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Optimization of GMAW Using Combination of Adaptive Simulated Annealing and Artificial Intelligent Approach

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Abstract

This paper prescribes that ANN shall be used to determine optimum process parameters for gaseous metal arc welding technology. On the semiautomatic MIG welding system the intended experiments were carried out. The connections are determined between the parameters of the equipment (arc current, arc voltage, welding rate, preheating temperature and protrusion electrode) and the soiling efficiency (depository, hardness and dilution). The Neural Network will use the adaptive simulated rinsing (ASA) optimization algorithm with an output index to look for the best parameters of the system. From the experimental results, it has been concluded that this new technique will help improve welding efficiency.

Keywords: GMAW, ANN, Optimisation, Adaptive Simulated Annealing.

1 Introduction

Welding is one of industry's main and most versatile manufacturing methods (Chandel et al. 1997). Welding is used in many different forms to add different industrial alloys. Most items, for instance, guided rockets, nuclear power stations, jet fighters, pressure vessels, chemical processing equipment, transport vehicles and literally tens of thousands more, cannot actually be created without the use of welding. A proper consideration of the specific characteristics and requirements of the process can prevent many problems inherent in the welding. The choice of a specific process involves an insight into the wide range of options available, the variety of potential joint configurations and the many variables to be defined for each operation. In order to achieve fluid solder efficiency, scientists tried to predict GMAW's system parameters (Yang et al. 1993). In the continuous casting of steels tools, due to the hard working conditions, steel milling rolls are certainly impaired. In terms of time and money, it is very difficult to purchase and reinstall a new steel mill sheet. Consequently, a method for repairing damaged rolls of steel mills has been suggested.

A neural network is a powerful tool for data processing which captures and portrays complex relations between input and output (Ingber, 1989). The drive towards the progress of neural networking technology is the wish to create an artificial device that is capable of performing "intelligent" jobs akin to those done by the human intelligence. They are capable of representing linear as well as nonlinear interactions and of explicitly learning from information modeled on which neural networks are actually powerful and beneficial. Consequently, neural network models for the tough GMAW program are included in this study. The solder performance (deposition frequency, hardening and dilution) can be determined using the defined

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neural network by process factors for instance, arc tension, joining rate, and conductor protrusion. The optimization algorithm with an index of results is then performed for the quest for optimal welding parameters once a GMAW system template has been built. In this article, the method of sound optimization Adaptive Simulated Annealing (ASA) was adopted (Crowther, 1984). An effective way to avoid the optimal local environment and to achieve an optimal global strategy was found in ASA. The ASA algorithm has therefore emerged to boost arbitrary functions as a general tool.

2 GMAW process description: Hardfacing

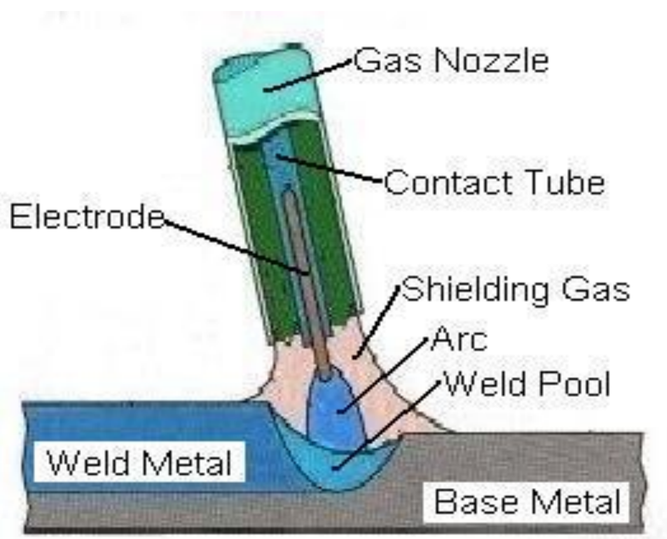

Fig 1. MIG Welding

GMAW is a welding community in which heat generated from an electric arc produced between a tungsten-unusable electrode and a working part are connected together in the presence of an inert gas atmosphere. During the welding process a filler material can be inserted when necessary. Differences in holding parameters such as arc current, voltage of the bow, welding speed, electrode blows and pre-heat temperature can influence each other's welding dilution and then impact the microstructure of the face layer (Pherson, 1997). Microstructures that are very important for evaluating quality, such as wear-resistance and thermal tiredness, influence the durability of the solder layer. A GMAW-process was deposited with a thickness of a 30 mm thick, mild sheet of steel with dimensions of 100 mm and 60 mm on martensitic stainless steel sheets. Table1 shows the chemical compounds of the lightweight steel sheets and the core electrode core in stainless steel with 4 mm diameter. The electrode was connected to the ESAB DC-LAF 1600 power supply with a NA-3A controller. The flow was baked 2.5 hours before use at 523 ° K. A 1 percent precision temperature indicator was used to preheat basket metals with an oxyacetylene gas torch containing a warming tube. The 420-520 A welding power spectrum of welding voltage, 26-30 V welding voltage, and 30-40 cm / min welder welding rate differ forty (Table 2) tests. The protrusion of the electrode in the 19-25 mm range and pre heat in the 180-205 K range. A total of 4 layers of 4 passes per layer with a deposit length of approximately 100 mm were mounted on every surface. The rough quality is measured by the measures below. Next, by multiplying the cross sections of the soil surface across the base metal region by the

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soiling velocity and weight, the deposition rate was simple to calculate. Second, 10 Rockwell C hardness measurements were taken on each 10 mm surface of the sold layer on each resilient deposit along the longitudinal line. Such tests have been used for the study on average. Thirdly, after polishing and grazing, the deposition dilution was measured. Table 2 lists the welding performance with the appropriate process parameters.

Table 1 Elemental composition of substrate material and electrode

Materials	C	Si	Mn	S	P	Cr
Mild steel base metal	0.13	0.2	0.8	0.014	0.02	0.03
Stainless steel Electrode	0.44	0.40	1.65	0.01	0.017	15.2

3 Modelling of the GMAW process

In this context, the GMAW process is shaped using a forward neural network. A neural feed network is a classification algorithm of biological inspiration. It comprises of a number of modest, layer-organized neuronal treatment units (Fig 2). Each unit in a layer will be associated to the previous layer of all units. Not all these connections are similar, each link can have a different weight or power. The weights of these ties represent network information. The modules are often also called nodes in a neural network. Data is entered on inputs and is sent layer by layer through the network until the output is reached. When it acts as a classifier, feedback between layers is not available during normal functioning. For this reason, it is called neural networks feeding. The weighted entries are combined with the sigmoid transfer function in order to determine the neuron output. The neuron output is then passed to the following neurons along the weighted output joints. The input surface neuron is measured using the device parameters of arc voltage, arc current, sounds, protrusion electrodes and pre-heating. For soldering efficiency, e.g. deposition, durability and dilution are used. As a consequence, the neural network has five input and three output variables. Test and error testing decides the number of neurons in the secret surface. The neural network is built with test data described in Table 2 for the correct determination of GMAW input and output relationships (Fig. 3). During training procedure, many neural network settings have been checked. Table 3 shows how much iteration different neural network parameters are used by the training process. Two hidden layers have been found to improve convergence by modeling the GMAW system. Hence, the process parameters are linked to the welding performance by a feed-forward neural network with a type 5-11-8-3.

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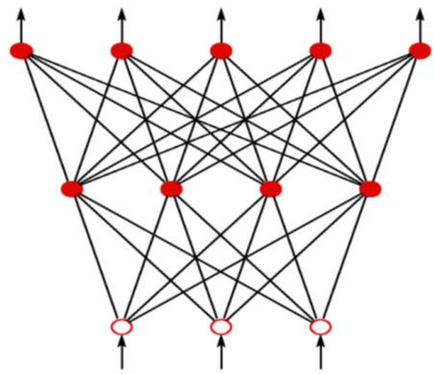

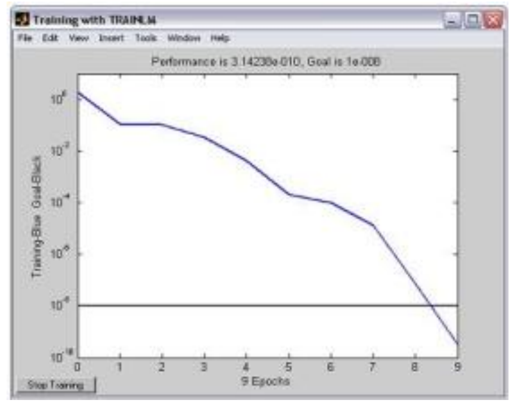

Fig 2. Example of feed forward neural network

4 Adaptive simulated annealing algorithm

This criterion simulates the refrigeration of a solid to achieve a new energy status (Metropolis et al. 1953). A new optimisation algorithm was developed based on the Metropolis criterion, known as "Simulated Adaptive Annealing." In contrast to conventional optimization (Ingber, 1989) it was shown that the Adaptive Simulated Annealing algorithm has numerous benefits. Firstly, for most customary optimization algorithms, need not compute the necessary downward slope. Thus, the adaptive simulated rinse algorithm can be used for all types of objective and complex tasks. Moreover, instead of capturing the destination function with local minimal obstacles, the adaptive simulated rinsing algorithm by probabilistic climb properties can discover the universal least additional effectually (Weimann, 1991). Nonetheless, the quest in the Adaptive Simulated Annealing depends on the first requirements.

Table 2 Input data and results of GMAW process for hardfacing

S. No.	Arc Current	Arc Voltage	Welding Speed	Electrode Propulsion	Preheat Temp	Deposition Rate(Kg/H)	Hardness (H_RC)	Dilution
1.	420	26	30	19	180	4.90	53.1	14.7
2.	520	26	30	19	180	5.15	55.3	16.7
3	420	28	30	19	180	4.62	54.1	19.7
4	420	26	40	19	180	4.95	54.1	18.4
5	420	26	30	25	180	5.35	54.2	17.1
6	420	26	30	19	200	4.90	54.9	14.9
7	520	28	30	19	160	6.05	54.2	19.4
8	520	26	40	19	180	6.62	53.5	19.7
9	520	26	30	25	180	6.97	54.2	15.7
10	520	26	30	19	200	7.50	50.0	17.5
11	420	28	40	19	180	6.04	52.4	17.1
12	420	28	30	25	180	7.05	54.8	8.9
13	420	28	30	19	205	6.65	53.0	11.7
14	420	26	40	25	180	5.85	51.8	17.0

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15	420	26	40	19	205	6.00	50.2	15.3
16	420	26	30	25	205	7.05	46.2	10.3
17	420	26	40	25	205	6.80	47.2	8.0
18	420	28	23	25	205	6.80	52.3	12.3
19	420	28	40	28	205	6.00	52.5	17.0
20	420	28	40	25	180	7.14	55.3	11.7
21	520	26	30	25	205	8.85	54.4	14.3
22	520	26	40	19	205	7.40	54.0	14.3
23	520	26	40	25	180	8.15	52.2	11.1
24	520	28	30	19	205	7.24	53.2	15.4
25	520	28	30	25	180	7.93	54.0	13.7
26	520	28	40	19	180	6.85	54.2	18.0
27	420	28	40	25	205	6.9	54.2	I8.3
28	520	26	40	25	205	7.85	51.0	14.8
29	520	28	30	25	205	8.00	50.9	10.4
30	520	28	40	19	205	7.40	53.2	19.8
31	520	28	40	25	180	8.05	53.0	20.8
32	520	28	40	25	205	8.29	51.5	19.9
33	420	27	35	22	195	5.80	52.9	15.6
34	470	27	35	22	195	6.10	49.9	17.4
35	520	27	35	22	195	7.60	47.8	17.0
36	420	26	35	22	195	5.50	46.4	15.3
37	470	26	30	22	195	6.40	53.4	15.4
38	470	27	30	19	195	6.63	50.9	15.7
39	470	27	35	25	195	6.50	53.2	12.7
40	520	28	35	22	205	7.7	48.6	19.7

Table 3 Various neural network configurations

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

This paper will use the Adaptive Simulated Annealing algorithm to look for optimum system parameters. The adaptive fluxing map is shown in Fig 4. In view of the initial set of temperatures, the final te and the initial parameters of Xo processes, an objective entity based on soldering effectiveness will be specified. The system parameters are influenced by a small random variance. Using deviated compensation parameters to recalculate the object feature.

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The deviation of process parameters will be accepted as the new process parameters and the temperature T slightly drops, that is

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

where C_T is the decaying ratio for the temperature ($C_T < 1$).
However, the probability of accepting deviated process parameters is given as if the objective function is larger:

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

where k_B is the Boltzmann constant and Δobj is the difference in the objective function. Repeat the phase above until T is near zero. The Pr probability (OBJ) in all energy states exceeds one, as is shown in equation (2). The temperature T is large. However, the probability of high-energy decreases as temperature increase compared to low energy levels.

Table 4 Optimization results for hardfacing

W 1	W 2	Arc current(Am)	Arc voltage (v)	Welding speed(cm/ min)	Electrode propulsion(mm)	Preheat Tempera ture	Deposit ion rate	Hardn ess	Dilution (%)
1	0	520	26	32	22	210	8.8	52.2	13.5
0	1	430	26	38	22	215	6.5	49.1	7.70
1	1	470	26	34	22	205	7.3	46.7	8.5
5	1	520	26	31	22	205	7.6	51.1	10.0

5 Optimal welding process parameters

To evaluate the optimum welding parameters and maintain an appropriate hardness level, the total deposited rate and the minimum dilution for optimizing welding efficiency in hardfacing must be considered. The object function class is therefore described as:

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

Where W1 and W2 are controlled by measuring deposition speed and dilution.
The disparity restraint on hardness is given as follows-

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

Initial TS= 100 ° C, final Te=0,001 ° C, decline ratio=0,99, Boltzmann kB=1,0 are used as the parameter for an adaptable rinsing render annealing algorithm. In the area shown in table 2.0, device parameters are picked. In Table 4 through the stimulating reinforcement search the optimal method factors with numerous weighting associations are indicated. Process parameters with the optimal solder effectiveness in hard surfaces have been demonstrated by this method.

6 Conclusions

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The paper outlines a neural network method to GMAW simulation and optimization. For creating a GMAW device prototype, a neural feedback network is used. The complex links between device parameters and the soldering power can be developed on this model. Used for the solution of optimal device parameters by means of a network objective function the global optimisation algorithm Adaptive Simulated Annealing (ASA). There are also significant improvements in the efficiency of deciding optimum GMAW process parameters.

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