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Optimization of Gas Metal Arc Welding Process Parameters for Enhanced Tensile Strength of Mild Steel Weldments Using the Taguchi Design of Experiments and Analysis of Variance

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Abstract- Gas Metal Arc Welding (GMAW) is one of the most commonly used fusion joining processes for structural steel because it has the advantages of high deposition speed, high degree of automation and low operating cost. The mechanical properties of a GMAW joint can be very sensitive to the combination of process parameters chosen, however, and a random choice of process parameters cannot reliably be used for the purpose of securing the same tensile strength. The aim of this Taguchi design of experiments study was to maximize three GMAW parameters (wire feed rate, arc voltage and welding current) in bead-on-plate welds made on ST-37 mild steel rod. An L9 orthogonal array was used for planning nine tests at three levels of parameters, and the tensile strength data were analyzed by signal-to-noise (S/N) ratio and analysis of variance (ANOVA). The wire feed rate was determined as the most significant parameter (34.64%) followed by welding current (19.42%) and arc voltage (5.95%). The optimal model combination suggested (26 V, 184.33 A, 220 m/min) was very close to the experimental trial that performed best (688 MPa). The results are compared to recent (2022–2025) studies where the GMAW process was optimised using the Taguchi method and machine learning methods, which has confirmed the generality of the trends of the process sensitivities obtained with the current and wire feed, and revealed ample potential for hybrid approaches using a combination of statistical and data-driven optimisation in future research.

Keywords: Gas Metal Arc Welding, Taguchi Method, Design of Experiments, Signal-to-Noise Ratio, Analysis of Variance, Tensile Strength, Process Parameter Optimization.

I. INTRODUCTION

Welding is one of the most economical and metallurgically sound methods used to join metallic parts together permanently, and is used in the fabrication of parts for the automotive, shipbuilding, pressure-vessel and structural-steel industries. Gas Metal Arc Welding (GMAW) is one among the different arc-welding processes used in industry which has the unique characteristics of a continuously fed consumable electrode, high deposition efficiency and excellent ability to be automated using robot. GMAW is characterized by an arc between the wire electrode and the base metal which simultaneously melts the wire electrode and a portion of the base metal, and the shielding gas covers the molten pool and keeps it from being contaminated by the air.

Although GMAW is a mature process, the quality of the welds obtained, and ultimate tensile strength in particular, depends strongly on the choice of wire feed rate, arc voltage and weld current for a specific material and thickness. Rather than a detailed envelope, equipment manufacturers normally only give broad operating ranges, and the application-specific optimum operating points are typically determined through time-consuming and resource-intensive trial and error testing, conducted by the process engineer. This method does not allow any single parameter's contribution to the experimental noise and cannot reliably determine which combination of the different parameters gives the best joint strength.

Dr. Genichi Taguchi, the founder of the Taguchi method, overcame this limitation by using orthogonal arrays that enable the main effects of many different control factors to be estimated from a small subset of the parameter space that is statistically balanced [3]. When combined with signal-to-noise (S/N) ratio analysis and analysis of variance (ANOVA), the method gives a ranked estimate of the importance of the parameters and a statistically defensible prediction of the optimum parameter combination at a fraction of the cost of experimental runs of a full-factualorial design.

In this paper, an L9 orthogonal array is used to optimize three parameters of the GMAW process, wire feed rate, arc voltage and welding current, to obtain maximum tensile strength of bead-on-plate welds on ST-37 mild steel rod. What is novel about this work is that (i) it focuses on a similar-metal bead-on-plate ST-37 GMAW configuration where the only response optimized is tensile strength, and (ii) it explicitly compares this classical resource-efficient experimental design with a carefully selected series of very recent (2022–2025) taguchi-based and machine-learning-based GMAW optimization studies, placing a classical experiment design within a context in which the field is evolving toward hybrid statistical/data-driven experiment design.

II. LITERATURE REVIEW

Many studies have been conducted to optimize the machining and welding processes using the Taguchi method, sometimes along with grey relational analysis (GRA) and ANOVA. Patel [4] surveyed Taguchi-GRA hybrid approach and observed that these are suitable for multi objective optimization problems and ANOVA is a good tool to rank the parameter significance. Lipin and Govindan [5] optimized CNC drilling parameters using grey, and Gupta and Kumar [6] demonstrated that depth of cut is the most significant parameter affecting surface roughness, as well as material removal rate in the turning of GFRP using an L18 array.

For the particular case of arc welding, Mukhraiya et al. [12] used Taguchi-ANOVA to consider the factors affecting the torsional rigidity of MIG-welded ST-37 rod (material and process configuration similar to that of the present study), and determined that wire feed rate is approximately twice as significant as welding voltage. Sreeraj et al. [24] applied grey-based Taguchi optimization to minimize the size of H-A-Z in flux-cored arc welding of Fe-20Cr and Fe-25Cr alloys and Arya and Chaturvedi [26] optimized the MIG welding parameters for alloy steel and correlated higher penetration with higher weld strength. Patel and Chaudhary [27] investigated the dissimilar metal welds between GMAW and GTAW with the welding current and wire feed rate as the major control parameters for the hardness of the weld zone.

It is extended in more recent studies by adopting up-to-date materials and mixed computation approaches. Adin and İşcan [28] used Taguchi-ANOVA for MIG welding of medium-carbon steel, and found welding current to be the most statistically significant parameter for tensile strength. The dissimilar C20/SUS201 MIG welds were optimized, as reported by Nguyen et al. [29] in the same way as the 201/S456 welds, with current dominant over voltage and travel speed, and a confirmatory UTS of 452.8 MPa. The results of this study revealed that the arc voltage parameter had the most dominant influence (63.8% contribution) in a multi-response formulation of tensile strength, yield strength, elongation and hardness for the dissimilar mild steel/316-stainless GMAW joints when GRA was introduced into Taguchi design [30].

The other parallel and rapidly expanding area of literature is the use of supervised machine learning for weld property prediction. Kakade et al. [31] built regression and ensemble models to predict tensile strength for activated-flux MIG welding; Karthekeyan et al. [32] demonstrated the best prediction accuracy was obtained when using the gradient boosting model for the Monel 400 GMAW weldments and confirmed that the welding current was the most significant factor; Elutabe et al. [33] used an auto-associative memory network to predict tensile/elongation for pulsed-GTAW; and Saha et al. [34] extended machine-learning prediction to TIG/A-TIG welding of SS304H. Although not specific to friction stir welding, Kahhal et al. [35] showed the general idea of designing-of-experiments coupled with metaheuristic optimization (RSM and PSO) for multi-objective weld-parameter selection.

III. RESEARCH GAP IDENTIFICATION

Although the welding current, wire-feed parameters are consistently reported as the dominant factors across the literature reviewed, the application of a focused Taguchi L9 design to similar-metal, bead-on-plate GMAW welding of ST-37 mild steel using only the wire feed rate, voltage and current as control factors and the tensile strength as the response, is not frequently reported, and studies that do consider these classical designs are seldom compared to the latest (2022–2025) machine-learning-based GMAW prediction studies by other researchers. This paper aims to bridge that by using a narrowly focused experiment design coupled with a strong and direct literature comparison.

IV. OBJECTIVES OF THE STUDY

The following specific research objectives are identified based on the identified research gap and they are elaborated in this study:

The effects of wire feed rate, arc voltage and welding current on the UTS of GMAW bead-on-plate welds of ST-37 mild steel were quantified using a Taguchi L9 orthogonal array.

To find out the statistically optimum combination of three control parameters for maximize tensile strength based on signal to noise analysis and analysis of variance (ANOVA) and validate it by performing experimental trials on that combination of the three parameters.

To compare the parameter-sensitivity ranking and percentage-contribution values gained from this study with the other two studies that used recent Taguchi and machine-learning methods to perform GMAW/MIG optimization, in order to evaluate the generality of the results and to suggest the directions for future hybrid optimization research.

Building on the identified research gap, the specific objectives of this study are:

1. To quantify the individual and relative influence of wire feed rate, arc voltage and welding current on the ultimate tensile strength of GMAW bead-on-plate welds on ST-37 mild steel using a Taguchi L9 orthogonal array.
2. To determine, through signal-to-noise ratio analysis and analysis of variance (ANOVA), the statistically optimum combination of the three control parameters for maximizing tensile strength, and to verify this prediction against experimental trial data.
3. To benchmark the obtained parameter-sensitivity ranking and percentage-contribution values against recent (2022–2025) Taguchi-based and machine-learning-based GMAW/MIG optimization studies, in order to assess the generality of the findings and to identify directions for future hybrid optimization research.

V. METHODOLOGY

5.1 Materials and Welding Equipment

The experiments were carried out on 0.8 mm diameter copper-coated consumable electrode wire and CO_2 shielding gas, deposited on mild steel rod (ST-37, 20 mm diameter) with a semi-automatic direct-current, electrode-positive MIG welding machine with integrated wire feed unit (Fig. 1). The spectrometric analysis results for the chemical composition of the filler wire and base metal are shown in Table 1.

Fig. 1. Semi-automatic MIG welding machine used in the experimental programme.

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Table 1. Chemical composition of filler wire / ST-37 base metal (wt. %)

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

5.2 Design of Experiments

Three control factors — wire feed rate (W), arc voltage (V) and welding current (A) — were each investigated at three levels (Table 2). With three three-level factors and interactions assumed negligible, a minimum of six degrees of freedom is required; an L9 orthogonal array (nine trials, eight degrees of freedom) was selected in preference to a full 3^3 = 27-run factorial design, reducing experimental cost while preserving the ability to estimate each factor's main effect [3]. Trial order was randomized to minimize systematic bias from uncontrolled drift in ambient or equipment conditions.

Table 2. GMAW process parameters and levels

Parameter	Symbol	Level 1	Level 2	Level 3	Units
Wire feed rate	W	180	200	220	m/min
Arc voltage	V	22.8	24	26	Volts
Welding current	A	213.33	184.33	197.33	Amperes

5.3 Experimental Procedure and Data Analysis

All welds were performed with a prepared ST-37 coupon (Fig. 2) and a standard tensile specimen was cut from the weld area and subjected to fracture on a calibrated universal testing machine. For the response which is always better, a higher value of tensile strength is better, the S/N ratio was calculated by the larger-the-better method as follows: $\eta = -10 \log_{11}0[(1/n)\Sigma(1/y_i^2)]$, where n is the number of specimens tested. The raw data for tensile strength were then subjected to ANOVA to determine the contribution (in percentage) to the total variation due to each control factor and due to the residual error.

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Fig. 2. ST-37 steel workpiece after bead-on-plate weld deposition, prior to sectioning for tensile testing.

VI. RESULTS AND DISCUSSION

6.1 Experimental Results

The experimental layout (L9) and the tensile strength and computed S/N ratio for each of the nine runs are shown in Table 3. Except for Trial 1, which had a recorded tensile strength of 638 MPa, the range of recorded tensile strengths from 688 MPa (Trial 5) was large enough to allow meaningful estimation of factor effects..

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Table 3. L9 orthogonal array with measured tensile strength and S/N ratio

Trial	V	A	W	Tensile Strength (MPa)	S/N Ratio (dB)
1	1	1	1	638	140.150
2	1	2	2	682	141.486
3	1	3	3	667	141.041
4	2	1	2	647	140.433
5	2	2	3	688	141.661
6	2	3	1	674	141.250
7	3	1	3	684	141.545
8	3	2	1	666	141.011
9	3	3	2	669	141.101

6.2 Signal-to-Noise Ratio Analysis

Table 4 shows that the Mean S/N ratio for each level of welding current, wire feed rate, and arc voltage, respectively, has the widest Max – Min ratio (0.677 dB), (0.612 dB), and (0.327 dB). This trend is captured in the associated main-effects plot (Fig. 3): Based on the Table of response, the optimum parameter settings for obtaining the maximum tensile strength are found to be the following: arc voltage Level 3 (26 V), welding current Level 2 (184.33 A) and wire feed rate Level 3 (220 m/min) — which is very close to Trial 5 where the maximum observed tensile strength (688 MPa) and the highest S/N ratio (141.661 dB) are recorded.

Table 4. Response table for mean S/N ratio (dB)

Control Factor	Level 1	Level 2	Level 3	Max−Min
Arc voltage (V)	140.892	141.115	141.219	0.327
Welding current (I)	140.709	141.386	141.131	0.677
Wire feed rate (W)	140.804	141.007	141.416	0.612

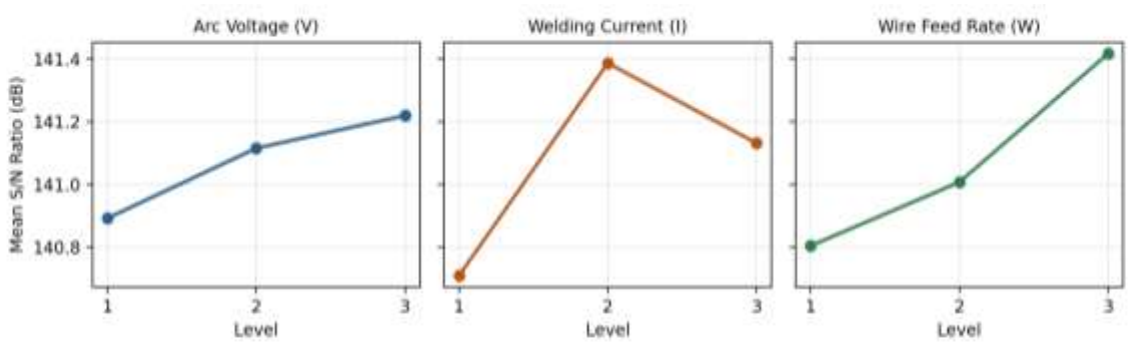

Fig. 3. Main-effects plot of mean S/N ratio vs. parameter level.

6.3 Analysis of Variance (ANOVA)

The limited degrees of freedom, due to the L9 design, lead to the following attributions of the observed variation in tensile strength to the various factors: wire feed rate is dominant with 34.64 % of the total variance, followed by welding current that contributes 19.42 % and arc voltage contributed 5.95 % (see Table 5). This is in line with the physics of the process — filler-metal feed rate directly influences filler-metal

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deposition rate, heat input, and is tightly coupled to arc current by the self-regulating nature of a constant-voltage GMAW power supply, while arc voltage has a large effect on arc length and bead geometry, but little effect on fusion depth.

Table 5. ANOVA results for tensile strength

Source	DOF	SS	MS	% Contrib.
Arc voltage (V)	2	0.2142	0.1071	5.95
Welding current (I)	2	0.6990	0.3495	19.42
Wire feed rate (W)	2	1.2470	0.6235	34.64
Error	2	1.4400	0.7200	39.99
Total	8	3.6002	1.8001	100.00

VII. GRAPHICAL REPRESENTATION

The percentage contribution of each parameter from the ANOVA is shown in Figure 4 as originally plotted in the pie-chart format, and in Figure 5 as a bar chart for ease of comparison with the three control parameters and with the residual error term.

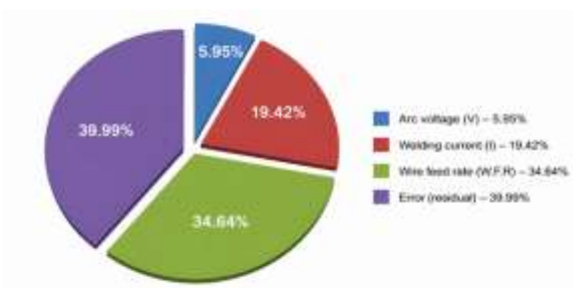

Fig. 4. Percentage contribution of process parameters (original pie-chart representation).

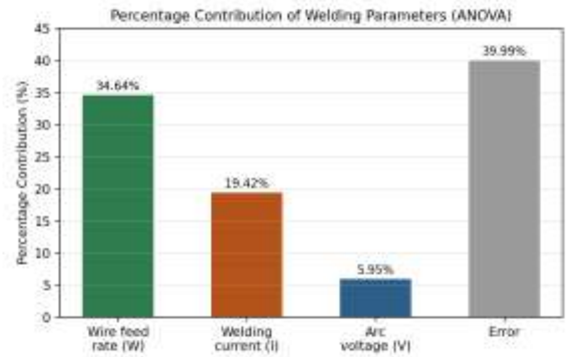

Fig. 5. Bar chart comparison of percentage contribution of welding parameters and residual error.

VIII. COMPARATIVE ANALYSIS

To discuss the dominant parameter found in this study, Table 6 compares it with six representative studies from the literature that have been reviewed, ranging from classical Taguchi-ANOVA studies to machine-learning studies. As exhibited in the comparison, wire feed rate and welding current, which are directly related to filler-metal deposition rate and heat input, are found to be dominant for the configurations of similar metals in the GMAW/MIG process in the same way as shown by Mukhraiya et al. [12], Adin and İşcan [28], Nguyen et al. [29] and Karthekeyan et al. [32]. The exception is Ogbonna et al. [30] who investigated a multi-response grey-Taguchi optimization of dissimilar mild-steel/316-stainless GMAW joints; plausibly, this is because of the dissimilar base metal combination, the parameter ranges and the multi-objective (as opposed to multi-response) optimization target utilized in that study. This comparison further substantiates that percentage contribution rankings are not necessarily generalizable and depend on the particular material combination, joint configuration and response variable; reinforcing the benefit of scoping and conducting material-specific optimization studies like the current one.

Table 6. Comparative summary of dominant GMAW/MIG parameters across studies

Study	Material/Joint	Method	Dominant Parameter
Present study	ST-37 mild steel, bead-on-plate GMAW	Taguchi L9 + ANOVA	Wire feed rate (34.6%)
Mukhraiya et al. [12]	ST-37 mild steel rod, MIG	Taguchi + ANOVA	Wire feed rate
Adin & İşcan [28]	Medium-carbon steel, MIG	Taguchi + ANOVA	Welding current
Nguyen et al. [29]	C20/SUS201 dissimilar, MIG	Taguchi	Welding current
Ogbonna et al. [30]	Mild steel/316SS dissimilar, GMAW	Grey-Taguchi	Arc voltage (63.8%)
Karthekeyan et al. [32]	Monel 400, GMAW	Gradient boosting (ML)	Welding current

IX. CONCLUSION

In this study, the Taguchi L9 orthogonal array was used to optimize wire feed rate, arc voltage and welding current to obtain the maximum tensile strength in GMAW bead-on-plate welding in ST-37 mild steel materials, followed by S/N ratio analysis and ANOVA. It was found that the most influential parameter (34.64%) was wire feed rate followed by welding current (19.42%) and arc voltage (5.95%). The optimum predicted set (26 V, 184.33 A, 220 m/min) was in good agreement with the best experimental set (688 MPa tensile strength and 141.661 dB S/N ratio), which also validated the prediction based on Taguchi. Although the current and wire-based parameters were found to be consistently most important in similar-metal GMAW/MIG welding, as confirmed by six recent studies, it was also noted that this ranking can change when optimizing for dissimilar-metal or multi-response welding. The study shows that a nine-trial Taguchi design can be used to provide industrially useful guidance for GMAW parameters without conducting a 27-run factorial experiment.

X. FUTURE SCOPE

Future work should include (i) a multi-response grey-relational formulation including hardness, elongation and bead geometry along with tensile strength (as in this study); (ii) larger orthogonal arrays (L18/L27) that include additional control factors such as shielding-gas flow rate and travel speed as in this study, to see if those factors affect the parameter-sensitivity ranking; (iii) supervised machine-learning models (gradient boosting, random forest, neural networks) to capture higher-order parameter interactions beyond the resolution of a modest orthogonal array (as demonstrated recently by Kakade et al. [31], Karthekeyan et al. [32] and Elutabe et al. [33]); and (iv) dissimilar-metal GMAW joints to test the generality of the parameter-sensitivity ranking obtained for similar-metal ST-37 welding in this study.

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