Enhancing Urban Flood Response: Traffic Flow Prediction with Field Theory-Inspired Physics-Informed Graph Neural Network

Xuhui Lin[1], Qiuchen Lu[1], Tim Broyd[1], Tao Cheng[2], Xianghui Zhang[2], Tohid Erfani[2], Trung Hieu Tran[3]

1 *The Bartlett School of Sustainable Construction, University College London, London, Unite Kindom*
2 *Department of Civil, Environmental and Geomatic Engineering, University College London, London, Unite Kindom*
3 *Centre of Design Engineering, Cranfield University, Cranfield, Unite Kindom*

THE BARTLETT SCHOOL OF SUSTAINABLE CONSTRUCTION

DAFNI Data & Analytics Facility for National Infrastructure

Motivation

Amidst global climate change, the increasing severity of flood disasters on transportation network systems has become a pressing concern. Existing methods to predict and manage traffic flow changes during floods often lack a comprehensive understanding of the dynamic alterations in complex transportation networks, particularly in real-time response situations. These models face significant challenges in addressing uncertainties and dynamic changes, such as road closures and emergency evacuation routes. There is a critical need for advanced predictive models that can accurately and dynamically capture the effects of floods on transportation networks to enhance flood resilience and improve decision-making in urban planning and disaster response.

Objectives

This paper aims to develop a novel traffic flow prediction model that combines ***Physics-Informed Neural Networks (PINNs) and Graph Neural Networks (GNNs), PINNs-GNN***, to overcome these limitations. By integrating physical equations and GNNs, the model abstracts the transportation network as a graph and introduces a diffusion equation describing traffic flow propagation within the GNN to enhance physical consistency. Inspired by field theory, the model also defines a field effect term to represent the impact of floods, which is extracted from node and edge features by the GNN, thereby improving the model's adaptability to dynamic environments. A new loss function combining data fitting errors and physical equation residuals is designed to optimize the model further. Through experiments on real flood event datasets, the proposed model demonstrates superior accuracy, real-time performance, and robustness compared to existing methods, proving its effectiveness in enhancing urban flood response capabilities. This innovative approach not only provides a new solution for traffic flow prediction but also explores the integration of physical knowledge and graph learning, contributing to the development of resilient urban transportation systems.

Graph Structure & PINNS Background

Line Graph of Transportation Networks

Treating roads as nodes and the connections between roads as edges (line graph, Fig 1b of the original graph, Fig 1a) allows for detailed road-level feature modeling, naturally captures interactions between roads, effectively handles complex intersections, and enhances the physical consistency of the model. This approach improves the model's adaptability to dynamic traffic conditions, resulting in more accurate and reliable traffic flow predictions.

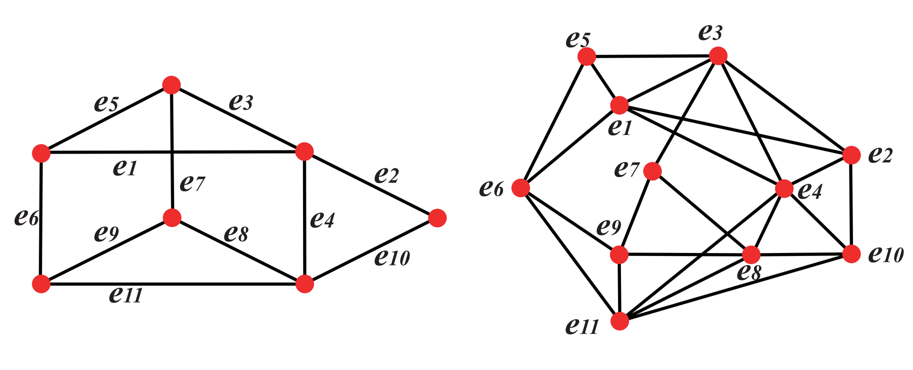

Figure 1. Comparison between the original network (a) and the corresponding line graph (b)

Physic-Informed Netural Networks

PINNs enhance this research by embedding physical laws(e.g. Partial differential equation, PDE) into the model, resulting in more accurate and reliable traffic flow predictions, especially with limited data. It improves generalization to new situations, such as dynamic flood conditions, and reduce the dependency on extensive historical data. Ensuring consistency with physical laws prevents unrealistic predictions, increase robustness and reliability.

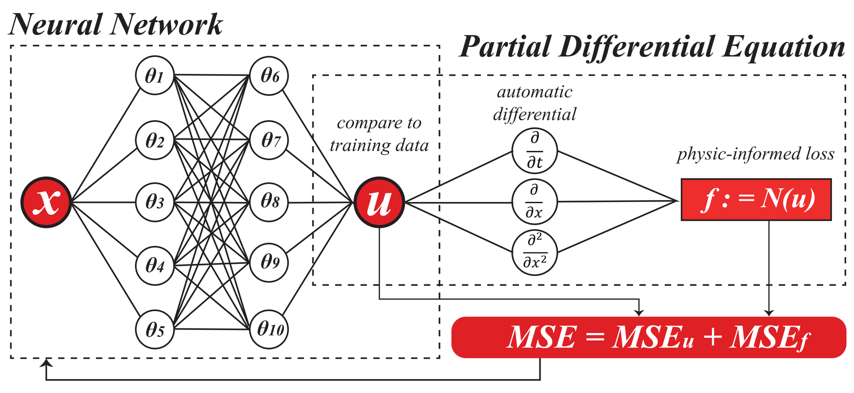

Figure 2. A general framework of PINNs

Methodology - Framework & Formulation

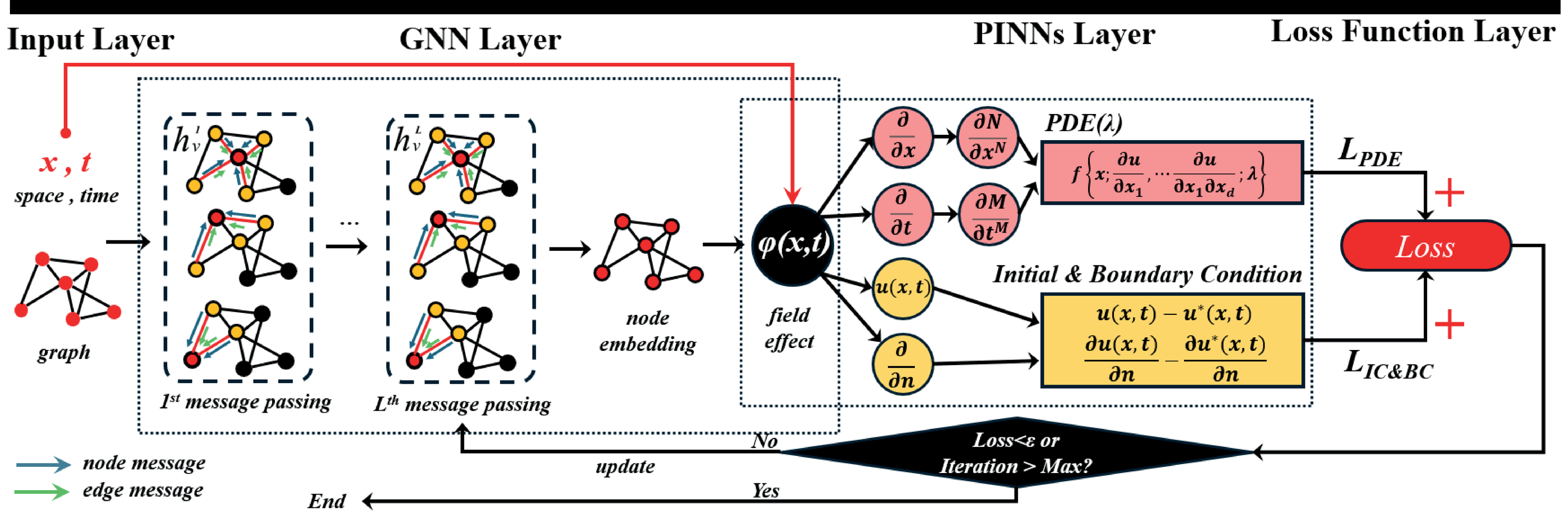

Figure 3. Frameork of field theory-inspired PINNs-GNN

This architecture integrates multiple layers: an **1) Input Layer** for node and edge features, a **2) GNN Layer** for message passing and feature updates, and field effect to capture cumulative impacts, a **3) PINNs Layer** for incorporating physical diffusion equations, and a **4) Loss Function Layer** to combine data errors and physics residuals, ensuring accurate and physically consistent traffic flow predictions during floods.

GNN Layer:

- Message Passing Aggregates information from neighboring nodes and edges

$$\mathbf{m}_i^{(k)} = \sum_{j \in \mathcal{N}(i)} \mathbf{e}_{ij} \odot \mathbf{h}_j^{(k)}$$

Each node gathers information from its neighboring nodes and the edges connecting them. This process helps in capturing the local context and relationships within the network.

- Feature Updaye Updates node features based on aggregated messages.

$$\mathbf{h}_i^{(k+1)} = \sigma\left(\mathbf{W}^{(k)}\mathbf{h}_i^{(k)} + \mathbf{m}_i^{(k)} + \mathbf{b}^{(k)}\right)$$

After message passing, each node's features are updated using a neural network layer, which combines the original features with the aggregated messages, applying weights and biases to refine the feature representation.

- Field Effect The final output of the GNN, representing the field effect.

$$\phi(x_i, t) = \mathbf{h}_i^{(L)}$$

This layer encapsulates the cumulative impact of the node's neighbors and its own features over multiple layers of message passing and feature updates.

PINNs Layer:

Incorporates the field effect into the physics-informed model.

$$\frac{\partial u}{\partial t} = \alpha \nabla^2 u + \beta \phi(x, t)$$

The PINNs layer integrates the field effect into the traffic flow diffusion equation, ensuring that the model adheres to the underlying physical principles governing traffic flow. This equation models how traffic density evolves over time and space, influenced by diffusion and external factors represented by the field effect.

Loss Function Layer:

- Data Error This component of the loss function quantifies the discrepancy between the predicted traffic flow and the actual observed data, guiding the model to minimize this error.

$$\mathcal{L}_{data} = \sum \left(u_{\text{pred}} - u_{\text{true}}\right)^2$$

- Physics Equation Residual This component of the loss function quantifies the discrepancy between the predicted traffic flow and the actual observed data, guiding the model to minimize this error.

$$\mathcal{L}_{physics} = \sum_j \left(\frac{\partial u(x_j, t_j)}{\partial t} - \alpha \nabla^2 u(x_j, t_j) - \beta \phi(x_j, t_j)\right)^2$$

- Total Loss Function The total loss function is a weighted sum of the data error and the physics residual, balancing the need to fit the data accurately with the need to comply with physical principles.

$$\mathcal{L} = \mathcal{L}_{data} + \lambda \mathcal{L}_{physics}$$

Result Analysis

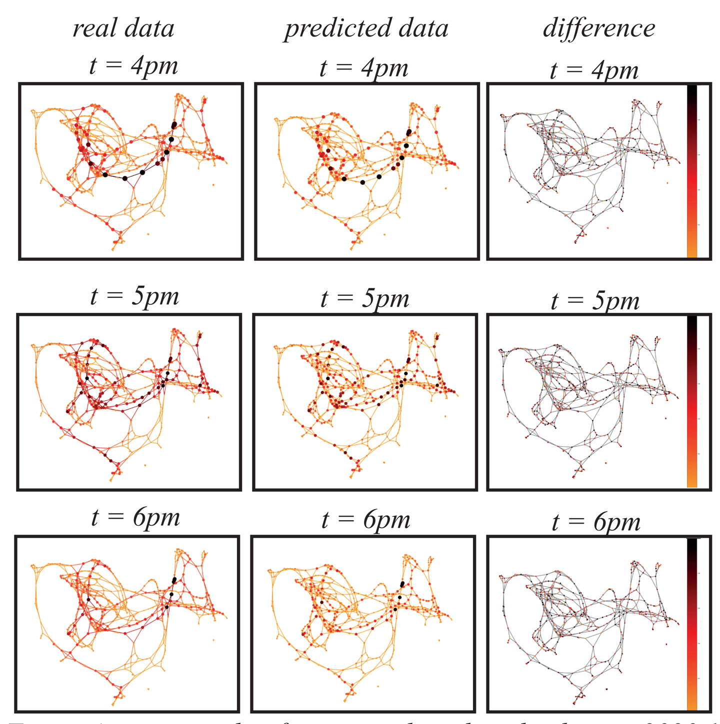

Figure 4a. x-t snapshot for true and predicted values at 2020.10.02

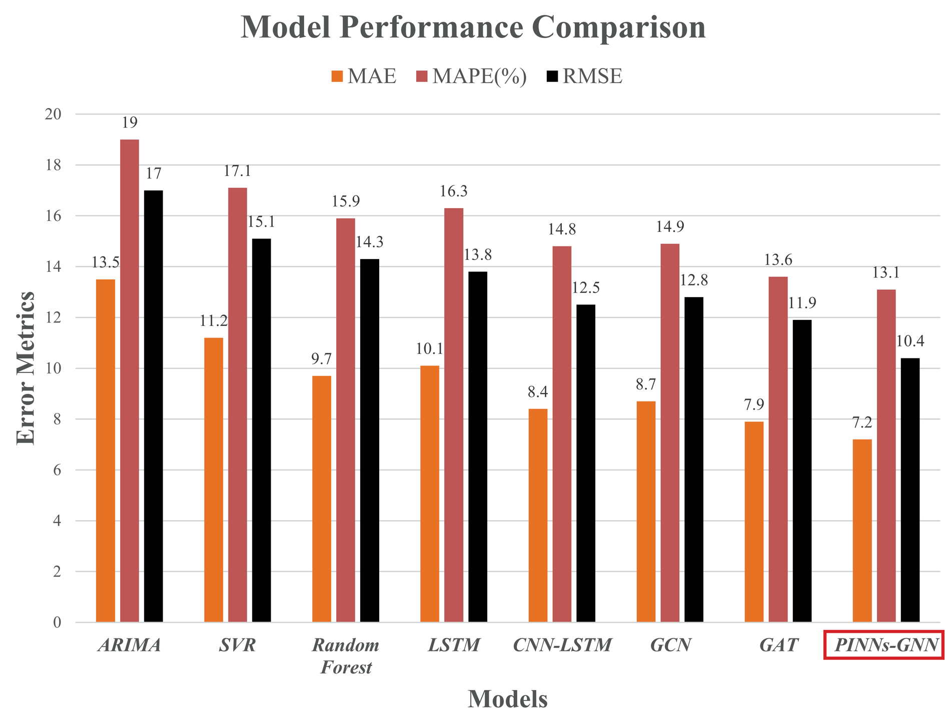

Figure 4b. Evaluation of error metrics across different models

Dataset: The dataset comprises 542 road nodes in Shoreditch(London's East End), with a time step of 1 hour, covering the period from 2020.09 - 2020.10. It includes days with rainfall exceeding 20 mm/h.

Description: These figures demonstrate the PINNs-GNN model's superior performance in predicting traffic flow during floods, effectively capturing spatiotemporal dynamics and reducing errors.

Transportation Timeseries Under Flooding

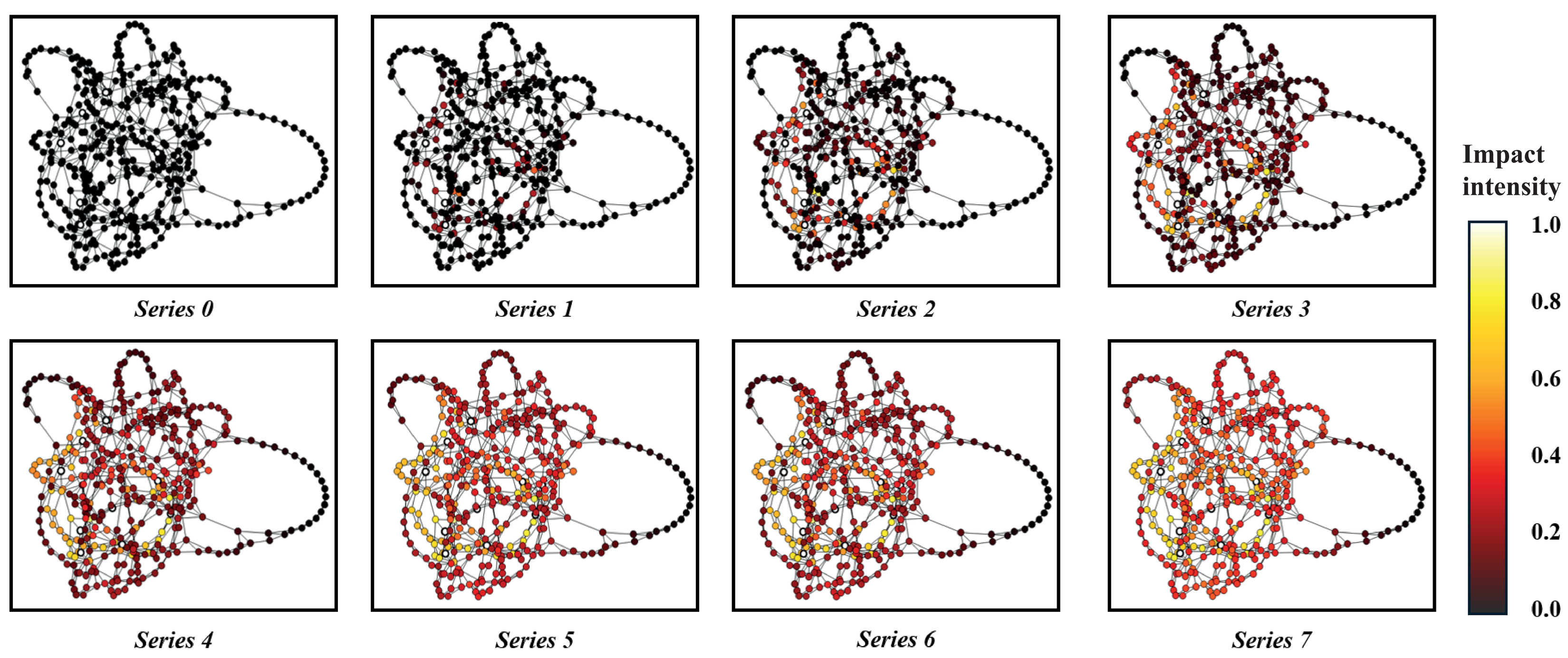

Figure 5. Spatiotemporal impact diffusion sequence of road network under flood impact generated by field theory-inspired PINNs-GNN

The PINNs-GNN model, by simultaneously modeling the topology of the road network and the message passing based on filed theory, learns the propagation patterns of flood impact within the road system. The generated time series accurately depict the dynamic evolution of the impact across different regions, reflecting both the interactions between nodes and the varying resilience of each area.

Future Work

Future work involves several key areas for enhancing the PINNs-GNN model. ***1) introducing additional physical constraints***, such as the conservation equation of traffic flow and velocity-density relationships, can further improve prediction accuracy and reliability. Incorporating other domain knowledge like traffic regulations and driving behavior patterns can also enrich the model's knowledge representation capabilities. ***2) optimizing the model structure*** by exploring different types of graph neural networks, such as graph attention networks and graph autoencoders, is expected to offer stronger feature extraction and generalization abilities. Additionally, optimizing the model's physical equation solver and adopting higher-order numerical methods are promising directions for improvement. ***3) validation with more public datasets and corresponding benchmarks*** is crucial for comprehensively evaluating the generalization performance of the PINNs-GNN model. Extensive comparisons with other advanced traffic flow prediction models are necessary to objectively assess the proposed method's advantages and limitations.

Acknowledgement :

This research is supported by the DAFNI's Sandpit Transport Projects