Parametric Modeling of SAW Process using Genetic Algorithms Based Technique

P Sahithi, V Srujana, S Khaleed Saifulla, D Kondayya

Abstract: ***The main aim of the present work paper is to apply a novel and efficient evolutionary technique in modeling welding responses which is very essential in subsequent optimization of the welding process. Submerged arc welding (SAW) being a highly efficient welding process owing to deep penetrant weld and smooth finish is used for the process modeling in the present research study. An empirical relationship is established between the significant input welding parameters and bead geometrical parameters (responses) by using a potential modeling tool namely, gene expression programming (GEP). Thus GEP gives the optimized model expressions to relate the responses to selected inputs. The various input parameters selected are Voltage, electrode wire feed, carriage speed and tube-end to work distance. These are altered to predict the responses namely, reinforcement, penetration and width of the bead. The models obtained have high correlation coefficients thus indicating the effectiveness of the GEP algorithm.***

Keywords : ***weld bead geometry, welding parameters, empirical modeling, genetic algorithms***

I. INTRODUCTION

Submerged arc welding is a widely used metal joining process having significant applications in ship building, pressure vessels, structural welding, surfacing etc. In this environmentally sustainable process the flux used is recyclable and also the arc is submerged underneath the flux resulting in no toxic fumes and arc exposure to the operator. SAW machines have been operated in semiautomatic or automatic mode in these industries due to the necessity to attain greater throughput and having emphasis on strict safety norms. The mechanical strength of the weld depends to large extent on not only the chemical composition of the weld metal but also the resultant weld bead geometry shape generated due to the welding procedure. Hence it is essential to monitor and control the weld bead shape by correct selection of weld parameters specifically in automated welding processes such as SAW. The weld bead shape shown in fig 1 is generally identified by three factors namely weld penetration, reinforcement and bead width and hence these parameters dimensionally control the weld bead shape.

Satisfactory weld bead shape is governed by number of weld factors. Some of these significant factors include Power input or the heat energy induced through the weld arc to the base plate, speed of weld carriage holding the electrode, weld joint preparation another factors.

In order to obtain this it is necessary to establish well defined relationships between the weld controlling parameters and weld bead parameters.

These relationships can be developed in the form mathematical models which relate the weld bead parameters to weld control parameters. Also the established expressions can be utilized to optimize the weld process parameters to achieve required weld bead shape and enhance the weld quality.

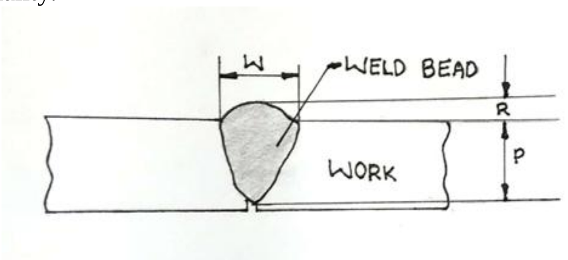

Fig 1: Weld bead Parameters (W – bead width; R – bead reinforcement; P – bead penetration)

A considerable number of researchers carried out various investigations for improving the process performance by proper selection of parameters. : Several researchers have studied the SAW process for enhancing the process performance by selecting proper weld parameters. Gupta and Parmar (1989) developed mathematical models for bead geometrical parameters using fractional factorial techniques. the models adequacy were statistically tested for their adequacy and significance. Datta et.al.(2008) have formulated and solved a multi-response optimization problem for obtaining a favorable bead geometry for bead on plate welding. Taguchi method with Grey relational analysis was used to obtain the optimal solution. Benyounis and Olabi (2008) have presented an exhaustive literature review on optimization of wide-ranging welding processes. They have systematically presented the various techniques used for modeling and optimization of several responses of the SAW process. N. Murugan and V. Gunaraj (2005) have presented the fractional factorial techniques for development of mathematical models to predict weld bead dimensions and shape relationships in SAW. The effect of process parameters on responses have been analyzed using main and interaction effects. Sensitivity analysis of SAW process parameters was presented by Serdar Karaoğlu, and Abdullah Seçgin (2008). The mathematical models for bead width and bead height in their study were developed using multi curvilinear analysis. Recently, Ankush Choudhary et.al (2019) have developed mathematical models for bead geometrical parameters in SAW of AISI 1023 plates.

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They have additionally included the flux condition and plate thickness in their work and used three optimization algorithms for comparing the results and reported that the Jaya algorithm is superior in performance.
Survey of the existing literature reveals that modeling of SAW process was based on statistical regression based techniques. But for a complicated welding process such as SAW regression based methodologies may not capture the implicit complex relationship between the responses and inputs. Hence in the present work a novel approach namely gene expression programming is used to model the complex relationship in SAW process and this approach has not been used in SAW process. Moreover genetic based approaches do not presuppose any model and allow the evolutionary model to predict the optimum ones [7].
This paper attempts to present an unconventional approach for modeling of responses in SAW. GEP [8] is used to obtain non- linear regression based empirical models for relating the responses of the weld bead geometry parameters ie., reinforcement, penetration and bead width with the input parameters.

II. METHODOLOGY

GEP is data driven regression modeling technique in which the training and validation data sets are inputs to the algorithm. The algorithm parameters are: number of generations, number of chromosomes, head size, number of genes, linking function and functions to generate model tree. Initial trial runs are performed by keeping the linking function, number of genes, head size and the functions used constants whereas number of generations and number of chromosomes are altered simultaneously to achieve desired results.
The finalized ranges of the above parameters are shown in the table- I.

Table- I: GEP Parameter ranges

Parameter	Symbol
Functions	+, -, / ,*
Number of generations	1000-10,000
Number of chromosomes	40-150
Number of genes	3
Size of head	8

After selecting the optimal parameters a model tree is generated and regression formula is obtained for the output parameters and the target values and the model values are plotted and compared.
SAW involves several control variables which affects the weld bead geometry. Review of previous research works lead to identification of four significant variables, namely, voltage (open circuit), electrode wire feed, carriage speed, tube-end to work distance were considered as the decision (control) variables and the reinforcement (R) , penetration (P) , bead width (B) are considered were output responses. Experimental trials were conducted to establish the best operating range of the SAW machine. Based on trials, working range finalized as shown in Table II. By combining the working ranges 100 experimental data was generated which were divided into the training data set and testing data set. These experiments work as the data bases for GEP to provide the model tree.

Data of 70 experiments were used for training while 30 experimental data were used to validate the models generated. Apportioning the experimental data in this way helps in achieving generalized expressions for the responses.

Table- II: Working range

Process Parameter	voltage (volts)	electrode wire feed (mm/min)	carriage Speed (mm/min)	tube-end to work distance (mm)
Working Range	31 - 39	1.7 - 3.7	0.25 - 0.75	29-37

By selecting a suitable working range for experiments weld effects such as porosity and slug inclusions can be eliminated. By combining the working ranges experiments were conducted to generate the training and validation data sets.

III. EXPERIMENTAL DETAILS

For measuring the bead geometry, after each experiment the welded joint was sectioned perpendicular to the weld directions. To expose the bead geometry, the sectioned weld specimens were thoroughly polished through the usual metallurgical polishing route and then etched in a 3% nital solution. This process reveals the bead shape which is then put under a profile projector and the bead geometrical parameters are traced and precisely measured. The base metal used for the experiments is IS2062 quality structural steel of dimensions 6mm×110mm×65mm. Electrode used is Automelt Gr. A 5(EL8) (AS-1), Ø 3.15mm, Coil form and SAW flux is Automelt (A55) (AWS F7AZ/PZ-EL8), Baked flux. The joint type is square butt joint with 1mm root opening. The SAW machine is of ADOR make.

Fig. 2 SAW machine used for experiments

IV. RESULTS AND DISCUSSION

genetic operators namely reproduction, mutation and cross-over to solve the problem. Genetic programming is based on the principles of Genetic algorithms and is symbolic regression based implementation of the GA philosophy in which the algorithm establishes the empirical relationship between input parameters and process responses with great correlation.

GEP algorithm is a further step in evolutionary computation for solving symbolic regression problems. This algorithm is much superior and improved implementation of the original GP methodology.
The GEP model was established using four prominent input parameters as follows:

BGP = f (d_0, d_1, d_2, d_3).
where BGP is bead geometry parameter (penetration/reinforcement/width)

(a) voltage (open circuit) (d_0), electrode wire feed (d1), carriage speed (d2), tube-end to work distance (d_3)

Table- II: Trials

Bead Reinforcement				*Bead Penetration*				*Bead width*			
G	*C*	*R^2*	*α*	*G*	*C*	*R^2*	*α*	*G*	*C*	*R^2*	*α*
100	*40*	*0.5782*	*0.7604*	*0*	*40*	*0.4377*	*0.666*	*1000*	*40*	*0.7368*	*0.8583*
1000	*50*	*0.6435*	*0.8022*	*1000*	*50*	*0.4613*	*0.6792*	*2000*	*40*	*0.856*	*0.8976*
2000	*0*	*0.6126*	*0.7827*	*2000*	*40*	*0.4093*	*0.6398*	*2000*	*50*	*0.75*	*0.866*
2000	*50*	*0.651*	*0.8068*	*5000*	*40*	*0.4557*	*0.675*	*3000*	*50*	*0.6699*	*0.8185*
2000	*80*	*0.6058*	*0.7783*	*5000*	*50*	*0.5879*	*0.7667*	*3000*	*40*	*0.765*	*0.8746*
3000	*40*	*0.6488*	*0.8054*	*5000*	*80*	*0.4782*	*0.6915*	*5000*	*40*	*0.7566*	*0.8698*
3000	*50*	*0.5852*	*0.7649*	*5000*	*100*	*0.4695*	*0.6852*	*5000*	*50*	*0.7579*	*0.8705*
4000	*40*	*0.6736*	*0.8207*	*5000*	*120*	*0.4689*	*0.6848*	*5000*	*80*	*0.793*	*0.8905*
4000	*50*	*0.5817*	*0.7627*	*6000*	*40*	*0.4702*	*0.6857*	*5000*	*100*	*0.7789*	*0.8825*
5000	*40*	*0.6779*	*0.8233*	*8000*	*40*	*0.4551*	*0.6746*	*7000*	*40*	*0.7249*	*0.8514*
5000	*50*	*0.6407*	*0.8004*	*8000*	*50*	*0.46*	*0.6782*	*7000*	*50*	*0.79909*	*0.8939*
5000	*80*	*0.6729*	*0.8203*	*8000*	*70*	*0.4875*	*0.6982*	*8000*	*40*	*0.7719*	*0.8785*
5000	*100*	*0.6488*	*0.8055*	*8000*	*80*	*0.4729*	*0.6877*	*8000*	*50*	*0.7532*	*0.8678*

After selecting the required working ranges and experiments are performed to generate Training and validation sets. These datasets are used by GEP to build the empirical model. GEP being heuristic algorithm several trials are needed to determine the optimum model. After performing these trials it can be observed that the model tree with highest R^2 and correlation value are selected to represent the bead geometry. R^2 and correlation coefficient can be calculated using following formula:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(X_i - x_i)^2}{N}}$$

Where X= predicted value, x= actual value

$$R = \frac{N(\sum ab) - (\sum a)(\sum b)}{\sqrt{(N\sum a^2 - (\sum a)^2)(N\sum b^2 - (\sum b)^2)}}$$

Where N= number in data set;

a= first variable, b= second variable

The R^2 coefficient and correlation coefficient values from the several trials are tabulated as shown in the table (3).

It can be seen that in reinforcement, trial with 5000 generations and 40 chromosomes is seen to have highest values, similarly in penetration it is 5000 generations and 50 chromosomes, in bead width it is 2000 generations and 40 chromosomes. Taking these trials into consideration, the target values and the model values are noted and compared. Simultaneously, expression trees are generated.

The comparison between the training data and GEP model output for the three bead geometry parameters are shown in fig 3 to fig 8. The figures are shown both for the training dataset and validation dataset as well. From the figures it can be inferred that that the generated models through GEP adequately represent the outputs. Hence it can be concluded with confidence that the generated models accurately represent the process responses within the experimental domain.

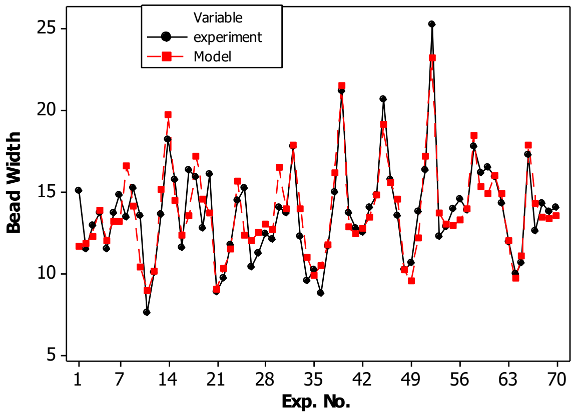

Fig. 3 Bead Width Training Vs GEP predicted

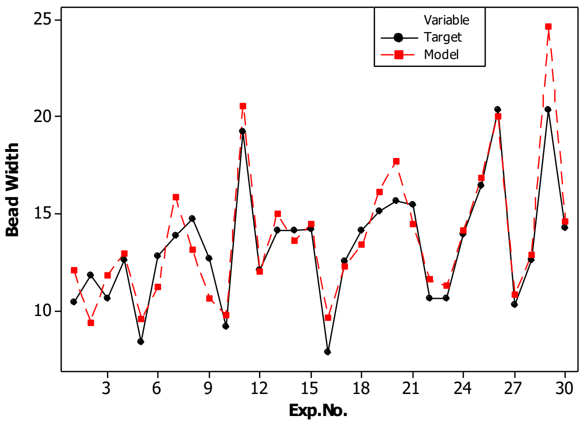

Fig. 4 Bead Width Validation Vs GEP predicted

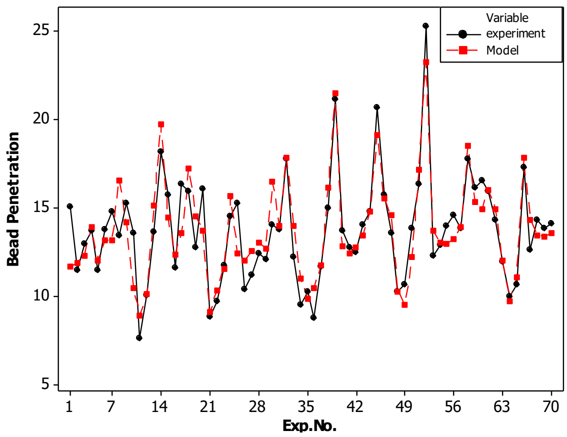

Fig. 5 Bead Penetration Training Vs GEP predicted

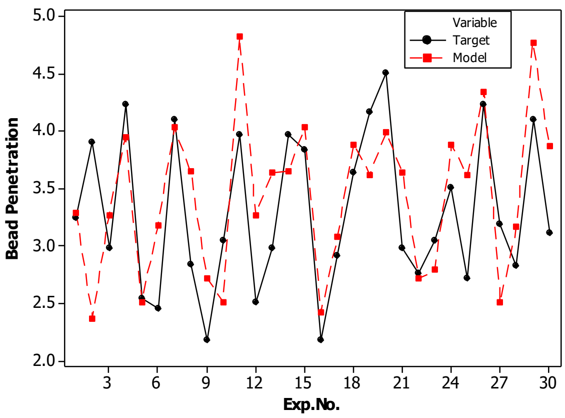

Fig. 6 Bead Penetration Validation Vs GEP predicted

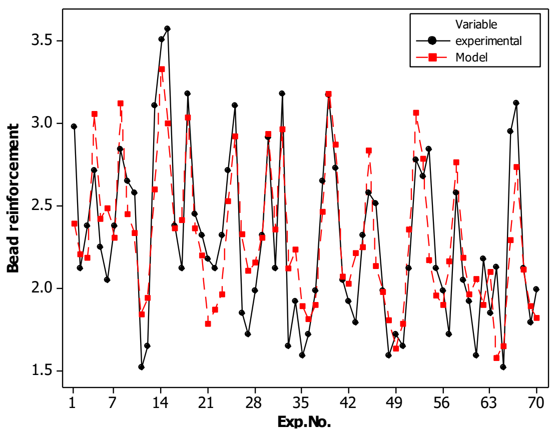

Fig. 7 Bead reinforcement Training Vs GEP predicted

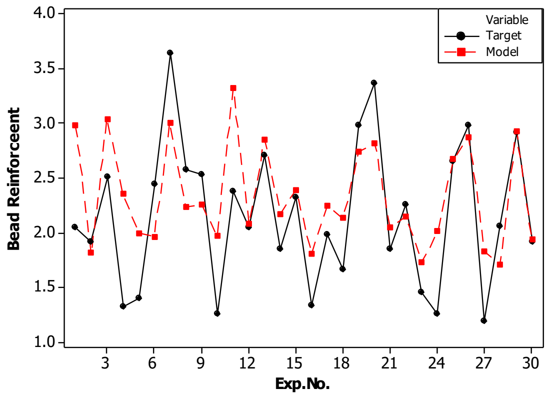

Fig.8 Bead reinforcement Validation Vs GEP predicted.

Expression trees for the bead geometry parameters generated at the end of the trials as mentioned above are given in fig. 9, fig. 10, and fig. 11.

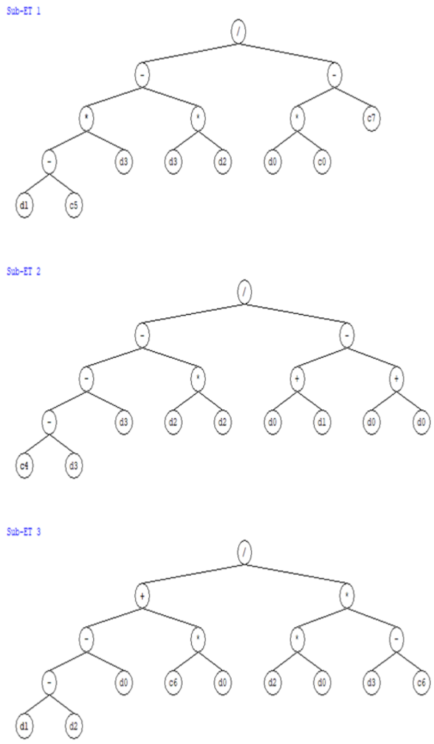

Fig 9 Model tree of reinforcement

The final expression tree is obtained by summing up the sub trees namely sub-ET1, sub-ET2, and sub-ET3. The individual expressions for all the bead geometrical parameters are evaluated in the similar procedure

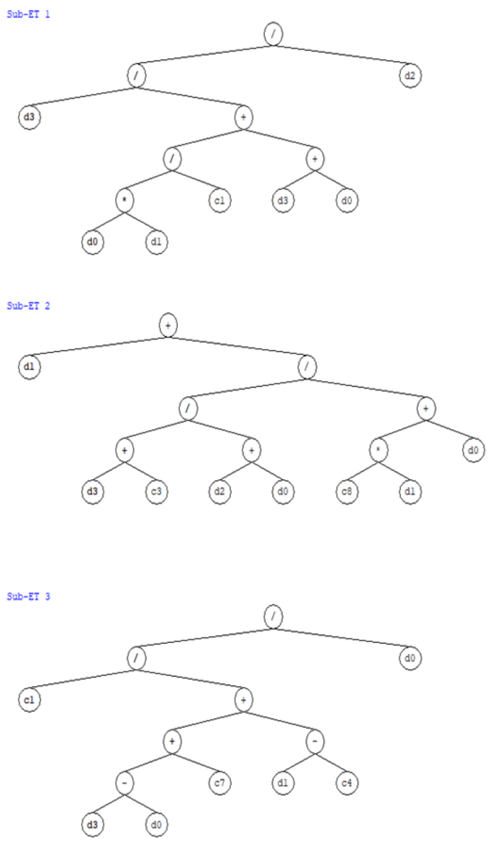

Fig 10. Model tree of penetration

These model trees generated for the bead geometrical parameters correspond to the respective expressions, where voltage (open circuit) (d_0), electrode wire feed (d_1), carriage speed (d_2), tube-end to work distance (d_3)

The expression trees are converted into mathematical expressions by evaluating the expressions tress independently from the right branch and left branch and them combining these braches by the appropriate arithmetic operator connecting the two sides. For each of the three bead geometry parameter based on the superior correlation coefficient, three sub trees were obtained. These are sub-ET1, sub-ET2 sub-ET3. These independent expressions trees are then summed up to obtain the overall expression tree for the particular response parameter.

Parametric analysis of the effects of weld parameters namely, voltage, electrode wire rate, carriage speed and tube end to work distance on bead geometry presented in fig 8, fig 9 and fig 10. From Fig 8 it can be inferred that, the effect of electrode wire feed on bead width is positive while with the increase in carriage speed the width decreases. Similar trend is observed in bead penetration ie., as electrode wire feed increases the penetration also increases. The effect of voltage on the three bead parameters is almost the same trend in which the increase in voltage decreases all the three to a large extent.

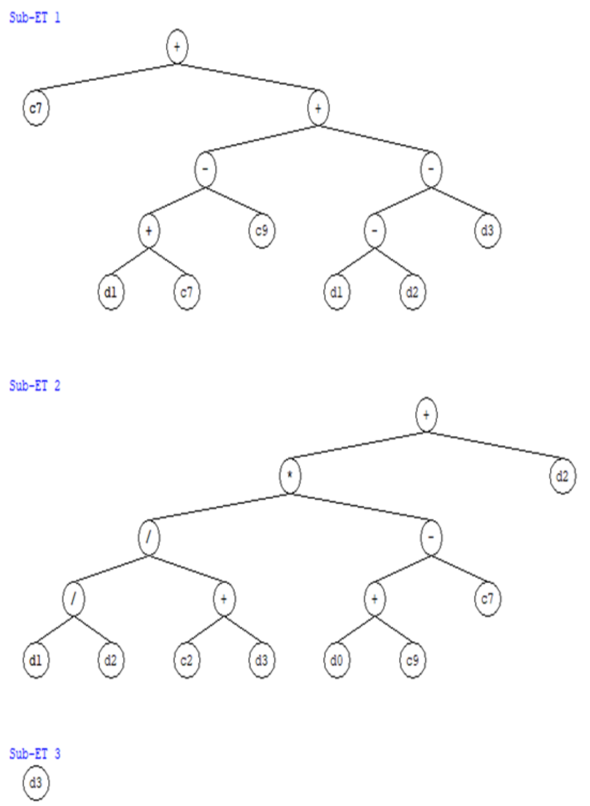

Fig 11. Model tree of bead width

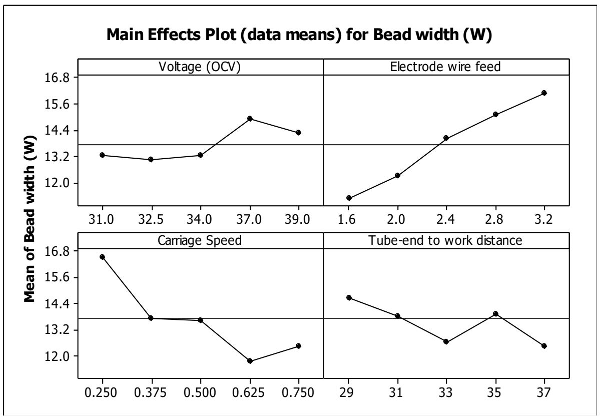

Fig 12 Effect of weld parameters on bead width

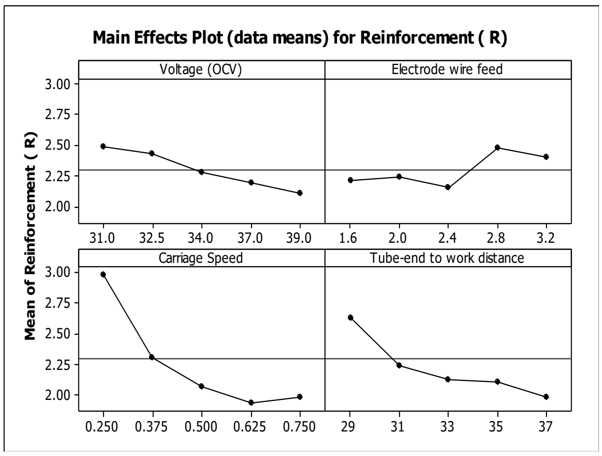

Fig 13 Effect of weld parameters on bead reinforcement

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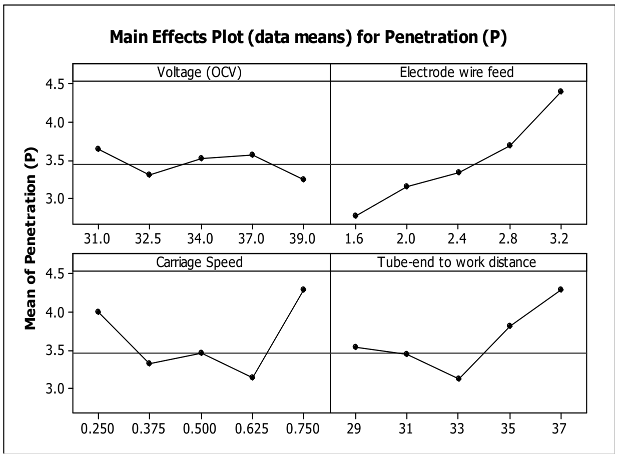

Fig 14 Effect of weld parameters on bead penetration

V. CONCLUSIONS

The main aim of the present study is to obtain the explicit formulation of weld bead geometry (bead width, bead reinforcement, bead penetration) as a function of weld process parameters voltage (open circuit) (d_0), electrode wire feed (d_1), carriage speed (d_2), tube-end to work distance (d_3) by applying a novel non-traditional algorithm namely the gene expression programming. SAW process has been chosen due to its importance in several engineering fields. The accuracy of the developed models were statistically tested for their significance and prediction accuracy of the model is good with validation datasets as well as. R^2 and correlation coefficient which are tabulated, ascertain the ability of the GEP to predict the bead parameters. The major advantage of using evolutionary methods like GEP is they do not assume any order or degree of the model expression apriori as it happens in regression based techniques. These developed models may be used to optimize the process so as to obtain the best working ranges of the machine to suit our bead geometry requirement.

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