Using a back propagation neural network based modeling and heuristic algorithms based optimization technique in activated gas tungsten arc welding process

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Original Article

Keywords: Activated gas tungsten arc welding (A-GTAW) process, Response surface methodology (RSM), design of experiments (DOE), Back propagation neural network (BPNN), particle swarm optimization (PSO) algorithm, and simulated annealing (SA) algorithm

Posted Date: August 25th, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-812301/v1>

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Abstract

In this study, a modeling method based on an artificial neural networks model combined with a back propagation algorithm (BPNN) and an optimization procedure based on heuristic algorithms (particle swarm optimization (PSO) and simulated annealing (SA) algorithms) have been proposed for modeling and optimization of activated gas tungsten arc welding (A-GTAW) process in order to tackle the poor penetration drawback occurs during GTAW process. In this study effect of the most important process adjusting variables including welding current (C), welding speed (S) and percentage of activating fluxes (TiO_2 and SiO_2) combination (F) on the most important quality characteristics (weld bead width (WBW), depth of penetration (DOP), and consequently aspect ratio (ASR)) in welding of AISI316L austenite stainless steel parts have been investigated. Box-behnken and central composite designs (BBD and CCD) based on response surface methodology (RSM) in design of experiments (DOE) method have been employed to gather the required data for modeling and optimization purposes. Then, BPNN has been used to determine the relations between A-GTAW process input variables and output responses. To determine the proper BPNN model architecture (the proper hidden layers' number and their corresponding neurons/nodes in each layer) PSO algorithm has been used. Next, PSO and SA algorithms have been used to optimize the proposed BPNN model in such a way that desired AR, minimum WBW, and maximum DOP achieved. Finally, confirmation experimental tests have been conducted to evaluate the proposed procedure performance. Based on the results, the proposed method is efficient in modeling and optimization (less than 7% error) of A-GTAW process.

1. Introduction

There are different merits (a spatter free process with high weld quality) have been introduced for gas tungsten arc welding (GTAW) process considering of which turned this process for fabricating different alloys including aluminum, magnesium, stainless steel and titanium. However, shallow (poor) penetration has been introduced as a demerit for GTAW process [1 – 3]. To tackle the drawback of poor penetration in GTAW process, different procedures have been introduced. Among the proposed procedures activated GTAW (A- GTAW) is the most important ones. In A-GTAW process a coating of activating fluxes is prepared and applied on the surface of the weldment before the welding process begins [4, 5]. As the welding process proceeds, the coated layer is melted and vaporized. Due to two phenomena known as arc constriction and reversal of Marangoni convection, depth of penetration (DOP) increases and consequently weld bead width (WBW) decreases. These phenomena have been well documented in refs [1, 2].

In GTAW process, when the thickness of specimens exceeds 3 mm, to fill the welding gap a filler metal is required. Whereas, specimens of around 8 mm could be fabricated in a single welding pass and without even edge preparation in A-GTAW process [6– 11]. There is a great deal of studies in which different aspects of A-GTAW process have been taken into account.

Microstructural and mechanical properties, and corrosion behavior in dissimilar A-GTAW process of AISI316L and P91 steel parts have been investigated by Vidyarthi et al [1]. Ramkumar et al [2], investigated the effect of an activating flux on DOP and mechanical and microstructure properties in GTAW process of titanium alloy (Ti-6Al-4V). An improvement in mechanical and microstructural properties and DOP values in A-GTAW process in comparison to GTAW process have been reported. Zou et al [3], investigated the effect of activating fluxes in GTAW process. Based on this study results, the performance of GTAW process has been enhanced in dissimilar welding of duplex stainless steel and ferrite steel parts. Kulkarni et al [4], investigated the effect of adding activating fluxes on mechanical properties in dissimilar welding of Inconel 800 and Inconel 600. Furthermore, an enhancement for microstructural and mechanical properties in A-GTAW process of P91 weldments have been reported [5, 6]. Kumar et al. [12] investigated the effect of adding activating fluxes in GTAW process. Results of this study illustrated that a full penetration for A-GTAW process reported. Furthermore, the performance of GTAW process could be improved by decreasing WBW and increasing DOP simultaneously using oxide-based activating fluxes. Elimination of edge preparation (required for specimens with more than 3mm thickness) and reduction of welding passes for accomplishing fabricating in GTAW process has been reported by Venkatesan et al. [13], using activating fluxes (A-GTAW process). Mechanical properties improvement and distortion reduction were introduced by Chern et al. [14] as the main assets of A-GTAW process. Effect of using different fluxes (including oxide, chloride, and fluoride ones) have been studied by Tathgir et al. [15] in dissimilar welding process of stainless steel and low alloy parts to improve DOP. Based on the research results, using oxide fluxes results in the largest DOP. Whereas, other fluxes had trivial and negligible effect on DOP.

Based on the A-GTAW process literature survey, there are different studies in which the influence of using activating fluxes on different process characteristics (e.g. DOP, WBW, and microstructural and mechanical properties) have been studied. In these papers the lack of modeling and optimization of the process output measures senses. To the best of our knowledge, there is no study in which modeling and optimization of DOP, WBW and AR are considered simultaneously using RSM-based (BBD and CCD) designs of experiments approach, ANN-based modeling, and heuristic algorithms-based (SA and PSO algorithms) optimization technique. As different activating fluxes have different effects on weld bead geometry, mechanical and metallurgical properties of weldments, therefore, in this study the percentage of activating fluxes combination 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 AR achieved simultaneously. In this study based on the preliminary experimental tests carried out using DOE (screening) approach and literature survey studied, three inputs parameters (welding current (I), welding speed (S) and percentage of activating fluxes combination (F)) have been taken into account as adjusting parameters and their corresponding intervals and levels determined. According to the number of input variables and their predetermined levels, the most appropriate design matrix (CCD and BBD based on RSM) have been considered. Next, to determine the relationships between process input variables and output characteristics, back propagation neural network (BPNN) has been used. Next, PSO algorithm has been used to find the best BPNN architecture (number of hidden layers and nodes/neurons

in each layer). Finally, the optimal values of process input variables for multi-response optimization have been determined using PSO algorithm. The SA algorithm has also been used to check the adequacy of PSO algorithm and avoid getting trapped in local minima. The proposed approach has been carried out on AISI316L austenitic stainless steel parts. Based on the achieved results, an optimized formula ($\text{TiO}_2 + \text{SiO}_2$) has been proposed in such a way a desired ASR with minimum WBW and maximum DOP achieved.

2. Experimental Set Up

2.1. Equipment and material used

To carry out the experimental tests based on the CCD and BBD design matrixes proposed by RSM, a DIGITIG 250 AC/DC welding machine has been employed (Fig. 1). Furthermore, in this study, Argon (with 99.7% purity) has been used as the shielding inert gas.

AISI316L stainless steel sheets with dimension of 100 mm×50 mm×5 mm have been considered as specimens (Fig. 1). In this study, a combination of Nano oxide fluxes (TiO_2 , SiO_2) (+ 99%, 20–30 nm, amorphous) have been used as activating fluxes. Firstly, to assure the powder particle size, FESEM test has been employed (Fig. 2). Figure 3 represents the FESEM results of the oxide-based activating fluxes used which confirmed the Nano-scale claimed by provider. Next, a paste like coating of fluxes prepared by adding a mixture of fluxes (20-grams of TiO_2 and SiO_2) with 20 ml of methanol (as a carrier solvent) using approximately 20 minutes of mechanical, magnetic and ultrasonic mixers (Fig. 4)) [1, 2]. Then, the paste like flux has been applied on the surface of the specimen with a brush and dried before the welding process begins (Fig. 5).

2.2. Response surface methodology (RSM)

Defining a proper experimental design matrix using of which experiments required for modeling and optimization purposes are conducted, is the next step after selecting the main process input variables and their corresponding intervals and levels. In this study, the main process variables and their corresponding intervals and levels have been determined based on the literature survey and preliminary experimental tests using screening procedure. Generally, to facilitate the identification of each individual process variables influences, establish the relations between process input variables and output measures, and determine the optimal levels of input variables in order to get the desired responses (in this study, minimum WBW, maximum DOP, and desired ASR), DOE approach is employed.

There are different approaches in DOE method, among which response surface methodology (RSM) acts as a powerful tool. RSM comprises different designs, including central composite design (CCD) (spherical CCD, rotatable CCD, and etc.), box–behnken design (BBD), and hybrid designs (Fig. 6) [20].

2.3. Determination of adjusting variables and their corresponding intervals and levels

There are different variables affecting the A-GTAW process among which, the most influential ones based on the literature review and screening method used are welding speed (S) and welding current (I). Furthermore, percentage of activating fluxes combination (F) has been considered as a process input variable to achieve the merits of both in this regard [1–3]. Similarly, process quality characteristics including DOP, WBW, and ASR are the most important responses of A-GTAW process. To determine the possible working intervals of each process input variables, welding references studied and some preliminary tests have been carried out [8–15]. The process input variables and their possible intervals and levels have been shown in Tables 1, 2 considered for CCD and BBD designs respectively. Other input variables with trivial effects have been considered at an optimum fixed level. In this study, a CCD's L_{20} and a BBD's L_{17} matrix have been opted (Tables 3 and 4).

Table 1
Process input variables and their corresponding intervals and levels considered for CCD

Process parameter	Flux combinations (SiO_2 - TiO_2)	Welding current	Welding speed
Symbol	F	C	S
Unit	%	Amps	mm/sec
Interval	0-100	90–130	110–190
Level 1	0-100	90	110
Level 2	25–75	100	130
Level 3	50–50	110	150
Level 4	75 – 25	120	170
Level 5	100-0	130	190

Table 2
Process input variables and their corresponding intervals and levels considered for BBD

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

2.4. Experimental results

A random order in conducting experiments has been used to increase the accuracy of the experiments. After welding, three types of responses (DOP, WBW, and ASR) have been measured from each specimen (Tables 3 and 4).

Two cross sections on each sample have been made in order to measure DOP, WBW, and consequently ASR. Next, to clearly show DOP and WBW, the cut faces have been polished smoothly and etched (Figs. 7). Then, for taking images an optical microscope has been used (Fig. 7). To determine samples' DOP and WBW, images have been processed by MIP software (Fig. 7). Results of the measuring process has been illustrated in Figs. 8 and 9.

Table 3
Experimental conditions based on CCD and their corresponding measured outputs

No.	Welding speed (mm/sec)	Welding current (Amp)	Flux combination (SiO ₂ - TiO ₂)	Depth of penetration (mm)	Weld bead width (mm)	Aspect ratio (AR)
1	130	120	25	5.755	7.693	1.337
2	150	110	50	5.041	7.905	1.568
3	170	100	75	5.367	7.224	1.346
4	170	100	25	3.142	9.466	3.013
5	150	110	50	4.711	7.617	1.617
6	150	130	50	6.827	7.703	1.128
7	170	120	25	3.92	8.425	2.149
8	170	120	75	5.524	5.923	1.072
9	130	100	25	4.873	8.125	1.667
10	150	110	50	4.321	7.92	1.833
11	150	110	50	4.85	7.51	1.548
12	130	100	75	6.356	6.676	1.051
13	150	110	50	4.95	7.847	1.585
14	150	110	100	6.124	5.604	0.915
15	110	110	50	6.254	6.393	1.022
16	150	90	50	4.61	7.778	1.687
17	150	110	50	4.906	7.803	1.591
18	130	120	75	7.894	6.91	0.875
19	150	110	0	3.133	9.985	3.187
20	190	110	50	3.85	7.46	1.938

To relate the process input variables and output responses for CCD and BBD matrixes, regression equations proposed for DOP, WBW, and ASR (Equations 1–6).

$$\text{DOP} = 24.19 + 0.03358 \times F - 0.381 \times C + 0.000230 \times (S \times S) - 0.000960 \times (S \times C) + 0.002608 \times (C \times C) \quad (1)$$

$$\text{WBW} = -28.83 + 0.0549 \times F + 0.3483 \times S + 0.1842 \times C - 0.000628 \times (F \times S) - 0.000526 \times (S \times S) - 0.001340 \times (S \times C) \quad (2)$$

$$W/D = -15.39 + 0.1125 \times S + 0.1634 \times C + 0.000155 \times (F \times F) - 0.000448 \times (F \times S) + 0.000280 \times (F \times C) - 0.000109 \times (S \times S) - 0.000395 \times (S \times C) - 0.000615 \times (C \times C) \quad (3)$$

$$DOP = -21.9 + 0.1187 \times F + 0.425 \times C - 0.001189 \times (F \times F) - 0.000189 \times (F \times S) + 0.000435 \times (F \times C) + 0.000251 \times (S \times S) - 0.000879 \times (S \times C) - 0.001251 \times (C \times C) \quad (4)$$

$$WBW = -97.8 - 0.1743 \times F + 0.4264 \times S + 1.338 \times C + 0.000561 \times (F \times S) + 0.000761 \times (F \times C) - 0.001564 \times (S \times S) + 0.000381 \times (S \times C) - 0.00630 \times (C \times C) \quad (5)$$

$$ASR = e^{-6.60} \times F^{-0.2853} \times S^{2.005} \times C^{-0.392} \quad (6)$$

Table 4
Experimental conditions based on BBD and their corresponding measured outputs

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

3. Back Propagation Neural Network (Bpnn)

In order to relate a set of input-output parameters in a system (a manufacturing process such) different procedures are being employed among which ANNs are the most extensively used ones. ANNs are embrace of a set of connecting processing units named neurons/nodes, organized in each layer (input, hidden and output). An illustration of a perceptron is shown in Fig. 9 (a), where each input variable (defined as x_i) is related with a weight (w_i) which indicates a portion of the input variable to the neuron for processing. Furthermore, b is the bias and y the output signal.

Fig 9 (a), represents a linear perceptron's inputs (x_1-x_n) combination. Next, a signal $(v = \sum_{i=1}^N x_i \times w_i + b)$ is obtained and transferred using function (f) in order to obtain the output signal (y) [17, 18].

Different structures for ANN have been proposed among which multi-layer perceptron (MLP) has been extensively used due to its ability to solve different problems (including non-linear separable/continuous). MLP networks embraces an input layer, hidden layer/s (one or more), and an output layer (Figure 9 (b)). In the training stage, a supervised way is used to determine the biases and weights, based a set of input-output data pairs, which allows the MLP to learn the input-output parameters relations (in this study, process input variables and output responses). In BPNN, an algorithm (back propagation) is employed in which error of each MLP's input-output pair is calculated and then propagated from the last (output) layer to the first (input) layer, adjusting the biases and weights of the MLP network to the error devoted by its neuron proportionally, is used [15]. The details in this regard are well documented in Refs. [16, 19].

Commonly, the architecture of ANN models is determined based on trial and error. Whereas, in this study in order to eradicate this error, PSO algorithm has been used to determine the proper BPNN's architecture. The hidden layers' number was varied from 1 to 3; hence a **3** (number of process input variables)– n_1 – n_2 – n_3 –**3** (number of process output characteristics) structure was constructed; where the number of neurons/ nodes for the 1st to 3rd hidden layers are n_1 , n_2 , and n_3 respectively. The training stage acts as a way to find the proper weights and architecture of net that leads to minimum error between the desired (or predetermined) and predicted measures.

The comparison between process responses and the proposed model based on CCD matrix prediction has been shown in Fig. 10. Fig.11 shows the variation of mean squared error (MSE) during the training process of BPNN model. The performance of the proposed model has been illustrated in Fig.12.

4. Problem Definition

Obtaining the best set of A-GTAW process variables to simultaneously maximize DOP, minimize WBW and attain desired ASR, is the main objective of this study. Consequently, process output measures could be considered together to build a multiple process response in the optimization procedure. Thus, the optimal design could be formulated as a multi-response optimization problem illustrated as Eq. (7):

Maximum DOP = DOP (F, I, S) (7)

Minimum WBW = - WBW (F, I, S)

Desired AS= [1-1.4]

In this study achieving low WBW, high DOP and desired AR simultaneously required for multi-criteria optimization. Therefore, process multi-responses are changed into a single measure using Eq. (8), where w_1 and w_2 are weighting coefficients to show the importance of DOP and WBW respectively. Based on the literature survey which has been confirmed via experimental tests, in order to avoid solidification cracks the best interval for AR is [1.0-1.4] [20]. Solidification cracking tendency is significantly influenced by width to depth ratio (WBW to DOP (W/D)), which can be minimized by ensuring that this ratio is between 1 and 1.4. (Fig. 13).

Minimize F (F, C, S) = ($w_1 \times \text{DOP}$) - ($w_2 \times \text{WBW}$), ($1.0 < \text{AR} < 1.4$) (8)

5. An Introduction To Heuristic Algorithms

Nowadays different heuristic algorithms for different optimization purposes have been proposed (including simulated annealing (SA), genetic (GA), Tabu search (TS), ant colony (AC), bee colony (BC), particle swarm optimization (PSO), and etc.,) among them PSO and SA, due to their advantages are mostly being employed. Easy programming (few input parameters to adjust) and fast convergence are the major merits of PSO algorithm. Whereas, in high dimensional space, falling into local optimum traps may be considered as a weakness for PSO algorithm. Based on the SA mechanism this algorithm could avoid getting trapped into local optimum which can be considered as a major excellence over other algorithms [19].

In this study, PSO and SA algorithms due to their mentioned merits, have been employed as the heuristic algorithms to optimize A-GTAW process variables in order to achieve maximum DOP, minimum WBW and proper value of ASR. In this study, PSO has been used twice (to determine the most appropriate architecture for BPNN and optimize the process measures). Next, SA algorithm has been used to evaluate the performance of PSO algorithm. Furthermore, a set of validation experiments has been conducted in order to confirm the proposed approach.

5.3. Simulated annealing algorithm

To interpolate between the process input variables intervals to select the most appropriate values of process input parameters reaching the desired output characteristics (e.g. minimum WBW and maximum DOP), different procedures have been introduced among which heuristic algorithms have been extensively employed for different optimization problems. All heuristic algorithms are reminiscent of biological or physical processes. In this regard, SA algorithm is reminiscent of annealing in heat treatment process [21, 22]. In annealing process, metals are heated up to a specific and pre-determined

temperature (near the melting point), at which all metal particles are in random motion. Then, all metal particles rearranged by cooling down slowly toward the lowest energy state. As the cooling process is conducted appropriately slowly, lower and lower energy states are achieved until the lowest energy state is reached. Similarly, in A-TIG welding process the lowest energy level gives the optimized value for variables based on an energy function is created and minimized. The mechanism of SA algorithm is defined as follows [23]:

Defining an acceptable answer space and generating an initial random solution in this space. Next, the new solution's objective function (C_1) is computed and compared with the current ones (C_0). A move to a new solution is made either the new solution has better value or the value of SA probability function (Eq. (9)) is higher than a randomly generated number between 0 and 1 [22]:

$$P_r = \exp \left(-\frac{\Delta C}{T_k} \right) \quad (9)$$

Where, temperature parameter is shown by T_k , which acts as the temperature in the physical annealing process does [21]. Eq. (10), is used as a temperature reduction rate to cool down the pre-determined temperature at each iteration.

$$T_{k+1} = \alpha \times T_k \quad k=0,1,\dots \text{ and } 0.9 \leq \alpha < 1 \quad (10)$$

Where, the current and former temperatures are shown by T_{k+1} and T_k respectively. The cooling rate also presented by parameter α . Consequently, at the first iterations of SA due to higher temperature, most of the not improving (or even worsening) moves may be accepted. Nonetheless, as the algorithm proceeds and temperature is reduced only improving moves are likely to be accepted. This strategy could help the algorithm avoid being trapped in local minimum and jump out of it. After a specific number of iterations, a number of iterations in which no development is detected, and a pre-determined run time, the algorithm may be dismissed.

5.4. Particle swarm optimization (PSO) algorithm

PSO is a heuristic algorithm proposed by Kennedy and Eberhart [24]. It begins with a population of random solutions which is updated and searched for optimum ones. The current optimum particles are followed by the random solutions (known as particles) through the problem space. The problem space is connected with the best obtained solution and its corresponding location shown by "pBest" and "gBest" respectively. Each particle keeps track of the "pBest" and "gBest" in the problem space by changing its velocity towards them. The following Equations (11 and 12) used updating the particles [25–27].

$$V_{i+1} = w \times V_i + (C_1 \times r_i \times (pBest_i - X_i)) + (C_2 \times r_i \times (gBest - X_i)) \quad (11)$$

$$X_{i+1} = X_i + V_{i+1} \quad (12)$$

Where, (V_{i+1}) for each particle has been determined based on its previous velocity (V_i) , global best solution (pBest) and location (gBest). Eq. (9) has been used for updating the particle's position (X_i) [27]. The terms " r_1 " and " r_2 " are two random numbers generated independently in the range of [0, 1]. There are acceleration constants (" c_1 " and " c_2 ") using which pull each particle (solution) towards "pBest" and "gBest" positions. Inertia weight " w ", acts as an important parameter in PSO algorithm convergence behavior. In order to explore the answer space globally, the large amount of " w " required, while the small amounts explore nearby regions of the space [28].

Based on the literature survey, the architecture (number of hidden layers and nodes in hidden layers) of BPNN in most studies has been determined using trial and error. Whereas, in this study PSO algorithm has been employed to determine the PBNN architecture. Furthermore, the optimization of the proposed BPNN models have been carried out using PSO algorithm. Moreover, SA algorithm has been used to confirm the performance of PSO algorithm (avoiding getting trapped in the local optima).

The performance of each evolutionary algorithm is affected by its own distinctive adjusting parameters. The details of the PSO performance are well documented in Refs [23–27].

The adjusting parameters used for controlling the SA and PSO algorithms are carried out as the following.

PSO variables: Population: 50; Learning factor c_1 and c_2 : 2; Number of iteration performed: 30.

SA variables: Temperature reduction rate: 0.91; Processing time: 30; seconds Initial temperature: 700.

6. Results And Discussion

Different weights (W_1 and W_2) may have been considered for A-GTAW process responses (DOP and WBW) based on the importance considered. In this study the value of 0.5 has been considered for W_1 and W_2 for DOP and WBW. In this study optimization procedure has been used for two conditions. In the first condition the demotion of weld bead geometry has not been restricted. In the second condition the dimensional restriction has been imposed to the optimization procedure. In the second condition, the maximum value for DOP has been considered 5 mm. At the same token desired AR ([1.0-1.4]) has been taken into account as the second limitation. Figure 14, illustrates the cross section of weldment for optimization of the second condition. 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. In this paper, the performance of PSO algorithm has been checked by SA algorithm. The convergence of PSO and SA algorithms has been shown by Fig. 15. Tables 5 and 6, represents the results of PSO and SA optimization for the both mentioned conditions. Based on the results, PSO and SA could accurately optimize the process responses (with less than 7% error).

Table 5

Optimal A-TIG welding process variables and coressponding process measures for CCD matrix

Output	Algorithm	Process variables			Predicted	Experimental	Error (%)
		F	S	C			
W _{DOP} =0.50 and W _{WBW} =0.50		Considering weld bead geometry restriction					
DOP	SA	60	190	129	4.96	5.11	3.0
DOP	PSO	71	190	128	4.95	5.07	2.4
WBW	SA	60	190	129	5.70	5.56	2.7
WBW	PSO	71	190	128	5.68	5.55	2.1
AR	SA	60	190	129	1.14	1.08	5.2
AR	PSO	71	190	128	1.14	1.09	5.1

Table 6

Optimal A-GTAW welding process variables and coressponding process measures for BBD matrix

Output	Algorithm	Process variables			Predicted	Experimental	Error (%)
		F	S	C			
W _{DOP} =0.50 and W _{WBW} =0.50							
DOP	SA	74	133	100	4.92	4.62	6.0
DOP	PSO	75	134	100	4.94	4.68	5.5
WBW	SA	74	133	100	5.61	5.36	4.3
WBW	PSO	75	134	100	5.62	5.40	4.0
ASR	SA	74	133	100	1.14	1.16	1.8
ASR	PSO	75	134	100	1.13	1.15	1.8

7. Conclusion

An important factor which affects the weldments' quality in different welding processes is the proper selection of process variables levels. The modeling and optimization of A-TIG welding process for AISI316L austenite stainless steel parts considering both the process variables and percentage of activating fluxes combination has been addressed throughout this study. First, CCD based on RSM has been employed to determine the experimental design matrix required for data gathering, modeling and optimization purposes. Next, DOP and WBW values have been measured using MIP software. Based on the results of WBW and DOP, AR values have been computed. Then, BPNN has been employed to

establish the relations between process input variables (welding speed, current and percentage of activating fluxes combination) and output responses (DOP, WBW and AR). Moreover, in order to determine the proper BPNN architecture, PSO algorithm has been used. Then, PSO algorithm has been used again to optimize the proposed proper BPNN model in such a way that DOP increased and WBW decreased simultaneously and achieved the desired AR. Furthermore, the PSO algorithm performance has been checked using SA algorithm. Using the proposed hybrid BPNN-PSO approach either process input variables have been optimized (190 mm/sec for welding speed and 128 Amp for welding current) and the optimum formula (71% SiO₂ and 29% TiO₂) for activating fluxes combination has been determined in order to achieve the desired process output measures (maximum DOP, minimum WBW and desired AR). The result of proposed optimization procedure showed that the proposed method can precisely simulate and optimize (with less than 7% error) the A-TIG welding process.

Nomenclature

Artificial neural network	ANN
Particle swarm optimization	PSO
Activated gas tangent arc welding	A-GTAW
Gas tangent arc welding	GTAW
Design of experiments	DOE
Box-behnken design	BBD
Central composite design	CCD
Weld bead width	WBW
Welding current	I
Welding speed	S
Back propagation neural network	BPNN
Microstructural image processing	MIP
Multi-layer perceptron	MLP
Mean squared error	MSE
New solution	C_1
Current solution	C_0
Current temperatures	T_{k+1}
Former temperatures	T_k
Cooling rate	α
Velocity	V_j
Position	X_j
Random numbers	r_1 and r_2
Acceleration parameters	c_1 and c_2
Inertia weight	γ
Best position of particle	p_j
Best position of group	p_g
Particle	j^{th}

Current velocity	V_{j+1}
Former velocity	V_j
Particle's position	X_i
Global best location	gBest
Current best location	pBest
Inertia weight	w

Declarations

Acknowledgments

We are thankful to the editor and reviewer of this journal for suggesting the valuable improvements and allowing appropriate time for updating the manuscript.

Conflicts of interest

The authors whose names are listed immediately below certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

Funding

Not applicable' for this section

Availability of data and material

The data and material could be available if is required

Code availability

The Code could be available if is required

Ethics approval

The manuscript will not be submitted elsewhere until the editorial process is completed.

Consent for publication

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Figures

Figure 1

Workpieces and welding machine used

Figure 2

FESEM test equipment used

Figure 3

Nano activating flux (SiO_2) and results of FESEM tests

Figure 4

Magnetic and ultrasonic mixers and electronic balance used

Figure 5

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

Figure 6

Schematic illustration of full factorial; box-behnken and central composite designs

Figure 7

Optical microscope and electro polish machine used

Figure 8

A-TIG weld cross-sectional profile for CCD matrix

Figure 9

A-GTAW weld cross-sectional profile for BBD matrix (a) Example of perceptron and (b) architecture of proposed ANN model

Figure 10

Comparison of process responses and proposed BPNN model predictions based on CCD matrix

Figure 11

Variation of mean squared error (MSE) for CCD matrix

Figure 12

Performance of the proposed BPNN model in training, validation and test stages for CCD matrix

Figure 13

Effect of aspet ratio values on tendency of occuring solidification cracking

Figure 14

Evaluation of DOP and WBW for the optimized condition based on BBD and CCD matrix

Figure 15

Convergence of heuristic (PSO and SA) algorithms