Some Studies of Optimal Process Parameters For Solid Wire Gas Metal Arc Welding Using Neural Network Technique And Simulation Using Ansys

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***Abstract* – GMAW (Gas Metal Arc Welding) is an arc welding process which is widely used in industry to join the metals. In this present work we have investigated the effect of varying welding parameters on the weld bead quality of Mild Steel flat having 12mm thickness. The chosen input parameters for the study are Welding Voltage, Welding Current and the travel speed of welding torch. The output parameters chosen are Weld Bead Width, Weld Bead Height, Depth of Penetration and Depth of Heat Affected Zone (HAZ). The four levels of experimental set-ups for each of the input parameters are considered and other process parameters are kept constant for the study. Hence the total numbers of experimental set-ups are 64 and the corresponding values of output parameters are found. As this is a Multi-Response Problem, it is being optimized to Single-Response Problem using Weighted Principal Components (WPC) Method. Artificial Neural Networks (sANN), Error Back Propagation Procedure is being used for the prediction of optimal process parameters for GMAW process in this present work. The finite element analysis of residual stresses in butt welding of two similar plates is performed with the ANSYS software.**

Keywords- Gas Metal Arc Welding, Heat Affected Zone, Multi-Response Problem, Weighted Principal Components Method, Artificial Neural Networks, Error Back Propagation Procedure, ANSYS, Finite Element Analysis.

I. INTRODUCTION

The increase of welding productivity has a significant economic impact, estimated in order of several hundred million dollars in yearly worldwide saving. Gas Metal Arc Welding (GMAW) is widely used in the automotive industry. The process's high metal deposition rate makes it well suited to automatic and robotic welding. Modeling weld quality according to welding process parameters is increasingly important since great financial savings are possible, especially in manufacturing where improved weld process conditions lead to losses in production and necessitate time-consuming and expensive use of materials. In order to reduce man-power working hours, increase efficiency and enhance weid quality, the use of automated welding processes, especially those using robots is increasing. More recently, in the welding of large structures that have relied on manual welding, such as bridges, heavy equipment and ships, welding robots are being used applying the artificial intelligence. Applying the artificial intelligence technology requires the introduction of input and output data to the network. The task of modeling welding process by neural network is to use input data, such as welding voltage and current, speed travel and output data, such as Weld Bead Width, Weld Bead Height, Depth of Penetration and Depth of Heat Affected Zone can be used as variables. Weighted Principal Component method is being used to optimize the Multi-Response problem to Single-Response problem as the ANN model used is Error Back Propagation Procedure. After this, the data are being processed by neural network model to obtain the best prediction. The main functions of the proposed model are: to simulate the process for purposes of training operators; to improve welding process performance by identifying regions that are insensible to variations on input parameters; and finally to increase the flexibility of a robotic welding cell. The concrete benefits obtained from the GMAW process model development are: optimization of critical variables of the welding process, support for development of virtual process and prototypes, definition of a robust welding procedure, quick response to product change and support in welding training. The validation of Neural Network models predicted responses has been done by simulation using finite element analysis. The finite element analysis is used to perform welding simulation and to predict weld-induced residual stresses in butt welding of two similar mild-steel plates. The simulation is being done by conducting the thermal and structural analysis of the welded mild-steel plates.

II. LITERATURE SURVEY

Gupta, P.C.Raina, C.L. and Singh K. (Ref.1) done the individual study and comparative study of bead geometry taking solid wire CO_2 welding with fixed electrode diameter, variable voltage, current and welding speed taking flux cored CO_2. He also became interested to find arc characteristics during welding process.

A.C.Lahari (Ref.2) gives idea about the development of control system in arc welding. The importance of control systems has grown in welding side by side with the high performance a requirement mainly arising out of the basic demands on the output functions like speed and accuracy.

Chandel and Orr. concluded (Ref.3) that except preheat temperature all other variables had an influence on one or more feature of weld deposits. Moreover, they have studied microstructure in and adjacent to the fusion line and hardness distribution in these areas. A marked drop in hardness was found at the fusion line which was also revealed from the micro structural change in that zone.

Bush and Colvin (Ref.4) have done the similar type of experiment to show the effects of process variables on bead geometry. They have found that between 22v and 32v the voltage has no effect on penetration dilution.

Artificial Neural Networks (ANNs) are widely used for modeling and investigating the effects of process parameters. The laser butt welding of Ti6Al4V material on a 2.2 KW CO2 laser is investigated. The experiments were designed using a five level Response surface Method (RSM). Effects of process parameters including laser power, welding speed and focal point position on butt weld geometries were carried out using Artificial neural Network. Results indicate that the welding speed and laser power have significant effect, whereas, the focal point position show low effect on the process. The welding speed has an opposite effect on all responses while the laser power has a positive effect. [5]

The development of a robotic arc welding system, wherein a three-degree of freedom Selective Compliance Assembly Robot Arm (SCARA) is interfaced to a GMAW process. The entire system is composed of a robot linked to a GMAW system. Set points are derived using the desired mass and heat input, along with the weld speed. The stick-out and the current of the welding process are controlled using an Adaptive Neural Network Controller (ANNC). The trajectory of the robot or the weld profile is also controlled by implementing a Mixed Fuzzy-GA Controller (MFGAC) on a three axis SCARA robot. The system is, then, analyzed and the result shows adequate improvement in the efficiency and performance of the proposed controller in welding a curvilinear weld profile. [6]

Taguchi method is a very popular offline quality design. However, it cannot solve the multi-response problems which occur often in today’s society. Research shows that the multi-response problem is still an issue with the Taguchi method. Researchers have tried to find a series of theories and methods in seeking a combination of factors/levels to achieve the situation of optimal multi-response instead of using engineers judgment to make a decision in Taguchi method. In 1997, Su et al. submitted the multivariate method, and in 2000 Anatomy proposed Principal Component Analysis (PCA), to solve this problem [7]. But with the PCA method, there are still two main shortcomings. In his study, the Weighted Principal Components (WPC) method is proposed to overcome these two shortcomings. The result shows that the WPC method offers significant improvements in quality.

Finite Element Analysis of Residual Stresses in Butt welding of two similar plates (Ref.8s), by Dragi Stamenkovic and Ivana Vasovic.

III. NEURAL NETWORK TECHNIQUE

An Artificial Neural Network is a computational model of human brain, where information processing is distributed over several interconnected processing elements called neurons or nodes, structured in layers (input, hidden and output layer) which operate in parallel. The output of the nodes in one layer is transmitted to the nodes in another layer through connections which amplify or attenuate the outputs through weights. The net input to each node, except the input nodes, is the sum of the weighted output of the nodes feeding that node. Each node is activated in accordance with the input to the node through the activation function. Thereby the network provides a mapping through which points in the input space are connected to the corresponding points in the output space. Neural Networks can capture domain knowledge from examples, cannot achieve knowledge explicitly, can handle both continuous and discrete data and have a good generalization capability. Knowledge is built into

ANNs through training with typical input patterns and the corresponding output patterns. The output of a neuron is given as

$$o=f\,(net)$$

$$\text{in which} \quad net = \sum_{i=1}^{n} w_i x_i \qquad (1)$$

f (net) is referred to as an activation function. Typical activation functions used are

$$f(net) = (2/1 + e^{-\lambda.net}) - 1 \qquad (2)$$

or

$$f(net) = (2/1 + e^{-\lambda.net}) \qquad (3)$$

In which the parameter λ (λ > 0) is used to control the steepness of the function f(net) near net = 0. There are also other types of activation functions that can be used. Readers may refer to [1],[2] for more details about model neurons and activation functions.

A Neural Network may be distinguished on the basis of directions in which the signal flows. Basically there are two types of networks, i.e., Feedforward Network and Recurrent Network. In Feedforward network the signals propagate in only one direction from an input stage through intermediate neurons to the output stage. While in a Recurrent network signals can propagate from output of any neuron to the input of any neuron. They can also be classified as Unsupervised and Supervised, in terms of the amount of guidance that the learning process receives from an outside agent. An Unsupervised learning network learns to classify the input into sets without being told anything. A Supervised learning network adjusts weights on the basis of the difference between the values of output units and the desired values given by the user as an input pattern. Neural Network is further classified as shown in Fig-1, which summarizes the taxonomy of the most important network models.

Since the proposed work is focused on the application of Neural Networks for the optimization of welding process, we will introduce three types of network models that are very popular in manufacturing applications. They are Back-propagation network, Hopfield network and ART network. Readers may refer to [1], [3] for detailed information about different network models and learning algorithms. Back-propagation networks are multi-layered Feedforward neural networks that apply the error back-propagation procedure for learning. The back-propagation method uses the gradient descent method which adjusts the weight in its original and simplest form by an amount proportional to the partial derivative of the error function with respect to the given weight.

$$E_{training} = \sum_{i=1}^{n} |(Y_{oi} - Y_i)/Y_{oi}|/n \qquad (4)$$

where $E_{training}$ is the training error, Y_{oi} is the target value of i-th training vector(the one the ANNs must learn, Y_i the ANNs response to the i-th training data vector(the one the ANN has learned) and n is the number of training data. The formula used for adjustment is

$$w_{ij}(t + 1) = w_{ij}(t) - \eta(\delta E / \delta w_{ij}) \qquad (5)$$

In which η is a user selected, positive constant called learning rate.

The learning procedure of a back-propagation network is as follows:

1. Initialize the weights of the network at small random values.
2. Start the learning cycle by exposing the network to a certain input pattern paired with the desired output.
3. Compare the networks output and compare it with the desired output so that the error can be calculated.
4. Adjust the weights of the network using the error back-propagation algorithm so that a certain amount of detected error is removed.
5. Repeat the steps 2,3, and 4 with all the input patterns and their correspondent desired outputs(training examples), compute the cumulative error.
6. If the cumulative error is within a tolerable range, terminate the training process; otherwise, go back to step 2. This is shown in Fig – 2.

Back-propagation networks can be applied to almost all applications in the manufacturing domain. Readers can refer to [4], [5], and [6], for details about Hopfield and ART networks.

IV. WEIGHTED PRINCIPAL COMPONENT METHOD(WPC)

Weighted Principal Component (WPC) method is used to optimize the multi-response problem, by using the explained variance as the weight to combine all principal components in order to form a multi-response performance index (MPI). Then the best combination of factors/levels will easily be obtained. The principal components can be obtained by transforming the normalized multi-response values into uncorrelated linear combinations. If n linear combinations are obtained, then n principal components will also be formed. Let Y_i be the normalized value of the i-th response, for i=1,2,………..,p.. To compute principal components, k (k ≤ p) components will be obtained to explain the variance in the p responses. Principal components are correlated from each other. Simultaneously, the explained variance of each principal component for the total variance of responses is also gained. The formed j principal component is a linear combination.

$$Z_j = \sum_{i=1}^{p} a_{ji} Y_i \qquad j = 1,2, \ldots\ldots, k \qquad (6)$$

Subjecting to

$$\sum_{i=1}^{p} x_{ji}^2 = 1 \qquad (7)$$

also the coefficient a_{ij} is called eigenvector.

To achieve the objective, first all the principal components will be used, so that the explained variance can be completely explained in all responses. Second because different principal components have their own variance to account for the total variance, the variance of each principal component is regarded as the weight. Because these principal components are independent to each other (i.e., in an additive model), the multi-response performance index is

$$MPI = \sum_{j=1}^{p} W_j Z_j \qquad (8)$$

Where W_j is the weight of j-th principal components. The larger the MPI is, the higher the quality. Readers can refer to [8] and [9] for details about principal components and MPI.

V. GAS METAL ARC WELDING

American Welding Society (AWS) defines Gas Metal Arc Welding (GMAW) as “an arc welding process that produces coalescence of metals by heating them with an arc between a continuous filler metal electrode and the workpiece. Shielding is obtained entirely from an externally supplied gas.” The essential elements of a basic GMAW process are shown in **Figure 3**. GMAW is an arc welding process that incorporates the automatic feeding of a continuous, consumable electrode that is shielded by an externally supplied gas (see **Figure**). Since the equipment provides for automatic control of the arc, the only manual controls required by the welder for semiautomatic operation are the gun positioning, guidance, and travel speed. GMAW is used to weld all the commercially important metals, including steel, aluminum, copper, and stainless steel. The process can be used to weld in any position, including flat, vertical, horizontal, and overhead. It is usually connected to use direct current electrode positive (DCEP).

The specific focus of the present work is the automation of GMAW process by the combination of a robot integrated gas metal arc welding system and by the use of intelligent controllers, such as neural networks and fuzzy method. The use of control in the GMAW process can eliminate much of the guess work often used by welding engineers to specify welding parameters for a given task. Advanced and intelligent methods for controlling the welding process can lead to significant improvements in the economic competitiveness of an industry.

VI. FINITE ELEMENT ANALYSIS

In tis present work, the process of welding is simulated by the FEA method. The welding process computation can be split into two solution steps: thermal and structuraal analysis. First the temprature & phase evolution are determined as a function of time in the thermal analysis. Then the structural analysis employs the previous results to get displacements at nodes & stresses integration points. Since the thermal field has a strong influence on the stress field with little inverse influence, a sequential coupled analysis works very well. Moreover a 3D FE analysis in the optimum method of ascertaining the thermal cycle of welding. Therefore, in this paper, the welding process is simulated using a sequentially coupled 3D thermostructural FE formulation based on the ANSYS code. For both the thermal and structural analyses, temprature dependent thermo-physical & structural properties of the materials are incorporated.

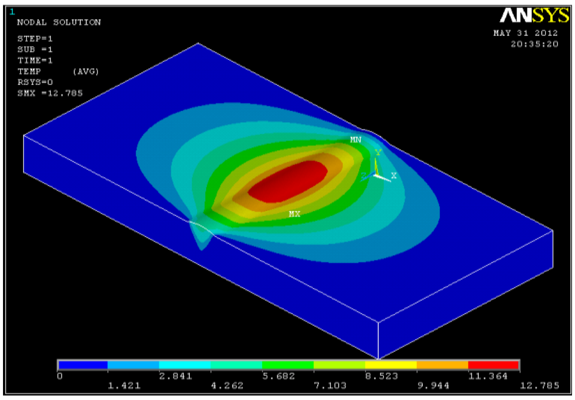

Fig.1 Finite Element Model

VII. EXPERIMENTAL PROCEDURE

STEP – 1

In the present investigation only three process variables, single material(Mild Steel) of constant thickness (12mm), only one electrode diameter is considered, constant gas flow rate of 14 l/min. is maintained and wire feed rate is kept at 1.5 mm/sec.. The process parameters that are considered; welding voltage, welding current and welding speed, at four levels each, refer Table-1. These parameters are combined in 64 numbers of patterns to obtain the results for depth of penetration, width of weld bead, weld bead height and heat effected zone thickness.

TABLE – 1

Welding Voltage In volts	***Welding Current In amps***	***Travel Speed In cm/min***
20	130	15
25	180	25
30	230	40
35	280	55

STEP -2

The experimental results for four performance factors has been combined to a single response so as to optimize the performance. As this is a multi-response problem it has been solved using Weighted Principal Component(WPC) method, to obtain multi-response performance index (MPI). By checking the correlation between the experimental results normalized data, the data is un-correlated by using the rotated loading matrix; principal components are obtained for four responses. The principal components of four responses are then combined using the total explained variance, to form multi-response performance index (MPI).

STEP -3

Neural Network model is trained and tested for predicting the optimum results using the experimental data by Error Back-propagation method. The experimental data with three input variables and the combined experimental output factor i.e. MPI is given at a time for training and testing. The Back-propagation model consists of four input nodes and one output node (i.e., the predicted output). The training has been conducted for number of hours till the error reduces to a minimum.

STEP -4

The MPI response is then trained and tested using Back-propagation method for obtaining the responses with minimum error. These values can be used for testing the performance of the welding output parameters, the optimum values of input parameters can be taken as the required experimental setup to get the desired weld bead quality.

STEP -5

The simulation of the predicted Neural Network data has been done by using ANSYS, this analysis includes a finite element model for the thermal & structural welding simulation. The finite element method is the conventional means of calculating the residual stresse.

VIII. CONCLUSIONS

1. The neural network model for correlate the influence of GMAW process parameters on the join characteristics has been developed.
2. The model shows excellent information about the relationship of independent and dependent variables.
3. The model shows some important inflexion points, but those will be smooth when increase the input data.
4. The neural network model can calculate the GMAW process parameters to obtain a specific joint, with defined characteristics.
5. The models learning itself, this permit decrease the error.
6. The use of Artificial Intelligence in general and Neural Network in particular, permit to increase the productivity, eliminate excessive expenses by materials, energy, people, etc.
7. Ansys presents the finite element model for numerical simulation of welding residual stresses in mild-steel butt welds. The finite element method is an efficient technique in analysing residual stresses in welding processes. The finite element analysis results of residual stress distribution of two butt welded plates in the axial directions are shown. The results shown by finite element method are very close to the experimental results.

IX. REFERENCES

[1] Ref 1 - Gupta, P.C.Raina, C.L. Singh K. – Effect of welding parameters on mechanical properties, Welding Journal – 1998. June, 1969.

[2] Ref 2 – A.C.Lahiri – Development of control systems in arc welding, Indian Welding Journal, January – 1991.

[3] Ref 3 – Chandel, R.S. and Orr.R.F. – Effect of process variables on bead-geometry of the submerged arc strip overlay welds, Indian Welding Journal, January, 1984.

[4] Ref 4 – Bush, A.F. and Colvin – Welding and metal fabrication. Vol. – 37, June – 1969.

[5] Ref 5 – A.Khorram, M.r.Soleymani Yazdi, M.goreishi & M.Moradi, " Using ANN approach to investigate the weld geometry of Ti6Al4VTitanium alloy", International Journal of Engineering and Technology, vol.2, no.5, Oct.2010 ISSN:1793-8236.

[6] Ref 6 – H.Sayyadi & A.A.eftekharian, "Modelling and Intelligent Control of a robotic gas metal arc welding system", Scienta Iranica, vol.15, no.1, pp 75-93, (c) Sharif University of Technology, Februaary2008.

[7] Ref 7 – Hung-Chang-Liao, "Multi-Response Optimization using Weighted Principal Component", 15 May 2004/ Published online :23 February 2005 (c) Springer-Verlag London Limited 2005. [8] Dragi Stamenkovic and Ivana Vasovic, "Finite Element Analysis of Residual Stresses in Butt welding of two similar plates", Scientific Technical Review, Vol.LIX,No.1,2009.

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