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# Estimation and Comparison of Welding Performances using MRA and GMDH in P-GMAW for ASTM 106 Material

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**Abstract**

The Pulsed Gas Metal Arc Welding (P-GMAW) process is one of the most significant arc welding processes, used in high-technology industrial applications. In order to understand and control the P-GMA welding process parameters, it is necessary to determine the input and output relationship of the welding processes. P-GMAW is widely used process, especially in thin sheet metal industries. It offers an improvement in quality and productivity over regular Gas Metal Arc Welding (GMAW). The process enables stable spray transfer with low mean current and low net heat input. This paper describes the estimation and comparison of welding process parameters viz., current, gas flow rate and wire feed rate on ultimate yield strength, ultimate tensile strength, percentage of elongation and hardness. Experiments have been performed based on Taguchi's $L_{27}$ standard orthogonal array. Estimation of welding performances have been carried out using sophisticated mathematical models viz., MRA and GMDH, and, compared. The GMDH algorithm is designed to learn the process by training the algorithm with the experimental data. Three different criterion functions, viz., regularity, unbiased and combined criterions were considered for estimation in GMDH. Different GMDH models can be obtained by varying the percentage of data in the training set and the best model can be selected from these, viz., 50%, 62.5% & 75%. Estimation and comparison of welding performances were carried out using MRA and GMDH techniques.



*Keywords:* Welding, P-GMAW, Estimation, MRA and GMDH.

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## 1. Introduction

Pulsed Gas Metal Arc Welding (P-GMAW) is widely used process, especially in thin sheet metal industries. It offers an improvement in quality and productivity over regular Gas Metal Arc Welding (GMAW). The process enables stable spray transfer with low mean current and low net heat input. It applies waveform control logic to produce a very precise control of the arc through a broad wire feed speed range. With precise control of arc dynamics, P-GMAW can be used as a fast-follow process at high travel speeds, or it can be run as a high deposition rate, fast-fill process. A variation of the spray transfer mode, pulse-spray is based on the principles of spray transfer but uses a pulsing current to melt the filler wire and allow one small molten droplet to fall with each pulse. The pulses allow the average current to be lower, decreasing the overall heat input and thereby decreasing the size of the weld pool and heat-affected zone while making it possible to weld thin work pieces. The pulse provides a stable arc and no spatter, since no short-circuiting takes place. This also makes the process suitable for nearly all metals, and thicker electrode wire can be used as well. The smaller weld pool gives the variation greater versatility, making it possible to weld in all positions. In comparison with short arc GMAW, this method has a somewhat slower maximum speed (85 mm/s or 200 in/min) and the process also requires that the shielding gas be primarily argon with a low carbon dioxide concentration. Additionally, it requires a special power source capable of providing current pulses with a frequency between 30 and 400 pulses per second. However, the method has gained popularity, since it requires lower heat input and can be used to weld thin work pieces, as well as nonferrous materials.

Analysis on optimization of P-GMAW parameters using Taguchi method was performed. The experiments were conducted under varying pressure, welding current and welding time. The output characteristic considered was tensile strength of the welded joint. The material used was low carbon steel sheets of 0.9mm. Their conclusion leads that the contribution of welding current holding time and pressure towards tensile strength is 61%, 28.7% and 4 % respectively as determined by the ANOVA method [1]. An optimization of MIG welding parameters for improving welding strength was carried out. The influence of welding parameters welding current, welding voltage, welding speed on ultimate strength of welded joints of AISI mild steel materials was studied. A plan of experiments using Taguchi has decided. Experiments were performed and result was confirmed. From this study they concluded that the welding current and welding speed are the major factors affecting tensile strength of welded joints [2].An optimization of MIG welding parameters in order to improve yield strength of AISI 1040 mild steel was carried out. The process parameters welding current, voltage, gas flow rate and wire speed were studied. The experiments were conducted based on four factors, three level orthogonal arrays. The empirical relationship can be used to predict the yield strength of welded material [3].The optimization of MIG welding parameters using Taguchi design method was carried out. In their research they considered welding current, welding voltage and welding speed as input variables and penetration depth as output variable.MS C20 was selected as work piece material. An orthogonal array, signal to noise(S/N) ratio and ANOVA were employed to investigate the welding characteristics of MS C20 material and optimize the welding parameters. Their experimentation results that the lower current, medium voltage and lower welding speed leads to better penetration in the welding of MS C20 material [4]. Both MIG and TIG welding on low alloy steel AISI 1020 or C20 was conducted. Welding current was found to have effect on hardness [5]. The effect of welding processes such as GTAW, GMAW and FSW on mechanical properties of AA6061 aluminium alloy was studied. It was found that hardness was lower in the weld metal (WM) region compared to the HAZ and BM regions irrespective of welding technique [6].The optimization of MIG welding parameters for improving strength of welded joint was studied. It was observed that welding speed has major influence on tensile strength of welded joints [7].The optimization methods used in this study are appropriate for modeling, control and optimizing the different welding process [8]. Comparison of machining performances using multiple regression analysis and group method data handling technique in wire EDM of Stavax material, parameters like, pulse on time, pulse off time, bed speed on the responses material removal rate as well as surface roughness while machining [9]. The surface roughness and cylindricity of aluminium silicon nitride material using MRA GMDH & pattern recognition technique in drilling was conducted [10].Estimation of machining performances using MRA, GMDH and Artificial Neural Network (ANN) in wire EDM of EN-31 was carried out [11]. This literature survey is carried out to understand the various welding process parameters like Current, Gas Flow Rate, Welding Speed, Wire Diameter, Voltage, Stick out distance and wire feed rate.

## 2. Experimental work

Experiments were conducted using Lorch welding machine (pulsed) by DC electrode positive power supply. Test pieces of size outer diameter of 25mm, length of 300 mm with wall thickness of 3mm were cut in to length of each 150 mm initially with an edge preparation of 45º and tack welded. Copper coated mild steel electrode of 1.2 mm diameter was used for welding. Argon (85%) and $CO_2$ (15%) gas mixture was used for shielding. The experimental setup used consists of a rotating disk in to which work sample was attached. The working ranges for the process parameters were selected from the American Welding Society hand book. Single pass welding was performed on ASTM A106 pipes by varying the process parameters as shown in Table 1. The photograph of the experimental set up is shown in Fig 1 and Fig 2. Ultimate Tensile Strength, Yield Stress, Percentage Elongation and Hardness are considered as objectives. Hardness test was performed using Vickers Hardness testing machine. Experiments were performed according to $L_{27}$ orthogonal array.

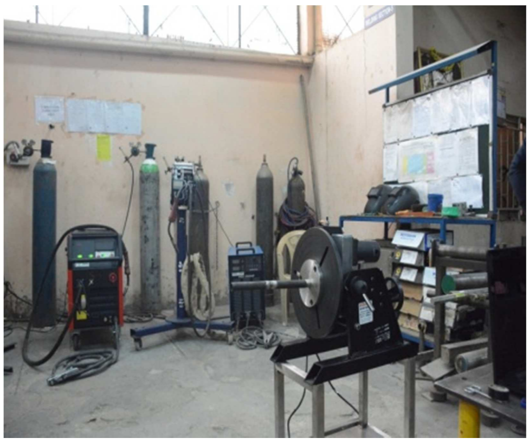

Fig1. Welding Experimental Setup

Fig2. Tensile Experimental Setup

Table1. Welding settings used in experiments

| | | Level | | |
|---|---|---|---|---|
| Input parameters | | I | II | III |
| A | Current (Amp) | 55 | 60 | 65 |
| B | Gas Flow Rate (LPM) | 12 | 13 | 14 |
| C | Wire Feed Rate (mm/min) | 110 | 115 | 120 |

## 3. Result and Discussions

### *3.1 Multiple Regression Analysis*

The objective of multiple regression analysis is to construct a model that explains as much as possible, the variability in a dependent variable, using several independent variables. The model fit is usually a linear model, though some timer non linear models such as log-linear models are also constructed. When the model constructed is a linear model, the population regression equation is

$$Y_i = \alpha + ß_1 X_{1i} + \ldots\ldots\ldots\ldots + ß_m X_{mi} + e_i \tag{1}$$

Where $Y_i$ is the dependent variable and $X_{1i}$ …………… $X_{mi}$ are the independent variables for $i^{th}$ data point and $e_i$ is the error term. Error term is assumed to have zero mean. This error term is the combined effect of variables that are not considered explicitly in the equation, but have an effect on the dependent variable. The co-efficient$\alpha$,

$ß_1$,………$ß_m$ are not known and estimates of these values, designated as a, $b_1$……$b_m$ have to be determined from the sampled data. For this least squares estimation is used, which consists of minimizing.

$$SS = \sum_{i=1}^{n} e_i^{\,2} = \sum_{i=1}^{n} \left(Y_i - a - b_i X_{1i} ............. - b_m X_{mi}\right)^2 \tag{2}$$

With respect to each of the co-efficient a, $b_1$…..$b_m$. This will give k+1 equations from which a, $b_1$…..$b_m$. can be obtained. These least squared estimates are the best linear unbiased estimates and hence gives the best linear unbiased estimate of the dependent variable.

$$Y = a + b_1X_1 + b_2X_2 + \ldots\ldots\ldots\ldots + b_mX_m \tag{3}$$

The obtained regression model for estimating Ultimate Tensile Strength (UTS) for ASTM A-106 material is,

$$UTS=5.74 \text{ x } A -24.74 \text{ x } B -4.37 \text{ x } C +720.69 \tag{4}$$

The obtained regression model for estimating *Yield Stress* for ASTM A-106 material is,

$$Yield\ Stress = 2.34 \text{ x } A - 8.11 \text{ x } B -9.4e\text{-}1 \text{ x } C + 221.87 \tag{5}$$

The obtained regression model for estimating % *of Elongation* for ASTM A-106 material is,

$$\%\ of\ Elongation = 2.2e\text{-}1 \text{ x } A - 4.5e\text{-}1 \text{ x } B - 1.38e\text{-}1 \text{ x } C +12.12 \tag{6}$$

The obtained regression model for estimating *Hardness* for ASTM A-106 material is,

$$Hardness = 4.45e\text{-}1 \text{ x } A + 3.45 \text{ x } B + 8.75e\text{-}1 \text{ x } C - 61.88 \tag{7}$$

### *3.2 Group Method of Data Handling*

Group method of data handling (GMDH) is a family of inductive algorithms for computer-based mathematical modeling of multi-parametric datasets that features fully automatic structural and parametric optimization of models. GMDH is used in such fields as data mining, knowledge discovery, prediction, complex systems modeling, optimization and pattern recognition. GMDH algorithms are characterized by inductive procedure that performs sorting-out of gradually complicated polynomial models and selecting the best solution by means of the so-called external criterion.

A GMDH model with multiple inputs and one output is a subset of components of the base function *(8)*.

$$Y(x_1,......,x_n) = a_0 + \sum_{i=1}^{m} a_i f_i \tag{8}$$

Where f are elementary functions dependent on different sets of inputs, a are coefficients and m is the number of the base function components. In order to find the best solution GMDH algorithm consider various component subsets of the base function *(8)* called partial models. Coefficients of these models estimated by the least squares method. GMDH algorithm gradually increase the number of partial model components and find a model structure with optimal complexity indicated by the minimum value of an external criterion. This process is called self-organization of models. The most popular base function used in GMDH is the gradually complicated Kolmogorov-Gabor polynomial *(9)*.

$$Y(x_1,.......,x_n) = a_0 + \sum_{i=n}^{n} a_i x_i + \sum_{i=1}^{n}\sum_{j=1}^{n} a_{ij} x_i x_j + \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n} a_{ijk} x_i x_j x_k + ...... \tag{9}$$

GMDH is also known as polynomial neural and statistical learning networks thanks to implementation of the corresponding algorithms in several commercial software products.

### *3.3 Prediction of response variables of MS ASTM A- 106 material*

The prediction of responses was carried out using MRA and GMDH, for various training sets of 50%, 62.5% and 75% of data is used in GMDH for automatic level. There are three criteria's, viz., regularity, unbiased and combined criterions was used in GMDH. When the training is completed, it is necessary to check the network performance and determine if any changes need to be made to the training process, network architecture or the data sets. Table 2 shows the welding performances.

Table 2.Welding performances using L27 orthogonal array

| Run | Current (Amps) | Gas flow rate (LPM) | Wire feed rate (mm/min) | Ultimate tensile strength ($N/mm^2$) | Yield stress ($N/mm^2$) | % Elongation | Hardness (VHN) |
|---|---|---|---|---|---|---|---|
| 1 | 55 | 12 | 110 | 303 | 161 | 5.1 | 102.83 |
| 2 | 55 | 12 | 115 | 235 | 156 | 3.1 | 103.83 |
| 3 | 55 | 12 | 120 | 207 | 140 | 1.9 | 111.91 |
| 4 | 55 | 13 | 110 | 215 | 135 | 2.6 | 106.30 |
| 5 | 55 | 13 | 115 | 204 | 130 | 2.3 | 102.56 |
| 6 | 55 | 13 | 120 | 225 | 159 | 3.1 | 112.90 |
| 7 | 55 | 14 | 110 | 195 | 124 | 1.9 | 108.34 |
| 8 | 55 | 14 | 115 | 232 | 160 | 2.8 | 112.07 |
| 9 | 55 | 14 | 120 | 172 | 115 | 1.6 | 118.23 |
| 10 | 60 | 12 | 110 | 258 | 154 | 4.1 | 102.71 |
| 11 | 60 | 12 | 115 | 229 | 144 | 2.5 | 104.44 |
| 12 | 60 | 12 | 120 | 245 | 155 | 4.5 | 113.18 |
| 13 | 60 | 13 | 110 | 210 | 133 | 2.2 | 104.40 |
| 14 | 60 | 13 | 115 | 256 | 158 | 4.1 | 114.35 |
| 15 | 60 | 13 | 120 | 189 | 112 | 2.0 | 117.90 |
| 16 | 60 | 14 | 110 | 250 | 159 | 5.5 | 110.30 |
| 17 | 60 | 14 | 115 | 202 | 118 | 2.7 | 112.07 |
| 18 | 60 | 14 | 120 | 162 | 105 | 1.5 | 118.23 |
| 19 | 65 | 12 | 110 | 303 | 164 | 6.1 | 107.35 |
| 20 | 65 | 12 | 115 | 375 | 189 | 6.5 | 108.89 |
| 21 | 65 | 12 | 120 | 255 | 166 | 4.0 | 111.69 |
| 22 | 65 | 13 | 110 | 335 | 169 | 6.9 | 114.87 |
| 23 | 65 | 13 | 115 | 276 | 159 | 3.5 | 112.07 |
| 24 | 65 | 13 | 120 | 209 | 142 | 3.5 | 113.56 |
| 25 | 65 | 14 | 110 | 245 | 158 | 5.1 | 108.91 |
| 26 | 65 | 14 | 115 | 251 | 166 | 3.6 | 114.44 |
| 27 | 65 | 14 | 120 | 256 | 178 | 5.0 | 127.20 |

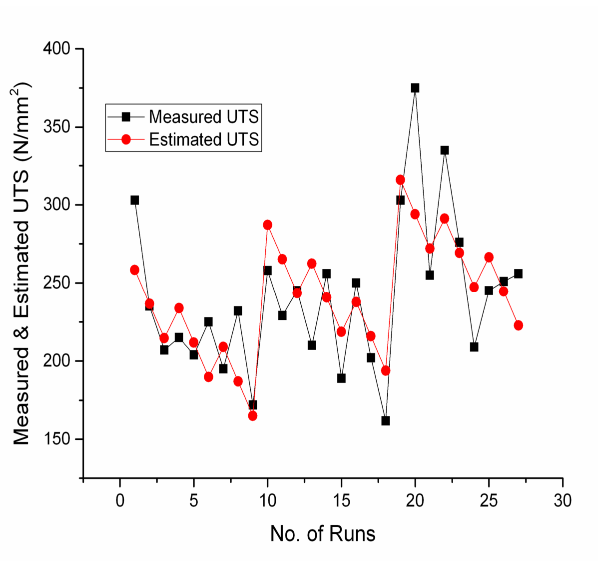


Fig. 3. Measured and estimated UTS by MRA

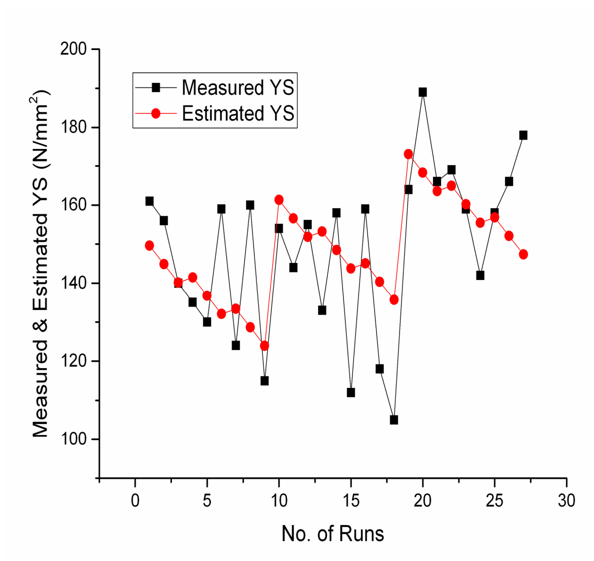


Fig. 4. Measured and estimated YS by MRA

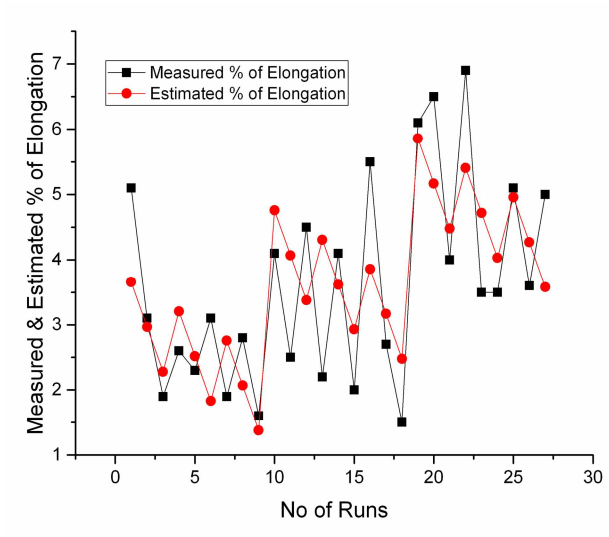


Fig. 5. Measured and estimated % of elongation by MRA

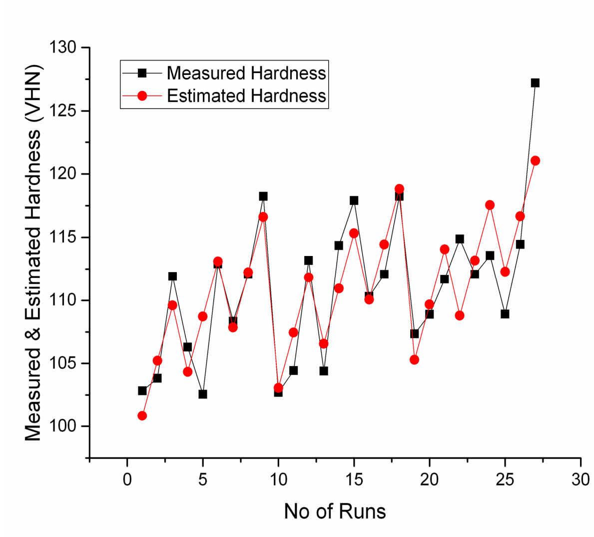


Fig. 6. Measured and estimated hardness by MRA

Fig. 3, Fig. 4,Fig. 5 and Fig. 6 shows the comparison of measured and estimated ultimate tensile strength, yield strength, % age of elongation and hardness using MRA. It is moderately correlating well.

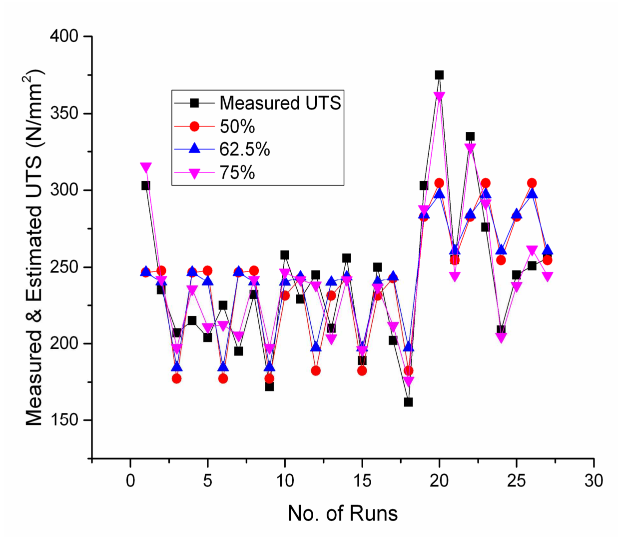


Fig. 7. Measured and estimated UTS by varying the percentage of data in GMDH

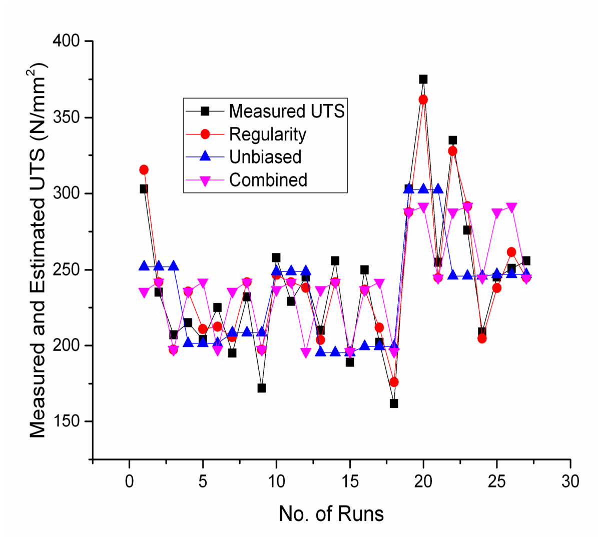


Fig. 8. Measured and estimated UTS by varying the criterions in GMDH

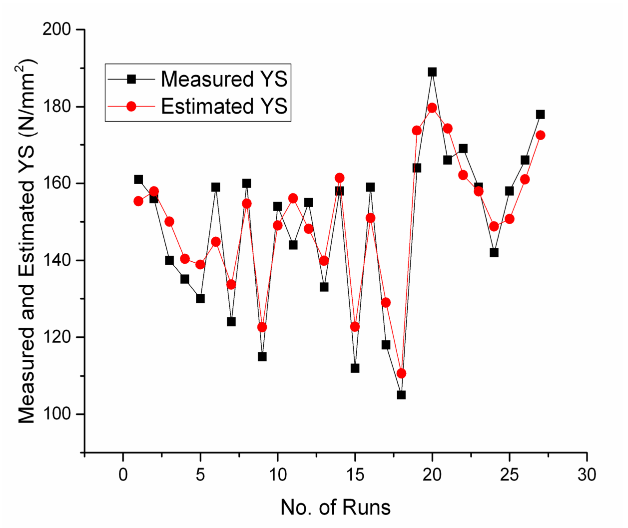


Fig. 9. Measured and estimated YS by GMDH

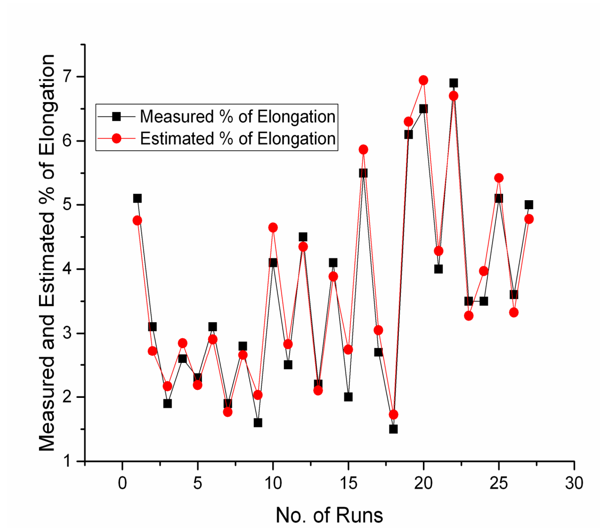


Fig. 10. Measured and estimated % of elongation by GMDH

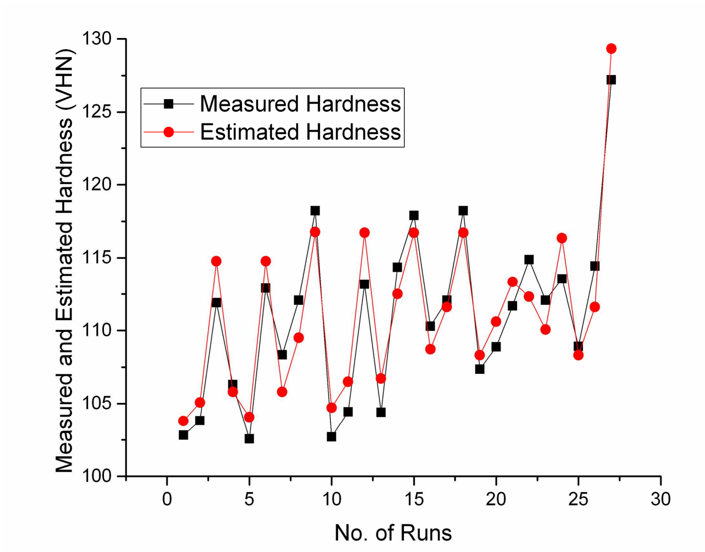


Fig. 11. Measured and estimated hardness by GMDH

Three different criterion functions of GMDH viz., Regularity (RMS), Unbiased and Combined have been tried for estimation of welding performances ASTM A-106. The results from the GMDH show that the regularity criterion function provides good estimation than the other two functions. Different models of GMDH were built by varying the number of data in the training set to 50%, 62.5% and 75% of the total data.

From the Fig. 7 its clearly observed that 75% of data was correlates with the measured one when compared to 50% and 62.5% of data for UTS. The least error and best fit was found at 75% of data for UTS.

Fig. 8 shows the regularity criteria were correlates well with the measured one when compared to unbiased and combined criterions for UTS.

It was found that the least error of estimation and best-fit was found for 75% of data in training set for on ultimate tensile strength, ultimate yield strength, percentage of elongation, as shown in Fig. 7, Fig. 8, Fig. 9 and Fig. 10and 62.5% of data in training set for hardness as shown in Fig. 11.

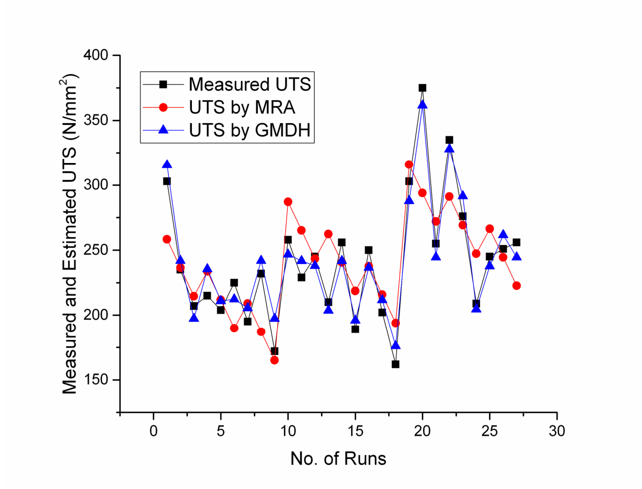


Fig. 12. Measured and estimated UTS by MRA and GMDH

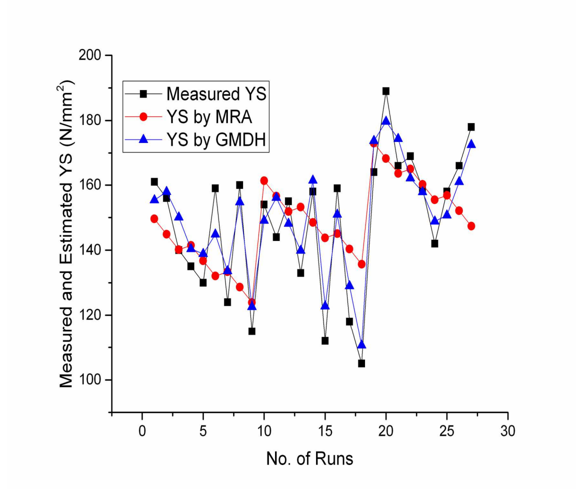


Fig. 13. Measured and estimated YS by MRA and GMDH

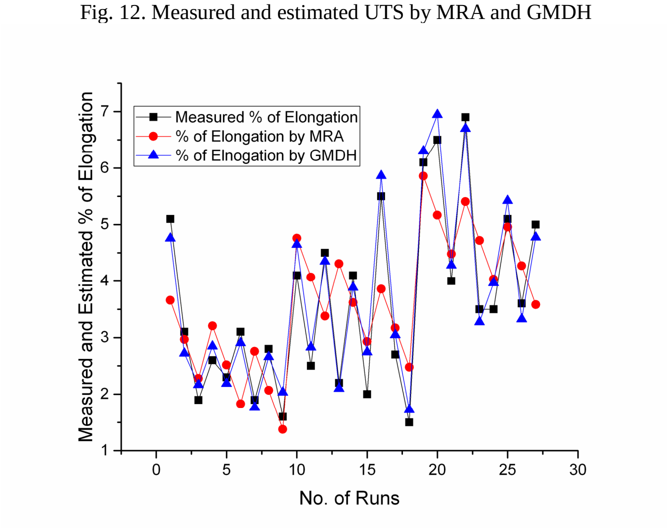


Fig. 14. Measured and estimated % of elongation by MRA and GMDH

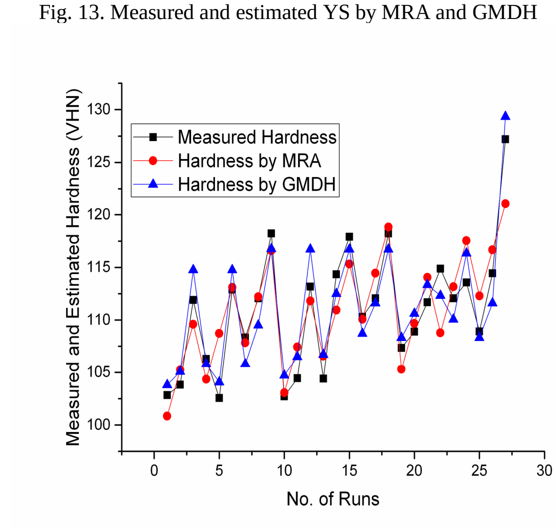


Fig. 15. Measured and estimated hardness by MRA and GMDH

It is observed from the Fig. 12, Fig. 13 and Fig. 14 predicted UTS, YS and % of elongation of regularity criteria with 75% of the data set exhibits better correlation with the measured UTS, YS and % of elongation than 50% and 62.5% of the data set using GMDH when compared to the MRA.

From the Fig. 15 predicted hardness of regularity criteria with 62.5% of the data set exhibits better correlation with the measured hardness than 50% and 75% of the data set using GMDH when compared to the MRA.

## 4. Conclusion

This paper has presented an investigation on the estimation and prediction of welding parameter on ultimate yield strength, ultimate tensile strength, percentage of elongation, and hardness. It was found that, each control factors are affecting the response variables to different extent. We have also seen that multiple regression analysis is a preferred tool for estimating the welding performances of ASTM A-106 material. Three different criterion functions of GMDH viz., regularity (RMS), unbiased and combined have been tried for estimation of welding performances ASTM A-106.

The results from the GMDH show that the regularity criterion function provides good estimation than the other two functions. Different models of GMDH were built by varying the number of data in the training set to 50%, 62.5% and 75% of the total data. It was found that the least error of estimation and best-fit was found for 75% of data in training set for on ultimate tensile strength, ultimate yield strength, percentage of elongation and 62.5% of data in training set for hardness. Comparison of the two theoretical methods for estimation of welding performances, it was found that, GMDH technique has an edge over MRA. Thus, predicted response variables of 62.5% and 75% of data in training set correlates well with the measured response variables. GMDH technique gave better prediction than MRA.

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