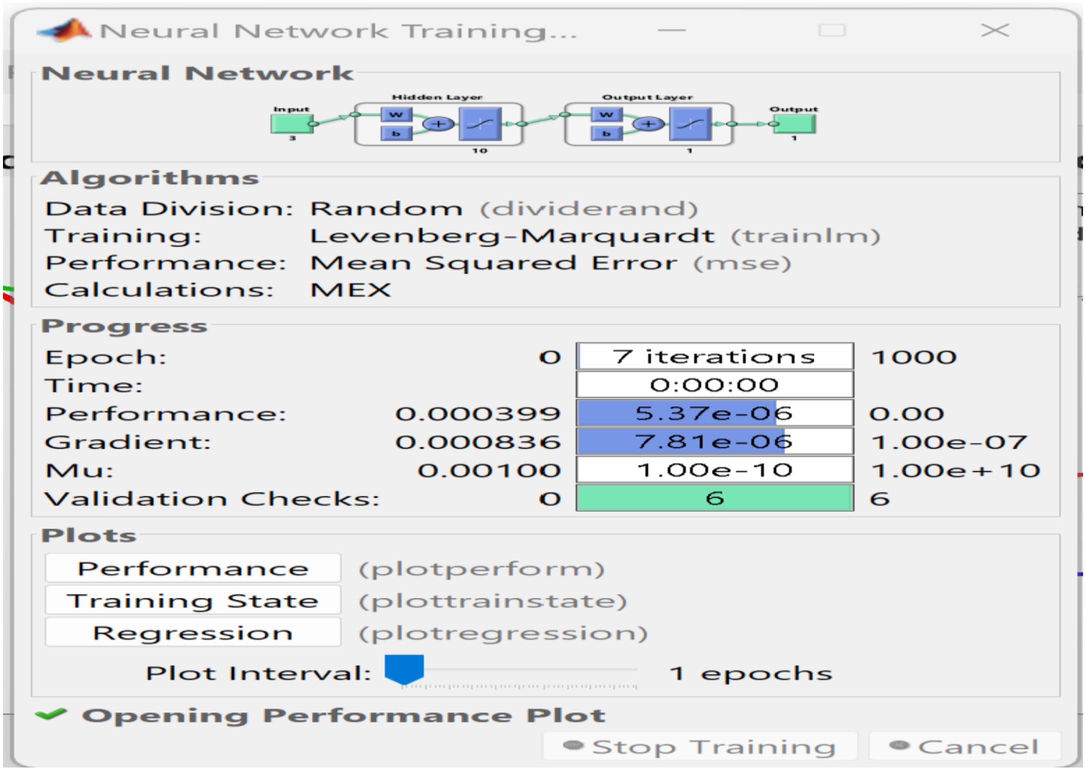

Figure 5: Network training diagram for predicting Weld Undercut responses

To effectively train the network, Figure 4 present the configuration interphase for neural network, where all parameters were set and the feed forward backprop was chosen amongst other network type to yield the best results. Current, voltage and weld speed information provided in Table 1 were inputted into ANN to output the Weld Undercut.

Figure 5 present the neural network diagram for predicting the Weld Undercut responses. Data division algorithm was set to random (dividerand), training algorithm was set to Levenberg-Marquardt (trainlm), and performance algorithm was set to Mean squared error (mse).

Figure 6 presents the performance curve for the trained network. The best validation performance was obtained at epoch 1.

In MATLAB software, an epoch can be

thought of as a completed iteration of the training procedure of your artificial neural network. Which means, once all the vectors in your training set have been used or gone through your training algorithm, one epoch has been attained. Thus, the "real-time duration" of an epoch is dependent on the training method used. The best prediction for the Weld Undercut responses was achieved at epoch 1, although, a total of 7 epochs where used in the iteration process.

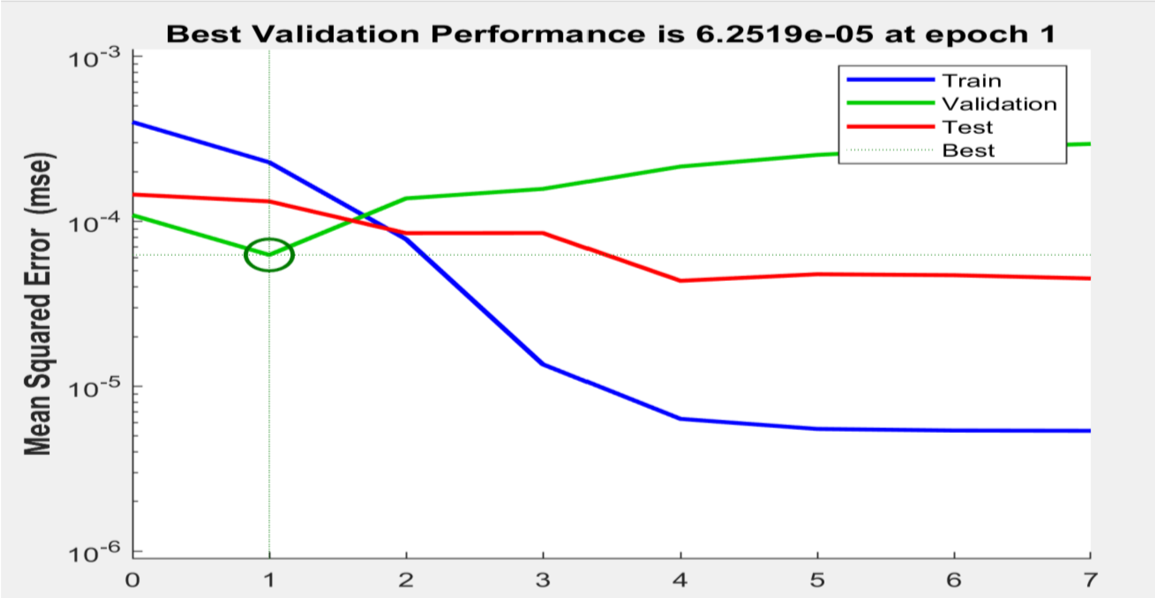

Figure 6: Performance curve for trained network to predicting Weld Undercut responses

Figure 7 shows the number of epochs used up during the training process. 1 epoch, signifies one complete algorithm training. 1 epoch was used and Figure 7 and shows that at the 1stepoch, best prediction was achieved. From the dotted red lines for validation checks in Figure 7, it could be seen that the lowest failure was at epoch 1. Figure 8 present the training, validation and testing plot with correlation coefficient (R) of over 80% which signifies a robust prediction for the Weld Undercut. The dotted diagonal line on each plot indicates the line of best fit which indicate a perfect prediction and a correlation of 1.

The comparison plote between the training results and validation results from Figure 8 is given in Table 4.

In comparing the prediction strength of ANN to the experimental results, Regression Analysis based on the fitted line plot shown in Figure 9for Weld Undercut were performed to produce equation 1 with Table 5 as its model summary

$EXP = 0.000144 + 0.9985 * ANN$

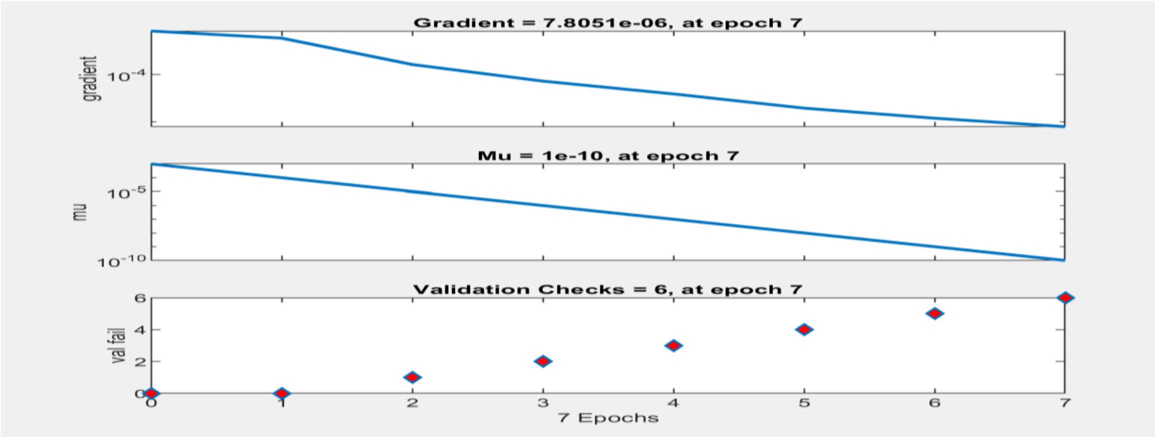

Figure 7: Neural network gradient plot for predicting Transverse responses

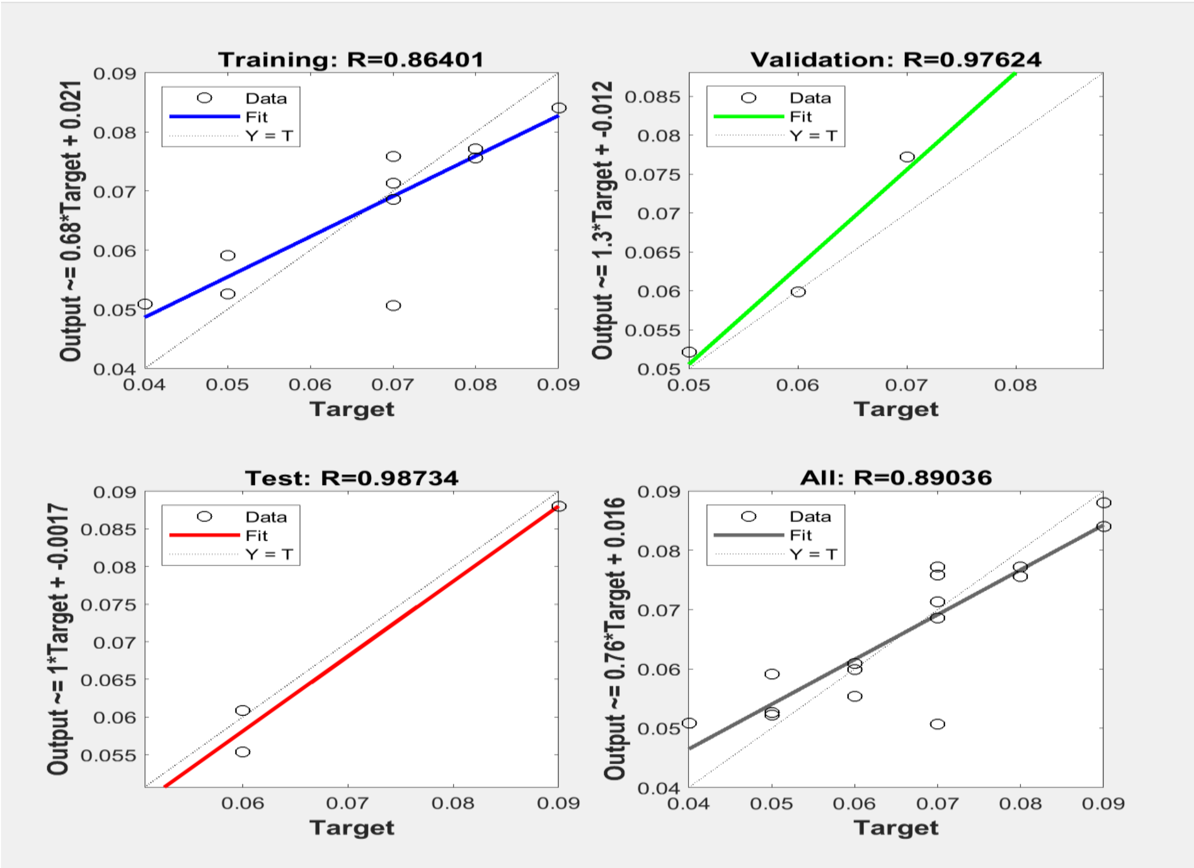

Figure 8: Regression plot of training, validation and testing for Weld Undercut responses

Table 4: Comparison Table between Experimental value vs ANN trained result of weld undercut responses.

S/N	Input parameters			Exp Responses	ANN Prediction
	Current (ampere)	Voltage (Volts)	GFR (Lit/min)	Weld Undercut (mm)	Weld Undercut (mm)
1	165.000	17.500	14.500	0.080	0.078
2	180.000	16.000	16.000	0.060	0.061
3	150.000	19.000	16.000	0.060	0.063
4	165.000	17.500	14.500	0.070	0.078
5	165.000	17.500	14.500	0.080	0.078
6	165.000	20.023	14.500	0.050	0.046
7	180.000	19.000	16.000	0.050	0.051
8	165.000	17.500	14.500	0.080	0.078
9	150.000	19.000	13.000	0.070	0.071
10	165.000	17.500	14.500	0.080	0.078
11	180.000	16.000	13.000	0.080	0.078
12	139.773	17.500	14.500	0.090	0.089
13	180.000	19.000	13.000	0.040	0.043
14	165.000	14.977	14.500	0.070	0.072
15	190.227	17.500	14.500	0.070	0.068
16	165.000	17.500	11.977	0.070	0.069
17	165.000	17.500	17.023	0.050	0.048
18	150.000	16.000	13.000	0.090	0.091
19	150.000	16.000	16.000	0.060	0.058
20	165.000	17.500	14.500	0.080	0.078

Table 5: Model Summary for ANN

S	R-sq	R-sq(adj)
0.0027717	96.34%	96.14%

The model summary values obtained in Table 5 and fitted line plot presented in Figure 9 for ANN shows that ANN has an R^2 prediction strength of 96.34% which is robust enough to predict beyond the given input ranges.

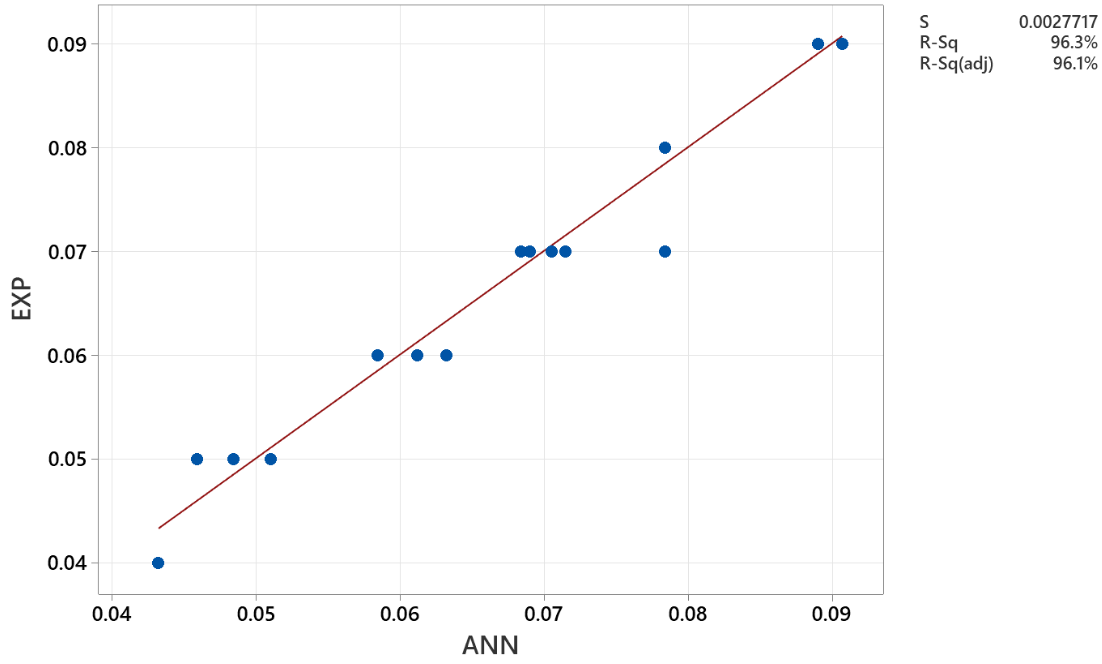

Figure 9: Regression plot of Experimental versus predicted Weld Undercut responses

4. CONCLUSION

Weld undercut is a defect in welded metal which can lead to quick failure of the weld component under loading and predicting its magnitude would be a great preventive measure to mitigate against failure. The study has developed and applied predictive expert models to estimateWeld undercut of TIG mild steel weld using ANN. This research demonstrates the predictive effectiveness of ANN in the field of welding.

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