



- Limitations of current forecasting methods
- Proposed methodology
- Training data
- Results
- Future work



Limitations of Travel Demand Models

- Fail to capture rapid short-term trends.
- Aggregate inputs and fixed response functions.

Limitations of Time-Series Deep Learning Models

- Work only when the network is stationary.
- Performance drops when capacity changes.

Hybrid Framework

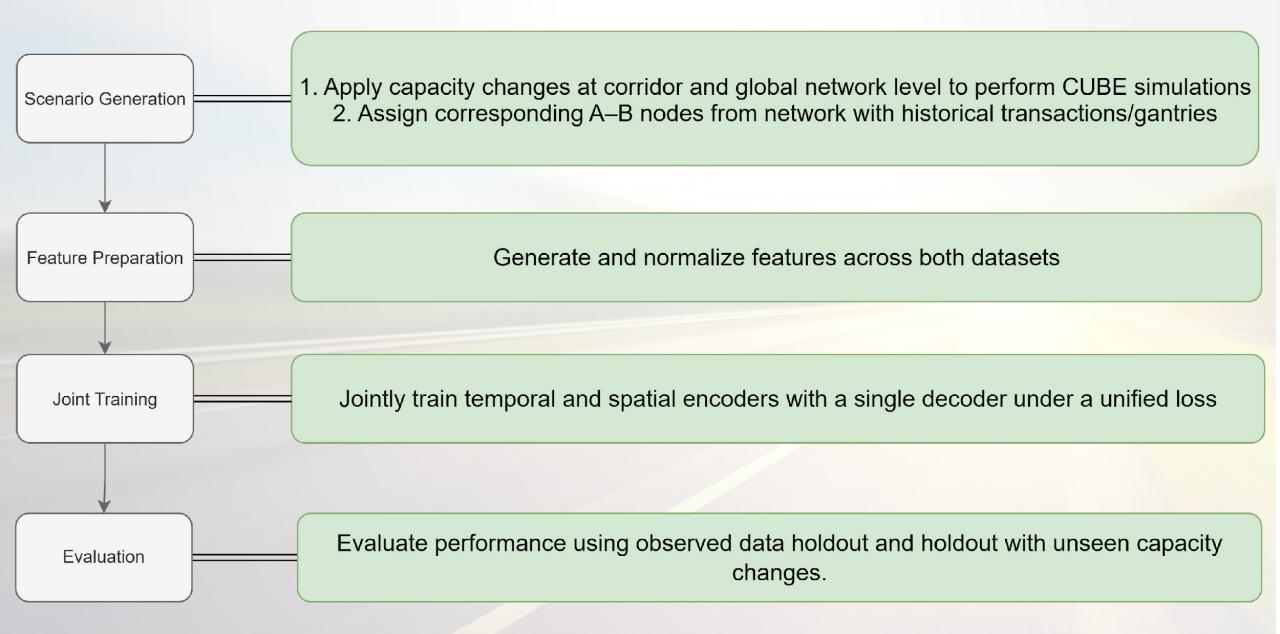
- Combine historical observations (i.e., demand changes) for real temporal patterns with
- CUBE simulations (i.e., network changes) for counterfactual scenarios (e.g., capacity changes).

Outcome

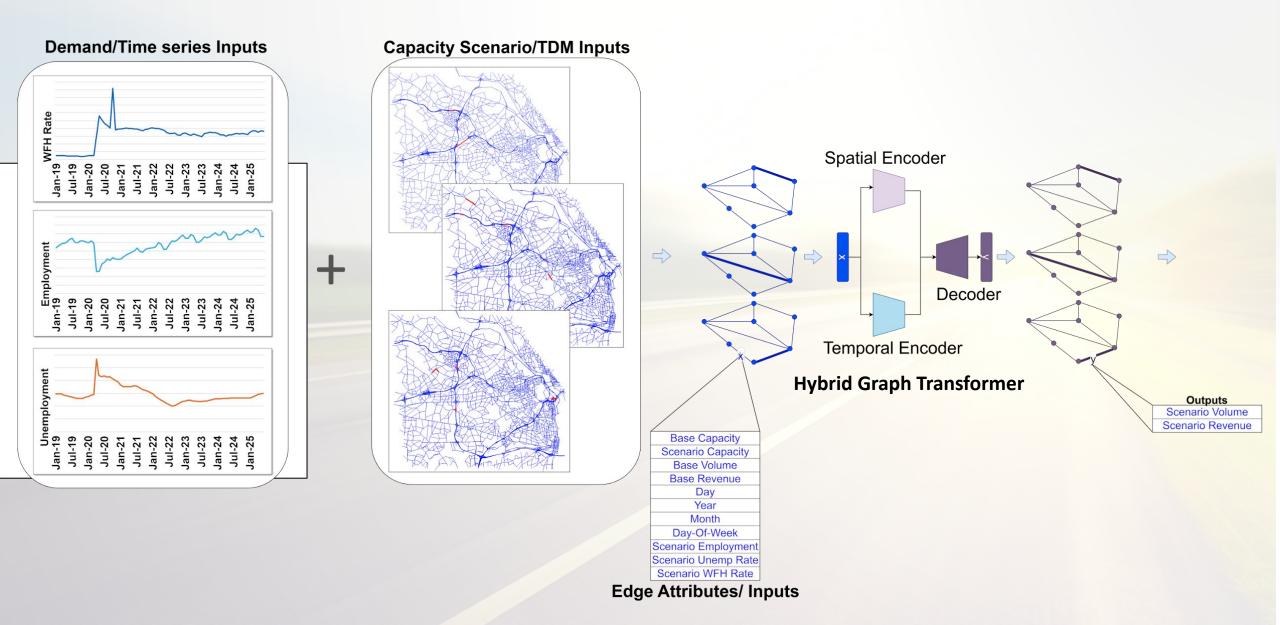
Link-level volume and revenue forecasts under dynamic network conditions.

Methodology Overview











Existing Literature

- DCRNN's graph diffusion + RNN encoder-decoder
- STGCN's graph conv + gated TCN
- Graph Transformers
- Separate space and time modules

Cross-domain feature alignment:

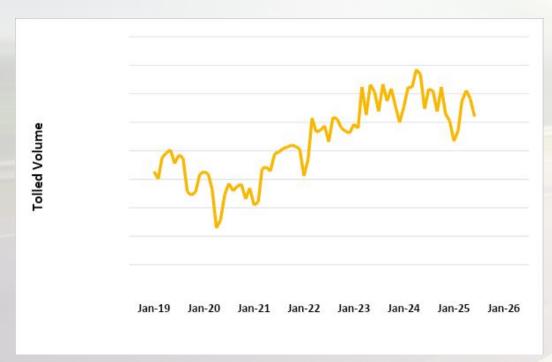
- We used two transformer blocks (one spatial, one temporal encoder) tied by a shared MLP decoder.
- Produce a single latent representation for both historical and simulation inputs.
- This enables weighting of these evidence sources during forecasting.

Architectural scalability:

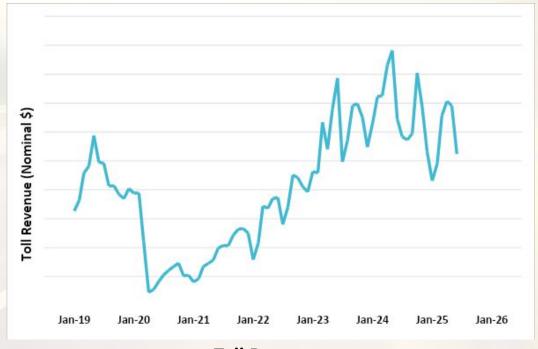
- Supports varying network sizes, time resolutions, and forecasting windows without redesign.
- Makes it practical for corridor-level, region-level, or systemwide applications.



• Detailed 1-minute transaction and toll revenue data for gantries along major express lane corridors in the Northern Virginia Area, from Jan 2019 to Jun 2025.



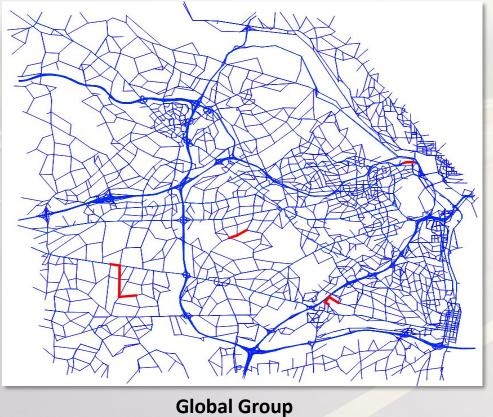
Tolled Transactions

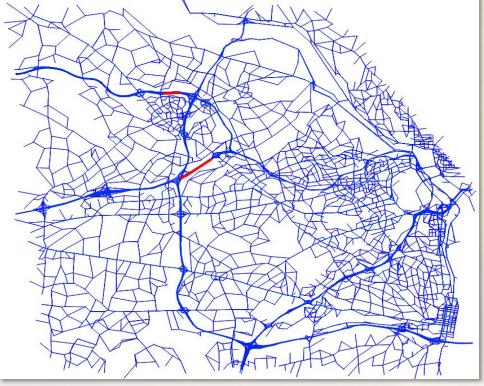


Toll Revenue



- 500 random capacity change scenario runs over a subarea of 2019 year calibrated travel demand model's subarea network:
 - 11,704 edges and 5,973 nodes
 - Corridor-level changes
 - Global changes



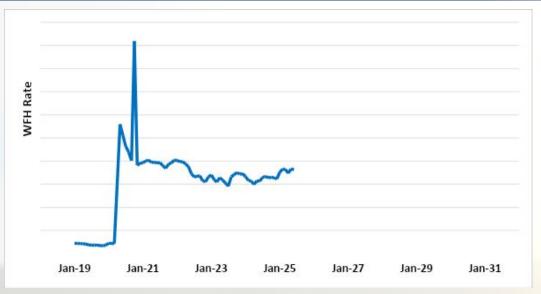


p Corridor Group

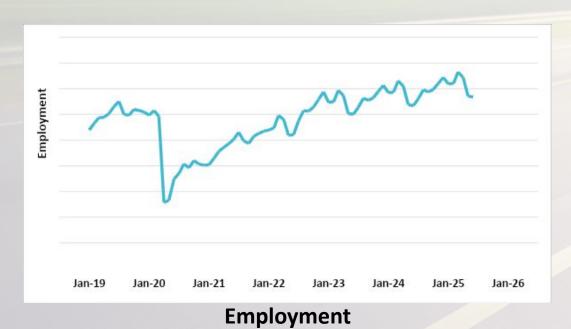
Datasets - Socioeconomic Data

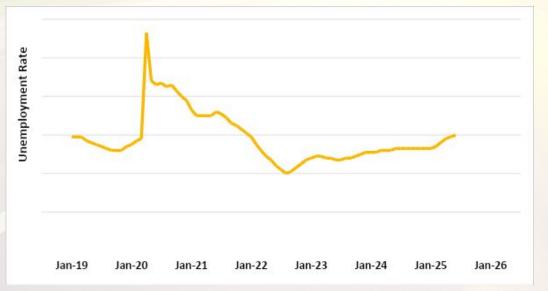


* All data corresponds to the project area



Work-From-Home Rate

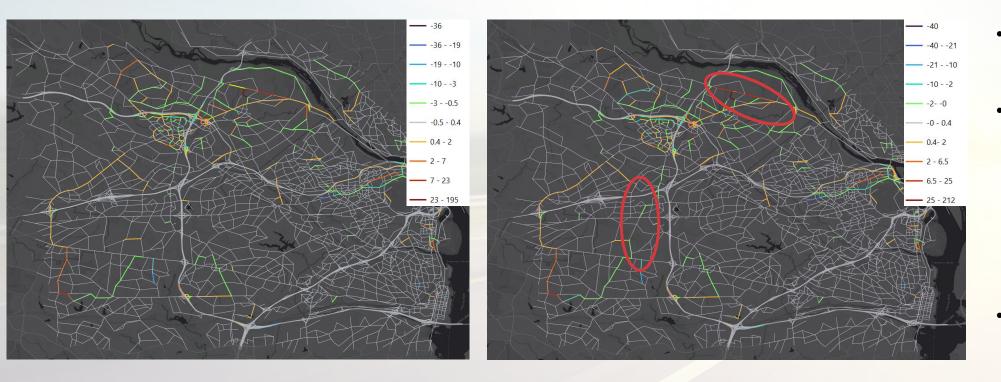




Unemployment Rate



Comparison of percentage change in volume compared to Base Scenario under capacity change



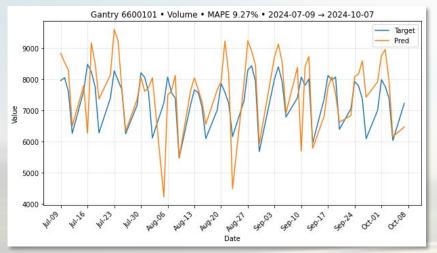
- Validated on 64 capacity change scenarios
- Av. Diff. between model predicted and CUBE predicted scenarios not used during training was 3.4% MAPE, indicating strong robustness to network perturbations
- Highest error for a link observed at 10.03% MAPE.

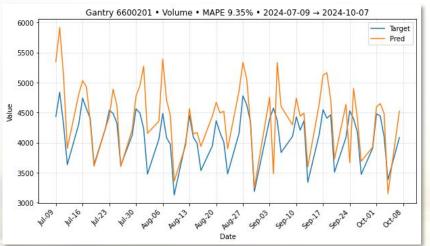
CUBE

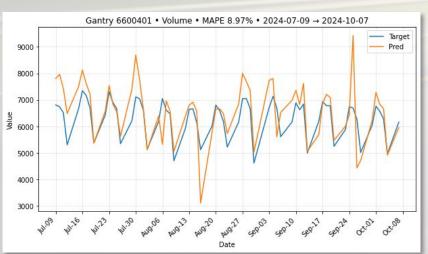
Hybrid Graph Transformer

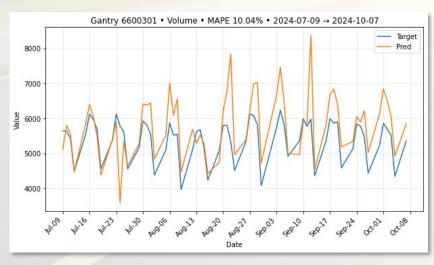


Comparison of Predicted Volume compared to Observed Historical under demand change







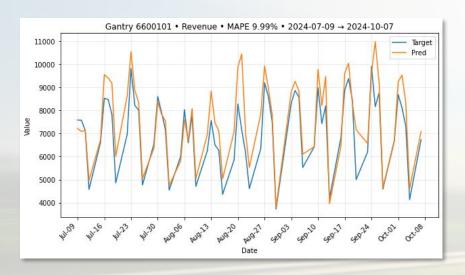


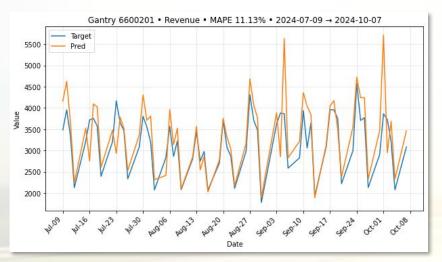
 Validated on 64 days of historical data across 4 gantries.

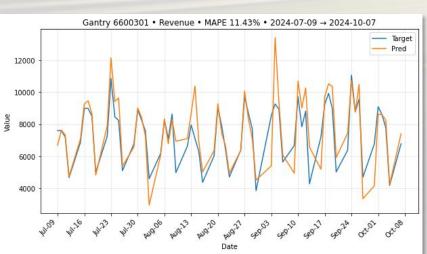
 Av. Diff. between predicted vs actual gantry volumes was 9-10% MAPE, indicating strong robustness to temporal variations

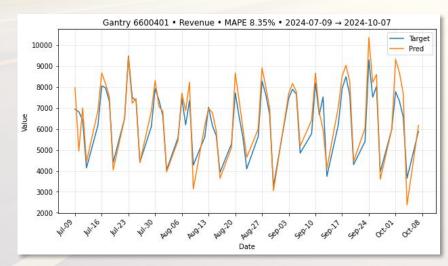


Comparison of Predicted Revenue compared to Observed Historical under demand change









- Validated on unseen 64 days of historical data across 4 gantries
- Av. Diff. between predicted and actual gantry revenues was 8-11% MAPE, indicating strong robustness to temporal variations



- More real-world validation
 - Create capacity-change scenarios reflecting observed impacts: phased lane closures, temporary reversible lanes, ramp detours, and traffic pattern shifts.
- Test performance on other architectures:
 - DCRNN's graph diffusion + RNN encoder-decoder
 - STGCN's graph conv + gated TCN
- Support downstream optimization (e.g., maximizing throughput or revenue)
- Mid-term to long-term forecasting



- The proposed framework explicitly handles joint demand and network changes:
 - Robust short-term forecasting
 - Credible what-if analysis under capacity changes
- This method:
 - Scales to larger multi-facility networks
 - Can be fine-tuned using real-world capacity change/network scenarios

