Estimation and Comparison of Welding Performances in P- GMAW using MRA and ANN for SS 304L 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. P-GMAW welding input process parameters are the most important factors affecting the quality, productivity and cost of welding 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 tensile strength, yield strength, percentage of elongation and hardness. Experiments have been performed based on Taguchi's L27 standard orthogonal array. Estimation of welding performances have been carried out using sophisticated mathematical models viz., MRA and ANN, and, compared. The output developed by artificial neural network model is used to compare with the output obtained through multiple regression analysis. Estimation and comparison of welding performances were carried out using MRA and ANN techniques.

1. Introduction

Pulsed gas metal arc welding (P-GMAW) is widely used process in manufacturing due to its high deposition rate and with better welding quality. It offers an improvement in productivity and quality over regular Gas Metal Arc Welding (GMAW). The stability of welding process and weld quality are closely associated with the Metal Droplet Transfer (MDT) and its stability. The arc stability is affected by phase matching (Pulse timing control) between the two pulse arcs, background current and shielding gas composition. The welding input parameters affect the MDT mode as well as the weld quality in P-GMAW. Pulsed Gas Metal Arc Welding (P-GMAW) can be used as a fast-follow process at high travel speeds, a high deposition rate, and fast-fill process with precise control of arc dynamics. 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. P-GMAW MAW process suitable for nearly all metals due to pulse provides a stable arc and no spatter, since no short-circuiting takes place.

A comparison in a back-bead prediction of gas metal arc welding using multiple regression analysis and artificial neural network was performed. The system configuration consists of the 3-axis

table system, welding machine and measuring system. The CO_2 arc welding machine was used as a welding power source, and CO_2 was used as a shielding gas. A laser vision sensor was used to measure the geometry of the back-bead. The flow rate of the shielding gas was 15 l/min, and the Contact Tip to Workpiece Distance (CTWD) was determined at 15 mm. The feed wire which was used had a diameter of 1.2 mm. In the experiment, SS41 mild steel was used as the specimen [180mm (width) 100 mm (length) 6mm (thickness)]. Butt welding was performed on the specimen and the different welding parameters and welding conditions used in the experiment. The results when using the multiple regression analysis and the artificial neural network to predict the geometry of the back-bead in gas metal arc welding it can be seen that compared to the multiple regression analysis, the artificial neural network is a more accurate system for predicting the width and depth of the back-bead [1]. Comparative study of surface roughness and cylindricity of aluminium silicon nitride material using MRA, GMDH & pattern recognition technique in drilling was performed. The experimental work consists of drilling aluminium silicon nitride composite using High-Speed Steel drill bit. The machining was carried out in an automatic drilling machine tool. The experiments were conducted for different cutting speeds and feeds combinations. The cutting speeds considered are 11.309 m/min, 15.39 m/min and 21.36 m/min. Feeds considered are 0.095 mm/rev, 0.190 mm/rev and 0.285 mm/rev. Pattern Recognition Technique uses Neural Network to know the status of drilled hole based on surface roughness. Comparison of the two theoretical methods for estimation of surface roughness and cylindricity, it was found that regularity criterion function of GMDH had an edge over Multiple Regression Analysis method. The estimation capability of the Multiple Regression Analysis method was better at lower cutting conditions than at higher cutting conditions, due to the lesser value of measured parameters at those conditions [2].

Estimation of machining performances using MRA, GMDH and Artificial Neural Network in Wire EDM of EN-31was established. The experiments were performed on CONCORD DK7720C four axes CNC WED machine. The basic parts of the WED machine consist of a wire electrode, a work table, a servo control system, a power supply and dielectric supply system. The CONCORD DK7720C allows the operator to choose input parameters according to the material and height of the work piece. The gap between wire and work piece is 0.02 mm and is constantly maintained by a computer controlled positioning system. Molybdenum wire having diameter of 0.18 mm was used as an electrode. It was found that, each control factors are affecting the response variables to different extent. They have also seen that multiple regression analysis is a preferred tool for estimating the machining performances EN-31 material. ANN is used to predict the response variable viz., surface roughness, VMRR and accuracy. Back propagation feed forward neural network (BPNN) and Levenberg–Marquardt Algorithm (LMA) are used to build and train the network [3].

Artificial neural network modeling studies to predict the friction welding process parameters of Incoloy 800H joints was established. Incoloy 800H in the form of bars of diameter 12 mm and length 100 mm was used. The samples were received in cylindrical rod of 1000 mm length. They were cut into 100 mm length by abrasive cutting machine. Later they were cleaned with acetone to ensure clean faying surface and the chemical composition of the as received base material. An artificial neural network for friction welding of Incoloy 800H has been optimized through a proper selection of the training algorithm. Different ANNs, trained with standard or incremental back propagation (IBP), Batch Back Propagation (BBP), Quick Propagation (QP), LM and Genetic Algorithm (GANN), have been evaluated with respect to their predictive Ability [4]. Optimization of machining parameters of Al/SiC-MMC with ANOVA and ANN analysis was performed. In order to achieve the objective of this experimental work, MMCs of type A356/SiC/20p (aluminium with 7.5% silicon, 2.44% magnesium, reinforced with 20% volume particles of silicon carbide (SiC)) were tested. The silicon carbide particle size ranges from 56 to 185_m. A medium duty lathe with 2 kWspindle powerwas used to perform the experiments. The CNMA 120408 inserts with PCLNR 25 X25 M12 tool holder with PCD were used to turn the billets of 150-mm diameter. For the performance of ANN when testing all the training and testing pattern is 1.47%. ANN is suitable tool, which is used to predict the surface roughness in machining process. ANN model has been tested using the training data and graphs were plotted using predicted and tested values. The results indicate that ANN model has been successfully

applied to the machining parameters of MMC composites. Two modeling techniques were used to predict the surface roughness namely ANOVA and ANN. ANOVA and ANN approach provide a systematic and effective methodology for the optimization [5]. Automated diagnosis of rolling bearings using MRA and neural networks was established. FAG 7206 B single ball bearings were tested. The sampling rate was set at 5000 Hz, and each acquired signal had 5120 points. A pit 2mm long was artificially induced in the inner or outer race by an electric pen. In the case of the rolling ball, multiple slots in the surface were performed to simulate the flacking phenomenon. The radial and axial loads were 2.5 and 3 bars, respectively. A total of 196 bearings measured were obtained, 49 for each condition at 600 RPM. Parallel studies were performed at 1200 and 1800RPM. The network has been trained with three different numbers of neurons (10, 20 and 30) in the hidden layer, in order to obtain the best results and to study the influence of the number of processing units in the hidden layer in the training and classification process. An automatic fault classification technique based on MRA and neural networks has been developed. The difficulty in classifying bearing conditions from data provided by a real machine is also stated in this work. The neural network MLP can be used to classify the bearing condition in a very incipient stage with a success rate of up to 80% [6].

A multi-stage MRA-artificial neural network approach was performed. The 160 respondents demographic profile were taken, of which 36.3% of them were male and 63.7% were female. Most of respondents were fairly young which 45% were below 21 years and 53.8% were between 21 and 25 years; all of their marital statuses were single. In terms of academic qualification, majority of the respondents were degree holder with 45.6%, followed by high school leaver at 43.1%, diploma holder at 10.0% and PhD holder at 1.3%. With the use of a multi-stage MRA-ANN approach, the findings of this study have contributed in closing the literature gaps of the current body of knowledge with respect to technology adoption from the contexts of mobile music adoption. With the use of MLP and ANN models, the findings have provided a novel perspective in understanding of the motivators of mobile music adoption. The use of this multi-stage MRA-ANN approach has enabled us to capture the linear and non-linear relationships between the predictor and the criterion variables. It has also provided the opportunity for us to compare the accuracy and predictive power of both techniques. Obviously, ANN has been able to out-performed MRA in the sense of RMSE scores and the ability to capture both linear and non-linear predictors [7].

2. Experimental work

Lorch welding machine was used to conduct experiments using by DC electrode positive power supply. Experimental test specimens are in the size length of 300 mm, outer diameters of 25 mm, inner diameter of 19 mm with pipe wall thickness of 3mm were cut in to length of each 150 mm each initially with an edge preparation of 60º angle and tack welded. 1.2 mm diameter of copper coated mild steel electrode was used for welding. CO_2 (15%) and Argon (85%) 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 SS 304L pipes by varying the process parameters as shown in Table 1. The Fig 1 & 2 shows the experimental set up. Ultimate tensile strength, yield stress, percentage elongation and hardness are considered as output variables. Experiments were performed according to L27 orthogonal array.

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

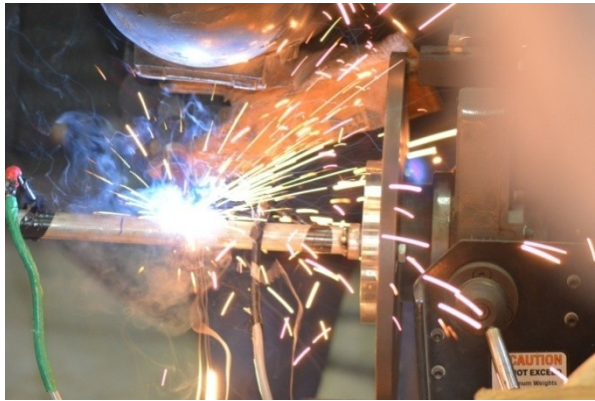$$Yi = \square + ß1\ X1i + \ldots\ldots\ldots\ldots + ß\ mXmi + ei \qquad (1)$$

Fig. 1. Welding Experimental Setup
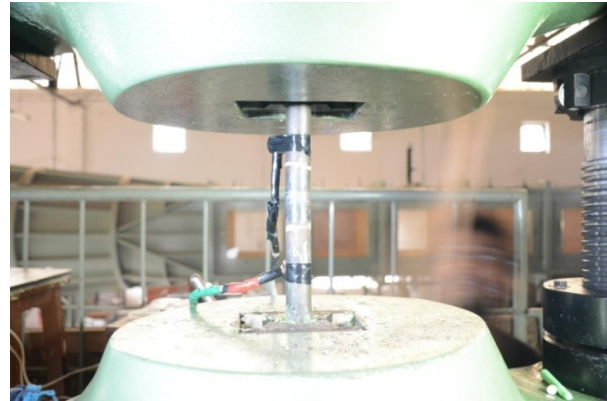
Fig. 2. Tensile Experimental Setup

Table1. Welding settings used in experiments

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

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 coefficient α, β_1,………βm 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.

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

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 give the best linear unbiased estimate of the dependent variable.

Y = a + b1X1 + b2X2 +………….+ bm Xm   (3)

The obtained regression model for estimating Ultimate Tensile Strength (UTS) for SS 304L material is,

UTS=5.74 x A -24.74 x B -4.37 x C +720.69   (4)

The obtained regression model for estimating Yield Stress for SS 304L material is,

Yield Stress = 2.34 x A – 8.11 x B –9.4e-1 x C+ 221.87   (5)

The obtained regression model for estimating % of Elongation for SS 304L material is,

% of Elongation = 2.2e-1 x A – 4.5e-1 x B - 1.38e-1 x C +12.12   (6)

The obtained regression model for estimating Hardness for SS 304L material is,

Hardness = 4.45e-1 x A + 3.45 x B + 8.75e-1 x C – 61.88   (7)

3.2. Artificial Neural Network

A neural network is an artificial representation of human brain that tries to simulate its learning process. ANN is an interconnected group of artificial neurons that uses a mathematical model or computational models for information processing based on a connectionist approach to computation. The ANN are made of inter connecting neurons which may share some properties of biological neurons. ANN is an information processing paradigm that is inspired by procedure in the biological nervous system. Neural networks are non linear mapping systems that consist of simple processors

which are called neurons, linked by weighed connections. Each neuron has inputs and generates an output that can be seen as the reflection of local information that is stored in connections. The output signal of a neuron is fed to other neurons as input signals via interconnections Fig. 3 shows the network architecture of ANN.

The neuron has a bias b, which is summed with the weighted inputs to form the net input n.

$$n = w1,1p1 + w1,2\ p2 + ... + w1,R\ pR + b \qquad (8)$$
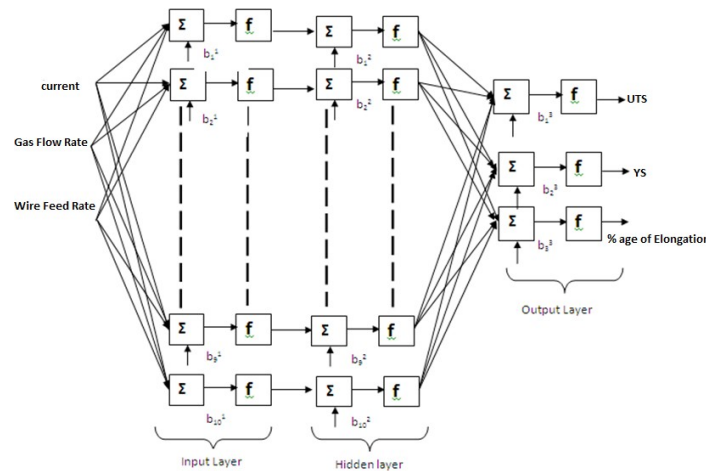
Fig. 3. Network architecture

Various input to the neurons are represented by 'X_n'. Each of these inputs is multiplied by a connection weighed, represented by 'W_n' and added to the bias 'φ' to compute activation 'a_n' which is converted into the output 'O_n' via transfer function. Various input to the neurons are represented by 'X_n'. Each of these inputs is multiplied by a connection weighed, represented by 'W_n' and added to the bias 'φ' to compute activation 'a_n' which is converted into the output 'O_n' via transfer function.

$$a_n = W_n\ Xn^T + \varphi \qquad (9)$$

$$O_n = f\ (a_n) \qquad (10)$$

After conducting the experiment, response values are noted down and analysis has been done. The experiment was conducted in the same environmental condition for all the runs so that environmental noise factors can be minimized.

3.3. Prediction of response variables of SS304L material

The prediction of responses was carried out using MRA and ANN. 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.

Fig. 4 gives the measured and estimated responses with the number of runs using MRA. Referring to the below figure, it was observed that most of these estimates are correlating well with the measured responses at lower and higher welding conditions than at intermediate welding conditions.

Comparison of responses using MRA and ANN were carried out. It is observed from the Fig. 5, Fig. 6, Fig. 7 and Fig. 8 predicted UTS, YS, % elongation and hardness of 70% of the data set by ANN exhibits better correlation with the measured UTS, YS, % elongation and hardness when compared to the GMDH.
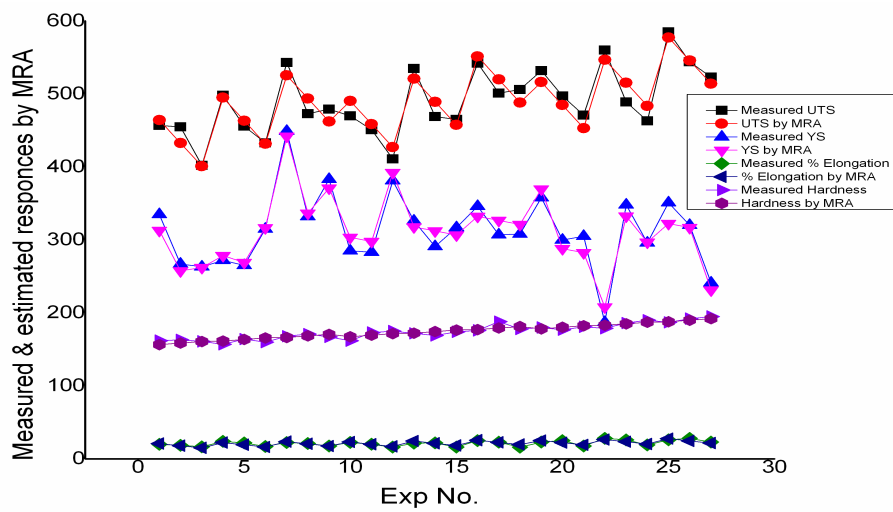
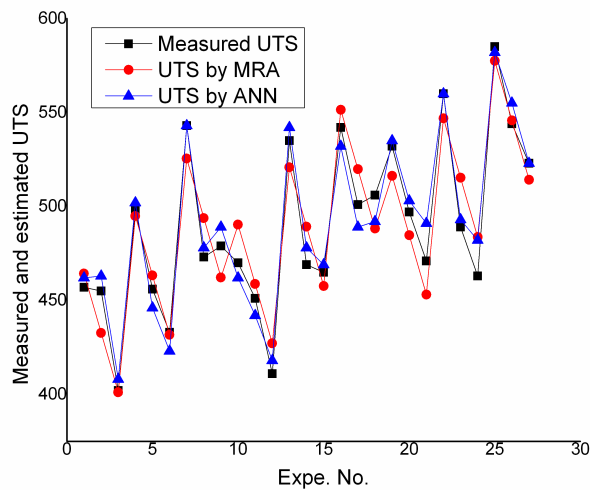Fig. 4. Measured and estimated responses by MRA
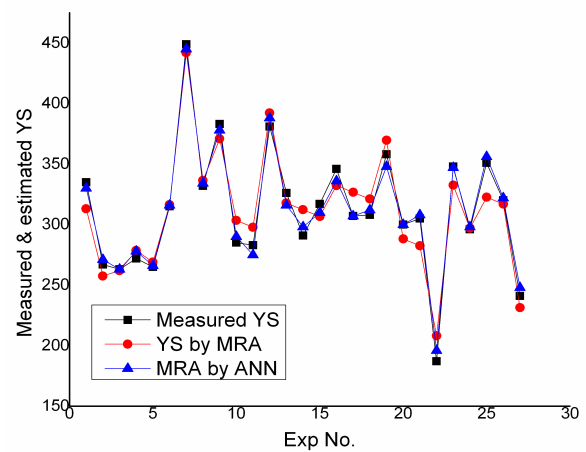

Fig. 5. Comparison of UTS by MRA & ANN
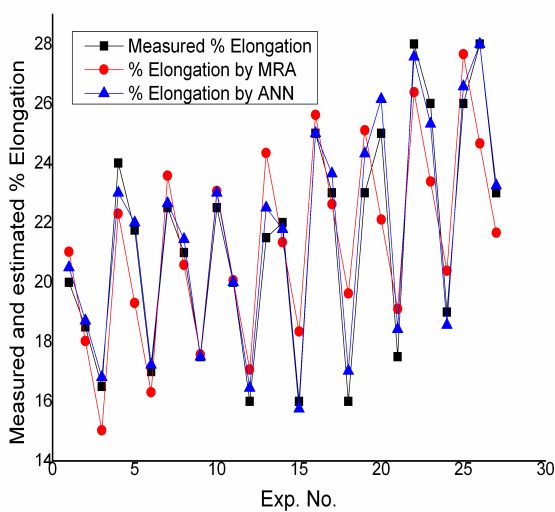

Fig. 6. Comparison of YS by MRA & ANN

Fig.7. Comparison of %elongation by MRA & ANN

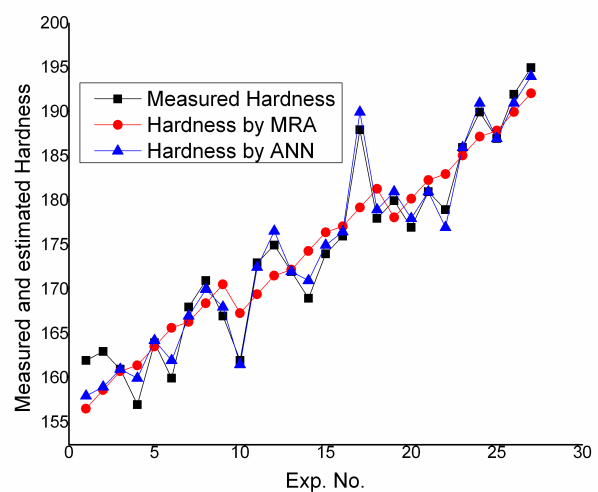Fig. 8. Comparison of hardness by MRA and ANN

4. Conclusion

This paper has presented an investigation on the estimation and prediction of welding parameter on ultimate tensile strength, yield 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 MRA and ANN is a preferred tool for estimating the welding performances for SS 304L material. Comparison of the two theoretical methods for estimation of welding performances, it was found that, ANN fitting function has an edge over MRA method. Thus, predicted response variables of 70% training set correlates well with the measured response variables. ANN function gave better prediction than GMDH.

Acknowledgements

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