Multi-Source Spatiotemporal Deep Learning Framework for Non-Recurring Traffic Congestion Forecasting

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Abstract

Unexpected events, such as car crashes, result in non-recurring congestion (NRC), which does not follow repetitive patterns in space and time and increases the challenge of traffic management. Current NRC prediction methods are predominantly qualitative, leading to information loss, or quantitatively limited to single-step, short-term forecasts. This research proposes advanced quantitative, interpretability-enhanced, spatio-temporal prediction approaches tailored separately for highway and urban network NRC.

For highway NRC, two novel deep learning models are introduced: the Dual-Stream Autoencoder Sequence-to-Sequence (DS-AE-Seq2Seq) model and the 2-Encoder-Decoder model with Attention mechanism (Att-2ED). Both models utilize Long Short-Term Memory (LSTM) and Multilayer Perceptron (MLP) encoders to independently process time-series speed data and static crash-related features, subsequently employing an LSTM-based decoder to generate spatio-temporal predictions. The Att-2ED model incorporates an attention layer to prioritize input sequences, enhancing predictive interpretability. Tested on a real-world dataset from highways I-5 and I-405 in the United States, these models outperform existing benchmarks. These results demonstrate robust performance under various traffic conditions and exhibiting consistent reliability across varying prediction horizons and spatial distances, as confirmed by sensitivity analyses.

For urban network NRC, this thesis introduces a hybrid predictive framework combining an attention-enhanced Graph Convolutional Network with LSTM (Att-GCN-LSTM) and linear regression for forecasting NRC and associated network-level excessive emissions. The Att-GCN-LSTM integrates historical traffic data, road network graph structures, and non-recurring event details to predict traffic conditions. Subsequently, emissions are estimated using a linear regression model based on these predicted conditions. This approach is evaluated using a simulated dataset, demonstrating superior predictive performance compared to baseline models.

This research provides transportation agencies and traffic management professionals with powerful, interpretable predictive tools for effectively managing and mitigating congestion caused by non-recurring traffic events.

Keywords

Spatio-temporal prediction, Non-recurring congestion, Attention mechanism, Explainable neural network, Multi-step-ahead prediction

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1 Introduction

Traffic congestion is a critical problem that plagues most cities worldwide. Existing research has shown the impacts of traffic congestion on the environment and economy of cities [4]. NRC can happen randomly at any time and location, significantly increasing the difficulty of congestion management [2]. [3] reported that highway accidents cause a 7.8 km/h (7.5%) reduction in average speed and a 17.8% increase in travel time. Additionally, NRC negatively affect road safety and driver mental health. According to [1], normal and steady drivers are more likely to exhibit aggressive behaviour following NRC, particularly during the early stages of trips.

While most exciting research has focused on predicting recurring congestion, only a limited number of studies have paid attention to NRC prediction. However, accurate and intelligent traffic prediction approaches under non-recurrent events are crucial research fields that need attention. Predicting NRC presents several distinct challenges compared to recurring congestion and general traffic prediction:

(1) Irregularity of non-recurring events makes NRC much harder to model and forecast accurately. (2) Infrequency of Non-Recurring Congestion. Most traffic prediction models, which do not explicitly account for non-recurring congestion, tend to ignore or remove anomalies that may result from non-recurring events [5]. (3) Data Limitations. Accurate prediction of non-recurring congestion requires detailed traffic data along with event-specific information (e.g. traffic accident data), which is often unavailable or incomplete in most traffic prediction or recurring congestion studies. (4) Spatio-temporal complexity. Non-recurring events affect traffic both spatially and temporally, requiring models to predict its impact over both dimensions. Longer prediction horizons with fine spatial granularity (e.g., segment or link-level) are important for providing decision-makers and road users with sufficient information to manage and alleviate congestion.

2 Research Objectives

The primary objectives of this research are to provide single-corridor level and road-network level prediction for NRC, more specifically:

(1) Develop a quantitative, multi-step-ahead, high-resolution, spatio-temporal model for predicting freeway non-recurring congestion (FNC), applicable at specific locations, including crash sites and upstream/downstream regions. (2) Evaluate the effectiveness of the developed highway-level model under various scenarios. (3) Introduce novel multi-source data processing frameworks for non-recurring congestion prediction. (4) Benchmark the proposed model against state-of-the-art methods to demonstrate superior performance and robustness. (5) Incorporate an attention mechanism into the model design to enhance interpretability and prediction accuracy of FNC forecasting. (6) Develop a quantitative, multi-step-ahead, high-resolution, spatio-temporal model for predicting road-network non-recurring congestion. (7) Propose a novel hybrid framework to quantitatively estimate the impact of non-recurring congestion events on excessive greenhouse gas (GHG) emissions at the road network level.

3 Methodology

For highway-level prediction, the Att-2ED model is proposed to predict FNC up to 60 minutes by using 65-min historical data. The time interval of two datasets is 5 minutes. Thus, the model uses 13 previous time steps, including the time of the occurrence of the traffic crash, as the sequence input. Figure 1 illustrates the architecture of the Att-2ED model. The code for the proposed Att-2ED model has been made publicly available and can be accessed at: https://github.com/Paper688/Att-2ED_for_NC_prediction.

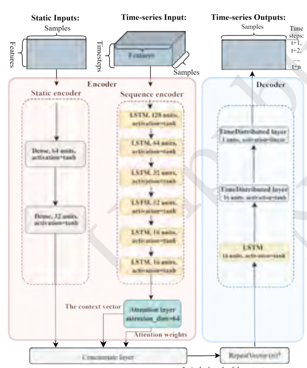

Figure 1: The Att-2ED model architecture

For road-network-level prediction, a multi-branch Att-GCN-LSTM model and a linear regression model are proposed to achieve the objectives. Figure 2 illustrates the framework of the models.

4 Result and Discussion

The temporal performances of the Att-2ED model and benchmark models on I-5 datasets across different prediction horizons are compared in Tables 1. The Att-2ED model outperformed all benchmark models, showcasing the efficacy of integrating spatial-temporal sequences with static data through two-encoder-decoder architectures. This result not only confirms the critical role of the 2-encoder-decoder architecture in processing traffic flow sequences and crash data for FNC prediction but also emphasizes that the incorporation of an attention layer can improve prediction accuracy.

Table 2 shows the performance of the proposed Att-GCN-LSTM and baseline models for 240-minute-ahead prediction in the test dataset. Att-GCN-LSTM achieves the lowest RMSE and MAE among state-of-the-art methods in both the small-scale and city-level networks, demonstrating robust predictive performance across different network scales. The better performance of Att-GCN-LSTM compared with TwoEncoder demonstrates the importance of including event information in traffic condition prediction of a road network after a non-recurring event occurs.

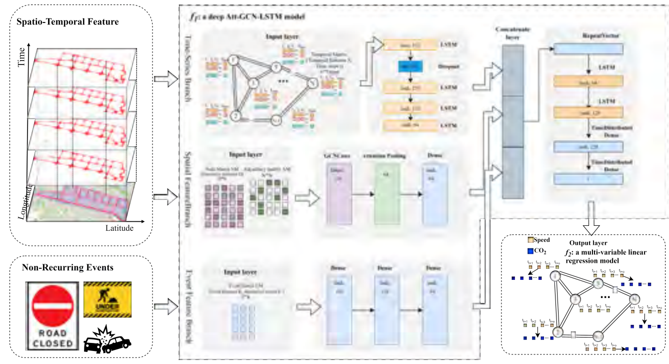

Figure 2: The architecture of the proposed multi-branch Att-GCN-LSTM model

Table 1: Temporal prediction performance: Att-2ED vs. benchmarks on dataset I-5 (15, 35, and 55 min omitted)

Metrics	MAPE			
Prediction Horizon (min)	5	25	45	60
Single-Step-LSTM	12.6%	/	/	/
CNN-LSTM	17.1%	21.6%	23.8%	26.4%
1DCNN	17.5%	24.1%	23.9%	27.9%
Stacked LSTM	19.9%	23.3%	25.5%	26.9%
2ED	8.1%	15.5%	18.4%	21.7%
ConvLSTM	13.3%	17.7%	20.8%	21.9%
2DCNN	9.1%	16.2%	19.5%	20.8%
Att-2ED	**7.7%**	**14.8%**	**17.7%**	**20.1%**

Table 2: Model Performance on Two Network Scales

	Small-Scale Network		City-Level Network	
Model	RMSE	MAE	RMSE	MAE
Att-GCN-LSTM	6.68	2.93	3.88	1.50
TwoEncoder	7.03	3.16	4.57	1.71
FC-LSTM	6.73	3.08	5.28	2.11
CNN-LSTM-Att	7.44	3.93	6.28	2.69
Autoencoder-1D-CNN-LSTM	6.93	3.33	14.56	9.10

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