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Estimation of Dependent Parameters of Saw Process

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Abstract

This paper is an attempt to develop a model to predict the output responses of Submerged Arc Welding (SAW) process with the help of neural network technique. Also a mathematical model has been developed to study the effects of input variable (i.e. current, voltage, travel speed) on output responses (i.e. reinforcement height, weld bead width, metal deposition rate). SAW process has been chosen for this application because of the complex set of variables involved in the process as well as its significant application in the manufacturing of critical equipments which have a lot of economic and social implications. Under this study the neural network model is trained according to the actual inputs and outputs. When the training is completed then the desired inputs are given to the model and it gives the estimated output value. And according to this we can also estimate the error between the actual and predicted results. Neural network is implemented here because of having remarkable ability to derive meaning from complicated or imprecise data and can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. Hence a trained neural network can be thought of as an "expert" in the category of information it has been given to analyses.

Keywords: SAW; Neural network; Confounded parameters; Bead width; Reinforcement height

Introduction

Submerged arc welding (SAW) is commonly used for joining plate because of high deposition rate welding process. Here an arc is formed between a continuously fed wire electrode and the work piece, and the weld is formed by the arc melting the work piece and the wire. To shield the arc from atmospheric contamination, the arc is completely submerged under a blanket of granular, fusible flux.

During welding the intense heat of the arc simultaneously melts the tip of the bare wire electrode and a part of the flux. The electrode tip and the welding zone are always surrounded and protected by molten flux, while all of them are covered by the top layer of unfused flux. As the arc progresses along the joint, the molten metal settles down while the lighter molten flux rises from the puddle in the form of slag. The weld metal, having a higher melting point solidifies first while the slag above it takes some more time to freeze. The solidified slag continues to protect the weld metal while it is still hot, and is capable of reacting with the atmospheric oxygen and nitrogen. After the weld has solidified, the unfused flux is removed manually or by a vacuum pick up system, to be screened and reused [1].

The process can be fully automatic or semi-automatic. The submerged-arc welding (SAW) process is popular because of its ability to match the chemistry and physical properties of the base material. This ability allows a multitude of possible weld-wire and flux combinations. These combinations can be easily sorted and matched to specific applications.

SAW process is one of the major fabrication processes in industry because of its inherent advantages, including deep penetration and a smooth bead. In this parameters yield characteristics of SAW process have been predicted through Neural Network [2], which help to reduce the cost and time as well as to obtain the required information about the main and interaction effects on the yield characteristics.

This model is useful for selecting correct process parameters to predict desired weld bead parameters so this model facilitate optimization of the process and sensitivity analysis, also help to improve the understanding of the effect of process parameters on bead quality and to evaluate the interaction effect of bead parameters and to optimization the bead quality to obtain a high quality welded joint at a relatively low cost with productivity.

The most common neural network model is the multilayer perception (MLP). This type of neural network is known as a supervised network because it requires a desired output in order to learn. The goal of this type of network is to create a model that correctly maps the input to the output using historical data so that the model can then be used to produce the output when the desired output is unknown.

Set. No.	Travel Speed (Cm/Min)	Voltage (In Volts)	Current (In Ampere)	Reinforcement Height (Mm)	Bead Width (Mm)	Metal Deposition Rate (Gm/Sec)
1	25	25	300	3.2	13	0.81
2	28	26	320	2	12.5	0.909
3	24	28	280	2.6	13	0.759
4	27	24	300	3.5	13.6	0.55
5	20	20	400	5	11.7	1.5
6	16	20	280	1.7	10	1.25
7	17	19	380	2	12	0.909
8	21	38	450	2.6	21.9	0.792
9	21	30	320	2	15.5	0.681
10	17	24	300	2.3	13.8	0.869
11	16	24	280	1	16.3	1
12	12	23	300	0.6	23	0.877
13	17	22	320	2.3	18.7	0.869
14	20	25	340	2.4	13.8	1.224

Table 1: Experimental Data.

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Experimental Procedure

The output variable was decided based on the guidelines in the reference material. The bead parameters were considered for measuring the response output. Three output parameters considered are (figure 1): P-penetration (mm) H-reinforcement height (mm)w, width(mm).

Sample preparation for the experiment

Now the first thing for conducting the experiment was to prepare the sample for experiment. For this purpose a long mild steel piece was selected and was brought to the welding shop for cutting it to the required dimensions and shape. The mild steel piece was having thickness more than 10 mm. Now here with the help of oxy-acetylene flame it was cut in the desired length. After cutting it into pieces it was left for cooling. After few hours of cooling the pieces were welded in pairs so that they remain together during the experiment. This was done with the help of welding. These samples were having a V-groove over which submerged arc welding was to be done [3].

Now the initial weight of each sample was taken and noted. Also the Submerged Welding Machine was started. Flux was filled in the machine so that there may be no problem in between the experiment.

The machine was fully automatic. Now the welding was done on each sample. The welding parameters travel speed, current [4], voltage were varied each time. Total time taken during the welding was noted and weight after each welding was also taken.

Conducting the experiment

This experimental study was conducted at ISM workshop (Dhanbad). For this study MEMCO semiautomatic welding equipment with constant voltage rectifier was used. The welding parameters were noted during actual welding to determine the fluctuations if any. The slag was removed and the job as allowed to cool down. The values of the reinforcement height, and width were taken using venire caliper of least count 0.02 mm. And metal deposition rate was also calculated with the help of stop watch and weighing machine. Finally the readings obtained are tabulated in table 1

Alternative approach-multi regression method

Reinforcement height, Weld bead width, Metal deposition rate are denoted by RH, W and MDR for this purpose.

As, RH, W, MDR are the response the function, can be expressed as

y=f(T,V,C) where T-Travel speed, V-Voltage-Current. The relationship selected being third degree response surface. The expression as follows:

Sl. No.	Experimental Input			Experimental Output			Estimated Output from NN Model			ESTIMATED ERROR IN %		
	Travel Speed	voltage	current	Reiforcement Height	Bead Width	Metal Deposition Rate	Reiforcement Height	Bead Width	Metal Deposition Rate	Reiforcement Height	Bead Width	Metal Deposition Rate
	Cm/s	Volt	Ampere	Mm	Mm	Gm/s	Mm	Mm	Gm/s	Mm	Mm	Gm/s
1	25	25	300	3.2	13	0.81	3.086965	11.93201	0.917307	3.5323	8.2153	-13.2487
2	28	26	320	2	12.5	0.909	3.301979	11.40573	1.096024	-65.0989	8.7542	-20.5747
3	24	28	280	2.6	13	0.759	2.926106	12.27045	0.847951	-12.5425	5.6119	-11.7195
4	27	24	300	3.5	13.6	0.55	2.960678	12.38977	0.798028	15.4092	8.8987	-45.096
5	20	20	400	5	11.7	1.5	3.732686	10.78969	1.433275	25.3463	7.7188	4.4483
6	16	20	280	1.7	10	1.25	1.607609	12.44933	1.268276	5.4383	-24.4933	-1.4621
7	17	19	380	2	12	0.909	2.863566	13.8952	0.923675	-43.1783	-15.7933	-1.6144
8	21	38	450	2.6	21.6	0.792	2.285657	19.34244	0.659527	12.0901	11.6784	16.7264
9	21	30	320	2	15.5	0.681	2.334672	16.61227	0.641438	-16.7336	-7.1759	9.7827
100	17	24	300	2.3	13.8	0.869	1.868067	15.45693	0.763443	18.7796	-12.0067	12.1469
11	16	24	280	1	16.3	1	1.103829	16.21997	0.962939	-10.3829	0.49098	3.7061
12	12	23	30	0.6	23	0.877	0.627393	2.1554	0.841575	-4.5655	3.6722	4.03934
13	17	22	320	2.3	18.7	0.869	2.473048	13.70641	0.878619	-7.5238	26.7037	-1.069
14	20	25	340	2.4	13.8	1.224	3.090822	12.31951	1.07047	-28.78425	10.7543	12.5433

Table 2: Predicted Data and Estimated Error in Percentage for the Case of Neural Network Model.

Constant	Value For Case Reinforcement Height	Value For Case Of Weld Bead Width	Value For Case Of Metal Deposition Rate
B0	-139.8519	201.2225	83.6786
B1	-7.51767	-38.9009	-1.7873
B2	-16.788	211.0884	-2.5428
B3	2.81482	-16.4002	-0.404
B4	-0.0322	0.942	0.015
B5	0.3517	-8.348	0.0588
B6	-0.011	0.0525	0.0008
B7	0.3951	0.4321	0.0515
B8	0.0309	0.0661	0.004
B9	0.0281	-0.0259	0.0035
B10	0.0003	-0.015	-0.0003
B11	-0.0046	0.1131	-0.0009
B12	0.00001	-0.00005	-0.0000007
B13	-0.0014	-0.0014	-0.0001

Table 3: Values of Constants of Equation 1.

Sl.No	Travel Speed (Cm/Min)	Voltage (In Voltes)	Current (In Ampere)	Reinforement Height (Mm) (Experimental Value)	Reinforcement Height (Mm) (Estimated Value)	Bead Width (Mm) (Experimental Value)	Bead Width (Mm) (Estimated Value)	Metal Deposition Rate (Experimental Value)	Metal Deposition Rate (Estimated Value)	Estimation Error In %		
										Reinforcement Height	Bead Width	Metal Deposition Rate
1	17	24	320	2.4	2.46	14	14.3	0.87	0.88	-2.3	-2.1	-1.6
2	20	22	340	2.6	2.65	24	25	1	1.04	-1.8	-4.2	-4
3	21	28	320	2.4	2.51	8.5	8.76	0.92	0.95	-4.4	-3	-3
4	24	26	280	2.7	2.71	13.3	13.7	0.81	0.83	-0.3	-2.8	-1.2
5	25	26	320	2.5	2.38	13.7	14	1.1	1.08	4.7	-2.4	2.4

Table 4: Estimation of Error in % for the Case of Mathematical Model

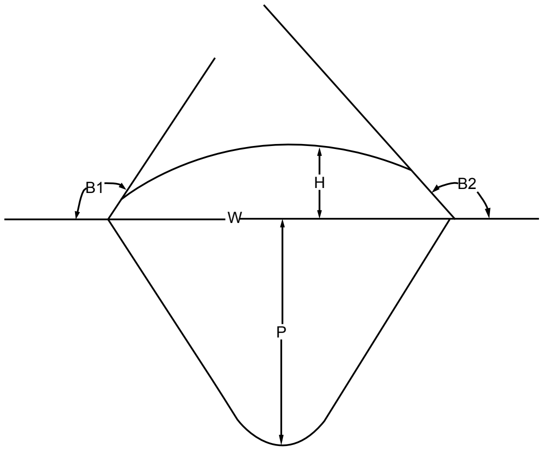

Figure 1: Bead Geometry, P-Penetration (Mm) H-Reinforcement Height (Mm)W, Width(Mm).

Relation between the input and output variables of saw process

Let, $y=B_0+B_1.T+B_2.V+B_3.C+B_4.T_2+B_5.V_2+B_6.C_2+B_7.T.V+B_8.T.C+B_9.V.C+B_{10}T_3+B_{11}.V_3+B_{12}.C_3+B_{13}.T.V.C$----------- (i)

Where B0, B1, B2 …… are constants. Values of theses constants have been calculated (with the help of MATLAB) putting the experimental values which are tabulated in the table 1.

Calculated values are shown in table 3

For checking accuracy of result again five no. of experiments have been done by taking different values input variables which are shown in table 4 A comparisons has been made between estimated values and experimental values and errors also have been calculated and shown in this table. The results show that this model (is made with the help of equation (1)) accuracy is above 95%.

Result and Discussion

Prediction of weld bead parameters Model was developed using neural network. This model was first trained with the help of actual experimental data. And when the training is completed then it is used to predict the values of the output on the same input data to estimate the percentage of error between the experimental result and the result predicted with the help of neural network model.

Also mathematical model has been developed which gives 95% correct result (Table 4). From these two models, we can get a comparative idea of predicted output responses of saw process.

Conclusion

From table 1 we can say that travel speed has a negative effect on all the three bead parameters. An increase in travel speed substantially reduces the heat input resulting in lower burn off rate. This reduced burn off rate decreases the metal deposition at the weld joint thereby lowering all the bead parameters. It has been seen that the penetration increases with increase in the current, the reinforcement height also increases marginally with an increase in the current but the width decreases i.e. it has a negative effect. It is generally observed that as the arc voltage increases, the weld bead becomes wider and flatter and the penetration decreases .Also understood that there are interactions present among the input parameters for output parameters.

A soft computing model was developed in C with the help of neural network. In which we first feed our actual experimental values which includes both inputs and outputs. And on the bases of these values the model is train. And when the training is completed then the desired value of inputs parameters is given to the model and it gives the predicted value of the outputs according the trend. On the bases of these actual and predicted values we can estimate the optimum value of the welding parameters. Also we can estimate the % of error (Table 2). Side by side a mathematical model, comparison of the predicted and observed values of bead parameters revealed the models' accuracy above 95% (Table 4), has been developed by which we can also predict output responses of saw process.

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