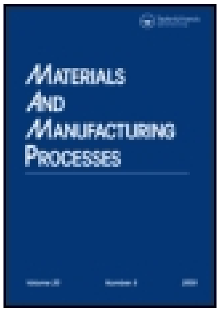


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# Optimization of the GTA Welding Process Using Combination of the Taguchi Method and a Neural-Genetic Approach

Hsuan-Liang Lin [a] & Chang-Pin Chou [b]

[a] Vehicle Engineering , Army Academy , Taoyuan, Taiwan

[b] Mechanical Engineering , National Chiao Tung University , Hsinchu, Taiwan

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# Optimization of the GTA Welding Process Using Combination of the Taguchi Method and a Neural-Genetic Approach

Hsuan-Liang Lin[1] and Chang-Pin Chou[2]

[1]*Vehicle Engineering, Army Academy, Taoyuan, Taiwan*
[2]*Mechanical Engineering, National Chiao Tung University, Hsinchu, Taiwan*

Many parameters affect the quality of the gas tungsten arc (GTA) welding process. It is not easy to obtain optimal parameters of the GTA welding process. This paper applies an integrated approach using the Taguchi method, artificial neural network (ANN), and genetic algorithm (GA) to optimize the weld bead geometry of GTA welding specimens. The proposed approach consists of two stages. First stage executes initial optimization via Taguchi method to construct a database for the ANN. In second stage, an ANN is used to provide the nonlinear relationship between factors and the response. Then, a GA is applied to obtain the optimal factor settings. The experimental results showed that the weld bead geometry of the optimal welding parameters via the proposed approach is slender than apply Taguchi method only.

*Keywords* Gas tungsten arc welding; Genetic algorithm; Neural networks; Taguchi method.

## Introduction

The gas tungsten arc (GTA) welding is one of the mainly applied welding processes in industry to carbon steels and stainless steels for high quality weld and low investment. However, the relatively shallow penetration capability and low productivity are the main disadvantages in the GTA welding process. Achieving full penetration of welds and increasing productivity are the main objectives in the welding industry. In order to achieve single pass welds with no edge preparation, instead of multipass procedures, one of the most notable techniques is to use activating flux with GTA welding process [1]. Several parameters influence the quality of GTA welding process. Conventionally, engineers apply the Taguchi method to conduct parameter design in a variety of industrial practices. The usage of Taguchi method in the welding process has been proven to be very beneficial to process modeling, optimization, and control. For example, Juang et al. [2] used the Taguchi method to optimize the weld pool geometry in the GTA welding of stainless steel. However, the Taguchi method has some limitations when adopted in practice. It can find optimal solutions only within the specified level of control factors. The Taguchi method cannot find the real optimal values when the specified parameters are continuous. Artificial neural network (ANN) is a nonlinear function, and can accurately represent a complex relationship between inputs and outputs [3, 4]. A trained ANN model has also been used to predict accurately the response (output) for specified parameter settings (input). For example, Ciurana et al. [5] used the ANN to select appropriate machining conditions to achieve desired dimensions, angles, and roughness features in the pulsed Nd:YAG laser micromachining process. In addition, Khaw et al. [6] demonstrated that advantages could be gained using the Taguchi concept for ANN design. First, it is the only known method for ANN design that considers robustness as an important design criterion, increasing the quality of the ANN. Second, the Taguchi method uses orthogonal arrays (OAs) to design an ANN systematically, markedly reducing the design and development time for ANN. In this work, a global optimization method, genetic algorithm (GA), is used to converge a global optimum among several possible local optimums [7]. GA simulates the biological evolutionary process, Darwin's theory of survival of the fittest. The solution of the optimization problem with GA begins with a set of potential solutions or chromosomes that are randomly generated or selected. The entire set of these chromosomes comprises a population. The chromosomes evolve during several iterations or generations. New generations are generated using crossover and mutation technique. Crossover involves splitting two chromosomes and then combining one half of each chromosome with the other pair. Mutation involves flipping a single bit of a chromosome. The chromosomes are then evaluated using a certain fitness criteria, and the best ones are kept while the others are discarded. This process is repeated until one chromosome has the best fitness and thus is taken as the best solution to the problem. For example, Chakraborti et al. [8] applied the GA to resolve the complex optimization of $Li^+$ ions contained in carbon nanotubes.

To solve the above optimization problem, a combing ANN and GA (Neural-Genetic) approach is proposed to model and optimize the GTA welding process in this work. Ozcelik et al. [9] used the ANN and GA to minimize warpage of thin shell plastic parts manufactured by injection molding. Su et al. [3] present an integrated approach of an ANN and GA for the integrated circuit (IC) wire bonding optimization problem. This work combines the Taguchi method and a Neural-Genetic approach to determine the

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Address correspondence to Hsuan-Liang Lin, Vehicle Engineering, Army Academy, No. 113, Sec. 4, Jungshan E. Rd., Jungli City, Taoyuan, Taiwan; E-mail: alaniin@ms47.hinet.net

optimal conditions of GTA welding process. The proposed approach consists of two stages. First stage executes initial optimization via Taguchi method to construct a database for the ANN. Second stage applies an ANN with the Levenberg–Marquardt back-propagation (LMBP) algorithm to construct an ANN model. The process conditions are optimized using GA, and the fitness function used in the process conditions optimization of GTA welding is based on the ANN model. The outline of the combining the Taguchi method and a Neural-Genetic approach is given in Fig. 1. An initial population is generated at random, and the fitness function based on ANN model is used to calculate the fitness for all initial individuals. Then, selection, crossover and mutation are used to reproduce a new generation. The process is repeated until the maximum generation number or population convergence is reached. The ANN and GA software of MATLAB toolbox were used to develop the required network model and search global optimization in this work.

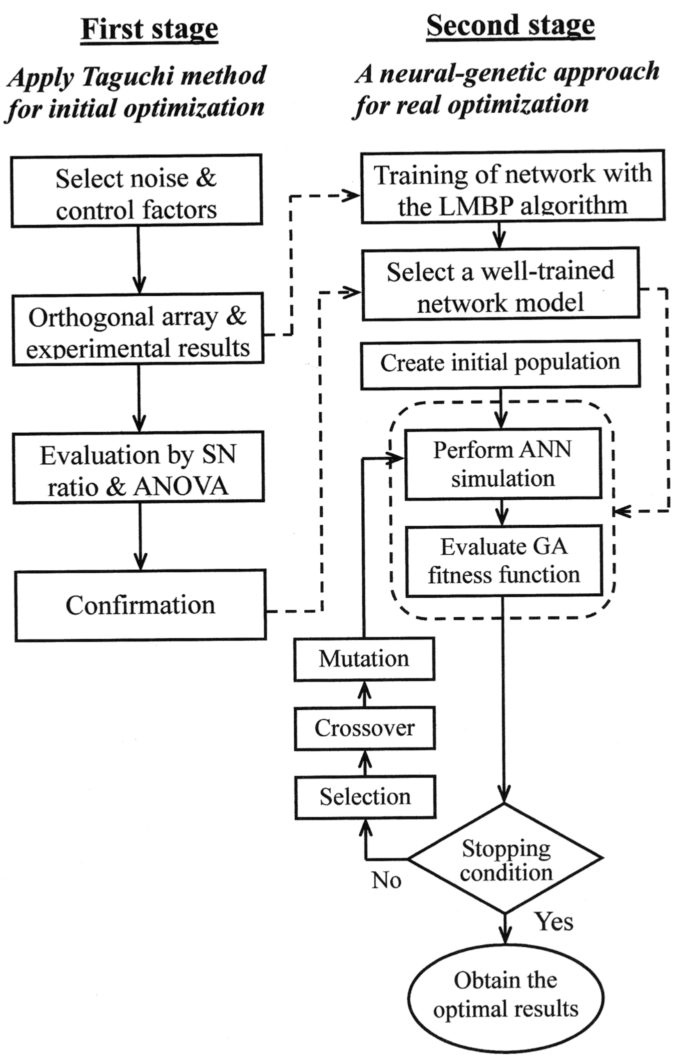



FIGURE 1.—Schematic diagram of experimental procedure.

## INITIAL OPTIMIZATION VIA THE TAGUCHI METHOD

### *Parameter of the GTA Welding Process*

The GTA welding quality is strongly characterized by the weld bead geometry. The weld bead geometry plays an important role in determining the mechanical properties of the weld [2, 10]. Measurements of the weld bead geometry were performed for evaluation of the quality of GTA welds. This work took the width of weld bead and the depth of penetration to describe the weld bead geometry. The depth-to-width ratio (DWR) of the weld bead geometry of each specimen was selected as the quality characteristic of GTA welding process. The previous experiment [11] showed that the most significant parameters for DWR of weld bead geometry are welding current, travel speed of the welding torch, and electrode angle in GTA welding process. Results from the literature [12] indicate that oxide flux $TiO_2$ has the most pronounced effect on welds morphology, resulting in a large DWR on low carbon steel. In addition, Huang et al. [13] and Yang et al. [14] proved that oxide flux $SiO_2$ cause an important increase in penetration on JIS SUS 304 stainless steel in bead-on-plate GTA welding process. Therefore, welding current, travel speed of the welding torch, electrode angle, and the different proportion of oxide $TiO_2$ and $SiO_2$ for mixed fluxes were selected as the control factors. The values of the welding process parameters at the different levels are listed in Table 1. Cleanliness of the weld joint areas was selected as the noise factor in this work. The surface impurities were removed, and the surface was cleaned with acetone at level one (N1). The specimens at level two (N2), without any cleaning treatment, may have been tarnished with dirt and/or grease.

### *Orthogonal Array Experiment and ANOVA*

Four four-level control factors, as well as one noise factor, were considered in this work. The interaction effect between the welding parameters is not considered. Therefore, the four control factors yield 12 degrees of freedom. The L16 ($4^5$) OA that has 15 degrees of freedom was employed in this work. Table 2 presents an experimental layout with an inner array for control factors and an outer array for a two-level noise factor (N1 and N2). The DWR of weld bead geometry of the specimens, as discussed earlier, is a higher-is-better (HB) quality characteristic. The signal-to-noise

TABLE 1.—Control factors and their levels.

| Factor | Process parameter | Level 1 | Level 2 | Level 3 | Level 4 |
|---|---|---|---|---|---|
| A | Electrode angle | 60° | 65° | 70° | 75° |
| B | Welding current | 165 A | 170 A | 175 A | 180 A |
| C | Travel speed | 165 mm min$^{-1}$ | 160 mm min$^{-1}$ | 155 mm min$^{-1}$ | 150 mm min$^{-1}$ |
| D | Proportion of mixed flux | 20% $TiO_2$ 80% $SiO_2$ | 40% $TiO_2$ 60% $SiO_2$ | 60% $TiO_2$ 40% $SiO_2$ | 80% $TiO_2$ 20% $SiO_2$ |

TABLE 2.—Experimental layout using an L16 orthogonal array and results.

| | Control factor | | | | Noise factor | | |
|---|---|---|---|---|---|---|---|
| | | | | | N1 specimen | N2 specimen | |
| Trial no. | A | B | C | D | DWR | DWR | SNR, dB |
| 1 | 1 | 1 | 1 | 1 | 0.738 | 0.735 | −2.655 |
| 2 | 1 | 2 | 2 | 2 | 0.520 | 0.507 | −5.791 |
| 3 | 1 | 3 | 3 | 3 | 0.526 | 0.562 | −5.299 |
| 4 | 1 | 4 | 4 | 4 | 0.686 | 0.656 | −3.468 |
| 5 | 2 | 1 | 2 | 3 | 0.559 | 0.544 | −5.166 |
| 6 | 2 | 2 | 1 | 4 | 0.454 | 0.419 | −7.220 |
| 7 | 2 | 3 | 4 | 1 | 0.736 | 0.757 | −2.541 |
| 8 | 2 | 4 | 3 | 2 | 0.664 | 0.640 | −3.847 |
| 9 | 3 | 1 | 3 | 4 | 0.408 | 0.450 | −7.377 |
| 10 | 3 | 2 | 4 | 3 | 0.704 | 0.660 | −3.342 |
| 11 | 3 | 3 | 1 | 2 | 0.623 | 0.604 | −4.250 |
| 12 | 3 | 4 | 2 | 1 | 0.725 | 0.673 | −3.126 |
| 13 | 4 | 1 | 4 | 2 | 0.608 | 0.696 | −3.775 |
| 14 | 4 | 2 | 3 | 1 | 0.653 | 0.578 | −4.262 |
| 15 | 4 | 3 | 2 | 4 | 0.532 | 0.520 | −5.582 |
| 16 | 4 | 4 | 1 | 3 | 0.616 | 0.633 | −4.091 |

Average SNR of total trial $\hat{\eta}$ is −4.487 (dB).

ratios (SNR), which condense multiple data points in a trial, depend on the characteristic that is being evaluated [15]. The equation for the SNR of HB characteristic is

$$SNR = -10\log\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right), \tag{1}$$

where $n$ is the number of tests in a trial (which equals number of repetitions regardless of noise levels) and $y_i$ is the DWR of weld bead geometry of the specimens. The value of $n$ is two in this work. Table 2 corresponds to the SNR of each trial. Figure 2 plots the SNR graph obtained from Table 2. The initial optimal combinations of GTA welding process parameter levels, $A_1B_4C_4D_1$, are obtained from Fig. 2. Table 3 is the results of ANOVA for the weld bead geometry in first stage. The travel speed and

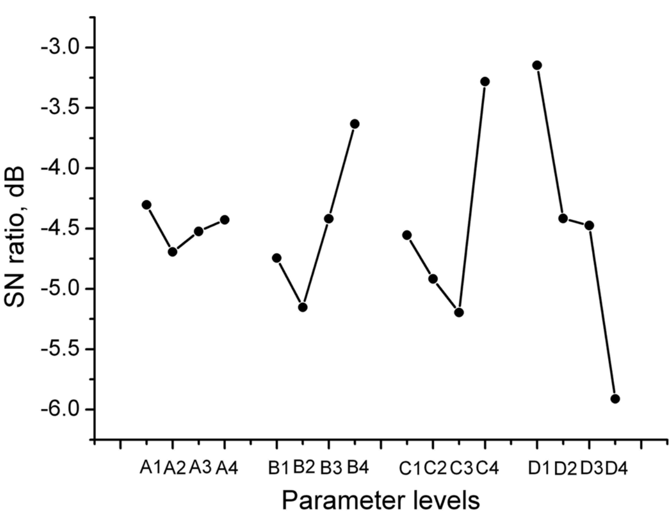



FIGURE 2.—SNR graph for the weld bead geometry.

TABLE 3.—Results of ANOVA for the weld bead geometry.

| Factor | Degree of freedom | Sum of square | Mean square | F-Test | Pure sum of square | Percent contribution |
|---|---|---|---|---|---|---|
| A | 3 | 0.325# | – | – | – | – |
| B | 3 | 4.977 | 1.659 | 2.87 | 3.24 | 10.01 |
| C | 3 | 8.581 | 2.860 | 4.94 | 6.84 | 21.14 |
| D | 3 | 15.339 | 5.113 | 8.83 | 13.60 | 42.02 |
| Error | 3 | 3.149 | | | | |
| $\text{Error}_{(\text{pooled})}$ | (6) | (3.474) | (0.579) | | 8.68 | 26.83 |
| Total | 15 | 32.371 | | | 32.371 | 100 |

# The factors are treated as pooled error.

the different proportion of oxide $TiO_2$ and $SiO_2$ for mixed fluxes were the significant welding parameters in affecting the quality characteristic, with the different proportion of mixed fluxes being the most significant, as indicated by Table 3.

### *Confirmation Tests*

The final step of first stage is to compare the estimated value with the confirmative experimental value, using the optimal levels of the control factors to confirm experimental reproducibility. The estimated SNR $\eta_{opt}$ using the optimal level of the control factors, is calculated as

$$\eta_{opt} = \hat{\eta} + \sum_{j=1}^{q}\left(\eta_j - \hat{\eta}\right), \tag{2}$$

where $\hat{\eta}$ is the total average SNR of all the experimental values, $\eta_j$ is the mean SNR at the optimal level, and $q$ is the number of the control factors that significantly influence the quality characteristic. Table 3 reveals that control factor A has the least effect on the quality characteristic. In order to prevent an over-estimate [16], control factor A is not considered and the estimated SNR $\eta_{opt}$ is computed as

$$\begin{aligned}\eta_{opt} &= -4.487 + (-3.633 + 4.487)\\ &\quad + (-3.281 + 4.487) + (-3.146 + 4.487)\\ &= -1.086 \text{ (dB)}.\end{aligned}$$

The confidence limits on the above estimation can be calculated using the following equation:

$$CI = \sqrt{F_{\alpha;1;v_e} V_{ep}\left(\frac{1}{n_{eff}}\right)}, \tag{3}$$

where $F_{\alpha;1;v_e}$ is the $F$-ratio required for $\alpha = 0.05$ (with a confidence of 95%); $v_e$ is the degrees of freedom for pooled error; $V_{ep}$ is the pooled error variance, and $n_{eff}$ is the effective sample size;

$$n_{eff} = \frac{N}{1 + DOF_{opt}}, \tag{4}$$

TABLE 4.—Confirmation results of the Taguchi method.

| | Depth-to-width ratio, DWR | | | | |
|---|---|---|---|---|---|
| Trial no. | N1 specimens | N2 specimens | SNR, dB | Average | Confidence interval (95%) |
| 17 | 0.785 | 0.778 | −2.146 | 0.781<br>$D = 5.806$<br>$W = 7.432$ | $-1.086 \pm 1.472$ (dB) |

where $N$ is the total number of trials, and $DOF_{opt}$ is the total degrees of freedom that are associated with the items used to estimate $\eta_{opt}$.

Given a CI of 95% for the DWR, $F_{0.05;1;6} = 5.99$, and $V_{ep} = 0.579$, $N = 16$, $DOF_{opt} = 9$, and the effective sample size $n_{eff}$ is 1.6. Therefore, the CI is computed to be CI = 1.472 (dB). The experimental results (Table 4) confirm that the initial optimizations of the GTA welding process parameters were achieved in first stage of the proposed approach.

## Optimization using a neural-genetic approach

ANNs are used to model complex manufacturing processes, typically for process and quality control [17]. Several well-known supervised learning networks use a back-propagation (BP) neural network. Funahashi [18] proved that the BP neural network may approximately realize any continuous mapping. Back propagation learning employs a gradient descent algorithm to minimize the mean square error between the target data and the predictions of a neural network. However, one of the major problems with basic BP algorithm (gradient descent algorithm) has been the extended training time required. The techniques for accelerating convergence have fallen into two main categories: heuristic methods and standard numerical optimization methods such as the LMBP algorithm [19].

An ANN with the LMBP algorithm is used to provide the nonlinear relationship between factors and the response. Then, a GA is applied to obtain the optimal factor settings. The LMBP algorithm is similar to the quasi-Newton method, in which a simplified form of the Hessian matrix (second derivatives) is used. When the cost function has the form of a sum of squares, then the Hessian matrix H can be approximated as

$$H = J^T J, \tag{5}$$

and the gradient $g$ can be computed as

$$g = J^T e, \tag{6}$$

where $J$ is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases, and $e$ is a vector of network errors. The Jacobian matrix can be computed through a standard BP technique that is much less complex than computing the Hessian matrix [20]. An iteration of this algorithm can be written as

$$X_{K+1} = X_K - [J^T J + \mu I]^{-1} J^T e, \tag{7}$$

when the scalar $\mu$ is zero, this is just Gauss–Newton, using the approximate Hessian matrix. When $\mu$ is large, this becomes gradient descent with a small step size. The algorithm begins with $\mu$ set to some small value (e.g., $\mu = 0.01$). If a step does not yield a smaller value for $e$, then the step is repeated with $\mu$ multiplied by some factor $\theta > 1$ (e.g., $\theta = 10$). Eventually, $e$ should be decreased, since we would be taking a small step in the direction of steepest descent. If a step does produce a smaller value for $e$, then $\mu$ is divided by $\theta$ for the next step, ensuring that the algorithm will approach Gauss–Newton, which should provide faster convergence [19]. The LMBP algorithm is the fastest algorithm that has been tested for training multilayer networks of moderate size, even though it requires a matrix inversion at each iteration. It requires two parameters, but the algorithm does not appear to be sensitive to this selection.

### *Training of Back Propagation Network*

Multilayer feed-forward ANNs are commonly used for solving difficult predictive modeling problems [21]. They typically consist of an input layer, one or more hidden layers, and one output layer. The neurons in the hidden layers are computational units that perform non-linear mapping between inputs and outputs. A feed-forward ANN was used in this work. It takes a set of four input values (control factors A, B, C, and D) and predicts the value of two outputs (depth and width of the weld bead geometry). The transfer functions for all hidden neurons are tangent sigmoid functions, and a linear function is used for the output neurons. Determining the number of hidden neurons is critical in the design of neural networks. An over abundance of hidden neurons give too much flexibility that usually leads to over-fitting. On the other hand, too few hidden neurons restrict the learning capability of a network and degrade its approximation performance [21]. A total of 32 input–output data patterns were separated into a training set and a testing set. Functionally, 80% (26 patterns) were randomly selected to train the neural network; 20% (6 patterns) were randomly selected for testing. An efficient algorithm, the Levenberg–Marquardt algorithm, was adopted to improve classical BP learning in the training process.

### *Select a Well-Trained Network Model*

Table 5 presents ten options for the ANN architecture. After comparing all the data for the mean square error (MSE) value, the structures 4-8-2, 4-10-2, 4-12-2, 4-18-2, and 4-20-2 are the five best convergence criteria. The structure 4-10-2 showed the least simulating error and was, therefore, selected to obtain a better performance. The simulating errors were compared with average D and W value of confirmation experimental results (as shown in Table 4). Figure 3 presents the topology of the network 4-10-2 with a $\mu$ value of 0.001 and a $\theta$ value of 10. This well-trained network was employed to create the fitness function.

TABLE 5.—Options for different networks.

| Architecture | Mean square error for training | Rank of MSE | Simulating error, % (Compare with the average value in Table 4) | |
|---|---|---|---|---|
| | | | D value (%) | W value (%) |
| 4-2-2 | 0.162199 | | | |
| 4-4-2 | 0.158015 | | | |
| 4-6-2 | 0.346066 | | | |
| 4-8-2 | 0.0950624 | 5 | −16.01 | 0.13 |
| 4-10-2 | 0.0723461 | 3 | −11.43 | −1.47 |
| 4-12-2 | 0.0637613 | 1 | −13.77 | −10.37 |
| 4-14-2 | 0.0968101 | | | |
| 4-16-2 | 0.0953464 | | | |
| 4-18-2 | 0.0637613 | 1 | −41.52 | −10.87 |
| 4-20-2 | 0.077998 | 4 | 20.45 | −5.30 |

*Optimization via a Neural-Genetic Approach*

In order to use the GA to optimize welding process parameters, an index to evaluate the next generation's survival fitness was needed. This work made a fitness function using the weld bead geometry, which based on a well-trained network model. Excessive welding bead width and penetration do not produce good weld quality. Therefore, this study used the following objective function, with bead width and depth of penetration

$$F_{\mathrm{Object}} = w_1 \times (W_s - W_d)^2 + w_2 \times (D_s - D_d)^2 \qquad (8)$$

where $W_d$ and $D_d$ are the desired bead width and depth of penetration by the designer, $W_s$ and $D_s$ are the bead width and depth of penetration obtained from the simulation results of ANN model. As to $w_1$ and $w_2$, they are the weights reflecting the importance of weld bead geometry. In this work, the desired values used were $W_d = 5.5\,\mathrm{mm}$, $D_d = 5\,\mathrm{mm}$, the weights $w_1 = 0.1$, $w_2 = 0.5$. Thus, to obtain the desired bead geometry was to find the welding parameters that minimize the $F_{\mathrm{Object}}$. An initial population is generated at random, and the fitness function based on ANN model and objective function is used to calculate the fitness. The critical parameters of the GA are the size of the population, mutation rate, number of the iterations (i.e., generations) etc. In this work, population size = 20, crossover rate = 1.0, mutation rate = 0.1, bit number for each variable = 16, and the number of iterations = 50 are utilized.

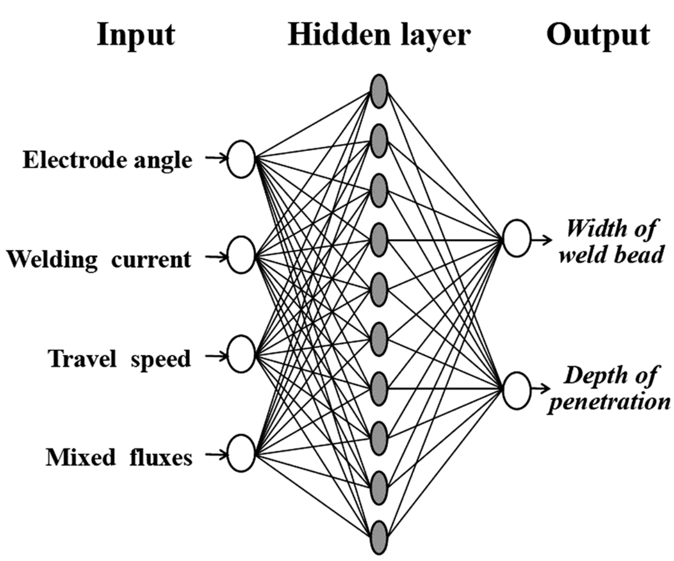


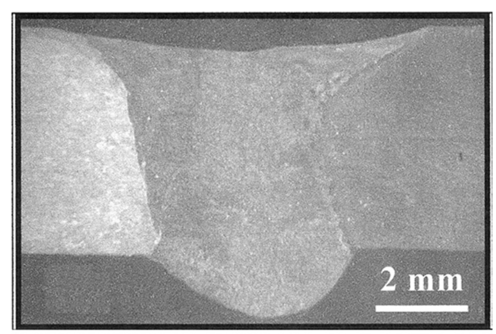

FIGURE 3.—The BP network topology.

TABLE 6.—Results of the proposed approach.

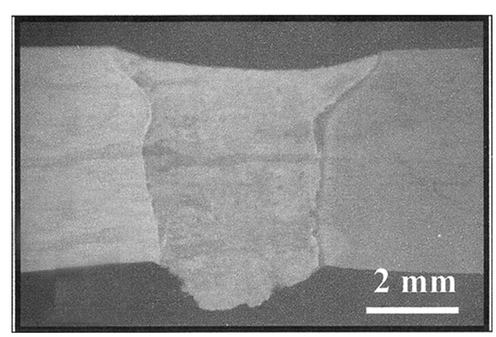
| Trial no. | Depth-to-width ratio, DWR | | |
|---|---|---|---|
| | N1 specimens | N2 specimens | Average |
| 18 | 0.915 | 0.910 | 0.912 |

*The Comparison*

The proposed approach yielded the welding condition that optimized the DWR of a GTA welding specimen: electrode angle = 64.7°, welding current = 177.5 A, travel speed = 147.8 mm min$^{-1}$ and proportion of mixed fluxes = 18%$TiO_2$ + 82%$SiO_2$. Table 6 presents the experimental results obtained using these optimal welding parameters. Comparing Table 4 with 6 reveals that the improvement in the average DWR when the initial optimal parameters are changed to the real optimal parameters is 0.131. In summary, the proposed approach efficiently improves the quality of the GTA welding process. Comparison of Fig. 4(a) with 4(b) shows the improvement of average DWR of weld bead geometry from initial optimization via the




(a)




(b)

FIGURE 4.—Weld bead geometry for validating: (a) apply Taguchi method, DWR = 0.785; (b) apply proposed approach, DWR = 0.915.

Taguchi method to real optimization using the proposed approach is 16.77%.

## Conclusions

This paper presents an integrated approach of the Taguchi method, ANN and GA for the GTA welding optimization problem. The Taguchi method is first used to construct a database. An ANN with the LMBP algorithm is used to develop the nonlinear relationship model between factors and response. Then, a GA is applied to obtain the optimal factor settings. The proposed approach is relatively effective and easy for engineers to follow. This paper also conducts a comparison between the proposed approach and the Taguchi method. The improvement of the average DWR from initial optimal parameters (applying Taguchi method only) to the real optimal parameters (applying proposed approach) is about 16.77%.

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