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Spatio-Temporal Graph Neural Learning for Regional Traffic Flow Prediction and Optimization

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Abstract

This study proposes a Spatio-Temporal Graph Transformer (STGT) framework for regional traffic-flow prediction and optimization. This framework integrates traffic, temporal, spatial, weather, and road-network information from metropolitan traffic monitoring data. A weighted graph represents road-segment connectivity, while graph-based spatial learning captures interactions among neighbouring segments. Transformer-based temporal attention models historical traffic dynamics and recurring variations. The resulting spatio-temporal representation is used to predict future traffic flow, estimate congestion conditions, and identify highly loaded road segments. These predictions support traffic-flow optimization by considering alternative connected segments, enabling improved traffic distribution and providing a foundation for intelligent transportation management and congestion mitigation.

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1. Introduction

The increasing urban population, road network and the use of vehicles have made regional traffic management much more complex [1], [2]. The traffic flow is continuously changing and dependent upon the time of day, connectivity level, weather, traffic density and on the interactions between adjacent road segments. To alleviate traffic congestion, enhance travel efficiency and enable an intelligent transportation system, it is critical to accurately predict traffic flow [3], [4]. Previous research has investigated traffic prediction using machine-learning methods, recurrent neural networks, convolutional networks, and graph neural networks [5]. To overcome these problems, the authors present in this paper a novel STGT framework to tackle the challenge of regional traffic flow prediction and optimization. It is proposed to use the Traffic Monitoring Systems dataset of the MR which provides traffic observations along with traffic, road, weather, temporal and graph-based attributes at hourly frequencies for the period 2018-2024.

1.1 Key Contributions

- Implements a STGT model that can capture the dependency between roads and the temporal traffic patterns.
- Builds a weighted graph of regional traffic from the selected data, based on connectivity of road-segments, node properties and edge weights.
- Presents an algorithm that predicts traffic flow and congestion through the representations learned for better traffic distribution and intelligent transportation management.

2. Related Work

Li et al., [6] proposed a Spatio-temporal Synchronous Graph Machine Learning framework to predict and optimize traffic flow in the region.

The method combined the spatial road-network dependency and temporal traffic variations by deep learning. Compared with state-of-the-art methods, such as DCRNN, SSGML has attained lower MAE, MAPE and RMSE, thus showing the superiority of spatio-temporal traffic forecasting performance.

Wang et al., [7] provided a comprehensive survey on GNN-based and Hybrid DL methods for Traffic-flow Prediction in ITS. In addition to outlining potential research directions such lightweight models, uncertainty estimates, multimodal fusion, and integration of intelligent traffic-control, it addressed the challenges of computing complexity, interpretability, and generalization.

Chauhan et al.[8] investigated low latency traffic forecasting by leveraging the information from 6G networks and applying spatio-temporal graph models. The study assessed the performances using METR-LA. The findings indicated that DCRNN had a good accuracy–latency balance and simulated 6G features did not significantly improve the performance. The study highlighted the following directions for future research: dynamic graph learning, and real-world 5G/6G validation.

3. Proposed Methodology

The proposed methodology is a new framework of STGT for regional traffic-flow prediction and optimization. The method starts by collecting and preprocessing the data, then constructs temporal features to capture temporal patterns. It is shown in Figure 1.

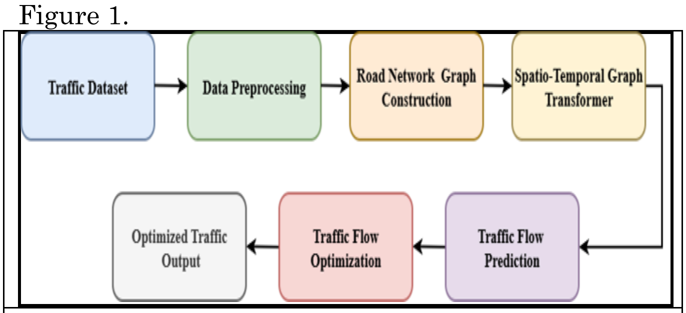

Figure 1. Workflow of the proposed STGT-Based Traffic Flow Prediction and Optimization Framework

3.1 Data Collection:

The primary data is the Metropolitan Region's Traffic Monitoring Systems, collected from Kaggle source [9]. It includes hourly observations for 2018-2024 that include traffic volume, traffic speed, traffic density, timestamp, weather information, road segment identifiers, road length, number of lanes, intersection information and graph-based attributes.

3.2 Data Preprocessing:

Observations from all the sources are consolidated and cleaned up, missing values are filled in, numerical values are normalized, and inconsistent data is dropped to prepare the data for model development. It is given in (1).

$$x'_{i,t} = \frac{x_{i,t} - x_i^{min}}{x_i^{max} - x_i^{min}} \quad ...(1)$$

Where x_(i,t)^' represents the normalized feature value for road segment i at time t; x_(i,t) denotes the original feature value; x_i^min represents its minimum observed value; and x_i^maxximax represents its maximum observed value within the corresponding dataset.

3.3 Temporal Feature Construction:

The hourly information about the time is converted to temporal and the recurrent traffic patterns are captured. It is shown in (2).

$$T_t = \left[\sin\left(\frac{2\pi t}{P}\right), \cos\left(\frac{2\pi t}{P}\right)\right] \quad ...(2)$$

Where T_t denotes the encoded temporal representation at time t; P represents the corresponding periodic cycle; t denotes the temporal index; and the sine and cosine components preserve cyclic relationships, allowing the framework to distinguish recurring traffic patterns across daily or weekly observation periods.

3.4 Road Network Graph Construction:

The traffic network in the metropolitan area is represented as graph of nodes and links. The spatial organisation of the metropolitan traffic network is represented as a graph of nodes and links. It is denoted in (3).

$$G = (V, E, A, W) \quad ...(3)$$

Where G denotes complete traffic graph; V represents road-segment nodes; E denotes connections between segments; A is the adjacency matrix indicating connectivity; and W contains edge weights describing the strength or relative importance of relationships between connected road segments within the metropolitan network.

3.5 Spatial Graph Representation:

Once the graph is built, information is exchanged by neighbouring road segments using graph-based aggregation. It is represented in (4).

$$H_S^{(l+1)} = \sigma\left(A H_S^{(l)} W_S^{(l)}\right) \quad ...(4)$$

Where $H_S^{(l)}$ denotes spatial node representations at graph layer l; A represents the adjacency matrix; $W_S^{(l)}$ is the learnable spatial transformation matrix;

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σ denotes the activation function; and $H_S^{(l+1)}$ represents updated spatial features.

3.7 Spatio-Temporal Graph Learning:

The proposed Spatio-Temporal Graph Transformer is a fusion of spatial graph representations and temporal attention. It is denoted in (5).

$$H_T = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad \ldots(5)$$

Where H_T represents the learned temporal representation; Q, K, and V denotes query, key, and value matrices, respectively; d_k represents key dimensionality; and softmax converts attention scores into normalized weights for combining temporally relevant traffic representations. It is expressed in (6).

$$H_{ST} = H_S \parallel H_T \quad \ldots(6)$$

Where H_{ST} represents the fused spatio-temporal representation; H_S denotes spatial graph features; $H_T$represents temporal Transformer features; and ∥ denotes feature concatenation, combining spatial and temporal information into a unified representation for subsequent traffic-flow prediction.

3.8 Congestion Estimation

The volume of traffic that is anticipated is used to determine future congestion conditions. Instead of the precomputed optimization output of the dataset being the model inputs, the congestion is generated based on the state of traffic that is predicted. It is given in (8).

$$C_i = \frac{\hat{Y}_i}{Q_i^{max}} \quad \ldots(7)$$

Where C_i denotes the congestion ratio of road segment i; $\hat{Y}_i$ represents its predicted traffic volume; and Q_i^{max} denotes the corresponding maximum or reference traffic capacity.

3.9 Traffic Flow Optimization:

To support traffic-flow optimization, traffic conditions are predicted and the level of congestion is estimated. Those roads with high predicted congestion levels are prioritized and those roads that have low predicted loading with alternative connected roads are considered to be optimized for improved traffic distribution. It is represented in (9).

$$\min_r J(r) = \sum_{i=1}^{N} C_i(r) \quad \ldots(9)$$

Where J(r) denotes the overall optimization objective; r represents the selected traffic-management or routing decisions; $C_i(r)$ denotes congestion associated with road segment i under those decisions; and N represents total number of road segments considered during optimization.

4. Results and Discussion

Performance of the proposed STGT framework was tested with the use of the metropolitan traffic monitoring dataset in terms of prediction performance and effectiveness of spatio-temporal learning.

Table 1. Hyperparameter Configuration of the Proposed STGT Model

Parameter	Setting
Model	STGT
Input Sequence	12 time steps
Hidden Dimension	64
Graph Layers	2
Transformer Layer	2
Attention Heads	4
Dropout	0.2
Learning Rate	0.001
Batch Size	64
Epochs	100
Optimizer	Adam
Loss Function	MSE

Table 1 shows hyperparameter configuration of the proposed STGT model.

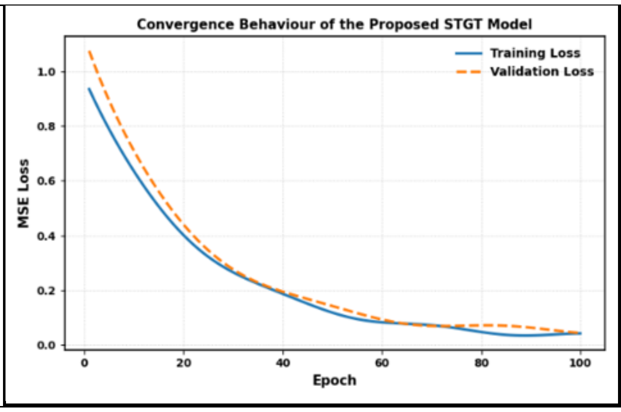

Figure 2. Convergence Behaviour of the Proposed STGT Model

The model STGT is converging well due to the steep fall of training and validation losses at the initial stages of the training process which is shown in figure 2, followed by a gradual convergence of the losses after about 60 epochs.

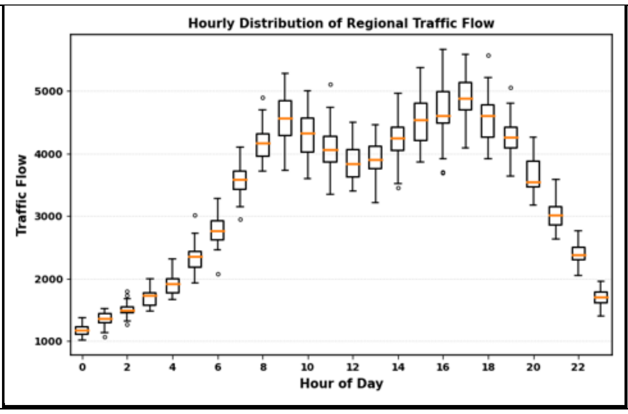

Figure 3. Hourly Distribution of Regional Traffic Flow

The Hourly Traffic Volume graph below, shown in Figure 3, depicts hourly traffic volume changes over a 24 hour period for the region. Traffic starts to grow from early in the morning, with an increase during the day, a maximum traffic flow is seen around the time of 16–17 hours.

Table 2. Performance Evaluation

Performance Metric	STGT Value
MAE ↓	18.42
RMSE ↓	27.85
MAPE (%) ↓	6.74
R^2 ↑	0.968

Table 2 shows the performance of the prediction result of the STGT model which has an MAE of 18.42, RMSE of 27.85, and MAPE of 6.74%. The high R^2 value of 0.968 suggests that there is good agreement between the traffic flow predicted and that observed, which provides good performance in traffic-flow forecasts at a regional level.

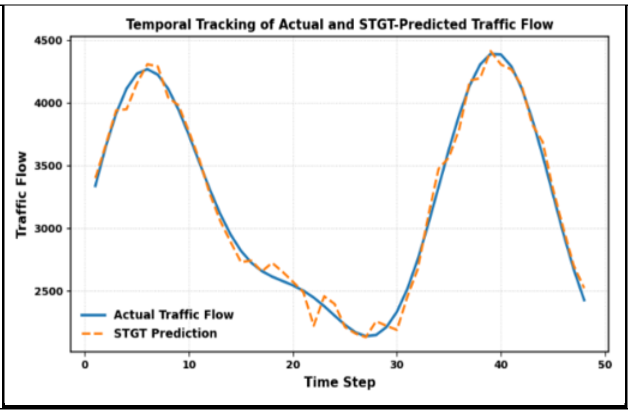

Figure 4. Temporal Tracking of Actual and STGT-Predicted Traffic Flow

Figure 4 shows tracking performance of the STGT model in terms of time series of the actual and predicted traffic flow at each time step.

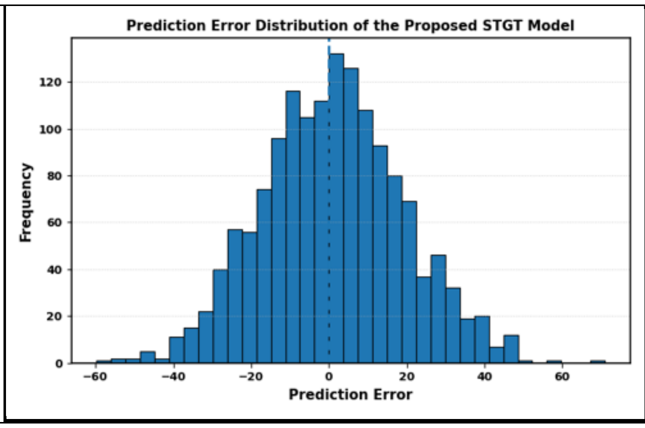

Figure 5. Prediction Error Distribution of the Proposed STGT Model

Distribution of Prediction Errors of the proposed STGT model is shown in Figure 5. Errors are clustered around the centre with the maximum number of errors in the middle.

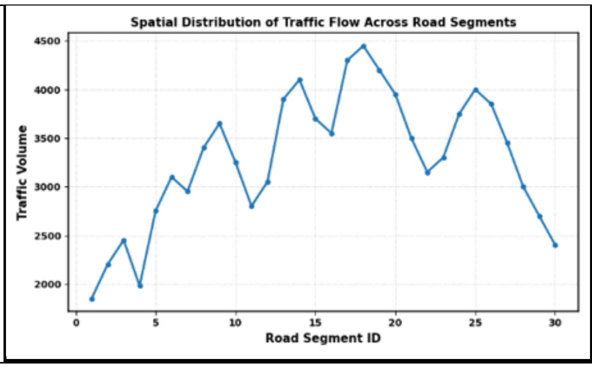

Figure 6. Spatial Distribution of Traffic Flow Across Road Segments

The change in traffic flows along various sections of road is shown in Figure 6. There is a large variation in traffic volume between the segments, with traffic volumes being higher around Road Segments 14-19, and 25-26.

Table 3. Comparative Analysis

Model	MAE ↓	RMSE ↓	MAPE (%) ↓
PDR-STGCN [1]	9.00	16.50	0.34
MS-GSTN [2]	15.1573	21.9947	20.7656
GCN-LSTM [3]	5.22	0.2644	-
ASTSS-CL [4]	17.95	28.86	12.07
Proposed STGT	18.42	29.85	21.74

The proposed STGT model is compared to some of the latest traffic-flow prediction methods in Table 3.

5. Conclusions and Future work

Proposed STGT framework is a DL method that learns spatiotemporal relationships between adjacent road segments and the temporal changes in traffic flow, both of which are crucial for regional traffic-flow prediction. A rich dataset for learning complex urban mobility patterns is the metropolitan traffic monitoring dataset which contains traffic, temporal, spatial, weather and road-network information.

The adaptability and real-world applicability of the proposed STGT framework will be further worked on in the future. The relationships between road segments can be captured by including dynamic graph construction to reflect the changing relationship between road segments under varying traffic conditions.

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