Data Fusion: Traffic Flow Estimation Based on a GNN Approach for Loop Detector Data

Leveraging Spatio-Temporal Features and Floating Car Data – A work in progress

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European Transport Conference 2025

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Why Accurate Traffic Data is Crucial for ITS

Accurate traffic state variables—flow, speed, and density—are the bedrock of modern Intelligent Transportation Systems (ITS) [1]. They directly enable:

Real-Time Operations

- Adaptive traffic signal control
- Incident detection & management [2]
- Dynamic route guidance [3]

Strategic Planning & Analysis

- Identifying congestion bottlenecks [4]
- Infrastructure investment planning [5]
- Environmental impact modeling [6]

Without a complete and accurate picture of the traffic state, these applications fail or become unreliable.

The Data Reality: Two Imperfect Sources

To understand the traffic state, we primarily rely on two data types, each with significant limitations:

Eulerian Data(Fixed Sensors)

- E.g., Loop Detectors [7]
- Provide point-based "ground truth".
- Problem: Suffer from frequent failures, creating spatial and temporal data gaps.

Lagrangian Data (Mobile Sensors)

- E.g., Floating Car Data (FCD) [8]
- Provides wide network coverage.
- Problem: A biased sample with unknown and variable penetration rates.

The core challenge is to fuse these imperfect sources to create a complete and accurate picture.

Related Work: Forecasting Methods & Their Limits

Classical approaches struggle with the complex nature of traffic networks:

- **Simulation-based Models** (e.g., micro/meso/macro) [9] *Limit:* Often computationally expensive for large networks or they oversimplify vehicle behavior.
- **Deterministic Models** (e.g., Kinematic Wave Theory) [10] *Limit:* Struggle to capture the stochastic, non-linear dynamics of real-world traffic.
- **Statistical & Classic ML** (e.g., ARIMA, SVR) [11, 12] *Limit:* Often treat sensors as independent time-series, failing to model the crucial spatial relationships between them.

The fundamental limitation

Traffic is inherently a **graph**—a network of interconnected sensors. Models that ignore this topology will have limited success.

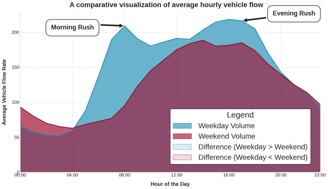
Presentation Outline

This presentation of our work-in-progress is structured in three parts:

1. **Data Pipelines & Ground Truth Creation**
   Detailing the study area, data sources (LDD, FCD), and the fusion process.
2. **Analysis of FCD Penetration Rate Dynamics**
   Investigating the key factors that influence the representativeness of FCD.
3. **GNN-based Data Imputation**
   Presenting the spatio-temporal model design, experimental setup, and key results for filling data gaps.

Data Pipeline I: Loop Detector Data (LDD)

Map of the study area and loop detectors



Average hourly traffic flow; typical weekday vs. a weekend day.

Source: High-Resolution LDD [13]

- More than 500 detectors, providing minute-by-minute flow (q) and occupancy (o).
- Serves as our ground truth for total vehicle counts (N_{Total}).

Pre-processing Pipeline:

- Flagging of invalid data based on physical constraints (e.g., $o \notin [0, 100]$, $q > C_{max}$).
- Removal of detectors with less than 5% data availability.
- Imputation and aggregation to 10-minute intervals.

Data Pipeline II: Floating Car Data (FCD)

Source: Commercial FCD [14]

- ≈ 19M raw trips
- ≈ 3M unique devices
- Provides probe counts (N_{FCD})

Preprocessing Pipeline:

- Geospatial filtering
- Large-scale map-matching to OSM using Valhalla [15, 16]

Raw FCD trajectories (left) vs. map-matched network volume (right).

Data Pipeline III: Fusion for Ground Truth Analysis

To analyze FCD representativeness, we fuse the two data streams at co-located points on the OSM network.

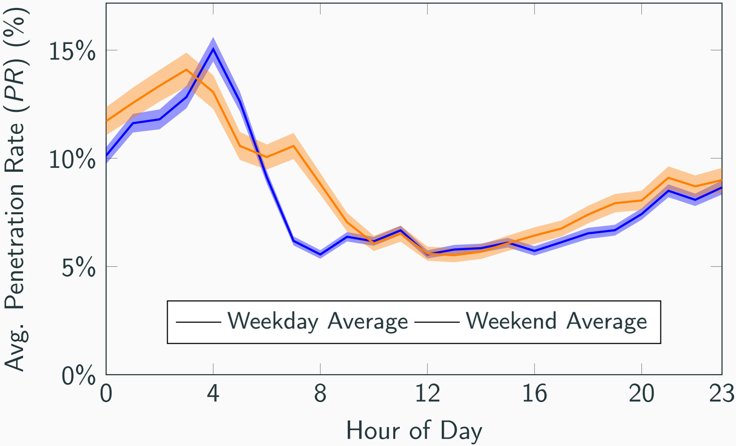
- LDD sensors are spatially mapped to their corresponding OSM road segments.
- FCD trips are counted as they traverse these same segments.

This allows us to calculate the empirical **Penetration Rate (PR)** for any location l at time t:

$$PR(l,t) = \frac{N_{FCD}(l,t)}{N_{Total}(l,t)}$$

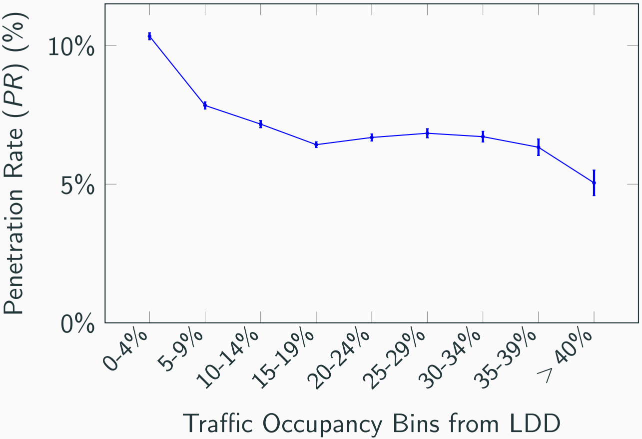
This fused dataset is the foundation for both understanding FCD bias and for training our GNN.

FCD Analysis I: Temporal Dynamics of Penetration Rate



- While both day types follow a similar daily pattern, with peaks in the early morning and evening, **weekends** show a significantly **higher PR** during the day.

FCD Analysis II: Impact of Congestion on PR



- Increased traffic congestion causes a significant drop in the Penetration Rate.
- This is likely due to the traffic avoidance behavior of taxi and fleet drivers.

GNN Model Design for Data Imputation

To capture the network's spatio-temporal nature, we designed a GATGRU model.

1. **Graph Representation**
   - Sensors are nodes (V).
   - Connectivity forms edges (E).
   - Edge weights are a Gaussian kernel on distance:

$$A_{ij} = \exp\left(-\frac{\text{dist}(i,j)^2}{\sigma^2}\right)$$

2. **Input Features**
   - LDD history (flow, occ, speed)
   - Temporal Embeddings (time of day, day of week)

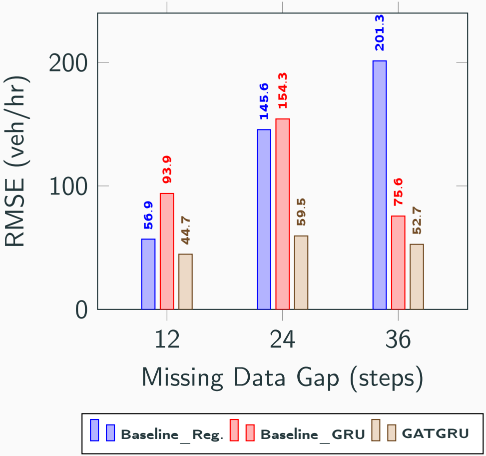
3. **GATGRU Architecture**
   - A **Graph Attention (GAT)** layer aggregates spatial information from important neighbors.
   - A **Gated Recurrent Unit (GRU)** layer processes the output as a time-series to learn temporal patterns.

GNN Experiment: Setup & Flow Imputation Results

Setup

- **Task:** Impute artificially created data gaps in the test set.
- **Models Compared:**
  - ‘Baseline_Reg.‘: Statistical
  - ‘Baseline_GRU‘: Temporal
  - ‘GATGRU‘: Spatio-Temporal
- **Scenarios:** 2, 4, and 6-hour gaps (12, 24, 36 steps).
- **Metric:** RMSE

Flow Imputation (RMSE)

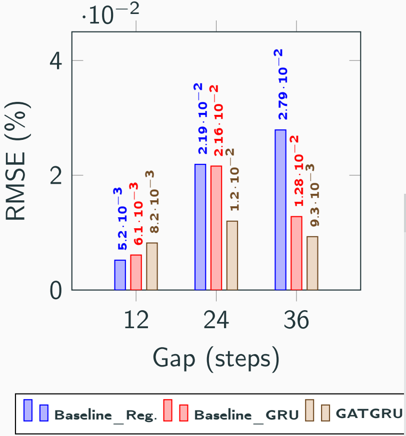


Insight: The spatio-temporal GATGRU model consistently and significantly outperforms both baselines, especially for longer gaps.

GNN Experiment: Occupancy Results & Performance Gain

The GATGRU model's advantage becomes more pronounced as the imputation task becomes more difficult.

Occupancy Imputation (RMSE)



GATGRU Advantage over Best Baseline (Flow RMSE)

- At 2-hour gap: **21%** lower error
- At 4-hour gap: 59% lower error
- At 6-hour gap: 74% lower error

Key Takeaway

The GNN's ability to leverage spatial information from neighboring sensors provides a massive advantage when local temporal data is missing for extended periods.

Discussion

Why does the GNN-based fusion approach work?

- **Spatial Learning (GAT):** The model learns which neighboring sensors are most influential.
- **Temporal Learning (GRU):** The model captures recurring patterns (e.g., rush hours), allowing it to make context-aware predictions.
- **Feature Fusion Value:** The model is enhanced by exogenous features. Temporal embeddings provide crucial time context.

- **FCD such as counts and speed can provide an "independent witness" signal, and could be potentially beneficial for model accuracy**

Applications & Future Work

Our trained models enables several practical applications:

- Enables investigating the features changing PR
- Estimation of traffic flow on street level granularity
- Enhanced inputs for emission models and traffic models.

Future Work:

- Directly integrate FCD counts and speed as a feature to quantify its impact.
- Explore features proven to be important in PR estimation

Conclusion

1. **Problem:** Missing data from physical sensors is a significant barrier for effective Intelligent Transportation Systems.
2. Our experiments demonstrate that FCD and LDD have variable spatial and temporal relations.
3. We proposed a spatio-temporal GNN model that learns from the sensor network structure and temporal patterns to impute missing data.

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Thank You

Questions?