International Journal of Advances in Engineering and Management (IJAEM)
Volume 3, Issue 9 Sep 2021, pp: 686-699 www.ijaem.net ISSN: 2395-5252

Performance of RSM and ANN in Optimizing and Predicting Heat Input needed to Eliminate Crack Formation in Mild Steel Weldment

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Submitted: 01-09-2021 Revised: 09-09-2021 Accepted: 12-09-2021

ABSTRACT

The aim of the study is to optimize and predict the optimal combination of current, voltage and welding speed needed to maximize heat input in order to eliminate crack formation in mild steel weldment using response surface methodology (RSM) and artificial neural network (ANN).

The key input parameters considered in this work are welding current, welding voltage and welding speed while the response or measured parameter is preheat temperature (PT). Using the range and levels of the independent variables, statistical design of experiment (DOE) using central composite design (CCD) method was employed to randomize the input variables. Hundred (100) pieces of mild steel coupons measuring 60 x 40 x10 were used for the experiments. The experiment was performed 20 times, 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. The tungsten inert gas welding equipment was used to weld the plates after the edges have been bevelled and machined. 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 and thereafter, the response (preheat temperature) was measured and recorded. To optimize the welding process, numerical optimization based on response surface methodology was employed while the prediction of heat input using input variables not captured by the design of experiment was done using artificial neural network.

From the result, it was observed that; for a current of 190.00amp, voltage of 21.95volts and welding speed of 5.00mm/s the maximized heat input was computed to be 1.69076KJ/mm. In addition, the reliability plot of observed heat input versus ANN predicted heat input yielded a coefficient of determination (R^2) value of 0.9940 thus supporting the application of ANN and RSM for the optimization and prediction of heat input

Keyword: Heat input (HI), Design of experiment, Central composite design, Response surface methodology and artificial neural network

I. INTRODUCTION

Filler metal alloys, such as elemental aluminum and chromium, can be lost through the electric arc from volatilization. This loss does not occur with the GTAW process. Because the resulting welds have the same chemical integrity as the original base metal or match the base metals more closely (Watkins and Mizia, 2003). GTAW welds are highly resistant to corrosion and cracking over long time periods, making it the welding procedure of choice for critical operations like sealing spent nuclear fuel canisters before burial (Weman, 2003).

The metallurgical and mechanical properties of a weld depend on the bead geometry which is directly related to welding process parameters (Kimchi et al. 2002). It is pertinent to

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note that; post weld defects such as cracks are generated on the weld line when the weld product is subjected to a bending stress or shocks (Tarun et al. 2014).

The quality and strength of a weld is characterized by the reduction and elimination of weld defects such as cracks, undercut, deformation, porosity in addition to controlling the heat input which is a very strong determining factor needed to produce a reliable weld (Shubhavardhan and Surendran, 2012). One of the fundamental issues facing Engineers in the manufacturing sector is the problem of choosing the most suitable combinations of input process parameters in order to achieve the required optimum weld bead quality (Springer et al. 2011). It is a well-known fact that most welders mainly focused on bead geometry and aesthetics of the weld structure, but the reduction in post weld cracks which determines the overall quality of weldment has not been paid much attention (Navid and Jill, 2016). These problems can be solved with the development of mathematical models through effective and strategic planning, design and execution of experiments (Vikram, 2013)

Numerous supervised machine learning algorithm are available for achieving these task. Popular among them is response surface methodology (RSM), support vector machine (SVM), random forest algorithm and artificial neural network (ANN) (Ghosh et al., 2016). Response surface methodology is an advance statistical technique which involves the incorporation of the second order effects of non-linear relationships (Cerino-Cordova et al., 2011). It is a popular optimization technique employed in most process industries to determine the best possible combination of variables needed to optimize a specific response while artificial neural network is a predictive technique that employs different training algorithm and neurons to learn on a particular task. Numerous literatures on the application of machine learning algorithm were reviewed in the course of this study. Notable among the literatures includes;

II. RESEARCH METHODOLOGY

The key input parameters considered in the study includes; welding current, welding voltage and welding speed while the response or measured variable is heat input (HI). The range and level of the experimental variables used for statistical design of experiment 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	170	190
Welding Voltage (Volt) X_2	21	25
Welding Speed (mm/s) X_2	2	5

Using the range and levels of the independent variables presented in Table 1, statistical design of experiment (DOE) using central composite design (CCD) method was done. The total number of experimental runs that can be generated using the CCD is defined as;

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

Where;
N; is the number of experimental runs based on CCD design
2^n; is the number of factorial points
n_0; is the number of center points
2n; is the number of axial points
n; is the number of variables
Using Equation 1, twenty (20) experimental runs were generated based on the central composite design method and presented in Table 2

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Table 2: Design of experiment (DOE)

Std	Run	Type	Current (A)	Voltage (V)	Welding Speed (mm/s)
15	1	Center	180	23	3.5
16	2	Center	180	23	3.5
17	3	Center	180	23	3.5
18	4	Center	180	23	3.5
19	5	Center	180	23	3.5
20	6	Center	180	23	3.5
9	7	Axial	163.1820717	23	3.5
10	8	Axial	196.8179283	23	3.5
11	9	Axial	180	19.63641434	3.5
12	10	Axial	180	26.36358566	3.5
13	11	Axial	180	23	0.977310754
14	12	Axial	180	23	6.022689246
1	13	Fact	170	21	2
2	14	Fact	190	21	2
3	15	Fact	170	25	2
4	16	Fact	190	25	2
5	17	Fact	170	21	5
6	18	Fact	190	21	5
7	19	Fact	170	25	5
8	20	Fact	190	25	5

Applying the design of experiment presented in Table 2, 100 pieces of mild steel coupons measuring 60 x 40 x10 were used for the experiments. The experiment was performed 20 times, 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.

The tungsten inert gas welding equipment was used to weld the plates after the edges have been bevelled and machined. 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 and thereafter, the responses were measured and recorded. The measured response corresponding to the input variable is presented in Table 3

Table 3: Design of experiment (DOE)

Run	Type	Current (A)	Voltage (V)	Welding Speed (mm/s)	Heat Input (KJ/mm)
1	Center	180	23	3.5	1.667
2	Center	180	23	3.5	1.667
3	Center	180	23	3.5	1.667
4	Center	180	23	3.5	1.667
5	Center	180	23	3.5	1.665
6	Center	180	23	3.5	1.768
7	Axial	163.1820717	23	3.5	1.203
8	Axial	196.8179283	23	3.5	0.944
9	Axial	180	19.63641434	3.5	1.012
10	Axial	180	26.36358566	3.5	0.806
11	Axial	180	23	0.977310754	0.756
12	Axial	180	23	6.022689246	1.412

13	Fact	170	21	2	1.203
14	Fact	190	21	2	2.009
15	Fact	170	25	2	0.755
16	Fact	190	25	2	1.12
17	Fact	170	21	5	0.88
18	Fact	190	21	5	1.173
19	Fact	170	25	5	1.258
20	Fact	190	25	5	1.775

For analysis of design data, Design Expert Statistical Software, Version 7.01, was employed in order to obtain the effects, coefficients, standard deviations of coefficients, and other statistical parameters of the fitted models. The behaviour of the system which was used to evaluate the relationship between the response variables (Y_1, Y_2, Y_3, Y_4 and Y_5) and the independent variables (X_1, X_2, and X_3) was explained using the empirical second-order polynomial equation proposed by Nuran, (2007) and presented as;

$$Y = \beta_0 + \sum_{i=1}^{q} \beta_i x_i + \sum_{i=1}^{q} \beta_{ii} x_i^2 + \sum_{i=1, i<j}^{q-1} \sum_{j=2}^{q} \beta_{ij} x_i x_j + \varepsilon \qquad (2)$$

Where;
X_1, X_2, X_3… X_k = input variables
Y, β_0, β_i, β_{ii}, and β_{ij} = the known parameters and ε = the random error.

To predict the heat input (HI) beyond the scope of experimentation; artificial neural network (ANN) was employed. The step by step methodology of applying neural network is discussed as follows;

2.1 Generation of input data

Input data employed in the training, validation and testing were obtained from series of batch experiments based on the central composite design of experiment under varied welding current, welding voltage and welding speed. A full factorial central composite design of an experiment with 6 center points and 3 replicates resulted in a total of 60 experimental runs was used as the input data. The data were randomly divided into three subsets to represent the training (60%), validation (25%) and testing (15%). The validation data were employed to assess the performance and the generalization potential of the trained network while the testing data were used to test the quality of the network. To avoid the problem of weight variation which can subsequently affect the efficiency of the training process, the input and output data were first normalized between 0.1 and 1.0 using the normalization equation proposed by Sinan et al., 2011 presented in Equation 2.3

$$x_i = \frac{x - x_{\min}}{x_{\max} - x_{\min}} + 0.1 \qquad (2.2)$$

Where;
x_i; is the normalized value of the input and output data
x_{min}; and x_{max} are the minimum and maximum value of the input and output data
x is the input and output data.

2.2 Selection of training algorithm and hidden neurons

Input and output data training resulting in the design of network architecture is of paramount importance in the application of neural network to data modelling and prediction. To obtain the optimal network architecture that possess the most accurate understanding of the input and output data, two factors were considered. First was the selection of the most accurate training algorithm and secondly, the number of hidden neurons. Based on this consideration, different training algorithm and hidden neurons were selected and tested to determine the best training algorithm and accurate number of hidden neurons that will produce the most accurate network architecture. Selectivity was based on (r^2 and MSE).

2.3 Network Training/Performance of MNN

To train the network, 3 runs of 1000 epochs, each were used. In addition, cross validation data representing about 15% of the total input data were introduced to monitor the progress of training and prevent the network from memorizing the input data instead of leaning which was a common problem associated with overtraining. The progress of the training was checked using the mean square error of regression (MSE) graph for training and cross validation

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2.4 Network Testing/Validation

To test the efficiency of the trained network, 25% of the input data was introduced to the network.

III. RESULTS AND DISCUSSION

The target of the optimization model was to maximize the heat input by optimizing the input variables. Using the method of numerical optimization based on response surface methodology, a second order polynomial equation was generated using the quadratic model. To validate the suitability of the quadratic model in analyzing the experimental data, the sequential model sum of squares for heat input (HI) was calculated and presented in Table 4

Table 4: Sequential model sum of square for heat input (HI)

Response 2 HI Transform: None

*** WARNING: The Cubic Model is Aliased! ***

Sequential Model Sum of Squares [Type I]

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Mean vs Total	34.87	1	34.87			
Linear vs Mean	0.68	3	0.23	1.62	0.2244	
2FI vs Linear	0.70	3	0.23	1.99	0.1647	
Quadratic vs 2FI	1.51	3	0.50	289.48	< 0.0001	Suggested
Cubic vs Quadra	3.832E-003	4	9.580E-004	0.42	0.7882	Aliased
Residual	0.014	6	2.268E-003			
Total	37.78	20	1.89			

"Sequential Model Sum of Squares [Type I]": Select the highest order polynomial where the additional terms are significant and the model is not aliased.

The sequential model sum of squares table shows the accumulating improvement in the model fit as terms are added. Based on the calculated sequential model sum of square, the highest order polynomial where the additional terms are significant and the model is not aliased was selected as the best fit. From the results of Tables 4, it was observed that the cubic polynomial was aliased hence cannot be employed to fit the final model. In addition, the quadratic and 2FI model with p-value <0.0001, F-value of 289.48, mean square value of 0.50 and sum of square value of 1.51 were suggesed as the best fit.

To test how well the quadratic model can explain the underlying variation associated with the experimental data, the lack of fit test was estimated for heat input (HI). Model with significant lack of fit cannot be employed for prediction. A result of the computed lack of fit for heat input is presented in Table 5.

Table 5: Lack of fit test for heat input (HI)

Lack of Fit Tests

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Linear	2.23	11	0.20	118.16	< 0.0001	
2FI	1.52	8	0.19	111.07	< 0.0001	
Quadratic	8.867E-003	5	1.773E-003	1.03	0.4856	Suggested
Cubic	5.035E-003	1	5.035E-003	2.94	0.1473	Aliased
Pure Error	8.571E-003	5	1.714E-003			

"Lack of Fit Tests": Want the selected model to have insignificant lack-of-fit.

From the results of Tables 5, it was observed that the quadratic polynomial with p-value of 0.4856, F-value of 1.03, mean square value of 0.001.773 and sum of square value of 0.008867 had a non-significant lack of fit and was suggested for model analysis while the cubic polynomial with p-value of 0.1473, F-value of 2.94, mean square value of 0.005035 and sum of square value of 0.005035 had a significant lack of fit hence aliased to model analysis. The model summary statistics computed for heat input based on the different model sources is presented in Table 6

Table 6: Model summary statistics for heat input (HI)

Model Summary Statistics

Source	Std. Dev.	R-Squared	Adjusted R-Squared	Predicted R-Squared	PRESS	
Linear	0.37	0.2329	0.0890	-0.2162	3.55	
2FI	0.34	0.4746	0.2322	-0.1520	3.36	
Quadratic	0.042	0.9940	0.9886	0.9721	0.081	Suggested
Cubic	0.048	0.9953	0.9852	0.6152	1.12	Aliased

"Model Summary Statistics": Focus on the model maximizing the "Adjusted R-Squared" and the "Predicted R-Squared".

With R-squared value of 0.9940, Adjusted R-squared value of 0.9886, predicted R-squared value of 0.9721 and the predicted error sum of square (PRESS) value of 0.081, the quadratic model was acclaimed the best fit model. Low standard deviation, R-Squared near one and relatively low PRESS is the optimum criteria for defining the best model source. Based on the results of Tables 6, the quadratic polynomial model was suggested

In assessing the strength of the quadratic model towards maximizing heat input (HI), one-way analysis of variance (ANOVA) was generated for and presented in Table 7.

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Table 7: ANOVA table for validating the model significance towards maximizing heat input (HI)

Response 2 HI

ANOVA for Response Surface Quadratic Model

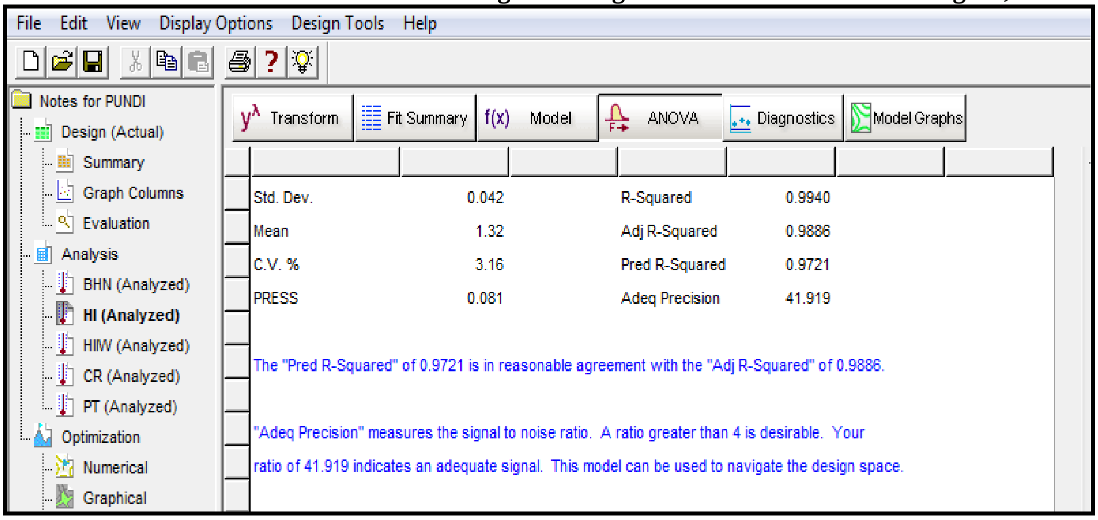
Analysis of variance table [Partial sum of squares - Type III]

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	2.90	9	0.32	184.67	< 0.0001	significant
A-Current	0.19	1	0.19	108.96	< 0.0001	
B-Voltage	0.11	1	0.11	61.25	< 0.0001	
C-Welding speed	0.38	1	0.38	219.14	< 0.0001	
AB	5.151E-003	1	5.151E-003	2.95	0.1164	
AC	0.46	1	0.46	266.18	< 0.0001	
BC	0.24	1	0.24	135.13	< 0.0001	
A^2	0.94	1	0.94	538.95	< 0.0001	
B^2	0.72	1	0.72	414.32	< 0.0001	
C^2	0.037	1	0.037	21.21	0.0010	
Residual	0.017	10	1.744E-003			
Lack of Fit	8.867E-003	5	1.773E-003	1.03	0.4856	not significant
Pure Error	8.571E-003	5	1.714E-003			
Cor Total	2.92	19				

Analysis of variance (ANOVA) was needed to check whether or not the model is significant and also to evaluate the significant contributions of each individual variable, the combined and quadratic effects towards each response. From the result of Table 4.10b, the Model F-value of 184.67 implies the model is significant. There is only a 0.01% chance that a "Model F-Value" this large could occur due to noise. Values of "Prob > F" less than 0.0500 indicate model terms are significant. In this case A, B, C, AC, BC, A^2, B^2, C^2 are significant model terms. Values greater than 0.1000 indicate the model terms are not significant. The "Lack of Fit F-value" of 1.03 implies the Lack of Fit is not significant relative to the pure error. There is a 48.56% chance that a "Lack of Fit F-value" this large could occur due to noise. Non-significant lack of fit is good as it indicates a model that is significant.

To validate the adequacy of the quadratic model based on its ability to maximize heat input, the goodness of fit statistics presented in Tables 8 was employed;

Table 8: GOF statistics for validating model significance towards maximizing HI,



Std. Dev.	0.042	R-Squared	0.9940
Mean	1.32	Adj R-Squared	0.9886
C.V. %	3.16	Pred R-Squared	0.9721
PRESS	0.081	Adeq Precision	41.919

The "Pred R-Squared" of 0.9721 is in reasonable agreement with the "Adj R-Squared" of 0.9886.

"Adeq Precision" measures the signal to noise ratio. A ratio greater than 4 is desirable. Your ratio of 41.919 indicates an adequate signal. This model can be used to navigate the design space.

From the result of Table 8, it was observed that the "Predicted R-Squared" value of 0.9721 is in reasonable agreement with the "Adj R-Squared" value of 0.9886. Adequate precision measures the signal to noise ratio. A ratio greater than 4 is desirable. The computaed ratio of 41.919 as observed in Table 8 indicates an adequate signal. This model can be used to navigate the design space and adequately maximize heat input. Based on the goodness of Fit statistics, the optimized mathematical model which shows the relationship between current, voltage, welding speed and heat input (HI), was generated and presented as follows;

$$HI = -94.50168+0.84575X_1+2.19053X_2-3.93715X_3+0.00126875X_1X_2+0.016058X_1X_3+0.057208X_2X_3-0.00256372X_1^2-0.055977X_2^2-0.022518X_3^2 \text{ ------------------------------------ } (1)$$

Using the optimal equations, the response variable (heat input) was predicted and a reliability plot of observed versus predicted values of heat input was obtained and presented in Figure 2

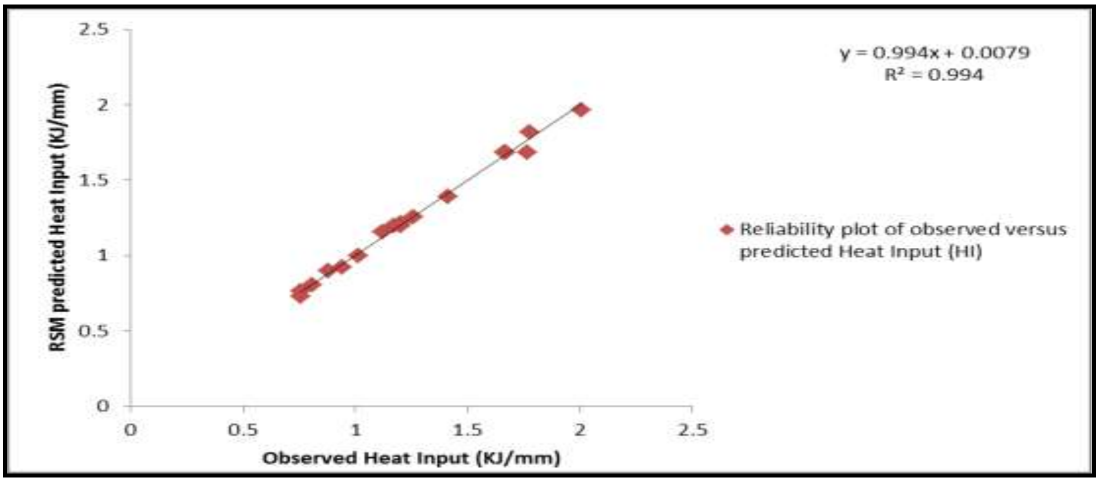


Figure 2: Reliability plot of observed versus predicted heat input

The high coefficient of determination (R^2 = 0.994) as observed in Figure 2 was used to established the suitability of response surface methodology in maximizing heat input. Finally, numerical optimization was performed to ascertain the desirability of the overall model. The optimization objective was to maximize heat input (HI). The relative importance was set at the optimum value of 5.0 and the lower and upper boundary conditions were set at 0.1 and 1.0 for maximization. Lower boundary of 0.1 constrains the optimization tool to maximize the response

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Volume 3, Issue 9 Sep 2021, pp: 686-699 www.ijaem.net ISSN: 2395-5252

variable. The final solution of numerical optimization is presented in Table 9

Table 9: Optimal solutions of numerical optimization

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Notes for PUNDI; Design (Actual); Summary; Graph Columns; Evaluation; Analysis; BHN (Analyzed); HI (Analyzed); HIW (Analyzed); CR (Analyzed); PT (Analyzed); Optimization; Numerical; Graphical; Point Prediction

Solutions Tool: Report; Ramps; Bar Graph

Criteria | Solutions | Graphs

Solutions 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22

Solutions

Number	Current	Voltage	Welding speed	BHN	HI	HIW	CR	PT	Desirability	
1	190.00	21.95	5.00	200.959	1.69076	12.3562	72.0727	150.677	0.964	Selected
2	189.99	21.93	5.00	201.01	1.68603	12.3393	72.1133	150.636	0.964	
3	190.00	21.98	5.00	200.885	1.69761	12.3822	72.0463	150.759	0.964	
4	190.00	22.05	5.00	200.684	1.71503	12.4468	71.9447	150.906	0.964	
5	190.00	21.78	5.00	201.42	1.64389	12.1757	72.3076	150.375	0.964	
6	190.00	21.89	4.99	201.146	1.67386	12.2933	72.2494	150.776	0.964	
7	189.79	22.04	5.00	200.707	1.71709	12.4963	72.5994	150.864	0.964	
8	189.72	22.14	5.00	200.394	1.74348	12.6062	72.704	151.153	0.963	
9	190.00	22.78	5.00	198.042	1.86833	12.9467	70.9786	154.175	0.963	
10	190.00	22.15	4.88	200.645	1.72186	12.4971	72.7981	153.308	0.963	
11	188.89	22.42	5.00	199.435	1.81586	13.0105	74.9173	152.134	0.960	
12	190.00	22.48	4.66	200.005	1.74949	12.6864	74.0488	157.624	0.959	
13	170.00	23.03	2.00	193.099	1.33013	12.7828	70.7123	134.014	0.956	
14	170.00	23.00	2.00	193.104	1.33181	12.8047	70.6133	134.093	0.956	
15	170.00	23.05	2.00	193.097	1.32927	12.7716	70.7665	133.989	0.956	
16	170.00	23.09	2.00	193.09	1.32681	12.7404	70.9074	133.885	0.956	
17	170.00	23.16	2.00	193.065	1.32138	12.6757	71.1856	133.718	0.956	
18	170.05	22.96	2.00	193.155	1.336	12.8437	70.6588	134.269	0.956	
19	170.00	23.10	2.01	193.087	1.32589	12.7277	71.0106	134.083	0.956	
20	170.00	22.77	2.02	193.088	1.34154	12.9622	69.8452	135.224	0.956	
21	170.00	22.60	2.00	193.005	1.34457	13.0446	69.222	135.546	0.956	

From the results of Table 9, it was observed that a current of 190.00amp, voltage of 21.95volts and welding speed of 5.00mm/s will produce a weld material with heat input (HI) of 1.69076KJ/mm. The optimal solution was selected by design expert with a desirability value of 96.40%. To study the effects of combine input variables on heat input(HI), 3D surface plots was generated and presented in Figure 3

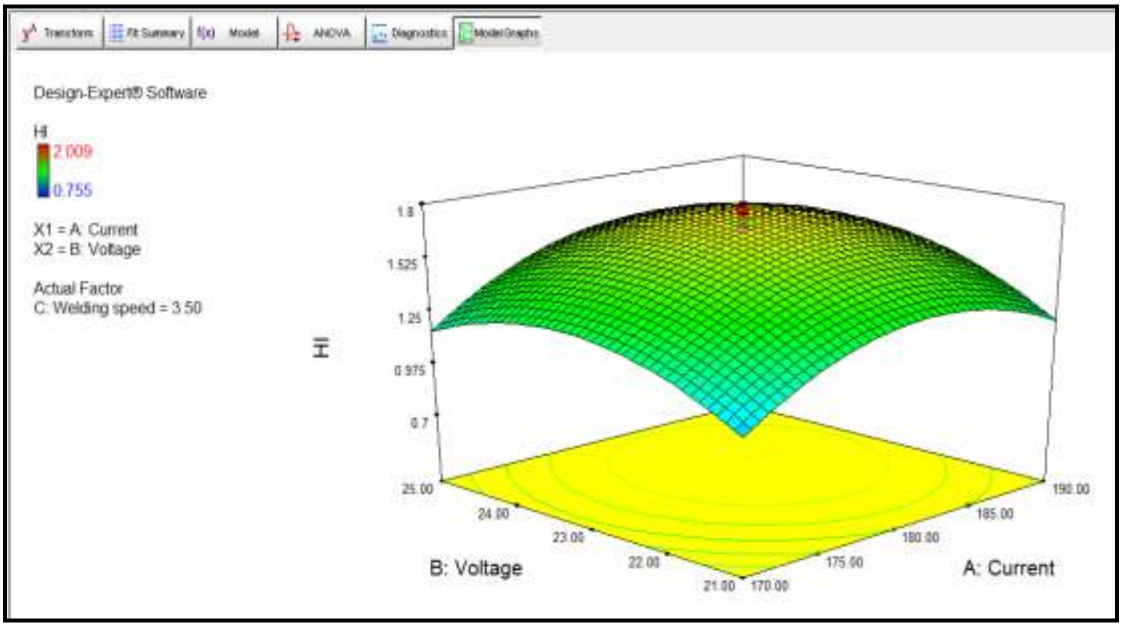

Figure 3: Effect of current and voltage on heat input (HI)

The 3D surface plots presented in Figures 3 shows the relationship between the input variables (current and voltage) and the response variable (heat input). It is a 3 dimensional surface plot which was employed to give a clearer concept of the response surface. Although not as useful as the contour plot for establishing responses values and coordinates, the view can provide a clearer picture of the interactions between the input and the response variables. In Figure 3, the colour of the surface was observed to be darker towards current and voltage. The implication is that an increase in current and voltage will bring aboaut a proportionate increase in heat input (HI).

To apply ANN for the prediction of heat input (HI), two important factors were considered and they include; selection of the most accurate training algorithm and determination of the exact number of hidden neurons. Table 10 shows the different training algorithm that were tested and their performance.

Table 10: Selection of optimum training algorithm for ANN

S/No	Training Algorithm (Learning Rule)	Training MSE	Cross Validation MSE	R-Square (r^2)
1	Gradient information (Step)	0.05489	0.04905	0.74
2	Gradient and weight change (Momentum)	0.05339	0.08097	0.78
3	Gradient and rate of change of gradient (Quick prop)	0.06894	0.04467	0.68
4	Adaptive step sizes for gradient plus momentum (Delta Bar Delta)	0.07602	0.00335	0.82
5	Second order method for gradient (Conjugate gradient)	0.03367	0.06703	0.79
6	Improved second order method for gradient (Levenberg Marquardt)	0.00028*	0.00012*	0.98*

Based on the result of Table 10, improved second order method of gradient also known as Levenberg Marquardt Back Propagation training algorithm (LMBPTA) was selected as the best since it has the highest coefficient of determination (R^2) and the lowest mean square error of regression (MSE). To determine the exact numbers of hidden neuron, different numbers of hidden neurons were tested to create a trained network using Levenberg Marquardt Back Propagation training algorithm. The number of hidden neuron corresponding to the lowest MSE and the highest R^2 as presented in Table 11 was selected to design the network architecture.

Table 11: Selection of optimum number of hidden neurons for ANN

S/No	**Number of Hidden Neurons**	**Training MSE**	**Cross Validation MSE**	**R-Square (R^2)**
1	2	0.0345	0.00453	0.75
2	3	0.0269	0.03367	0.67
3	5	0.0306	0.04051	0.88
4	8	0.0178	0.02241	0.71
5	10	0.0009	0.00033	0.97

Based on the results of Tables 10 and 11, Levenberg Marquardt Back Propagation training algorithm having 10 hidden neurons in the input layer and output layer was used to train a network of 3 input processing elements, namely; current, voltage and welding speed and one response variable (heat input).

The network training diagram generated for the prediction of amount of diffusible hydrogen (H_{IIW}) using back propagation neural network is presented in Figure 4.

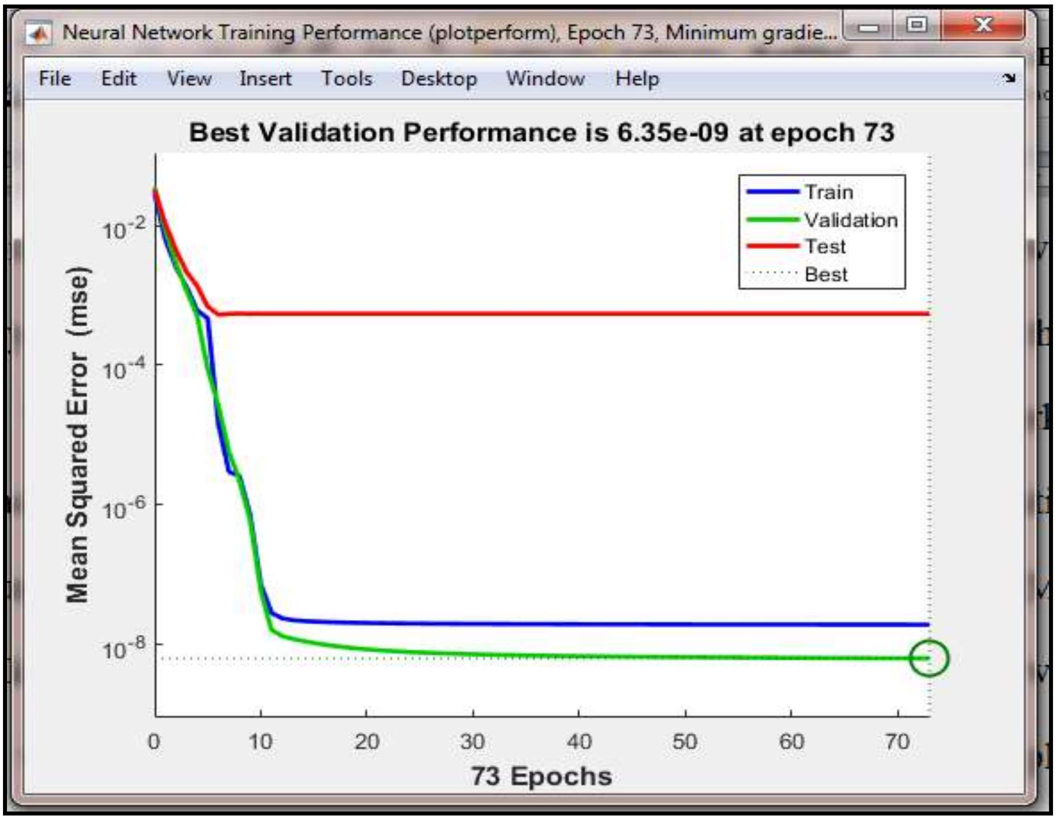

Figure 4: Performance curve of trained network for predicting heat input

From the performance plot of Figure 4., no evidence of over fitting was observed. In addition similar trend was observed in the behaviour of the training, validation and testing curve which is expected since the raw data were normalized before use. Lower mean square error is a fundamental criteria used to determine the training accuracy of a network. An error value of

International Journal of Advances in Engineering and Management (IJAEM)
Volume 3, Issue 9 Sep 2021, pp: 686-699 www.ijaem.net ISSN: 2395-5252

6.3500e-09 at epoch 73 is an evidence of a network with strong capacity to predict heat input.

The regression plot which shows the correlation between the input variables (current, voltage and welding speed) and the target variable (heat input) coupled with the progress of training, validation and testing is presented in Figure 5

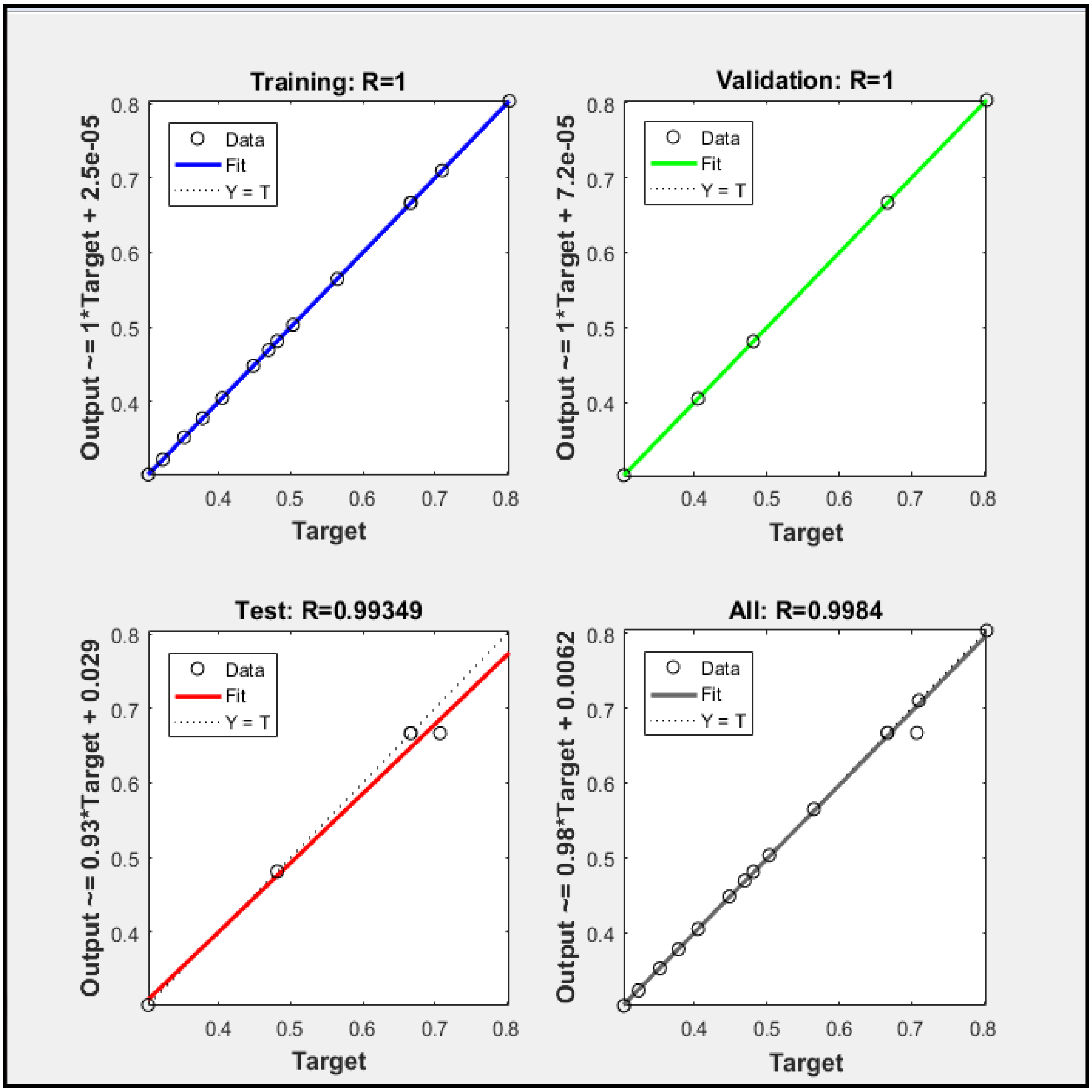

Figure 5: Regression plot showing the progress of training, validation and testing for maximizing heat input (HI)

International Journal of Advances in Engineering and Management (IJAEM)
Volume 3, Issue 9 Sep 2021, pp: 686-699 www.ijaem.net ISSN: 2395-5252

Based on the computed values of the correlation coefficient (R) as observed in Figure 5, it was concluded that the network has been adequately trained and can be employed to predict heat input of the welded material. To test the reliability of the trained network, the network was thereafter employed to predict its own values of heat input (HI) using the same set of input parameters (current, voltage and welding speed) generated from the central composite design. Based on the observed and the predicted value of heat input, a regression plot of outputs was thereafter generated and presented in Figure 6

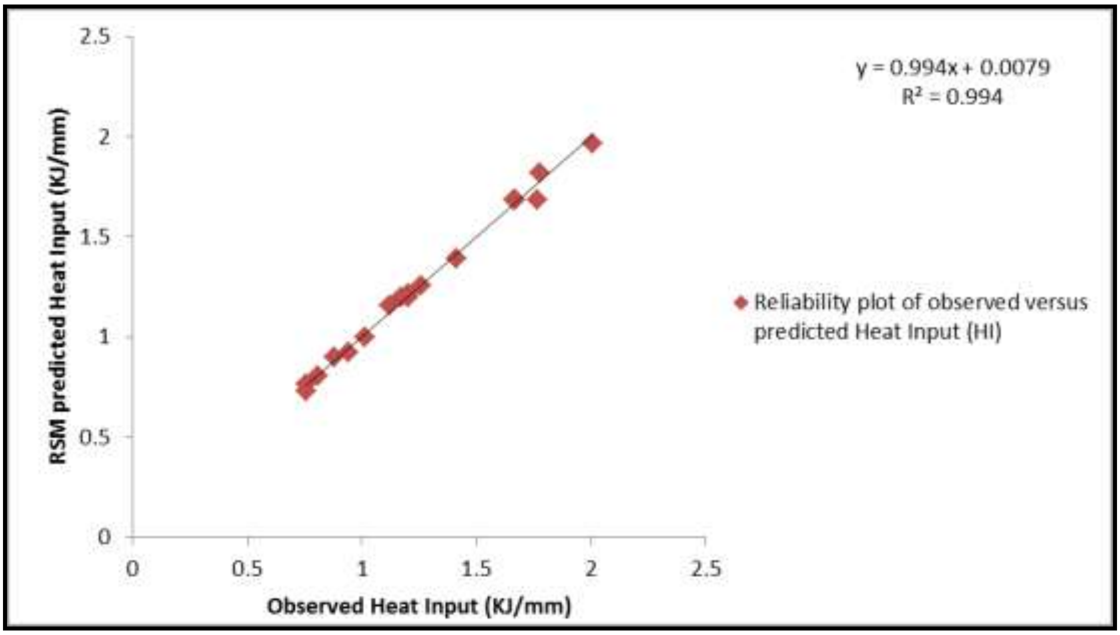

Figure 6: Regression plot of observed versus predicted heat input

Coefficient of determination (r^2) values of 0.9940 as observed in Figure 6 was employed to draw a conclusion that the the trained network can be used to predict heat input (HI) beyond the scope of experimentation.

IV. CONCLUSION

In this study, optimization and prediction of heat input using response surface methodoloy (RSM) and artificial neural network have been implemented successfully. The study will not only provide additional information to the already existing literatures and optimization and prediction of welding process, it will also form the bases for future research in related field of study. It is interesting to note that determining the optimum conditions for any welding process is completely beyond the scope of the traditional methods of experimentation hence, the need to optimize all the controlling variables collectively using statistical design of experiment (DOE) which allows a large number of factors to be screened simultaneously. In this study, response surface methodology (RSM) has been successfully applied to optimize selected welding variables, namely; current, voltage and welding speed in order to maximize the heat input and eliminate crack formation. The outcome of the study revealed that; for a current of 190.00amp, voltage of 21.95volts and welding speed of 5.00mm/s, the maximized heat input was computed to be 1.69076KJ/mm. In addition, the reliability plot of observed heat input versus ANN predicted heat input yielded a coefficient of determination (R^2) value of 0.9940 thus supporting the application of ANN and RSM for the optimization and prediction of heat input

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