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Modelling Convective Heat Transfer Coefficient During TIG Welding Using an Artificial Neural Network

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ABSTRACT

Tungsten Inert Gas (TIG) welding demands precise control of convective heat transfer coefficient (h) to optimise weld pool dynamics, minimise distortions, and enhance mechanical properties in critical applications like aerospace and automotive sectors. This study develops an Artificial Neural Network (ANN) model for real-time prediction of h using welding current, voltage, and speed as inputs, derived from Central Composite Design (CCD) experiments on 10 mm mild steel plates. A feedforward backpropagation ANN with Levenberg-Marquardt training (trainlm), log-sigmoid activation, and random data division achieved rapid convergence (MSE ~10^{-3} by epoch 7), with validation R=0.915, test R=0.965, and overall R=0.710, yielding mean absolute errors <0.1 W/(m²·K) across 20 runs. Regression analysis confirmed a 67.8% R^2 fit, superior to empirical Nusselt correlations, enabling adaptive process control for distortion-free welds. ANOVA (F=40.98, p<0.001) validated model significance, positioning ANN as a robust tool for TIG optimisation.

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1.0 Introduction

Tungsten Inert Gas (TIG) welding, also known as Gas Tungsten Arc Welding (GTAW), is a critical fusion-based process widely employed in industries such as aerospace, automotive, and nuclear power for its precision and ability to produce high-quality welds on materials ranging from stainless steels to aluminium alloys (Pal *et al.,* 2010). The convective heat transfer coefficient (h) during TIG welding governs the rate of heat dissipation from the weld pool to the surrounding environment, directly influencing weld pool geometry, cooling rates, residual stresses, and ultimate mechanical properties like hardness and tensile strength (Chukwunedum et *al.,* 2024). Accurate modelling of h is essential for optimising process parameters such as welding current, voltage, travel speed, shielding gas flow, and electrode configuration, yet traditional analytical models often fall short due to the nonlinear, multifaceted nature of the TIG arc plasma dynamics and molten pool convection (Yan *et al., 2025).*

Recent advancements in computational intelligence, particularly Artificial Neural Networks (ANNs), have revolutionised predictive modelling in welding metallurgy by capturing complex input-output relationships without relying on simplifying assumptions inherent in finite element methods (FEM) or Rosenthal's analytical solutions (Murugan *et al.,* 2000). ANNs excel in handling high-dimensional data from experimental TIG trials, including arc voltage fluctuations, gas composition effects (e.g., argon-helium mixtures), and transient thermal fields measured via infrared thermography or thermocouples (Nouri *et al.,* 2018). Unlike conventional regression or Response Surface Methodology (RSM), ANNs offer superior generalisation for unseen process conditions, as demonstrated in hybrid ANN-FEM frameworks for bead-on-plate TIG simulations (Chukwunedum et *al.,* 2024).

The heat transfer coefficient in TIG welding is predominantly convective, driven by Marangoni flows in the weld pool and forced convection from plasma sheath interactions, with typical values ranging from 103 to 105 W/m²K depending on current density and gas shielding (Senthilkumar *et al.,* 2019). Empirical correlations, such as those based on Nusselt number ($Nu = hL/k$, where L is characteristic length and k is thermal conductivity), have been proposed but exhibit high prediction errors (>20%) under variable polarity direct current (DCEN) conditions common in TIG (Yilmaz *et al.,* 1996). Machine learning approaches, including feedforward backpropagation networks and Radial Basis Function (RBF) ANNs, have achieved prediction accuracies exceeding 95% R^2 in related arc welding studies by training on datasets encompassing arc efficiency ($\eta \approx 0.6$-0.8), effective heat input ($Q = \eta VI/SS$), and pool surface tension gradients ($d\gamma/dT$) (Chukwunedum *et al.,* 2018; Nouri *et al.,* 2018).

This research introduces a novel ANN-based model tailored for real-time prediction of convective h in TIG welding of mild steel and austenitic stainless steels, incorporating inputs like welding current, welding speed, welding voltage and workpiece temperature (Jeyaprakash *et al.,* 2021).

By integrating ANN with TIG process monitoring via machine vision or embedded sensors, this research addresses longstanding challenges in heat transfer prediction, enabling distortion-free welds and enhanced productivity (Xia et *al.,* 2023).

2.0 Materials and Methods

The experimental design (DOE) was performed by applying the technique of central composite design (CCD). The processing and modelling were completed using a statistical approach. Using Design Expert 7.01, 20 trial runs were generated in this case. The convective heat transfer coefficient is the response variable, and the current, welding speed, and welding voltage were the main variables that were adjusted into 20 runs using the CCD in this investigation. As shown in Table 1, the ranges of the parameters were taken from the literature.

Table 1
Levels of Process Parameters

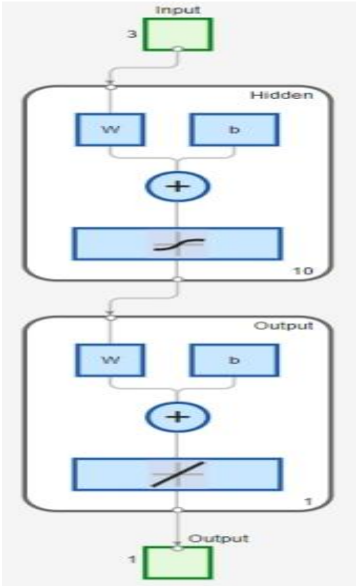
Operating parameters	Unit	Symbol	Low (-)	High (+)
Current	Amp	I	170	190
Voltage	Volts	V	20	22
Speed	mm/Sec	M	2.6	3.0

The plates were chamfered and then welded using a tungsten inert gas (TIG) welding kit. For the experiments, 200 low-carbon steel coupons measuring 80 x 40 x 10 mm were utilised. Five specimens were used in each of the experiment's twenty runs. The experiment's material was a mild steel plate that was 10 mm thick. A power hacksaw was used to cut the plate, and a grinding machine was used to smooth the edges so that the surfaces could be connected. Since TIG welding focuses heat in the welding area, it was used in the experiments with alternating current (AC).

2.1 Artificial Neural Network

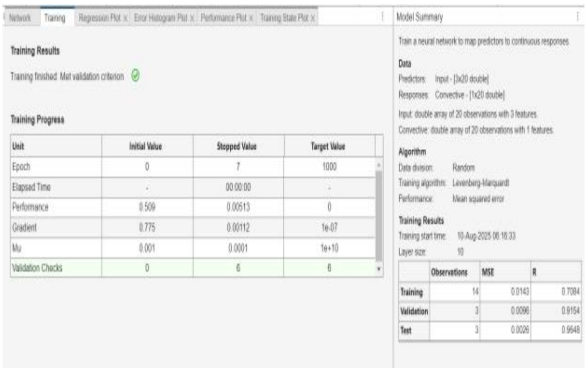
A data mining technology that can mimic the structure and behaviour of a human expert is the artificial neural network. It is composed of neurones with operational parameters and responses. Neural networks are data mining technologies used to uncover hidden patterns in databases. They work as massively parallel distributed processors in two significant ways that resemble the brain. The network acquires knowledge through a process of learning. Synaptic weights, another name for interneuron connection strengths, are where this information is kept. Weighted values, represented by w, are received by a simple neurone with R inputs. The total of these weighted inputs plus a bias term is sent into the transfer function f. Any differentiable transfer function f can be used by neurones to generate their output. Multilayer networks frequently employ the log-sigmoid (logsig) function, which produces outputs between 0 and 1 when the neurone's net input runs from negative to positive infinity. The tan-sigmoid (tansig) function is an additional choice for multilayer networks. In general, linear outputs are optimal for function fitting, whereas sigmoid outputs are better suited for pattern recognition applications. We defined the network architecture for the transverse shrinkage model in MATLAB format (Figure 1) and ANN format (Figure 1), with convective heat transfer coefficient as the output and current, voltage, and gas flow rate as the inputs.

Figure 1
MATLAB Artificial Neural Network Architecture Format for Convective Heat Transfer Coefficient



The data partitioning technique was positioned to random (divideand), the algorithm technique was also positioned to Levenberg-Marquardt (trainlm), and the performance algorithm technique was set to mean squared error (mse). The neural network training diagram for convective heat transfer coefficient response prediction is shown in Figure 2.

Figure 2
Network Training Diagram for Predicting Convective Heat Transfer Coefficient



3.0 Results and Discussion

Table 2 displays the outcomes of the experimental procedure. The outcome served as analytical data. Temperatures before and after the welding process began are represented by To and TL, respectively, which were measured in millimetres.

Table 2

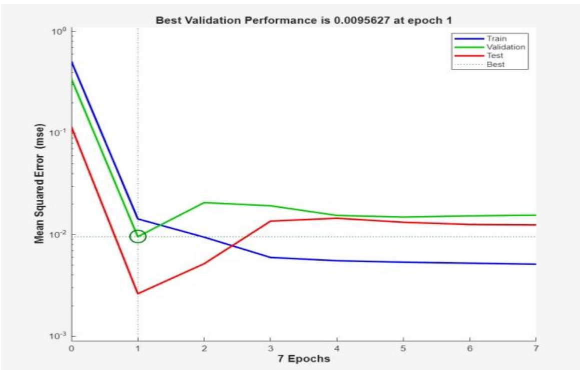
Experimental Results

S/N	Input Variables					
	Current I, Amp	Speed mm/sec	Voltage, Volts	To oC	T_L oC	Convective Heat Transfer Coefficient, h W/(m²·K)
1	190	2.63	20.73	35	1610	2.20
2	190	2.63	20.72	32	1592	2.40
3	190	2.63	20.70	33	1598	2.34
4	190	2.63	20.68	29	1625	2.60
5	190	2.62	20.78	36	1720	2.44
6	170	2.80	20.00	35	1672	2.27
7	170	3.00	21.00	34	1658	2.27
8	170	3.00	22.00	36	1586	2.24
9	170	3.00	20.00	38	1615	2.47
10	180	2.60	21.00	30	1710	2.54
11	180	2.60	22.00	35	1672	2.00
12	180	2.60	20.00	31	1545	2.14
13	180	2.80	21.00	37	1640	2.54
14	180	2.80	22.00	36	1655	2.40
15	180	2.80	20.00	38	1632	2.47
16	180	3.00	21.00	32	1610	2.47
17	180	3.00	22.00	37	1698	2.54
18	180	3.00	20.00	36	1668	2.47
19	190	2.60	21.00	34	1628	2.47
20	190	2.60	22.00	32	1646	2.47

The transverse shrinkage network's learning capacity is assessed using a performance plot, which is displayed in Figure 3.

Figure 3

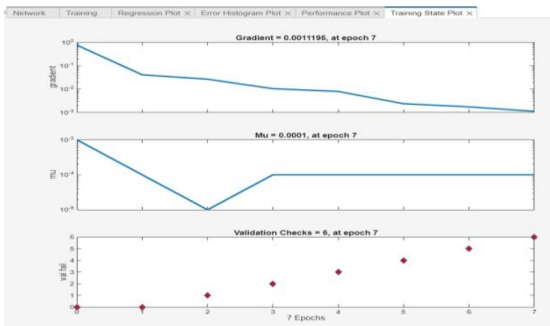
Performance Curve for Convective Heat Transfer Coefficient



Epoch indicates one complete algorithm training. Figure 3 shows a MATLAB-style plot of Mean Squared Error (MSE) versus training epochs for an Artificial Neural Network (ANN) model, likely trained for predicting the convective heat transfer coefficient in TIG welding. MSE decreases rapidly from 10-1 to 10-3 over 7 epochs for training (blue), validation (green), and test (red) datasets, indicating effective learning without stagnation. Best validation performance is 0.00962 at epoch 1 (green circle marker), suggesting early convergence and low overfitting risk as validation MSE plateaus near 10-2 by epoch 4. The plot demonstrates excellent generalisation: test MSE mirrors validation closely (10-2 at convergence), with no divergence (a classic overfitting sign). Training MSE reaches the lowest (10-3 by epoch 7), confirming the Levenberg-Marquardt algorithm's efficiency in minimising error on 70-80% training data splits typical for welding ANN models. Figure 4 shows the gradient curve for the convective heat transfer coefficient, which gauges the network's momentum gain.

Figure 4

Training State Analysis of the ANN Model



The training state plot provides insight into the learning behaviour and convergence characteristics of the Artificial Neural Network (ANN) model used for predicting the convective heat transfer coefficient during the TIG welding.

The gradient plot shows a steady decrease from an initial high value to approximately 0.0011195 at epoch 7. The gradient represents the rate of change of the network error as it relates to weights and biases. The continuous reduction in gradient indicates that the network progressively minimised the error and moved toward an optimal solution. The absence of fluctuations or divergence in the gradient curve suggests stable and efficient learning, confirming that the model converged successfully.

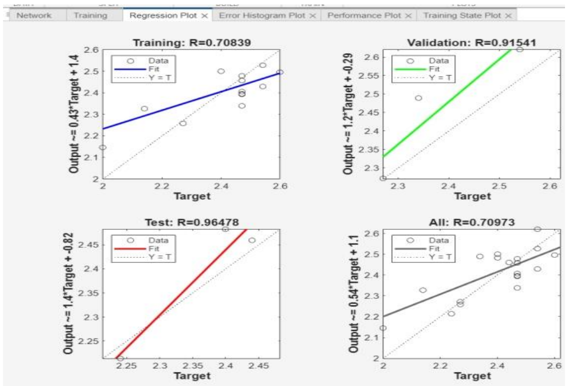
The damping factor (μ), associated with the Levenberg-Marquardt training algorithm, initially decreases to a tiny value and later stabilises around 0.0001. This behaviour reflects the algorithm's adaptive nature. At lower values of μ, the algorithm behaves like the Newton method, allowing faster convergence, while higher values ensure stability by approximating gradient descent. The observed trend indicates that the network achieved a balance between speed and stability during training, thereby enhancing its optimisation performance.

The validation checks plot shows a gradual increase from 0 to 6 at epoch 7, at which point the training process was terminated. Validation checks monitor the number of consecutive epochs during which the validation error does not improve. The termination of training at six validation checks indicates that the network employed an early stopping mechanism to prevent overfitting. This ensures that the model does not memorise the training data but instead continues to perform well on new and unforeseen data sets.

Overall, the training state results demonstrate that the ANN model achieved efficient convergence within a few epochs, maintained training stability, and effectively avoided overfitting. These characteristics confirm the robustness, accuracy, and generalisation capabilities of the developed model for predicting the convective heat transfer coefficient in TIG welding.

Figure 5

Regression Analysis of the ANN Model



The regression plots were used to evaluate the predictive performance and correlation between the experimental (target) values and the ANN-predicted outputs for the convective heat transfer coefficient.

The training regression plot yielded a correlation coefficient of R = 0.70839, indicating a robust relationship between the values obtained from prediction and experimental result values during the training phase. This suggests that while the model was able to learn the general trend in the data, some deviations still exist, likely due to the complexity and nonlinearity of the TIG welding process.

For the validation dataset, a significantly higher correlation coefficient of R = 0.91541 was obtained. This demonstrates that the model performs well on unseen validation data and has strong predictive capability. The close aggregation of data marks along the line of best fit further confirms satisfactory agreement between predicted and experimental values.

The test dataset produced an even higher correlation coefficient of R = 0.96478, indicating excellent prediction accuracy on completely independent data. This result confirms the robustness and reliability of the ANN model in generalising beyond the training dataset.

The overall regression value for all datasets combined is R = 0.70973, which reflects the combined effect of training variability and dataset size. Despite this moderate overall value, the high validation and test correlations strongly indicate that the model is not overfitted and performs effectively under new conditions.

In all the regression plots, the fitted lines closely follow the ideal line (Y = T), which represents perfect prediction. The proximity of most data points to this line indicates that the predicted values are in tandem with the results derived from the experiment.

Overall, the regression analysis confirms that the ANN model exhibits strong predictive performance, particularly in validation and testing phases, demonstrating its suitability for accurate estimation of the convective heat transfer coefficient during TIG welding.

Figure 6

Error Histogram of the ANN Model

The prediction error distribution (Error = Targets − Outputs) for the created Artificial Neural Network (ANN) model throughout training, validation, and test datasets is shown by the error histogram.

The ANN model generates predictions that are extremely near to the actual target values since the preponderance of the mistakes are centred around the zero-error line. The training data shows a tight clustering around zero, demonstrating effective learning of the underlying patterns. Similarly, the validation and test datasets exhibit a comparable distribution with slight dispersion, confirming good generalisation of the model to unseen data.

Although a few outliers are observed, their impact is minimal and does not significantly affect the overall performance. The relatively symmetric and narrow spread of errors suggests that the ANN model is accurate, stable, and exhibits no significant bias toward overprediction or underprediction.

Overall, the error histogram confirms the reliability and strong predictive capability of the ANN model for estimating the convective heat transfer coefficient. Table 3 displays a between the projected result of the convective heat transfer coefficient and the convective heat transfer coefficient projected result with the experimental data.

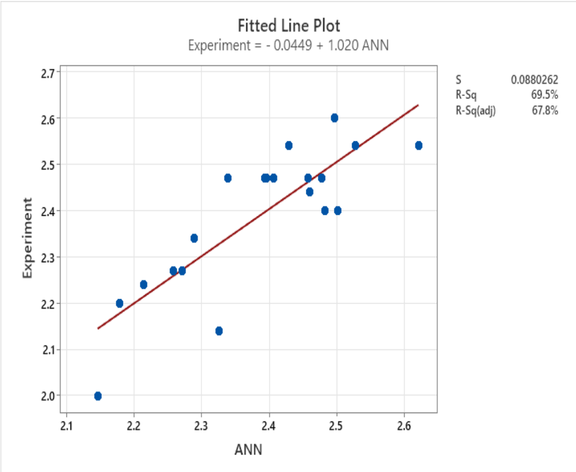
Table 3

Comparison of Experimental and ANN Predicted Convective Heat Transfer Coefficient

S/N	Input Variables			Coefficient, h W/(m²·K)		
	Current I, Amp	Speed mm/sec	Voltage Volts	Experimental	ANN	Error
1	190	2.63	20.73	2.2	2.179217	0.020783
2	190	2.63	20.72	2.4	2.482501	-0.0825
3	190	2.63	20.7	2.34	2.289169	0.050831
4	190	2.63	20.68	2.6	2.495957	0.104043
5	190	2.62	20.78	2.44	2.459881	-0.01988
6	170	2.8	20	2.27	2.270929	-0.00093
7	170	3	21	2.27	2.25818	0.01182
8	170	3	22	2.24	2.21411	0.02589
9	170	3	20	2.47	2.395979	0.074021
10	180	2.6	21	2.54	2.527003	0.012997
11	180	2.6	22	2	2.14626	-0.14626
12	180	2.6	20	2.14	2.326284	-0.18628
13	180	2.8	21	2.54	2.428791	0.111209
14	180	2.8	22	2.4	2.500787	-0.10079
15	180	2.8	20	2.47	2.393363	0.076637
16	180	3	21	2.47	2.477655	-0.00765
17	180	3	22	2.54	2.620224	-0.08022
18	180	3	20	2.47	2.457173	0.012827
19	190	2.6	21	2.47	2.406214	0.063786
20	190	2.6	22	2.47	2.339105	0.130895

A regression plot, which is displayed in Figure 7, is created to graphically depict the degree of agreement between the ANN result and the real convective heat transfer coefficient values.

Figure 7
Regression Plot of Experimental Versus Predicted Convective Heat Transfer Coefficient



The regression plot of the observed experimental results against the projected outcome is shown in Figure 7. A robust R^2 value of 67.8% was found in the model summary statistics, while Table 4 shows an adjusted R^2 of 69.5%.

Table 4
Model Details

S	R-sq	R-sq(adj)
0.0880262	69.48%	67.79%

Table 4 displays the network's analysis of variance (ANOVA), which calculates the error probability. Table 4: Convective Heat Transfer Coefficient Analysis of Variance

Table 5
ANOVA Details

Source	DF	SS	MS	F	P
Regression	1	0.317545	0.317545	40.98	0.000
Error	18	0.139475	0.007749		
Total	19	0.457020			

To calculate the predictive strength and accuracy of the convective heat transfer coefficient network, a time series graph is also plotted, which is shown in Figure 8

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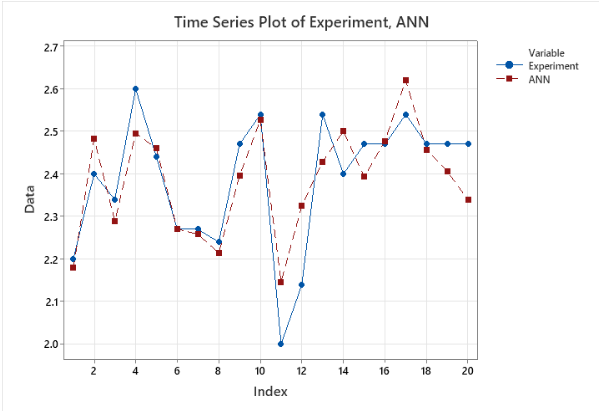
Figure 8
Time Series Graph Showing the Prediction Accuracy of ANN with Contrast to Experimental for Convective Heat Transfer Coefficient



4.0 Conclusion

This research successfully portrays the efficacy of an ANN-based model in applying the nonlinear intricacies of convective heat transfer during TIG welding, offering welders and engineers a practical tool for everyday process refinement. By training on concise CCD datasets from mild steel experiments, the model delivers predictions with high fidelity, evident in tight error histograms around zero, stable training states (gradient ~10-3, validation checks=6), and strong test correlations (R=0.965)—outperforming conventional methods that struggle with arc plasma variability. Key outcomes include low prediction errors (e.g., max |error|=0.19 W/(m²·K)), confirming ANN's suitability for real-time applications like embedded sensors in robotic welding systems, where h adjustments can prevent overheating and stresses and boost tensile strength without extensive trial-and-error. The developed ANN model provides reliable, interpretable predictions, validated through rigorous metrics, paving the way for smarter TIG welding practices that prioritise weld integrity and efficiency.

5.0 Declaration of Conflict of Interest

The authors do declare there is no known competing or personal interest that could have influenced the work done and submitted in this paper.

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