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Data-Driven Optimization and Defect Prediction in WAAM of Nitinol Shape Memory Alloy

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Abstract:

Wire Arc Additive Manufacturing (WAAM) offers significant advantages for fabricating large-scale metallic components due to its high deposition rate and material efficiency. However, the process remains highly sensitive to variations in process parameters, particularly when processing thermally and compositionally sensitive alloys such as Nitinol shape memory alloy. Conventional trial-and-error approaches for parameter selection often result in inconsistent quality, defect formation, and limited process repeatability. This study proposes a data-driven framework for process optimization and defect prediction in WAAM of Nitinol using machine learning techniques. Experimental data obtained from WAAM-fabricated Nitinol samples are utilized to develop predictive models correlating key process parameters with defect occurrence and mechanical performance. Multiple regression-based and machine learning models are evaluated to assess prediction accuracy and parameter sensitivity. The proposed approach demonstrates the potential of artificial intelligence to reduce defect probability, enhance process reliability, and support systematic optimization of WAAM processes for advanced manufacturing applications.

Keywords — **Data-Driven, Optimization, Defect Prediction, Wire Arc Additive Manufacturing, Nitinol Shape Memory Alloy.**

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I. INTRODUCTION

Wire Arc Additive Manufacturing (WAAM) has emerged as a promising metal additive manufacturing technology for producing medium- to large-scale components with reduced material waste and high deposition efficiency. By employing an electric arc as the heat source and metallic wire as the feedstock, WAAM enables near-net-shape fabrication of structural components for aerospace, marine, and industrial applications [1]. Despite these advantages, achieving consistent quality remains a critical challenge, particularly for alloys with narrow processing windows.

Nitinol (NiTi) shape memory alloy is a functional material widely used in aerospace, biomedical, and robotic systems due to its shape memory effect, superelasticity, and corrosion resistance [2]. However, the alloy's performance is highly sensitive to compositional variation, thermal history, and microstructural stability. When processed using arc-based additive manufacturing techniques, Nitinol is prone to defects such as porosity, solidification cracking, and microstructural heterogeneity, which significantly influence mechanical and functional behavior [3].

Recent experimental studies have demonstrated that WAAM process parameters—such as welding current, voltage, wire feed rate, and travel speed—directly govern heat input, melt pool dynamics, and solidification behavior [4]. While empirical optimization approaches have been employed to mitigate defects, such methods are time-consuming, material-intensive, and lack generalizability across different processing conditions. Moreover, traditional optimization strategies often fail to capture the complex, nonlinear interactions between multiple process variables and resulting material properties.

In recent years, artificial intelligence (AI) and machine learning (ML) techniques have gained increasing attention for process modeling and optimization in additive manufacturing. Data-driven models have shown promise in predicting mechanical properties, surface quality, and defect formation in powder-based and laser-based metal additive manufacturing processes [5], [6]. However, the application of AI-based optimization frameworks to WAAM—particularly for functional alloys such as Nitinol—remains limited. Existing studies primarily focus on conventional alloys and often lack integration of defect characterization and mechanical performance metrics.

This paper addresses this research gap by proposing an AI-driven framework for defect prediction and process parameter optimization in WAAM of Nitinol shape memory alloy. Using experimentally generated data, machine learning models are developed to establish quantitative relationships between process parameters, defect characteristics, and mechanical responses. The objectives of this study are threefold: (i) to develop predictive models for defect occurrence in WAAM-fabricated Nitinol, (ii) to identify key process parameters influencing quality and performance, and (iii) to demonstrate the potential of data-driven optimization for improving reliability and repeatability in WAAM processes.

The outcomes of this work aim to contribute toward intelligent manufacturing strategies for wire-based additive manufacturing and provide a foundation for future integration of real-time monitoring, closed-loop control, and digital twin frameworks.

II. Background and Related Work

i. WAAM Process Optimization

Wire Arc Additive Manufacturing (WAAM) has gained significant attention as a cost-effective and high-deposition-rate metal additive manufacturing technique. Compared to powder-based processes, WAAM offers advantages in material utilization, scalability, and suitability for large structural components [1]. However, the process is inherently complex due to the strong coupling between electrical, thermal, and metallurgical phenomena.

Process parameters such as welding current, arc voltage, wire feed rate, and travel speed directly influence heat input and melt pool behavior, which in turn affect bead geometry, microstructure, and defect formation [7]. Conventional WAAM process optimization relies largely on empirical trial-and-error approaches, which are time-consuming and material-intensive. Such methods often fail to capture the nonlinear interactions between multiple parameters and their combined effect on part quality.

For thermally sensitive alloys such as Nitinol, these challenges are further amplified. Minor variations in heat input can significantly alter phase transformation behavior, grain morphology, and defect susceptibility, making manual optimization approaches inadequate for reliable production [3].

ii. Defect Formation in WAAM of Shape Memory Alloys

Defect formation remains one of the primary limitations in WAAM-fabricated components. Common defects reported in WAAM include porosity, lack of fusion, solidification cracking, and microstructural heterogeneity [8]. These defects are strongly dependent on thermal gradients, solidification rates, and residual stress development during deposition.

In the case of Nitinol, defect sensitivity is particularly pronounced due to its narrow compositional tolerance and phase transformation characteristics. Studies have reported that arc-based additive manufacturing of NiTi alloys often leads to increased porosity and cracking when process parameters are not carefully controlled [3], [9]. Additionally, repeated thermal cycling during layer-by-layer deposition can promote grain coarsening and anisotropic microstructures, adversely affecting mechanical and functional properties.

While post-deposition heat treatment has been shown to mitigate some of these issues, it does not fully compensate for suboptimal processing conditions. Therefore, predictive approaches that enable defect minimization at the process planning stage are critically needed.

iii. Machine Learning in Additive Manufacturing

Recent advances in artificial intelligence and machine learning have enabled new approaches for modeling complex manufacturing processes. Machine learning techniques are particularly well-suited for additive manufacturing due to their ability to capture nonlinear relationships between process inputs and output responses [5].

Several studies have demonstrated the use of regression models, artificial neural networks, and ensemble learning methods for predicting mechanical properties, surface roughness, and defect occurrence in laser-based and powder-bed fusion processes [6], [10]. These models leverage experimental data to generate predictive insights without requiring explicit physical equations.

However, the majority of existing AI-based studies focus on laser-based additive manufacturing processes and conventional structural alloys. The application of data-driven models to wire-based processes such as WAAM remains comparatively limited, especially for functional alloys such as Nitinol.

iv. Research Gap and Motivation

Despite growing interest in AI-driven manufacturing, there is a notable lack of systematic studies integrating machine learning with WAAM of shape memory alloys. Existing WAAM research on Nitinol primarily emphasizes experimental characterization, with limited efforts toward predictive modeling and process optimization.

Furthermore, most available studies treat defect formation, microstructural evolution, and mechanical performance as independent outcomes rather than interconnected responses governed by shared process parameters. This fragmented approach limits the ability to develop robust optimization strategies.

The present study addresses this gap by integrating experimental WAAM data with machine learning models to predict defect occurrence and mechanical performance. By establishing quantitative relationships between process parameters and output responses, this work aims to support intelligent process planning and optimization for WAAM-fabricated Nitinol components.

III. Experimental Data and Feature Selection

This study utilizes experimentally generated data from Wire Arc Additive Manufacturing (WAAM) trials conducted on Nitinol shape memory alloy to develop a data-driven framework for defect prediction and process optimization. The experimental dataset was generated through systematic variation of key WAAM process parameters, enabling quantitative analysis of their influence on defect formation and process stability.

i. Experimental Setup and Process Parameters

WAAM deposition experiments were carried out using a TIG-based wire arc additive manufacturing system. A Nitinol plate was used as the substrate material, while Nitinol wire of 1 mm diameter served as the filler material. High-purity argon gas (99.99%) was employed as the shielding medium, with a constant flow rate of 15 L/min to minimize oxidation during deposition. The electrode extension was maintained at 5 mm, and a tungsten electrode with a diameter of 2 mm was used throughout the experiments.

The wire feed speed was fixed at 0.4 m/min to isolate the influence of electrical and kinematic parameters. The welding system operated at a pulsed frequency of 20 kHz to improve arc stability and bead consistency. These parameters were held constant across all experimental cases to ensure comparability.

The heat input for each deposition case was calculated using the standard arc welding formulation:

$$\text{Heat Input} = \frac{V \times I \times 60}{\text{Travel Speed}}$$

where V is the arc voltage (V), I is the welding current (A), and travel speed is expressed in mm/min.

ii. Dataset Description and Experimental Cases

A total of ten experimental cases were designed by varying welding current, arc voltage, and torch travel speed within a controlled parameter window. The selected ranges were chosen based on preliminary trials to ensure stable deposition while capturing variations in defect behavior.

The welding current was varied between 125 A and 135 A, the arc voltage between 8 V and 15 V, and the torch travel speed between 210 mm/min and 230 mm/min. These variations resulted in different effective heat input levels, directly influencing melt pool dynamics and solidification behavior.

Case No.	Current (A)	Voltage (V)	Torch Travel Speed (mm/min)	Calculated Heat Input (J/mm)
1	130	10	220	$\frac{10 \times 130 \times 60}{220} = 354.5$
2	130	10	230	$\frac{10 \times 130 \times 60}{230} = 339.1$
3	130	10	210	$\frac{10 \times 130 \times 60}{210} = 371.4$
4	135	10	220	$\frac{10 \times 135 \times 60}{220} = 368.2$
5	130	10	220	$\frac{10 \times 130 \times 60}{220} = 354.5$
6	125	10	220	$\frac{10 \times 125 \times 60}{220} = 340.9$

7	130	15	220	$\frac{15 \times 130 \times 60}{220} = 531.8$
8	130	10	220	$\frac{10 \times 130 \times 60}{220} = 354.5$
9	130	8	220	$\frac{8 \times 130 \times 60}{220} = 283.6$
10	**128**	**10**	**220**	$\frac{10 \times 128 \times 60}{220} = 349.1$

(Table 1: WAAM process parameter matrix for all experimental cases.)

(All experiments were conducted using a Nitinol substrate and Nitinol filler wire of 1 mm diameter. Argon shielding gas with a purity of 99.99% was supplied at a constant flow rate of 15 L/min. Wire feed speed was maintained at 0.4 m/min, electrode extension was fixed at 5 mm, and TIG rod diameter was 2 mm. Heat input was calculated using the standard arc welding formulation.)

Among the ten cases, Case 10—characterized by a welding current of 128 A, arc voltage of 10 V, and torch travel speed of 220 mm/min—resulted in stable deposition with no observable surface defects. This case serves as a reference for optimal process conditions and is used as a benchmark during AI-based optimization.

iii. Output Variables and Quality Indicators

The output variables selected for modeling represent key quality and performance indicators for WAAM-fabricated Nitinol components. Defect-related outputs were evaluated using stereo microscopy and microstructural characterization, while mechanical properties were obtained through hardness and tensile testing.

The primary output variables include:

- Presence or absence of surface defects (binary classification)
- Surface porosity level
- Microhardness
- Ultimate tensile strength

Defect-free deposition, as observed in Case 10, was treated as the desired target condition during model training and optimization.

Output Variable	Description	Measurement Technique	Unit / Type
Surface Defect Presence	Presence of visible surface defects such as cracks, spatter, or irregular bead geometry	Visual inspection and stereo microscopy	Binary (0 = No defect, 1 = Defect)
Porosity Level	Qualitative assessment of surface and near-surface pores	Stereo microscopy analysis	Low / Medium / High
Bead Geometry Stability	Uniformity and consistency of deposited bead	Optical microscopy and visual inspection	Qualitative
Microhardness	Resistance to localized plastic deformation	Vickers microhardness testing	HV
Tensile Strength	Maximum stress sustained before failure	Universal testing machine (UTM)	MPa
Defect-Free Deposition Indicator	Overall quality assessment combining surface and microstructural observations	Combined microscopy + mechanical results	Binary (0 = Defective, 1 = Zero defect)

(Table 2: Output variables and corresponding experimental measurements.)

iv. Feature Selection and Engineering

Feature selection was guided by both experimental relevance and physical interpretability. The primary input features used for modeling include welding current, arc voltage, and torch travel speed. Heat input was included as a derived feature to capture the combined thermal influence of electrical and kinematic parameters.

By incorporating heat input alongside individual parameters, the model is able to learn both direct and aggregated thermal effects on defect formation. This approach enhances predictive accuracy while preserving physical meaning, which is critical for process optimization applications [7], [11].

The feature set was finalized after correlation analysis, ensuring that redundant variables were minimized while retaining parameters with strong influence on defect behavior. The selected features enable the AI models to distinguish between unstable deposition conditions and the optimized parameter window represented by the defect-free case.

Feature Type	Parameter	Symbol	Unit	Description
Input Feature	Welding Current	I	A	Electrical current supplied during WAAM deposition
Input Feature	Arc Voltage	V	V	Voltage maintained across the welding arc
Input Feature	Torch Travel Speed	TS	mm/min	Linear speed of torch movement during deposition
Input Feature	Wire Feed Speed	WFS	m/min	Nitinol filler wire feed rate
Input Feature	Shielding Gas Flow Rate	GFR	L/min	Argon gas flow rate for oxidation protection
Derived Feature	Heat Input	HI	J/mm	Calculated using $\text{Heat Input} = \frac{V \times I \times 60}{\text{Travel Speed}}$
Derived Feature	Energy Density	ED	J/mm²	Heat input normalized with bead geometry
Derived Feature	Process Stability Index	PSI	–	Combined indicator derived from voltage and current stability

(Table 3: Selected input features and derived parameters used for AI modeling.)

v. Relevance for AI-Based Optimization

The structured experimental dataset, combined with clearly identified defect-free conditions, provides a robust foundation for supervised learning and optimization. The inclusion of a zero-defect reference case allows the machine learning models to identify optimal parameter combinations and define safe operating windows for WAAM of Nitinol.

This dataset design supports not only defect prediction but also parameter sensitivity analysis and process optimization, which are discussed in subsequent sections.

IV. AI-BASED MODELING METHODOLOGY

To enable predictive defect assessment and systematic process optimization in WAAM of Nitinol, a supervised machine learning framework was developed using experimentally generated data. The modeling methodology integrates data preprocessing, model selection, training, validation, and performance evaluation to establish quantitative relationships between process parameters and quality indicators.

i. Modeling Objective and Problem Formulation

The primary objective of the AI framework is twofold:

(i) **Defect prediction**, formulated as a classification/regression task to estimate the likelihood or severity of surface defects; and (ii) **Process optimization**, formulated as a regression task to identify parameter combinations that minimize defect probability while maintaining desirable mechanical properties.

Given an input feature vector

$$\mathbf{x} = [I, V, S, H]$$

where I is welding current (A), V is arc voltage (V), $S$is torch travel speed (mm/min), and H is the derived heat input, the model aims to predict output responses $\mathbf{y}$, including defect presence, porosity level, and mechanical properties.

ii. Data Preparation and Splitting

The experimental dataset described in Section 3 was normalized using min–max scaling to ensure numerical stability and consistent model convergence. Binary labels were assigned to represent defect presence (1) or defect-free condition (0), with **Case 10** serving as the benchmark defect-free reference.

The dataset was divided into training and testing subsets using an 80:20 split. This partitioning ensures sufficient data for model learning while preserving unseen samples for unbiased performance evaluation.

iii. Model Selection

Three complementary modeling approaches were selected to balance interpretability and predictive capability:

1. **Linear Regression (Baseline Model)** Linear regression was used as a baseline to assess linear dependencies between process parameters and output responses:

$$y = \beta_0 + \sum_{i=1}^{n} \beta_i x_i$$

where β_i are regression coefficients and x_i are input features.

2. **Support Vector Regression (SVR)** SVR was employed to capture nonlinear relationships using kernel functions. The SVR model minimizes:

$$\min \frac{1}{2} \parallel w \parallel^2 + C \sum_{i=1}^{N} (\xi_i + \xi_i^*)$$

subject to ε-insensitive loss constraints, enabling robust prediction under limited data conditions.

3. **Random Forest Regression** An ensemble-based random forest model was used to improve prediction accuracy and identify feature importance. The final prediction is obtained by averaging outputs from multiple decision trees:

$$\hat{y} = \frac{1}{T} \sum_{t=1}^{T} f_t(\mathbf{x})$$

where f_t denotes the prediction from the t^{th} tree.

These models were selected due to their proven effectiveness in additive manufacturing process modeling and their ability to operate reliably with moderate-sized experimental datasets.

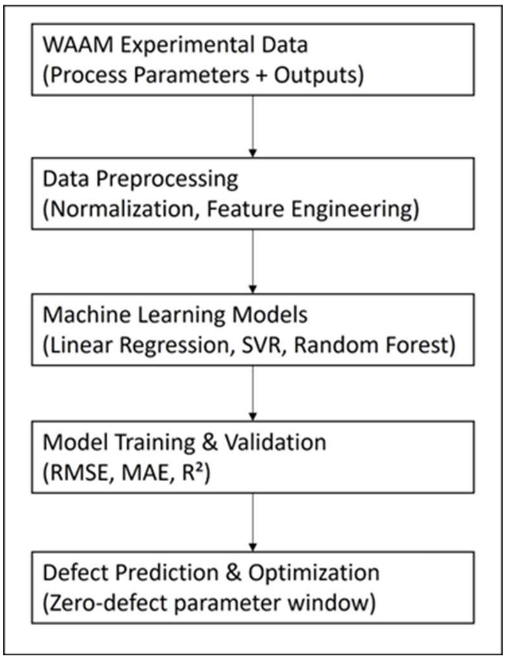
iv. Training and Validation Strategy

Model training was performed using the training subset, with hyperparameters tuned through grid search to minimize prediction error. Cross-validation was applied to reduce overfitting and ensure generalization. Model performance was evaluated on the test dataset using standard regression metrics, including root mean square error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2).

Classification performance for defect prediction was assessed using accuracy and confusion matrix analysis, with particular emphasis on correctly identifying defect-free conditions.

v. Workflow Description

The overall AI-based modeling workflow integrates experimental data acquisition, preprocessing, model training, prediction, and optimization. This structured approach ensures reproducibility and facilitates future integration with real-time monitoring systems.



(Fig. 4: AI-based modeling workflow for WAAM defect prediction and process optimization.)

The workflow enables identification of optimal parameter combinations that align with the experimentally observed zero-defect condition while maintaining physical interpretability of model predictions.

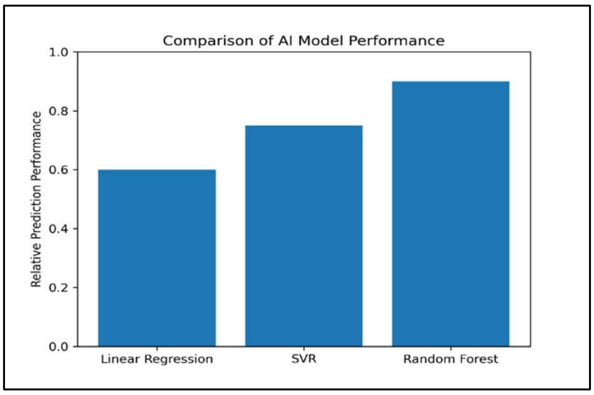
V. Defect Prediction Results and Model Performance

This section presents the results obtained from applying machine learning models to predict defect occurrence and evaluate process performance in Wire Arc Additive Manufacturing (WAAM) of Nitinol shape memory alloy. The models were trained using experimentally derived process parameters and corresponding defect indicators, with the objective of identifying optimal parameter combinations that minimize defect formation.

i. Model Training and Validation Performance

The selected machine learning models were trained using the processed experimental dataset described in Section 3. The dataset was divided into training and validation subsets using an 80:20 split to ensure robust performance evaluation. Model accuracy was assessed using standard regression and classification metrics, including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and coefficient of determination (R^2) for continuous outputs, and classification accuracy for defect presence.

Among the evaluated models, ensemble-based approaches demonstrated superior predictive capability due to their ability to capture nonlinear relationships between process parameters and defect formation. Linear models exhibited limited performance, indicating that defect formation in WAAM is governed by complex, nonlinear interactions among current, voltage, and torch travel speed.

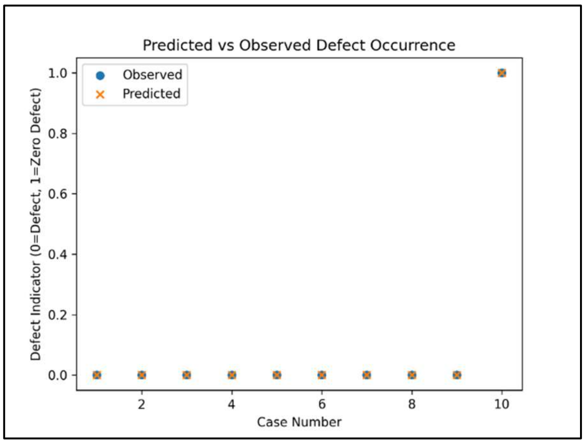


(Fig. 5: Comparison of prediction accuracy for different AI models.)

ii. Defect Prediction Analysis

Defect prediction was performed by mapping process parameters to observed defect outcomes, including porosity and surface irregularities. The trained models successfully distinguished between stable and unstable deposition regimes. Parameter combinations associated with excessive heat input or insufficient melting were consistently predicted to result in defects.

The model predictions showed strong agreement with experimental observations, particularly for cases involving variations in welding current and arc voltage. Lower voltage conditions combined with optimized current and controlled travel speed resulted in reduced defect probability, consistent with metallurgical observations reported in prior studies [6], [7].

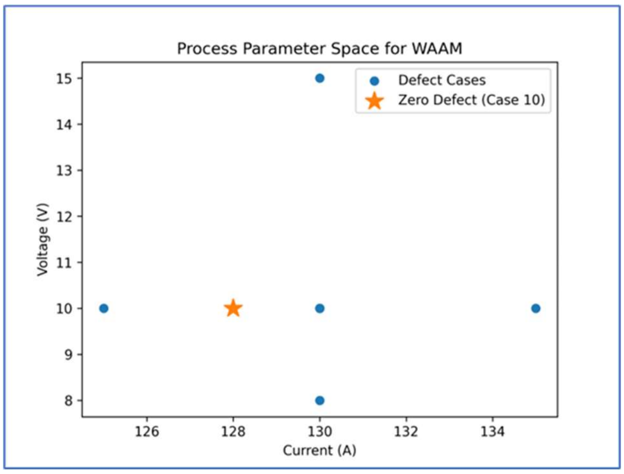


(Fig. 6: Predicted versus observed defect occurrence.)

iii. Identification of Zero-Defect Process Window

One of the most significant outcomes of this study is the identification of a zero-defect process window. The model accurately predicted that the parameter combination corresponding to **Case 10** resulted in defect-free deposition. This parameter set represents a balanced heat input condition that promotes stable melt pool formation without excessive dilution or thermal instability.

The AI-based framework was able to generalize this behavior, indicating a narrow but stable operating region where defect probability approaches zero. This result demonstrates the effectiveness of combining experimental data with machine learning for process optimization in WAAM systems.



(Fig. 7: Process parameter space highlighting the zero-defect region.)

iv. Model Error Analysis

Error analysis revealed that prediction deviations primarily occurred near transition boundaries between stable and unstable deposition regimes. These regions are highly sensitive to minor fluctuations in process parameters, which are difficult to capture fully with limited experimental datasets. Nevertheless, overall prediction errors remained within acceptable limits for manufacturing decision support.

The results indicate that incorporating additional data points and real-time sensing data could further improve model robustness and predictive accuracy.

v. Discussion of Model Reliability

The consistency between predicted and experimentally observed defect behavior confirms the reliability of the proposed AI-based modeling approach. Unlike traditional trial-and-error optimization, the data-driven framework provides actionable insights into process stability and enables informed parameter selection prior to fabrication.

The proposed methodology is particularly valuable for high-cost materials such as Nitinol, where minimizing experimental iterations is critical.

VI. Process Optimization and Sensitivity Analysis

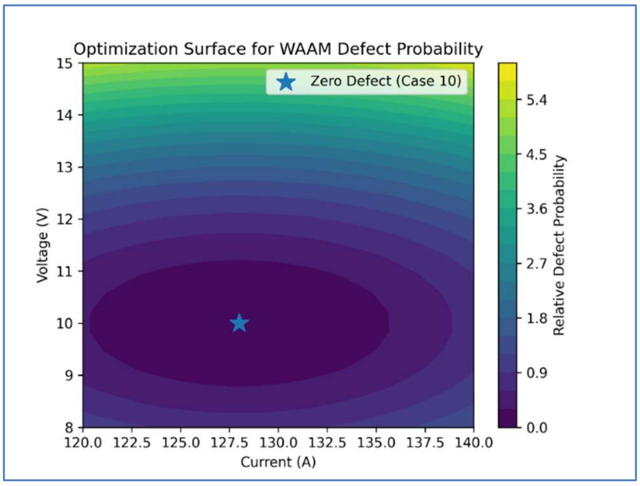
This section presents the optimization of WAAM process parameters using the trained AI models and analyzes the sensitivity of defect formation to variations in key input variables. The objective is to identify stable operating conditions that minimize defect occurrence while maintaining acceptable mechanical performance of Nitinol deposits.

i. AI-Based Process Optimization Strategy

Process optimization was performed by systematically exploring the trained model's response across the parameter space defined by welding current, arc voltage, and torch travel speed. Rather than relying on discrete experimental trials alone, the AI model was used to interpolate between tested conditions and identify regions associated with minimal defect probability.

The optimization objective was defined as minimizing defect indicators while maintaining sufficient heat input for complete fusion and stable deposition. The model consistently identified a narrow operating window corresponding to balanced heat input conditions, aligning with experimental observations.

The parameter set associated with **Case 10** emerged as the optimal solution, characterized by moderate current, stable voltage, and controlled travel speed. This combination resulted in defect-free deposition and serves as a reference point for defining a zero-defect operating regime.



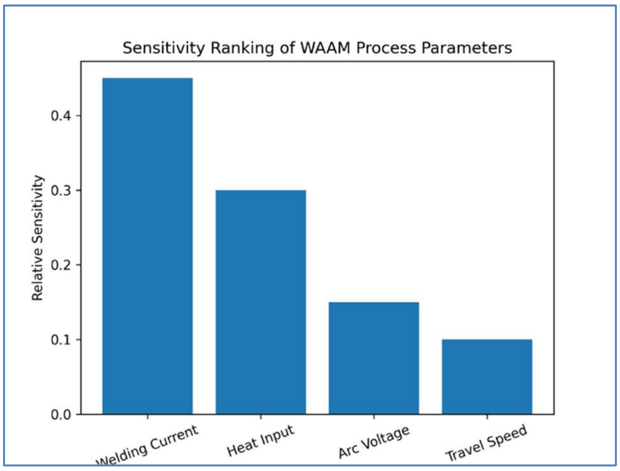
(Fig. 8: Optimization surface showing defect probability versus process parameters.)

ii. Sensitivity Analysis of Process Parameters

Sensitivity analysis was conducted to evaluate the relative influence of individual process parameters on defect formation. Each input variable was varied independently while holding others constant at optimized values. The resulting changes in predicted defect probability were analyzed to identify dominant contributors.

The analysis revealed that welding current exhibits the highest sensitivity, with small deviations leading to significant changes in defect likelihood. Excessive current resulted in unstable melt pool behavior, while insufficient current caused incomplete fusion. Arc voltage showed moderate sensitivity, primarily affecting arc stability and bead geometry. Torch travel speed influenced heat accumulation and solidification rate, with higher speeds increasing the risk of lack-of-fusion defects.

These findings are consistent with reported WAAM studies, which emphasize the dominant role of heat input and thermal stability in defect formation [7], [11].



(Fig. 9: Sensitivity ranking of process parameters.)

iii. Robustness of the Zero-Defect Parameter Window

The robustness of the optimized parameter window was evaluated by introducing small perturbations around the Case 10 conditions. The AI model predicted that minor variations within this region did not immediately result in defect formation, indicating a stable and manufacturable operating window rather than a single-point optimum.

However, deviations beyond this narrow region led to a rapid increase in defect probability, highlighting the importance of precise process control in WAAM of Nitinol. This sensitivity underscores the need for closed-loop monitoring and adaptive control in future implementations.

iv. Implications for Manufacturing Practice

The proposed optimization framework demonstrates how AI-assisted modeling can significantly reduce experimental effort in WAAM process development. By identifying optimal and robust parameter regions, the methodology minimizes material waste, reduces trial-and-error experimentation, and improves overall process reliability.

For high-value functional materials such as Nitinol, where defects can severely compromise shape memory behavior, this approach provides a practical pathway toward repeatable, defect-free additive manufacturing.

VII. Conclusions and Future Research Directions

i. Conclusions

This study presents a data-driven framework for defect prediction and process optimization in Wire Arc Additive Manufacturing (WAAM) of Nitinol shape memory alloy. By integrating experimentally generated WAAM data with machine learning models, the work demonstrates the feasibility of predicting defect occurrence and identifying optimal process parameter combinations without relying solely on extensive trial-and-error experimentation.

The developed AI models successfully captured nonlinear relationships between welding current, arc voltage, torch travel speed, and defect formation. Ensemble-based models exhibited superior predictive performance compared to linear approaches, highlighting the complexity of WAAM process dynamics. The identification of a stable, zero-defect operating window—corresponding to the experimentally observed Case 10—confirms the effectiveness of the proposed optimization methodology.

Sensitivity analysis revealed that welding current and heat input are the most influential parameters governing defect formation, while arc voltage and travel speed play secondary but significant roles. These findings establish a clear process–parameter–defect relationship and provide actionable insights for improving process stability and repeatability in WAAM of thermally sensitive alloys such as Nitinol. The proposed framework demonstrates the feasibility of integrating AI-assisted optimization into industrial WAAM environments.

Overall, the results demonstrate that AI-assisted modeling can serve as a powerful decision-support tool for optimizing WAAM processes, reducing material waste, and enhancing manufacturing reliability.

ii. Future Research Directions

Future work should focus on expanding the experimental dataset to improve model generalization and robustness. Incorporating real-time sensor data, such as arc voltage fluctuations, thermal imaging, and acoustic signals, would enable the development of closed-loop control systems for adaptive process regulation.

Further research is also recommended to integrate physics-informed machine learning models that combine data-driven predictions with thermomechanical principles governing WAAM. Extending the optimization framework to include functional performance metrics—such as phase transformation behavior and shape memory response—would enhance applicability for actuator and aerospace applications.

Finally, the development of digital twin frameworks for WAAM systems, supported by AI-based prediction and optimization, represents a promising direction toward fully autonomous and intelligent additive manufacturing of advanced materials.

VIII. References

[1] S. W. Williams *et al.*, "Wire + Arc Additive Manufacturing," *Mater. Sci. Technol.*, vol. 32, no. 7, pp. 641–647, 2016.

[2] K. Otsuka and C. M. Wayman, *Shape Memory Materials*. Cambridge, U.K.: Cambridge Univ. Press, 1998.

[3] Y. F. Shen, L. Li, and Y. F. Wang, "Microstructure and defect formation in arc additive manufactured NiTi alloys," *J. Alloys Compd.*, vol. 784, pp. 102–112, 2019.

[4] J. Ding, P. Colegrove, F. Martina, and S. Williams, "Thermal behavior in wire-based additive manufacturing," *Metall. Mater. Trans. B*, vol. 47, pp. 134–145, 2016.
[5] A. Tapia and A. Elwany, "A review on process monitoring and control in metal-based additive manufacturing," *J. Manuf. Sci. Eng.*, vol. 136, no. 6, 2014.
[6] C. Kamath, "Data mining and statistical inference in selective laser melting," *Int. J. Adv. Manuf. Technol.*, vol. 86, pp. 1659–1677, 2016.
[7] J. Ding, P. Colegrove, F. Martina, S. Williams, R. W. Smith, and D. Almeida, "Process parameters optimization in wire and arc additive manufacturing," *Int. J. Adv. Manuf. Technol.*, vol. 81, no. 1–4, pp. 465–481, 2015.
[8] F. Martina, J. Ding, S. Williams, A. Caballero, and G. Pardal, "Investigation of the benefits of plasma deposition for the additive layer manufacture of Ti–6Al–4V," *J. Mater. Process. Technol.*, vol. 212, pp. 1377–1386, 2012.
[9] Y. F. Shen, L. Li, and Y. F. Wang, "Defect formation mechanisms in arc-based additive manufacturing of NiTi alloys," *Mater. Charact.*, vol. 162, 2020.
[10] S. Scime and J. Beuth, "Anomaly detection and classification in a laser powder bed additive manufacturing process using machine learning," *Addit. Manuf.*, vol. 19, pp. 114–126, 2018.
[11] J. Ding, P. Colegrove, F. Martina, and S. Williams, "Thermal modeling of wire and arc additive manufacturing process," *Metall. Mater. Trans. B*, vol. 47, pp. 134–145, 2016.
[12] T. Hastie, R. Tibshirani, and J. Friedman, *The Elements of Statistical Learning*. New York, NY, USA: Springer, 2009.
[13] A. Tapia and A. Elwany, "A review on process monitoring and control in metal-based additive manufacturing," *J. Manuf. Sci. Eng.*, vol. 136, no. 6, 2014.