Prediction of Temperature on the Substrate During Wire Arc DED Through Physics Informed Neural Network

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ABSTRACT

Accurate prediction of the substrate temperature during Wire Arc Directed Energy Deposition (Wire Arc DED) is critical for managing thermal gradients, avoiding residual deformation, and maintaining the dimensional correctness and mechanical performance of manufactured metallic components. The research introduces a new physics-informed neural network (PINN) framework designed for predicting a time-dependent temperature distribution in the substrate using only the data obtained by numerical simulations. To start with, a three-dimensional heat model in transient mode was created using COMSOL Multiphysics to study heat transfer processes throughout deposition. The temperature data obtained from four selected areas on the substrate were used to train the PINN system based on the theory of heat transfer used in WA-DED. It was proven that the proposed model was able to produce accurate predictions when tested against finite element modelling data. additionally, the effect of the main process factors on the temperature in the substrate was analysed. In addition, comparative analysis revealed that the PINN model consistently outperformed a conventional data-driven Deep Neural Network (DNN), achieving lower values of Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and MAPE, thereby confirming its superior accuracy, robustness, and generalization capability. The proposed PINN framework offers a computationally efficient and physics-consistent approach for thermal field prediction, providing a promising tool for real-time thermal monitoring, process optimization, and intelligent control of WA-DED manufacturing.

KEYWORDS: Additive manufacturing; PINN; Wire arc DED; Substrate temperature.

1. INTRODUCTION

The dimensional accuracy, mechanical integrity, and long-term dependability of manufactured components are negatively impacted by the substantial residual stresses produced by Wire Arc-Direct Energy Deposition's rapid heat cycles and steep temperature gradients. In remanufacturing, the present component itself acts as the substrate, making its thermal condition crucial to process success. The substrate plays a crucial role by functioning as a heat sink to manage temperature gradients. Therefore, enhancing process accuracy, component quality, and the service life of remanufactured parts requires precise substrate thermal behaviour prediction and management [1]. The Finite Element Method (FEM) and Computational Fluid Dynamics (CFD) models have been widely used to forecast the thermal behaviour in metal additive manufacturing [2]. FEM offers an effective substitute for thermal and residual stress analysis, while CFD offers high-fidelity Multiphysics simulations at a significant computational cost [3]. Data-driven thermal prediction is now possible because to recent developments in machine learning, however traditional models frequently need a lot of labelled data and don't follow the underlying physical principles [4]. By including heat transfer equations into deep learning, Physics-Informed Neural Networks (PINNs) get beyond these restrictions and enable precise thermal field prediction with much less training data and computing effort [2]. This study proposes a Physics-Informed Neural Network (PINN) framework for rapid transient thermal prediction in WA-DED using computationally efficient numerical COMSOL simulation data. The model accurately predicts the substrate temperature distribution at four monitoring locations throughout the ten-layer deposition process and exhibits strong generalization under previously unseen deposition conditions. Its predictive capability was validated against finite element simulation results, demonstrating high accuracy and reliability for transient thermal analysis.

2. MATERIALS AND METHODS

A three-dimensional transient thermal model of the WA-DED process was developed in COMSOL Multiphysics to simulate heat transfer during ten-layer deposition. Temperature histories were

© The Author(s) 2026
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_7

extracted from four predefined locations on the substrate and used to construct the training dataset for the PINN. A spatiotemporal thermal dataset was generated from COMSOL simulations, comprising spatial position (x) in mm, time (t) in seconds, and corresponding temperature (T) in K values to capture the transient thermal behaviour. The variables were subsequently normalized (x_norm), (t_norm), and (T_norm)) and used as inputs/outputs for PINN modelling. The PINN was trained by incorporating the governing heat conduction equation and relevant boundary conditions into the learning framework. The predictive performance of the model was evaluated by comparing its results with finite element simulations using MSE, RMSE, MAE, and MAPE as accuracy metrics.

3. RESULTS AND DISCUSSION

Figure 1 shows the COMSOL simulations results, which were set up on COMSOL multi-physics 6.1.0. The boundary conditions are set up as per the literature [1]. The absolute error between predictions of the COMSOL and PINN model is less than 22°C, demonstrating that the PINN model exhibits excellent precision in predicting the temperature field for the first layer whereas it increases for the subsequent layers. The PINN model demonstrated higher prediction accuracy, resilience, and reliability in thermal field estimation by achieving lower values of MSE, RMSE, and MAPE than the traditional DNN model.

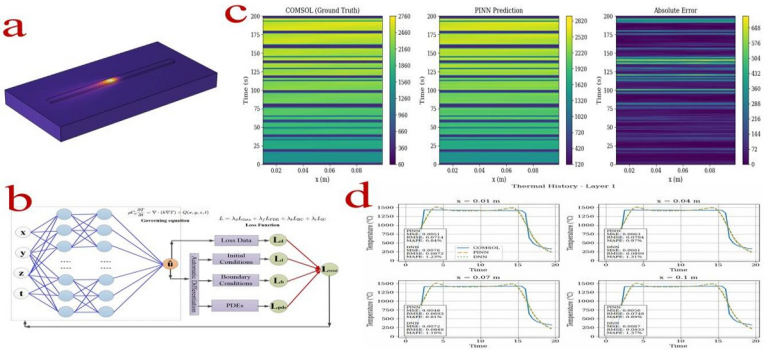


Figure 1. (a) COMSOL Simulation, (b) PINN architecture, (c) Comparison of Substrate temperature calculated by PINN and COMSOL, (d) Statistical Comparison of PINN, DNN and COMSOL results for Layer 1.

4. CONCLUSION

The proposed PINN accurately predicted the transient substrate temperature during WA-DED with high agreement to finite element simulations while requiring only simulation-generated training data. Compared with the conventional DNN, the PINN consistently achieved lower MSE, RMSE, and MAPE values, demonstrating superior predictive accuracy and reliability. These findings highlight the potential of PINNs as an efficient and physics-consistent approach for thermal prediction and process optimization in WA-DED.

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