[illegible] of Control Parameters in Submerged Arc Welding Using GA

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[illegible] is one of the most [illegible] industries. In [illegible] parameters is vital in [illegible] paper, modeling and [illegible] have been addressed. [illegible] between important [illegible] specifications, [illegible] technique is [illegible] is also verified [illegible] are then implanted [illegible] SAW process [illegible] geometries. The [illegible] method is quite [illegible] for any desired weld [illegible]

[illegible] Submerge Arc Welding, [illegible] Genetic Algorithm.

[illegible]

[illegible] techniques are [illegible] metal-to-metal joints. [illegible] Welding (SAW) [illegible] because of its [illegible] and smooth [illegible] of process- [illegible] weld bead [illegible] in SAW [illegible] welding speed and [illegible] the bead quality [illegible] reinforcement, bead [illegible] [2]. In the [illegible] methods were [illegible] for a given [illegible] were limited in [illegible] process changes [illegible].

[illegible] have been [illegible] through [illegible] the relationship [illegible] weld bead [illegible] and numerical [illegible] welding processes. [illegible] (NN) have [illegible] parameters.

Most of such models are developed based on regression analysis for a given set of experimental welding data.

Using regression analysis, Kim et al. [4] carried out a set of statically designed experiments based on factorial technique to study the relationship between process variables and bead penetration for CO_2 arc welding. Xue, et al., [5] have employed a fuzzy linear regression approach to investigate the effects of process parameters on the bead width and weld quality in the robotic arc welding. Statistically designed experiments based on the factorial technique were also used to gather the required information about different process parameters and their mutual interactions [6]. The mathematical models developed are useful for selecting proper process parameters to achieve the desired weld bead quality or to predict weld bead quality for the given process parameters.

Numerous other research works exist on the modeling and optimization of process parameters in welding. Nevertheless, most of the proposed models are complicated and highly non linear. They require comprehensive and time consuming mathematical manipulations. The new trend in welding parameters optimization is to use evolutionary algorithms such as Genetic Algorithm [7], and Simulated Annealing [8]. Other search methods have also been used for this purpose [9].

Along this line, Genetic Algorithms (GAs) are well known evolutionary computation methods that have been adapted for a large number of applications in different areas [10]. These include from image processing in medicine, to optimization of bonding parameters in material science and determination of heat transfer coefficients in energy-related fields. Genetic algorithms also provide a robust and powerful optimization technique for multi-modal nonlinear structural problems. Studies conducted on modeling and predicting the mechanical properties using GA are very limited, while the application of the GA approach to the estimation of predicting the mechanical properties is quite new. Previous work in welding, used genetic algorithm for optimization by sweeping a region of interest and select the optimal (or near optimal) setting to welding process [11, 7].

In this paper, a GA approach is proposed to determine the best values for process parameters with respect to a desired bead geometry.

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In summary, developing more accurate models and providing more efficient solution procedure is the main objective of this research. For illustrative purposes, the data presented by Gunaraj and Murugan [2] is used here.

II. MODEL DEVELOPMENT

The following steps are needed in the proposed approach. First, the mathematical model to relate the bead geometry to the process parameters should be developed and verified. Then, a proper objective function is needed to facilitate the prediction process with respect to any desired Weld bead specification. The implementation of Genetic Algorithm to optimally determine process variables through minimization of such objective function is the final step.

The most important process parameters in SAW are the voltage (V); the wire feed rate (F); the welding speed (S) and the nozzle-to-plate distance (N). To develop the mathematical model with the minimum number of trial experiments, a design matrix should be constructed. Trial runs are then conducted based on this matrix by varying one of the process parameters at a time; while keeping the rest constant. To facilitate design matrix construction, a coding system is employed to indicate different ranges of parameters. The upper and lower limits are coded as +2 and −2, respectively. The intermediate values are calculated using the following formula:

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

Where X_i is the coded value of variable X, and X [illegible] value between X_{min} and X_{max}. Using this procedure, [illegible] coded process parameters are given in Table I.

TABLE I
PROCESS PARAMETERS LIMITS AND CODE

Parameters	Units	Notation	−2	−1	0	[illegible]	[illegible]
Welding voltage	Volts	V	24	26	28	[illegible]	[illegible]
Wire feed rate	m/min	F	0.70	0.93	1.16	[illegible]	[illegible]
Welding speed	m/min	S	0.43	0.51	0.59	[illegible]	[illegible]
Nozzle-to-plate	mm	N	30.0	32.5	35.0	[illegible]	[illegible]

The design matrix, shown in Table II, is a standard [illegible] composite rotatable four-factor five-level factorial [illegible]

These 31 experimental runs are sufficient to [illegible] relationship between weld bead characteristics and [illegible] parameters.

TABLE II
DESIGN OF EXPERIMENTS MATRIX FOR BEAD GEOMETRY PARAMETERS WITH RESPECT TO PROCESS PARAMETERS

No	V	F	S	N	P mm	R mm	W mm	Ap (mm^2)	Ar (mm^2)	D (%)	[illegible]
1	−1	−1	−1	−1	3.52	1.70	10.15	20.7	24.48	42.40	[illegible]
2	+1	−1	−1	−1	3.40	1.51	13.47	22.1	21.52	46.80	[illegible]
3	−1	+1	−1	−1	4.75	2.32	11.05	24.5	22.80	47.50	[illegible]
4	+1	+1	−1	−1	4.10	1.85	15.64	26.3	24.15	50.30	[illegible]
5	−1	−1	+1	−1	3.25	1.38	08.28	18.3	23.17	40.70	[illegible]
6	+1	−1	+1	−1	3.18	1.18	10.10	19.5	23.42	41.90	[illegible]
7	−1	+1	+1	−1	3.52	1.50	09.15	21.5	18.90	48.60	[illegible]
8	+1	+1	+1	−1	3.33	1.82	09.86	23.2	19.25	49.80	[illegible]
9	−1	−1	−1	+1	3.85	1.61	10.66	20.2	27.48	39.40	[illegible]
10	+1	−1	−1	+1	3.60	1.48	14.55	21.8	26.24	40.50	[illegible]
11	−1	+1	−1	+1	4.10	1.92	13.38	23.1	27.82	42.10	[illegible]
12	+1	+1	−1	+1	3.80	1.80	15.96	26.5	31.16	42.90	[illegible]
13	−1	−1	+1	+1	3.20	1.37	08.70	17.7	24.52	38.60	[illegible]
14	+1	−1	+1	+1	3.00	1.10	09.28	18.9	25.34	39.70	[illegible]
15	−1	+1	+1	+1	4.10	1.75	09.01	20.3	25.55	40.80	[illegible]
16	+1	+1	+1	+1	3.88	1.50	10.00	21.1	23.87	42.30	[illegible]
17	−2	0	0	0	4.10	1.62	10.28	19.4	24.25	41.10	[illegible]
18	+2	0	0	0	3.75	1.43	15.30	25.4	29.45	42.90	[illegible]
19	0	−2	0	0	3.26	1.41	09.95	19.1	17.95	38.10	[illegible]
20	0	+2	0	0	4.97	1.75	10.96	27.7	21.53	51.00	[illegible]
21	0	0	−2	0	4.25	2.30	16.11	25.3	31.33	41.30	[illegible]
22	0	0	+2	0	3.48	1.40	08.50	18.4	21.05	43.00	[illegible]
23	0	0	0	−2	3.82	1.31	11.17	22.5	19.68	48.70	[illegible]
24	0	0	0	+2	3.58	1.27	12.05	23.2	27.83	42.50	[illegible]
25	0	0	0	0	3.45	1.15	11.20	20.9	21.80	47.00	[illegible]
26	0	0	0	0	3.47	1.30	10.58	21.7	21.40	46.50	[illegible]
27	0	0	0	0	3.66	1.27	09.92	21.9	19.80	48.20	[illegible]
28	0	0	0	0	3.60	1.31	11.13	21.2	19.90	47.60	[illegible]
29	0	0	0	0	3.30	1.16	10.56	20.5	21.10	45.70	[illegible]
30	0	0	0	0	3.60	1.27	10.84	22.6	21.50	47.30	[illegible]
31	0	0	0	0	3.92	1.45	11.05	22.1	24.60	48.50	[illegible]

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ABSTRACT- Submerged Arc Welding (SAW) is one of the most important metal joining processes in metal forming industries. In this technique, optimal selection of process parameters is vital in achieving high quality joints. In this paper, modeling and optimization of process parameters in SAW have been addressed. To establish the mathematical relationships between important process-control variables and the bead-quality specifications, regression analysis based on a five-level factorial technique is employed. The adequacy of the developed models is also verified using ANOVA method. The proposed models are then implanted into a Genetic Algorithm (GA) to determine the best SAW process parameters for any target values of weld bead geometries. The computational results demonstrate that GA method is quite effective in predicting process parameters for any desired weld bead geometry.

KEYWORDS- Weld Bead Geometry, Submerge Arc Welding, Process Parameters Optimization, Modeling, Genetic Algorithm.

I. INTRODUCTION

In metal forming industries, various welding techniques are employed to produce permanent metal-to-metal joints. Among these techniques, Submerged Arc Welding (SAW) is one of the most widely used processes because of its inherent advantages, including deep penetration and smooth bead [1] In this technique, appropriate selection of process-control variables is crucial for achieving required weld bead quality. The important controlling parameters in SAW include welding voltage, wire feed rate, welding speed and nozzle-to-plate distance. By the same token, the bead quality is determined by weld penetration, reinforcement, bead width, bead volume and the percentage of dilution [2]. In the past, cost and time-intensive trial and error methods were used to determine the best process parameters for a given bead quality [3]. However, these methods were limited in the sense they could not take into account process changes such as different materials and welding environments.

More recently, various optimization methods have been applied to define the best output parameters through developing mathematical models to specify the relationship between the process parameters and the weld bead specifications. Design of Experiment (DOE) and numerical methods are employed to model welding processes. Evolutionary algorithms and Neural Networks (NN) have also been adopted to predict the best process parameters. Most of such models are developed based on regression analysis for a given set of experimental welding data.

Using regression analysis, Kim et al. [4] carried out a set of statically designed experiments based on factorial technique to study the relationship between process variables and bead penetration for CO_2 arc welding. Xue, et al., [5] have employed a fuzzy linear regression approach to investigate the effects of process parameters on the bead width and weld quality in the robotic arc welding. Statistically designed experiments based on the factorial technique were also used to gather the required information about different process parameters and their mutual interactions [6]. The mathematical models developed are useful for selecting proper process parameters to achieve the desired weld bead quality or to predict weld bead quality for the given process parameters.

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In this paper, a GA approach is proposed to determine the best values for process parameters with respect to a desired bead geometry.

In summary, developing more accurate models and providing more efficient solution procedure is the main objective of this research. For illustrative purposes, the data presented by Gunaraj and Murugan [2] is used here.

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The following steps are needed in the proposed approach. First, the mathematical model to relate the bead geometry to the process parameters should be developed and verified. Then, a proper objective function is needed to facilitate the prediction process with respect to any desired Weld bead specification. The implementation of Genetic Algorithm to optimally determine process variables through minimization of such objective function is the final step.

The most important process parameters in SAW are the voltage (V); the wire feed rate (F); the welding speed (S) and the nozzle-to-plate distance (N). To develop the mathematical model with the minimum number of trial experiments, a design matrix should be constructed. Trial runs are then conducted based on this matrix by varying one of the process parameters at a time; while keeping the rest constant. To facilitate design matrix construction, a coding system is employed to indicate different ranges of parameters. The upper and lower limits are coded as +2 and −2, respectively. The intermediate values are calculated using the following formula:

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

Where X_i is the coded value of variable X, and X has a value between X_{min} and X_{max}. Using this procedure, the coded process parameters are given in Table I.

TABLE I
PROCESS PARAMETERS LIMITS AND CODE

Parameters	Units	Notation	–2	–1	0	+1	+2
Welding voltage	Volts	V	24	26	28	30	32
Wire feed rate	m/min	F	0.70	0.93	1.16	1.39	1.62
Welding speed	m/min	S	0.43	0.51	0.59	0.67	0.75
Nozzle-to-plate	mm	N	30.0	32.5	35.0	37.5	40.0

The design matrix, shown in Table II, is a standard central composite rotatable four-factor five-level factorial design. These 31 experimental runs are sufficient to establish the relationship between weld bead characteristics and welding parameters.

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1	–1	–1	–1	–1	3.52	1.70	10.15	20.7	24.48	42.40	48.8
2	+1	–1	–1	–1	3.40	1.51	13.47	22.1	21.52	46.80	47.3
3	–1	+1	–1	–1	4.75	2.32	11.05	24.5	22.80	47.50	51.5
4	+1	+1	–1	–1	4.10	1.85	15.64	26.3	24.15	50.30	52.2
5	–1	–1	+1	–1	3.25	1.38	08.28	18.3	23.17	40.70	44.9
6	+1	–1	+1	–1	3.18	1.18	10.10	19.5	23.42	41.90	46.5
7	–1	+1	+1	–1	3.52	1.50	09.15	21.5	18.90	48.60	44.3
8	+1	+1	+1	–1	3.33	1.82	09.86	23.2	19.25	49.80	46.6
9	–1	–1	–1	+1	3.85	1.61	10.66	20.2	27.48	39.40	51.3
10	+1	–1	–1	+1	3.60	1.48	14.55	21.8	26.24	40.50	53.8
11	–1	+1	–1	+1	4.10	1.92	13.38	23.1	27.82	42.10	54.9
12	+1	+1	–1	+1	3.80	1.80	15.96	26.5	31.16	42.90	61.8
13	–1	–1	+1	+1	3.20	1.37	08.70	17.7	24.52	38.60	45.5
14	+1	–1	+1	+1	3.00	1.10	09.28	18.9	25.34	39.70	47.6
15	–1	+1	+1	+1	4.10	1.75	09.01	20.3	25.55	40.80	49.8
16	+1	+1	+1	+1	3.88	1.50	10.00	21.1	23.87	42.30	49.1
17	–2	0	0	0	4.10	1.62	10.28	19.4	24.25	41.10	47.2
18	+2	0	0	0	3.75	1.43	15.30	25.4	29.45	42.90	59.2
19	0	–2	0	0	3.26	1.41	09.95	19.1	17.95	38.10	40.1
20	0	+2	0	0	4.97	1.75	10.96	27.7	21.53	51.00	54.3
21	0	0	–2	0	4.25	2.30	16.11	25.3	31.33	41.30	61.2
22	0	0	+2	0	3.48	1.40	08.50	18.4	21.05	43.00	42.8
23	0	0	0	–2	3.82	1.31	11.17	22.5	19.68	48.70	46.2
24	0	0	0	+2	3.58	1.27	12.05	23.2	27.83	42.50	54.6
25	0	0	0	0	3.45	1.15	11.20	20.9	21.80	47.10	44.4
26	0	0	0	0	3.47	1.30	10.58	21.7	21.40	46.50	46.6
27	0	0	0	0	3.66	1.27	09.92	21.9	19.80	48.20	45.4
28	0	0	0	0	3.60	1.31	11.13	21.2	19.90	47.60	44.5
29	0	0	0	0	3.30	1.16	10.56	20.5	21.10	45.70	44.9
30	0	0	0	0	3.60	1.27	10.84	22.6	21.50	47.30	47.8
31	0	0	0	0	3.92	1.45	11.05	22.1	24.60	48.50	47.6

The weld bead geometry includes penetration (P), width (W), reinforcement (R), area of penetration (AP), area of reinforcement (AR), percentage of dilution (D) and total volume (T.V) of the weld bead (assuming the length of the bead (L) as unity). The last seven column of Table II are the observed values for the weld bead geometry resulted from 31 trial runs adopted from Gunaraj, V., and Murugan, N., [2]. These data can be used to develop the mathematical models.

Any of the above weld bead characteristics is a function of process parameters ($Y = F(V, F, S, N)$) which can be expressed in general form as:

$$Y = b_0 + b_1V + b_2F + b_3S + b_4N + b_{11}V^2 + b_{22}F^2 + b_{33}S^2 + b_{44}N^2 + b_{12}VF + b_{13}VS + b_{14}VN + b_{23}FS + b_{24}FN + b_{34}SN \quad (2)$$

Based on the above data, the coefficients values ($\boldsymbol{b}_i$) can be calculated using regression analysis. These coefficients are tabulated in Table III. Now, the mathematical models representing the relationship between process parameters and weld bead geometry can be stated as follows:

Penetration (P) $= 3.57 - 0.113V + 0.33F - 0.217S - 0.001N + 0.048V^2 + 0.1F^2 + 0.03S^2 - 0.01N^2 - 0.05VF + 0.06VS + 0.038VN - 0.011FS - 0.01FN + 0.083SN \quad (3)$

Reinforcement (R) $= 1.27 - 0.08V + 0.16F - 0.18S - 0.03N + 0.07V^2 + 0.08F^2 + 0.15S^2 + 0.01N^2 + 0.02VF + 0.03VS - 0.014VN - 0.003FS - 0.02FN + 0.03SN \quad (4)$

Width of weld bead (W) $= 10.76 + 1.19V + 0.45F - 1.9S + 0.23N + 0.41V^2 - 0.17F^2 + 0.29S^2 + 0.12N^2 - 0.05VF + 0.64VS - 0.15VN - 0.35FS + 0.091FN - 0.29SN \quad (5)$

Area of penetration (Ap) $= 21.56 + 1.05V + 1.85F - 1.61S - 0.21N + 0.041V^2 + 0.29F^2 - 0.097S^2 + 0.15N^2 + 0.14VF - 0.21VS + 0.056VN - 0.24FS - 0.16FN - 0.16SN \quad (6)$

Area of reinforcement (Ar) $= 21.44 + 0.443V + 0.187F - 1.76S + 2.11N + 1.39V^2 - 0.39F^2 + 1.22S^2 + 0.62N^2 + 0.41VF - 0.047VS + 0.14VN - 0.94FS + 0.77FN - 0.33SN \quad (7)$

Percentage of dilution (Pd) $= 47.27 + 0.74V + 2.5F + 0.25S - 2.23N - 1.31V^2 - 0.71F^2 - 1.31S^2 - 0.44N^2 - 0.09VF - 0.28VS - 0.31VN + 0.43FS - 0.9FN + 0.17SN \quad (8)$

Total weld bead volume (Tv) $= 45.78 + 1.58V + 2.2F - 3.5S + 2.0N + 1.67V^2 + 0.17F^2 + 1.34S^2 + 0.97N^2 + 0.28VF - 0.21VS + 0.48VN - 0.87FS + 0.64FN - 0.77SN \quad (9)$

To ensure the accuracy of these empirical models, analysis of variance technique (ANOVA) is performed. According to ANOVA, models are adequate within the confidence limit of 95%. For illustrative purposes, the distributions of real data around regression lines for four of the above models are shown in Figures 1 through 4. These figures illustrate a good conformability of the developed models to the real process. For other three models the same pattern was observed.

For any given weld bead geometry, this set of equations must be solved simultaneously to find the suitable process parameters. As can be seen, the only feasible way to solve these equations is the use of numerical methods. Such methods require large computational efforts and are porn to errors. In the following sections, we propose a GA based approach to predict the best values for process parameters by minimizing a fitness function.

TABLE III
COEFFICIENTS FOR MODELS CONSTANTS

No.	Coefficient	P (mm)	R (mm)	W (mm)	Ap (mm^2)	Ar (mm^2)	D (%)	Tv (mm^3)
1	b_0	3.572	1.27	10.76	21.56	21.44	47.27	45.78
2	b_1	–0.113	–0.08	1.19	1.05	0.443	0.74	1.58
3	b_2	0.33	0.16	0.45	1.85	0.187	2.50	2.20
4	b_3	–0.217	–0.18	–1.90	–1.61	–1.76	0.25	–3.50
5	b_4	–0.001	–0.03	0.23	–0.21	2.11	–2.23	2.00
6	b_{11}	0.05	0.07	0.41	0.04	1.39	1.31	1.67
7	b_{22}	0.10	0.08	–0.17	0.29	–0.39	–0.71	0.17
8	b_{33}	0.03	0.15	0.29	–0.097	1.22	–1.31	1.34
9	b_{44}	–0.01	0.01	0.12	0.15	0.62	–0.44	0.97
10	b_{12}	–0.05	0.02	–0.05	0.14	0.41	–0.09	0.28
11	b_{13}	0.06	0.03	–0.64	–0.21	–0.047	–0.28	–0.21
12	b_{14}	0.038	–0.014	–0.15	0.056	0.14	–0.31	0.48
13	b_{23}	–0.011	–0.003	–0.35	–0.24	–0.94	0.43	–0.87
14	b_{24}	–0.01	–0.02	0.09	–0.16	0.77	–0.90	0.64
15	b_{34}	0.083	0.03	–0.29	–0.16	–0.33	0.17	–0.77

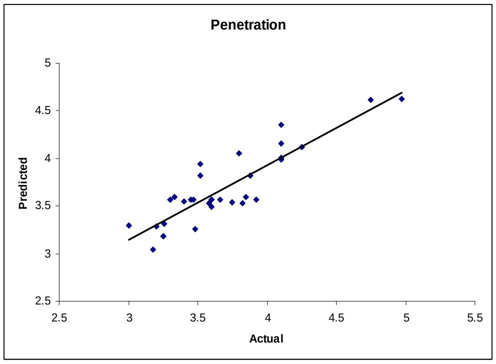

Fig. 1 Predicted Penetration vs. Actual Values

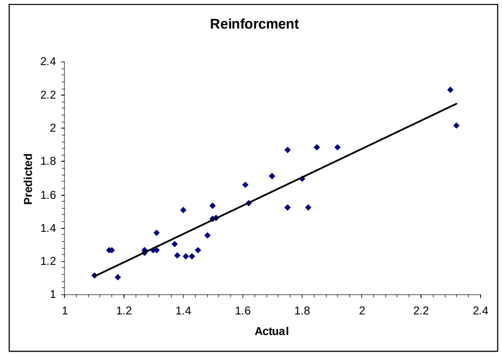

Fig. 2. Predicted Reinforcement vs. Actual Values

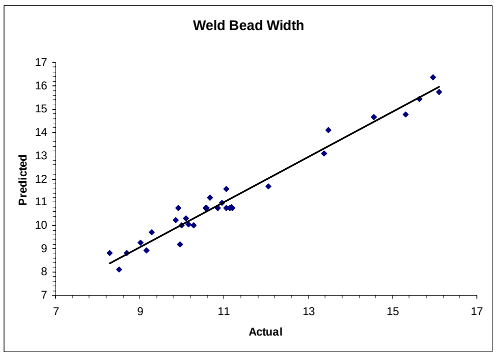

Fig. 3. Predicted Weld bead width vs. Actual Values

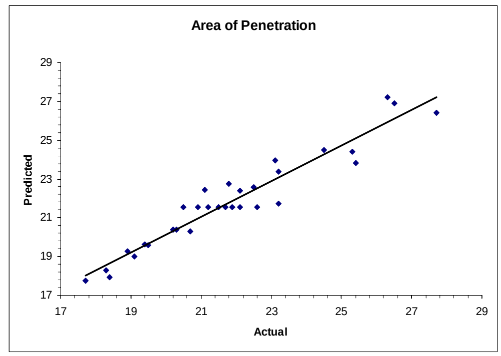

Fig. 4. Predicted Area of penetration vs. Actual Values

A. THE PREDICTION FUNCTION

The mathematical models furnished above provide one to one relationships between process parameters and weld bead geometry. They can be used in two ways:

1) Predicting weld bead geometry based on input parameters

2) Predicting process parameters for a desired weld bead specification.

The later one is more practical since the welding parameters are usually set based on desired bead geometry. For this purpose, the set of non-linear equations must be solved simultaneously for all the process parameters. Evolutionary algorithms are powerful optimization techniques widely used for solving combinatorial problems. Nevertheless, other capabilities of these techniques have rarely been explored. As a new and promising approach, one of these algorithms, called GA, is implemented for prediction purposes in this research.

To predict the process parameters based on a desired bead quality, we first define the prediction function as follow:

$$of(i) = \alpha_1 \frac{(P_t - P_{Equ})^2}{P_t} + \alpha_2 \frac{(R_t - R_{Equ})^2}{R_t} + \alpha_3 \frac{(W_t - W_{Equ})^2}{W_t} + \alpha_4 \frac{(Ap_t - Ap_{Equ})^2}{Ap_t} + \alpha_5 \frac{(Ar_t - Ar_{Equ})^2}{Ar_t} + \alpha_6 \frac{(Pd_t - Pd_{Equ})^2}{Pd_t} + \alpha_7 \frac{(Tv_t - Tv_{Equ})^2}{Tv_t} \quad (10)$$

Where:

$P_{Equ}, R_{Equ}, W_{Equ}, Ap_{Equ}, Ar_{Equ}, Pd_{Equ}, Tv_{Equ}$ are bead specifications namely penetration, reinforcement, width of weld bead, area of penetration, area of reinforcement, percentage of dilution and total bead volume respectively which are given by (3) to (9). In the same manner, we define $P_t, R_t, W_t, Ap_t, Ar_t, Pd_t, Tv_t$ as the target values for the desired weld bead geometry.

The coefficients α_i represent weighing importance of different parameters in the objective function. In the prediction process, the purpose is to minimize this objective function. By doing so, the process parameters are calculated in such way that the bead geometry parameters approach their desired values. A GA method is employed to find the best welding variables with respect to process specifications.

III. GENETIC ALGORITHM

Genetic Algorithm, first proposed by John Holland in 1975, has been adapted for large number of applications in different areas. This method has its philosophical basis in Darwin's theory of survival of the best and most fitted individuals. It belongs to a general category of stochastic search methods. This algorithm encodes a potential solution to a specific problem on simple chromosome string like data structure and applies specified operators to these structures so as to preserve critical information, and to produce a new set of population with the purpose of generating strings which map to high function values. The basic operations which affect the binary strings makeup in natural evolution are a selection, a crossover of genetic information between reproducing parents, a mutation of genetic information and an elitist strategy that keeps the best individual in the next generation.

The main characteristic of the GA and its several variations is that they operate simultaneously with a large set of search space points, instead of a single point (as the conventional optimization techniques). Besides, the applicability of the GAs is not limited by the need of computing gradients and by the existence of discontinuities in the objective function (performance indexes). This is so because the GAs works only with function values, evaluated for each population individual. Moreover, GA employs multiple starting points to search for a solution simultaneously, speeding up the search process.

Genetic algorithm repeatedly modifies a population of individual solutions. At each step, it selects individuals at random from the current population to be parents and uses them to produce the children for the next generation. Over successive generations, the population "evolves" toward an optimal solution.

Genetic algorithm uses three main types of rules at each step to create the next generation from the current population:

- **Selection rules** select the individuals, called parents, which contribute to the population at the next generation.
- **Crossover rules** combine two parents to form children for the next generation.
- **Mutation rules** apply random changes to individual parents to form children.

Genetic algorithm can be applied to solve a variety of optimization problems including problems in which the objective function is discontinuous, non differentiable, stochastic, or highly nonlinear [10]. The major drawback of GA includes its many search parameters which need to be properly selected and tuned. A complete description of this algorithm and some of its applications can be found in [10] and [15].

IV. AN ILLUSTRATIVE EXAMPLE

In this section a numerical example is presented to illustrate the performance of proposed procedure and solution technique. The target values for desired weld bead geometry are given in Table IV [2].

TABLE IV
TARGET VALUES FOR WELD BEAD GEOMETRY

Weld Bead Geometry	Target Value
P_t	3.07 mm
R_t	1.28 mm
W_t	8.33 mm
Ap_t	18.13 mm^2
Ar_t	20.21 mm^2
Pd_t	38%
Tv_t	41.33 mm^3

Without lose of generality, all elements of the bead geometry are assumed to be of the same importance and therefore constants α_1 to α_7 are set to unity.

The prediction function given in (10) along with weld bead modeling (3) to (9) are embedded into GA algorithm. The parameters for the algorithm are set as follows:

Generation number	200
Population size	30
Crossover rate	80%
Crossover mechanism	Scatter
Mutation rate	1%

The objective is to minimize the perdition function which is used as the fitness criterion in evaluation each generation of solutions. The best values found by proposed GA for process parameters are presented in Table V. By setting these parameters in SAW, the target weld bead geometry specifications may be achieved.

TABLE V
PREDICTED VALUES BY GA ALGORITHM

Process Parameters	Predicted Value By GA
Welding Voltage (V)	27.34102
Wire Feed Rate (F)	0.70055
Welding Speed (S)	0.63756
Nozzle to plate distance (N)	34.36322

The performance of the solution procedure was tested by substituting parameters values obtained by GA into the weld bead models and comparing the results with the desired values of bead geometry. The comparison of the calculated and desired values is shown in Table VI. The largest error is around 5.5% while most parameters deviate much less than 1% from their desired values. The computational results show that GA can be used efficiently and with good accuracy as a prediction technique.

TABLE VI
COMPARISON BETWEEN TARGET AND CALCULATED VALUES

$Error = \frac{Target - Predicted}{Predicted} \times 100$	Target Value	Predicted Value By GA	Error %
Penetration (mm)	3.07	3.193	-3.85
Reinforcement (mm)	1.28	1.213	5.52
Width of weld (mm)	8.33	8.35	-0.24
Area of Penetration (mm^2)	18.13	18.12	0.06
Area of Reinforcement (mm^2)	20.21	20.25	-0.197
Percentage of Dilution (%)	38	37.94	0.1
Total Weld Bead Volume	41.33	41.41187	-0.198

V. CONCLUSION

Weld bead geometry is the most important quality measure in welding processes. In order to achieve a high quality weld, welding parameters should be set in such way that the desired bead geometry is obtained. The relationship between bead geometry and welding parameters is quite complicated involving many mutual interactions. The main trust of this research was to explore the possibility of using GA algorithm in predicting welding parameters values in Submerged Arc Welding (SAW). Along this line, first the mathematical relationships between welding parameters and weld bead geometry were established. Then a GA based procedure was developed to predict the best process parameters values for desired weld bead specifications. Computational results show that the proposed GA method can efficiently and accurately predict welding parameters so that a desired weld bead is obtained. The extension of this research may include employing GA, and other heuristic techniques, to predict optimal parameters for other kinds of welding processes.

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VII. BIOGRAPHIES

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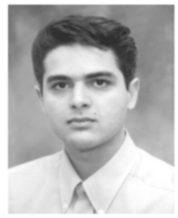

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