International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 1 Issue 10, December- 2012

Multi-Response Optimization For Heat Effected Zone Parameters In CO_2 Welding Using Weighted Principle Components

K.Lalitnarayan
Associate Professor Sir C.R.Reddy College of Engineering
Department of Mechanical Engineering, Eluru 534007, lndia

M M M.Sarcar
Professor, A U College o{ Englneering,
Department of Mechanical Engineering, AU, Visakhapatnam_530003, lndia

K.Mallikarjuna Rao
Professor, J N.T.U.College of Engineering,
Department of Mechanical Engineering, Kakinada-533003, lndia

IJERT

Abstract

Applying the artificial intelligence technology to CO_2 welding 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, travel speed 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 validation of the Neural Network Models predicted responses has been done by conducting the experiments, varying welding voltage, welding current and the travel speed of the torch other parameters are kept constant. The microstructure and hardness has been checked for the specimens at weld bead, heat affected zone and at the base metal.

1. Artificial Neural Network:

The human brain provides proof of the existence of massive neural networks that can succeed at those cognitive, perceptual, and control tasks in which humans are successful. The brain is capable of computationally demanding perceptual acts (e.g. recognition of faces, speech) and control activities (e.g. body movements and body functions). The advantage of the brain is its effective use of massive parallelism, the highly parallel computing structure, and the imprecise information-processing capability. The human brain is a collection of more than 10 billion interconnected neurons. Each neuron is a cell (Figure 1) that uses biochemical reactions to receive, process, and transmit information. Treelike networks of nerve fibers called dendrites are connected to the cell body or soma, where the cell nucleus is located. Extending from the cell body is single long fibers called the axon, which eventually branches into strands and sub-strands, and are connected to other neurons through synaptic terminals or synapses. The transmission of signals from one neuron to another at synapses is a complex chemical process in which specific transmitter substances are released from the sending end of the junction. The effect is to raise or lower the electrical potential inside the body of the receiving cell. If the potential reaches a threshold, a pulse is sent down the axon and the cell is ‘fired’. Artificial neural networks (ANN) have been developed as generalizations of mathematical models of biological nervous systems. A first wave of interest in neural networks (also known as connectionist models or parallel distributed processing) emerged after the introduction of simplified neurons by McCulloch and Pitts (1943). The basic processing elements of neural networks are called artificial neurons, or simply neurons or nodes. In a simplified mathematical model of the neuron, the effects of the synapses are represented by connection weights that modulate the effect of the associated input signals, and the nonlinear characteristic exhibited by

ISSN: 2278-0181
Vol. 1 Issue 10, December- 2012

neurons is represented by a transfer function. The neuron impulse is then computed as the weighted sum of the input signals, transformed by the transfer function. The learning capability of an artificial neuron is achieved by adjusting the weights in accordance to the chosen learning algorithm.

A typical artificial neuron and the modeling of a multilayered neural network are illustrated in **Fig.1**. Referring to **Fig.1**, the signal flow from inputs *x*1, . . . , *xn* is considered to be unidirectional, which are indicated by arrows, as is a neuron's output signal flow (*O*). The neuron output signal *O* is given by the following relationship o=f (net)

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

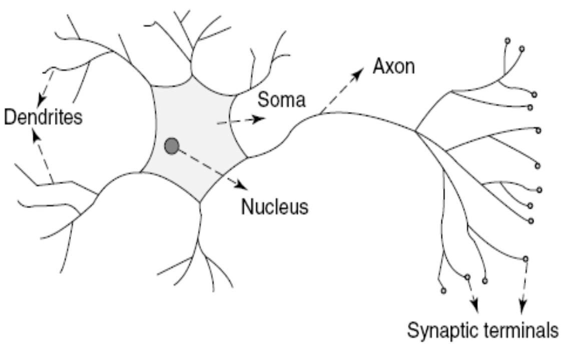

Figure 1. Mammalian Neuron

Where w_j is the weight vector, and the function f(net) is referred to as an activation (transfer) function. The variable net is defined as a scalar product of the weight and input vectors,

$$\text{net} = w^T x = w_1 x_1 + \ldots\ldots\ldots + w_n x_n \qquad (2)$$

Where T is the transpose of a matrix, and, in the simplest case, the output value *O* is computed as

$$0 = f(\text{net}) = \begin{cases} 1 \text{ if } w^T x \geq \theta \\ 0 \text{ otherwise} \end{cases} \qquad (3)$$

Where θ is called the threshold level; and this type of node is called a linear threshold unit.

2. Weighted Principal Component method

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

$$Z_j = \sum_{i=1}^{p} a_{ji} Y_i \qquad j = 1,2,\ldots\ldots.,k \qquad (4)$$

Subjecting to

$$\sum_{i=1}^{p} x_{ji}^2 = 1 \qquad (5)$$

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

$$MPI = \sum_{j=1}^{p} W_j Z_j \qquad (6)$$

Where Wj is the weight of j-th principal components. The larger the MPI is, the higher the quality.

The application of artificial neural networks is employed for process modeling and control issues extensively, however not much work is reported in area of welding processes selected issues.

3. Literature Review

Artificial Neural Networks (ANNs) are widely used for modeling and investigation the effects of process parameters. Khorram et al [1] have investigated the weld geometry of T16 A14V Titanium alloy using ANN approach. The laser butt welding of Ti 6Al 4V 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 indicated 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.

An artificial neural network (ANN) model was developed for the analysis and simulation of the correlation between the friction stir welding (FSW) parameters of aluminum (Al) plates and mechanical properties by Yousif et

IJERT

al [2]. The input parameters of the model consist of weld speed (Ws) and tool rotation speed (Rs). The outputs of the ANN model include property parameters namely: tensile strength, yield strength and elongation. Good performance of the ANN model was achieved. The model can be used to calculate mechanical properties of welded Al plates as functions of weld speed and tool rotation speed. The combined influence of weld speed and tool rotation speed on the mechanical properties of welded Al plates was simulated. Simulated annealing technique was used to prevent the network from getting stuck in local minima. A comparison was made between measured and calculated data. The calculated results were in good agreement with measured data.

ANN has been used not only in welding, but in various engineering and non-engineering streams. Mohsen Hayati et al [3] have applied ANN for the prediction of natural convection heat transfer from a confined horizontal elliptic tube.

Ajit Abraham [4] in his book has presented the biological motivation and fundamental aspects of modeling artificial neural networks. Performance of feed-forward artificial neural networks for a function approximation problem has been demonstrated. Advantages of some specific neural network architectures and learning algorithms have also been discussed [4].

Neural Network architecture and learning algorithms with reference to biological motivations and material science were elaborately discussed [5-7]. These papers were used as basis for the present research work.

The results of a research carried out to evaluate the correlation between GMAW process parameters and weld quality parameters are presented by Reyes et al [8] in their publication. The GMAW weld process was carried out and quality parameters according to automotive Industry were measured; the leg size, depth of fusion and gap (root opening) were determined. A neural network model was proposed by the authors to explain the contribution of the various welding process parameters (Amperes, Voltage and Travel speed) on weld quality parameters. The authors found that the neural network model presented an excellent correlation to predict the weld quality; the leg size was enhanced with the increase of amperage and reduced with the increase of the travel speed and voltage. The relationships of all variables were explained. Hung Chang Lio [9] proposed the weighted principal components (WPC) method to overcome shortcomings that arose by the earlier methods. The result showed that the WPC method offers significant improvements in quality. RajaKumar et al have studied the tensile & Mechanical properties of friction stir welded AA 6061-T6 aluminum alloy joints and also established their corrosion rate [10]. Benyounis et al have established optimization of CO_2 laser welding process of austenitic stainless steel by using multi-response optimization technique [11]. Kumanan et al have determined submerged arc welding process parameters using taguchi method and regression analysis [12]. Noorossana et al have used artificial neural network approach to multiple response optimization for their research work [13].

4. Experimental Procedure:

Testing is typically performed on flat or cylindrical samples. Cutting and/or machining are often required to obtain suitable test specimens from complex shaped components. Smooth parallel surfaces, free of coatings, scale and gross contamination, are required for testing, the specific finish requirements.

In this present work mild steel of 12mm thickness, 60mm X 60mm flat plates are prepared for the CO_2 welding. Single V-groove has been prepared; having an included angle of 35^0 - 45^0 as per the AWS standards and the edges are polished before welding. The welding has been performed by setting the voltage and current, the travel speed of the torch is calculated with the help of a stop-watch. The obtained specimens are then used to view the micro-structure at three (on weld bead, heat affected zone, adjacent to the heat affected zone), the specimens are being polished and followed by etching, the micro-structures are observed. Rockwell Hardness Test (HRC) has been done at the said zones for all the specimens for studying the variation of hardness at the zones.

The detailed experimental procedure is explained in the following steps :

Step – 1

In the present investigation three important process variables, material of constant thickness (12mm), filler wire of diameter (1.2mm) are 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 considered are; 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 - 2)**.

Table – 1 Input Parameters

Welding Voltage(V) in Volts	Welding Currents in Amps	Travel Speed(Ws) in cm/min
20	130	15
25	180	25
30	230	40
35	280	55

Table – 2

IJERT

Sl. No.	V	I	Ws	WBH	DOP	DHAZ	WWB
1	20	130	15	4	1.8	1.4	8
2	20	130	25	3.7	1.6	0.9	7
3	20	130	40	2.4	1.3	0.7	6.2
4	20	130	55	2	1	0.6	4.5
5	20	180	15	4.5	2.3	1.7	11.4
6	20	180	25	3.9	1.9	1	9
7	20	180	40	2.9	1.5	1	7.4
8	20	180	55	2.1	1.3	0.7	6
9	20	230	15	4.6	2.6	2.5	12.5
10	20	230	25	4.2	2.4	1.3	9.1
11	20	230	40	3.8	2	0.6	7.7
12	20	230	55	3	1.6	0.5	7.3
13	20	280	15	5.6	3.2	2.5	13.5
14	20	280	25	4.9	2.8	1.4	8.7
15	20	280	40	4.4	2.4	0.7	7.8
16	20	280	55	3.4	2.1	0.4	7.3
17	25	130	15	3.6	3.4	1.5	9.7
18	25	130	25	3.3	1.6	1.1	7.9
19	25	130	40	2.4	1.3	0.9	7
20	25	130	55	1.8	1.1	0.7	4.6
21	25	180	15	4.1	2.4	1.9	12..3
22	25	180	25	3.6	2.1	1.3	9.4
23	25	180	40	2.8	1.7	1.1	8.2
24	25	180	55	2.1	1.5	0.9	6.2
25	25	230	15	4.4	2.8	2.7	12.5
26	25	230	25	4.2	2.5	1.4	10.5
27	25	230	40	3.7	2.3	1.2	8.5
28	25	230	55	2.6	2.1	1.1	8
29	25	280	15	5.2	3.4	2.7	13.7
30	25	280	25	4.6	2.8	1.5	11.5
31	25	280	40	4.2	2.5	1.3	9.1
32	25	280	55	2.9	2.3	1.2	8
33	30	130	15	3.2	2.8	1.5	11.5
34	30	130	25	2.8	2.4	1.2	9.1
35	30	130	40	2.4	1.9	1	7.2
36	30	130	55	1.5	1.7	0.4	4.7
37	30	180	15	3.9	3.6	1.7	12.5
38	30	180	25	3.3	2.9	1.4	10.8
39	30	180	40	2.4	2.2	1.2	8.4
40	30	180	55	1.6	2	1	6.4
41	30	230	15	4.2	4	2.1	13.4
42	30	230	25	4	3	1.5	11.1
43	30	230	40	3.2	2.5	1.3	9
44	30	230	55	2.5	2.3	1.1	8.2
45	30	280	15	4.7	4.2	2.3	14.6
46	30	280	25	4.2	3.7	1.8	12.5
47	30	280	40	3.4	2.9	1.5	9.6
48	30	280	55	2.5	2.6	0.9	9.3
49	35	130	15	2.8	3	1.9	12.6
50	35	130	25	2.6	2.7	1.4	9.8
51	35	130	40	1.9	2	1.1	8.5
52	35	130	55	1.5	1.8	0.4	8.2
53	35	180	15	3.4	4	1.9	17.1
54	35	180	25	3	3.2	1.6	14.7
55	35	180	40	2.3	2.6	1.2	9.7
56	35	180	55	1.6	2.4	1.1	8.3
57	35	230	15	3.6	4.7	2.2	18.1
58	35	230	25	3.2	4	1.7	12.3
59	35	230	40	2.8	3.2	1.4	10.5
60	35	230	55	2	3	1.1	10.5
61	35	280	15	3.7	5	2.8	19.5
62	35	280	25	3.4	4.1	2.1	17.5
63	35	280	40	2.9	3.8	1.6	15.3
64	35	280	55	2.2	3.6	1.2	13.5

IJERT

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 percent of 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

ISSN: 2278-0181
Vol. 1 Issue 10, December- 2012

values of input parameters can be taken as the required experimental setup to get the desired weld bead quality.

Step – 5

Validation of the predicted Neural Network data has been done by conducting the experiments with varying voltage, current and the speed of travel of the torch. These specimens are used for studying the microstructures at different zones (weld bead, heat affected zone and on the base metal) and the Rockwell hardness test for checking the hardness values at the zones.

5. Experimental Work

The experimental work has been conducted using CO_2 welding machinery and its specifications are mentioned in the Table-3.

The base metal pieces for welding has been prepared as per the AWS standards for 12mm thick mild-steel plates of 60mm X 60mm dimension as shown in Fig.-3.

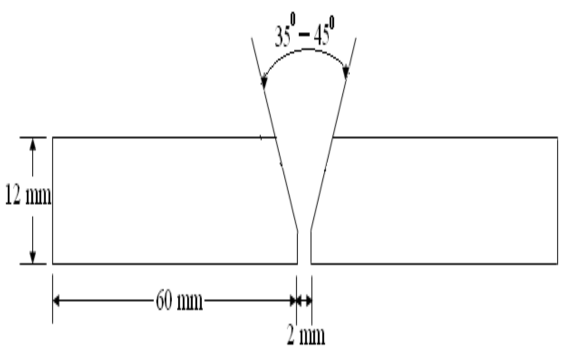

Fig.-3 Edge Preparation for Single V weld

The experiments has been conducted by following the standards, of fixing the metal pieces on the welding table in-order to restrict the changes in the gap between the pieces, the welding torch is held by the hands, settings for coarse and fine has been altered for different specimens, the wire feed rate and the gas flow rate has been kept at 2.5-3mm/sec and 14 l/min respectively. The welding is of single pass and the time for welding has been observed with the help of a stop-watch.

The specimens are examined for shape distortion, presence of blow holes, under cuts and over-fill. Then specimens are cut along the normal to the weld bead for observing of micro-structures and for testing the hardness at three zones namely: on the weld bead, heat affected zone and on the base metal.

The cut-pieces of specimens are polished on four grades of polishing papers; etching has been carried out using 2% Nital as the etchant and then the micro-structures are observed. Then the Rockwell hardness test has been

Table 3

Technical Specifications :	
Specifications	MIG- 400
Input	415 VAC / 3 Phase
Current	20A
KVA (100)	15
Output Current (Duty Cycle 100%)	320A
Output Current	400A
OCV	15-42V

conducted using the C scale with Brale penetrator at a load of 150 Kg, the corresponding results are shown in Table-8.

IJERT

RESULTS AND DISCUSSIONS

In order to get the correlation matrix for the output parameters namely weld bead height, weld bead width, depth of penetration, depth of heat affected zone the data has been normalized and is applied to Statistical software (SYSTAT 7.0). The matrix shown in Table-4 shows the correlation between the four output parameters.

The normalization of data for the four output parameters has been done by choosing the highest value in that corresponding column and then by dividing it to all the corresponding column parameters.

Table – 4 Pearson Correlation Matrix

	NWBH	NDOP	NDHAZ	NWWB
NWBH	1.000			
NDOP	0.416	1.000		
NDHAZ	0.632	0.760	1.000	
NWWB	0.465	0.916	0.838	1.000

This matrix shows the correlation between the four output parameters and it is clear from the table that all the parameters are correlated to each other and has been un-correlated using the rotated loading matrix.

Where NWBH is normalized data of weld bead height, NDOP is the normalized data of depth of penetration, NDHAZ is the normalized data of depth of heat affected zone and NWWB is normalized data of width of weld bead.

ISSN: 2278-0181
Vol. 1 Issue 10, December- 2012

The rotated loading matrix obtained by checking the correlation of the normalized CO_2 experimental data is used to form the corresponding Principal Components.

The corresponding Principal components are formed by using the relation mentioned below

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

Where Y_i be the normalized value of the i-th response, for i=1, 2,……….., p.. To compute principal components, k ($k \leq p$) components will be obtained to explain the variance in the p responses. The coefficient a_{ij} is called eigenvector, Z is the principal components and j is the number of principal components.

The rotated loading matrix is as follows:

Table – 5 Rotated Loading Matrix (VARIMAX, Gamma = 1.0000)

	1	2	3	4
NWBH	0.188	0.956	0.224	0.025
NDOP	0.940	0.189	0.269	-0.094
NDHAZ	0.515	0.379	0.768	0.033
NWWB	0.842	0.218	0.406	0.280

By un-correlating the normalized data of four output parameters the corresponding principal components are used to get the multi-response performance index.

The Multi-Response Performance Index (MPI) is formed using the total explained variance to the obtained Principal Components by using the relation mentioned below

$$MPI = \sum_{j=1}^{p} W_j Z_j$$

Where W_j is the weight of j-th

Table – 7 Neural Network Models Predicted Data

MPI	Predicted	Difference	V	I	Ws	IndexCounter1
0.8467376	0.88	0.03	20	230	40	11
0.7106691	0.71	0.00	20	230	55	12
1.639662	1.62	0.02	20	280	15	13
1.199469	1.21	0.01	20	280	25	14
0.9595607	0.94	0.02	20	280	40	15
0.7805607	0.79	0.01	20	280	55	16
1.222001	1.12	0.10	25	130	15	17
0.8614402	0.90	0.04	25	130	25	18
0.6969891	0.70	0.00	25	130	40	19
0.5236413	0.53	0.00	25	130	55	20
1.289051	1.32	0.03	25	180	15	21
1.022557	1.04	0.02	25	180	25	22
0.8450797	0.86	0.01	25	180	40	23
0.6757874	0.67	0.00	25	180	55	24
1.512916	1.52	0.01	25	230	15	25
1.163887	1.17	0.01	25	230	25	26
1.009288	0.98	0.03	25	230	40	27
0.8719718	0.83	0.04	25	230	55	28
1.676828	1.67	0.01	25	280	15	29
1.27585	1.31	0.03	25	280	25	30
1.105374	1.06	0.05	25	280	40	31
0.9362603	0.95	0.01	25	280	55	32
1.172994	1.18	0.01	30	130	15	33
0.9720919	0.96	0.02	30	130	25	34
0.7922254	0.76	0.04	30	130	40	35
0.5195685	0.57	0.05	30	130	55	36
1.384711	1.39	0.00	30	180	15	37
1.153604	1.09	0.06	30	180	25	38
0.8991069	0.91	0.01	30	180	40	39
0.7224678	0.73	0.01	30	180	55	40
1.554112	1.58	0.03	30	230	15	41
1.24401	1.23	0.01	30	230	25	42
1.029055	1.02	0.01	30	230	40	43
0.8939698	0.88	0.01	30	230	55	44
1.685906	1.71	0.02	30	280	15	45
1.437178	1.41	0.03	30	280	25	46
1.145348	1.12	0.03	30	280	40	47
0.9235827	1.00	0.08	30	280	55	48
1.273025	1.30	0.03	35	130	15	49
1.050027	1.04	0.01	35	130	25	50
0.8229753	0.83	0.01	35	130	40	51
0.6311612	0.63	0.00	35	130	55	52
1.563601	1.54	0.02	35	180	15	53
1.315411	1.24	0.08	35	180	25	54
0.9761049	1.00	0.03	35	180	40	55
0.8425208	0.81	0.03	35	180	55	56
1.745366	1.69	0.05	35	230	15	57
1.374869	1.45	0.08	35	230	25	58
1.143783	1.18	0.04	35	230	40	59
1.005552	0.99	0.01	35	230	55	60
1.939713	1.74	0.01	35	280	15	61
1.624034	1.61	0.01	35	280	25	62
1.396099	1.37	0.02	35	280	40	[illegible]
1.195299	1.19	0.01	35	280	55	64
	0.88		20	230	40	11

The row marked yellow at the bottom of table shows optimal process parameters among the given input data set. It shows that if the welding voltage, welding current and the travel speed of torch is being set at 20V, 230A and 40cm/min respectively then a quality weld bead can be obtained.

The **Fig 4** shown below shows the scattered data around the actual data curve. The graph shows that the error has been minimized, as the maximum values lies approximately on the actual data curve. The actual data curve is shown as the blue line and the yellow lines shows the distribution of the predicted data around the actual data. The red points indicate the predicted data set.

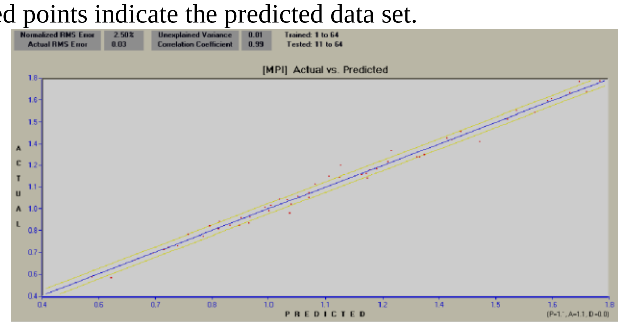

Fig 4 Scattered Graph

The time graph shown in **Fig 5** below also shows the predicted responses versus the actual values that are approximately nearer to the actual values. The blue curves are the actual values and the red curves are predicted responses.

IJERT

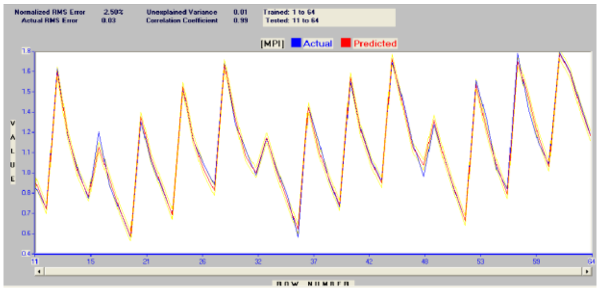

Fig 5 Time Graph

The **Fig 6** shown below is the factor loadings for the four output parameters i.e. weld bead height is the factor (1), depth of penetration as the factor (2), depth of heat affected zone as factor (3) and width of weld bead as factor (4). It shows the dependency and independency of the four output parameters.

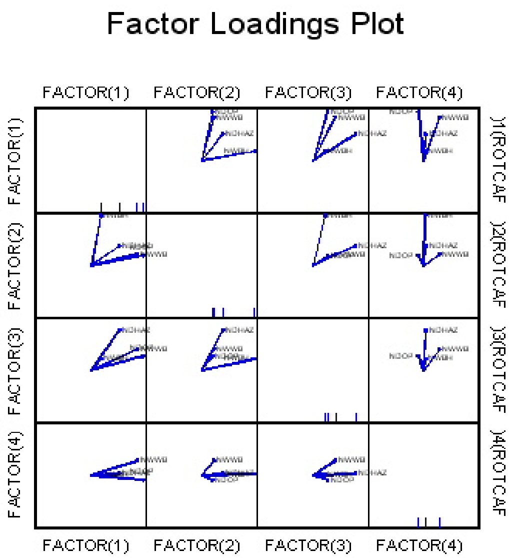

Fig 6 Factor Loadings Plot

The correlation between the four output parameters is shown in **Fig 6**, obtained from the statistical software correlation of normalized data for the corresponding output parameters. It shows that all the four data sets are correlated as the maximum points are within the closed envelop.

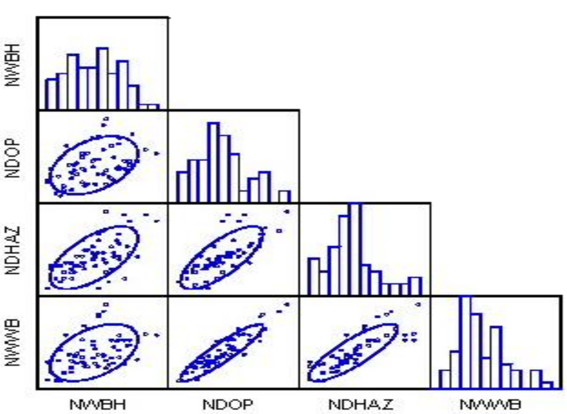

Figure.7 Correlation Graph

The scree plot i.e. between eigenvalue and number of factors is shown in **Fig 8**. As we have four factors i.e. factor 1, factor 2, factor 3 and factor 4 corresponding to the four output parameters, the eigenvalues relation is shown. The eigenvalues or the coefficient a_{ij} is called eigenvector and the corresponding values are shown in Table-6.

Fig 8 Scree Plot

The Table-8 below shows the output data of the Rockwell Hardness test for the welded specimens obtained after the experimentation done for the validation of ANN predicted responses for optimal process parameters. As per the ANN prediction the below mentioned experimental process parameters has been set and the corresponding hardness values at three different zones are found. In HRC values ‘a’ indicates the zone adjacent to the heat affected zone, ‘b’ is on weld bead and ‘c’ is on the heat affected zone.

IJERT

Table – 8 Rockwell Hardness Values (HRC)

Sl. No.	Welding Voltage in Volts	Welding Current in Ampere	Travel Speed mm / sec	HRC values		
				a	b	c
1	22.5	180	1.07	50.67	52.83	49
2	20	180	1	51	50	51
3	25	130	1.22	52	50	50.33
4	25	130	1.09	51.17	51.5	51.5
5	30	130	1.30	34.83	52	50.5
6	30	130	1.39	48.5	51	51.67
7	35	140	1.33	53.25	50	49.17
8	35	150	1.39	48.87	50.17	50.5
9	20	130	0.73	51	52.5	52.17
10	20	150	1.03	53.75	52	50.33
11	25	130	1.5	52.25	51.83	52.17

6. Conclusion

- The Error Back Propagation Neural Network model shows the optimal process parameters for the desired weld bead quality for a single V groove butt weld of mild-steel of thickness 12mm, predicted optimal process parameter values are; 20V, 230A and 40cm/min as welding voltage, welding current and the travel speed of torch respectively to obtain a quality weld bead.
- The output parameters obtained by ANN model i.e. weld bead height, depth of penetration, depth of heat affected zone and width of weld bead for the corresponding optimal process parameters are 3.8, 2, 0.6 and 7.7 respectively that are the desired weld bead qualities.
- The ANN model has reduced the error to a minimum of 2% after testing the complete given input data and training 80% of the data set for several hours. As a result the predicted responses are very close to the actual data set that is observed from the scattered graph **Fig 4** and time graph **Fig 5**.
- The validation data obtained by observing the micro-structures and the Rockwell hardness values at three zones namely on the weld bead, on the heat affected zone and on the base metal shows good results that are in accordance with the Neural Network Models predicted responses.
- The neural network model to correlate the influence of CO_2 process parameters on the joint characteristics has been developed.
- The model shows excellent information about the relationship of independent and dependent variables among the chosen parameters i.e. width of weld bead, weld bead height, depth of penetration and depth of heat affected zone.
- The model shows some important inflexion points, but those will be smooth when we increase the input data i.e. if the experimental set-ups has been increased more than 64 by taking other output parameters into consideration and also by increasing the levels of input parameters.
- The neural network model can calculate the CO_2 process parameters to obtain a specific joint, with defined characteristics.
- The models learning itself, this permit decrease the error.
- 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.
- Hence it has a wide scope for the automation of CO_2 to obtain the quality weld beads.

7. Scope for future improvement

In this present work we have considered single material (Mild-steel) of thickness 12mm, single V groove butt weld joint, CO_2 gas for shielding, constant electrode diameter of 1mm, constant gas flow rate of 14 l/min, four level process parameters namely welding voltage, welding current and travel speed of torch and the weld bead height, weld bead width, depth of penetration and depth of heat affected zone with 64 experimental set-ups only for predicting the optimal process parameters.

By considering the other process parameters like electrode stick out, electrode diameter, thickness of the material, joining of different materials, shielding gases, for other edge preparations like V groove, for other joints like lap joints, by increasing the levels of input parameters,…etc, can lead to more comprehensive results for the optimal process parameters. The other techniques of artificial intelligence can also be used like fuzzy logic and genetic algorithms for the best prediction and comparison of optimal process parameters. This can lead to more comprehensive results for performing the corner joints, double hulled structures,…etc.. As a result we can obtain more comprehensive optimal process parameters that can be incorporated to the neuro controllers to automate the CO_2 Welding process.

IJERT

8. References:

[1] Khorram A, Soleymani yazdi M.R, Ghoreishi M and Moradi M, "Using ANN approach to investigate the weld geometry of T16 Al4V Titanium Alloy", I ACSIT, International Journal of Engineering and Technology. Vol.2, No.5, 2010.

[2] Yousif Y.K, Daws K.M, Kazem B.I, "Prediction of Friction stir welding characteristics using Neural Network, 2008. Jordon Journal of Mechanical and Industrial Engineering, Vol 2, No.3, , pp 151-155, 2008.

[3] Mohsen Hayati, Tooraj Yousefi, Mehdi Ashjaee, Abdul Samad Hamidi & Yazdan shixvany, "Application of artificial neural networks for prediction of Natural convection Heat Transfer from a confined Horizontal Elliptic tube", World academy of science and technology 28, pp 269-274, 2007.

[4] Ajith Abraham, "Artificial Neural networks", Oklahoma state University, Stillwater, U.S.A.

[5] Bhadesh H.K.D.H. , "Neural Networks in Material Science", ISIJ International, Vol.39, No.10, pp 966-979, 1999.

[6] Welding Hand book, 8th edition, Vol.1

[7] Lancaster, J.F., 'The Physics of Welding', 2nd ed., Pergamon Press, 1996

[8] Reyes F.A – Valdes, Torres-Trevino L, Lopez-Cortez V.H, F.de la cruz-Marquez, Briceno-Ramixez F, "Correlation between GMAW process and weld quality parameters - A neural network approach applied in the automotive industry". Session 8A: Arc and weld pool observation, Measurement and sensing, pp 177-186

[9] Hung-chang Lio 'Multi-Response Optimization using weighted principal component", International Journal of Advanced Manufacturing Technology. Vol 27, PP 20-725, 2005

[10] Rajakumar S, Muralidharan C, Bala Subramanian V (2011) "Predicting tensile strength, hardness and corrosion rate of friction stir welding AA 6061-T6 aluminum alloy joints, material Design; 32: 2878-2890

[11] Benyounis KY, Olabi AG, Hashmi MSJ (2008) "Multi Response optimization of co_2 laser-welding process of austenitic stainless steel, optics laser technology; vol 40: 76-87

[12] Kumanan S, Dhas JER, Gowthaman K (2007) "Determination of submerged arc welding process parameters using taguchi method and regression analysis" Indian journal Engineering Material science; 12:177-183

[13] Noorossana R, Tajbakhsh S D, Saghaei A (2008) An artificial neural network approach to multiple-response optimization, International Journal of Advanced Manufacturing Technology; 40 (11-12): 1227-1238.

IJERT
IJERT