

103rd Annual Meeting of Transportation Research Board
ACP50 – Traffic Flow Theory and Characteristics Committee
3002 – Network Modeling and Control

A Bi-level Method for Link Speed Estimation Based on Macroscopic Fundamental Diagram Using Deep Learning

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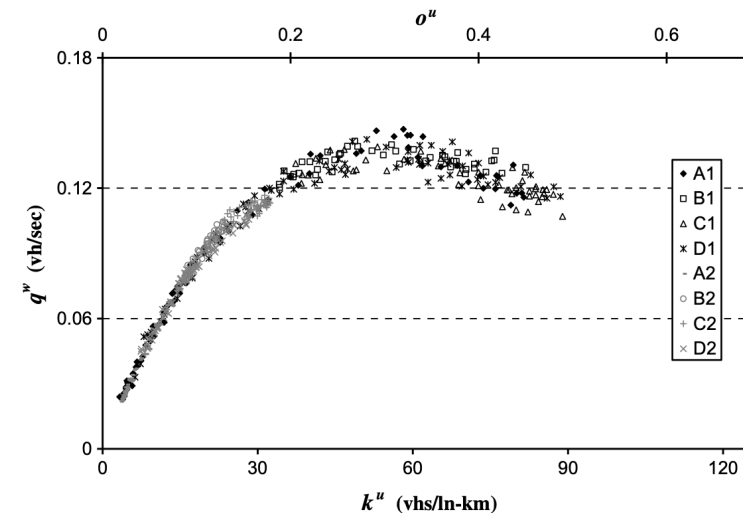


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Introduction

Background

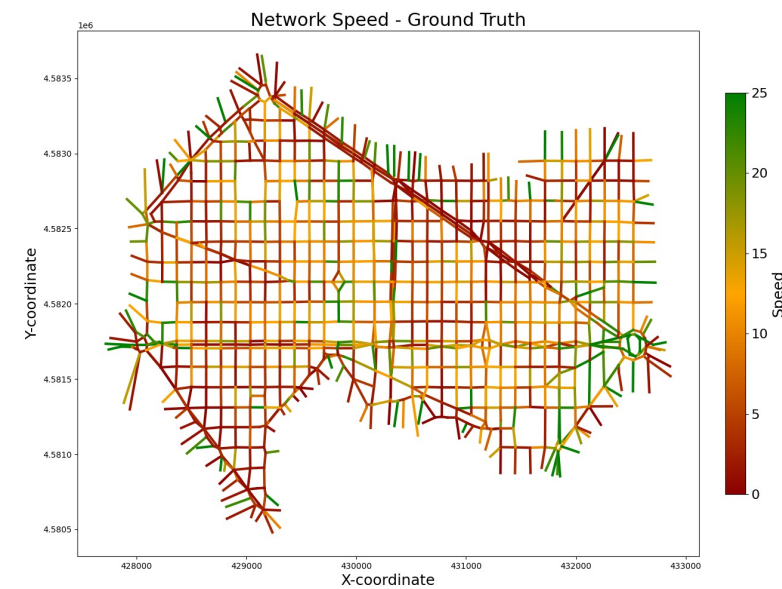
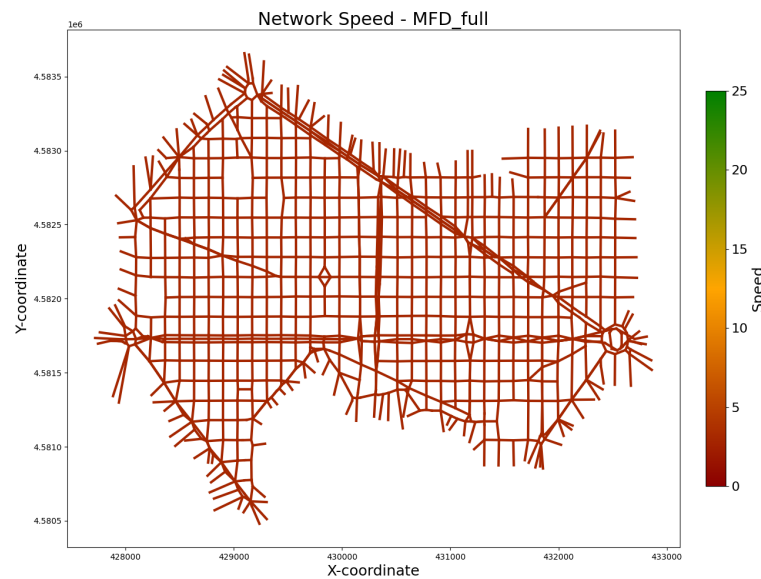
- **Urban Traffic Challenges:** Rapid urbanization and increasing vehicular usage exacerbate traffic congestion in cities.
- **Large-Scale Optimization:** Macroscopic Fundamental Diagram (MFD)^[1,2] offers a holistic perspective and efficient approach for optimizing traffic across urban networks.
 - Fast for large-scale optimization ^[3,4]



Introduction

Limitation of MFD-based simulator

- **Aggregated Data:** MFD uses aggregated traffic data, which ignores the unique conditions of individual road links
- **Limited Spatial Diversity**
 - Can't reflect the spatial diversity of road networks
 - A comprehensive traffic management approach may require integrating MFDs with more granular levels.



Problem Definition

Research Objective

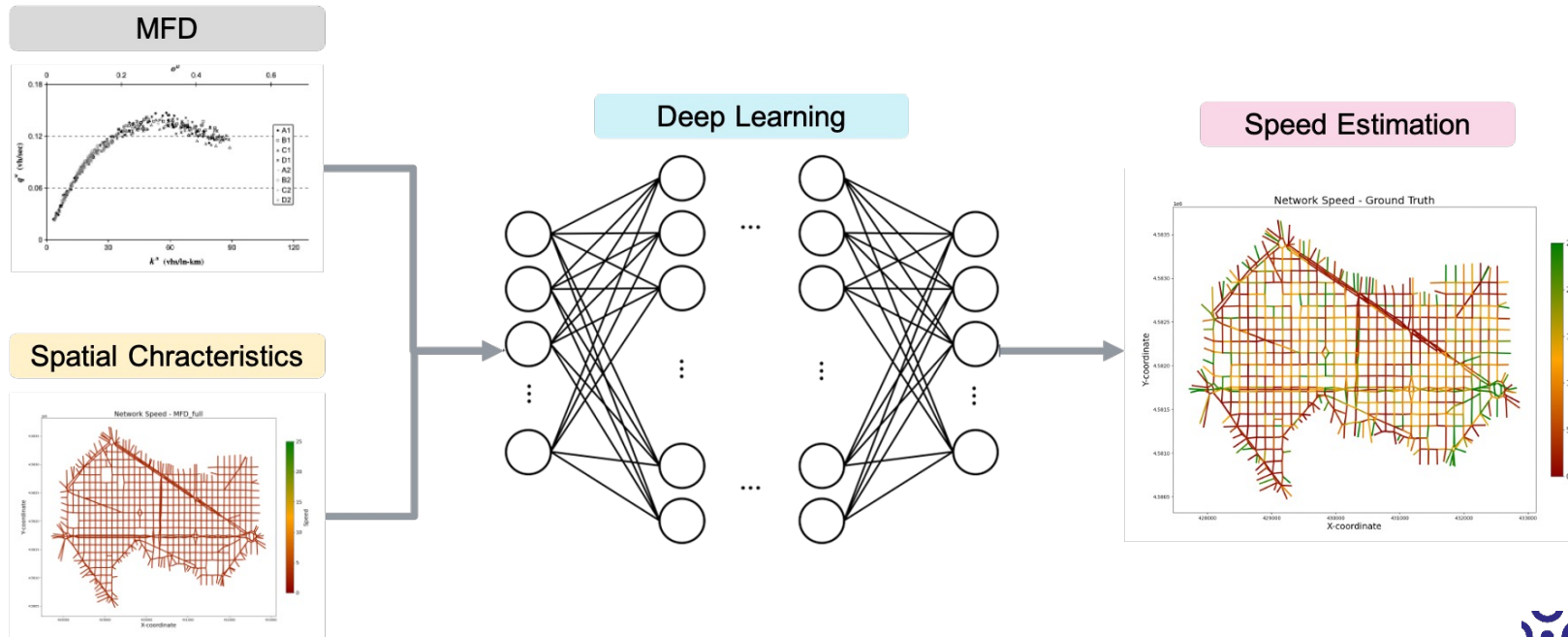
- **Objective:** Estimate the speed of each link in the road network for the MFD-based simulator
 - Local correction factor (f_{LCF})
 - Input:
 - ✓ Spatial characteristic of each link ($S_{spatial}$)
 - ✓ Average speed information of network from speed MFD (V_{S-MFD})
 - Output:
 - Speed of each link in the network (V_{link})
 - $V_{link} = f_{LCF}(S_{spatial} + V_{S-MFD})$



Methodology

Deep learning approach

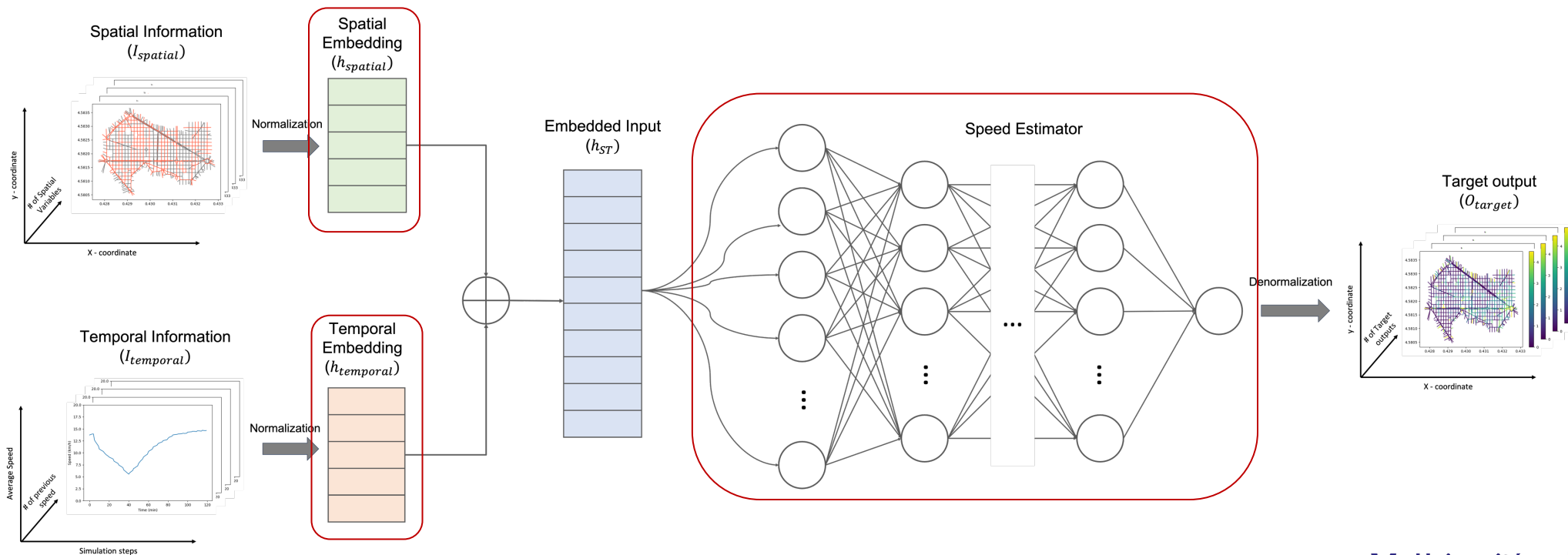
- Deep learning approach in speed estimation
 - Powerful techniques to solve complex non-linear problem
 - Popular approach in speed prediction^[5,6,7,8]
 - Multilayer-Perceptron (MLP), Recurrent Neural Network (RNN), Graph Neural Network (GNN) ...
 - Leverage information from aggregated data (MFD) and spatial characteristics to estimate the speed of the network.



Methodology

Model framework – STGNN (Spatio-Temporal Graph Neural Network)

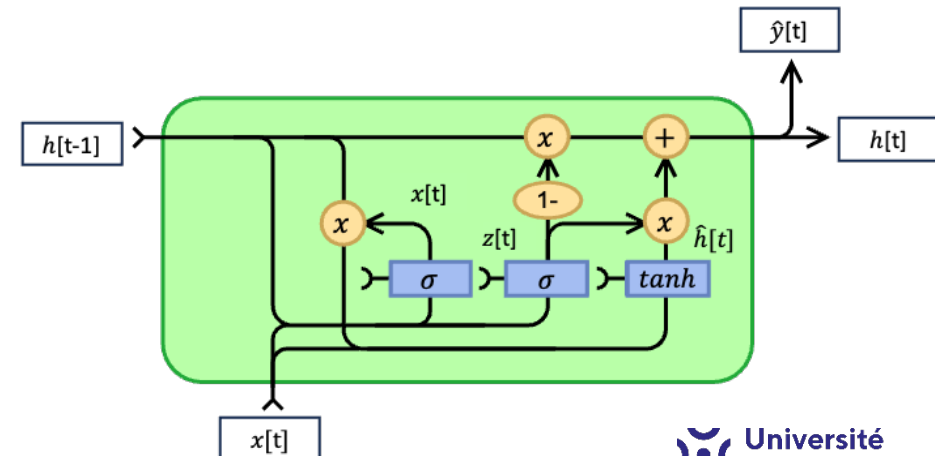
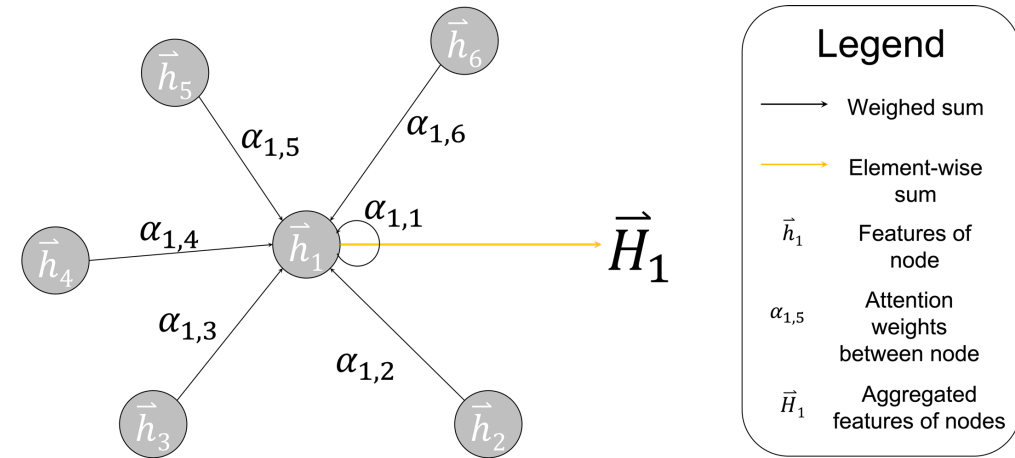
- Use three deep neural network models to estimate the speed of each link
 - Spatial Embedding: Graph Attention network (GAT)
 - Temporal Embedding: Gated Recurrent Unit (GRU)
 - Speed Estimator: Multi-layer Perceptrons (MLP)



Methodology

Description of Spatial and Temporal Embedding

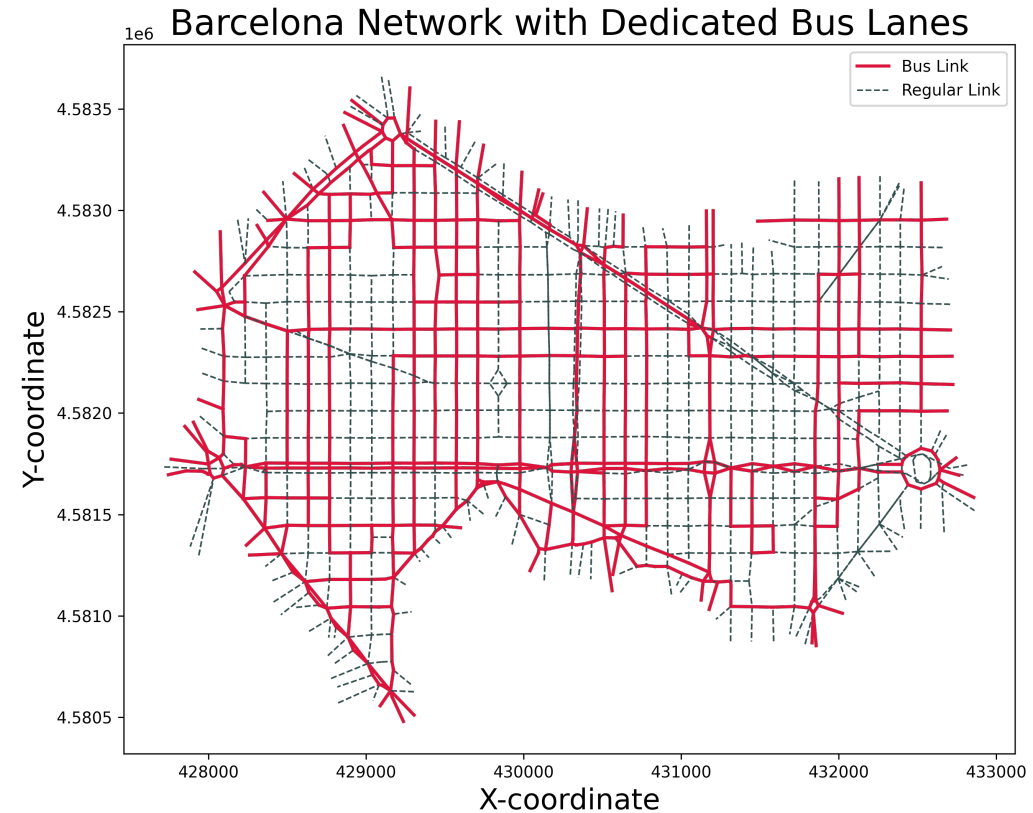
- GAT: dynamically weigh the influence of different nodes in a network
 - Spatial features: (10 features)
 - ✓ Length of link, number of lanes, number of upstream/downstream links, number of virtual links in upstream/downstream, ratio of lane reduction, number of bus lanes at upstream/downstream, label of partitioned sub-network
- GRU: efficiently captures temporal dependencies by using gates to regulate the flow of information
 - Average speed of speed MFD
 - Temporal features: average speed of each sub-network at previous time steps (4 steps)



Performance Evaluation

Target area – Barcelona Network

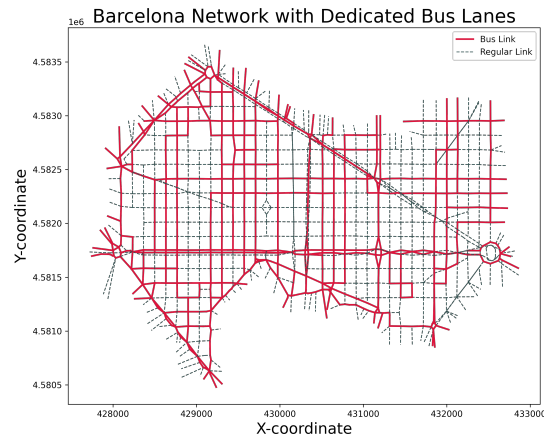
- Number of links: 1570
- Number of nodes: 933
- Number of lanes: 1 to 5
- Number of dedicated bus lanes: 818
 - At least 2 lanes included in the link
 - Adjust the existence of bus lanes to change the road configuration
- Number of signalized junctions: 565



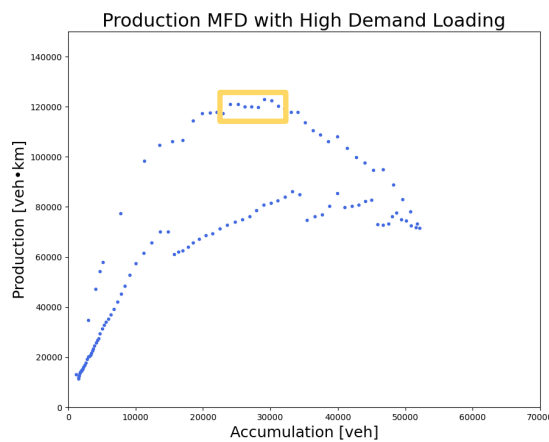
Performance Evaluation

Network partitioning

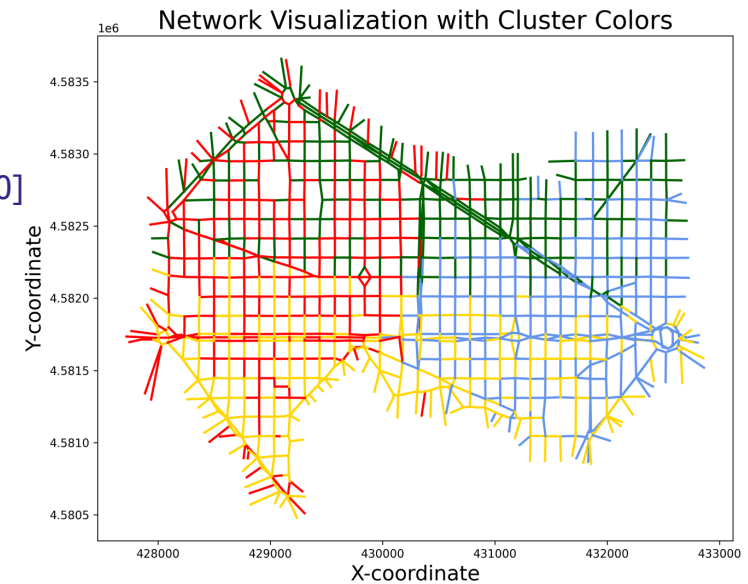
Link coordination
(X_{link}, Y_{link})



Average speed
at maximum
production
(V_{avg})



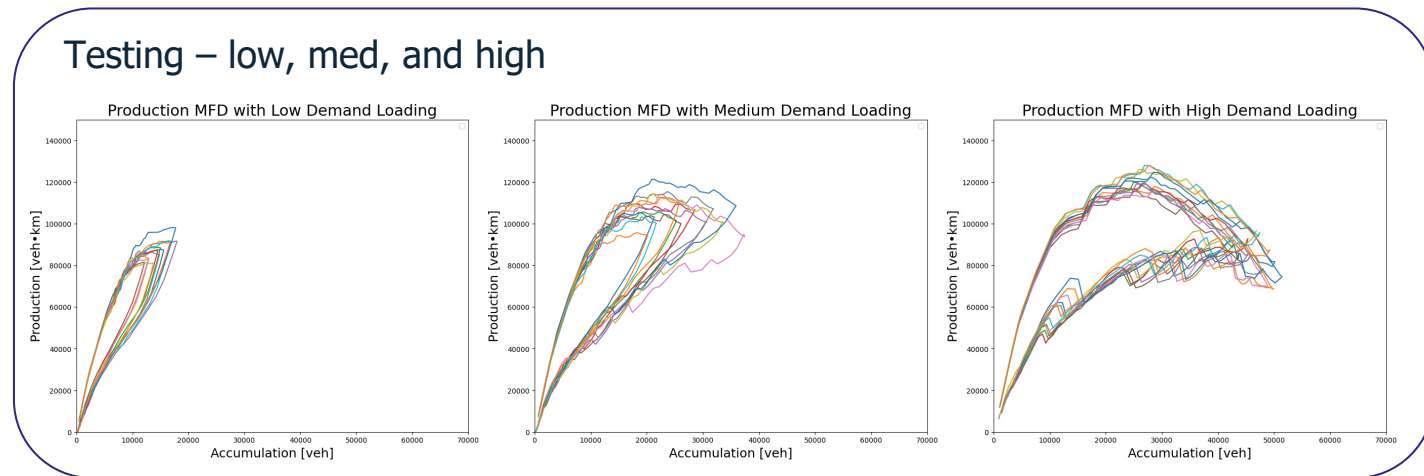
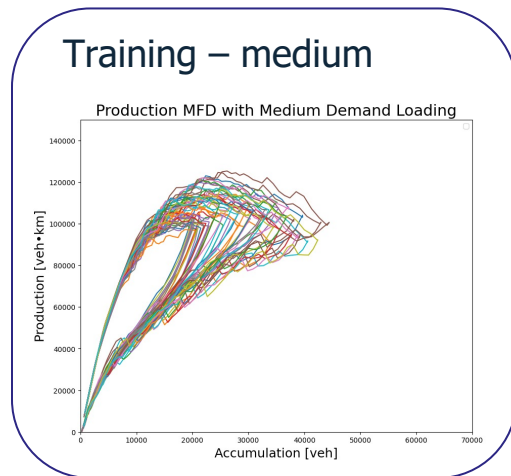
Clustering^[9,10]



Performance Evaluation

Data generation - Simulation

- Macroscopic, Queue-based Store-and-Forward (SaF) paradigm with enhanced structural properties derived by S-Model^[11]
- Various scenario
 - Different OD, demand, road configuration
 - 6h simulation, 120 time steps, 3min aggregated/step
 - **Estimate the speed of the link at each time step**
- Three types of demand cases
 - Training: Medium demand, general scenarios (50 scenarios, 6000 steps)
 - Testing: 1. Normal: Medium demand, 2. Extreme: low and high demand (12 scenarios, 1440 steps)



Performance Evaluation

Data generation – Baseline models & Metrics

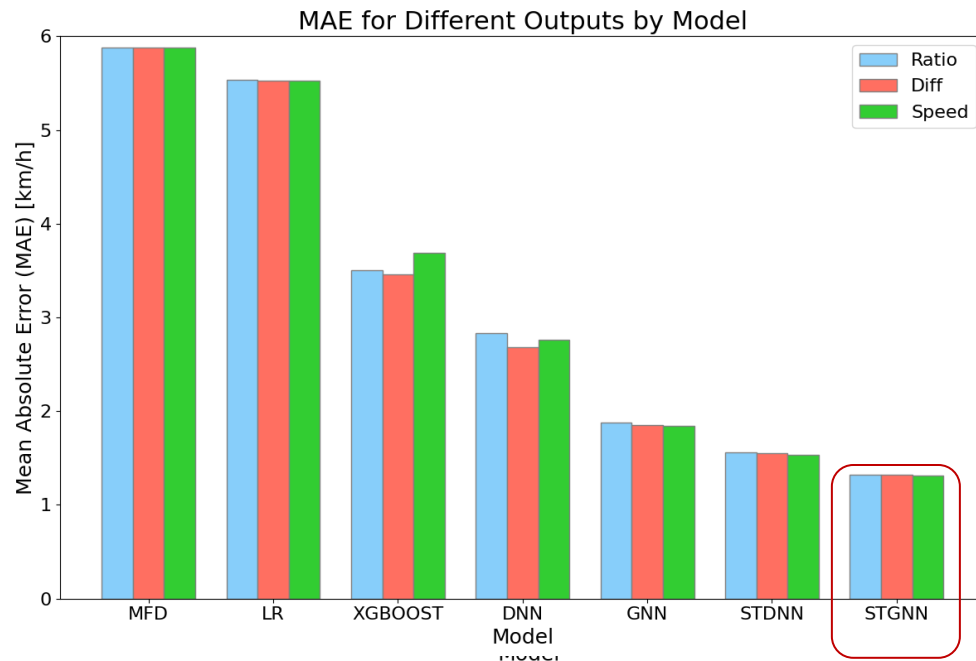
- Baseline models
 - Linear Regression, XGBoost,
 - Deep Neural Network (DNN), Graph Neural Network (GNN), Spatio-Temporal Deep Neural Network (ST-DNN), and Spatio-Temporal Graph Neural Network (ST-GNN)
- Evaluation metrics
 - **Mean Absolute Error (MAE)**, Mean Squared Error (MSE) and Root Mean Squared Error (RMSE)
- Output format
 - Ratio: Actual speed / average speed
 - Diff: Actual speed - average speed
 - Speed: Actual speed



Performance Evaluation

Result (1) – Test in normal scenario (median demand loading)

- Deep learning-based model → high performance
 - STGNN: 1.3131 km/h error
- Temporal information → improve performance
 - DNN vs STDNN, GNN vs STGNN
- Different output → small performance differences



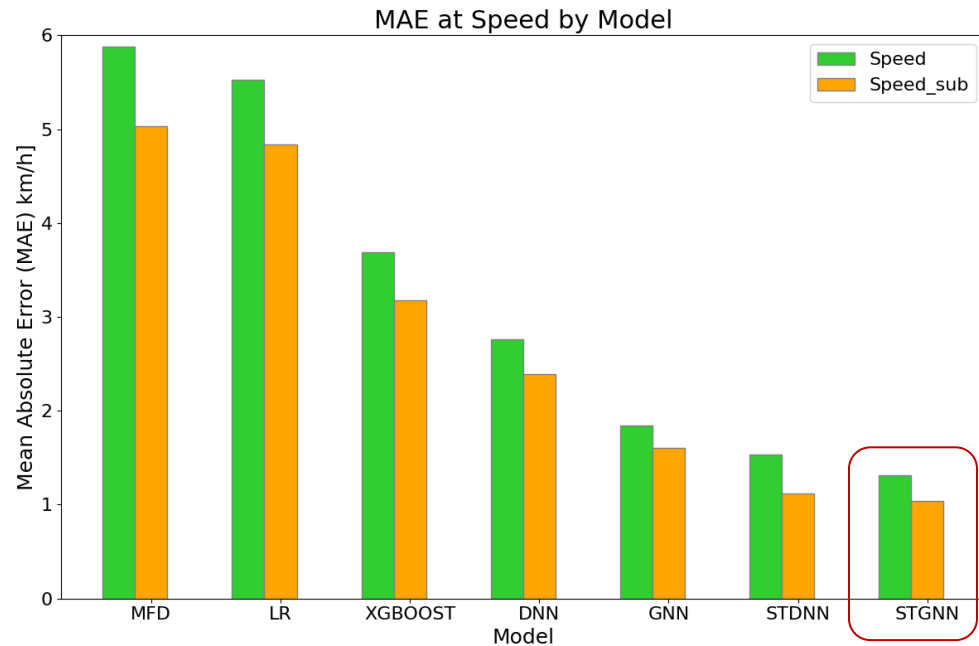
Tab 1: Performance evaluation with medium demand [km/h]

| Model | Output | MAE | MSE | Error Mean | Error STD |
|---------|--------------|---------------|---------------|----------------|---------------|
| MFD | - | 5.8808 | 48.7415 | 0.0000 | 6.9815 |
| LR | Ratio | 5.5348 | 44.1518 | 0.0119 | 6.6447 |
| | Diff | 5.5225 | 43.8645 | 0.0058 | 6.6230 |
| | Speed | 5.5226 | 43.8645 | 0.0066 | 6.6230 |
| XGBOOST | Ratio | 3.5032 | 25.0235 | 0.0934 | 5.0015 |
| | Diff | 3.4632 | 24.7820 | 0.0661 | 4.9777 |
| | Speed | 3.6887 | 27.2620 | 0.1501 | 5.2191 |
| DNN | Ratio | 2.8330 | 20.7619 | 0.2742 | 4.5483 |
| | Diff | 2.6806 | 19.7136 | 0.1808 | 4.4363 |
| | Speed | 2.7575 | 20.5260 | 0.2339 | 4.5245 |
| GNN | Ratio | 1.8784 | 12.8576 | 0.0471 | 3.5854 |
| | Diff | 1.8540 | 12.6814 | 0.0673 | 3.5605 |
| | Speed | 1.8466 | 12.8286 | 0.0954 | 3.5804 |
| STDNN | Ratio | 1.5591 | 8.8222 | 0.0806 | 2.9691 |
| | Diff | 1.5492 | 8.8086 | 0.0628 | 2.9587 |
| | Speed | 1.5338 | 8.7474 | 0.0538 | 2.9571 |
| STGNN | Ratio | 1.3250 | 7.6582 | 0.0649 | 2.7683 |
| | Diff | 1.3251 | 7.3392 | 0.0649 | 2.7083 |
| | Speed | 1.3131 | 7.3091 | -0.0124 | 2.7073 |

Performance Evaluation

Result (2) – Effect of network partitioning (median demand loading)

- Add network partitioned information → improve overall performances
 - STGNN: 1.0404 km/h error → 0.3km/h improvement
 - Efficient in model performance



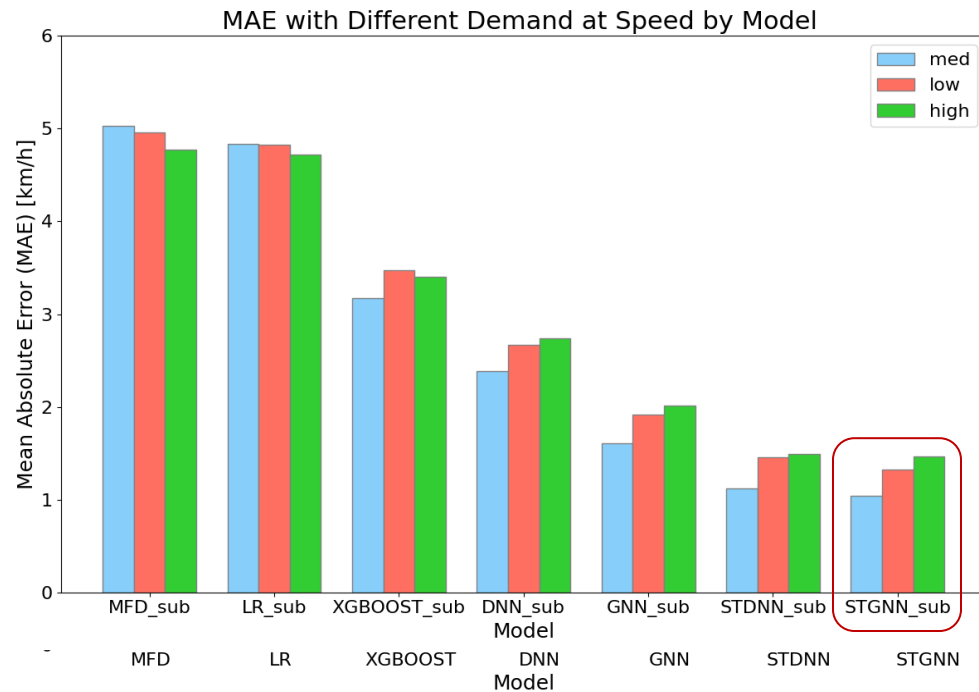
Tab 2: Performance evaluation with medium demand [km/h]

| Type | Model | MAE | Improve | Error Mean | Error STD |
|--------------|------------------|---------------|---------------|----------------|---------------|
| Origin | MFD | 5.8808 | - | 0.0000 | 6.9815 |
| Origin + sub | MFD_sub | 5.0319 | 14.44% | 0.0000 | 6.1299 |
| Origin | LR | 5.5226 | - | 0.0066 | 6.6230 |
| Origin + sub | LR_sub | 4.8373 | 12.41% | 0.0048 | 5.9290 |
| Origin | XGBOOST | 3.6887 | - | 0.1501 | 5.2191 |
| Origin + sub | XGBOOST_sub | 3.1742 | 13.94% | 0.1341 | 4.7334 |
| Origin | DNN | 2.7575 | - | 0.2339 | 4.5245 |
| Origin + sub | DNN_sub | 2.3885 | 13.40% | 0.1513 | 4.1213 |
| Origin | GNN | 1.8466 | - | 0.0954 | 3.5804 |
| Origin + sub | GNN_sub | 1.6075 | 12.95% | 0.0895 | 3.1966 |
| Origin | STDNN | 1.5338 | - | 0.0538 | 2.9571 |
| Origin + sub | STDNN_sub | 1.1184 | 27.08% | 0.0321 | 2.3836 |
| Origin | STGNN | 1.3131 | - | -0.0124 | 2.7073 |
| Origin + sub | STGNN_sub | 1.0404 | 23.84% | -0.0265 | 2.3160 |

Performance Evaluation

Result (3) – Test in extreme scenarios (low and high demand loading)

- Performance slightly decreases
 - STGNN - Low: 1.3206 km/h error, high: 1.4678 km/h error
 - Robustness of model in different scenarios (demand + OD distribution+ road configuration)

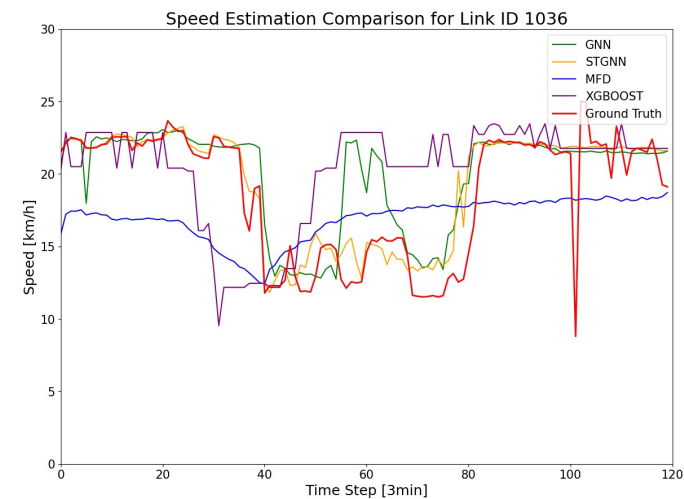
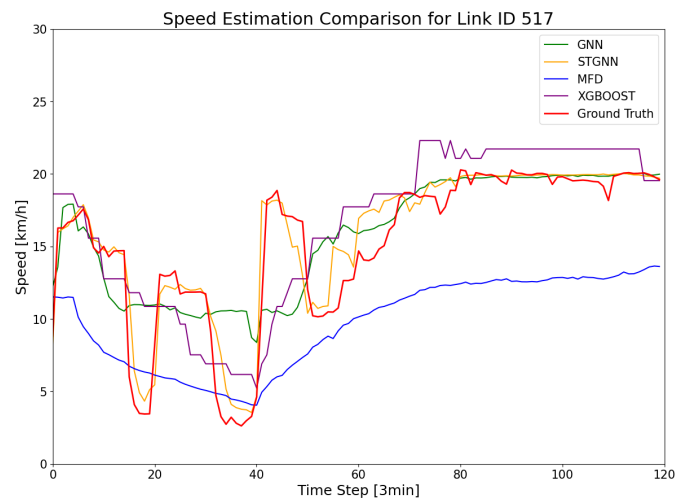
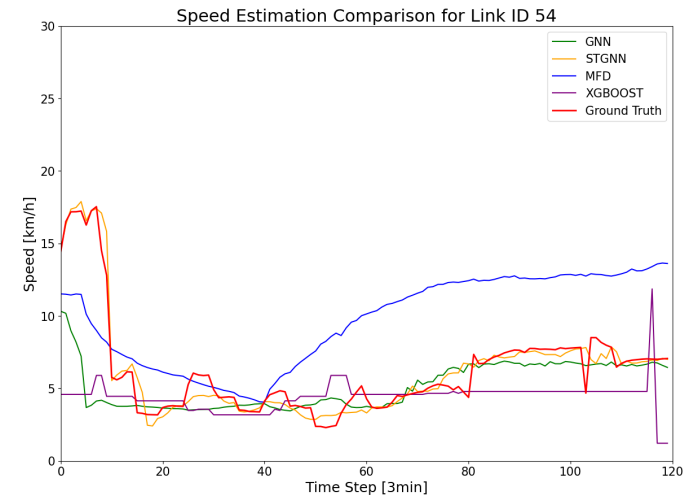
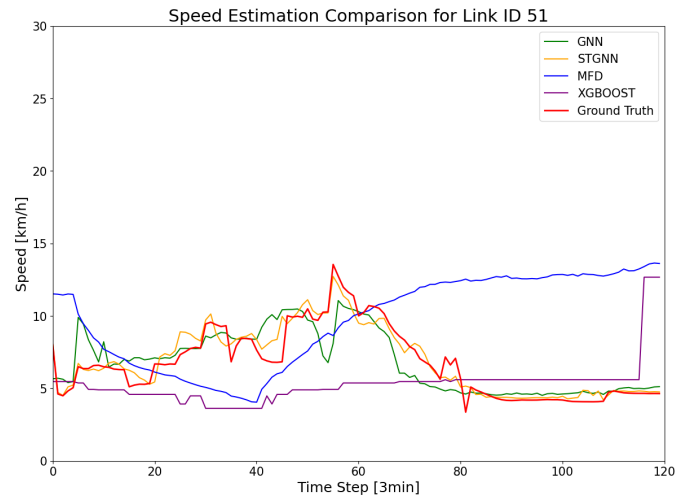


Tab 3: Performance evaluation with various demand [km/h]

| Model | Demand | MAE | Improve | Error Mean | Error STD |
|------------------|-------------|---------------|----------------|----------------|---------------|
| MFD_sub | med | 5.0319 | - | 0.0000 | 6.1299 |
| | low | 5.5052 | -9.41% | 0.0000 | 6.7059 |
| | high | 5.8304 | -15.87% | 0.0000 | 6.9921 |
| LR_sub | med | 4.8373 | - | 0.0048 | 5.9290 |
| | low | 4.8244 | -0.27% | 0.1385 | 5.9418 |
| | high | 4.7180 | -2.47% | -0.1045 | 5.8952 |
| XGBOOST_sub | med | 3.1742 | - | 0.1341 | 4.7334 |
| | low | 3.4769 | -9.54% | 0.0459 | 5.1713 |
| | high | 3.3997 | -7.10% | 0.0894 | 5.0446 |
| DNN_sub | med | 2.3885 | - | 0.1513 | 4.1213 |
| | low | 2.6696 | -11.77% | 0.1226 | 4.6639 |
| | high | 2.7350 | -14.51% | 0.0771 | 4.5994 |
| GNN_sub | med | 1.6075 | - | 0.0895 | 3.1966 |
| | low | 1.9137 | -19.05% | 0.0833 | 3.8190 |
| | high | 2.0134 | -25.25% | 0.1276 | 3.8436 |
| STDNN_sub | med | 1.1184 | - | 0.0321 | 2.3836 |
| | low | 1.4564 | -30.22% | 0.0625 | 3.1447 |
| | high | 1.4951 | -33.68% | -0.0689 | 3.1206 |
| STGNN_sub | med | 1.0404 | - | -0.0265 | 2.3160 |
| | low | 1.3206 | -26.93% | 0.1021 | 2.6330 |
| | high | 1.4678 | -41.08% | -0.0034 | 2.9863 |

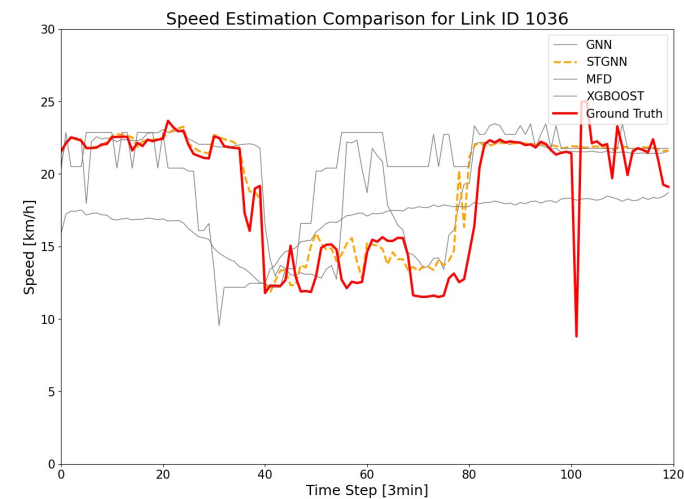
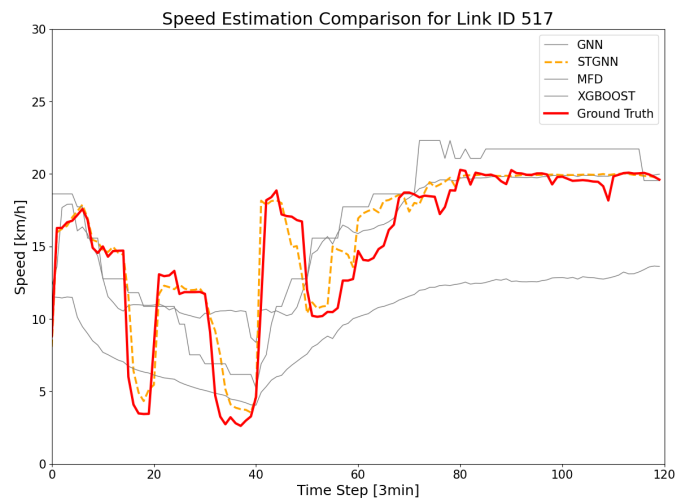
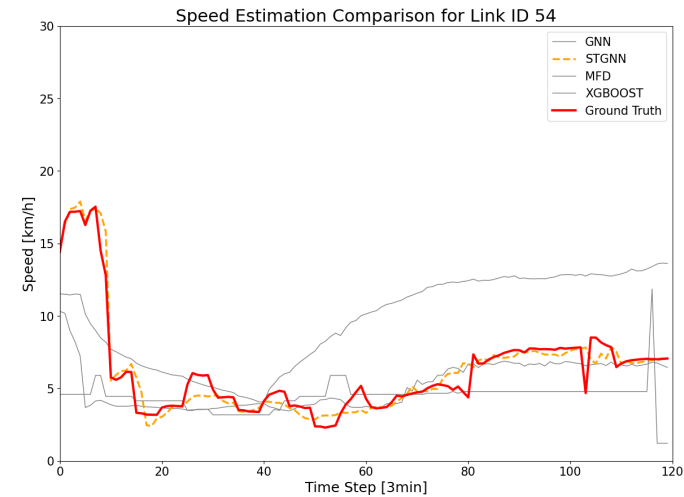
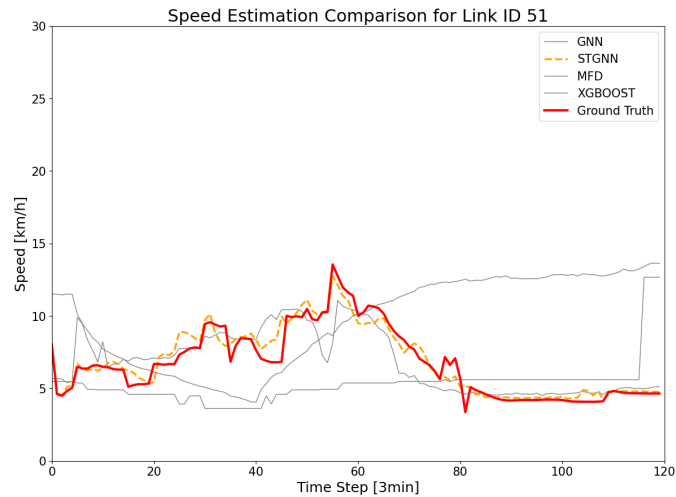
Performance Evaluation

Result (4) – Speed Visualization



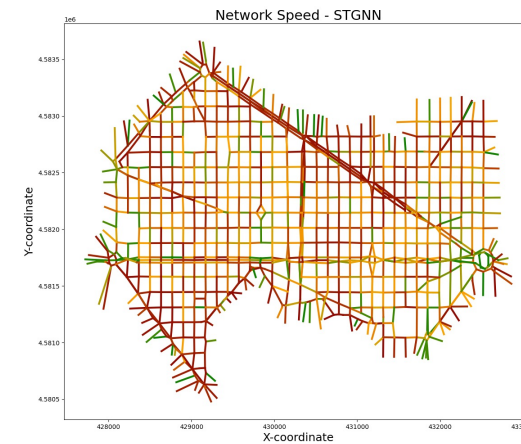
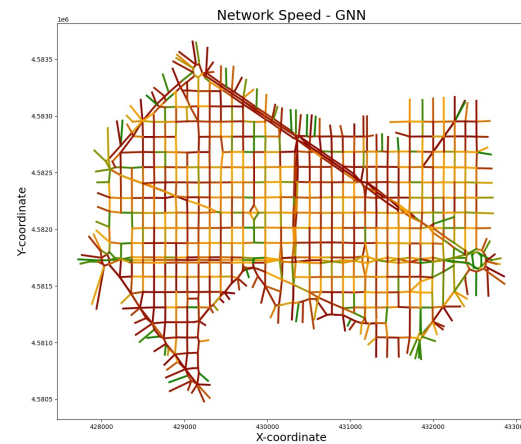
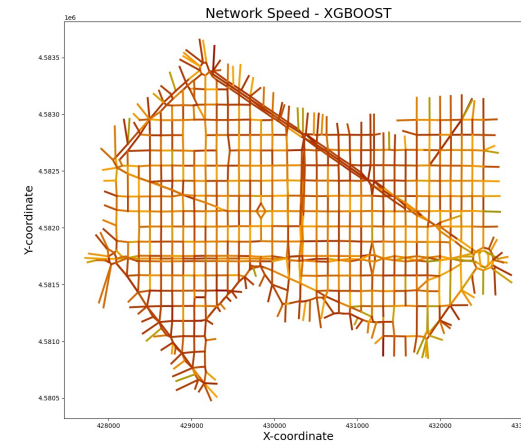
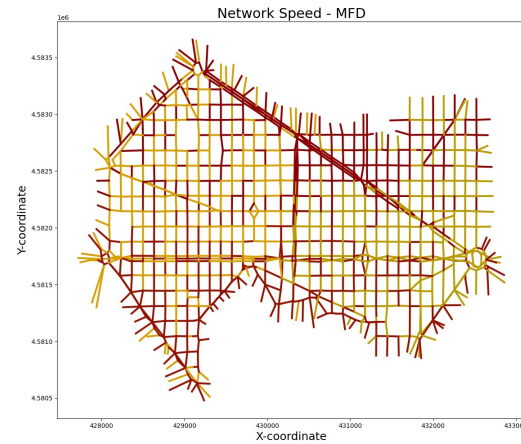
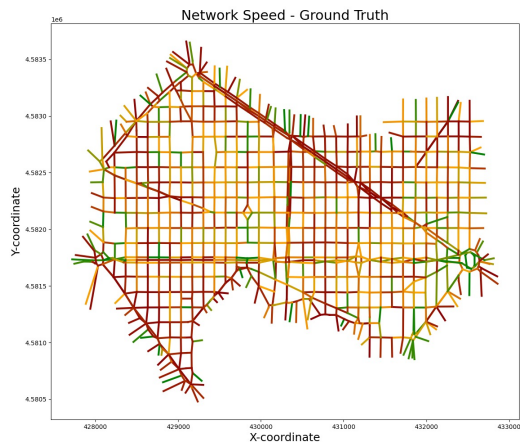
Performance Evaluation

Result (4) – Speed Visualization



Performance Evaluation

Result (5) – Network Visualization



Conclusion

Summary & Future study

- Propose a deep learning method to estimate link speed based on spatial characteristics of the network and Macroscopic Fundamental Diagram (MFD)
 - **Local correction factor**
 - STGNN shows high performance among various baseline models
 - Apply network partitioning to improve model performance
 - Robust in various scenarios (demand + OD distribution + road configuration)
- Application in future study
 - Different city networks
 - Solve traffic optimization problems



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Thank you for your attention

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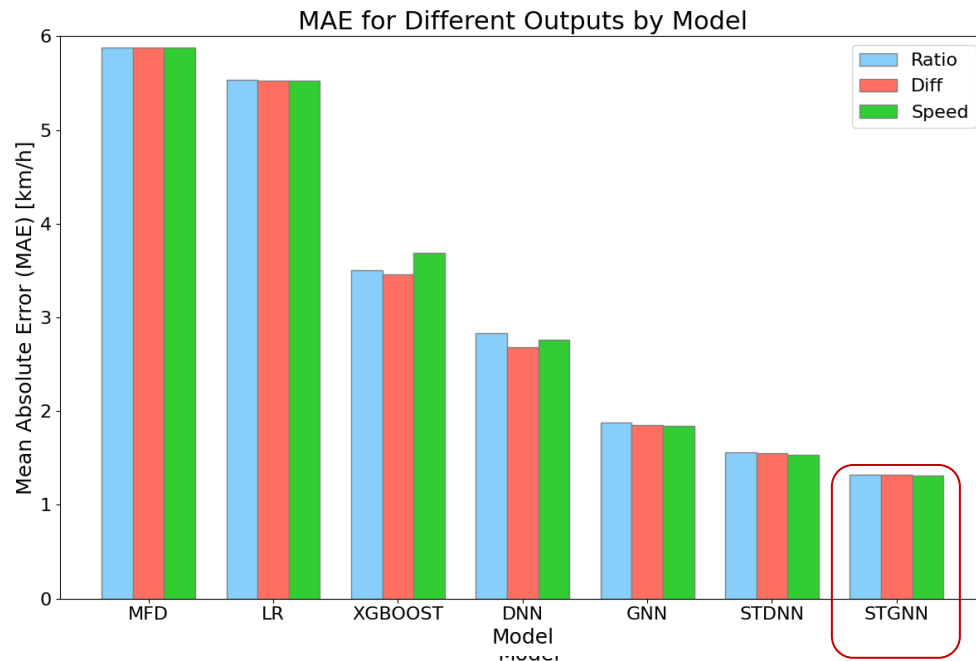
Reference

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Performance Evaluation

Result (1) – Test in normal scenario (median demand loading)

- Deep learning-based model → high performance
 - STGNN: 1.3131 km/h error
- Different output → small performance differences
- Temporal information → improve performance
 - DNN vs STDNN, GNN vs STGNN



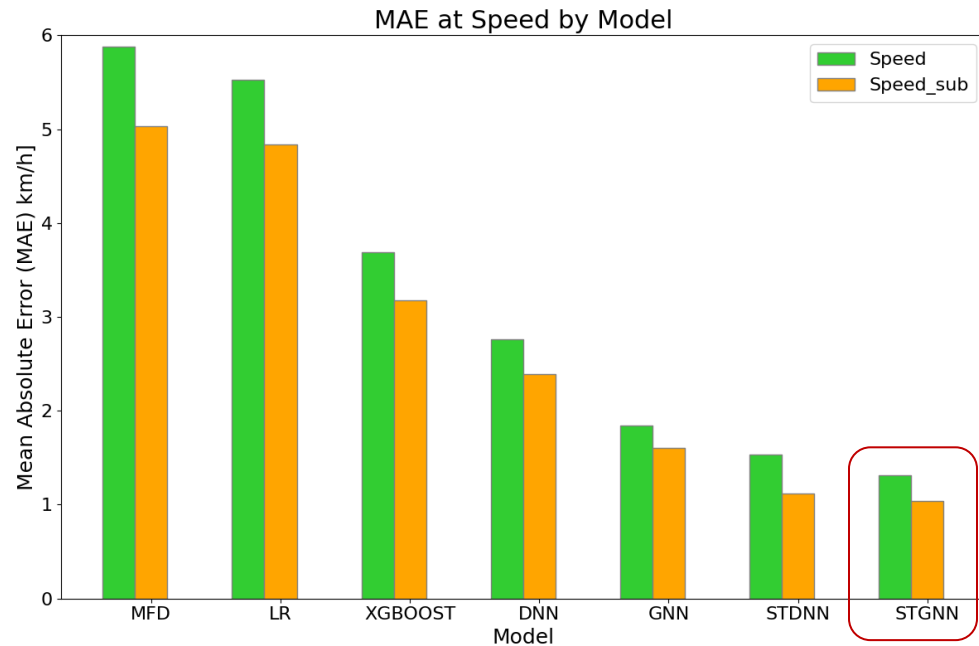
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| | Diff | 5.5225 | 43.8645 | 0.0058 | 6.6230 |
| | Speed | 5.5226 | 43.8645 | 0.0066 | 6.6230 |
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| | Diff | 3.4632 | 24.7820 | 0.0661 | 4.9777 |
| | Speed | 3.6887 | 27.2620 | 0.1501 | 5.2191 |
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| | Diff | 2.6806 | 19.7136 | 0.1808 | 4.4363 |
| | Speed | 2.7575 | 20.5260 | 0.2339 | 4.5245 |
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| | Diff | 1.3251 | 7.3392 | 0.0649 | 2.7083 |
| | Speed | 1.3131 | 7.3091 | -0.0124 | 2.7073 |

Performance Evaluation

Result (2) – Test in normal scenario (median demand loading)

- Add network partitioned information → improve overall performances
 - STGNN: 1.0404 km/h error → 0.3km/h improvement
 - Efficient in model performance



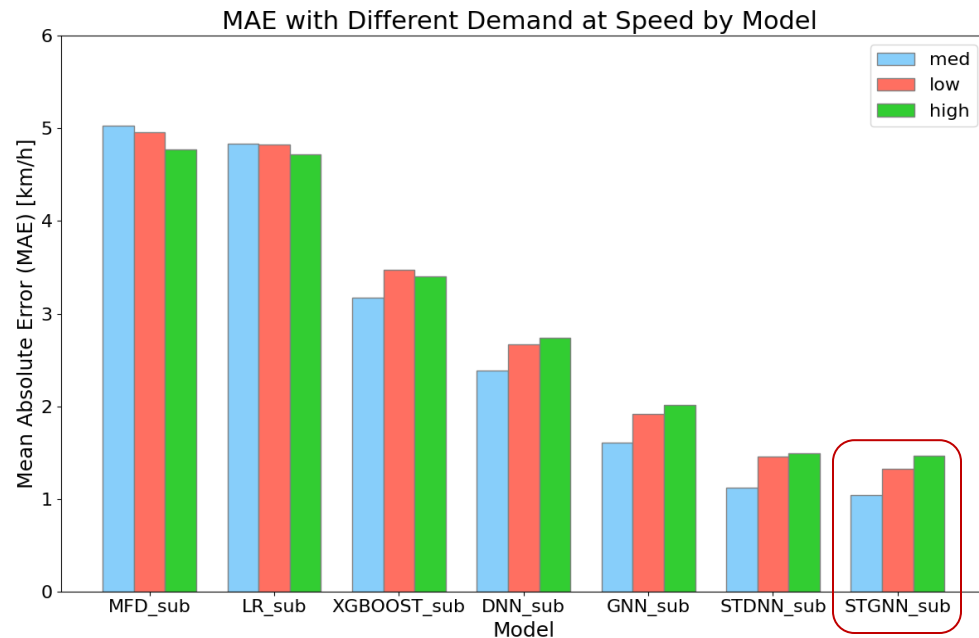
Tab 2: Performance evaluation with medium demand [km/h]

| Model | MAE | MSE | Error Mean | Error STD |
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| MFD | 5.8808 | 48.7415 | 0.0000 | 6.9815 |
| MFD_sub | 5.0319 | 37.5756 | 0.0000 | 6.1299 |
| LR | 5.5226 | 43.8645 | 0.0066 | 6.6230 |
| LR_sub | 4.8373 | 35.1528 | 0.0048 | 5.9290 |
| XGBOOST | 3.6887 | 27.2620 | 0.1501 | 5.2191 |
| XGBOOST_sub | 3.1742 | 22.4228 | 0.1341 | 4.7334 |
| DNN | 2.7575 | 20.5260 | 0.2339 | 4.5245 |
| DNN_sub | 2.3885 | 17.0077 | 0.1513 | 4.1213 |
| GNN | 1.8466 | 12.8286 | 0.0954 | 3.5804 |
| GNN_sub | 1.6075 | 10.2265 | 0.0895 | 3.1966 |
| STDNN | 1.5338 | 8.7474 | 0.0538 | 2.9571 |
| STDNN_sub | 1.1184 | 5.6825 | 0.0321 | 2.3836 |
| STGNN | 1.3131 | 7.3392 | -0.0124 | 2.7073 |
| STGNN_sub | 1.0404 | 5.3646 | -0.0265 | 2.3160 |

Performance Evaluation

Result (3) – Test in extreme scenarios (low and high demand loading)

- Performance slightly decreases
 - STGNN - Low: 1.3206 km/h error, high: 1.4678 km/h error
 - Robustness of model in different scenarios (demand + OD + road configuration)



Tab 3: Performance evaluation with various demand [km/h]

| Model | Demand | MAE | MSE | RMSE | Error Mean | Error STD |
|-------------|--------|--------|---------|--------|------------|-----------|
| MFD_sub | med | 5.0319 | 37.5756 | 6.1299 | 0.0000 | 6.1299 |
| | low | 5.5052 | 44.9693 | 6.7059 | 0.0000 | 6.7059 |
| | high | 5.8304 | 48.8893 | 6.9921 | 0.0000 | 6.9921 |
| LR_sub | med | 4.8373 | 35.1528 | 5.9290 | 0.0048 | 5.9290 |
| | low | 4.8244 | 35.3243 | 5.9434 | 0.1385 | 5.9418 |
| | high | 4.7180 | 34.7639 | 5.8961 | -0.1045 | 5.8952 |
| XGBOOST_sub | med | 3.1742 | 22.4228 | 4.7353 | 0.1341 | 4.7334 |
| | low | 3.4769 | 26.7450 | 5.1716 | 0.0459 | 5.1713 |
| | high | 3.3997 | 25.4555 | 5.0453 | 0.0894 | 5.0446 |
| DNN_sub | med | 2.3885 | 17.0077 | 4.1240 | 0.1513 | 4.1213 |
| | low | 2.6696 | 21.7672 | 4.6655 | 0.1226 | 4.6639 |
| | high | 2.7350 | 21.1608 | 4.6001 | 0.0771 | 4.5994 |
| GNN_sub | med | 1.6075 | 10.2265 | 3.1979 | 0.0895 | 3.1966 |
| | low | 1.9137 | 14.5917 | 3.8199 | 0.0833 | 3.8190 |
| | high | 2.0134 | 14.7896 | 3.8457 | 0.1276 | 3.8436 |
| STDNN_sub | med | 1.1184 | 5.6825 | 2.3838 | 0.0321 | 2.3836 |
| | low | 1.4564 | 9.8931 | 3.1453 | 0.0625 | 3.1447 |
| | high | 1.4951 | 9.7429 | 3.1214 | -0.0689 | 3.1206 |
| STGNN_sub | med | 1.0404 | 5.3646 | 2.3162 | -0.0265 | 2.3160 |
| | low | 1.3206 | 6.9429 | 2.6349 | 0.1021 | 2.6330 |
| | high | 1.4678 | 8.9182 | 2.9863 | -0.0034 | 2.9863 |