MODELING OF TIG WELDING PROCESS BY REGRESSION ANALYSIS AND NEURAL NETWORK TECHNIQUE

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ABSTRACT

In the present paper, neural network-based expert systems have been developed for process parameter to weld bead geometry for tungsten inert gas (TIG) welding process welding. However linear regression analysis is used for the process modeling and analysis of numerical data consisting of the values of dependent variables (responses) and independent variables (input parameters). The numerical data are utilized to obtain an approximation model correlating the outputs and inputs by showing the influences of the parameters on responses. Once trained, the neural network-based expert systems could make the predictions in a fraction of a second. The analysis of variance for all factor a pareto chart of effect of the responses on parameter and their interaction, which effect maximum on the welding process responses on weld bead geometry. Here, a performance analysis has been attempted to check the viability and performance of regression analysis and back propagation neural network (BPNN) based tool for predicting modeling of TIG welding process.

Key word: TIG Welding, Linear Regression, Neural Network, Modelling, Pareto Chart.

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1. INTRODUCTION
To ensure high productivity, process control as well as good quality of product, a manufacturing process is to be automated. In order to automate a process, a proper model has to be constructed and tested before implementing process control. This paper deals with a modelling of a TIG welding process. TIG welding is an inert gas (like He, Ar.) shielded arc welding process using a non-consumable tungsten electrode. It is mainly used for aluminium, stainless steel, magnesium, titanium etc. Here a relation has to be establishing in between input and output of welding parameter.

1.1 Background
L. Nele et al. [1] presents a neuro-fuzzy modeling approach to provide adaptive control for the automatic process parameter adjustment. Three input parameters are modeled with welding current output, providing control over weld bead formation during the welding. In order to ascertain the effectiveness of the neuro-fuzzy modeling approach, multiple regression models were also developed to compare the performances and some other weld quality majors such as dilution ratio and hardness of fusion zone have been incorporated in the model. D. Katherasan et al. [2] Addresses the simulation of weld bead geometry in FCAW process using artificial neural networks (ANN) and optimization of process parameters using particle swarm optimization (PSO) algorithm. The input process variables and output process variables considered for weld bead geometry. K.N. Gowtham et al. [3] In this work, adaptive neuro fuzzy inference system is used to develop independent models correlating the welding process parameters like current, voltage, and torch speed with weld bead shape parameters like depth of penetration, bead width, and HAZ width. Then a genetic algorithm determines the optimum A-TIG welding process parameters to obtain the desired weld bead shape parameters and HAZ. Dongcheol kim et al.[4] Proposed a method to optimize the variables for an arc welding process using the genetic algorithm and the response surface methodology. In this study, systematic experiments done without the use of models to correlate the input and output variables. Hsuan-Liang et al. [5] applies an integrated approach of Taguchi method, ANN and GA to optimize the weld bead geometry of GTA welding specimens. In first stage executes initial optimization via Taguchi method to construct a database for the ANN. In second stage, an ANN is used to provide the nonlinear relationship between factors and the response. Then, a GA is applied to obtain the optimal factor settings. J.P.Ganigatti, D.K.Pratihar et al.[6] gives a relationships with input-output of the MIG welding process by using regression analysis based on the data collected as per full-factorial design of experiments. The effects of the welding parameters and their interaction terms on different responses have been analyzed using statistical methods (both linear and non-linear). D.S.Nagesh, G.L.Datta [7] An integrated approach based on the use of Design of Experiment (DOE), Artificial Neural Networks (ANN) and Genetic Algorithm (GA) for modeling of Gas Metal Arc Welding (GMAW) process has been done. Back-propagation neural networks are used to associate the welding process variables with the features of the weld bead geometry and Genetic Algorithms are used for optimizing the process parameters. Asfak Ali Mollah & Dilip Kumar Pratihar [8] determined Input-output relationships of TIG welding and abrasive flow machining (AFM) processes using radial basis function networks (RBFNs). The performances of RBFN tuned by a BP algorithm and that trained by a GA were compared. Young Whan Park & Sehun Rhee[9] Did the laser welding experiments for AA5182 aluminium alloy and AA5356 filler wire were
performed according to various laser powers, welding speeds, and wire feed rates. Tensile tests were carried out by NN model to evaluate the weld ability. The process variables were optimized using a genetic algorithm. Y.S.Tarng et al. [10] gives an application of NN and simulated annealing (SA) algorithm to model and optimize the GTAW process. The relationships between welding process parameters and weld pool features are established based on NN. The counter-propagation network (CPN) is selected to model the GTAW process due to the CPN equipped with good learning ability. Y.S Tarng and W.H Yang [11] determine the welding process parameters for obtaining optimal weld bead geometry in TIG welding is presented. The Taguchi method is used to formulate the experimental layout, to analyze the effect of each welding process parameter on the weld bead geometry, and to predict the optimal setting for each welding process parameter. J Edwin raja dhas &s kumanan [12] gives an intelligent technique, adaptive neuro-fuzzy inference system, to predict the weld bead width in submerged arc welding process for a given set of welding parameters. Experiments are designed according to Taguchi’s principles and their results are used to develop a multiple regression model. Multiple sets of data from regression analysis are utilized to train the intelligent network to predict the quality of weld. S.Vishnuvaradhan et al. [13] Developed a independent models correlating the welding parameters like current, voltage and torch speed with bead shape parameters like weld bead width, depth of penetration, and HAZ width using adaptive neuro-fuzzy inference system. During ANFIS modeling, various membership functions were used. N. Chandrasekhar and M.vasudevan [15] developed an intelligent modelling for optimization of A-TIG welding process, by combining artificial neural network (ANN) and genetic algorithm (GA) for determining the optimum process parameters for achieving the desired depth of penetration and weld bead width during Activated Flux Tungsten Inert Gas Welding (A-TIG) welding of type 316LN and 304LN stainless steels. N. Raghavendra et al. [16] gives the joint strength prediction in pulse MIG welding using hybrid soft computing technique. ACO and BPNN models are combined to predict the ultimate tensile strength of but welded joints. A large number of experiments have been conducted, and comparative study shows that the hybrid neuro-ant colony-optimized model produces faster and also better weld-joint strength prediction than the conventional back propagation model. Reza Teimouri & Hamid Baseri [17] Attempts to carry out both forward and backward mapping of friction stir welding (FSW) process using FL models. Fuzzy approaches were applied to anticipate tensile strength, elongation and hardness of Friction stir welded aluminium joints according to variation of tool rotational speed and welding. Tae Wan Kim &Young Whan Park [18] determine the optimal welding conditions in terms of the productivity and weldability for laser welding of aluminium alloy AA5182 using filler wire AA 5356. For tensile strength estimation, three regression models are proposed. In above, the second order polynomial regression model had the best estimation performance with respect to ANOVA (analysis of variation) and average error rate. S.C.Juang, Y.S. tarang et al. [19] applies NN to model the TIG welding process. They developed both back-propagation and counter-propagation networks to establish the relationships of welding process parameters with the features of weld-pool geometry and showed that both the back-propagation and counter-propagation networks can model the TIG welding process with a reasonable accuracy. Mohammadhosein Ghasemi Baboly et al. [20] Deals with modeling and analysis of laser material processing technologies which were commonly used in the recent past. The characteristics of laser machining and laser welding have been determined using response surface method (RSM), artificial neural network (ANN) and adaptive neuro-
fuzzy inference system (ANFIS). For each process, an experimental setup was
designed and site-conducted using central composite design (CCD). Then their
performance measures (responses) have been modeled and predicted based on RSM,
ANN and ANFIS. Hamed Pashazadeh, Yousof Gheisari et al. [21] used three welding
parameters in Resistance spot welding and identified as the main effective parameters
on the weld nugget dimensions including the weld nugget diameter and height using
full factorial design of experiments. Then using hybrid combination of the ANN and
multi-objective genetic algorithm, the optimized values of the aforementioned
parameters was specified. Norasiah Muhammad, Yupiter HP Manurung et al. [22]
gives alternate way to optimize process parameters of resistance spot welding (RSW)
towards weld zone development. It consider the multiple quality characteristics,
namely weld nugget and heat affected zone (HAZ), using multi-objective Taguchi
method (MTM). The optimum value was analyzed by means of MTM, which
involved the calculation of total normalized quality loss (TNQL) and multi signal to
noise ratio (MSNR).

1.2 Problem

In previous work the modeling of the TIG welding process, by regression analysis has
been done only considering main factor and their two or three level interaction. Also,
the modeling of the TIG welding has been done in forward direction only (i.e. from
input to the output), reverse modeling of the process is yet to be done. Determining
the set of input parameters to achieve a set of pre-specified outputs may sometimes
become very difficult when the transformation matrix relating the outputs with the
inputs becomes singular.

1.3 Objectives

The main objective of this research is:

- To develop Regression equation model for the TIG welding process to relate the input
  process parameters to the process output variables. Also uses ANOVA determine
  which factor has more effects on the weld bead geometry.
- To developed forward and reverse modeling of the Tungsten inert gas welding
  process using back propagation neural network (BPNN).
- A comparative analysis has been attempted to check the viability and performance of
  statistical regression and NN based tool for predicting the input parameters, as well as
certain outputs of TIG welding process.

2. MODELING PROCESS TECHNIQUES

Modeling is one of the major contributors to the TIG welding, which governed by a
number variables, which may be interrelated. Accurate and comprehensive
measurements of the process are difficult and sometimes impossible. Hence, process
modeling is a prerequisite to automation. A process is characterised by several
independent input parameter, process control and various responses. The weld quality
of TIG welding is characterising by the weld bead geometry, mechanical properties
and distortion. Weld modeling is important for predicting the quality of welds and
also there are not any mathematical formulae to relate the process parameters
(welding speed, wire feed rate, cleaning percentage, arc gap, and welding current) to
weld bead geometry(front height, front width, back height and back width). Here
forward and reverse modelling is employed for TIG welding. In this forward
modeling, the relationship in between the input process variable, to output process for
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TIG welding process. In forward modeling investigation are made to how the output parameters are changed when changes are made in input process parameters.

In case of reverse modeling, it relates for TIG welding from the output parameters of the process, to input parameter, as shown by reverse arrow. [refer fig 1.]

2.1. Conventional Linear regression analysis
To determine a response equation, a conventional linear regression model can be considered, the response functions involving all linear and interaction terms is given by the following expression.  

\[ Y = f(X_1, X_2, X_3, X_4, X_5) \]

Where, 

\[ Y \]  is the estimated response (output) value; the coefficients (b values) are estimated by using a least square technique.

2.2 Artificial neural network
An Artificial Neural Network (ANN) is an information processing paradigm inspired by the way biological nervous systems, such as the brain, process information and learns from experience. In other words, ANNs focus on replicating the learning process performed by the brain. Humans have the ability to learn new information, store it, and return to it when needed. Humans also have the ability to use this information when faced with a problem similar to that they have learned from in the past.

2.3 Back propagation neural network (BPNN)
This is a multilayer feed forward network where learning rule based on gradient decent technique with backward error propagation. All the neurons units are connected in a feed-forward fashion with input units fully connected to units in the hidden layer and hidden units fully connected to units in the output layer. When a back prop network is cycled, an input pattern is propagated forward to the output units through the intervening input-to-hidden and hidden-to-output weights. The output of a back propagation network is interpreted as a classification decision. With back propagation networks, learning occurs during a training phase.
2.3.1 Forward propagation
In the forward propagation of the BPNN network, error is calculated. That error is used in the back-propagation. The function used in 1st step output of input layer (i.e. input to hidden layer) linear transfer, 2nd step output of hidden layer tan sigmoid, 3rd output of output layer linear transfer and finally error is calculated at the kth output neuron, average error, and average mean square error.

2.3.2 Back-propagation algorithm
In back propagation the weights are the function of error and the hidden-output weights are updated to minimize the error, as given below:

\[ W_{\text{new}} = W_{\text{old}} + \Delta W, \quad \text{Where} \quad \Delta W = -\eta \frac{\partial E}{\partial W} \]

3. PROBLEM FORMULATION
A sample of TIG welding is taken that shows the bead geometric parameters in TIG welding process. In this work, Regression analysis is done to identify the relationship between welding input process variable to the output responses and also identify their effect.

![Figure 2 A schematic diagrams showing the weld bead geometric parameters](image)

Back-propagation neural network (BPNN) will be use for modeling of TIG welding in both forward and reverse. The process input parameters selected for this process is welding speed, wire feed rate, cleaning percentage, arc gap, and welding current. These are the parameters which affect the weld bead quality. The output parameters is weld bead geometry, which is front height, front width, back height, and back width.

Fig.1. shows a schematic diagram indicating the inputs (namely, welding speed A, wire feed rate B, % cleaning C, gap D, welding current E) and weld bead geometric parameters (such as front height FH, front width FW, back height BH and back width BW), in a TIG welding process. The ranges of the input process parameters considered for the purpose of analysis are shown in table 1.
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Table 1 Input welding parameters and their ranges

<table>
<thead>
<tr>
<th>Input process parameters</th>
<th>units</th>
<th>Notation</th>
<th>Maximum value(+)</th>
<th>Minimum value(-)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Welding speed</td>
<td>cm/min</td>
<td>A</td>
<td>46</td>
<td>24</td>
</tr>
<tr>
<td>Wire feed rate</td>
<td>Cm/min</td>
<td>B</td>
<td>2.5</td>
<td>1.5</td>
</tr>
<tr>
<td>% cleaning</td>
<td></td>
<td>C</td>
<td>70</td>
<td>30</td>
</tr>
<tr>
<td>Gap</td>
<td>mm</td>
<td>D</td>
<td>3.2</td>
<td>2.4</td>
</tr>
<tr>
<td>current</td>
<td></td>
<td>E</td>
<td>110</td>
<td>80</td>
</tr>
</tbody>
</table>

In forward modeling, the number of nodes of the input layer is kept equal to the number of input process parameters (refer fig 3.).

![Figure 3 Configuration of the back-propagation network for the forward modeling](image)

Figure 3 Configuration of the back-propagation network for the forward modeling

The number of neurons in the output layer is made equal to the number of output parameters of the process, i.e., four neurons. The number of hidden layer is kept equal to one. In reverse modeling, the number of neurons in the input and output layers will be kept equal to four and five, respectively (Refer Fig 4.).

![Figure 4 Configuration of the back-propagation network for the reverse modelling](image)

Figure 4 Configuration of the back-propagation network for the reverse modelling

The number of neurons in the output layer is made equal to the number of output parameters of the process, i.e., four neurons. The number of hidden layer is kept equal to one. In reverse modeling, the number of neurons in the input and output layers will be kept equal to four and five, respectively (Refer Fig 4.).
4. RESULT AND DISCUSSION
Regression analysis carried out first to establish input-output relationship based on the experiments of a TIG welding process.

4.1 Linear Regression Analysis
The response functions involving all linear and interaction terms obtained through Minitab statistical software is given below.

\[
FH = -17.2504 + 0.620178A + 4.67616B + 0.0866466C + 7.44792D + 0.043108E - 0.186955AB - 0.00579205AC - 0.220992AD - 0.00291231AE + 0.00181288BC - 1.83959BD + 0.0191386BE - 0.0585772CD + 0.00178852CE - 0.0352192DE + 0.00140606ABC + 0.0622964ABD + 0.000205682ABE + 0.0022313ACD - 0.00000676136ACE + 0.00114086ADE + 0.00609754BCD - 0.0013628BCE - 0.00303314BDE - 0.000275331CDE - 0.0004237699ABCD + 0.0000189015ABCE - 0.000045928ABDE - 0.00000875947ACDE + 0.000376231BCDE - 0.00000686553ABCDE.
\]

\[
FW = -329.676 + 8.25394A + 167.104B + 5.81867C + 101.462D + 3.99527E - 4.07073AB - 0.141415AC - 2.54891AD - 0.0991439AE - 2.91505BC - 54.1378BD - 1.9883BE - 1.851CD - 0.0686438CE - 1.21499DE + 0.0699894ABC - 1.31749ABD + 0.0485682ABE + 0.0441117ACD + 0.0169773ACE + 0.0308099ADE + 0.939865BCD + 0.0345468BCE + 0.652385BDE + 0.0222935CDE - 0.0222604ABCD - 0.000839242ABCE - 0.0159427ABDE - 0.00054259ACDE - 0.0112937BCDE + 0.000271828ABCDE.
\]

\[
BH = 20.7999 - 0.383051A - 3.57449B + 0.107945C - 9.32839D - 0.092436E + 0.00582955AB - 0.00543087AC + 0.166515AD + 0.000490909AE - 2.92361BD + 0.016822BE - 0.00915199CD - 0.00368345CE + 0.057682DE + 0.0044629ABC - 0.0237311ABD + 0.00145682ABE + 0.00155777ACD + 0.000124015ACE - 0.000552324ABDE + 0.0262282BCD + 0.00236962BCE - 0.00413068CDE + 0.00095CDE - 0.00134848ABCD - 0.0000768939ABCE - 0.000314867ABDE - 0.0000393229ACDE + 0.00068428BCDE + 0.0000249527ABCDE.
\]

\[
BW = -179.435 + 4.12091A + 104.771B + 4.11129C + 52.8753D + 2.43685E - 2.54736AB - 0.0946174AC - 1.26952AD - 0.057292AE - 2.22725BC - 34.1677BD - 1.29734BE -1.3856CD - 0.0508243CE - 0.719793DE + 0.0520439ABC + 0.818774ABD + 0.032125ABE + 0.0318464ACD + 0.0012161ACE + 0.0181802ADE + 0.768436BCD + 0.0268395BCE + 0.435309BDE + 0.0175575CDE - 0.017848ABC - 0.000642652ABCE - 0.0107846ABDE - 0.000421188ACDE - 0.00935019BCDE + 0.000224574ABD.
\]

For the significant factor which affect on responses for this analysis variance for factor has calculated.

4.2 Analysis of variance for FH, FW, BH and BW
Analysis of variance is carried out to find the variance in the data and significant factors which affect on the responses. Considering (Fig.5 to Fig.8) the various main factors, Out of different interaction terms, pareto chart of effect is summarized in table 2.
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Figure 5 Pareto chart of effects of the responses on FH

Figure 6 Pareto chart of effects of the responses on FW

Figure 7 Pareto chart of effects of the responses on BH

Figure 8 Pareto chart of effects of the responses on BW
Table 2 Summary of pareto chart effect

<table>
<thead>
<tr>
<th>Analysis of variance</th>
<th>Factor 1</th>
<th>Factor 2</th>
<th>interaction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Front height (FH)</td>
<td>E</td>
<td>A</td>
<td>BCE</td>
</tr>
<tr>
<td>Front width (FW)</td>
<td>E</td>
<td>A</td>
<td>AE</td>
</tr>
<tr>
<td>Back height (BH)</td>
<td>A</td>
<td>E</td>
<td>ABCD</td>
</tr>
<tr>
<td>Back width (BW)</td>
<td>E</td>
<td>A</td>
<td>AE</td>
</tr>
</tbody>
</table>

4.3. Testing the regression equation model

To obtain responses equation considering all the interaction terms are tested with the test case to analyze the prediction capability of the linear regression analysis equation. The predicted output of regression, their compressions between targeted and predicted values are shown in fig 9 to fig 12. When put the result of test cases into the regression equation to obtain the corresponding responses (i.e. front height, front width, back height and back width).

4.3.1 Result of the test cases in regression analysis for FH, FW, BH and BW

Figure 9 Plot between target and predicted values for FH

From the fig. 9 it is noticed that in test cases 4, 20 and 27 there is high % deviation, which is due to some experimental error.

Figure 10 Plot between target and predicted values for FW

From figure10 it is that for front width the regression model predicts the responses accurately.
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4.3.2 Comparison between the predicted values with their respective target values

The Scatter plots between predicted value and the target value are plotted for the various responses namely Front Height, Front Width, Back Height and Back Width are shown below (refer 13 to 16). It is important to note that the better predictions are obtained in case of Front Width and Back Width (refer Fig 14 & fig 16) compared to those of the Front Height and Back Height (refer Fig 13 & 15) and as a result of which, the points shown in Figs. 14 & 16 are found to lie closer to the ideal line (the line on which all points should lie), whereas the points are seen to be slightly scattered in Figs. 13 & 15 from the ideal line.

Figure 11 Plot between target and predicted values for BH

Figure 12 Plot between target and predicted values for BW

Figure 13 scatter plot between targets and predicted for FH
4.4 Result of forward modeling using Back propagation neural network (BPNN)

The performance of BPNN depends on its architecture; in this case only one parameter was varied at a time after keeping the other parameters unchanged. In this approach, the number of hidden neurons is varied from five to twenty. The process is done until we got the minimum mean square error (MSE). During the training, the parameters: learning rate (η), momentum factor (α) and hidden output connecting weights are varied in the ranges of (0.01, 0.8), (0.2, 0.9) and (-1, 1). The following optimal parameters are obtained through a careful training of network: Number of hidden neurons = 7, Learning rate of BP algorithm (η) = 0.3 and Momentum factor of 

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**Figure 14** scatter plot between targets and predicted for FW

**Figure 15** scatter plot between targets and predicted for BH

**Figure 16** scatter plot between target and predicted for BW
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BP algorithm \((\alpha) = 0.56\). The performance of the trained BPNN was tested on 36 test cases, the trained BPNN predict the corresponding response of the welding process.

4.4.1 Result of the test cases in BPNN for FH, FW, BH and BW

In fig 17 to fig 20 show the graph between target values and network (BPNN) predicted values front height, front width, back height, back width.

**Figure 17** Plot between target and predicted values for FH

**Figure 18** Plot between target and predicted values for FW

**Figure 19** Plot between target and predicted values for BH
4.4.2 Comparison between the predicted values with their respective target values

Figure 20 Plot between target and predicted values for BW

Figure 21 scatter plot between targets and predicted for FH

Figure 22 scatter plot between targets and predicted for FW

Figure 23 scatter plot between targets and predicted for BH
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From the scatter plot (Fig.21 to Fig. 24) of the predicted and target values for Front height, Front width, back height and Back width, it is clear that the back propagation network predict the responses precisely in case of Front width (fig.22) and Back width (fig. 24). In case of Front height (fig21) and Back height (fig.23) there are some data which are slightly scattered from the ideal line (the line on which all points should lie), whereas, the points shown in Figs.22 and 24 are found to lie closer to the ideal line.

4.5 Comparison of the regression analysis & BPNN approaches in forward modelling

The RMS deviation and average % deviation for all test cases for the responses has been calculated and are shown below (table 3).

Table 3 Comparison of the regression analysis and BPNN approaches

<table>
<thead>
<tr>
<th>Forward mapping Approaches</th>
<th>RMS Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>FH</td>
</tr>
<tr>
<td>Regression</td>
<td>0.13</td>
</tr>
<tr>
<td>BPNN</td>
<td>0.225</td>
</tr>
<tr>
<td>Average % Deviation</td>
<td>-128.07</td>
</tr>
<tr>
<td>Regression</td>
<td>40.72</td>
</tr>
</tbody>
</table>

4.6 Result of reverse modeling using Back propagation neural network

Reverse modelling using BPNN, aims to determine the set of input process parameters, corresponding to a set of desired output parameters (refer fig 4). The statistical method might fail to carry out the said reverse modeling because of the fact that the transformation matrix might not be invertible at all. The following optimal parameters are obtained through a careful training of network: Number of hidden neurons = 7, Learning rate of BP algorithm (η) = 0.2 and Momentum factor of BP algorithm (α) =0.6. After the network has been trained properly all the 36 cases are passed through the optimized neural network. The predicted values of the network corresponding to their target values are observed, and their RMS deviation and average % deviation in reverse modelling shown in table 4.
### Table 4 RMS deviation and average % deviation in reverse modeling

<table>
<thead>
<tr>
<th></th>
<th>RMS Deviation</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Welding speed</td>
<td>7.87</td>
<td>0.188</td>
<td>20.53</td>
<td>0.57</td>
<td>10.07</td>
</tr>
<tr>
<td>Wire feed speed</td>
<td>-0.816</td>
<td>-6.11</td>
<td>0.48</td>
<td>4.19</td>
<td></td>
</tr>
<tr>
<td>% cleaning</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gap</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Welding current</td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>

In reverse modeling, Back propagation neural network predicts a good result for wire speed and electrode to work piece gap.

### 5. CONCLUSION AND FUTURE WORK

For estimating weld bead parameters like Front height, Front width, back height and Back width in TIG welding process, input-output relationships determined by regression analysis were carried out based on full factorial DOE and forward-reverse modeling by controlling the five welding processes such as welding speed, wire feed rate, percentage of cleaning, work-piece to electrode gap and welding current through NN were developed. Comparisons were made of the above approaches, after testing their performances. It has to be observed that the regression analysis considering all the interaction term predict the responses very well in some of the test cases. But regression analysis is not capable of modeling the process in Reverse. But in the other hand back propagation neural networks predict the responses better and yield a good result in prediction. The reverse modeling for TIG welding can be done by using back propagation neural network.

The back propagation neural networks have some drawbacks like it is sometimes struck with local minima, so it can be integrated with global optimization techniques like simulated annealing, particle swarm optimization etc. also Clustering techniques will be used as pre-processing phase to find the optimum adjustable parameters of the BPNN.

### REFERENCES


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