Design of Experiment and Goal Programming Application for the GMAW Process

An integrated experimental design and goal programming combination are proposed to determine critical process variables

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ABSTRACT

The gas metal arc welding (GMAW) process is extensively used in manufacturing for a variety of ferrous and nonferrous metals because it greatly increases the quality of welding. The objective of this study is to develop an approach that enables the determination of critical GMAW variables and optimization of process variables by using integrated design of experiment (DoE) and goal programming (GP) methods conjunctively. This paper presents a methodology for simultaneously determining the variables of a GMA process with multiple performance objectives utilizing full-factorial design of experiments, regression analysis and goal programming. Three GMAW process variables formulated using regression analysis, are simultaneously optimized utilizing the GP method. Results were validated and showed that the proposed method provided more accurate approximations, increasing the quality of the GMA welding process.

Introduction

Gas metal arc welding (GMAW) is an arc welding process in which the electrode is a consumable bare metal wire, and shielding is accomplished by flooding the arc with gas (Ref. 1). When the process was first introduced, it was applied to the welding of aluminum using inert gas (argon) for arc shielding. The name given to this process at that time was MIG (metal inert gas) welding. Shielding gases for the GMAW process include inert gases such as argon and helium for aluminum welding, and active gases such as CO_2 for steel welding. The development of GMAW for steel welding has led to the use of gas mixtures, such as CO_2 and argon, or oxygen and argon (Ref. 1).

Gas metal arc welding is affected by various variables such as welding geometry, groove angle, and shielding gas type and mixture. Although many experimental design approaches are now available to facilitate the understanding of the effects of process variables on the welding performance selection, this paper attempts to explore the applicability of integrated design of experiment (DoE) and goal programming (GP) methods to determine the optimal GMAW variables in a real-time industrial application.

There are previous studies that aimed to increase welding process performance. However, a search of the *Science Direct* (Ref. 2) electronic database from 2000 to the present determined there has been no study that particularly combines DoE and GP simultaneously in the welding process design. In this regard, the method of integrating DoE, regression analysis, and GP is applied to determine optimum welding parameters for the first time. In this study, DoE and GP methods are implemented together to identify critical factors of the GMA variables by fitting a polynomial to the experimental data in a multiple linear regression analysis.

The main objective of this study is to present an integrated GMA welding design approach by 1) addressing both design and process variables simultaneously, 2) modeling performance responses of the GMAW process using DoE and regression analysis, and 3) achieving desired levels of multiple performance responses through a GP formulation with the regression equations of welding variables. Application steps of this study are illustrated in Fig. 1.

The basic welding variables used in this study were groove angle and joint geometry to determine the effect on mechanical properties for tension and compression loading of butt-joint-welded armor steel. Armor steel plates used in the study were prepared using V- and double-V-groove joint geometries and two different groove angles: 48 and 60 deg. Welding was performed with the GMA process. During the study, tension and compression tests of the welded joints were performed, and tensile properties and compression strength of the welded plates were examined.

KEYWORDS

Gas Metal Arc Welding
Armor Steel
Design of Experiment
Goal Programming
Process Variables

Literature Review

In a welding process, the primary task is to select a combination of process variables that produces an acceptable quality level for production. In a number of published studies, several methods have been proposed to predict and understand the effects of the process variables on welding performance. Generally, two major independent research areas are utilized to improve welding performance. These areas include the empirical method based on studies of real welding situations, and mathematical model- or experimental design-based studies. As an example of the empirical method-based studies, Alam et al. (Ref. 3) presented a study on understanding the interacting geometrical causes for the value and location of the peak stress in manifold laser weld geometries. Using finite element analysis (FEA), they endeavored to provide applicability of the findings to a much wider range of joint and root designs. In another study, Kim et al. (Ref. 4) proposed a method for determining the near-optimal settings of welding process parameters using a controlled random search (CRS) in which the near-optimal settings of the welding process parameters were determined through experiments.

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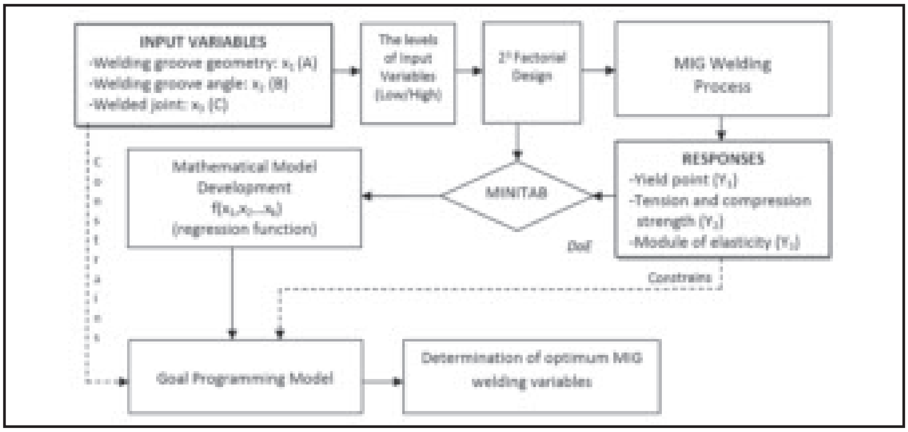

Fig. 1 — The DoE-GP model application steps.

Fig. 2 — Armor steel plates were prepared using V- and double-V-groove welding geometries.

Recently, DoE has a wide application area in understanding the effects of the process variables on the welding performance. As evidenced in published studies, it can be seen that DoE is the most common approach used in determining welding variables. For example, Gunaraj and Murugan (Ref. 5) presented the application of response surface methodology (RSM) in developing mathematical models for submerged arc welding (SAW) of pipes. They plotted contour graphs related to important input variables, namely the open-circuit voltage, the wire feed rate, the welding speed, and the nozzle-to-plate distance, to the penetration, the width, and the percentage dilution of the weld bead. In another study, Tarng et al. (Ref. 6) used gray-based Taguchi methods for the optimization of the SAW process parameters. In their application, the gray relational analysis was employed to solve the SAW process with multiple weld qualities. Similarly, Kim et al. (Ref. 7) developed an algorithm that enabled the determination of process variables for optimized bead geometry for robotic GMA welding processes. In another study, Tarng et al. (Ref. 8) used fuzzy logic in the Taguchi method to optimize the SAW process with multiple performance characteristics. Jing-Shiang et al. (Ref. 9) utilized the principal component analysis (PCA) approach integrated with the Taguchi method to improve the GMAW process for welding aluminum foam plate. They produced a set of optimized parameter combinations to ensure that the GMAW process exhibited the best multiple performance characteristics for welding aluminum foam plate. Tay and Butler (Ref. 10) described an application of an integrated method using experimental designs and neural network technologies for modeling and optimizing the GMAW process. Cho et al. (Ref. 11) analyzed the effects of various welding conditions on the quality of aluminum welds employing the DoE and statistical modeling approach. Cho et al. also examined process parameters and abnormalities, such as electrode misalignment and poor fit up, in their study.

Experimental Work

In the experiment, armor steel plates were prepared using V- and double-V-groove welding geometries and two different types of groove angles using the GMAW process. Tension and compression tests of welded joints were performed and tensile properties and compression strength of the welded plates were examined (Ref. 12).

The selection of the welding electrode wire was based principally upon matching the mechanical properties and physical characteristics of the base metal, weld size, and existing electrode inventory. An austenitic stainless steel electrode 1.6 mm in diameter was used. The chemical compositions and mechanical properties of armor steel and welding material used in the tests are given in Tables 1 and 2.

The welding parameters were arc current: 150 A; arc voltage: 24.5 V; welding speed: 4.9 m/min; welding electrode diameter: 1.6 mm; and weld sequence: 3 passes. A shielding gas mixture of 97% argon-3% CO_2 was used. To cut the plates to the required dimensions, welding grooves were prepared in a horizontal machining center using V- and double-V-groove geometries with 48- and 60-deg groove angles in accordance with TS EN ISO 9692-1 standard — Fig. 2.

The welding and test specimen preparation were carried out at 1st Main Maintenance Center facility, while test fixtures were designed and produced at Baskent University, and the testing facility of Gazi University in Turkey was used for tensile and compressive tests. Examples of these tests are illustrated in Figs. 3 and 4.

These samples were joined with the GMAW process until the predetermined full-factorial experimental runs were

Table 1 — Chemical Compositions of Armor Steel and Welding Electrode

Material	Armor Steel					Welding Electrode						
Chemical composition (%)	C	Cr	Ni	Mb	Mn	C	Si	Mn	P	S	Cr	Ni
	0.272	0.92	0.301	0.249	0.699	0.066	0.622	6.819	0.017	0.012	18.633	8.801

completed. Among these welded parts, a total of 120 (8×5×3) test samples were prepared in accordance with standards.

DoE and Regression Analysis

DoE Methodology

Recently, DoE has been more widely used in quality control, manufacturing, and system engineering disciplines for design or development of a new product and redesign of an existing product (Ref. 13). Due to the highly competitive global industry, companies need to possess a swift and strong understanding of the impact of both operational and environmental variables and their interactions on system or product performance. Therefore, mathematical model–based optimization employing DoE is a powerful design technique for use by system analysts, engineers, and designers (Ref. 13). For the optimization models, there are various papers and tutorials using stochastic optimization, DoE, RSM, modern heuristic methods, and statistical methods. Compared to many methods, DoE is a more efficient method among optimization models in terms of number of required experiments. Also, its applications, as well as computations, are more time efficient (Refs. 14, 15).

In this study, the effects of GMAW variables were studied employing DoE and GP approaches simultaneously. DoE was used to identify critical welding variables and their interactions of all experiments by fitting a polynomial to the experimental data in a multiple linear regression analysis. A 2^3 full–factorial design provided the main effect and interactions of three variables at two levels. The 2^3 full–factorial design required 8 weld runs with 5 replications for fitting each regression equation. This factorial design also enabled us to investigate the existing interactions between three selected factors that affect GMAW performance on armor steel plates. The regression equations were obtained for the GMAW responses, namely, yield point (Y_1), tension or compression strength (Y_2), and modulus of elasticity (Y_3), where welding groove angle is (x_1), welding groove geometry is (x_2), and welded joint is (x_3). The structure of the regression equations is given below.

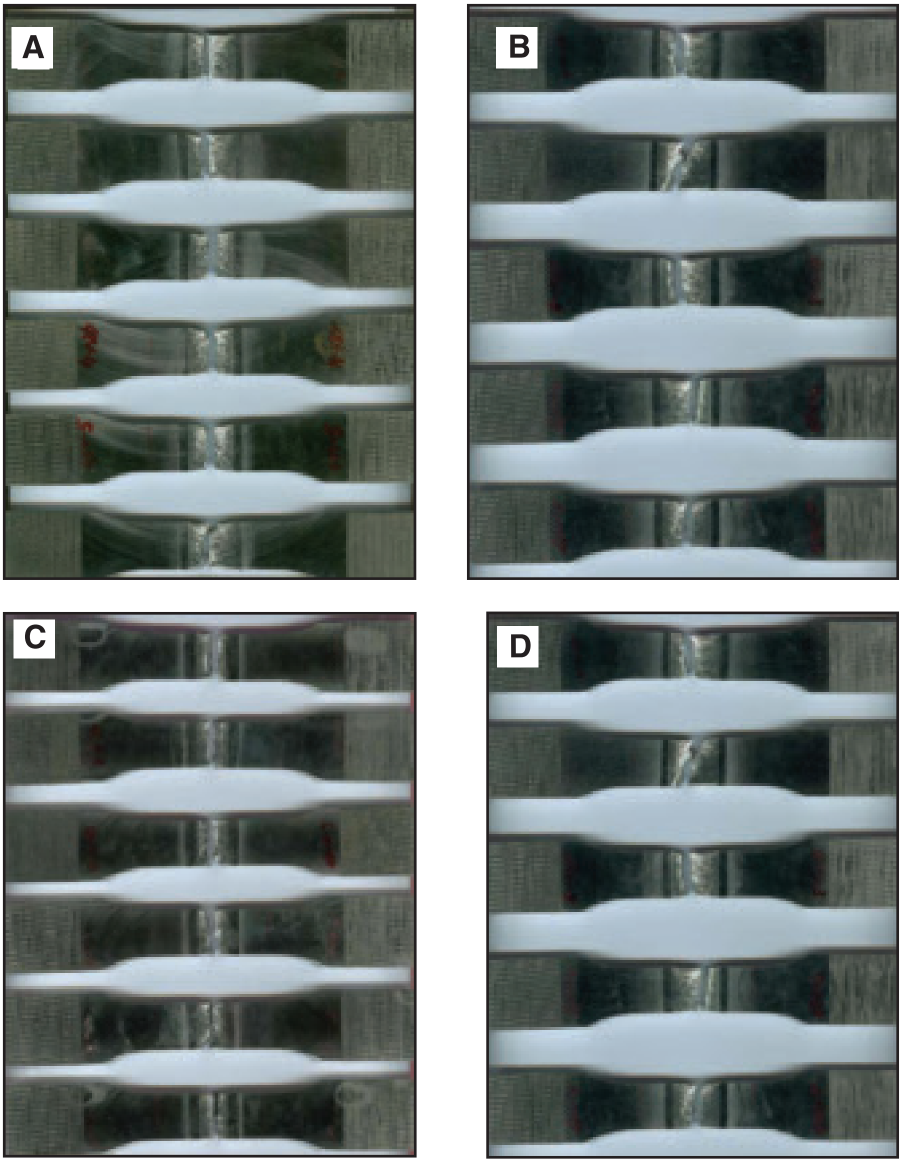

Fig. 3 — A — Tension test results for 48-deg, V-groove geometry; B — tension test results for 60-deg, V-groove geometry; C — tension test results for 48-deg, double-V-groove geometry; D — tension test results for 60-deg, double-V-groove geometry.

Table 2 — Mechanical Properties of Armor Steel and Welding Electrode

Mechanical Properties	Armor Steel	Welding Electrode
Tensile strength (MPa)	1660	612
Yield strength (MPa)	1396	407
Elastic modulus (GPa)	211.3	130
Elongation (%)	11	40
Poisson ratio	0.28	0.3

Table 3 — Variable Levels and Codes for DoE

Variables	Minimum Level	Maximum Level	Minimum Cod	Maximum Cod
Welding groove angle: x_1 (A)	48 deg	60 deg	–1	1
Welding groove geometry: x_2 (B)	V	double-V	–1	1
Welded joint: x_3 (C)	tensile	compression	–1	1

Table 4 — The Results of 2^3 Factorial Design

Design of Experiment Points	Factor Levels A (x_1)	B (x_2)	C (x_3)	Replication 1	2	3	4	5
				Yield Point (Y_1) (MPa)				
1	1	–1	1	417.32	297.08	292.54	400.29	418.80
2	1	–1	–1	305.36	307.54	313.03	426.09	274.01
3	1	1	1	723.73	289.07	473.20	485.07	267.84
4	1	1	–1	261.61	713.69	475.40	301.94	712.17
5	–1	1	–1	317.67	445.91	672.88	707.98	289.12
6	1	–1	1	422.29	304.13	479.82	268.23	314.24
7	1	1	1	636.67	302.71	552.35	279.54	271.41
8	–1	–1	1	471.21	478.51	304.42	699.23	301.51
				Tension or Compression Strength (Y_2) (MPa)				
1	1	–1	1	962.76	366.81	375.07	932.93	945.97
2	1	–1	–1	460.54	438.18	398.47	952.08	415.30
3	1	1	1	898.15	481.60	1042.35	989.73	385.92
4	1	1	–1	419.79	885.60	1076.18	487.58	989.69
5	–1	1	–1	410.17	1072.61	1078.00	993.63	398.01
6	1	–1	1	976.51	496.55	971.28	425.70	496.42
7	1	1	1	980.34	468.86	1048.96	390.34	397.17
8	–1	–1	1	886.40	975.56	448.78	989.21	470.49
				Modulus of Elasticity (Y_3) (GPa)				
1	1	–1	1	50.79	42.94	36.35	50.92	51.57
2	1	–1	–1	43.12	35.65	45.24	51.52	47.36
3	1	1	1	52.83	39.70	53.40	52.58	48.18
4	1	1	–1	47.42	50.78	52.97	42.09	53.06
5	–1	1	–1	52.89	49.85	53.20	52.96	45.49
6	1	–1	1	51.77	38.14	52.49	46.43	39.64
7	1	1	1	53.87	39.38	54.03	44.87	46.50
8	–1	–1	1	52.32	50.77	43.44	53.66	40.62

Determination of the Regression Equations

The first stage of building a regression function is the selection of the input variables and their levels, taking into account process constraints. Since it is not possible to identify the effects of all variables, it is important to determine the variables that have a more significant effect on the response. The GMAW variables and variable levels employed in this study are given in Table 3.

These determined factors (A, B, C) are the independent variables that are used as input values to the GMAW process to generate the dependent variables, which are the yield point, tension or compression strength, and module of elasticity of the weld joint. It is possible to represent all combinations using a regression model instead of time-consuming GMAW experiments. Each combination was run five times, and the runs were independent of each other. The polynomial regression models took into account three input GMAW process variables.

The experiment results for the 2^3 full-factorial designs were collected (Table 4) and the coefficients β of the polynomial regression model were estimated. Table 4 shows the combination matrix for 2^3 factorial designs with outputs as yield point (Y_1), tension or compression strength (Y_2), and modulus of elasticity (Y_3) in the GMAW process. Analysis of the main,

Table 5 — Estimated Effects and Coefficients for Y_1

Term	Effect	Coef	SE Coef	T	P
Constant		431.89	6.289	68.67	0.000
A	–55.25	–27.63	6.289	–4.39	0.000
B	86.90	43.45	6.289	6.91	0.000
C	247.48	123.74	6.289	19.68	0.000
AB	–24.54	–12.27	6.289	–1.95	0.060
AC	–36.78	–18.39	6.289	–2.92	0.006
BC	105.29	52.65	6.289	8.37	0.000
ABC	–12.35	–6.17	6.289	–0.98	0.334

S = 39.7762 R–Sq = 94.38% R–Sq (adj) = 93.15%

Table 6 — Estimated Effects and Coefficients for Y_2

Term	Effect	Coef	SE Coef	T	P
Constant		721.991	7.320	98.63	0.000
A	–5.386	–2.693	7.320	–0.37	0.715
B	–15.005	–7.503	7.320	–1.02	0.313
C	550.811	275.405	7.320	37.62	0.000
AB	24.378	12.189	7.320	1.67	0.106
AC	3.837	1.919	7.320	0.26	0.795
BC	46.634	23.317	7.320	3.19	0.003
ABC	–0.861	–0.431	7.320	–0.06	0.953

S = 46.2962 R–Sq = 97.81% R–Sq(adj) = 97.33%

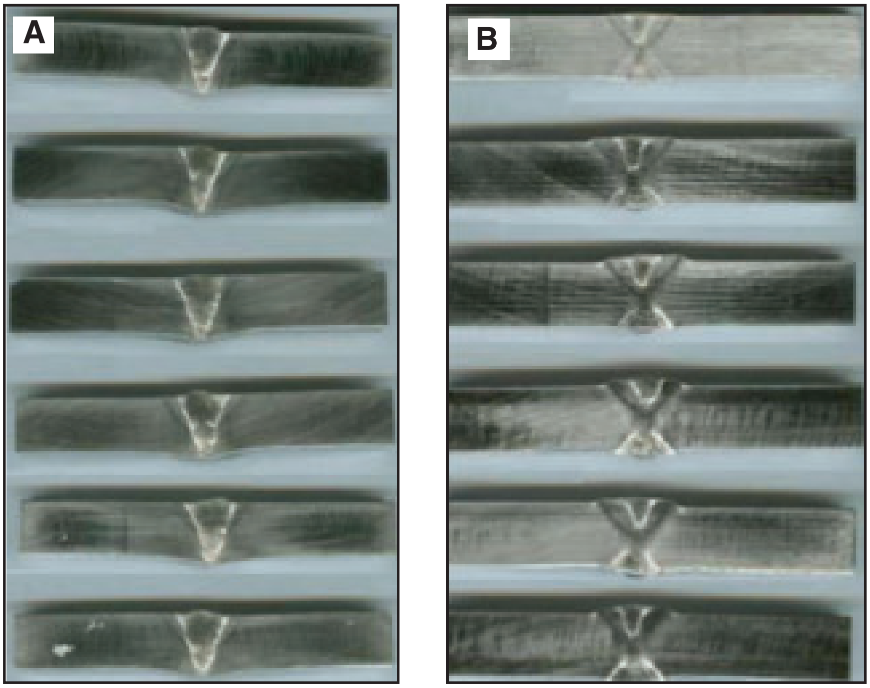

Fig. 4. — A — Compression test results for V-groove geometries; B — compression test results for double-V-groove geometry.

two-way interactions and three-way interactions were obtained at 0.05 significance level, and the coefficients and *p* values are presented in Tables 5–7.

The results of the experimentations are analyzed by ANOVA procedures (Ref. 16). Tables 8–10 show the results of the ANOVA.

ANOVA results give a summary of the main effects and interactions (Tables 8–10). In Tables 6–8, the main effects and two-way interactions are significant on the *p* response since the *p*-values are lower than 0.05. After identifying the significant effects in ANOVA tables (Tables 8–10), estimated effects and coefficients (Tables 5–7) were analyzed. These tables show the *p*-values associated with each individual model term.

Table 7 — Estimated Effects and Coefficients for Y_3

Term	Effect	Coef	SE Coef	T	P
Constant		52.770	0.3194	165.20	0.000
A	–0.038	–0.019	0.3194	–0.06	0.953
B	4.270	2.135	0.3194	6.68	0.000
C	8.996	4.498	0.3194	14.08	0.000
AB	0.829	0.415	0.3194	1.30	0.204
AC	0.238	0.119	0.3194	0.37	0.712
BC	–2.650	–1.325	0.3194	–4.15	0.000
ABC	–0.343	–0.171	0.3194	–0.54	0.595

S = 2.02023 R–Sq = 89.13% R–Sq (adj) = 86.75%

Table 8 — MINITAB Analysis of Variance Results for Y_1 (coded units)

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Main Effects	3	718524	718524	239508	151.38	0.000
2–Way Interactions	3	130419	130419	43473	27.48	0.000
3–Way Interactions	1	1525	1525	1525	0.96	0.334
Residual Error	32	50629	50629	1582		
Pure Error	32	50629	50629	1582		
Total	39	901097				

Table 9 — MINITAB Analysis of Variance Results for Y_2 (coded units)

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Main Effects	3	3036465	3036465	1012155	472.23	0.000
2–Way Interactions	3	27838	27838	9279	4.33	0.011
3–Way Interactions	1	7	7	7	0.00	0.953
Residual Error	32	68587	68587	2143		
Pure Error	32	68587	68587	2143		
Total	39	3132897				

The "Term" column in Tables 5–7 presents the main effects and all interactions. The second column displays the relative strength of the effects of the terms. Coefficients and their standard deviations are shown in the third and fourth columns, respectively. The last two columns display the *t*-ratios and *p*-values. The rows of all significant factors ($p < 0.05$) are shown in bold in Tables 5–7. As a result, the regression Equations 1–3 have been derived through Tables 5–7 for the Y_1, Y_2, and Y_3. The regression equations are as follows:

$$Y_1 = 431.89 - 27.63A + 43.45B + 123.74C - 18.39AC + 52.65BC \quad (1)$$

$$Y_2 = 721.991 + 275.405C + 23.317BC \quad (2)$$

$$Y_3 = 52.770 + 2.135B + 4.498C - 1.325BC \quad (3)$$

The coefficients of determination R-square (93.15, 97.33, and 86.75%, respectively) are high enough in that the single effects and the interactions could be explained by the model satisfactorily.

Decision Model and Optimization

Goal programming is a multiobjective decision-making model that can efficiently handle multiple objectives simultaneously (Refs. 17, 18). Goal programming evaluates so as to minimize an objective function that can be defined as a combination of multidimensional absolute deviations from the goal value. Goal programming has wide usability and flexibility because of its capability to admit nonhomogeneous units of measure (Ref. 18). Goal programming can be classified into two widely used applications that are distinguished by the way they determine priorities and objective functions (Ref. 17). First, the pre-emptive GP model is formed when goals are clearly ranked and deviation variables are ranked. Second, the weighted GP model, also called the nonpreemptive GP model, attempts to minimize the total weighted deviations from all goals (Refs. 19, 20). The second model is useful when the relative weights of decision factors for goals are available. In this study, we used the weighted GP model with additional constraints and integer decision variables that was formulated below. With the regression equations for three welding performance responses presented previously in this paper, the GMAW design problem can be formulated via the GP method. The GP model for the GMAW design problem is given in the equations below.

Objective Function:

$$Min\ Z = P_s\, d_s^- + P_{tcs}\, d_{tcs}^- + P_{me}\, d_{me}^- \quad (4)$$

Strength Limit:

$$431.89 - 27.63x_1 + 43.45x_2 + 123.74x_3 - 18.39x_1x_3 + 52.65x_2x_3 + d_s^- - d_s^+ = 432 \quad (5)$$

Tension or Compression Strength Limit:

$$721.991 + 275.405x_3 + 23.317x_2x_3 + d_{tcs}^- - d_{tcs}^+ = 722 \quad (6)$$

Modulus of Elasticity Limit:

$$52.77 - 2.135x_2 + 4.498x_3 - 1.325x_2x_3 + d_{me}^- - d_{me}^+ = 52.8 \quad (7)$$

Constraints:

$$48 \le x_1 \le 60 \ \textit{and integer-valued} \quad (8)$$

$$x_2 \text{ and } x_3 \text{ are binary (0 or 1)} \quad (9)$$

$$d_s^-, d_s^+; d_{tcs}^-, d_{tcs}^+; d_{me}^-, d_{me}^+ \ge 0 \quad (10)$$

$$P_s >> P_{tcs} >> P_{me} \ \textit{(absolute dominance)} \quad (11)$$

The presented GP formulations can easily be rearranged or modified depending on the priorities of the decision makers and circumstances of the decision environment. The GP objective function (Equation 4) includes the positive and negative deviational variables that represent the deviations from the desired goal levels (i.e., overachievement of a goal is represented by d^+ and underachievement of a goal is shown as d^-) with preemptive priority levels ($P_s >> P_{tcs} >> P_{me}$).

The solution of the GP model minimizes the objective function (Equation 4) and satisfies goal constraints (Equations 5–11). The solution set also must satisfy the system constraints. The GP model was solved using LINGO® and the model determined the optimal combination as follows:

- Welding groove angle: 48 deg
- Welding groove geometry: double–V
- Welded joint: tension

Discussion of the Proposed Model

In order to demonstrate the usability and potentiality of the integrated DoE-GP application in solving GMAW process optimization in real–time manufacturing environment and loading conditions, the following comparative analysis is considered. This comparative analysis for the GMAW process is presented as how well the DoE-GP model represents a real-world manufacturing application. To ensure the validity of the DoE-GP model built in this study, the DoE-GP model's results were tested against different solutions of the same problem using FEA methods taken from the literature (Ref. 12). For the same GMA welding design problem, Ipek (Ref. 12) obtained similar welding design conditions for the GMAW process with FEA method-based analysis, which produced optimal welding conditions. Ipek (Ref.12) examined the effects of basic GMAW parameters such as welding groove angle and geometry on mechanical properties for tension and compression loading of butt-joint-welded armor steel. In Ipek's experiment, armor steel plates were prepared using V- and double-V-groove welding geometries and 48-, 54-, and 60-deg groove angles with the GMAW process. The shielding gas mixture was 97% argon-3% CO_2.

The effects of welding parameters such as groove geometry and groove angle on tension and compression strength were analyzed numerically using FEA software MSC.MARC®, and three–dimensional, elastic–plastic FEA was applied to determine the strength of armor steel. Ipek (Ref. 12) also compared the experimental results and FEA solutions in her study and her results were found consistent with experimental and FEA findings. The results are shown in Tables 11 and 12. The readers are referred to Ipek and Elaldi (Ref. 21),

Table 10 — MINITAB Analysis of Variance Results for Y_3 (coded units)

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Main Effects	3	991.67	991.671	330.557	80.99	0.000
2–Way Interactions	3	77.65	77.650	25.883	6.34	0.002
3–Way Interactions	1	1.18	1.176	1.176	0.29	0.595
Residual Error	32	130.60	130.602	4.081		
Pure Error	32	130.60	130.602	4.081		
Total	39	1201.10				

Table 11 — Experimental Results and FEA Solution's Comparison for Tension Strength (Ref. 12)

Grove Geometry	Yield Stress – Experimental Results (MPa)	Yield Stress – FEA Results (MPa)	Modulus of Elasticity – Experimental Results (GPa)	Modulus of Elasticity – FEA Results (GPa)
48 V	500.5	478.5	70.0	69.8
54 V	512.7	494.5	72.2	77.0
60 V	483.4	473.4	67.8	63.1
48 Double–V	477.4	480.8	78.6	74.4
54 Double–V	456.3	451.6	74.5	69.1
60 Double–V	439.2	461.9	80.5	61.7

Table 12 — Experimental Results and FEA Solution's Comparison for Compression Strength (Ref. 12)

Grove Geometry	Yield Stress – Experimental Results (MPa)	Yield Stress – FEA Results (MPa)	Modulus of Elasticity – Experimental Results (GPa)	Modulus of Elasticity – FEA Results (GPa)
48 V	747.4	750.2	87.2	92.8
54 V	768.1	723.6	86.5	97.1
60 V	68.2	729.2	86.8	84.0
48 Double–V	1103.0	1092.5	89.1	91.9
54 Double–V	1056.3	1054.2	90.3	90.4
60 Double–V	858.8	1007.7	89.9	90.1

Table 13 — Optimal Levels of GMAW Process Variables

Welding Variables	DoE-GP Model Optimal results for all possible conditions	FEA method-based analysis (Ref. 12) Absolutely Tension Condition	Absolutely Compression Condition
Welding groove angle	48 deg	54 deg	48 deg
Welding groove geometry	double-V	V	double-V
Welded joint	tension	tension	compression

for detailed explanations and application steps of the FEA results.

As a result, a welding groove angle of 54 deg and a V-groove geometry were found to be the best mechanical properties for tension strength. Additionally, welding groove angle of 48 deg and a double-V-groove geometry were found to be the best solution for compression strength of butt-joint-welded armor steel.

Therefore, it can be seen in Table 13 that in the results of the DoE-GP model, the optimal GMAW conditions are similar to those derived by Ipek's (Ref. 12) study. It was concluded that the DoE-GP model could be employed to determine the optimal conditions for the GMAW process since it was computationally efficient enough to explore all possible combinations among three primary welding variables.

As a result of the DoE-GP model, x_1 = 48 deg, x_2 = double-V-groove geometry, and x_3 = tension loading were found to be the best mechanical properties for tension and compression strength of butt-joint-welded armor steel. Unlike Ipek's study (Ref. 12), this study presents an integrated model for simultaneously determining optimum process variables for all possible combinations of a GMAW process.

However, the proposed DoE-GP model demonstrated some implementation difficulties. The decision–maker must be aware that proper utilization of the developed DoE-GP approach depends strongly on the following issues: 1) the limitations and dependencies within the decision-maker formulated as constraints in the GP have great importance in the determination of optimum GMAW process variables; 2) inappropriate determination of the constraints will result in recommendation of an inappropriate solution set; and 3) in the developed approach, the solution is sensitive to the variations in the priority procedure. If the determination of priority level of objectives is not judged correctly, then the priority will be assigned inefficiently, which directly affects the outcomes of the DoE–GP approach.

Conclusions

In this study, DoE and GP methods were combined to identify critical variables of the GMAW process by fitting a polynomial to the experimental data in a multiple linear regression analysis. A 2^3 full-factorial design was employed in this study to test an experimental design for the multiple-objective GMAW process. This is a new approach in solving a multiple-objective GMAW design problem by employing the DoE method, regression analysis, and a multiobjective decision making method conjunctively.

For the first time, the method of integrating DoE, regression analysis, and GP is applied to determine optimum welding parameters. This combined method provides a new and alternative solution to the FEA. It is also a more practical and easier method for welding parameter optimization for engineers working in a manufacturing environment.

The combined use of DoE and GP approaches allowed us to solve a multiobjective decision making problem that considers multiple conflicting goals along with resource limitations and dependencies among the welding process variables. The DoE-GP model's results were tested against the solution of the same problem using FEA methods found in the literature (Ipek, Ref. 12). It was found that FEA method-based analysis, which gives optimal welding conditions, yielded similar results to those derived from the DoE-GP model. In addition to this similarity, the proposed model in some respects has additional further benefits. For example, use of the regression model greatly reduced the cost, time, and amount of experimental steps. Furthermore, this study presents an integrated model for simultaneously determining optimum process variables for all possible combinations of a GMAW process. Application of the combined model produced a structure that enables decision-makers to see different facets of the problem and keep track of the effects their decisions made at various stages of their solution process on the solution sets. Therefore, the developed approach possesses flexibility of adding new constraints, aspiration levels, improvement objectives or alternatives, and modifying them whenever necessary.

Application of the DoE-GP method in a wider range of welding or manufacturing processes, which have a large number of variables, in manufacturing or other possible application areas, remains for future research.

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