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Research Paper

Development of Welding Fumes Velocity Predictive Models Using Artificial Neural Network

Usman .F[1], Achebo .J .I[2], Ozigagun A[3]

[1]Department of Production Engineering, Faculty of Engineering, University of Benin, P.M.B 1154, Benin City, Edo State
[2]Department of Production Engineering, Faculty of Engineering, University of Benin, P.M.B 1154, Benin City, Edo State
[3]Department of Production Engineering, Faculty of Engineering, University of Benin, P.M.B 1154, Benin City, Edo State, Nigeria

Corresponding Author: Usman .F

ABSTRACT

This research study concentrates on predictive models for welding fumes velocity using artificial neural network. The experiment was optimized using an expert design software, which produced thirty runs of tungsten inert gas mild steel weld specimen, thereafter measuring the welding fumes velocity response. The fume velocity data collected was trained, validated and tested. Analysis of variance ANOVA and model summary statistics helped to check for the models accuracy and reliability. The result obtained from the model indicates that the network developed can predict the fumes velocity adequately with a very low mean square error.

Keywords: development, welding, fume velocity, models artificial neural network, predictive

INTRODUCTION

Welding process is recognized as the most common and reliable industrial process used to join metals [1] about 300,000 workers in the American continent and over three million workers in the world have exposure to welding fumes daily [2]. welding aerosols contain a large proportion of ultrafine particles, which are defined as particles less than 100nm in all dimensions [3] Research studies shows that welding fumes are complex aerosol made up of different metals and the total amount emitted from the welding industry is estimated at about 5000 tons per year [4] The welding fume hazard contains both acute and has long-term chronic effects on Welders. Welding fumes are solid particles that originate from welding consumables, the base metal and coatings present on the base metal. Welding fumes occurs when the intense heat of the arc or flame vaporizes the base metal and electrode coating. The vaporized metal condenses into tiny particles called fumes that can be inhaled. [5] Welding thermal effects can cause agglomeration of the particles into particle chains and clusters that can be deposited in the human respiratory tract [6]. Welding and related hot processes such as thermal cutting can generate a variety of potentially hazardous airborne contaminants including metal fumes containing Manganese (Mn) and /or hexavalent Chromium (Cr VI), ozone, oxides of nitrogen, and carbon monoxide among others. [7] quadratic models was developed to explain the effects of current and voltage on the fume formation rate in Gas Tungsten Arc Welding ,Several statistical tools such as box cox plot, cooks distance and surface plots were employed to check for significance, compatibility and strength of the model. [8] Welding fume particles react with air when they are vaporized and their sizes vary from 0.1 to 5 micrometers, categorizing fumes in the ultrafine and fine particle ranges [9] lung cancer due to welding fumes exposure is inconclusive due to the difficulty in assessing exposure due to different welding settings, materials such as stainless steel welding in confined spaces, and additional carcinogens exposure. The United States Environmental Protection Agency (EPA) classifies Cr (VI) as a Group A carcinogen through the inhalation exposure route. [10] Trivalent chromium has a lower toxicity level because it does not enter cells, while hexavalent chromium has been associated with mutagenic effects [11] The relationship between lung cancer and Cr (VI) exposure remains unclear. Some studies suggest an excess risk of lung cancer and adverse health effects due to acute occupational exposure. However, other studies did not show a statistically significant correlation between lung cancer and the exposure. [12]

2. RESEARCH METHODOLOGY

An appropriate selection of welding parameters and materials is of great importance for optimum experimentation .In this study thirty sets of weld samples was produced. The Gas tungsten arc welding process was used to join the weld specimen made of low carbon steel. The central composite design experimental matrix was developed and used as a guide,

2.1 experimental procedure

150 pieces of mild steel coupons measuring 60 x 40 x10 was used for the experiments, the experiment was performed 30 times, using 5 specimen for each run. The tungsten inert gas welding equipment was used to weld the plates after the edges have been bevelled and machined.

2.2 *Welding Process Parameters*

The key parameters considered in this work are welding current, welding speed, gas flow rate, welding voltage. The range of the process parameters obtained from literature is shown in the table 1.

Table 1: process parameters

Parameters	Unit	Symbol	Coded value	Coded value
			Low (-1)	High (+1)
Current	Amp	A	180	240
Gas flow rate	Lit/min	F	16	22
Voltage	Volt	V	18	24
Wire diameter	Mm	W	1.5	4

2.3 method of data analysis

Table 2: Experimental data

Runs	Current	Voltage	Wire diameter	Gas flow rate	Fume velocity
1	180.00	20.00	2.80	13.00	0.82
2	180.00	16.00	2.80	13.00	0.6
3	220.00	20.00	2.80	13.00	0.89
4	180.00	20.00	0.40	13.00	0.7
5	200.00	22.00	1.60	11.00	0.72
6	180.00	20.00	2.80	13.00	0.82
7	200.00	18.00	4.00	11.00	0.88
8	180.00	20.00	2.80	9.00	0.77
9	200.00	22.00	4.00	11.00	0.92
10	200.00	18.00	1.60	15.00	0.65
11	160.00	18.00	1.60	11.00	0.65
12	160.00	18.00	4.00	15.00	0.62
13	180.00	20.00	2.80	13.00	0.82
14	160.00	22.00	4.00	15.00	0.62
15	200.00	18.00	4.00	15.00	0.88
16	180.00	20.00	2.80	13.00	0.77
17	180.00	20.00	2.80	13.00	0.77
18	160.00	22.00	1.60	15.00	0.62
19	160.00	22.00	4.00	11.00	0.62
20	160.00	18.00	4.00	11.00	0.65
21	180.00	20.00	2.80	13.00	0.82
22	160.00	22.00	1.60	11.00	0.65
23	200.00	22.00	4.00	15.00	0.92
24	180.00	20.00	5.20	13.00	0.82
25	180.00	20.00	2.80	17.00	0.83
26	160.00	18.00	1.60	15.00	0.65
27	200.00	22.00	1.60	15.00	0.65
28	200.00	18.00	1.60	11.00	0.86
29	180.00	24.00	2.80	13.00	0.48
30	140.00	20.00	2.80	13.00	0.52

Neural network are data mining tool for finding unknown patterns in databases, a neural network is a massively parallel distributed processor that has a natural propensity for storing experimental knowledge and making it available for use. Neural Networks are the artificial representation of biological neurons of human brain. This neuron system is circulated in parallel around processing system. These neurons are highly interconnected among them and have the ability to learn from real life experiences and adapt information and make it available for future use.

3 RESULTS AND DISCUSSION

Appropriate network selection and training was done for the fume velocity output which is shown in figure 1

Figure 1 present the neural network diagram for predicting the Fume Velocity. Data division algorithm was set to random (dividerand), training algorithm was set to Levenberg-Marquardt (trainlm), and performance algorithm was set to Mean squared error (mse). A performance plot was produced to check if the network is learning, the plot is shown in figure 2

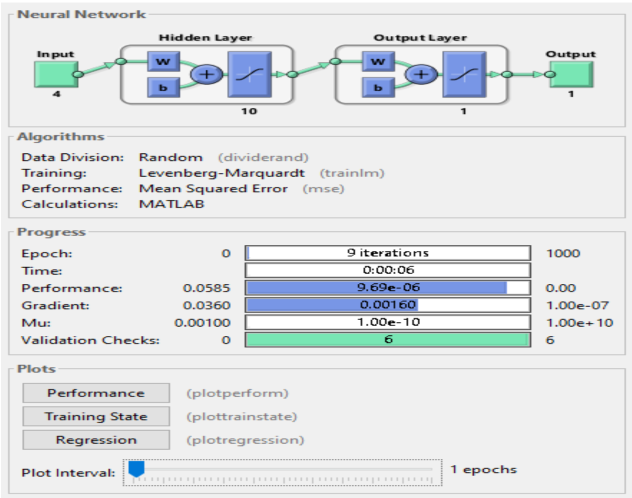

Figure 1: Network training diagram for predicting Fume Velocity

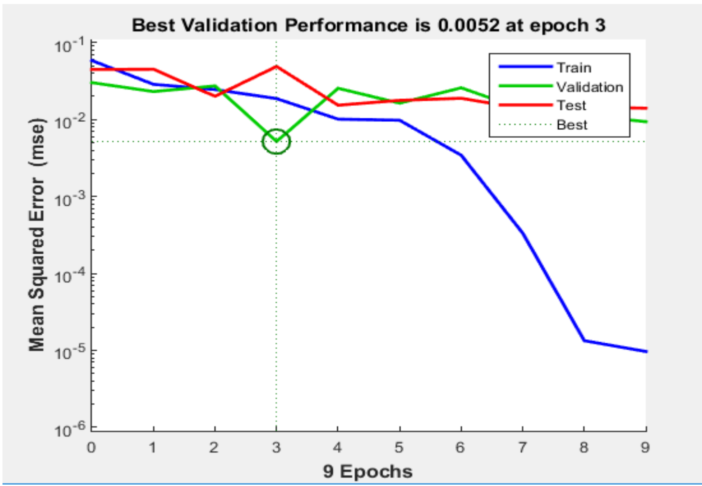

Figure 2: Performance curve for trained network to predicting Fume Velocity

Figure 2 presents the performance curve for the trained network. The best validation performance was obtained at epoch 3.In MATLAB software, an epoch can be thought of as a completed iteration of the training procedure of your artificial neural network. Which means, once all the vectors in your training set have been used or gone through your training algorithm, one epoch has been attained. Thus, the "real-time duration" of an epoch is dependent on the training method used. The best prediction for the Fume Velocity was achieved at epoch 3. The gradient curve which measures the momentum is presented in figure 3.

Figure 3 shows the number of epoch used up during the training process. 1 epoch, signifies one complete algorithm training. 9 epochs were used and figure 12 shows that at the 3th epoch, best prediction was achieved. A regression plot which measures th3 correlation between the network output and the experimental values is shown in figure 4.

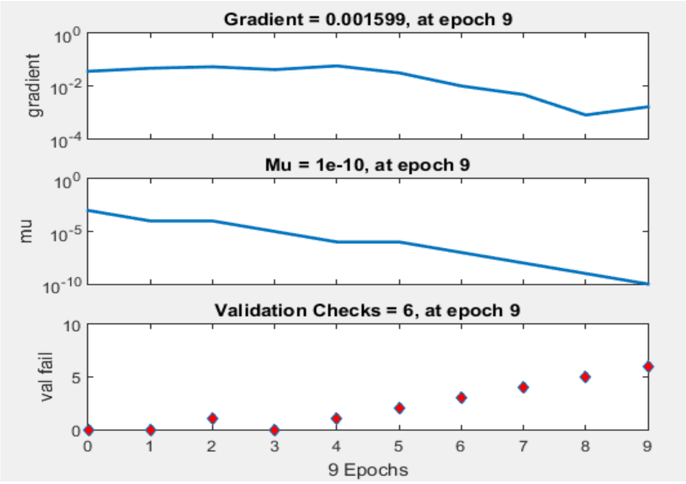

Figure 3: Neural network gradient plot for predicting Fume Velocity

Table 3 : Experimental observed value vs ANN predicted result for Fume Velocity

Runs	INPUT PARAMETERS				EXP Observed	ANN Predicted
	Current (I)	Voltage (V)	Wire Diam (WD) mm	Gas Flow Rate (GFR) L/min	Fume Velocity m/s	Fume Velocity m/s
1	160	18	1.6	11	0.65	0.5858
2	160	19	2.0	12	0.56	0.5189
3	160	20	2.4	13	0.52	0.5226
4	160	21	3.2	14	0.74	0.7399
5	160	22	4.0	15	0.62	0.6209
6	170	18	2.0	13	0.73	0.7294
7	170	19	2.4	14	0.72	0.7129
8	170	20	3.2	15	0.64	0.6420
9	170	21	4.0	11	0.78	0.7799
10	170	22	1.6	12	0.81	0.8110
11	180	18	2.4	15	0.83	0.8297
12	180	19	3.2	11	0.66	0.6598
13	180	20	4.0	12	0.82	0.8200
14	180	21	1.6	13	0.77	0.7311
15	180	22	2.0	14	0.50	0.5646
16	190	18	3.2	12	0.54	0.5400
17	190	19	4.0	13	0.63	0.6266
18	190	20	1.6	14	0.81	0.8752
19	190	21	2.0	15	0.79	0.7806
20	190	22	2.4	11	0.84	0.8359
21	200	18	4.0	14	0.88	0.8802
22	200	19	1.6	15	0.65	0.8912
23	200	20	2.0	11	0.90	0.9990
24	200	21	2.4	12	0.86	0.8579
25	200	22	3.2	13	0.92	0.9111

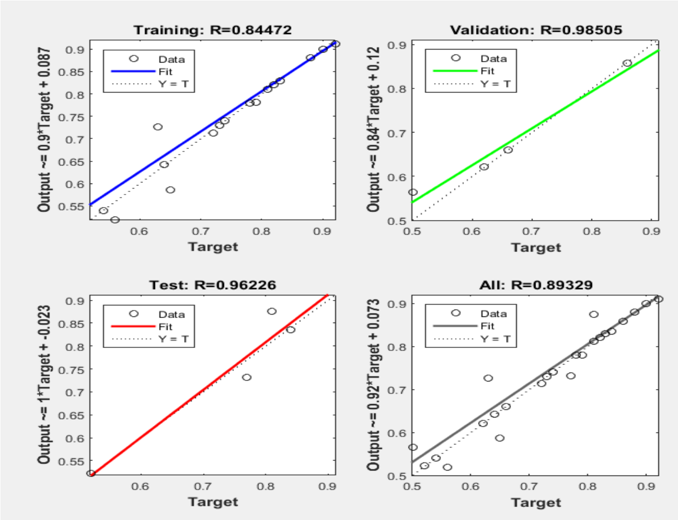

Figure 4.: Regression plot of training, validation and testing for Fume Velocity

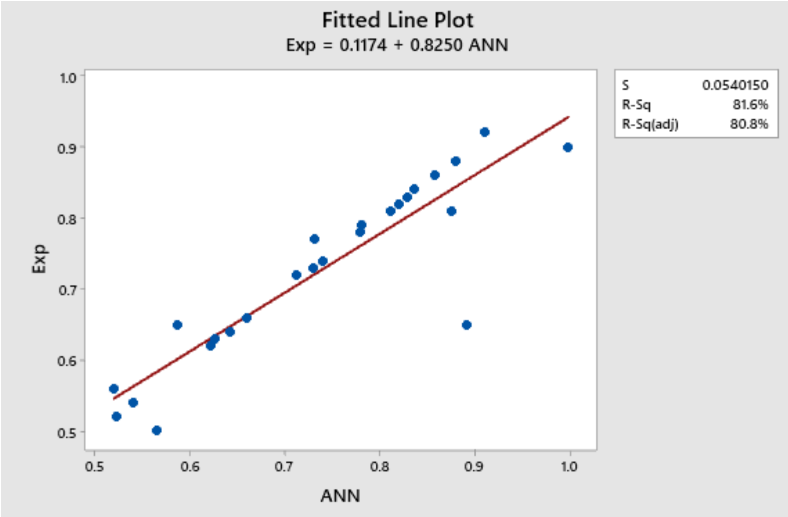

Figure 5: Regression plot of Experimental versus predicted Fume Velocity

Figure 4 present the training, validation and testing plot with correlation coefficient (R) of over 80% which signifies a robust prediction for the Fume Velocity. A comparison between the network output and the actual values is presented in table 3

A regression plot which measures the strength of the neural network prediction is shown in figure 5.

Figure 5 presents the regression plot for the experimental observed results versus the predicted result. It was observed that a robust R^2 value of81.6% (approximated) was obtained. With an adjusted R^2 of 80.81% p. the model summary statistics for the fume velocity network is presented in Table 4.

Table 4: Model Summary statistics

S	R-sq	R-sq(adj)
0.0540150	81.61%	80.81%

The analysis of variance table for the fume velocity network is presented in table 5.

Table 5: Analysis of Variance for fume velocity

Source	DF	SS	MS	F	P
Regression	1	0.297839	0.297839	102.08	0.000
Error	23	0.067105	0.002918		
Total	24	0.364944			

3.2 DISCUSSION

The artificial neural network predictive model was l developed in this study to accurately predict welding fume velocity, the ANOVA results shows that the model selected is very significant with the p values of 0.000 indicating minimum error probability, the model showed very high correlation with the experimental results It was observed that a robust R^2 value of 81.6% (approximated) was obtained. With an adjusted R^2 of 80.81%.

4. CONCLUSION

This study reveals the successful use of Artificial neural network ANN to predict welding fume velocity of TIG welded mild steel plates and the results reported are in good agreement with other researchers. The ANN Predicted results shows a mean squared error of 0.002918, the model summary statistics and the ANOVA table showed the significance and strength of the model.

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