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Prediction of Weld Quality by Artificial Neural Network Modeling of Parameters of MIG Welding Process

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ABSTRACT
The study aims to predict the weld quality of MIG welding by Artificial Neural Network Modeling of the process parameters. Due to the lack of any direct analytical mathematical relation among the welding factors, the paper focused on establishing a co-relation among the welding parameters and responses. Tensile strength and Hardness of the welding joints are taken as welding responses. Welding current, welding voltage and wire feed rate are selected among the MIG welding parameters as the inputs to form a multilayer perception (MLP) neural network. The training of the model has been done through Back-propagation (BP) algorithm. The result shows that with the rise of welding current and voltage, the Tensile strength and Hardness of the weld joints have been increased but the best result is obtained at moderate wire feed rate. It is found that the proposed adaptive Artificial Neural Network is capable of mapping the complex relationship among the welding parameters and corresponding weld quality as output.

Keywords: MIG welding, Artificial Neural Network, Multilayer Perception Neural Network, Back-propagation, Welding response.

1. Introduction

Metal joining processes are really very much used processes by the manufacturers now-a-days. Welding is a fabricating process of joining materials which includes basically metal and thermoplastics by fusion of heated and molten materials. Gas Metal arc welding (GMAW) is a welding process in which an electric arc forms between a consumable wire electrode and work piece metals, which heats the work piece metals, causing them to melt and join [12]. Manufacture Engineers often face the problems of process optimization, most of them are multiple response process optimization. And in many manufacturing systems and processes boundary conditions and physical phenomena are so complex that they exceed the current technical capability of system to perform satisfactory analytical or numerical models or approaches which make these problems more complicated [1]. In these cases experimentation is necessary to describe the optimal behavior of the system. One such example of multiple responses is optimization of GMAW parameters. There are lots of tools for optimizing tools for GMAW like Taguchi methods, Response Surface Methods, Artificial Neural networking, Among them Artificial Neural networking is used for more complex problems and reliable solutions.

K. Abbassi et.al studied the effect of MIG welding parameters on the weld bead and shape factor characteristic of bright drawn mild steel specimen of dimensions 144 31 10 mm. The welding current, arc voltage, welding speed, heat input rate are chosen as welding parameters. MIG welding parameters are the most important factors affecting the quality, productivity and cost of welded joint [2]. Metal transfer in MIG welding refers to the process of transferring material of the welding wire in the form of molten liquid droplets to the work-piece [2,4]. The input variables directly affect the shape factor.

Welding current is the most important variable for welding, because it controls the burn off rate of electrodes, fusion depth and weld geometry [2].

Welding voltage determines the shape of fusion zone and weld reinforcement height. Welding speed is defined as the rate of travel work piece under electrode.

Speed of welding(s) = Travel of electrode/ arc time mm/min. Heat input rate = $(V\times A\times 60)$ /S joules per mm, Where, V is arc voltage in volts, A is welding current in ampere, S is speed of welding in mm/min [2, 11].

Shape Factor is the ratio of Penetration Depth to Weld Width. Width The above factor i.e. arc current, arc voltage and welding speed and their interactions play a significant role in determining the weld bead shape characteristics [9,10].

Process optimization is the discipline of adjusting a process so as to optimize some specified set of parameters without violating some constraint. The most common goals are minimizing cost and maximizing throughput and/or efficiency. This is one of the major quantitative tools in industrial decision making. In their study, Aktepe et.al used Pareto Analysis for determining uncontrollable input parameters of the welding process based on expert views. With the help of these analyses, 9 uncontrollable parameters are determined among 22 potential parameters. Then, the welding process of ammunition is modeled as a multi-input multi-output process with 9 input and 3 output parameters [5]. The study of K. Anand et.al focuses on friction welding process parameter optimization using a hybrid technique of ANN and different optimization algorithms. This optimization techniques are not only for the effective

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process modelling, but also to illustrate the correlation between the input and output responses of the friction welding of Incoloy 800H. In addition the focus is also to obtain optimal strength and hardness of joints with minimum burn off length [6]. Asif Iqbal et al, investigated the weld bead geometry (front bead width and height, and back bead width and height) is a significant physical characteristic of a welding [7]. Several welding parameters such as welding speed, weld current, voltage, and shielding gas flow rate affect the weld bead geometry [8].

2. Methodology

2.1 Problem Definition

All welding processes are non-linear and highly coupled multivariable systems. The task of determination of weld quality is difficult because the welding process is a complex process with a lack of analytic mathematical description [1]. The present welding theories are inadequate to model the weld quality (penetration, tensile strength and hardness). In addition, not all the process variables affecting the weld quality are known, nor easily quantified, e.g. contamination, heat absorption and environmental conditions. Unfortunately, few of these factors are simply related to weld quality or to one another. It is seldom possible to establish a simple mathematical equation for weld quality as a function of these variables [12]. In order to solve this inherent weld quality complexity, a new tool is required to find an ‘equation’ to relate these various parameters to determine weld quality.

2.2 Artificial Neural Network

Artificial Neural Network or **connectionist systems** are computing systems inspired by the biological neural system that constitutes animal brains. Such systems learn (progressively improve performance) to do tasks by considering examples, generally without task-specific programming [12].
Artificial Neural Networks (ANN) are programs designed to solve any problem by trying to mimicking the structure and function of our nervous system. An Artificial Neural Network consists of following components-

- A set of processing unit (cell).
- A set of activation unit (inputs) for each unit.
- Connection between every units, generally marked by weights, w_{ji}
- A propagation rule.
- An activation function, f()
- A learning rule.
- An environment where the system must operate providing input signals and error signals if required.

The working principle of an artificial neuron is shown in the figure 1-

1. The inputs are the activity of collecting data from the relevant sources. These data are fed to the neural network. A set of synapses (i.e. connections) brings in activations from other neurons.
2. A processing unit sums the inputs, and then applies a non-linear activation function (which is also often called a threshold or transfer or squashing function). An ANN saves its information in its links and each link has weight (w_{jk}). The weights are constantly varied while trying to optimize the relation between inputs and outputs.
3. An output line transmits the result to other neurons.

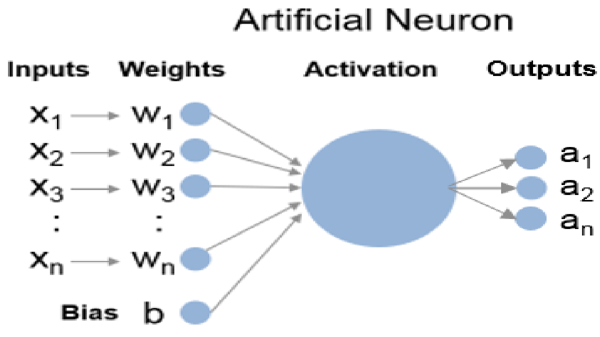

Fig.1 Structure of an Artificial Neuron

2.3 Architecture of Artificial Neural Networking

The architecture of an artificial neural network defines how its several neurons are arranged, or placed, in relation to each other. Training a particular architecture involves applying a set of ordinated steps to adjust the weights and thresholds of its neurons. The network required for our study is constructed with the following components-

Table 1 Architecture of ANN

Type	**Multilayer Perception free forward ANN**
Input Neurons	Current, Voltage and Wire feed rate
Output Neurons	Tensile strength and Hardness of specimen
Performance function	MSE
Activation function	‘relu’, ‘tanh’
Solver	‘lbgfs’
Test function	Test
Software and language	Anaconda Prompt and Python

2.4 Steps of formulating the model

- Using the experimental data as the inputs to train the mode.
- Finding out the smallest mean square error (mse) from input data by altering the combinations of the number of weights, activation function type and iteration number.

- Using the set of weights, activation functions and mean square error the result is predicted by the model.
- The deviation of the predicted values from the real data is determined by graphs.

3. Experimental Investigation

By the present setup of the foundry lab, three parameters of MIG welding were available to vary. These parameters are welding current, welding voltage and wire feed rate. As welding responses tensile strength and hardness of the weld pieces were investigated. For the experimental investigation we have prepared V shaped groove in a square bar.

3.1 Preparation of work piece

After selecting the material types the work piece dimension and types of joint for the experimental welding are fixed. The dimensions are given below:
Work piece dimension: 200mm × 10mm × 10mm.
Types of joint: V Type Butt Joint of 45° angle.

Fig.2 Prepared Work-piece.

3.1.1 Process of work piece preparation

After selecting the material and dimensions of the work piece there need to be started to prepare it. The preparation is done by three steps and three types of machines were used here and shown in figure 3.

1. At first the work piece is cut according to their dimension in disc cutter.
2. The grinded the work piece in grinding machine.
3. The aligned the vertical milling machine at 22.5° for cutting the V shape in work piece. Here end mill cutter is used for this operation.

Fig.3 Prepared Work-piece after grinding, surface finishing and milling.

3.2 Data collection

3.2.1 Mean square value

Mean square error (MSE) is the performance function which determines the best solution for the problem from the data.

Table 2 Determination of smallest Mean Square Value.

Serial	a	b	c	d	Activation	Iterations	MSE
1	10	5	5	10	relu	100	38.96712
2	5	5	5	15	relu	100	44.202
3	5	5	5	5	relu	200	37.670
4	5	5	5	5	relu	100	33.67
5	5	5	5	5	relu	300	33.51

Here a,b,c,d denote the weights. And the smallest mse value obtained is 30.94 with weights (10, 5, 5, 10) and activation function relu with 260 iterations.

3.2.2 Welding Responses

Welding responses are those who can show the result of the effect of the varying of the parameters. In this experimentation, only three parameters were possible to vary within their range. As mentioned earlier they are welding current, arc voltage and wire feed rate. And the two welding responses are considered. They are- **Tensile Strength** and **Hardness.** In current setup, welding current was varied from 100amp-120amp, voltage was (20V-25V) and Welding speed (8cm/m-14 cm/m).

Table 3 Data collection for Tensile Strength.

Sample number	current ampere	voltage volt	wire feed rate cm/min	output Tensile Strength MPa	Predicted values MPa
1	100	20	8	289.5	295.599
2	100	20	12	315.7	316.299
3	100	20	14	303.8	306.721
4	110	20	8	389.65	384.647
5	110	20	12	404.3	404.744

Table 4 Data collection for Hardness.

Sample no	current ampere	Voltage volt	wire feed rate cm/min	Hardness HRB	Predicted values HRB
1	100	20	8	69	68.579
2	100	20	12	73	72.858
3	100	20	14	70.5	69.512
4	110	20	8	389.65	384.647
5	110	20	12	404.3	404.744

All data from the experiment of Tensile Strength and Hardness test of the weld joints weren't possible to be shown in the Table 3 and Table 4 for convenience of the paper. They are shown in the graphs later.

3.2.3 Graphical representation of the deviation of the predicted value from the actual value for tensile strength and hardness

Almost forty samples were used to check the real obtained values for weld responses and real and predicted values are plotted against sample numbers.

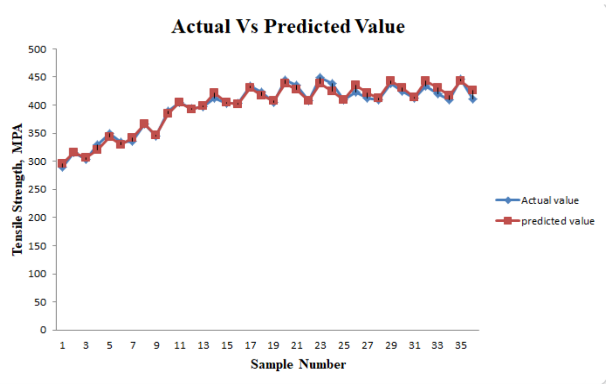

Fig.4 Deviation of predicted values from actual values (Tensile strength)

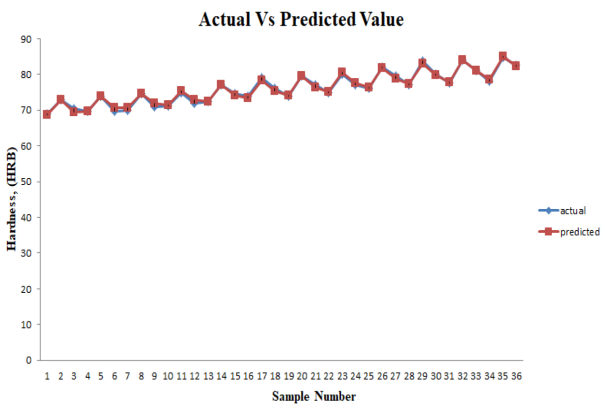

Fig.5 Deviation of predicted values from actual values (Hardness)

In Fig.4 and Fig.5 the blue lines represent the actual values and the red ones do the predicted values. It's clearly seen that the values of both real and predicted results are rising as the sample numbers. Because the from the tables containing the values it gets to know that the welding current and voltage have been increased by the way the sample numbers go forward. But fluctuations happened because in these experiments three varying wire feed rates e.g. 8, 12 and 14 cm per minute have been used. And the result is satisfactory when the moderate wire feed rate was in use. So it is clearly evident that with the rise of the welding voltage and current and with a moderate wire feed rate the tensile strength of MIG weld joints increases. And the graph shows a very negligible deviation of the predicted values from the actual ones. In the Fig 3.4, like tensile strength, both the real and predicted values of hardness are plotted again sample numbers. This graph behaved in the same way like tensile strength. But the deviation is more negligible, the line of predicted values almost coincides with the line of real values.

3.2.4 Error Calculation

The differencs between the actual and predicted value of are showed in percentage value to demonstrate the error. The percentage of error is showed in the Table 5.

Table 5 The percentage of error (%)

Sample Number	Tensile Strength (%)	Hardness (%)
1	2.1067	1.25
2	0.1897	0.852
3	0.9614	0.0190
4	1.2839	0.734
5	0.1098	0.758

3.2.5 Graphical representation of the percentage of error for tensile strength and hardness.

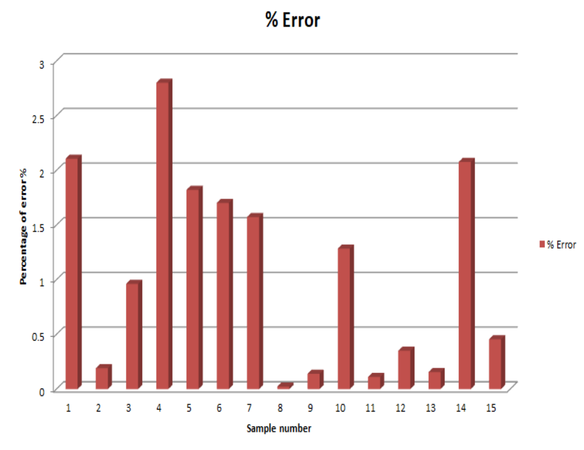

Fig.6 Percentage of error % for Tensile strength.

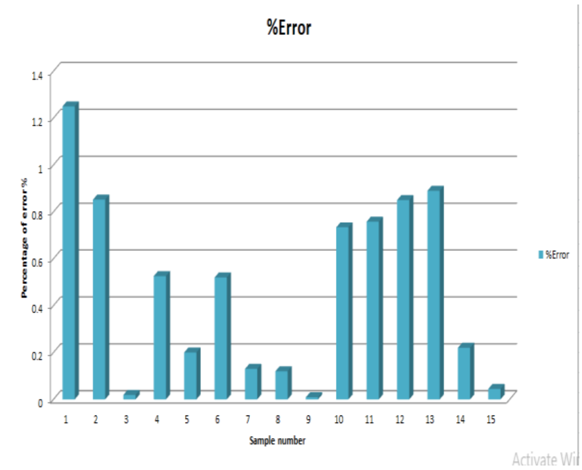

Fig.7 Percentage of error % for Hardness

The figures 6 and 7 show that the accuracy of the model while predicting the results after being trained. The range remains 0.0019%-3.89%.

3.3 Destructive Tests

For finding the welding quality and performance of the welded work piece, two types of destructive test was performed in the laboratory. These are:

1) Macro etching tests
2) Nick break tests

3.3.1 Macro Etching Test

For this test the work piece need to be prepared. The steps involved in preparation of the work piece are described below:

1. At first grind the work piece in the grinding machine
2. Than shaped the work piece in shaper machine
3. At last finished the surface with surface grinding machine

After preparation of work piece for testing than applied 5% nitrile solution in it so that it can be seen the shape and defects of welding. 5% nitrile solution contains 5% nitric acid and 95% methanol. Than observed the welding with the help of magnifying glass.

Fig.8 at 110 A, 20 V, 8 cm/min

Fig.9 at 110 A, 20 V, 12 cm/min

Fig.10 at 110 A, 20 V, 14 cm/min

Results of the macro Etching tests for figure 8, 9 and 10 are mentioned in Table 6 later.

3.4 Nick break test

This type of testing involves breaking a sample fillet weld that is welded on one side only. The sample has a load applied to its unwedded side, typically in a press, and the load is increased until the weld fails. The failed sample is then inspected to establish the presence and extent of any welding discontinuities. This type of weld inspection can detect such items as lack of fusion, internal porosity, and slag inclusions

To compare the results and of four tests together, three samples keeping welding current 110A, voltage 20 V constant and at the three varying wire feed rates are taken. Thus the optimized conditions for these parameters are obtained by comparing the results. During the experiments, the defects those are detected are shown in Fig.11.

110 A, 20 V, 8 cm/min | 110 A, 20 V, 12 cm/min | 110 A, 20 V, 14 cm/min

Fig.11 Nick Break Test.

3.5 Result

The results found from all destructive tests are given bellow-

Table 6 Results of tests

Type of tests	**Specimen 1 110A, 20 V, 8cm/min**	**Specimen2 110A, 20V, 12cm/min**	**Specimen 3 110A, 20 V, 14 cm/min**	**Remarks**
Tensile Strength	389.65	404.3	395.5	Specimen 2 is better
Hardness test	71.23	75	72	Specimen 2 is better
Marco Etching test	Cracks with burnt areas.	No cracks, only heat affected zones.	Blow holes with cracks.	Specimen 2 is better
Nick break test	Cracks and slag inclusions	No cracks and little spatter	Voids with slag and porosity.	Specimen 2 is better

3.6 Discussion

i. It is clearly seen that specimen 2 in each case of having the wire feed rate 12 cm per min has the highest tensile strength and better hardness value.
ii. In case of Macro Etching test, showing no cracks and only little heat affected zone. And the results of the Nick break test reveal also that at 12 cm per min they have no cracks and little spatter.
iii. The highest and lowest percent error from the predicted values of the tensile strength and hardness are found 3.89% for Tensile Strength and 0.0019% for hardness tests.

4. Recommendation and Conclusion

4.1 Recommendation

1. There are a number of parameters which can be varied for MIG welding. But in our current setup only three parameters i.e. welding

current, welding voltage and wire feed rate were possible to vary for experimentation.

2. If The number of inputs can be increased than present, the Mean Square Error will be less than the results obtained in this experiment
3. The available inputs of our current set up (current, voltage and wire feed rate) can provide limited sets of data. If the range of variation could be increased, more data would have been collected.
4. As we know, Artificial Neural Network Modeling can predict closer results to actual ones only when a huge set of data is available. That's why increasing the size of data can provide a more accurate and reliable prediction than the present model.

4.2 Conclusion

This model was able to demonstrate the successful use of Artificial Neural Network in predicting the weld responses i.e. tensile strength and hardness of the weld joints of mild steel by MIG welding and the result reported are in good agreement with other researches. The mean square error for tensile strength and Hardness obtained are 30.004 and 0.295354 respectively. And the highest and lowest percentages of error among the actual and predicted data are obtained. These values are in good agreement within the range of errors predicted by other researches though they were conducted under different conditions and media. Predicted values show that Tensile strength and Hardness values obtained are in range and can be achieved by combination of certain factors shown in the model. Thus the set of factors have been found which are capable of obtaining quality weld joints.

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