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OPTIMIZATION OF MAG WELDING PARAMETERS USING MATHEMATICAL AND VARIOUS SIMULATION MODELS

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Abstract

In the process of active metal gas (MAG), this research uses a genetic algorithm to control weld metal deposition on a predefined set of parameters. By using ANFIS and AI Technique, it can render the model consisting input-output in its range for a given set of data. Experiments were conducted in comprehensive experimental design and the obtained results are adopted to create a model which is termed as ANFIS. The intelligent network is tested, validated and trained using multiple sets of data from experiments. In order to estimate, how much weld metal gets deposited, the qualified network is used. The proposed ANFIS, which was created using MATLAB functions, is adaptable and has the potential to become a better online monitoring system. The projected results are optimized using a genetic algorithm, which has been tested with these observations and simulations, and found to be adequate enough. The model's efficiency reveals the proper input range in order to achieve optimal weld metal deposition so that we can get the expected results. By constructing a mathematical model for a welding specimen's deposition area, this experimental work intends to MAG welding parameters such as, welding current, and welding speed welding voltage should be optimized.

Keywords: Genetic Algorithm, Weld Metal Deposition, MAG, Artificial Intelligence, mathematical model. Adaptive Neuro Fuzzy Interference System (ANFIS)

1. INTRODUCTION

For industrial arc welding the most usual method is Metal active gas welding, and its input and output parameters are predicted and continuously monitored to regulate the process in order to achieve consistent weld efficiency. MAG comprises mechanical-metallurgical welding features that rely upon the geometry of the bead in the weld, the deposition of weld metal, the penetration and strengthening of the weld bead, the wetting, the fusion angle etc. The process parameters used as the input are in direct relation with this welding process. In the past around 6 decades the different process parameters, the optimization processes, welding with inert gases in metals, various models, different simulations have been studied and this is well defined in the literature [1-2]. Various studies are also performed because researchers are trying to build a relationship among the parameters such as those used as input, deposition of metal in the weld, the efficiency of weld, and this relationship occurred will lead to the optimized method. For this process various techniques are used which are rule base for the fuzzy logic controller, such as ANFIS, and GA etc. For fuzzy logic controller, two researchers [3-4] have used the fuzzy logic concept and this they have done after established By using the Artificial Neural Network, the notion of fuzzy logic has evolved ANFIS theory and the principle [5] in combination with engineering applications. With the idea of local and global hybrids, clarified GA's search technique to maximize the result [6]. With the support of GA, demonstrated how the number of fuzzy rules can be reduced and demonstrated how a collection of numerical data can be used to produce fuzzy rules using a heuristic approach. Comparison was made among GMAW (Gas Metal Arc Welding) welding genetic algorithms and response surface methodologies.[7]. An altered Taguchi system in which the process parameters used in welding are analyzed, specifically the welding parameters having Tungsten Inert Gas (TIG) with the combination of optimal welding pool geometry are observed.

The effect on bead geometry AISI 304 stainless steels of the welding parameters have been investigated have been working on influence of electrodes as one of the significant parameters in the process of arc welding by integrating one of standard statistical analysis procedures, developed and validated the use of ANFIS model which is multi-input, single-output and is based on fuzzy logic in order to estimate the tensile strength of tubular joints which are welded by using the radial friction welding technique, used a factorial design approach to optimise the various parameters of the Gas Metal Arc Welding process.[8-10]. The research had optimized various GMAW parameters for the sound solder deposit region of a mild steel specimen, including welding tightness, welding tension, welder speed and the plate-distance (NPP) nozzle. The effect of weld parameters on sold bead geometry in low carbon steel MIG welding has been studied, a neuro hybrid model was adopted for the prediction of perforation width in the arc. The Bead Geometry of the Submerged A. Arc Welding was optimized by Biswas et al. and is based on the orthogonal array concept of Taguchi and combined with the parameters of the process control. [11-13]. Various parameters of bead geometry have been optimized and the optimum conformation results have been verified. This study proposes a hybrid ANFIS intelligent technique for prediction of sold metal deposition during a MAG welding phase in order to achieve the correct results by means of a specific set of parameters used in welding and optimization by making the use of GA.[14-15].

2. MAG WELDING

MAG, a joint arc welding method, uses input variables such as welding current, weld speed, electrode stick out diameter of electrode, polarity, form etc. weld current affects directly the deposition of the weld metal, which gives greater penetration depth and base metal fusion, shows in fig. 1The electrode diameter is affected at a given current by the welding metal deposition. Metal deposition on the weld must be minimum without disturbing the strength and desired penetration because parent material is not that much fragile as much weld is. Weld metal deposition should be kept to a minimum because too much deposited weld metal wastes the welding electrode and lengthens the process. There is therefore a need for adequate attention to choose the parameters which will be used in the process of welding, to achieve a minimum deposition of weld metal with the necessary welding quality.

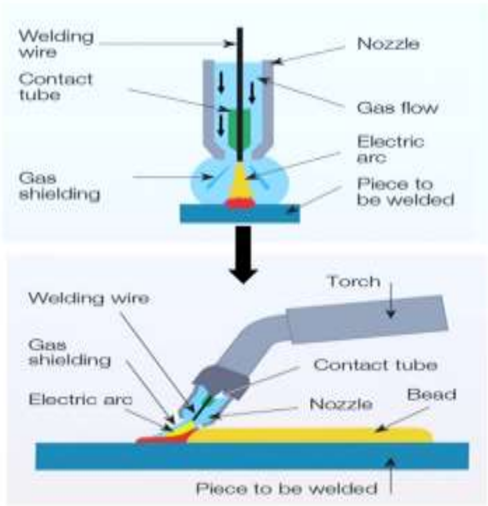

Fig. 1 MAG welding process

3. SUGGESTED METHODOLOGY

3.1 Data Collection

Full factorial experimental design means the systematic application of experiment design in order to increase the quality of product by using all set of combinations which are possible for the input levels to thoroughly assess the essence of the output. A three-level experimentation design was carried out in four factors where (3)4 = 81 number of tests participated in the welding system shown in fig 2 MAG (POWERMIG T400). This experiment was conducted on, by using a pair of 100mm x 5mm x 100mm work parts, IS2962 grade steel is taken for performing the butt welding and this steel is commercially available and its composition has 0.2 % silicon, 0.25 % carbon, 0.75 % manganese and iron in balanced amount. Shown in fig 3Edge preparation was needed prior to welding. CO_2 gas was used as a shielding gas with the 1.2 mm of electrode diameter (ER 70S-6: AWS/SFA 5.18) and a flow rate of 11 lit/min. Weights were taken before and after welding to determine how much weld metal was deposited on the metal which is taken as the base and this is illustrated in tab. 1.

Fig. 2 Depiction of Model of Power MIG T400

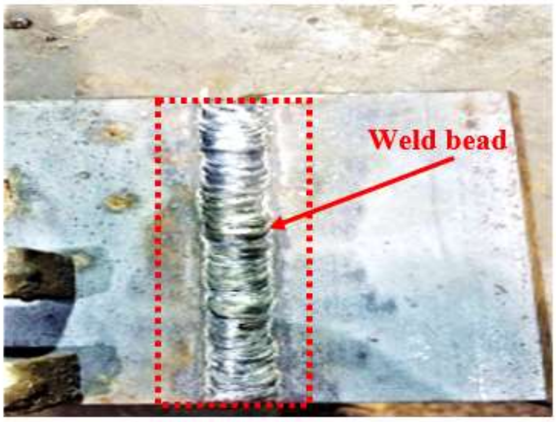

Fig. 3 Weld specimen

3.2 Optimization Using GA

Genetic algorithm (GA) is a heuristic search which imitates a natural development process. This heuristic system is commonly used to produce helpful solutions to search and optimization problems. A population of cords (called genome or genotype), that encodes solutions for an optimization issue (called individuals or phenotypes) evolves into better solutions in a genetic algorithm. Solutions typically are expressed in binaries as 0s and 1s strings, but other encodes are also available. The population of randomly generated individuals is taken for the evolution. Every generation evaluates each individual's fitness in the populace, selecting many individuals from the existing populations (according to their fitness) and changing them to create a new population (recombined and likely mutated randomly). In the next iteration of the algorithm, the new population is used. Usually, the algorithm is terminated by either producing the highest number of generations or by achieving a good population fitness level.

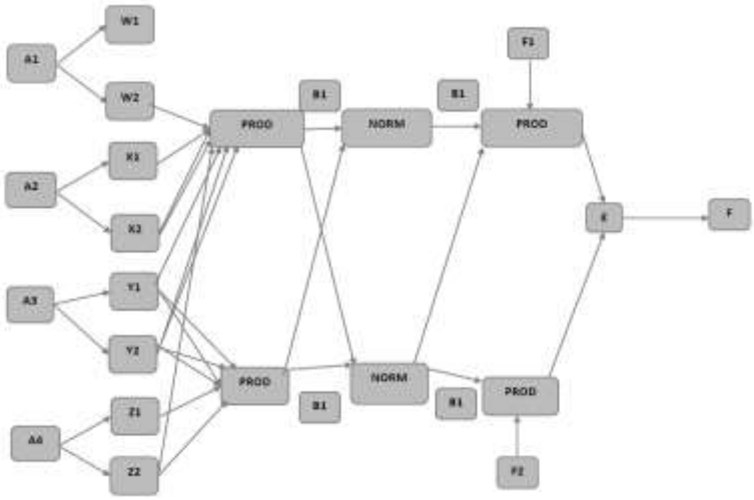

Fig:5. Depiction of 4 inputs Single output ANFIS architecture used in MAG process to estimate the weld mass deposition.

The aim of this study is to look at using a genetic algorithm (GA) to optimize welding parameter selection. In order to optimize an objective aim like the deposition of welding metals, the algorithm tries to find out the most suitable data which is defined in terms of welding current, electrode stick out, arc voltage, and speed of welding. The goal here is minimum deposition that is determined by multiple input single objective Genetic Algorithm for each input process data combination. In order to obtain the values of the size of population, the number of people produced by assuming criterion including minimum value of deposition, the objective function was written in MATLAB and the project was implemented. Fig:5. Figure showing 4 inputs Single output ANFIS architecture used in MAG process to estimate the weld mass deposition.

3.3 Forecasting for the use of ANFIS for Weld Metal Deposition

The method used by Adaptive Neuro Fuzzy Interference System (ANFIS) employs Neural Network architecture, modeling approach for learning knowledge about a collection of data to obtain a rules base to pick fuzzy rules. A database specifies the membership functions in the laws, which establishes a framework for the logic of the rules and the facts. The advantages of the fuzzy system and the Neural network are combined in this approach. Metal Active Gas welding simulation of welding metal deposition is achieved by taking into account 1 parameter at the output and 4 parameters at the input. The hybrid system is used to tune the parameters of the membership functions which combines back and lower square process. Through the learning process, the parameters of the membership functions will change. A gradient vector, which calculates how well the input/output data are modelled for a specific range of constraints by the inference system, allows these variables to be calculated. Any of the numerous optimization functions might be used to alter the parameters to eliminate any incorrect measurements if the gradient vector had been obtained.

TABLE 1. Observation Table

Experiment no	Electrode stick out	Arc voltage	Welding speed	Weight before welding (gm)	Weld deposition	Weight after welding	Welding current
1	10	20	3.25	765	12	777	180
2	6	20	3.25	770	10	780	180
3	6	24	4.54	768	13	781	180
4	10	24	3.65	775	17	792	180
5	6	20	3.64	778	8	786	180
6	10	20	5.44	780	10	790	180
7	6	24	3.65	771	17	788	200

8	6	24	3.64	767	15	782	180
9	6	24	5.44	769	16	785	200
10	10	20	3.65	780	14	794	200
11	6	20	3.85	776	12	788	200
12	10	24	3.85	777	19	796	200
13	6	22	4.16	773	13	786	200
14	8	22	3.85	776	11	787	200
15	6	20	4.16	773	10	783	200
16	10	24	3.85	770	10	780	200
17	10	20	4.16	776	10	786	200
18	10	24	4.16	768	15	783	180
19	6	22	3.85	775	13	788	190
20	8	20	4.54	773	10	783	190
21	10	22	4.16	781	15	796	200
22	8	24	3.85	771	17	788	190
23	6	22	4.54	777	11	788	190
24	8	22	3.85	772	15	787	200
25	8	20	4.16	777	12	789	200
26	6	20	3.85	772	10	782	190
27	10	24	4.16	769	17	786	190
28	10	22	3.85	774	15	789	190
29	6	24	4.16	768	15	783	190
30	8	24	4.16	775	15	790	180
31	10	20	3.85	774	12	786	190
32	8	20	4.16	778	10	788	180
33	10	22	4.54	773	13	786	190
34	8	24	4.54	776	15	791	190
35	8	22	4.54	774	11	785	180
36	8	20	3.85	780	12	792	190
37	10	22	3.26	776	13	789	180
38	8	22	3.25	771	13	784	180
39	8	24	4.30	777	17	794	200
40	6	22	4.25	773	11	784	180

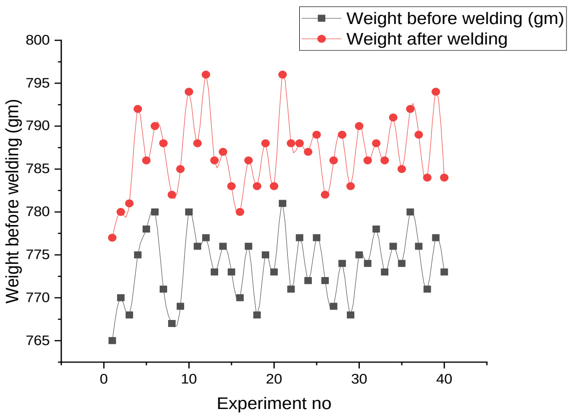

Fig:4 Graphical Representation of Weld Metal Deposition (Experimental Results)

The structure proposed by ANFIS (Fig: 2) uses Sugeno type fluid-type interference systems and in order to execute training group of data it uses bell-shaped membership which is Gaussian generalized. It contains 120 total parameter numbers, 30 nonlinear,90 linear,70 nodes, 60 training pairs, 10 control pairs of data and 24 floating rules for predicting weld metal deposition. The ANFIS modeling process begins with the acquisition of a pair of input-output data sets and the division into training and data monitoring. For finding the initial membership function this information of training data is taken.

$$\text{final output (f)} = \sum_1^N w_1 f_1 / \sum_1^N w_i \qquad (1)$$

where, f_i = level for output level for each rule, w_i = firing strength of the rule

4. Developed Mathematical model

The RA for treatment combinations of 1, 2, 3, 4, 5, 6, 7, 8 and 8, 9,10 is the optimal response value as RA (R1, R2, R3, R4, R5, R6, R7, R8, R9, R10) RE
The following equation depicts the relationship between main effects, interactions, and response:

$$R = A_0 + A_1M_1 + A_2M_2 + A_3M_3 + A_4M_4 + A_{12}(M_1M_2) + A_{13}(M_1M_3) + A_{14}(M_1M_4)) + A_{23}(M_2M_3) + A_{24}(M_2M_4)) + A_{34}(M_3M_4)$$

R_i (i = 1 to 10) is reacted by the i^{th} -treated coefficient, b0 is mean of reactions, and A_w (w = 1 to 4) is the coefficient of j_{th} main factor. The interaction factor is the coefficient (w= 1 for voltage, 2 for current, 3 for speed, 4 for weld deposition), and A_{wl} (w, L=1 to 4) values were calculated as follows for all these coefficients:

$$A_0 = \Sigma R_{i/10}$$
$$= [(R_1+R_2+R_3+R_4+R_5+R_6+R_7+R_8+R_9+R_{10})] / 10$$
$$A_1 = [(R1-R2+R_3-R_4+R_5-R_6+R_7-R_8-R_9-R_{10})] / 10$$
$$= [(R_1+R_3+R_5+R_7)-(R_2+R_4+R_6+R_8+R_9+R_{10})] / 10$$
$$A_2 = [(R_1+R_2-R_3-R_4+R_5+R_6-R_7-R_8+R_9+R_{10})] / 10$$
$$[(R_1+R_2+R_5+R_6+R_{10})-(R_3+R_4+R_7+R_8+R_9)] / 10$$
$$A_3 = [(R_1+R_2+R_3+R_4-R_4-R_5+R_7-R_8-R_9-R_{10})]/10$$
$$= [(R_1+R_2+R_3+R_4+R_5)-(R_6+R_7+R_8+R_9+R_{10})] / 10$$
$$A_4 = [(R1-R2-R_3+R4-R5-R_6+R_7-R_8-R_9+R_{10})] / 10$$
$$= [(R_1+R_4+R_6+R_7+R_{10})-(R_2+R_3+R_5+R_8+R_9] / 10$$
$$A_{12} = [(R1-R2+R_3+R_4+R_5+R_6+R_7+R_8+R_9+R_{10})] / 10$$
$$= [(R_1+R_4+R_5+R_8+R_9)-(R_2+R_3+R_6+R_7+R_{10})] / 10$$
$$A_{13} = [(R_1-R_2+R_3-R_4-R_5+R_6-R_7+R_8+R_9+R_{10})] / 10$$
$$= [(R_1+R_3+R_6+R_8+R_{10})-(R_2+R_4+R_5+R_7+R_9)] / 10$$
$$A_{14} = [(R_1+R_2-R_3-R_5-R_6+R_7+R_8+R_9+R_{10})] / 10$$
$$= [(R_1+R_2+R_7+R_8+R_9)-(R_3+R_4+R_5+R_6+R_{10})] / 10$$
$$A_{23} = [(R_1+R_2-R_3-R_4-R_5-R_6+R_7+R_8+R_9+R_{10})] / 10$$
$$= [(R_1+R_2+R_7+R_8+R_{10})-(R_3+R_4+R_5+R_6+R_9)] / 10$$
$$A_{24} = [(R_1-R_2+R_3-R_4-R_5+R_6-R_7+R_8+R_9+R_{10})] / 10$$
$$= [(R_1+R_3+R_6+R_8+R_{10})-(R_2+R_4+R_5+R_7+R_9)] / 10$$
$$A_{34} = [(R_1-R_2-R_3+R_4+R_5-R_6-R_7+R_8-R_9+R_{10})] / 10$$
$$= [(R_1+R_4+R_5+R_8)-(R_2+R_3+R_6+R_7-R_9+R_{10})] / 10$$

As noted above, the values of distinct impacts can be determined as follows:
$A_0 = 18.235$, $A_1 = -1.6325$, $A_2 = 3.3251$, $A_3 = -0.0452$, $A_4 = 0.2236$, $A_{12} = -3.2536$, $A_{13} = 1.02740$, $A_{14} = 0.8798$, $A_{23} = 0.8956$, $A_{24} = 1.0860$, $A_{34} = -2.8525$

This means that the actual model can be described by:
$$R = 18.235 + (-1.6325)M_1 + (3.3251)M_2 + (-0.0452)M_3 + (0.2236)\,M_4 + (-3.2536)\,(M_1M_2) + 1.02740(M_1M_3) + 0.8798(M_1M_4)) + 0.8956(M_2M_3) + 1.0860(M_2M_4)) + -2.8525(M_3M_4)$$

4. RESULTS AND DISCUSSION

Given that the input data range differ considerably from the numerical value standard to a standardized input scale for the ANFIS model, this was accomplished by normalization with a range (2) of 0.1-0.10. Table 2 shows the comparison of experimental results and ANFIS predictions including the normalized input parameters

$$y = 0.1 + 0.10\left(\frac{\text{X}-\text{Xmin}}{\text{X max}-\text{Xmin}}\right) \qquad (2)$$

TABLE 2. Weld Metal Deposition with Error (Normalized Predicted Results)

Experiment No.	Electrode stick out	ANFIS prediction	Arc voltage	Welding speed	Weld metal deposition	error	Welding current
1	0.1	0.62	0.9	0.1	0.61	0.01	0.1
2	0.1	0.38	0.1	0.1	0.39	-0.01	0.9
3	0.10	0.21	0.1	0.9	0.25	-0.03	0.1
4	0.10	0.61	0.1	0.1	0.54	0.07	0.9
5	0.1	0.2	0.1	0.9	0.25	-0.04	0.9
6	0.1	0.27	0.1	0.1	0.25	0.02	0.1
7	0.1	0.08	0.1	0.9	0.1	-0.02	0.1
8	0.1	0.47	0.9	0.9	0.46	0.01	0.1
9	0.10	0.37	0.1	0.1	0.39	-0.02	0.1
10	0.10	0.77	0.9	0.1	0.75	0.01	0.1
11	0.9	0.21	0.1	0.9	0.25	-0.03	0.9
12	0.1	0.49	0.9	0.9	0.68	-0.19	0.9
13	0.1	0.46	0.5	0.46	0.46	0	0.9
14	0.1	0.79	0.9	0.1	0.75	0.04	0.9
15	0.10	0.61	0.9	0.9	0.61	0	0.1
16	0.10	0.77	0.9	0.1	0.9	-0.13	0.9
17	0.5	0.69	0.9	0.1	0.75	-0.07	0.5
18	0.10	0.21	0.9	0.9	0.25	-0.04	0.9
19	0.5	0.26	0.5	0.9	0.32	-0.06	0.9
20	0.5	0.16	0.1	0.9	0.25	-0.09	0.5
21	0.1	0.45	0.5	0.1	0.46	-0.01	0.5
22	0.1	0.27	0.5	0.9	0.32	-0.05	0.5
23	0.1	0.59	0.9	0.46	0.61	-0.02	0.5
24	0.5	0.36	0.1	0.46	0.39	-0.03	0.9
25	0.5	0.58	0.5	0.1	0.61	-0.03	0.9
26	0.5	0.43	0.9	0.9	0.61	-0.18	0.5
27	0.10	0.58	0.5	0.1	0.61	-0.03	0.5
28	0.5	0.31	0.5	0.9	0.32	0	0.1
29	0.5	0.6	0.9	0.46	0.75	-0.16	0.9
30	0.10	0.5	0.5	0.46	0.61	-0.11	0.9
31	0.10	0.29	0.5	0.9	0.46	-0.17	0.5
32	0.5	0.6	0.9	0.46	0.61	-0.01	0.1
33	0.10	0.47	0.5	0.46	0.46	0	0.1
34	0.10	0.6	0.9	0.46	0.75	-0.16	0.5
35	0.10	0.36	0.1	0.46	0.39	-0.03	0.5
36	0.5	0.23	0.1	0.46	0.25	-0.01	0.1
37	0.1	0.25	0.1	0.46	0.25	0.01	0.5
38	0.1	0.33	0.5	0.46	0.32	0.01	0.1
39	0.5	0.45	0.5	0.1	0.46	-0.01	0.1
40	0.5	0.36	0.1	0.1	0.39	-0.03	0.5
41	0.10	0.46	0.5	0.46	0.54	-0.07	0.5

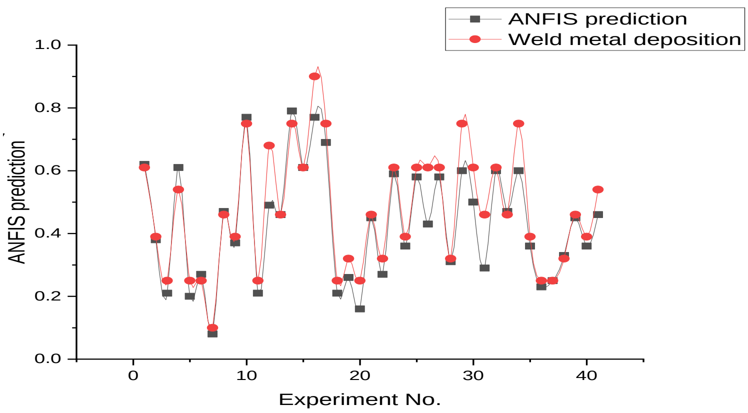

Fig:6 Graphical Representation of Weld Metal Deposition with Error (Normalized Predicted Results By ANFIS)

The first 41 sets of data are taken in order to train the ANFIS model, to test the model the next 16 sets of data are used, and the last 17 set of data is taken for network validation. Using ANFIS estimated data, GA was used to optimize the operation. MATLAB is used to write the objective function of Genetic Algorithm, and the software was run to obtain values for population size and generation number by using minimum deposition as a criterion. As output of the executed program, population size v/s graphs were produced with the minimum average reaction and the average number of generations v/s. The best appropriate values for generational number and population size are 65 for fig: 3 and 50 for fig. 5 and this is the minimum deposition.GA gets converged in the selected generation with the best appropriate minimal value of the sold metal deposition and 50 is selected for the generation. The optimized welding condition can be achieved by using the multi input single objective genetic algorithm, so that welding metal deposition can be reduced. The input conditions for the optimization are set out below (Table III). Lower arc voltage, welding current and electro magazine are observed, and higher welding speed values are minimal to the metal deposition

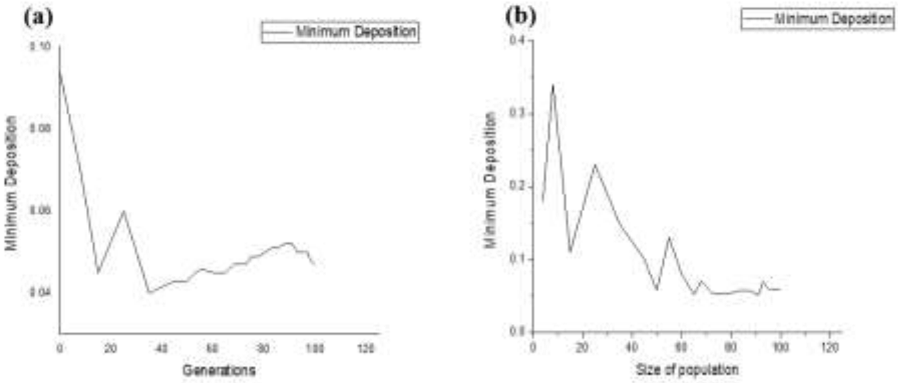

Fig: 7. (a) Graph showing Minimum Deposition v/s No. of generations, b) Graph showing Minimum Deposition v/s population size

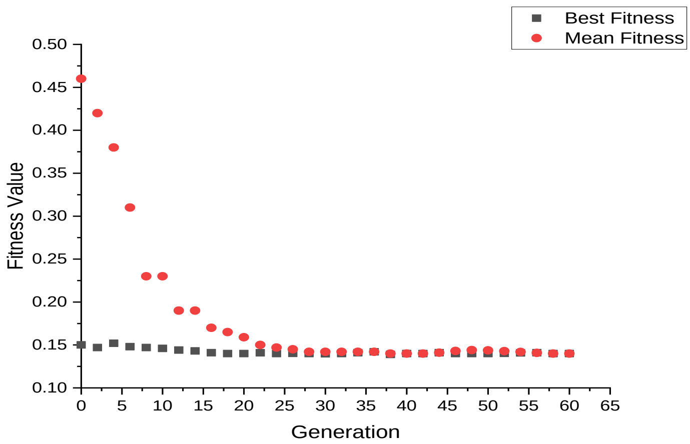

Fig: 9. Graph showing Fitness values v/s generation

The MATLAB Software evaluated the sold metal deposition in order to obtain minimum deposition criteria for the normalized value of the input parameters. The results showing genetic algorithm are presented in Fig. 7 and these are obtained using MATLAB. An example of the results of Optimization validated with the experimental outcome is the contrast between Fig: 7 and table III. It is observed that for the 5th set of experiment, the output results obtained from genetic algorithm and the range of data given for input are both different. Fig:8 Graph showing Minimum Deposition v/s population size and Fig: 9. Graph showing Fitness values v/s generation.

Table 3 Comparative analysis of normalized, Experimental, Optimized Input data

Val. / Par.	Normalized Input Data	Optimized Input Data	Experimental Input Data
Welding speed	0.9	0.7985	5.21
Electrode stick	0.1	0.1125	5
Arc voltage	0.1	0.1010	24
Welding current	0.1	0.1110	200
Weld's ANFIS Prediction	Experimental Weld Metal	Weld Metal GA output	Normalized Value of Weld Metal
0.09	9	0.0965	0.2

5. CONCLUSION

- Fuzzy Interference System is the basis of the proposed ANFIS, which was designed to prevent the deposition of soil metal in a MAG phase. Corrected data range from Neuro Genetic modelling and optimization has been achieved. Table III indicates the difference which is shown for the optimized and normalized input data.
- This achieved data will leads to the machine achieving accurate results that are not possible to be produced by the normal human observations. The difference or the error which occurred between the two sets of data that is optimized and experimental, can be used to be applied as the error to the system through the feedback and this process goes on in order to achieve minimum error.
- This current work will be developed further by this process. If it is needed to extend this work, we can make use of other welding parameters as well which includes form of material, its effect on deposition of weld metal, electrode diameter, thickness of base metal etc.
- Simultaneously in order for the device environment to be more realistic simultaneously, and in order to optimise deposition of the soft metal along with penetration depth, weld power etc. with multi-target GA, here we are using genetic algorithm.

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