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Improved Welding Quality Prediction for Metal Inert Gas Welding using Artificial Intelligence

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ABSTRACT

Welding is widely used by manufacturing engineers and production personnel to quickly and effectively set up manufacturing processes for new products. The MIG welding parameters are the most important factors affecting the quality, productivity and cost of welding. This paper presents the influence of welding parameters like welding current, welding voltage, Gas flow rate, wire feed rate, etc. on weld strength, ultimate tensile strength, and hardness of weld joint, weld pool geometry of various metal material during welding. By using DOE method, the parameters can be optimize and having the best parameters combination for target quality. The analysis from DOE method can give the significance of the parameters as it give effect to change of the quality and strength of product.

Keywords: ANFIS, ANN, Welding Quality, MIG Welding

I. INTRODUCTION

Metal Inert Gas welding as the name suggests, is a process in which the source of heat is an arc formed between a consumable metal electrode and the work piece, and the arc and the molten puddle are protected from contamination by the atmosphere (i.e. oxygen and nitrogen) with an externally supplied gaseous shield of inert gas such as argon, helium or an argon-helium mixture. No external filler metal is necessary, because the metallic electrode provides the arc as well as the filler metal. It is often referred to in abbreviated form as MIG welding. MIG is an arc welding process where in coalescence is obtained by heating the job with an electric arc produced between work piece and metal electrode feed continuously. A metal inert gas (MIG) welding process consists of heating, melting and solidification of parent metals and a filler material in localized fusion zone by a transient heat source to form a joint between the parent metals. Gas metal arc welding is a gas shielded process that can be effectively used in all positions. MIG Welding is a widely used industrial arc welding process needs a better prediction and monitoring of its parameters to produce consistent weld quality. Quality of welding plays an important role as it improves material strength, hardness and toughness of the product. Weld quality of a product is evaluated by different parameters like weld bead geometry, hardness, deposition rate etc. All these characteristics are controlled by weld parameters like welding speed, welding current, arc voltage and electrode stick out.

To obtain good quality, is necessary to set the proper welding process parameters. Researchers attempted many techniques to establish MIG process. The effects of welding variables upon bead shape and size, bead width and height , dilution and bead geometry , weld deposit area, element transfer behavior and weld-metal chemistry in submerged-arc welding was explored. Also the effect of increasing deposition rate on bead geometry and flux component on softening temperature was examined [1] for MIG weld. Usually, the desired welding parameters are determined using traditional methods like welder's experiences, charts and handbooks (preferred values) which are simple and economical. However this does not ensure that the selected welding parameters result in satisfactory welding and this method is not applicable to new welding process. To overcome this problem, various methods of obtaining the desired output variables through models to correlate input variables with output variables have been developed. Fractional factorial techniques, Mathematical modeling, curvilinear regression equations, linear regression equations [2], response surface methodology [3], finite element modeling [3, 4], grey-based Taguchi method [5] and sensitivity analysis [6] were used to model MIG process. All These techniques are limited in application due to difficulties in modeling, time consuming and weighty. For this reason, inadequacy and inefficiency of the mathematical models to explain the nonlinear properties existing between the input and output parameters of welding lead to the development of intelligent modeling techniques. Precise simulation and analysis of the process needs attention which helps to predict the wide variety of process parameters to set the factory floor in real time.

II. RELATED WORK

Hossein Towsyfyan et al(2013), In this study, three parameters including the current, speed and welding voltage were selected as the input variables and the weld bead penetration, width and height were modeled by the regression and neural network methods. Obtained results show that quadratic regression equations for bead weld penetration, width and height have the coefficients of determination 0.901, 0.6 and 0.739, respectively and they imply the accurate modeling, acceptable fitting and proper accuracy of quadratic model. Further, despite the accuracy of regression equations, designed neural network is significantly more accurate in predicting the weld bead geometry, so that the difference in relative error of two methods reaches 83%. Also by increasing the welding current, the weld bead penetration and height will be increased and the weld width will be reduced. By increasing the welding voltage, the weld bead penetration, height and width will be increased and by increasing the welding speed, the bead penetration will be decreased, while the bead width and height will be increased

Chandrasekhar Neelamegam et al(2013), HereGenetic algorithm in combination with ANFIS models has been used for optimizing the A-TIG welding process parameters to achieve the target weld bead geometry and HAZ width in RAFM steel. The methodology is imple- mented in two steps. First, independents ANFIS models were developed correlating the welding process parame- ters like current, torch speed and arc voltage with weld bead parameters like depth of penetration, bead width and HAZ width. Second, a GA code was developed to optimize the process variables to achieve the desired tar- get depth of penetration and HAZ width. The ANFIS models were used to evaluate the objective function in the GA code. A close agreement was achieved between the target and the actual values of depth of penetration and HAZ width. Thus, the present work shows that the GA has the capability to optimize and produce multiple sets of welding process parameters that can lead to the desired weld bead profile and HAZ width accurately in RAFM steel.

I.U. Abhulimen et al(2014), revealed that the successful use of ANN to in predicting tensile and yield strength of TIG welded mild steel pipe joints and the results reported are in good agreement with other researchers. Predicted results shows a mean squared error of 34.2 for overall performance, a maximum and minimum absolute errors of 22MPa and 0.09 MPa respectively. Relative errors were 18% and 0.02% for largest and smallest errors respectively. The calculated average absolute error of 15.35% with an average percentage error of 3.5. These values are in agreement within the ranges of errors predicted by other researchers though they were conducted under different conditions. Barclay et al, (2012), reported a minimum percentage error of 0.0859 and a maximum absolute error of 0.0469 in predicting weld distortions using induced welding. They also recorded an average percentage error of 6.51%. Predicted values shows that tensile and yield strength as good as 508 MPa and 388 MPa can be achieved by a combination of certain factors as shown in the model.

P. Sreeraj et al (2013), showed that the developed model can be used to predict clad bead geometry within the applied limits of process parameters. This method of predicting process parameters can be used to get minimum percentage of dilution. In this study, ANN and GA were used for achieving optimal clad bead dimensions. In the case of any cladding process bead geometry plays an important role in determining the properties of the surface exposed to hostile environments and reducing cost of manufacturing. In this approach the objective function aimed for predicting weld bead geometry within the constrained limits.

Parth D Patel et al(2012), with the studies of MAG-CO2 welding technique and their test reports, they found that welding current has great impact on Hardness of Weld joint but other parameter like wire diameter of electrode and wire feed rate of electrode also play role in Weld Hardness. The tool use in this work NeuroXL Predictor proves as very handy tool for Different Welding Technique.The Artificial Neural Network has shown its effectiveness as a tool to predict various parameters in both MAG-CO2 and TIG welding technique.

J. Edwin Raja Dhas et al(2012), applied Taguchi method for experimentation. Relationship between the input weld parameters Weld bead width, weld reinforcement, depth of penetration and bead hardness and output weld parameters are modeled through regression analysis and additional data's are generated to train the neural network models. Validity of the developed equations is checked for adequacy. It is found that the result from neural network trained with PSO seems to have an edge over the other developed models in terms of computational accuracy and time. Confirmative experiments are done for validation. The developed model scopes for online weld quality monitoring system. To ensure high quality of welding SEM analysis is done on the weld samples indicating a good grain structure

III. METHODOLOGY

MIG Welding is a widely used industrial arc welding process needs a better prediction and monitoring of its parameters to produce consistent weld quality. Weld quality plays an important role as it improves material strength, hardness and toughness of the product[8]. Quality of a weld product is evaluated by different parameters like weld bead geometry, deposition rate, hardness etc. These characteristics are controlled by weld parameters like welding current, welding speed, arc voltage and electrode stick out. In order to attain good quality, is necessary to set the proper welding process parameters. Researchers attempted many techniques to establish MIG process. The effects of welding variables upon bead shape and size, bead width and height, dilution and bead geometry , weld deposit area, element transfer behavior and weld-metal chemistry in submerged-arc welding was explored[8]. Also the effect of increasing deposition rate on bead geometry and flux component on softening temperature was examined for MIG weld. Investigations were done to analyze the effect of welding parameters on chemical composition and mechanical properties, heat affected zone and bead geometry of MIG weld.

Usually, the desired welding parameters are determined using traditional methods like welder's experiences, charts and handbooks (preferred values) which are simple and inexpensive. But this does not ensure that the selected welding parameters result in satisfactory welding and this method is not applicable to new welding process. To overcome this problem, various methods of obtaining the desired output variables through models to correlate input variables with output variables have been developed.

Fractional factorial techniques, Mathematical modeling, curvilinear regression equations, linear regression equations, response surface methodology, finite element modeling, grey-based Taguchi method and sensitivity analysis were used to model MIG process[8]. These methods are limited in application due to difficulties in modeling, time consuming and cumbersome. Due to the inadequacy and inefficiency of the mathematical models to explain the nonlinear properties existing between the input and output parameters of welding lead to the development of intelligent modeling techniques. Precise simulation and analysis of the process needs attention which helps to predict the wide variety of process parameters to set the factory floor in real time. The type of artificial intelligence capable of responding to changes in the automated manufacturing environment, and having the ability to capture vast manufacturing knowledge is Adaptive Neuro Fuzzy Inference System (ANFIS). It is becoming widely used in all aspects of manufacturing process to assist humans.

Realizing that matter, ANFIS a state of the art artificial intelligent method, has the possibility to enhance the prediction of weld quality to find the best combination of independent variables which is welding current (I), speed (S) and welding voltage (V) as the input variables in order to achieve desired weld quality. Thus the main objectives of this project is to develop ANFIS model to predict weld bead width.

Performance Criteria Used

The first step in the ANN development process is the choice of performance criteria, as this determines how the model is assessed and will consequently affect many of the subsequent steps such as training and the choice of network architecture. Performance criteria may include measures of training and processing speed; however, the most commonly used performance criteria used is the prediction accuracy.

Performancecriteriawhichmeasurepredictionaccuracy generallymeasurethefit (or lack thereof) between the model outputs $\hat{y} = \left(\hat{y},\ldots\ldots,\hat{y}_N\right)$ and the observed data $y = \left(y_i,\ldots\ldots,y_N\right)$ by some error measure E_y. They are used during training as objective functions and after training to evaluate the trained ANFIS, where the criterion used for each purpose need not necessarily be the same.

1. Root Mean Squared Error (RMSE)

The RMSE is a measure of general model performance. It is the most easily interpreted statistic, since it has the same units as the parameters estimated. The RMSE is thus the difference, on an average, of an observed data and the estimated data. RMSE evaluates the residual between measured and forecasted values[1][2]. RMSE is a frequently-used measure of the difference between values predicted by a model or an estimator and the values actually observed from the thing being modelled or approximate. These differences are also called residuals. Hypothetically, if this criterion equals zero then model represents the perfect fit, which is not possible at all.

$$\mathrm{R}MSE = \left(\frac{1}{N} \sum_{i=1}^{N} \left(y_i - \hat{y}_i \right)^2 \right)$$

(2) Magnitude of Relative Error (MRE)

It is defined as

MRE = [Modulas of (Actual Value – Predicted Value)/ Actual Value] * 100

For MRE a higher score means worse prediction accuracy. When using MRE as a means of prediction accuracy, it is supposed that the error is proportionl to the size of the project.

Model Inputs and Structure

The modelling approach used to develop forecasting model along with details on input and output parameters is presented in this section. One of the most important steps in the development of any prediction model is the selection of appropriate input variables that will allow an ANFIS to successfully produce the desired results. Good understanding of the system under consideration is an important prerequisite for successful application of data driven approaches. The main reason for this is that ANFIS belongs to the class of data-driven approaches [2][4][5]. Physical understanding of the process being studied leads to better choice of the input variables. Here since predicting surface roughness is a complicated problem that involves multiple interacting factors. In order to build a reasonably accurate model for prediction, proper parameters must be selected. Some practical considerations in parameter selections are firstly, the selected parameters must affect the target problem, i.e., strong relationships must exist among the parameters and target (or output) variables, and secondly, the selected parameters must be well-populated, and corresponding data must be as clean as possible. Since the soft computing methods model problems based on available data, the availability and quality of data are both essential.

In the present work, the experimental data for predicting the weld bead width using MIG process has been taken from the published paper[7]. The experiment has been conducted on MS 1018 Steel using the dominant factors which are having greater influence on the responses as open circuit voltage (OCV), welding current (I) , wire feed rate (F), welding speed (S) and nozzle- to- plate distance (C). Different combinations of open circuit voltage (OCV), welding current (I) wire feed rate (F), welding speed (S) and nozzle- to- plate distance (C) were used to observe their effect on the desired response. The weld deposits were visually inspected to identify the working limits of the welding parameters.

Table 1 presents the working range of factors considered. For the convenience of the recording and processing the experimental data the upper and lower levels of the factors are coded as -1 and +1 respectively.

Table-1 Important Process Control Variables with Notations and Range.

S.no	Parameters	Units	Notations	High (+1)	Low (-1)
1	Voltage	volts	V	35	29
2	Current	amp	I	550	400
3	Wire feed rate	mm/min	F	3400	1600
4	Welding speed	mm/min	S	600	360
5	Nozzle to plate distance	mm	C	30	25

Developing the experimental design matrix

The feasible limits of the parameters were selected in such a way that the welds obtained were free from surface defects. A two level full factorial design of (2^5 = 32) thirty two experimental runs, which is a standard statistical tool to investigate the effects of five independent direct welding parameters. This technique reduces the experimentation costs and provides the required information about the main and interaction effects. The commonly employed method of varying one parameter at a time, though popular, does not give any information about interaction among parameters.

Generation of Train and Test Data

In this study, 20 data set were used for training and 12 data set were used for testing the network respectively. Normally, the data set for ANFIS needs to be divided into three parts. The first part is for the training, the second part for validation and the third part for testing. However, because the length of our sample data was not very big, we considered only two parts: training and testing. The only difference between a testing phase and a validation phase is that if the error rate of the validation phase increases, then the training stops. In this study, those two terms are used synonymously.

ANFIS Model Development

Model Selection

In the present work ANFIS Network Structure model consisting of one input layer with five input variables and an output layer consisting of weld bead width as the output variable.

Parameter Selection

As discussed earlier, ANFIS is a judicious integration of FIS and ANN, capable of learning, high-level thinking and reasoning [4][5][6] and it combines the benefits of these two techniques into a single capsule[2]. Identification of the rule base is the key of a FIS. The problems are (1) there are no standard methods for transformimg human knowledge or experience into rule base; and (2) it is required to further tune the MFs to minimise the output error and to maximise the performances. Thus when generating a FIS using ANFIS, it is important to select proper parameters, including the number of membership functions (MFs) for each individual antecedent variables. It is also important to select proper parameters for learning and refining process, including the initial step size (ss). In the present work commonly used rule extraction method i.e. subtractive clustering has been applied for FIS identification and refinement [2]. The ANFIS is simulated using the MATLAB version R2012a Fuzzy Logic Toolbox[1].

In ANFIS, the initial parameters of the ANFIS are identified using the subtractive clustering method. However, the parameters of the subtractive clustering algorithm still need to be specified. The clustering radius is the most important parameter in the subtractive clustering algorithm and is optimally determined through a trial and error procedure. By varying the clustering radius $r_a$between 0.1 and 1 with a step size of 0.01, the optimal parameters are sought by minimizing the root mean squared error obtained on a representative validation set. Clustering radius $r_b$is selected as 1.5 r_a. Default values are used for other parameters in the subtractive clustering algorithm [3]. Gaussian membership functions are used for each fuzzy set in the fuzzy system. The number of membership functions and fuzzy rules required for a particular ANFIS is determined through the subtractive clustering algorithm. Parameters of the Gaussian membership function are optimally determined using the hybrid learning algorithm. Each ANFIS is trained for 1000 epochs.

Gaussian membership function has been used as the input membership function and linear membership function for the output function. Here separate sets of input and output data has been used as input arguments. In MATLAB genfis2 generates a Sugeno-type FIS structure using subtractive clustering. Since there is only one output, genfis2 has been used to generate an initial FIS for ANFIS training. genfis2 accomplishes this by extracting a set of rules that models the data behaviour [1]. The rule extraction method first uses the subclust function to determine the number of rules and antecedent membership functions and then uses linear least squares estimation to determine each rule's consequent equations. This function returns a FIS structure that contains a set of fuzzy rules to cover the feature space.

The membership function type and the number of membership functions used in ANFIS model are given in **table 2**. The input membership function curves for the model based on performance criteria for ANFIS are shown in **figure 2**. The rule extraction method used for training ANFIS model are given in **table 3**. **Table 4** summerizes the results of types and values of model parameters used for training ANFIS.

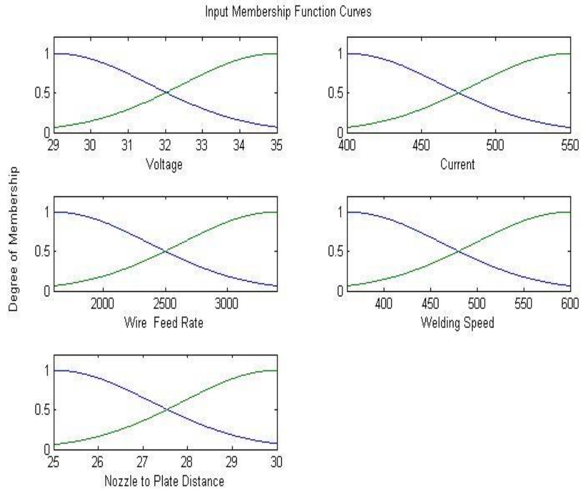

Fig:- 1 Input Membership function curves for the ANFIS model

Table 2 Parameters used in all the models for training ANFIS

Rule extraction method	Parameters used
Input MF type	Gaussian membership ('gaussmf')
Input partitioning	variable
Output MF Type	Linear
Number of output MFs	one
Training algorithm	Hybrid learning
Training epoch number	20
Initial step size	0.01

Table 3 Rule extraction method used for training ANFIS

Rule Extraction Method	Type
And method	'prod'
Or method	'probor'
Defuzzy method	'wtever'
Implication method	'prod'
Aggregation method	'max'

Figure 3 and 4 shows the comparative plots of observed and predicted bead width both for training and testing phases. The figures wisely demonstrate that (1) the model performance are in general accurate, where all data points roughly fall onto the line of agreement; (2) model using subtractive clustering is consistently superior in training phase than in testing phase.

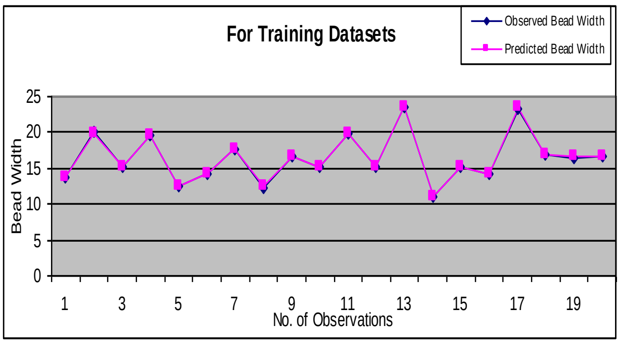

Fig.:- 2 Comparative plot ofPredicted vs. Observed Bead Width

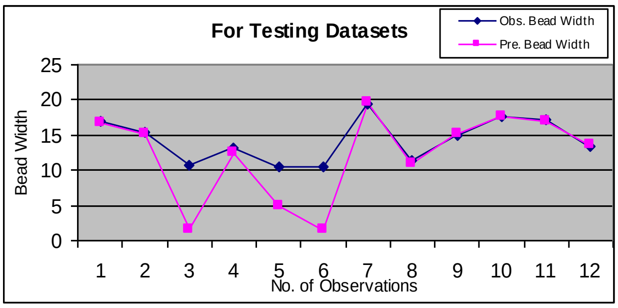

Fig.:- 3 Comparative Plot of Predicted vs. Observed Bead Width

IV. RESULTS AND DISCUSSIONS

ANFIS model having five input variables are trained and tested by ANFIS method and their performances compared and evaluated based on training and testing data. The best fit model structure is determined according to criteria of performance evaluation. The performances of the ANFIS model are shown in **Fig. 6&7** and their RMSE values both for training and testing data are 0.072 and 3.964 respectively (Table 5 below).

Table 4:- RMSE Values for Datasets after using ANFIS

	Training Datasets	**Testing Datasets**	**Total Datasets**
RMSE	0.072	3.964	3.068

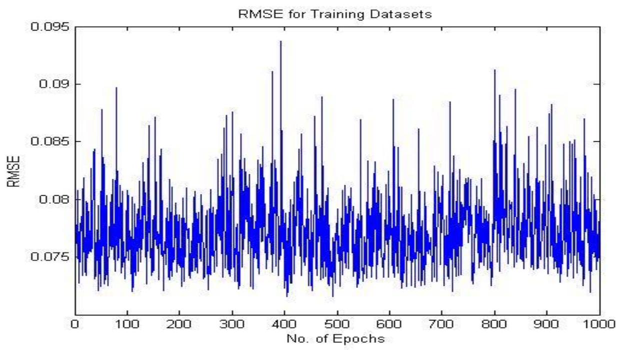

Fig.:- 4 RMSE Plot of Training Datasets during ANFIS Training

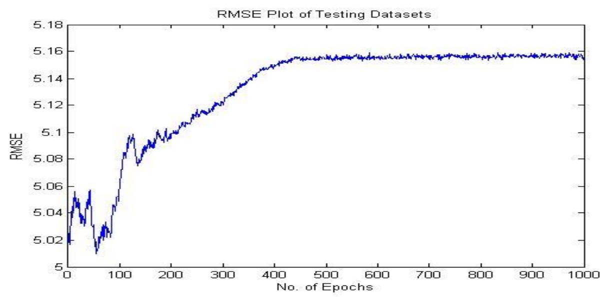

Fig.:- 5 RMSE Plot of Testing Datasets during ANFIS Training

A comparative chart of both observed and predicted (ANFIS_Output) bead width values for training and testing data are summerised in table 6 below.

Table 6:- Observed & Predicted Bead Width using ANFIS

Obs. BW	**Pre. BW**	14.12	14.13151
13.68	13.67376	23.31	23.40949
20.01	19.92199	16.97	16.96034
15.29	15.1841	16.49	16.58522
19.57	19.57124	16.69	16.58522
12.52	12.42666	16.95	16.76193
14.32	14.33816	15.42	15.12796
17.62	17.63331	10.61	1.622157
12.32	12.42666	13.2	12.5732
16.75	16.76489	10.41	4.94761
15.09	15.1841	10.41	1.622157
19.81	19.92199	19.37	19.58761
15.15	15.17991	11.29	11.03887
23.51	23.40949	14.95	15.22682
11.09	11.0812	17.62	17.60717
15.22	15.22565	17.17	16.95672
		13.48	13.71444

Further in order to judge the ability and efficiency of the model to predict the Bead Width values MRE has been used. MRE is an indication of the average deviation of the predicted values from the corresponding measured data and can provide information on long term performance of the models; the lower MRE the better is the long term model prediction. A positive MRE value indicates the amount of overestimation in the predicated Bead Width and vice versa.

The MRE of training and testing data sets for bead width are shown in fig. 8 and 9 below.

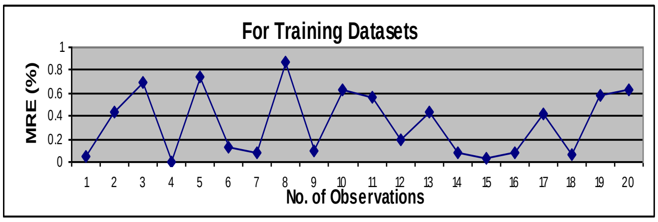

Fig. 6:- Magnitude of Relative Error for Training Datasets

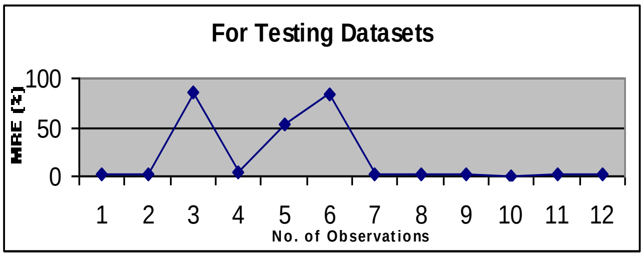

Fig.7 :- Magnitude of Relative Error for Testing Datasets

The average MRE for bead width of training data and testing data are calculated as 0.3393 and 19.0 respectively. It is an indication of deviation of the predicted values from the corresponding measured data and can provide information on long term performance of the models. The lower deviation, the better is the long term model prediction. A positive value indicates the amount of overestimation in the predicted surface roughness and vise-versa.

Further from the perusal of the scatter plot given in fig. 5 below it is evident that there is a good correlation between the predicted and the observed bead width values, as depicted by more or less straight trend line.

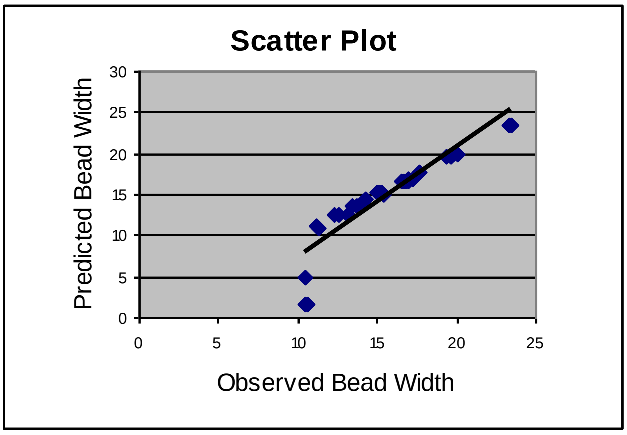

Fig.:- 8 Scatter Plot of predicted versus observed Bead Width

Further from the analysis of the observed and predicted values as given in table 6 and as also from the corresponding graph given in fig. 3 & 4 above, both for training and testing data sets, it is clear that the ANFIS model has been able to perform better for both training and testing datasets. From the perusal of Fig. 3 it is evident that all the data points corresponding to observed and predicted bead width values fall on the same line, whereas in case of Fig. 4 for testing datasets out of 12 data points, almost 75% of the values are in unison, which again shows an excellent ANFIS output.

V. CONCLUSION

In the present paper, applicability and capability of ANFIS techniques for weld bead width prediction has been investigated. It is seen that ANFIS models are very robust, characterised by fast computation, capable of handling the noisy and approximate data that are typical of data used here for the present study. Due to the presence of non-linearity in the data, it is an efficient quantitative tool to predict effort estimation. The studies has been carried out using MATLAB simulation environment. The present investigation uses arc voltages, current, welding speed, wires feed rate and nozzle-to-plate distance as process parameters and one output variable as weld bead width.

Here the initial parameters of the ANFIS are identified using the subtractive clustering method. Gaussian membership functions (given in earlier section) are used for each fuzzy set in the fuzzy system. The number of membership functions and fuzzy rules required for a particular ANFIS is determined through the subtractive clustering algorithm. Parameters of the Gaussian membership function are optimally determined using the hybrid learning algorithm. Each ANFIS has been trained for 1000 epochs.

From the analysis of the above results, given under heading Results and Discussions, it is seen that the weld bead width prediction model developed using ANFIS technique has been able to perform well. This can be concluded from the analysis of the results given under the heading "Results and Discussions". The overall RMSE value obtained from ANFIS model is 3.068. Further from Fig. 3 & 4 and Table 6 it is seen that ANFIS model line almost closely follows the observed line. This again depicts the predictive superiority of ANFIS technique.

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