Taguchi-based optimization technique for activated tungsten inert gas welding process

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Abstract

In order to improve the performance of TIG welding process different methods have been proposed among which, activated tungsten inert gas (A-TIG) welding process is the most important one. In this study, Taguchi method, regression modeling and analysis of variance have been used to model and optimize A-TIG welding process. In this paper SiO_2, nano-particles have been considered as an activating flux. To gather the required data, Taguchi method has been employed. Then, process response parameters have been measured and their corresponding signal to noise (S/N) ratio values have been calculated. Different regression equations have been applied to model the process. Based on statistical findings, the most fitted models have been selected as an authentic representative of the process. Next, S/N analysis, in such a way that weld width minimized and depth of penetration is maximized has been used. Finally, experimental performance evaluation tests have been carried out, based on which it can be concluded that the proposed procedure is quite efficient (with less than 7% error) in modeling and optimization of A-TIG welding process.

Keywords: activated TIG welding process, depth of penetration, weld bead width, design of experiments, and signal to noise analysis.

Introduction

Tungsten inert gas (TIG) welding is one of the most widely used welding processes for fabricating stainless steels parts due to its good quality and surface finish. As TIG welding process produces a shallow penetration, its application for fabricating of thick parts in a single pass has been restricted [1−3]. To cope with this problem different procedures has been introduced among which hybrid welding (e.g. Laser-TIG) and activated TIG (A-TIG) welding processes are the most important ones [4, 5].

Laser-TIG hybrid butt joint welding process parameters have been investigated using surface methodology (RSM) by Moradi et al [6]. Welding speed, welding current and distance of heat sources have been considered as input process variables. Furthermore, the weld surface width, weld seam area, and weld penetration were assumed as the process responses. Results of ANOVA indicated that the welding speed is the most important parameter. The desirability approach has also been utilized for optimization purpose.

Effect of hybrid laser – TIG welding variables (TIG current, laser power, pulse frequency, pulse duration) on the process responses (DOP and WBW) for welding of AISI316LN have been investigated by Ragavendran et al [7]. Central composite design (CCD) has been employed to design the experimental matrix required for gathering data. To correlate the process variables with the responses, regression modeling procedure has been used. For optimization purpose, the desirability approach has been employed. Then, determined process optimum variables have been validated using confirmation experiments. Based on the results, there was a good agreement between the predicted and measured values.

There are different studies in which A-TIG welding process has been considered. Nonetheless, to the best of our knowledge, there is no published study in which modeling and optimization of DOP and WBW are considered using design of experiments (OA-Taguchi method), mathematical modeling (regression), statistical analysis (ANOVA), and signal to noise (S/N) approach for optimization of process response parameters (DOP and WBW). Therefore, in this article, three process inputs variables (welding current (I), welding speed (S) and welding gap (G)) has been taken into account. Moreover, DOP and WBW have been considered as process response parameters. In the proposed approach, experimental test matrix gathered base on the OA-Taguchi method. Regression modeling has been performed to establish a relation between process input variables and process response parameters. Then, in order to choose the most fitted derived regression equations as the authentic representatives of the process, ANOVA technique has been performed. Furthermore, significance of the process input variables and their corresponding percent contribution (68% and 88% percent contribution reported for welding current affects DOP and WBW respectively) on the process response parameters measures have been determined based on the ANOVA results. Next, in order to maximize DOP and minimize WBW signal to noise (S/N) analysis has been used.

Experimental set-up

To carry out the experiments, a welding machine (DIGITIG 250 AC/DC) equipped with an automatic bed has been used. Furthermore, Argon (with 99.7% purity) as welding shield gas has been used. AISI316L stainless steel sheets (100 mm×50 mm×10 mm) have been considered as specimens. In this study, SiO_2 Nano-powder has been used as the activating flux. The powdered oxide used has an average particle size of 20-30 nm with 99% purity.

Prior to welding, 1000 mg of flux powder was mixed with 2 ml of carrier solvent (ethanol), and the mixture was stirred using a glass rod in a beaker until a paste-like flux attained. Then, the flux was coated on the specimen with a brush. Upon evaporation of the carrier solvent, the flux layer remained attached to the surface of the specimen. Fig. 1 illustrates the preparation process of the paste-like flux [2].

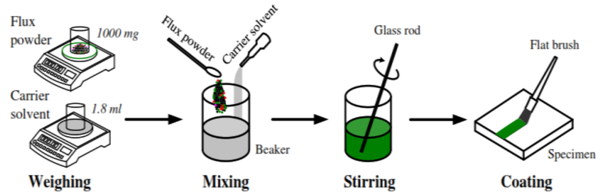

Figure 1. Activating flux preparation procedure [2]

Process input variables and their levels

Table 1, lists the process input parameters and their corresponding intervals and levels. Other input parameters with trivial effects have been considered at a fixed level. Based on the process input parameters and their corresponding levels an OA-Taguchi's L_{32} design matrix has been chosen.

Table 1. A-TIG welding process input variables and their levels

Process parameter	Welding speed (S)	Welding current (I)	welding gap (G)
Unit	mm/sec	Amps	mm
symbol	S	I	G
Interval	1.00-3.00	100-280	0.75-1.50
Level 1	1.00	100	0.75
Level 2	1.67	160	1.50
Level 3	2.34	220	-
Level 4	3.00	280	-

For measuring DOP and WBW, on each samples two transverse cross sections were made. Next, to clearly show DOP and WBW, the cut faces were smoothly polished and etched (Fig. 2). A stereo microscope M 80 (with zoom magnification of 7.5x - 60x and 2.34x - 120x for total magnification with additional, ATM Co.) has been used to measure the DOP and WBW. Fig. 2 (a), illustrates a cut face which has smoothly polished and etched after welding by TIG welding process. Full penetration for A-TIG welding process has been presented by Fig. 2 (b). The average of two measurements for each sample was reported in Table 2.

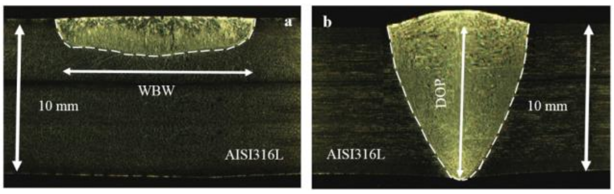

Figure 2. Comparison of TIG and A-TIG weldments cross sections under the same welding condition
(a) Incomplete penetration using TIG welding process
(b) Full penetration using A-TIG welding process

Signal to noise analysis

Experimental matrix based on DOP approach is used by OA-Taguchi method to study the whole process input parameters space with small numbers of experiments. Taguchi method also uses signal–to–noise (S/N) ratios as performance measures to optimize the process response parameters. To calculate the deviation between the experimental and desired value, a loss function is introduced. The loss function is transformed into S/N ratio. The S/N ratio calculation may be decided as "Smallest is the Best, (SB)" or "Largest is the Best, (LB)" based on the process under consideration, as given in Equations 1, 2 [8].

$$\mathbf{SB}:\ S/N(\eta) = -10\log\left(\frac{1}{n}\sum_{K=1}^{n} x_K^{2}\right) \tag{1}$$

$$\mathbf{LB}:\ S/N(\varphi) = -10\log\left(\frac{1}{n}\sum_{K=1}^{n}\frac{1}{x_K^{2}}\right) \tag{2}$$

Where number of iteration in a trial shown as n, in this study, n =1 and x_K is the j^{th} measured value in a run. Therefore, as the lowest WBW and the highest DOP are desired, Eq. 1 and Eq. 2 are considered to calculate WBW and DOP respectively. The experimental results of 32 experiments and their corresponding S/N ratio values based on the Taguchi method are reported in Table 2.

Regression modeling and analysis of variance

Regression modeling is a statistical procedure for approximating the relationships between process input variables and response parameters. To carry out this procedure the following stages are to be taken in to account [9, 10].

Table 2. Experimental conditions based on Taguchi method

No.	G	I	S	DOP	WBW	S/N DOP	S/N WBW
1	0.75	100	1.00	2.97	4.10	21.771	-28.219
2	0.75	100	1.67	2.71	4.19	19.939	-28.654
3	0.75	100	2.34	2.32	3.75	16.831	-26.435
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
30	1.50	280	1.67	8.52	11.05	42.848	-48.048
31	1.50	280	2.34	5.95	9.76	35.667	-45.565
32	1.50	280	3.00	4.70	9.31	30.953	-44.243

The first three columns of Table 2 are the process input variables. The next two columns are the measured process responses (DOP and WBW) based on the conducted experiments in each rows. The last two columns are the calculated S/N ratio values for the measured responses. Any of the above output is a function of process parameters which are expressed by linear, logarithmic and second order functions; as stated in Equations 3 to 5 respectively [10].

$$Y_1 = a_0 + a_1B + a_2C + a_3D \tag{3}$$

$$Y_2 = a_0 + a_1B + a_2C + a_3D + a_{11}BB + a_{22}CC + a_{33}DD + a_{12}BC + a_{13}BD + a_{23}CD \tag{4}$$

$$Y_3 = a\,0 \times B^{a1} \times C^{a2} \times D^{a3} \quad (5)$$

Where, regression constants are shown with a_0, a_1, a_2 and a_3 and are to be predicted. Furthermore, B, C and D are the input parameters (I, S, G) and Y_1, Y_2 and Y_3 are the process response parameters (S/N ratio values for DOP and WBW). Based on the calculated S/N ratios for DOPs and WBWs data given in Table 2, the regression equations are developed using MINITAB software.

To determine how well a model fits the experimental data and represents the authentic process under study ANOVA is performed [10]. ANOVA procedure within 95% of confidence limit has been employed to check the adequacies of proposed regression models (Table 3) [10].

Table 3. ANOVA results of different models

Model	Variable	R^2	R^2 (adj)	F-value	Pr>F
Linear	DOP	95.7%	95.2%	185.90	<0.0001
logarithmic	DOP	92.2%	91.6%	152.83	<0.0001
Second order	DOP	99.4%	99.2%	489.21	<0.0001
Linear	WBW	95.7%	95.4%	258.86	<0.0001
logarithmic	WBW	92.6%	92.0%	161.88	<0.0001
Second order	WBW	98.1%	97.8%	271.16	<0.0001

Obviously, Equations 6 and 7, the second order model (with elimination of unimportant parameters) for DOP and WBW are the superior models to other models based on the required confidence limit (Pr), the correlation factor (R^2) and the adjusted correlation factor (R^2-adj). Thus, these superior models are considered as the best authentic representative of the A-TIG welding process in this paper.

$$S/N\,(DOP) = 6.82 + 0.243\times I - 5.08\,S - 0.000329\times I\times I + 1.13\times S\times S + 0.0221\times G\times I - 1.74\times G\times S - 0.0138\times I\times S \quad (6)$$

$$S/N\,(WBW) = -13.1 - 5.68\times G - 0.136\times I + 0.000125\times I\times I + 1.41\times G\times S - 0.00182\times I\times S \quad (7)$$

The residual plots for DOP and WBW have been shown in Figs 3 and 4 respectively. This Figs demonstrate a good conformability of the developed model to the real process (normal probability plot). Moreover, histogram plots show the normal distribution of the residuals. Based on the residual-fitted value plots, there is no pattern to be followed by the residuals. Furthermore, order of observation versus residuals show that the residual changes is accidentally.

The percent contributions of each parameter may be provided by ANOVA results (Equation 8) [10]. The percent contributions of the A-TIG process parameters are shown in Figs. 5 and 6.

$$P_i\,(\%) = \frac{SS_i - (DOF_i \times MS_{error})}{Total\ Sum\ of\ Squre} \quad (8)$$

Where, P_i is percentage of contribution for each parameters under consideration, SSi is sum of square, DOFi is degree of freedom of ith factor, and MSerror is mean sum of square of error [10].

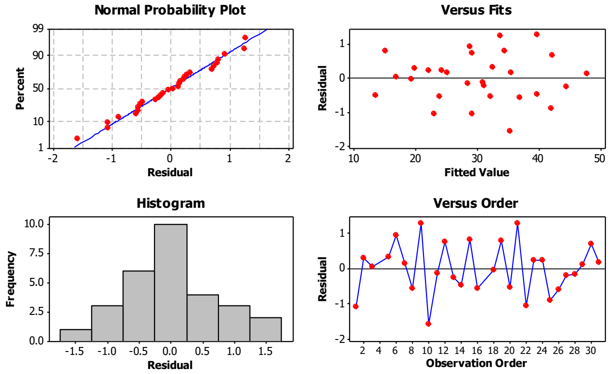

Figure 3. Residual plot for depth of penetration (DOP)

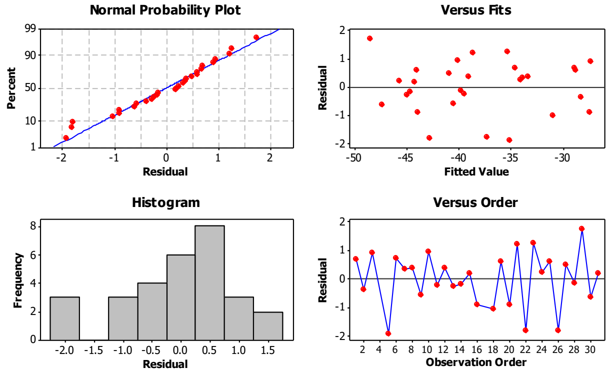

Figure 4. Residual plot for weld bead width (WBW)

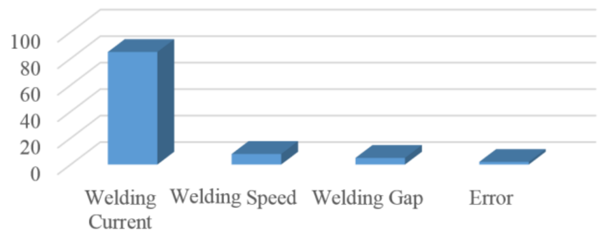

Figure 5. Percent contributions of welding parameters to the DOP

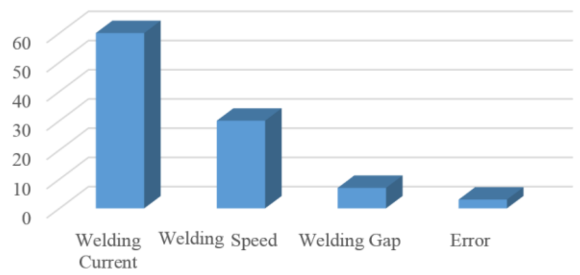

Figure 6. Percent contributions of welding parameters to the WBW

According to Fig 5, welding current is the major factor affecting DOP at 68% contribution. It is followed by welding speed at 29%. Welding gap has a trivial effect on DOP (at 1% contribution). The rest (2%) is due to error and uncontrollable parameters. Based on the nature of the process and the equipment used, it is acceptable. By the same token, welding current with 88%, welding speed with 7% and welding gap with 2% are the most important parameters affecting WBW respectively.

Taguchi based optimization method

To define the effect of each process input variables on the process response parameters, the mean of S/N ratios for each test containing this parameter in desired level are calculated. Moreover, the calculated means for each level of input parameter under consideration are compared and the level to which the highest value belongs considered as the desired level in order to optimize the process characteristic [10]. For example mean effect of welding speed in level 1 is gained from averaging test runs number 1, 2 up to 16. Along these lines, the mean effects of parameters are computed and listed in Tables 4 and 5.

Table 4. Response (mean) of S/Ns for depth of penetration

Symbol	Level 1	Level 2	Level 3	Level 4
G	**29.47433**	29.47216	-	-
I	17.86305	27.60055	33.98006	**38.44933**
S	**35.4727**	31.1149	26.82146	24.48393

Table 5. Response (mean) of S/Ns for weld bead width

Symbol	Level 1	Level 2	Level 3	Level 4
G	**-36.6224**	-38.5828	-	-
I	**-28.7466**	-35.2511	-40.9238	-45.4889
S	-38.8268	-38.8153	**-36.2404**	-36.5281

Since the higher value of mean S/N is favorable, with respect to the data in Table 4 optimal set of parameters for optimization of DOP are: G at level 1, I at level 4 and S at level 1. Similarly, optimal set of parameters for optimization of WBW are: G at level 1, I at level 1 and S at level 3 based on results of Table 5.

Table 6 indicates that for resulting in maximum possible DOP, the welding current and welding gap should be considered at their highest levels. Likewise, for achieving lower WBW, welding current and welding gap should be approximately set at their lower ranges.

Table 6. Results of optimization based on the Taguchi method

parameters	Set of Parameters			Predicted value	Experimental value	Error (%)
	S	I	G			
	1.00	280	1.50	46.052	43.127	6.3
Taguchi optimization	3.00	100	0.75	-27.013	-28.816	6.7

Conclusion

In this study the problem of modeling and optimization of A-TIG welding process for AISI316L austenite stainless steel has been addressed. First, A-TIG welding modeling has been performed based on experimental data gathered as per L32 Taguchi method based DOE approach. Major findings drawn from the study are listed below.

- The process characteristics (DOP and WBW) as a function of input parameters (welding current, welding speed and welding gap) has been formulated using regression modeling.
- The most fitted models have been determined based on ANOVA results. Moreover, important parameters and their corresponding percent contribution on each process characteristics has been determined.
- Based on the results illustrated, welding current is the most important parameter affects DOP and WBW with 68% and 88% percent contribution respectively. Furthermore, the minor effect belong to welding gap.
- Taguchi optimization procedure (signal to noise analysis) have been used to optimize the selected models and results confirmed using experimental tests. The result of optimization procedure shows that the proposed method can accurately simulate and optimize the A-TIG welding process authentically (with less than 7% error).

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