

Can Information about Road Conditions Improve Rail Delay Forecasting? A Heterogenous Spatiotemporal Graph Neural Network model approach

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Background and Motivation

Accurately forecasting rail delay has value at various operational levels from supporting dispatcher decision-making to emergency response capability to improving customer satisfaction.

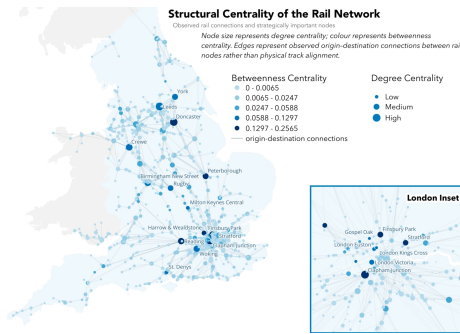


Figure 1: Map of the National Rail Network

This study employs a heterogenous Spatio-Temporal Graph Convolution Network (STGCN) model that propagates dynamic conditions on the Strategic Road Network (SRN) in England to rail station nodes on the National Rail network (Figure 1) with endogenous rail performance history to forecast short-term rail delays.

Data and Methods

This study uses 3 main open-source secondary datasets: (1) Historic Rail Delay from the Rail Data Marketplace, (2) and (3) Traffic flow data and National Highways disruptions (Unplanned Lane closures and Speed Managed Areas) from the National Highways Digital Lab websites.

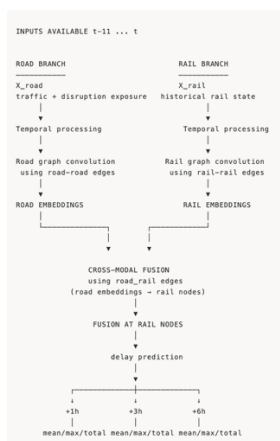


Figure 2: Schematic of the heterogenous STGCN model architecture

Using a Cross-Modal (Road_Rail edges) graph as a static topological foundation on which dynamic attributes were attached, all variables were aggregated to an hourly resolution before input features were selected (see Figure 2). The final STGCN was trained on a rolling sequence of the previous 12-hours of input data to predict rail delay at 1-hour, 3-hour and 6-hour forecast horizons and compared against conventional benchmark models. Additionally, a scenario experiment was conducted to test the counterfactual sensitivity of the model using simulated perturbations. Scenario A tested

sensitivity to different traffic conditions. Scenario B examined how specific types of road disruptions affected the model's rail response. Scenario C tested the temporal persistence of rail delay responses after unplanned lane closures. Scenario D synthesised the node level responses to create a station vulnerability score; this determined which railway stations were the most vulnerable to road disruptions according to the model

Key Findings

The heterogenous STGCN had a lower error rate than every other benchmark model demonstrating its superior predictive capability (Figure 3).

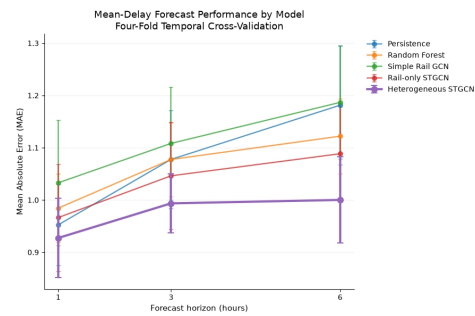


Figure 3: Mean-Delay Forecast performance by Model

The most vulnerable stations according to the model are not spatially concentrated in one part of the network (Figure 4). Among the most vulnerable are, London Euston, Birmingham New Street, Bristol Temple Meads and Manchester Piccadilly.

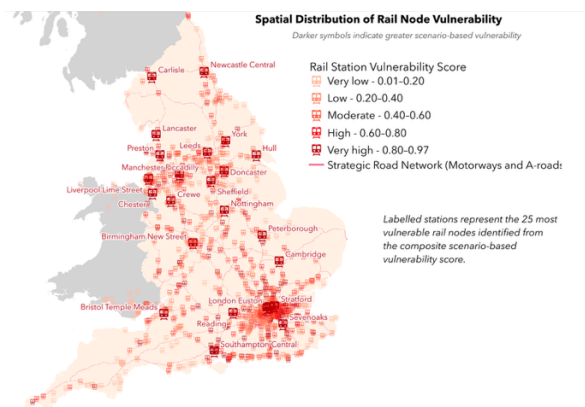


Figure 4: Map of the most vulnerable stations according to the STGCN model

Value of the research

This study demonstrates the value of incorporating heterogenous cross-modal data into transport forecasting studies; it improves predictive performance when compared to conventional mode-specific methods. Furthermore, the findings of this analysis have identified which Network Rail stations are the most vulnerable to road disruptions in terms of delay, according to the model response. This framework can be employed as a practical outcome for stakeholders as it can aid in awareness and adaptation to delays at the most vulnerable stations in the National Rail network, based on associated road conditions.

