Welding Quality Prediction using Advanced Artificial Intelligence Techniques

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Abstract: Submerged Arc 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. 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. 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. 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).

Keywords: ANFIS, ANN, Welding Quality, Submerged Arc Welding

1. Introduction

Submerged Arc Welding is a widely used industrial arc Welding manner desires a higher prediction and monitoring of its parameters to provide consistent weld pleasant. Quality of welding plays an vital function as it improves material power, hardness and toughness of the product. Weld first-class of a product is evaluated by means of special parameters like weld bead geometry, hardness, deposition price etc. All these characteristics are controlled by means of weld parameters like welding pace, welding current, arc voltage and electrode stick out. To attain right first-rate, is important to set the proper welding process parameters. Researchers attempted many strategies to set up SAW system. The results of welding variables upon bead form and length, bead width and height , dilution and bead geometry , weld deposit region, detail switch conduct and weld-metallic chemistry in submerged-arc welding turned into explored. Also the effect of increasing deposition rate on bead geometry and flux aspect on softening temperature turned into tested [1] for submerged arc weld. Usually, the favored welding parameters are decided using traditional strategies like welder's reviews, charts and handbooks (desired values) that are easy and inexpensive. However this does not make certain that the selected welding parameters bring about exceptional welding and this technique isn't applicable to new welding procedure. To overcome this hassle, diverse strategies of obtaining the preferred output variables via fashions to correlate input variables with output variables were developed. Fractional factorial techniques, Mathematical modeling, curvilinear regression equations, linear regression equations [2], response floor method [3], finite detail modeling [3, 4], gray-based Taguchi technique [5] and sensitivity analysis [6] had been used to version SAW procedure. All These techniques are limited in software because of problems in modeling, time ingesting and weighty. For this reason, inadequacy and inefficiency of the mathematical fashions to provide an explanation for the nonlinear houses current between the enter and output parameters of welding lead to the development of wise modeling techniques. Precise simulation and analysis of the technique wishes interest which enables to are expecting the extensive form of process parameters to set the factory floor in actual time.

2. Related Work

Hossein Towsyfyan et al(2013), In this examine, 3 parameters including the contemporary, speed and welding voltage had been decided on because the input variables and the weld bead penetration, width and top were modeled through the regression and neural community techniques. Obtained consequences display that quadratic regression equations for bead weld penetration, width and peak have the coefficients of determination 0.901, zero.6 and zero.739, respectively and they imply the correct modeling, suited fitting and right accuracy of quadratic model. Further, regardless of the accuracy of regression equations, designed neural community is extensively extra correct in predicting the weld bead geometry, in order that the distinction in relative error of two strategies reaches eighty three%. Also by using growing the welding current, the weld bead penetration and height could be multiplied and the weld width will be decreased. By increasing the welding voltage, the weld bead penetration, top and width might be elevated and by increasing the welding velocity, the bead penetration could be decreased, at the same time as the bead width and peak could be elevated

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Chandrasekhar Neelamegam et al(2013), HereGenetic set of rules in aggregate with ANFIS fashions has been used for optimizing the A-TIG welding manner parameters to gain the target weld bead geometry and HAZ width in RAFM steel. The methodology is implemented in steps. First, independents ANFIS models had been developed correlating the welding manner parame- ters like present day, torch speed and arc voltage with weld bead parameters like depth of penetration, bead width and HAZ width. Second, a GA code become developed to optimize the method variables to acquire the desired tar- get intensity of penetration and HAZ width. The ANFIS models have been used to evaluate the objective feature inside the GA code. A close agreement turned into carried out between the goal and the real values of depth of penetration and HAZ width. Thus, the existing work shows that the GA has the capability to optimize and convey more than one sets of welding procedure parameters which can cause the preferred weld bead profile and HAZ width appropriately in RAFM metallic.

I.U. Abhulimen et al(2014), found out that the a success use of ANN to in predicting tensile and yield electricity of TIG welded slight metal pipe joints and the outcomes stated are in good agreement with other researchers. Predicted effects suggests an average squared error of 34.2 for overall overall performance, a maximum and minimal absolute mistakes of 22MPa and 0.09 MPa respectively. Relative mistakes have been 18% and 0.02% for biggest and smallest errors respectively. The calculated common absolute errors of 15.35% with a mean percentage error of 3.Five. These values are in settlement inside the degrees of mistakes expected by different researchers even though they have been carried out beneath distinct situations. Barclay et al, (2012), reported a minimal percent blunders of zero.0859 and a most absolute mistakes of 0.0469 in predicting weld distortions the usage of brought about welding. They additionally recorded a median percentage blunders of 6.Fifty one%. Predicted values suggests that tensile and yield strength as properly as 508 MPa and 388 MPa can be completed by way of a aggregate of positive elements as proven in the model.

P. Sreeraj et al (2013), confirmed that the developed version can be used to expect clad bead geometry inside the carried out limits of technique parameters. This method of predicting manner parameters may be used to get minimal percentage of dilution. In this study, ANN and GA have been used for reaching premiere clad bead dimensions. In the case of any cladding method bead geometry plays an essential position in figuring out the houses of the surface uncovered to opposed environments and decreasing cost of producing. In this approach the objective characteristic aimed for predicting weld bead geometry within the constrained limits.

Parth D Patel et al(2012), with the research of MAG-CO2 welding technique and their test reports, they discovered that welding present day has fantastic impact on Hardness of Weld joint but other parameter like twine diameter of electrode and wire feed charge of electrode also play function in Weld Hardness. The tool use on this paintings NeuroXL Predictor proves as very accessible tool for Different Welding Technique.The Artificial Neural Network has shown its effectiveness as a tool to predict diverse parameters in each MAG-CO2 and TIG welding method.

J. Edwin Raja Dhas et al(2012), applied Taguchi method for experimentation. Relationship among the enter weld parameters Weld bead width, weld reinforcement, intensity of penetration and bead hardness and output weld parameters are modeled thru regression analysis and additional information's are generated to educate the neural network fashions. Validity of the advanced equations is checked for adequacy. It is observed that the result from neural community trained with PSO seems to have an facet over the opposite evolved models in phrases of computational accuracy and time. Confirmative experiments are executed for validation. The developed model scopes for on-line weld quality tracking device. To make sure high best of welding SEM evaluation is finished on the weld samples indicating a good grain structure.

3. Methodology

Submerged Arc Welding is a broadly used industrial arc welding method needs a higher prediction and tracking of its parameters to provide steady weld quality. Weld first-class performs an critical role because it improves material power, hardness and durability of the product[8]. Quality of a weld product is evaluated through exceptional parameters like weld bead geometry, deposition price, hardness and so forth. These characteristics are controlled through weld parameters like welding present day, welding velocity, arc voltage and electrode stick out. In order to achieve right first-class, is important to set the right welding method parameters. Researchers tried many techniques to establish SAW system. The consequences of welding variables upon bead form and length, bead width and peak, dilution and bead geometry , weld deposit region, detail switch behavior and weld-metal chemistry in submerged-arc welding turned into explored[8]. Also the impact of increasing deposition rate on bead geometry and flux factor on softening temperature became examined for submerged arc weld. Investigations have been finished to investigate the effect of welding parameters on chemical composition and mechanical homes, warmth affected area and bead geometry of submerged arc weld.

Usually, the desired welding parameters are decided the usage of traditional techniques like welder's reviews, charts and handbooks (desired values) which can be simple and inexpensive. But this doesn't make certain that the chosen welding parameters bring about exceptional welding and this method isn't applicable to new welding manner. To conquer this trouble, diverse strategies of obtaining the desired output variables through fashions to correlate enter variables with output variables had been developed.

Fractional factorial strategies, Mathematical modeling, curvilinear regression equations, linear regression equations, reaction surface methodology, finite element

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modeling, grey-primarily based Taguchi method and sensitivity evaluation have been used to version SAW technique[8]. These techniques are limited in software due to difficulties in modeling, time ingesting and bulky. Due to the inadequacy and inefficiency of the mathematical models to give an explanation for the nonlinear residences present among the enter and output parameters of welding result in the improvement of sensible modeling techniques. Precise simulation and evaluation of the technique needs interest which facilitates to expect the huge variety of system parameters to set the factory floor in real time. The type of synthetic intelligence capable of responding to modifications within the computerized production surroundings, and having the capacity to seize enormous production knowledge is Adaptive Neuro Fuzzy Inference System (ANFIS). It is turning into broadly used in all components of producing system to assist humans.

Realizing that matter, ANFIS a nation of the artwork synthetic smart method, has the opportunity to decorate the prediction of weld exceptional to locate the nice combination of independent variables that is welding modern (I), speed (S) and welding voltage (V) as the enter variables so one can attain desired weld nice. Thus the principle goals of this venture is to develop ANFIS model to expect 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 $\hat{y} = \left(\hat{y},........,\hat{y}_N\right)$ and the observed data $y = \left(y_i,......,y_N\right)$ 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.

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

(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 Manner being studied ends in better preference of the enter variables. Here due to the fact that predicting surface roughness is a complex trouble that includes more than one interacting factors. In order to build a reasonably correct model for prediction, right parameters need to be selected. Some practical considerations in parameter picks are first of all, the selected parameters must have an effect on the goal problem, i.E., strong relationships must exist the various parameters and goal (or output) variables, and secondly, the chosen parameters should be nicely-populated, and corresponding information need to be as easy as possible. Since the soft computing techniques version problems based on to be had information, the provision and first-class of statistics are each vital.

In the existing work, the experimental records for predicting the weld bead width the usage of SAW process has been taken from the posted paper[7]. The test has been conducted on MS 1018 Steel using the dominant factors that are having greater influence on the responses as open circuit voltage (OCV), welding modern-day (I) , wire feed price (F), welding speed (S) and nozzle- to- plate distance (C). Different mixtures of open circuit voltage (OCV), welding current (I) twine feed charge (F), welding speed (S) and nozzle- to- plate distance (C) were used to examine their impact at the desired response. The weld deposits were visually inspected to become aware of the working limits of the welding parameters.

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Table 1 affords the running range of factors taken into consideration. For the ease of the recording and processing the experimental information the top and lower stages 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 have been decided on in such a manner that the welds obtained had been unfastened from floor defects. A two stage complete factorial layout of (25 = 32) thirty experimental runs, which is a fashionable statistical tool to investigate the results of 5 impartial direct welding parameters. This technique reduces the experimentation charges and gives the specified statistics approximately the main and interplay effects. The generally hired technique of varying one parameter at a time, though popular, does no longer give any statistics about interplay amongst parameters.

Generation of Train and Test Data

In this study, 20 statistics set have been used for schooling and 12 records set have been used for testing the network respectively. Normally, the records set for ANFIS desires to be divided into 3 elements. The first element is for the education, the second one part for validation and the 0.33 component for testing. However, because the period of our pattern statistics changed into no longer very huge, we taken into consideration most effective parts: training and checking out. The only difference between a checking out section and a validation segment is that if the error price of the validation phase increases, then the education stops. In this observe, the ones two phrases are used synonymously.

ANFIS Model Develoment

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 in advance, ANFIS is a really appropriate integration of FIS and ANN, able to getting to know, high-degree questioning and reasoning [4][5][6] and it combines the blessings of these two techniques right into a single capsule[2]. Identification of the rule base is the important thing of a FIS. The problems are (1) there are no general techniques for transformimg human information or revel in into rule base; and (2) it is required to further music the MFs to minimise the output mistakes and to maximise the performances. Thus whilst generating a FIS the usage of ANFIS, it's far important to choose proper parameters, such as the number of club functions (MFs) for every individual antecedent variables. It is likewise important to choose proper parameters for learning and refining procedure, which include the preliminary step length (ss). In the prevailing work normally used rule extraction method i.E. Subtractive clustering has been implemented for FIS identity and refinement [2]. The ANFIS is simulated the use of the MATLAB version R2012a Fuzzy Logic Toolbox[1].

In ANFIS, the preliminary parameters of the ANFIS are recognized using the subtractive clustering method. However, the parameters of the subtractive clustering algorithm nonetheless want to be unique. The clustering radius is the maximum vital parameter within the subtractive clustering set of rules and is optimally determined thru a trial and mistakes method. By various the clustering radius ra among 0.1 and 1 with a step length of zero.01, the ultimate parameters are sought by minimizing the basis imply squared errors obtained on a representative validation set. Clustering radius rbis decided on as 1.Five ra. Default values are used for different parameters inside the subtractive clustering algorithm [3].

Gaussian club features are used for every fuzzy set in the fuzzy machine. The range of membership functions and fuzzy rules required for a specific ANFIS is decided via the subtractive clustering algorithm. Parameters of the Gaussian club function are optimally determined the usage of the hybrid gaining knowledge of algorithm. Each ANFIS is educated for one thousand epochs .

Gaussian club characteristic has been used because the input club characteristic and linear membership feature for the output characteristic. Here separate sets of enter and output facts has been used as enter arguments. In MATLAB genfis2 generates a Sugeno-kind FIS structure the usage of subtractive clustering. Since there's handiest one output, genfis2 has been used to generate an preliminary FIS for ANFIS education. Genfis2 accomplishes this with the aid of extracting a set of policies that models the statistics behaviour [1]. The rule extraction approach first makes use of the subclust feature to decide the quantity of regulations and antecedent club functions and then uses linear least squares estimation to determine each rule's consequent equations. This feature returns a FIS structure that contains a hard and fast of fuzzy policies to cover the function space.

The membership feature type and the range of club features utilized in ANFIS model are given in table 2. The enter club feature curves for the model primarily based on overall performance standards for ANFIS are proven in parent 2. The rule extraction approach used for education ANFIS version are

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given in table three. Table 4 summerizes the effects of sorts and values of model parameters used for schooling ANFIS.

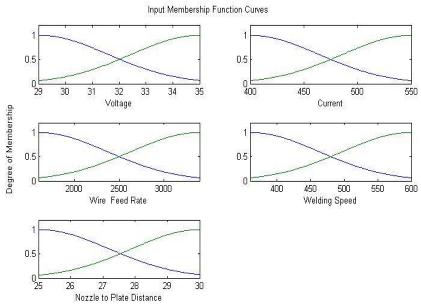

Fig:- 1 Input Membership function curves for the ANFIS model

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.

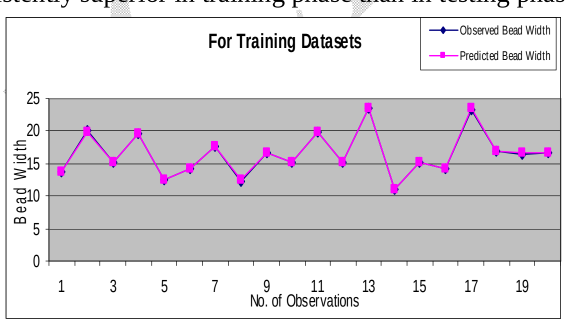

Fig.:- 2 Comparative plot of Predicted vs. Observed Bead Width

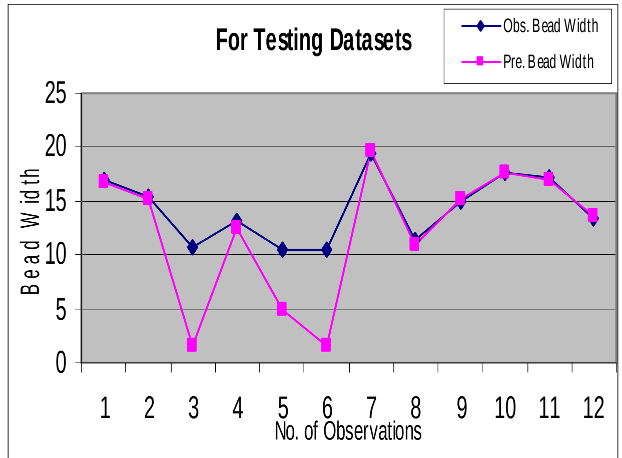

Fig.:- 3 Comparative Plot of Predicted vs. Observed Bead Width

4. Results And Discussions

ANFIS model having 5 enter variables are educated and tested by means of ANFIS method and their performances as compared and evaluated based totally on training and testing facts. The first-rate fit version shape is decided in line with criteria of overall performance evaluation. The performances of the ANFIS model are proven in Fig. 6&7 and their RMSE values both for schooling and trying out information are 0.072 and 3.964 respectively (Table five underneath).

Table 4:- RMSE Values for Datasets after using ANFIS

	Training Datasets	Testing Datasets	Total Datasets
RMSE	0.072	3.964	3.068

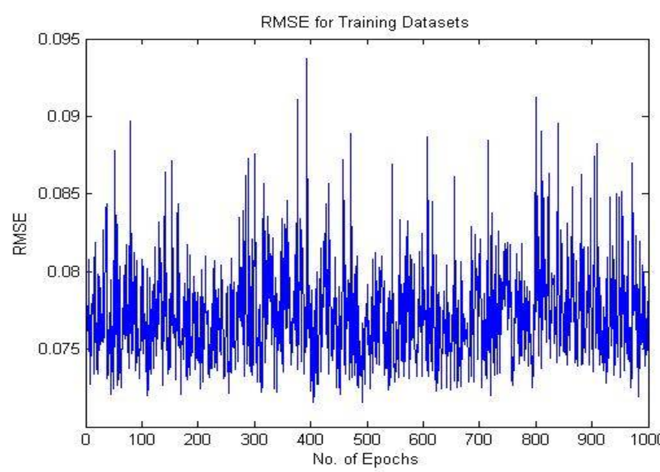

Fig.:- 4 RMSE Plot of Training Datasets during ANFIS Training

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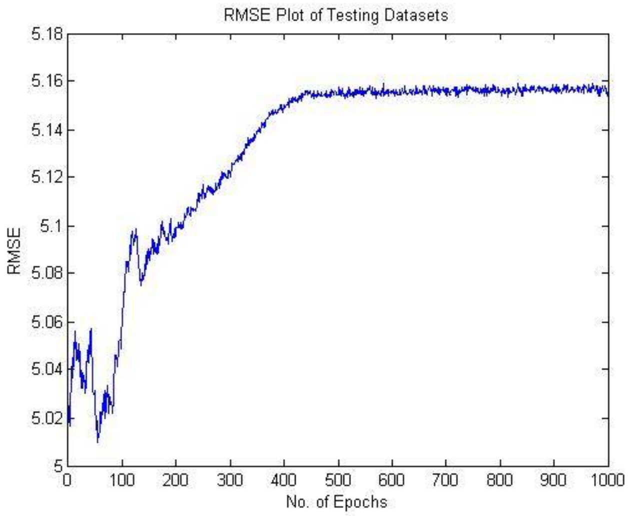

Fig.:- 5 RMSE Plot of Testing Datasets during ANFIS Training

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 with a view to judge the capability and performance of the model to predict the Bead Width values MRE has been used. MRE is an indication of the common deviation of the anticipated values from the corresponding measured facts and might offer facts on long term performance of the models; the decrease MRE the better is the long time model prediction. A positive MRE cost suggests the quantity of overestimation within the predicated Bead Width and vice versa.

The MRE of training and testing information units for bead width are proven in fig. 8 and 9 under.

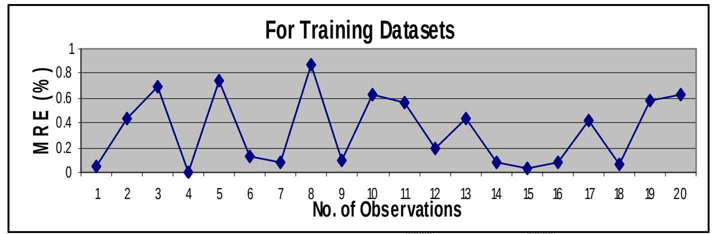

Fig. 6:- Magnitude of Relative Error for Training Datasets

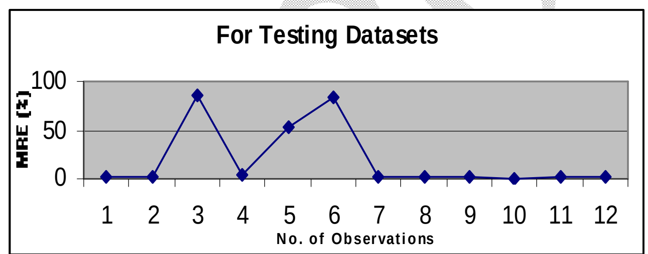

Fig.7 :- Magnitude of Relative Error for Testing Datasets

The average MRE for bead width of training statistics and checking out data are calculated as 0.3393 and 19.0 respectively. It is an indication of deviation of the anticipated values from the corresponding measured information and can provide statistics on long term performance of the fashions. The decrease deviation, the better is the long time version prediction. A high-quality cost indicates the amount of overestimation inside the anticipated floor roughness and vise-versa.

Further from the perusal of the scatter plot given in fig. Five below it is evident that there is a great correlation among the anticipated and the discovered bead width values, as depicted by way of greater or much less straight fashion line.

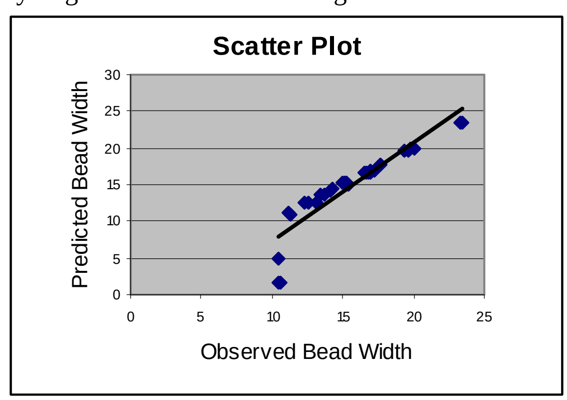

Fig.:- 8 Scatter Plot of predicted versus observed Bead Width

Further from the evaluation of the found and predicted values as given in table 6 and as also from the corresponding graph given in fig. 3 & 4 above, each for schooling and checking out records sets, it is clear that the ANFIS model has been capable of carry out higher for both education and checking

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out datasets. From the perusal of Fig. 3 it is evident that all the statistics factors similar to observed and anticipated bead width values fall on the equal line, whereas in case of Fig. 4 for checking out datasets out of 12 records factors, almost 75% of the values are in unison, which once more indicates an excellent ANFIS output.

5. Conclusion

In the present paper, applicability and functionality of ANFIS techniques for weld bead width prediction has been investigated. It is visible that ANFIS models are very robust, characterized by means of fast computation, capable of managing the noisy and approximate records that are ordinary of information used right here for the present examine. Due to the presence of non-linearity inside the statistics, it's far an green quantitative tool to expect attempt estimation. The research has been accomplished the use of MATLAB simulation environment. The present research uses arc voltages, modern-day, welding pace, wires feed charge and nozzle-to-plate distance as manner parameters and one output variable as weld bead width.

Here the initial parameters of the ANFIS are recognized using the subtractive clustering approach. Gaussian membership functions (given in earlier segment) are used for each fuzzy set in the fuzzy machine. The number of club features and fuzzy policies required for a specific ANFIS is determined thru the subtractive clustering algorithm. Parameters of the Gaussian membership feature are optimally decided the use of the hybrid gaining knowledge of set of rules. Each ANFIS has been trained for 1000 epochs.

From the analysis of the above consequences, given under heading Results and Discussions, it is visible that the weld bead width prediction version developed the usage of ANFIS technique has been capable of perform well. This can be concluded from the analysis of the results given underneath the heading "Results and Discussions". The overall RMSE value acquired from ANFIS model is three.068. Further from Fig. Three & 4 and Table 6 it is visible that ANFIS model line nearly carefully follows the located line. This once more depicts the predictive superiority of ANFIS approach.

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ICRAST 2020

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