MM Science Journal | www.mmscience.eu
ISSN 1803-1269 (Print) | ISSN 1805-0476 (On-line)
Special Issue | CUTTING TOOLS 2024
1st International Conference on Cutting Tools
November 20-22, 2024, Trnava, Slovakia
DOI: 10.17973/MMSJ.2025_10_2025098

CUTTINGTOOLS2024-00016

ANALYSIS OF THE INFLUENCE OF ARC LENGTH AND DYNAMICS CORRECTION ON THE DIMENSIONAL CHARACTERISTICS OF WELD OVERLAYS USING THE DOE METHOD

Milan Maronek[1]*, Bohdan Savytskyi[1], Jozef Barta[1], Janette Kotianova[1]
[1]Slovak University of Technology in Bratislava, Faculty of Materials Science and Technology, Trnava, Slovakia
*Corresponding author; e-mail: milan.maronek@stuba.sk

Abstract
Wire Arc Additive Manufacturing (WAAM) is an arc-based additive manufacturing process used for the layer-wise fabrication of metallic components. The used process parameters significantly affect process stability, deposition quality, and surface integrity of the manufactured parts. Welding power source manufacturers allow some of the process parameters to be corrected, but they do not quantify these corrections in more detail. The objective of this study is to apply the Design of Experiments (DOE) methodology to assess the effect of selected process parameters such as arc length and arc dynamics on the geometrical features of the deposited layers, specifically bead height, bead width and deposition bead angle.
Keywords:
WAAM, DOE, Arc length, Dynamics correction, Dimensional characteristics

1 INTRODUCTION

Additive Manufacturing (AM) has become a transformative technology in recent decades, fundamentally changing traditional paradigms of manufacturing and design across various industries. This advanced manufacturing method is based on the layer-by-layer deposition of material, effectively building the final component from scratch. Among the various AM technologies, metal-based processes have gained significant importance due to their ability to fabricate functional parts with high mechanical integrity and material efficiency [Dinovitzer 2019, Shukla 2025].

Directed Energy Deposition (DED) methods, especially Wire Arc Additive Manufacturing (WAAM), have demonstrated notable potential due to their capability to produce large and complex metallic parts with reduced material waste and lower operational costs. WAAM uses an electric arc as a heat source to melt a metal wire, which is then deposited layer by layer. In addition to flexibility in design, WAAM enables hybrid manufacturing, structural repairs, reinforcement, and remanufacturing, making it an attractive solution for industries such as aerospace, energy, and tooling [Kumar 2024].

Despite these advantages, the WAAM process still faces challenges in achieving dimensional accuracy and consistent geometric quality. The final shape of the deposited bead is highly sensitive to various process parameters, including thermal input, wire feeding behavior, and arc stability. [Grandvallet 2025]

Arc welding is a dynamic process in which electrical parameters fluctuate rapidly even under constant settings, influenced by inherent process instabilities. Recent advances in digital control and electronics have enabled real-time monitoring and active regulation of critical parameters such as current, voltage, wire feed speed, arc length, and waveform shape. These improvements have enhanced process stability, reduced heat input, and minimized welding defects [Xu 2022, Sahane 2022, Hamzeh 2020].

Although manufacturers allow adjustment of arc length and arc dynamics corrections, technical documentation typically does not provide sufficient information on how these changes influence the process and the resulting weld bead geometry. This lack of clarity limits the user's ability to predict and optimize process outcomes based solely on the available equipment settings.[Yadav 2025]

Several studies have explored the influence of arc length or arc dynamics in conventional welding processes, including waveform control and droplet transfer. However, these investigations have primarily focused on standard arc welding applications. To date, no comprehensive study has combined WAAM technology with a structured Design of Experiments (DOE) methodology to systematically evaluate the effects of arc length and dynamics correction settings on geometric output parameters. [Montgomery 2016, Berger 2018, Xu 2022, Sahane 2022].

This research aims to fill this gap by analyzing the isolated and combined effects of these two key parameters on weld bead characteristics within the WAAM process. By applying a DOE-based experimental design, it provides a statistically supported insight into process behavior, which can serve as a basis for further optimization and adaptive control strategies. [Schiefer 2021; Alaboudi 2025]

2 EXPERIMENT

The experiment was designed to analyze the effect of selected process parameters on the quality of weld deposition using the MIG welding method. This fusion-based process is highly automatable and suitable for application in metal additive manufacturing.

The Minitab software was used for processing and visualizing the experimental data. It supports statistical analysis, model development, and interpretation in accordance with the principles of Design of Experiments (DOE).

The study focused on two primary factors:

- Arc length (Factor A).
- Arc dynamics (Factor B).

Each factor was tested at three levels: low (–10), center (0), and high (+10). This three-level structure allowed the model to capture both linear and quadratic effects, which are essential for identifying curvature and interactions in the system response.

A face-centered design (FCD), a specific form of central composite design (CCD), was selected based on findings from pilot experiments. This approach allowed for efficient modeling of curvature and interaction effects, while ensuring that factor levels remained within the practically feasible range of -10 to 10.

The design included:

- Factorial points (4 points located at the corners of the design space),
- Axial points (4 points located at the center of each edge of the square design space),
- Center point (1 point located at the geometric center of the design space).

These points are shown in Figure 1, with:

- red for factorial points,
- blue for axial points,
- and green for the center point.

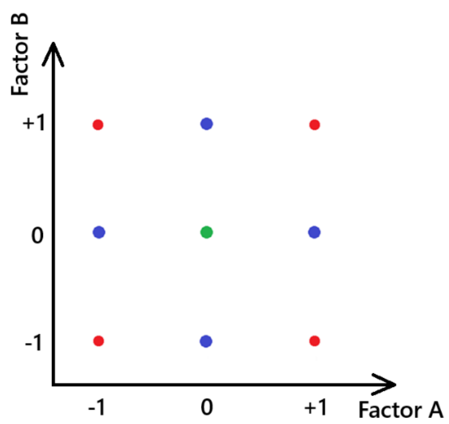

Fig. 1: Distribution of experimental points in coded units for FCD.

The factor levels in the figure are represented in coded units, where the interval [-1; 1] corresponds to the actual physical range [-10; 10] given by equipment. Coding simplifies statistical modeling and improves the interpretability of the results.

Each experimental point represented a specific set of welding conditions, where arc length and arc dynamics were systematically varied. During the process, the actual values of welding current, arc voltage, and wire feed rate were continuously measured and recorded. From these measurements, the specific heat input was calculated, serving as an indicator of the process's energy level.

A total of 9 samples were produced. On each sample, a single weld bead was deposited. Each experimental point was measured with one replication, and a center point was included to improve the estimation of experimental error and to verify the stability of the process.

Experimental weld overlays were produced using Inconel 718 filler wire with a diameter of 1.2 mm. Inconel 718 is designed for welding applications that require excellent mechanical performance and corrosion resistance at elevated temperatures. The chemical composition of the Inconel 718 filler material is provided in Table 1 based on the 3.1 inspection certificate delivered by the producer according to EN10204.

Tab. 1: Chemical composition of Inconel 718 filler wire (wt.%).

C	Cr	Ni	Mo	Nb+Ta	Ti	Fe
0.07	17.50	52.00	3.00	5.00	0.9	balance

Based on the technical capabilities of the Fronius TPS 600i welding system and the properties of the base material S235 with dimensions of 170×30×20 mm, which was used for the deposition of the components, appropriate welding parameters were selected. The welding was performed in the Pulse Synergic mode. The main WAAM process parameters used in this study were as follows: average welding current 252 A, average arc voltage 17 V, wire feed speed 8 m/min, and travel speed 5 mm/s. These parameters were selected based on preliminary trials and adjusted to ensure stable arc behavior and consistent bead formation throughout the deposition process. The shielding gas used was argon (Ar) with a purity of 99.999%.

After fabrication, the samples were subjected to 3D scanning using the GOM ATOS II Triple Scan system. To improve scanning quality and surface detection, the samples were matted with a chalk-based spray prior to measurement. The scanned geometry of the sample is shown in Figure 2.

Following data processing, 10 cross sections were generated for each sample. These sections enabled precise measurement of the bead width, bead height, and deposition bead angle. In total, 90 cross sections were analyzed using this method. For each section, three measurements were recorded: width, height, and deposition bead angle. This resulted in 270 individual data points, providing a sufficiently large dataset for reliable statistical analysis and objective assessment of the influence of the investigated process parameters.

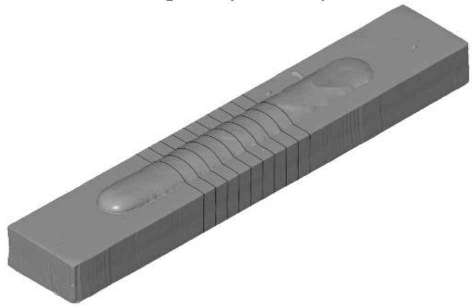

Fig. 2: 3D scan of the sample with a single weld bead and cross-section layout for dimensional analysis.

This method provided a consistent, objective, and reproducible way to evaluate the weld geometry across all samples. An illustrative example of such a cross-sectional view, with all measured parameters marked, is shown in Fig. 3

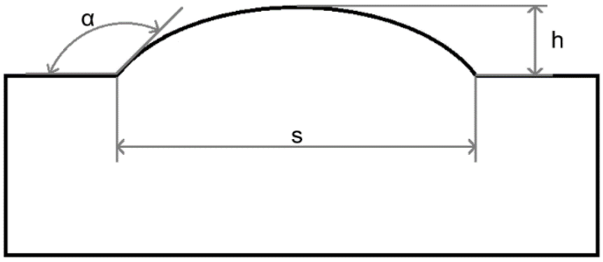

Fig. 3: Cross-sectional view of a single weld bead with measured width (s [mm]), height (h [mm]), and deposition bead angle (α [°]).

3 ANALYSIS OF THE MEASURED DATA

The aim of this section is to analyze the experimental data and assess the influence of individual process parameters – arc length (Factor A) and arc dynamics (Factor B) on the dimensional characteristics of the deposited layers. The observed responses include bead width, bead height, and deposition bead angle, all of which are closely related to weld quality, process repeatability, and energy efficiency.

To evaluate the data, a combination of multiple regression analysis and statistical visualization tools such as the Pareto chart of standardized effects and contour plots was applied. This analytical framework, based on ANOVA and statistical significance tests of regression coefficients, allows the identification of significant main effects and interactions, while also generating a predictive regression model that describes the relationship between input factors and system responses.

The resulting model is evaluated in terms of its statistical quality using indicators such as R^2, adjusted R^2, predicted R^2, and the standard error of residuals. Special attention is given to the predictive capability of the model and its potential application in the real-time control and optimization of the WAAM process.

3.1 Model Summary

The "Model Summary" tables present essential statistical indicators that evaluate the overall quality and performance of the regression models developed for each response variable. These metrics provide insight into how well the model fits the experimental data, how reliably it explains variation, and how effectively it can predict future outcomes.

S – standard error of the regression: This value represents the average magnitude of residuals, i.e., the differences between observed and predicted values. A lower S value indicates that the predicted values are closely aligned with actual measurements, reflecting a higher level of model accuracy.

R-sq – coefficient of determination (R^2): This metric quantifies how much of the variability in the response variable can be explained by the model. Values closer to 100% indicate that the model effectively captures the underlying trends in the data.

R-sq (adj) – adjusted R^2: Unlike R^2, this value adjusts for the number of predictors used in the model. It helps to prevent overestimation of model quality when irrelevant or redundant variables are included, offering a more realistic measure of explanatory power.

R-sq (pred) – predicted R^2: This statistic estimates how well the model is likely to perform on unseen data. If the predicted R^2 is considerably lower than the regular R^2, it may indicate that the model is overfitted, meaning it performs well on the current dataset but poorly on new inputs.

Together, these metrics form the foundation for evaluating the suitability and robustness of each regression model and guide the interpretation of how process parameters influence the studied responses [Madsen 2012].

Response – bead width [mm]

Tab. 2: Model summary for response – weld bead width [mm]

S	R-sq	R-sq(adj)	R-sq(pred)
0,814702	93,19%	92,87%	92,25%

The model for bead width achieved excellent statistical indicators. The coefficient of determination R^2 = 93.19% shows that over 93% of variability in the data is explained by the model. The adjusted R^2 = 92.87% indicates that the model is well-structured without overfitting. The predicted R^2 = 92.25% confirms strong predictive capability. The standard error S = 0.814 mm is reasonable given the measurement range (Tab. 2).

Response – bead height [mm]

Tab. 3: Model summary for response – weld bead height [mm]

S	R-sq	R-sq(adj)	R-sq(pred)
0,149083	93,71%	93,49%	93,25%

For bead height, the regression model also performed with high accuracy. The values R^2 = 93.71% and R^2 (adj) = 93.49% indicate consistency and model adequacy. The predicted R^2 = 93.25% confirms excellent generalization. The standard error S = 0.149 mm is very low, suggesting high precision in both measurement and estimation (Tab. 3).

Response – deposition bead angle [°]

Tab. 4: Model summary for response – deposition bead angle [°]

S	R-sq	R-sq(adj)	R-sq(pred)
5,86613	90,43%	89,67%	90,10%

The model for the bead angle yielded slightly lower but still very strong performance. R^2 = 90.43% indicates that a significant portion of variability is captured. R^2 (pred)= 89.67% and R^2(adj) = 90.10% confirm reliable model structure and predictive performance. The standard error S = 5.87° reflects a naturally higher variation in this response type (Tab. 4).

Based on the evaluation of the regression models, it can be concluded that all three models – for bead width, height, and deposition angle achieved a high level of accuracy and reliability. The coefficient of determination (R^2) exceeded 90% in all cases, indicating excellent agreement between the models and the experimental data. All models demonstrated strong predictive capability, confirming their suitability for further analysis and process optimization.

3.2 Pareto Chart of the Standardized Effects

The Pareto chart of standardized effects is a key visualization tool used to identify the most impactful factors and their interactions on the measured responses within an experiment. Its primary advantage lies in its ability to clearly highlight which input parameter changes result in statistically significant variations in the output.

On the vertical axis, the chart displays standardized absolute effect values for each factor and interaction, arranged in descending order. A red dashed line represents the threshold of statistical significance. Effects that extend beyond this line are considered statistically significant and indicate a meaningful influence on the response variable. Conversely, effects below this threshold are regarded as negligible and may be excluded from further model interpretation. Thus, the Pareto chart is an effective tool for narrowing down relevant factors, simplifying the regression model, and supporting more targeted and efficient optimization of the experimental process [Kenett 2014].

Response – bead width [mm]

The most dominant influence on bead width was observed from factor A – arc length correction (Fig. 4).

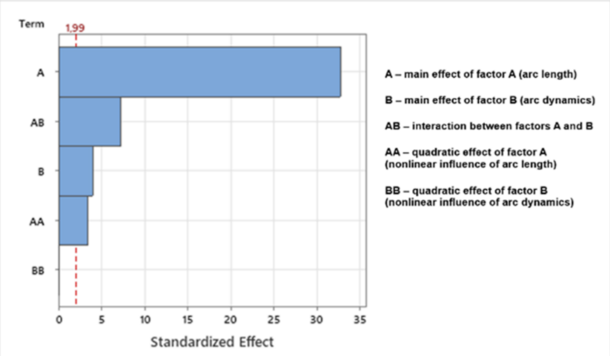

Fig. 4: Pareto chart of the standardized effects bead width.

Other terms such as the AB interaction (combined influence of factors A and B), factor B – arc dynamics, and the quadratic term AA (second-degree effect of factor A) also exceeded the threshold of statistical significance.

While these effects are not as strong as factor A, they still contribute to the variability in results and should be taken into account during process optimization. The quadratic term BB showed no significant influence (Fig. 4).

Response – bead height [mm]

For bead height, factor A – arc length correction was again identified as the dominant influence (Fig. 5).

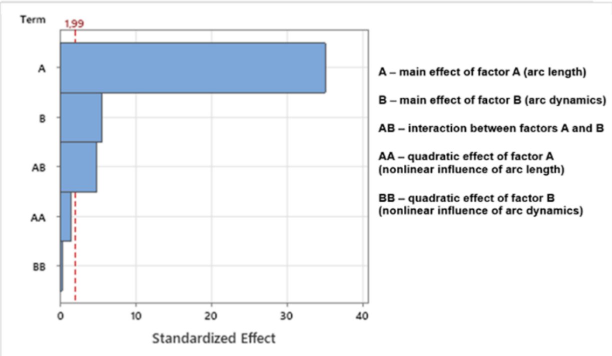

Fig. 5: Pareto chart of the standardized effects bead height.

In addition, factor B – arc dynamics and the AB interaction were statistically significant. These factors work in synergy with factor A and contribute to the overall response. Quadratic terms AA and BB remained below the significance threshold and had a negligible effect on bead height (Fig. 5).

Response – deposition bead angle [°]

The deposition bead angle was primarily affected by factor A – arc length correction, which exhibited the strongest influence. However, both factor B – arc dynamics and the AB interaction also exceeded the threshold of statistical significance, indicating that they play a relevant role in shaping the angle of the weld bead. The quadratic terms AA and BB were again statistically insignificant for this response (Fig. 6).

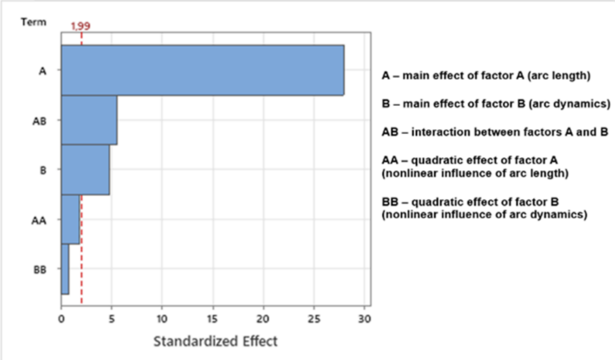

Fig. 6: Pareto chart of the standardized effects deposition bead angle.

Based on the presented findings, it can be concluded that factor A – arc length correction is the most dominant and consistent influence across all evaluated geometric characteristics of the weld bead. However, other factors should not be disregarded, as several reached statistical significance and contributed additional effects. This highlights the importance of considering not only primary factors but also interactions and quadratic terms when aiming for reliable optimization of the WAAM process to ensure consistent bead geometry and final part quality.

Moreover, the statistically significant interactions particularly the combined effect of factors A and B play an important role in how the system responds when multiple input parameters change simultaneously. These interaction effects should be carefully addressed in process design, especially when high deposition accuracy is required.

Additionally, the presence of quadratic terms indicates possible nonlinear behavior of the system, particularly at the boundary values of the factor ranges. Ignoring such effects may lead to underestimated risks of deviation beyond the optimal window. Therefore, these terms must be taken into account when extending process limits or implementing adaptive control strategies.

The combined influence of multiple statistically relevant terms confirms that weld bead geometry is governed by complex interdependencies rather than isolated effects. This supports the need for holistic process tuning and data-driven optimization in advanced WAAM applications.

3.3 Interaction Plot

The interaction plot is a statistical tool used to visualize the relationship between two input factors and their combined effect on the response variable. The main purpose of this graphical representation is to determine whether the effect of one factor depends on the level of another factor, indicating the presence of an interaction. This type of analysis is particularly valuable in the framework of Design of Experiments (DOE), where understanding both main effects and interaction effects is essential for accurate modeling and optimization. The plot consists of two axes, representing levels of factor A and factor B, respectively. For each combination, the mean value of the response is calculated and plotted. If the resulting lines are parallel, there is no significant interaction – meaning the effect of one factor is independent of the other. Conversely, if the lines cross or diverge, this indicates a significant interaction, meaning the influence of one factor changes depending on the level of the other.

From a methodological perspective, interaction plots serve as a critical validation tool for regression models and are fundamental for designing robust process settings. They allow researchers to detect combinations of input parameters that may lead to unexpected or amplified effects on the response. This insight is crucial for optimizing complex manufacturing processes such as WAAM. Interaction plots complement the findings from Pareto charts, helping to form a comprehensive understanding of the experimental structure and system behavior [Lambiase 2025].

Response – bead width [mm]

The interaction plot for bead width clearly illustrates the dominant influence of factor A – arc length correction. As the value of factor A increases, the mean bead width also increases significantly. This trend exhibits noticeable curvature, particularly due to the significant quadratic term A^2, as evidenced by the large difference in mean bead width between the extreme levels of factor A (-10 and +10). Additionally, the non-parallel nature of the effect curves in the interaction plot suggests the presence of an interaction between factors A and B. Although factor B does not have a strong individual effect, it contributes to this interaction and to the overall curvature of the response (Fig. 7).

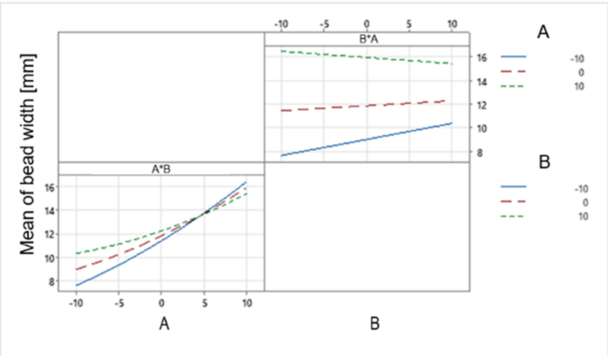

Fig. 7: Interaction Plot – bead width [mm].

From the plot, it is evident that the minimum bead width occurs when factor A is at its lowest level and factor B is also set to its lower level (-10), as indicated by the blue line in the interaction plot. Conversely, the maximum width is achieved with high values of factor A and low values of factor B. This implies that optimizing bead geometry requires careful coordination of both factors, with primary emphasis on controlling arc length. The interaction effect between A and B is particularly noticeable at medium and high levels of factor A, where differences between the levels of factor B become more prominent (Fig. 7).

Response – bead height [mm]

For bead height, factor A again shows the strongest influence. An increase in A results in a linear decrease in bead height. Factor B has a similar but less pronounced trend. Maximum bead height occurs at low values of both A and B, while the minimum is observed at a high level of factor A, regardless of the setting of factor B (Fig. 8).

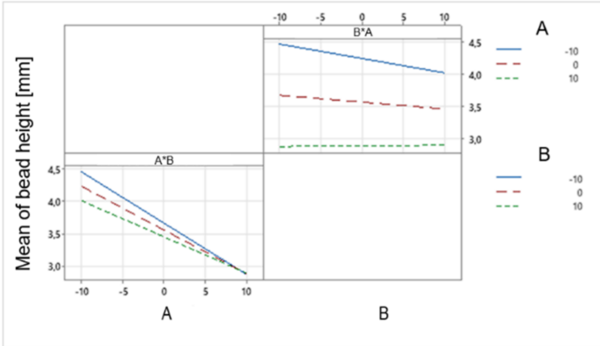

Fig. 8: Interaction Plot – bead height [mm].

Response – deposition bead angle [°]

The behavior of the deposition bead angle mirrors the previous responses. Factor A has a strong linear effect – higher A leads to a greater angle. Factor B does not exhibit a major direct effect but contributes through interaction with A (Fig. 9).

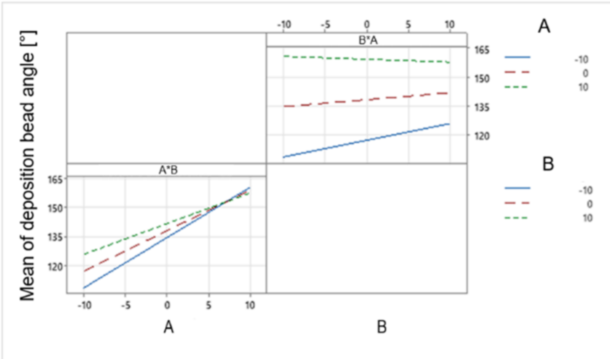

Fig. 9: Interaction Plot – deposition bead angle [°]

The interaction plots confirm the dominant influence of factor A – arc length correction on all geometric responses of the weld bead. While factor B does not exert a strong independent effect, it plays a crucial role through interactions and nonlinear system behavior, which is essential for optimizing the WAAM process. Additionally, the combined effect of factors A and B can lead to unexpected shifts in the response, highlighting the importance of tracking interactions. These insights are critical for fine-tuning process parameters to achieve consistent weld bead quality. From a practical perspective, these findings support the need for adaptive process control strategies that account for interaction effects.

Furthermore, interaction plots help visually validate the regression model and reinforce the presence of significant AB terms. The identification and interpretation of these interactions represent the most important contribution of the study, as they reveal complex relationships that would otherwise remain hidden in purely linear analysis.

3.4 Regression Equation in Uncoded Units

The result of regression analysis is a mathematical model that describes the relationship between input factors and the response variable. For practical applications, this model must be expressed in uncoded (real-world) units, as opposed to the normalized values used during statistical processing. By expressing the regression equations in uncoded units, it becomes possible to directly predict response values based on actual process parameters. This also provides a foundation for generating visual tools, such as contour and surface plots, which can be based either on coded or uncoded values to aid in evaluating and optimizing process behavior [Alshukur 2025].

Equations (1) to (3) are regression models in uncoded units for bead width, height, and angle. They describe the influence of arc length correction (factor A) and arc dynamics correction (factor B), with some models including quadratic and interaction terms, indicating nonlinear system behavior. These equations enable direct prediction of responses based on actual process parameters and form the basis for creating visualization tools such as contour and surface plots.

3.5 Surface Plot

Surface plots provide a three-dimensional visualization of system behavior under the influence of two simultaneous input factors. These plots are generated from regression equations expressed in uncoded (real) units. Their main advantage lies in visually identifying areas where the response increases or decreases depending on the parameter combinations. When the model includes interaction terms (e.g., AB) or quadratic terms (e.g., AA, BB), these appear as curvature in the surface. The curvature reveals nonlinear behavior and helps interpret the combined influence of input factors. Surface plots are therefore a valuable tool for WAAM process control and optimization, enabling fine-tuning of settings to achieve the desired bead geometry. They allow quick assessment of response extrema and help locate regions of optimal settings. Surface curvature confirms the presence of interaction or nonlinear effects [Myers 2016].

The 3D models illustrate how the output responses depend on factors A and B. For bead width (Fig. 10), factor A shows a dominant effect, while the surface curvature results from both the interaction term (AB) and the quadratic term (A^2) present in the regression model, manifesting as a parabolic shape. Bead height (Fig. 11) decreases with increasing values of both factors, and the curvature confirms the interaction behavior. The deposition angle (Fig. 12) increases significantly with factor A, while the curvature observed in the surface is primarily caused by the interaction between factors A and B, rather than the direct effect of factor B alone.

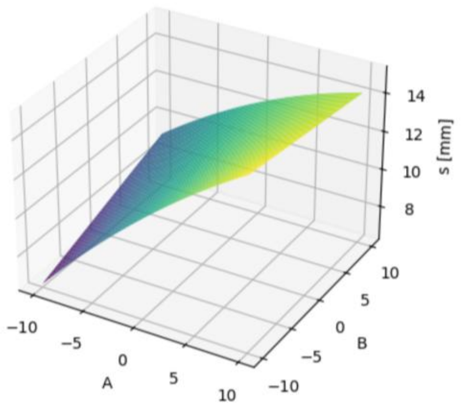

Fig. 10: Surface plot – bead width as a function of factors A and B

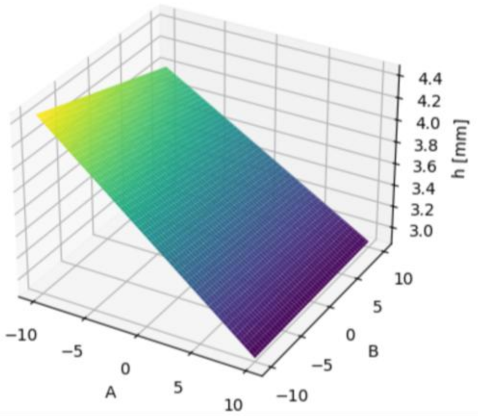

Fig. 11: Surface plot – bead height as a function of factors A and B.

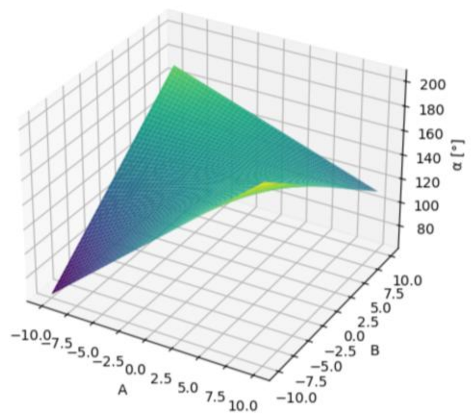

Fig. 12: Surface plot – bead angle as a function of factors A and B.

$$s=11.829 + 0.3461 \cdot A + 0.0419 \cdot B - 0.00621 \cdot A^2 - 0.00936 \cdot A \cdot B \quad (1)$$

$$h=3.5597 - 0.06739 \cdot A - 0.01059 \cdot B + 0.001160 \cdot A \cdot B \quad (2)$$

$$\alpha=138.140 + 2.0891 \cdot A + 0.33587 \cdot B - 0.5052 \cdot A \cdot B \quad (3)$$

s – bead width [mm]

h – bead height [mm]

α – deposition bead angle [°]

A – arc length [-]

B – arc dynamics [-]

3.6 Contour Plots

Contour plots are effective visual tools that provide an intuitive representation of how two independent variables jointly influence a single dependent response. These plots are a two-dimensional projection of a three-dimensional response surface, where isolines (contours) connect points of equal response values.

This method is particularly helpful in identifying regions of optimal parameter combinations as well as detecting transition zones or unstable behavior. When contour lines are straight and evenly spaced, it typically suggests independent (linear) effects of the input factors.

In contrast, curved or distorted contours usually indicate an interaction between the factors or a quadratic influence of one factor, reflecting the nonlinear nature of the system. In addition, contour plots reveal nonlinear system behavior and interaction effects between input factors.

When used in combination with Pareto charts, they become a powerful instrument for interpreting experimental results, supporting process optimization, and contributing to reliable decision-making in engineering practice [Myers 2016, Antony 2014].

Response – bead width [mm]

The contour plot for bead width shows that factor A – arc length correction has the most dominant influence (Fig. 13).

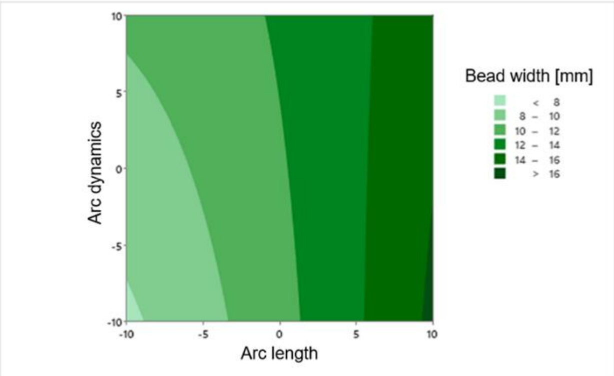

Fig. 13: Contour plot of bead width as a function of factors A and B.

Increasing A significantly increases the bead width. Factor B – arc dynamics correction also contributes, though to a lesser extent. To maximize bead width, A must be maximized and B minimized.

The minimum bead width occurs when both A and B are at their lowest settings. The curvature of the contour lines suggests the presence of interaction effects (AB) and a quadratic influence of A (AA) (Fig. 13).

Response – bead height [mm]

The contour plot for bead height shows that increasing factor A leads to a decrease in height. Similarly, increasing factor B also causes a reduction in height.

The maximum bead height is achieved when both A and B are at their minimum values, while the minimum height occurs when A is at its maximum. Factor B alone has a weaker effect but introduces curvature, indicating an interaction or nonlinear contribution (Fig. 14).

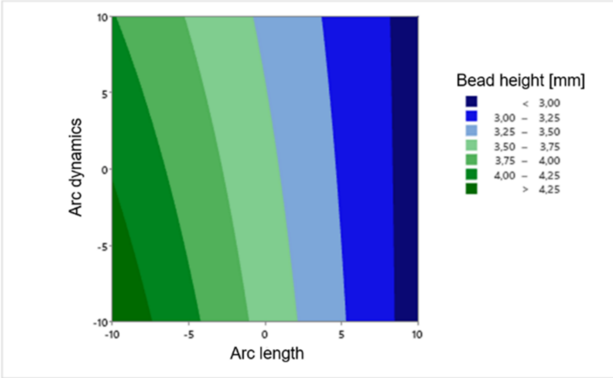

Fig. 14: Contour plot of bead height as a function of factors A and B.

Response – deposition bead angle [°]

The deposition angle increases with rising values of factor A, confirming its dominant role. Factor B also has a direct linear effect, although it is smaller compared to factor A. Curvature in the response surface suggests the presence of interaction between the factors. The maximum angle is achieved at high values of factor A, regardless of the setting of factor B, while the minimum angle occurs when both A and B are at their lowest levels (Fig. 15).

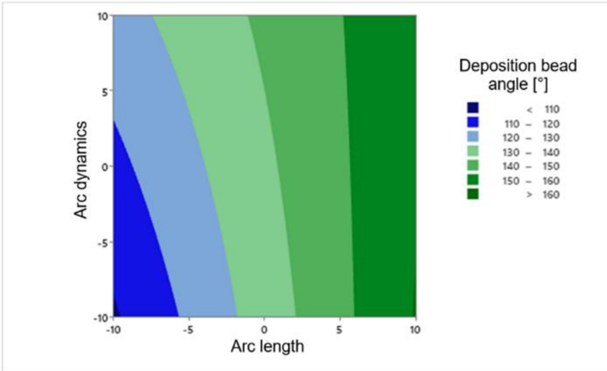

Fig. 15: Contour plot of deposition bead angle as a function of factors A and B.

Contour plots provide a clear and intuitive visualization of how input parameters influence the geometric characteristics of the deposited weld bead. The analysis demonstrated that arc length correction (factor A) is the dominant influence across all three observed responses: bead width, height, and deposition bead angle. It shows a strong and direct linear effect. Arc dynamics correction (factor B) also has a statistically significant effect, although it is considerably smaller compared to factor A. In addition to its direct linear contribution, factor B influences the system through interaction with factor A, as indicated by the curvature of the contour lines, reflecting nonlinear behavior.

Changes in the input factors directly influence the resulting bead geometry. Interactions between factors and quadratic terms manifest as curvature in the contour lines, indicating nonlinear behavior of the investigated process, particularly near the boundary values of the factor ranges. Both types of terms, interaction and quadratic, contribute to the curvature of the response surface and must be considered in accurate modeling and process optimization. Recognizing these effects is essential for reliable process control.

4 CONCLUSION

This work focused on the application of the Design of Experiments (DOE) methodology to analyze the influence of two process parameters – arc length correction (factor A) and arc dynamics correction (factor B) on the geometric characteristics of weld beads produced by the WAAM method. The main objective was to quantitatively assess main effects, interactions, and nonlinear system behavior, and subsequently to create predictive models suitable for process control and optimization.

Based on the conducted analysis, the following key conclusions can be drawn:

1. **DOE enabled quantitative analysis of effects of factors and interactions**

The Face Centered Design (FCD) provided a statistically sound foundation for evaluating the influence of individual factors as well as their interactions. All responses (bead width, height, and angle) showed strong dependence on arc length correction, while interaction and quadratic terms revealed nonlinear system behavior.

2. **Accurate and practical regression models were developed**

The resulting regression equations in uncoded units achieved R^2 values above 90%, confirming their high reliability. These models allow for direct prediction of the responses and can be used for process optimization and adaptive control.

3. **Graphical tools confirmed model consistency**

Pareto charts, contour plots, and surface plots visualized the dominance of factor A and identified regions of optimal settings. The curvature observed in the plots confirmed the presence of interaction and quadratic effects, which is essential for reliable process control.

4. **Significant reduction in the number of required experiments**

Thanks to the DOE methodology, the number of experimental points was minimized without losing informational value, saving time, material, and resources.

5. **The study established a foundation for further research and WAAM optimization**

The findings provide a valuable basis for future experiments, model extension to include more factors, or validation through simulation methods, contributing to improved quality and repeatability of the WAAM technology.

5 ACKNOWLEDGMENTS

This work was supported by the Slovak Research and Development Agency (contract No. APVV-20-0259) and by the Slovak Cultural and Educational Grant Agency (project No. 009STU-4/2023).

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