Intelligent Modeling Combining Adaptive Neuro Fuzzy Inference System and Genetic Algorithm for Optimizing Welding Process Parameters

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Modified 9Cr-1Mo ferritic steel is used as a structural material for steam generator components of power plants. Generally, tungsten inert gas (TIG) welding is preferred for welding of these steels in which the depth of penetration achievable during autogenous welding is limited. Therefore, activated flux TIG (A-TIG) welding, a novel welding technique, has been developed in-house to increase the depth of penetration. In modified 9Cr-1Mo steel joints produced by the A-TIG welding process, weld bead width, depth of penetration, and heat-affected zone (HAZ) width play an important role in determining the mechanical properties as well as the performance of the weld joints during service. To obtain the desired weld bead geometry and HAZ width, it becomes important to set the welding process parameters. In this work, adaptative neuro fuzzy inference system is used to develop independent models correlating the welding process parameters like current, voltage, and torch speed with weld bead shape parameters like depth of penetration, bead width, and HAZ width. Then a genetic algorithm is employed to determine the optimum A-TIG welding process parameters to obtain the desired weld bead shape parameters and HAZ width.

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I. INTRODUCTION

MODIFIED 9Cr-1Mo steels are mainly used in high-temperature structural applications. These steels have high creep resistance, good oxidation resistance, and excellent corrosion resistance at elevated temperatures coupled with good thermal conductivity and a low thermal expansion coefficient that result in excellent resistance to thermal stress. Thus, these steels are mostly preferred in petrochemical and chemical plants, gas turbines, power plants, as well as for nuclear fission and fusion reactor components. Modified 9Cr-1Mo steel in normalized and tempered condition has been chosen as a steam generator structural material for prototype fast breeder reactors. The fabrication of steam generator components made of modified 9Cr-1Mo steel is generally done by arc welding processes. Owing to the high-quality weld metal deposits, great precision, superior surfaces, and excellent strength, gas tungsten arc welding (GTAW) is widely used among all arc welding processes. In GTAW of modified 9Cr-1Mo steels, the depth of penetration achievable during autogenous welding is limited, and hence, for welding large thickness plates, several passes are required, thus reducing productivity.

This limitation problem can be overcome by implementing a modified GTAW process called flux-assisted GTAW or activated flux tungsten inert gas (A-TIG) welding process in which a thin coating of the activating flux is applied to the surface of the joint area just prior to welding, causing a drastic increase in the depth of penetration even up to 300 pct, and thus, improved productivity can be achieved.[1–3] The A-TIG process has many advantages like a decrease in the number of weld passes, thereby shortening welding time, as well as reduced consumption of filler wire and reduced distortion.[4] The welding costs also can be reduced by up to 50 pct in the A-TIG process. It has a wide range of applications in the fabrication of pressure vessels, pipe welds, and tube-to-tube sheets in heat exchangers in power and chemical industries.

The weld bead shape parameters like depth of penetration, bead width, and heat-affected zone (HAZ) width play an important role in deciding the mechanical properties, creep properties, and weld quality. These shape parameters are decided by A-TIG welding process parameters like current, arc voltage, and torch speed. Experimental optimization of the process parameters requires many trials and is time consuming. Therefore, it becomes necessary to devise a computational methodology to optimize the welding process parameters to achieve the desired weld bead geometry and HAZ width.

Soft computing is a natural option for solving nonlinear and complex problems in welding.[5,6] Fundamental areas of soft computing are artificial neural networks (ANNs), fuzzy logic, genetic algorithms (GA), *etc.*

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The application of these techniques offers new opportunities in solving complex problems. Artificial neural networks are parallel-distributed processing systems comprising nonlinear process elements that perform in a similar manner to biological neurons. ANNs possess the ability to learn from experience and generalize new data from previous data sets. They are particularly useful for problems in which a lack of complete understanding exists of relationships among the variables. Fuzzy logic predicts the complex characteristics of the problem based on the concept of relative importance of precision of solutions. Fuzzy logic offers a powerful frame of reasoning as how human reasoning works. These systems employ a rule-based approach and interpolative reasoning as well as perform nonlinear mapping of inputs. In fuzzy logic, experts' knowledge also can be added to bring out the results accurately. GAs are nondeterministic stochastic optimization methods that use theories of evolution and natural selection to solve a problem within a complex solution space.[7] GA possesses a population of solutions that evolve according to the rules of selection and other operators such as recombination and mutation. GA represents an efficient global method of optimizing nonlinear problems.

Numerical models of heat and fluid flow provide significant insights into the mechanisms of welding processes and welded materials. Although numerical models provide significant insight into the mechanisms governing the welding processes, their application has been limited for several reasons. They require a significant amount of computer time and are unidirectional in nature. They cannot give multiple process variables to achieve a particular weld bead geometry.[8] Also, limitations are associated with the soft computing techniques. For example, neural networks suffer from a lack of transparency as the calculations are encoded in weights. The generalization ability for the new inputs is limited by the range defined by the training data. Fuzzy systems have been missing adaptation and learning capabilities, whereas the genetic algorithm requires specification of a good fitness function. Badly written fitness function will result in erroneous results. These techniques cannot be used to understand the mechanisms of the processes and are generally data driven. However, systematic correlations between welding process variables and the weld attributes such as weld bead geometry have been brought out by combining numerical models of heat and fluid flow with soft computing techniques such as neural networks and genetic algorithm.[8,9]

The soft computing techniques also can be combined to exploit the strengths that each possess. Therefore, today, hybrid techniques such as a combination of ANN and GA or fuzzy logic and GA are emerging as effective tools for producing solutions to nonlinear problems.[10] These systems bring out the advantages of both techniques. Datta *et al*.[11] worked on a similar hybrid system consisting of ANN and multiobjective GA for designing high-strength multiphase steels. Dey *et al*.[12] modeled the mechanical properties of TRIP-assisted steels using a fuzzy inference system (FIS).

The adaptive neuro fuzzy inference system (ANFIS), a modified FIS, works similar to that of neural networks. With the help of ANFIS, tuning of membership function parameters can be done by either using a back propagation algorithm or in combination with the least-square type method. This allows the FIS to learn from the data that are to be modeled. Several attempts were made to model complex problems using this advanced tool. Hancheng *et al*.[13] modeled material properties using fuzzy neural networks. Chen and Linkens[14] predicted impact toughness for alloy steels.

Hybrid computing techniques hence are used for modeling nonlinear and complex problems involving welding process parameters and welding bead shape parameters. Dhas and Kumanan[15] have predicted weld bead width in submerged arc welding using ANFIS. Kovacevic and Zhang[16] modeled weld pool geometry experimentally using neurofuzzy. Vasudevan *et al*.[17] used hybrid techniques along with GA to optimize process parameters for GTAW of austenitic stainless steels. Bag and De[18] coupled GA with a heat-transfer model to predict process variables in GTA spot welding. GAs are being applied increasingly in the field of welding in recent times to solve the nonlinear problems in welding.

In the present work, welding process parameters like current, voltage, and torch speed are correlated, using ANFIS, which incorporates effective learning from given data, to weld bead shape parameters like depth of penetration, bead width, and HAZ width. Then these ANFIS models are employed in GA to evaluate the objective function and to arrive at the optimal solutions for obtaining target weld bead geometry and HAZ width during A-TIG welding of modified 9Cr-1Mo steels.

II. DATA GENERATION

Bead-on welding was carried out on modified 9Cr-1Mo steel plates of 6-mm thickness. Several experiments were conducted to generate 54 data sets by altering the process parameters. The current was adjusted between a minimum value of 80 amps and a maximum value of 240 amps in steps of 20 amps (*e.g.*, 80, 100, 120…240). Torch speed was set in the range of 1.33 mm/s to 4 mm/s and arc voltage was set in the range of 10.1 V to 14.1 V. A thoriated tungsten electrode of 3-mm diameter was used. The arc gap was fixed at 1 mm. Argon at a flow rate of 10 L/min was used for shielding. Multicomponent specific activated flux was used. The samples cut from the bead-on plate welds

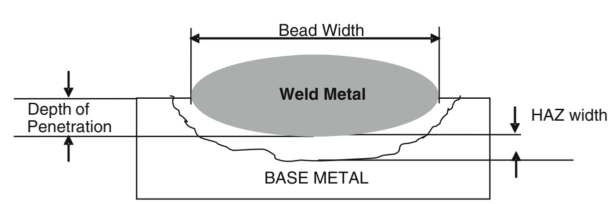

Fig. 1—Schematic figure depicting weld bead shape parameters.

were polished and etched to see the cross section for making measurements on depth of penetration, weld bead width, and HAZ width. A machinist's microscope was used for making the measurements. Figure 1 describes the various weld bead shape parameters and HAZ width in a typical weld.

III. METHODOLOGY

The methodology applied for optimizing weld bead geometry using GA models is shown in Figure 2. Using the generated data, initially three different models were created using ANFIS correlating welding process parameters like current, torch speed, and arc voltage with depth of penetration, bead width. and HAZ width, respectively. Then these models were incorporated in GA to evaluate the multiobjective function, and hence, the GA code was developed to optimize the welding process parameters to achieve target weld bead geometry and HAZ width.

IV. RESULTS AND DISCUSSION

A. *Development of ANFIS Models*

ANFIS embeds the FIS into the framework of the adaptive networks. It serves as a basis for constructing a set of fuzzy if–then rules with appropriate membership functions to attain the stipulated input–output data pairs. It models or remodels the entire FIS whose membership function parameters are tuned by using either a back propagation algorithm or in combination with the least-square method. It learns and hence trains the FIS based on the given input data sets. This fuzzy system mainly has the following components: (1) A rule base that has a collection of rules, (2) a database with the help of which the membership functions can be decided and its parameters are to be tuned, and (3) a decision-making mechanism that carries out an inference procedure to map the inputs and the rules.[15,19]

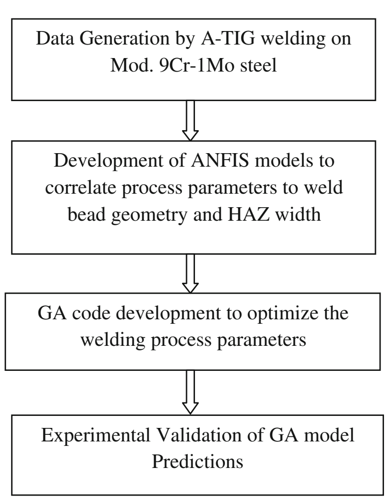

Fig. 2—Flowchart describing the methodology involved.

The schematic network-like structure used in ANFIS is shown in Figure 3, indicating the essential input and the output parameters.

In this current work, out of the 54 input data pairs, 42 data pairs are used to train the FIS and 7 data pairs are used for testing it. The remaining five data pairs are used for checking the FIS. These checking data are mainly used to check for the overfitting of the model by the training data sets. Takagi-Sugeno type FIS of zero order is used in this case. The Sugeno model represents the FIS compactly with high computational efficiency. It works well for nonlinear problems and with optimization and adaptive techniques The triangular function, which maps this nonlinear problem with high efficiency, is used for each welding process parameter, and the number of membership functions is fixed at three, representing the linguistic variables like low, medium, and high. Then, the new FIS is generated implementing a grid partitioning technique that clusters all data sets and creates the rules accordingly. The following are some basic rules in the model predicting depth of penetration:

(a) If current is low and torch speed is medium and voltage is medium, then depth of penetration is r_5.
(b) If current is medium and torch speed is low and voltage is high, then depth of penetration is r_{12}.
(c) If current is medium and torch speed is high and voltage is low, then depth of penetration is r_{16}.

where r_5, r_{12}, and r_{16} are the consequent parameters of the ith rules. Thus, an initial FIS is created by the grid partitioning technique that clusters the entire region and describes the behavior of the consequent within the fuzzy region. The membership function parameters initially are assigned by ANFIS and are changed after training of the FIS. The combination of back propagation and the least-square technique (hybrid optimization method) is used for the training process at the least error value for about 250 to 300 iterations. The following are the parameters of the FIS developed:

(a) Total number of nodes: 78
(b) Number of linear parameters: 27
(c) Number of nonlinear parameters: 27
(d) Number of fuzzy rules: 27
(e) Total number of parameters: 54
(f) Training data pairs: 42
(g) Checking data pairs: 05

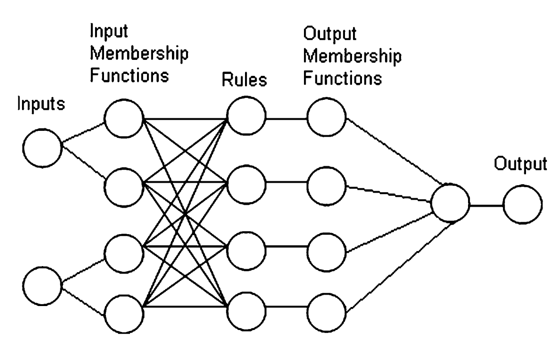

Fig. 3—Schematic sketch of ANFIS network.

Table I. RMS Error Values for the Training and Test Data Set Predicted by ANFIS Models

Weld Bead Shape Parameter that the Model Predicts	RMS Error of Training Data	RMS Error of Testing Data
Depth of penetration	0.145	0.329
Bead width	0.158	0.135
HAZ width	0.074	0.232

Then the rules that do not contribute to the output value are deleted. Ultimately, the number of rules are 24, 26, and 21 in models predicting depth of penetration, bead width, and HAZ width, respectively. Three independent ANFIS models predicting the depth of penetration, bead width, and HAZ width as a function of welding process parameters have been developed, respectively. The root mean square (RMS) error values, obtained in these ANFIS models for the training and test data sets are given in Table I.

Figure 4 clearly shows that a good agreement exists between the actual values and the predicted weld bead shape parameters using the models developed by ANFIS. The values of correlation coefficients determined show that an excellent correlation exists between the actual and the predicted values. Furthermore, this correlation also is depicted in the RMS error values that were mentioned in Table I. Thus, the weld bead geometry and HAZ width predicted by the models created by ANFIS are good.

B. *Development of Genetic Algorithm Code*

The GA code was developed in Matlab for optimizing the welding process parameters like current, torch speed, and arc voltage of modified 9Cr-1Mo steel plates. The flowchart that represents the steps[7] involved in the code development by GA is given in Figure 5.

C. *Multiobjective Function*

To attain the target values of the weld bead shape parameters like depth of penetration, bead width, and HAZ width, the GA code should be made to converge for solutions. To facilitate the objective function and to converge at the solutions with less iterations, the least-square error minimization is used as the objective function. In this present work, the sum of the least-square error values of the weld bead shape parameters multiplied by weights, which are assigned based on their relative importance, is chosen as the objective function as in Eq. [1]. Thus, the weighted sum converts the multiobjective optimization problem into a scalar one.[20] Equation [1] is expressed as follows:

$$\mathrm{ObjV} = (w1)\frac{[\mathrm{DOPT} - \mathrm{DOP(i)}]^2}{\mathrm{DOPT}} + (w2)\frac{[\mathrm{BWT} - \mathrm{BW(i)}]^2}{\mathrm{BWT}} + (w3)\frac{[\mathrm{HAZWT} - \mathrm{HAZW(i)}]^2}{\mathrm{HAZW}} \quad [1]$$

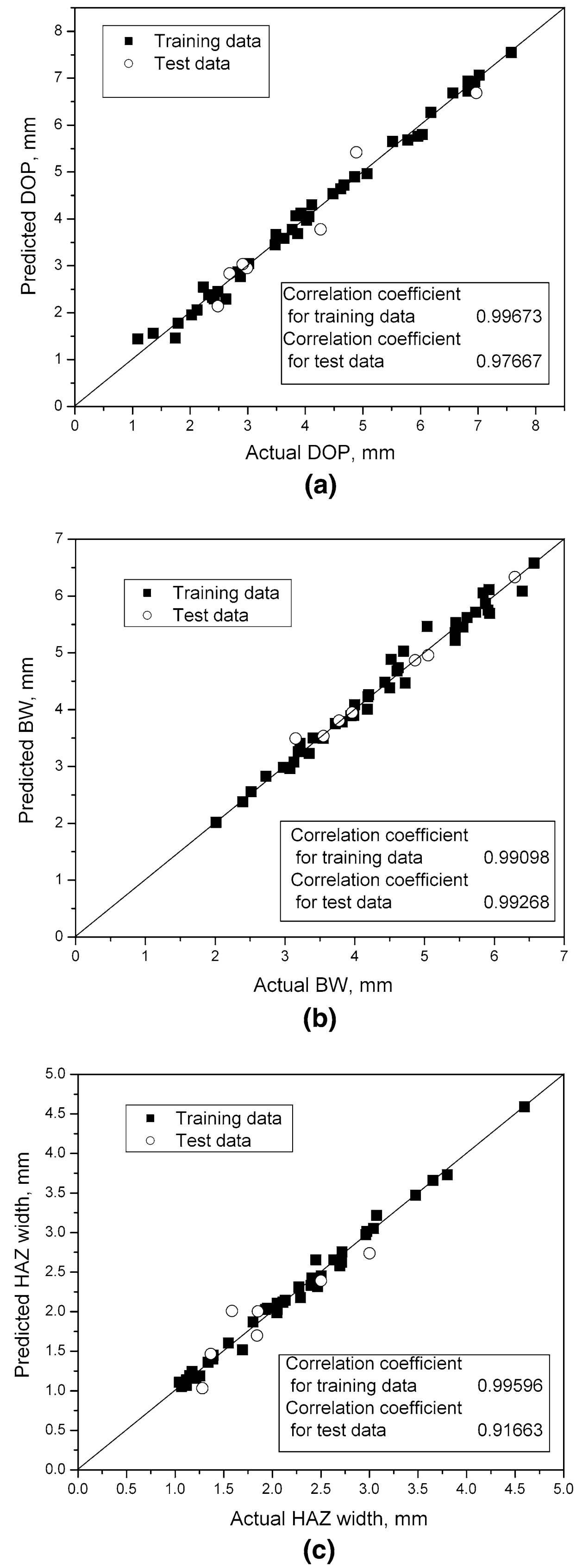

Fig. 4—Plots depicting the comparison between actual values and predicted values by the ANFIS model for (*a*) depth of penetration, (*b*) bead width, and (*c*) HAZ width.

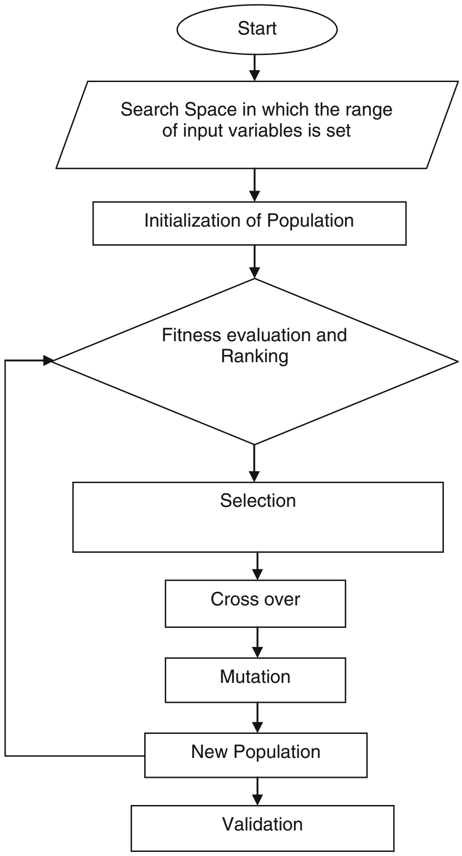

Fig. 5—Flowchart describing various steps in GA.

Where ObjV is the objective function; DOPT, BWT, and HAZWT are target values of depth of penetration, bead width, and HAZ width, respectively; DOP, BW, and HAZ are the depth of penetration, bead width, and HAZ width values, respectively, of the ith individual; and $w1$, $w2$, and $w3$ are the weights that are attributed to those parameters. Although the objective function is mainly for minimizing the error values, GA always strives to maximize the solutions. Thus, the solutions are ranked based on the fitness index, which is defined as the inverse of the objective function value, such that the solution with the low-objective function value has a high fitness index value. The solutions with the higher fitness values are selected for the next generation.

D. *Selection of Genetic Algorithm Parameters*

Several parameters are involved in a GA like the number of individuals, number of generations, crossover type, crossover rate, and mutation rate that control the speed of convergence. Deb[21] neatly explained the different terminologies that are used in GA. These parameters are varied in the following ranges before arriving at the optimum values:

(a) Number of individuals: 50–100
(b) Number of generations: 100–500
(c) Crossover type: Single point/Double point/Multi-point

Table II. Genetic Algorithm Parameters Selected for Optimizing Welding Process Parameters

Genetic Algorithm Parameters	Value
Number of individuals	60
Number of generations	100
Crossover type	multipoint crossover
Crossover rate	0.76
Mutation rate	0.001
Selection strategy	roulette wheel selection
Length of individual chromosome	8
Number of variables	3
$w1$	0.5
$w2$	0.2
$w3$	0.3

(d) Crossover rate: 0.05–0.08
(e) Mutation rate: 0.001–0.005
(f) Weights assigned ($w1$, $w2$, and $w3$): 0-0.5

The best set of parameters that lead to a fast convergence was selected based on the trial-and-error method, and the influence of the parameters on the convergence of the solutions is studied. The parameters that produced the exact convergence at a faster rate were chosen and are listed in Table II.

The maximum and the minimum values (the range) for each welding process parameter like current, torch speed, and arc voltage also were specified. The initial population, in binary form, is randomly selected within the specified values for the iteration process. Each individual in the initial population represents each welding process parameter. In the present case, the maximum value among all independent parameters was 240 (*i.e.*, the value of current); therefore, the length of each individual gene in the chromosome is chosen as eight ($2^8 = 256$). Because three parameters are controlling the target process variables, the total length of the chromosome is 24 (8×3). Standard gray coding is employed for decoding the binary representation of the strings along with logarithmic scaling. Then the binary strings that are converted to real values are evaluated for their fitness using the objective function. The weights are selected in such a way that their sum accounts to one, and the optimum weight values are determined such that they facilitate faster convergence of solutions. Based on the fitness index values that are calculated as the inverse of the objective function value, these chromosomes are ranked.

To select the best chromosomes from this population, roulette wheel selection is used. In this method, the parents are selected based on their fitness index values. The better the chromosomes, the more chances to be selected. A virtual roulette wheel (pie chart) is created in which each individual is assigned a portion proportional to the normalized fitness value. An unbiased spinning of the roulette pointer is simulated through a random number generator, and the individual corresponding to the region where it points is picked up for additional processing often with an assigned probability.[21] The chromosomes with higher fitness values are selected more times because they occupy more space on the pie.[7]

This algorithm works similarly until it has generated the entire population for the next generation.

Then multipoint crossover was carried out on these selected chromosomes. The basic idea behind this multipoint crossover is that the parts of the chromosome representation that contribute most to the performance of a particular individual may not necessarily be contained in adjacent substrings. This method takes two parent strings from the mating pool and performs an exchange at some positions between them to form a new string (children). The crossover proceeds in three steps. First, the two parent strings are selected randomly. Second, several positions (as crossover sites) are chosen randomly in both strings. Finally, the portions of the strings at the crossover sites are exchanged between both the parents to form the offsprings. This crossover is limited only to certain parents, which is determined by the crossover rate. Based on the error values in the predicted weld bead parameters, the crossover rate was fixed at 0.76, implying that crossover was carried out only on 76 chromosomes among the 100 chromosomes, and the remaining chromosomes were carried over to the next generation without any alteration.[22]

After the crossover, mutation was carried out on the offsprings in which one allele of the gene is randomly replaced by another to produce a new genetic structure. The mutation probability is kept low at a rate of 0.001 to avoid any possible perturbations. The offsprings then are decoded into real values. Then the objective function is evaluated for this new set of chromosomes, and they are ranked based on their fitness index values. From this mix of parents and offsprings, the 100 best chromosomes are selected based on their fitness ranking. Then these newly selected chromosomes were reinserted for the next iteration. Similar iterations continue until no more changes take place in the value of the optimized process parameters, or any of the terminating conditions like attaining a fixed number of generations, getting a solution with the highest fitness ranking, and lapsing the fixed computational time is achieved. In this case, arriving at the fixed number of generations was used as a terminating condition.

E. *Validation of Genetic Algorithm Model*

In this present work, to prove the proper working of the computational model based on GA code, a few weld bead geometry parameters and a few HAZ width parameters are chosen from the experimentally generated database. The GA model was used to optimize the A-TIG welding process parameters for attaining the target weld bead shape parameters and the target HAZ width. The optimized genetic parameters as quoted in Table II were used. One hundred iterations (generations) are used to determine the optimized process parameters. Each time, the GA model predicts different optimized process parameters for achieving the same target parameters. These results are reported in Table III. Thus, the GA proves to have the potential to produce multiple process parameters that converge to a similar weld bead profile. Similar observation has been reported earlier.[22]

Table III. Multiple Welding Process Parameters for Achieving the Same Target Weld Bead Shape Parameters

	Target Parameters			Welding Process Variables		
S.No.	Depth of Penetration (mm)	Bead Width (mm)	HAZ Width (mm)	Current (A)	Torch Speed (mm/s)	Arc Voltage (V)
1	2.028	2.979	1.045	87.5294	1.9687	10.602
				97.5686	2.7331	11.4647
				100.0784	2.398	10.6804
				103.8431	2.7749	10.4451
				108.2353	2.7959	10.9941
2	3.108	3.194	1.932	98.8235	2.4189	11.1667
				135.2157	2.6912	12.3118
				167.8431	3.2566	12.4843
				179.1373	3.6021	12.6569
				184.1569	3.7906	12.7667
3	4.027	4.201	2.052	132.0784	1.6232	11.2137
				143.3725	1.8431	11.8882
				162.8235	2.4608	12.5000
				182.902	2.7854	11.4961
				201.098	3.4032	12.7039
4	5.076	5.877	2.425	199.8431	2.5551	13.2686
				201.098	2.6707	12.9392
				218.0392	2.9739	13.3471
				222.4314	3.1205	13.1588
				236.8627	3.3194	13.5824
5	6.035	5.442	2.718	196.0784	2.3561	12.8137
				206.1176	2.4608	13.1275
				212.3922	2.8273	12.4373
				226.1961	2.9948	12.798
				230.5882	3.0576	12.6569

Table IV. Comparison of the Target and the Actual Depth of Penetration and HAZ Width

GA Optimized Welding Process Parameters			Target Weld Bead Shape Parameters		Actual Weld Bead Shape Parameters obtained	
Current (A)	Torch Speed (mm/s)	Arc Voltage (V)	Depth of Penetration (mm)	HAZ Width (mm)	Depth of Penetration (mm)	HAZ Width (mm)
198.5882	2.3771	12.9235	6.035	2.718	6.023	2.458
228.0784	3.0995	13.6294	5.076	2.425	4.588	2.024
180.3922	3.0262	12.3275	4.027	2.052	4.069	1.840
137.7255	2.6284	12.5784	3.018	1.932	2.933	1.616
88.7843	1.9059	10.649	2.028	1.045	2.250	1.478

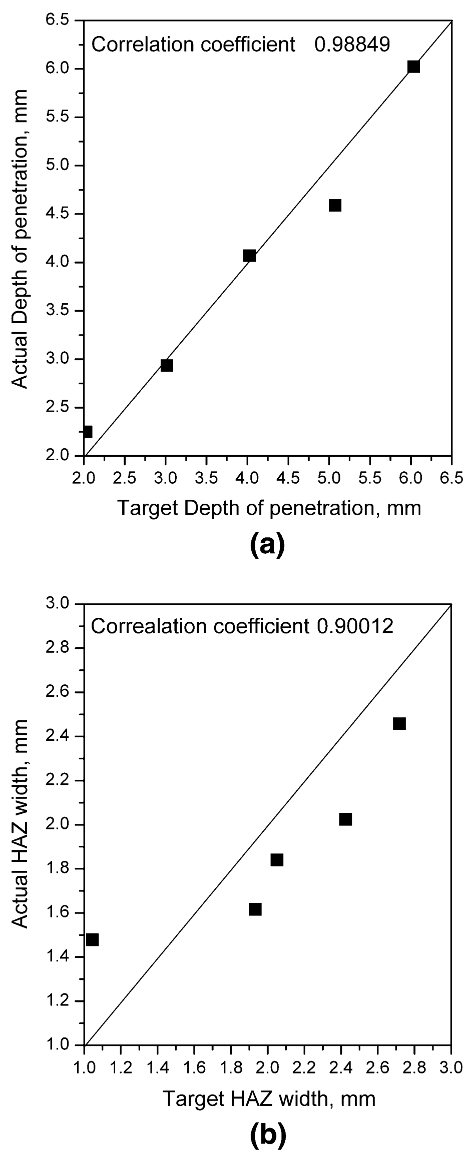

Fig. 6—Comparison plots between the target and the actual values of (*a*) depth of penetration and (*b*) HAZ width using the MOGA code.

For the purpose of experimentally validating the model, a set of process parameters is considered. The target and the actual depth of penetration, bead width, and HAZ width using the multiobjective GA model are given in Table IV. The comparison plots between the target and the actual weld bead shape parameters are presented in Figure 6. This figure clearly shows that an excellent agreement exists between the target and the actual values for depth of penetration, whereas the agreement is not so good for HAZ width. The reason could be a result of the choice of weight values in the fitness function. A higher weight value 0.5 was chosen for depth of penetration, whereas 0.3 was chosen as the weight value for HAZ width. This choice was made because, in the A-TIG welding process, the primary aim was to enhance the depth of penetration as much as possible. Therefore, the present work proves that the developed GA model can be optimized to give multiple process parameters that accurately ensure the desired/target weld bead geometry and HAZ width.

V. SUMMARY

A methodology has been developed using a GA for optimizing the A-TIG welding process parameters to achieve the target weld bead geometry and HAZ width. This methodology consists of two steps. Initially, independent models were developed using an ANFIS correlating the welding process parameters like current, torch speed, and arc voltage with weld bead parameters like depth of penetration, bead width, and HAZ width. Second, a GA code was generated to optimize the process variables to achieve the desired target weld bead shape parameters and HAZ width. The ANFIS models were used to evaluate the objective function in this GA code. Furthermore, the parameters that are used in the GA code also were optimized by the trial-and-error method to attain faster convergence. A close agreement was achieved between the target and the actual values of depth of penetration and HAZ width. Thus, the present work shows that the GA has the capability to optimize and produce multiple sets of welding process parameters that can lead to the desired weld bead profile and HAZ width accurately.

REFERENCES

1. W. Lucas: *Welding Metal Fabrication*, 2000, vol. 68 (2), pp. 7–10.
2. T. Paskell, C. Lundin, and H. Castner: *Welding J.*, 1997, vol. 76 (4), pp. 57–62.

3. M. Vasudevan: Ph.D. Thesis, Indian Institute of Technology, Chennai, India, 2007.
4. M. Vasudevan, A.K. Bhaduri, and B. Raj: *Proc. International Institute of Welding, International Congress*, January 8–10, 2008, Chennai.
5. M. Vasudevan and B. Raj: *IIM Metal News*, 2009, vol. 12, pp. 15–21.
6. M. Vasudevan: *Mater. Manuf. Process.*, 2009, vol. 24, pp. 209–18.
7. N. Chakraborti: *Int. Mater. Rev.*, 2004, vol. 49 (3–4), pp. 246–60.
8. S. Mishra and T. DebRoy: *Welding J.*, 2006, vol. 85 (11), pp. 231s–242s.
9. A. Kumar and T. DebRoy: *Metall. Mater. Trans. A*, 2005, vol. 36A, pp. 2725–35.
10. O.A. Odejobi and L.E. Umoru: *Afr. J. Math. Comput. Sci. Res.*, 2009, vol. 2 (7), pp. 104–31.
11. S. Datta, F. Pettersson, S. Ganguly, H. Saxen, and N. Chakraborti: *ISIJ Int.*, 2007, vol. 47, pp. 1193–2001.
12. S. Dey, S. Datta, P.P. Chattopadhyay, and J. Sil: *Computat. Mater. Sci.*, 2008, vol. 43, pp. 501–11.
13. Q. Hancheng, X. Bocai, L. Shangzheng, and W. Fagen: *J. Mater. Process. Technol.*, 2002, vol. 122, pp. 196–200.
14. M.Y. Chen and D.A. Linkens: *ISIJ Int.*, 2006, vol. 46, pp. 586–90.
15. J.E.R. Dhas and S. Kumanan: *J. Sci. Ind. Res.*, 2007, vol. 66, pp. 335–38.
16. R. Kovacevic and Y.M. Zhang: *IEEE Control Sys.*, 1997, vol. 17 (2), pp. 30–42.
17. M. Vasudevan, M.V. Kuppuswamy, and A.K. Bhaduri: *Trans. Indian Inst. Metals*, 2010, vol. 63 (1), pp. 1–10.
18. S. Bag and A. De: *Sci. Technol. Welding Joining*, 2009, vol. 14, pp. 633–45.
19. P. Ghanty, S. Paul, A. Roy, D.P. Mukherjee, N.R. Pal, M. Vasudevan, H. Kumar, and A.K. Bhaduri: *Sci. Technol. Welding Joining*, 2008, vol. 13, pp. 167–75.
20. M. Vasudevan, V. ArunKumar, N. Chandrasekhar, and V. Maduraimuthu: *Sci. Technol. Welding Joining*, 2010, vol. 15, pp. 117–23.
21. K. Deb: *Sadhana*, 1999, vol. 24, pp. 239–315.
22. M. Vasudevan, A.K. Bhaduri, B. Raj, and K.P. Rao: *Mater. Manuf. Process*, 2007, vol. 22, pp. 641–49.