Publishing House
AKAPIT

COMPUTER METHODS IN MATERIALS SCIENCE
Informatyka w Technologii Materiałów

Vol. 11, 2011, No. 1

INTELLIGENT MODELING USING GENETIC ALGORITHM FOR OPTIMIZING A-TIG WELDING PROCESS PARAMETERS OF MOD. 9Cr-1Mo STEEL

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Abstract

Modified 9Cr-1Mo ferritic steel is used as structural material for stream generator components of power plants. Generally, Tungsten Inert Gas (TIG) welding is preferred for welding these steels in which the depth of penetration achievable during autogenous welding is very limited and hence productivity is less. Therefore, Activated flux Tungsten Inert Gas (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 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 and also the performance of the weld joints during service. To obtain the desired weld bead geometry, HAZ width and make a good weld, it becomes important to set up the welding process parameters. Since the experimental optimization of these parameters is time consuming, Genetic Algorithm based computational model is developed for optimization of the welding process parameters. First Adaptive Neuro Fuzzy Inference System (ANFIS), one of the soft-computing tools is used to develop independent models correlating the welding process parameters like current, voltage and speed with weld bead shape parameters like depth of penetration, bead width and HAZ width. Then Genetic Algorithm is employed to determine the optimum A-TIG welding process parameters in order to obtain the desired weld bead shape parameters and HAZ width. Validation of the GA model is completed by carrying out experiments to compare the target values with that of the actual values of the weld bead shape parameters obtained. There is good agreement between the target values and the actual values.

Key words: ANFIS, genetic algorithm, A-TIG welding, welding process optimization, mod. 9Cr-1Mo steel

1. 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 low thermal expansion co-efficient. These steels are commonly used in petrochemical and chemical plants, gas turbines, power plants and for nuclear fission and fusion reactor components. Gas Tungsten Arc Welding (GTAW) is widely used among all the arc welding processes for fabricating components made of mod. 9Cr-1Mo steel as the process produces weld joints of high quality with superior surface finish and excellent strength. However, during autogenous GTAW of Mod. 9Cr-1Mo steels, the depth of

 ISSN 1641-8581

penetration achievable is limited and hence for welding large thickness plates, a number of passes are required thus reducing productivity.

The above limitation can be overcome by implementing a modified GTAW process called as 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. Use of flux increases drastically the depth of penetration up to 300% and resulting in improved productivity (Lucas 2000; Paskell et al 1997; Vasudevan 2007). The A-TIG process has many advantages, as reported by Vasudevan et al (2008), like decrease in number of weld passes, there by shortening of welding time, reduced consumption of filler wire, and reduced distortion. The welding costs can also be reduced by up to 50% in A-TIG process.

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 of joints made by A-TIG welding process. These shape parameters are decided welding process parameters like current, arc voltage and torch speed. Experimental optimization of the process parameters requires many trials and are 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 for mod. 9Cr-1Mo steel.

Soft computing (Vasudevan and Baldev Raj 2009; Vasudevan 2009) is a natural option for solving non linear and complex problems in welding. Fundamental areas of soft computing are Artificial Neural Networks (ANNs), Fuzzy Logic, Genetic Algorithms (GA), etc.. Artificial Neural Networks are parallel-distributed processing systems composed of non-linear 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 where there is a lack of complete understanding of relationship 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 rule based approach and interpolative reasoning and perform non-linear mapping of inputs. In fuzzy logic, experts' knowledge can also be added to bring out the results accurately. Genetic Algorithms (Chakraborti 2004) are nondeterministic stochastic optimization methods that utilize theories of evolution and natural selection to solve a problem within a complex solution space. 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 non-linear problems.

Nowadays, hybrid techniques (Odetunji A. Odejobi and Laisisi E. Umoru, 2009) such as combination of ANN and GA or Fuzzy Logic and GA are emerging as effective tools for producing solutions to non-linear problems. Datta et al (2007) have worked on a similar hybrid system consisting of ANN and Multi-Objective GA for designing high strength multi phase steels. Dey et al (2008) have modeled the mechanical properties of TRIP assisted steels using Fuzzy Inference System. Adaptive Neuro Fuzzy Inference System (ANFIS), a modified Fuzzy Inference System (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 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 (2002) modeled material properties using fuzzy neural networks. Chen and Linkens (2006) have predicted impact toughness for alloy steels using ANFIS. Dhas and Kumanan (2007) have predicted weld bead width in Submerged Arc Welding using ANFIS. Kovacevic and Zhang (1997) have experimentally modeled weld pool geometry using Neurofuzzy. Vasudevan et al (2010) have used hybrid techniques along with GA to optimize process parameters for GTAW of austenitic Stainless steels. Bag and De (2009) have coupled GA with heat transfer model to predict process variables in GTA spot welding. GAs are being increasingly applied in the field of welding in recent times to solve the non-linear problems in welding.

In the present work, welding process parameters like current, voltage and torch speed are correlated, using ANFIS 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 mod. 9Cr-1Mo steels.

2. DATA GENERATION

Bead-on plate welding was carried out on Mod. 9Cr-1Mo steel plates of 6 mm thickness. Current was adjusted between a minimum value of 80 amps and a maximum value of 240 amps in steps of 20 amps (say 80, 100, 120…240). Torch speed was set in the range of 1.33 mm/s – 4 mm/s and arc voltage in the range of 10.1 v to 14.1 v. Thoriated Tungsten electrode of 3 mm diameter was used. Arc gap was fixed as 1mm. Argon at a flow rate of 10 l/min was used for shielding. Multi-component specific activated flux was used. The samples cut from the bead-on plate welds were polished and etched to see the cross section for making measurements on depth of penetration, weld bead width and HAZ width. Machinist's microscope was used for making the measurements. Totally 54 numbers of data set were generated.

3. RESULTS AND DISCUSSION

The computational model developed for optimizing weld bead geometry involved two steps. In the first step, 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. The ANFIS models are then converted into 'C' (C programming language) code for incorporation in the Genetic Algorithm code. In the second step, the generated models in the form of C code were incorporated into genetic algorithm code to evaluate the multi objective function. Then the entire genetic algorithm code was implemented in MATLAB tool box.

3.1. Development of Adaptive Neuro Fuzzy Inference System Models

Adaptive Neuro Fuzzy Inference System embeds the Fuzzy Inference System 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 fuzzy inference system whose membership function parameters are tuned by using either back propagation algorithm or in combination with least square method. It learns and hence trains the fuzzy inference system based on the given input data sets. This fuzzy system has mainly three components: i) A rule base that has a collection of rules ii) A database with the help of which the membership functions can be decided and its parameters are to be tuned and iii) A decision making mechanism which carries out inference procedure to map the inputs and the rules (Dhas and Kumanan 2007; Ghanty et al 2008). The schematic network like structure that is used in ANFIS is shown in figure 1 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 for testing it. The remaining 5 data pairs are used for checking the FIS. These checking data is mainly used to check for the over-fitting 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 non-linear problems and with optimization and adaptive techniques The triangular function, that maps this non-linear problem with high efficiency, is utilized for each welding process parameter and the number of membership functions is fixed as three representing the linguistic variables like Low, Medium and High. Then, the new FIS is generated implementing Grid partitioning technique which clusters all the data sets and creates the rules accordingly. The membership function parameters are initially assigned by ANFIS and are changed on training of the FIS. The combination of back propagation and least square technique is used for the training process at the least error value for about 250-300 iterations.

Then the rules that do not contribute to the output value are deleted. Ultimately, the number of rules are found to be 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 1.

Table 1. *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

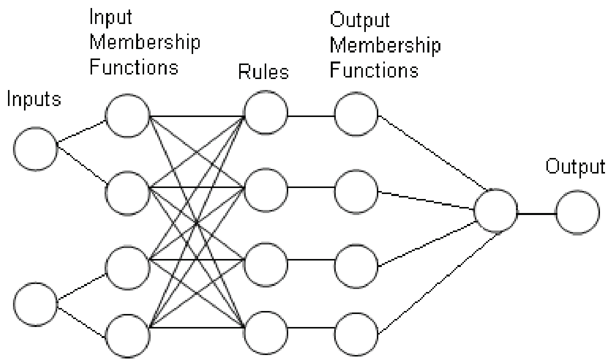

Fig. 1. Schematic Sketch of ANFIS network.

The figure 2 clearly shows that there is a good agreement 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 there is an excellent correlation between the actual and the predicted values. Further, this correlation is also depicted in the RMS error values that were mentioned in table 1. Thus, the weld bead geometry and HAZ width predicted by the models created by ANFIS are found to be quite good.

3.2. Development of Genetic Algorithm Code

The Genetic Algorithm code was developed in Matlab for optimizing the welding process parameters like current, torch speed and arc voltage of Mod. 9Cr-1Mo steel plates. To attain the target values of the weld bead shape parameters like depth of penetration, bead width and heat affected zone width, GA code should be made to converge for solutions. To facilitate the objective function, 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 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 equation 1. Thus, the weighted sum converts the multi-objective optimization problem into a scalar one (Vasudevan et al 2010).

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

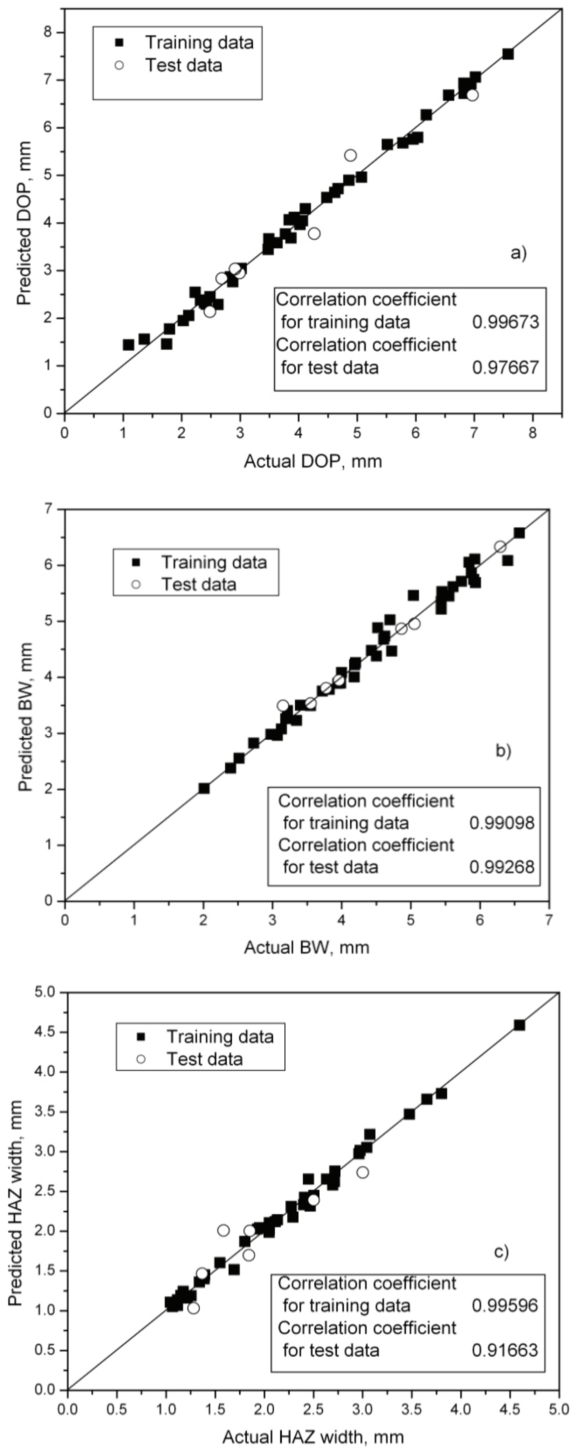

Fig. 2. Plots depicting the comparison between actual values and predicted values by the ANFIS model for a Depth of penetration b Bead width and c HAZ width.

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 i^{th} 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.

3.3. Selection of Genetic Algorithm Parameters

There are several parameters in Genetic Algorithm like number of individuals, number of generations, crossover type, crossover rate and mutation rate that control the speed of convergence. Deb (1999) clearly explains the different terminologies that are used in GA. 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 exact convergence at a faster rate were chosen and are listed in table 2.

Table 2. *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

The maximum and the minimum values (the range) for each welding process parameter like current, torch speed and arc voltage were also 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 one set of welding process parameters. 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.

For selection of the best chromosomes from this population, roulette wheel selection is used. In this method, the parents are selected based on their fitness index values. In roulette wheel selection, chromosome with bigger fitness will be selected more times. Therefore, the better the chromosomes are, the more chances to be selected they have. 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 further processing often with an assigned probability (Deb 1999). The chromosomes with higher fitness values are selected more times since they occupy more space on the pie (Chakraborti 2004). Then multipoint crossover was carried out on these selected chromosomes. This method takes two parent strings from the mating pool and performs exchange at some positions between them to form a new string (children). 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 as 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 (Vasudevan et al 2010).

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 are then 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, 100 best chromosomes are selected based on their fitness ranking. Then these newly selected chromosomes were reinserted for the next iterations. The iterations continue till the fixed number of generations are completed.

3.4. Validation of Genetic Algorithm Model

In this present work, in order to validate the predictions of the computational model based on GA, a few weld bead geometry parameters and a few HAZ width parameters are chosen from the experimentally generated database. 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. Each time when the GA model was run, the model predicts different optimized process parameters for achieving the same target parameters. Thus, Genetic Algorithm has the capability to produce multiple process parameters that result in similar weld bead profile. Similar observation has been reported earlier (Vasudevan et al, 2007). The comparison plots between the target and the actual weld bead shape parameters are presented in figure 3. This figure shows clearly that there is an excellent agreement between the target and the actual values. Therefore, the present work proves that the developed Genetic Algorithm model can be optimized to give multiple process parameters that accurately ensure the desired/target weld bead geometry and HAZ width.

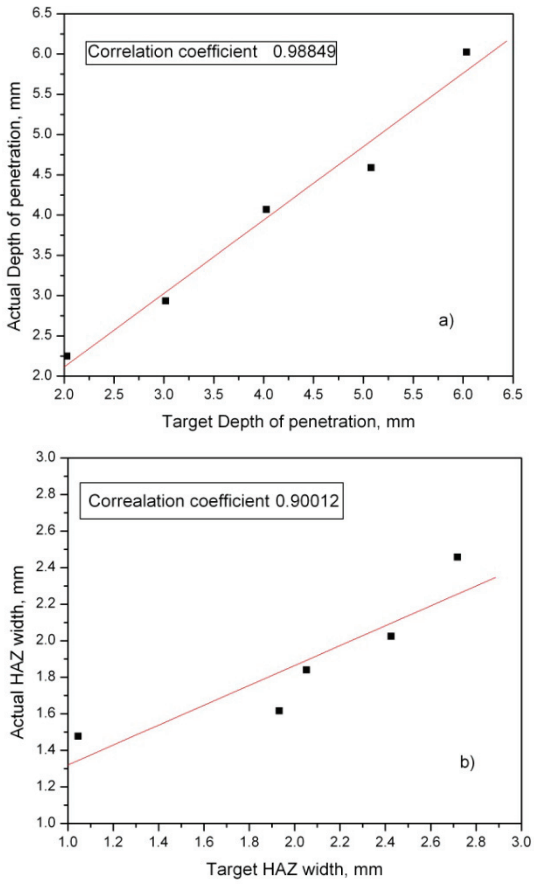

Fig. 3. Comparison plots between the target and the actual values of (a) Depth of penetration and (b) HAZ width using the MOGA code.

4. CONCLUSIONS

A computational model combining ANFIS and GA has been developed for optimizing the A-TIG welding process parameters to achieve the target weld bead geometry and HAZ width for mod. 9Cr-1Mo steel. The development of the model involved two steps. Initially independent models were developed using Adaptive Neuro Fuzzy Inference System correlating the welding process parameters like current, torch speed and arc voltage with weld bead parameters like depth of penetration and bead width and HAZ width. Secondly, a Genetic Algorithm code was developed in which the ANFIS models were used to evaluate the objective function. A close agreement was achieved between the target and the actual values of depth of penetration, and HAZ width obtained using the GA model suggested process parameters. Thus, the present work shows that Genetic Algorithm has the capability to optimize welding process parameters that can produce the desired weld bead profile and HAZ width accurately.

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OPTYMALIZACJA PARAMETRÓW PROCESU SPAWANIA METODĄ A-TIG MODYFIKOWANYCH STALI 9CR-1MO W OPARCIU O INTELIGENTNE MODELOWANIE WYKORZYSTUJĄCE ALGORYTMY GENETYCZNE

Streszczenie

Modyfikowana stal ferrytyczna 9Cr-1MoDo wykorzystywana jest do budowy generatorów stosowanych w elektrowniach. Tego typu stale spawane są najczęściej metodą TIG (Tungsten Inert Gas), charakteryzującą się bardzo małą głębokością przetopu podczas spawania, a tym samym niską sprawnością. Dla zwiększenia głębokości przetopu opracowana została nowa technika spawania, tzw. A-TIG (Activated flux Tungsten Inert Gas). Własności mechaniczne oraz jakość wykonania spawów metodą A-TIG zależy w dużej mierze od szerokości spoiny, głębokości przetopu oraz wielkości strefy wpływu ciepła (Heat Affected Zone). Kontrola jakości spawu, czyli dobranie odpowiedniej szerokości spoiny oraz utrzymanie strefy ciepła HAZ, zależy od parametrów procesu. Ze względu na czasochłonności optymalizacji doświadczalnej, do określenia optymalnych parametrów spawania zastosowano model obliczeniowy procesu połączony z algorytmem genetycznym (GA). Do wyznaczenia niezależnych modeli korelacji pomiędzy parametrami procesu: natężeniem i napięciem prądu oraz prędkością spawania, a szerokością spawu, głębokością przetopu oraz wielkością HAZ wykorzystano jedno z narzędzi ANFIS (Adaptive Neuro Fuzzy Interface System). Następnie za pomocą algorytmu genetycznego oszacowano optymalne parametry procesu spawania metodą A-TIG. W celu weryfikacji modelu wykonano doświadczenia i porównano wartości otrzymane z rzeczywistymi potwierdzając poprawność otrzymanych wyników obliczeń.

Received: September, 16, 2010
Received in a revised form: October 1, 2010
Accepted: November 8, 2010