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Parameter Optimization of SAW in Hardfacing Process Using Hybrid Approach of Adaptive Stimulated Annealing and Neural Networks

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Abstract - **This paper details the application of ANN in hardfacing technique to determine the optimal process parameters for submerged arc welding (SAW). The planned experiments are conducted on the semiautomatic submerged arc welding machine. The relationships between process parameters (arc current, arc voltage, welding speed, electrode protrusion, and preheat temperature) and welding performance (deposition rate, hardness, and dilution) are established. A Adaptive Simulated Annealing (ASA) optimization algorithm with a performance index is then applied to the neural network for searching the optimal process parameters. Experimental results have shown that welding performance can be enhanced by using this new approach**

***Keywords*: SAW, Hardfacing, ANN, Optimization, Adaptive Simulated Annealing**

I. Introduction

SAW is one of the oldest automatic welding processes introduced in 1930s to provide high quality of weld. It is a multi-input multi- output process since the output variables being closely coupled together, a great deal of time and cost are expanded by trial-and-error methods to obtain optimal weld conditions through the combination of the various welding process parameters to produce consistent weld quality. SAW hardfacing process is a widely used industry and needs a better prediction and monitoring of its parameters. Process planers use different techniques to estimate the influence of the welding parameters (welding current, arc voltage, and welding speed) on bead hardness and deposition rate which are the most sought weld quality indicator in the SAW hardfacing process [1]. Usually, the desired welding parameters are determined based on welder's experience which is simple and inexpensive. However, the obtained result may not guarantee optimal performance. It is necessary to select most appropriate weld parameter settings to improve weld efficiency, process at low cost and produce high quality products. Researchers have made many attempts to predict the process parameters of SAW to get a smooth quality of weld. Weimann[6]elaborates the study of welding procedure generation for the submerged arc welding process. The structure of the dissimilar welds by SAW was studied by McPherson *et al*[5]. The effect of increasing deposition rate on the bead geometry of submerged arc welds was studied by Chandel *et al.*[2] Yang *et al*[8]. A neural network is a powerful data modeling tool that is able to capture and represent complex input/output relationships. The motivation for the development of neural network technology derived from the desire to develop an artificial system that could perform "intelligent" tasks similar to those performed by the human brain. The true power and advantage of neural networks lies in their ability to represent both linear and non linear relationships and in their ability to learn these relationships directly from the data being modeled. Therefore, neural networks are considered in this paper for modeling the SAW process in hardfacing. Based on the developed neural network, the effect of the process parameters (arc current, arc voltage, welding speed, electrode protrusion, and preheat temperature) on the welding performance (deposition rate, hardness, and dilution) can be obtained. Once the SAW process model is constructed, an appropriate optimization algorithm with a performance index is then carried out for searching the optimal welding parameters. In this paper, a sound optimization method of Adaptive Simulated Annealing (ASA) [3] is adopted. It has been found that ASA can provide an effective way to escape from a local optimum and to approach a global optimum. As a result, the ASA algorithm has emerged as a general tool for optimization of arbitrary functions.

II. Saw Process Description: Hardfacing

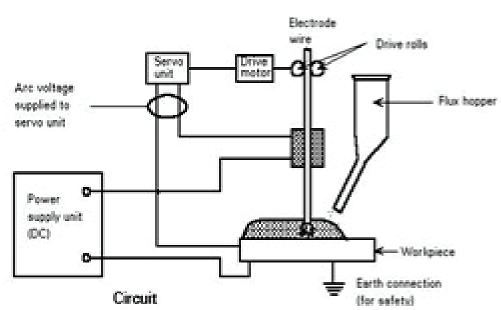

Fig. 1 Process diagram for Submerged arc welding

SAW uses the arc struck between a continuously fed electrode and the work piece to melt the metal in the joint area and provide additional filler metal under a blanket of granular flux. This arc is completely submerged under the molten flux, which protects the molten metal from the atmosphere. There is no visible arc, spatter or fume during the welding operation. The variations in welding parameters, such as arc current, arc voltage, welding speed, electrode protrusions, and preheat temperature, may mutually influence the dilution behavior of the weldment and subsequently affect the microstructure of the hardfacing layer. The hardness of the weld deposit depends directly on the microstructure which is very important in determining the performance such as wear resistance and thermal fatigue resistance. In this study, a martensitic stainless steel hardfacing layer was deposited by the SAW process on the surface of 30 mm thick mild steel plates having dimensions of 100 mm× 60 mm. the working ranges for the process parameter were selected from American society welding handbook. The chemical compositions of the mild steel plates and the stainless steel flux cored electrode of 4 mm diameter used in this work are shown in Table I.

Table I Chemical Composition of Base Metal and Electrode

Materials	C	Si	Mn	S	P	Ni	Cr	Cu
Mild Steel BaseMeta l	0.13	0.20	0.8	0.014	0.02	-	0.03	0.02
Stainless Steel Electrode	0.44	0.40	1.65	0.01	0.017	0.09	15.2	-

The electrode was connected to the positive terminal of an ESAB DC- LAF 1600 power source with a NA-3A controller. The flux (neutral) was baked for 2.5 hrs at 523° K before use. The base metal preheat was carried out by an oxyacetylene gas torch with heating nozzle, and measured using a temperature indicator with 1% accuracy of rated temperature. Forty hardfacing experiments (Table 2) were carried out by varying the welding current in the range of 425- 525 A, the welding voltage in the range of 28-30 V, the welding speed in the range of 30 to 40 cm/min. The electrode protrusion in the range of 19-25 mm, and the preheat temperature in the range of 180-205 K.

In the experiments, a total of 4 layers with 4 passes on each layer were deposited on each plate with length of deposit was about 100 mm. The hardfacing performance is evaluated by the following measurements. First, the deposition rate was simply calculated by multiplying the cross-section area of weld deposit above the surface of the base metal by the welding speed and the density of steel. Secondly, 10 Rockwell C hardness measurements were taken on the surface of the weld deposit along the longitudinal direction at every 10 mm for each hardfacing deposit. These measurements were averaged for use in the analysis. Thirdly, the deposition dilution was measured after a weld cross-section was polished and etched. The welding performance with the corresponding process parameters is listed in Table II.

III. Modelling Of The Saw Process

A feed forward neural network is adopted here to model the SAW process. It consists of a (possibly large) number of simple neuron-like processing units, organized in layers (Figure 2). Every unit in a layer is connected with all the units in the previous layer. These connections are not all equal; each connection may have a different strength or weight. The weights on these connections encode the knowledge of a network. Often the units in a neural network are also called nodes. Data enters at the inputs and passes through the network, layer by layer, until it arrives at the outputs. During normal operation, that is when it acts as a classifier, there is no feedback between layers. This is why they are called feedforward neural networks. The weighted inputs are summed to determine the output of the neuron using a sigmoidal transfer function. The output of the neuron is then transmitted along the weighted outgoing connections to serve as an input to subsequent neurons. In this study, the neurons of the input layer are used to receive the process parameters, that is, arc voltage, arc current, welding speed, electrode protrusion, and preheat temperature. The neurons of the output layer are used to send out the welding performance, that is, deposition rate, hardness, and dilution. As a result, there are 5 input variables and 3 output variables in the neural network. The number of neurons in the hidden layer is determined by trial-and-error experimentation. To properly establish the input and output relationships of the SAW process with the neural network, finite discrete samples of experimental data listed in Table II are used to train the neural network (Figure 3). During the training process, several neural network configurations are studied. Table III shows the number of iterations during the training process using various neural network configurations. It is found that two hidden layers can provide better convergence in modeling the SAW process. The best neural network is the network with the fastest convergence speed. Therefore, a feedforward neural network with a 5-11-8-3 type is adopted here to associate the process parameters with the welding performance.

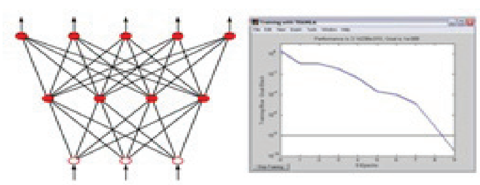

Fig 2 Example of feed forward neural network

IV. Adaptive Simulated Annealing Algorithm

1953, Metropolis *et al*[6] proposed a criterion used to simulate the cooling of a solid for reaching a new energy state . Based on the Metropolis criterion, an optimization algorithm called “Adaptive Simulated Annealing” was developed by Ingber [3]. It has been shown that the Adaptive Simulated Annealing algorithm possesses several advantages in comparison with traditional optimization algorithms. First, the Adaptive Simulated Annealing algorithm does not need to calculate the gradient descent that is required for most traditional optimization algorithms. This means that the Adaptive Simulated Annealing algorithm can be applied to all kinds of objective and constraint functions. Next, the

Adaptive Simulated Annealing algorithm with probabilistic hill climbing characteristics can find the global minimum more efficiently instead of trapping in a local minimum where the objective function has surrounding barriers. Furthermore, the Adaptive Simulated Annealing search is independent of the initial conditions.

TABLE II INPUT DATA OF THE SAW PROCESS FOR HARDFACING

SNo.	Arc current (Am)	Arc voltage (V)	Welding Speed (cm/min)	Electrode Protrusion (mm)	Preheat Temperature (^{0}C)	Deposition Rate (Kg/h)
1.	425	28	30	19	180	5.30
2.	525	28	30	19	180	5.55
3.	425	30	30	19	180	5.02
4.	425	28	40	19	180	5.35
5.	425	28	30	25	180	5.35
6.	425	28	30	19	200	5.30
7.	525	30	30	19	160	6.45
8.	525	28	40	19	180	7.02
9.	525	28	30	25	180	7.37
10.	525	28	30	19	200	7.90
11.	425	30	40	19	180	6.44
12.	425	30	30	25	180	7.45
13.	425	30	30	19	205	7.05
14.	425	28	40	25	180	6.25
15.	425	28	40	19	205	6.40
16.	425	28	30	25	205	7.45
17.	425	28	40	25	205	7.20
18.	425	30	30	25	205	7.20
19.	425	30	40	19	205	6.40
20.	425	30	40	25	180	7.54
21.	525	28	30	25	205	9.25
22.	525	28	40	19	205	7.80
23.	525	28	40	25	180	8.55
24.	525	30	30	19	205	7.64
25.	525	30	30	25	180	8.33
26.	525	30	40	19	180	7.25
27.	425	30	40	25	205	7.30
28.	525	28	40	25	205	8.25
29.	525	30	30	25	205	8.40
30.	525	30	40	19	205	7.80
31.	525	30	40	25	180	8.45
32.	525	30	40	25	205	8.69
33.	425	29	35	22	195	6.20
34.	475	29	35	22	195	6.50
35.	525	29	35	22	195	8.00
36.	425	28	35	22	195	5.90
37.	475	28	30	22	195	6.80
38.	475	29	30	19	195	7.03
39.	475	29	35	25	195	6.90
40.	525	30	35	22	205	8.10

TABLE III RESULTS OF THE SAW PROCESS FOR HARDFACING

S.No.	Hardness (H_R C)	Dilution (%)
1.	54.1	16.2
2.	56.3	18.2
3.	55.1	21.2
4.	55.1	19.9
5.	54.2	17.1
6.	55.9	16.4
7.	55.2	20.9
8.	54.5	21.2
9.	55.2	17.2
10.	51.0	19.0
11.	53.4	18.6
12.	55.8	10.4
13.	54.0	13.2
14.	52.8	18.5
15.	51.2	16.8
16.	47.2	11.8
17.	48.2	9.5
18.	53.3	13.8
19.	53.5	18.5
20.	56.3	13.2
21.	55.4	15.8
22.	55.0	15.8
23.	53.2	12.6
24.	54.2	16.9
25.	55.0	15.2
26.	55.2	19.5
27.	55.2	9.8
28.	52.0	16.3
29.	51.3	11.9
30.	54.2	21.3
31.	54.0	22.3
32.	52.5	21.4
33.	53.9	17.1
34.	50.9	18.9
35.	48.8	18.5
36.	47.4	16.8
37.	54.4	16.9
38.	51.9	17.2
39.	54.2	14.2
40.	49.6	21.2

TABLE IV VARIOUS NEURAL NETWORK CONFIGURATIONS FOR MODELING THE SAW PROCESS

Configuration	Number of iterations	R.M.S error
5-11-8-3	31926	0.9757
5-11-7-3	32356	0.9547
5-11-8-3	22147	0.9575
5-11-11-3	28756	0.8661
5-16-3	134567	6.4785
5-20-3	152688	4.3256
5-8-8-5-3	47866	0.9910

In this paper, the Adaptive Simulated Annealing algorithm is used to search the optimal process parameters. Figure 4 shows the flowchart for the Adaptive Simulated Annealing. First, given an initial temperature T_s, final temperature T_e, and a set of initial process parameter vector X_o, the objective function *obj* is defined based on the welding performance. A small randomly generated deviation is applied to the process parameters. The objective function *obj* is recalculated using the deviated compensation parameters. If the new objective function becomes smaller, the deviated process parameters are accepted as the new process parameters and the temperature T drops a little, that is

$$T_{new} = T_{old}\ CT \qquad (1)$$

Where CT is the decaying ratio for the temperature ($C_T < 1$). However, if the objective function becomes larger, the probability of the acceptance of the deviated process parameters is given as

$$P_r = \exp(- \Delta obj / k_B\ T) \qquad (2)$$

where k_B is the Boltzmann constant and Δobj is the difference in the objective function. Repeat the above procedure until the temperature T approaches zero. As shown in equation (2), the probability P_r (*obj*) approaches one for all energy states when the temperature T is high. However, as the temperature T drops the probability of high-energy states decreases as compared to the probability of low energy states. This implies that the Boltzmann distribution concentrates on the low energy states as the temperature decreases.

V. Optimal Welding Process Parameters

To determine the optimal welding parameters maximum deposition rate and minimum dilution should be considered for optimizing welding performance in hardfacing, while hardness should be kept at an acceptable level. Therefore, the objective function *obj* is defined as:

$$obj = -W_1 \text{ deposition rate} + W_2 \text{ dilution} \qquad (3)$$

Where W_1 and W_2 are the weights of the deposition rate and dilution in optimization.

The inequality constraint on hardness is given as follows

$$46\ (H_RC) < \text{hardness} < 56\ (H_RC) \qquad (4)$$

The process parameters are chosen in the same domain as shown in Table II. The parameters used in the Adaptive Simulated Annealing algorithm are given as follows: the initial temperature T_s=100°C, the final temperature T_e=0.001°C, the decaying ratio C_T = 0.99, and the Boltzmann constant k_B = 10.0. Through the stimulated annealing search, the optimal process parameters with several weighting combinations are listed in Table IV. It is shown that the process parameters with an optimum welding performance in hardfacing can be systematically obtained through this approach.

VI. Conclusions

The effects of welding parameters and the optimum welding parameters for SAW hardfacing process are systematically investigated in this research. The paper describes a neural network approach for modeling and optimization of the SAW process. A feed forward neural network is used to construct the SAW process model. Based on this model, the complicated relationships between the process parameters and welding performance can be obtained. A global optimization algorithm, Adaptive Simulated Annealing (ASA), is then applied to this network for solving the optimal process parameters based on an objective function. Therefore, the efficiency of determining optimal SAW process parameters in hardfacing can be dramatically improved by using this approach. The following conclusions are made:

- Approach of ANN and ASA is very effective in optimization of SAW hardfacing.
- Least dilution 9.21% is obtained when welding current is 435 amps, arc voltage is 28 and welding speed is 38cm/min.
- Through the optimum procedure of ANN and ASA optimize weld parameters are obtained and verified by confirmation test. Final results verify that the multiple objectives are improved simultaneously through this approach.

Table IV Optimization Results For Hardfacing

W1	W2	Arc current (Amp)	Arc voltage (V)	Welding Speed (cm/min)	Electrode Protrusion (mm)	Preheat Temperature (^{0}C)	Deposition Rate (Kg/h)	Hardness (H_RC)	Dilution (%)
1	0	525	28	32	22	210	9.21	53.2	15.0
0	1	435	28	38	22	215	7.01	50.1	9.21
1	1	475	28	34	22	205	7.76	47.7	10.0
5	1	525	28	31	22	205	8.02	52.1	11.56

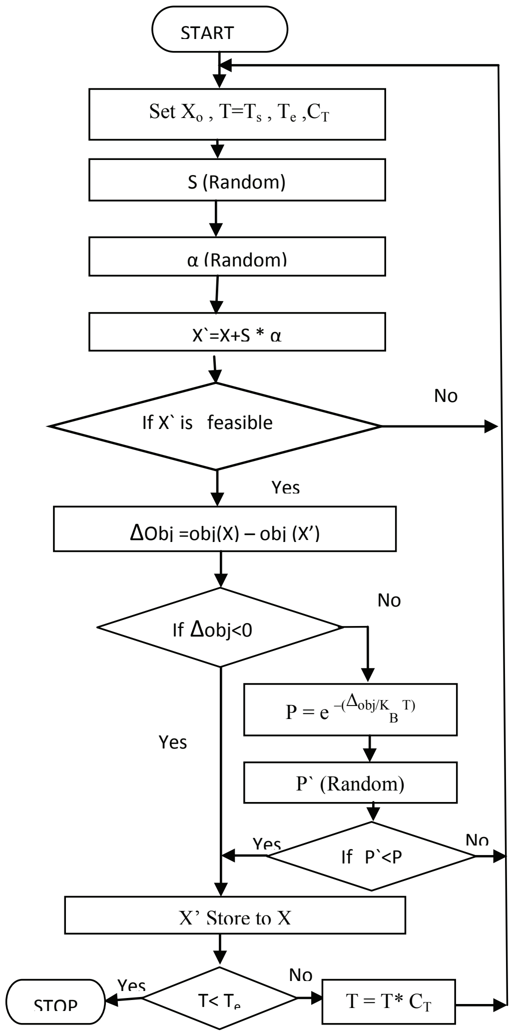

Fig. 4 Flow chart for Adaptive Simulated Annealing (ASA)

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