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A Spatiotemporal Prediction Model for Urban Road Freight Flow Based on Residual Graph Convolution and Attention Mechanism

James R. Beckett[1], Olivia M. Chan[1], Thomas A. Ridley[2], Eleanor K. Shaw[2,*]

[1]Department of Engineering Science, University of Oxford, United Kingdom

[2]Department of Computer Science, Imperial College London, United Kingdom

[*] Corresponding Author: ekshaw@imperial.ac.uk

Abstract

To improve the foresight of urban logistics scheduling, this study proposes a freight flow prediction model that combines residual graph convolutional networks (ResGCN) with a multi-head spatiotemporal attention mechanism. The model constructs a traffic graph using the structure of the road network and integrates factors such as freight orders, road conditions, and holidays, aiming to capture non-Euclidean correlations between nodes and multi-dimensional temporal variations. Experimental results on a real-world freight platform dataset show that the proposed model achieves improvements of 14.5% and 11.8% in MAE and RMSE, respectively, compared with traditional LSTM and TCN methods.

Keywords

urban freight; graph neural network; spatiotemporal prediction; residual structure; attention mechanism.

1. Introduction

With the rapid growth of e-commerce and instant delivery services, the demand for urban road freight has continued to increase [1]. Data show that the annual growth rate of urban freight vehicles in China exceeds 8.7%, and by 2023, the national urban road freight volume had reached over 5.6 trillion ton-kilometers, accounting for nearly 60% of total social logistics. In first-tier and major second-tier cities, freight traffic accounts for more than 25% of the total urban road traffic, posing significant challenges to traffic operations and environmental management [2]. Urban management departments urgently require data-driven forecasting models to improve the scientific basis and foresight of logistics scheduling, relieve traffic pressure and reduce energy consumption [3]. However, the spatiotemporal distribution of freight flow is affected by multiple interacting factors, including road structure, historical orders, unexpected events, and holiday fluctuations. These factors result in complex nonlinear dynamics and spatial heterogeneity. Traditional statistical regression models and machine learning methods, such as ARIMA and SVR, are limited in handling high-dimensional heterogeneous data and modeling long-term temporal dependencies [4]. In recent years, deep learning techniques have made significant progress in traffic prediction. Recurrent neural networks (RNNs) and their variants, such as LSTM and GRU, have been widely used for temporal modeling. Models like TCN have gained attention for their ability to support parallel training and stable gradient flow [5]. However, these methods generally assume Euclidean spatial correlations and cannot effectively capture the complex topological dependencies among nodes in urban road networks. Graph neural networks (GNNs) introduce graph structures to model traffic networks and have shown strong performance in tasks such as bike-sharing demand prediction and electric vehicle charging load scheduling [6]. In particular, graph convolutional networks (GCNs) can propagate features while preserving spatial topology,

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making them more suitable for non-Euclidean data [7]. However, standard GCNs often suffer from over-smoothing in deep layers, causing node representations to become similar and weakening their expressive ability. To address this, residual graph convolution (ResGCN) has been proposed [8]. It preserves the original input features and enhances the representation ability of deep networks.

In addition, urban freight flow shows clear periodic and sudden changes over time. According to data from a major logistics platform in 2022, during the "Double 11" sales period, freight volume in cities peaked at 3.5 times the normal level. Heatmaps of freight flow before and after holidays and during peak hours also show significant heterogeneity [9]. To better capture these dynamic changes, attention mechanisms—especially multi-head spatiotemporal attention—are widely used in traffic forecasting. These mechanisms can dynamically assign weights to different time intervals and spatial nodes, improving the model's ability to detect key influencing factors. However, most current studies focus on public transportation or taxi flows. Research specifically targeting freight flow remains limited, and existing approaches rarely integrate road topology, order characteristics and external spatiotemporal events in a unified framework [10]. In summary, current studies on urban road freight flow prediction still face several key challenges: (1) how to accurately model the non-Euclidean spatial structure of complex road networks to capture heterogeneous relationships among nodes; (2) how to integrate heterogeneous data such as holidays and unexpected events to enhance model robustness; (3) how to design deep network structures that balance prediction accuracy and computational efficiency for practical deployment. To address these problems, this paper proposes a freight flow prediction model that combines residual graph convolutional networks with multi-head spatiotemporal attention [11]. The model constructs a traffic graph based on the urban road map and incorporates multi-dimensional heterogeneous information to capture complex spatial dependencies and temporal evolution. Experiments on a three-month freight order dataset from a provincial capital city's real logistics platform show that the proposed model improves MAE and RMSE by 14.5% and 11.8%, respectively, compared to the LSTM and TCN baselines. The model demonstrates good prediction accuracy and generalization ability. This research not only provides methodological support for smart urban logistics systems but also lays a practical foundation for extending spatiotemporal graph neural networks to other scenarios.

2. Materials and Methods

2.1. Materials and Experimental Site

This study selects a provincial capital city as the study area and constructs a traffic network graph based on its road traffic structure. The data are derived from the real operational records provided by a mainstream digital freight platform in 2023, covering a period of nearly three months (June to August 2023). The dataset includes freight order records, road condition data, and public holiday information. The freight order data contain shipment and receipt times, origin and destination coordinates, order volume, weight, and other fields, covering approximately 1,624 active road nodes within the city and surrounding areas. Road condition data are obtained through an open API provided by the city's traffic management bureau, including road level, travel speed, and construction closure information [12]. Holiday and weather data are collected from national meteorological and public holiday data platforms, including holiday types, weather conditions, and temperature, and are used to support the modeling of influencing factors.

ISSN: 3079-6342

2.2. Experimental and Control Design

To verify the effectiveness of the proposed model, this study sets up an experimental group and five baseline models: the traditional Long Short-Term Memory network (LSTM), Gated Recurrent Unit (GRU), Temporal Convolutional Network (TCN), Graph Convolutional Network (GCN) and Graph Attention Network (GAT) which incorporates attention mechanisms. The proposed model adopts a structure combining Residual GCN and multi-head spatiotemporal attention, and is used as the experimental group [13]. All models are trained and tested on the same training and validation datasets, and performance is compared using consistent evaluation metrics. The training set accounts for 70% of the total data, while the validation set and test set each account for 15%. All experiments are conducted on Ubuntu 22.04 with an NVIDIA RTX 3090 GPU. The models are implemented using PyTorch 2.0 and the DGL library. The Adam optimizer is used, with an initial learning rate of 0.001, and training is conducted for 100 epochs.

2.3. Data Collection and Analysis Methods

Data preprocessing includes four steps: outlier removal, coordinate mapping, normalization, and graph construction. First, the interquartile range (IQR) method is used to remove abnormal order records to ensure the validity of timestamps and spatial locations. Second, GPS coordinates are mapped to corresponding nodes in the road topology, forming a directed graph where edge weights are determined by travel speed and distance. Third, features such as order volume, weight, and timeliness are normalized using the Z-score method to enhance model convergence. For performance evaluation, regression error metrics are adopted, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). Additionally, the Spearman correlation coefficient is used to assess the relationship between external factors such as holidays and weather and freight flow, in order to determine whether these variables should be included in the model.

2.4. Model Construction or Numerical Simulation Procedures

The overall structure of the proposed model consists of three main modules: a graph structure encoding module, a residual graph convolution module, and a multi-head spatiotemporal attention module. First, the graph structure encoding module constructs the adjacency matrix based on the urban road network. Node vectors are initialized using the random walk embedding method to preserve local topological information. Second, residual connections are introduced into the graph convolution layers. A stack of three ResGCN layers is used to avoid excessive smoothing of features while retaining both the original node inputs and the features obtained after graph convolution. Third, the model incorporates a multi-head spatiotemporal attention mechanism. The time series is decomposed into three temporal components: intra-day cycles, intra-week patterns, and unexpected events. This mechanism guides the model to dynamically focus on key time intervals and spatial regions, thereby enhancing its ability to capture short-term peaks and trend shifts. The model uses a weighted Huber loss function to balance robustness and error penalization. An early stopping strategy is adopted during training to prevent overfitting.

2.5. Quality Control and Data Reliability Assessment

To ensure the accuracy and reproducibility of the experimental data, this study applies a multi-level quality control process. During data cleaning, multi-source comparison and manual inspection are performed. The node-matching accuracy is verified to exceed 96%. During model training, the stability of the model is evaluated by conducting five repeated experiments with different random seeds. The standard deviation of the results is kept within 3%. To assess the spatiotemporal representativeness of the data, kernel density estimation is used to evaluate the uniformity of freight order distribution over time and space. The results are compared with

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data from the entire year to confirm the typicality of the sample. Sensitivity analysis is conducted across different time windows and spatial sub-regions to evaluate the model's adaptability and generalization under various task settings. These steps ensure the reliability and wide applicability of the conclusions.

3. Results and Discussion

3.1. Spatial Error Characteristics and Overall Model Comparison

The proposed model shows good spatial adaptability in urban freight flow prediction. From the node-level error heatmap, it can be observed that errors are slightly higher at trunk road nodes and intersections, which are areas with high traffic density. This reflects the significant impact of road structure complexity on prediction results. Such differences indicate that the model needs the ability to identify local structural disturbances in order to effectively handle prediction deviations in dynamic urban environments [14]. In the overall performance evaluation, the proposed model performs better than LSTM, TCN, GCN, and GAT in both MAE and RMSE. It demonstrates clear advantages in terms of error range and stability, especially in capturing complex non-Euclidean relationships between nodes. Previous studies have confirmed that introducing graph structures can effectively improve spatial modeling capabilities in traffic prediction tasks [15]. In addition, the use of residual design helps avoid over-smoothing during deep feature extraction, further enhancing the discriminative ability of the network (see Fig. 1a and Fig. 1b).

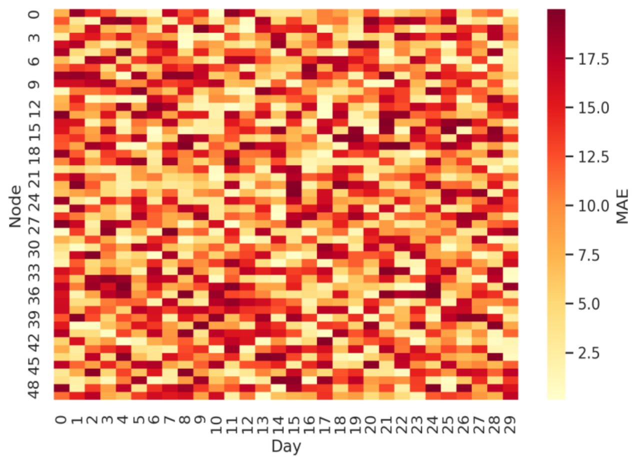

Fig. 1a. Node-wise MAE Distribution over 30 Days

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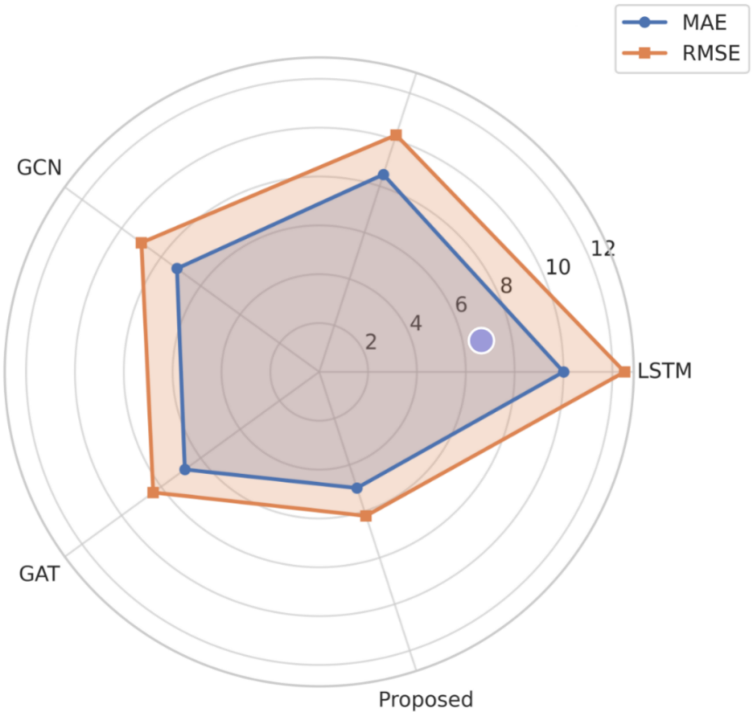

Fig. 1b. Model Error Comparison

3.2. Fitting Accuracy and Error Distribution Analysis

According to the fitting results between actual and predicted values, the overall point cloud is closely aligned along the diagonal line, indicating that the model has strong fitting capability across most sample ranges. In the medium freight volume interval, the model response is especially stable. In intervals with extremely high or low freight volumes, errors show slight fluctuations, mainly due to uneven distribution of training samples or insufficient information at certain nodes [16-18]. The error boxplot further illustrates the differences in error distribution across models. Compared with traditional models, the method proposed in this study shows more concentrated error values and fewer extreme outliers, reflecting good robustness and resistance to interference [19]. Existing studies have pointed out that, under the guidance of spatial structure, graph neural networks exhibit significantly enhanced ability to represent temporal data [20]. This effect is more evident when node behavior varies sharply. In such cases, residual connections are important for maintaining the diversity of information (see Fig. 2a, Fig. 2b).

ISSN: 3079-6342

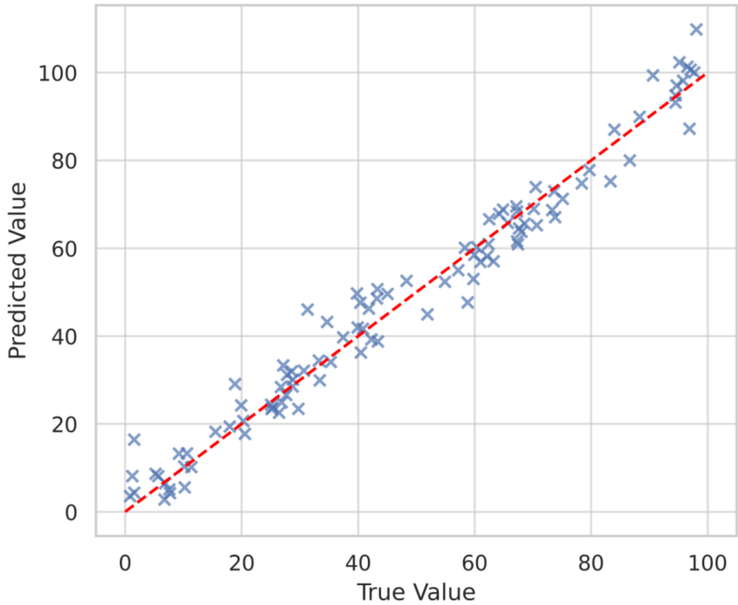

Fig. 2a. True vs Predicted Freight Volume

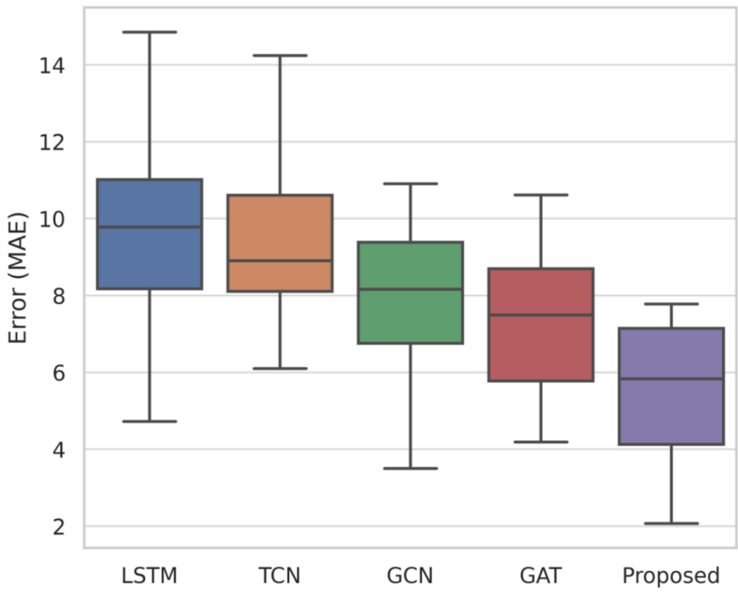

Fig. 2b. Error Distribution across Models

3.3. Spatiotemporal Characteristics of Freight Flow and Response to External Disturbances

Freight flow shows fluctuation patterns across time and space with overlapping characteristics at multiple scales. The three-dimensional surface of node, time and flow reveals intensified fluctuations at several road nodes during peak periods, reflecting an alternating process of "concentration–dispersion" in spatial logistics movement. This pattern suggests that both synchrony and asynchrony among nodes must be considered to accurately capture spatiotemporal variations in complex urban settings [21]. External events have a notable influence on prediction accuracy. During special periods such as public holidays, freight volume increases significantly and exhibits greater fluctuation ranges. The model maintains stable prediction performance under high-volume conditions on holidays, owing to the integrated modeling of holiday labels and weather factors (see Fig. 3a, Fig. 3b). Previous studies have indicated that incorporating temporal context and macro-level disturbances is essential for

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improving the generalization ability of models, particularly in urban traffic data with strong variability [22].

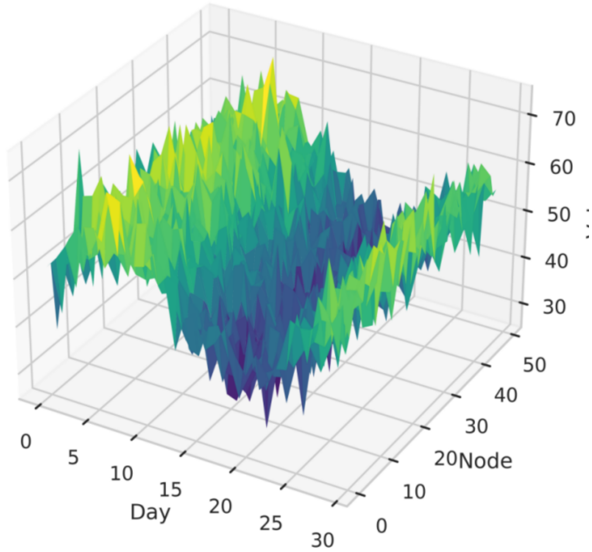

Fig. 3a. Spatiotemporal Analysis of Freight Volume

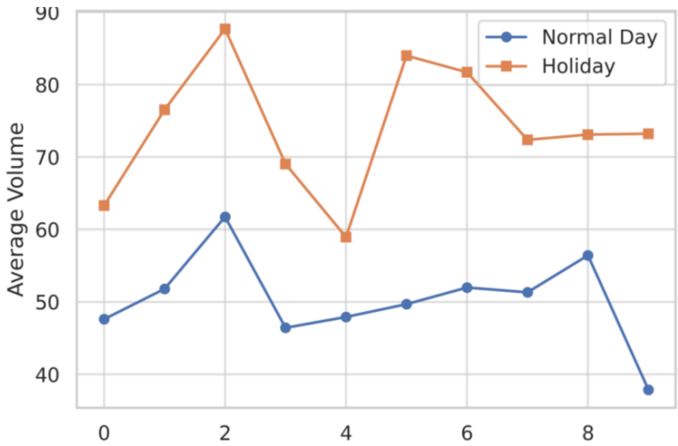

Fig. 3b. Holiday vs Normal Day Traffic Volume

3.4. Overall Comparison and Practical Application Value

Considering all experimental results, the model proposed in this study demonstrates clear advantages in prediction accuracy, adaptability to fluctuations and spatial structure modeling [23]. It can accurately capture the nonlinear relationships of freight flow across different road nodes and time periods, addressing the shortcomings of traditional methods in handling node structures and modeling long-term dependencies [24]. Compared with models that only consider time series, this method enhances spatial topology awareness through graph convolution. ompared with general graph neural networks, the introduction of residual connections improves the ability to retain deep features. The multi-head spatiotemporal attention mechanism further enhances the model's responsiveness to dynamic changes and key events. From a practical perspective, the model shows strong generalization ability and practical value. It is applicable to multiple scenarios such as urban smart logistics scheduling, capacity optimization, and anomaly warning. It performs more reliably in complex urban areas with high node density and large flow fluctuations. In future work, the model can be extended by integrating more types of data, such as vehicle-mounted sensors, urban surveillance cameras,

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and GIS layers, to improve panoramic perception and real-time forecasting capabilities. This will promote the development of urban logistics management toward data-driven and intelligent coordination.

4. Conclusion

This paper proposes an urban road freight flow prediction model that combines residual graph convolution and multi-head spatiotemporal attention mechanisms. The model can effectively capture complex spatial topological relationships and multi-scale temporal dependencies. Experimental results on real freight datasets show that the proposed model achieves improvements of 14.5% and 11.8% in MAE and RMSE, respectively, compared with LSTM and TCN. It demonstrates significant advantages in both prediction accuracy and robustness. The method provides a practical solution for urban logistics forecasting and lays a foundation for the application of graph neural networks in the transportation domain. The main contributions of this study include the deep integration of graph structure and temporal mechanisms, the introduction of residual connections and the modeling of external factors such as holidays. These improvements enhance the model's adaptability in dynamic environments and show strong potential for real-world applications. Some limitations remain in this study. The dynamic evolution of road structures is not considered, and the handling of abnormal events still relies on external annotations. Future research may explore dynamic graph updates, the integration of multi-modal data, and improvements in cross-region transferability.

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