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APPLICATION OF ARTIFICIAL NEURAL NETWORK TO PREDICT THE HEAT INPUT OF TIG MILD STEEL WELDS

Uwoghiren F.O. and Achebo J.I.

Department of Production Engineering, University of Benin, Benin City, Nigeria.

Abstract

With the rapidly changing scenario in the manufacturing industry, the optimization of process parameters is essential for a manufacturing unit. Heat input affects the quality of the weld. The aim of this study is to apply expert systems such as artificial neural network to predict weld metal heat input of low carbon steel using the tungsten inert gas welding process in order to produce a better weldment. Mild steel plate was cut into dimension 60mm x 40mm x 10mm with a power hack saw, grinded and cleaned before the welding process. The experimental data was divided into three parts, which is training 60%,validating25% and testing 15%. The network output has a Momentum gain of 1.0e-16 and an error value of 1.2134e-6 at epoch 9 is an evidence of a network with strong capacity to predict the heat input. A Coefficient of determination (r^2) values of 0.9974 was employed to draw a conclusion that the the trained network can be used to predict the heat input beyond the limit of experimentation

1.0 Introduction

As the demand for welding new materials and larger thickness components increased, mere gas flame welding, which was utilized by earlier welding engineers, is no longer up to par with current demands [1]. Over the years welding has improved by incorporating better suited welding methods such as Metal Inert Gas Welding, Tungsten Inert Gas Welding (TIG), and Electron and Laser Beam Welding. Tungsten inert gas (TIG) welding is a thermal process that depends upon heat conducted through the weld joint materials [2] .The melting temperature necessary to weld materials in the TIG welding is obtained by inducing an arc between a tungsten electrode and the work piece. The weld pool temperatures can advance up to 2500^o. In TIG welding, a non-consumable tungsten electrode of diameter between 0.5 to 6.5 mm is employed with an inert shielding gas .The shielding gas shields both the tungsten electrode and the weld pool from the detrimental effects of surrounding atmospheric gases. Argon is the most common shielding gas employed in welding low carbon steels and stainless steels. The mechanical properties of AA 5456 Aluminum alloy welds through pulsed Tungsten Inert Gas (TIG) welding process has been improved on [3]. Taguchi method was employed to optimize the pulsed TIG welding process parameters of AA 5456 Aluminum alloy welds for increasing the mechanical properties. A new approach using experimental design matrix of experimental designs technique has been developed [4]. They used the artificial neural network method for predicting the weld bead geometric descriptors and use of genetic algorithm for optimization of process parameters.

Optimization of gas tungsten arc welding process by response surface methodology was reported in which effects of process parameters on tensile strength and hardness were evaluated [5].

2. Materials and Methods

2.1 Materials

100 pieces of mild steel coupons measuring 60mm x 40mm x 10mm were used for the experiments. The experiment was performed 20 times, using 5 specimens for each run. The tungsten inert gas welding equipment was used to weld the plates after the edges have been bevelled and machined.

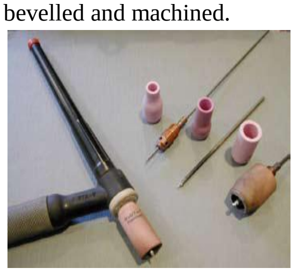


Plate 1: Welding torch

Plate 2: Welding in progress

Corresponding Author**:** Uwoghiren F.O., Email: frank.uwoghiren@yahoo.com, Tel: +2348052561414, +2348174726239 (AJI)

A thermocouple is a sensor used for measuring temperature, it consists of a pair of dissimilar wires joined at one end .The type K-thermocouple is a nickel-chromium and nickel–alumel thermocouple is suitable for inert atmospheres at temperatures up to 1260^{o}c,the K-type thermocouple is shown in plate 3.

Plate 3: K-Type Thermocouple

A digital thermometer is a mercury free thermometer containing thermal sensor in them, it used to take quick and highly accurate temperature readings from the weld samples. They are easy to read with LCD display on them. The digital thermometer is shown in plate 4.

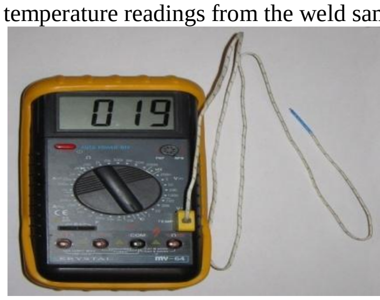


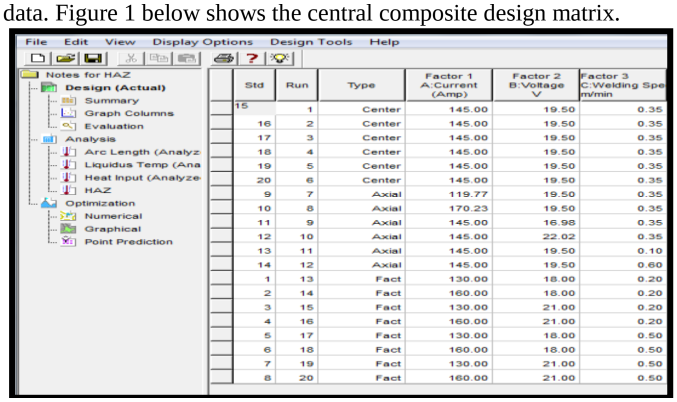
Plate 4: Digital thermometer

Table 1: Process parameters and their levels

Parameters	Unit	Symbol	Coded value	Coded value
			Low(-1)	High(+1)
Current	Amp	A	100	180
welding speed,	M/min	F	0.10	0.6
Voltage	Volt	V	16	22

3.5 Method of Data Collection

The central composite design matrix was developed, using the design expert software, producing 20 experimental runs. The input parameters and output parameters make up the experimental matrix and the responses recorded from the weld samples were used as the data. Figure 1 below shows the central composite design matrix.



Std	Run	Type	Factor 1 A:Current (Amp)	Factor 2 B:Voltage V	Factor 3 C:Welding Spe m/min
15	1	Center	145.00	19.50	0.35
16	2	Center	145.00	19.50	0.35
17	3	Center	145.00	19.50	0.35
18	4	Center	145.00	19.50	0.35
19	5	Center	145.00	19.50	0.35
20	6	Center	145.00	19.50	0.35
9	7	Axial	119.77	19.50	0.35
10	8	Axial	170.23	19.50	0.35
11	9	Axial	145.00	16.98	0.35
12	10	Axial	145.00	22.02	0.35
13	11	Axial	145.00	19.50	0.10
14	12	Axial	145.00	19.50	0.60
1	13	Fact	130.00	18.00	0.20
2	14	Fact	160.00	18.00	0.20
3	15	Fact	130.00	21.00	0.20
4	16	Fact	160.00	21.00	0.20
5	17	Fact	130.00	18.00	0.50
6	18	Fact	160.00	18.00	0.50
7	19	Fact	130.00	21.00	0.50
8	20	Fact	160.00	21.00	0.50

Figure 1: Central Composite Design Matrix (CCD)

Result and discussion

The network training diagram generated for the prediction of heat input using back propagation neural network is presented in figure 2

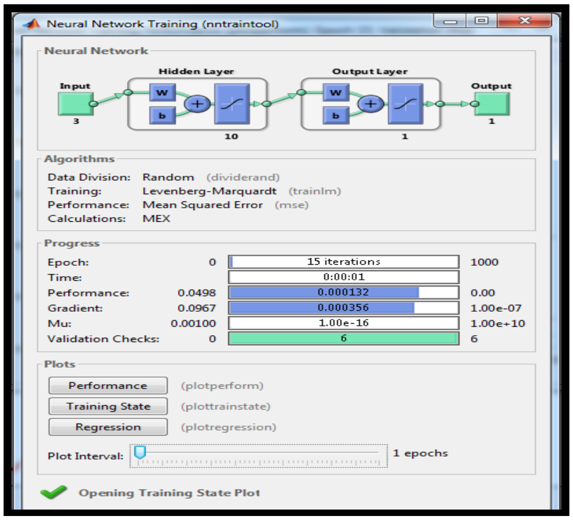


Figure 2: Network training diagram for predicting liquidus temperature

From the network training diagram of figure 2, it was observed that the network performance was significantly good with a performace error of 0.000132 which is far lesser than the set target error of 0.01. The maximum number of iteration needed for the network to reach this performance was observed to be 15 iterations which is also less than the initial 1000 epochs. The gradient function was calculated to be 0.000356 with a training gain (Mu) of 1.00e-16. Validation check of six (6) was recorded which is expected since the issue of wieght biased had been addressed via normalization of the raw data.

The performance evaluation plot which shows the progress of training, validation and testing is presented in figure 3

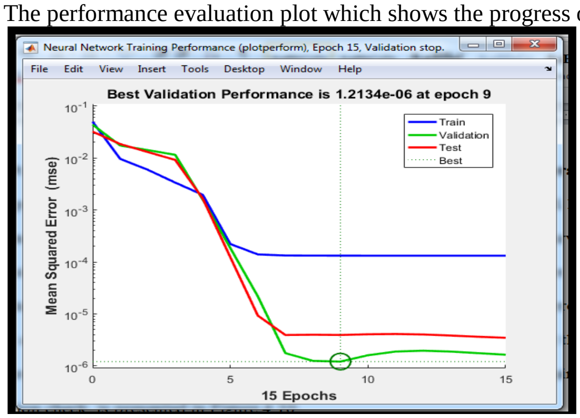


Figure 3: Performance curve of trained network for predicting heat input

From the performance plot of figure 3, no evidence of over fitting was observed. In addition similar trend was observed in the behavior of the training, validation and testing curve which is expected since the raw data were normalized before use. Lower mean square error is a fundamental criteria used to determine the training accuracy of a network. An error value of 1.2134e-6 at epoch 9 is an evidence of a network with strong capacity to predict the heat input. The training state, which shows the gradient function, the training gain (Mu) and the validation check, is presented in figure 4.

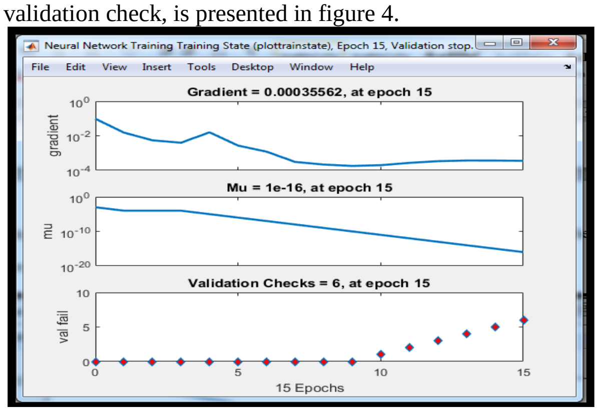


Figure 4: Neural network training state for predicting heat input

Back propagation is a method used in artificial neural networks to calculate the error contribution of each neuron after a batch of data training. Technically, the neural network calculates the gradient of the loss function to explain the error contributions of each of the selected neurons. Lower error is better. Computed gradient value of 0.00035562 as observed in figure 4 indicates that the error contributions of each selected neurons is very minimal. Momentum gain (Mu) is the control parameter for the algorithm used to train the neural network. It is the training gains and its value must be less than unity. Momentum gain of 1.0e-16 shows a network with high capacity to predict the heat input.

The regression plot which shows the correlation between the input variables (current, voltage and welding speed) against the target variable (Heat Input) coupled with the progress of training, validation and testing is presented in figure 5.

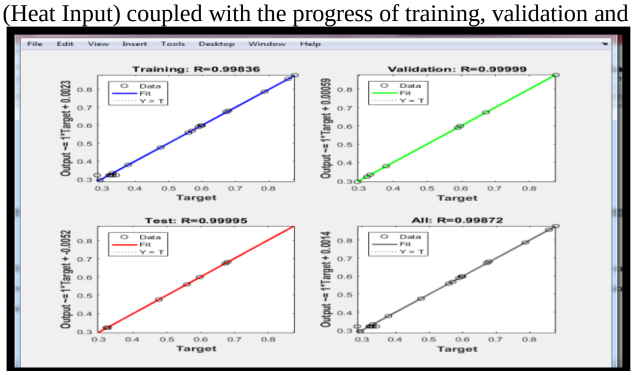


Figure 5: Regression plot showing the progress of training, validation and testing for heat input

Based on the computed values of the correlation coefficient (R) as observed in figure 5, it was concluded that the network has been accurately trained and can be employed to predict the heat input.

To test the reliability of the trained network, the network was thereafter employed to predict its own values of heat input using the same sets of input parameters (current, voltage and welding speed) generated from the central composite design. Based on the observed and the predicted values of heat input, a regression plot of outputs was thereafter generated as presented in Figure 6.

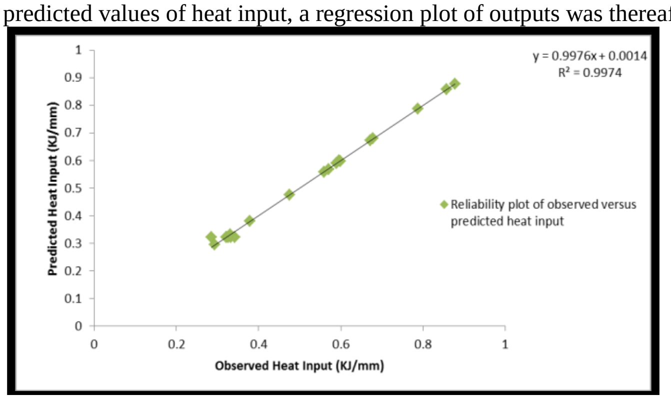


Figure 6: Regression plot of observed versus predicted heat input

Coefficient of determination (r^2) values of 0.9974 as observed in figures 6 was employed to draw a conclusion that the the trained network can be used to predict the heat input beyond the limit of experimentation.

Conclusion

The quality and integrity of welded joints is highly influenced by the optimal combination of the welding input parameters. This study developed a model using Artificial Neural Network as the expert system to predict heat input from input parameters such as current, voltage and welding speed. The Artificial Neural Network produced appreciable predictions with 99.8% closeness to the experimental for heat input.

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