ANFIS Model for Interaction of Parameters of Submerged Arc Welding Process for Mild Steel Plates of Higher Thickness

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ABSTRACT

The interactions of welding input parameters are studied by an ANFIS model in MATLAB of Submerged Arc Welding process. SAW is a high quality, very high deposition rate welding process commonly used to joint plates. The main objective is to identify the main input factors, to determine the interaction amongst the input factors and finally establish the optimum model for predicting the weld bead parameters that leads to the desired weld quality. This paper proposes an Adaptive Neuro Fuzzy Inference System (ANFIS) technique of fuzzy based systems for modelling and simulation of the Submerged Arc Welding process. The performance of the ANFIS model developed is validated by comparing the predicted results with the actual experimental results.

Keywords: SAW, ANFIS, FIS, Submerged Arc Welding, bead width and reinforcement height

INTRODUCTION

Submerged arc welding (SAW) is a widely used industrial process particularly in heavy equipment industries and machinery which have high economic and social implications. SAW provides a purer and cleaner high volume weld with deposition rate much higher than the traditional welding methods. To predict suitable values for various welding parameters that provide consistent weld quality an improved understanding of complex parameters of SAW process is required. Research has been carried out to predict the process parameters of the SAW that provide consistent quality for weld.

Extensive studies have already been reported on effect of welding parameters on the bead geometry and properties of the weld metal produced by SAW process. Mc Pherson et al (1997) studied the structure of the dissimilar welds by SAW process. Chandel et al (1997) studied the effect of increasing deposition rate on the bead geometry of SAW. Yang et al (1993) studied the effects of SAW process variables on the weld deposition area. Revaandra and Parmar (1987) used mathematical model to predict the weld bead geometry for the flux cored welding process. Gunaraj et al. (2000a,b) used mathematical models for prediction and optimization of weld bead volume for the SAW. Multiple regression analysis has been used (Tarng & Yang,1998; Lee & Rhee, 2000; Lee & Um, 2000; Jeongick & Kiwoam, 2000) to predict process parameters for gas arc welding. Kim et al (2002) studied the effects of welding process parameters on weld bead width in GMAW processes. Nagesh and Datta (2002) & Kim et al (2002) trained Artificial Neural Networks to predict the weld bead geometry and penetration in shielded metal arc welding. Di et al (2002) applied neural network based Fuzzy logic to control arc welding process. Radovan and Yu (1997), Luo et al (2002), Dilthey & Hichri (2003), Gao & Yu (2003) used Neuro Fuzzy models to control the fusion state of fully penetrated welds in gas tungsten arc (GTA) welding, optimize the weld pool geometry, to monitor and control the on line checking of GMA welding processes and control weld penetration in GTA welding. Prediction and control of weld bead geometry and shape relationships in SAW of pipes was studied by Murugan et al (2005). Raja and Kumanan (2007) used hybrid intelligent technique to predict weld quality in SAW process for a given set of welding parameters. Kummanan et al (2007) used Taguchi method and regression analysis to determine SAW process parameters. Raja Dhas, J.E. and Kumanan, S.. (2007) used ANN to determine the weld bead in SAW process. ANFIS model has been used in this present work to predict the welding parameters in SAW process.

SUBMERGED ARC WELDING

In this process, the arc is covered by the flux heat loss is minimum. The thermal efficiency of the process is as high as 95%. Welding current for submerged arc welding can vary from as low as 50 amperes to as high as 2000 amperes. The stability of the arc depends on the flux. Chemical and mechanical properties of the weld can be controlled by the flux. The quality of the weld may be affected by the quality and quantity of the flux used over the arc.

WELDING VARIABLES

Selection of the correct welding conditions for the plate thickness and joint preparation to be welded is very important, if satisfactory joints free from defects such as cracking, porosity and undercut are to be obtained. The important process variables are Electrode polarity, Welding current, Electrode diameter, Arc voltage, Welding speed, Electrode extension, Electrode angle, Flux depth. These are the variables that determine bead size, bead shape, depth of penetration, metal deposition rate, reinforcement height and in some circumstances metallurgical effects such as incidence of cracking, porosity and weld metal composition. In the present work welding speed, voltage and current are considered as important input variables and metal deposition rate, bead width and reinforcement height are the response variables.

EXPERIMENTAL

This experimental study was conducted at the ISM workshop (Dhanbad). For this study MEMCO semi-automatic welding equipment with constant rectifier was used as shown in Figure 1. The flux used is ADOR auto melt Gr. II AWS/SFA 5.17 (Granular flux) mad a electrode of ADOR 3.15 diameter copper coated wire. To prepare the sample for experiment a long mild steel piece was selected and cut it to the required dimension and shape with the help of oxy-acetylene in the welding shop. The mild steel piece was having thickness more than 10mm. After cutting it into pieces one of the edges of each of these plates were prepared in such a way that with two such prepared edges from two plates can produce a V groove required for welding when assembled together. The plates were tack welded at the V groove and subsequently welded by SAW process by depositing weld metal in the groove.

The submerged arc welding machine was started. Flux was filled in the machine so that there may be no problem between the experiments. The machine is fully automatic. The welding was done on each sample. The welding parameters travel speed, current, voltage were varied each time. Total time taken for the welding was recorded and weight of sample before and after each welding was also recorded.

The welding parameters were noted during the actual welding to determine the fluctuations if any. The slag was removed and the job was allowed to cool down. The values of the reinforcement height, and the bead width were taken with the help of vernier callipers of least count 0.02mm. And the metal deposition rate was also calculated with the help of a stop watch and the weighing machine. The readings obtained are presented in Table 1.

ADAPTIVE NEURO FUZZY INFERENCE SYSTEM (ANFIS) MODEL

Fuzzy logic theory is one of the most innovative, active and fruitful areas of research for science and engineering applications, especially in the field of industrial processes. The fuzzy logic represents a methodology that allows us to obtain defined solutions from vague, ambiguous or uncertain information. The rule-based character of fuzzy models allows for a model interpretation in a way that is similar to the one humans use to describe reality.

The modeling of submerged arc welding has been done using Adaptive Neuro Fuzzy Inference System (ANFIS) by considering three input parameters and three output parameters. The Adaptive Neuro-Fuzzy inference system (ANFIS) is an advanced technique of fuzzy based systems for modeling and simulation of the complex systems. It has been employed here for predicting the metal deposition rate, bead width and reinforcement height. In order to compute the input membership function parameters subtractive clustering method is used. Using the genfis2 command in MATLAB the three input parameter's membership functions are determined. These membership functions parameters are tuned using a hybrid system that contains the combination of back propagation and least squares type method. 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. This system is based on Sugeno-type system and can simulate and analyze the mapping relation between the input and output data through a hybrid learning to determine the optimal distribution of membership function. The fuzzy logic is based on the determination of the fuzzy-set that represents the possible values of the variables. Figure 2 shows the fuzzy model for prediction of metal deposition rate from three input variables of submerged arc welding. The number of fuzzy rules is 2.

The fuzzy theory with respect to the traditional logic theory, according to which an element can belong or not to a particular set, allows the partial membership of an element to a set. Each value of the variables is characterized by a membership value which changes with continuity from zero to one. Thus, it is possible to define a membership function for each variable that establishes the membership rate of a variable at a certain set. In the present study there are three input variables and one output variable. Figure 3 shows the Membership function plots of three input variables for metal deposition rate prediction model.

RESULTS AND DISCUSSION

Effect of Travel Speed on Bead Parameters

Travel speed has a negative effect on all the three bead parameters. An increase in the travel speed substantially reduced the heat input resulting in lower burn off rate. This reduced burn off rate decreases the metal deposition at the weld joint thereby lowering all the three parameters i.e. penetration, reinforcement height and the width.

Effect of current on bead parameters

It is seen that the penetration increases with the current, the reinforcement height also increases marginally with the increase in the current but the width decreases. The increase in current results in decreasing arc length as well as prevents the spreading of the cone which results in higher melting temperature at the tip and the parent material, resulting in deeper penetration at the cost of the bead width. The decrease in bead width helps in marginally increasing the reinforcement height.

Effect of Voltage on Bead Parameters

It is generally observed that the arc voltage increases, the weld bead becomes wider and flatter and the penetration decrease.

The effects of changing voltage are explained as follows:

1. Increasing the voltage
   a) Produces a flatter and wider bead
   b) Increases flux consumption
   c) Helps bridge up the gap when the fit up is poor
   d) increase the pickup of the alloy from the flux: this can be used to advantage to raise the alloy content of the weld when welding is performed with the alloy or hard surfacing fluxes.
2. Excessively high voltage
   a) Produces poor slag removal in the groove welds
   b) Produces a hat shaped bead that is subjected to crack
   c) Increase undercut on fillet welds

The number of ANFIS rules used for the present models is 2. The results of the three fuzzy models developed for three responses (metal deposition rate, bead width, and reinforcement height) are presented in Table 2. The experimental values and the ANFIS model predicted values are plotted for comparison in Figure 4.The maximum absolute percentage error for metal deposition rate model is 5.38%. The absolute testing error is less than 2.5%.

The deviation of the predicted values for each experimental value is plotted in Figure 5. It is possible to design a model to get very low error by changing the radius of the cluster and the number of epochs. The model is designed to get maximum error in the range of experimental measurement error. The comparison of the experimental values and the predicted values of the bead width is presented in Figure 6. The maximum absolute error for bead width ANFIS model is 9.58% for a deviation of about 1.3 mm of bead width as shown in Figure 7. The predicted values of the reinforcement height are plotted in Figure 8 along with the experimental values. The maximum absolute error for reinforcement height ANFIS model is 3.05% (for a deviation of 0.07 mm) as shown in Figure 9. The models can be used to predict the metal deposition rate, bead width and reinforcement height for a given set of speed, voltage and current without conducting experiments. Table 3 shows the summary of the of the ANFIS models and the respective R-square values, Training and Checking Root Mean Square values for corresponding radii for different parameters.

CONCLUSIONS

The ANFIS model developed is based on first order Sugeno-fuzzy inference system using MATLAB toolbox. The proposed ANFIS models predict the metal deposition rate, bead width, and reinforcement height of submerged arc welding process for a given input parameter values of speed, voltage, and current. The model predicted results matched well that of experimental values thus validating the models. The trained network is used to predict the quality parameters of the weld. The ANFIS model is flexible and accurate enough to consider for a online monitoring system.

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Table 1 : Experimental Data

Travel speed (cm/min)	Voltage (Volts)	Current (amp)	Metal deposition rate (gm/sec.)	Bead width (mm)	Reinforcement height (mm)
25	25	300	0.810	13.0	3.2
28	26	320	0.909	12.5	2.0
24	28	280	0.759	13.0	2.6
27	24	300	0.550	13.6	3.5
20	20	400	1.500	11.7	5.0
16	20	280	1.250	10.0	1.7
17	19	380	0.909	12.0	2.0
21	38	450	0.792	21.9	2.6
21	30	320	0.681	15.5	2.0
17	3	300	0.869	13.8	2.3
16	23	280	1	16.3	1.0
12	23	300	0.877	23.0	0.6
17	22	320	0.869	18.7	2.3
20	25	340	1.224	13.8	2.4

Table 2 : Predicted data and Percentage error

Metal deposition rate (gm/sec.)	predicted metal deposition rate (gm/sec.)	percentage effor of metal deposition rate (gm/sec.)	bead width (mm)	predicted bead width (mm)	percentage bead width error	reinforcement height (mm)	predicted reinforcement height (mm)	percentage reinforcement height error
0.81	0.8536	-5.382716	13	12.7631	1.82230769	3.2	3.2233	-0.72812
0.909	0.9114	-0.2640264	12.5	13.5618	-8.4944	2	2.0017	-0.085
0.759	0.7314	3.63636364	13	13.5739	-4.41461538	2.6	2.5971	0.111538
0.55	0.5275	4.09090909	13.6	12.2969	9.58161765	3.5	3.4845	0.442857
1.5	1.5144	-0.96	11.7	11.8278	-1.09230769	5	5.0006	-0.012
1.25	1.2612	-0.896	10	10.0464	-0.464	1.7	1.6863	0.805882
0.909	0.9043	0.51705171	12	12.0909	-0.7575	2	1.9977	0.115
0.792	0.7838	1.03535354	21.9	21.7137	0.85068493	2.6	2.6001	-0.00385
0.681	0.7327	-7.5917768	15.5	15.4012	0.63741935	2	1.999	0.05
0.869	0.8698	-0.0920598	13.8	13.82	-0.14492754	2.3	2.2297	3.056522
1	0.9711	2.89	16.3	16.2295	0.43251534	1	1.0437	-4.37
0.877	0.8844	-0.8437856	23	23.0173	-0.07521739	0.6	0.5951	0.816667
0.869	0.8808	-1.3578826	18.7	18.6469	0.28395722	2.3	2.3476	-2.06957
1.224	1.1726	4.19934641	13.8	13.8113	-0.08188406	2.4	2.3934	0.275

Table 3 : Overall model performance parameters

	Radius	TRSE	CRSE	R-square
Metal deposition rate	1.003	0.0267	0.0698	0.98755
Bead Witdth	0.9706	0.4848	0.6593	0.98279
Reinforcement height	0.9241	0.027	0.1886	0.99932

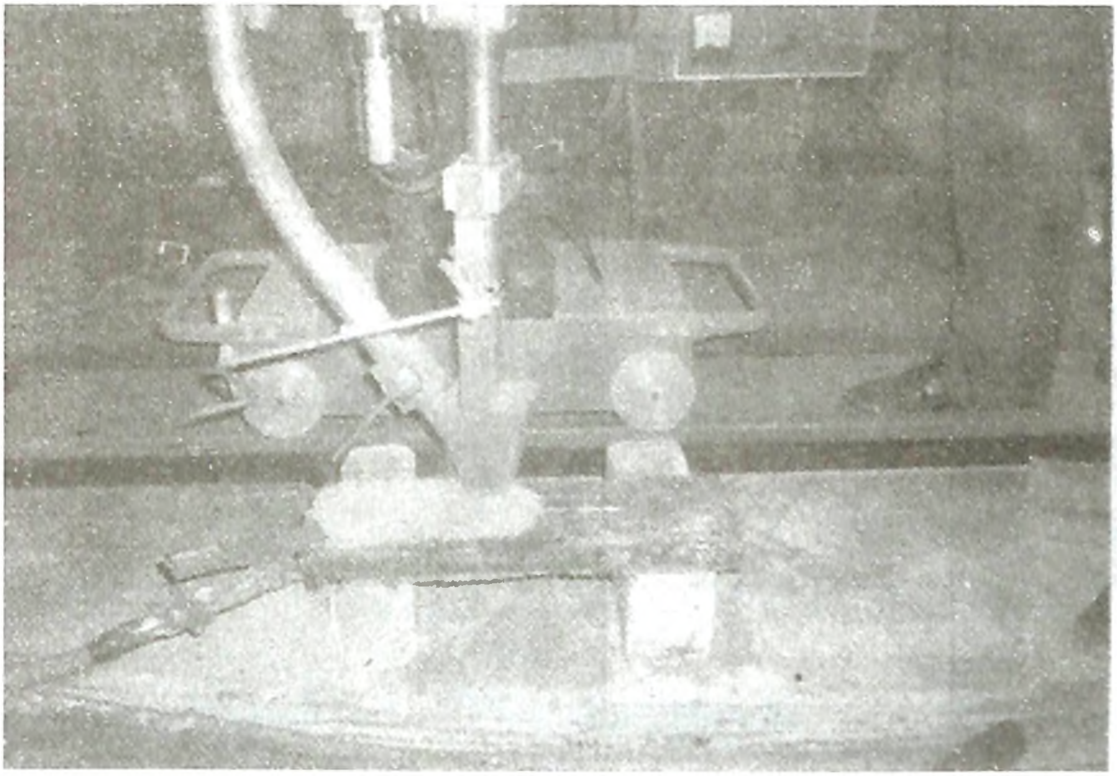

Fig. 1 : SAW Welding in process

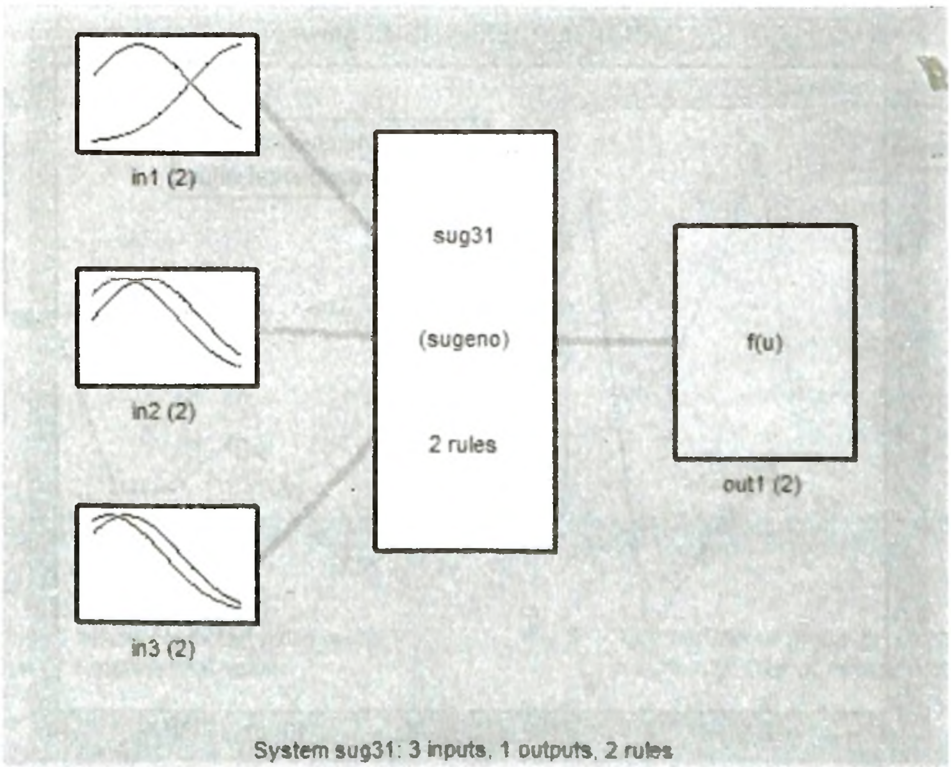

Fig. 2 : Structure of ANFIS for Metal Deposition Rate

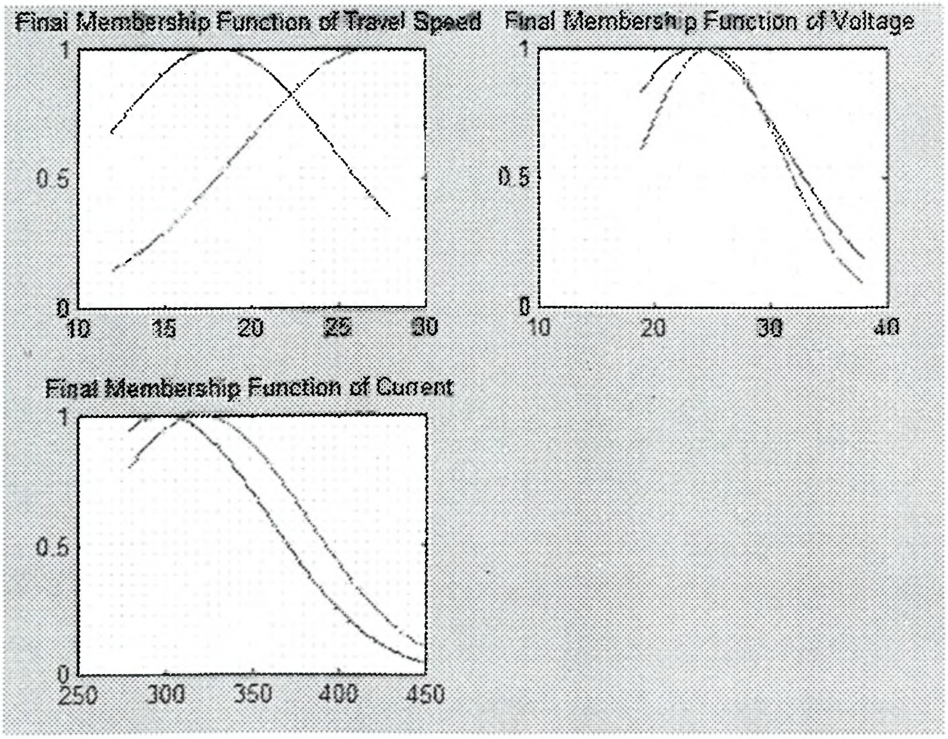

Fig. 3 : Membership functions for input parameters for Metal Deposition Rate

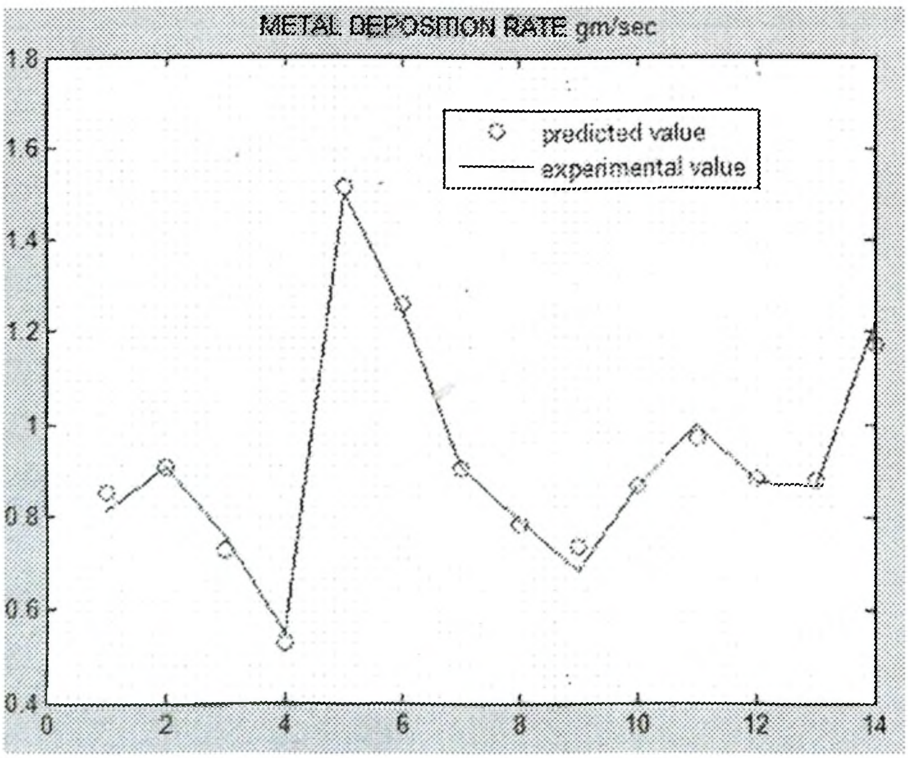

Fig. 4 : Comparison of model predicted metal deposition rate with that of experimental value

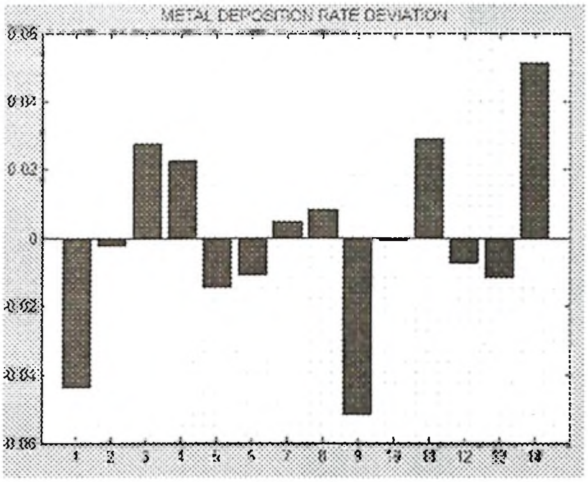

Fig. 5 : Deviation model predicted metal deposition rate with that of experimental value

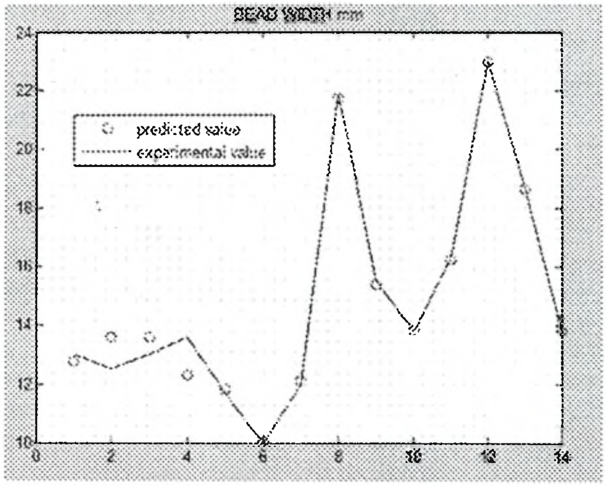

Fig. 6 : Comparison of model predicted bead width with that of experimental value

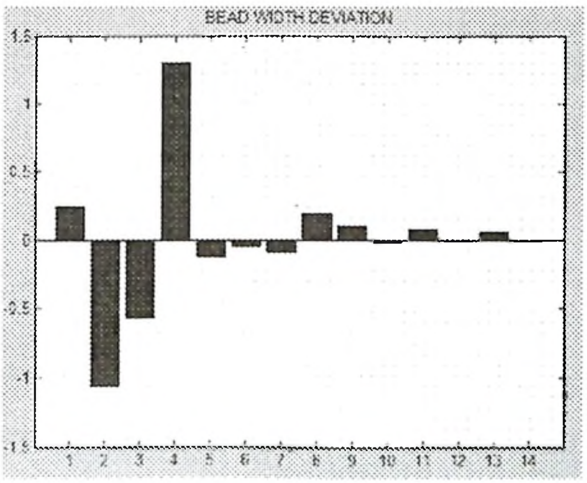

Fig. 7 : Deviation of model predicted head width with that of experimental value

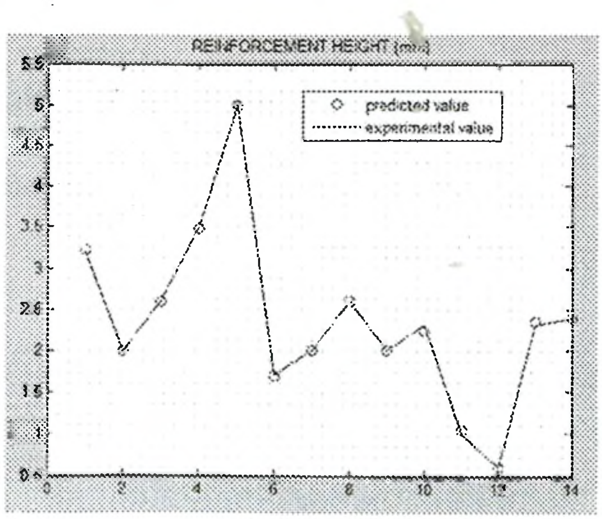

Fig.8 : Comparison of model predicted reinforcement height with that of experimental value

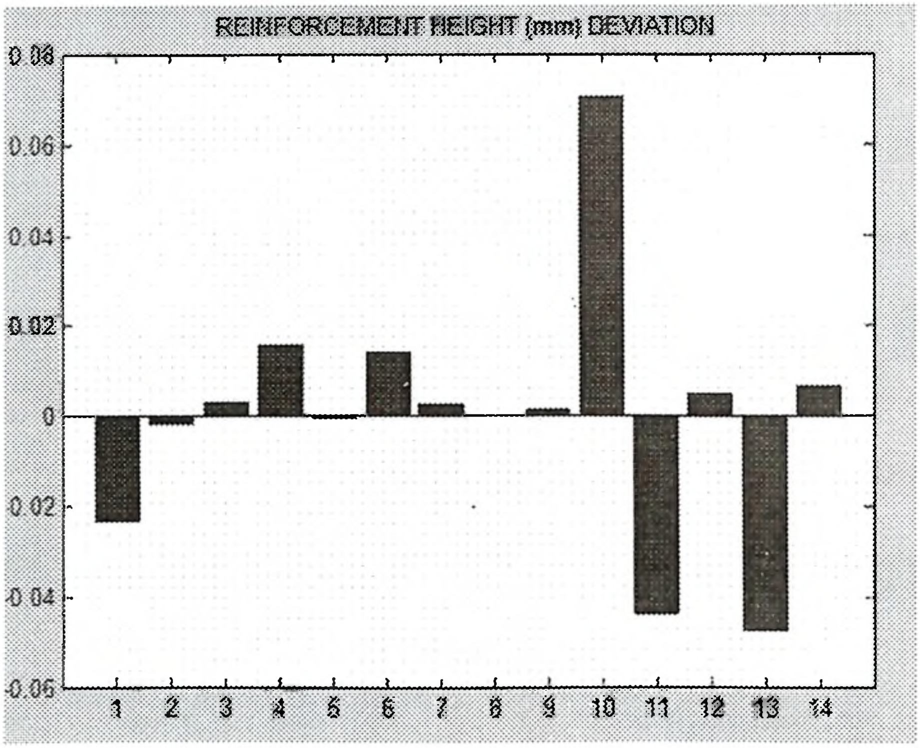

Fig. 9 : Deviation of model predicted reinforcement height with that of experimental value