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Prediction of tungsten inert gas welding process parameter using design of experiment and fuzzy logic

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ABSTRACT

The focus of this study is to predict tungsten inert gas (TIG) welding process parameter such as heat input for stabilizing heat and removing post weld crack formation in mild steel weldment. The main input parameters examined are the welding current, voltage and speed whereas the measured (response) parameter is heat input. Statistical design of experiment was done by means of central composite design method using the range and levels of independent variables. The experiment was carried out 20 times (with 5 specimens per run) using 60 mm x 40 mm x 10 mm mild steel coupons. The plate samples were cut longitudinally with a Single-V joint preparation, with the edges beveled. The welding process utilizes 100% pure argon as a protecting gas to shield the weld specimen from external interaction. The interaction between the input and response variables was analyzed using a fuzzy logic system. The result showed that for a welding current, voltage and speed of 190 A, 21 V, and 2.0 mm/s respectively, the predicted heat input was 0.912 kJ/mm whereas for input parameters of (170 A, 25 V, and 2.0 mm/s) and (180 A, 23 V, 0.98 mm/s), the predicted heat inputs were 1.07 kJ/mm and 1.380 kJ/mm, respectively.

1. Introduction

Although, welding process parameters are often chosen on the basis of expert judgment or from a welding handbook, this choice does not guaranty the best or near best weld bead profile for that particular welding environment [1]. The quality of a weld depends on several factors including the mechanical properties and reduced post weld defects of the weld, which depends on the chemical composition and metallurgical characteristics of the weld metal [2]. The metallurgical and mechanical properties of a weld depend on the bead geometry, which is directly related to welding process parameters [3]. It is pertinent to note that post weld defects such as cracks are generated on the weld line when the weld product is subjected to either a bending stress or shocks [4].

However, metallurgical variations linked with fusion welding processes such as solidification cracking, segregation, presence of porosities and grain growth in the heat affected area frequently result in poor mechanical properties of the weldment [5]. Tungsten inert gas (TIG) welding is a process of welding, which involves an arc between non-consumable tungsten electrode and the work piece. The arc, electrode and molten pool are all shielded

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from contamination by an inert gas, normally argon. Hydrogen is likely to be attracted to areas of high triaxial tensile stress where the metal structure is dilated. As a consequence, it is drawn to such areas ahead of cracks or notches that are under stress [6]. The dissolved hydrogen can possibly help in the fracture of the metal, either by making cleavage easier or assisting in the progress of intense local plastic deformation [7]. Crack growth rates are usually fairly rapid but in extreme cases can be up to 1 mm/s [8].

Heat input is a comparative measure of the energy transferred per unit length of weld and is one of the essential parameters, which is of great concern during welding procedure specification (WPS) preparations [9]. Due to its ability to create improved microstructure weldment with less tension and distortion, low heat input is the most widely used welding parameter in industries. Low heat input, on the other hand, limits penetration and can weaken the weldment joint. Consequently, high heat input has recently become common in the shipping industry where it allows for deeper penetration joint [10].

2. Methodology

The main input parameters examined in this study are the welding current, voltage and speed whereas the response parameter is heat input (HI). Statistical design of experiment was done by means of central composite design (CCD) method using the range and levels of independent variables, shown in Table 1 to generate the randomized designed needed for data collection. The number of experimental runs, which can be generated by the CCD was estimated using equation (1).

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

Where, N is the number of experimental runs based on CCD design, 2^n is the number of factorial points, n_o is the number of center points, $2n$ is the number of axial points, and n is the number of variables.

Twenty (20) experimental runs were generated using equation (1). Each experiment was carried out with 5 specimens mild steel coupons each with the dimension (60 mm x 40 mm x 10 mm). The plate samples were cut longitudinally with a Single-V joint preparation. The edges were beveled, grinded and surfaces polished with emery paper and the joints welded and thereafter, the responses were measured and recorded.

The TIG welding equipment used is presented in Fig. 1. The welding process utilizes 100 % pure argon as a protecting gas to shield the weld specimen from external interaction. The interaction between the input and response variables was analyzed using a fuzzy logic system. The measured response corresponding to the input variable of the experimental runs generated based on the CCD method is shown in Table 2.

Fig. 1 A TIG welding equipment.

2.1. Fuzzy Logic Modeling

The underlying equations of fuzzy logic adopted from [11] is presented as equation (2); where $a_{ij} = (l_{ij}, m_{ij}, u_{ij}) = a_{ij} = (1/u_{ji},\ 1/m_{ji},\ 1/l_{ji})$ for $i, j = 1, \ldots, n$ and $i \neq j$. To compute a priority vector shown in equation (2), equations (3) – (7) were utilized [12]. First, a fuzzy comparison operation was used to sum up each row of the fuzzy comparison matrix using equation (3). Then, the row sums were normalized using equation (4). The degree of possibility of $S_i \leq S_j$ was computed with the aid of equation (5); where, the possibility degree is $S_i = (l_i, m_i, u_i)$ and $S_j = (l_j, m_j, u_j)$. Subsequently, the degree of possibility of S_i over all the other (n – 1) fuzzy member was computed by equation (6). Finally, the priority vector $W = (w_1, \ldots, w_n)^T$ of the fuzzy comparison matrix A was defined as equation (7).

Table 1 Range and levels of independent variables.

Independent Variables	Lower Range (-1)	Upper Range (+1)
Welding current (A), X_1	170	190
Welding voltage (V), X_2	21	25
Welding speed (mm/s), X_3	2	5

Table 2 Design of experiment.

Std	Run	Type	Current (A)	Voltage (V)	Speed (mm/s)	Heat input (kJ/mm)
15	1	Center	180	23	3.5	1.667
16	2	Center	180	23	3.5	1.667
17	3	Center	180	23	3.5	1.665
18	4	Center	180	23	3.5	1.667
19	5	Center	180	23	3.5	1.667
20	6	Center	180	23	3.5	1.768
9	7	Axial	163.1820717	23	3.5	0.755
10	8	Axial	196.8179283	23	3.5	1.12
11	9	Axial	180	19.63641434	3.5	0.88
12	10	Axial	180	26.36358566	3.5	1.173
13	11	Axial	180	23	0.977310754	1.258
14	12	Axial	180	23	6.022689246	1.775
1	13	Fact	170	21	2	1.203
2	14	Fact	190	21	2	0.944
3	15	Fact	170	25	2	1.012
4	16	Fact	190	25	2	0.806
5	17	Fact	170	21	5	0.756
6	18	Fact	190	21	5	1.412
7	19	Fact	170	25	5	1.203
8	20	Fact	190	25	5	2.009

$$A = (a_{ij})_{nxn} = \begin{bmatrix} (1,1,1) & (l_{12}, m_{12}, u_{12}) & \cdots\cdots\cdots & (l_{1n}, m_{1n}, u_{1n}) \\ (l_{21}, m_{21}, u_{12}) & (1,1,1) & \cdots\cdots\cdots & (l_{2n}, m_{2n}, u_{2n}) \\ \vdots & \vdots & \vdots & \vdots \\ (l_{n1}, m_{n1}, u_{n1}) & l_{n2}, m_{n2}, u_{n2} & \cdots\cdots\cdots & (1,1,1) \end{bmatrix} \quad (2)$$

$$RS_i = \sum_{j=1}^{n} a_{ij} = \left(\sum_{j=1}^{n} l_{ij}, \sum_{j=1}^{n} m_{ij}, \sum_{j=1}^{n} u_{ij}\right), \qquad i = 1, \dots, n \quad (3)$$

$$S_i = \frac{RS_i}{\sum_{j=1}^{n} RS_j} = \left(\frac{\sum_{j=1}^{n} l_{ij}}{\sum_{j=1}^{n} l_{ij} + \sum_{k=1,k\neq i}^{n} + \sum_{j=1}^{n} u_{kj}}, \frac{\sum_{j=1}^{n} m_{ij}}{\sum_{k=1}^{n}\sum_{j=1}^{n} m_{kj}}, \frac{\sum_{j=1}^{n} u_{ij}}{\sum_{j=1}^{n} ui_j + \sum_{k=1,k\neq i}^{n} 1 \sum_{j=1}^{n} l_{kj}}\right), \quad i = 1, \dots, n \quad (4)$$

$$V(Si \geq Sj) = \begin{cases} 1 & mi \geq mj \quad 1 \\ \frac{ui - lj}{(ui - mi)(mj - lj)}, & lj \leq uj \quad 1 \\ 0 & others \quad 1 \end{cases} \qquad i, j = 1, \dots, n; j \neq i \quad (5)$$

$$V(S_i \geq S_j j = 1 \ldots\ldots, n; j \neq i) = V(S_i \geq S_j), \qquad i = 1, \ldots, n \quad (6)$$

$$wi = \frac{V(S_i \geq S_j j = 1, \ldots, n; j \neq i)}{\sum_{k=1}^{n} V(S_k \geq S_j j = 1, \ldots, n; j \neq k)}, \qquad i = 1, \ldots, n \quad (7)$$

The fundamental steps in the usage of fuzzy logic [12] for predicting the TIG process parameters required to eliminate post weld crack formation and stabilize heat input in mild steel weldment are described as follow:

Definition of input and output variables. First, sets of input variables, namely, current, voltage and welding speed were selected. Then, the range and values of the selected input variables were defined based on expert knowledge. For a fuzzy logic model aimed at predicting the heat input (HI), it is assumed that the weld factors namely, current (c), voltage (v) and welding speed (ws) be termed the linguistic variables. To qualify the current, voltage and welding speed, terms such as (very low, low, moderate, high and very high) were used. Hence, the linguistic values of the current, voltage and welding speed as well as the output variable, HI are given as:

$$\text{C (c)} = \{\text{very low, low, moderate, high and very high}\}$$

$$\text{V (v)} = \{\text{very low, low, moderate, high and very high}\}$$

$$\text{WS (ws)} = \{\text{very low, low, moderate, high and very high}\}$$

$$\text{HI} = \{\text{very low, low, moderate, high and very high}\}$$

The terms in bracket represent the set of decompositions for the linguistic variable current, voltage, welding speed and heat input. Each member of this decomposition is called a linguistic term. For this problem, the linguistic variables and their range of values include: current, (from 170 to 190 A); voltage (from 21 to 25 V); welding speed (from 2 to 5 mm/s); and HI (from 0.755 to 2.009 kJ/min). The fuzzy logic tool box, which defines the input and output variables is shown in Fig. 2.

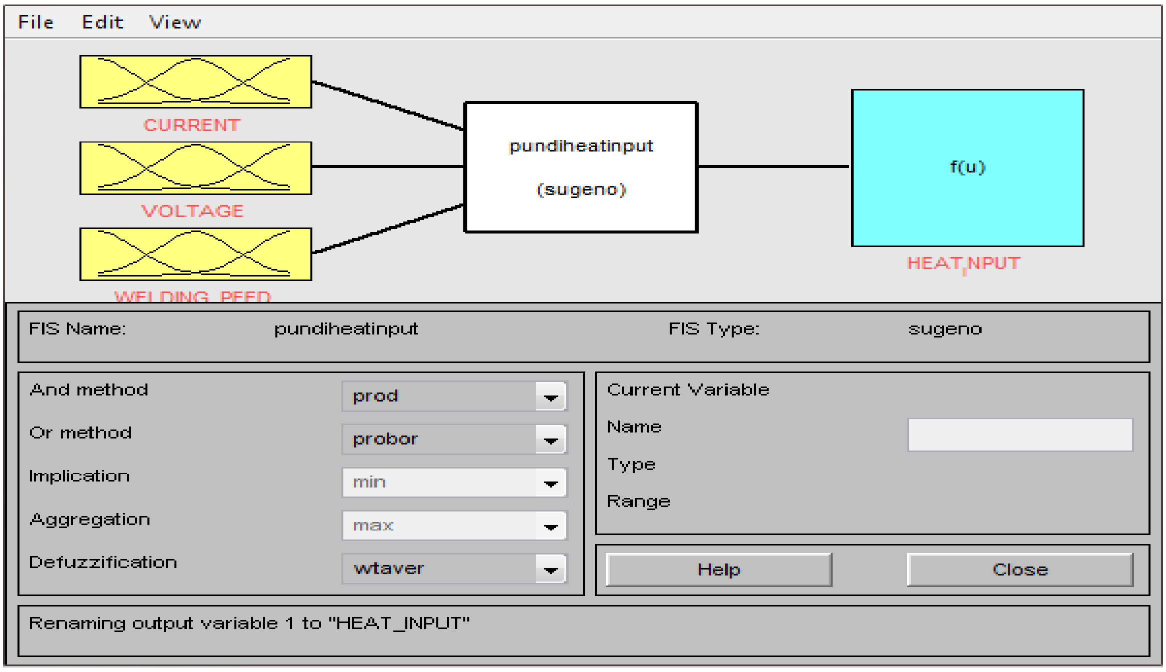

Fig. 2 Fuzzy logic tool box containing the input and output variables.

Conversion of crisp variables to fuzzy sets. The adaptive neuro-fuzzy inference system (ANFIS) was used to convert the crisp variables into fuzzy sets. The main steps are: the three vital input variables coded as a, b, c; members of the variables also defined; and MATLAB codes written to connects the input and output variables. A grid partition technique was used to construct the fuzzy inference systems (FIS) due to its proven capacity to generate the desired fuzzy sets from large input variables [12].

Definition of membership function. For each input and output variables, five membership functions (very low, low, moderately high, high and very high) were chosen as shown in Table 3. The triangular membership function (trimf) was utilized for the input variables whereas constant membership function (conmf) was applied for the output variable.

Creation of fuzzy rules and simulation. A fuzzy rule is a simple IF-THEN rule with a condition and a conclusion [13]. On the basis of the summary results presented in Table 2, eight (8) decisive rules were formed to simulate the fuzzy-logic-based HI as follows:

1. If current is low, voltage is moderate and welding speed is moderate, then heat input is (<< very low heat input)
2. If current is high, voltage is low and welding speed is low, then heat input is (< very low heat input)
3. If current is low, voltage is high and welding speed is low, then heat input is (very low heat input)
4. If current is moderate, voltage is moderate and welding speed is low, then heat input is (low heat input)
5. If current is high, voltage is low and welding speed is high, then heat input is (moderate heat input)
6. If current is moderate, voltage is moderate and welding speed is moderate, then heat input is (high heat input)
7. If current is moderate, voltage is moderate and welding speed is very high, then heat input is (> very high heat input)
8. If current is high, voltage is high and welding speed is high, then heat input is (>> very high heat input).

Series of simulation were performed, based on these rules, to assess the ability of fuzzy logic in estimating the heat input of the welding material.

Table 3 Summary of membership function and membership sets.

Membership function	Membership set			
	Current	Voltage	Welding speed	HI
Very Low	[154.8 163.2 171.6]	[17.96 19.64 21.32]	[-0.28 0.980 2.240]	[1.069]
Low	[163.2 171.6 180.0]	[19.64 21.32 23.00]	[0.980 2.240 3.500]	[1.225]
Moderate	[171.6 180.0 188.4]	[21.32 23.00 24.68]	[2.240 3.500 4.760]	[1.382]
High	[180.0 188.4 196.8]	[23.00 24.68 26.36]	[3.500 4.760 6.020]	[1.539]
Very High	[188.4 196.8 205.2]	[24.68 26.36 28.04]	[4.760 6.020 7.280]	[1.696]

3. Results and Discussion

3.1. Fuzzy Sets Generated from Crisp Variables

Fig. 3 displays the ANFIS interface containing the fuzzy sets for the three input variables, namely, current, voltage and welding speed including the single output variable, which is the HI. The ease and flexibility of the usage of triangular membership function together with its capability to identify a wider range of decomposed sets of linguistic variables justify its selection. Also, the constant membership function was utilized due to its simplicity. Fig. 4 presents the defined membership functions for the input and output variables.

3.2. Inputs and Output Membership Function

Fig. 5 shows the membership function for current. The current range is stated as [163.2 196.8]. The membership set, which defines low current is [163.2 171.6 180]. The membership function type is the triangular membership function.

Fig. 6 displays the membership function for voltage. The voltage range is stated as [19.64 26.36] whereas the membership set, which defines low voltage is [19.64 21.32 23]. The membership function type is the triangular membership function. Fig. 7 presents the membership function for welding speed (WS). The WS range is stated as [0.98 6.02] while the membership set defining low welding speed is [0.98 2.24 3.50]. The membership function type is triangular. Fig. 8 presents the membership function for heat input. The range for heat input is [0.755 2.009] while the membership set, which defines (>> very high heat input is [2.009]. The membership function type is the constant membership function. Using the information on Fig. 7, the following additional membership sets were generated and presented in Table 4.

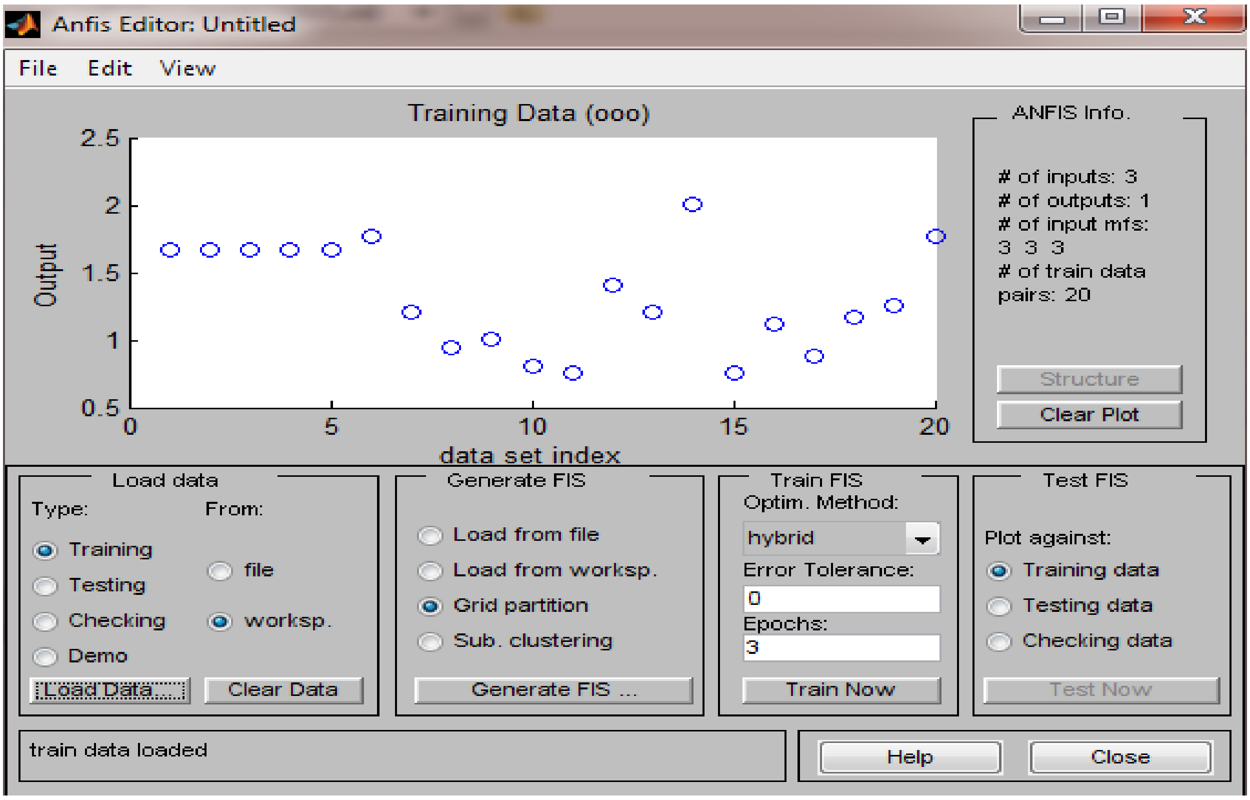

Fig. 3 ANFIS edit tool box showing the crisp data.

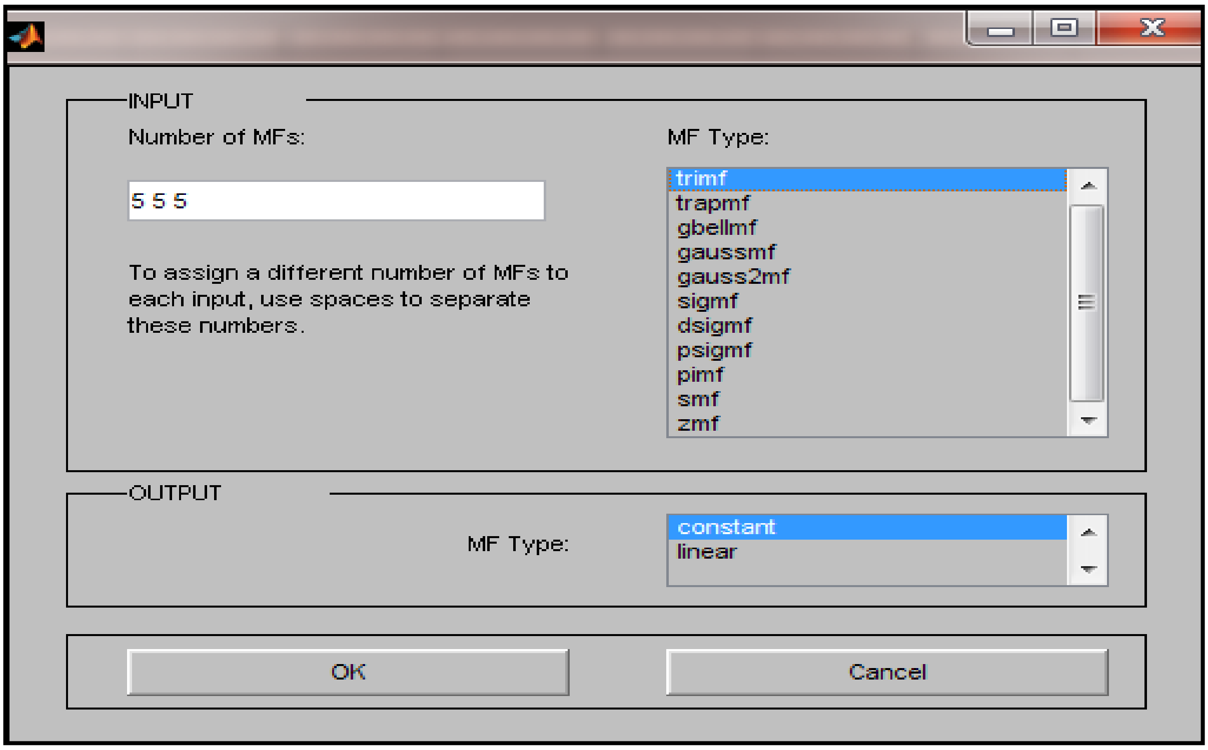

Fig. 4 Input and output membership functions.

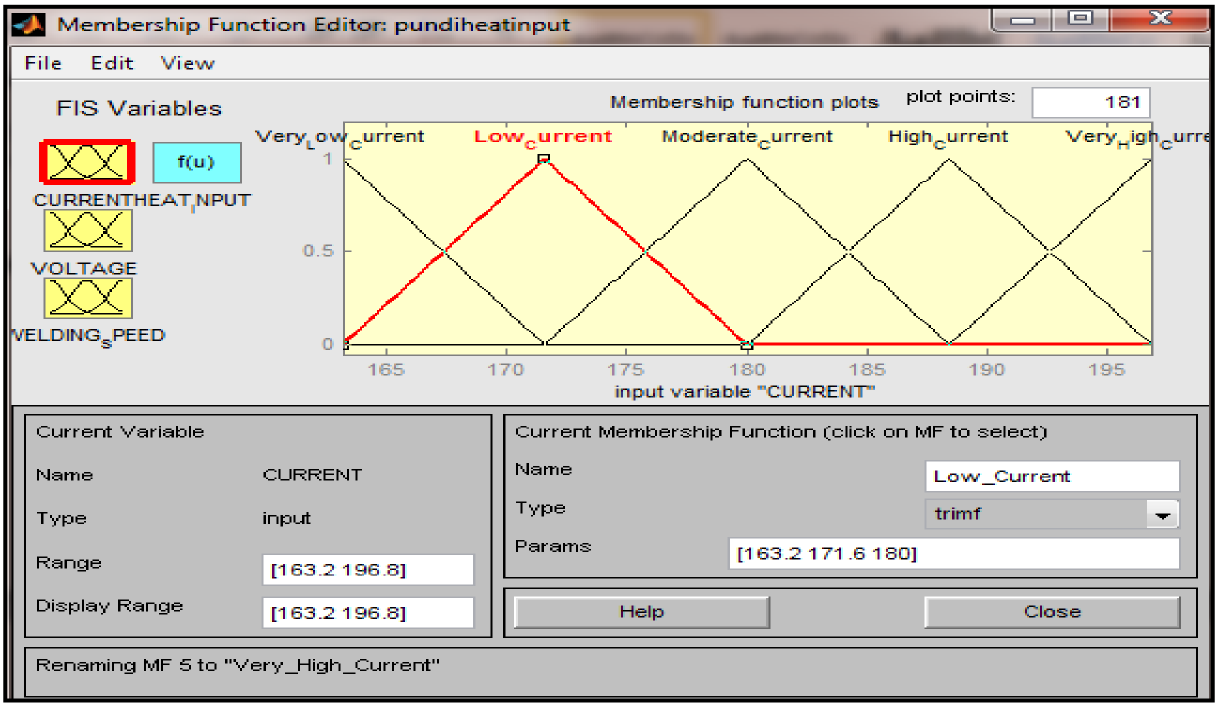

Fig. 5 Membership function for current (low current).

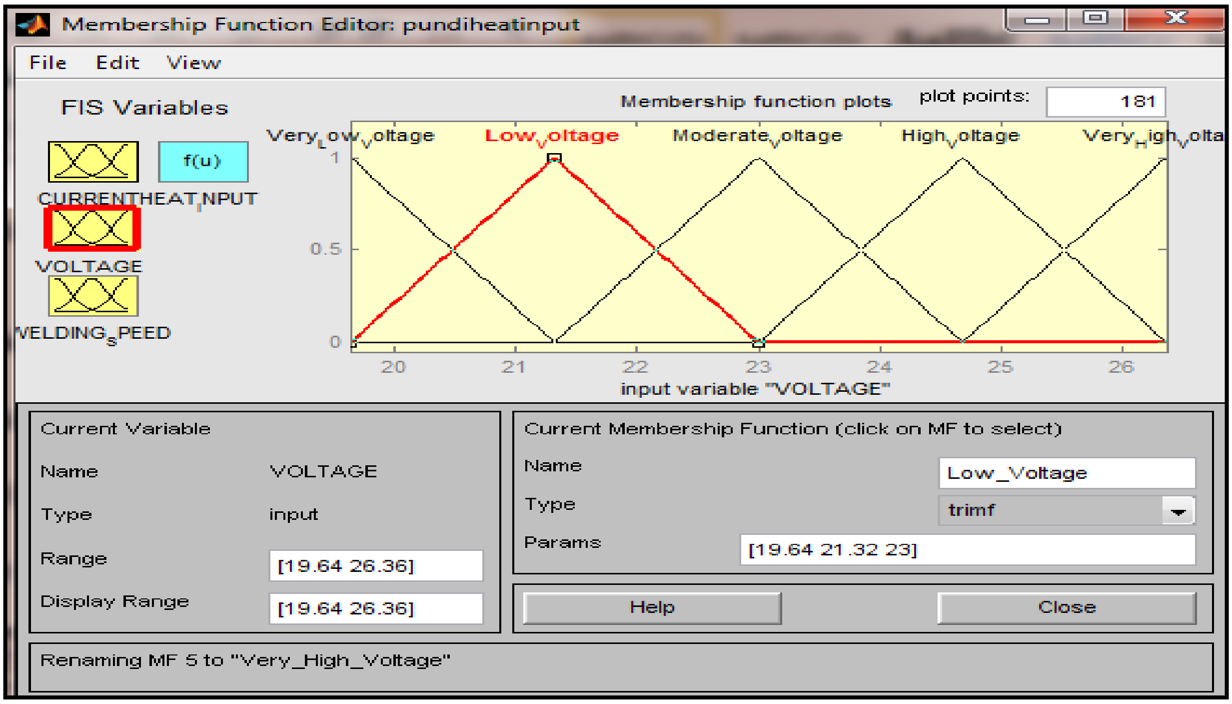

Fig. 6 Membership function for voltage (low voltage).

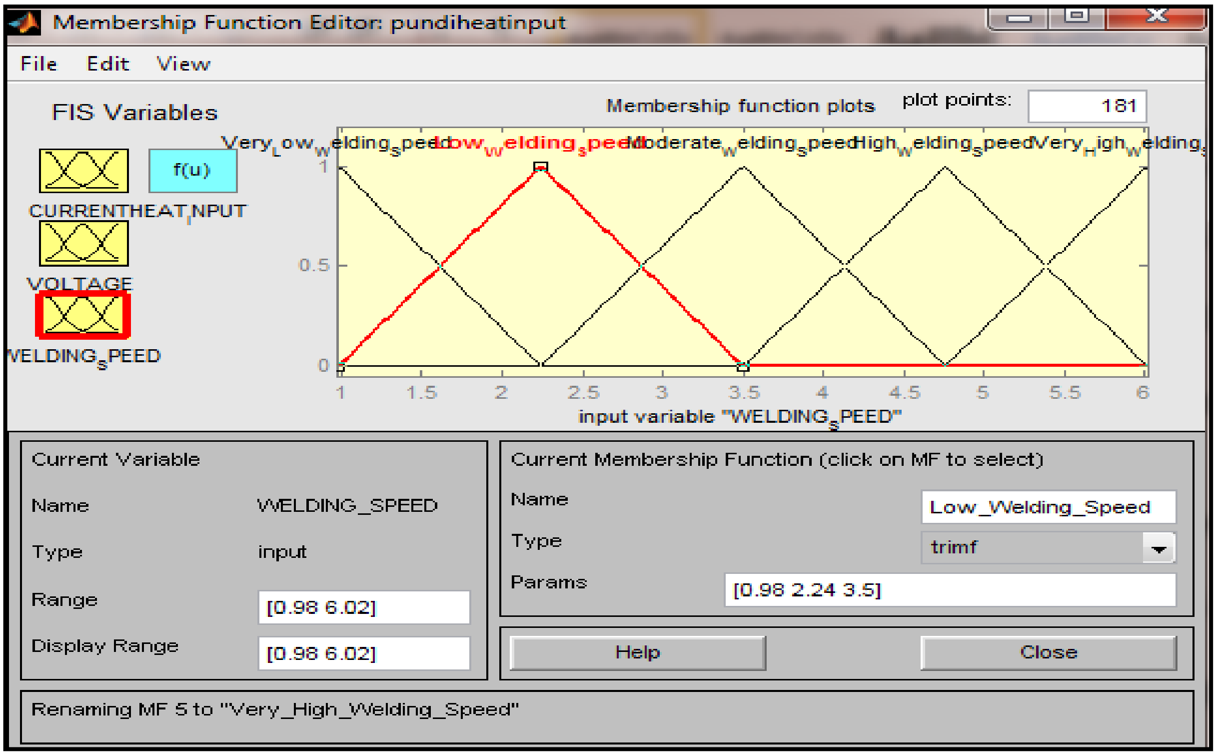

Fig. 7 Membership function for welding speed (low welding speed).

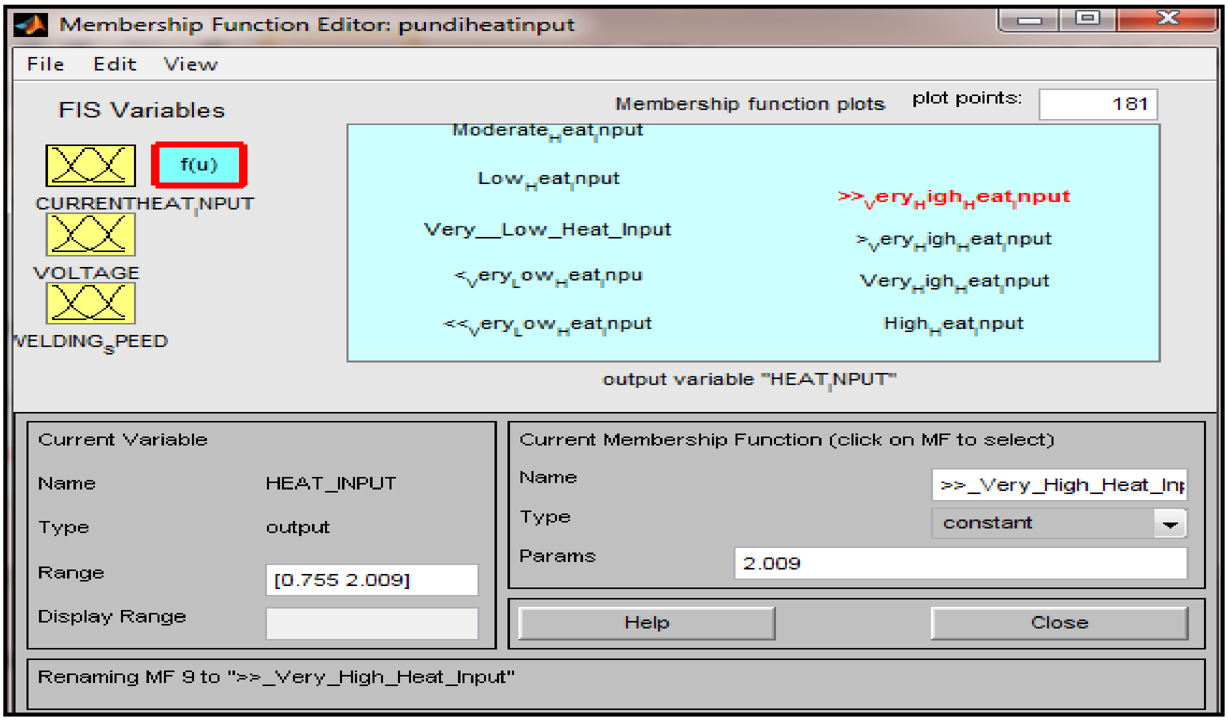

Fig. 8 Membership function for heat input.

Table 4 Membership sets generated for HI.

S/No	Index	Description	Fuzzy Membership Set Value
1	<< Very Low	Least Heat Input	0.7550
2	< Very Low	Lowest Heat Input	0.9118
3	Very Low	Lower Heat Input	1.0690
4	Low	Low Heat Input	1.2250
5	Moderate	Moderate Heat Input	1.3820
6	High	High Heat Input	1.5390
7	Very High	Higher Heat Input	1.6960
8	> Very High	Highest Heat Input	1.8520
9	>> Very High	Upmost Heat Input	2.0090

3.3. Predicting Heat Input using Fuzzy Logic

The results of the fuzzy prediction of heat input (HI) using the eight critical rules (presented in section 2.1), under varied conditions of welding current, voltage and speed are presented in Figs. 9 – 12. From Fig. 9, it was noticed that for a current of 190 A, voltage of 21 V, and welding speed of 2.0 mm/s, the predicted HI was 0.912 kJ/mm. Also, it was observed (Fig. 10) that for a 170 A, 25 V, and 2.0 mm/s, the predicted heat input was 1.07 kJ/mm. Similarly; for a current of 180 A, voltage of 23 V, and speed of 0.98 mm/s, the predicted heat input of 1.380 kJ/mm was observed (Fig. 11) while for a 180 A, 23 V, and 3.5 mm/s, the predicted heat input was 1.540 kJ/mm as observed (Fig. 12). From the other simulations, it was seen that with 180 A, 23 V, and 6.02 mm/s, the predicted HI was 1.850kJ/mm while for 190 A, 25 V, and 5.0 mm/s, the predicted HI was 2.010 kJ/mm.

To assess the overall performance of fuzzy logic in predicting the HI, a regression plot of output between the observed heat input and fuzzy logic predicted HI was obtained and presented in Fig. 13. With a coefficient of determination, R^2 value of 0.9502, it was concluded that Fuzzy logic systems can be employed for the prediction of heat input and other weld parameters.

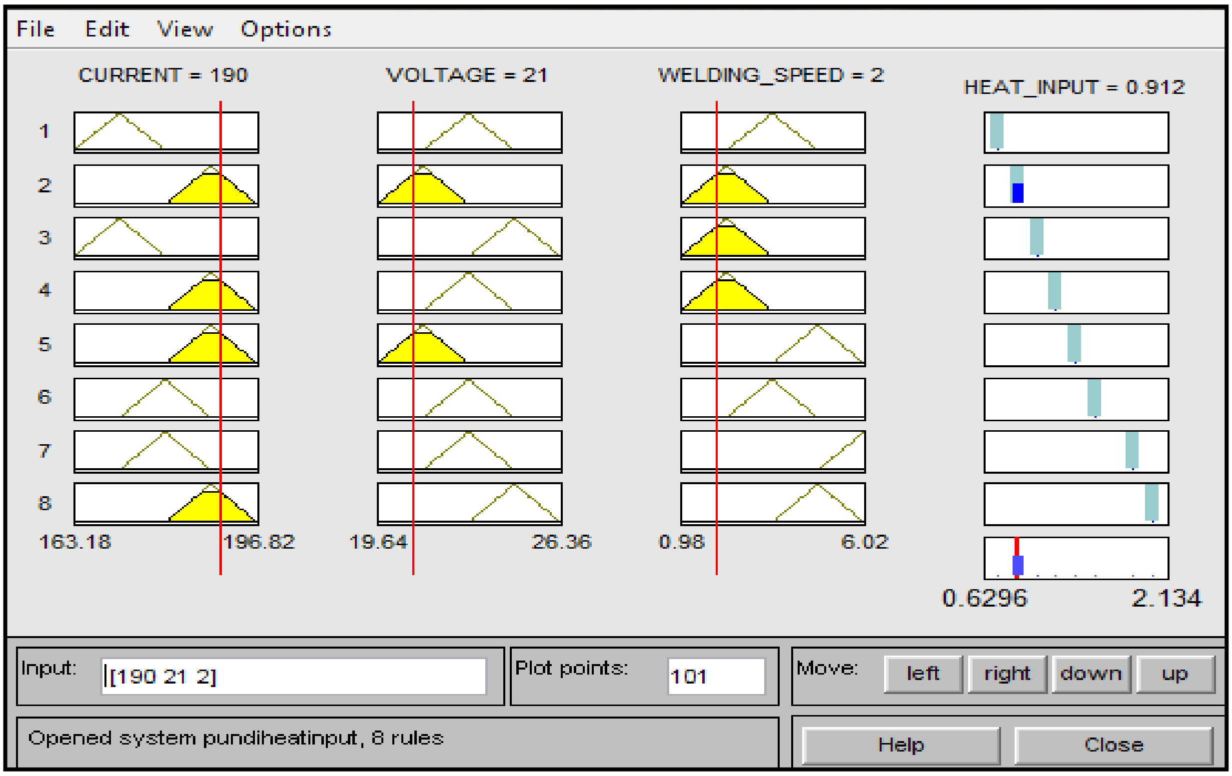

Fig. 9 Prediction of HI using fuzzy logic under welding current, voltage and speed of 190 A, 21 V and 2 mm/s respectively.

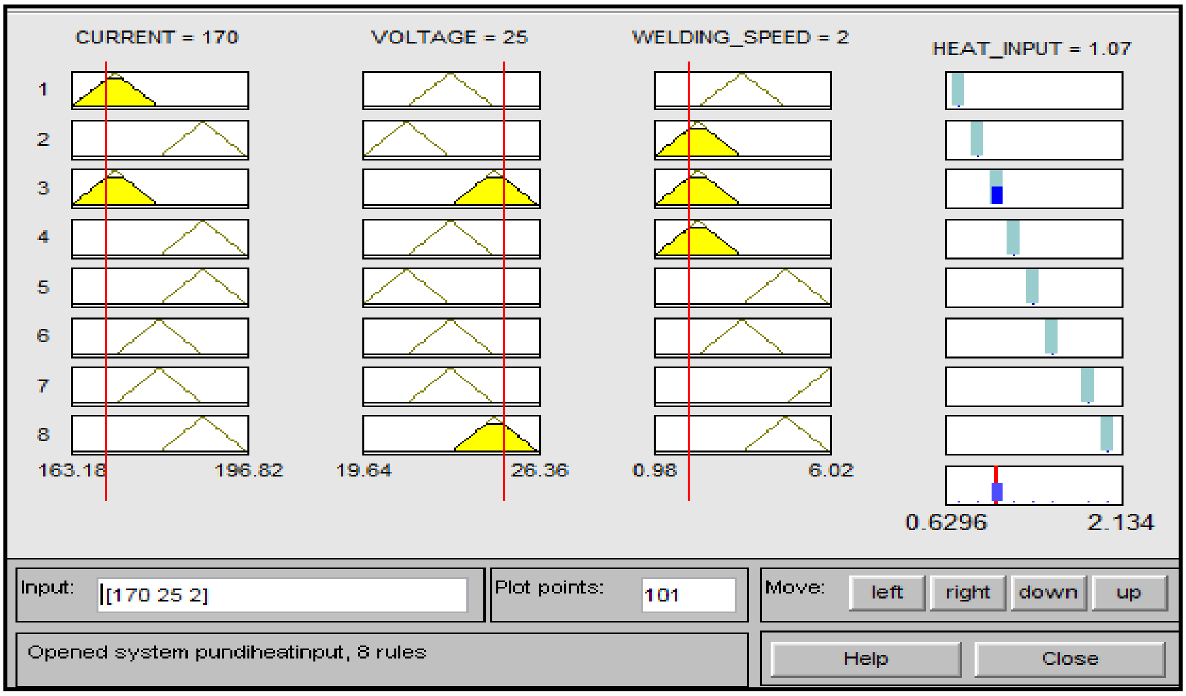

Fig. 10 Prediction of HI using fuzzy logic under welding current, voltage and speed of 170 A, 25 V and 2 mm/s respectively.

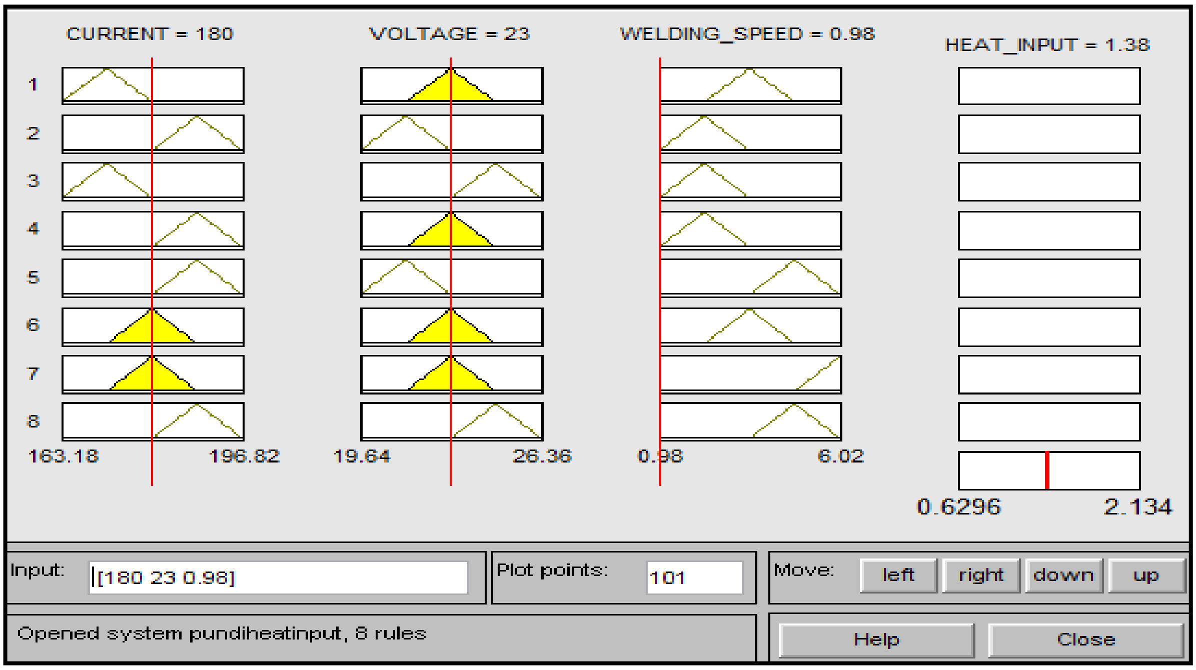

Fig. 11 Prediction of HI using fuzzy logic under welding current, voltage and speed of 180 A, 23 V and 0.98 mm/s respectively.

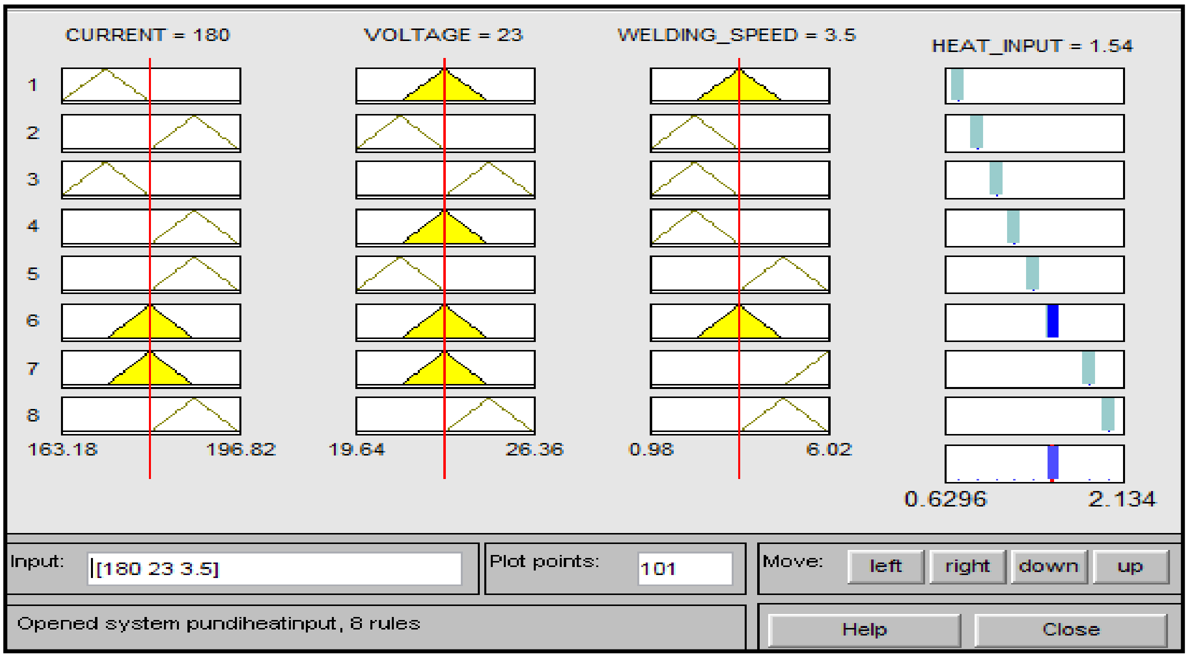

Fig. 12 Prediction of HI using fuzzy logic under welding current, voltage and speed of 180 A, 23 V and 3.5 mm/s respectively.

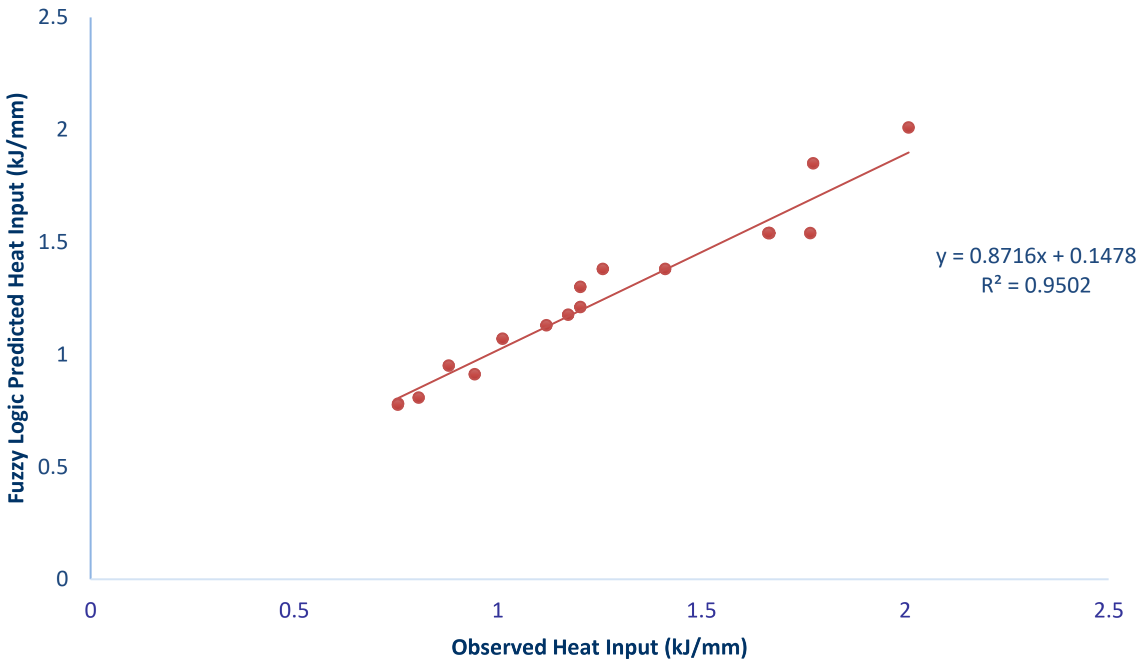

Fig. 13 Regression plot of output.

4. Conclusion

The use of a suitable welding heat input that could lower the degree of residual stress caused during welding, can avoid deleterious formation of heat affected zone cracking during TIG welding process especially when the optimum values of the welding variables are adequately determined. To ensure adequate determination of the welding variables, fuzzy logic was employed. The fuzzy logic estimation scheme developed in this paper provides an alternative to the general but complex machine learning algorithm such as random forest for the prediction of weld parameters. In addition, since fuzzy logic is a rule-based prediction model, it is important that adequate preference is given to parameter randomization in order to arrive at the precise rules that will generate accurate prediction.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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