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Development of Predictive Models to Improve Weld Bead Surface Profile Formation and Weld Arc Temperature in Tig Welding

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ABSTRACT

The quality, integrity, dimensional accuracy and mechanical performance of welded joints is highly influenced by the weld bead profiles formation resulting from a combined optimal welding input parameter. This study developed a model using Response Surface Methodology (RSM) and Adaptive Neuro Fuzzy Inference System (ANFIS) to optimize and predict weld bead surface profiles formation considering the welding arc temperature of a TIG welding process used to produce 10mm thick mild steel plate coupons with current, voltage and gas flow rate as input parameter. The experimental matrix design was developed using the central composite design (CCD) of a version 13.05 design expert. The weld bead profile and formation factor was measured and calculated, the welding arc temperature was measured using a mercury free thermal sensor digital thermometer. Response surface methodology (RSM) and Adaptive Neuro Fuzzy Inference System (ANFIS) was employed to predict the optimal arc temperature response. The predictive strength and adequacies of both models was compared. ANFIS prediction for the arc temperature response had a higher R^2 value of 98.54% with an adjusted R^2 value of 98.46% while RSM prediction had a R^2 value of 79.72% with an adjusted R^2 value of 78.59%, the signal to noise ratio in the model was also higher in the RSM prediction when compared with the ANFIS which selected FIS grid partitions having epochs numbers changed from 3 to 1000 using the triangular membership function for the range of input variables and trained constant membership function for response; was the performance criterion that produced the best ANFIS predictions giving it a better and higher prediction accuracy.

1. Introduction

Welding is a process of joining of two metals either same or different with the application of heat and/or with pressure with or without a filler rod. Welding technology is used in diverse branch of industries. The tendency for the atoms to bond is the fundamental basis of welding [1]. In addition to melting the base metal, a filler material is often added to the joint to form a weld pool (pool of molten metal) which after cooling, forms a joint which is referred to as weldment. There are different types of welding techniques. such as Submerge Arc Welding (SAW), Gas Metal Arc Welding (GMAW) otherwise known as Metal Inert Gas (MIG) Welding, Metal Active Gas (MAG) Welding and Gas Tungsten Arc Welding (GTAW) otherwise known as Tungsten Inert Gas (TIG) Welding etc. The TIG welding is a thermal process which depends on heat conducted through the metal. It makes use of the TIG machine, a non-consumable tungsten electrode which varies in diameter from 0.2 - 6.5mm, shielding gas which protects the weld pool from detrimental atmospheric effects. Argon gas is mostly used as the shielding gas and the use of a filler metal is optional in this process. In tungsten inert gas welding, an electric arc is formed when electric current is passed through the system connection of the electrode and work piece in the presence of an inert gas, TIG welding process is well known and its characterized with low heat input, low fumes, lesser spatter and also gives a pure quality weld product thus fabrication experts prefer this welding technique.

Weldments or weld quality is affected by different factors ranging from heat input, arc temperature, bead surface geometry, surface tension, molten metal fluidity, molten metal viscosity, liquidus temperature, arc length, weldments impact toughness etc. It has been proven by researchers that accurate prediction of bead surface profile formation of weldments improves the productivity of the welding process as well as the integrity of fabricated structures. The mechanical properties of welded joints are dictated mainly by heat input during welding, the heat affected zone (HAZ) area, precipitation process and weld bead geometry. Micro structure of weldment base material is also affected by high temperatures during the welding process, this reduces the integrity of the weldment heat affected zone (HAZ). According to Juang and Trang [2], weld quality is systematically structured by the weld bead geometry because the mechanical properties of welded joints are determined by the dimensions of weld bead profile hence it is very essential to select the welding process parameters for obtaining the most favorable weld bead profile. The bead geometry and surface profiles relationships affect the load carrying capacity of weldment as the shape and sizes of weldments has significant influence on its stress distribution during its shrinkage and solidification periods. The integrity of a weld bead is hinged on its surface profiles and their effects on the dimensional accuracy and quality of weldments. Adequate knowledge of bead surface profiles formation with proper consideration of the arc temperature during welding process is essential as the mechanical properties of weldments are affected by the bead formation. Welding happens to be a non - linear manufacturing process, which requires an advanced model that can predict the interaction between the welding input parameters and their various outputs. According to Oussaid and Ouafi [3], predictive modelling for quality analysis is one of the most critical requirements for a continuous improvement of reliability, efficiency and safety of welding process. Exploring certain aspects of the application of expert systems such as response surface method (RSM) and adaptive neuro fuzzy inference system (ANFIS) to predict and control the quality of bead surface profiles during the tungsten inert gas welding process aimed at improving the service life of structures is the motive of this study. The RSM and ANFIS were chosen because of its ability to adequately handle/develop models for both single and multi-response cases and also generate an optimal equation. Process parameters such as welding current, welding voltage, gas flow rate etc. has various effect on the surface profiles of weld beads during TIG welding. Karunakaran [4] compared weld bead profiles and temperature distribution of constant current and pulsed current gas tungsten arc weldment of AISI 304L grade stainless steel joints and reported on the effects of pulsed current welding on the tensile properties, micro structural features, hardness profile and residual stress distribution of stainless-steel joints. Panji *et al.* [5] studied the effect of welding current and welding speed on the weld bead geometry and distortion in TIG welding process using the A36 mild steel pipe as experimental material. Odoemelam *et al* [6]. A study on the expert optimization and prediction of bead volume of mild steel butt welded joint plate measuring 60mm x 40mm x 10mm was carried out by employing central composite design matrix using a Design Expert 7.01 software on a produced set of 20 experimental runs. RSM was used as the predictive modeling tool to obtain an optimum weld bead. According to Kshirsagar *et al* [7], Researchers have used artificial neural networks (ANNs) to predict the bead geometry based on the input parameters for a welding process; however, the number of hidden layers used in these ANNs are limited to one due to the small amount of data usually available through experiments and this leads to a reduction in the accuracy of prediction. Such ANNs are also incapable of capturing sudden changes in the input–output trends; Akkas *et al.* [8] did a study on modeling and analysis of the weld bead geometry in submerged arc welding by using adaptive neuro-fuzzy inference system with the aim of obtaining a relationship between the values defining bead geometry, The relationship between the welding parameters is modeled by using ANN and neuro fuzzy system approach and test data selected from experimental result was used to check for the adequacy of each model after which each model was compared with regard to accuracy. Ojika *et al* [9] developed a model for predicting incomplete penetration in tungsten inert gas welding using response surface methodology and artificial network while ANOVA was used to analyse the statistics of the main composite design, surface plots alongside cook's distance and quasi newton neural network was used to examine and forecast the aim if the reaction. The result obtained from the models showed that the partial penetration was adequately forecasted with the artificial neural being a better predictive model with least mean square error. High temperature in the welding zone during the welding process leads to generation of unwanted residual stresses which results in weld distortion. Arora *et al.* [10] presented a critical review of the thermal and structural modelling of the arc welding process because measurement of the temperature distribution was a huge challenge in time past. Enegide *et al*. [11] stated that microstructure alteration of the weld area is one of the major effects of excessive heat input on weldments therefore one need to take into cognizance the amount of heat being introduced into a weld zone in order to obtain a quality weld. A research on heat input optimization and prediction analysis for TIG welding process with the aim of predicting and optimizing and predicting heat input needed during mild steel plate fusion welding using response surface methodology (RSM) was carried out.

2.0. Methodology

2.1 Identification of Input Parameters Range

The key parameters considered in this work are welding current (A), welding voltage (V), Gas Flow Rate (L/Min) with considerations on bead width, bead depth and bead form factor. The range of the process parameters used for this study is as presented in Table 1.

Table 1: Process parameters and their levels

PARAMETERS	UNITS	SYMBOL	CODED VALUE	CODED VALUE
			LOW (-1)	HIGH (+1)
WELDING CURRENT	Amps	I	-1 ↔ 160.00	+1 ↔ 190.00
WELDING VOLTAGE	Volts	V	-1 ↔ 22.00	+1 ↔ 25.00
GAS FLOW RATE	L/Min	GFR	-1 ↔ 14.00	+1 ↔ 17.00

2.2 Experimental Data Collection

The input parameters (Current, Voltage and Gas flow rate) were used as factors for the design matrix, the output parameters (bead width, bead depth, form factor and arc temperature) which are the responses recorded during and after the welding of the mild steel coupons which forms the weld samples make up the experimental matrix that was used as the data. Design expert software version 13.05 was employed to carry out the experimental design. The face centered central composite design was used to develop a statistical design of experiment (DOE) by setting each numerical factor to 5 levels: plus and minus alpha (axial), plus and minus 1 (factorial points) and then the center point. When these categoric factors are added, the central composite design will be duplicated for every combination of the categorical factor levels. This generated an experimental design matrix having six (6) center points (n_o), six (6) axial points (2n) and eight (8) factorial points (2^n) which when imputed into Equation 1 resulted in twenty (20) experimental runs as presented in Table 2. The total number of experimental runs as generated by the CCD is given as: Owolabi *et al* [12].

$$N = 2^n + n_o + 2n \qquad (1)$$

Table 2: Central Composite Design (CCD) Experimental Matrix.

Run	Factor 1	Factor 2	Factor 3
	A: Current (Amp)	B: Voltage (Volt)	C: Gas Flow Rate (lit/min)
1	170	22	14
2	170	23	15
3	190	24	16
4	170	25	17
5	180	22	15
6	170	23	16
7	180	24	17
8	160	25	14
9	180	22	16
10	160	23	17
11	160	24	14
12	160	25	15
13	180	22	17
14	170	23	14
15	170	24	15
16	170	25	16
17	170	25	17
18	170	24	14
19	160	23	15
20	170	22	16

To analyze the effect of arc temperature on bead surface profiles, the bead width, bead depth and the bead form factor has to be observed during experimentation. These alongside the measured arc temperature make up the responses to be analyzed in other to successfully predict and control bead surface profiles formation considering the effect of arc temperature during TIG welding process on mild steel.

2.3 Experimental Procedure

Two hundred (200) coupons of mild steel plates were cut into the desired shape and size with their edges smoothened and cleaned with emery paper before a TIG welding machine (Fig 1) with a tungsten electrode and argon gas as weld pool shield was used to carry out welding to form one hundred (100) welded samples using the combination of input parameters as stated by the CCD, five (5) experimental runs was carried out for each range of input parameter and the average recorded as the response value to avoid error. The weld bead width and depth was measured using a digital Vernier caliper, the form factor was calculated while the arc temperature was measured using a mercury free digital thermometer (Fig 2).

Figure 1: TIG welding Machine

Figure 2: Digital thermometer

3. Results and Discussion

The Measured and recorded value for each experimental run with the different combination of process parameter and the observed response is presented in Table 3.

Table 3: Experimental Results

Std	Run	PROCESS PARAMETER			RESPONSE			
		A	B	C	1	2	3	4
		Current	Voltage	Gas Flow Rate	Bead Width	Bead Depth	Form Factor	Arc Temp
		(Amp)	(Volt)	(lit/min)	(mm)	(mm)		(^{0}C)
13	1	170	22	14	12.7	10.1	1.2233	1514
14	2	170	23	15	12.5	10.1	1.205	1388
2	3	190	24	16	16.2	13.1	1.5565	1434
6	4	170	25	17	15.9	12.8	1.5245	1514
11	5	180	22	15	14.5	11.7	1.3921	1438
15	6	170	23	16	13.5	10.8	1.4294	1420
8	7	180	24	17	16	12.9	1.5359	1339
1	8	160	25	14	12.4	10	1.1913	1586
18	9	180	22	16	14.2	11.5	1.3693	1485
17	10	160	23	17	17.1	13.8	1.6432	1632
12	11	160	24	14	12.6	10.2	1.2164	1468
5	12	160	25	15	12.5	10.1	1.2073	1547
3	13	180	22	17	15.4	12.4	1.4789	1565
7	14	170	23	14	13.7	11	1.3145	1377
10	15	170	24	15	12.9	10.4	1.2392	1383
19	16	170	25	16	13.2	10.7	1.2712	1494
16	17	170	25	17	15.4	12.5	1.4903	1496
9	18	170	24	14	13.8	11.1	1.3237	1403
20	19	160	23	15	12.3	10	1.1845	1512
4	20	170	22	16	12.9	10.4	1.2392	1597

3.1 Model Prediction using Response Surface Methodology (RSM)

The RSM optimization process was to determine the optimum value of each input variable that will predict and optimize the weld bead profile while considering the arc temperature on the weld bead formation factor during TIG welding process. The summary of input factors and responses generated by the CCD matrix with their range of values including the mean and standard deviation reveals that the model is of the quadratic type therefore requiring adequate polynomial analysis as depicted by the response surface design.
To check for the suitability and adequacy of the quadratic model on the experimental data analysis, a goodness of fit statistics was computed as shown in Table 4.

Table 4. Goodness of Fit Statistics for Arc Temperature

Std. Dev.	13.51	**R^2**	0.9854
Mean	1479.6	**Adjusted R^2**	0.9723
C.V. %	0.9133	**Predicted R^2**	0.7744
		Adeq Precision	28.2616

It is observed that the **Predicted R^2** of 0.7744 is in reasonable agreement with the **Adjusted R^2** of 0.9723; i.e. the difference is less than 0.2. implying that the developed can be used to navigate the design space and adequately predict the target response.
The optimal equation showing the individual effects and combine interactions of the input variables: current, voltage and gas flow rate (A, B and C) against the measured arc temperature response based on the coded factors is presented in Equation 2.

$$arc\ temp = 1338.09 - 47.36A + 7.68B + 6.94C + 115.02AB - 45.59AC - 66.44BC + 91.56A^2 + 176.64B^2 + 30.06C^2 \qquad (2)$$

The equation in terms of coded factors can be used to make predictions about the response for given levels of each factor. The coded equation is useful for identifying the relative impact of the factors by comparing the factor coefficients.
To establish the suitability of response surface methodology in using the quadratic model and to asses the prediction accuracy, a reliability plot of the predicted and actual values of each responses was developed to access the accuracy of prediction is presented in Figure 3.

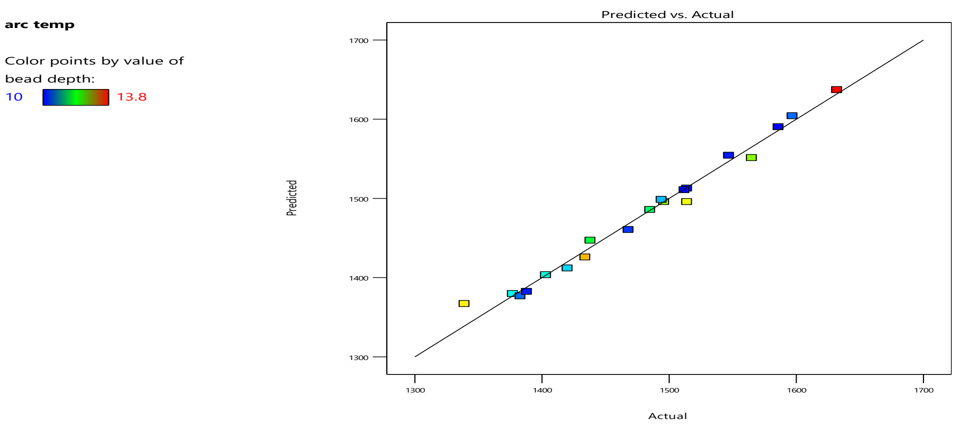

Figure 3: Reliability Plot of Predicted Values vs Actual Values for Arc Temperature

Obervations from Figure 4.8 shows that the data points all cluster along the line of best fit therefore establishing the prediction accuracy degree of RSM.

3.2 Model Prediction using Artificial Neuro Fuzzy Inference System (ANFIS)

Development of ANFIS for prediction of bead surface profiles considering its arc temperature on the weld bead formation factor during TIG welding process is a fuzzy inference system implemented in the framework of neural networks. The proposed model applies two techniques in updating parameters. ANFIS first employs gradient descent to fine-tune premise parameters that define membership functions then uses the hybrid learning method in combination with the gradient descent method and least squares method to identify the consequent parameters that define the coefficients of each output equations. The three input (current, voltage, gas low rate) and one output (arc temperature) variables were created as presented in Figure 4.

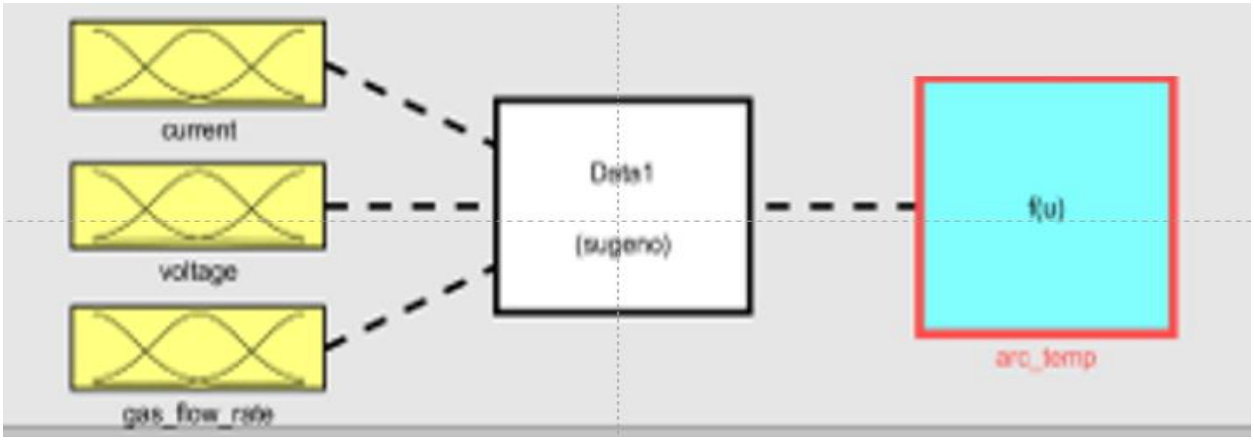

Figure 4: ANFIS Simulation Setting for Arc Temperature Analysis

After creating the variables, 70% of the research data being 14 runs were employed to train the network, while 30% being 6 runs were employed to test the network. The appropriate architecture needed to predict arc temperature was automatically generated. The triangular membership function can take only three arguments therefore it was selected based on the three (3) input variables to produce 27 possible argumets for a better prediction.

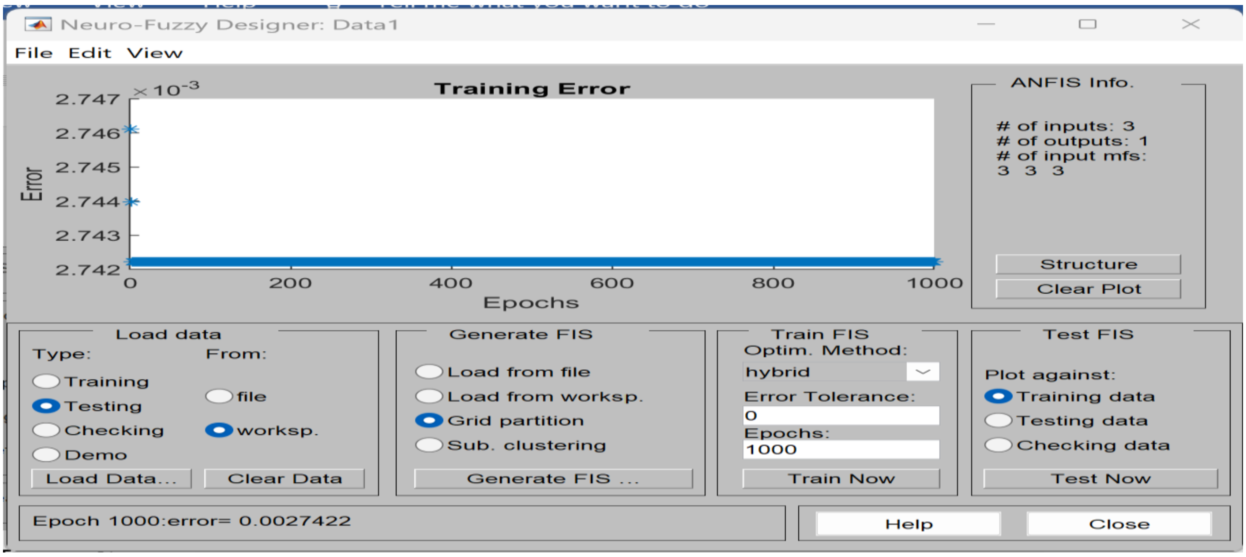

Figure 5: Neuro-Fuzzy Design Interphase for Arc Temperature

The linguistic values of current, voltage, and gas flow rate was qualified (low, moderate and high) while that of the arc temperature was also qualified (very low, low, moderate, high, very high). The terms in bracket is known as the linguistic terms, it represents the set of decompositions for the input variables and output responses. The fuzzy logic tool box that defines the input parameters and output variables applied the constant membership function because ANFIS can only carry out prediction on one response at a particular time. The constant membership function for arc temperature response was defined and trained by allowing the ANN function in ANFIS apply the appropriate governing rules for the arc temperature response as presented in Figure 6.

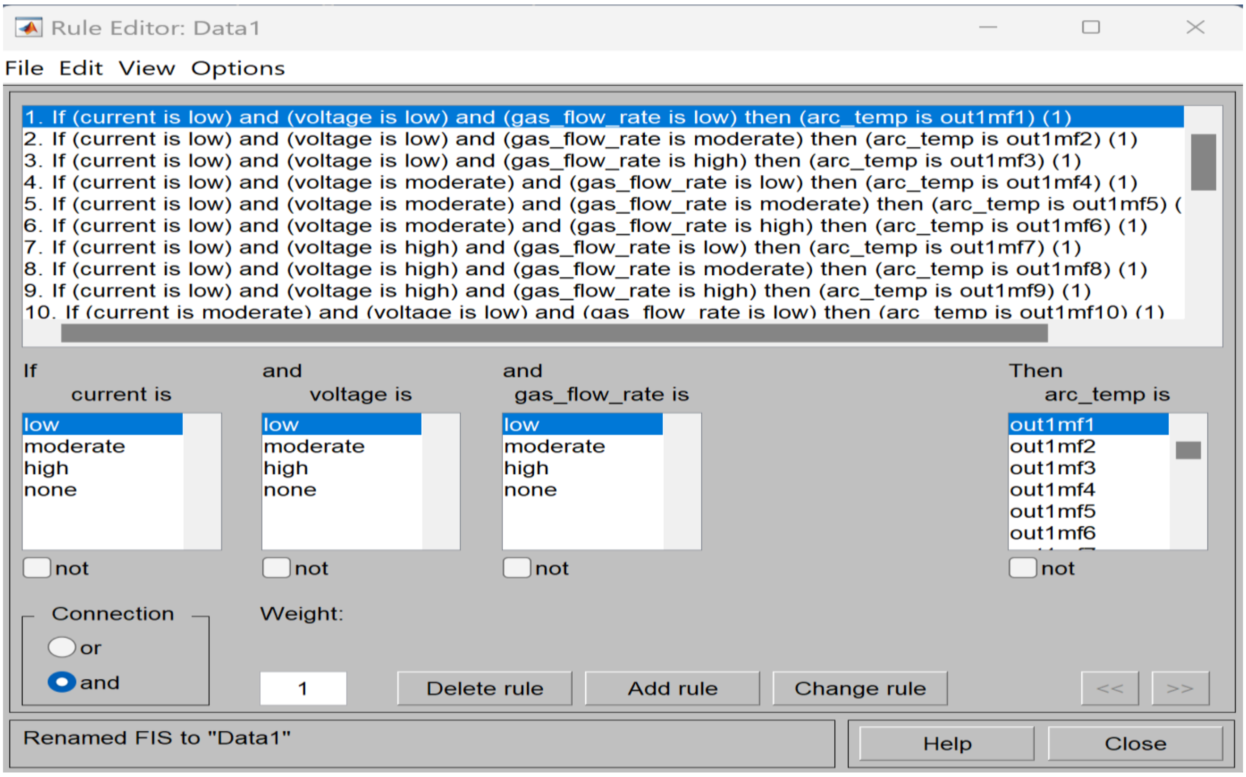

Figure 6: Rules Editor Window for Arc Temperature Response

The predicted arc temperature can be viewed using the rule viewer interphase as presented in Figure 7.

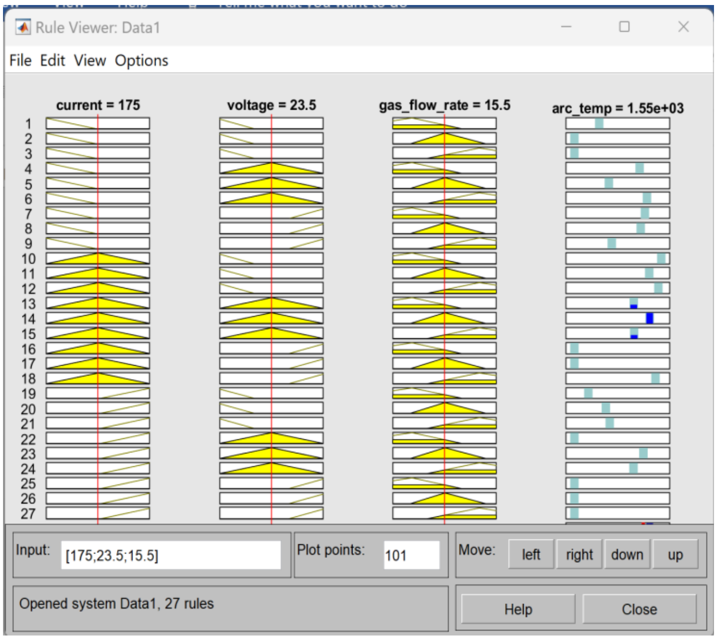

Figure 7: Rule Viewer for Arc temperature Prediction

3.3 Comparison of Expert Systems Predictions to Experimental Results.

To compare the predicting strength of RSM and ANFIS, the summary of their corresponding predicted values was developed and the regression equation showing the relationship between the actual values and ANFIS predicted value for the arc temperature is presented in Equation 3.

$$\text{Actual Values} = -0.01 + 1.000\ \text{ANFIS} \tag{3}$$

while the regression equation showing the relationship between the actual values and RSM predicted value for the arc temperature is presented in Equation 4.

$$\text{Actual Values} = 149.9 + 0.9009\ \text{RSM} \tag{4}$$

The regression model summary showing the signal to noise ratio (S) alongside their prediction adequacy R^2 is presented in Table 5.

Table 5: Regression Model Summary for Arc Temperature Predictions.

Source	**S**	$\mathbf{R^2}$	**Adj** $\mathbf{R^2}$
ANFIS	10.0736	98.54%	98.46%
RSM	37.5967	79.72%	78.59%

A fitted line plot was used to graphically depict the relationship between the actual and predicted values of the two expert methods based on a line of best fit as shown in Fig 8a and 8b.

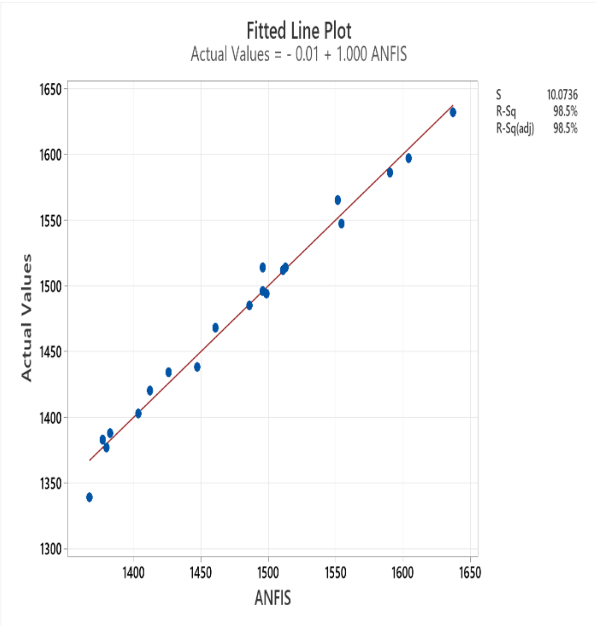

Figure 8a: Fitted Line Plot of Actual vs ANFIS Prediction for Arc Temperature

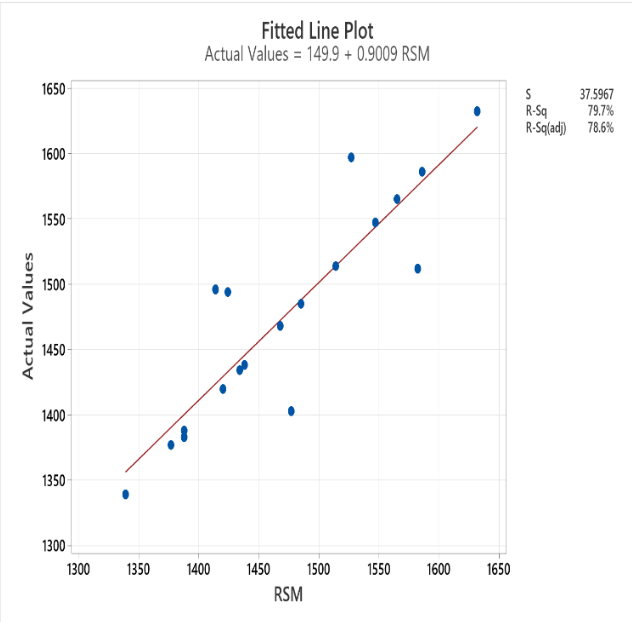

Figure 8b: Fitted Line Plot of Actual vs RSM Prediction for Arc Temperature

A time series plot was used to compare and illustrate the trend at which both expert methods (ANFIS & RSM) carry out their predictions in comparison to the experimemta data as presented in Figure 9.

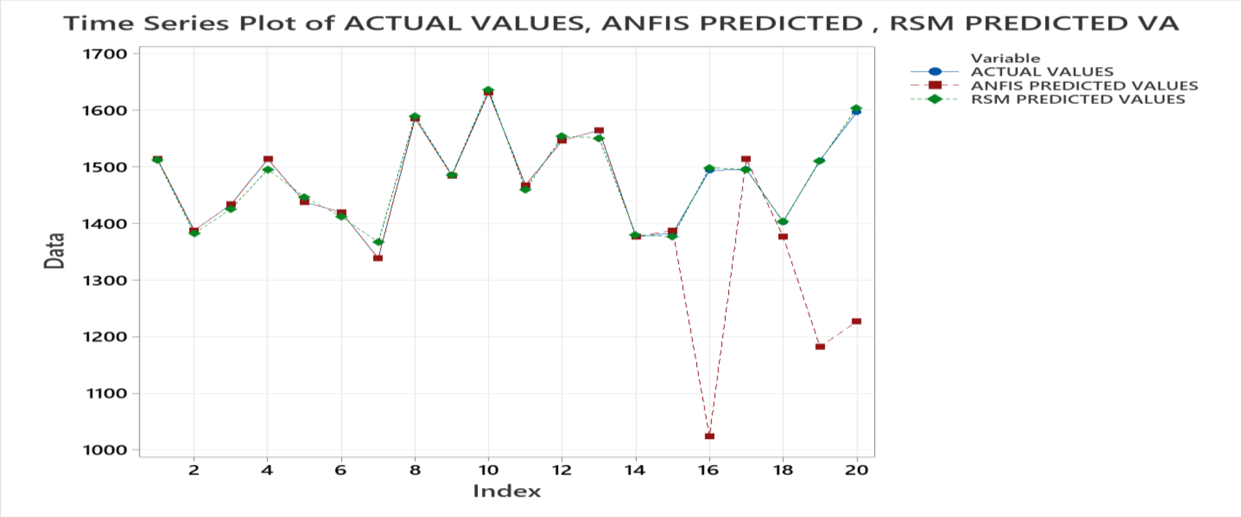

Figure 9: Time Series Comparison of Actual Values, ANFIS and RSM predictions

4. Conclusion

Observations from Table 5 shows that the ANFIS prediction for the arc temperature response has a higher R^2 value of 98.54% with an adjusted R^2 value of 98.46% while RSM prediction has a R^2 value of 79.72% with and adjusted R^2 value of 78.59%, the maximum error which signifies the signal to noise ratio in the model was also observed to be higher in the RSM prediction when compared with the ANFIS prediction implying that ANFIS has a better predictive strength with a prediction having current of 175amps, voltage of 23.5v and a gas flow rate of 15.5L/min to produce an optimal weld arc temperature of 1.550^{o}C. To get a better graphical insight on the process drift points during prediction as can be observed from the time series plot in Figure 9, both expert systems predictions mimicked the experimental actual values, both predictors shows a good correlation trend or agreement. However, ANFIS also showed a better predictive correlation trend.

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