Neuro Genetic Optimization of Weld Metal Deposition in MAG Welding Process Using Genetic Algorithm and Adaptive Neuro Fuzzy Interference System

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Abstract

This work uses Genetic Algorithm to predict the weld metal deposition in the Metal Active Gas (MAG) welding process for a given set of welding parameters; with the help of Adaptive Neuro Fuzzy Interference System (ANFIS), an artificial intelligent technique to make the input-output model a standard one for given set of data into its input range. Experiments are designed according to full factorial design of experiments and its experimental results are used to develop an ANFIS model. Multiple sets of data from experiments are utilized to train, test and validate the intelligent network. The trained network is used to predict the amount of weld metal deposition. The proposed ANFIS, developed using MATLAB functions, is flexible, and it scopes for a better online monitoring system. Genetic algorithm is used to optimize the predicted results which is validated with experimental results and found satisfactory. The optimization of the model shows the correct input range to achieve the optimized weld metal deposition for the desired result.

Keywords:

Genetic Algorithm, ANFIS, MAG, Weld Metal Deposition.

I. INTRODUCTION

Metal Active Gas (MAG) welding is a widely used industrial arc welding procedure, which needs prediction and continuous monitoring of its input and output parameters to control the process in a better way to produce consistent weld quality. MAG involves mechanical-metallurgical features of the weldment, which depend upon the weld bead geometry, weld metal deposition, penetration and reinforcement of weld bead, wetting and fusion angle etc. These are directly related to combination and values of input process parameters of welding. Literature shows that a work has been explored since the last six decades on various aspects of modeling, simulation and process optimization in Metal Inert Gas (MIG) welding. Researchers are attempting many techniques to establish relationships between welding input parameters and weld metal deposition and weld quality leading to an optimal process by the application of different techniques like Genetic Algorithm (GA) and Adaptive Neuro Fuzzy Interference System (ANFIS) which is a rule base of fuzzy logic controller (FLC). After the development of the concept of Fuzzy Logic by Lofti Zadeh [1] [2] [3] Mamdani et al. [4] and Sugeno et al. [5] [6] extended the concept of fuzzy logic to the FLC. The theory and concept of ANFIS was developed by J.S.R. Jang [7] with an engineering application using Artificial Neural Network [8][9]. Goldberg [10] [11] explained the search technique of GA to optimize the result with a concept of local and global hybrids. Ishibuchi et al. [12] explained that how the nos. of fuzzy rules can be made minimized with the help of GA. Nozaki et al. [13] extended the concept of Ishibuchi and showed how a set of numerical data can generate fuzzy rule by heuristic method. Davi et al. [14] made a Comparison between genetic algorithms and response surface methodology in Gas Metal Arc Welding (GMAW) welding optimization. Juang and Tarng [15] adopted a modified Taguchi method to analyze the effect of each welding process parameter on the weld pool geometry and then to determine the Tungsten Inert Gas (TIG) welding process parameters combination associated with the optimal weld pool geometry. Manonmani [16] investigated the effect of the welding parameters on the bead geometry AISI 304 stainless steel. S. Datta et al. [17] have worked on the influence of electrode stick out as an one of the important process parameters of submerged arc welding by incorporating one of the traditional methods of statistical data analysis (ANOVA). Jagdev Singh and Simranpreet Singh Gill [18] has designed and demonstrated the use of fuzzy logic based multi input and single output ANFIS model to predict the tensile strength of tubular joints, welded by the technique of radial friction welding. Manoj Singla et al. [19] have optimized the different parameters of Gas Metal Arc Welding process by using factorial design approach. The study had optimized various GMAW parameters including welding voltage, welding current, welding speed and nozzle to plate distance (NPD) by developing a mathematical model for sound weld deposit area of a mild steel specimen. P. Kumari et al. [20] has made a study on the effect of welding parameters on weld bead geometry in MIG welding of low carbon steel. J Raja Dhas and S Kannan [21] have adopted a neuro hybrid model to predict bead width in submerged arc welding. A. Biswas et al. [22] has optimized the bead geometry in Submerged Arc Welding which was conducted based on Taguchi's L_{25} orthogonal array design with combinations of process control parameters.

Different bead geometry parameters was optimized and optimal result has been verified by confirmatory. This study proposes a hybrid intelligent technique, ANFIS, to predict weld metal deposition in a MAG welding process for a given set of welding parameters and optimization of the same using genetic algorithm to have an corrected result.

II. METAL ACTIVE GAS (MAG) WELDING

MAG, a common arc welding process has welding current, arc voltage, welding speed, electrode stick out (extension), electrode diameter, polarity, current type etc. as input variables. Welding current directly influences the weld metal deposition which gives better depth of penetration and base metal fusion. At a given current, weld metal deposition is affected by the electrode diameter. Since the weld is more brittle than the parent material, it is vital that the weld metal deposition must be minimal without disturbing desired penetration and strength. Minimization of the weld metal deposition is necessary because excessive deposited weld metal leads to wastage of the welding electrode and the process consumes more time. Therefore sufficient attention is required to select the process parameters in welding to get a minimized weld metal deposition with having desired weld quality as required.

III. PROPOSED METHODOLOGY

A. Data Acquisition

Full factorial design of experiments is a systematic application of design of experiments to improve the product quality which uses the all possible combinations of levels of the input factors to make a meticulous investigation of the nature of the output. A four factors three levels design of experiments was done where $(3)^4 = 81$ numbers of experiments were involved in the MAG (POWERMIG T400) welding machine (Fig: 01). The experiment was conducted at M/s. Hind Engineering, Badu, Madhyamgram, West Bengal. Single pass butt welding is performed on the commercially available steel of IS2962 grade (C 0.25%, Si 0.20%, Mn 0.75% and balance Fe) on a pair of 100mm × 100mm × 5mm work piece. Before welding required edge preparation was done. Electrode (Dia 1.2 mm) (AWS/SFA 5.18: ER 70S-6) was used with CO_2 gas at 11 lit/min flow rate as shielding gas. The weights were recorded before and after welding to measure the amount of weld metal deposition on the base metal (Table I).

Fig: 01. PowerMIG T400 model (Make: Powercon Electric Company)

B. Development of ANFIS for weld metal deposition prediction

ANFIS is a fuzzy interference system which uses the framework of Neural Network. This technique provides a method for fuzzy modeling procedure to learn information about a data set in order to achieve a rule base for selection of fuzzy rules. A database defines the membership functions used in the rules which creates a reasoning mechanism to carryout interference procedure on the rules and the given fact. This methodology combines the advantages of fuzzy system and Neural Network. The modeling of weld metal deposition by Metal Active Gas welding is done by considering four input parameters and one output parameter. The membership functions parameters are tuned using a hybrid system which is the combination of back propagation and the method of least squares. The parameters associated with the membership functions will change through the learning process. The computation of these parameters is facilitated by gradient vector, which provides a measure of how well fuzzy inference system is modeling the input/output data for a given set of parameters. Once the gradient vector is obtained, any of the several optimization routines could be applied in order to adjust the parameters so as to reduce some error measure. The proposed ANFIS

TABLE I
EXPERIMENTAL RESULTS FOR WELD METAL DEPOSITION

Exp. No.	Arc Voltage	Welding current	Welding Speed	Electrode Stick out	Weight before welding	Weight after welding	Weld Deposition	Exp. No.	Arc Voltage	Welding current	Welding Speed	Electrode Stick out	Weight before welding	Weight after welding	Weld Deposition
1	20	180	3.85	6	770	780	10	42	22	190	3.85	8	773	787	14
2	24	180	3.85	6	767	782	15	43	22	190	4.54	8	771	783	12
3	20	180	3.85	10	765	777	12	44	22	190	4.16	6	772	784	12
4	20	200	3.85	6	776	788	12	45	22	180	4.16	8	773	785	12
5	20	180	4.54	6	778	786	8	46	24	190	4.16	8	775	791	16
6	20	180	4.54	10	780	790	10	47	22	200	4.16	8	778	792	14
7	24	180	4.54	6	768	781	13	48	20	190	4.16	8	779	790	11
8	20	200	3.85	10	780	794	14	49	22	190	4.16	8	773	786	13
9	24	180	3.85	10	775	792	17	50	20	180	4.54	8	776	785	9
10	20	200	4.54	6	773	783	10	51	20	190	4.54	6	775	784	9
11	24	200	3.85	6	771	788	17	52	20	180	4.16	6	778	787	9
12	20	200	4.54	10	776	786	10	53	22	180	3.85	6	777	789	12
13	24	200	3.85	10	777	796	19	54	24	200	4.54	8	773	785	12
14	24	200	4.54	6	769	785	16	55	22	200	4.54	10	771	781	10
15	24	180	4.54	10	768	783	15	56	20	180	3.85	8	770	781	11
16	24	200	4.54	10	770	780	10	57	24	190	4.54	10	769	781	12
17	22	200	4.16	6	773	786	13	58	20	200	4.54	8	773	783	10
18	20	190	4.54	8	773	783	10	59	24	200	3.85	8	776	794	18
19	24	190	3.85	8	771	788	17	60	22	200	4.54	6	775	787	12
20	22	190	3.85	6	775	788	13	61	20	190	4.54	10	778	788	10
21	22	200	4.54	8	776	787	11	62	24	200	4.16	10	768	786	18
22	22	200	3.85	8	772	787	15	63	24	190	3.85	10	765	783	18
23	22	190	3.85	10	774	789	15	64	24	190	4.54	6	764	778	14
24	20	200	4.16	8	777	789	12	65	20	180	4.16	10	778	789	11
25	22	200	4.16	10	781	796	15	66	22	180	3.85	10	776	790	14
26	24	190	4.16	10	769	786	17	67	20	200	4.16	10	779	792	13
27	24	190	4.16	6	768	783	15	68	24	180	4.16	6	777	791	14
28	20	190	4.16	6	772	782	10	69	20	200	4.16	6	771	782	11
29	20	190	4.16	10	774	786	12	70	22	200	3.85	6	776	790	14
30	22	190	4.54	6	777	788	11	71	22	180	4.54	10	772	784	12
31	22	190	4.54	10	773	786	13	72	24	180	4.54	8	776	790	14
32	24	190	4.54	8	776	791	15	73	24	180	3.85	8	773	789	16
33	24	180	4.16	8	775	790	15	74	20	190	3.85	6	772	783	11
34	22	180	4.54	8	774	785	11	75	22	200	3.85	10	776	792	16
35	20	180	4.16	8	778	788	10	76	20	200	3.85	8	778	791	13
36	22	180	4.16	10	776	789	13	77	24	190	3.85	6	775	791	16
37	24	200	4.16	8	777	794	17	78	20	190	3.85	10	778	791	13
38	22	180	4.16	6	773	784	11	79	24	200	4.16	6	776	792	16
39	22	180	3.85	8	771	784	13	80	22	180	4.54	6	779	789	10
40	20	190	3.85	8	780	792	12	81	24	180	4.16	10	773	789	16

(Fig: 02) structure utilizes Sugeno type fuzzy interference systems and generalized Gaussian bell-shaped membership function to execute a given training data set. It employs 55 nodes, 80 linear parameters, 24 nonlinear parameters, 104 total numbers of parameters 57 training data pairs, 8 checking data pairs and 16 fuzzy rules to predict weld metal deposition. ANFIS modelling process starts by obtaining an input-output pair of data sets and dividing it into training and checking data. The training data are used to find out the initial premise parameters for membership functions by equally spacing membership functions.

The final output of the system is the weighted average of the all rule outputs, computed as

$$\text{Final output } (f) = \Sigma_1^N w_i f_i / \Sigma_1^N w_i \qquad \ldots\ldots\ldots.. (1)$$

Where w_i = firing strength of the rule
f_i = output level of each rule

C. Optimization using Genetic Algorithm

A Genetic Algorithm (GA) is a search heuristic that mimics the process of natural evolution. This heuristic is routinely used to generate useful solutions to optimization and search problems. In a Genetic Algorithm, a population of strings (called Genome or Genotype) which encode candidate solutions (called Individuals or Phenotypes) to an optimization problem evolves toward better solutions. Traditionally, solutions are represented in binary as strings of 0s and 1s, but other encodings are also possible. The evolution usually starts from a population of randomly generated individuals and happens in generations. In each generation, the fitness of every individual in the population is evaluated, multiple individuals are stochastically selected from the current population (based on their fitness), and modified (recombined and possibly randomly mutated) to form a new population. The new population is then used in the next iteration of the algorithm. Commonly, the algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population.

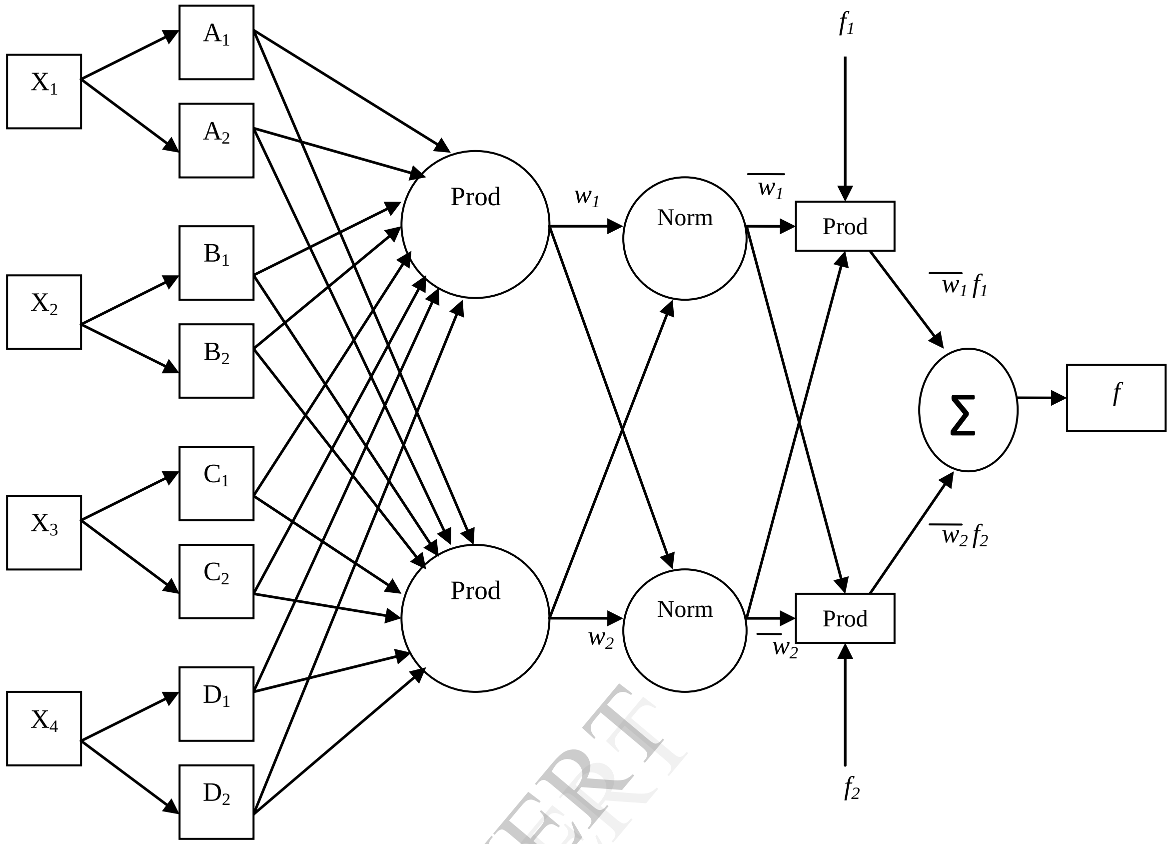

Fig: 02. Proposed ANFIS structure for four inputs, single output to predict weld mass deposition in MAG welding process.

The present work aims to explore genetic algorithm (GA) as a method for optimizing welding parameters selection. The algorithm searches for the best solution in terms of arc voltage, welding current, welding speed and electrode stick out with the aim of optimizing an objective function i.e. weld metal deposition. Minimum Deposition is the objective here which is calculated for each input process data combination invoked as the result of multiple input single objective Genetic Algorithm. The objective function of Genetic Algorithm was written in MATLAB and the program was executed to acquire the values of population size, number of generation by taking minimum deposition as the criteria.

IV. RESULTS AND DISCUSSION

As there is a considerable variation in the input data range in terms of numerical value, the input data is normalized to a uniform scale for input to the ANFIS model and this has been achieved by normalizing, using (2) for a range varying from 0.1 to 0.9.

$$y = 0.1 + 0.8\left(\frac{x - x_{min}}{x_{max} - x_{min}}\right) \quad (2)$$

The normalized input parameters along with the error comparison between experimental results and ANFIS prediction is given in Table II.

TABLE II

NORMALIZED PREDICTED RESULTS BY ANFIS FOR WELD METAL DEPOSITION WITH ERROR

Exp. No.	Arc Voltage	Welding current	Welding Speed	Electrode Stick out	Weld metal deposition	ANFIS Prediction	Error	Exp. No.	Arc Voltage	Welding current	Welding Speed	Electrode Stick out	Weld metal deposition	ANFIS Prediction	Error
1	0.1	0.1	0.1	0.1	0.25	0.27	0.02	42	0.5	0.5	0.1	0.5	0.54	0.49	-0.04
2	0.9	0.1	0.1	0.1	0.61	0.62	0.01	43	0.5	0.5	0.9	0.5	0.39	0.28	-0.11
3	0.1	0.1	0.1	0.9	0.39	0.37	-0.02	44	0.5	0.5	0.46	0.1	0.39	0.38	-0.01
4	0.1	0.9	0.1	0.1	0.39	0.38	-0.01	45	0.5	0.1	0.46	0.5	0.39	0.39	0
5	0.1	0.1	0.9	0.1	0.1	0.08	-0.02	46	0.9	0.5	0.46	0.5	0.68	0.58	-0.1
6	0.1	0.1	0.9	0.9	0.25	0.21	-0.03	47	0.5	0.9	0.46	0.5	0.54	0.46	-0.08
7	0.9	0.1	0.9	0.1	0.46	0.47	0.01	48	0.1	0.5	0.46	0.5	0.32	0.28	-0.03
8	0.1	0.9	0.1	0.9	0.54	0.61	0.07	49	0.5	0.5	0.46	0.5	0.46	0.41	-0.06
9	0.9	0.1	0.1	0.9	0.75	0.77	0.01	50	0.1	0.1	0.9	0.5	0.17	0.14	-0.03
10	0.1	0.9	0.9	0.1	0.25	0.2	-0.04	51	0.1	0.5	0.9	0.1	0.17	0.13	-0.04
11	0.9	0.9	0.1	0.1	0.75	0.79	0.04	52	0.1	0.1	0.46	0.1	0.17	0.2	0.03
12	0.1	0.9	0.9	0.9	0.25	0.21	-0.03	53	0.5	0.1	0.1	0.1	0.39	0.4	0.01
13	0.9	0.9	0.1	0.9	0.9	0.77	-0.13	54	0.9	0.9	0.9	0.5	0.39	0.35	-0.05
14	0.9	0.9	0.9	0.1	0.68	0.49	-0.19	55	0.5	0.9	0.9	0.9	0.25	0.21	-0.04
15	0.9	0.1	0.9	0.9	0.61	0.61	0	56	0.1	0.1	0.1	0.5	0.32	0.3	-0.02
16	0.9	0.9	0.9	0.9	0.25	0.21	-0.04	57	0.9	0.5	0.9	0.9	0.39	0.41	0.02
17	0.5	0.9	0.46	0.1	0.46	0.46	0	58	0.1	0.9	0.9	0.5	0.25	0.2	-0.05
18	0.1	0.5	0.9	0.5	0.25	0.16	-0.09	59	0.9	0.9	0.1	0.5	0.83	0.75	-0.08
19	0.9	0.5	0.1	0.5	0.75	0.69	-0.07	60	0.5	0.9	0.9	0.1	0.39	0.32	-0.07
20	0.5	0.5	0.1	0.1	0.46	0.45	-0.01	61	0.1	0.5	0.9	0.9	0.25	0.2	-0.04
21	0.5	0.9	0.9	0.5	0.32	0.26	-0.06	62	0.9	0.9	0.46	0.9	0.83	0.55	-0.28
22	0.5	0.9	0.1	0.5	0.61	0.58	-0.03	63	0.9	0.5	0.1	0.9	0.83	0.74	-0.09
23	0.5	0.5	0.1	0.9	0.61	0.58	-0.03	64	0.9	0.5	0.9	0.1	0.54	0.46	-0.08
24	0.1	0.9	0.46	0.5	0.39	0.36	-0.03	65	0.1	0.1	0.46	0.9	0.32	0.3	-0.02
25	0.5	0.9	0.46	0.9	0.61	0.5	-0.11	66	0.5	0.1	0.1	0.9	0.54	0.54	0
26	0.9	0.5	0.46	0.9	0.75	0.6	-0.16	67	0.1	0.9	0.46	0.9	0.46	0.46	0
27	0.9	0.5	0.46	0.1	0.61	0.59	-0.02	68	0.9	0.1	0.46	0.1	0.54	0.54	0
28	0.1	0.5	0.46	0.1	0.25	0.25	0.01	69	0.1	0.9	0.46	0.1	0.32	0.32	0
29	0.1	0.5	0.46	0.9	0.39	0.36	-0.03	70	0.5	0.9	0.1	0.1	0.54	0.54	0
30	0.5	0.5	0.9	0.1	0.32	0.27	-0.05	71	0.5	0.1	0.9	0.9	0.39	0.39	0
31	0.5	0.5	0.9	0.9	0.46	0.29	-0.17	72	0.9	0.1	0.9	0.5	0.54	0.54	0
32	0.9	0.5	0.9	0.5	0.61	0.43	-0.18	73	0.9	0.1	0.1	0.5	0.68	0.68	0
33	0.9	0.1	0.46	0.5	0.61	0.6	-0.01	74	0.1	0.5	0.1	0.1	0.32	0.32	0
34	0.5	0.1	0.9	0.5	0.32	0.31	0	75	0.5	0.9	0.1	0.9	0.68	0.68	0
35	0.1	0.1	0.46	0.5	0.25	0.23	-0.01	76	0.1	0.9	0.1	0.5	0.46	0.46	0
36	0.5	0.1	0.46	0.9	0.46	0.47	0	77	0.9	0.5	0.1	0.1	0.68	0.68	0
37	0.9	0.9	0.46	0.5	0.75	0.6	-0.16	78	0.1	0.5	0.1	0.9	0.46	0.46	0
38	0.5	0.1	0.46	0.1	0.32	0.33	0.01	79	0.9	0.9	0.46	0.1	0.68	0.68	0
39	0.5	0.1	0.1	0.5	0.46	0.45	-0.01	80	0.5	0.1	0.9	0.1	0.25	0.25	0
40	0.1	0.5	0.1	0.5	0.39	0.36	-0.03	81	0.9	0.1	0.46	0.9	0.68	0.68	0
41	0.5	0.5	0.46	0.9	0.54	0.46	-0.07								

The first 48 data sets are used for training the ANFIS model, next 16 data sets are used to check the model and the last 17 data sets are used to validate the network.

ANFIS predicted data were used to optimize the process using Genetic Algorithm. The objective function of Genetic Algorithm was written in MATLAB and the program was executed to acquire the values of population size, number of generation by taking minimum deposition as the criteria. The graphs of population size v/s minimum average response and number of generation v/s minimum average response was generated as an output of the executed program. The best suitable values of number of generation and population size, could be found as 65 (Fig: 03) and 50 (Fig: 04) respectively where the minimum deposition is in its minimum values.

The genetic algorithm converges to the best suitable minimum value of weld metal deposition in the selected generation. The generation was selected as 50. The next result (Fig. 05) shows how the genetic algorithm is fitted in generation with beat fitness and mean fitness.

With the help of multi input single objective Genetic Algorithm we can get the optimized welding condition to make the weld metal deposition minimized. Following (Table III) is the set of input conditions for the optimization. It is observed at lower values of arc voltage, welding current and electrode stick out and higher values of welding speed weld metal deposition is minimized.

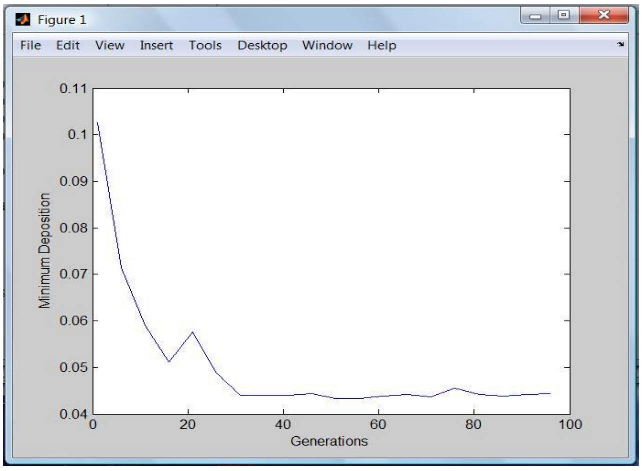

Fig: 03. Variation of Minimum Deposition with no. of generations

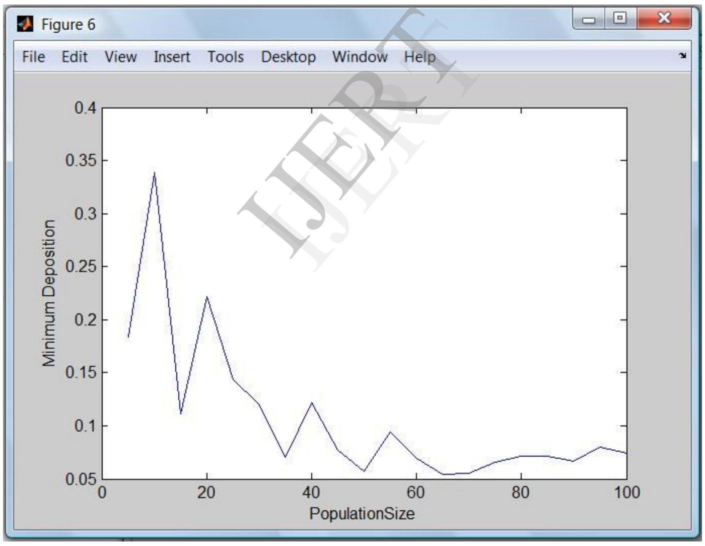

Fig: 04. Variation of Minimum Deposition with population size

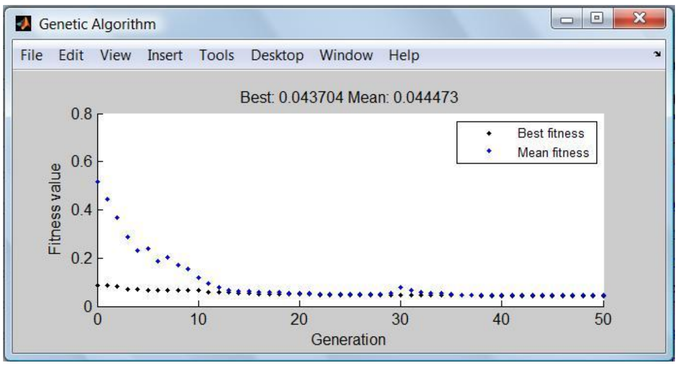

Fig: 05. Fitness values v/s generation graph

The result of the Genetic Algorithm in MATLAB environment is shown in following Fig: 06 where for the normalized values of the input parameters the MATLAB program has estimated the weld metal deposition for the minimum deposition criteria. A comparison between Fig: 06 and table III gives the idea of the validated result of the optimization with the experimental result. It is seen that there is a little variation of input data range of the data set of experiment no. 05 and the optimization result from the Genetic Algorithm.

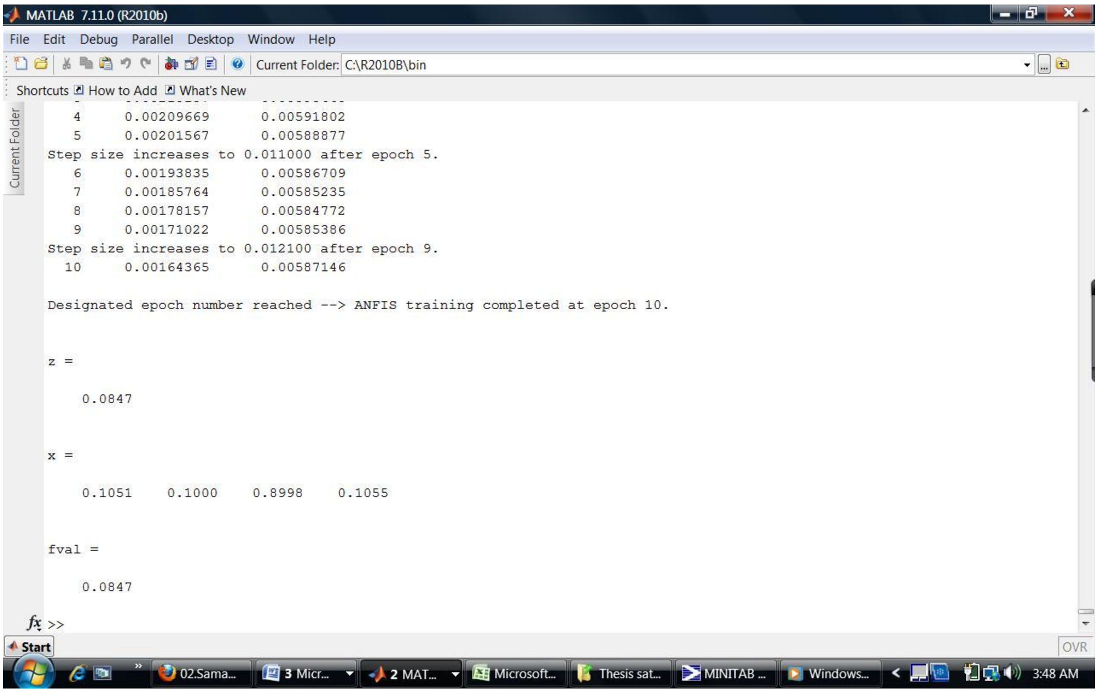

Fig: 06. MATLAB result for Genetic Algorithm optimization

TABLE III

Exp No.	Arc Voltage	Welding Current	Welding Speed	Electrode Stick out	Arc Voltage	Welding Current	Welding Speed	Electrode Stick out	Arc Voltage	Welding Current	Welding Speed	Electrode Stick out	Experimental Weld Metal Deposition	Normalized Value of Weld Metal Deposition	ANFIS Prediction for Weld Metal Deposition	GA output for Weld Metal Deposition
	Experimental Input Data				Normalized Input Data				Optimized Input Data							
5	20	180	4.54	6	0.1	0.1	0.9	0.1	0.1051	0.1000	0.8998	0.1055	8	0.1	0.08	0.0847

V. Conclusion

Proposed ANFIS is based on first order Sugeno fuzzy interference system and developed to predict weld metal deposition in a MAG process. Corrected set of input data range has been achieved from the Neuro Genetic modeling and optimization. The difference can be seen in Table III where it is observed that there is a little deviation between the normalized input data and optimized input data. This correction is leading the system to achieve precision results which can't be done by the normal human observations. The residue between the experimental and optimized data can be used as feedback to the system to minimize error. This may lead to the further development of this present work. The present work also could be extended with the involvement of more welding parameters such as electrode diameters, base metal thickness, material type and their effect on the weld metal deposition. The Genetic Algorithm may be extended to multi objective GA to optimize weld metal deposition with depth of penetration, weld strength etc. simultaneously to make the system environment, a more practical one.

References

[1] L. A. Zadeh, "Fuzzy Sets", Information and Control, Vol.8, pp.338-353, 1965.

[2] L. A. Zadeh, "Outline of a new approach to the analysis of complex systems and decision processes", IEEE Transactions on Systems, Man, and Cybernetics, Vol. 3, No. 1, pp. 28-44, Jan 1973.
[3] L. A. Zadeh, "Fuzzy Logic", IEEE Computer, pp. 83-89, 1988.
[4] E.H. Mamdani and S. Assilian, "An experiment in linguistic synthesis with a fuzzy logic controller." International Journal of Man-Machine studies, 7(1):1-13,1975.
[5] T. Takagi and M. Sugeno, "Fuzzy identification of systems and its applications to modeling and control." IEEE Transactions on Systems, Man, and Cybernetics, 15:116-132, 1985.
[6] M. Sugeno and G. T. Kang, "Structure identification Fuzzy model." Fuzzy Sets and Systems, 28:15-33, 1988.
[7] Jyh-Shing Roger Jang, "ANFIS: Adaptive-Network-Based Fuzzy Interference System", IEEE transactions on systems, man, and cybernetics, Vol. 23, no. 3, pp. 665-685, May/June 1993
[8] J. Hopfield, "Neural networks and physical systems with emergent collective computational abilities", Proc. Natl. Acad. Sci. USA, Vol. 79, pp. 2554–2558, 1982.
[9] J. Hopfield and D. Tank, "Computing with neural circuits: A model", Science, Vol. 233, pp. 625–633, 1986.
[10] D.E. Goldberg, "Genetic algorithms for search, optimization and machine learning", Reading, MA: Addison-Wesley, 1989.
[11] D.E. Goldberg, "Optimizing global-local search hybrids", Proceedings of the Genetic and Evolutionary Computation Conference (GECCO), pp. 220-228, 1999.
[12] H. Ishibuchi, T. Murata, "Minimizing the fuzzy rules and maximizing its performance by a multi objective genetic algorithm.", Proceedings of the Sixth International Conference on Fuzzy Systems, pp. 259-264, 1997.
[13] Ken Nozaki, Hisao Ishibuchi, Hideo Tanaka, "A simple but powerful heuristic method for generating fuzzy rules from numerical data", Fuzzy Sets and Systems 86 (1997) Elsevier Science pp. 251-270, 1995.
[14] Davi Sampaio Correia, Cristiene Vasconcelos Gonçalves, Sebastiao Simoes da Cunha, Jr., "Comparison between genetic algorithms and response surface methodology in GMAW welding optimization", Journal of Materials Processing Technology 160, pp. 70-76, 2005.
[15] Y.S Tarng., S.C. Juang, C.H. Chang, "The use of grey-based Taguchi methods to determine submerged arc welding process parameters in hardfacing", Journal of Materials Processing Technology,128,I-6, 2002.
[16] K. Manonmani, N. Murugan, G. Buvanasekaran "Effect of process parameters on the weld bead geometry of laser beam welded stainless steel sheets", Mt J Joining Mater 2005:l7(4):l03 9, 2005.
[17] S. Datta et al., "Effect of electrode stick out on quality and performance of submerged arc weldment - experimental and statistical analyses", International Conference on Mechanical Engineering 2005 Dhaka, Bangladesh ICME05-AM-39, 2005.
[18] Jagdev Singh and Simranpreet Singh Gill, "Multi input single output fuzzy model to predict tensile strength of radial friction welded GI pipes", International Journal of Information and Systems Sciences, Volume 4, Number 3, pp. 462-477, 2006.
[19] Manoj Singla, Dharminder Singh, Dharmpal Deepak, "Parametric optimization of gas metal arc welding processes by using factorial design approach", Journal of Minerals & Materials Characterization & Engineering, Vol. 9, No.4, pp.353-363, 2010.
[20] P. Kumari, K. Archna and R.S. Parmar, "Effect of Welding Parameters on Weld Bead Geometry in MIG Welding of Low Carbon Steel", International Journal of Applied Engineering Research ISSN 0973-4562 Volume 6, Number 2 (2011) pp. 249–258, 2011.
[21] Dhas J. E. R. and Somsundaram Kumanan, "Neuro hybrid model to predict weld bead width in submerged arc welding process", Journal of Scientific & Industrial Research Vol. 69, May 2010, pp. 350-355, 2010.
[22] A. Biswas, "Bead geometry optimization of Submerged Arc Weld: Exploration of Weighted Principal Component Analysis (WPCA)", 2nd International Conference on Mechanical, Industrial and Manufacturing Technologies (MIMT 2011), Singapore 2011.