

Prediction and optimization of processing parameters in wire and arc-based additively manufacturing of 316L stainless steel

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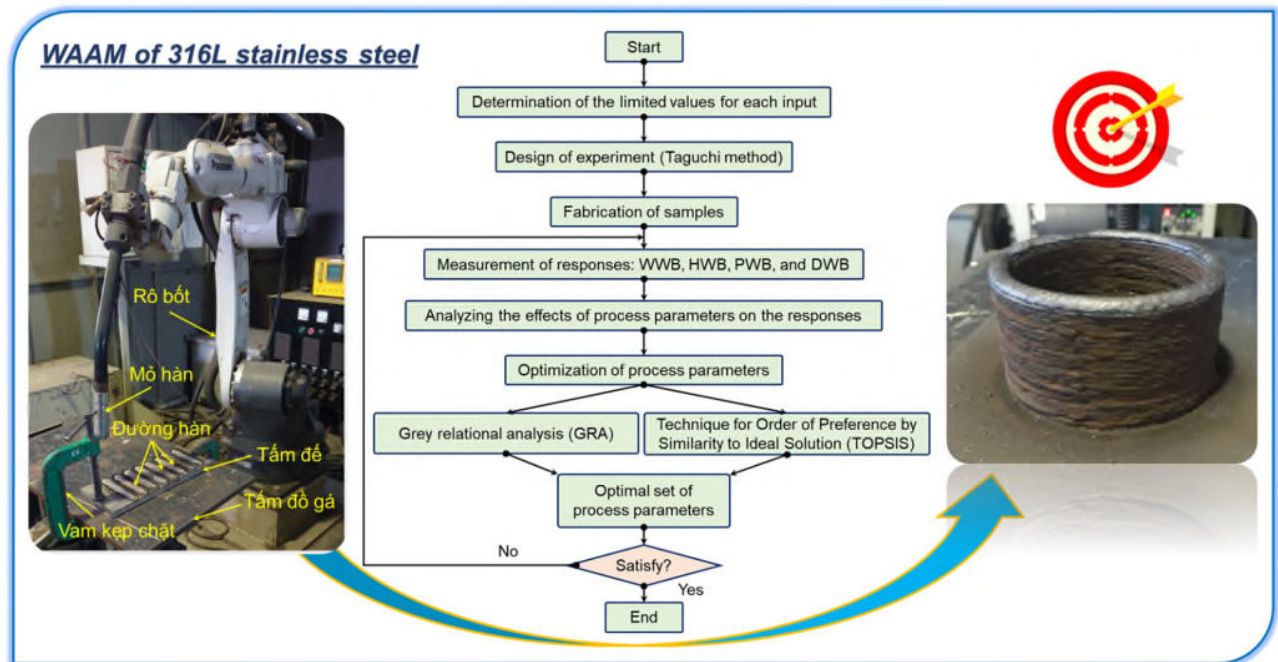
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Abstract. Wire and arc-based additively manufacturing (WAAM) is a potential metallic additively manufacturing (AM) technologies for producing large-size metallic components. 316L is one of the most common stainless-steel grades used in WAAM. However, most of previous studies normally adopted process parameters for the WAAM process based on recommendations of welding wire manufacturers for traditional welding processes. In this article, we focus on predicting and optimizing process parameters for the WAAM process of 316L stainless steel. The experiment was designed by using Taguchi method and L16 orthogonal array. Three parameters, consisting of voltage (U), welding current (I), and travel speed (v) were considered as the input variables, and the responses are four geometrical characteristics of single weld beads, including width, height, penetration, and dilution of weld beads (WWB, HWB, PWB, and DWB, respectively). The effects of each input variable on the responses were determined through analysis of variance (ANOVA). The optimal process parameters were identified by using GRA (Grey-Relational Analysis) and TOPSIS (Techniques for Order-Preferences by Similarity-to-Ideal Solution) methods. The obtained results show that the travel speed has the most important effect on WWB and HWB, while the voltage has the highest impact on PWB and DWD. Both GRA and TOPSIS methods give the same optimum process parameters, namely $U = 22$ V, $I = 110$ A, and $v = 0.3$ m/min, which are validated by confirmation experiments. The predicted models of WWB, HWB, PWB, and DWB were also demonstrated to be adequate for selecting the process parameters in specific applications.

Keywords: WAAM, Stainless steel, Optimization, Process parameter, GRA, TOPSIS.

Graphical abstract:



1. Introduction

Wire and arc-based additively manufacturing (WAAM) has emerged as an effective additive manufacturing (AM) technology to manufacture large-dimensional components [1]. This technique features some unique advantages as compared to other metallic AM processes, such as high deposition speed, high material usage efficiency, and inexpensive production and device investment costs [2]. In the WAAM process, the energy sources can be gas-metal-arc welding (GMAW) [3], cold-metal transfer (CMT) [4], gas-tungsten-arc welding (GTAW) [5], and plasma-arc welding (PAW) [6]. However, the GMAW-WAAM process is the most suitable and preferable for producing metal parts with large dimensions, because its high deposition rate capacity, up to 10 kg per hour [7]. In the GMAW-WAAM process, an electrical arc is generated between the wire tip (a consumable electrode) and the substrate. The metal wire is melted by the high heat of the electrical arc, and the molten metal is deposited into the workpiece in the X-Y plane to create layers. The part is built up along the Z direction by adding the material according to the deposition paths. Within the deposition process, the shielding gas is used to isolate the arc and the deposited metal from the surrounding ambience, as described in [3,8].

Among the materials used in the WAAM process, 316L stainless steel is the most common one that has been investigated, because it reveals a good weldability and high corrosion resistance. This material also has a large range of applications, such as nuclear reactor, marine engineering, and biomedical implants. Most of recently published studies have focused on analyzing the metallurgical characteristics and mechanical properties of 316L stainless steel thin-walled or thick-walled components fabricated by WAAM [9]. For examples, Chen et al. [10] analyzed the microstructural characterization and tensile properties of WAAM 316L thick-walled components. The authors found that the microstructures of components feature three phases (δ , γ , and σ), in which the austenite γ phases were dominant, while δ and σ phases possessed a little amount in grain boundaries of austenite. Wang et al. [11] also studied on the microstructural and tensile properties of WAAM 316L thick-walled parts. In that work, the authors focused on analyzing the microstructures in the remelting zones (RZ) and overlapped zones (OZ) of weld beads in the transversal and building directions. The microstructures in RZs revealed the grains perpendicular to the fusion lines, whereas the grains developed along the build direction in OZs. That distribution of microstructures resulted in anisotropic mechanical properties. Wu et al. [12] fabricated 316L stainless steel thin-walled parts by WAAM. They observed that the mechanical properties of parts varied along the vertical direction of thin walls.

Other research works have aimed at exploring the effects of processing parameters and conditions on the quality of 316L steel parts. Chakkravarthy et al. [13] explored the printability of multi-walled

316L components by CMT-WAAM. They found that an increase in the inclination angle of the torch increased could reduce the surface roughness. Wen et al. [14] studied the impact of heat input on microstructure characteristics and corrosion of WAAM 316L components. They observed that with a raise in heat input the primary dendrite spacing in microstructures and the corrosion resistance increased, but the ferrite content remained similar. Other authors and Wu et al. demonstrated that the different arc modes (i.e., speed pulse and speed arc) [15] and the different welding-current processes (i.e., speed cold and speed arc) [16] in WAAM generated different heat input and cooling rate levels, resulting in the inhomogeneity in microstructures and mechanical properties of 316L stainless steel. In the work of Cunningham et al. [17], the authors assessed the effects of LN₂ cryogenic cooling on the quality of WAAM 316L parts. They found that that the parts fabricated with LN₂ cooling revealed more equiaxed grains than those produced under a normal air-cooling condition with an interlayer temperature of 160°C, therefore enhancing the stiffness and tensile properties of as-built parts.

Until now, very few studies have focused on predicting and optimizing processing parameters in WAAM of 316L stainless steel to obtain proper geometrical characteristics of weld beads. The quality and shape of single welding beads (e.g., stable and smooth shape and less spatter) play an important role and assure the deposition stability and the final shape of products [3,18–20]. The width and height of weld beads (denoted by WWB and HWB) are also two essential parameters for the generation of deposition paths for the WAAM process of thin-walled and thick-walled components [21–28]. That is why many works have been carried out for predicting the geometry of weld beads for the WAAM processes. For instance, Suryakumar et al. [27] modelled the geometry (i.e., WWB and HWB) of weld beads in the case of mild steel (ER70S6) as a parabola and validated through experiments. Their models have been successfully applied in the prediction and optimization of process parameters for hybrid layer manufacturing. Xiong et al. [20] developed predictive models of WWB and HWB of a low carbon steel by utilizing an ANN (artificial-neural network) and a second-order-regression model. They demonstrated that their models had a good accuracy and can be used to estimated desirable geometry of weld beads for the slicing process in AM. Wang et al. [19] also used an ANN model to predict the geometry of weld beads in functions of wire feed speed, travel speed, and interpass temperature for the CMT-WAAM of a high strength steel (ER100). Geng et al. [29] predicted the bead shape for the GTAW-WAAM of 5A06 aluminum alloy by using the response-surface methodology (RSM). Youheng et al. [30] analyzed the effects of the wire-feed speed and the travel speed on WWB and HWB. The authors also found optimal process parameters to fabricate single weld beads with smooth surface, less spatters, and defects for the WAAM of bainite steel. Kumar and Maji [31] developed geometry models for single weld bead in WAAM of 304L stainless steel using RSM and optimized the bead geometry using the desirability

approach (DA). Sarathchandra et al. [32] also researched the effects of processing parameters on geometrical characteristics of 304 stainless steel weld beads produced by CMT-WAAM. The RSM and DA method were also adopted to determine optimal process parameters. Recently, Venkatarao [33] used the TLBO (teaching and learning based optimization) technique to optimize the weld bead geometry in the GMAW-WAAM of mild steel. They showed that the TLBO revealed stronger performance as compared to Taguchi and RMS methods. In the work of Veiga et al. [34], the regressive models for the bead geometries (bead width, bead height, and the symmetry coefficients) were developed with a high accuracy level for the WAAM process of Invar alloy (nickel–iron and manganese alloy). The developed models could be used to optimize the depositing condition to achieve the proper weld bead shape.

From the above literature survey, it can be confirmed that the influences of processing parameters on geometrical characteristics of weld beads in WAAM of 316L stainless steel are not yet explored. The WAAM 316L components were generally produced with the process parameters recommended by the welding wire manufacturers for conventional welding processes. In this paper, we aim at predicting the geometrical characteristics of weld beads and identifying optimum process parameters for the WAAM of 316L steel. The experiments were designed by using Taguchi method and L16 orthogonal array with the consideration of three process parameters, including the voltage (U), welding current (I), and travel speed (v). The responses consist of the width of weld beads (WWB), the height of weld beads (HWB), the penetration of weld beads (PWB), and the dilution of weld beads (DWB). The significance and effects of each input variable on the responses were determined through the ANOVA (analysis of variance). The optimal processing parameters were identified by using GRA (Grey-Relational Analysis) and TOPSIS (Techniques for Order Preferences by Similarity-to-Ideal Solution) methods. They have been widely used in different manufacturing fields, for example in machining and welding [35–38].

2. Materials and methods

2.1. Materials

In the experiments, a welding wire of 316L steel with a diameter of 1.2 mm supplied by Kiswel was used. Two 316L-stainless-steel plates with dimensions of 220 x 80 x 10 mm were employed as the substrates. The chemical composition of the wire and the base plate is shown in Table 1.

Table 1. Chemical elements of the wire and the substrate materials (in wt.%).

Element	C	Si	Mn	Ni	Cr	Mo
Stainless steel 316L wire	0.02	0.40	1.73	11.17	18.15	2.22
Stainless steel 316L plate	≤ 0.03	≤ 0.75	≤ 2.00	10 - 14	16 - 18	≤ 3.00

To fabricate samples, a GMAW-WAAM system, which consists of a 6-axis welding robot (Panasonic TA1400) and a YD-350GR3 power was utilized (Fig. 1a). In this system, the feed speed of the welding wire is adjusted based on the current values. During the welding process, a gas of argon with a purity of 99.99% and a flow rate of 15 L/min was applied to protect the molten metal from the oxidization.

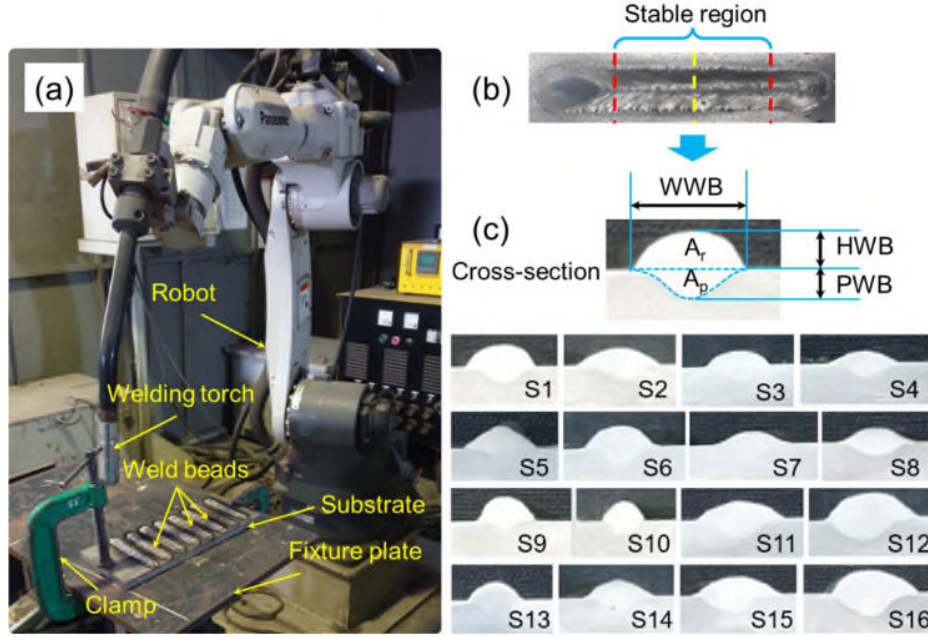


Fig. 1. (a) the WAAM system, (b) a single weld bead, and (c) cross-section images of all single welds.

2.2. Research procedure

As above mentioned, this work focuses on assessing the effects of input parameters $\{I, U, v\}$ on the geometrical characteristics of single weld beads $\{WWB, HWB, PWB, \text{ and } DWB\}$, and determining the optimum processing parameters in the WAAM of 316L stainless steel. To achieve these objectives, the research methodology is proposed, as illustrated in Fig. 2. The main steps are depicted as follows:

Step 1: Determining the limited values of the input variables. The limited values (i.e., the lowest and highest values) of each input variable were determined. For that purpose, we carried out several trials of single weld beads with the process parameter values taken in value ranges recommended by the wire supplier for conventional welding processes. After some running tests, the value ranges for welding current, voltage, and travel speed were determined as follows: $I = 110 - 140$ A, $U = 22 - 28$ V, and $v = 0.3 - 0.6$ m/min, which allows producing continuous weld beads with less spatters (as shown in Fig. 1b).

Step 2: Design of experiment and data acquisition. the experiments were designed by using Taguchi method with L16 orthogonal array. As compared to other experimental design methods such as RSM and full factorial design, the Taguchi method enables optimizing multiple factors simultaneously, and extracting more quantitative information from fewer experimental runs. Therefore, the Taguchi experimental design can reduce costs, improve quality, and provide robust design solutions [39]. In this study, three input variables with four levels were selected as presented in Table 2. As a results, there were 16 experimental runs of single weld beads for acquiring the data of considered responses (i.e., WWB, HWB, PWB, and DWB). Each weld bead with a length of about 60 mm were produced by the above GMAW-WAAM system on two substrates. After each run, the substrate was cooled down to room temperature for the next runs. As a result, we assumed that the run of the previous weld bead has no effects on the geometrical responses of next weld beads. The experimental plan and measurement results were shown in Table 3.

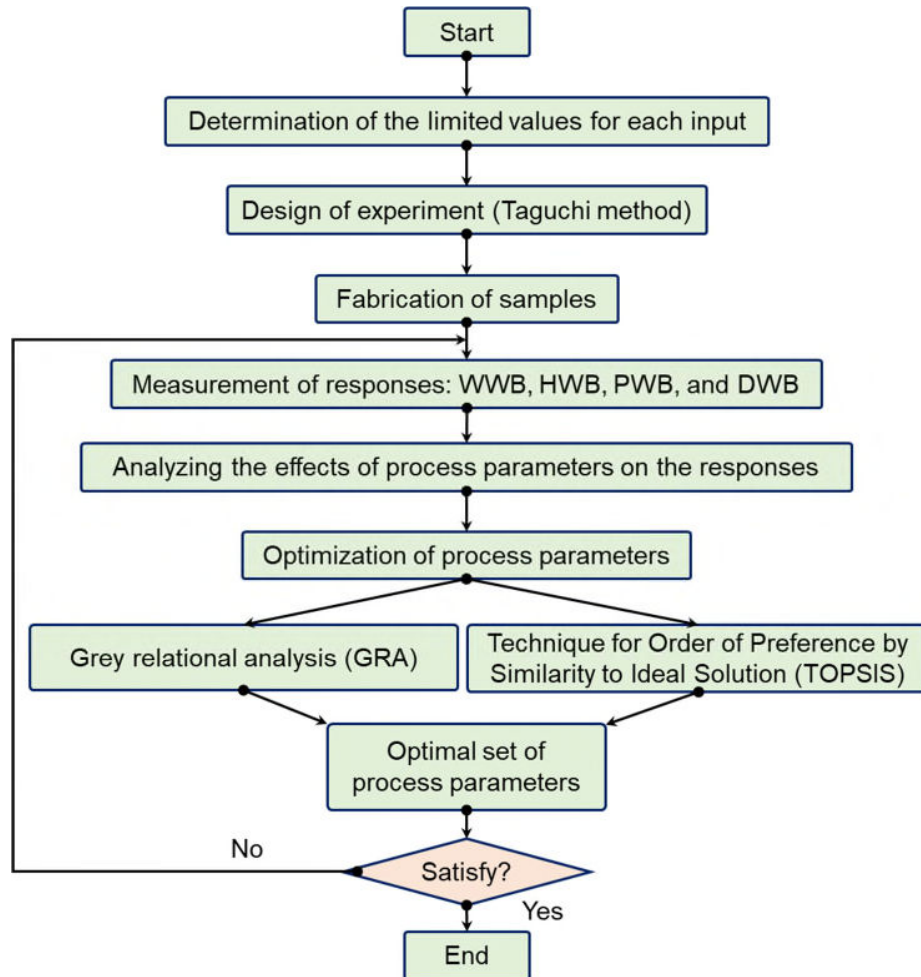


Fig. 2. Research methodology.

The values of WWB and HWB were the average values of five measurements at five locations in a stable region of weld beads (Fig. 1b). The WWB and HWB at a location were measured by using a digital Mitutoyo caliper with an accuracy of ± 0.02 mm and 0.01 mm in resolution. To measure PWB and DWB, a cross-section of each weld bead (Fig. 1c) was cut at a stable location (Fig. 1b), and then it was ground and polished. The PWB value was directly measured on the optical image of the cross-section by using ImageJ software, while the DWB value was calculated by Eq. (1):

$$DWB (\%) = 100\% * \frac{A_p}{A_r + A_p} \quad (1)$$

where A_r and A_p are the area of reinforcement and the area of penetration of the weld bead, respectively (Fig. 1c). A_r and A_p were also measured by using ImageJ software on the image of the weld bead cross-section.

Table 2. Process parameters and their levels used for the design of experiment.

Process parameter	Levels			
	1	2	3	4
I (A)	100	120	130	140
U (V)	22	24	26	28
v (m/min)	0.3	0.4	0.5	0.6

Table 3. Experimental plan and the measurement results of responses.

Run	I (A)	U (V)	v (m/min)	WWB (mm)	HWB (mm)	PWB (mm)	DWB (%)
1	110	22	0.3	8.76	2.89	1.28	23.51
2	110	24	0.4	9.11	2.43	1.45	25.87
3	110	26	0.5	8.27	2.02	1.82	27.89
4	110	28	0.6	8.7	1.37	1.88	35.99
5	120	22	0.4	8.42	2.92	1.57	28.66
6	120	24	0.3	9.87	2.82	2.11	32.71
7	120	26	0.6	8.53	1.59	1.57	34.59
8	120	28	0.5	9.42	1.63	1.97	39.24
9	130	22	0.5	7.29	2.75	1.62	26.88
10	130	24	0.6	7.46	2.12	1.58	30.00
11	130	26	0.3	11.17	2.89	2.32	39.35
12	130	28	0.4	11.32	2.15	2.61	45.20

13	140	22	0.6	6.96	2.54	1.45	26.48
14	140	24	0.5	9.11	2.47	1.93	32.48
15	140	26	0.4	10.22	2.59	2.47	39.17
16	140	28	0.3	11.65	3.17	3.06	40.42

Step 3: Analysis of the impacts of processing parameters on the responses. The influence of process parameters on the responses were evaluated by using the ANOVA (analysis of variance). The ANOVA and the prediction models of each response were performed with a confidence level of 95% by using Minitab software.

Step 4: Optimization of processing parameters. In this work, two approaches for the multi-response optimization problems were adopted – i.e., GRA (Grey-Relational Analysis) and TOPSIS (Techniques for Order Preferences by Similarity-to-Ideal Solution). These methods are applied effectively in many manufacturing fields, for example in machining and welding [35–38]. For the WAAM process, the multi-response optimization problem of weld beads was defined as follows [32]:

Find $X = \{U, I, V\}$ that
 Maximize $\{BH, BW\}$ and minimize $\{PWB, DWB\}$
 Subject to $110 \leq I \leq 130$ A, $20 \leq U \leq 22$ V, and $0.3 \leq V \leq 0.5$ m/min.

2.3. Grey Relational Analysis (GRA)

The first step in the GRA method is to normalize the responses. There are two kind of quality characteristics – i.e., the large-the-better (LTB) and the smaller-the-better (STB) [40]. In this case, the WWB and HWB values were normalized according to the LTB, Eq. (2):

$$y_{ij}^{(n)} = \frac{y_{ij}^{(0)} - \text{Min}_i\{y_{ij}^{(0)}\}}{\text{Max}_i\{y_{ij}^{(0)}\} - \text{Min}_i\{y_{ij}^{(0)}\}}, i = 1, 2, \dots, m \text{ and } j = 1, 2, \dots, n \quad (2)$$

On the other hand, the PWB and DWB values were normalized according to the STB, Eq. (3):

$$y_{ij}^{(n)} = \frac{\text{Max}_i\{y_{ij}^{(0)}\} - y_{ij}^{(0)}}{\text{Max}_i\{y_{ij}^{(0)}\} - \text{Min}_i\{y_{ij}^{(0)}\}}, i = 1, 2, \dots, m \text{ and } j = 1, 2, \dots, n \quad (3)$$

where $y_{ij}^{(0)}$ is the initial response measured in the experiments, $\text{Max}_i\{y_{ij}^{(0)}\}$ is the maximum value of $\{y_{ij}^{(0)}\}$, $\text{Min}_i\{y_{ij}^{(0)}\}$ is the minimum value of $\{y_{ij}^{(0)}\}$, “ m ” is the number of experimental runs, and “ n ” is the number of responses.

In the second step, the grey relational coefficient (GRC) was computed by Eq. (4):

$$\epsilon_{ij} = \frac{\delta_{\min} + \omega \delta_{\max}}{\delta_{0i}(k) + \omega \delta_{\max}} \quad (4)$$

where δ_{0ij} is the absolute deviation between the comparability $y_{ij}^{(n)}$ and the reference $y_{0j}^{(n)}$, as described in Eq. (5); δ_{max} and δ_{min} are the maximum and minimum values of $\delta_{0i}(k)$, as shown in Eqs. (6) and (7), respectively; and ω is a distinguishing coefficient, $0 \leq \omega \leq 1$. Generally, the value of ω is set to 0.5.

$$\delta_{0ij} = |y_{ij}^{(n)} - y_{0j}^{(n)}| \quad (5)$$

$$\delta_{min} = \min_{\forall i} \{ \min_{\forall j} \delta_{0ij} \} \quad (6)$$

$$\delta_{max} = \max_{\forall i} \{ \max_{\forall j} \delta_{0ij} \} \quad (7)$$

Finally, the grey relational grade was calculated by Eq. (8):

$$\zeta_i = \sum_{j=1}^n w_j * \epsilon_{ij} \quad (8)$$

where w_i refers to the weight of the i^{th} objective and $\sum_{i=1}^n w_i = 1$. The value of ζ_i falls in the range from 0 to 1, and the optimal solution is corresponding to the highest value of ζ_i .

2.4. Techniques for Order Preferences by Similarity-to-Ideal Solution (TOPSIS)

In this method, the responses were first arranged in a decision matrix $\mathbf{M} = [y_{ij}^{(0)}]_{m \times n}$, where $y_{ij}^{(0)}$ is the initial value of the j^{th} response in the i^{th} experiment, $1 \leq i \leq m$ and $1 \leq j \leq n$.

Second, the matrix $\mathbf{M}$ was normalized according to Eq. (9):

$$r_{ij} = \frac{y_{ij}^{(0)}}{\sqrt{\sum_{i=1}^m (y_{ij}^{(0)})^2}} \text{ with } i = 1, 2, \dots, m \text{ and } j = 1, 2, \dots, n \quad (9)$$

Third, a set of weights $\{w_j, j = 1, 2, \dots, n\}$ is used to compute the weighted-normalized-decision matrix, Eq. (10), where $w_j \in (0, 1)$ and $\sum_{j=1}^n w_j = 1$.

$$v_{ij} = w_j r_{ij}, (i = 1, 2, \dots, m; j = 1, 2, \dots, n) \quad (10)$$

The next step is to determine ideal solutions (IS) and non-ideal solutions (NIS) based on v_{ij} , as shown in Eqs. (11) and (12), respectively.

$$IS = \left\{ \left(\max_i v_{ij} | j \in J \right), \left(\min_i v_{ij} | j \in J \right) i = 1, 2, \dots, m \right\} = \{IS_1, IS_2, \dots, IS_n\} \quad (11)$$

$$NIS = \left\{ \left(\min_i v_{ij} | j \in J \right), \left(\max_i v_{ij} | j \in J \right) i = 1, 2, \dots, m \right\} = \{NIS_1, NIS_2, \dots, NIS_n\} \quad (12)$$

The distance of feasible solutions from ISs or NISs is computed as Eq. (13) and (14), respectively.

$$DIS_i = \sqrt{\sum_{j=1}^n (v_{ij} - IS_j)^2}, i = 1, 2, \dots, m \quad (13)$$

$$DNIS_i = \sqrt{\sum_{j=1}^n (v_{ij} - NIS_j)^2}, i = 1, 2, \dots, m \quad (14)$$

Finally, the closeness degree of ideal solution $CDIS_i$ is determined by Eq. (15):

$$CDIS_i = \frac{DNIS_i}{(DIS_i + DNIS_i)}, i = 1, 2, \dots, m \quad (15)$$

The value of $CDIS_i$ is in the range from 0 to 1. The optimal solution is corresponding to the highest value of $CDIS_i$.

It is noted that the weight value of each response used both in GRA and TOPSIS (w_i in Eqs. (8) and (10), respectively) was calculated by using the CRITIC method [41]. This method combines the conflict nature and the contrast intensity when calculating the weight fraction of each response. The steps and formulas related to this method can be found in previous publications [41–44].

In this investigation, the Taguchi method, the predictive models, the results of analysis of variance (ANOVA) were implemented with the aid of Minitab 19 software. Moreover, the steps of CRITIC, GRA and TOPSIS techniques were performed by Microsoft Excel software.

3. Results and discussion

3.1. Influence of process parameters on the responses

a. Parameter effects on the width of welding beads (WWB)

Figure 3 shows the direct influences of process parameters on WWB. It can be found that WWB increases with an augmentation in welding current (from 110 to 140 A) and in voltage (from 22 to 28 V). On the other hand, an increase in the travel speed (from 0.3 to 0.6 m/min) causes a decrease in WWB.

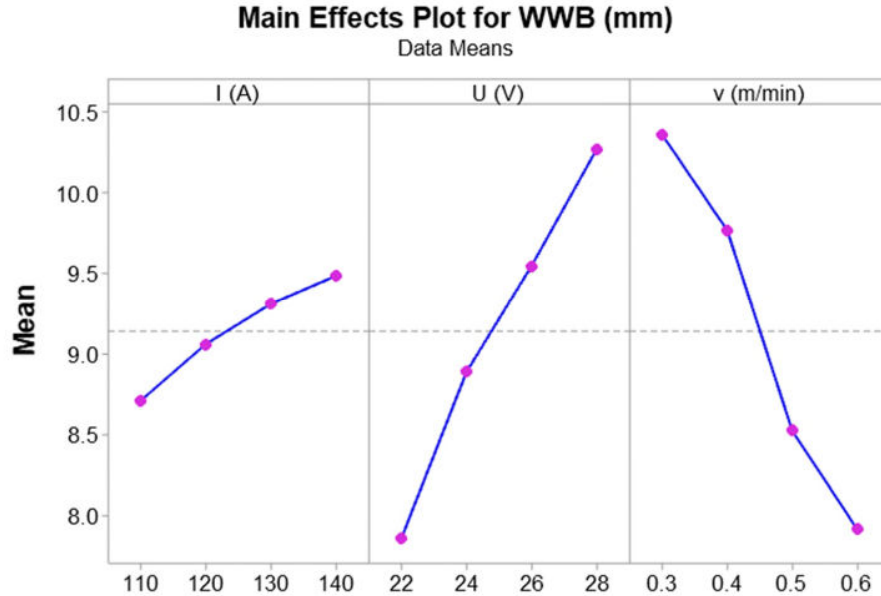


Fig. 3. Direct effects of process parameters on WWB.

The reasons for these phenomena can be explained as follows [18,32,45]: An increase in welding current leads to an increase in wire feed speed and the material deposition, resulting in an augmentation in melting pool size and in the width of weld beads (WWB). An increase in voltage also makes an increase in length and spreading of the arc. Therefore, WWB becomes larger with a higher level of the voltage. Oppositely, an augmentation in travel speed leads to a decrease in material deposition quantity per length unit. Therefore, the WWB becomes narrow as the travel speed increases.

Table 4 shows the results obtained through the ANOVA on the significance of each parameter for WWB. It is indicated that the travel speed has the most importance impact on WWB, with the highest contribution percentage (49.36%) and followed by the voltage with 41.75% of contribution percentage. On the other hand, the welding current features the lowest impact, with only 4.43% of contribution percentage. The Eq. (16) present the predicted model of WWB. The determination coefficients (i.e., $R^2 = 95.53\%$, $R^2(\text{adj}) = 94.42\%$, $R^2(\text{pred}) = 92.43\%$) indicate that this model has a high accuracy and can be used for the prediction.

$$\text{WWB (mm)} = -0.09 + 0.02575 \times I + 0.3953 \times U - 8.595 \times v \quad (16)$$

Table 4. ANOVA for WWB.

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Regression	3	28.599	95.53%	28.599	9.5329	85.57	0.000
I (A)	1	1.326	4.43%	1.326	1.3261	11.90	0.005
U (V)	1	12.498	41.75%	12.498	12.4978	112.19	0.000
v (m/min)	1	14.775	49.36%	14.775	14.7748	132.62	0.000
Error	12	1.337	4.47%	1.337	0.1114		
Total	15	29.936	100.00%				

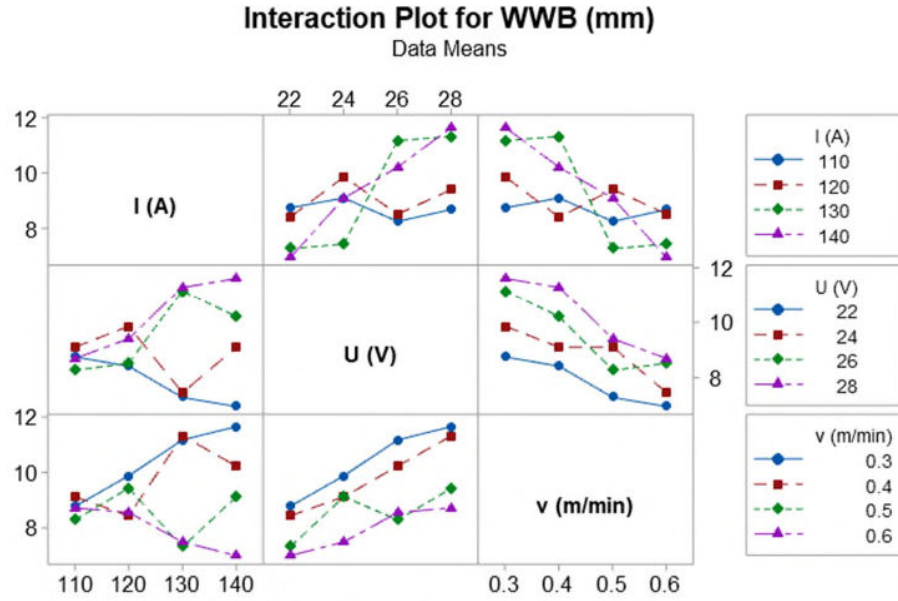


Fig. 4. Interaction effects of process parameters on WWB.

Figure 4 presents the interaction influences of process parameters on WWB. Due to the important contribution percentages of travel speed and voltage on WWB, it is found that the WWB generally increases/ decreases as the voltage and the welding speed increase, respectively, in the design space of experiments. Meanwhile, the WWB only increases with an augmentation in welding current for the cases of low travel speeds and high voltages. When the travel speed is high (e.g., 0.6 m/min) or the voltage is low (e.g., 22V), the WWB show a decreasing trend with the raise in the welding current.

b. Parameter effects on the height of weld beads (HWB)

The main effects of process parameters on the HWB are described in Fig. 5. It is revealed that the HWB increases with an increase in welding current from 110 to 140 A. Oppositely, HWB decreases as the voltage increases from 22 to 28 V and/or the travel speed increases from 0.3 to 0.6 m/min. As discussed above, when the welding current increases, the wire feed speed increases too. As a result, the volume of materials deposited increases, leading to an increase in HWB [32,45,46]. Moreover, the welding current increases, leading to an increase in the convexity of weld beads. This also enhances the HWB. On the other hand, when increasing the travel speed, the quantity of deposited materials per length unit is reduced. Hence, the HWB is reduced [32,47]. With an increase in voltage, the spreading area of the arc is larger, leading to flatter weld beads [48]. Hence, the HWB reveals a decreasing trend with an increase in voltage.

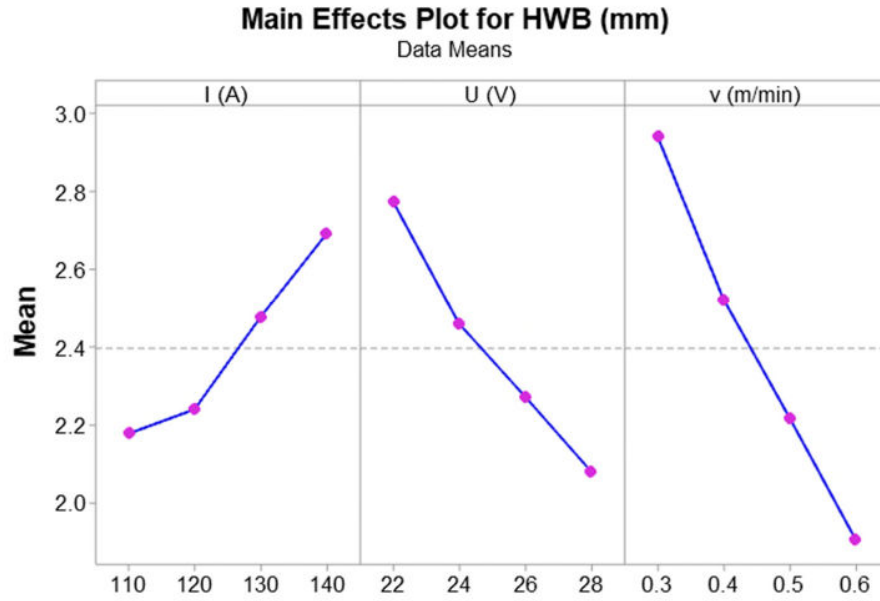


Fig. 5. Direct effects of process parameters on HWB.

Table 5 shows the ANOVA results for HWB. It is found that the travel speed exhibits the most impact on HWB with 54.34% of contribution. The voltage and the welding current show 24.03% and 14.78% of impact contribution, respectively. These results are also consistent with the results plotted in Fig. 5. The developed model of HWB is also adequate for the prediction with a reasonable accuracy ($R^2 = 93.14\%$, $R^2(\text{adj}) = 91.43\%$, $R^2(\text{pred}) = 85.57\%$).

$$\text{HWB (mm)} = 4.547 + 0.01782 \times I - 0.1136 \times U - 3.417 \times v \quad (17)$$

Table 5. ANOVA for HWB.

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Regression	3	4.0042	93.14%	4.0042	1.33472	54.34	0.000
I (A)	1	0.6355	14.78%	0.6355	0.63546	25.87	0.000
U (V)	1	1.0329	24.03%	1.0329	1.03285	42.05	0.000
v (m/min)	1	2.3359	54.34%	2.3359	2.33586	95.09	0.000
Error	12	0.2948	6.86%	0.2948	0.02456		
Total	15	4.2989	100.00%				

The interaction influences of input parameters on the HWB are shown in Fig. 6. Like the case of WWB, the HWB generally decreases when the traveling speed increases in the entire design space of experiment. This indicates the highest impact of the travel speed on the HWB, as shown in Table 5. The

HWB also reveals a decreasing trend with an increase in voltage. However, at a high level of current (e.g., $I = 140$ A) and at a low value of travel speed (e.g., $v = 0.3$ m/min), the HWB shows an increasing trend with an increase in voltage. On the other hand, the welding current reveals a complexly interaction with other parameters on the HWB.

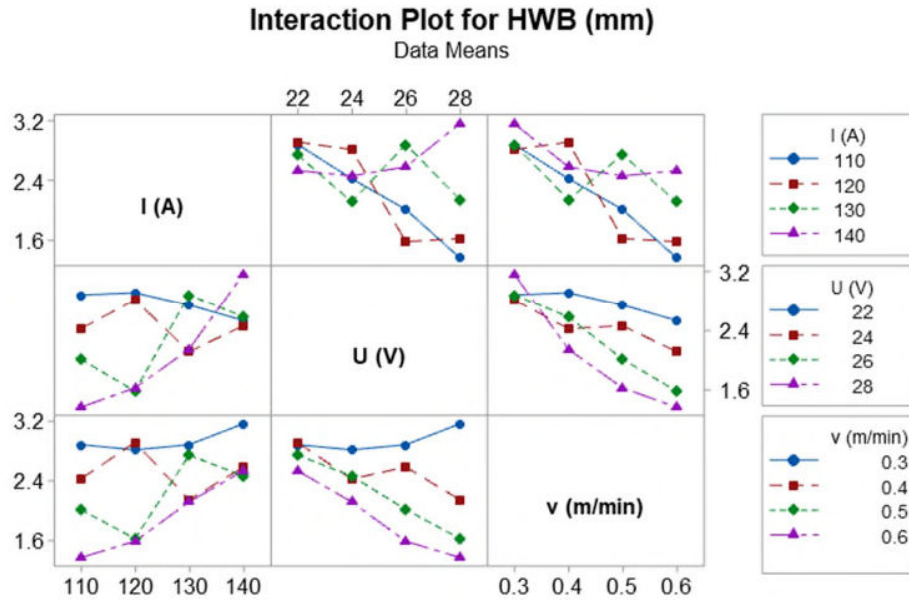


Fig. 6. Interaction effects of process parameters on HWB.

c. Parameter effects on the penetration depth of weld beads (PWB)

Figure 7 indicates the main impacts of process parameters on the PWB. It is indicated that the PWB increases with an increase in welding current (from 110 to 140 A) and with an augmentation in voltage (from 22 to 28 V). Meanwhile, the PWB decreases as the travel speed increases in the design space. Indeed, when the welding current and the voltage increase, the heat input increases, and more quantity of the substrate material is melted. As a result, the PBW becomes deeper. On the other hand, when the travel speed increases, the head input per unit length reduces, resulting in a smaller melting pool and a decrease in PWB. These observations are in line to that reported in previous works [32,45,48].

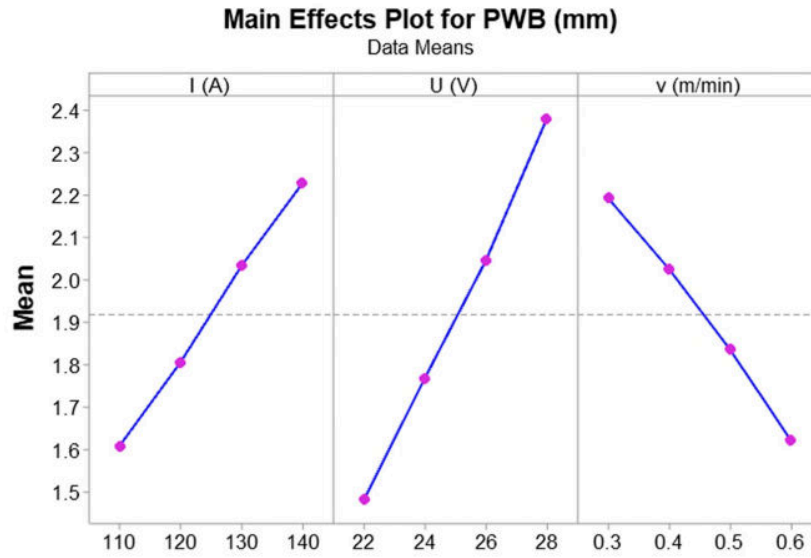


Fig. 7. Direct effects of process parameters on PWB.

Based on the ANOVA results presented in Table 6, it is shown that the voltage features the highest impact on the PWB with 49.38% of contribution. The welding current and the travel speed reveal a lower impact contribution of 24.27% and 20.27%, respectively. Moreover, the developed model of PWB, Eq. (18), with high determination coefficients (i.e., $R^2 = 93.93\%$, $R^2(\text{adj}) = 92.41\%$, $R^2(\text{pred}) = 88.76\%$) can be applied to predict the PWB with an acceptable accuracy.

$$\text{PWB (mm)} = -3.555 + 0.02087 \times I + 0.1489 \times U - 1.908 \times v \quad (18)$$

Table 6. ANOVA for PWB.

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Regression	3	3.3723	93.93%	3.3723	1.12411	61.85	0.000
I (A)	1	0.8715	24.27%	0.8715	0.87153	47.95	0.000
U (V)	1	1.7731	49.38%	1.7731	1.77310	97.56	0.000
v (m/min)	1	0.7277	20.27%	0.7277	0.72771	40.04	0.000
Error	12	0.2181	6.07%	0.2181	0.01817		
Total	15	3.5904	100.00%				

The interaction effects of processing parameters on the PWB are depicted in Fig. 8. It can be found that an increase in voltage, which has the highest level of impact contribution yields a raise in PWB. At high voltages (e.g., 26 and 28 V) and low travel speeds (e.g., 0.3 and 0.4 m/min), the PWB reveals an increasing trend with an augmentation in welding current. However, at low levels of voltage (e.g., 22 and 24 V), the PWB only increases as the welding current increases to certain values and then

PWB decreases. At high travel speeds (e.g., 0.5 and 0.6 m/min), the PWB reveals a decreasing trend with a raise in welding current. Similarly, the welding speed exhibits complex interaction impacts with I and U on PWB. The PWB decreases with an increase in travel speed at high levels of welding current and at high levels of voltage. At low voltage and low welding current, the PWB shows an augmentation trend when the travel speed increases.

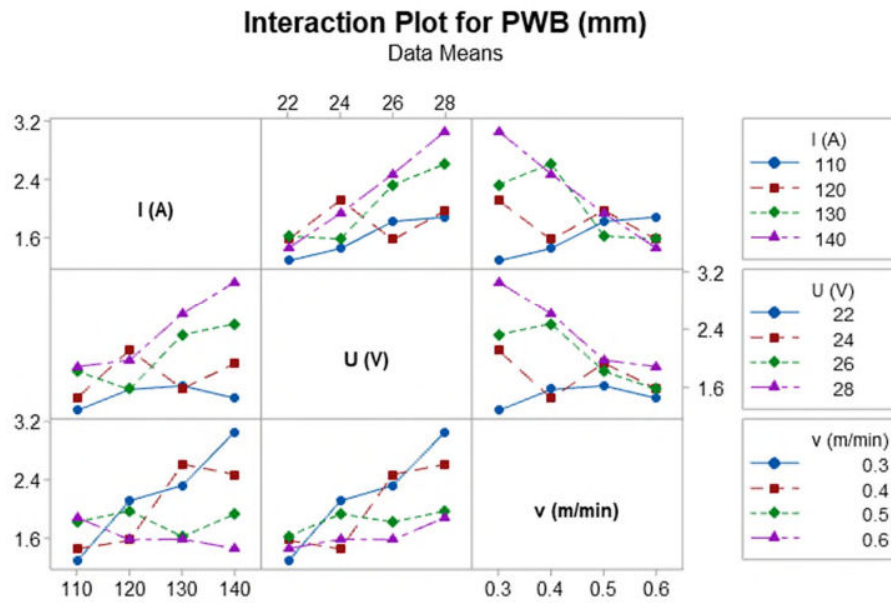


Fig. 8. Interaction effects of process parameters on PWB.

d. Parameter effects on the dilution of weld beads (DWB)

Figure 9 depicts the main influences of process parameters on the DWB. It is indicated that the DWB increases with an increase in voltage. The DWB also increases as the welding current increases up to 130 A. However, DWB becomes decreasing with the raise of the welding current from 130 to 140 A. On the other hand, when the travel speed increases, the DWB shows a decreasing trend. As discussed above, the heat input augments with the welding current and the voltage, resulting in deeper penetration and an increase in penetration area. Hence, the DWB increases with the voltage and welding current. When the travel speed increases, the DWB also reveals a diminishing trend. At an elevated travel speed, the quantity of metal deposited into the substrate is reduced, thus the reinforcement and penetration areas are reduced. These observations are similar those reported in the literature [32,45,48,49]. According to the ANOVA results for the DWB (Table 6), it is indicated that the voltage shows the highest impact on DWB with 71.07% of contribution. The welding current and the travel speed feature 13.87% and 3.16% of contribution, respectively.

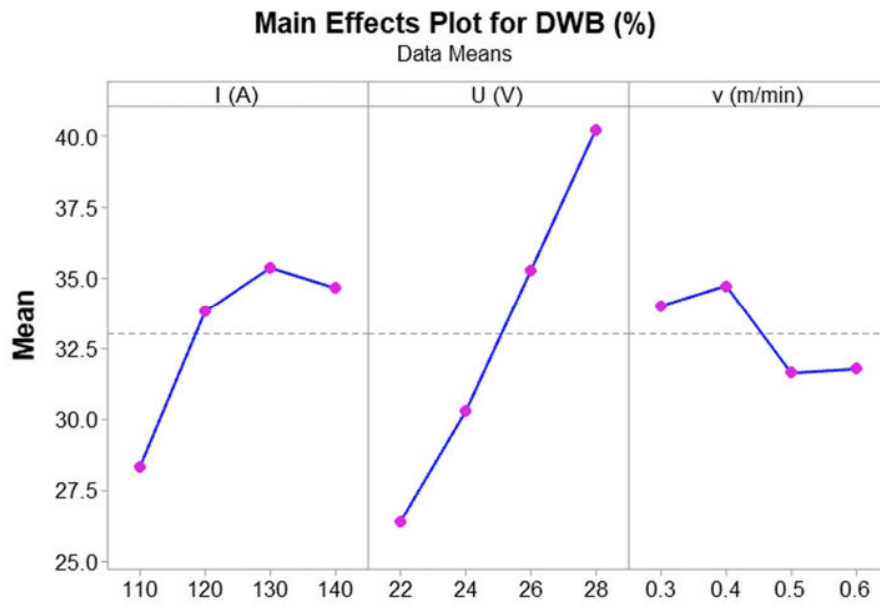


Fig. 9. Direct effects of process parameters on DWB.

Table 6. ANOVA for DWB.

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Regression	3	535.64	88.10%	535.64	178.546	29.63	0.000
I (A)	1	84.32	13.87%	84.32	84.315	13.99	0.003
U (V)	1	432.09	71.07%	432.09	432.092	71.70	0.000
v (m/min)	1	19.23	3.16%	19.23	19.231	3.19	0.099
Error	12	72.32	11.90%	72.32	6.027		
Total	15	607.96	100.00%				

$$\text{DWB (\%)} = -46.3 + 0.2053 \times I + 2.324 \times U - 9.81 \times v \quad (19)$$

The Eq. (19) represents the predicted model for the DWB. This model features an acceptable of determination coefficients - i.e., $R^2 = 88.10\%$, $R^2(\text{adj}) = 85.13\%$, $R^2(\text{pred}) = 77.50\%$. Therefore, it can be used for the prediction of DWB in the design space of experiments.

Figure 10 illustrates the interaction impacts of process parameters on the DWB. As the voltage has the highest contribution impact on the DWB, the DWB rises with the voltage for all levels of other parameters in the design space. For all levels of voltage or at low levels of travel speed, the DWB rises with an augmentation in the welding current. However, it becomes decreasing at high levels of welding

current. On the other hand, at high levels of travel speed, the DWB decreases with an augmentation in the welding current.

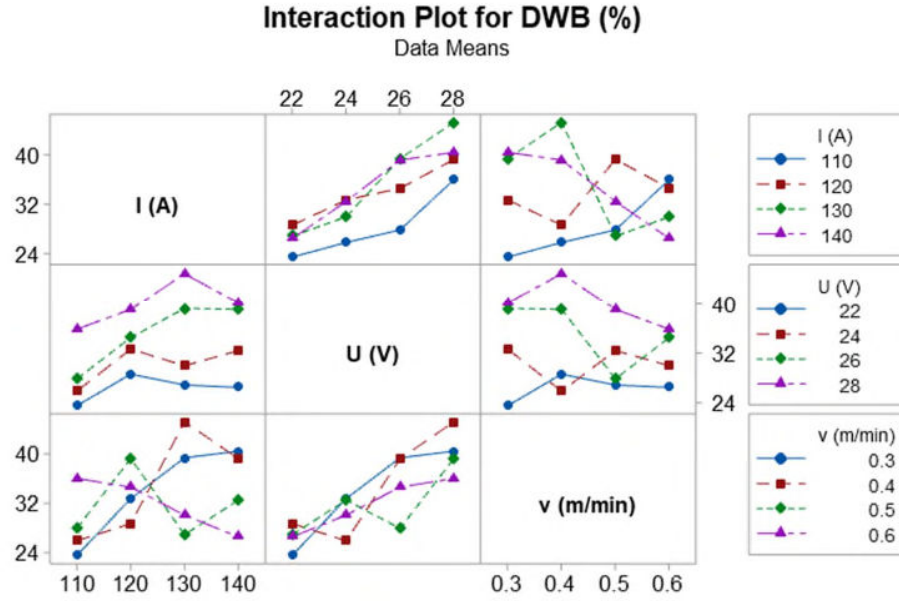


Fig. 10. Interaction effects of process parameters on DWB.

3.2. Optimizations results

a. Optimization with GRA

Table 7 presents the computation results with the GRA method, in which the normalized responses were obtained with Eq. (2) (for WWB and HWB) and Eq. (3) (for PWB and DWB). The values of GRC were calculated by Eq. (4), and lastly the GRG values were achieved with the aid of Eq. (8). It is noted that the weight for each response in Eq. (8) was obtained by using the CRITIC method. In this study, the weights for WWB, HWB, PWB, and DWB are 0.345, 0.214, 0.231, and 0.210, respectively. Based on the GRG values, the rank for all alternatives is given in the last column of Table 7. The Run 1 with the highest value of GRG is considered as the optimal condition. Therefore, the set of process parameters related to the Run 1 is the optimal combination of process parameters.

The mean values of GRG according to each level of input variables given in Table 8 and illustrated in Fig. 11 are also reveal the optimal condition with the highest GRG (marked in bold numbers), namely $U = 22$ V, $I = 110$ A, and $v = 0.3$ m/min are the optimal process parameters. The ANOVA for GRG indicates that the voltage and the welding speed have significant impacts on GRG (P-value < 0.05) with 51.49% and 16.91% of contribution, respectively, while the welding current features an insignificant impact (P-value > 0.05) with only 0.10% of contribution.

Table 7. Calculation results of normalized responses, GRC, GRG, and ranking.

Run	Normalized Response				Grey Relational Coefficient				GRG	Rank
	WWB	HWB	PWB	DWB	WWB	HWB	PWB	DWB		
1	0.384	0.844	1.000	1.000	0.448	0.763	1.000	1.000	0.759	1
2	0.458	0.589	0.904	0.891	0.480	0.549	0.840	0.821	0.649	3
3	0.279	0.361	0.697	0.798	0.410	0.439	0.622	0.712	0.529	12
4	0.371	0.000	0.663	0.425	0.443	0.333	0.597	0.465	0.460	16
5	0.311	0.861	0.837	0.763	0.421	0.783	0.754	0.678	0.629	5
6	0.620	0.806	0.534	0.576	0.568	0.720	0.517	0.541	0.583	8
7	0.335	0.122	0.837	0.489	0.429	0.363	0.754	0.495	0.504	14
8	0.525	0.144	0.612	0.275	0.513	0.369	0.563	0.408	0.472	15
9	0.070	0.767	0.809	0.845	0.350	0.682	0.724	0.763	0.594	7
10	0.107	0.417	0.831	0.701	0.359	0.462	0.748	0.625	0.527	13
11	0.898	0.844	0.416	0.269	0.830	0.763	0.461	0.406	0.641	4
12	0.930	0.433	0.253	0.000	0.877	0.469	0.401	0.333	0.565	9
13	0.000	0.650	0.904	0.863	0.333	0.588	0.840	0.785	0.600	6
14	0.458	0.611	0.635	0.586	0.480	0.563	0.578	0.547	0.534	10
15	0.695	0.678	0.331	0.278	0.621	0.608	0.428	0.409	0.529	11
16	1.000	1.000	0.000	0.220	1.000	1.000	0.333	0.391	0.718	2

Table 8. Average values of GRG according to the input variable levels.

Level	I (A)	U (V)	v (mm/min)
1	0.5992	0.6454	0.6754
2	0.5470	0.5735	0.5933
3	0.5819	0.5508	0.5321
4	0.5953	0.5537	0.5225
Delta = Max – Min	0.0522	0.0946	0.1529
Rank	3	2	1

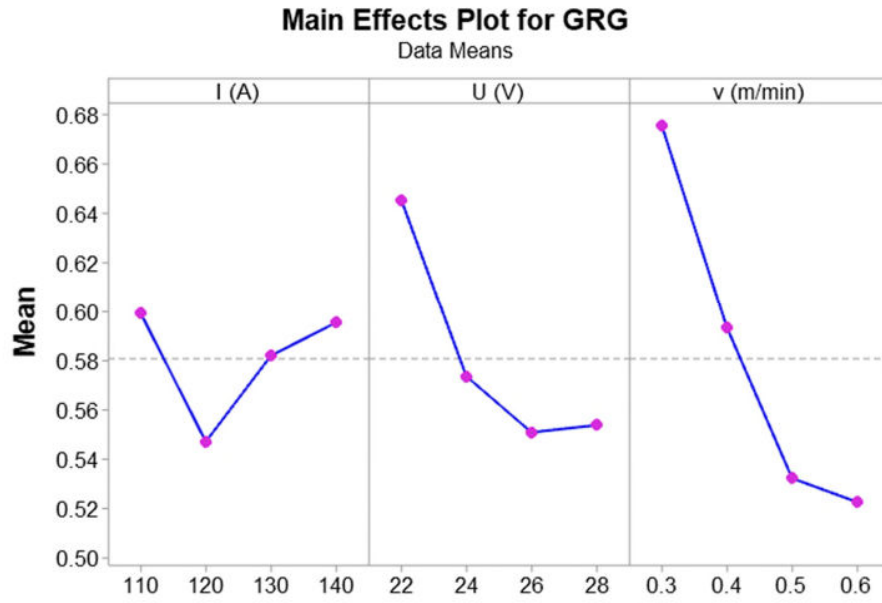


Fig. 11. Effects of process parameters on GRG.

Table 9. ANOVA for GRG.

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Regression	3	0.072	68.50%	0.071926	0.023975	8.70	0.002
I (A)	1	0.000	0.10%	0.000110	0.000110	0.04	0.845
U (V)	1	0.018	16.91%	0.017752	0.017752	6.44	0.026
v (mm/min)	1	0.054	51.49%	0.054065	0.054065	19.62	0.001
Error	12	0.033	31.50%	0.033073	0.002756		
Total	15	0.105	100.00%				

b. Optimization with TOPSIS

Table 10 show the calculation results in the TOPSIS method, the elements of the normalized decision matrix and the weighted normalized decision matrix were obtained by Eq. (9) and Eq. (10), respectively. The weight for each response was also calculated by the CRITIC method, as mentioned in the GRA method. The ideal solutions (IS) for each response are $IS_{(WWB)} = 0.1087$, $IS_{(HWB)} = 0.0692$, $IS_{(PWB)} = 0.0374$, and $IS_{(DWB)} = 0.0367$. The non-ideal solutions (NIS) for each response are $NIS_{(WWB)} = 0.0649$, $NIS_{(HWB)} = 0.0299$, $NIS_{(PWB)} = 0.0894$, and $NIS_{(DWB)} = 0.0706$. The distance of feasible solutions from ISs or NISs (DIS_i and $DNIS_i$) is computed as Eq. (13) and (14), respectively. Based on the values of CDIS, it is found that the Run 1 is considered as the best solution for the multi-objective optimization problem, followed by the Run 2, 5, 6, and so on, as depicted by the Rank in the last column of Table 10.

Table 10. Calculation results of normalized and weighted normalized decision matrices, distance values (DIS_i and $DNIS_i$), and $CDIS_i$ values.

Run	Normalized Decision Matrix				Weighted Normalized Decision Matrix				DIS_i	$DNIS_i$	$CDIS_i$	Rank
	WWB (mm)	HWB (mm)	PWB (mm)	DWB (%)	WWB (mm)	HWB (mm)	PWB (mm)	DWB (%)				
1	0.24	0.29	0.16	0.17	0.08	0.06	0.04	0.04	0.028	0.072	0.724	1
2	0.25	0.25	0.18	0.19	0.09	0.05	0.04	0.04	0.029	0.064	0.685	2
3	0.22	0.21	0.23	0.21	0.08	0.04	0.05	0.04	0.044	0.049	0.528	9
4	0.24	0.14	0.24	0.27	0.08	0.03	0.05	0.06	0.055	0.041	0.427	16
5	0.23	0.30	0.20	0.21	0.08	0.06	0.05	0.04	0.033	0.062	0.656	3
6	0.27	0.29	0.27	0.24	0.09	0.06	0.06	0.05	0.034	0.054	0.615	4
7	0.23	0.16	0.20	0.26	0.08	0.03	0.05	0.05	0.049	0.049	0.500	12
8	0.25	0.17	0.25	0.29	0.09	0.04	0.06	0.06	0.051	0.041	0.445	15
9	0.20	0.28	0.20	0.20	0.07	0.06	0.05	0.04	0.043	0.059	0.578	6
10	0.20	0.22	0.20	0.22	0.07	0.05	0.05	0.05	0.047	0.052	0.525	10
11	0.30	0.29	0.29	0.29	0.10	0.06	0.07	0.06	0.040	0.057	0.586	5
12	0.31	0.22	0.33	0.34	0.11	0.05	0.08	0.07	0.056	0.046	0.450	14
13	0.19	0.26	0.18	0.20	0.06	0.06	0.04	0.04	0.046	0.061	0.568	8
14	0.25	0.25	0.24	0.24	0.09	0.05	0.06	0.05	0.037	0.050	0.574	7
15	0.28	0.26	0.31	0.29	0.10	0.06	0.07	0.06	0.046	0.045	0.492	13
16	0.32	0.32	0.39	0.30	0.11	0.07	0.09	0.06	0.058	0.059	0.504	11

Table 11. Average values of CDIS according to the input variable levels.

Level	I (A)	U (V)	v (mm/min)
1	0.590	0.631	0.607
2	0.554	0.600	0.571
3	0.535	0.527	0.531
4	0.535	0.457	0.505
Delta = Max - Min	0.055	0.174	0.102
Rank	3	1	2

Figure 12 and Table 11 shows the mean values of CDIS. They also reveal the optimal condition for the highest value of CDIS (marked in bold numbers in Table 11) – i.e., $I = 110$ A, $U = 22$ V, and $v =$

0.3 m/min. The ANOVA for CDIS indicates that all input variables have significant impact on CDIS (P-value < 0.05 at the confidence level of 95%). The voltage has the highest level of impact contribution on CDIS (63.99%), followed by the welding speed (21.41%), and the welding current (6.30%).

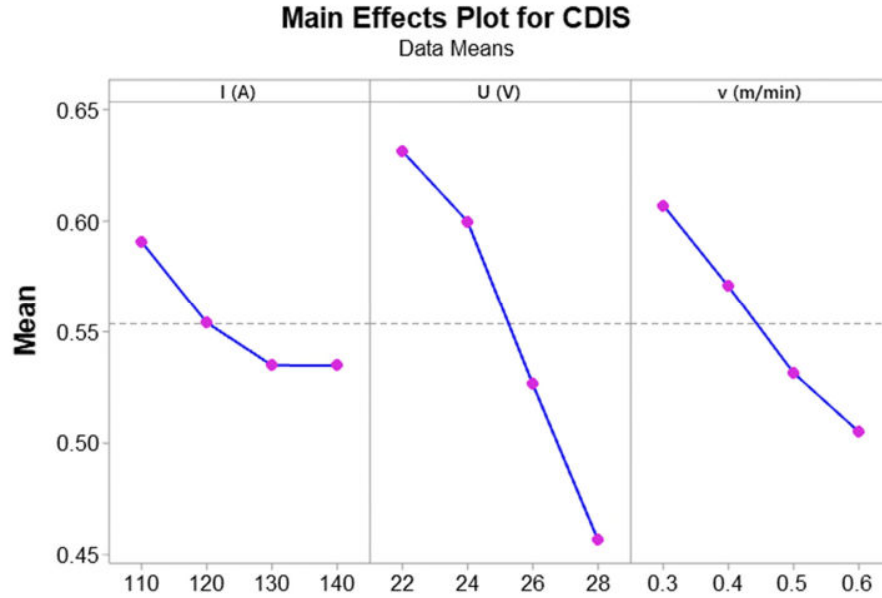


Fig. 12. Effects of process parameters on CDIS.

Table 11. ANOVA for CDIS.

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Regression	3	0.102	91.70%	0.102	0.034	44.21	0.000
I (A)	1	0.007	6.30%	0.007	0.007	9.11	0.011
U (V)	1	0.071	63.99%	0.071	0.071	92.54	0.000
v (m/min)	1	0.024	21.41%	0.024	0.024	30.96	0.000
Error	12	0.009	8.30%	0.009	0.001		
Total	15	0.112	100.00%				

From the obtained results, it is observed that the GRA and TOPSIS methods recommend the similar set of optimal process parameters. Therefore, we can conclude that the optimal process parameters for the WAAM process of 316L stainless steel according to the defined optimal criteria are $I = 110$ A, $U = 22$ V, and $v = 0.3$ m/min.

To validate the optimal process parameters, these parameters have been used to build a cylinder wall with 20 layers of single beads, as shown in Fig. 14. It is revealed that the single weld bead is

continuous and smooth with a regular width (Fig. 14a). The cylinder wall also has a good shape and regular height and width (Fig. 14b).

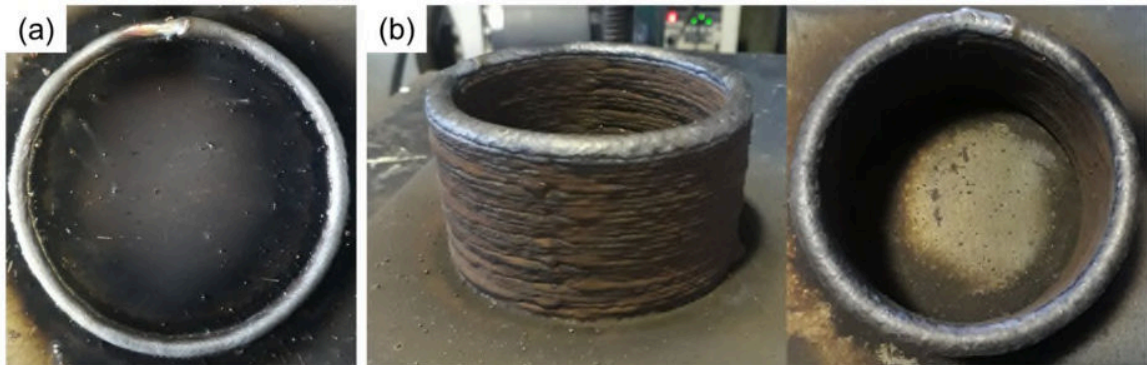


Fig. 14. (a) single weld bead and 20-layer cylinder wall produced by the WAAM process with the optimal process parameters.

4. Conclusions

This study aimed at investigating the influences of process parameters in the GMAW-WAAM process of 316L stainless steel on the characteristics of welding beads (including the width, height, penetration, and dilution of weld beads - WWB, HWB, PWB and DWB). The Taguchi method with L16 orthogonal array were adopted for the design of experiments. The ANOVA was applied to identify the significance of input variables on each response. The optimal process parameters were also determined by using GRA and TOPSIS methods. The main conclusions of this research can be depicted as follows:

- The process parameters feature significant influences on the characteristics of single weld beads. The ANOVA results indicate that the travel speed shows the most significant effect on the WWB and HWB. On the other hand, the voltage has the highest impact on PWB and DWD.
- The models of WWB, HWB, PWB, and DWB are also adequate for predicting the process parameters in specific applications (e.g., in generation of deposition paths, slicing layers from 3D CAD models for AM, and thermo-mechanical simulations of the WAAM process).
- GRA and TOPSIS are two effective solutions for multi-objective decision-making problems. Both the GRA and TOPSIS methods give the same optimal process parameters in WAAM of 316L stainless steel - i.e., $U = 22$ V, $I = 110$ A, and $v = 0.3$ m/min, which were used to successfully build a cylinder wall with 20 deposited layers. The regular and stable geometry of the built part demonstrates the suitability of optimal process parameters.

Declarations

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Completing interests

The authors have no competing interests to declare that are relevant to the content of this article.

Data availability statements

All data generated or analyzed in the study are included in this paper.

Author contributions

Conceptualization, Methodology: Van Thao Le; Formal analysis and investigation: Van Thao Le, Quang Thanh Doan, Dinh Si Mai, Manh Cuong Bui; Writing - original draft preparation: Van Thao Le; Writing - review and editing: Van Thao Le, Hoang Son Tran, Xuan Van Tran, Van Anh Nguyen; Funding acquisition: Van Thao Le.

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