A Data-Driven Approach for Thermal Modelling of Wire Arc Additive Manufacturing: Combining the Finite Element Method and Machine Learning

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ABSTRACT

During the fabrication of large components using Wire Arc Additive Manufacturing (WAAM), the process involves a unique thermal cycle that results in significant heat accumulation in the deposited layers. This research proposes a data-driven technique that combines finite element analysis (FEA) and Machine learning for predicting the temperature history layer by layer in the WAAM process. Four machine learning algorithms were employed to train the dataset derived from the FEA results, thereby developing the surrogate models. The models predicted the thermal profile with minimal error, with an RMSE of 5.49 °C and an MSE of 4.17 °C, and achieved a higher computational speed than the FEA simulation.

KEYWORDS: *Wire arc additive manufacturing; Finite element analysis; Machine learning*

1. INTRODUCTION

The deposition of layer-by-layer metal in Wire Arc Additive Manufacturing (WAAM) undergoes thermal cycle and heat accumulation problems, which can potentially compromise its mechanical and microstructural properties [1]. Controlling layer-by-layer properties plays a critical role in improving the overall properties of WAAM-fabricated parts [2]. In this context, computational tools such as Finite Element Analysis (FEA), Computational Fluid Dynamics (CFD), and Data-Driven and AI-based tools can help in understanding more complex thermal phenomena before the fabrication process more efficiently.

2. MATERIALS AND METHODS

The work combines FEA and machine learning to understand the thermal cycle behaviour during the fabrication of a multi-layer deposited wall using the WAAM process. In the first step, the FEM software is used to simulate the WAAM process and obtain the thermal history of the different layers under varying process parameters with experimental validation. In the second step, machine learning algorithms were developed by training them on a dataset from FEA simulations to predict the temperature history during the WAAM process.

2.1. Simulation condition

The COMSOL Multiphysics was used to obtain the thermal history of a multi-layered walled structure. The substrate material is Aluminium 5083 alloy, and the filler material is Aluminium 5356 alloy. The material properties are kept constant to avoid complex simulation conditions. The substrate and bead dimensions are based on an experimental parameter used in welding trials conducted bead-on-plate, where input parameters such as current, wire feed rate, and travel speed were varied. The single deposited dimension of the bead was assumed to be a rectangular cross-section with dimensions 5.98 × 7.92 mm^2, and a length of 150 mm. The dimension of the substrate plate was 370 ×185 × 5 mm^3. Each layer takes 43 seconds to complete single-layer deposition, and the dwell time between layers is 40 seconds to maintain the thermal cycle. A double-ellipsoidal heat source model was used for carrying out the FEA. On the bead, heat distribution through convective heat flux through the body, in which the heat transfer coefficient in layers is used 35 W/m^2 K on all 10 layers, and the substrate convective

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D. Nikam et al. (eds.), *Proceedings of the Global Symposium on Adaptive Manufacturing (GSAM 2026)*, Advances in Engineering Research 308,
https://doi.org/10.2991/978-94-6239-813-9_17

heat flux is used 400 W/m². Four machine learning algorithms were employed to train the dataset derived from the FEA results, thereby developing the surrogate models.

3. RESULTS

The FEA model for the WAAM deposition process was simulated using the governing equation and boundary conditions discussed in the last section. The temperature history was obtained at defined points from the FEA results. Figure 1 shows the temperature history of the two target points, P1 and P2, recorded after the simulation.

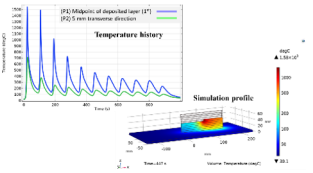


Figure 1: A sample of performed simulation and data of the temperature history

The four ML models i.e., Random Forest, XGBoost, KNN, and AutoML, were trained using the data obtained from FEM simulation work. The models were trained on 80% of the dataset, and the remaining 20% was used to test the models and verify their robustness in predicting the temperature history for the unseen dataset.

Table 1 Comparison of ML results for training and testing for different ML models

ML Model	Training			Testing		
	RMSE	MAE	R^2	RMSE	MAE	R^2
XGBoost	8.41	4.43	0.9935	5.49	4.17	0.9814
Random Forest	4.77	3.10	0.9979	5.77	4.55	0.9795
KNN	6.04	3.94	0.9967	5.63	4.52	0.9806
AutoML	15.51	8.08	0.9780	8.58	6.63	0.9550

4. DISCUSSION

A comparison of machine learning algorithms used to predict temperature, with training and testing results for different ML models, is shown in Table 1. Among the four ML models, Random Forest results show the best overall performance, attaining the lowest training RMSE of 4.77 and MAE of 3.10. The XGBoost and KNN have also yielded comparable results; however, the error rate is slightly higher than that of Random Forest. Overall, the results highlight that all ML Models achieved high R2 scores greater than 0.95, with Random Forest consistently achieving the best trade-off between accuracy and generalisation across datasets.

5. CONCLUSION

In this study, a data-driven approach combined with FEA and machine learning was developed and tested for predicting the thermal history of deposited layers in the WAAM process. The simulation dataset predicted the thermal history using a machine learning algorithm. The models predicted the thermal profile with minimal error, RMSE of 5.49 °C and MSE of 4.17 °C, with higher computational speed than the FEA simulation.

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