Real-Time Analysis on Spatio-Temporal Vehicle Graphs

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Introduction: The Need for Urban Transport to Have Real-Time Spatio-Temporal Analytics

As the city expands, traffic becomes more and more complicated within it, and problems such as traffic congestion, hazardous intersections, and pollution are aggravated. Hence, the capacity to estimate traffic flow in real time is most important now, not only for coordinating current infrastructure but also for the future optimization of urban mobility using ITS and smart city initiatives. For improving traffic, unclogging roads, and improving public and commercial transport safety, real-time prediction is the most important aspect. This functionality not only enhances traffic management, but also contributes to the efficiency of autonomous cars and other intelligent transportation systems.

The research in this field has graduated from issues of prediction to more aggressive measures that entail maximizing systems for a variety of applications, including autonomous vehicles and dynamic traffic management. Forecasting techniques for traffic have developed from simple statistical approaches to complex deep learning approaches.

Earlier models, either Auto-Regressive Integrated Moving Average (ARIMA) or machine learning algorithms such as Support Vector Machines (SVM), were adequate but maybe not impactful enough to capture the advanced patterns of traffic flows. These models had difficulty with the inherent level of urban mobility that entailed complex, nonlinear, and non-Euclidean relationships that are impossible to model through the conventional models. The development of Graph Neural Networks (GNNs) has been one such step forward. Since road networks by definition are analogous to graphs—road intersections as nodes and highways as edges—GNNs introduce a more natural and intuitive way of modeling the inter-connections between various road segments and traffic sensors.

As opposed to Convolutional Neural Networks (CNNs) conventionally employed to manage grid-based data (e.g., images), GNNs come naturally equipped to represent non-Euclidean road network topology. A shift of this kind revolutionized traffic forecasting, and GNNs are now an integral component of traffic analysis today. In spite of all these advancements, future traffic states (e.g., traffic speed, vehicle flow, or motion behavior) remain difficult to predict. This is largely due to the dynamic and intricate interdependencies in spatial (road segments influencing one another) and temporal spaces (prior states affecting subsequent states). The need for models that can accommodate such detailed, large numbers of relationships in real-time is the motivating force behind much of the state-of-the-art work and developments in this field.

1 Literature Review: Urban Intersection and Citywide Traffic Flow Prediction

1.1 Urban Intersection Traffic Flow Forecasting: A Physics-Guided Step-by-step Process Based on Spatio-Temporal Graph Neural Network Algorithms

Authors & Year: Y. A. Pan et al., 2025.
Venue: Multimodal Transportation (Elsevier)

The paper by Pan et al. is devoted to the strange problems at urban intersections where signal phases, stop-and-go traffic, and turning movements of vehicles create unstable flow regimes. Unlike employing a generic STGNN directly, the authors introduce a physics-guided spatio-temporal parsimonious framework (PG-STGNN) which synthesizes traffic flow theory into model design. The pipeline begins with stage-wise feature processing according to shockwave propagation, queue discharge, and signal coordination. Graph edges are defined in terms of lane-arm connectivity and signal phase relations rather than spatial proximity. The temporal module is designed to predict multi-step traffic conditions under rapid phase changes. Integrating domain-relevant traffic dynamics, the model significantly improves short-term prediction quality at advanced signalized intersections.

However, reliance on reliable signal timing plans as well as saturation flow parameters is a portability issue. Many intersections in emerging cities lack such structured metadata, limiting immediate deployment. Additionally, the model generalizes poorly to unsignalized intersections or mixed-priority junctions characterized by pedestrian flow and informal traffic behavior.

1.2 Long-Term Spatio-Temporal Graph Attention Network for Traffic Forecasting (LSTGAN)

Authors & Year: B. Remmouche et al., 2025.
Venue: Expert Systems with Applications (Elsevier)

Remmouche et al. address the long-term prediction horizon gap problem in traffic forecasting, arguing that most STGNN architectures lose accuracy with increasing prediction horizons because of the accumulation of errors and the temporal gradient drop. Their Long-Term Spatio-Temporal Graph Attention Network (LSTGAN) integrates graph attention with temporal convolution to capture periodic daily and weekly mobility patterns. The attention mechanism selectively assigns weight to noteworthy spatial neighbors, while residual temporal blocks maintain long-range dependencies. The model exhibits better performance on 15–60-minute prediction windows than traditional GCN-GRU hybrids.

Although effective, the architecture entails high computational cost due to attention applied over large time sequences. The reliance on continuous historical sensor data means that missing values or irregular sampling critically influence stability. Furthermore, while the model enhances deterministic prediction, it is not fitted with uncertainty estimation.

1.3 Spatio-Temporal Interactive Graph Convolution Network for Vehicle Trajectory Prediction (STI-GCN)

Authors & Year: G. Shen et al., 2023.
Venue: Patterns (Cell Press)

Shen et al. shift the focus from network-level flow prediction to fine-grained vehicle trajectory prediction. STI-GCN varies from typical grid-based LSTM or CNN-based motion models in that it builds a dynamic interaction graph where each vehicle is represented as a node, and influence is captured via learned interaction kernels rather than basic Euclidean distances. Temporal history is represented by a CNN, while dynamic spatial interactions are modeled by GRU and GCN layers. The adaptive graph changes dynamically when cars enter and exit the perception range, representing more realistic on-road behavior.

The model performance, however, depends heavily on stable multi-agent tracking. ID switches, occlusions, or partial visibility violate graph coherence, lower the quality of predictions. There is also no explicit use of roadway semantics such as lane regulations or priority logic, which can help with infrequent-case scenarios such as U-turns or forceful maneuvers.

1.4 Dynamic Multi-Graph Spatio-Temporal Graph Traffic Flow Prediction in Bangkok (DMST-GNODE)

Authors & Year: P. Promsawat et al., 2024–2025.
Venue: Computer Modeling in Engineering & Sciences (CMES)

Proomsawat et al. note that single-graph STGNNs cannot capture the diverse relations present in complex megacities such as Bangkok. Their DMST-GNODE model constructs personal distance-based, functional class-based, and statistical correlation-based graphs separately, which are then merged using attention layers. Neural Ordinary Differential Equations are used to model continuous-time transitions to facilitate robustness against asymmetrical sampling and diffusion delay effects. Experimental application to Bangkok yields higher accuracy compared to STGCN and DCRNN.

The model introduces engineering complexity due to demands for ODE solver tuning and construction of multiple graph structures. Training involves high memory usage and latency, which makes it difficult to carry out streaming in real time without the use of acceleration.

1.5 Attention-Based Dynamic Multi-Graph Module for Citywide Prediction (ADMGM)

Authors & Year: A. Ali et al., 2025.
Venue: Chaos, Solitons & Fractals

Ali et al. propose ADMGM as an extension of dynamic graph learning with a focus on scalability and privacy retention. The method integrates different adjacency types—spatial neighborhoodbased, and time-dependent—and learns attention weights to adaptively combine them. Federated Learning is integrated into an edge computing platform, enabling distributed updating. The Adaptive Enhancement Module learns long-term edge-level embeddings to uncover hidden correlations.

Despite its novelty, federated learning and dynamic graph attention introduction in both examples poses synchronization challenges when deployed on heterogeneous edge devices. Local model update non-uniformity and communication delays induce convergence instability.

2 Implementation

The PG-STGNN framework has been implemented as an end-to-end Python system that accurately mirrors the methodology outlined in the research paper with added practical optimizations for real-world implementation. The implementation adheres to the four-step framework laid out in the original research:

2.1 Step 1: Network Graph Construction

The model builds an intersection graph with each node capturing a traffic movement (through, left, right turns) from various approaches. The graph constructor establishes spatial relations among nodes utilizing PyTorch Geometric, with node features being lane structure, road type, speed limit, and movement feature. The adjacency matrix encodes the connectivity among various traffic movements in an intersection.

2.2 Step 2: Physics Traffic Performance Embedding

This module applies traffic flow theory to the machine learning paradigm by computing:

- Volume-to-capacity (V/C) ratios to estimate intersection saturation
- Queue dynamics based on simplified traffic flow equations
- Flow characteristics such as mean flow, standard deviation, and peak flows
- Congestion levels from real-time traffic conditions

2.3 Step 3: PG-STGNN Model Architecture

The central model incorporates three essential components:

- **Spatial Feature Modeling**: utilizes Graph Convolutional Networks (GCN) to learn relations between various traffic movements.
- **Temporal Series Modeling**: utilizes Long Short-Term Memory (LSTM) networks to learn temporal patterns in traffic flow.
- **Physics Integration Layer**: combines the spatial-temporal characteristics with physics-inspired constraints to ensure predictions obey traffic flow principles.

2.4 Step 4: Performance Assessment

The framework includes evaluation metrics (MAE, RMSE, MAPE, R^2) and compares PG-STGNN to baseline models such as:

- Naive baselines (last value, seasonal)
- Spatial regression models
- Classic time series (ARIMA)
- New-style forecasting (Prophet)

3 Results and Analysis

3.1 Performance Comparison

Model	MAE	RMSE	MAPE	R^2
Naive (Last Value)	23.1342	28.3776	71.16%	-1.6727
Naive (Seasonal)	22.2462	27.4768	68.20%	-1.5057
Spatial Regression	4.0005	5.6291	16.04%	0.8948
ARIMA	29.1438	33.9214	100.00%	-2.8190
Prophet	16.9044	20.3570	92.26%	-0.3754
PG-STGNN	9.3096	12.1757	40.20%	0.5238

3.2 Key Findings

- **Spatial Regression Dominance:** Unexpectedly, the Spatial Regression model performed best on every criterion.
- **PG-STGNN Intermediate Performance:** The PG-STGNN model showed excellent performance but did not outperform Spatial Regression.
- **Impact of Physics Guidance:** PG-STGNN's physics-based elements added interpretability.
- **Conventional Model Limitations:** ARIMA and Prophet models had poor performance.
- **Computational Trade-offs:** PG-STGNN is more computationally expensive but more scalable for complex patterns.

4 Conclusion

In this, we discussed the requirement of real-time spatio-temporal analytics for city transit systems in terms of optimizing traffic forecasting based on advanced Graph Neural Networks (GNNs). Ambiguity of city traffic, driven by congestion, unpredictable driver behavior, and environmental constraints, calls for real-time prediction models that can cope with spatial and temporal correlations. Previously used models like ARIMA and SVM were not capable of preserving the intricate, non-Euclidean relations inherent to traffic networks but GNNs provide a good alternative.

Literature review discovered numerous methods in the literature, such as physics-guided models and dynamic multi-graphs, that sought to address different facets of traffic forecasting with variable degrees of success. Of particular interest was the PG-STGNN (Physics-Guided Spatio-Temporal Graph Neural Network) approach constructed in this paper that demonstrated how deep learning might be supplemented by domain knowledge to improve short-term traffic prediction, especially in complex city intersection contexts.

But while the positive outcomes are welcome, there are a few challenges. Although the PG-STGNN model is beneficial, computation complexity and generalizability to unsignalized intersections challenge it. Moreover, real-time feasibility remains a challenge, especially in those local administrations that lack unstructured traffic metadata or whose computation costs for stream-based prediction are prohibitively expensive. Although the physics-based aspects of the model are useful in the sense that they provide more interpretability, they do have trade-offs in terms of scalability and adaptability.

On the performance side, comparing PG-STGNN with baseline models revealed its intermediate performance levels—better than simple models such as Naive and ARIMA but unable to outperform Spatial Regression in general. This suggests that while PG-STGNN provides beneficial interpretability and additional enhancement in realistic modeling of traffic flow dynamics, further improvements are necessary to extend its predictive quality and reduce its computational requirements.

In conclusion, this research validates the greater applicability of real-time spatio-temporal analytics to urban transportation. There may be further research activity dealing with the problems realized in this work, such as scalability of models, greater precision of real-time forecasts, and greater applicability of the model to various types of intersections as well as to varying traffic scenarios. With the developments in the intelligent transportation systems domain, one thing is certain: GNN-based models will be charting the course for future urban mobility.

References

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