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Multi-variable measurements and optimization of GMAW parameters for API-X42 steel alloy using a hybrid BPNN–PSO approach

M. Azadi Moghaddam, R. Golmezergi, F. Kolahan *

Ferdowsi University of Mashhad, Department of Mechanical Engineering, P.O. Box 91775-1111, Mashhad, Iran

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ABSTRACT

This research addresses multi criteria modeling and optimization procedure for Gas Metal Arc Welding (GMAW) process of API-X42 alloy. Experimental data needed for modeling are gathered as per L_{36} Taguchi matrix. Model inputs include work piece groove angle as well as the five main GMAW process parameters. The proposed back propagation neural network (BPNN) simultaneously predicts weld bead geometry (WBG) and heat affected zone (HAZ). Image processing technique along with Bridge Cam and AWS gauges are used to take accurate measurements of WBGs and HAZs. The adequacy of the developed BPNN is established through comparisons against measured process outputs. Measurements indicate that the BPNN model simulates GMAW process with average errors of 0.33 to 0.82%. Next, the BPNN model is implanted into a particle swarm optimization (PSO) algorithm to simultaneously optimize HAZ and WBG characteristics. The hybrid BPNN–PSO determines process parameters values and groove angle so as a desired WBG is achieved while HAZ is minimized. Verification tests demonstrate that the proposed BPNN–PSO is quite efficient for in multi-criteria modeling and optimization of GMAW.

1. Introduction

Nowadays, Gas Metal Arc Welding (GMAW) process is widely used in various industries including gas pipelines, petrochemical plants, automotive and ship buildings. High productivity rate due to the continuous feed of wire electrode, low weld discontinuity, no slag inclusion and low thermal hazard on base metal are the main merits of this process [1].

In welding processes the quality of the joint is usually determined by such process quality measures as weld bead geometry (WBG) and heat affected zone (HAZ) [2]. Weld bead geometry is a significant factor as it strongly affects the mechanical properties of the joint [3]. Another key quality indicator of the joint is HAZ that determines the microstructural and metallurgical changes of the weldment due to the heat generated during welding process. Usually, because of large grain microstructure, ductility and toughness of this area is poor. In addition, HAZ is prone to such defects as hydrogen diffused crack, blue brittleness and laminar tearing (toe crack). The proper microstructural and metallurgical properties could be yield through controlling the heat input and the subsequent heat affected zone [4].

Various factors influence the size of HAZ and the shape of weld bead in GMAW process. An important group consists the process parameters to be set on the welding machine; namely, welding speed (*S*), welding voltage (*V*), wire feed rate (*F*) and nozzle-to-plate distance (*D*) [5]. In addition in all diffusion welding processes, involving thicker plates, the selection of groove angle (*A*) is an important variable affecting WBG. Without suitable groove angle, the entire internal portion of the joint would not be fused and causing a weak joint. To this end, proper selection of groove angle as well as the values of GMAW input parameters, plays a very significant role in determining the quality of the final weldment. Therefore, to achieve full penetrated weld with desired bead geometry, process parameters selection and joint edge preparation must be carefully considered.

The inherent nonlinearity of GMAW process and various interactions between its input parameters, have motivated the researchers to employ data-driven or artificial intelligence based methods [5–8]. Artificial Neural Networks (ANNs) have demonstrated ample potential in modeling of the input–output relationships of complicated nonlinear systems such as welding processes. In this regard, ANN may be used to predict the behavior of process under different parameters settings. There are many types of ANNs which vary in architecture, implementation of transfer functions and strategy of learning. In view of their universal approximation capabilities, back propagation neural

* Corresponding author. Tel.: +98 9153114112; fax: +98 5138763304.
E-mail address: kolahan@um.ac.ir (F. Kolahan).

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network (BPNN) has received considerable attention. The main architectural features of BPNN include the number of hidden layers and the number of processing elements in each hidden layer. These factors have to be determined in advance of the process modeling. Moreover, to gather experimental data needed for regression or ANN modeling, design of experiments (DOE) technique has been employed in many studies [7–9].

Along this line, artificial neural network has been used by Nagesh and Datta [10] to model the WBG and penetration in GMAW. It has been reported that depth of penetration is mostly affected by current, voltage and welding speed. Shallower penetration has been produced by longer arc-length and too small arc-length may also result in poor penetration. It was observed that poor fusion has been produced by high arc travel rate or low arc power. Higher electrode feed rate produced higher bead width. Campbell et al. [11] developed an ANN model for the prediction of WBG in GMAW process with alternating shielding gases. The models were used to predict the penetration, width and effective throat thickness under a set of weld parameters and alternate frequency of shielding gas. Ates [12] presented a technique based on ANNs to model GMAW parameters. The proposed ANN predicts mechanical properties of the weldment such as tensile strength, impact strength, elongation and weld metal hardness. Results showed that, ANN can be used as an alternative way to calculate the gas mixture to the presented conventional method.

In recent years, various heuristic algorithms and mathematical methods have also been applied to find the desired process parameters settings. Meta-heuristic algorithms such as simulated annealing (SA), particle swarm optimization (PSO), and etc., have proven to be a powerful skill for solving large combinatorial optimization problems such as multi objective optimization of manufacturing processes. Kolahan and Heidari [13], modeled and optimized GMAW process using regression modeling and SA algorithm. Various regression functions have been fitted on the experimental data to develop mathematical models. The developed models have been optimized using SA algorithm. Computational results indicated that the proposed SA method could efficiently and accurately determine welding parameters so as a desired bead geometry specification was obtained. Multiple linear regression technique has been used to develop mathematical models for weld bead shape parameters of tungsten inert gas (TIG) welding process. Also by using the same experimental data, an attempt has been made to model the process using BPNN. Then, genetic algorithmic (GA) coupled with BPNN has been applied to optimize the process parameters [14]. Dhas and Kumanan [15] simulated the input–output relationships for flux cored arc welding of the mild steel plates through regression modeling technique. They embedded the developed model into a PSO algorithm to determine optimal process parameters for minimizing of bead width. The optimized values obtained from this technique were compared with experimental results which illustrated a good agreement. Katherasan et al. [16] proposed an ANN model coupled with PSO algorithm to simulate and optimize WBG of 316L nickel based super alloys in flux cored arc welding process. The process modeling was established via ANN and then the developed model embedded into a PSO algorithm which optimized the process parameters. The performances of the conventional regression analysis approach, BPNN and an ANN model coupled with GA (ANN–GA) have been compared for TIG welding process. It has been shown that, ANN-based approaches could yield predictions that were more adaptive in nature compared to those of the more conventional regression analysis approach. It could be due to the fact that ANN-based approaches are able to bring adaptability, which is missing in the conventional regression analysis [17]. Chaki et al. [18] has combined ANNs, GA, SA and Quasi Newton line search techniques to develop three integrated soft computing based models such as ANN–GA, ANN–SA and ANN–Quasi Newton for modeling and optimization of welding strength for hybrid CO_2 laser–MIG welded joints of aluminum alloy. Best performance has been shown for ANN–GA technique.

There exist an extensive body of research on modeling and optimization of GMAW. However, to the best of our knowledge, there is no study in which modeling and optimization of both process parameters and groove angle are simultaneously considered. Therefore, in this article an artificial neural network has been developed to establish the relations between multi-input, multi-output parameters of GMAW. The proposed BPNN model has five inputs and four outputs in which we have jointly taken into account the WBG as well as HAZ specifications. Both of these features are important quality measures in GMAW process. In the proposed integrated BPNN–PSO approach, multi-objective optimization is carried out to simultaneously determine optimal groove angle as well as the values of process parameters (to be set on the welding machine). These settings would results in minimum HAZ while a desired WBG is achieved. The proposed approach has been implemented on API-X42 steel sheets, a widely used alloy in various industries including petrochemical and oil pipelines.

Generally, to construct an ANN model several sets of experimental data (inputs–outputs) are needed. In this paper, the 36 data sets needed for the BPNN training and testing, are gathered as per L_{36} Taguchi design matrix. Taguchi scheme has been selected since it could provide much useful information about the system under study with minimal number of trials. Then, a BPNN model has been developed and tested to simulate actual GMAW process. The BPNN could closely simulate the real GMAW process. Hence, no additional experiments are required if the process responses are to be estimated under various parameters settings. Finally, the BPNN model was embedded (as the objective function) into a multi-criteria PSO optimization algorithm to specify the optimized process parameters and groove angle. In this way after a certain number of iterations, the proposed optimization procedure would determine the best set of process parameters setting that result in a desired WBG with minimum HAZ.

2. Experimental procedure and results

2.1. Material and equipment

In this study, A GAAM-PARS MIG-SP 501W (GAAM-Co, Iran) semi-automatic welding machine with a 2000 ampere capacity, constant voltage and rectifier type power source has been employed to carry out the experiments. The electrode was in the form of a copper-coated coil with 1 mm diameter (ER70S-6G4Si1). Welding shield gas consisted of a mixture of 75% Ar and 25% CO_2, with the flow rate of 12 l/min. Fig. 1 shows a schematic illustration of GMAW process.

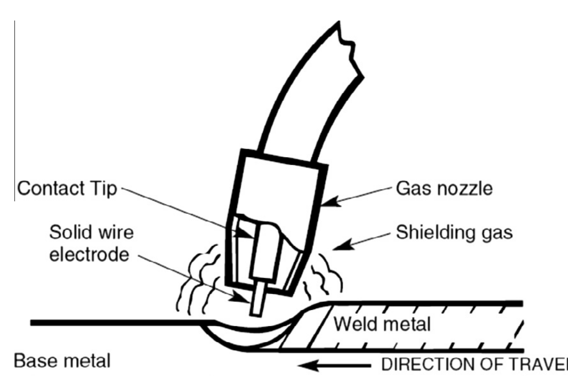

Fig. 1. A schematic representation of GMAW process.

Experiments were carried out on API-X42 steel plates with dimension of 120 mm × 50 mm × 10 mm. The chemical composition and mechanical properties of this alloy are reported in Table 1.

This steel is widely used in such industries as oil pipelines and petrochemical plants. In many of these applications the welded parts are subjected to high stresses or corrosive environments that demand high quality weldments. In all welding processes, the quality of welded joints are greatly affected by the values of process parameters. Moreover, joint edge preparation is often necessary when plates with more than 6 mm thickness are to be welded. This edge modification concentrates heat in the area to be melted and allows for the reduction in the arc power necessary for penetration. This results is lower heat input rate and hence reduces the risk of unforeseen distortions or metallurgical structure alterations. The joint edge geometry is usually specified by groove angle, root face and root opening, as shown in Fig. 2.

For the specimens in this study, joint edge geometries have been prepared by milling process in the form of V-beveled based on ANSI/AWS D 1.1 standard [19].

2.2. Process input variables and their levels

The most prominent parameters in GMAW process include nozzle-to-plate distance (D), welding voltage (V), wire feed rate (F) and welding speed (S) [1,3,5]. Likewise, process quality measures include bead penetration (BP), bead width (BW), bead height (BH) and heat affected zone (HAZ). To determine the feasible working ranges of each input variable, several preliminary tests were conducted. The variable limits were then evaluated by inspecting the weldment for a smooth appearance and good penetration without any visible defects such as surface porosities and undercut. According to the preliminary test results, the input variables and their corresponding levels are listed in Table 2.

2.3. Design of experiments and the results

Once the process variables and their ranges are selected, the next step is to select an appropriate design matrix for carrying out the experiments. Design of experiments (DOE) approach facilitates the identification of the influence of individual parameters, establishing the relationships between process parameters and output responses, and finally determining the optimum levels. Taguchi is one of the effective techniques that can dramatically reduce the number of experiments required to gather necessary data [20]. Given the number of input variables and their levels, in this study Taguchi's L_{36} has been selected to provide a well-balance design for test runs. It consists of 36 sets of process parameters, based of which the experiments have been performed. To increase accuracy, tests were carried out in random orders.

After welding, four types of measurements have been taken from each sample. For measuring BHs and BWs, two types of special gauges; namely Bridge Cam (TWI model) and AWS (G.A.L model), were employed (Fig. 3). Measurements were taken in three places along the weld lines and then averaged out.

Table 1
Chemical composition and mechanical properties of API-X42 steel alloy.

Chemical composition		Mechanical properties	
Fe	97.25%	Yield Stress (YS)	486 MPa
C	0.6%	Ultimate Tensile Strength (UTS)	513 MPa
Mn	1.2%	YS/UTS	0.95
Si	0.45%	Fracture energy in 30 °C	117 J
Other elements: Si + Mg + Cr + Ti	0.5%	Total elongation	21%

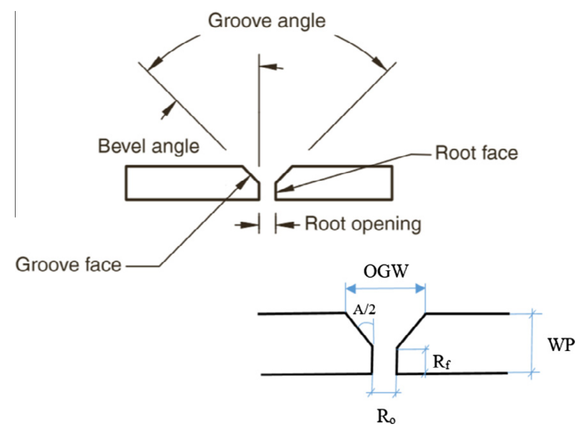

Fig. 2. Joint edge specifications for GMAW of plates with more than 6 mm thickness.

Table 2
GMAW process input variables and their levels.

Level	Welding speed (S) (cm/min)	Wire feed rate (F) (m/min)	Voltage (V) (V)	Groove angle (A) (degree)	Nozzle-work distance (D) (mm)
Level 1	15	5	30	50	6
Level 2	20	7	35	70	12
Level 3	25	9	40	90	–

As shown, welding speed (S), wire feed rate (F), voltage (V) and groove angle (A) would be evaluated at three levels each; while nozzle-work distance (D) is considered at two levels.

For measuring HAZs and BPs, two transverse cross sections were made on each samples. Next, the cut faces were smoothly polished and etched using 10% Nital solution to clearly show bead geometry specifications and heat affected zones.

Then, images were taken using an optical microscope with ×10 magnification (OLYMPUS-530 (Fig. 4)). These images were subsequently processed by Microstructural Image Processing (MIP) software, developed at Metallurgy Lab of Ferdowsi University of Mashhad, to determine samples HAZs and BPs. For each sample the average of two measurements are reported. It is noted MIP software was also used to verify the BHs and BWs dimensions already measured.

Fig. 5 illustrates a sample of transverse cross-section weldment processed by MIP software in which bead geometry specifications and HAZ are clearly shown.

The GMAW parameters settings along with their corresponding outputs are reported in Table 3. In this table, besides the test numbers, the first five columns represent parameters settings used to perform experiments and the last four columns are the measured process outputs.

In the following sections, these measured process outputs are used to model the GMAW using BPNN.

3. BPNN model of GMAW process

Traditional modeling methods are mostly relied on assumptions for model simplifications, and consequently may lead to imprecise results. Recently, ANN has become a powerful and useful method to model complex non-linear systems. The basis of ANN modeling is to capture the underlying trend of the data set presented to it, in the form of a complex nonlinear relationship between the input parameters and the process quality measures. Learning, generalization, and parallel processing are important advantages of ANN that make them suitable for GMAW process modeling [21].

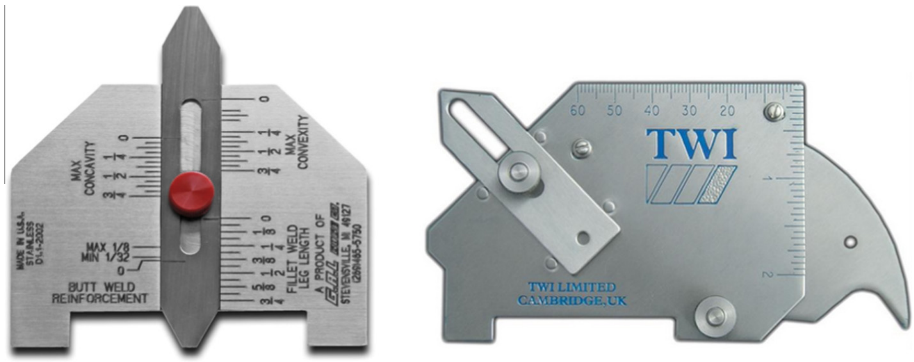

Fig. 3. Bridge Cam and AWS gauges used to measure BHs and BWs of the welded specimens.

Fig. 4. GMAW machine and optical microscope used.

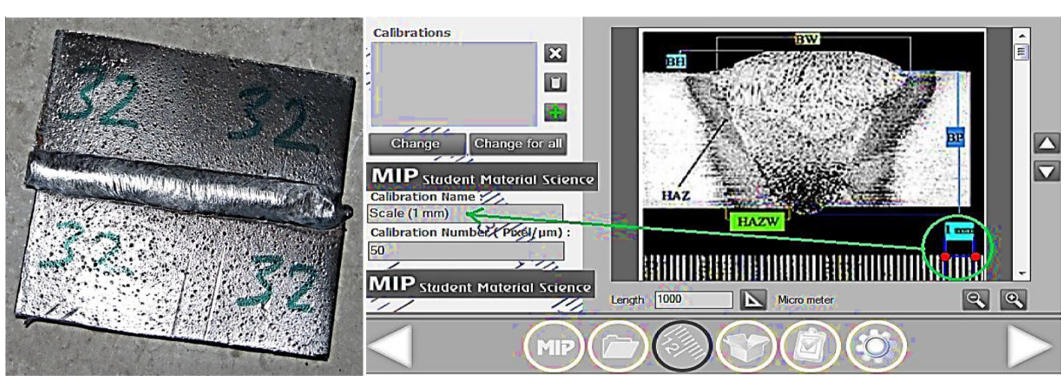

Fig. 5. Quantitative evaluation of WBG and HAZ using microstructural image processing software.

ANNs are built by connecting processing units, called nodes or neurons. Each of the input (X_i) is associated with some weight (W_i) which takes a portion of the input to the node for processing. The node combines the inputs (X_iW_i) and produces net input which in turn is transformed into output with the help of transfer/activation function [21,22].

Many researchers have reported multilayered networks are capable of computing a wider ranges of nonlinear functions than the networks with a single layer [16,21,22]. However, the computational effort needed for modeling a system increases substantially when more complicated architectures are considered. The BPNNs are found most appropriate for handling such large learning

Table 3
L_{36} orthogonal array of GMAW experimental conditions.

No.	D (mm)	A (Degree)	V (V)	F (m/min)	S (cm/min)	BW (mm)	BP (mm)	BH (mm)	HAZ (mm)
1	6	50	30	5	15	8.99	5.55	2.43	3.51
2	6	70	35	7	20	8.61	5.28	2.64	3.99
3	6	90	40	9	25	10.33	5.14	2.85	4.25
4	6	50	30	5	15	8.99	5.55	2.43	3.93
5	6	70	35	7	20	9.69	5.28	2.64	3.99
6	6	90	40	9	25	10.03	5.14	2.85	4.33
7	6	50	30	7	25	7.26	4.48	2.30	3.02
8	6	70	35	9	15	11.44	6.13	4.01	4.92
9	6	90	40	5	20	10.80	4.71	2.21	4.17
10	6	50	30	9	20	8.33	5.79	3.04	3.63
11	6	70	35	5	25	8.37	3.94	2.26	3.25
12	6	90	40	7	15	11.03	6.6	3.10	5.26
13	6	50	35	9	15	10.25	6.76	4.06	4.73
14	6	70	40	5	20	10.22	5.24	2.45	4.05
15	6	90	30	7	25	8.26	3.50	1.84	3.25
16	6	50	35	9	20	9.25	5.74	3.54	4.09
17	6	70	40	5	25	9.16	4.49	2.21	3.62
18	6	90	30	7	15	10.62	4.98	2.33	4.22
19	12	50	35	5	25	8.50	4.81	2.54	2.98
20	12	70	40	7	15	13.37	6.70	3.77	4.88
21	12	90	30	9	20	10.37	4.14	2.60	3.72
22	12	50	35	7	25	8.83	4.76	3.00	3.26
23	12	70	40	9	15	13.74	6.43	4.40	5.21
24	12	90	30	5	20	9.72	3.25	1.82	3.63
25	12	50	40	7	15	12.41	6.82	5.35	5.49
26	12	70	30	9	20	9.81	4.60	2.89	2.59
27	12	90	35	5	25	9.68	3.24	1.91	3.20
28	12	50	40	7	20	10.78	6.33	3.80	4.06
29	12	70	30	9	25	8.80	3.94	2.51	3.22
30	12	90	35	5	15	12.43	4.61	1.93	4.16
31	12	50	40	9	25	9.94	6.02	3.99	3.87
32	12	70	30	5	15	9.72	4.4	2.31	3.57
33	12	90	35	7	20	11.20	4.34	2.60	3.93
34	12	50	40	5	20	10.39	5.51	3.09	3.71
35	12	70	30	7	25	8.56	3.55	2.23	3.00
36	12	90	35	9	15	11.29	6.07	3.47	5.73

problems. This type of neural network is known as a supervised network because it requires a desired process quality measures in order to learn. A BPNN consists of multiple layers of nodes in a directed scheme, with each layer fully connected to the next one. Except for the input nodes, each node is a neuron (or processing element) with a nonlinear activation function defined by [22]:

$$F_{i,j} = \frac{1}{1 + \exp^{-P\left(W_{i,j-1}, O_{i,j-1}\right)}} \tag{1}$$

where for ith neuron in the jth layer, $P\,(W_{i,j-1}, O_{i,j-1})$ is given by:

$$P\left(W_{i,j-1}, O_{i,j-1}\right) = \sum_{j=1}^{m}\sum_{i=1}^{n} W_{i,j-1} \cdot O_{i,j-1} \tag{2}$$

where n and m are number of hidden layers and neurons in each layer respectively. $W_{i,j-1}$ is the weight of the ith neuron in $(j-1)$th. In this study for modeling of the GMAW process the total number of input nodes is five (nozzle-to-plate distance, groove angle, welding voltage, wire feed rate and welding speed). The best architecture of model the (number of hidden layers and number of nodes in each hidden layer) have been chose by trial and error method. Furthermore, the transfer function of each processing element is identified and next network is trained to interrelate the process parameters to output responses. The outputs of trained model are BW, BP, BH and HAZ.

Network training involves two phases through different layers of the network; a forward and a backward phase. In the forward phase, input vectors are presented and propagated forward to compute the outputs and the mean square error (MSE) via the following relation.

$$\mathrm{MSE} = \frac{1}{n}\sum_{k=1}^{n}\left(Y_k - y_k\right)^2 \tag{3}$$

The backward phase is an iterative error reduction performed in the backward direction from the output layer to the input layer. The Levenberg–Marquardt algorithm is used to minimize the MSE [21,22]. Several tests are carried out to find the best neural network architecture, training parameters and learning algorithm coefficients. Appropriate BPNN architecture with three hidden layers is selected. A 5–***5–3–6***–4 architecture results in the best interpolation performance and less MSE value. Configuration of the developed BPNN is schematically illustrated in Fig. 6.

Fig. 7 depicts the comparison between the capability of responses prediction by developed model and experiments. The good agreement with the small negligible error exists; so the developed BPNN predicts the process in the favorable level.

As clearly demonstrated in Fig. 7, the predicted outputs given by BPNN closely follow the experimentally measured data. The relative errors between predicted and measured BW, BP, BH and HAZ are 0.52%, 0.33%, 0.43%, 0.82% respectively. The maximum error is less than 6% for all 36 data sets. Consequently, the developed BPNN model may appropriately substitute the actual GMAW process. In the following, this model has been used as the process estimator in the proposed BPNN–PSO optimization process to find the optimal parameters settings.

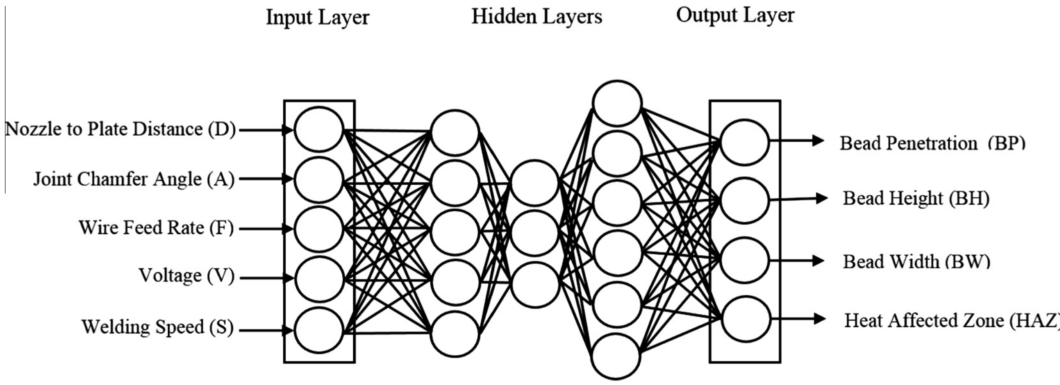

Fig. 6. Architecture of proposed BPNN model.

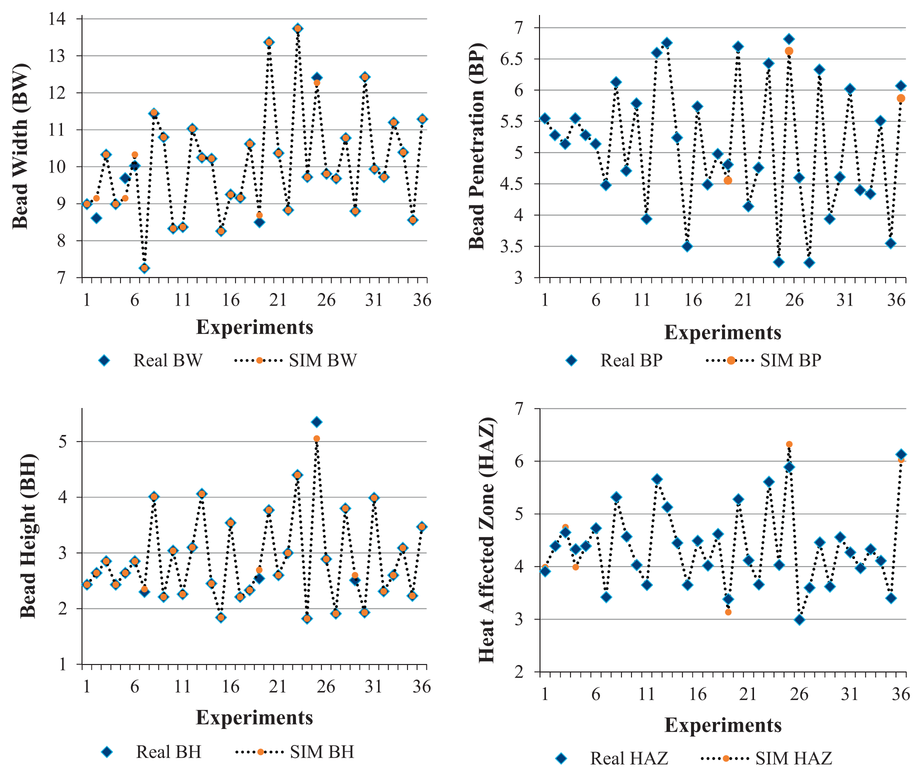

Fig. 7. Comparison between experimental and predicted BW, BP, BH and HAZ by the BPNN models.

4. GMAW process optimization

4.1. Problem definition

The goal of process optimization is to seek the best design by changing variables that satisfies the best process performance while don't disturb the design constraints. A suitable weld shall be such that the completed weld has a substantially uniform cross section. At no point shall the crown surface of bead be below the outside surface the parent plate, nor should it be raised above the parent by more than an upper limit value. Also the width of bead should be a few bigger than the original groove (crown width). On the other hand the optimum value of bead penetration is equal to thickness of sample plates while greater penetration require to larger heat input; so the risk of undercut and high overlap and heat caused defects in parent material increase.

A standard weld pool is defined in American petroleum institute (user's manual No 1104 released by the API) by its appearance (Fig. 8) [19].

Thus, based on API standard [19], the following rules may be used to achieve a high quality WBG.

$$\mathrm{OGW} < \mathrm{BW} < \mathrm{OGW} + 1.6\ \mathrm{mm},\quad \mathrm{BP} \geqslant 6\ \mathrm{mm},\quad 0.8\ \mathrm{mm} < \mathrm{BH} < 1.6\ \mathrm{mm} \tag{4}$$

The WBG specifications are directly influenced by the settings of GMAW parameters. Moreover, the parameter Original Groove

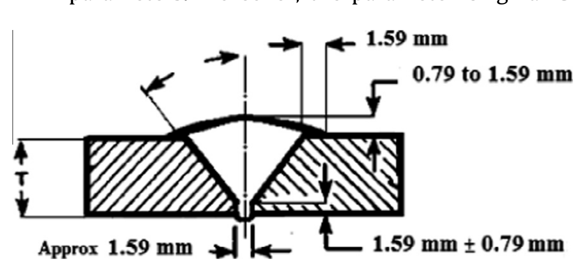

Fig. 8. Desirable V-beveled butt joint for gas pipeline and related facilities [19].

Width (OGW) is directly associated with the groove angle (A), root opening (R_O), root length (R_L) and work piece thickness (T). It is given by:

$$OGW = 2 \times (T - R_L) \times tg\left(\frac{A}{2}\right) + R_o \tag{5}$$

The need for the best compromise within various (sometimes conflicting) objectives, calls for an effective multi objective optimization approach. The best level of each process parameter may be specified through Taguchi Signal to Noise (S/N) analysis. However, this method is limited by the fact that S/N could only specify the best level of each parameter out of those originally included in the Taguchi design matrix. In other words, if the true optimal value of a given parameter fall within any two levels, S/N analysis could not identify it. To overcome this shortcoming, an integrated ANN–PSO algorithm has been proposed to make it possible for interpolation of entire permissible ranges of process parameters.

4.2. Solution method: particle swarm optimization

Particle swarm optimization (PSO) algorithm, a population based stochastic optimization proposed by Eberhart and Kennedy in 1995, has been inspired by social behavior of birds flocking [23]. The intelligence of swarm is based on the principle of social and psychological behavior of the swarm. The optimization procedure is initialized with a population of random solutions and searches for optima by updating generations. The potential solutions called particles fly through the problem space by following the current optimum particles. PSO is very easy to implement and there are few parameters to adjust. The algorithm can be explained based on the following scenario: a group of birds are randomly searching food in an area. There is only one piece of food in the area being searched. All the birds do not know where the food is. But they know how far the food is in their search [24]. The best strategy to attain the food is to simply follow the bird, which is nearest to the food. In optimization problems, each bird in the search space is referred to as 'particle'. All the particles are evaluated by the fitness function to be optimized and have velocities for the particles. The particles fly through the problem space by following the current optimum particles. The problem is initialized with a group of random particles and then searches for optima by updating generations [25]. Although conventional PSO can rapidly find out good solutions, it may be trapped in local minimum and fails to converge to the best position [13]. To obviate this problem and improve resolving capacity, an improved PSO algorithm with mutation is used. Using both the best and worst particle positions in the improved PSO algorithm accelerate the finding of the optimal solution. The particle positioning is accomplished by modifying the particle parameters including the speed and position (V_i and X_i), defined by the following expressions [26,27].

$$\begin{aligned} X_i(k+1) &= X_i(k) + V_i(k+1) \\ V_i(k+1) &= \gamma \cdot V_i(k) + c_1 r_1 (p_i - x_i(k)) + c_2 r_2 (p_g - x_i(k)) \end{aligned} \tag{6}$$

where c_1, c_2 and c_3 are acceleration parameters, r_1 and r_2 are random numbers ranged between 0 and 1, and γ represents the inertia weight which decreases linearly from 1 to near 0 as the search progresses. In addition, p_i and p_g denote the best position of the ith bird and the best position of the entire colony, respectively. Each heuristic algorithm has its own parameters that affect its performance in terms of solution quality and computational speed. It is noted that, the parameters of PSO also have to be tuned to achieve the best performance.

4.3. Optimization results and confirmation tests

The proposed multi objective BPNN–PSO procedure has been employed in order to obtain a weldment with desired WBG specifications and minimum HAZ on API-X42 steel plates. Here, Eq. (4) is used to define the ideal dimensions of WBG based on API standard [19]. The feasible ranges of GMAW parameters have been displayed in Table 2. According to Table 4, plates groove angle can vary between 50 and 90 degrees ($50° < A_i < 90°$), welding voltage may take any values in the range of 30–40 V ($30 < V_i < 40$) etc. In each iteration, the BPNN model, incorporated into PSO algorithm, acts as the objective function to calculate the GMAW outputs values. The algorithm would search through feasible solution space for the best set of parameters values so as HAZ is minimized and pre-defined dimensions of WBG are obtained.

As mentioned, to enhance the performance of the optimization algorithm, its parameters values must properly be determined. Based on the results of several test runs, inertia weight was set at 0.5 and the best population size found to be 20 for all generations. To avoid local optima, the computer code of BPNN–PSO algorithm was run several times using various set of initial populations. The algorithm was terminated after a pre-determined number of non-improving generations was observed. Fig. 9 demonstrates the convergence curve of a sample run in which the code was terminated after 35 generations, including five consecutive generations with no improvement in the objective function.

Table 4 lists two sets of the best GMAW parameters settings for which the value of the multi-criteria objective function is minimized. It should be mentioned that both sets result in the same values for the objective function. In Table 4, the first five column show optimal process parameters given by PSO algorithm. To assess the performance of the proposed BPNN–PSO method, experiments were carried out based on the optimized settings whose measured outputs are reported in the last four column of the table. By comparing GMAW test results it becomes evident that optimized HAZs are at least 75% smaller than all those reported in Table 3 (1.64 and 1.69 mm vs. 3.00 mm of test No. 35). Furthermore, the measured weld beads are well within the proper ranges delineated by API standard (Eq. (4)). By the same token, the WBGs resulted from optimized parameters settings are much better than all those of the 36 tests performed based on Taguchi scheme. These findings confirm that the proposed approach is quite efficient in finding the best set of parameters settings for multi objective optimization of GMAW.

In GMAW, large heat affected zones may cause fracture and corrosion due to pronounced metallurgical changes in this region [28]. On the other hand, bigger weld beads (especially larger BW and BP) are more favorable because of their higher strength. A favorable WBG is often defined by the specific applications and industries for which the welded parts are intended. In most cases WBG and HAZ are conflicting performance measures in which pre-defined WBGs and small HAZs are to be obtained. Achieving such conflicting objectives requires careful selection of parameters settings. Given the vast number of possible combinations for parameters settings, trial and error is quite inefficient. In contrast, multi-objective modeling and optimization proved to be more both efficient and effective in finding the best set of GMAW parameters.

With respect to the two performance measures used in this research, optimal parameters settings should produce a weldment with a small HAZ and WBG characteristics close to those given by Eq. (4). The optimized parameters values listed in Table 4 indicate that both nozzle to plate distance (D) and welding voltage (V) should be at their lower permissible ranges, resulting in minimum

Table 4
Optimal parameters and their measured responses.

Optimal process setup	Process parameters					Experimental responses			
	D (mm)	*A* (Degree)	*V* (V)	*F* (m/min)	*S* (cm/min)	BW	BP	BH	HAZ
Setting 1	6	70	33	6	21	6.91	6.10	1.23	1.64
Setting 2	7	75	34	6.2	20	6.96	6.12	1.49	1.69

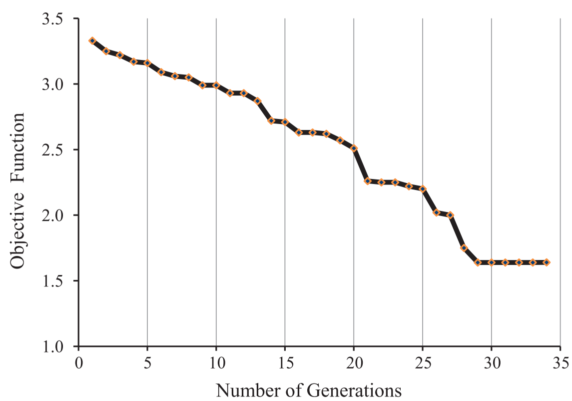

Fig. 9. Convergence curve for the proposed PSO algorithm.

possible HAZ. These, together with the values of other optimized process parameters, ensure that the pre-defined WBG is obtained. Therefore, the proposed BPNN–PSO approach a well-balanced welded joint may be achieved; satisfying both distinct objectives.

5. Conclusion

The quality of final product in GMAW process is significantly affected by the selection of process parameters levels. On the other hand, the interactions of these parameters and the conflicting nature of various quality measures, call for simultaneous selection of their optimal values. In this research the problem of multi-criteria modeling and optimization of GMAW process for API X42 steel sheets has been addressed. First, GMAW modeling has been carried out using experimental data gathered as per L_{36} Taguchi design matrix. Bead height and bead width has been measured using Bridge Cam and AWS gauges. Moreover, the MIP software has been used for measurement of bead penetration, width of heat affected zone and verification of measured bead height and bead width. The proposed BPNN model simultaneously takes into account five process input variables to predict four outputs responses. The BPNN predicted results were in a good agreement with the experimental data which illustrate the proposed model can accurately simulate the actual GMAW process. Next, the BPNN model has been coupled with a PSO procedure to determine the optimal set of process settings. The multi-objective optimization procedure involves finding a certain combination of welding parameters so as HAZ is minimized and a WBG with specific dimensions is obtained. The most important factors affecting HAZ is heat input rate. Usually high welding voltage (*V*) and nozzle to plate distance (*D*) would produce larger heat input rates which in turn increases the size of HAZ. The optimized parameters values, given by BPNN–PSO, indicate that both nozzle to plate distance and welding voltage should be set at their lower ends (6 m/min and 33 V respectively). Such settings, along with the values for other three parameters, would also produce a WBG with desired specifications while keeping HAZ to its minimal. The results depict that WBGs are well within the desired ranges whilst HAZs have been decreased considerably creating a near perfect balance among the conflicting objectives. These further illustrate that optimization results are consistent with the inherent characteristics of GMAW process. It is noted that in this research both performance measures were given equal weights of 50%. Based on the relative importance of the HAZ and WBG and with minor modifications in the objective function, any other combinations of these two objectives may also be achieved.

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