

Demand Forecasting in Transportation: A Graph Attention Networks for Predicting Bus Ridership

Tsetsentsengel Munkhbayar*, Zolzaya Dashdorj*, Zoljargal Jargalsaikhan*, Kang Tae-Koo**, Erdenebaatar Altangerel*

*Department of Computer Science, Mongolian University of Science and Technology, Ulaanbaatar, Mongolia

**Department of Human Intelligence and Robot Engineering, Sangmyung University, Seoul, Republic of Korea

tsetsentsengelm@must.edu.mn, zolzaya@must.edu.mn, j.zoljargal@must.edu.mn, tkkang@smu.ac.kr, erka@must.edu.mn

Abstract— Demand prediction in transportation systems plays a critical role in optimizing resources and improving service efficiency. This study explores demand prediction for Ulaanbaatar's public transportation network using Graph Attention Networks (GATs), Convolutional Neural Networks (CNNs), and Generative Adversarial Networks (GANs). GATs effectively capture spatial relationships, achieving the best performance while GANs struggle with stability and convergence issues. The findings emphasize the potential of using graph-based methods that incorporate key stations in the analysis of public transportation networks for predicting transit demand.

Keywords— Generative Adversarial Networks, Convolutional neural networks, Intelligent transportation systems, Deep learning

I. INTRODUCTION

Ulaanbaatar, the capital city of Mongolia, has seen rapid urbanization, with its population increasing by over 50% in the past two decades [2] which is depicted in Figure 1. This demographic shift has resulted in greater demand for public transportation services, particularly bus ridership, which is the primary mode of transportation for many residents as depicted in Figure 2. With only 1,300 buses currently in service, the system is struggling to cope, especially during peak hours, resulting in frequent overcrowding. In 2021, the city's traffic was moving at an average speed of just 8.9 km/h during peak hours, with residents spending an average of 2.5 hours daily stuck in traffic. This congestion has a direct impact on the efficiency and reliability of public transportation, as buses are caught in the same traffic jams, leading to delays and an unreliable service. With a daily ridership of around 480,000 to 500,000 passengers, Ulaanbaatar's public transportation system often becomes overcrowded, especially during peak hours. In fact, 61% of the city's population relies on public transport. The insufficient number of buses, combined with the increasing demand, results in packed buses, making the travel experience uncomfortable for passengers.

This overcrowding is particularly noticeable in the central areas of the city, where the demand for public transportation is highest. Traditional demand forecasting methods, such as time series analysis and regression models, have been proven inadequate for predicting the dynamic and nonlinear nature of

bus ridership demand [12].

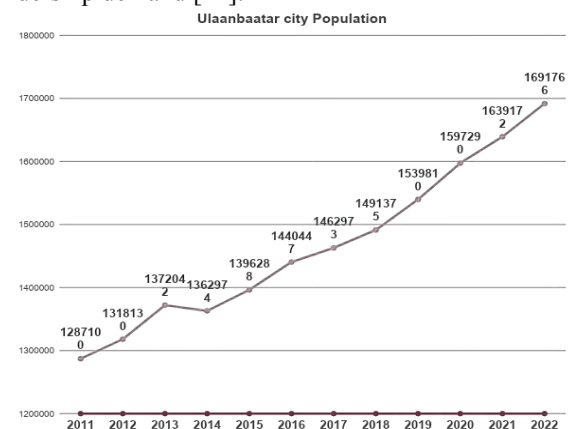


Figure 1. Ulaanbaatar city population

However, experts struggle to capture complex, non-linear relationships in the data, especially in cases with varying passenger flows or irregular demand patterns.

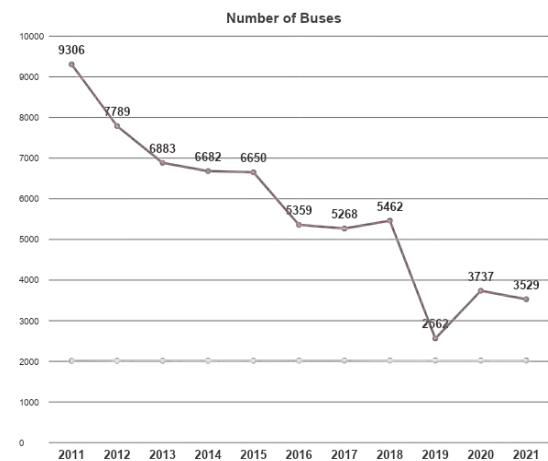


Figure 2. Number of public transportation

The need for efficient demand forecasting models has become crucial for optimizing the management of bus routes and schedules in Ulaanbaatar. Accurate demand prediction in public transportation systems is critical for optimizing

operations, improving passenger experience, and supporting urban planning initiatives. With increasing urbanization, cities face challenges in managing their public transit networks, which require robust data-driven solutions to address fluctuating demand and resource allocation [14]. Deep learning approaches, on the other hand, are promising approaches to handle these complexities, making them ideal for modeling bus ridership. Graph-based learning allows for the representation of transportation networks that captures both spatial and temporal interactions [4,5,11]. In this study, we focus on predicting bus ridership demand in the public transportation network of Ulaanbaatar city, Mongolia. To address this challenge, we explore and compare the performance of three deep learning approaches: Graph Attention Networks (GATs), Convolutional Neural Networks (CNNs), and Generative Adversarial Networks (GANs). Our findings offer valuable insights into the intelligent transportation applications that enable transportation authorities to make informed decisions about adjusting bus schedules, reallocating resources, or optimizing routes, thereby improving service efficiency and reducing operational costs.

II. RELATED WORKS

Demand prediction in public transportation has been extensively studied, with advancements driven by machine learning and deep learning techniques. Traditional methods, such as time series analysis and regression models, were initially used for forecasting ridership. For example, Holt-Winters exponential smoothing and ARIMA models were widely applied in early studies for transit demand forecasting, offering interpretable solutions but limited by their inability to capture non-linear and spatial-temporal relationships in the data [1]. Graph-based learning methods have shown significant promise in modeling transportation networks due to their ability to represent spatial and structural relationships effectively. [3] introduced Graph Convolutional Networks (GCNs), which have since been adapted for traffic flow and ridership prediction tasks. Recent work by [4] combined GCNs with temporal modeling to predict traffic demand, demonstrating the effectiveness of graph-based models in capturing complex spatial dependencies. Similarly, [5] proposed Graph Attention Networks (GATs), which further enhanced the ability to focus on important spatial relationships, making them suitable for public transportation networks. Convolutional Neural Networks (CNNs), initially developed for computer vision tasks, have been applied to sequential data for demand prediction. By treating temporal ridership patterns as 1D sequences, CNNs effectively capture local trends over time. [6] utilized CNNs to model spatiotemporal relationships in taxi demand prediction, demonstrating their capability to learn fine-grained temporal features. Similar applications in bus networks have shown that CNNs can capture both route-specific and time-dependent variations in demand [7]. Generative Adversarial Networks

(GANs) have been explored in transportation research for generating synthetic data and addressing data sparsity issues. For instance, [8] utilized GANs to generate synthetic traffic flow data, highlighting their potential in augmenting real-world datasets. However, GANs are prone to challenges such as training instability and mode collapse, which limit their effectiveness in tasks like ridership demand prediction. [9] noted that GANs require extensive hyperparameter tuning to achieve convergence, especially in applications involving highly imbalanced datasets. Comparative studies have highlighted the advantages of different modeling approaches based on task-specific requirements. [10] compared GCNs, Recurrent Neural Networks (RNNs), and CNNs for spatiotemporal forecasting, concluding that graph-based models excel in capturing network structures, while CNNs are better suited for sequential data. Similarly, [11] evaluated GANs against other deep learning models and found that GANs performed poorly in scenarios with unstable data distributions, reinforcing the need for further optimization. [13] introduced spatiotemporal graph neural networks (ST-GNNs) for travel demand forecasting. This model combines spatial and temporal data, making it highly effective for transportation applications like bus ridership prediction, where both geographic and time-related variables play a significant role.

III. METHODOLOGY

We utilize the following deep learning approaches for demand prediction using the passenger flow dataset.

A. Data preprocessing

The dataset used in this study consists of historical transportation data for 3 months including route id, sequence of bus stations, bus id, date time, number of passengers (adult, child, student, senior, donor, inspector, disabled person) who ride the bus, number of passengers (adult, child, student, senior, donor, inspector, disabled person) who take off the bus, number of passengers (adult, child, student, senior, donor, inspector, disabled person) who transit to the bus. In total 31 features are involved. The dataset was preprocessed by performing one-hot label encoding on the features; the number of passengers (demand) values were normalized between 0 and 1 using Min-Max scaling to improve training stability and model performance. In total, we collected 15,648 aggregated daily samples for 3 months, equivalent to 5,216 datasets per month, representing ridership statistics for each month. Thus, data for 133 bus routes, along with the geographical locations of the bus stations, were collected.

B. GAT Architecture

The Graph Attention Network (GAT) model [15] for predicting bus trip demand is designed to capture relationships between bus stations and the number of passengers traveling between them using a graph-based approach. The input graph contains nodes representing bus stations and edges

representing trips, with passenger counts as edge attributes. The GAT Convolution layer processes node features with 1 input channel, 8 output channels, and 8 attention heads. It concatenates the attention heads to capture significant relationships between bus stations, ensuring better predictions of demand. A fully connected layer maps the 64-dimensional output from the GAT layer to a single scalar value representing the predicted passenger demand. The ELU activation function is applied after the GAT layer to introduce non-linearity. The Adam optimizer updates the model parameters with a learning rate of 0.005, ensuring effective training across 50 epochs.

C. CNN Architecture

We modeled a 1-dimensional CNN for regression. The model uses 1-dimensional convolutional layers to capture spatial features from the input data. The first Conv1D layer has 64 filters with a kernel size of 3 and a ReLU activation function. This helps in detecting basic patterns in the input sequence. A subsequent MaxPooling1D layer with a pool size of 2 reduces the dimensionality and computation. Next, another Conv1D layer with 32 filters also uses a kernel size of 3. It is followed by another MaxPooling1D layer, which further down samples the features while maintaining important spatial information. After flattening the output from the convolutional layers, fully connected layers capture global relationships among the data. The first dense layer has 128 units with ReLU activation, followed by another dense layer with 64 units and ReLU activation. These layers help in learning complex interactions across the input features. The final layer is a Dense layer with a single neuron and a linear activation function, as it's designed for a regression task. This ensures that the model outputs a continuous value rather than a classification probability. The batch size is set to 32.

D. GAN Architecture

The GAN model consists of a generator and a discriminator. The generator takes random noise and one-hot encoded consecutive station information to generate synthetic demand data. The discriminator, on the other hand, takes both real and generated demand data along with route information, classifying it as real or fake. The batch size is set to 64. Both components are trained together using a binary cross-entropy loss function, ensuring adversarial training.

1) Generator:

The generator network takes two inputs: a random noise vector and one-hot encoded contextual features representing station information. It processes these inputs through a series of fully connected layers with ReLU activations, moving from smaller to larger layers (64, 32, 128, 256 neurons). The final output layer uses a linear activation function to produce continuous, non-negative demand predictions. The architecture aims to capture both fine-grained and high-level demand patterns. The learning rate is 0.0002, and the Adam optimizer.

2) Discriminator:

The discriminator network classifies inputs as real or fake by taking both generated and real demand data, along with contextual station information. It uses a series of fully connected layers with ReLU activations, gradually decreasing in size (256, 128, 64, and 32 neurons). The output layer contains a single neuron with a sigmoid activation, which outputs a probability indicating whether the input data is real or synthetic. The learning rate is 0.0001, and the Adam optimizer.

IV. EXPERIMENTAL RESULTS

We first analyse the transportation network as in Figure 3. In total, 133 bus routes are designed. In total, 1,253 nodes and 5,216 edges were represented per month. We prepared the training data by selecting a dataset from one month and used it to evaluate the demand prediction model on data from a different month. For the GAT-Demand Prediction Model, the dataset was processed by representing the transportation network as a graph, consisting of nodes and edges. The ridership data was aggregated based on the origin and destination stations, capturing passenger flow between consecutive stations along the bus routes. Each node in the graph corresponds to a bus station, while each edge represents a directed trip between two stations (origin and destination). The average in-degree and out-degree for a bus station are 2.17, with the maximum in-degree being 16 across 163 stations and the maximum out-degree being 13 across 417 stations. An average in-degree and out-degree of 2.17 indicates that, on average, each bus station has approximately two incoming and two outgoing connections. This suggests that the network has a relatively low level of connectivity, with most stations directly interacting with only a few others.



Figure 3. Public bus transportation network of Ulaanbaatar city, Mongolia

A maximum in-degree of 16 across 163 stations highlights that certain stations act as hubs, receiving significantly more incoming trips than others. These stations may serve as major transfer points or destinations with high passenger demand. A maximum out-degree of 13 across 417 stations indicates that some stations are primary origins for trips, dispatching buses to a wide range of destinations. This suggests an asymmetry in

the network, where certain stations are busier in terms of outgoing traffic than others. The larger number of stations with significant out-degree (417 stations) compared to in-degree (163 stations) may reflect a radial or hub-and-spoke network structure. In such structures, a few central nodes handle most of the incoming traffic, while many peripheral nodes primarily send outgoing trips. Stations with high in-degrees or out-degrees are critical for smooth operations and may require additional infrastructure or management to handle traffic efficiently.

The disparity between in-degree and out-degree hubs could indicate opportunities to balance traffic flow by adding new connections or redistributing routes. Critical bus stations are the nodes in the network graph that play a vital role in maintaining the connectivity and functionality of the bus network. Disruptions or failures at these stations could cause significant disruptions in transit flow, resulting in delays, reduced accessibility, or complete route breakdowns. Critical stations analysis plays a crucial role in enhancing demand prediction models, particularly those based on deep learning, in transportation systems.

TABLE 1. CRITICAL BUS STATIONS

Measurements	STATION ID	Interpretation
Overall Degree Centrality	379	A major hub with high activity
In-Degree Centrality	163	A primary destination or bus connections
Out-Degree Centrality	417	A key source hub for outgoing bus connections
Betweenness Centrality	21	An essential bridge node connecting multiple routes
Closeness Centrality	20	A centrally connected node ensuring quick transit routes

We estimated the critical stations by centrality measures as Figure 4. The result of centralities is explained briefly as Table 1. Overall degree centrality is bus station 379 that is the highest overall connectivity in the network that represents a hub with a high number of bus trips passing through it, both arriving and departing.

Station 163 has the highest incoming bus connections. This suggests that it is a major destination where many bus routes terminate. Such a station is usually a transfer point or terminal, where passengers converge, making it a significant point for network operations and transit planning. Station 417 has the highest number of outgoing connections. This indicates it serves as a major source hub for bus routes. Many buses depart from Station 417 to other stations, making it a key distribution point in the network, ensuring connections are distributed across different destinations. Station 21 has a high betweenness centrality score, meaning it acts as a critical

bridge in the network. It connects multiple routes and destinations, ensuring that transit flow remains smooth across different connections.

TABLE 2. MODEL EVALUATION METRICS

Model	Validation error
GAT-Demand	MAE = 0.059, MSE = 0.013
CNN-Demand	MAE = 0.0139, MSE = 0.0006
GAN-Demand	d_loss = 0.68, g_loss = 0.69

Disruptions at Station 21 could significantly impact network connectivity, causing delays and disjoint routes. Station 20 has the highest closeness centrality, meaning it can connect to every other station more quickly than any other node. It is centrally positioned in the network, ensuring efficient travel routes and minimal transit times. Passengers can access other stations with fewer connections and shorter paths, which improves overall transit speed and convenience.



Figure 4. Critical bus stations highlighted in red and large circle

By incorporating centrality analysis, deep learning models can better capture the dynamic relationships between different stations and their influence on overall demand. The GAT-Demand Prediction Model was successfully trained by epoch 50, achieving low loss values: Mean Absolute Error (MAE) = 0.036 and Mean Squared Error (MSE) = 0.006, indicating strong model performance. Validation was conducted using ridership data from a different month. Table 2 presents the evaluation metric results, comparing the performance of the GAT-Demand, CNN-Demand, and GAN-Demand prediction models.

To compare the results, the CNN-Demand model was trained for 50 epochs on the training dataset, where the dataset was formatted into a 1D tensor containing all 31 features. The model's performance was then evaluated using bus ridership data from a different month, comparing the predicted and actual demand. The MSE was found to be 6.1942e-04, and the MAE was 0.0141, suggesting that the model made reasonable predictions. While the model demonstrated potential, further adjustments to the architecture and training process are

required to reduce errors, particularly in low-demand scenarios. CNNs outperformed GATs in terms of error metrics, achieving the lowest MAE (0.0139) and MSE (0.0006), indicating superior accuracy in predicting temporal demand variations. The model was effective in capturing sequential trends in ridership, such as daily and weekly fluctuations. GATs achieved an MAE of 0.059 and MSE of 0.013, demonstrating effective modeling of spatial dependencies within the transportation network. Its ability to leverage graph structures makes GATs highly suitable for transportation networks with complex spatial interactions.

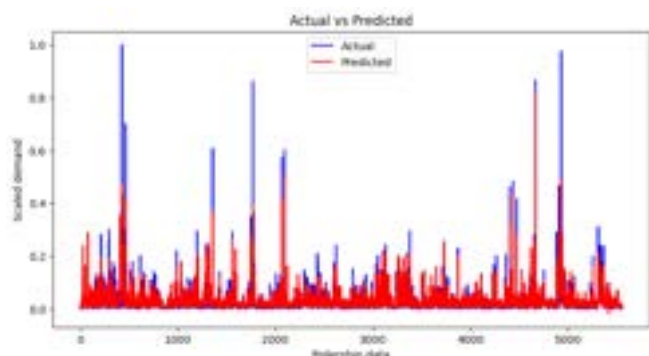


Figure 5. Demand prediction on the validation dataset

Figure 5 illustrates the comparison between the actual and predicted demand values for a subset of test data. It is evident that the predicted demand values closely match the actual demand, with minor discrepancies that may be attributed to the model's limited training data.

A discriminator loss of 0.68 indicates that the discriminator is reasonably effective at distinguishing between real and generated data. While the discriminator is learning to differentiate the two, it is not yet fully confident. The generator loss of 0.69 suggests that the generator is somewhat successful in creating outputs that could potentially deceive the discriminator. The generator aims to reduce this loss by generating increasingly realistic synthetic data. The similarity between the generator and discriminator losses (both around 0.68–0.69) signals a balanced adversarial training process, suggesting that both the generator and discriminator are evolving together. The models excelled at identifying demand patterns influenced by network topology, particularly at high-centrality nodes such as hubs and transfer stations.

V. DISCUSSION

The experimental results emphasize the varying performance of deep learning models in predicting bus ridership demand, highlighting their strengths and limitations. The Graph Attention Network (GAT) model demonstrated superior performance, achieving the lowest error metrics (MAE = 0.036, MSE = 0.006). By representing the transportation network as a graph, GAT effectively modeled the spatial dependencies between bus stations and routes. The model's ability to consider both the node-level (station) and

edge-level (trip) relationships enabled accurate predictions, particularly in a network characterized by hub-and-spoke dynamics. Stations with high degrees of centrality, such as hubs and key transfer points, were critical in shaping ridership patterns, and GAT's architecture was well-suited to account for these complexities. The CNN model also exhibited strong performance, particularly in capturing temporal patterns in the ridership data. With an MAE of 0.0141 and MSE of 0.0006, CNN effectively modeled sequential variations, reflecting its strength in identifying localized and time-specific demand trends. However, its reliance on 1D convolution limits its ability to explicitly model the spatial relationships inherent in transportation networks. This makes it less effective in contexts where spatial dependencies significantly influence demand. Generative Adversarial Networks (GANs), on the other hand, struggled with training instability and convergence challenges. The GAN model produced balanced generator and discriminator losses ($d_loss = 0.69$, $g_loss = 0.69$), indicating effective adversarial learning, yet its predictive performance was notably inferior to the other models. These limitations can be attributed to mode collapse, sensitivity to data imbalance, and the complex nature of ridership dynamics, which require extensive tuning of GAN architectures. The analysis of network centrality measures further illuminated the structural dynamics of Ulaanbaatar's transportation system. Key stations with high in-degree and out-degree centrality played pivotal roles in network connectivity. These stations often acted as major hubs for incoming and outgoing trips, influencing overall demand patterns. The GAT model excelled in capturing these relationships, which contributed to its predictive accuracy. The findings suggest that while CNNs are effective for capturing temporal demand variations, GATs are better equipped to handle the spatial complexities of graph-based networks. GANs, though less effective in this context, may serve as valuable tools for generating synthetic data to augment training datasets. The performance differences underscore the importance of selecting models aligned with the structural and temporal characteristics of the data.

VI. CONCLUSION

The analysis of centrality measures and degree distribution in Ulaanbaatar's public transportation network provided critical insights into its structural dynamics, which significantly influenced ridership demand prediction. Centrality analysis revealed the role of high-degree stations—those with significant in-degree or out-degree connections—as vital hubs in the transportation network. For instance, stations with the highest in-degree often served as major convergence points for passengers, while those with the highest out-degree acted as primary origins for trips. Stations with high betweenness centrality played critical bridging roles, ensuring connectivity across disparate parts of the network, whereas those with high closeness centrality facilitated efficient passenger flow by minimizing transit times

to other stations. This study evaluated the performance of three deep learning models—Graph Attention Networks (GATs), Convolutional Neural Networks (CNNs), and Generative Adversarial Networks (GANs)—for predicting bus ridership demand in Ulaanbaatar's public transportation network. The integration of centrality measures into predictive modeling highlights the importance of understanding network structure in demand forecasting. High-centrality nodes were identified as key predictors of overall ridership, enabling better resource allocation and operational planning. While GATs emerged as the best-performing model for spatially complex systems, CNNs offered complementary strengths in time-series prediction. GANs, despite their current limitations, have potential as auxiliary tools for addressing data challenges.

Overall, the findings emphasize that Graph-based approaches, such as GATs, are particularly well-suited for public transportation networks due to their ability to capture complex spatial dependencies effectively. In the future, we improve the GAT-Demand prediction model considering the spatial dependencies and temporal dependencies in real-time. By leveraging these advanced techniques, transportation systems can achieve more accurate ridership forecasts, leading to better resource allocation, optimized scheduling, and improved service quality for passengers.

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Tsentsengel Munkhbayer He received the B.C.A. degree in software engineering from Bangalore University, Bangalore, India, in 2013 and M.S. degree in software engineering from Mongolian University of Science and Technology, Ulaanbaatar, Mongolia. He is currently pursuing the Ph.D degree in Computer science at the Mongolian University of Science and Technology, Ulaanbaatar, Mongolia. His PhD thesis focused on issues related to public transportation computing.



Zolzaya Dashdorj received the Ph.D. in ICT from the University of Trento, Italy, in 2015. She is currently an associate professor in the Department of Computer Science at the Mongolian University of Science and Technology. She has conducted research at MIT, Korea University, United Nations and Yonsei University and has been involved in various international AI and data science projects. An IEEE member since 2020, her research interests encompass artificial intelligence, big data, urban computing, and biomedical analytics.



Zoljargal Jargalsaikhan is a PhD student at the Department of Computer Science, Mongolian University of Science and Technology. His research focuses on intelligent systems.



Tae-Koo Kang received his BS in applied electrical engineering, MS in visual image processing, PhD in electrical engineering from Korea University, in 2001, 2004, and 2012 respectively. Since 2015, he has been a Professor in the Department of Human Intelligence and Robot Engineering at Sangmyung University. His research interests include computer vision,

robotics, artificial intelligence, and machine learning.



Erdenebaatar Altangerel holds a Ph.D. in Computer Science (Artificial Intelligence) from Ural State Technical University. He previously served as the president of the Mongolian University of Science and Technology and is currently a senior professor in its Department of Computer Science. His research interests include artificial intelligence, big data analysis, software project development, and higher education management.