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Modeling and optimization of integrated flux assisted-welding process using a hybrid ANN-SA approach

(A case study in Rumaila combined cycle power plant, Basra, Iraq)

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Abstract
In this study an artificial neural network (ANN) based modeling and a heuristic based optimization procedure using simulated annealing (SA) algorithm for modeling and optimization of flux assisted TIG welding process known as activated TIG (A-TIG) have been addressed. In this study effect of the most important process variables (welding current (C), welding speed (S)) and percentage of activating fluxes (TiO_2 and SiO_2) combination (F) on the most important quality characteristics (depth of penetration (DOP), weld bead width (WBW), and consequently aspect ratio (ASR)) in welding of AISI316L austenite stainless steel parts have been considered. To gather the required data for modeling and optimization purposes, box-behnken design (BBD) in design of experiments (DOE) approach has been used. In order to establish a relation between process input variables and output characteristics, back propagation neural network (BPNN) has been employed results of which have been compared with regression modeling outputs. Particle swarm optimization (PSO) algorithm has been used for determination of BPNN architecture (number of hidden layers and neurons/nodes in each hidden layer). Simulated annealing (SA) and PSO algorithms have been employed for process optimization in such a way that desired AR, minimum WBW, and maximum DOP achieved simultaneously. Finally, confirmation experimental tests have been carried out to evaluate the performance of the proposed method. Based on the results, the proposed procedure is efficient in modeling and optimization (with less than 4% error) of A-GTAW process.

Keywords: Activated TIG (A-TIG) welding process, optimization, design of experiments (DOE), and simulated annealing (SA) algorithm.

Introduction

To tackle the problem of poor penetration in TIG welding process of thick plates, different procedures have been introduced [1−3]. Using paste-like activated fluxes coated on the weld surface before welding begins, known as activated TIG (A-TIG) welding process is one of the important methods used to increase depth of penetration (DOP) and consequently reduce weld bead width (WBW) in TIG welding process [4, 5]. This process can be taken in to account as the TIG welding process in which a layer including activating fluxes (including oxide, fluoride, and chloride) used on the weld surface before welding process started. These fluxes, are melted and vaporized during the process and due to arc constriction and reversal of Marangoni convection phenomena, DOP and WBW are increased and decreased respectively (Figure 1). These phenomena have been well documented in refs [1, 2].

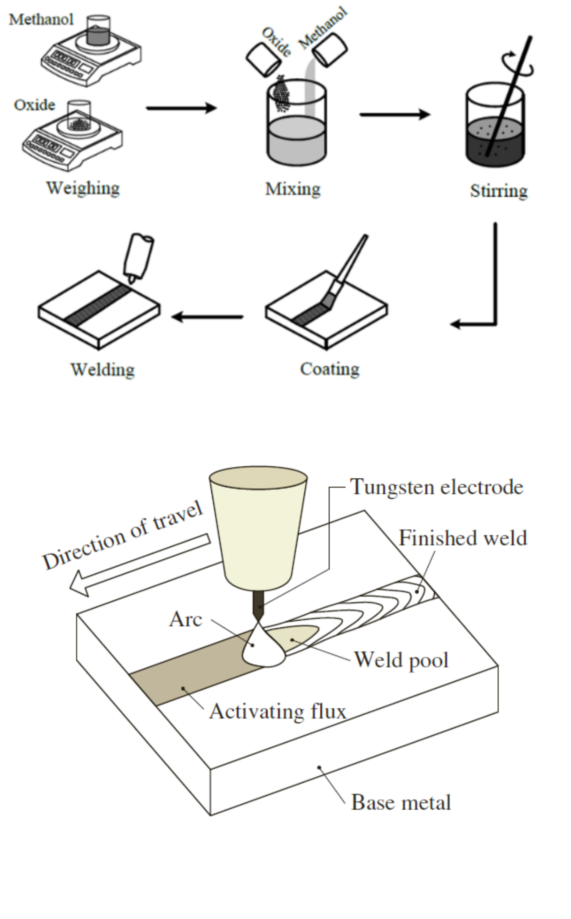

Figure 1 Schematic illustration of preparation of activating paste-like flux and A-GTAW process

To the best of our knowledge, there is no study in which modeling and optimization of A-GTAW process output characteristics (especially DOP, WBW and AR) have been considered simultaneously using BBD-based design of experiments approach, BPNN-based modeling method, and heuristic algorithm-based optimization (SA and PSO) technique. As different activating fluxes have different effects on WBG, mechanical and metallurgical properties, therefore, in this study effect of combination of the two most crucial activating fluxes has been considered as the process input variable (apart from welding speed and current) and optimized in such a way that DOP increases, WBW decreases and proper value for ASR achieved simultaneously. Based on the preliminary experimental tests carried out using DOE (screening) approach and literature survey studied, as mentioned three process inputs parameters (welding current (I), welding speed (S) and percentage of activating fluxes combination (F)) have been taken into account and their corresponding intervals and levels have been determined. According to the number of process input variables and their predetermined levels, the most appropriate design matrix (BBD) has been considered as the way of carrying out experiments and gathering data required for modeling and optimization purposes. Next, to establish the relations between process input variables (I, S and F) and output characteristics (DOP, WBW and ASR), back propagation neural network (BPNN) has been used. Next, the best BPNN architecture including number of hidden layers and number of nodes/neurons in each hidden layer has been determined using PSO algorithm. Furthermore, results of regression modeling have been used to evaluate the BPNN performance in modeling of the process. Finally, multi-response optimization (in order to achieve desired ASR, maximum DOP and minimum WBW simultaneously) has been carried out using SA and PSO algorithms to determine the values for process input variables. BBD approach has also been used to optimize the process. The proposed approach has been carried out on AISI316L austenitic stainless steel parts which is extensively used in power plants piping system (Fig. 2). Based on the achieved results, an optimized formula for activating fluxes (TiO_2 + SiO_2) has been proposed in such a way a desired ASR with minimum WBW and maximum DOP achieved simultaneously.

Figure 2 Piping used in Rumaila combined cycle power plant

Process input parameters and their corresponding interval and levels

There are different parameters affecting the A-TIG welding process among which, welding current (I), speed (S) and gap (G) are the most influential ones based on the literature review and screening method used [1-3]. Similarly, process quality characteristics include DOP and WBW are the most important responses of A-TIG welding process. To determine the possible working intervals of each process input variables, welding references studied and some preliminary tests were conducted [6-7]. Table 1, lists the process input variables and their corresponding intervals and levels based on the initial test findings. Other input variables with trivial effects have been considered at an optimum fixed level.

Table 1. A-GTAW process input variables and their corresponding intervals and levels

Process parameter	Welding speed	Welding current	Flux combinations (SiO_2- TiO_2)
Unit	mm/sec	Amps	%
Symbol	S	C	F
Interval	125-175	100-120	25-75
Level 1	125	100	25
Level 2	150	110	50
Level 3	175	120	75

Design of experiments (DOE) and Experimental results

Generally, to facilitate the identification of the influence of individual variables, establish the relationships between process input variables, output responses, and finally determine the optimal levels of input variables in order to get the desired responses, DOE approach is used. In DOE, there are different approaches among which response surface methodology (RSM) due to its merits is the most extensively used ones. There are different RSM designs, including the central composite design (CCD) and its variations (spherical CCD, rotatable CCD, small composite design, etc.), box–behnken design (BBD) and hybrid family of designs [8] In this study, based on the number of input variables and their corresponding levels a BBD's L17 matrix has been opted (Table 2).

To conduct the experimental tests, a DIGITIG 250 AC/DC welding machine has been used. Furthermore, in this study, Argon (with 99.7% purity) acted as the shielding inert gas.

Experimental tests have been conducted on AISI316L stainless steel specimens with dimension of 100 mm×50 mm×5 mm. In this study a combination of Nano oxide fluxes (TiO_2, SiO_2) (+99%, 20-30 nm, amorphous) has been used as activating flux to enhance the welding process. In order to prepare a paste-like activating flux coating, prior to welding process begins, 20 grams of flux has been mixed for approximately 20 minutes with 20 ml of a carrier solvent (methanol) using mechanical and magnetic mixers [1, 2]. Then, the paste like flux was coated on the specimen with a brush and dried before the welding process begins. When the carrier solvent evaporated, the flux layer remained attached to the surface of the specimen and the welding process could be started. The tests have been conducted in Rumaila combined cycle power plant, Basra, Iraq.

For measuring DOP and WBW, on each samples two transverse cross sections were made. Next, to clearly show DOP and WBW, the cut faces were smoothly polished and etched.

Then, for taking images an optical microscope has been used. To determine samples' DOP and WBW, images were consequently processed by MIP (microstructural image processing) software (Figure 3). The average of two measurements for each sample was reported (Table 2).

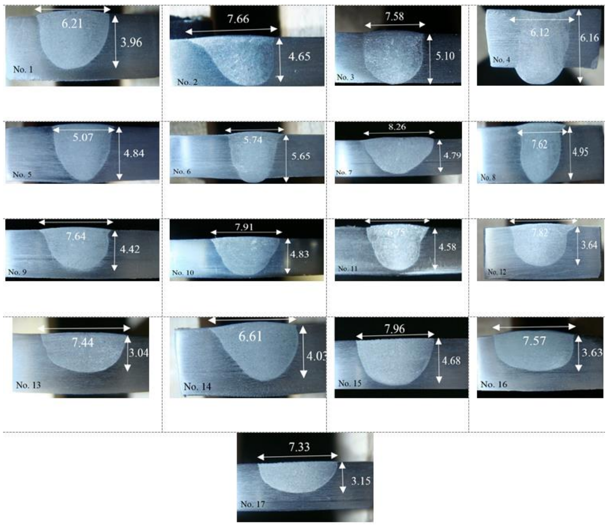

Figure 3 Cross section of the 17 specimens

Table 2. Experimental conditions based on BBD and their corresponding measured outputs

No.	Welding speed	Welding current	Flux combination	DOP (mm)	WBW (mm)	Aspect ratio (ASR)
1	(mm/sec)	(I)	(SiO_2 -TiO_2)	3.96	6.21	1.57
2	50	175	100	4.65	7.66	1.65
3	50	150	110	5.10	7.58	1.48
4	50	150	110	6.16	6.12	0.99
5	50	125	120	4.84	5.07	1.05
6	50	125	100	5.65	5.74	1.02
7	75	125	110	4.79	8.26	1.72
8	50	150	110	4.95	7.62	1.54
9	75	150	120	4.42	7.64	1.73
10	50	175	120	4.83	7.91	1.64
11	50	150	110	4.58	6.75	1.47
12	25	125	110	3.64	7.82	2.15
13	75	175	110	3.04	7.44	2.44
14	25	175	110	4.03	6.61	1.64
15	75	150	100	4.68	7.96	1.70
16	50	150	110	3.63	7.57	2.08
17	25	150	120	3.15	7.33	2.32

Back propagation neural network

Artificial neural networks (ANNs) has been proposed by McCulloch and Pitts for the first time [9]. The ability to learn and obtain information and make it accessible for use is the main merit of the ANNs. ANNs embrace of connecting processing units named nodes or neurons. Each input parameter (defined as xi) is related with a weight (wi) which indicates a portion of the input to the neuron for processing. The inputs and weights are multiplied (xi×wi) by neurons and input values transformed into output values (Figure 4) using transfer functions or activation functions (considered as (f)) [8].

In most of the studies, the architecture of the ANN is determined using trial and error procedure. Whereas, in this study PSO algorithm has been used for determining the suitable architecture for BPNN. The number of hidden layers was diverse from 1 to 3; hence a 3–n1–n2–n3–2 structure was constructed; where n1, n2, and n3 are the number of nodes/neurons for the 1st to the 3rd hidden layers respectively. The training of a NN denotes finding desired architecture and weights of net that leads to minimum error between the desired and predicted outputs. Figure 5 represents the comparison of process responses and proposed model prediction

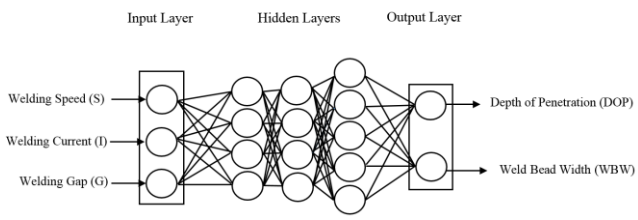

Figure 4 Architecture of proposed artificial neural network model

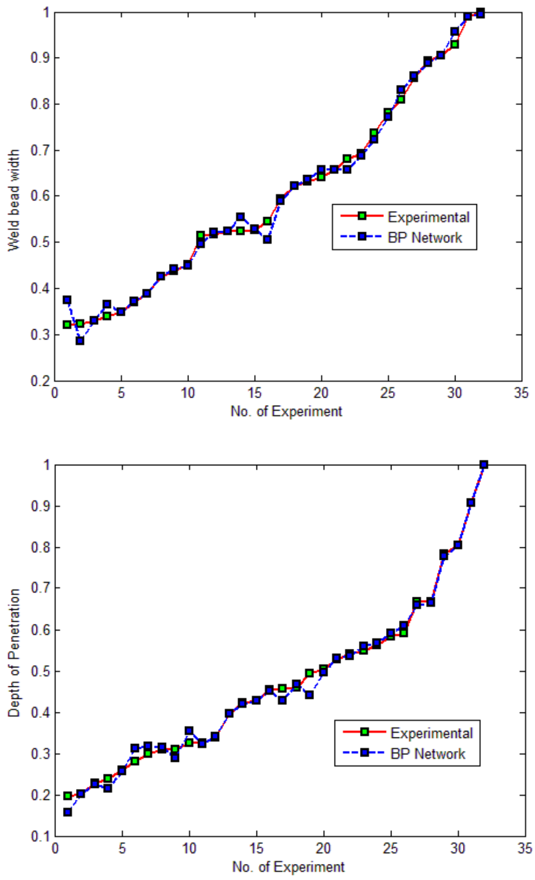

Figure 5 Comparison of process responses and proposed model prediction

The comparison between process responses and the model prediction has been shown in Fig. 5. The performance of the proposed model has been illustrated in Fig.6. Fig.7 shows the variation of mean squared error (MSE) during the training process of BPNN.

Based on the literature survey which has been confirmed via experimental tests, the weld bead geometry (including DOP, WBW and ASR) has a noticeable influence on solidification cracking and in order to avoid solidification cracks in welding process the best interval for ASR is [1.0-1.4].

Heuristic algorithms

Nowadays, different heuristic algorithms for different optimization purposes have been proposed (including ant colony (AC), genetic algorithm (GA), bee colony (BC), tabu search (TS), simulated annealing (SA), particle swarm optimization (PSO), and etc.,) among which SA and PSO, based on their merits are being extensively used. Few input parameters to adjust (easy programming) and fast convergence are the major advantages of PSO algorithm. SA is employed for optimization of a wide range of problems in different research areas (simple and easy to implement). Moreover, having few parameters for tuning, reasonable time of convergence are other merits of SA over other heuristic algorithms.

Based on the mentioned reasons SA and PSO algorithms have been considered as the heuristic algorithms to optimize A-GTAW process variables in order to achieve maximum DOP, minimum WBW and desired value of ASR simultaneously. The details of these algorithms' procedures are well documented in Ref. [8]

In this regard, SA is reminiscent of annealing process in heat treatment [9].

In annealing process, heated metals are slowly cooled down to make them reach a state of low energy. First, metals are heated up to a specific and pre-determined temperature, which is above the melting point. Therefore, at this temperature, all particles of the metal are in intense random motion. Then, the metal is slowly cooled down. All particles rearrange themselves and tend to be toward a low energy state. As the cooling process is conducted appropriately slowly, lower and lower energy states are gained until the lowest energy state is reached. Flowchart of SA algorithm used for the TIG welding process optimization has been shown in Fig 6.

The performance of SA has been checked using particle swarm optimization (PSO) algorithm.

Particle swarm optimization (PSO) is a random-generated and population-based evolutionary heuristic algorithm proposed by Kennedy and Eberhart. [21] First, a population of random solutions initialized and generations for optimum searching updating. Next, the current optimum solutions (called particles) followed by potential particles through the problem space. The best solution achieved and the corresponding location obtained named "pBest" and "gBest" respectively. The PSO algorithm procedure comprises changing the velocity of each particle toward its "pBest" and "gBest". Acceleration toward "pBest" and "gBest" is being done using a random term with separate random numbers for weighing velocity generated.

SA variables:

Initial temperature: 700, Temperature reduction rate: 0.91, Processing time: 30 seconds

PSO variables:

Number of iteration performed: 30, Population: 50, Learning factor c_1: 2, learning factor c_2: 2

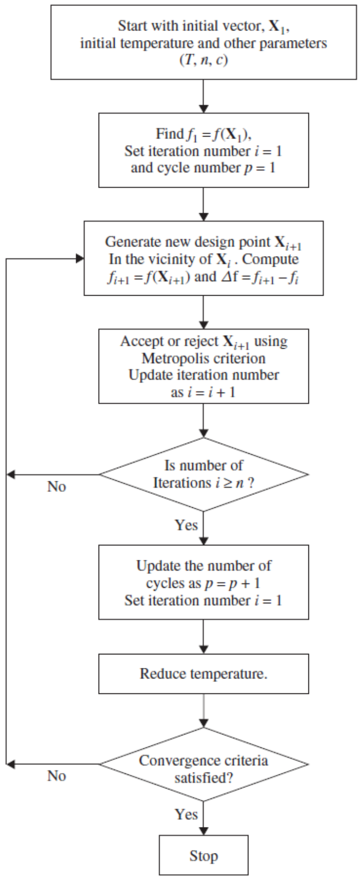

Figure 6 Flowchart of SA algorithm used for the TIG welding process optimization

Based on the nature of the PSO algorithm, its convergence is faster than SA algorithm. Furthermore, as the PSO drawback is falling into optimum traps, its performance could be better to be checked by another algorithm. The convergence of PSO and SA algorithms has been shown in Figure 7. Table 3. Represents the results of optimization using PSO and SA. Based on the results, PSO and SA could accurately optimize the process responses (with less than 4% error). Based on the optimized condition has been obtained using ANN-PSO algorithm an experimental test has been conducted to measure the accuracy of the proposed approach in an experimental test. The experimental test was in a quite efficient agreement with the proposed approach result.

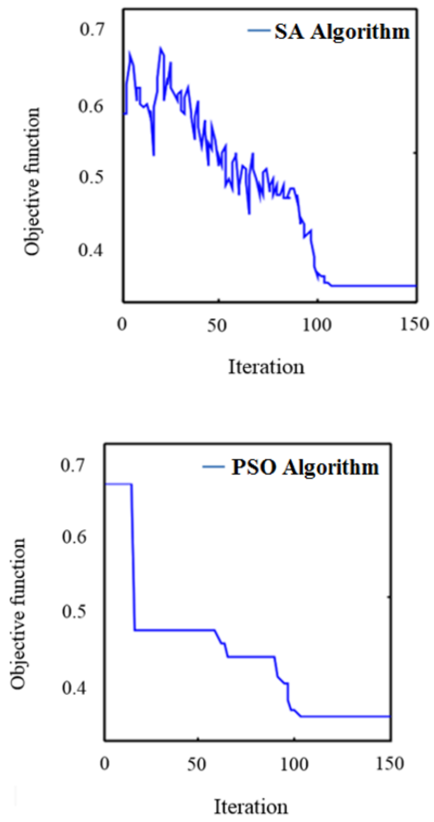

Figure 7 convergence of PSO and SA algorithms

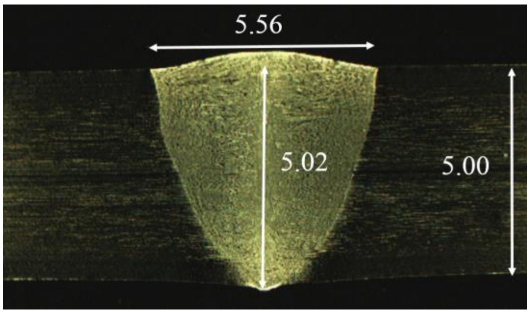

Figure 8 Results of optimization condition

Table 3 Optimal welding variables and corresponding process quality measures for equal weighing

Output	Method	Process variables			Predicted	experiment	Error (%)
		F	S	C			
DOP	PSO-ANN	75	134	100	3.40	3.40	3.40
WBW	PSO-ANN	75	134	100	2.60	2.60	2.60
ASR	PSO-ANN	75	134	100	1.11	1.11	1.11

Conclusion

The problem of modeling and optimization of A-TIG welding process for AISI316L austenite stainless steel parts has been addressed throughout this study. First, experimental tests matrix required for modeling and optimization purposes has been determined using OA-Taguchi method. Next, DOP and WBW values have been measured using MIP software. Then, BPNN has been employed to establish the relations between process input variables and output responses. Furthermore, in order to determine the architecture (number of neurons/nodes and hidden layers) PSO algorithm has been used. Then, PSO algorithm has been used to optimize the proposed model in such a way that DOP increases and WBW decreases simultaneously (based on the importance of WBW and DOP). Furthermore, the performance of PSO has been checked using SA algorithm.

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