ANFIS BASED WELD METAL DEPOSITION PREDICTION SYSTEM IN MAG WELDING USING HYBRID LEARNING ALGORITHM

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Abstract:
This work proposes a soft computing based artificial intelligent technique Adaptive Neuro Fuzzy Interference System (ANFIS), to predict the weld metal deposition in the Metal Active Gas (MAG) welding process for a given set of welding parameters using hybrid learning algorithm to have a correct amount of weld metal deposition to meet the correct welding requirement. Total 81 nos. of experiments are designed according to full factorial design of experiments with varied input parameters and its results are used to develop an ANFIS model. Multiple sets of data from experiments are utilized to train, check and validate the intelligent network, which is used to predict the amount of weld metal deposition. The proposed ANFIS, developed using MATLAB functions, is flexible, and it scopes for a better online monitoring system to achieve better welding requirement.

Keywords:
ANFIS, Hybrid Learning Algorithm, MAG, Weld Metal Deposition.

1. Introduction

Metal Active Gas (MAG) welding, a widely used industrial arc welding procedure needs a better prediction and monitoring of its parameters to produce consistent weld quality. The mechanical-metallurgical features of the weldment depend on the weld bead geometry and weld metal deposition, which are directly related to welding process parameters. Literature shows that work has been explored on various aspects of modeling, simulation and process optimization in MIG welding. Researchers are attempting many techniques to establish relationships between welding parameters and weld metal deposition and weld quality leading to an optimal process by the application of adaptive neuro fuzzy interference system (ANFIS) which is a rule base of fuzzy logic controller (FLC). After the development of the concept of Fuzzy Logic by Lofti Zadeh [1] [2] [3] Mamdani et al [4] and Sugeno et al [5] [6] extended the concept of fuzzy logic to the FLC. The theory and concept of ANFIS was developed by J.S.R. Jang [7] with an engineering application using Artificial Neural Network [8][9]. Nozaki et al [9] showed how a set of numerical data can generate fuzzy rule. Manonmani [11] investigated the effect of the welding parameters on the bead geometry AISI 304 stainless steel. Juang and Tarng [12] adopted a modified Taguchi method to analyze the effect of each welding process parameter on the weld pool geometry and then to determine the TIG welding process parameters combination associated...
with the optimal weld pool geometry. S. Datta et al [13] have worked on the influence of electrode stick out as an one of the important process parameters of submerged arc welding by incorporating one of the traditional methods of statistical data analysis (ANOVA). Jagdev Singh and Simranpreet Singh Gill [14] has designed and demonstrated the use of fuzzy logic based multi input and single output ANFIS model to predict the tensile strength of tubular joints, welded by the technique of radial friction welding. Manoj Singla et al [15] have optimized the different parameters of Gas Metal Arc Welding process by using factorial design approach. The study had optimized various Gas Metal Arc welding parameters including welding voltage, welding current, welding speed and nozzle to plate distance (NPD) by developing a mathematical model for sound weld deposit area of a mild steel specimen. P. Kumari et al [16] has made a study on the effect of welding parameters on weld bead geometry in MIG welding of low carbon steel. J Raja Dhas and S Kannan [17] have adopted a neuro hybrid model to predict bead width in submerged arc welding. A. Biswas et al [18] has optimized the bead geometry in Submerged Arc Welding which was conducted based on Taguchi’s L25 orthogonal array design with combinations of process control parameters. Different bead geometry parameters was optimized and optimal result has been verified by confirmatory. This study proposes a hybrid intelligent technique, ANFIS, to predict weld metal deposition in a MAG welding process for a given set of welding parameters and optimization of the same using genetic algorithm.

2. Metal Active Gas (MAG) Welding

MAG, a common and popular arc welding process in industries has welding current, arc voltage, welding speed, electrode stick out (extension of the electrode), electrode diameter, polarity, current type etc as input variables. Welding current directly influences the weld metal deposition which gives better depth of penetration and base metal fusion. The temperature at the welding zone is also directly depends upon welding current. At a given current, weld metal deposition is affected by the electrode diameter. Electrode stick out also have a varied relation with the weld metal deposition. Welding speed is also play a vital role, when weld metal deposition is considered. Since the weld is more brittle than the parent material, it is vital that the weld metal deposition must be minimal without disturbing desired penetration and strength. Minimization of the weld metal deposition is necessary because excessive deposited weld metal leads to wastage of the welding electrode and the process consumes more time and money. Therefore necessary attention is required to select the process parameters in welding to get a minimized weld metal deposition with having desired weld quality as required.

3. Sugeno Fuzzy Model

Unlike Mamdani model, Sugeno output membership functions are either linear or constant. If a fuzzy system under consideration has two inputs x and y and one output f, then for a first order Sugeno fuzzy model, a common rule set with two fuzzy if-then rules is as follows:

Rule 1: If x is $A_1$ and y is $B_1$, then $f_1 = p_1x + q_1y + r_1$
Rule 1: If x is $A_2$ and y is $B_2$, then $f_2 = p_2x + q_2y + r_2$

For a zero-order Sugeno model, the output level is a constant ($p_i = q_i = 0$). But for a first order Sugeno model, output is not a constant, but linear. The output level $f_i$ of each rule is weighted by the firing strength $w_i$ of the rule. For example, for an AND rule with Input 1 = x and Input 2 = y, the firing strength is

\[ w_i = \text{AND method} \left( A_i(x), B_i(y) \right) \]
where $A_i$ and $B_i$ are the membership functions for Input 1 and Input 2 respectively. The final output of the system is the weighted average of all rule outputs, computed as

$$\text{Final Output} = \frac{\sum_{i=1}^{n} w_i f_i}{\sum_{i=1}^{n} w_i}$$

(1)

Fig: 1. A two-input first-order Sugeno fuzzy model with two rules;

4. ANFIS architecture

Fig: 1 illustrates the reasoning mechanism for the Sugeno model discussed above while the corresponding ANFIS architecture is as shown in Fig: 2, where nodes of the same layer have similar functions. The output of $i^{th}$ node in layer $l$ is denoted as $O_{l,i}$.

Fig: 2. Equivalent ANFIS architecture

Layer 1: Every node $i$ in this layer is an adaptive node with a node function

- $O_{1,i} = \mu_{A_i}(x)$ for $i=1,2$
- $O_{1,i} = \mu_{B_i}(y)$ for $i=3,4$
where \( x \) (or \( y \)) is the input to node \( i \) and \( A_i \) (or \( B_{i-2} \)) is a linguistic label (“small” or “large”) associated with the node. Here the membership function for \( A \) (or \( B \)) can be any parameterized membership function. In this paper, generalized bell shaped Gaussian membership function is taken as follows:

\[
\mu_{A_iB_{i-2}} = \frac{1}{1 + \left(\frac{x-a_i}{b_i}\right)^2}
\]  

\( \{a_i, b_i, c_i\} \) is the parameter set which defines the curve for the above equation, which takes a form of bell shaped Gaussian distribution. These parameters are called premise parameters or antecedent parameters. These parameters adapt the fuzziness of the input parameters into the ANFIS network.

Layer 2: Every node in this layer is a fixed node labeled \( \Pi \), whose output is the product of all the incoming signals.

\[ O_{2,i} = w_i = \mu_{A_i}(x) \times \mu_{B_i}(y) \text{ for } i = 1, 2 \]  

Layer 3: Here, the \( i^{th} \) node calculates the ratio of the \( i^{th} \) rule’s firing strength to the sum of all rule’s firing strengths.

\[ O_{3,i} = \frac{w_i}{w_1+w_2} \]  

Layer 4: Every node in this layer is an adaptive node with a following node function:

\[ O_{4,i} = w_if_i = w_i(p_ix + q_iy + r_i) \]  

Here, \( w_i \) is a normalized firing strength from layer 3 and \( f_i = p_ix + q_iy + r_i \)

where, \( \{p_i, q_i, r_i\} \) is the parameter set. Parameters in this layer are referred to as consequent parameters.

Layer 5: The single node in this layer is a fixed node labeled \( \sum \), which computes the overall output as the summation of all incoming signals:

\[ O_{5,i} = \sum w_if_i = \frac{\sum w_if_i}{\sum w_i} \]  

5. Hybrid Learning Algorithm

The Hybrid Learning Algorithm is a combination of least square and backpropagation method. In the least square method, the output of a model \( y \) is given by the parameterized expression:

\[ y = \theta_1f_1(u) + \theta_2f_2(u) + \ldots + \theta_nf_n(u) \]  

where \( u = [u_1, u_2, \ldots u_n]^T \) is the model input vector, \( f_1, f_2, \ldots, f_n \) are known functions of \( u \), and \( \theta_1, \theta_2, \ldots, \theta_n \) are unknown parameters to be optimized. To identify these unknown parameters \( \theta_i \) usually a training data set of data pairs \( \{(u_i, y_i); i=1,2,\ldots,m\} \) is taken; substituting each data pair in (8) a set of linear equations is obtained, which can be written as

\[ A\theta = y \]
In matrix form, where A is a mXn matrix we can write

\[
A = \begin{bmatrix}
    f_1(u_1) & \cdots & f_n(u_1) \\
    \vdots & \ddots & \vdots \\
    f_1(u_m) & \cdots & f_n(u_m)
\end{bmatrix}
\] (10)

θ is an nX1 unknown parameter set and we can write the same as following

\[
\theta = \begin{bmatrix}
    \theta_1 \\
    \vdots \\
    \theta_n
\end{bmatrix}
\] (11)

And, y is an mX1 output set which can be written as following

\[
y = \begin{bmatrix}
    y_1 \\
    \vdots \\
    y_n
\end{bmatrix}
\] (12)

Since generally \(m > n\), instead of exact solution of (9) an error vector e is introduced to account for the modeling error, as

\[
A \theta + e = y
\] (13)

Our objective is to search for \(\theta = \theta^*\) which minimizes sum of squared values, expressed as follows

\[
E(\theta) = \sum_{i=1}^{m} (y_i - a_i^T \theta)^2
\] (14)

where \(E(\theta)\) is called the objective function. The squared error in (14) is minimized when \(\theta = \theta^*\), called Least Squares Estimator (LSE) that satisfies the normal equation

\[
A^T A \theta^* = A^T y
\] (15)

If \(A^T A\) is non singular, \(\theta^*\) is unique and is given by

\[
\theta^* = (A^T A)^{-1} A^T y
\] (16)

This is also known as the pseudo inverse of \(\theta\) as because ‘A’ being a non-square matrix, this pseudo inverse is taken. In case of backpropagation learning rule the central part concerns how to recursively obtain a gradient vector in which each element is defined as the derivative of an error measure with respect to a parameter. Assuming that a given feedforward adaptive network has \(L\) layers and layer \(l\) has \(N(l)\) nodes, then the output function of node \(i\) in layer \(l\) can be represented as \(x_{l,i}\) and \(f_{l,i}\) respectively. For the node function \(f_{l,i}\) we can write:

\[
x_{l,1} = f_{l,i}(x_{l-1,1}, \ldots, x_{l-1,N(l-1)}, \alpha, \beta, \gamma, \ldots)
\] (17)

where \(\alpha, \beta, \gamma\) etc. are the parameters of this node. Assuming that the given training data set has \(P\) entries, an error measure can be defined for the \(p^{th} (1 < p < P)\) entry of the training data set as the sum of squared errors:

\[
E_p = \sum_{k=1}^{N(L)} (d_k - x_{L,k})^2
\] (18)
where \( d_k \) is the \( k^{th} \) component of the \( p^{th} \) desired output vector and \( x_{l,k} \) is the \( k^{th} \) component of the actual output vector produced by presenting the \( p^{th} \) input vector to the network. The task here is to minimize an overall error measure, which is defined as \( E = \sum_{k=1}^{p} E_p \). The basic concept in calculating the gradient vector is to pass a form of derivative information starting from the output layer and going backward layer by layer until the input layer is reached. To facilitate the discussion the error signal \( E_{l,i} \) is defined as

\[
E_{l,i} = \frac{\partial E_p}{\partial x_{l,i}}
\]  
(19)

This is actually ordered derivative and is different from ordinary partial derivative.

For \( i^{th} \) output node (at layer \( L \))

\[
E_{L,i} = \frac{\partial E_p}{\partial x_{L,i}}
\]  
(20)

Therefore, we can write, \( E_{L,i} = -2 (d_i - x_{L,i}) \)  
(21)

For the internal node at the \( i^{th} \) position of layer \( l \), the error signal can be derived iteratively by the chain rule:

\[
E_{l,i} = \frac{\partial E_p}{\partial x_{l,i}} = \sum_{m=1}^{N(l+1)} \frac{\partial E_p}{\partial x_{(l+1),m}} \times \frac{\partial f_{(l+1),m}}{\partial x_{l,i}} = \sum_{m=1}^{N(l+1)} E_{(l+1),m} \times \frac{\partial f_{(l+1),m}}{\partial x_{l,i}}
\]  
(22)

The gradient vector is defined as the derivative of the error measure with respect to each parameter. If \( \alpha \) is a parameter of the \( i^{th} \) node at layer \( L \), we have

\[
\frac{\partial E}{\partial \alpha} = \frac{\partial E_p}{\partial x_{l,i}} \times \frac{\partial f_{l,i}}{\partial \alpha} = E_{l,i} \frac{\partial f_{l,i}}{\partial \alpha}
\]  
(23)

The derivative of the overall error measure \( E \) with respect to \( \alpha \) is

\[
\frac{\partial E}{\partial \alpha} = \sum_{p=1}^{P} \frac{\partial E_p}{\partial \alpha}
\]  
(24)

Accordingly, for simplest steepest descent without line minimization, the update formula for generic parameter \( \alpha \) is

\[
\Delta \alpha = -\eta \frac{\partial E}{\partial \alpha}
\]  
(25)

In the above equation \( \eta \) is the learning rate, which is defined as

\[
\eta = \frac{k}{\sqrt{\sum_{\alpha} \frac{\partial^2 E}{\partial \alpha^2}}}
\]  
(26)

Here, \( k \) = step size, the length of each transition along the gradient direction in the parameter space. We can change the step size to vary the speed of convergence. Therefore, from (25) we can write for parameter \( \alpha \)

\[
\alpha_{\text{new}} = \alpha_{\text{old}} + \Delta \alpha
\]
In this type of learning, the update action occurs only after the whole set of training data pair is presented. This process of presentation of whole set of training data pair is called epoch. It is assumed that ‘S’ is the total set of parameters and ‘S₁’ and ‘S₂’ are the sets of input and output parameters respectively. For hybrid learning algorithm, each epoch consists of a forward pass and a backward pass. In the forward pass, when a vector of input data pair is presented, the node outputs of the system are calculated layer by layer till the corresponding row in the matrices \( A \) and \( y \) of equation (9) are obtained. The process is repeated for all the training data pair to form the matrices \( A \) and \( y \) completely. Then the output parameters of set \( S₂ \) are calculated according to the equation (16). After this, the error measure for each training data pair is to be calculated. The derivative of those error measures w.r.t. each node output are calculated following equations (20) and (22). Thus the error signal is obtained. In the backward pass, these error signals propagate from the output end towards the input end. The gradient vector is found for each training data entry. At the end of the backward pass for all training data pairs, the input parameters are updated by steepest descent method as given by equation (27).

6. Proposed Methodology

Full factorial design of experiments is a systematic application of design of experiments to improve the product quality which uses the all possible combinations of levels of the input factors to make a meticulous investigation of the nature of the output. A four factors three levels design of experiments was done where \((3)^4 = 81\) numbers of experiments were involved in the MAG (POWERMIG T400) welding machine (Fig: 3.). The experiment was conducted at M/s. Hind Engineering, Badu, Madhyamgram, West Bengal. Single pass butt welding is performed on the commercially available steel of IS2962 grade (C 0.25%, Si 0.20%, Mn 0.75% and balance Fe) on a pair of 100mm \( \times \) 100mm \( \times \) 5mm work piece. Electrode (dia 1.2 mm) (AWS/SFA 5.18: ER 70S-6) was used with CO₂ gas at 11 lit/min flow rate as shielding gas. The weights were recorded before and after welding to measure the amount of weld metal deposition on the base metal.
Fig: 4. Edge Preparation before welding

Fig: 5. Welding Operation

Fig: 6. Samples after welding
7. Development of ANFIS for weld metal deposition prediction

ANFIS is a fuzzy interference system which uses the framework of Neural Network. This technique provides a method for fuzzy modelling procedure to learn information about a data set in order to achieve a rule base for selection of fuzzy rules. A database defines the membership functions used in the rules which creates a reasoning mechanism to carryout interference procedure on the rules and the given fact. This methodology combines the advantages of fuzzy system and Neural Network. The modelling of weld metal deposition by Metal Active Gas welding is done by considering four input parameters and one output parameter. The membership functions parameters are tuned using a hybrid system which is the combination of back propagation and the method of least squares. The parameters associated with the membership functions will change through the learning process. The computation of these parameters is facilitated by gradient vector, which provides a measure of how well fuzzy inference system is modelling the input/output data for a given set of parameters. Once the gradient vector is obtained, any of the several optimization routines could be applied in order to adjust the parameters so as to reduce some error measure. The proposed ANFIS (Fig. 1) structure utilizes Sugeno type fuzzy interference systems and generalized Gaussian bell-shaped membership function to execute a given training data set. It employs 55 nodes, 80 linear parameters, 24 nonlinear parameters, 104 total numbers of parameters 57 training data pairs, 8 checking data pairs and 16 fuzzy rules to predict weld metal deposition. ANFIS modelling process starts by obtaining an input-output pair of data sets and dividing it into training and checking data. The training data are used to find out the initial premise parameters for membership functions by equally spacing membership functions.

The final output of the system is the weighted average of the all rule outputs, computed as (1)

$$\text{Final output } (f) = \frac{\sum_{i=1}^{N} w_i f_i}{\sum_{i=1}^{N} w_i}$$

where $w_i =$ firing strength of the rule

$f_i =$ output level of each rule

Fig: 7. Proposed ANFIS structure for four inputs, single output to predict weld mass deposition in MAG welding process.
8. Results

As there is a considerable variation in the input data range in terms of numerical value, the input data is normalized to a uniform scale for input to the ANFIS model and this has been achieved by normalizing, using (28) for a range varying from 0.1 to 0.9.

\[ y = 0.1 + 0.8 \left( \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}} \right) \]

(28)

Where, \( x \) = actual value,
\( x_{\text{max}} \) = maximum value of \( x \),
\( x_{\text{min}} \) = minimum value of \( x \),
\( y \) = normalized value corresponding to \( x \).

The normalized input parameters along with the error comparison between experimental results and ANFIS prediction for 17 nos. Checking data set is given in Table I.

<table>
<thead>
<tr>
<th>Exp. No.</th>
<th>Actual Arc Voltage</th>
<th>Welding Current</th>
<th>Welding Speed</th>
<th>Electrode Stick out</th>
<th>Weld Deposition</th>
<th>ANFIS Prediction</th>
<th>Error</th>
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<td>4.16</td>
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</table>

Among the total 81 input-output data set the first 48 data sets are used for training the ANFIS model, next 17 data sets are used to check the model and the last 16 data sets are used to validate the network. The error between the experimental data and the predicted ANFIS model is well under tolerance limit which indicates an efficient modelling of the welding process. During ANFIS training in the forward pass, initial antecedent or premise membership functions is generated by using (3) and Fig:4 describes the nature of initial membership functions. Fig: 5 describes the values of premise parameters in matrix form.
Using equations (4) to (7) nodal calculations are done in layer 2 to 5 of ANFIS network and during backward pass consequent parameters are calculated using (16). In backward pass, error signals propagate from the output end towards the input end using backpropagation learning rule. The gradient vector is calculated for each training data pair. At the end of the backward pass for all training data pairs, the input parameters are updated by steepest descent method as given by equation (27). Fig: 6 and Fig: 7 describe the nature of revised membership function and the values of final antecedent or premise parameters in matrix form.

The consequent parameters is updated after each epoch and after the training of ANFIS completed the matrix of consequent parameters takes the form of a matrix as described in Fig: 8

\[
\begin{bmatrix}
0.4209 & 2.001 & 0.1252 \\
0.3702 & 2.000 & 0.9307 \\
0.4142 & 2.001 & 0.1167 \\
0.3822 & 2.000 & 0.9189 \\
0.4195 & 2.002 & 0.1269 \\
0.3558 & 2.000 & 0.9403 \\
0.3991 & 2.000 & 0.0901 \\
0.4009 & 2.000 & 0.899
\end{bmatrix}
\]
The overall error is measured using (18) and updated by steepest descent technique. Fig: 8 describe the values of root mean square error for the each epoch for initial and final pass.

![Surface plot of weld metal deposition (output) v/s arc voltage (input1) and welding current (input2)](image)

### Fig: 12. Matrix of consequent parameters

<table>
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<tr>
<th></th>
<th>Matrix Values</th>
<th>Matrix Values</th>
<th>Matrix Values</th>
<th>Matrix Values</th>
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Table II summarize the validating data sets and the normalized values with a comparison between the experimental data and ANFIS prediction, showing zero error for the predicted values.

9. Conclusion

Proposed ANFIS is based on first order Sugeno fuzzy interference system and developed to predict weld metal deposition in a MAG process. It could be extended with more welding parameters such as electrode diameters, base metal thickness, material type and their effect on the weld metal deposition. The ANFIS modelling may be extended to multi output to investigate the nature of weld metal deposition with depth of penetration, weld strength simultaneously.

10. Acknowledgement

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References