# Flux assisted tungsten inert gas welding process optimization using design of experiments approach and heuristic algorithm

**Hamid Dalir**[1], **Masoud Azadi Moghaddam**[2], **Farhad Kolahan**[3]

[1]Ferdowsi Combined Cycle Power Plant, Operation and maintenance (O&M) Company, MAPNA Group
[2] PhD. Student, Department of Mechanical Engineering, Ferdowsi University of Mashhad, Mashhad, Iran
[3] Associate Professor, Department of Mechanical Engineering, Ferdowsi University of Mashhad, Mashhad, Iran

**Abstract**
This paper reports a regression modeling and optimization procedure for activated tungsten inert gas (A-TIG) welding process of AISI316L austenitic stainless steel parts using Taguchi design of experiments (DOE), regression modeling, analysis of variance (ANOVA) and simulated annealing (SA) algorithm. Welding current (I), torch speed (S) and welding gap (G) are the most significant process input parameters has been considered in this study. Depth of penetration (DOP) and weld bead width (WBW) have been taken in to account as the most essential quality measures of the process under study. $SiO_2$ surface activating flux powder (in scale of nano-particles) have been used to enhance TIG welding process characteristics. To gather required data for modeling and statistical analysis purposes, DOE based on orthogonal array (OR) Taguchi method has been used. Then, modeling has been performed using different regression equations (including linear, curvilinear and logarithmic models). Statistical analysis based on analysis of variance (ANOVA) has been performed and the most fitted models were selected as an authentic representative of the process characteristics. Next, these models were used for optimization of process parameters in such a way that DOP is maximized and WBW minimized using simulated annealing (SA) algorithm. Finally, a set of experimental tests has been carried out through which the proposed method has been validated. Furthermore, results of SA optimization method have been compared with ones gained using signal to noise (S/N) analysis based on Taguchi procedure. Results shown the proposed procedure is quite efficient in modeling and optimization of the A-TIG process.

**Keywords:** Activated TIG (A-TIG) welding process, depth of penetration (DOP), weld bead width (WBW), Taguchi method, Regression modeling, Analysis of variance (ANOVA), Optimization, Simulated annealing (SA) algorithm.

## Introduction
Gas tungsten arc welding (GTAW) known as Tungsten inert gas (TIG) welding, is one of the most widely used welding processes for aluminum, manganese and stainless steels parts fabricating due to its good quality (surface finish and spatter free). Nonetheless, welding of thick plates in a single pass, results in an incomplete welding (lack of penetration or shallow penetration) [1−3]. Therefore, application of TIG welding process for welding of thick plates in a single pass is restricted by poor penetration produced which can be tackled using time consuming multi pass welding process and edge preparation. One of the most important procedures to tackle this problem and improve penetration of TIG welding process is using activated fluxes coated on the weld surface before welding process begins, known as activated TIG (A-TIG) or flux assisted TIG welding process which has first been proposed by the Paton institute of electric in 1960 [4]. Using activating fluxes (especially oxide based fluxes) ends in enhanced depth of penetration (DOP) and minimum weld bead width (WBW) in comparison with conventional TIG (C-TIG) welding process used especially for stainless steels parts [5]. This process can be considered as the TIG welding process in which an activating flux layer coated on the weld surface before welding process started. This layer of flux, is melted and vaporized during welding and DOP and WBW are increased and decreased due to arc constriction and reversal of Marangoni convection phenomena respectively. The details of these phenomena are well documented in Refs. [1, 2] in which DOP has been reported to be increased up to about 3 times in comparison with the C-TIG welding process [2–4]. Using A-TIG welding process, allowed steel specimens (of around 6 mm) to be fabricated with single pass welding without using filler metal and even edge preparation [6]. A-TIG welding process has also been effectively employed on different materials namely: alloy steels, stainless steels (including austenite and austenite duplex), and also dissimilar metals welding [7].

**Experimental set up and equipment used**

In this study to conduct the experiments based on OA-Taguchi DOE approach, a DIGITIG 250 AC/DC welding machine (GAAM-Co, Iran) has been employed. The tungsten electrodes and argon (with 99.7% purity) as shielding gas were used. Experiments were carried out on AISI316L stainless steel sheets with dimension of 100 ×50 ×12 (mm). Silicon dioxide ($SiO_2$) nano-powder (+99%, 20-30 nm, amorphous) has been used as the activating flux. First, activating fluxes prepared by mixing 20 grams of SiO2 with 20 mL of a solvent (ethanol, methanol or acetone) for 20 min. Then, the mixed paint like flux deposited on the specimens surfaces of which has been cleaned using acetone and dried before the welding process begins (Fig. 1). Fig. 4 shows a schematic illustration of A-TIG welding process.

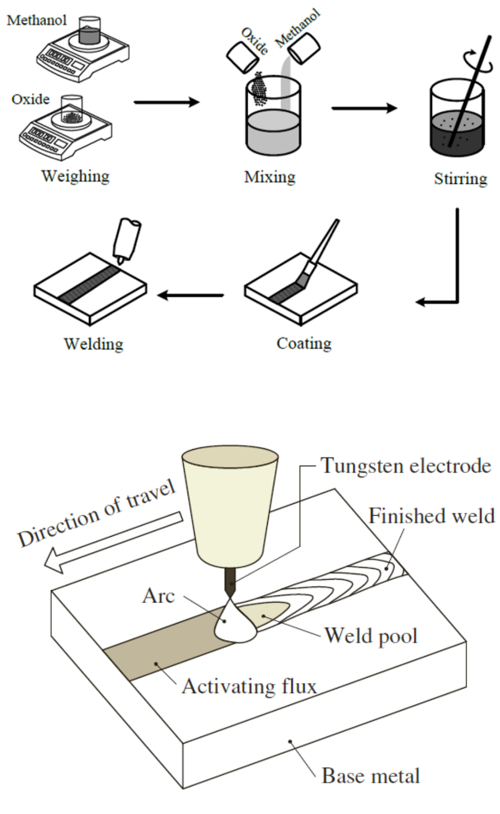


Fig. 1. Activated flux preparation and schematic diagram of A-TIG welding process [8]

**Design of experiments (DOE) approach**

After the main process input parameters have been selected and their corresponding intervals determined, an appropriate design matrix for conducting the experiments and data gathering must be determined. To facilitate the identification of the influence of individual parameters, establish the relationships between process input parameters and output characteristics, and finally determine the optimal levels of input parameters in order to get the desired characteristics, DOE approach is used. One of the effective methods that can intensely reduce the number of experiments required to gather necessary data is OA-Taguchi technique [9]. Based on the number of input parameters and their levels, a Taguchi's $L_{32}$ design matrix has been chosen using MINITAB software.

**Signal to noise (S/N) ratio**

Taguchi technique has been used 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 optimizing the process input characteristics for desired output measures. 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)" (used for measures in which the smallest amount is desired, e.g. WBW) or "Largest is the Best, (LB)" (used for measures in which the largest amount is desired, e.g. DOP) based on the process under consideration, as given in Equations 1, 2 [10].

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

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

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 smallest WBW and the larger DOP are desired, Eq. 1 and Eq. 2 are considered to calculate WBW and DOP respectively. The experimental results of 32 experiments (fifth and sixth columns) and their corresponding S/N ratio values (seventh and eighth columns) based on the OA-Taguchi DOE method are reported in Table 1.

Table 1. Experimental measured outputs and S/N ratios

| **No.** | DOP (mm) | WBW (mm) | S/N for DOP | S/N for WBW |
|---|---|---|---|---|
| 1 | 3.25 | 4.42 | 23.5731 | -29.7228 |
| 2 | 2.99 | 3.84 | 21.9055 | -26.9094 |
| 3 | 2.28 | 3.95 | 16.4835 | -27.4743 |
| 4 | 1.95 | 3.86 | 13.3566 | -27.0133 |
| 5 | 5.48 | 6.26 | 34.0221 | -36.6836 |
| 6 | 4.94 | 5.40 | 31.9473 | -33.7280 |
| . | . | . | . | . |
| . | . | . | . | . |
| . | . | . | . | . |
| | | | | |
| 27 | 4.60 | 8.14 | 30.5211 | -41.9358 |
| 28 | 4.23 | 7.68 | 28.8440 | -40.7724 |
| 29 | 10.00 | 11.97 | 46.0517 | -49.6481 |
| 30 | 6.67 | 11.12 | 37.9524 | -48.1749 |
| 31 | 5.27 | 10.25 | 33.2406 | -46.5456 |
| 32 | 5.04 | 9.69 | 32.3481 | -45.4219 |

**Regression modeling**

Regression modeling is a statistical procedure for approximating the relationships between process input parameters and output characteristics. To carry out regression modeling and corresponding analysis (e.g. ANOVA) the following stages must be taken in to account [11].

Models representing the relationship between process input parameters and output characteristics can be stated in Equations 3 to 8. Results of ANOVA has been reported in Table 2 and 3.

Linear Model

S/N (DOP) = 20.6 + 0.103×I - 5.07×S (3)

S/N (WBW) = - 20.9 - 2.64×G - 0.0970×I + 1.85×S (4)

Logarithmic model

S/N (DOP) = e- 3.05 × I0.697 × S - 0.347 (5)

S/N (WBW) = e- 1.69 × G0.0807 × I0.461 × S- 0.0965 (6)

Modified second order Model

S/N (DOP) = 9.28 + 0.276×I - 9.07×S - 0.000402× (I×I) + 1.32×(S×S) - 0.00906× (I×S) (7)

S/N (WBW) = - 19.9 - 2.64×G - 0.166×I + 7.08×S + 0.000181× (I×I) - 1.21×(S×S) (8)

Table 2. Result of ANOVA for S/N of Depth of Penetration

| Welding variables | Degree of freedom (Dof) | Sum of square ($SS_j$) | Mean Square | F-Value | Percent contribution (%) |
|---|---|---|---|---|---|
| G | 1 | 0.40 | 0.40 | 0.17 | 1 |
| I | 3 | 1605.2 | 535.09 | 226.40* | 68 |
| S | 3 | 677.60 | 225.87 | 95.57* | 29 |
| Error | 24 | 56.72 | 2.36 | - | 2 |
| Total | 31 | 2340.0 | - | - | 100 |
| Significant Parameter * | | | | | |

Table 3. Result of ANOVA for S/N of Weld Bead Width

| Welding variables | Degree of freedom (Dof) | Sum of square ($SS_j$) | Mean Square | F-Value | Percent contribution (%) |
|---|---|---|---|---|---|
| G | 1 | 31.48 | 31.48 | 12.70 | 2 |
| I | 3 | 1369.9 | 456.63 | 184.26* | 88 |
| S | 3 | 103.18 | 34.39 | 13.88* | 7 |
| Error | 24 | 59.48 | 2.48 | - | 3 |
| Total | 31 | 1564.0 | - | - | 100 |
| Significant Parameter * | | | | | |

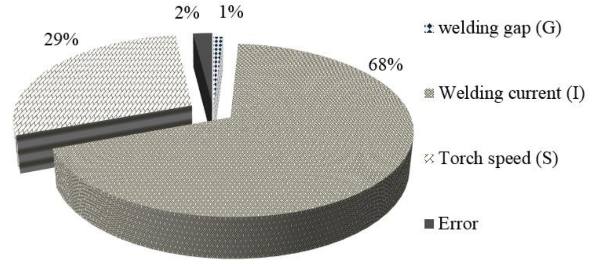


Fig. 2. Percent contributions of welding parameters to the DOP

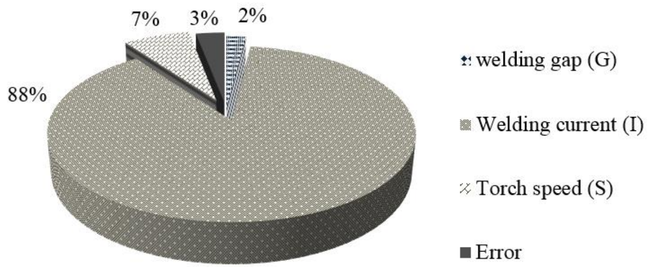


Fig. 3. Percent contributions of welding parameters to the WBW

According to table 2, welding current is the major factor affecting DOP at 68% followed by torch speed and welding gap at 29% and 1% contribution respectively. The rest (2%) is due to error and uncontrollable parameters based on the nature of the process and the equipment used is acceptable. By the same token, welding current at 88%, torch speed at 7% and welding gap at 2% are the most important parameters affecting WBW respectively (Table 3).

Percent contribution has been reported in Fig 2 and 3.

**Optimization procedures**

To define the effect of each process input parameters on the output characteristics, 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 is belongs considered as the desired level in order to optimize the process characteristic [12]. For example mean effect of torch 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 7 and 8. Since the higher value of mean S/N is favorable, with respect to the data in Table 7, optimal set of parameters for optimization of DOP are: G at level 2, I at level 4 and S at level 1, i.e., ($G_2$ $I_4$ $S_1$). Similarly, optimal set of parameters for optimization of WBW are: G at level 1, I at level 1 and S at level 4, i.e., ($G_1I_1$ $S_4$) based on results of Table 5. Moreover, Figs 5 and 5 also illustrate the optimum parameters settings in order to achieve the maximum DOP and minimum WBW.

As the signal to noise method in optimization procedure could determine the best set of process input parameters levels from the pre-determined ones on the design matrix used (Table 2). Using heuristic algorithms would help interpolating the answer space in order to find the best solution which may not be one of the determined levels considered in Table 2. In this study the most fitted models selected, consider as the objective functions for the heuristic algorithm used. Therefore, in order to optimize the objective functions simulated annealing (SA) algorithm has been used.

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

| Symbol | Level 1 | Level 2 | Level 3 | Level 4 |
|---|---|---|---|---|
| G | 29.119 | **29.344** | - | - |
| I | 18.512 | 27.493 | 33.866 | **37.057** |
| S | **35.859** | 31.064 | 25.911 | 24.094 |

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

| Symbol | Level 1 | Level 2 | Level 3 | Level 4 |
|---|---|---|---|---|
| G | **-37.353** | -39.3364 | - | - |
| I | **-28.929** | -36.1777 | -41.812 | -46.460 |
| S | -41.243 | -38.439 | -36.905 | **-36.791** |

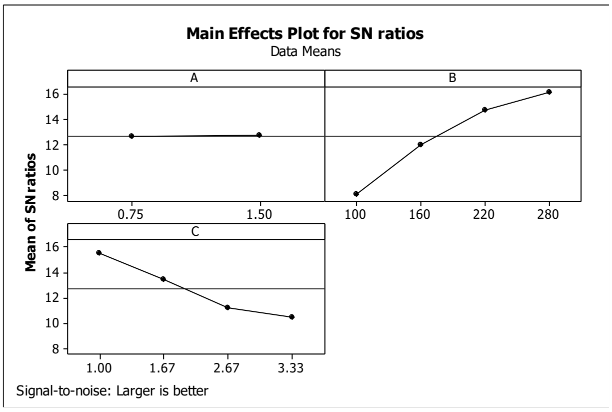


Fig. 4 The effect of A-TIG input process parameters on signal to noise (S/N) values of DOP

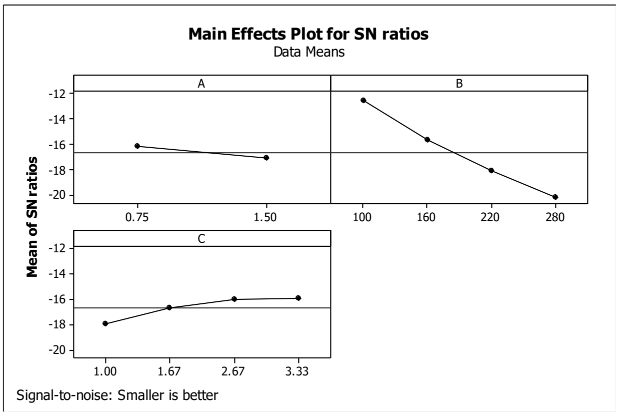


Fig. 5 The effect of A-TIG input process parameters on signal to noise (S/N) values of WBW

## Simulated annealing algorithm

Simulated annealing (SA) algorithm is a reminiscent of the physical annealing process in metal work and effectively used in optimization problems [12]. In Annealing process, metals are slowly cooled to make them reach a state of low energy. First, metals are heated up to a temperature which is about the melting point. Therefore, at this temperature, all particles of the metal are in intense random motion. Then, the metal is slowly cooled down. All particles rearrange themselves and tend toward a low energy state. As the cooling process is carried out appropriately slowly, lower and lower energy states are gained until the lowest energy state is reached. Similarly, in A-TIG welding process an energy function is created which is minimized. The lowest energy level gives the optimized value of A-TIG welding process parameters, while minimizing efforts are made to avoid local minima and to achieve global minima. Recently, the SA algorithm has developed as a leading tool for complex optimization problems [13].

The mechanism of SA algorithm is defined as the following sentences. Firstly, an initial random solution within the acceptable answer space is generated. Then, the objective function of new solution ($C_1$) is calculated and compared with that of current solution ($C_0$). Either, it has better value or the probability function implemented in SA has a higher value than a randomly generated number between 0 and 1, a move is made to the new solution [13]:

Consequently, at the first iterations of SA, most worsening moves may be accepted due to higher temperature, but at the end of the procedure only improving ones are likely to be allowed. This can help the process avoid getting trapped in local minimum and jump out of it. After a certain number of iterations or after a pre-determined run time or after a number of iterations in which no development is detected the algorithm may be terminated. Flowchart of SA algorithm for A-TIG welding process optimization is shown in Fig.6.

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.

The convergence of SA algorithm for DOP is shown in Fig. 15.

Table 6. Results of optimization based on the Taguchi and SA algorithm methods

| Set of Parameters | | | | Predicted S/N value | Experimental S/N value | Error (%) |
|---|---|---|---|---|---|---|
| Input parameters | G | I | S | | | |
| DOP | 1.50 | 280 | 1.036 | 49.6648 | 48.2256 | 2.9 |
| WBW | 1.00 | 153 | 2.85 | -21.7038 | -20.9952 | 3.3 |

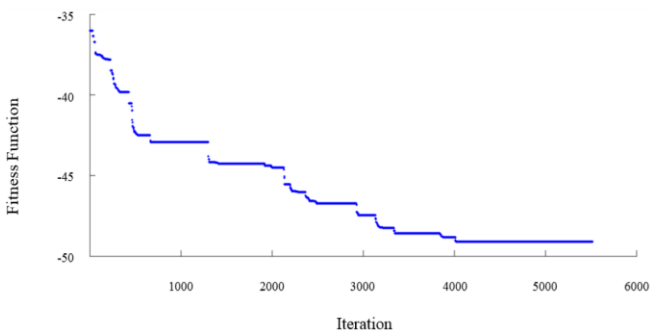


Fig. 6 Simulated annealing algorithm convergence for DOP optimization

**Conclusion**

Proper selection of process parameters levels positively affect the quality of weldments in A-TIG welding process. 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 experimental tests have been performed based on experimental data gathered as per L32 Taguchi DOE. Then, DOPs and WBWs have been measured using MIP software. Then, regression modeling has been used to formulate the process characteristics (DOP and WBW) as a function of input parameters (welding current, torch speed and welding gap). Next, ANOVA has been used in order to determine the most fitted models. Moreover, significant parameters and their corresponding percent contribution on each process characteristics have been determined using statistical analysis. Results showed that welding current is the most important parameter affects DOP and WBW at 68% and 88% percent contribution respectively. Furthermore, the minor effect belong to welding gap. Next, SA algorithm and 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 the proposed procedure can accurately simulate and optimize the TIG welding process.

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