A Thesis

on

TITLE

‘PARAMETRIC OPTIMIZATION OF MIG WELDING FOR TENSILE STRENGTH, HARDNESS AND SUFACE ROUGHNESS’

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CERTIFICATE

This is to certify that Mr. **Anoop Kumar Mishra** (Enrollment No.**-1900102579**) has carried out the research work presented in the thesis titled **"Parametric Optimization for MIG Welding for Tensile Strength, Hardness and Surface Roughness"** submitted for partial fulfillment for the award of the **Degree of Master of Technology in 2022** from **Integral University, Lucknow** under my supervision.

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DECLARATION

I hereby declare that the thesis titled **"Parametric Optimization for MIG Welding for Tensile Strength, Hardness and Surface Roughness"** is an authentic record of the research work carried out by me under the supervision of **Er. Mahmood Alam** Department of Mechanical Engineering for the period from 2019 to 2022 at Integral University, Lucknow. No part of this thesis has been presented elsewhere for any other degree or diploma earlier.

I declare that I have faithfully acknowledged and referred to the works of other researchers wherever their published works have been cited in the thesis. I further certify that I have not willfully taken other's work, para, text, data, results, tables, figures etc. reported in the journals, books, magazines, reports, dissertations, theses, etc., or available at websites without their permission, and have not included those in this M. Tech thesis citing as my own work.

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Abstract

Welding is widely used by manufacturing engineers and production personnel to set up manufacturing processes quickly and effectively 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 optimized and having the best parameters combination for target quality. The analysis from DOE method can give the significance of the parameters as it gives effect to change of the quality and strength of product.

Chapter 1

Introduction

1.1 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.

1.2 Key MIG process variables

- Wire feed speed (main factor in welding current control)
- Arc voltage
- Travel speed
- Electrode stick-out (ESO) or contact tip to work (CTTW)
- Polarity and current type (AC or DC) and variable balance AC current

1.3 Material applications

- Carbon steels (structural and vessel construction)
- Low alloy steels
- Stainless steels
- Nickel-based alloys
- Surfacing applications (build-up, wear-facing, and corrosion defiant overlay of steels)

1.4 Advantages

- High deposition rates (over 45 kg/h (100 lb/h) have been reported).
- Deep weld penetration.
- High operating factors in mechanized applications.
- Sound welds are readily made (with good process design and control).
- Minimal welding fume or arc light is emitted.
- High speed welding of thin sheet steels up to 5 m/min (16 ft/min) is possible.
- Practically no edge preparation is necessary.
- Low distortion
- The process is suitable for both indoor and outdoor works.
- Welds produced are sound, uniform, ductile, corrosion resistant and have good impact value.

- Single pass welds can be made in thick plates with normal equipment.
- 50% to 90% of the flux is recoverable, recycled and reused
- The arc is always covered under a blanket of flux, thus there is no chance of spatter of weld.

1.5 Limitations

- Limited to ferrous (steel or stainless steels) and some nickel-based alloys.
- Normally limited to long straight seams or rotated pipes or vessels.
- Normally limited to the 1F, 1G, and 2F positions.
- Requires relatively troublesome flux handling systems.
- Requires inter-pass and post weld slag removal.
- Flux and slag residue can present a health and safety concern.

1.6 Objective and scope of the present work

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, response surface methodology, finite element modeling, grey-based Taguchi method and sensitivity analysis were used to model MIG method. All the methods are limited in application due to difficulties in modeling, time consuming and weighty. Owing 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. Here artificial intelligence capable of responding to changes in the automated manufacturing surroundings, it also has 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 quality.

1.7 Brief Outline about ANFIS

Adaptive neuro-fuzzy inference system is a fuzzy inference system implemented in the framework of an adaptive neural network. The hybrid learning method, ANFIS preserve construct an input-output mapping based on both human-knowledge as fuzzy if-then rules and approximate membership functions from the stipulated input-output data pairs for neural network training. The process of developing a FIS using the framework of adaptive neural network is called an adaptive neuro fuzzy inference system (ANFIS) [9][10][11]. There are two methods that ANFIS learning employs for updating membership function parameters: 1) backpropagation for all parameters (a steepest descent method), and 2) a hybrid method consisting of backpropagation for the parameters associated with the input membership and least squares estimation for the parameters associated with the output membership functions. As a consequence, the training error is reduced at least locally, all through the learning process. It applies the least-squares method to identify the consequent parameters that define the coefficients of each output equation in the Sugeno-type fuzzy rule support. Here the training process continues till the desired number of training steps (epochs) or the desired root mean square error (RMSE) between the desired and the generated output is achieved. This study uses a hybrid learning algorithm, to recognize foundation and consequent parameters of first order Takagi-Sugeno type fuzzy system for predicting surface roughness in ball end milling.

1.8 Data to be used

The various input parameters which are going to be used are namely open circuit voltage (OCV), welding current (I) , wire feed rate (F), welding speed (S) and nozzle- to- plate distance (C) [12]. The output of the model is Weld Bead Width. Practical data according to the design of experiment are going to be used for training and testing different ANFIS architectures. For developing the ANFIS models MATLAB platform will be used.

1.9 Layout and content of the thesis

The second chapter is about the literature review, followed by chapter three dealing with research methodology used for ANFIS model development. Here a detailed description about Adaptive Neuro Fuzzy Inference System (ANFIS) is given. The fourth chapter is about Forecast model development using Artificial Neural Network. Here ANFIS model has been developed using experimental data obtained from published journal paper using MATLAB platform. Finally, the fifth chapter is all about conclusion of the present work and future recommendations.

Chapter 2

Literature Review

2.1 Introduction:

MIG Welding (MIG) is one of the major metal fabrication techniques in industry due to its reliability and capability of producing good quality weld. The ability to join thick plates (as thick as 1.5 inch) in a single pass, with high metal deposition rate has made this process useful in large structural applications. Indeed various research works have been explored on various aspects of MIG welding, yet investigations are still being carried on to study the phenomenon that occurs during the process of submerged arc welding, and many other related matters, so that the process becomes controllable more precisely, and can be monitored well, both manually as well as automatically. In MIG welding, various process parameters interact in a complicated manner, and their interactions influence the bead geometry, bead quality as well as metallurgical characteristics and mechanical properties of the weldment. Acceptability of the weldment depends on various quality characteristics that confirm functional requirements of the welded joint in the intended area of application. In most of the cases, quality of the weld is left to depend on the past experience and working skill of operator. But, with the advent of automation, it is now possible to design a machine capable of selecting optimal process parameters to provide desired yield. Research in the field of MIG welding is not new.

Farhad Kolahan et al (2009), In this research a procedure was proposed to model and optimize weld bead geometry in GMAW process. Since, the relationships between bead geometry characteristics and welding output variables are complicated; a regression based method was employed to model the process. The experimental data for model development were gathered using the actual tests carried out by the authors. Along this line, using DOE approach and regression analysis, different mathematical models were developed to establish the relationships between welding input parameters and weld bead geometry outputs. A Simulated Annealing technique was developed to minimize the error function consisting of desired and calculated weld bead geometry. By minimizing such a function, the process parameters can be determined so as the resultant bead geometry has the least deviation from its desired value. Computational results indicate that the proposed SA method can efficiently and accurately determine welding parameters so as a desired bead geometry specification is obtained.

Shahnwaz Alam et al (2012), showed that the two level full factorial designs are an effective tool for quantifying the main and interaction effect of variables on weld width. The developed model can be effectively used to predict the weld width in the MIG welding within the range of parameters used. Proposed models are adequate to predict the weld width with a confidence level of 95%. Weld width rapidly increases with voltage, slowly increases with current and wire feed rate and decreases with welding speed and nozzle to plate distance. The F-test indicates that the regression model as a whole is significant. Cross- validation test full-fills the validity of the models developed.

Karuna et al (2011), Here the combined effect of welding parameters on weld metal composition in MIG process was examined. Accordingly, the following conclusions can be drawn: It is interesting to note that chromium, molybdenum & silicon elements displaying a increasing trend & manganese element displaying a decreasing trend with an increase in any parameter, viz voltage, current & speed. An attempt was made to determine important welding parameters for composition of weld like Cr, Mn & Si in the MIG process. For controlling the weld metal composition, welding voltage is more effective than is welding current.

K. Lalitnarayan, et; al, (2011), showed that in gas metal arc welding where a gap exists, regression model questions of welding parameters which were thought to produce the desired geometry of the back-bead can be obtained. Both sides of the process regression model equation of the geometry parameters of the back-bead and welding process parameters are found and, after analysis it was found that whereas the correlation between parameters for the bead shape and welding process parameter has until now been
applied generally to bead-on-plate welding, this study extends the range of the research to the geometry prediction of the back-bead in butt welding where a gap exists. In order to obtain the geometry of the back-bead using the welding process parameters, the multiple regression analysis is modelled into a linear equation. The error rate of analysis had a maximum value of 9.5 percent. Also, the groove gap had the largest error rate for prediction, followed by the depth of the back-bead and the width of the back-bead. Thus, the groove gap was thought to be the most difficult parameter to predict. The multiple regression analysis of the welding process

parameters which were though to produce the desired back-bead was modeled into a linear equation and the error rate of analysis was under 6.5 percent. Also, the normalized welding speed had the largest error rate for prediction, followed by the normalized arc voltage and the normalized welding current. In this case, the welding speed was thought to be the most difficult parameter to predict.

A. K. LAKSHMINARAYANAN et. al (2009), have described the use of design of experiments(DOE) for conducting experiments. Two models were developed for predicting tensile strength of friction stir welded AA7039 aluminium alloy using response surface methodology and artificial neural network(ANN). From this investigation important conclusions derived was that rotational speed is the factor that has greater influence on tensile strength, followed by welding speed and axial force. Further, a maximum tensile strength of 319 MPa is exhibited by the FSW joints fabricated with the optimized parameters of 1 460 r/min rotational speed, 40 mm/min welding speed and 6.5 kN axial force. The predictive ANN model is found to be capable of better predictions of tensile strength within the range that they had been trained. The results of the ANN model indicate it is much more robust and accurate in estimating the values of tensile strength when compared with the response surface model.

Suneel Ramachandra Joshi, (2014), The literature review provides insight into the application of DOE, ANN, GA, Taguchi method and other techniques for modeling and optimizing different welding processes. It was noted that RSM performs better than other techniques, especially ANN and GA, when a large number of experiments are not affordable. The trend in the modeling using RSM has a low order non-linear behavior with a regular experimental domain and relatively small factors region, due to its limitation in a model building to fit the data over an irregular experimental region. The main advantage of RSM is its ability to exhibit the factor contributions from the coefficients in the regression model. This ability is powerful in identifying the insignificant factors, main effect, insignificant interactions or insignificant quadratic terms in the model and thereby can reduce the complexity of the problem. But, this technique requires good definition of ranges for each factor to ensure that the response(s) under consideration is changing in a regular manner within this range. The most popular designs within RSM designs are the central composite design (CCD) and Box-Behnken design. RSM uses model to make contour plots of predicted behavior.

2.2 ANN approach:

Another approach used for modelling, simulation and prediction in MIG welding is the Artificial Neural Network. ANN creates a mapping between set of inputs and corresponding responses. ANN is very efficient to model and simulate process behaviour, while the nature of response variation, with varying inputs, is very much complicated. Depending on huge data set obtained from experiments (combination of inputs and outputs), ANN itself establishes a correlation among inputs and outputs, into its internal architecture, that consists of input, output, hidden layers and connection between the layers (nodes/neuron). ANN then predicts output for a given combination of factor settings (inputs). The perfection of network prediction or network performance depends on the data set used to train the network, and selection of its internal features viz. number of hidden layers, number of nodes in a layer, leaning rate, training algorithm, performance goal and so on. Adequate data set with optimal network architecture can predict results with minimum error. An important step in building the network is selection of input variables. In the field of welding, some studies have been made with the neurons of the input layer to receive the input process parameters, while the neurons of the output layer were used to send out the features of quality characteristics of the weldment viz. weld bead and HAZ geometry, mechanical properties of the weldment, metallurgical features of the weld metal as well as HAZ.

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 implemented 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.

José Manuel Arroyo Osorio, et al(2007), have proposed a fuzzy logic method to suggest a reference tool geometry for different work-tool materials pairs by interpolating between empirically optimized tool geometries. With this method it is possible to suggest a tool geometry for not tested work-tool material pairs, diminishing the amount of experimental work necessary to optimize the tool tip geometry. The system can be improved by retraining it each time that the knowledge base of optimized tool geometries is increased or improved. In order to model the empirical knowledge about recommended cutting tool geometry, the reliable available data to train the fuzzy logic system was very few compared with the space of the problem, therefore was not made the normal procedure of using a percentage of the data to verify the system. Alternatively it was used a method found in the literature for tool geometry reliability evaluation.

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

Alice E. Smith et al (1993), demonstrated that neural networks can be comparable to Shewhart X-bar and R control charts for large shifts in mean or variance, and can out perform them for small shifts. For shape interpretation and prediction, networks performed best with minimal noise and maximum number of inputs. All neural networks proved capable of good quality decisions regarding pattern identification even in light of sparse and noisy data.

Literature summary

The critical review of the literature indicates that a lot of work has been done in the field of MIG Welding. Many investigators like Farhad Kolahan et al (2009), Shahnwaz Alam et al (2012), Karuna et al (2011), Hossein Towsyfyan et al(2013), Chandrasekhar Neelamegam et al(2013), etc., have studied the various responses like bead geometry, quality of weld, hardness and HAZ etc., and developed mathematical and theoretical models. The value and nature of the responses depend upon the range and selection of the input parameters i.e., current, voltage, electrode stick out, flux composition, travel speed, polarity etc. Many researchers Alice E. Smith et al (1993), J. Edwin Raja Dhas et al (2012), Parth D Patel et al(2012), P. Sreeraj et al (2013), José Manuel Arroyo Osorio, et al(2007), I.U. Abhulimen et al(2014), etc. have developed optimization models of the MIG welding process using the various like ANN, RSM, fuzzy logic etc.

2.3 Conclusion:

From the critical review of relevant literature, it has been found that no systematic work on an integrated approach of studying the effects of various welding process variables (welding current, voltage, welding speed, wire feed rate, nozzle-to-plate distance- all together) on bead geometric descriptors using full factorial technique and predicting the weld bead geometry using Artificial Neural Net work (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) has been found in the literature for MIG Welding.

Based on this literature review it has been found that a systematic work needs to be carried out to relate the welding parameters with weld bead geometry using Artificial Neural Network (ANN), Adaptive Neuro-Fuzzy Inference System (ANFIS) and Multiple Regression Analysis (MRA) on MIG Welding. Thus Mathematical relationships are needed to be developed between the welding process parameters viz. welding current, arc voltage, welding speed, wire-feed-rate, nozzle-to-plate distance and the important weld-bead geometrical variables viz. penetration depth, reinforcement height and weld width of the welded joint using full factorial design technique.

Chapter 3

Research Methodology

3.1 Adaptive Neural Fuzzy Inference System (ANFIS):

In 1965, Zadeh [11] published the first paper on a novel way of characterizing non-probabilistic uncertainties, which he called fuzzy sets. Recently resurgence in the field of artificial neural network has injected a new driving force into the fuzzy literature. The back-propagation learning rule which drew little attention till its application to ANN was discovered, is actually a universal learning paradigm for any smoothed parameterised model, including fuzzy inference systems (FIS)(or fuzzy models). As a result now fuzzy inference system can not only take linguistic information (linguistic rules) from human experts but also adapt itself using numerical (data inputs/outputs pairs) to achieve better performance. This gives fuzzy inference systems an edge over neural networks, which cannot take linguistic information directly. When represented as an adaptive network, FIS is called ANFIS [7][8].

3.2 Need for Adaptive Neuro Fuzzy Inference System (ANFIS)

A fuzzy inference system can utilize human expertise by storing its essential components in rulebase and database, and perform fuzzy reasoning to infer the overall output value. The derivation of fuzzy if then rules and corresponding membership functions depend heavily on the a priori knowledge about the system under consideration. However, there are still two basic but important problems concerning the preparation and manipulation of knowledge. Firstly, no systematic way exists to transform experience or knowledge of human experts to the knowledge base of a fuzzy inference system and secondly, there is still a need of adaptability or learning algorithms to tune the membership functions so as to minimise the discrepancy between models (calculated) output and desired output [7][8].These two problems greatly restrict the application domains of FIS. On the other hand, Neural Network modelling does not rely on human expertise. Instead, it employs a learning procedure and a given training data set to solve a set of parameters (i.e. weights) such that the required functional behaviour is achieved. No effective methods have been proposed to determine the initial weight values and network’s configuration (e.g. number of hidden layers and hidden nodes).

Thus the drawbacks pertaining to these two approaches seems complimentary. Therfore it seems natural to consider building an integrated system combining the concepts of fuzzy logic modelling and neural network modelling. In other words, the integrated approach, or neuro-fuzzy modelling, should incorporate the three most important features,

1. Meaning and concise representation of structured knowledge.
2. Efficient learning capability to identify parameters.

Clear mapping between parameters and structured knowledge.

3.3 ANFIS: Adaptive-Network-based Fuzzy Inference System:

(a) ANFIS Architecture

ANFIS has been shown to be powerful in modelling numerous processes such as time series, real-time reservoir operations and river flow forecasting [2][3][5]. ANFIS possesses properties such as capability of learning, constructing, expensing and classifying. It has the advantage of allowing the extraction of fuzzy rules from numerical data or expert knowledge and adaptively constructs a rule base. Moreover, it can adapt the complicated conversion of human intelligence to fuzzy systems. The main difficulty of the ANFIS predicting model is the time required for training structure and determining parameters. ANFIS uses the learning ability of the ANN to define the input-output relationship and construct the fuzzy rules by determining the input structure. The system results were obtained by thinking and reasoning capability of the fuzzy logic. The ANFIS architecture consists of five layers (***Figure 3.1***). Here the circles denote a fixed node whereas squares denote an adaptive node. For simplicity it is assumed that the examined FIS has two inputs and one output. For a first order Sugeno fuzzy model, a typical rule set with two fuzzy if-then rules can be expressed as

Rule 1: $IF\ x\ is\ A_1 and\ y\ is\ B_1 THEN\ f_1 = p_1x + q_1y + r_1$

Rule 2: $IF\ x\ is\ A_2 and\ y\ is\ B_2 THEN\ f_2 = p_2x + q_2y + r_2$

where, x and y are the crisp inputs to the node i , $A_i$and $B_i$are the linguistic labels (low, medium, high, etc.) characterized by convenient membership functions and p_i, $q_i$and r_i are the consequence parameters (i = 1 *or* 2) [1][7][8].

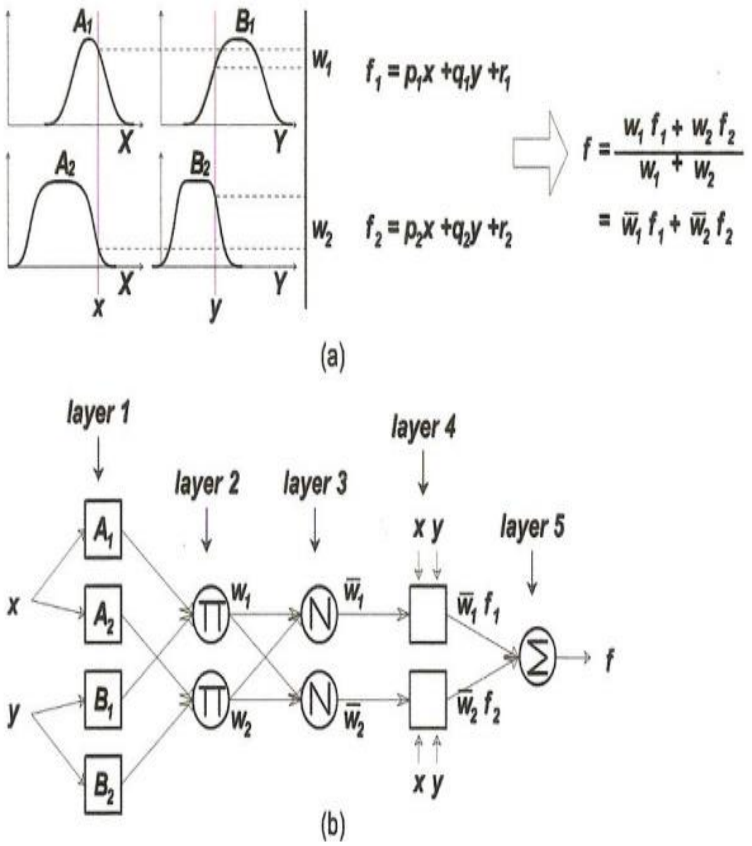

Fig 3.1 (a) A two input first-order Sugeno fuzzy model with two rules; (b) equivalent ANFIS architecture (Jang, 1993)

The model is briefly presented step by step in the following way;

Input nodes (Layer 1): Each node in this layer generates membership grades of the crisp inputs which belong to each of convenient fuzzy sets by using the membership functions. Each node's output $Oi^1$is calculated by:

$$O_i^1 = \mu_{A_i}(x) \text{ for i= 1,2 ; } \quad O_i^1 = \mu_{B_{i-2}}(y) \text{ for i= 3,4} \qquad (3.1)$$

Where $\mu_{Ai}$and $\mu_{Bi}$are the appropriate membership functions for $A_i$and $B_i$fuzzy sets, respectively. Many various membership functions such as trapezoidal, triangular, Gaussian function, etc. can be applied to determine the membership grades. The gauss membership function is used, as;

$$O_i^1 = \mu_{A_i}(x) = e^{\frac{-(x-c)^2}{2\sigma^2}} \quad (3.2)$$

Where, $\{a_i, b_i, c_i\}$ is the membership functions' parameter set that changes the shape of membership function from 1 to 0. These parameters are referred to as the premise parameters.

Rule nodes (Layer 2): In this layer, the AND/OR operator is applied to get one output that represents the results of the antecedent for a fuzzy rule, that is, firing strength. It means the degrees by which the antecedent part of the rule is satisfied and it indicates the shape of the output function for that rule. The outputs of the second layer, called as firing strengths O_i^2 are the products of the corresponding degrees obtaining from layer 1, named as *w* givenbelow.

$$O_i^2(x) = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \text{ i=1, 2} \quad (3.3)$$

Average nodes (Layer 3): Main target is to compute the ratio of firing strength of each ith rule to the sum of all rules' firing strength. Thus the firing strength in this layer is normalized as;

$$O_i^3 = \overline{w_i} = \frac{w_i}{\sum w_i} \text{ i=1, 2} \quad (3.4)$$

Consequent nodes (Layer 4): The contribution of ith rule's towards the total output or the model output and/or the function defined is calculated in Equation (4.21);

$$O_i^4 = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i x + r_i) \text{ i=1, 2} \quad (3.5)$$

Where, $w_i$is the ith node's output from the previous layer (i.e., demonstrated in the third layer). $\{p_i, q_i, r_i\}$is the parameter set in the consequence function and also the coefficients of linear combination in Sugeno inference system.

Output nodes (Layer 5): This layer is called as the output notes in which the single note computes the overall output by summing all the incoming signals and is the last step of the

ANFIS. Hence, each rule's fuzzy results are transformed into a crisp output in this layer by defuzzification process, as;

$$f\left(x,y\right)=\frac{w_1\left(x,y\right)f_1\left(x,y\right)+w_2\left(x,y\right)f_2\left(x,y\right)}{w_1\left(x,y\right)+w_2\left(x,y\right)}=\frac{w_1 f_1+w_2 f_2}{w_1+w_2} \tag{3.6}$$

$$O_i^5=f\left(x,y\right)=\sum_i w_i f_i=\overline{w_i} f_1+\overline{w_i} f_2=\frac{\sum_i w_i f_i}{\sum_i w_i} \tag{3.7}$$

There are two major phases for implementing the ANFIS for specific applications: the structure identification phase and the parameter identification phase. The structure identification phase involves finding a suitable number of fuzzy rules and fuzzy sets and a proper partition feature space. The parameter identification phase involves the adjustment of the premise and consequence parameters of the system. More detailed descriptions of the two phases are provided in the following two sections (b) and (c).

(b) Parameter indentification using hybrid learning algorithm

During the learning process, the premise parameters in the layer 1, {c ,σ }, and the consequent parameters in the layer 4, {p, q, r}, are tuned until the desired response of the FIS is achieved. The two frequently used training methods are the back-propagation (BP) algorithm and the hybrid learning algorithm [8]. The hybrid learning algorithm, which combines the least squares method (LSM) and the BP algorithm, is used to rapidly train and adapt the FIS. This algorithm converges much faster since it reduces the dimension of the search space of the original BP algorithm [8]. When the premise parameters are fixed, the overall output can be expressed as a linear combination of the consequent parameters. The output f can then be written as:

$$f=\frac{w_1}{w_1+w_2}f_1+\frac{w_2}{w_1+w_2}f_2=\overline{w_1}f_1+\overline{w_2}f_2 \tag{3.8}$$

$$=\left(\overline{w_1}x\right)p_1+\left(\overline{w_1}y\right)q_1+\left(\overline{w_1}\right)r_1+\left(\overline{w_2}x\right)p_2+\left(\overline{w_2}y\right)q_2+\left(\overline{w_2}\right)r_2$$

Which is linear in the consequent parameters p_1, q_1, r_1, p_2, q_2 and r_2. The hybrid learning algorithms of ANFIS consist of the following two parts [8]: (a) the learning of the premise parameters by back-propagation and (b) the learning of the consequence parameters by least-squares estimation. In the forward pass of the hybrid learning algorithm, functional signals go forward until layer 4 to calculate each node output. The nonlinear or premise parameters in the layer 2 remain fixed in this pass. The consequent parameters are identified by the least squares estimate. In the backward pass, the error rates propagate backward from the output end towards the input end, and the premise parameters are updated by the gradient descent. Jang [7][8] provided the detailed description and the mathematical background of the hybrid learning algorithm.

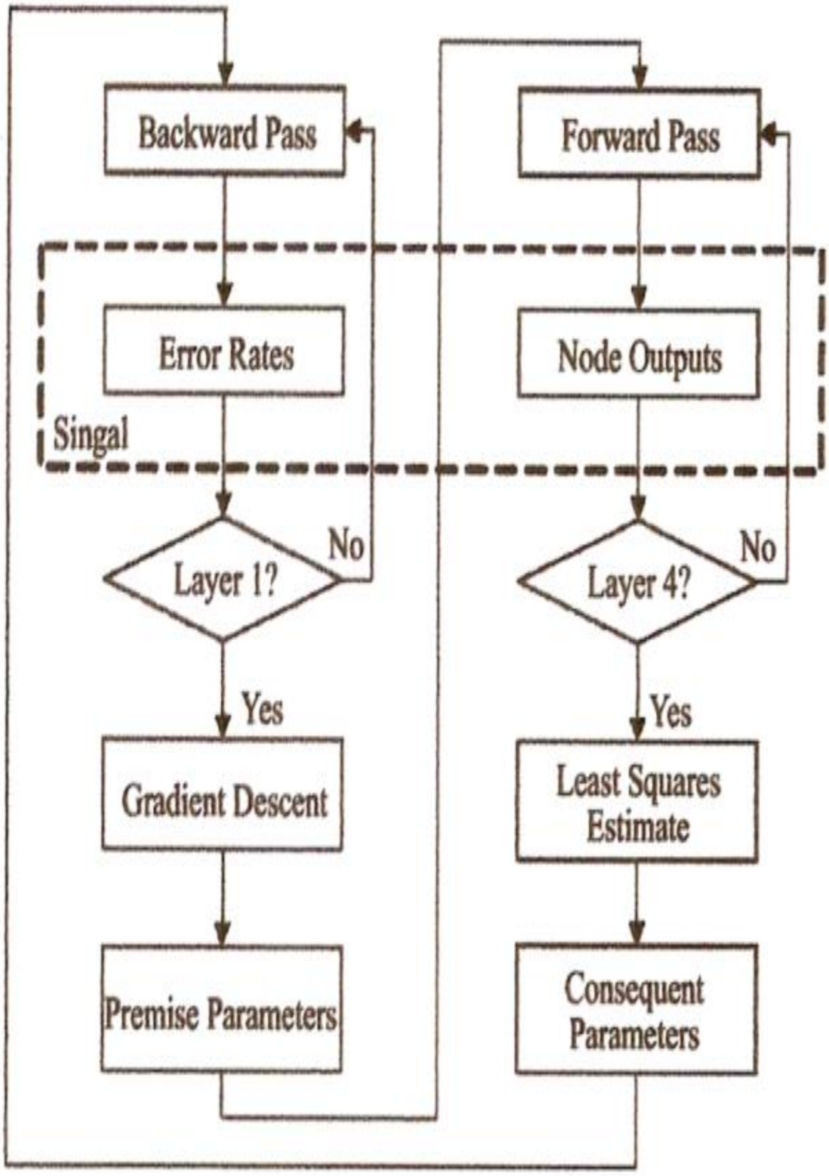

Fig. 3.2 Data Flow diagram for Hybrid learning algorithm (*Chih-Hsien Lin, 2007*)

(c) Structure identification

Clustering is a process in which data are placed into groups or clusters, such that data in a given cluster tend to be similar to each other, and data in different clusters tend to be dissimilar. When the clustering estimation is applied to a set of input output data, each cluster centre can be considered as a fuzzy rule that describes the characteristic behaviour of the system. Each cluster centre corresponds to fuzzy rule, and the cluster identified represents the antecedent of this rule. This step forms the structure identification [11].

Clustering algorithms are used extensively not only to organize and categorize data, but are also useful for data compression and model construction [6]. By finding similarities in data, one can represent similar data with fewer symbols. The density function for a data point is defined as the measure of potential for that data point. It is estimated based on the distance of this data point from all other data points, Therefore, a data point lying in a heap of other data points will have a high chance of being a cluster centre, while a data point which is located in an area of diffused and not concentrated data points will have a low chance of being a cluster centre.

Subtractive clustering is a technique for automatically generating fuzzy inference systems by detecting clusters in input-output training data. Subtractive clustering considers each data point as a potential cluster centre. The measure of potential for a data point is estimated based on the distance of this data point from all other data points. Therefore, a data point lying in a heap of other data points will have a high chance of being a cluster centre, while a data point which is located in an area of diffused and not concentrated data points will have a low chance of being a cluster centre [4][9].

After measuring the potential of every data point, the data point with the greatest potential value is elected as the first cluster centre. To find the next cluster centre, potentials of data points must be revised. For each data point, an amount proportional to its distance to the first cluster centre will be subtracted. This reduces the chance of a data point centre. After revising the potential of al1 data points, the data point with the maximum potential will be selected as the next cluster centre. The potential of data points in the first step is measured as given by Chiu [4]. Given a collection of *n* data points $\{x_1, \ldots\ldots x_n\}$, the subtractive clustering algorithm considers each data point as a potential cluster center. A density measure at a data point $x_i$is defined as

$$D_i = \sum_{j=1}^{n} e^{-\left|x_i - x_j\right|^2 / (r_a/2)^2} \tag{3.9}$$

where the cluster radius $r_a$is a positive constant. Thus, a data point that has many neighbouring data points will have a high potential of being a cluster center. The radius $r_a$defines a neighbourhood. Data points outside this radius have little effect on the density measure. The choice of $r_a$plays an important role in determining the number of clusters. Large values of $r_a$will generate a limited number of clusters, while small values of $r_a$will generate a large number of clusters. After the density measure of each data point has been calculated, the first cluster center is chosen to be the data point with the highest density measure. Suppose x_{c_1} is the point selected and D_{c_1} is its density measure, then the density measure for each data point $x_i$is revised by the formula

$$D_i = D_i - D_{c_i} e^{-\left|x_i - x_{c_i}\right|^2 / (r_b/2)^2} \tag{3.10}$$

where $r_b$is a positive constant. Note that the data points near the first cluster center x_{c_1} will have significantly reduced density measures, so that they are unlikely to be selected as the next cluster center. The constant $r_b$is usually greater than $r_a$to prevent closely spaced cluster centers. Generally $r_b$is specified as 1.5 times of r_a. After the density measure for each data point is revised, the next cluster center x_{c_2} is selected, and all of the density measures for data points are revised again. Subtractive clustering can be used as a standalone approximate clustering algorithm in order to estimate the number of clusters and their locations.

3.4 Working Principle Of MIG Welding:

The electrode in this process is in the form of coil and continuously fed towards the work during the process. At the same time inert gas (e.g. argon, helium, Co2) is passed around electrode from the same torch. Inert gas usually argon, helium, or a suitable mixture of these is used to prevent the atmosphere from contacting the molten metal and HAZ.

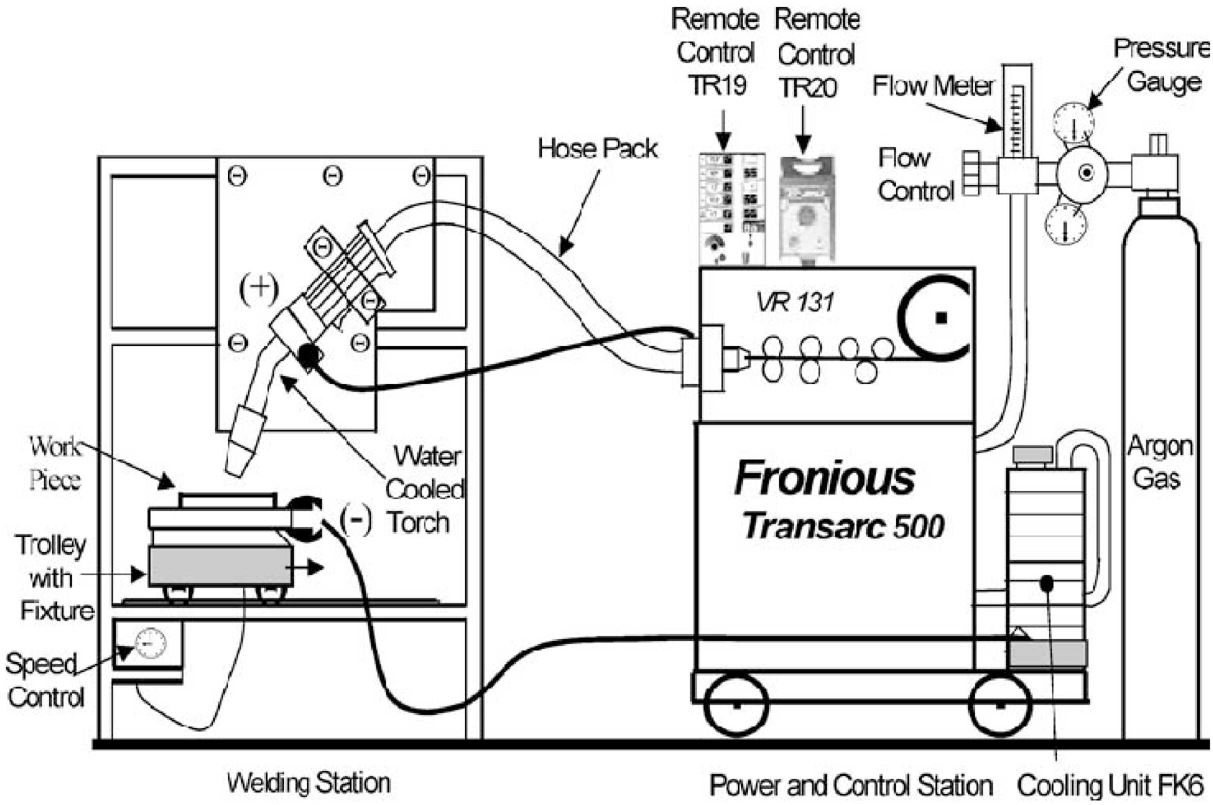

Fig 3.2: MIG welding Process Setup.

When gas is supplied, it gets ionized and an arc is initiated in between electrode and work piece. Heat is therefore produced.

Electrode melts due to the heat and molten filler metal falls on the heated joint. The weld bead geometry, depth of penetration and overall weld quality depends on the following operating variables.

- Electrode size, Welding current, Arc voltage
- Arc travel speed, welding position
- Gas Flow rate, Shielding Gas composition
- Electrode extension

Chapter 4

ANFIS Model Development

4.1 Introduction:

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.

4.2 Performance Criteria Used:

The first step in the ANN development process is the choice of performance criteria, as this determine show the model is assessed and will consequently affect many of the subsequent steps such straining 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.

Performance criteria which measure prediction accuracy generally measure the fit (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 MeanSquaredError R(MSE)

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.

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

(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.

4.3 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 4.1: 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

4.3.1 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.

4.3.2 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.

4.4 ANFIS Model Development:

4.4.1 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. This is shown in Fig. 1 below.

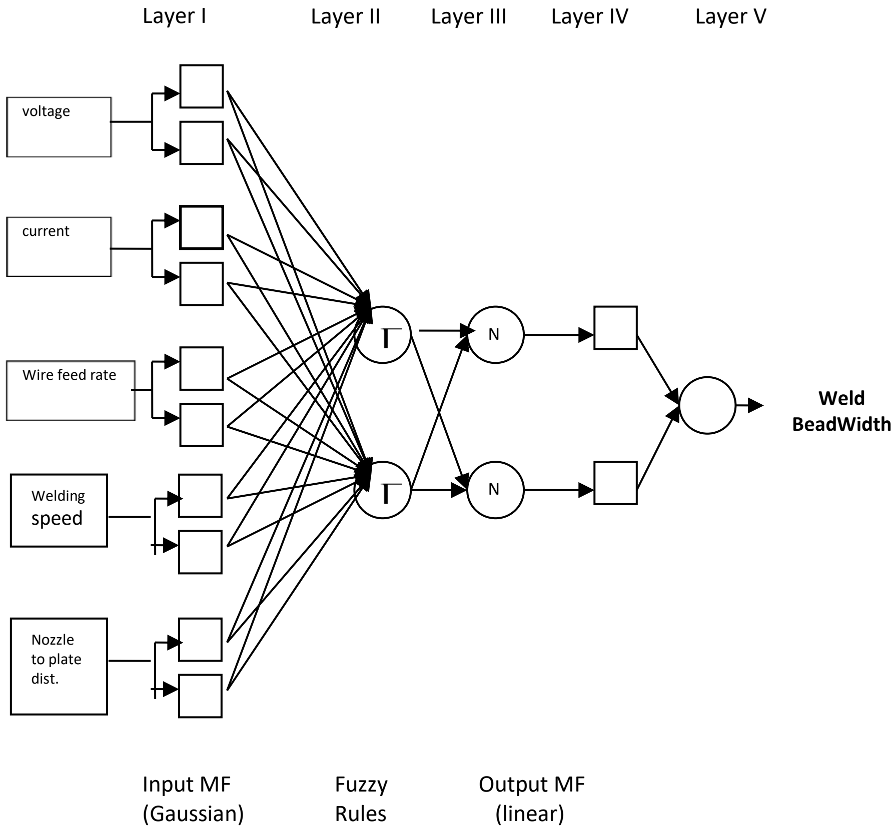

Fig. 4.1: ANFIS architecture

4.4.2 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.

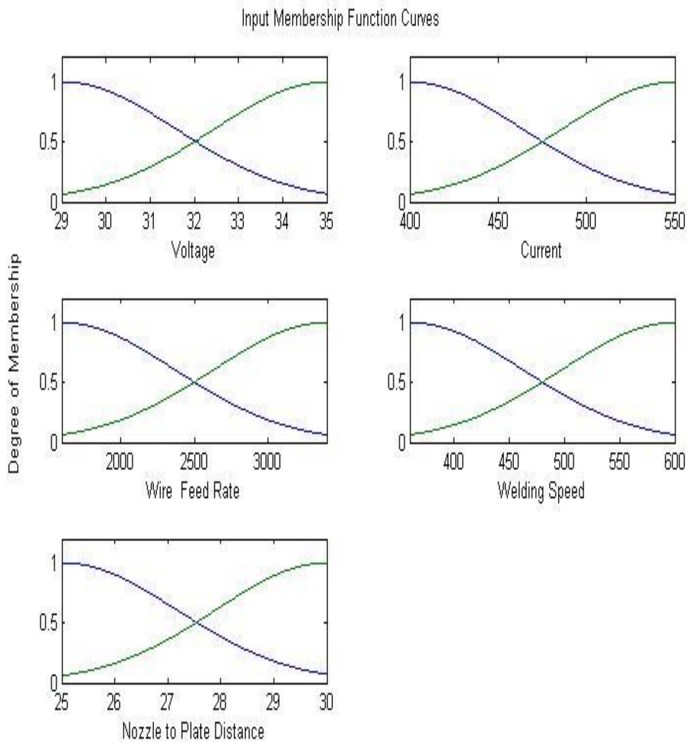

Fig. 4.2: Input Membership function curves for the ANFIS model

Table 4.2: 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 4.3: 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'

Table 4 Types and values of parameters used for training ANFIS model

No. of nodes	No. of linear parameters	No. of non-linear parameters	Total no. of prameters	No. of training data pairs	No. of testing data pairs	No. of fuzzy rules
92	190	20	212	20	12	32

Figure 4.3 and 4.4 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.

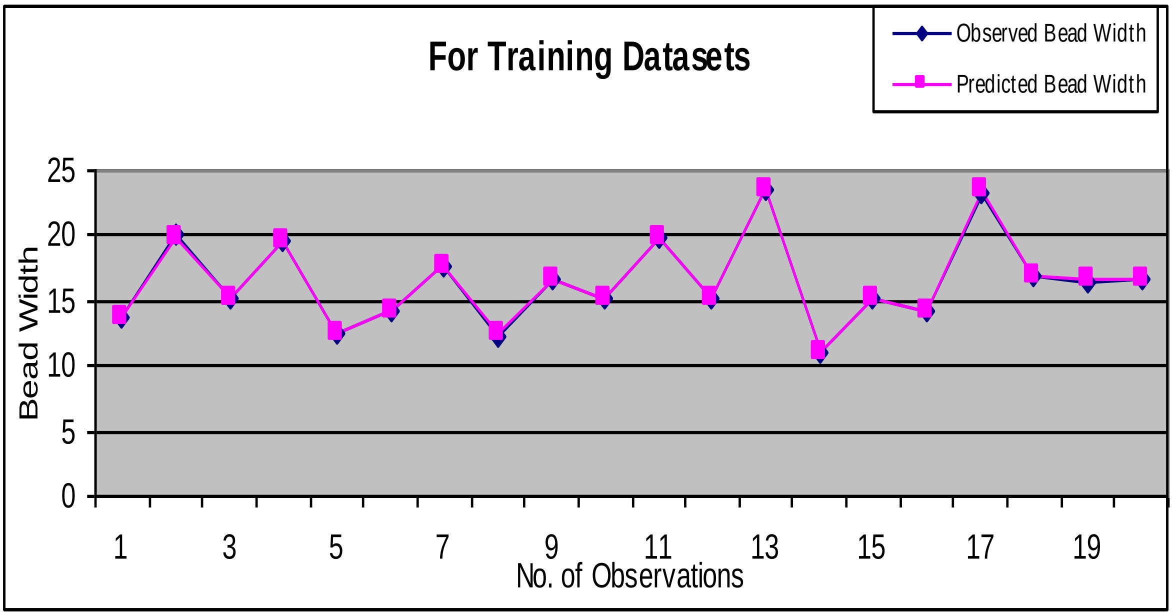

Fig. 4.3: Comparative plot ofPredicted vs. Observed Bead Width

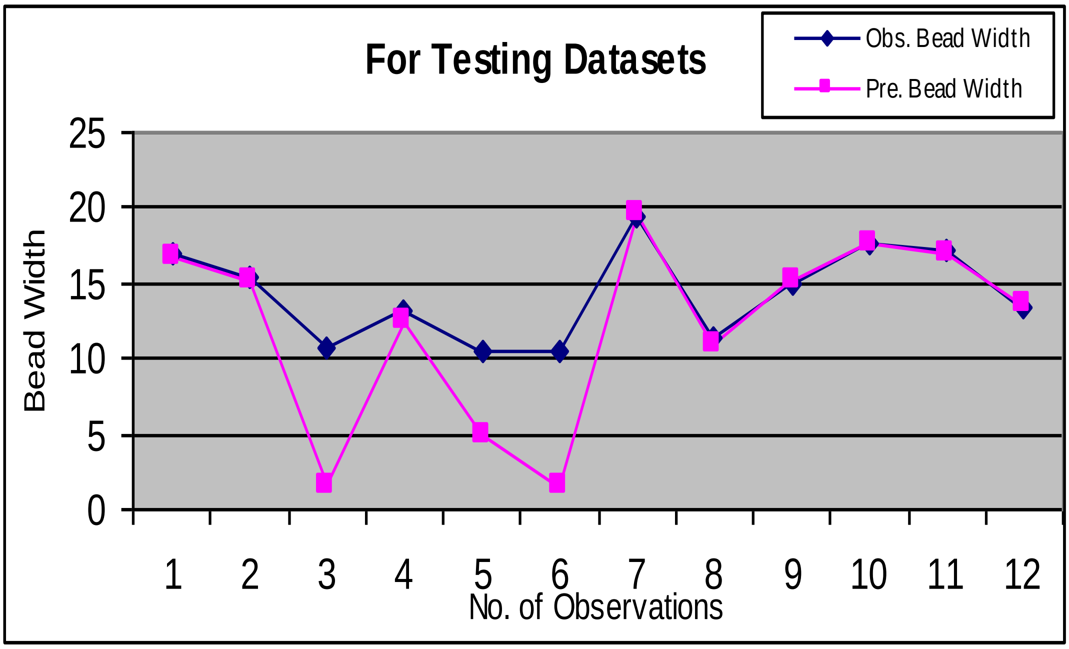

Fig. 4.4: Comparative Plot of Predicted vs. Observed Bead Width

4.5 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. 4.6&4.7*** and their RMSE values both for training and testing data are 0.072 and 3.964 respectively (Table 5 below)**.**

Table 4.5:- RMSE Values for Datasets after using ANFIS

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

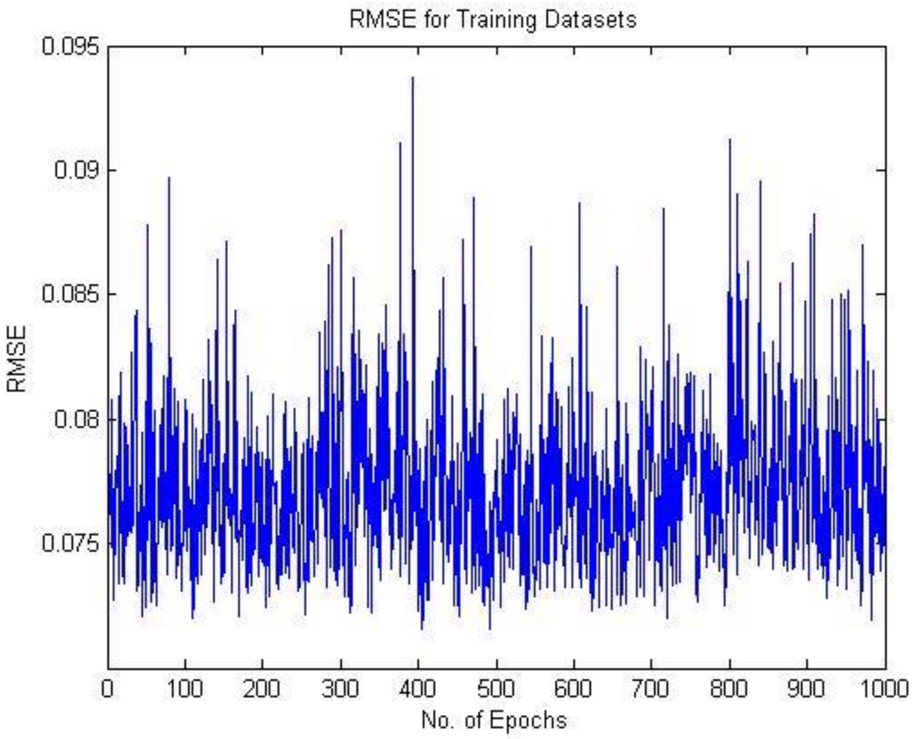

Fig. 4.6: RMSE Plot of Training Datasets during ANFIS Training

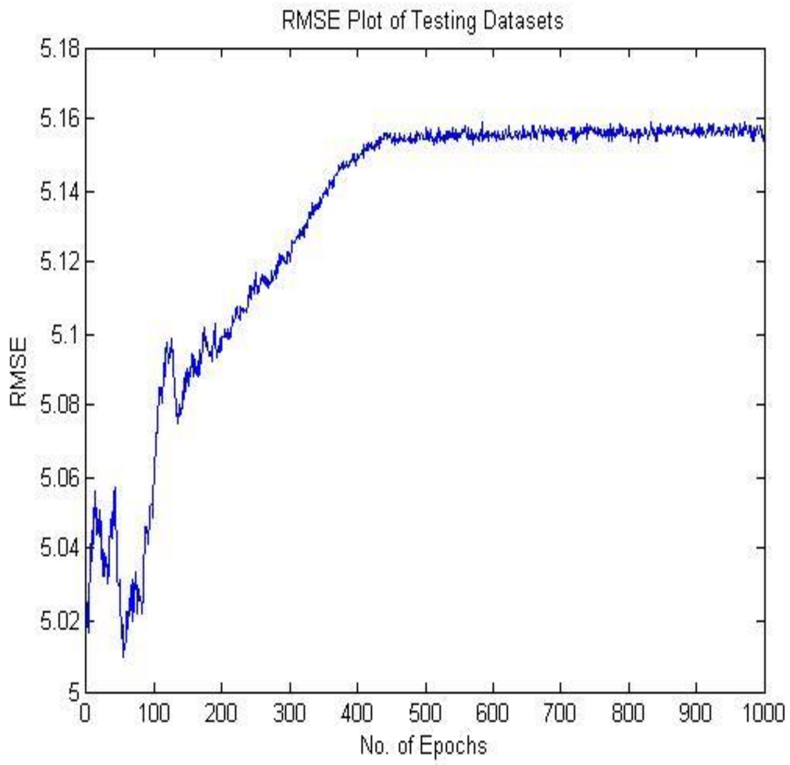

Fig. 4.7: RMSE Plot of Testing Datasets during ANFIS Training

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 4.6: 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.

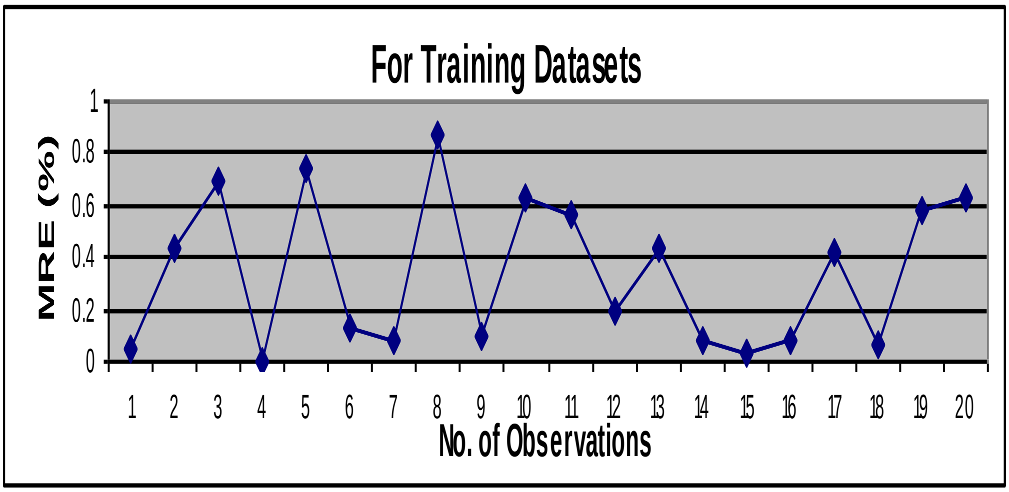

Fig. 4.8: Magnitude of Relative Error for Training Datasets

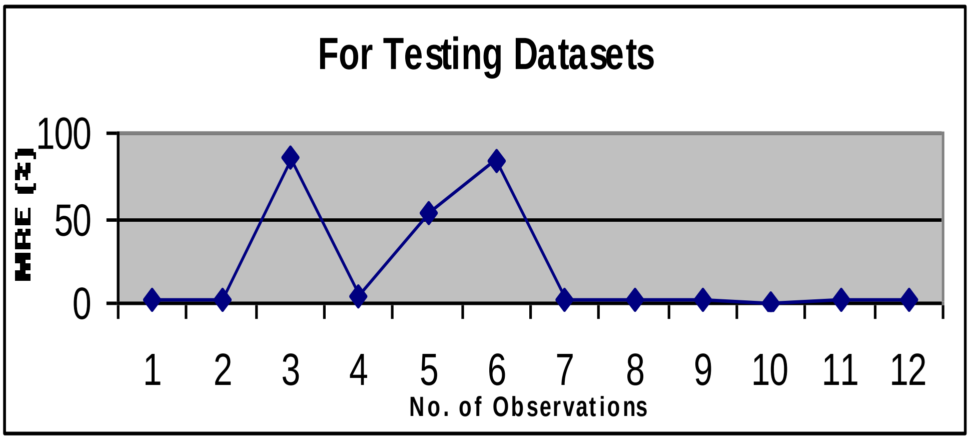

Fig. 4.9: Magnitude of Relative Error for Testing Datasets

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.

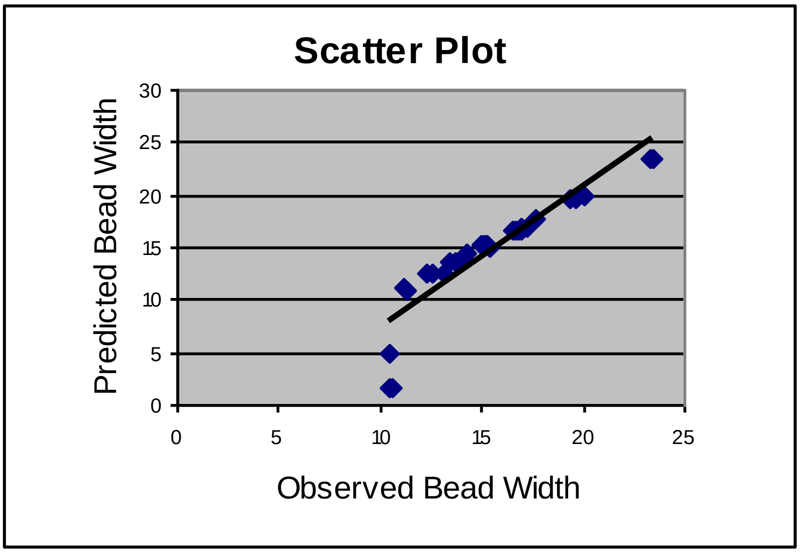

Fig. 4.10: Scatter Plot of predicted versus observed Bead Width

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 datapoints, almost 75% of the values are in unison, which again shows an excellent ANFIS output.

4.6 Conclusion:

In the present chapter, 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.

Chapter 5

Conclusions and recommendations

5.1 Need for the Research:

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. 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, it 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 hand books (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 outputvariables 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

5.2 Contributions of the research:

In this present work, applicability and capability of ANFIS techniques for weld bead width prediction has been investigated. For this experimental data from published paper has been taken for model development.

5.2.1 Model Development

A step-by-step approach for the successful development and implementation of ANFIS approach for weld bead prediction model has been carried out. 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 i.e. weld bead width. The various approaches include:

a) Selection of various input parameters, which have direct or indirect bearings on weld bead width of the material used.

b) Dividing the data into training and testing subsets using shuffling techniques during MATLAB code generation so that the training data has all the characteristics of the problem in order to get effective model development.

c) In case of ANFIS model development,

- For limited database, in order to reduce large computation time and decrease the number of rules, selection of appropriate rule extraction method viz. subtractive clustering is carried out for an effective partitioning of the input space. In case of subtractive clustering, proper selection of cluster radius through trial and error is done.
- Selection of parameterised functions, known as membership functions, is an important step in the development of an optimum model. Here Gaussian membership function has been selected for prediction model development.
- selection of training algorithm, initial step size and training epoch number;
- Validation and analysis of ANFIS models.

d) An analytical study of the technique followed by conclusions drawn regarding the model developed based on performance criteria.

5.3 Conclusions:

The overall objective of this thesis, as stated earlier in the introduction (chapter-1), was to use soft computing techniques viz. ANFIS for the development of weld bead width prediction model because weld quality plays an important role as it improves material strength, hardness and toughness of the product.

Through the work presented, it was shown that models developed in this thesis using ANFIS technique could be used to effectively address these issues. The work demonstrates that ANFIS can be trained to accurately predict weld bead width using variable process parameters. It is found that ANFIS models are very robust, characterised by fast computation, capable of handling the noisy and approximate data that are typical of hydrological data. The interpretation results in chapter 4 demonstrate one of the real strengths of ANFIS is that they perform well even when the training data contains noise and measurement errors. That is, during learning, ANFIS are able to filter out noise and measurement error and effectively generalise the system behaviour.

ANFIS modelling is an emerging computational tool that combines fuzzy logic and artificial neural network methods. Perhaps the most interesting feature of this approach is that we can cope scientifically with subjectivity and uncertainty in the welding process, rather than ignoring them. The ANFIS model provides nonlinear modelling capabilities and requires no assumption of the underlying model. By utilizing the fuzzy techniques, the linguistic relationship between the input and the output can be expressed using fuzzy rules. Through the ANN training, the ANFIS models tend to obtain missing fuzzy rules by drawing conclusions through the extrapolation of the existing data. Further, the adoption of Gaussian membership function for the development of ANFIS model show that Gaussian membership function performs well. ANFIS models save considerable computational time. In the current work, the ANFIS model reached convergence very early although 1000 epochs were used. Further, considering the complexity of the relationship between the input and the output, results obtained are very accurate and encouraging. The lower MRE and RMSE obtained by the ANFIS method suggests its good generalization capability.

From the analysis of the results, given under heading “Results and Discussions”, Chapter-4, it is seen that the weld bead width prediction model developed using ANFIS technique has been able to perform well. The overall RMSE value obtained from ANFIS model is 3.068, whereas individually both for training and testing datasets, the RMSE values are 0.072 and 3.964 respectively. Further from Fig. 3 & 4 and Table 6 of Chapter-4 it is seen that ANFIS model line almost closely follows the observed line. This again depicts the predictive superiority of ANFIS technique.

5.4 Recommendations for future work:

- The input variables could be extended with more welding parameters such as type of flux, width and depth of flux layer, polarity and type of current,
- In this work, regarding ANFIS model development the membership function (MF) types that has been used for ANFIS using subtractive clustering rule extraction methods is Gaussian MFs only. It may be recommended to use other types of MFs like Bell, Triangular, Trapezoidal, along with this MF so as to make a comparative study of the effect of these MFs on the model performance.

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Published Paper of My Thesis

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Artificial Intelligence-Enhanced Welding Quality Prediction for Metal Inert Gas Welding

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Abstract: Manufacturing engineers and production staff frequently employ welding to swiftly and efficiently set up manufacturing processes for new items. The most crucial elements impacting welding quality, output, and cost are the MIG welding parameters. The influence of welding parameters, such as welding current, welding voltage, gas flow rate, wire feed rate, etc. on the final tensile strength, hardness of the weld joint, weld pool geometry, and weld strength of various metal materials is discussed in this study. The parameters can be optimised and the best parameter combinations for the target quality can be achieved by employing the DOE approach. The relevance of the parameters can be determined by the DOE technique analysis since it can influence a product's strength and quality.

Keywords: ANFIS, ANN, Welding Quality, MIG Welding

1. Introduction: As the name implies, metal inert gas welding is a process in which the heat source is an arc formed between a wearable metal electrode and the work piece, and the arc and the molten puddle are shielded from 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. Since the metallic electrode also serves as the filler metal, no additional filler metal is required. MIG welding is a common acronym used to describe it. In the MIG welding process, an electric arc is continuously formed between the work piece and the metal electrode feed to heat the joint and achieve coalescence. In a localised fusion zone, parent metals and a filler material are heated, melted, and solidified during the metal inert gas (MIG) welding process to create a junction between the parent metals. A gas shielded process that works well in all positions is gas metal arc welding. MIG To generate consistent weld quality, welding, a widely used industrial arc welding method, needs better parameter prediction and monitoring. The product's material strength, hardness, and toughness are all enhanced by high-quality welding. A product's weld quality is assessed using a variety of factors, including weld bead geometry, hardness, deposition rate, etc. Weld parameters including welding speed, welding current, arc voltage, and electrode stick out control all of these characteristics. It's important to set the right welding process settings in order to get good quality. The impact of welding factors upon bead shape and size, bead breadth and height, dilution and bead geometry, weld deposit area, element transfer behaviour, and weld-metal chemistry in submerged-arc welding was examined by researchers in their several attempts to build the MIG method. Additionally, [1] for MIG welds, the impact of accelerating deposition rate on bead geometry and flux component on softening temperature was investigated. The classic, straightforward, and affordable methods of welder experience, charts, and handbooks (recommended values) are typically used to determine the appropriate welding parameters. However, this does not guarantee that the chosen welding settings produce adequate welding, and it cannot be used with new welding techniques. Many approaches to obtaining the appropriate output variables through models that correlate input variables with output variables have been developed to address this issue. Modeling of the MIG process included the use of fractional factorial approaches, mathematical modelling, curvilinear regression equations, linear regression equations, response surface methodology, finite element modelling, the grey-based Taguchi method, and sensitivity analysis [2–6]. All Due to modelling challenges, being time-consuming, and being heavy, these techniques have a limited range of applications. Because mathematical models can't adequately or effectively explain the nonlinear relationships between welding's input and output characteristics, intelligent modelling techniques have been developed as a result. Attention must be paid to accurate simulation and analysis of the process, which aids in the prediction of a wide range of process parameters to configure the factory floor in real time.

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Metal Inert Gas welding as the name suggests, is a process wherein the source of heat is an arc shaped among a consumable steel electrode a
the arc and the molten puddle are covered from infection via the atmosphere (I.E. Oxygen and nitrogen) with an externally furnished gaseous pr
argon, helium or an argon-helium mixture. No outside filler metallic is vital, due to the fact the steel electrode presents the arc as well as the filler
abbreviated shape as MIG welding. MIG is an arc welding process in which in coalescence is received through heating the task with an electric a
piece and metallic electrode feed continuously. A steel inert fuel (MIG) welding system consists of heating, melting and solidification of parent m
localized fusion region by means of a transient warmth supply to shape a joint between the discern metals. Gas metal arc welding is a gas shiel
efficiently used in all positions. MIG Welding is a extensively used industrial arc welding system desires a better prediction and monitoring of its
weld exceptional. Quality of welding plays an essential role as it improves material power, hardness and sturdiness of the product. Weld high-qu
via exclusive parameters like weld bead geometry, hardness, deposition charge etc. All those characteristics are managed with the aid of weld p
velocity, welding present day, arc voltage and electrode stick out. To achieve top first-rate, is essential to set the right welding technique paramet
many strategies to set up MIG manner. The outcomes of welding variables upon bead shape and length, bead width and top , dilution and bead
vicinity, element switch behavior and weld-metallic chemistry in submerged-arc welding become explored. Also the effect of growing deposition
flux factor on softening temperature changed into tested [1] for MIG weld. Usually, the preferred welding parameters are determined the usage o
welder's reports, charts and handbooks (preferred values) which might be simple and low cost. However this does not ensure that the chosen w
exceptional welding and this technique isn't applicable to new welding system. To conquer this problem, numerous strategies of obtaining the pr
fashions to correlate input variables with output variables were advanced. Fractional factorial strategies, Mathematical modeling, curvilinear regr
regression equations [2], reaction surface method [3], finite element modeling [3, 4], grey-primarily based Taguchi technique [5] and sensitivity e
to model MIG method. All These strategies are restricted in software due to problems in modeling, time ingesting and weighty. For this cause, in
the mathematical models to explain the nonlinear properties current among the enter and output parameters of welding result in the developmen
strategies. Precise simulation and evaluation of the system wishes interest which helps to are expecting the wide type of technique parameters t
actual time.

Key MIG process variables
- Wire feed velocity (important factor in welding cutting-edge manage)
- Arc voltage
- Travel velocity
- Electrode stick-out (ESO) or contact tip to work (CTTW)
- Polarity and present day type (AC or DC) and variable balance AC modern-day

Material applications
- Carbon steels (structural and vessel production)
- Low alloy steels
- Stainless steels
- Nickel-based alloys
- Surfacing programs (build-up, wear-going through, and corrosion defiant overlay of steels)

Advantages
- High deposition costs (over forty five kg/h (one hundred lb/h) were reported).
- Deep weld penetration.
- High running factors in mechanized programs.
- Sound welds are comfortably made (with right manner layout and manage).
- Minimal welding fume or arc mild is emitted.
- High speed welding of thin sheet steels up to 5 m/min (sixteen toes/min) is feasible.
- Practically no side coaching is vital.
- Low distortion
- The manner is suitable for both indoor and out of doors works.
- Welds produced are sound, uniform, ductile, corrosion resistant and have excellent impact price.
- Single bypass welds may be made in thick plates with ordinary equipment.
- 50% to ninety% of the flux is recoverable, recycled and reused
- The arc is constantly covered below a blanket of flux, accordingly there may be no hazard of spatter of weld.

Limitations
- Limited to ferrous (metal or stainless steels) and some nickel-based totally alloys.
- Normally restrained to lengthy immediately seams or rotated pipes or vessels.
- Normally confined to the 1F, 1G, and 2F positions.
- Requires enormously troublesome flux dealing with systems.
- Requires inter-bypass and publish weld slag removal.
- Flux and slag residue can gift a fitness and safety problem.

Objective and scope of the prevailing paintings

Usually, the preferred welding parameters are determined the use of traditional methods like welder's reports, charts and handbooks (favored va
cost. However this doesn't make certain that the chosen welding parameters bring about pleasant welding and this technique is not relevant to n
conquer this problem, diverse methods of obtaining the desired output variables thru models to correlate enter variables with output variables we
Fractional factorial techniques, Mathematical modeling, curvilinear regression equations, linear regression equations, reaction floor methodology
based totally Taguchi approach and sensitivity evaluation had been used to model MIG approach. All the methods are limited in application beca
time eating and weighty. Owing to the inadequacy and inefficiency of the mathematical models to provide an explanation for the nonlinear house
and output parameters of welding result in the improvement of smart modeling strategies. Precise simulation and evaluation of the t

Sources

(PDF) Effects of welding speed, energy input and heat source ...

Nov 16, 2020 — A metal inert gas (MIG). welding process consists of heating, melting and solidifica-. tion of parent metals and a filler material in localized ...

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Submerged arc welding

this helps fuse the toe of the weld to the base metal. key saw process variables wire feed speed (main factor in welding current control); arc voltage; travel speed; electrode stick-out or contact tip to work (cttw); polarity and current type (ac or dc) & variable balance ac current

http://ball1111.blogspot.com/2009/05/submerged-arc-welding.html

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MIG Welding is a widely used business arc welding system wishes a better prediction and monitoring of its parameters to provide consistent weld quality. Weld excellent plays an crucial position as it improves cloth power, hardness and sturdiness of the product. Quality of a weld product is evaluated with the aid of one-of-a-kind parameters like weld bead geometry, deposition charge, hardness etc. These characteristics are managed by means of weld parameters like welding present day, welding velocity, arc voltage and electrode stick out. In order to gain good first-class, it is important to set the right welding method parameters. Usually, the favored welding parameters are determined the use of traditional strategies like welder's reviews, charts and hand books (desired values) which can be simple and cheaper. But this does not ensure that the selected welding parameters result in nice welding and this approach isn't relevant to new welding method. To overcome this hassle, numerous methods of obtaining the desired output variables thru models to correlate enter variables with outputvariables have been developed. Fractional factorial techniques, Mathematical modeling, curvilinear regression equations, linear regression equations, reaction surface method, finite detail modeling, gray-primarily based Taguchi approach and sensitivity analysis have been used to model MIG procedure

five.2Contributions of the research

In this gift work, applicability and functionality of ANFIS techniques for weld bead width prediction has been investigated. For this experimental information from posted paper has been taken for model development.

Five.2.1 Model Development

A step-via-step technique for the successful improvement and implementation of ANFIS method for weld bead prediction model has been done. Different combinations of open circuit voltage (OCV), welding current (I) twine feed price (F), welding velocity (S) and nozzle- to- plate distance (C) had been used to have a look at their impact at the preferred response i.E. Weld bead width. The diverse processes encompass:

a) Selection of various enter parameters, that have direct or indirect bearings on weld bead width of the material used.

B) Dividing the records into education and checking out subsets the usage of shuffling strategies during MATLAB code generation in order that the training facts has all of the traits of the trouble to be able to get powerful version improvement;

c) In case of ANFIS model improvement,

• For confined database, so one can reduce huge computation time and reduce the variety of rules, selection of suitable rule extraction method viz. Subtractive clustering is done for an effective partitioning of the enter area. In case of subtractive clustering, right selection of cluster radius through trial and errors is carried out.

• Selection of parameterised features, called membership functions, is an vital step inside the development of an ideal version. Here Gaussian club feature has been selected for prediction model improvement.

• choice of education set of rules, initial step length and schooling epoch variety;

• Validation and analysis of ANFIS fashions.

D) An analytical have a look at of the approach accompanied by way of conclusions drawn regarding the version developed based totally on overall performance standards.

5.3Conclusions

The standard goal of this thesis, as stated earlier inside the creation (chapter-1), changed into to apply tender computing strategies viz. ANFIS for the improvement of weld bead width prediction model due to the fact weld quality plays an critical role because it improves fabric strength, hardness and longevity of the product.

Through the work presented, it turned into proven that fashions evolved in this thesis using ANFIS approach can be used to effectively deal with these troubles. The paintings demonstrates that ANFIS can be skilled to correctly expect weld bead width the use of variable method parameters. It is observed that ANFIS fashions are very sturdy, characterised through fast computation, capable of managing the noisy and approximate statistics which can be regular of hydrological facts. The interpretation results in bankruptcy four show one of the actual strengths of ANFIS is they carry out properly even if the schooling statistics consists of noise and dimension errors. That is, at some point of studying, ANFIS are capable of filter out noise and size error and successfully generalise the device behaviour. ANFIS modelling is an emerging computational tool that combines fuzzy common sense and synthetic neural network strategies. Perhaps the most interesting feature of this approach is that we will cope scientifically with subjectivity and uncertainty in the welding process, in place of ignoring them. The ANFIS version provides nonlinear modelling abilities and calls for no assumption of the underlying version. By utilizing the fuzzy techniques, the linguistic courting among the input and the output can be expressed using fuzzy policies. Through the ANN education, the ANFIS fashions generally tend to acquire lacking fuzzy guidelines by using drawing conclusions thru the extrapolation of the existing records. Further, the adoption of Gaussian membership feature for the development of ANFIS version show that Gaussian membership feature plays well. ANFIS fashions store vast computational time. In the cutting-edge paintings, the ANFIS version reached convergence very early despite the fact that 1000 epochs have been used. Further, considering the complexity of the connection among the enter and the output, results obtained are very accurate and inspiring. The lower MRE and RMSE received with the aid of the ANFIS method suggests its excellent generalization functionality.

F

Sources	Similarity

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MIG Welding is a broadly used commercial arc welding manner needs a higher prediction and monitoring of its parameters to provide steady weld first-rate. Weld high-quality plays an essential function because it improves cloth power, hardness and toughness of the product[8]. Quality of a weld product is evaluated by means of unique parameters like weld bead geometry, deposition rate, hardness and so on. These traits are controlled via weld parameters like welding modern-day, welding pace, arc voltage and electrode stick out. In order to obtain good first-class, is essential to set the right welding procedure parameters. Researchers attempted many strategies to set up MIG method. The effects of welding variables upon bead shape and size, bead width and top, dilution and bead geometry , weld deposit area, element switch conduct and weld-metallic chemistry in submerged-arc welding changed into explored[8]. Also the impact of growing deposition price on bead geometry and flux thing on softening temperature become examined for MIG weld. Investigations had been achieved to analyze the effect of welding parameters on chemical composition and mechanical properties, warmth affected quarter and bead geometry of MIG weld.
Usually, the favored welding parameters are determined the usage of conventional techniques like welder's experiences, charts and handbooks (desired values) that are easy and cheaper. But this does not ensure that the chosen welding parameters result in satisfactory welding and this approach isn't always applicable to new welding process. To overcome this hassle, diverse methods of obtaining the preferred output variables through fashions to correlate input variables with output variables had been evolved.
Fractional factorial strategies, Mathematical modeling, curvilinear regression equations, linear regression equations, response floor methodology, finite detail modeling, gray-based totally Taguchi approach and sensitivity evaluation were used to model MIG method[8]. These strategies are constrained in utility due to problems in modeling, time ingesting and bulky. Due to the inadequacy and inefficiency of the mathematical fashions to provide an explanation for the nonlinear properties existing among the enter and output parameters of welding lead to the improvement of wise modeling strategies. Precise simulation and analysis of the system desires interest which allows to are expecting the wide style of method parameters to set the manufacturing unit floor in real time. The type of artificial intelligence able to responding to adjustments within the automated production environment, and having the capacity to seize vast manufacturing understanding is Adaptive Neuro Fuzzy Inference System (ANFIS). It is turning into extensively used in all components of manufacturing procedure to help people.
Realizing that count number, ANFIS a country of the art artificial clever approach, has the opportunity to enhance the prediction of weld nice to find the high-quality combination of independent variables which is welding cutting-edge (I), pace (S) and welding voltage (V) because the enter variables for you to acquire favored weld pleasant. Thus the primary objectives of this project is to broaden ANFIS version to predict weld bead width.
Performance Criteria Used
The first step inside the ANN improvement process is the selection of overall performance standards, as this decide show the model is assessed and could therefore have an effect on a few of the subsequent steps suchastraining and the choice of community structure. Performance standards might also consist of measures of training and processing speed; but, the mos tcommonly used overall performance standards used is the prediction accuracy.
Performance standards which measure prediction accuracy usually measure the healthy (orlackthereof) among the modeloutputs and the observed data with the aid of a few error degree . They are used at some stage in schooling as objective functions and after training to assess the educated ANFIS, in which the criterion used for each purpose need now not necessarily be the same.

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1. Root MeanSquaredError R(MSE)
The RMSE is a measure of fashionable version performance. It is the maximum without difficulty interpreted statistic, since it has the identical gadgets as the parameters envisioned. The RMSE is consequently the distinction, on a mean, of an observed statistics and the estimated statistics. RMSE evaluates the residual between measured and forecasted values[1][2]. RMSE is a frequently-used measure of the distinction among values expected via a version or an estimator and the values simply discovered from the element being modelled or approximate. These variations also are called residuals. Hypothetically, if this criterion equals 0 then model represents an appropriate match, which isn't viable at all.
R 1/2
(2) Magnitude of Relative Error (MRE)
It is defined as
MRE = [Modulas of (Actual Value – Predicted Value)/ Actual Value] * a hundred
For MRE a better rating method worse prediction accuracy. When the usage of MRE as a means of prediction accuracy, it is supposed that the mistake is proportionl to the scale of the task.
Model Inputs and Structure
The modelling approach used to develop forecasting version along with information on enter and output parameters is supplied in this section. One of the most essential steps in the development of any prediction version is the selection of appropriate enter variables on the way to allow an ANFIS to efficaciously produce the favored effects. Good knowledge of the gadget below consideration is an essential prerequisite for a success application of facts driven processes. The foremost purpose for that is that ANFIS belongs to the magnificence of facts-driven tactics [2][4][5]. Physical knowledge of the manner being studied leads to better desire of the enter variables. Here due to the fact predicting floor roughness is a complicated trouble that includes multiple interacting elements. In order to build a reasonably accurate model for prediction, right parameters must be selected. Some practical considerations in parameter selections are first of all, the selected parameters must have an effect on the goal hassle, i.E., robust relationships ought to exist a few of the parameters and target (or output) variables, and secondly, the selected parameters ought to be well-populated, and corresponding data ought to be as easy as possible. Since the gentle computing techniques model troubles primarily based on

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MIG Welding (MIG) is one of the main steel fabrication techniques in industry because of its reliability and capability of producing true satisfactory weld. The capability to enroll in thick plates (as thick as 1.5 inch) in a unmarried pass, with excessive metal deposition price has made this manner useful in big structural applications. Indeed diverse studies works have been explored on various factors of MIG welding, yet investigations are nevertheless being carried on to look at the phenomenon that takes place for the duration of the manner of submerged arc welding, and lots of other associated topics, so that the technique turns into controllable greater exactly, and can be monitored properly, both manually in addition to robotically. In MIG welding, numerous technique parameters have interaction in a complicated manner, and their interactions impact the bead geometry, bead excellent as well as metallurgical characteristics and mechanical houses of the weldment. Acceptability of the weldment relies upon on various fine characteristics that verify purposeful requirements of the welded joint in the supposed region of application. In most of the instances, excellent of the weld is left to depend upon the past experience and operating ability of operator. But, with the advent of automation, it's far now possible to design a system capable of selecting superior procedure parameters to offer favored yield. Research inside the field of MIG welding is not new.

Farhad Kolahan et al (2009), In this research a method became proposed to model and optimize weld bead geometry in GMAW method. Since, the relationships between bead geometry traits and welding output variables are complex; a regression based totally method turned into employed to version the manner. The experimental statistics for version improvement were collected using the actual assessments executed via the authors. Along this line, using DOE technique and regression evaluation, distinctive mathematical fashions have been evolved to establish the relationships between welding input parameters and weld bead geometry outputs. A Simulated Annealing method become developed to limit the mistake function together with preferred and calculated weld bead geometry. By minimizing such a function, the technique parameters may be decided in order the resultant bead geometry has the least deviation from its favored cost. Computational consequences indicate that the proposed SA technique can successfully and as it should be determine welding parameters so as a desired bead geometry specification is obtained.

Shahnwaz Alam et al (2012), showed that the two stage full factorial designs are an effective tool for quantifying the primary and interaction effect of variables on weld width. The developed version can be effectively used to predict the weld width in the MIG welding in the variety of parameters used. Proposed models are ok to predict the weld width with a self assurance stage of ninety five%. Weld width rapidly will increase with voltage, slowly will increase with current and twine feed fee and decreases with welding pace and nozzle to plate distance. The F-take a look at suggests that the regression model as an entire is full-size. Cross- validation take a look at complete-fills the validity of the fashions developed.

Karuna et al (2011), Here the mixed effect of welding parameters on weld metal composition in MIG technique turned into tested. Accordingly, the subsequent conclusions may be drawn: It is thrilling to be aware that chromium, molybdenum & silicon factors showing a growing trend & manganese element displaying a lowering fashion with an increase in any parameter, viz voltage, current & velocity. An strive was made to determine crucial welding parameters for composition of weld like Cr, Mn & Si in the MIG technique. For controlling the weld metal composition, welding voltage is extra effective than is welding cutting-edge.

K. Lalitnarayan, et; al, (2011), confirmed that in gas metal arc welding wherein a gap exists, regression model questions of welding parameters which have been notion to supply the desired geometry of the back-bead may be acquired. Both sides of the technique regression version equation of the geometry parameters of the lower back-bead and welding

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manner parameters are determined and, after evaluation it become discovered that whereas the correlation among parameters for the bead shape and welding system parameter has until now been

applied normally to bead-on-plate welding, this study extends the range of the research to the geometry prediction of the back-bead in butt welding where a gap exists. In order to acquire the geometry of the again-bead the use of the welding process parameters, the a couple of regression analysis is modelled right into a linear equation. The errors price of evaluation had a most value of 9.5 percentage. Also, the groove gap had the largest mistakes charge for prediction, followed by means of the depth of the again-bead and the width of the again-bead. Thus, the groove gap became idea to be the most difficult parameter to predict. The a couple of regression evaluation of the welding technique parameters which had been though to provide the favored again-bead was modeled into a linear equation and the errors rate of analysis became underneath 6.5 percentage. Also, the normalized welding pace had the most important errors rate for prediction, accompanied by using the normalized arc voltage and the normalized welding current. In this example, the welding speed changed into thought to be the maximum difficult parameter to expect.

A. K. LAKSHMINARAYANAN et. Al (2009), have described using design of experiments(DOE) for engaging in experiments. Two models were advanced for predicting tensile strength of friction stir welded AA7039 aluminium alloy using response floor methodology and synthetic neural network(ANN). From this research vital conclusions derived changed into that rotational speed is the aspect that has more have an effect on on tensile energy, followed by using welding pace and axial force. Further, a most tensile strength of

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In 1965, Zadeh [11] posted the first paper on a unique manner of characterizing non-probabilistic uncertainties, which he called fuzzy sets. Recently resurgence within the field of artificial neural community has injected a brand new driving force into the fuzzy literature. The lower back-propagation learning rule which drew little interest till its application to ANN turned into found, is truely a widely wide-spread mastering paradigm for any smoothed parameterised version, inclusive of fuzzy inference systems (FIS)(or fuzzy fashions). As a result now fuzzy inference device can not simplest take linguistic records (linguistic regulations) from human experts however additionally adapt itself using numerical (information inputs/outputs pairs) to acquire better performance. This gives fuzzy inference structures an area over neural networks, which can't take linguistic facts directly. When represented as an adaptive community, FIS is known as ANFIS [7][8].

Need for Adaptive Neuro Fuzzy Inference System (ANFIS)

A fuzzy inference gadget can make use of human expertise by way of storing its crucial additives in rulebase and database, and carry out fuzzy reasoning to infer the general output value. The derivation of fuzzy if then policies and corresponding club features depend closely on the a priori understanding about the device underneath attention. However, there are nevertheless two primary however essential troubles regarding the education and manipulation of know-how. Firstly, no systematic manner exists to transform revel in or information of human experts to the expertise base of a fuzzy inference system and secondly, there's still a need of adaptability or studying algorithms to song the club capabilities in an effort to minimise the discrepancy among models (calculated) output and desired output [7][8].These problems significantly restrict the utility domains of FIS. On the other hand, Neural Network modelling does not depend on human information. Instead, it employs a studying process and a given training facts set to clear up a fixed of parameters (i.E. Weights) such that the desired practical behaviour is finished. No powerful techniques had been proposed to determine the preliminary weight values and network's configuration (e.G. Wide variety of hidden layers and hidden nodes).

Thus the drawbacks pertaining to these two strategies seems complimentary. Therfore it appears herbal to recollect building an incorporated gadget combining the standards of fuzzy common sense modelling and neural network modelling. In other phrases, the included approach, or neuro-fuzzy modelling, must contain the 3 most critical capabilities,

1. Meaning and concise representation of dependent knowledge.
2. Efficient studying functionality to perceive parameters.

Clear mapping among parameters and established expertise.

ANFIS: Adaptive-Network-primarily based Fuzzy Inference System

(a) ANFIS Architecture

ANFIS has been proven to be powerful in modelling numerous strategies including time collection, real-time reservoir operations and river glide forecasting [2][3][5]. ANFIS possesses residences including functionality of learning, building, expensing and classifying. It has the benefit of permitting the extraction of fuzzy regulations from numerical records or professional know-how and adaptively constructs a rule base. Moreover, it may adapt the complicated conversion of human intelligence to fuzzy structures. The main difficulty of the ANFIS predicting version is the time required for training structure and determining parameters. ANFIS makes use of the learning capability of the ANN to outline the input-output relationship and construct the bushy policies by figuring out the enter shape. The device results had been received by using thinking and reasoning functionality of the fuzzy common sense. The ANFIS architecture consists of

5 layers (Figure three.1). Here the circles denote a hard and fast node whereas squares denote an adaptive node. For simplicity it is assumed that the examined FIS has inputs and one output. For a primary order Sugeno fuzzy model, a standard rule set with fuzzy if-then guidelines can be expressed as

Rule 1: IF x is A1and y is B1THEN f1 = p1x + q1y + r1

Rule 2: IF x is A2and y is B2THEN f2 = p2x + q2y + r2

in which, x and y are the crisp inputs to the node i , Aiand Biare the linguistic labels (low, medium, excessive, and so forth.) characterized by using convenient membership capabilities and pi, qiand ri are the outcome parameters (i = 1 or 2) [1][7][8].

Fig three.1 (a) A input first-order Sugeno fuzzy version with guidelines;

(b) equivalent ANFIS architecture (Jang, 1993)

The version is briefly presented little by little inside the following manner;

Input nodes (Layer 1): Each node on this layer generates club grades of the crisp inputs which belong to each of handy fuzzy sets by means of the usage of the club functions. Each node's output Oi1is calculated by:

for i= 1,2 ; for i= three,4 (three.1)

Where μAiand μBiare the right club features for Aiand Bifuzzy units, respectively. Many various membership capabilities inclusive of trapezoidal, triangular, Gaussian characteristic, and so on. Can be implemented to determine the membership grades. The gauss club feature is used, as;

= (3.2)

Where, is the membership capabilities' parameter set that modifications the form of club characteristic from 1 to 0. These parameters are called the basis parameters.

Rule nodes (Layer 2): In this residue, the AND/OR operator is applied to get one output that represents the effects of the antecedent for a fuzzy rule, that is, firing strength. It approach the stages by using which the antecedent a part of the rule is glad and it indicates the shape of the output feature for that rule. The outputs of the second one layer, called as firing strengths are the goods of the corresponding tiers acquiring from layer 1, named as w givenbelow.

I=1, 2 (three.3)

Average nodes (Layer three): Main target is to compute the ratio of firing electricity of each ith rule to the sum of all rules' firing energy. Thus the firing power in this layer is normalized as;

i=1, 2 (three.4)

Consequent nodes (Layer four): The contribution of ith rule's closer to the overall output or the model output and/or the feature described

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f1 p1x q1y r1 Rule 2 if x is A2 and y is B2 then... | Course Hero this preview shows page 2 - 4 out of 7 pages. (f1 = p1x + q1y + r1) rule 2: if (x is a2) and (y is b2) then (f2 = p2x + q2y + r2) one possible anfis architecture to implement these two rules is shown in fig. 1. note that a circle indicates a fixed node whereas a square indicates an adaptive node (the... https://www.coursehero.com/file/p5779of/f1-p1x-q1y-r1-Rule-2-if-x-is-A2-and-y-is-B2-then-f2-p2x-q2y-r2-One-possible/	3%