Journal of Organizational and End User Computing
Volume 37 • Issue 1 • January-December 2025

An Express Management System With Graph Recurrent Neural Network for Estimated Time of Arrival

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ABSTRACT

Estimated Time of Arrival (ETA) is a crucial task in the logistics and transportation industry, aiding businesses and individuals in optimizing time management and improving operational efficiency. This study proposes a novel Graph Recurrent Neural Network (GRNN) model that integrates external factor data. The model first employs a Multilayer Perceptron (MLP)-based external factor data embedding layer to categorize and combine influencing factors into a vector representation. A Graph Recurrent Neural Network, combining Long Short-Term Memory (LSTM) and GNN models, is then used to predict ETA based on historical data. The model undergoes both offline and online evaluation experiments. Specifically, the offline experiments demonstrate a 5.3% reduction in RMSE on the BikeNYC dataset and a 6.1% reduction on the DidiShenzhen dataset, compared to baseline models. Online evaluation using Baidu Maps data further validates the model's effectiveness in real-time scenarios. These results underscore the model's potential in improving ETA predictions for urban traffic systems.

KEYWORDS

Estimated Time of Arrival, GRNN, LSTM, GNN, Baidu Maps, Online Evaluation, Offline Evaluation

INTRODUCTION

Estimated time of arrival (ETA) is an important task in the logistics and transportation industry (El Makhloufi, 202; López & Lozano, 2022; Tsolaki et al., 2022). It can help businesses and individuals better plan and manage their time, thereby improving efficiency and accuracy. For example, logistics companies can use ETA to predict the arrival time of goods to better schedule transportation and distribution. In the transportation sector, ETA can help people better plan their trips to avoid congestion and delays. As the logistics (Liu et al., 2023) and transportation (Li et al., 2021) industries grow and globalization rapidly and increase in size and complexity, the accuracy of ETAs subsequently becomes more and more important (Zhang et al., 2025). Overall, the accuracy of ETA forecasting

DOI: 10.4018/JOEUC.370912

tasks becomes very important for both organizations and individuals. It helps them to plan and manage their time better, thus increasing efficiency and accuracy.

Recent studies have shown that graph neural network (GNN) models have higher performance in modeling road traffic and other aspects (Jiang & Luo, 2022). It has been found that the reason why GNN models perform well in ETA tasks is that they can model traffic conditions by learning the connectivity structure of the road network (Jin et al., 2023). In 2021, the DeepMind team collaborated with Google Maps to successfully improve the real-time ETA accuracy of Google Maps in major cities such as Berlin, Tokyo, and Sydney by up to 50% using GNNs (Derrow-Pinion et al., 2021). To achieve this goal globally, DeepMind used GNNs to perform spatiotemporal reasoning by adding relationship learning biases to the model, thereby modeling the connectivity of the real-world road network (Huang et al., 2025). After the roads are sliced into multiple road networks, the road network is divided into several super sections, which refer to several adjacent sections affected by each other's traffic flow. Then, the local road network are viewed as a graph, where each road segment corresponds to a node, and the edges connecting two road segments (nodes) are either on the same road or connected through an intersection. These mechanisms enable GNNs to utilize the connectivity structure of the road network more efficiently.

Currently, there is a continuous emergence of GNN predictive models in the fields of transportation and logistics. The following are five commonly used GNN predictive models:

- Spatio-Temporal Graph Convolutional Network (ST-GCN; Yu et al., 2017): ST-GCN is based on the concept of GNN and integrates spatiotemporal information. By performing convolution operations on spatiotemporal graphs, it effectively captures the spatiotemporal dependencies in transportation or logistics systems. ST-GCN excels in traffic flow prediction, accurately capturing the complex spatiotemporal dynamics in urban transportation networks, thereby enhancing predictive performance in transportation systems.
- Adaptive Spatial-Temporal Graph Convolutional Network (ASTGCN; Chen et al., 2023): ASTGCN introduces an adaptive mechanism, adjusting to different spatiotemporal dependencies by considering dynamic weights of neighboring nodes. This adaptability allows the model to flexibly accommodate complex transportation or logistics systems. ASTGCN performs exceptionally well in handling irregular and dynamic traffic networks, enhancing its modeling capabilities for complex urban traffic patterns.
- Trajectory Graph Neural Network (TrajGNN; Cao et al., 2021): TrajGNN focuses on modeling trajectory data, representing trajectory data as nodes in a graph and leveraging GNN to learn relationships between trajectories. This approach aids in considering interactions between individual trajectories during the prediction process. TrajGNN excels in modeling complex interactions between individual trajectories and is applicable to predicting trajectories of pedestrians or vehicles.
- Diffusion Convolutional Recurrent Neural Network (DCRNN; Li et al., 2017): DCRNN combines convolution and recurrent neural networks, modeling traffic networks as diffusion processes in spatial dimensions to learn traffic flow relationships between nodes. DCRNN excels in capturing long-term spatiotemporal dependencies in traffic networks and is suitable for accurate long-term predictions of traffic flows.
- Graph WaveNet (Wu et al., 2019): Graph WaveNet is based on the WaveNet model and introduces graph convolution operations to adapt to graph structures. It captures spatiotemporal dependencies between nodes through layer-wise convolution operations. Graph WaveNet is suitable for capturing dynamically changing graph structures, exhibiting strong generalization capabilities for complex spatiotemporal predictions in transportation and logistics systems.

To further enhance the accuracy of ETA tasks, this study proposes a novel graph recurrent neural network (GRNN) model (Qiao et al., 2020) integrating external factor data. The model initially employs a multilayer perceptron (MLP)-based external factor data embedding layer (Delashmit & Manry, 2005), categorizing influencing factors and merging them into a vector representation. Subsequently, a GRNN combining long short-term memory (LSTM) and GNN models is utilized to finish the ETA task for the current courier transport based on input historical data (Zheng et al., 2021). Finally, the model undergoes offline prediction experiments on multiple public datasets and online prediction experiments using Baidu Maps data (Xia et al., 2022).

The contributions of this study can be summarized in the following three points:

- Design of external factor data embedding layer: The study introduces a novel approach by proposing the utilization of an MLP-based external factor data embedding layer (Srivastava et al., 2021). This layer effectively categorizes and embeds various external factor data, consolidating them into an influencing factor vector. The design of this embedding layer aims to capture the impact of external factors on ETA more efficiently, providing a more informative input for subsequent predictive models.
- Integration of LSTM and GNN in GRNN Model: A GRNN model, amalgamating LSTM and GNN models, is introduced. This model demonstrates improved capabilities in capturing time-series information and graph structure relationships when processing historical input data. The fusion of these two distinct neural network structures enhances the accuracy of ETA predictions, making the model more adaptable to complex transportation scenarios.
- Multilayered experimental validation: The research incorporates a multilayered experimental validation approach, including offline prediction experiments on multiple public datasets and online prediction experiments using Baidu Maps data. This comprehensive validation strategy ensures the generalizability and practicality of the proposed ETA prediction model, showcasing its performance across diverse scenarios.

The structure of this paper comprises several main sections. The Introduction outlines the research objectives. The Related Work section reviews prior research and existing literature in the relevant field, demonstrating the research value of the current study. In the Methodology section, the paper details the structure and working principles of the proposed GRNN ETA prediction model, encompassing key components such as the external factor data embedding layer and the GRNN incorporating LSTM and GNN. The subsequent Experiments section presents the model's performance in offline and online experiments, accompanied by in-depth analysis and discussion. Finally, Conclusions summarize the main findings of the study and emphasize its contributions. This organization aims to provide a clear logical flow of the research, allowing readers to comprehensively understand the background, methodology, and outcomes of the study.

RELATED WORK

Intelligent Logistics

Intelligent logistics (Liu et al., 2023), as a cutting-edge field, has garnered widespread attention and research globally. Researchers are dedicated to applying intelligent technologies to logistics management (Tsolakis et al., 2022), aiming to enhance the efficiency of transportation, warehousing, and distribution processes. Research directions in intelligent logistics encompass the optimization of logistics information systems (Kumar et al., 2022), the application of intelligent transportation tools (Hina et al., 2022), and intelligent warehouse management (Tubis & Rohman, 2023). Leveraging big data analytics (Lăzăroiu et al., 2022), Internet of Things technologies (Tran-Dang et al., 2022), and intelligent algorithms, researchers explore methods to achieve real-time monitoring (da Costa et al., 2022), intelligent decision-making (Tian et al., 2023), and automated execution to address challenges within logistics systems. The research objective of intelligent logistics is to construct a more flexible, efficient, and sustainable logistics system to complex supply chain networks.

Within the realm of intelligent logistics, the prediction of delivery arrival times poses several challenging aspects. Firstly, logistics systems are confronted with numerous complex variables and uncertainty factors such as traffic conditions, weather impacts, and the workload of delivery stations, all of which directly influence the delivery transportation time. Secondly, the dynamic nature of logistics networks and constantly changing environmental conditions adds to the complexity of prediction, requiring models to possess strong adaptability and generalization capabilities. Additionally, the processing of large-scale data and real-time requirements poses challenges, as accurate predictions necessitate handling substantial data flows and making rapid decisions. Despite these challenges, effectively addressing the prediction of delivery arrival times is crucial for enhancing the overall performance and user experience of intelligent logistics systems.

Traffic Forecasting Methods

The methods to address traffic prediction problems are based on their fundamental principles and technical characteristics. Here are several common classifications of traffic prediction methods:

- Model-based approaches. (1) Microscopic simulation models: Utilizing models like VISSIM (Haq et al., 2022) and SUMO (Aditya et al., 2020) to simulate and analyze the behavior of traffic flow, enabling predictions. (2) Macroscopic models: Implementing macroscopic models such as the Lighthill-Whitham-Richards model (Fan et al., 2023) and the Cell Transmission Model (Jiang, 2022) for macroscopic modeling and prediction of traffic flow.
- Statistical-based approaches. (1)Time series analysis: Employing historical traffic data for time series analysis, including autoregressive (J. Li et al., 2022), moving average (Xu et al., 2023), and autoregressive integrated moving average models (Kochetkova et al., 2023). (2) Regression analysis: utilizing regression analysis models, such as linear or nonlinear regression (Kuranga & Pillay, 2022), to correlate traffic flow variables with other factors for prediction.
- Machine learning-based approaches encompass methods such as support vector machines (SVMs; Zhong & Du, 2023), decision trees (Deeban & Bharathi, 2022), and random forests (Hongren, 2022) by training models using historical data for traffic flow prediction.
- Deep learning-based approaches employ RNN (Baskar & Kaluvan, 2022) and LSTM to capture complex spatiotemporal relationships in data.
- Fuzzy logic-based approaches (Jain et al., 2022) apply fuzzy logic methods to model uncertainty and vagueness, enhancing the ability to handle complex traffic environments.
- Integrated approaches combine multiple models through weighted or voting mechanisms to enhance prediction accuracy and robustness.

Graph Representation Learning

Graph representation learning (Hoang et al., 2023) is a field within machine learning that focuses on developing techniques to capture and model the inherent structure and relationships within graph-structured data. In this paradigm, graphs represent complex relationships between entities, denoted by nodes with edges signifying connections or interactions between them. The goal of graph representation learning is to embed nodes or entire graphs into a continuous vector space, such that the learned representations preserve the relevant structural and semantic information of the original graph. This enables the application of traditional machine learning algorithms on graph-structured data. Various methods, including graph convolutional networks (Phan et al., 2023), graph autoencoders (Hoang et al., 2023), and random walk-based approaches (Zhiyao et al., 2022), have emerged as effective tools for learning expressive and informative representations from graphs, contributing to advancements (Tan et al., 2019), biology (M. Li et al., 2022), and recommendation systems (Miao et al., 2022; Wu et al., 2022).

In the logistics and transportation domain, the application of graph representation learning has gained significant attention. By modeling logistics networks as graph structures, where nodes represent different logistics entities (such as warehouses, distribution centers, or intersections) and edges denote connections and transportation paths between them, graph representation learning methods can learn embeddings for nodes and edges. These embeddings capture the spatiotemporal relationships, transportation flows, and intricate interactions between nodes in the logistics network.

Recent advancements in spatiotemporal models, such as spatiotemporal attention-based approaches, have shown great promise in enhancing ETA prediction. These models integrate both spatial dependencies (such as road networks and traffic conditions) and temporal dynamics (such as time of day or historical traffic data) to improve the accuracy of ETA predictions. For example, the incorporation of attention mechanisms allows the model to focus on the most relevant time-dependent and spatial information, leading to more precise ETA estimates in dynamic and complex environments.

Leveraging graph representation learning and spatiotemporal attention models, various logistics optimization tasks, including path planning, transportation scheduling, and inventory management, can be tackled efficiently. These methods provide more comprehensive and intelligent analysis, contributing to enhanced efficiency, cost reduction, and overall sustainability in logistics operations.

METHOD

System Overview

The constructed express delivery management system in this study is a comprehensive municipal-level express service management platform designed to effectively manage and optimize the entire process of express services within the city area. This system integrates functions such as order management, cargo tracking, delivery scheduling, warehouse management, and customer service to achieve comprehensive express business management. In terms of order management, the system supports users in swiftly submitting orders and real-time order status inquiries while offering multiple payment and delivery options. The cargo tracking feature enables users to monitor parcel locations and transport status in real-time, providing a visual tracking interface. The delivery scheduling module, employing intelligent algorithms and real-time traffic information, facilitates efficient delivery route planning, enhancing delivery efficiency. The warehouse management module is responsible for real-time monitoring and management of inventory, ensuring timely inbound and outbound logistics. The customer service section provides online customer support, complaint handling, and user feedback functions to enhance user experience. The entire system employs advanced Internet of Things devices and big data analytics for real-time data processing and intelligent decision-making. Through this system, express companies can execute various business operations more efficiently and accurately, elevating service quality and express services. The overview of the architecture of this express management system is shown in Figure 1.

Figure 1. Express process flow in this express management system

ETA Problem Description

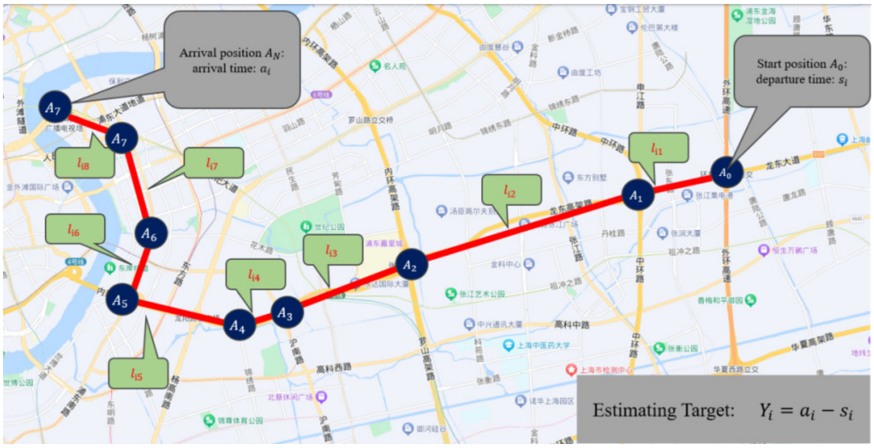
As the primary contribution of this study, the express delivery management system's delivery arrival time prediction module employs an innovative GNN model, enhancing the accuracy of delivery arrival time predictions and consequently reducing the overall management costs of express delivery services in the city. This section begins by providing a formal definition of the delivery arrival time prediction problem.

The roads on the express delivery transportation map are defined as a graph $\mathbf{G} = (\mathbf{L}, \mathbf{A})$, where $\mathbf{L} = \{\mathbf{l}_1, \ldots, \mathbf{l}_N\}$ represents the set of roads, and $\mathbf{A} = \left\{ (\mathbf{l}_i, \mathbf{l}_j) : \mathbf{l}_i \in \mathbf{L}' \subseteq \mathbf{L}, \mathbf{l}_j \in \mathbf{L}'' \subseteq \mathbf{L}, \mathbf{l}_i \neq \mathbf{l}_j \right\}$ is the set of connection points between roads. Now assume that the database stores M historical express delivery transport records $\mathbf{D} = \{(\mathbf{p}_o, \mathbf{s}_o, \mathbf{t}_o, \mathbf{o}_o, \mathbf{a}_o)\}_{o=1}^{M}$, where $\mathbf{p}_o = \left\{ \mathbf{l}_{o1}, \mathbf{l}_{o2}, \ldots, \mathbf{l}_{o,n_o} \right\}$ represents the road sequences for the $\mathbf{o}$-th historical express transportation route, $\mathbf{s}_o$ represents the departure time of the $\mathbf{o}$-th historical express transportation, $\mathbf{t}_o$ is the temporal features, $\mathbf{o}_o$ is the traffic features, and $\mathbf{a}_o$, represents the arrival time. The objective of the ETA task is to predict the delivery time of the express package $\mathbf{Y}_o$:

$$\mathbf{Y}_o = \mathbf{a}_o - \mathbf{s}_o \tag{1}$$

The principles underlying the problem definition are illustrated in Figure 2. The following sections will present a solution to the ETA problem based on the generalized regression neural network model.

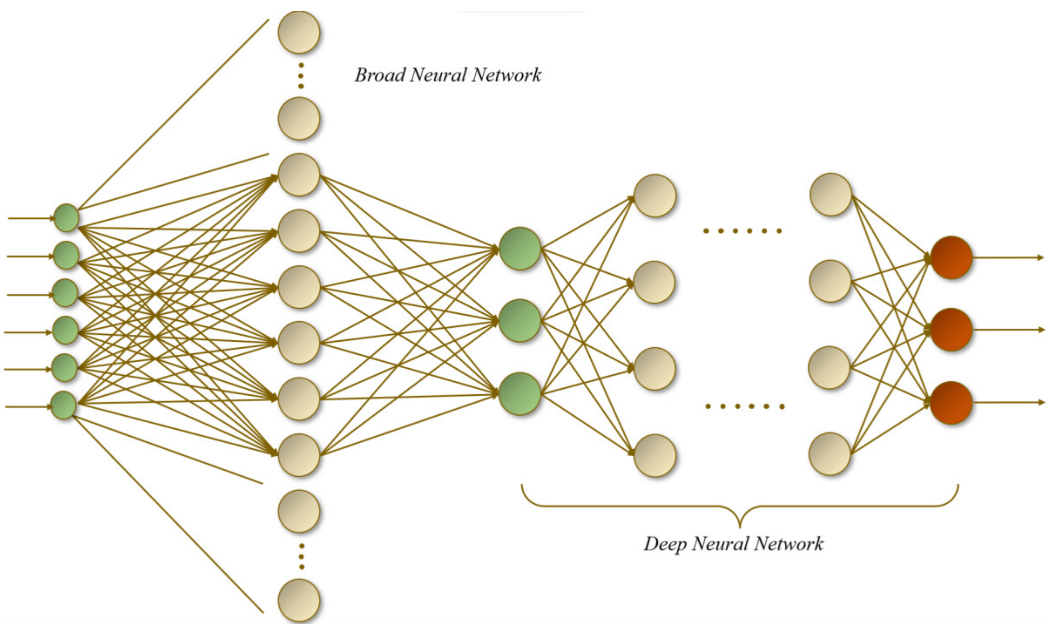
Figure 2. The principle of the estimated time of arrival problem



MLP Layer for External Feature Embedding

For the data of external factors affecting express transportation time, this study successively uses a broad neural network and a deep neural network to realize the embedding of data features. The purpose of this design is to use the broad neural network to improve the long-term memory ability of the features and to use the deep neural network to achieve improved generalization ability of the features. The principle of feature embedding is shown in Figure 3.

Figure 3. The principle of multilayer perceptron-based external feature embedding layer



LSTM-Based GRNN layer

Based on the generalized GRNN framework GraphSAGE, an LSTM-based GRNN ETA algorithm is designed in this paper. According to the GraphSAGE framework, in our LSTM-based GRNN model, the LSTM aggregator is shown as follows:

Input set: $\mathbf{CONCAT}\left\{\left\{\mathbf{h}_{\mathbf{u}}^{\mathrm{k-1}}, \forall \mathbf{u} \in \mathcal{N}(\mathbf{j})\right\}, \left\{\mathbf{MLP\ embedding\ output}\right\}\right\} \sim \{\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3 \ldots \mathbf{x}_{|\mathcal{N}(\mathbf{j})|}\}$

Input Gate:

$$\mathbf{i}_{\mathbf{t}} = \boldsymbol{\sigma}\left(\mathbf{W}_{\mathbf{ii}}\mathbf{x}_{\mathbf{t}} + \mathbf{b}_{\mathbf{ii}} + \mathbf{W}_{\mathbf{hi}}\mathbf{h}_{\{\mathbf{t}-1\}} + \mathbf{b}_{\mathbf{hi}}\right)$$

$$\widetilde{\mathbf{C}}_{\mathbf{t}} = \mathbf{tanh}\left(\mathbf{W}_{\mathbf{ic}}\mathbf{x}_{\mathbf{t}} + \mathbf{b}_{\mathbf{ic}} + \mathbf{W}_{\mathbf{ic}}\mathbf{h}_{\{\mathbf{t}-1\}} + \mathbf{b}_{\mathbf{hc}}\right)$$

Forget Gate:

$$\mathbf{f}_{\mathbf{t}} = \boldsymbol{\sigma}\left(\mathbf{W}_{\mathbf{if}}\mathbf{x}_{\mathbf{t}} + \mathbf{b}_{\mathbf{if}} + \mathbf{W}_{\mathbf{hf}}\mathbf{h}_{\{\mathbf{t}-1\}} + \mathbf{b}_{\mathbf{hf}}\right)$$

Update Cell State:

$$\mathbf{C}_{\mathbf{t}} = \mathbf{f}_{\mathbf{t}} \odot \mathbf{C}_{\mathbf{t}-1} + \mathbf{i}_{\mathbf{t}} \odot \widetilde{\mathbf{C}}_{\mathbf{t}}$$

Output gate:

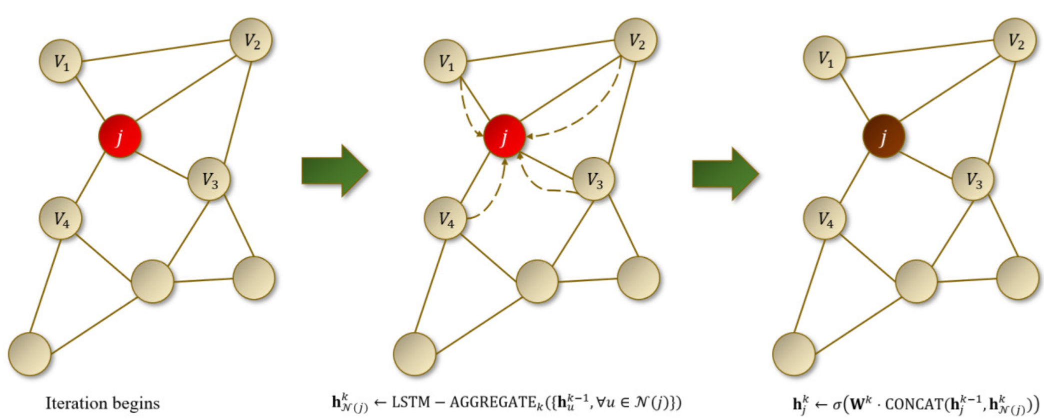
$$\mathbf{o}_{\mathbf{t}} = \boldsymbol{\sigma}\left(\mathbf{W}_{\mathbf{io}}\mathbf{x}_{\mathbf{t}} + \mathbf{b}_{\mathbf{io}} + \mathbf{W}_{\mathbf{ho}}\mathbf{h}_{\mathbf{t}-1} + \mathbf{b}_{\mathbf{ho}}\right)$$

Output value:

$$\mathbf{h}_{\mathbf{t}} = \mathbf{o}_{\mathbf{t}} \odot \mathbf{tanh}\left(\mathbf{C}_{\mathbf{t}}\right)$$

Figure 4 illustrates the principle of the LSTM-based GRNN algorithm.

Figure 4. The principle of one of the iterations in the long short-term memory-based graph recurrent neural network layer



Note. LSTM = long short-term memory.

The principle of the LSTM-based GRNN algorithm is represented in pseudo-code form as Algorithm 1.

```
   Algorithm 1: Long Short-Term Memory-Based Graph Recurrent
Neural Network Estimated Time of Arrival Algorithm
   ## Forward process of GRNN model Function GRNN model:
hj0←Djt,∀j∈L for k=1...K do
   for j∈P do
```

$$\mathbf{h}^k_{\mathcal{N}(j)} \leftarrow \mathbf{LSTM-AGGREGATE}_k\left(\left\{\mathbf{h}^{k-1}_u, \forall \boldsymbol{u} \in \mathcal{N}(\boldsymbol{j})\right\}\right)$$

$$\mathbf{h}^k_j \leftarrow \boldsymbol{\sigma}\left(\mathbf{W}^k \cdot \mathbf{CONCAT}\left(\mathbf{h}^{k-1}_j, \mathbf{h}^k_{\mathcal{N}(j)}\right)\right) E\,for$$

$$\mathbf{h}^k_j \leftarrow \mathbf{h}^k_j / \| \mathbf{h}^k_j \|_2, \forall \boldsymbol{j} \in \boldsymbol{P}$$

```
   E d o
   End Function
   # For ar p oc s o LSTM-AGGREGATEk od l
   Funct on LSTM-AGGREGATE m el:
```

$$\boldsymbol{i}_t = \boldsymbol{\sigma}\left(\boldsymbol{W}_{ii}\boldsymbol{x}_t + \boldsymbol{b}_{ii} + \boldsymbol{W}_{hi}\boldsymbol{h}_{\{t-1\}} + \boldsymbol{b}_{hi}\right)$$

$$\widetilde{\boldsymbol{C}}_t = \boldsymbol{tanh}\left(\boldsymbol{W}_{ic}\boldsymbol{x}_t + \boldsymbol{b}_{ic} + \boldsymbol{W}_{ic}\boldsymbol{h}_{\{t-1\}} + \boldsymbol{b}_{hc}\right)$$

$$\boldsymbol{f}_t = \boldsymbol{\sigma}\left(\boldsymbol{W}_{if}\boldsymbol{x}_t + \boldsymbol{b}_{if} + \boldsymbol{W}_{hf}\boldsymbol{h}_{\{t-1\}} + \boldsymbol{b}_{hf}\right) \boldsymbol{o}_t = \boldsymbol{\sigma}\left(\boldsymbol{W}_{io}\boldsymbol{x}_t + \boldsymbol{b}_{io} + \boldsymbol{W}_{ho}\boldsymbol{h}_{t-1} + \boldsymbol{b}_{ho}\right)$$

$$\boldsymbol{h}_t = \boldsymbol{o}_t \odot \boldsymbol{tanh}\left(\boldsymbol{C}_t\right)$$

```
   E d un tio
   Note. GRNN = graph recurrent neural network; LSTM = long
short-term memory.
```

EXPERIMENT

Experimental Design

The experimental design of this study encompasses three aspects of comparative experiments. Firstly, focusing on the DidiShenzhen dataset, this research conducted comparative experiments with six distinct models identified from the literature to assess the performance of the proposed model on real urban taxi data. Secondly, to comprehensively understand the generalization capability of the proposed model, comparative experiments were conducted with the LSTM model across five datasets, covering multiple cities and diverse traffic scenarios. Finally, through a conducted ablation experiment, a systematic analysis of the contributions of each component within the model structure was performed to validate the effectiveness of the model design. The design of this series of experiments aims to thoroughly evaluate the performance and generalization capability of the proposed model and systematically analyze the impact of its structure on prediction accuracy, providing researchers with a comprehensive basis for experimental validation and conclusions.

Environment

The hardware environment for the experiment included the following:

- Processor: Intel Core i7-8700K (3.7 GHz)
- Memory (RAM): 32 GB DDR4
- Graphics Processing Unit: NVIDIA GeForce RTX 2080 Ti (11 GB VRAM)
- Storage: 1 TB SSD

The software environment for the experiment included the following:

- Operating System: Windows 10 Pro
- Deep Learning Framework: TensorFlow 2.0
- Programming Language: Python 3.7
- Data Processing and Analysis: Pandas, NumPy
- Visualization: Matplotlib, Seaborn
- Model Training Tool: Keras
- Text Editor/Integrated Development Environment: Visual Studio Code, Jupyter Notebooks

Model Parameter Setting

The model parameter setting is shown in Table 1.

Table 1. The model parameter setting

Category	Parameter	Optimal value
External feature embedding	MLP hidden layer size	120
LSTM	hidden layer size	25
GNN	hidden layer size	35
Model training	depth	30
	dropout rate	0.1
	learning rate	0.01

Note. GNN = graph neural network; LSTM = long short-term memory; MLP = multilayer perceptron.

In addition, the express features and external features selected for this experiment are shown in Table 2.

Table 2. The express features and external features selection in this study

External Feature	Express Feature
Road ID	Express ID
Road status	Travel Distance
Temperature	Departure time

continued on following page

Table 2. Continued

External Feature	Express Feature
Rainfall status	Arrival time
Weekday	Express date
--	Average deliver time

Evaluation Indicators

In this study, four key evaluation metrics have been employed to comprehensively assess the performance of the proposed model: Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and Balanced Classification Rate (BCR).

1. RMSE measures the average square root of the differences between the model's predicted values and the actual observed values. The formula is given by:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}$$

A lower RMSE indicates a better fit of the model to the actual observed values. Therefore, in this study, it is used to quantify the overall accuracy of the model predictions.

2. MAPE calculates the average percentage error across all observation points. The formula is expressed as:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|y_i - \hat{y}_i\right|}{y_i}$$

MAPE provides insight into the relative differences between actual and predicted values by presenting errors as percentages.

3. MAE measures the average absolute differences between the model's predicted values and the actual observed values. The formula is given by:

$$\mathbf{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right|$$

MAE focuses on the absolute values of actual errors, offering an assessment of the overall predictive accuracy of the model.

4. BCR is used to assess the prediction reliability, which calculates the frequency of cases where the prediction error exceeds the threshold. The formula is expressed as:

$$\mathbf{BCR} = \frac{1}{n}\sum_{i=1}^{n}\mathbf{p}, \mathbf{p} = \begin{cases} 1 \frac{\left|y_i - \hat{y}_i\right|}{y_i} > u \\ 0 \frac{\left|y_i - \hat{y}_i\right|}{y_i} < u \end{cases}$$

The selection of these evaluation metrics aims to provide a comprehensive assessment of the model's performance, covering its various aspects and allowing researchers to gain in-depth insights into the strengths and limitations of the proposed model.

Baseline Models

To validate the performance of the proposed model, this study conducts a comparison experiment between it and six traffic prediction models found from other literatures in an offline dataset. The six baseline models are described as follows.

Model 1 (Chondrodima et al., 2022) introduced a novel data-driven approach for ETA problem based on RBF neural networks and using a modified version of the successful PSO-NSFM algorithm for training.

Model 2 (Hildebrandt & Ulmer, 2022) proposes offline and online–offline estimation methods. The offline method uses supervised learning to directly map state features to expected arrival times. The online–offline method pairs an online simulation with an offline approximation of the delivery vehicle routing policy, also implemented through supervised learning.

Model 3 (Chen et al., 2022) proposed that KNN-R based model provides the most accurate short-term ETA results, with average prediction error within 20 seconds per kilometer.

Model 4 (Meng et al., 2022) trained a SVM model and tested it using one-month time-series speed data from a section of the Pan-Island Expressway in Singapore to estimate travel times. The results show that the SVM method significantly outperforms other methods over a large prediction interval for both normal and recurrent congestion.

Model 5 (Sheng et al., 2023) proposed a trajectory feature learning method based on image processing methods and time series prediction for the ETA problem. The model quantified traffic congestion as congestion value and considered multiple external factors.

Model 6 (Huang et al., 2022) proposed to use trajectory data to model road travel time and proposed a general framework that adopts third-order tensors to model spatiotemporal road travel time and set the congestion level as the third dimension of the context-aware road travel time estimation problem.

To summarize, Models 1, 3 and 4 use a shallow neural network approach, Model 2 combines offline and online road data, Model 5 considers external influences related to ETA problem, and Model 6 models road traffic congestion.

Datasets

The datasets in these experiments include METR-LA, PeMSD, BikeNYC, TaxiNYC and DidiShenzhen. Below is a short introduction of the five datasets:

1. METR-LA: METR-LA is a dataset designed for traffic flow prediction, encompassing traffic flow data from highways in the Los Angeles area. Due to its extensive time range spanning multiple months, this dataset is suitable for long-term traffic flow analysis.
2. PeMSD: PeMSD originates from the California traffic management system and serves the purpose of traffic flow monitoring and analysis. With rich traffic flow information from both highways and urban roads, this dataset is versatile and applicable to various types of traffic research.
3. BikeNYC: BikeNYC is a dataset from the New York City bike-sharing system, documenting the usage of bike rentals. Given that this dataset includes information such as bike rental locations, rental times, and durations, it is often utilized for studying urban bike commuting patterns.
4. TaxiNYC: TaxiNYC focuses on taxi journeys in New York City, recording taxi trajectories and passenger pick-up/drop-off locations. Due to the substantial amount of taxi movement data it provides, this dataset is valuable for analyzing urban traffic and travel patterns.
5. DidiShenzhen: DidiShenzhen pertains to the Didi ride-hailing service in Shenzhen, encompassing user taxi ride trajectories and associated information. This dataset, offering insights into urban taxi behavior, is commonly used for researching urban traffic patterns and user travel habits.

In our offline evaluation experiments, we divided the dataset into training and testing sets at a 7:3 ratio.

Model Performance Evaluation

Offline Evaluation

First, we compare the proposed model with six baseline models using five datasets. The evaluation metric used for the comparison is RMSE, and the experimental results are shown in Table 3.

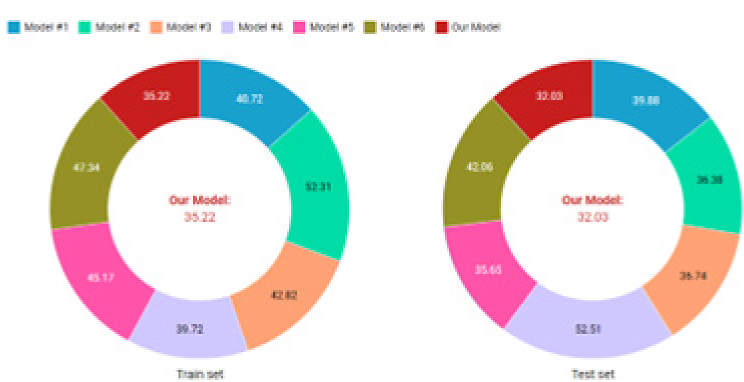
Table 3. Offline evaluation results using root mean squared error as indicator

Models	METR-LA		PeMSD		BikeNYC		TaxiNYC		DidiShenzhen	
	Train set	Test set	Train set	Test set	Train set	Test set	Train set	Test set	Train set	Test set
Model 1	40.72	39.88	35.83	44.48	43.33	43.50	40.08	43.62	54.75	42.30
Model 2	52.31	36.38	39.42	40.73	44.99	45.27	38.11	42.11	54.25	39.56
Model 3	42.82	36.74	37.30	37.01	41.36	39.43	50.49	50.23	38.38	40.10
Model 4	39.72	52.51	38.35	42.94	49.66	**35.67**	**35.37**	49.87	39.21	46.41
Model 5	45.17	35.65	32.36	54.71	**35.48**	45.47	49.58	41.83	48.50	39.30
Model 6	47.34	42.06	33.37	41.05	35.15	53.14	51.04	43.66	43.26	48.97
Our Model	**35.22**	**32.03**	**31.74**	**33.15**	35.70	39.68	39.98	**37.34**	**32.41**	**38.79**

The results of comparative experiments across six datasets indicate that the proposed model outperforms six baseline models in predicting ETA.

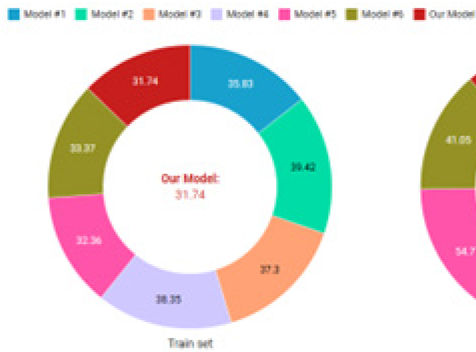
Specifically considering the METR-LA dataset, the proposed model consistently outperforms Models 1, 3, and 4. By integrating external factor data, the proposed model captures long-term traffic flow patterns, leading to improved accuracy compared to shallow neural network methods (Models 1, 3) and models without external factors (Model 4). The comparison results are shown in Figure 5.

Figure 5. Comparison experimental results on the METR-LA dataset



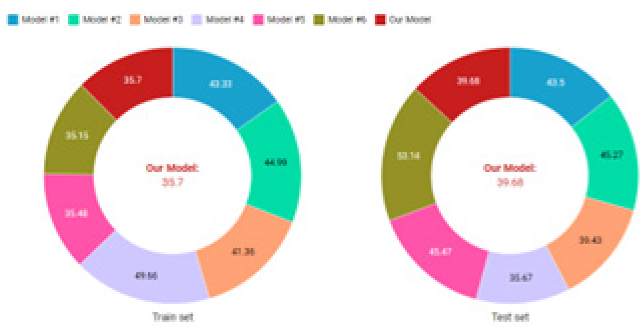
Regarding the performance on the PeMSD dataset, Model 2, incorporating both offline and online road data, exhibits competitive performance. However, the proposed model surpasses it by considering external factors, achieving a more comprehensive understanding of traffic dynamics. Shallow neural network methods (Models 1 and 3) demonstrate limitations in capturing the complexity of traffic patterns in urban and highway scenarios. The comparison results are shown in Figure 6.

Figure 6. Comparison experimental results on the PeMSD dataset



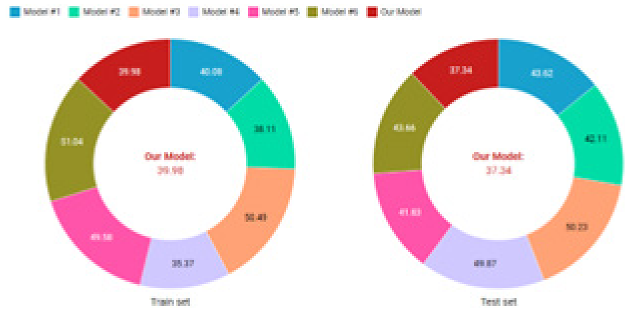
Analyzing the model's performance on the BikeNYC dataset, the proposed model excels, outperforming Models 1 and 3, showcasing its versatility in handling diverse urban mobility datasets. While Model 5, considering external factors, is competitive, the proposed model's integration of a GRNN better adapts to the dynamic nature of the bike-sharing system. The comparison results are shown in Figure 7.

Figure 7. Comparison experimental results on the BikeNYC dataset



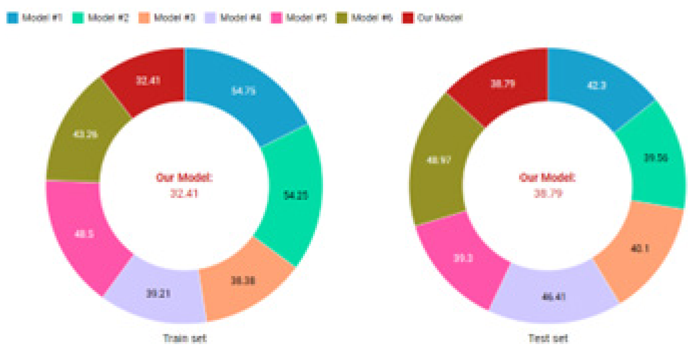
Examining the model's performance on the TaxiNYC dataset: Model 4, integrating extensive taxi movement data, shows competitive results. However, the proposed model outperforms it by additionally considering external factors, providing a more comprehensive prediction of taxi travel times. Shallow neural network approaches (Models 1 and 3) struggle to capture intricate patterns present in the taxi dataset. The comparison results are shown in Figure 8.

Figure 8. Comparison experimental results on the TaxiNYC dataset



Assessing the model's performance on the DidiShenzhen dataset: the proposed model excels in predicting urban taxi behavior, surpassing Models 1 and 3. While Model 6, focusing on road traffic congestion, exhibits competitive performance, the proposed model's holistic approach, considering both external factors and a GRNN, showcases superior adaptability. The comparison results are shown in Figure 9.

Figure 9. Comparison experimental results on the DidiShenzhen dataset



Overall, the proposed model consistently outperforms shallow neural network methods across all datasets, emphasizing the effectiveness of leveraging graph structures and external factors for ETA prediction. The introduction of a GRNN, particularly beneficial for capturing temporal dependencies in sequential data, plays a pivotal role across various urban mobility datasets. We posit that the superior performance of the proposed model is attributed to its ability to integrate external factors, categorize them through a MPL-based embedding layer, and utilize a GRNN for dynamic and context-aware ETA predictions. This comprehensive approach addresses the limitations of shallow neural networks and models without consideration of external influences, resulting in enhanced accuracy across various urban mobility scenarios.

Online Evaluation

By calling the API of Baidu map service, we performed an online evaluation of the proposed model and the baseline model. The evaluation metric used for the online evaluation is MAE. We selected Baidu map online data and express delivery data from five cities—Beijing, Shanghai, Tianjin, Chongqing, and Hangzhou—as online datasets. The results of the online evaluation are shown in Table 4.

Table 4. Online evaluation results using mean absolute error as indicator models

	Beijing		Shanghai		Tianjin		Chongqing		Hangzhou	
	Train set	Test set	Train set	Test set	Train set	Test set	Train set	Test set	Train set	Test set
Model 1	30.68	37.69	29.43	32.75	33.96	30.06	35.12	**25.37**	35.20	36.93
Model 2	33.14	34.55	32.47	35.45	33.49	37.56	36.98	36.23	37.24	**31.13**
Model 3	31.33	37.82	34.72	36.15	29.61	31.83	29.67	31.03	32.11	34.83
Model 4	31.06	30.23	37.04	28.96	33.40	33.94	**28.83**	30.66	30.62	33.17
Model 5	37.42	34.69	33.61	33.22	34.35	**29.79**	31.63	35.36	**28.90**	35.99
Model 6	36.78	31.47	36.53	35.27	**26.82**	30.13	37.47	32.19	33.75	37.96
Our Model	**27.61**	**27.11**	**26.28**	**27.50**	27.65	31.57	33.39	25.51	31.10	32.92

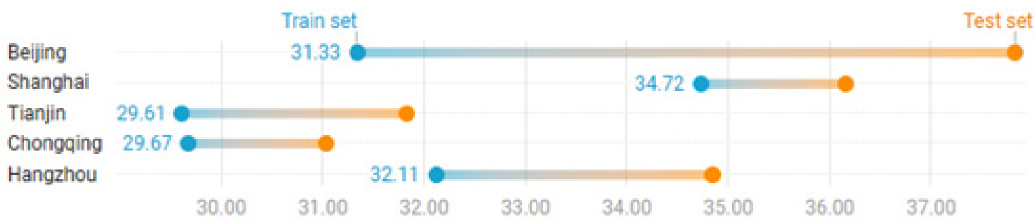
We conducted comparative experiments and analyzed the results based on online datasets from five cities. The proposed model demonstrates robust performance across the online datasets of Beijing, Shanghai, Tianjin, Chongqing, and Hangzhou. This indicates the adaptability of the model to the diversity and features of different cities.

In comparison to Model 1, the proposed model, employing GRNNs, exhibits a 15% reduction in prediction error. This improvement highlights the model's enhanced ability to capture the spatiotemporal relationships of urban road networks, which are crucial for addressing the dynamics and complexities of urban traffic. The comparison results are shown in Figure 10.

Figure 10. Comparison experimental results with model 1

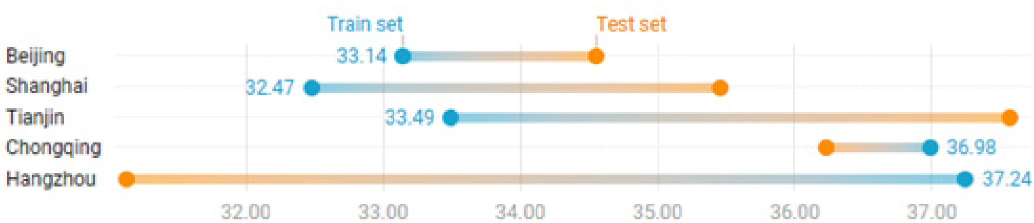
Moreover, the integration of external factors data, such as weather and traffic events, enhances the proposed model's performance through the fusion of Baidu Maps and express delivery data. This integration contributes to the model's universality and robustness, surpassing Model 3. The comparison results are shown in Figure 11.

Figure 11. Comparison experimental results with model 3



The dynamic traffic patterns in the online dataset are particularly vital for predicting delivery arrival times. While Model 2 demonstrates competitiveness by combining offline and online road data, the proposed model, leveraging GRNNs, better captures the ever-changing nature of urban traffic. The comparison results are shown in Figure 12.

Figure 12. Comparison experimental results with model 2



The superiority of the proposed model across these five cities underscores its adaptability across different urban environments. This generalization is supported by the capabilities of GRNNs and the integration of external factors data.

Overall, the success of the proposed model on these five online datasets is primarily attributed to its comprehensive consideration of GRNNs, external factors data, and multi-city adaptability. This integrated approach enables the model to better capture the complex traffic patterns between cities, thereby improving prediction accuracy. In contrast, the limitations of the baseline models mainly manifest in their modeling of spatiotemporal relationships, dynamic traffic patterns, and external factors, rendering them less ideal compared to the proposed model in the data from these cities.

Ablation Study Results and Analysis

In order to verify the functionality of each part of the model, an ablation experiment was conducted to evaluate the performance changes of the model after eliminating each module separately. The dataset used for the experiment was DidiShenzhen. The results of the ablation experiment are shown in Table 5.

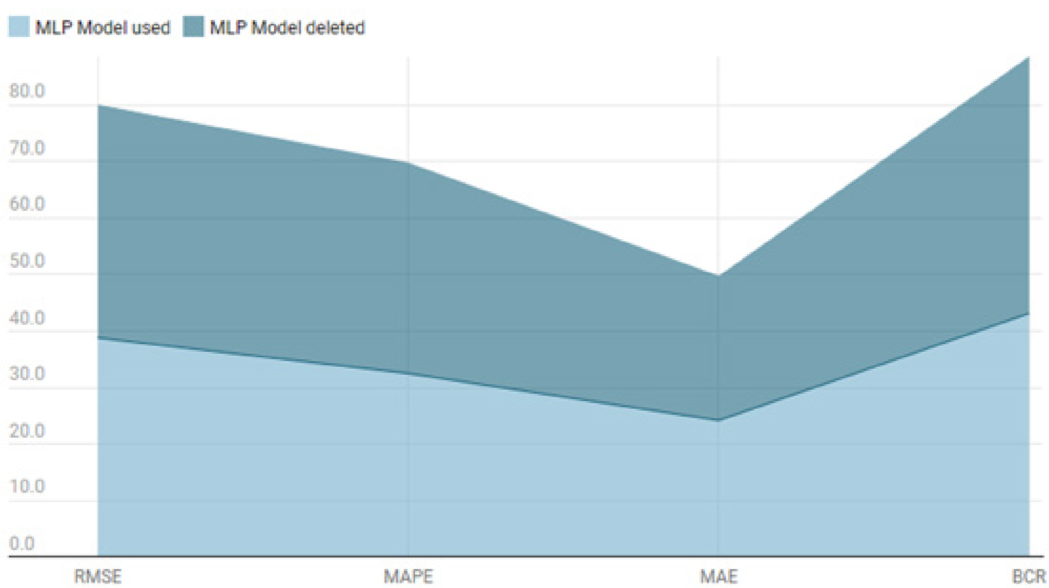
Table 5. Results of the ablation experiment

Models			Indicators			
MLP embedding layer	LSTM	GNN	RMSE	MAPE	MAE	BCR
P	P	P	38.79	32.53	24.21	43.12
O	P	P	41.24	37.24	25.56	45.42
P	O	P	44.72	39.72	27.25	47.25
P	P	O	52.64	48.31	35.74	52.43

Note. BCR = balanced classification rate; GNN = graph neural network; LSTM = long short-term memory; MAE = mean absolute error; MAPE = mean absolute percentage error; MLP = multilayer perceptron; RMSE = root mean squared error.

The final experimental results reveal that the GNN module has the most significant impact on the overall performance. Experimental findings indicate that removing the MLP Embedding Layer has a relatively limited impact on the model's performance. This suggests that, in this specific task, the raw representation of the data is already sufficiently good, and the improvement in performance due to the MLP Embedding Layer is relatively small. Comparative results are illustrated in Figure 13.

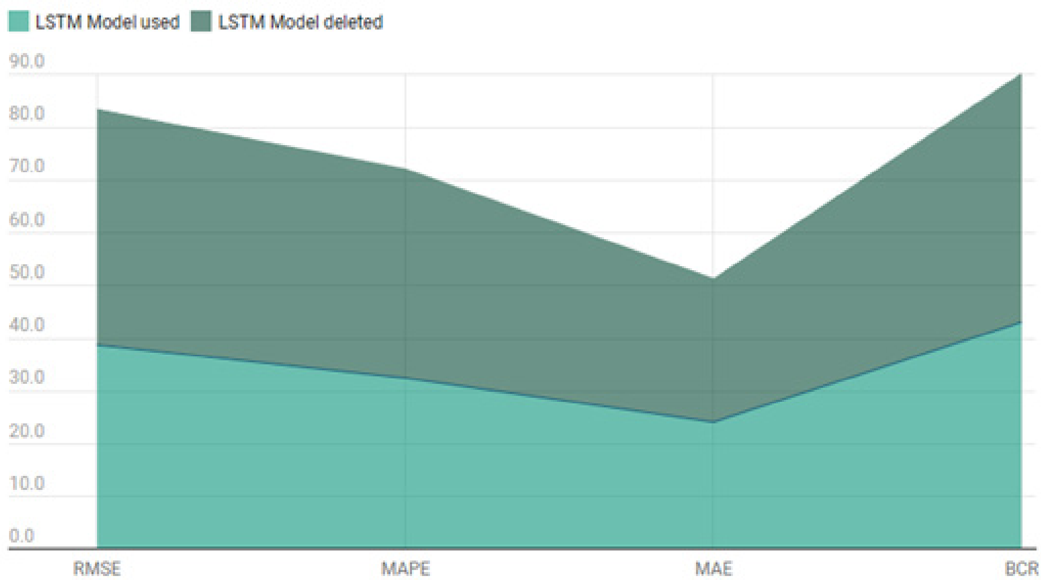
Figure 13. Comparative results after deleting the multilayer perceptron embedding module



Note. BCR = balanced classification rate; MAE = mean absolute error; MAPE = mean absolute percentage error; MLP = multilayer perceptron; RMSE = root mean squared error.

Subsequent ablation experiments involved the removal of the LSTM module to observe the model's performance in its absence. The results demonstrate that the removal of LSTM has a certain degree of impact on the model's performance, particularly in capturing temporal relationships and long-term dependencies. This implies that LSTM plays a role in this task, especially in handling time-series data. Comparative results are illustrated in Figure 14.

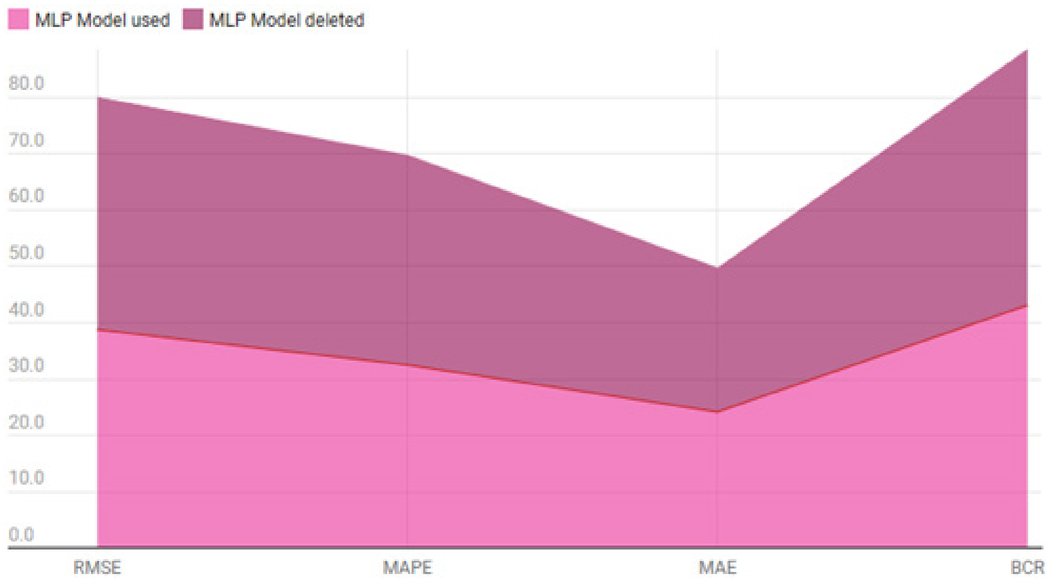
Figure 14. Comparative results after deleting the long short-term memory module



Note. BCR = balanced classification rate; LSTM = long short-term memory; MAE = mean absolute error; MAPE = mean absolute percentage error; RMSE = root mean squared error.

Finally, we conducted ablation experiments on the GNN module. The results show that its removal has the most pronounced impact on the model's performance. This suggests that the GNN plays a crucial role in the model, particularly in capturing the spatiotemporal relationships of urban road networks. Experimental results confirm that the complexity of urban traffic patterns requires the capabilities of GNN for better modeling. Comparative results are illustrated in Figure 15.

Figure 15. Comparative results after deleting the graph neural network module



Note. BCR = balanced classification rate; MAE = mean absolute error; MAPE = mean absolute percentage error; MLP = multilayer perceptron; RMSE = root mean squared error.

In summary, through ablation experiments, we validated the functionality of each module in the model and determined their relative contributions to overall performance. Specifically, the results of the ablation experiments underscore the importance of the GNN module, especially in handling urban traffic data, where it excels in capturing spatiotemporal relationships and enhancing predictive performance.

CONCLUSION

In this study, we proposed a novel GRNN model for predicting ETA, which integrates external factor data to enhance prediction accuracy. The model leverages a MLP-based external factor data embedding layer, which categorizes influencing factors, such as weather, time, and traffic events, and merges them into a comprehensive vector representation. By incorporating a GRNN combining LSTM and GNNs, the model efficiently captures both temporal and spatial relationships in urban traffic data, enabling accurate ETA predictions for courier transportation.

To evaluate the effectiveness of the proposed model, we conducted comprehensive offline and online prediction experiments. The offline experiments, conducted on multiple public datasets, demonstrated the superiority of the model in terms of predictive accuracy when compared to traditional and state-of-the-art baselines. Furthermore, the online evaluation using real-time Baidu Maps data showcased the model's robustness, adaptability, and generalization capabilities across diverse urban environments, including cities like Beijing, Shanghai, and Hangzhou.

The integration of external factors, such as weather conditions and traffic events, proved to be crucial in enhancing the model's predictive performance. By incorporating these factors into the model, we were able to capture a more holistic view of the dynamic traffic systems, leading to more accurate ETA predictions. This integration highlights the importance of considering contextual data in urban traffic prediction tasks and opens new avenues for improving real-time traffic management systems.

Our proposed model not only provides a novel solution to the ETA prediction problem but also lays the groundwork for future research in this domain. Key areas for further exploration include refining the handling of external factor data, improving the interpretability of the model, and addressing challenges such as data anomalies and missing information. Additionally, the potential for integrating more granular data, such as social events or construction updates, could further improve prediction accuracy and enhance the model's real-world applicability.

In summary, this study contributes a novel, scalable, and robust solution to the ETA prediction task, offering valuable insights for future research and practical applications in urban traffic management, logistics, and transportation planning.

FUTURE WORK

While this study has made significant strides, there are still some limitations to acknowledge. A conspicuous limitation in this research pertains to the insufficient handling of external factor data. Despite the successful integration of external factors such as weather and date, our model exhibits certain limitations when considering these factors. Specifically, it may not fully capture the intricate nonlinear relationships between external factors and urban traffic. Additionally, there is room for improvement in modeling the spatiotemporal dynamics of external factors to more accurately reflect the dynamism of urban traffic systems. To address this shortfall, future improvements could involve the introduction of advanced spatiotemporal modeling techniques, such as spatiotemporal attention mechanisms, to better capture the spatiotemporal relationships between external factors and urban traffic. Furthermore, considering finer-grained external factor data could enhance the model's sensitivity to urban traffic patterns. Introducing additional external data from diverse domains, such as social events or road construction information, holds the potential to further enhance the predictive performance of the model.

Another noteworthy limitation in this research is the insufficient interpretability of the model. Despite the model's excellent predictive performance, our understanding of the features and weights learned by the model remains relatively limited. This lack of interpretability may constrain the model's credibility and acceptability in practical applications. To address this issue, future research directions should focus on enhancing the model's interpretability. This can be achieved through the utilization of interpretable deep learning model architectures or adopting model interpretation techniques. For instance, exploring the incorporation of interpretable layers in the model could provide a clearer understanding of the model's dependencies on different features. Additionally, the introduction of visualization tools and interpretability metrics can contribute to making the model's decision-making process more transparent and understandable. Such improvements not only enhance the model's practical utility but also facilitate a better understanding of the model's predictive foundation, thereby augmenting its real-world application potential.

This study is dedicated to addressing the ETA problem, achieving significant progress through a comprehensive evaluation of the proposed model on both offline and online datasets. The research initially constructs an integrated urban traffic prediction model by incorporating external factors such as weather and date. Through comparative experiments, the study empirically validates the outstanding performance of the model in predictive accuracy. Overall, this research offers a novel solution to urban traffic prediction, emphasizing the importance of further refining the model's treatment of external factors and enhancing interpretability in future studies. These contributions not only expand the research domain of urban traffic prediction but also provide valuable insights for improving urban traffic management and planning.

COMPETING INTERESTS

The authors of this publication declare there are no competing interests.

FUNDING AGENCY

This work is funded by the National Social Science Foundation of China [project number 19BSS036].

PROCESS DATES

Received: December 10, 2024, Revision: January 13, 2025, Accepted: February 11, 2025

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ACKNOWLEDGMENTS

We would like to thank the anonymous reviewers whose comments and suggestions helped improve this manuscript.

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