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Experimental investigation and optimization analysis of weld penetration in SAW of mild steel plates of solar fin coated with TiO_2/Cr_2O_3 nano-particles by fuzzy logic

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ABSTRACT

Demands for improved productivity, efficiency, and quality pose challenges to the welding industry. In submerged arc welding (SAW) process, the weld quality is not only closely related to the geometry of weld bead but it is also, greatly affected by welding input parameters, a relationship which is complicated because of the non-linear nature of the welding processes. Nowadays, trial-and-error and statistical methods to determine optimal conditions incur considerable time and cost. In order to overcome these problems, a couple of non-traditional methods have been reported. This paper reports the applicability of fuzzy logic (FL) to predict the weld penetration in SAW process as affected by welding input parameters. FL is a computer technique which allows expressing, evaluating, and simplifying complexities in regard with the relationships in a process by describing the dependencies between outputs and input parameters in a linguistic form. For developing the fuzzy logic model, the arc voltage, welding current, welding speed, electrode stick-out, and weight percentage of TiO_2 / Cr_2O_3 nano-particles coated on mild steel plates before actual welding operation, were taken as the input parameters and the weld penetration as the response. In order to generating experimental data, a five-level five-factor central composite rotatable design (CCRD) of experiments was employed. Bead-on-plate welds were placed on mild steel plates using automatic SAW machine. Data were collected and FL modeling was carried out to establish input–output relationships of the process. The values obtained from this technique was compared with experimental results and presented in graphical forms.

1. INTRODUCTION

Demands for improved productivity, efficiency, and quality pose challenges to the welding industry. As materials become ever more sophisticated in their chemical composition to provide ever-better functionally specific properties, a more complete and precise understanding of how such materials can be joined for optimal effectiveness and efficiency will become essential.

One of the most widely used welding methods in industries and research organizations is the SAW. SAW is a high quality welding process commonly used for fabricating large diameter line pipes, pressure vessels and wind turbine towers due to its high deposition rate, ease of automation and low operator skill requirement. In order to achieve high melting efficiency required for high productivity, best weld quality and good mechanical properties in manufacturing industries, the welding process parameters need to be optimized. During SAW process, operator cannot observe the weld pool and cannot directly interfere with the welding process. To consistently produce high quality of welds, SAW requires skilled welding personnel with significant experience and a proper selection of welding parameters for a given task. Many attempts have been made by researchers to establish the SAW process for a desired weld quality. Traditionally the desired welding parameters are obtained either from experience, charts or handbooks which are difficult, cumbersome and they do not ensure that the chosen welding parameters are optimal for the particular environment. In recent years, mathematical models have been developed to correlate the welding performance such as weld bead width, shape and size [1–5] with welding parameters. Multiple regression techniques have been used to establish mathematical models for the weld bead geometry [6-7]. One of the weld quality characteristics extremely important for structural integrity is the weld bead geometry. One of the important dimensions in weld bead geometry is the weld penetration which is defined as the depth to which the molten metal penetrates into a weld, determines the size and stress carrying capacity of weld beads that hold the joints together [8].

Due to the inadequacy and inefficiency of the regression models to explain the non-linearity and other complexities existing in manufacturing processes between the responses and input parameters, the usage of artificial intelligence techniques in modeling of welding operations is getting more and more inescapable. These techniques can be considered as a branch of computer science and try to bridge the gap between humans and machines by giving the machines some aspects of human capabilities. One type of intelligent system that has found popularity recently is FL. FL is well suited for modeling complex and uncertain problems that can be controlled by humans. Several authors have performed the application of fuzzy methodology to estimate welding quality in different welding processes [9–13]. FL due to its capability in approximating the nonlinear functions and incorporating the human knowledge has been widely used to solve many

engineering problems [14]. FL is a mathematical theory of inexact reasoning that allows us to model the reasoning process of humans in linguistic terms and is very suitable in defining the relationship between the system inputs and the desired system outputs [15].

It has been reported that active fluxes such as TiO_2 and Cr_2O_3 when added to weld puddle, can modify fusion zone geometry dramatically in GTA welding [16]. On the other hand, it has been reported that addition of oxide nano-particles to the weld puddle can modify the fusion zone geometry in SAW process and have a significant role on improving the hardness [11]. What is then missing is the application of TiO_2, Cr_2O_3 and nano-particles in welding processes in general. Nano-materials are defined as particles having diameters ranging from 1 nm to 100 nm [17]. Their small size and large surface and volume effects offer unique mechanical, electrical, magnetic, optical, and physiochemical properties which make them suitable candidates for different applications in defense, electronic, aerospace, and chemical industries [18]. In recent years, a great deal of attention has been given to the application of nano-materials in welding research [9, 19–21] but the fact is that scientific investigations into the role of nano-materials in welding processes will still remain to be seen in the future.

Since it was not possible to mix up the TiO_2 and Cr_2O_3 nano particle with the flux due to its nano size therefore, it was decided to disperse them in ethanol and then apply the obtained paste on the low carbon plates in different weight percent as per the design matrix before welding operation.

2. EXPERIMENTATION AND DATA COLLECTION

2.1. Design of experiments

Table 1. The input parameters and their ranges

Notation	Parameter		Units	Code values				
				-2	**-1**	**0**	**+1**	**+2**
I	Welding current		Amp	500	550	600	650	700
V	Arc voltage		Volts	24	26	28	30	32
N	Electrode stick-out		mm	30	32.5	35	37.5	40
S	Welding speed		mm/min	300	350	400	450	500
F	Nano-Particles	TiO_2	Wt.%	10	30	50	70	90
		Cr_2O_3		90	70	50	30	10

Table 2. Design matrix

No	V	I	S	N	F	P
1	1	-1	-1	-1	-1	9.263
2	-1	-1	-1	1	-1	5.951
3	0	0	0	0	0	8.027
4	0	0	0	0	-2	5.982
5	1	1	-1	1	-1	10.005
6	1	1	1	-1	-1	7.746
7	-1	-1	1	1	1	6.442
8	0	-2	0	0	0	7.171
9	0	0	0	-2	0	7.697
10	1	1	-1	-1	1	10.738
11	-2	0	0	0	0	3.896
12	2	0	0	0	0	10.245
13	-1	1	1	1	-1	5.951
14	0	0	0	0	0	8.027
15	0	2	0	0	0	8.178
16	0	0	0	2	0	7.610
17	0	0	0	0	0	8.027
18	-1	1	1	-1	1	4.938
19	-1	1	-1	1	1	6.901
20	-1	1	-1	-1	-1	6.466
21	1	-1	-1	1	1	9.748
22	0	0	0	0	0	8.027
23	1	-1	1	1	-1	6.663
24	0	0	0	0	2	8.338
25	0	0	0	0	0	8.027
26	1	-1	1	-1	1	8.716
27	-1	-1	-1	-1	1	7.117
28	1	1	1	1	1	10.063
29	0	0	-2	0	0	8.439
30	0	0	2	0	0	6.380
31	-1	-1	1	-1	-1	6.209
32	0	0	0	0	0	8.027

RSM provides a powerful means to achieve breakthrough improvements in product quality and process efficiency. From the viewpoint of manufacturing fields, this can reduce the number of required experiments when taking into account the numerous factors affecting the experimental results. RSM can show how to conduct the fewest number of experiments while maintaining the most important information [22]. The experiments for the present work have been carried out using five-level CCRD [22]. In this investigation, the number of input parameters considered for the response surface modeling is five, and the number of experiments conducted is thirty two. The alpha value selected as per central composite design is 2.0. The independently controllable process parameters identified for the experimentation are: arc voltage (V), welding current (I), welding speed (S), electrode stick-out (C), and weight percent of TiO_2/Cr_2O_3 and the response, is the weld penetration (P). The working level for each input parameter was determined by doing one factor at a time welding technique and inspecting the weldments for absence of visible defects and good appearance. The coded value is calculated from the following relationship:

$$X_i = \frac{2[2X-(X_{max}+X_{min})]}{(X_{max}-X_{min})} \quad (1)$$

where X_i is the required coded value of a parameter X. X is any value of the parameter from X_{min} to X_{max}, X_{min} and X_{max} are the lower level and the upper level of the parameter respectively. The selected input parameters, their notations, and their limits are given in Table 1. The design matrix for all the 32 experiments is listed in Table 2.

2.2 Nano-particles

2.2.1 TiO_2

(AEROXIDE TiO_2 P 25) is a highly dispersed titanium dioxide manufactured according to the AEROSIL process,

obtained from the Degussa AG, Germany. Titanium Dioxide P 25 has an average primary particle size of about 21 nm and a specific surface of about 50 m^2/g.

2.2.2 Cr_2O_3

A simple synthesizing procedure was used to produce Cr_2O_3 nano-particles. In this procedure, some amount of ammonium dichromate $(NH_4)_2Cr_2O_7$ was placed in a crucible, and then by approaching a flame, it was ignited. Subsequently, its color changed to green and Cr_2O_3 powder was produced. In this reaction, the combustion liberated N_2 gas that affected the formation of Cr_2O_3 nano particles by obstructing the growth of particle sizes. Characterization of the Cr_2O_3 nano-particles and its grain size, was obtained by using XRD and SEM. The properties of Cr_2O_3 nano-particles are given in Table 3.

Table 3. Properties of Cr_2O_3 nano-particles

Name	Formula	Crystal system	Particle size	Density
Chromium Oxide	Cr_2O_3	Rhombohedral	68.568 nm	5.345 g/cm³

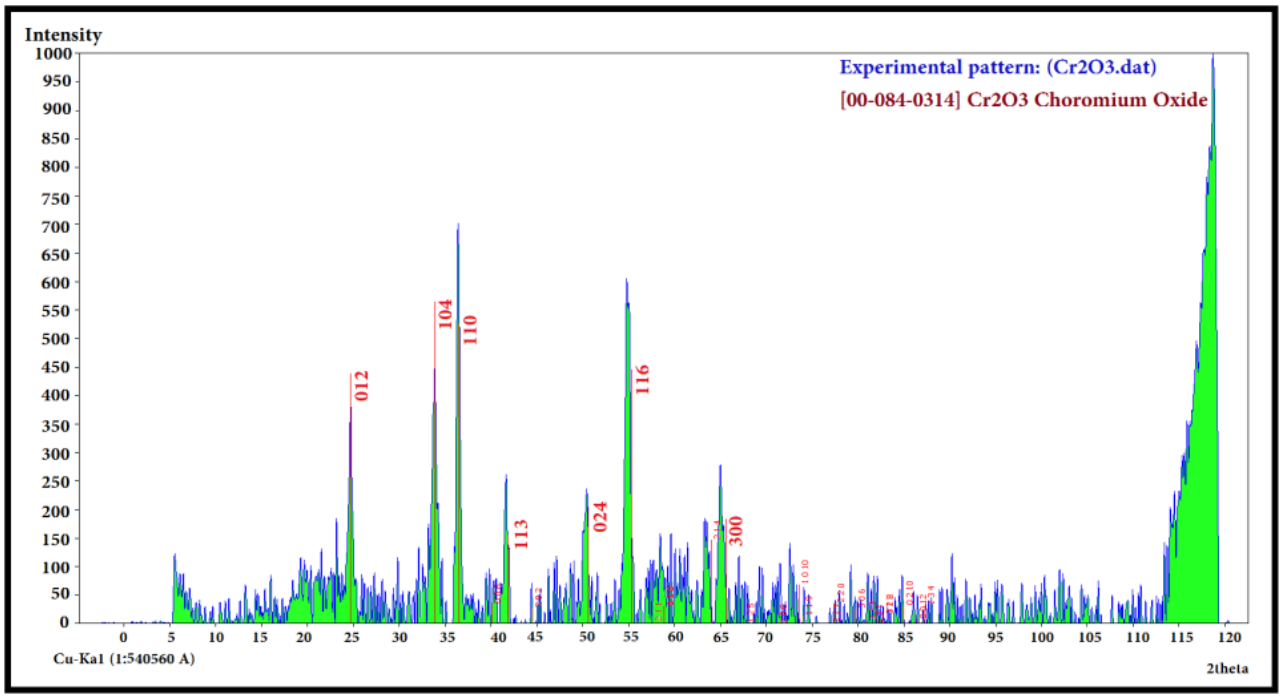

Figure 1. XRD of Cr_2O_3 nano-particles

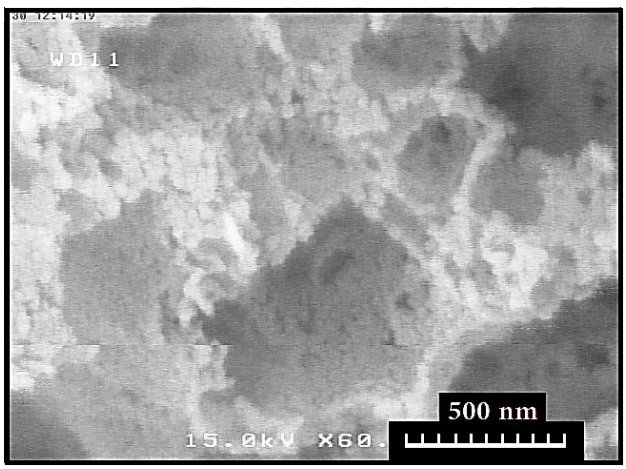

Figure 2. SEM of Cr_2O_3 nano-particles

2.3 Conducting the experiment as per the design matrix

The experiments were conducted at the Welding Research Center of Razi University with the following details:

- ✓ Polarity: Direct current reverses polarity
- ✓ Filler wire: 3.2 mm copper-coated electrode in coil form (DIN S1- AMA Co. Trade Name 50-11)
- ✓ Type of joint: Single bead-on-plate
- ✓ Flux: Agglomerated aluminate-rutile type with the basicity index of 0.4
- ✓ Electrode-to-work angle: 90°
- ✓ Work-piece dimensions: 150 mm × 50 mm × 15 mm

Thirty two specimens were prepared and their surfaces were thoroughly cleaned and the paste of TiO_2/Cr_2O_3 nano-particles according to Table 1, was coated on each plate as per the design matrix and welding was carried out at random order. Subsequent to welding, two transverse specimens were cut from each welded plate at mid length and were prepared by the usual metallurgical polishing methods and etched with 2% nital. The profiles of the weld penetration were traced by using Olympus optical microscope. The chemical composition of base plate is given in Table 4. The experimental set-up and the schematic illustration of weld penetration are shown in Fig. 3 and Fig. 4, respectively.

Table 4. Chemical composition of base metal

Element	Cr	P	S	Si	Ti	Mn	C	Fe
Wt%	0.031	0.007	0.01	0.024	0.002	0.417	0.113	Balance

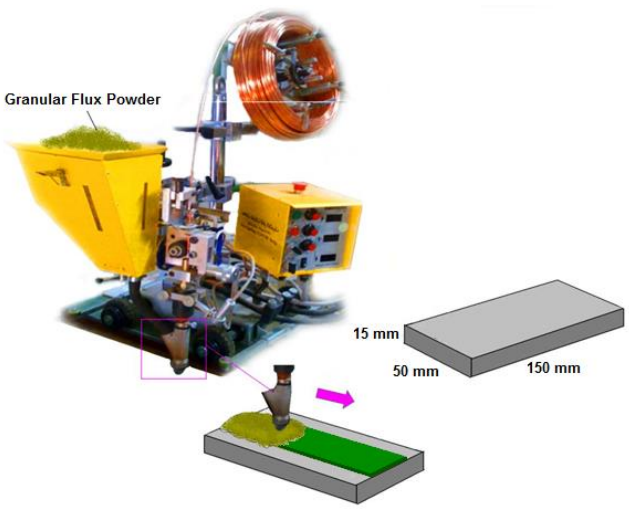

Figure 3. The experimental set-up

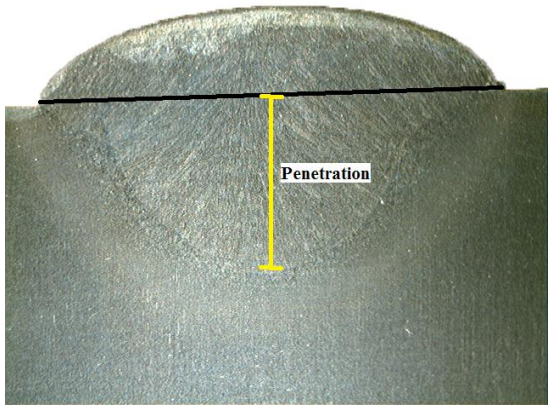

Figure 4. Weld penetration

3. MODELING APPROACH

3.1 Computational intelligence model

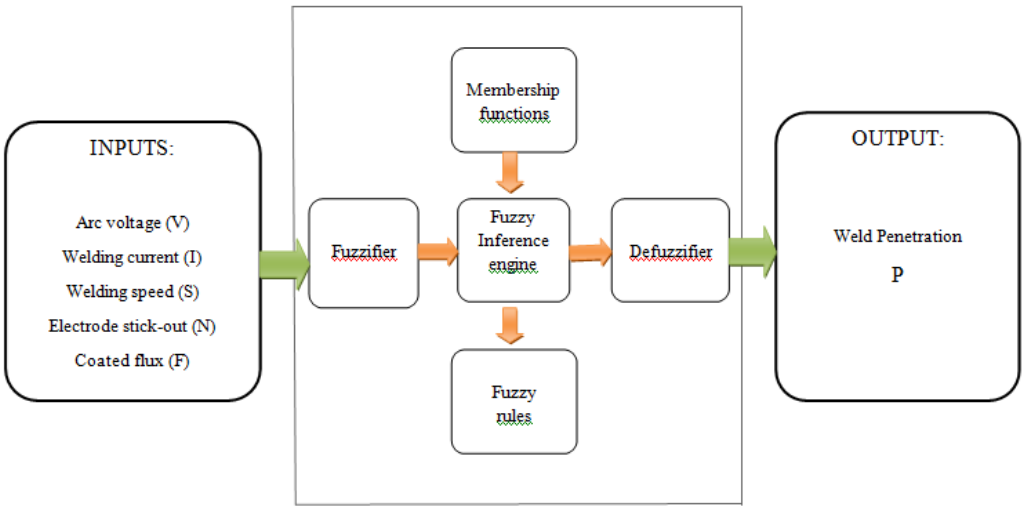

Figure 5. Model representation of the weld penetration using fuzzy logic

Fuzzy logic is a popular soft computing methodology Among various methods that are available. it is found effective and applied by many researchers for modeling and optimization.Fuzzy logic technique based on fuzzy set theory was first introduced by Lotfi Zadeh [23] and it is used as a tool for computing with language. Since then the number and variety of applications of fuzzy set theory in engineering field have grown significantly in the recent years including the area of artificial intelligence (AI). Here, in order to predicting the combined effect of coating flux and aforesaid welding parameters mentioned above on the weld bead penetration during the SAW of mild steel plates, a fuzzy model as shown in Fig.5 is used. In this study, the weld penetration, is adopted as a function of the five input parameters namely the arc voltage (*V*), welding current (*I*), welding speed (*S*), electrode stick-out (*N*) and coated flux (*F*).

3.2. Fuzzy logic

Fuzzy logic approach uses a fuzzy set that allows an infinite number of intervals between true and false. This means that there will be other stages besides true and false, [25]. Fuzzy approach encompasses fuzzy set theory, fuzzy logic and fuzzy measure theory. Many engineering fields have already benefited from the new methodological possibilities presented by fuzzy concepts. Fuzzy logic is based on imprecision and non numerical information, fuzzy logic mimics the way human make decisions using linguistic reasoning [25]. Fuzzy systems base their decisions on inputs and outputs in the form of linguistics variables. The variables are tested with IF-THEN rules, which produce one or more responses depending on which rules are asserted. Generally, the system inputs are passed to a process called fuzzification. In the fuzzification process, the input data will undergo some translation into linguistic quantity such as Low, Medium, High. The translated data will be sent to an inference mechanism that will apply the predefined rules. The inference mechanism will generate the output in linguistic form. The linguistic-output will go through defuzzification process, [24]. The output will then turn out to be in numerical normal data form. In fuzzy inference engine, the truth value for the premise of each rule is computed and applied to the conclusion part of each rule. The response of each rule is weighed according to the degree of membership of its inputs and the centroid of the response is calculated to generate the appropriate output. There are a lot of different shapes of fuzzy set. Some of the common shapes are Pi curve, beta curve, Gaussian curve and triangle. Triangle is the most preferred fuzzy shape as it can be easily represented with a

minimum of computing power. A set of fuzzy rules has to be developed by a fuzzy designer. A more complicated system will have more complex rules. The defuzzification process is defined as the conversion of a fuzzy quantity, represented by a membership function, to a precise or crisp quantity. There are two commonly used techniques for the defuzzification of fuzzy quantities [25]. They include the Max method and Centroid method. The fuzzy algorithm allows here building a nonlinear functional relationship between the input variables and the output. The membership functions and the rule base are defined to best represent the experimental results. In the present study, Isosceles triangles are used to represent the membership shape with a fixed base length. The membership functions are defined by the following general equation:

$$\text{triangle}(x; a, b, c) = \begin{cases} 0 & x \leqslant a \\ \frac{x-a}{b-a} & a \leqslant x \leqslant b \\ \frac{c-x}{c-b} & b \leqslant x \leqslant c \\ 0 & c \leqslant x \end{cases} \tag{2}$$

where a, b, c stand for the triangular fuzzy triplet which determine the x coordinates of the three corners of the underlying triangular membership function as shown in Fig(6).

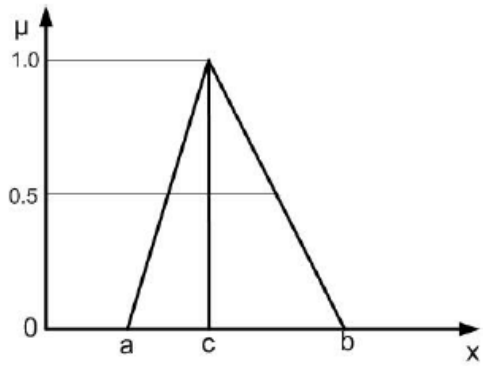

Figure 6. Triangular membership function

3.3 Fuzzy logic modeling

The optimum structure of the fuzzy model which is employed in this paper is described in Table 5. In order to performing FL, symmetric triangular membership functions for the input and output parameters are defined.

Table 5. Selected structure of the proposed fuzzy model

Type of fuzzy inference system (FIS)	Mamdani
Inputs / Output	5/1
Input membership function types	Triangular
Output membership function types	Triangular
Number of input membership functions	5/5/5/5/5
Number of output membership function	100
Rules weight	1
Number of fuzzy rules	27
And method	Min
Implication method	Min
Aggregation method	Max
Defuzzification method	Centroid

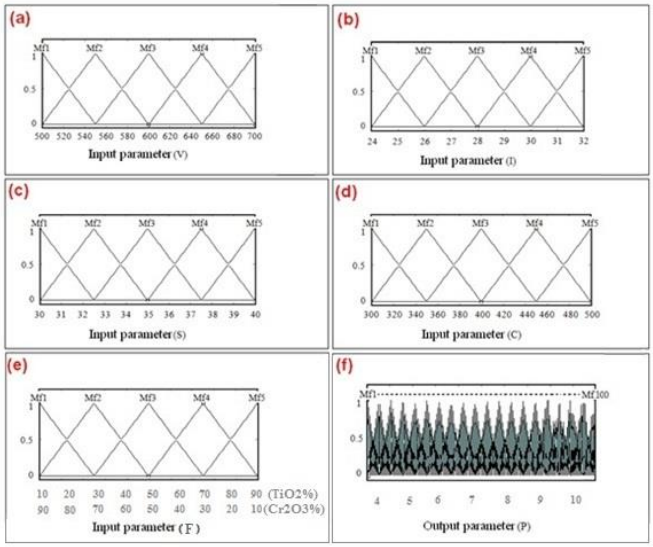

Figure 7. The membership functions of the inputs and output parameters

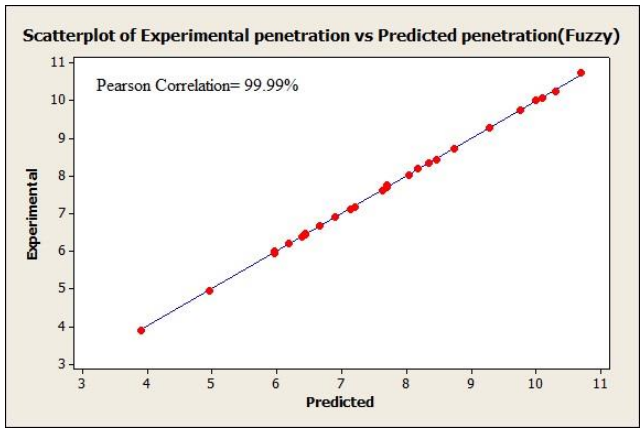

Figure 8. Comparison between the experimental and predicted values of the weld bead penetration using the fuzzy logic model

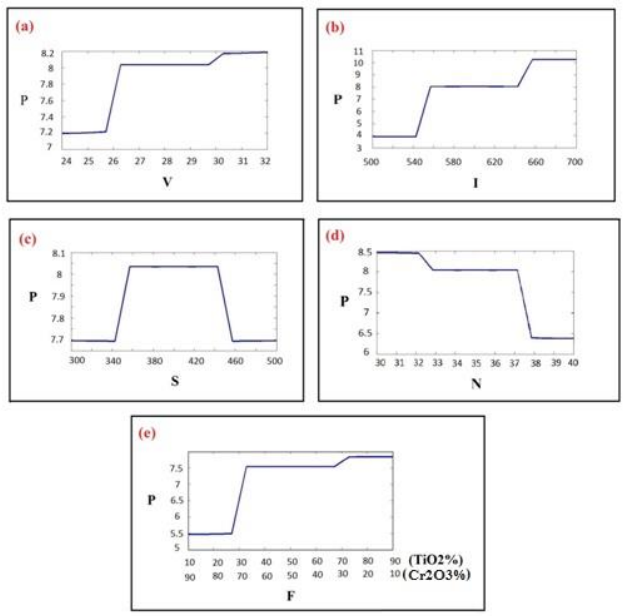

Figure 9. Fuzzy predicted weld penetration as a function of the input parameters

Table 6. Some of the rules involved in the fuzzy logic model

No	Rules
1	If (V is mf2) and (I is mf4) and (S is mf3) and (N is mf2) and (F is mf2) then (P is mf79)
2	If (V is mf4) and (I is mf2) and (S is mf4) and (N is mf4) and (F is mf2) then (P is mf31)
3	If (V is mf3) and (I is mf5) and (S is mf3) and (N is mf3) and (F is mf3) then (P is mf93)
4	If (V is mf3) and (I is mf3) and (S is mf5) and (N is mf3) and (F is mf3) then (P is mf55)
5	If (V is mf5) and (I is mf3) and (S is mf3) and (N is mf3) and (F is mf3) then (P is mf63)

Here, five symmetric triangles are used for building up the input membership functions. Where, the peak of each triangle indicates the main values in experiments. For establishing the output membership functions, one hundreds symmetrical triangular membership functions are used in the range of zero to 100, where 0,1,…, 99 indicate the locations of triangle peaks. Subsequently, the range of zero to 99 is marked as 3.896 mm to 10.738 mm, respectively. By doing this sort of replacements we, therefore, obtained one hundred symmetrical triangular membership functions for the weld penetration. Fig. 7a-e depict the membership functions for the input parameters. In addition, the membership functions of the output parameter are shown in Fig. 7f. Some parts of twenty seven rules, which are chosen for the fuzzy logic model, are shown in Table 6.

The results of the proposed fuzzy model are shown in Fig. 8 and Table 7, in which, the mean relative error (MRE) is defined by:

$$MRE = \frac{1}{N} \times \sum_{i=1}^{N} \left| \frac{P_{\exp} - P_{pred}}{P_{\exp}} \right| \tag{6}$$

where P_{exp} and P_{pred} are the experimental and predicted values of the weld penetration, respectively and N is the number of welding runs. According to the obtained results, it is to be concluded that the predictions made by fuzzy model are in excellent agreement with the experimental data.

Table 7. Comparison between the experimental and predicted values of the weld penetration using the fuzzy logic model

No	Experimentally measured penetration, P_{exp}	Fuzzy predicted penetration, P_{pred}	MRE%
1	9.263	9.28	0.184
2	5.951	5.96	0.151
3,14,17,22,25,32[a]	8.027	8.03	0.037
4	5.982	5.96	0.368
5	10.005	10.0	0.050
6	7.746	7.69	0.723
7	6.442	6.43	0.186
8	7.171	7.20	0.404
9	7.697	7.69	0.091
10	10.738	10.7	0.354
11	3.896	3.90	0.103
12	10.245	10.3	0.537
13	5.951	5.96	0.151
15	8.178	8.18	0.024
16	7.61	7.63	0.262
18	4.938	4.95	0.243
19	6.901	6.89	0.159
20	6.466	6.43	0.557
21	9.748	9.76	0.123
23	6.663	6.66	0.045
24	8.338	8.34	0.024
26	8.716	8.74	0.275
27	7.117	7.13	0.183
28	10.063	10.1	0.368
29	8.439	8.46	0.249
30	6.381	6.38	0.002
31	6.209	6.18	0.467

The average values of the experiments 3,14,17,22,25 and 32 are considered in order to be used for the modeling process

4. VALIDATION OF THE FUZZY MODEL

Accuracy of the FL model in actual welding conditions was obtained by conducting conformation tests. This was done by assigning different values to different input parameters within the working levels but different from those already present in

the design matrix. For this purpose, five welding runs were performed and their penetrations were measured. The percentage of error provided the deviation of predicted values from the actual measured values. It is found from Table 8 that the average error for the model is 1.43%.

Table 8. Comparison of the experimental and predicted values of the weld penetration

S. no.	Process variables in coded form					Predicted values	Experimental values	%Error
	V	I	S	N	F	P (mm)	P (mm)	P
1	-1	0	0	0	0	7.32	7.15	2.37%
2	0	0	0	-1	0	8.45	8.33	1.44%
3	0	1	0	0	0	9.41	9.24	1.84%
4	0	0	-1	0	0	7.69	6.74	0.64%
5	0	0	0	0	1	8.04	8.11	0.86%
Average error %								1.43%

The effects of the five input parameters on the weld penetration based on the fuzzy logic predictions are shown graphically in Fig. 9a-e.

As shown in Fig. 9a the weld penetration increases slightly with the increase in the arc voltage. This could be attributed to the slight increase in the heat input into the workpiece. However, quantitatively the effect is not very much. Many investigators [26] reported that arc voltage in a consumable electrode process has no significant effect on the weld penetration.

From Fig. 9b, it is observed that penetration increases with the increase in welding current. Basically, the increase in current gives rise to the increase in heat input into the weld bead causing greater volume of the base plate to melt and hence, achieving deeper penetration. Furthermore, the increase in welding current increases the temperature and the heat content of the droplets, resulting in more heat being transferred to the base metal. In addition, increase in the welding current also increases the momentum of the filler metal droplets striking the weld pool and results in a deeper penetration [27-28].

Fig. 9c shows that the welding speed has no significant effect on weld penetration. As shown in Fig. 9d, the weld penetration decreases with the increase in electrode stick-out because increase in the electrode stick-out increased the circuit resistance, which reduced the welding current. This decrease in the welding current reduced the heat input and hence reduced the penetration.

Fig. 9e shows that the weld penetration increases with the increase in weight percentage of the TiO_2 nano-particles pasted on the mild steel plates. Welding pool penetration can be improved significantly by preplacing a thin layer of coated flux of nano-oxides on the surface of substrate. Weld penetration can also be determined by the fluid flow mode in the weld pool, which is driven by the electromagnetic force, surface tension gradient and buoyancy force. Among them, the surface tension gradient on the welding pool is the principle variable that changes the convection mode. Generally, the surface tension decreases with the increasing temperature, $\partial\sigma/\partial T < 0$, for pure metal and many alloys. In the weld pool for such materials, the surface tension is higher in the relatively cooler part of the pool edge than that in the pool center under the arc, and hence the fluid flows from the pool center to the edge. Surface-tension-driven convection is also called Marangoni convection. The heat flux is easily transferred to edge and the weld pool shape is relatively wide and narrow as shown in Fig. 10a [29]. Heiple and Roper proposed that surface active elements such as oxygen, sulfur and selenium can change the temperature coefficient of the surface tension for steels from negative to positive, $\partial\sigma/\partial T > 0$, and further changes the direction of the fluid flow in the weld pool as illustrated in Fig. 10b [29]. In that case, a relatively deep weld was produced.

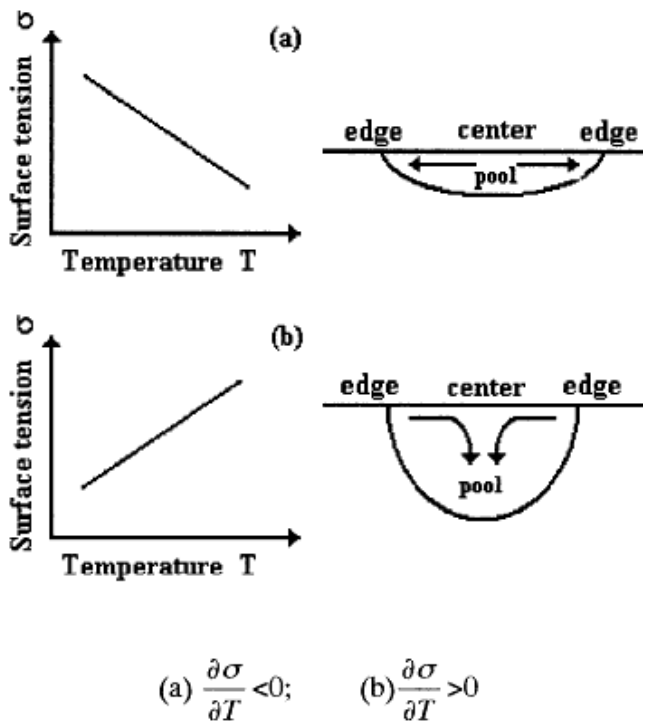

Figure 10. Marangoni convection mode by surface tension gradient in welding pool [16]
(a) $\partial\sigma/\partial T < 0$; (b) $\partial\sigma/\partial T > 0$

In our experiments, the oxygen in the weld from decomposition of the coated nano-oxide flux (TiO_2 and Cr_2O_3) played the important role as an active element and changed the Marangoni convection mode of the liquid weld pool. As the oxygen content in the weld increased, the Marangoni convection mode changed from outward to inward first, and then the inward convection becomes weaker or changed to the outward direction as the oxygen content increases in the weld [16] the Cr_2O_3 oxide is less stable than TiO_2 and more easily

decomposed under the arc. The decomposed oxygen would dissolve in the weld pool and quickly increase the oxygen content in the weld. If the oxygen content is too high, the inward Marangoni convection becomes weak or changes to the outward direction and the weld pool penetration decreases again. However, the TiO_2 oxide is more stable and not decomposed completely under the arc, which caused the oxygen content in the weld pool to be relatively low and the Marangoni convection mode is maintained in the inward direction [16].

6. CONCLUSIONS

In this paper, a fuzzy logic model is developed to predicting the weld penetration in submerged arc welding process. The model was designed to take into account the effect of the arc voltage (V), welding current (I), welding speed (S), electrode stick-out (N), coated flux (F). A model based on twenty seven fuzzy rules was able to reflect the effect of these input parameters, and resulted in a low estimation error.

The important parameters, which significantly affect the weld penetration, have also been identified by this technique. Within limitations of the present work, the following conclusions are summarized as follow:

1. Out of the five input parameters considered, welding current had a significant positive effect whereas, the welding speed had no significant effect on the weld penetration.
2. Arc voltage had a slightly positive effect on the weld penetration.
3. The electrode stick-out had a negative effect on the weld penetration.
4. Increasing weight percent increasing of TiO_2 nano particle had a positive effect on the weld penetration.

Based on the obtained results, it is concluded that the fuzzy logic is a reliable technique to predicting the weld penetration in SAW process due to its low error rate as indicated in the study.

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