PROJECT PROPOSAL

Title: Predicting WAAM Bead Geometry (Average and Variance) Using Machine Learning and Deep Learning

1. Problem Definition

Wire Arc Additive Manufacturing (WAAM) is a metal additive manufacturing process that builds structures layer-by-layer using an electric arc as the heat source. A critical factor influencing the dimensional accuracy and structural quality of WAAM components is bead geometry, particularly bead height stability and variation. Unstable bead height leads to poor surface finish, geometric distortion, defective layers, and reduced mechanical performance.

This project seeks to develop a dataset-driven AI system capable of predicting bead geometry AVERAGE and VARIANCE directly from WAAM process parameters: Voltage, Wire Feed Speed, Travel Speed, and CTWD (Contact Tip to Work Distance).

By building and comparing two AI models—a classical Machine Learning model and a Deep Learning model—the project will evaluate which approach provides the most accurate and robust geometry prediction. This contributes to improved understanding of WAAM behavior and supports future development of adaptive process control.

2. Theoretical Justification and Relevance

WAAM is governed by nonlinear thermal–fluid interactions that make analytical modeling of bead geometry extremely difficult. Small parameter variations can lead to large changes in bead height, and traditional linear models cannot capture the complex relationships.

Machine Learning (ML)

Models such as Random Forest and XGBoost can learn nonlinear mappings between WAAM process parameters and bead geometry. They perform well with small- to medium-sized datasets and offer interpretability through feature importance metrics.

Deep Learning (DL)

A fully connected neural network (multilayer perceptron) provides a more flexible function approximator that can learn deeper nonlinear relationships. While DL typically requires more data, it may outperform ML when subtle interactions exist between inputs.

Predicting both the average height and the variance improves understanding of stability and uniformity — key factors in real-world WAAM quality assurance.

3. Literature Review

1. Ding, D., Pan, Z., Cuiuri, D., & Li, H. (2015). Wire arc additive manufacturing: A review of processes, structures, and properties. Journal of Materials Science & Technology.

2. Xiong, J., & Zhang, G. (2014). Adaptive prediction and control of bead geometry in GMAW-based additive manufacturing. Welding Journal.

3. Wen, S. et al. (2022). Machine learning-guided prediction of melt-pool geometry in metal additive manufacturing. Additive Manufacturing.

4. Bao, Y., & Wang, L. (2021). Machine learning methods for predicting welding quality and bead characteristics. Int. Journal of Advanced Manufacturing Technology (Springer).

5. Zhan, H., et al. (2020). Neural-network-based modeling of bead geometry in arc welding processes. Journal of Intelligent Manufacturing (Springer).

4. Dataset Description

The dataset consists of **13 WAAM experiments**, each with repeated bead height measurements (Sz1–Sz13). For each experiment:

Inputs (4 features):

1. Voltage

2. Wire Feed Speed

3. Travel Speed

4. CTWD (Contact Tip to Work Distance)

Outputs (2 targets):

- **AVERAGE**: Mean bead height
- **VARIANCE**: Statistical variance of bead height

5. Proposed Methodology

Data Preprocessing

- Load dataset from Excel/CSV
- Normalize or standardize input features
- Shuffle and split into training/testing sets (80/20)
- Optional feature engineering (interaction terms)

Model 1: Machine Learning (Random Forest or XGBoost)

- Input: 4 process parameters
- Output: Average and Variance (dual regression)
- Metrics: RMSE, MAE, R^2 for each predicted target

Model 2: Deep Learning (Fully Connected Neural Network)

- Input: 4 normalized features
- Architecture:
  - Dense(32) → ReLU
  - Dense(16) → ReLU
  - Dense(2) for outputs
- Loss: MSE (multi-output regression)

Evaluation

- Compare ML vs. DL performance
- Provide error plots, scatter plots, and residual analysis
- Perform model robustness checks

Expected Contribution

- Demonstrate predictive capability of ML & DL for WAAM geometry
- Provide dual-prediction (average + variance) for better quality analysis
- Lay foundation for future real-time WAAM control systems

6. Expected Results

- Random Forest may outperform DL for small datasets
- DL may capture deeper interactions once tuned
- Strong prediction accuracy for AVERAGE
- Moderate prediction accuracy for VARIANCE
- Demonstration that AI can estimate bead stability from basic parameters