UJEAS

UNIZIK JOURNAL OF ENGINEERING AND APPLIED SCIENCES

UNIZIK Journal of Engineering and Applied Sciences 5(1), June (2025), 2204 - 2211
Journal homepage: https://journals.unizik.edu.ng/index.php/ujeas
PRINT ISSN: 2992-4383 || ONLINE ISSN: 2992-4391

Prediction of tensile strain in mild steel tig weld using artificial neural networks

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Abstract
Tensile strain is the relative length of deformation exhibited by a specimen subjected to a tensile force. An artificial neural network (ANN) was employed to predict the tensile strain of the weldment. One hundred welded specimens of mild steel, measuring 60mm x 40mm x10mm, were prepared and calculated using the VWACgauge. The results were employed to train ANN. The research produced an R^2 of 86% 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 was over 90%. Results of the study have shown that ANN is a robust predictive tool in welding, which could help reduce trial and error in welding processes.

Keywords: tensile strain, Tungsten Inert Gas (TIG), weldment, desirability, expert, deformation, welding current

1. Introduction

In welding, tensile strain can affect the quality and durability of the weld joint. In a study by Li et al. (2021), it was found that increasing the tensile strain of the weld joint resulted in a reduction in the fatigue life of the joint. Furthermore, in a related study by Zhang et al. (2021), it was observed that increasing the tensile strain of the weld joint also decreased its fracture toughness. A welded joint is obtained when two clean surfaces are brought into contact with each other, and either pressure, heat, or both are applied to create a strong metallurgical bond. The tendency of atoms to bond is the fundamental basis of welding. A non-linear relationship exists between welding process parameters and weld quality (Narang et al., 2017). Narang et al. (2011) explained that TIG welding is done in a controlled atmosphere using a tungsten electrode, which produces an arc to melt the metal. Direct current (DC) or Alternating Current of High Frequency (ACHF) enables the resulting continuous and stable arc without touching the metal electrodes. TIG is becoming the most preferred technology because it has the cleanest weld bead and produces no debris or metal slag. Other researchers also studied the TIG parameter using a Fuzzy Logic controller, and the result found that the fuzzy clustering technique was adequate for establishing the relationship between the input process parameters and the outputs.

Chkwunedum et al. (2024) developed models for optimizing (minimizing) the weld time of mild steel weldment using response surface methodology and an artificial neural network. The input factors used in this research study are current, voltage, and gas flow rate. The output parameter is the weld time. The welding process used for the experimental welding is tungsten inert gas (TIG) welding. An adequately optimized weld time will produce a quality weld with the desired strength. The RSM analysis gave the optimal solutions for each input factor with current as

180.00Amps, voltage as 21.672Volts, and gas flow rate as 15.504L/min. The optimal solution for the output factor, weld time, is 44.000 seconds. The optimum results were achieved with a desirability of 83.62%. Analysis of variance results indicated that the gas flow rate input factor has the most significant effect on the output variable under consideration. The artificial neural network predicted an optimal solution for the weld time response factor as 53.71292Secs. It showed an overall strong correlation (R) between the input factors and the output parameter of 99.893%. They recommended that the models be used for design and application. However, the optimal solution of the artificial neural network analyses will produce a better and higher quality weld because of its higher Regression (R) value, and thus, suggested for practical application and systematic decision making.

The shape and dimensions of the weld bead are essential because these factors determine the wall thickness limits that can be built and influence the quality of the surface finish. The four main welding parameters are the welding current, arc voltage, welding speed, and wire-feed speed. Three important keys to the welding process's success are preheating the substrate (base metal), arc-length monitoring, and controlling the heat input. The influence of welding parameters such as current ratio and pulse frequency on the weld pool shape shows that for stainless steel, the choice of the peak current, background current, and pulsed frequency considerably affects the weld pool shape.

2.0 Materials and methods

The study involved ameliorating mild steel heat-treated welded joints was carried out. This work considered three input parameters: welding current, welding voltage, and gas flow rate, with tensile strain as the response or measured parameter.

2.1 ANN Generation of input data

Input data employed in the training, validation, and testing were obtained from a series of batch experiments based on the central composite design of the experiment under varied welding currents, welding voltage, and gas flow rates. A complete factorial central composite design of an experiment with six center points and three replicates resulted in 20 experimental runs used as the input data for Amadhe et al. (2023). The data were randomly divided into three subsets to represent the training (70%), validation (15%) and testing (15%). The validation data were employed to assess the performance and the generalization potential of the trained network, while the testing data were used to test the quality of the network. To avoid the problem of weight variation, which can subsequently affect the efficiency of the training process, the input and output data were first normalized between 0.1 and 1.0 using the normalization equation (Sinan et al., 2011) presented in Equation 1

$$x_i = \frac{x - x_{\min}}{x_{\max} - x_{\min}} + 0.1 \tag{1}$$

where,

xi = the normalized value of the input and output data

min; and xmax the minimum and maximum value of the input and output data

x the input and output data.

2.2 Selection of training algorithm and hidden neurons

Input and output data training resulting in network architecture design is paramount in applying neural networks to data modeling and Prediction. Two factors were considered to obtain the optimal network architecture with the most accurate input and output data understanding. First was the selection of the most accurate training algorithm, and second, the number of hidden neurons. Based on this consideration, different training algorithms and hidden neurons were selected and tested to determine the best training algorithm and accurate number of hidden neurons that will produce the most accurate network architecture. Selectivity was based on (r2 and MSE).

2.3 Network Training/Performance of ANN

A learning rate of 0.01, momentum coefficient of 0.1, target error of 0.01, analysis update interval of 500, and a maximum training cycle of 1000 epochs was used. Three runs of 1000 epochs were used to train the network. In addition, cross-validation data representing about 15% of the total input data were introduced to monitor the training progress and prevent the network from memorizing the input data instead of learning, a common problem associated with overtraining. The training progress was checked using the mean square error (MSE) graph for training and cross-validation.

2.4 Network Testing/Validation

To test the efficiency of the trained network, 15% of the input data were introduced to the network Augustine et al. (2023). Plate 1 shows the Universal Pull Tester used to determine the tensile strain of the welded specimen.

Plate 1: Universal pull tester tester

3.0 Result and Discussion

3.1 Prediction of Responses Using Artificial Neural Network

One of the fundamental challenges with response surface methodology (RSM) is the inability to predict the response variables without the experiment's design accurately. Therefore, RSM's performance depends on the beauty of the experimental design. Therefore, a predictive model such as an artificial neural network (ANN) was employed to predict the response variables beyond the scope of experimentation. To train a neural network for predicting a feed forward back propagation algorithm was used. The network's input layer uses the hyperbolic target (tan-sigmoid) transfer function to calculate the layer output from the network input. In contrast, the output layer uses the linear (purely) transfer function. The number of hidden neurons was set at 10 neurons per layer, and the network performance was monitored using the mean square error of regression (MSEREG). The network interphase for predicting impact energy is presented in Figure 1.

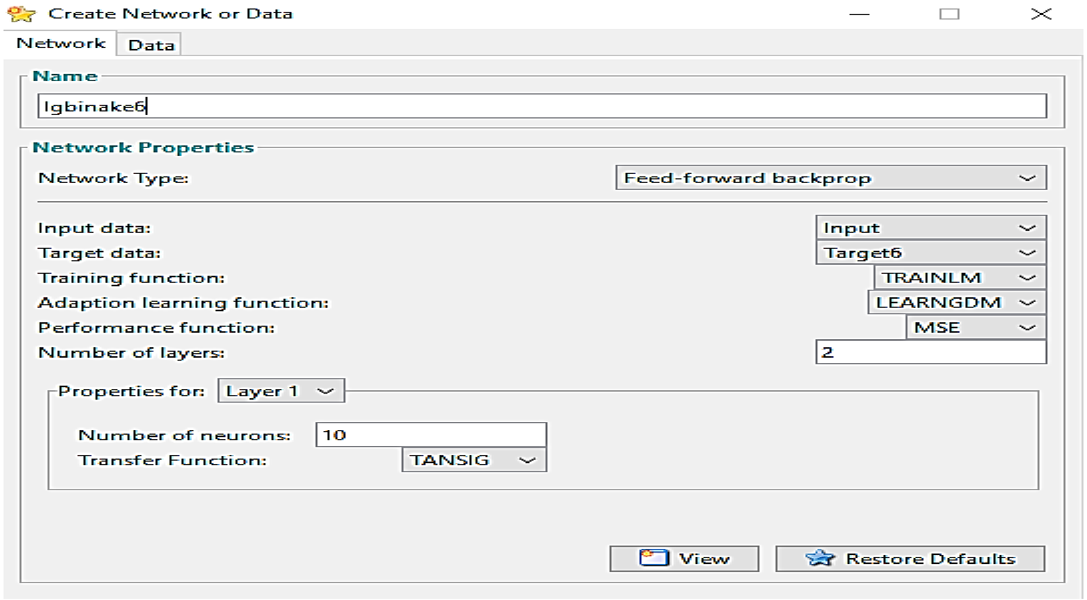

Figure 1: Network properties interphase for predicting weld Tensile Strain response

Figure 1 presents the configuration interphase for a neural network, where all parameters were set, and the feed-forward backdrop was chosen amongst other network types to yield the best results. Current, voltage, and gas flow rate information provided in Table 1 were inputted into ANN to output the Tensile Strain response obtained.

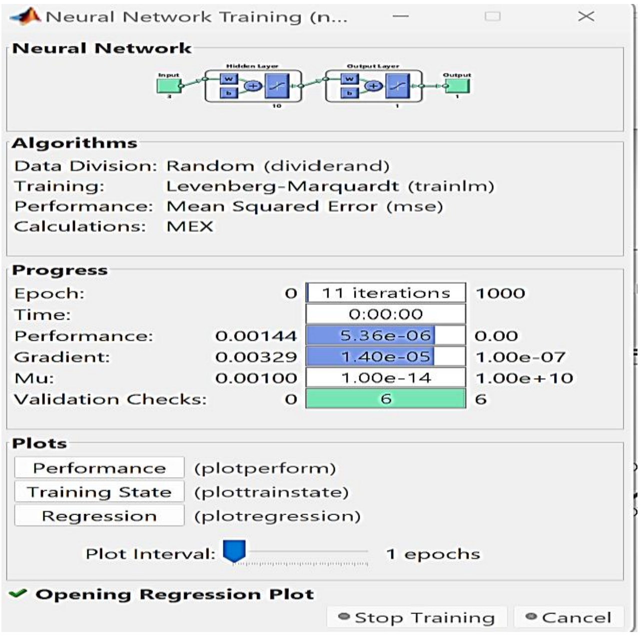

Figure 2: Network training diagram for predicting Tensile Strain responses

Figure 2 presents the neural network diagram for predicting the Tensile Strain responses. The data division algorithm was set to random (dividend), the training algorithm was set to Levenberg-Marquardt (trail), because in most cases it is robust and finds a solution even if it starts very far off the final minimum and the performance algorithm was set to Mean squared error (me).

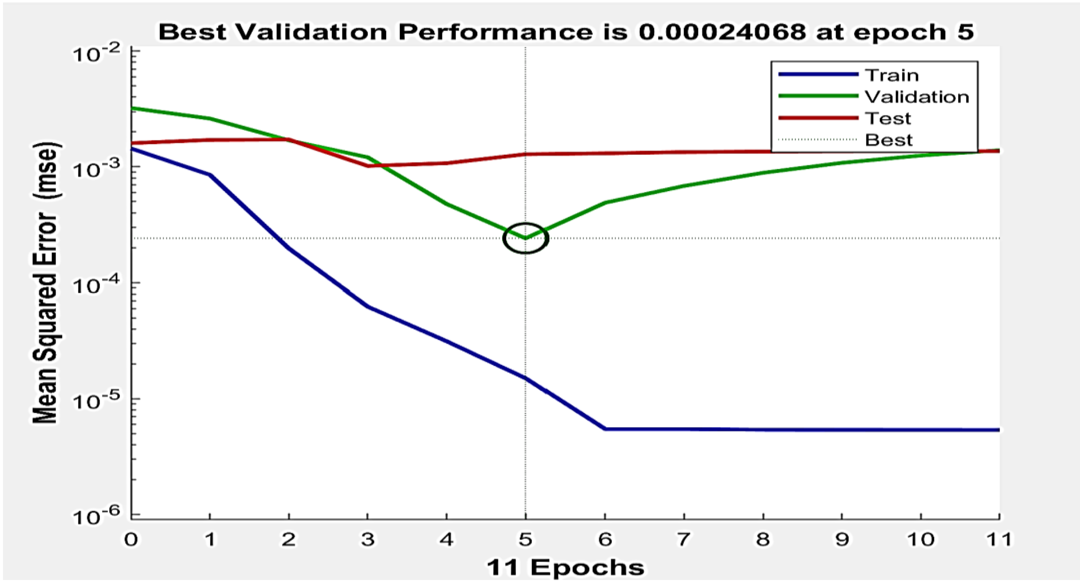

Figure 3: Performance curve for the trained network to predict Tensile Strain responses

Figure 3 presents the performance curve for the trained network. The best validation performance was obtained at epoch 5. In MATLAB software, an epoch can be thought of as a completed iteration of the training procedure of your artificial neural network. Once all the vectors in your training set have been used or gone through your training algorithm, one epoch has been attained Usman *et al*. (2021). Thus, an epoch's "real-time duration" depends on the training method used. The best Prediction for the Tensile Strain responses was achieved at epoch 5, although 11 epochs were used in the iteration process.

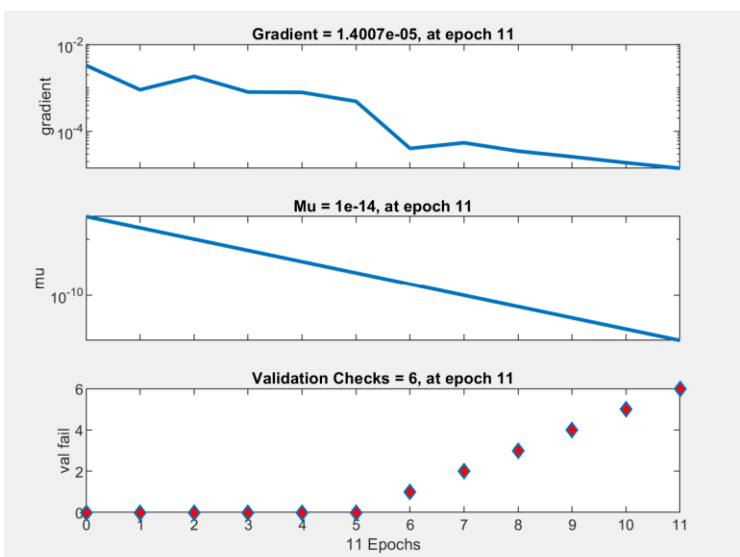

Figure 4: Neural network gradient plot for predicting Tensile Strain responses

Figure 4 shows the number of epochs used during the training process. One epoch signifies one complete algorithm training. 11 epochs were used, and Figure 4 shows that the best Prediction was achieved at the fifth epoch. From the dotted red lines for validation checks, it could be seen that the lowest failure was at epoch 5.

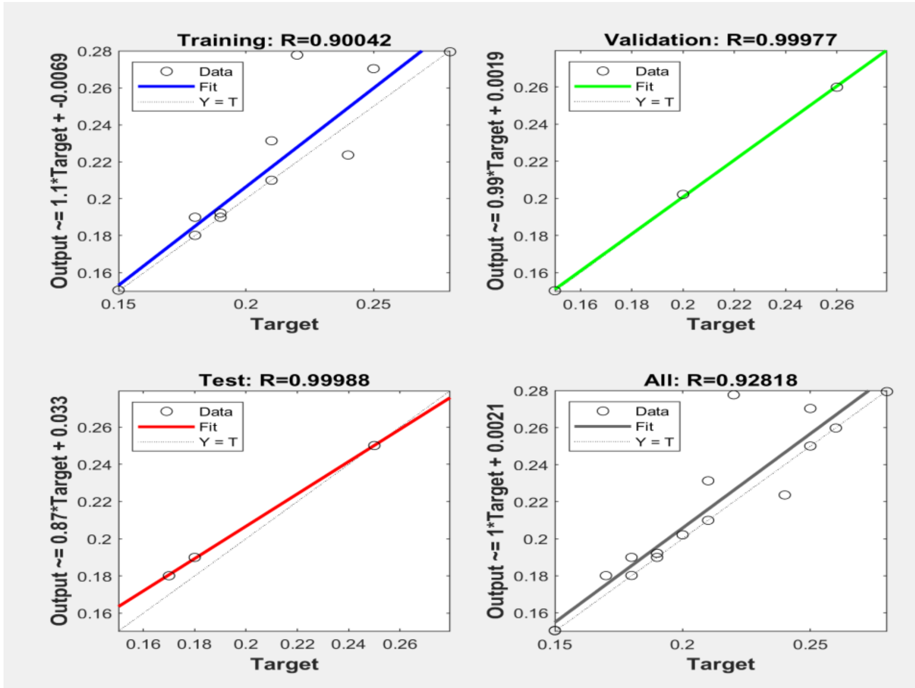

Figure 5: Regression plot of training, validation, and testing for Tensile Strain responses

Figure 5 presents the training, validation, and testing plot with a correlation coefficient (R) of over 90%, which signifies a robust prediction for the Tensile Strain. The dotted diagonal line on each plot indicates the line of best fit, which indicates a perfect prediction and a correlation of 1.

Table 1: Experimentally observed value vs. ANN predicted result of Tensile Strain responses.

S/N	Input parameters			Exp Responses	ANN Prediction
	Current	voltage	GFR	Tensile Strain	Tensile Strain
1	165.000	17.500	14.500	0.190	0.187
2	180.000	16.000	16.000	0.210	0.205
3	150.000	19.000	16.000	0.240	0.235
4	165.000	17.500	14.500	0.180	0.187
5	165.000	17.500	14.500	0.190	0.187
6	165.000	20.023	14.500	0.250	0.255
7	180.000	19.000	16.000	0.280	0.276
8	165.000	17.500	14.500	0.180	0.187
9	150.000	19.000	13.000	0.170	0.174
10	165.000	17.500	14.500	0.190	0.187
11	180.000	16.000	13.000	0.200	0.204
12	139.773	17.500	14.500	0.150	0.147
13	180.000	19.000	13.000	0.260	0.256
14	165.000	14.977	14.500	0.180	0.177
15	190.227	17.500	14.500	0.220	0.225
16	165.000	17.500	11.977	0.210	0.205
17	165.000	17.500	17.023	0.250	0.256
18	150.000	16.000	13.000	0.150	0.153
19	150.000	16.000	16.000	0.190	0.193
20	165.000	17.500	14.500	0.190	0.187

Table 1 compares the experimental and ANN-predicted values for Tensile Strain responses. The Regression Analysis for tensile strain obtained from the fitted line plot of EXP versus ANN produced equation 2 with Table 2 as its model summary

$$EXP = 0.02655 + 0.8457\ ANN \quad (2)$$

Table 2: Model Summary for ANN Tensile strain

S	R-sq	R-sq(adj)
0.0137181	86.16%	85.39%

4.0 Conclusion

The study has developed and applied a predictive expert model to optimize and predict the tensile strain of TIG mild steel weld using an artificial neural network. Consequently, the ANN model was observed to have a very high predictive reliability value and correlation coefficient (R) of over 90%, which signifies a robust prediction for the Tensile Strain.

5.0 Recommendation

. A model is recommended to be developed that will harmonize tensile strength and tensile strain

Nomenclature

ACHF	Alternating Current of High Frequency
ANN	Artificial Neural Network
DC	Direct Current
GFR	Gas Flow Rate
MSE	Mean Square Error
MSERG	Mean Square Error of Regression
R	Regression
RSM	Response Surface Methodology
TIG	Tungsten Inert Gas

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