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Comparison of Response Surface Methodology and Artificial Neural Networks in The Estimation Of Thermal Conductivity Mild Steel Tig Weld

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ABSTRACT

Thermal conductivity is a measure of heat flow per second per unit area per temperature gradient. This study compared Response surface Methodology to Artificial Neural Networks in the opitimisation of the thermal conductivity of mild steel weld using the TIG welding process, The input parameters considered in this study were welding current, welding voltage and gas flow rate, while the measured parameters was thermal conductivity. Twenty sets of experiment were performed using 5 specimens for each run. The plate samples were 60 mm long with a wall thickness of 10mm. The models RSM R^2 value for RSM was 92.38% and ANN 99.85%. This shows that ANN is a better predictor as compared to RSM.

1. Introduction

Thermal conductivity is heat flow per second per unit area per unit temperature gradient. Heat conduction / Heat energy is the transferred from the hot end of heat conductor to the cold end [1]. There are different methods to measure thermal conductivity [2]. In general, it can be classified as a steady-state method and transient or unsteady-state method. In a steady-state method, a steady-state condition is attained when the temperature at each point of the specimen is constant and the temperature does not change with time. A disadvantage is that it generally takes a long time to reach the required equilibrium. This method involves expensive apparatus since a well-designed experimental installation system is usually needed. Nevertheless, it is the primary and most accurate measurement method. In the Transient method, the measurement is taken during the healing process. Thermal conductivity is measured using sensors and probes. The measurement can be made quickly compared to the steady-state method. The transient method is more suitable for materials with heterogeneous properties and high moisture content. The arc length in GTAW is usually from 2 to 5 mm. If the arc length increases, the voltage to maintain the arc stability must increase, but the heat input to work-piece decreases due to radiation losses from the column of the arc [3]. Consequently, weld penetration and cross section area of melted material decrease with increasing arc length. Shielding gases are used in GTAW in order to prevent atmospheric contamination of the weld metal. This contamination can produce porosity, weld cracking, scaling and even change in the chemical composition of melted material. Besides shielding gas also has a large influence on the stability of the electric arc. Gases with low ionization potential facilitate the ignition of the electric arc and those with low thermal conductivity tend to increase the arc stability.

Thermal conductivity is a material property that determines how well a material conducts heat. In welding, the thermal conductivity of the base metal can affect the quality of the weld joint. It was found that the thermal conductivity of the base metal had a significant effect on the microstructure and mechanical properties of the weld joint [4]. The study observed that welding on materials with high thermal conductivity resulted in a fine-grained microstructure and increased strength, while welding on materials with low thermal conductivity resulted in a coarse-grained microstructure and decreased strength

Resistance spot welding (RSW) is included in the group of resistance welding processes in which the heat is generated by passage of electric current through the bodies to be joined [5]. According to Joule's law, other welding processes such as resistance seam welding, projection welding, flash or upset welding and high-frequency welding are of the same group. Spot welding is the resistance welding process most widely used in robotic applications all over the world in resistance spot welding overlapping sheets of metal are joined by applying electric current and pressure in the zone to weld with copper electrodes copper is used for electrodes because it has low electrical resistance and high thermal conductivity.

Response surface technique as a collection of rigorous mathematical and statistical operations utilized to build and optimize methods (RSM) [6]. The main use of RSM is described in unique conditions when many input variables affect certain execution phases and process quality elements. The response scale is referred to as the execution scale, while input variables are often referred to as independent variables, which engineers typically control. In order to construct a good typical model to estimate response and independent variables, this work focused on the RSM statistical modeling status. The approximation model is a tentative model that is developed built on either process or system information. The quantitative technique, including multiple regressions, is indeed a combination of very essential tools for constructing the required uncertain models for the RSM.

The present trend in the fabrication industries is the use of automated welding processes to obtain high production rates and high quality output.TIG welding, happens to be the best welding method employed in the manufacturing industry [7]. one of the problem facing the fabrication industry is the control of the process input parameters to obtain a good welded joint . however it is essential to establish the relationship between process parameters and weld quality output to predict and control weld bead quality .The aim of this study is to predict the impact energy of TIG mild steel welds using ANN.In this study, twenty experimental runs were carried out, each experimental run comprising the current, voltage and gas flow rate, the TIG welding process was used to join two pieces of mild steel plates measuring 60 x40 x10 mm , the impact energy was measured respectively. Thereafter the data collected from the experimental results was analysed with the ANN. The experimental results for the impact energy was analyzed with the Artificial Neural Networks. The overall R-value is shown to be 98.7%. The best validation performance is 0.48429 and occurred at epoch five (5). The coefficient of correlation for training shows of 99.9% closeness ,99.4% for validation and 89.8% for testing respectively.

Welded yield strength is designed to be large enough to handle all forces and pressures on the joint and is designed to be as strong as the tube itself [8]. Hence, was need to investigate the use of artificial neural network (ANN) to evaluate and forecast selected welding parameters on mild steel welded joints soldered by tungsten inert gas (TIG) using sixty (60) experimental data generated by replicating the design matrix from the Central composite Design (CCD) used for the ANN modelling. The welding current, welding voltage and gas flow rate were selected as process parameters and yield strength chosen as Response. The resulted obtained show that the R-value (coefficient of correlation) for training shows of 95.8% closeness, 99.2% for validation and 93.1% for testing respectively. The overall R-value obtained is 95.1% which showed that the developed model can accurately predict the value of strength. Results also showed that ANN is a more efficient tool for prediction of the Yield strength in TIG Mild steel weld. TIG Welding is a high quality form of welding which is very popular in industries. It is one of the few types of welding that can be used to join dissimilar metals. Here a weld joint is formed between stainless steel and monel alloy. It is desired to have control over the weld geometry of such a joint through the adjustment of experimental parameters which are welding current, wire feed speed, arc length and the shielding gas flow rate [9]. To facilitate the automation of the same, a model of the welding system is needed. However, the underlying welding process is complex and non-linear, and analytical methods are impractical for industrial use.

Therefore, artificial neural networks (ANN) are explored for developing the model, as they are well-suited for modelling non-linear multi-variate data. Feed-forward neural networks with backpropagation training algorithm are used, and the data for training the ANN taken from experimental work. There are four outputs corresponding to the weld geometry. Different training and testing phases were carried out using MATLAB software and ANN approximates the given data with minimum amount of error.

2. Material and Method

2.1 Design of Experiment

The key input parameters considered in this work were welding current, welding voltage and gas flow rate, while the response or measured parameters, thermal conductivity. The range and level [10,11] of the experimental variables were obtained and are presented in Table 1

Table 1: Range and Levels of independent variables

Independent Variables	Range and Levels of Input Variables	
	Lower Range (-1)	Upper Range (+1)
Welding Current (Amp) X_1	150	180
Welding Voltage (Volt) X_2	16	19
Gas flow rate (lit/min) X_3	13	16

2.2 Sample Preparation

Twenty sets of experiment were performed using 5 specimens for each run. The plate samples were 60 mm long with a wall thickness of 10mm. The samples were cut longitudinally with a single-V joint preparation as shown in Figure 1.

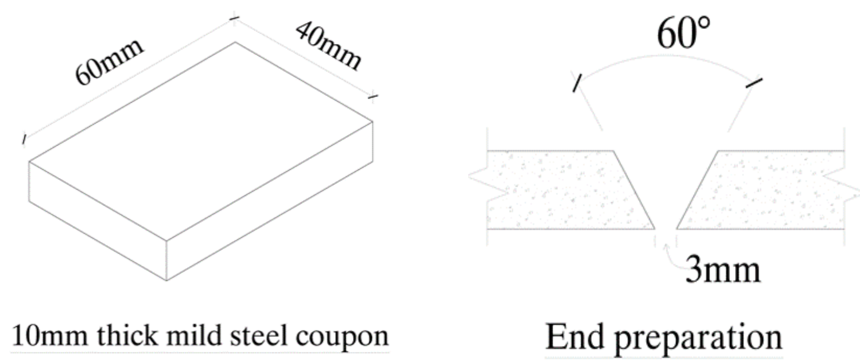

Figure 1: Weld specimen design

The set of tools including power hacksaw cutting and grinding machines, mechanical vice, emery (sand) paper and sander was used to prepare the mild steel coupons for welding.
The set of tungsten inert gas welding equipment was used to weld the plates after the edges have been machined and bevelled

The welding process uses a shielding gas to protect the weld specimen from atmospheric interaction. For this study, 100% pure Argon gas was used. The weld samples were made from 10mm thickness of mild steel plate; the plate was cut to size with the power hacksaw. The edges grinded and surfaces polished with emery paper and the joints welded.

2.3 Data Collection

After grinding and polishing of the sample edges, welding work was carried out, and the responses were measured and recorded. The measured response corresponding to the input variable is presented in Table 1

3. Results and Discussion

The experimental results utilized in the Response Surface Methodology are presented in Table 2

Table 2: Experimental observed value, RSM vs ANN predicted result of Thermal conductivity responses.

S/N	Input parameters			Exp Responses	RSM prediction	ANN Prediction
	Current	voltage	GFR	Thermal conductivity	Thermal conductivity	Thermal conductivity
1	165.000	17.500	14.500	51.780	51.791	51.783
2	180.000	16.000	16.000	51.854	51.881	51.850
3	150.000	19.000	16.000	51.791	51.775	51.787
4	165.000	17.500	14.500	51.786	51.791	51.783
5	165.000	17.500	14.500	51.788	51.791	51.783
6	165.000	20.023	14.500	51.885	51.868	51.887
7	180.000	19.000	16.000	51.995	51.967	51.995
8	165.000	17.500	14.500	51.783	51.791	51.783
9	150.000	19.000	13.000	51.756	51.783	51.760
10	165.000	17.500	14.500	51.781	51.791	51.783
11	180.000	16.000	13.000	51.749	51.788	51.752
12	139.773	17.500	14.500	51.738	51.749	51.736
13	180.000	19.000	13.000	51.937	51.894	51.934
14	165.000	14.977	14.500	51.759	51.757	51.757
15	190.227	17.500	14.500	51.911	51.919	51.913
16	165.000	17.500	11.977	51.787	51.795	51.784
17	165.000	17.500	17.023	51.886	51.913	51.889
18	150.000	16.000	13.000	51.751	51.758	51.751
19	150.000	16.000	16.000	51.812	51.789	51.815
20	165.000	17.500	14.500	51.781	51.791	51.783

Table 2: presents the comparison between the experimental value, RSM and the ANN predicted value for Thermal conductivity responses

The Regression Analysis for ambient temp obtained from the fitted line plot of Figure EXP versus ANN produced equation 1 with Table 3 as its model summary

The regression equation is

$$EXP = -4.363 + 1.084\ RSM \quad (1)$$

Table 3: Model Summary RSM model

S	R-sq	R-sq(adj)
0.0202043	92.38%	91.96%

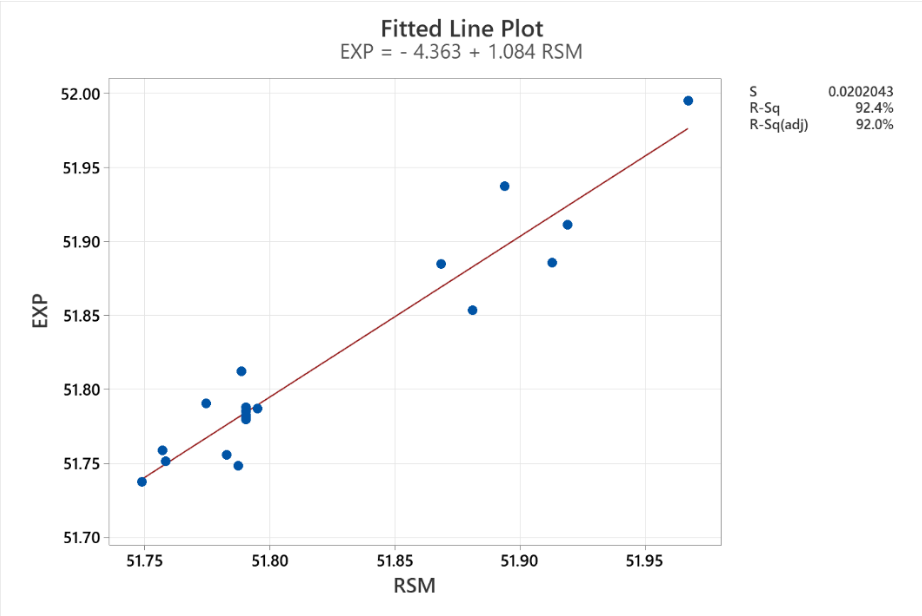

Figure 2: Regression plot of Experimental versus predicted Thermal Conductivity

The Regression Analysis for thermal conductivity obtained from the fitted line plot of Figure 2 EXP versus ANN produced equation 2 with Table 4 as its model summary

The regression equation is

$$EXP = - 0.0040 + 1.000\ ANN \quad (2)$$

Table 4: Model Summary for ANN model

S	R-sq	R-sq(adj)
0.0028572	99.85%	99.84%

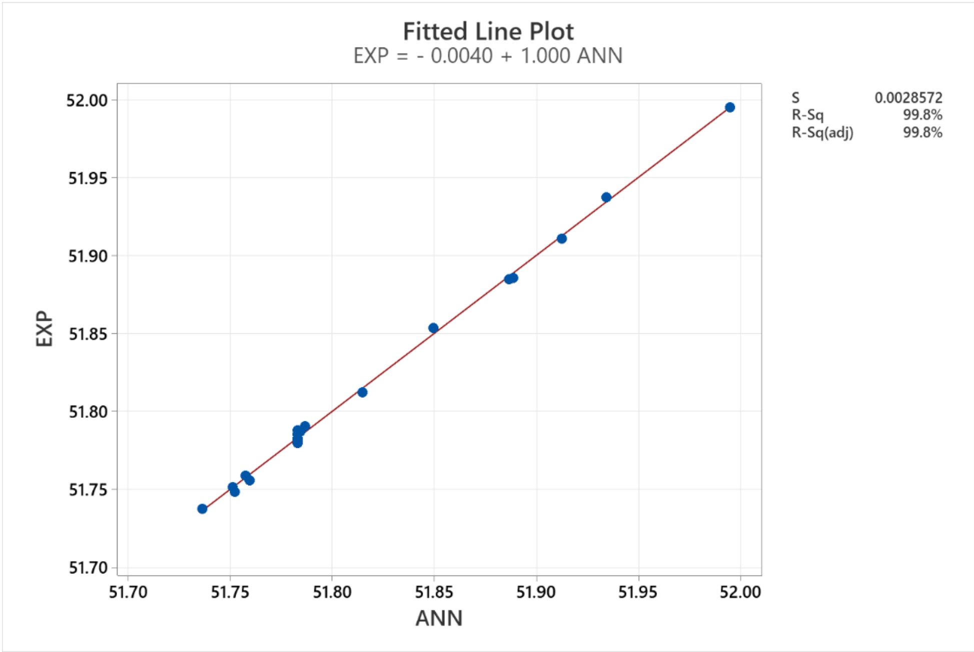

Figure 3: Regression plot of Experimental versus predicted Thermal conductivity responses

The model summary values between the experimental results compared to RSM (R^2 = 92.38%) and ANN (R2 = 99.85%) values. This shows that ANN is a better predictor as compared to RSM.

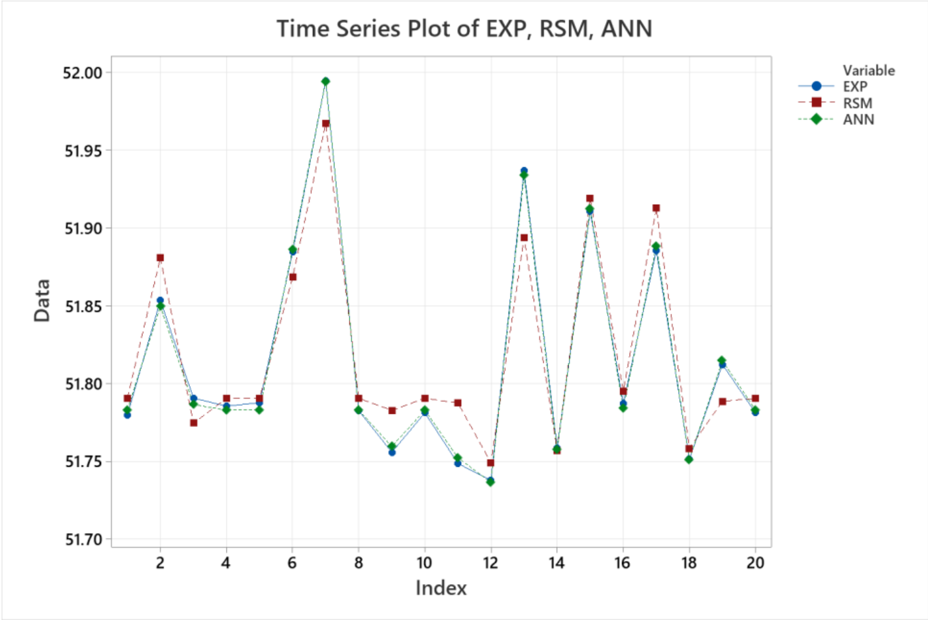

Figure 4: Time series plot showing the prediction accuracy of ANN with comparison to Experimental for Thermal conductivity responses

A time series plot is a graphical representation of data points collected over time, allowing for the visualization of trends, patterns, or seasonal variations in the data. Figure 4. shows the prediction accuracy of the two expert systems used against the experimental for predicting thermal conductivity response. By examining the plot, one can see, that even with the limited data set for training, ANN performance is also in slightly closer approximation with the experimental trend.

The model summary values between the experimental results compared to RSM ($R^2 = 92.38\%$) and ANN (R2 = 99.85%) values. This shows that ANN is a better predictor as compared to RSM.

5 Conclusion

The study has developed and applied predictive expert models to optimize thermal conductivity of TIG mild steel weld comparing the response surface methodology and artificial neural networks. The developed models shows that the ANN is a better predictor compared to the RSM with R^2 value of ANN (R2 = 99.85%) and RSM ($R^2 = 92.38\%$)

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