Enhancing Bus Arrival Time Predictions in Transit Networks through Spatio-temporal Forecasting

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***Keywords*—Spatio-temporal Forecasting, Bus Arrival Time Prediction, Graph Neural Networks, Transformer Models, Public Transportation Systems**

I. Introduction

Urban public transport is a key infrastructural element that tends to suffer from the variability of bus arrival times, leading to long wait times and increased passenger dissatisfaction. This research presents a sophisticated prediction framework that leverages the synergy of Graph Neural Networks (GNNs) and Transformer-based models to overcome these limitations. Utilizing comprehensive datasets from the New York City Metropolitan Transportation Authority (MTA), the model captures both the temporal dynamics of bus movements and the spatial interdependencies among stops. The integrated model not only performs better than traditional models that tend to study routes independently, but also provides real-time accurate forecasting. Experimental results demonstrate significant improvements in predictive accuracy over established baselines, validating the model's effectiveness. These promising outcomes highlight the potential of advanced machine learning techniques to revolutionize urban transit management and foster improved mobility.

II. Literature Review

Chien et al. [1] proposed an ANN-based model for bus arrival predictions but faced limitations in accounting for multi-route transit networks. Building on this, Jiang and Luo [2] showed that GNNs outperform traditional models like CNNs and RNNs in capturing spatial-temporal dependencies; however, their approach treats spatial and temporal factors independently by relying on static graphs, which restricts adaptability to real-time conditions.

Zhang et al. [3] proposed the ST-ResNet model, which effectively captures spatial patterns using deep residual CNNs but falls short in managing irregular transportation networks.

Rong et al. [4] introduced the GBTTE model, which employs a 3D cross-graph attention mechanism to capture spatial and temporal dependencies in an integrated manner, addressing the limitations of earlier approaches that handled these factors independently. While this joint modeling enhances forecast accuracy, GBTTE still faces challenges in adapting to real-time traffic changes.

Our approach builds on these advances by integrating both attention and self-attention mechanisms within a Transformer framework. This design not only enhances the joint modeling of spatial and temporal dynamics but also improves the model's responsiveness to real-time traffic changes, ultimately providing a more robust solution for bus arrival predictions.

III. Methodology

A. Data Collection

The New York City MTA bus network is the primary data source for this project. The dataset contains real-time bus locations, routes, scheduled and actual arrival times, and is recorded at 10-minute intervals. It provides a comprehensive view of the movement of buses across the city.

B. Data Preprocessing

Data preprocessing involved removing records with missing or erroneous values. Specifically, entries with absent timestamps, bus IDs, route numbers, or arrival times were discarded, while outliers in arrival times (values below the 5th or above the 95th percentile), unrealistic GPS coordinates,

https://doi.org/10.31705/ADScAI.2025.34

and implausible travel durations were filtered. Categorical features were encoded, and continuous variables normalized, with a stratified random sample of 500,000 records drawn from 5 million to ensure statistical representativeness and computational efficiency.

A correlation matrix was employed to inform feature weighting, prioritizing those strongly correlated with the target variable. Notably, distance from stop, arrival proximity text, and next stop-point name were weighted at 1.5, 1.3, and 1.2 respectively, ensuring that the most informative features were emphasized in subsequent analyses.

C. Model Development

The core of the model development involves the integration of GNNs and Transformer-based architectures, specifically the Spacetimeformer [5] model. The steps include:

- Graph Neural Networks (GNNs): Used to capture spatial relationships between bus stops by mapping their connectivity, transit routes, and interaction patterns, enabling a deeper understanding of spatial dependencies.
- Transformer-based Architectures: The Spacetimeformer model handles both spatial and temporal dependencies using a spatiotemporal attention mechanism, enabling dynamic learning of relationships without relying on predefined graphs.

D. Hyperparameter Tuning

Hyperparameter tuning was conducted using time-series cross-validation to optimize key settings for the Spacetimeformer model. The tuning process focused on parameters including the learning rate, batch size, number of layers, and dropout rate. These hyperparameters were iteratively adjusted to balance model complexity and generalization, thereby enhancing the predictive accuracy for bus arrival times.

E. Evaluation

The model is evaluated using key metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE).

IV. Results and Discussion

The study highlights Spacetimeformer's superior ability to predict bus arrival times using spatiotemporal forecasting. It outperformed GNNs and CNNs, achieving lower MAE and RMSE values, as shown in Table I.

TABLE I
PERFORMANCE COMPARISON OF MODELS (NORMALIZED METRICS)

Model	*MAE*	*MSE*	*RMSE*
Graph Neural Networks	0.1889	0.0630	0.2510
Convolutional Neural Networks	0.1978	0.0911	0.3019
Spacetimeformer	0.1187	0.0364	0.1907

Spacetimeformer recorded the lowest error rates, demonstrating its strength in capturing spatial and temporal dependencies. In contrast, GNNs and CNNs struggled with complex time-series relationships, limiting their accuracy. The system's strong performance supports real-world deployment, with future improvements focusing on local data integration, environmental factors, and mobile accessibility.

V. Limitations and Future Work

While effective, this study has some limitations. The model relies on NYC MTA data, which may not generalize well without retraining on local datasets. It does not incorporate real-time weather, traffic, or road conditions, which affect bus schedules. Spacetimeformer's computational demands pose challenges for real-time deployment, and the model lacks dynamic adaptation to transit changes. Additionally, the user interface could be expanded with more personalized features.

Future work will focus on addressing these limitations by integrating localized datasets, incorporating environmental and traffic data, and optimizing model performance through advanced tuning techniques. A mobile application will be developed for real-time transit updates, and alternative models like Temporal Graph Networks (TGNs) will be explored.

VI. Conclution

This study demonstrates how spatiotemporal forecasting algorithms can improve public transport by precisely predicting bus arrival times. Using NYC MTA data, a scalable solution was created to cut passenger wait times and improve transport reliability. Comparative investigation established Spacetimeformer as the most effective model, surpassing GNNs and CNNs due to its capacity to capture complicated spatial and temporal connections. The model has lower MAE, MSE, and RMSE, indicating higher predictive accuracy. In addition, an interactive dashboard was built to visualize bus arrival statistics, which increased user engagement. This study demonstrates the utility of predictive modeling for optimizing transit schedules and increasing commuter experience.

Acknowledgment

We extend our gratitude to our mentors, Dr. Uthayasanker Thayasivam and Ratneswaran Shiveswarran, for their guidance, support, and insights throughout this project. We also express our appreciation to all who contributed directly or indirectly to this work. This research was carried out independently without the support of external funding.

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