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Modelling and Prediction of Residual Stresses in Mild Steel Welded Joints using Artificial Neural Network

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Abstract: Residual stresses are those stresses that remain in a solid material even in the absence of external loading or thermal gradients. Residual stresses form a balanced force system within an object, as all forces and moments acting on one plane through the entire object must sum to zero. At cold temperatures, the stress after welding is not completely released because of the fast-cooling speed, which results in cracks. The central composite design model patterned the experimental matrix. The tungsten inert gas (TIG) welding kit was employed to weld the plates after chamfering their edges. 100 mild steel coupons, each measuring 80 x 40 x 10 mm, were used for the experiments. The experiment was conducted 20 times, with 5 specimens for each run. A 10 mm thick mild steel plate was chosen as the material for the experiment. This study is applying artificial neural networks to optimize and predict the residual stress of machined heat affected zone of mild steel welds using current, voltage and gas flow rate as the input variables. The Artificial neural network (ANN) was used to optimize and predict the residual stress of the weld specimen. 70% of the data was used for training, 15 % was used for validating and the remaining 15% for the actual test. It was observed from the analysis that it had 3 input neurons, 10 hidden neurons and 1 output neuron with gradient of 95.8669 at epoch 12 and validation check of 6 out of 6. It was also observed from the model summary statistics that a robust R^2 value of 86.4% was obtained, with an adjusted R^2 of 85.6%.

Keywords: *modelling, residual stress, weld specimen, artificial neural network*
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1. INTRODUCTION

Within material science and engineering, residual stress analysis is a crucial field that provides deep insights into the performance, longevity, and structural integrity of materials (Gong et al., 2023). Residual stresses have a major impact on the fatigue life, fracture resistance, and dimensional stability of materials (Tabatabaeian et al., 2022). They are frequently present in produced components as a result of operations like casting, welding, or heat treatment (Akinlabi et al., 2018). Intricate experimental techniques like X-ray diffraction or neutron scattering, as well as computationally demanding numerical simulations like finite element analysis (FEA), are commonly used in traditional approaches for assessing residual stress (Jiang et al., 2021). These traditional methods have drawbacks along with their effectiveness. Experimentation techniques can be costly, time-consuming, and difficult to obtain certain supplies or parts for (Carpenter and Tabei, 2020). Numerical simulations can need a significant amount of computer power and knowledge, which limits their use and accessibility in some situations (Qi et al., 2019) Furthermore, the study may contain errors and uncertainties due to the complicated data interpretation and calibration procedures that both approaches sometimes need (Beghini & Grossi, 2024). A strong alternative paradigm for residual stress analysis is presented by the development of machine learning, especially Artificial Neural Networks (ANNs), in light of these difficulties. ANNs are computer models that can recognize intricate patterns and relationships in data because they are modeled after the structure and operation of biological neural networks (Buscema et al., 2018). By utilizing ANNs, scientists may be able to overcome the drawbacks of conventional techniques and improve forecast accuracy and efficiency while streamlining the residual stress analysis procedure (Ghoroghi et al., 2022). This paper aims to investigate the application of artificial neural networks (ANN) to residual stress analysis, with a particular emphasis on the incorporation of gas flow rate, voltage, and current as input parameters. These factors are especially relevant in situations like additive manufacturing or welding, where they have a big impact on the material's mechanical and thermal history and hence residual stress distributions (Oliveira et al., 2020). Our goal is to create predictive models that can accurately represent the complex interactions between these input factors and the residual stress profiles that arise by utilizing ANNs. In the work by Lo et al., (2022), the control of residual stress in films is very important for the synthesis of mechanically stable AlN films as the AlN film may crack or peel from the substrate due to significant film residual stress. Tafarroj and Kolahan (2018) used a neural network and a regression model to establish the relationship between welding input variables and parameters of the Goldak heat source model. The results showed that the precision of the ANN model is slightly higher than that of the regression model. Lawal and Afolalu (2024) established that in the case of MIG welding, the effect of residual stress can be reduced after treatment. In the case of TIG welding process, increase in current will lead to deformation and residual stresses. The aim of this study is to provide engineers and researchers with a flexible and easily obtainable instrument for enhancing material processing, design, and performance, in addition to contributing to the growing knowledge of residual stress phenomena. Our goal is to promote innovation and advancement across several industries, such as aerospace, automotive, energy, and others, by establishing a connection between sophisticated machine learning methods and the complexities of material science and engineering.

2. METHODOLOGY

The central composite design (CCD) patterned the experimental matrix using the Design expert-13 software, producing 20 experimental runs. The major parameters varied into 20 runs using the CCD in the present study are the welding current, welding speed, gas flow rate, welding voltage while the residual stress (σ_R) in MPa is the response variable. The ranges of the parameters were obtained from literatures as described in Table 1.

Table 1: Process parameters and their levels

Factors	Unit	Symbol	Low (-1)	High (+1)
Welding Current	Ampere	I	130	170
Welding Voltage	Volts	V	20	24
Gas Flow Rate	Lit/min	GFR	13	17

The tungsten inert gas (TIG) welding kit was employed to weld the plates after chamfering their edges. 100 mild steel coupons, each measuring 80 x 40 x 10 mm, were used for the experiments. The experiment was conducted 20 times, with 5 specimens for each run. A 10 mm thick mild steel plate was chosen as the material for the experiment. The plate was cut using a power hacksaw and the edges were ground to smoothen the surfaces to be joined. The experiments were performed using the TIG welding process with alternating current (AC), as it concentrates the heat in the welding area.

2.1 Artificial Neural Network

The artificial neural network is a data mining tool that can replicate the behavior and structure of a human expert. It consists of neurons which are made up of inputs and outputs. Neural networks are tools for data mining that are used to find patterns in databases that are hidden. They are two important ways in which they mimic the brain, functioning as massively parallel distributed processors. Through a process of learning, the network gains knowledge. This knowledge is stored in interneuron connection strengths, also known as synaptic weights. A suitable weight, represented by the letter w, is applied to a basic neuron with R input. The input to the transfer function f is the sum of the weighted inputs plus the bias. Any differentiable transfer function f can be used by neurons to produce their output. The log-sigmoid transfer function, or logsig, is widely employed in multilayer networks and generates outputs in the 0 to 1 range when the net input of the neuron varies from negative to positive infinity. The tan-sigmoid transfer function, or tansig, is an additional option for multilayer networks. Whereas linear output neurons are typically employed for function fitting issues, sigmoid output neurons are frequently utilized for pattern recognition tasks.

Current, voltage and gas flow rate parameter were taken as input into ANN architecture while the residual stress was the output .the network architecture for the transverse shrinkage as described in the matlab architecture format in Figure 1 and the ANN architecture format in Figure 2.

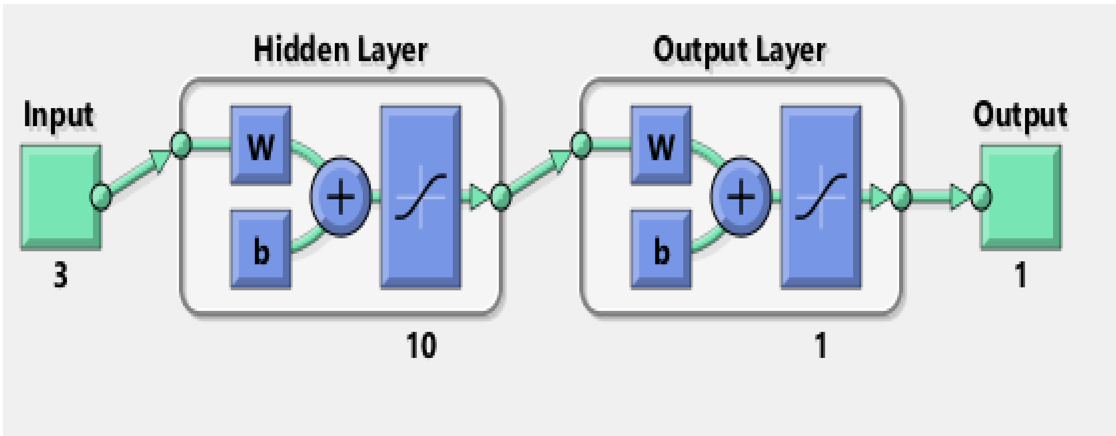

Figure 1: Matlab Artificial neural network architecture format for Residual stress

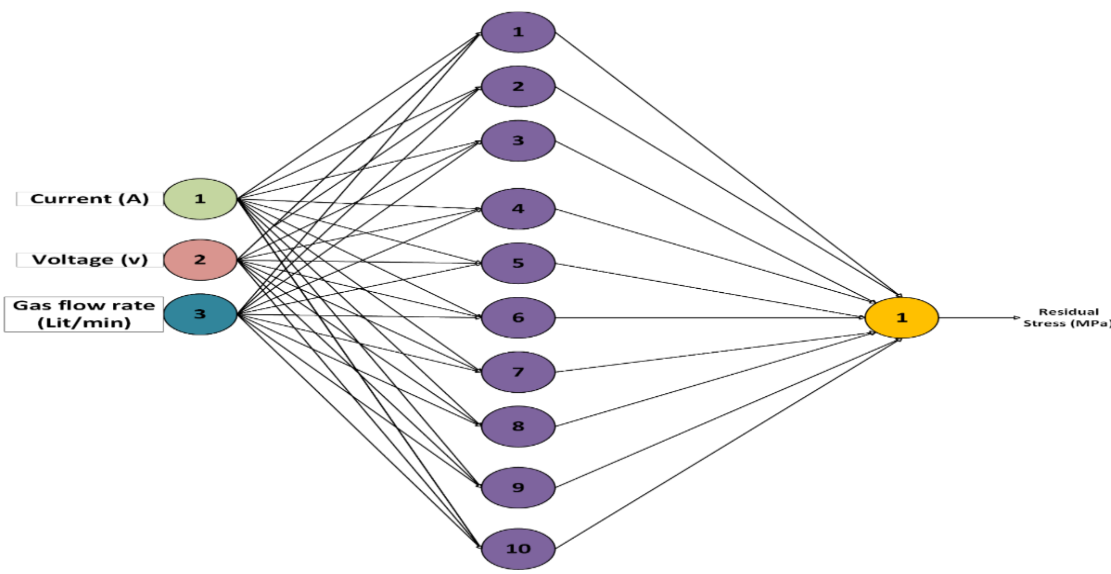

Figure 2: Artificial neural network architecture format for Residual stress

3. RESULTS AND DISCUSSION

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 3 describes the the neural network training diagram for predicting the residual stress responses.

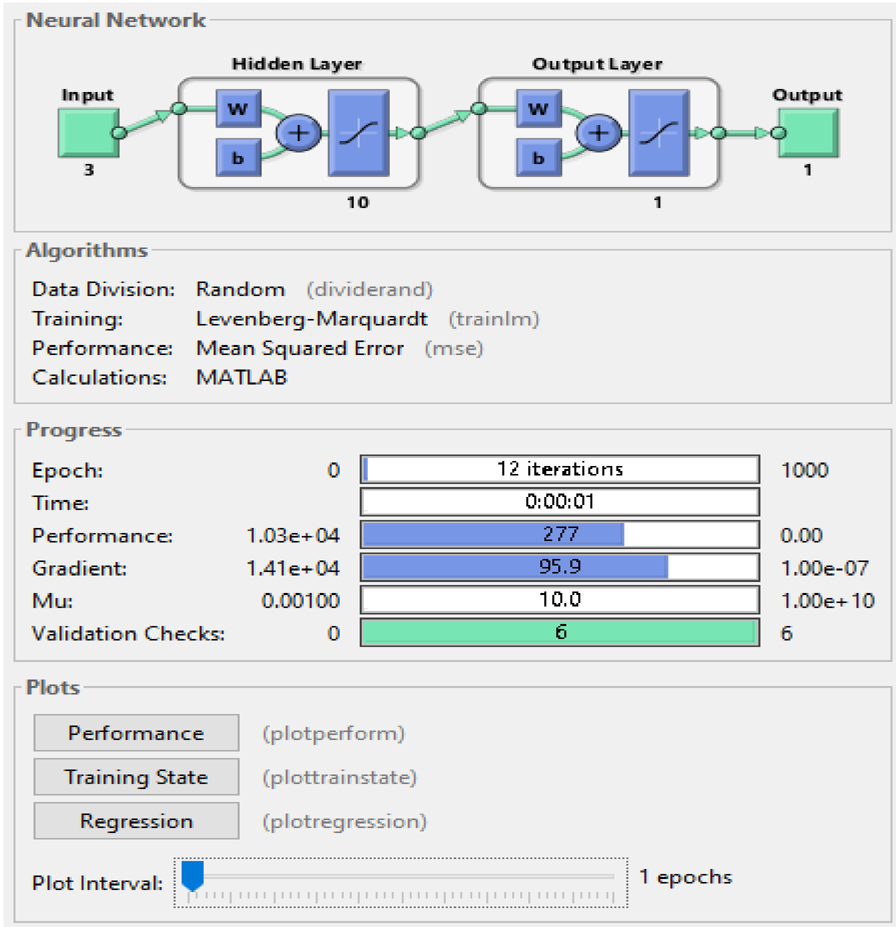

Figure 3: Network training diagram for predicting Residual stress

A performance plot is produced for the transverse shrinkage network to evaluate its learning capacity which is shown in Figure 4.

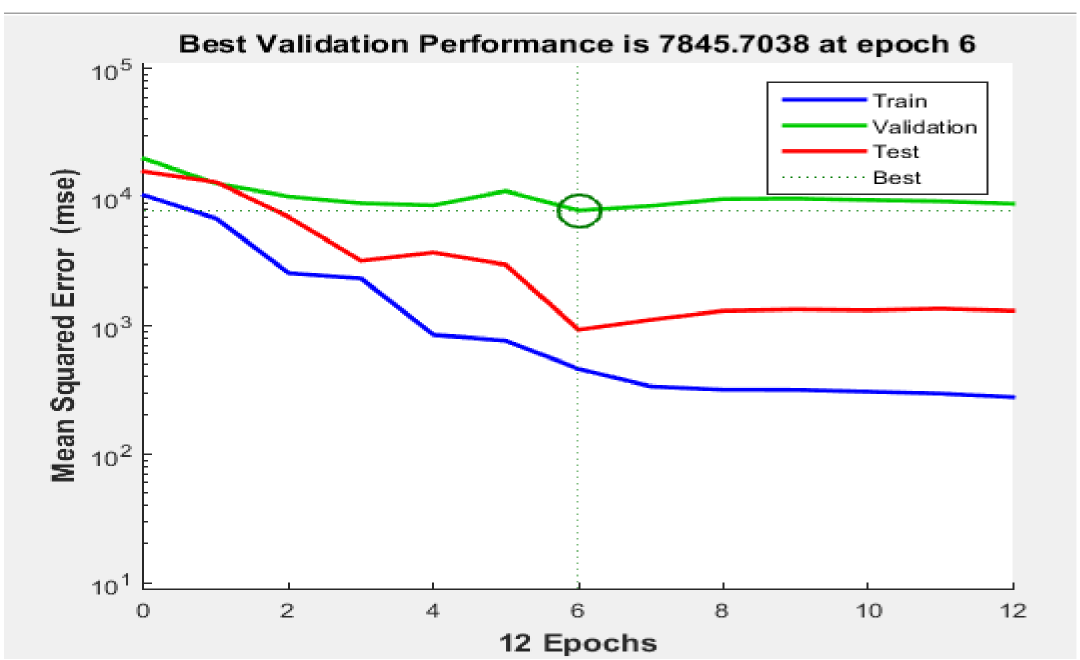

Figure 4: Performance curve for Residual stress

An epoch signifies one complete algorithm training, thus, from Figure 4, it can be observed that 12 epochs were used and in which at the 6th epoch, the best prediction was achieved. The best validation performance was obtained at epoch 1. In the 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 Transverse responses was achieved at epoch 1, although, a total of 7 epochs were used in the iteration process. The gradient plot for the residual stress which measures the momentum gain of the network is presented in Figure 5.

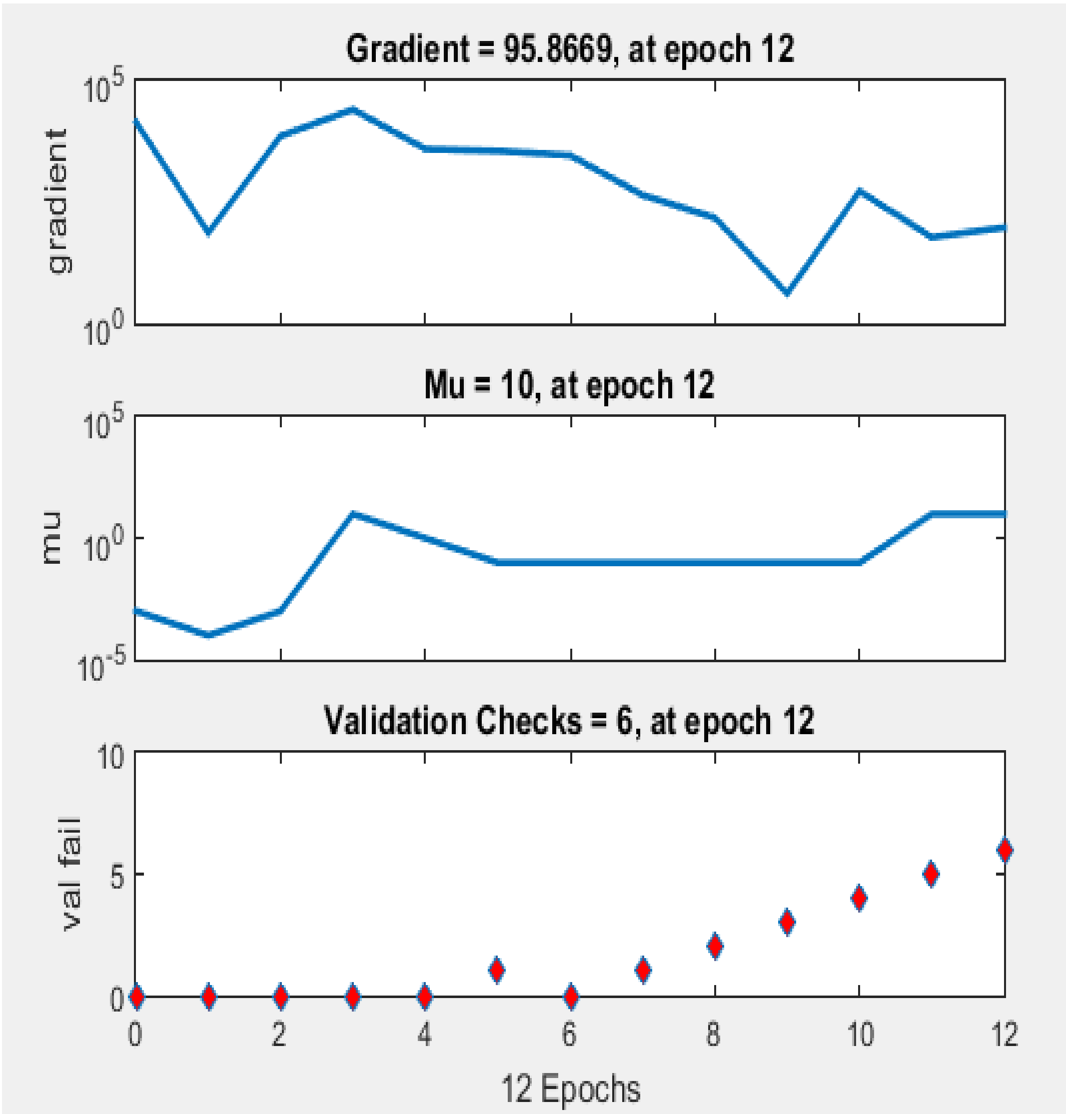

Figure 5: Gradient plot for residual stress

From Figure 5, it is observed that the number of epochs used up during the training process is 12. From the dotted red lines for validation checks, it could be seen that the lowest failure was at epoch 6 beyond which the validation failure rate increased.

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To measure the correlation between the network output and the actual results a correlation plot is produced for the residual stress is presented in Figure 6

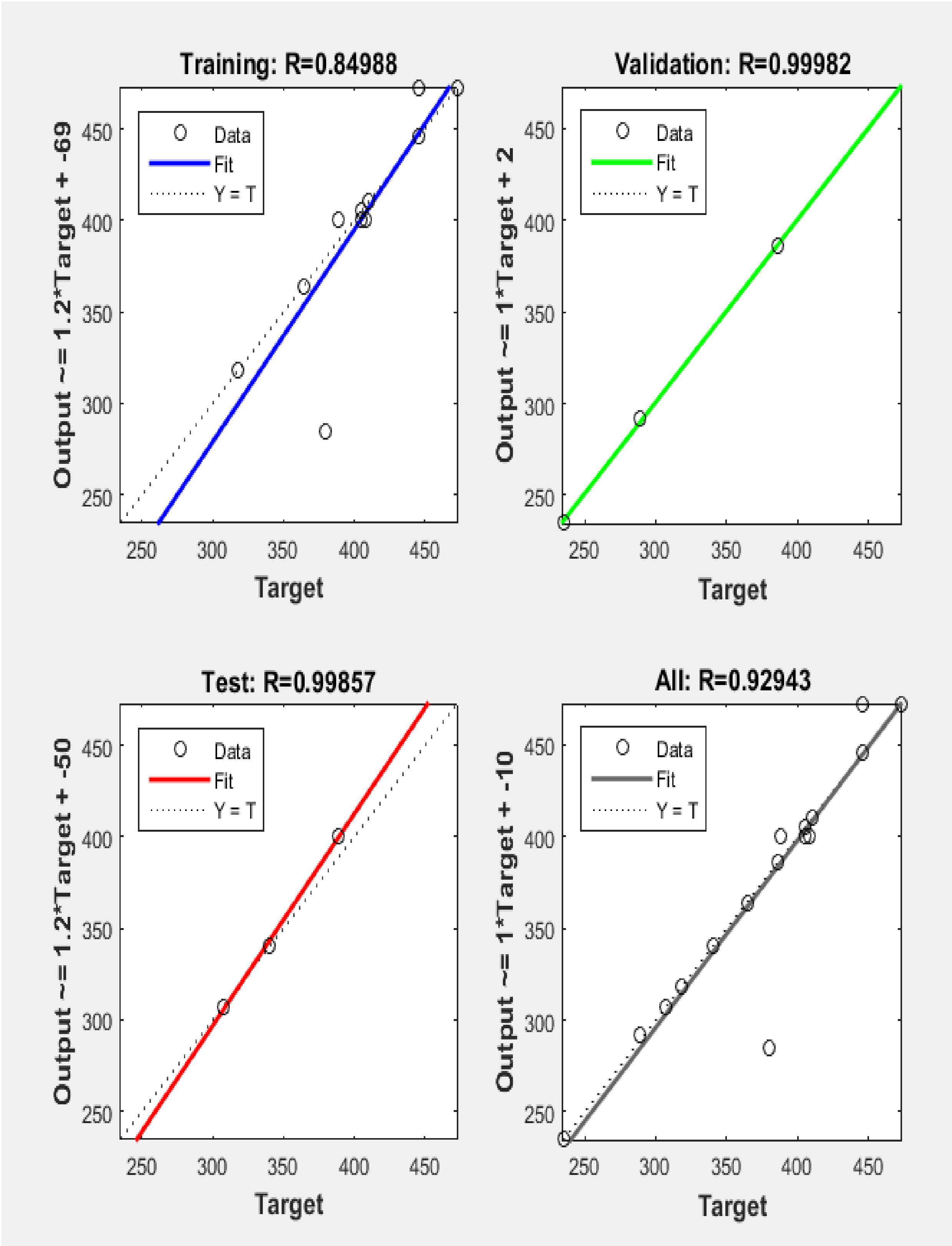

Figure 6: Regression plot of training, validation and testing for residual stress

Figure 4 presents the training, validation, and testing plot with correlation coefficient (R) of over 80% which signifies a robust prediction for the Residual stress. The dotted diagonal line on each plot indicates the line of best fit which indicates a perfect prediction. A comparison between the experimental results and the predicted result of the residual stress is presented in Table 2.

Table 2: Experimental value vs ANN predicted result of residual stress

S/N	Input parameters			Exp Responses	ANN Observed
	I Ampere	V Volts	GFR Lit/min	σ_R (MPa) Residual stress	σ_R (MPa) Residual stress
1	130.00	21.50	12.50	407.80	400.348
2	130.00	21.50	12.50	388.30	400.348
3	110.00	20.00	11.00	340.42	340.829
4	110.00	23.00	11.00	307.00	306.760
5	130.00	21.50	12.50	405.47	400.348
6	130.00	24.02	12.50	472.54	472.523
7	163.64	21.50	12.50	385.73	385.628
8	130.00	21.50	12.50	388.30	400.348
9	110.00	23.00	14.00	289.00	291.494
10	96.36	21.50	12.50	234.80	234.813
11	150.00	20.00	14.00	410.28	410.068
12	130.00	21.50	15.02	405.47	405.372
13	150.00	20.00	11.00	380.00	284.641
14	130.00	21.50	12.50	388.30	400.348
15	130.00	18.98	12.50	405.47	405.453
16	110.00	20.00	14.00	318.00	318.372
17	150.00	23.00	11.00	445.88	472.374
18	130.00	21.50	9.98	364.32	363.600
19	130.00	21.50	12.50	405.47	400.348
20	150.00	23.00	14.00	445.88	445.730

A graphical representation of the closeness between the ANN result and the actual values of the residual stress, a regression plot is produced which is shown in Figure 7
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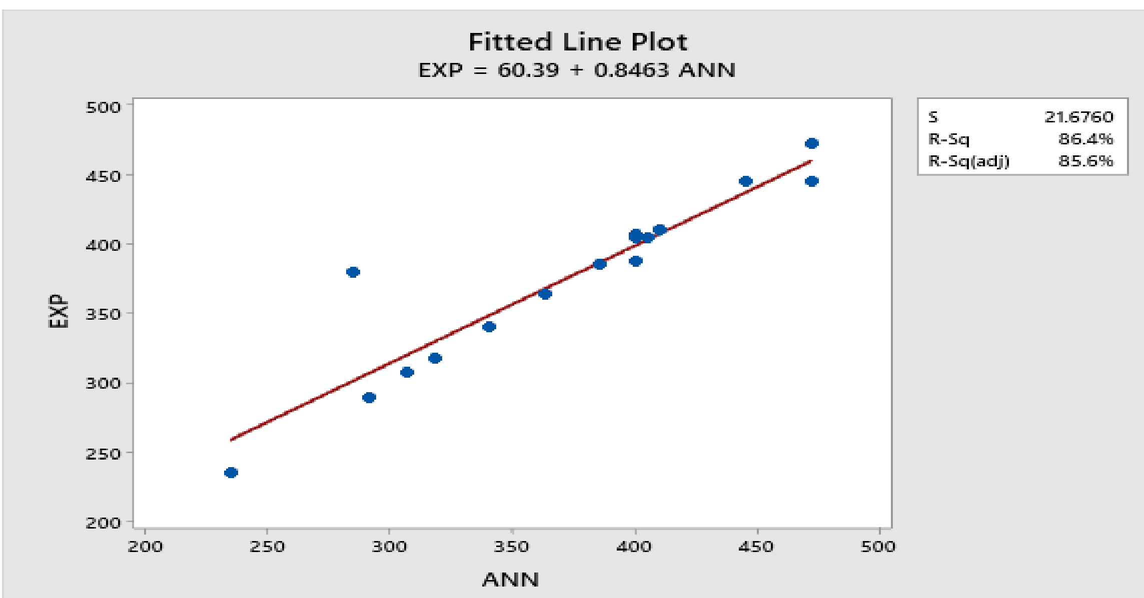

Figure 7: Regression plot of Experimental versus predicted residual stress

Figure 7 presents the regression plot for the experimental observed results versus the predicted result. It was observed in the model summary statistics that a robust R^2 value of 86.4% was obtained, with an adjusted R2 of 85.6% presented in Table 3.

Table 3: Model Summary statistics

S	R-sq	R-sq(adj)
21.6760	86.38%	85.63%

The analysis of variance ANOVA for the network which measures the error probability is presented in Table 4.

Table 4: Analysis of Variance for residual stress

Source	DF	SS	MS	F	P
Regression	1	53653.6	53653.6	114.19	0.000
Error	18	8457.3	469.8		
Total	19	62110.9			

To measure the predictive accuracy of the residual stress network a time series plot is produced as shown in Figure 8.

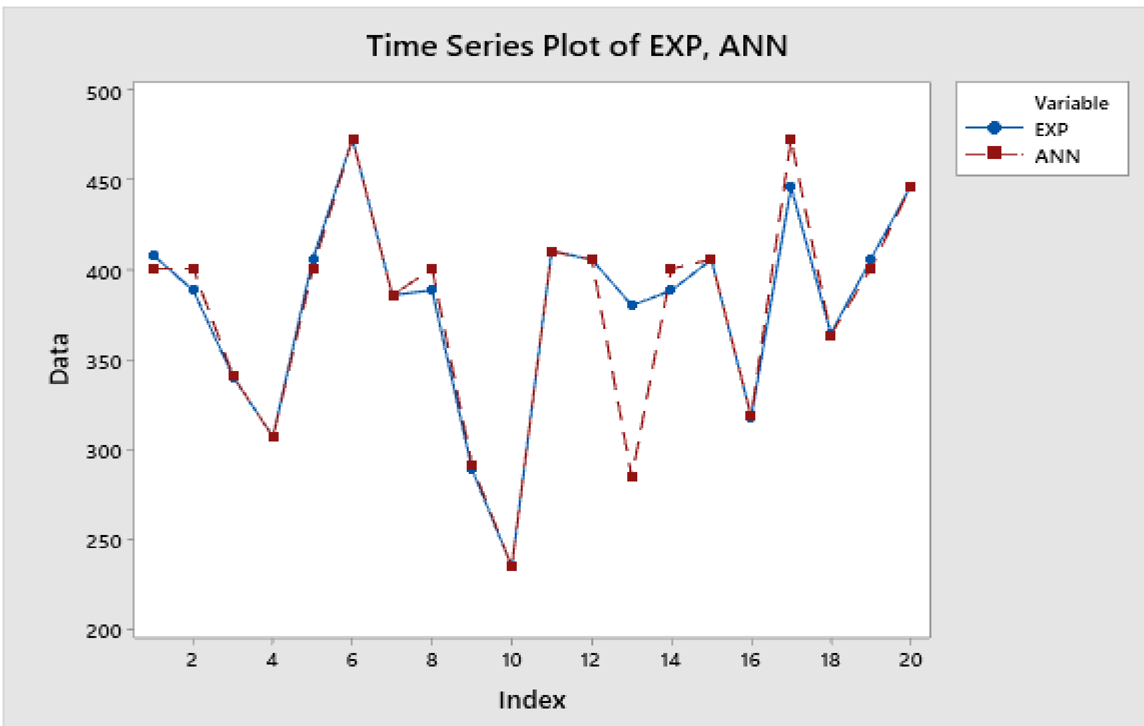

Figure 8: Time series plot showing the prediction accuracy of ANN with comparison to Experimental for residual stress.

4. CONCLUSION

The study has developed and applied a predictive expert model to model the residual stress of mild steel welded joints using the ANN model. An appropriate design of experiment was selected. The ANN model possesses satisfactory statistical results making it a highly effective tool to optimize and predict the target responses.

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