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Predicting Convective Heat Transfer Coefficient in TIG Welding via Adaptive Neuro-Fuzzy Inference System (ANFIS)

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Abstract

This study develops an Adaptive Neuro-Fuzzy Inference System (ANFIS) to predict the convective heat transfer coefficient (h) in Tungsten Inert Gas (TIG) welding of mild steel, overcoming limitations of traditional empirical correlations under variable arc conditions. Overtime, TIG welding has been used to produce high-quality welds for aerospace and precision applications. Mild steel plates were cut into 200 coupons (80 × 40 × 10 mm), machined, cleaned, ground, and butt-welded using TIG equipment with 100% pure argon shielding gas. A central composite design matrix via Design-Expert v7.01 generated 20 experimental runs, with five replicates per run yielding 100 data points. Input parameters included welding current (I), voltage (V), and speed (ws). ANFIS integrates fuzzy logic and neural networks for nonlinear mapping from inputs to h. Linguistic variables, current (c: 170-190 A), welding speed (ws: 2.6-3.0 mm/s), voltage (v: 20-22 V), employed triangular membership functions (trimf: low, moderate, high). Output h ranged 1.9-2.5 W/m².K with constant functions. Grid partition generated the fuzzy inference system (FIS); crisp training data optimized rules via ANFIS toolbox. This research finding established that ANFIS model effectively predicts the convective heat transfer coefficient (h) in TIG welding of mild steel using inputs of welding current (170-190 A), voltage (20-22 V), and speed (2.6-3.0 mm/s). Experimental h values ranged from 2.00 to 2.60 W/m².K across 20 runs, with ANFIS predictions matching closely (e.g., 2.20 vs. 2.20, 2.54 vs. 2.54). Regression analysis yielded the equation: Experimental h = 0.3632 + 0.8497 × ANFIS h, achieving R^2 = 97.47% and S = 0.0766300, confirming high predictive accuracy. Time series plots showed strong correlation trends with minimal drift, validating ANFIS for real-time process optimization.

Keywords: *ANFIS, TIG, Convection, Mapping, Nonlinear, Functions.*

1.0 Introduction

Tungsten Inert Gas (TIG) welding, or Gas Tungsten Arc Welding (GTAW), is widely employed in aerospace, automotive, and precision engineering due to its ability to produce high-quality, low-defect welds. The convective heat transfer coefficient representing the rate of heat transfer between the weld pool surface and the surrounding shielding gas, is a critical parameter governing weld pool morphology, penetration depth, and cooling rates [1]. Accurate prediction of Convective heat transfer coefficient is crucial for process parameter optimization, minimizing weld defects such as porosity and distortion, and ensuring dimensional accuracy in high-value components. Traditional empirical correlations are often inadequate under variable arc conditions, necessitating advanced data-driven modeling approaches.

Convective heat transfer in TIG weldments is quantitatively described by:

$$h = \frac{Nu \cdot k}{L} \tag{1}$$

where Nu denotes the Nusselt number, k represents thermal conductivity of the shielding gas, and L is the characteristic length of the weld pool which is typically the length of the plate (in the flow direction). The Nusselt number is influenced by booth Reynolds and Grashof numbers, thereby accounting for forced and natural convection phenomena within the plasma and the molten pool [1].

Variations in shielding gas flow rate, welding current, and voltage strongly affect h with reported values typically ranging from 50 to 300 W/m²K for forced convection and 2 to 25 W/m².K for free convection which is applicable to our study. Computational studies incorporating the Navier–Stokes equations demonstrate that Marangoni-driven surface tension effects can effectively boost convective heat transfer by up to 40% in activated TIG processes, underscoring the complexity of thermal-fluid interactions in welding [1].

Adaptive Neuro-Fuzzy Inference Systems (ANFIS) provide a robust framework for predicting convective heat transfer coefficient by integrating fuzzy logic with neural network learning, enabling accurate nonlinear mapping from welding parameters to heat transfer outcomes. These Models have proven to perform better in optimizing TIG heat input while minimizing prediction errors [2]. [3] Further confirmed the efficacy of combining ANFIS with response surface methodology (RSM) in predicting and optimizing convective heat transfer coefficient for mild steel weldments, achieving high predictive accuracy under variable process conditions.

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Recent computational and experimental advances have deepened understanding of convective effects in TIG welding. Unified computational fluid dynamics (CFD) simulations quantify transient convective heat transfer coefficient in stationary GTAW with filler wire, linking torch angle and melt flow efficiency to heat transfer rates [4]. Time-dependent thermal efficiency analyses incorporating convection loses which have also been reported [5], while FEM-based thermo-mechanical studies highlight the role of convection in penetration and residual stress development [6]. Parametric optimization studies further demonstrate that welding current and shielding gas flow are the primary levers for controlling convective heat transfer coefficient in practice [7]; [8].

Despite these advances, real-time prediction of convective heat transfer coefficient integrating multi-physics data remains limited, and post-2015 applications of ANFIS to TIG convective heat transfer are sparse [2]; [3]. This research work would address the limitations deduced from available literatures by developing an ANFIS-based parametric optimization framework for predicting the convective heat transfer coefficient in TIG welding. The proposed approach leverages key process parameters to enhance predictive accuracy and enable real-time process control for improved weld quality.

2.0 Materials and Methods / Methodology

Mild steel plate ASTM A36 was utilized for the test piece, and it was cut into pieces using a power hack saw. The samples were edge machined, cleaned, ground, and longitudinally cut. Tungsten inert gas welding equipment using direct current (DC) and straight polarity also referred to as direct current electrode negativity (DCEN) was used to generate the weld specimen after the edges were machined, in the welding process, an electrode of 2.0mm was used and torch was placed at an angle of between 10-15 degrees perpendicular to the work piece. 200 mild steel coupons measuring 80 x 40 x 10 mm were used to make the 100 weldment samples used in the investigations. Five specimens were used in each of the experiment's 20 runs.

Using the design expert application, a center composite design matrix was created, leading to 20 experimental runs. The experimental design process was aided by the use of Expert Design version 7.01. The input parameters (current I, welding speed M/s, and voltage V) and output parameters (convective heat transfer coefficient and it was calculated using equation 1 above) make up the experimental matrix. The responses recorded from the weld samples were the data used in the matrix. Shielding gas administered for this study was pure argon gas with which was 100% based content. The range and values of the process parameters utilized to create the experiment are shown in Table 1, which is based on previously published research.

Table 1: Input indices and their limits

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

3.0 Results and Discussions

3.1. Result

The obtained results during the experimental processes are outlined in Table 2 below, it summarizes the experimental readings recorded from the conducted welding experiments with 20 runs. The table lists the input parameters, including current, welding speed, and voltage, alongside the measured both the outside temperature and the temperature after welding. The table thus presents both the experimental conditions and the derived response (convective heat transfer coefficient) that is being investigated in this work.

Table 2 Experimental results

S/N	Current I, Amp	Speed mm/sec	Voltage, Volts	To ^oC	T_L ^oC	Convective Heat Transfer Coefficient, h $W/m^2.K$
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

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S/N	Current I, Amp	Speed mm/sec	Voltage, Volts	To °C	T_L °C	Convective Heat Transfer Coefficient, h W/m².K
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

3.2 Prediction of Convective Heat Transfer Using the Adaptive Neuro-Fuzzy Inference System Defining the Linguistic Variables and Terms

Linguistic variables are the system's input or output variables whose values are natural language words or sentences rather than numbers. Typically, a linguistic variable can be broken down into a collection of linguistic terms. Consider a welding process aimed at predicting the convective heat transfer. Let current (c), welding speed (ws) and voltage (v), be the linguistic variables which represents the weld factors.

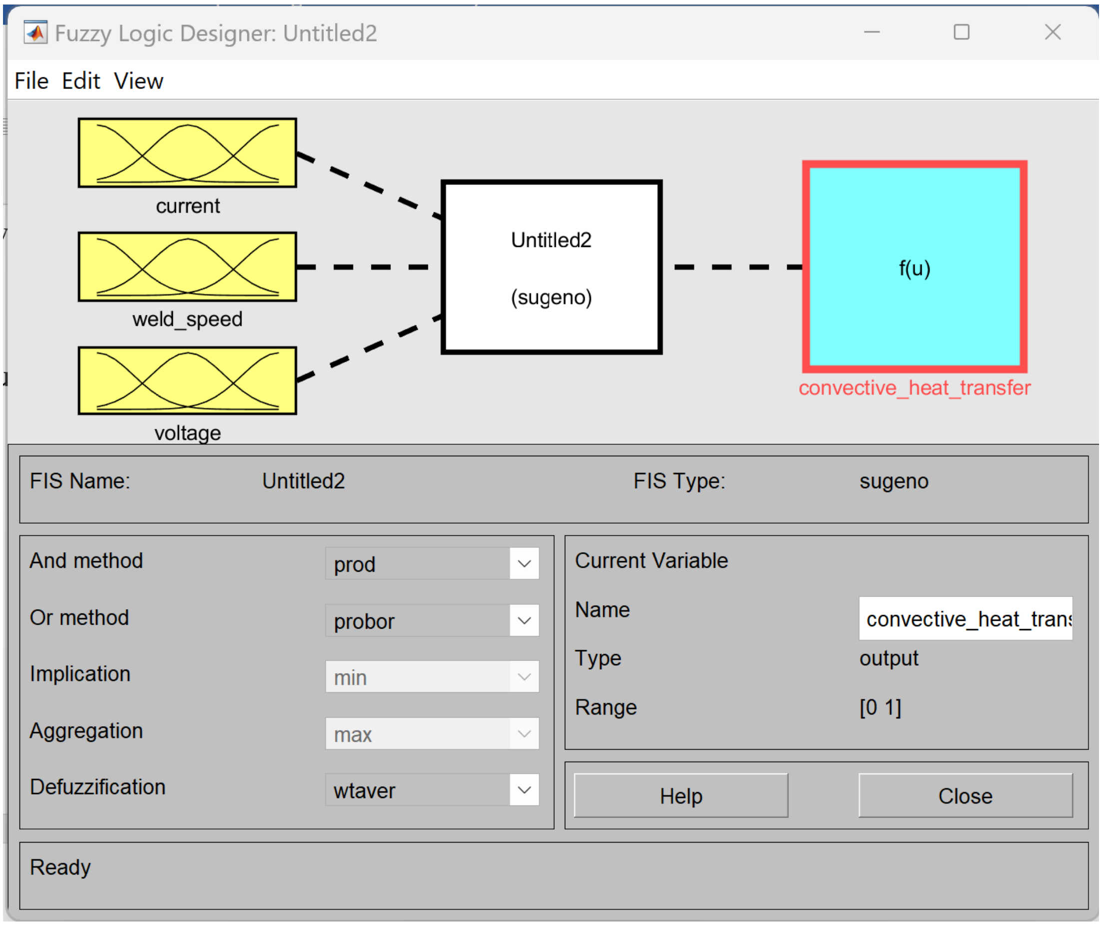

Figure 1: Defining the process parameters and investigated responses for convective heat transfer

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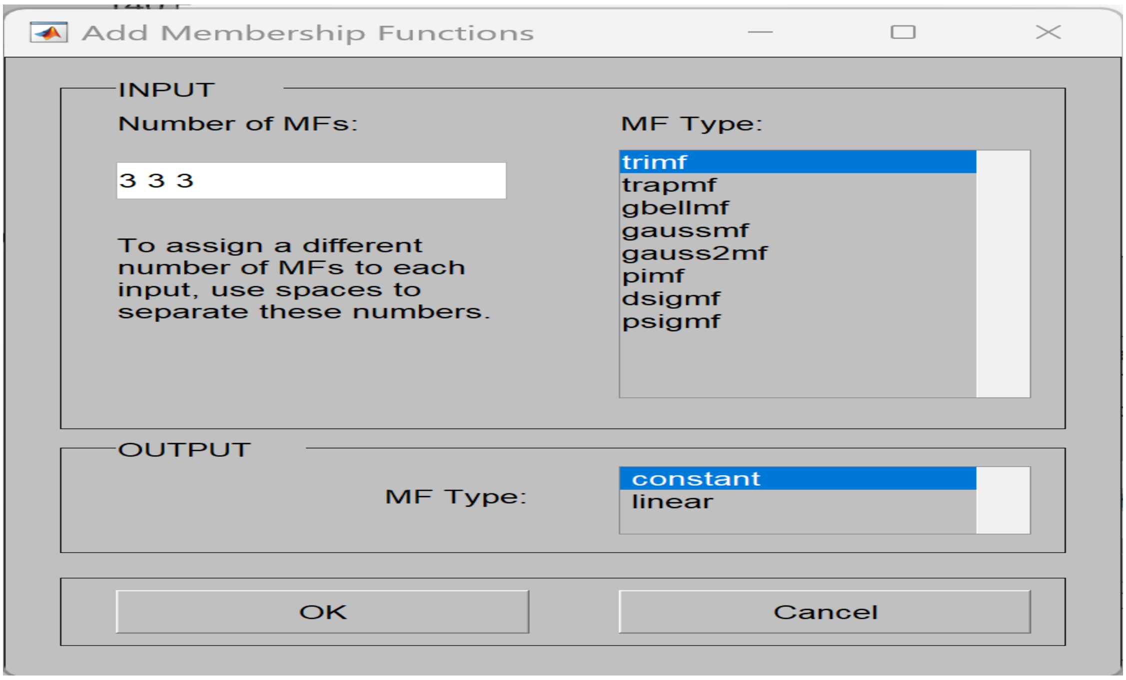

Figure 2: Description of input and output membership function for convective heat transfer

Figure 2 shows the member for function that was assigned to each linguistic variable and the kind of membership function that was chosen for every input and output variable. Ad observed in the figure above, three membership functions were defined for each process parameter and investigated response variable while the triangular and the constant membership function were selected.

3.3 Defining the input and output Membership function

Membership functions are used in the fuzzification and defuzzification steps of a fuzzy logic systems (FLS, to map the non-fuzzy linguistic terms and vice versa. A membership function is used in most cases to quantify a linguistic term. An important characteristic of ANFIS is that it doesn't have to be fuzzified using only one membership function. In other words, a value can belong to multiple sets at the same time. As mentioned earlier, three membership functions were selected for each inputs and output variables which is low.

To qualify the current, welding speed and voltage, the triangular membership function was employed having the following assignment (low, moderate and high). These are the linguistic values of the current, welding speed and voltage. Then,

C (c) = { low, moderate and high }
WS (ws) = { low, moderate and high }
V (v) = { low, moderate and high }

The terms in bracket represent the set of decompositions for the linguistic variable voltage, current, welding speed, gas flow rate and convective heat transfer. Each member of this decomposition is called a linguistic term. For this problem, the linguistic variables and their range of values include:

i. Current; this range from 180 to 200 amps
ii. Welding speed; this range from 2.6 to 3.2 mm/min
iii. Voltage; this range from 22 to 23volts
iv. convective heat transfer; this range from 1.9 to 2.4 h W/m².K

The ANFIS tool box that defines the input and output variables is presented in Figure

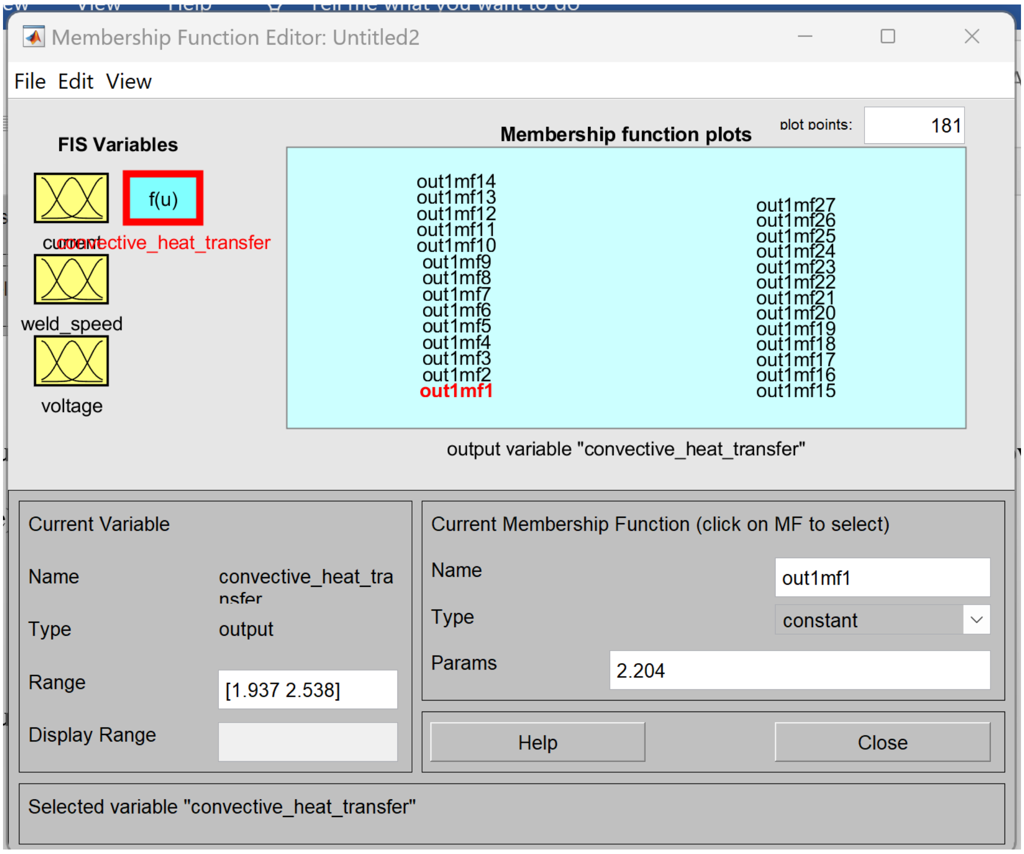

Figure 3: Definition of membership function for convective heat transfer

Figure 3 shows the membership function for convective heat transfer. The range is specified as [1.937 2.538] while the membership set that defines the low heat input is given as [2.204].

Employ the ANFIS tool to set membership functions and rules

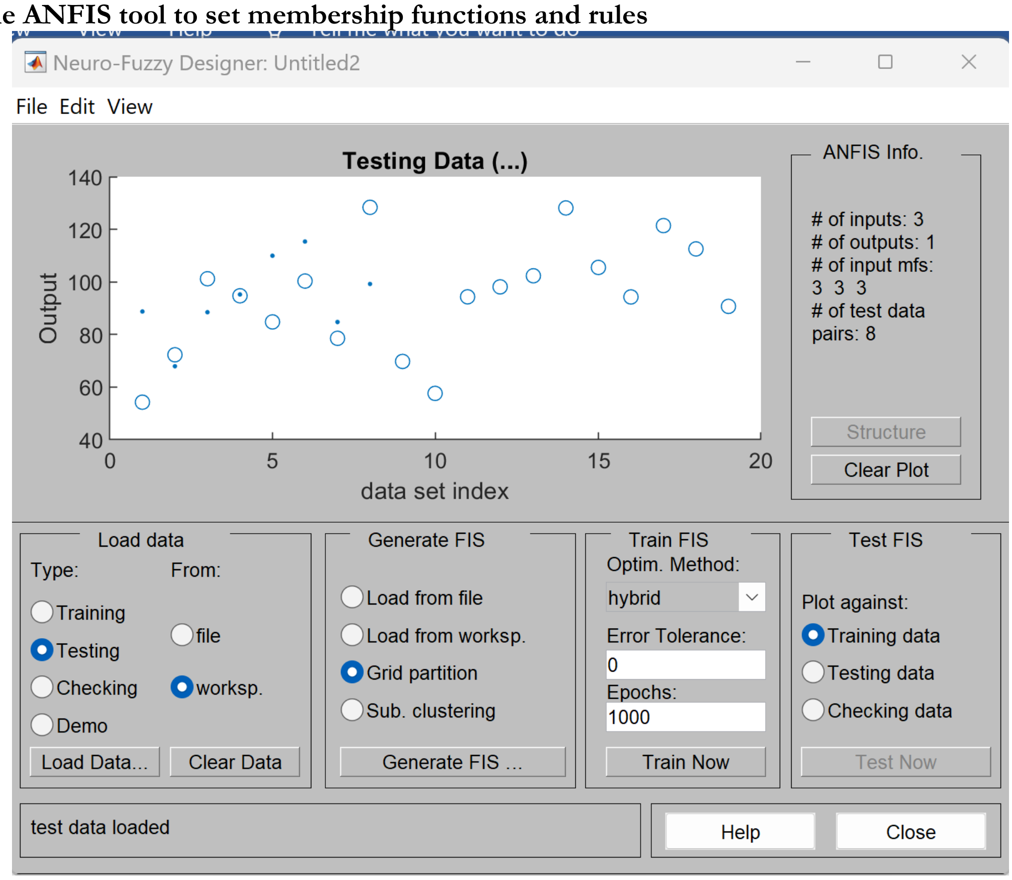

Figure 4: ANFIS Tool Box Showing the Crisp Data for Convective Heat Transfer

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Figure 4 shows the interface of ANFIS containing the crisp data for convective heat transfer. To generate the fuzzy interference system (FIS) grid partition was selected and the "generate FIS" button was activated. Three membership functions were selected for each input variable. For this problem, the triangular membership function (trimf) was used. The simplicity and flexibility of the triangular membership function coupled with its ability to define wider range of decomposed sets of linguistic variables accounts for its selection.

After carefully carrying out definitions of different input and output variables, setting of rules and membership functions as enumerated in previous chapter, the ANFIS prediction of convective heat transfer coefficient was carried out as shown in Figure 5.

The applied rules governing predicting convective heat transfer coefficient can be viewed using the rule viewer interphase presented in figure 5, from the result, it was observed that, for a current of 180Amp, Welding speed of 2.8mm/s and voltage of 21 votls, the predicted convective heat transfer is 2.4W/m².K

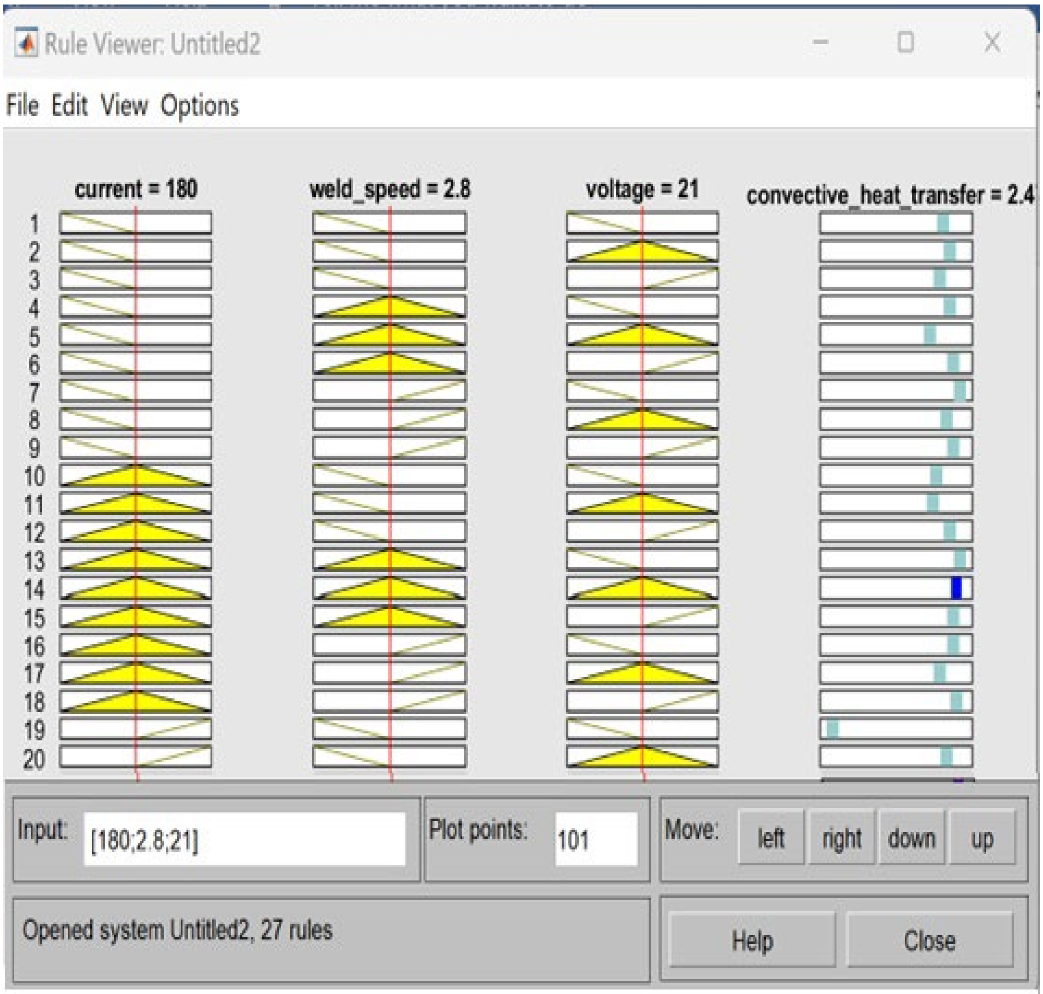

Figure 5: Rule viewer for prediction of convective heat transfer

To study the effects of combine input variables (welding speed and current) on convective heat transfer, 3D surface was generated as presented in Figure 6

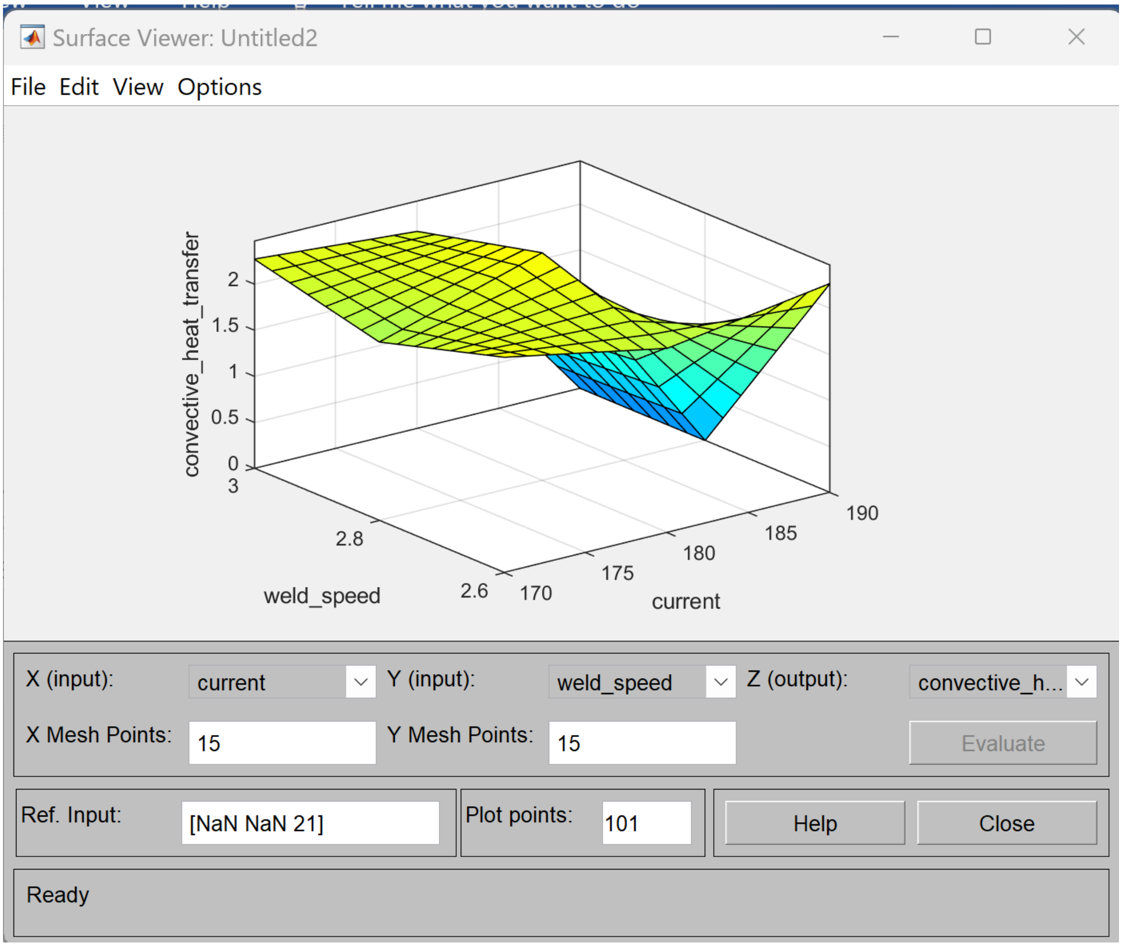

Figure 6: Influence of gas flow rate and voltage on convective heat transfer

Presented in Table 6 is the comparison made between the experimental research data of convective heat transfer to that of ANFIS predicted data of convective heat transfer

Table 3: Comparison between experiment convective heat transfer and ANFIS convective heat transfer

S/N	**Current, I, Amp**	**Speed, mm/sec**	**Voltage, Volts**	**Experiment convective heat transfer, h** W/m².K	**ANFIS convective heat transfer,h** W/m².K
1	190	2.63	20.73	2.20	2.20
2	190	2.63	20.72	2.40	2.40
3	190	2.63	20.70	2.34	2.34
4	190	2.63	20.68	2.60	2.60
5	190	2.62	20.78	2.44	2.44
6	170	2.80	20.00	2.27	2.251
7	170	3.00	21.00	2.27	2.27
8	170	3.00	22.00	2.24	2.24
9	170	3.00	20.00	2.47	2.47
10	180	2.60	21.00	2.54	2.54
11	180	2.60	22.00	2.00	2.00
12	180	2.60	20.00	2.14	2.14
13	180	2.80	21.00	2.54	2.54
14	180	2.80	22.00	2.40	2.42
15	180	2.80	20.00	2.47	2.47
16	180	3.00	21.00	2.47	2.47
17	180	3.00	22.00	2.54	2.54
18	180	3.00	20.00	2.47	2.47
19	190	2.60	21.00	2.47	2.46
20	190	2.60	22.00	2.47	2.49

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To compare the prediction strength of experimental values and ANFIS predicted values, a time series plot was generated to illustrate the trend at which the adopted expert method carry out its prediction in comparison to the experimental data. A time series plot is used to visually establish the trend of a process and observe outliers within the process. The time series plot showing comparison for experimental values for radiation heat loss and ANFIS predicted convective heat transfer is presented in figure 7.

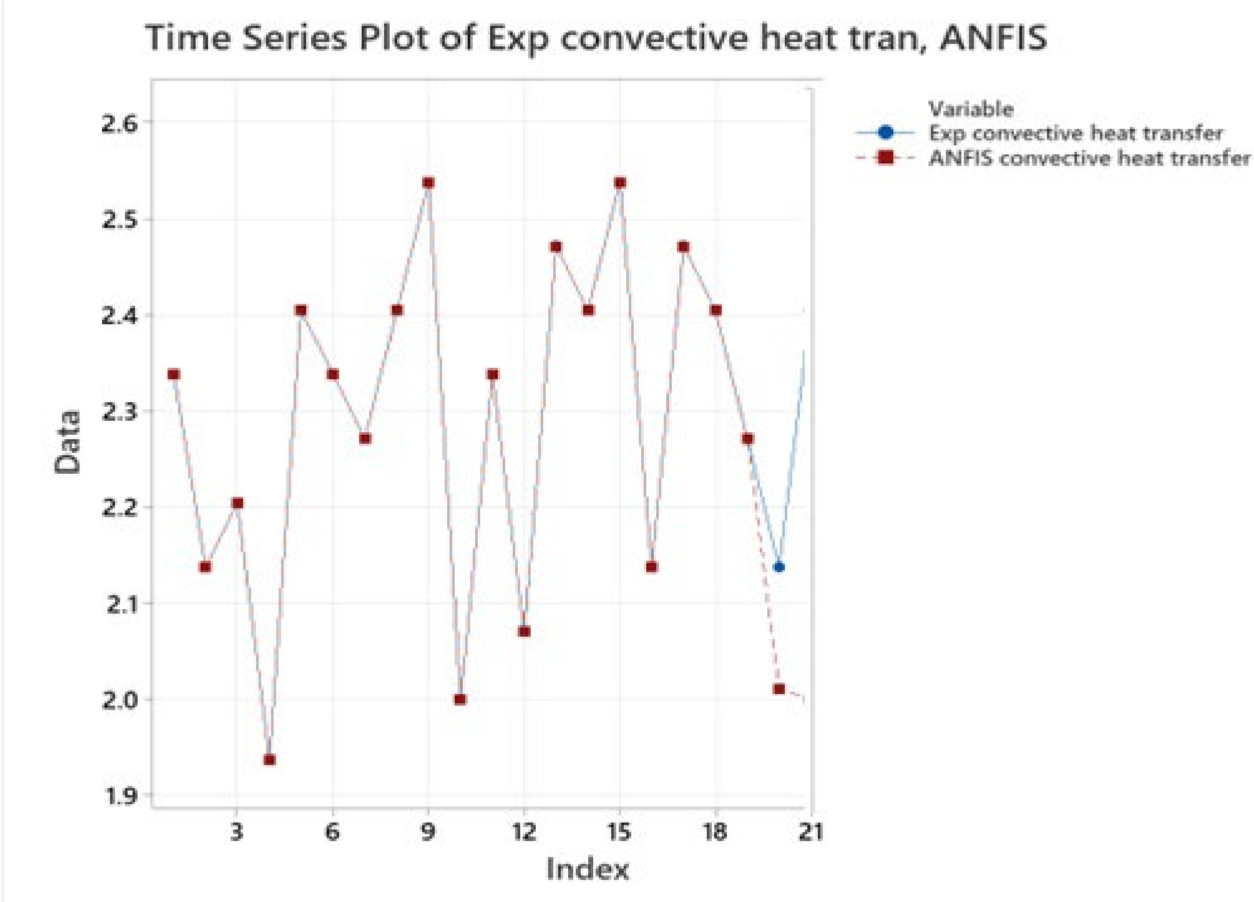

Figure 7: Time series plot of experiment convective heat transfer vs ANFIS convective heat transfer

As observed from the plot, the expert systems prediction acted like the actual experimental values, it can be seen that both variables show a good correlation trend and are in agreement with the actual value and gives a better graphical insight on the process drift points during prediction

3.4 Regression Analysis:

The regression equation of Experiment convective heat transfer versus ANFIS convective heat transfer is presented in Equation (2).

Experiment convective heat transfer = 0.3632 + 0.8497 ANFIS convective heat transfer (2)

Model summary presented in Table 4 shows an R^2 value of 97.47% obtained for the comparison of the experimental data to the ANFIS predicted data.

Table 4: Model Summary

S	R-sq
0.0766300	97.47%

Table 4 shows the model summary. It measures the strength and adequacy of the quadratic model. The results obtained shows that the model has 97.47% capacity to optimize convective heat transfer.

3.5 Conclusion

The ANFIS model effectively predicts the convective heat transfer coefficient (h) in TIG welding of mild steel using inputs of welding current (170-190 A), voltage (20-22 V), and speed (2.6-3.0 mm/s). Experimental h values ranged from 2.00 to 2.60 W/m².K across 20 runs, with ANFIS predictions matching closely (e.g., 2.20 vs. 2.20, 2.54 vs. 2.54). Regression analysis yielded the equation: Experimental h = 0.3632 + 0.8497 × ANFIS h, achieving $R^2 = 97.47\%$ and S = 0.0766300, confirming high predictive accuracy. Time series plots showed strong correlation trends with minimal drift, validating ANFIS for real-time process optimization.

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