Open Innovation Platform for Optimising Production Systems by Combining Product Development, Virtual Engineering Workflows and Production Data.

Temporal Graph Neural Operator

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TEMPORAL GRAPH NEURAL OPERATOR: A STATE-OF-THE-ART METHODOLOGY IN CONTROLLING DISTORTION FOR WIRE ARC ADDITIVE MANUFACTURING

In the landscape of Industry 4.0, particularly within complex sectors like aerospace and maritime engineering, the ability to control large-scale additive manufacturing processes in real-time is essential for maintaining efficiency and competitiveness. As part of the European Union's Horizon **PIONEER** initiative, researchers today unveiled a cutting-edge Artificial Intelligence solution designed to revolutionise Wire Arc Additive Manufacturing (WAAM): the **Temporal Graph Neural Operator (TGNO)**.

This new deep learning architecture solves one of the most persistent challenges in metal 3D printing, structural deformation due to thermal stress, by accurately predicting final cambering curves on the critical **Y (longitudinal)** and **Z (vertical)** axes.

INTRODUCTION: THE CHALLENGE OF "CAMBERING" IN WAAM

Wire Arc Additive Manufacturing (WAAM) is reshaping heavy industry by enabling the rapid production of large metal components. However, the integration of this technology into safety-critical supply chains faces a significant hurdle: the physics of heat.

Funded by the European Union

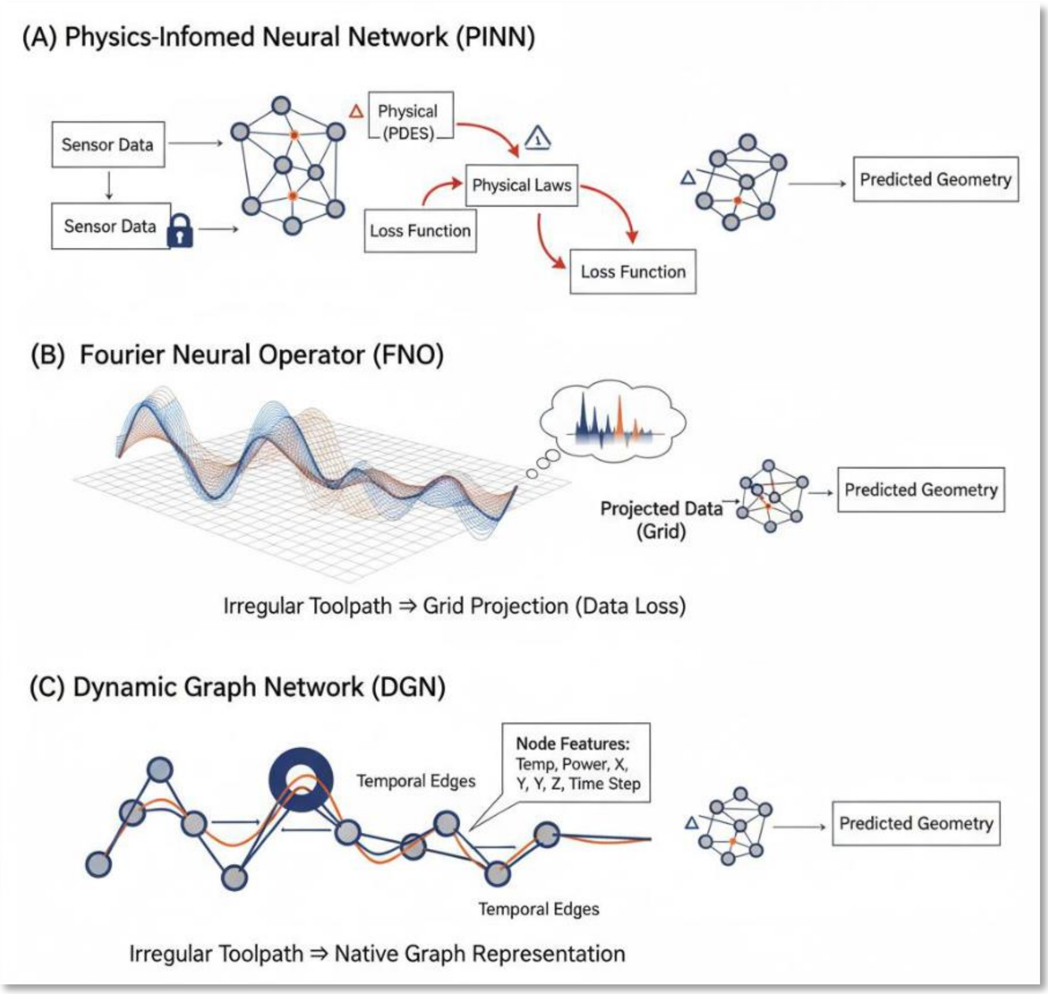
As the welding torch deposits molten metal layer by layer, the component undergoes intense, repeated heating and cooling cycles. These thermal gradients generate residual stresses that cause the part to warp or bend, a phenomenon known as **cambering**.

- **Y-Axis Distortion:** Affects the longitudinal straightness, potentially making the part impossible to assemble or requiring expensive post-process machining.
- **Z-Axis Distortion:** Affects the vertical layer height consistency, which can lead to arc instability and total print failure during the process.

Traditionally, detecting these distortions required waiting until the print was finished and cooled, or utilising Finite Element Analysis (FEA) simulations. While accurate, FEA is computationally heavy and too slow for real-time monitoring. To bridge this gap, CORE Innovation has developed a solution that combines the speed of AI with the physical accuracy of simulation.

THE SOLUTION: MODELLING TIME AND GEOMETRY

The core of the innovation is the **Temporal Graph Neural Operator (TGNO)**. Unlike standard "black box" machine learning models that simply map inputs to outputs based on statistical correlation, the TGNO is designed to learn the underlying partial differential equations (PDEs) that govern the cooling and warping of metal.



1. GRAPH-BASED REPRESENTATION

Standard Convolutional Neural Networks (CNNs) struggle with 3D printing because they expect data on a fixed grid (like pixels in an image). However, WAAM parts have complex, arbitrary geometries. The TGNO solves this by discretising the part geometry into a graph structure:

- **Nodes** represent physical coordinates along the deposition path.
- **Edges** represent the thermal and mechanical influence between those points.

This allows the model to "understand" the geometry of the part naturally, regardless of its shape complexity.

2. THE "TEMPORAL" ADVANTAGE

Heat in WAAM is cumulative. A distortion that appears at Layer 100 is often the result of heat retained from Layer 10. The architecture incorporates recurrent temporal layers that capture this history. By analysing the thermal state of the early layers, the model can forecast the deformation evolution over time.

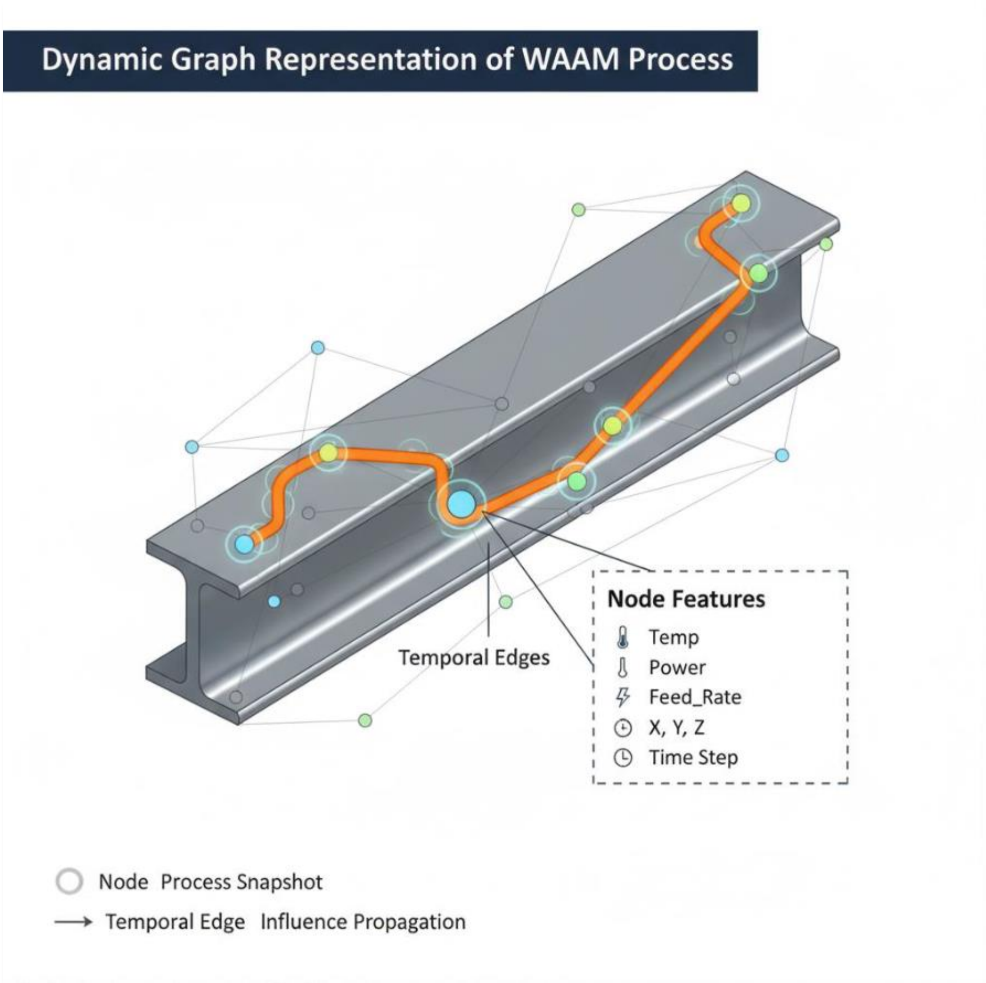
3. OPERATOR LEARNING

Perhaps the most significant technical advancement is the shift from "Function Learning" to "Operator Learning."

- **Standard AI**: Maps a low-resolution input to a low-resolution output. If the mesh resolution changes, the model fails.
- **Neural Operator**: Learns the mapping between infinite-dimensional function spaces. This means the TGNO is **resolution independent**. It can be trained on sparse sensor data but evaluated on a dense, high-resolution mesh, offering massive flexibility for industrial deployment where sensor configurations vary.

ARCHITECTURAL DESIGN OF THE PREDICTION WORKFLOW

To implement this solution in a production environment, the workflow mirrors the physical deposition process but operates in a predictive capacity.



Step 1: Data Ingestion

The system ingests time-series data from the early stages of the print. This includes process parameters (current, voltage, travel speed) and thermal history.

Step 2: The Encoder

Similar to the "Encoder" in auto-encoder architectures, this stage lifts the input data into a high-dimensional latent space. However, instead of just compressing data, it embeds the physical constraints of the Y and Z axes into the graph structure.

Step 3: The Temporal Graph Processing

The core processing block propagates information across the graph. It calculates how heat spreads from node to node (spatial) and how stress accumulates from layer to layer (temporal). This effectively simulates the physics of the print in milliseconds.

Step 4: The Decoder

The final stage projects the high-dimensional data back into the physical domain, outputting the predicted final cambering curves.

- **Outcome**: The system provides a specific curve showing exactly how much the part will deviate on the Y and Z axes before the print is even halfway done.

ADDED VALUE FOR EUROPEAN MANUFACTURING

The deployment of the Temporal Graph Neural Operator offers substantial added value compared to existing methodologies:

- **Early Detection**: By identifying critical distortions early, manufacturers can halt a doomed print immediately, saving significant energy and raw materials (wire).
- **Feed-Forward Control**: The speed of the TGNO (inference in milliseconds) opens the door to active control. The prediction can be fed back to the welding robot to adjust process parameters on the fly, effectively "counter-steering" against the predicted warp.
- **Sustainability**: This development contributes directly to the EU's goals for **Zero-Defect Manufacturing**, reducing the carbon footprint associated with scrap metal and re-work in heavy industry.

ABOUT THE PROJECT

This Horizon Europe project took off in January 2023. PIONEER develops and implements an interoperable Materials-Modelling-Manufacturing Ecosystem, enabling multidirectional dataflow throughout the material value chain by connecting the production's various stages. Combining a design-by-simulation approach with manufacturing and quality data, PIONEER optimises product development strategies in high-mix/low-volume production schemes.

Project Title: Open Innovation Platform for Optimising Production Systems by Combining Product Development, Virtual Engineering Workflows and Production Data.

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