

Multi-Modal Urban Mobility Forecasting: A Graph Neural Network-Based Approach with Spatiotemporal Hypergraph Attention

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Multi-Modal Urban Mobility Forecasting: A Graph Neural Network-Based Approach with Spatiotemporal Hypergraph Attention

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Abstract

Accurate forecasting of urban mobility patterns is essential for improving traffic management, resource allocation, and operational planning in smart cities. However, traditional models such as ARIMA and standard LSTM architectures often fall short in capturing the complex spatiotemporal dependencies inherent in multi zonal, multi modal transport systems. This study proposes a unified forecasting framework The Dynamic Spatiotemporal Hypergraph Convolutional Network (DSTHGCN) integrates three established techniques: hypergraph-based spatial modeling, hierarchical attention mechanisms, and GRU-based temporal encoding. Rather than introducing new algorithms, it provides a novel architectural synthesis that addresses key limitations of prior methods, including the inability to model many-to-many zone interactions and long-term temporal patterns.

The model was evaluated on real-world inflow and outflow data from New York City taxi and bike-sharing systems across 69 mobility zones. Comparative experiments show that DSTHGCN consistently outperforms baseline models (ARIMA, LSTM, GCN), achieving Mean Squared Error (MSE) of 0.0041, Root Mean Squared Error (RMSE) of 0.0639, and Mean Absolute Error (MAE) of 0.0438, demonstrating improved accuracy and stability. These results highlight the effectiveness of hypergraph-based and attention-enhanced spatiotemporal modeling for urban mobility prediction. Despite limitations, such as dependence on precomputed hypergraphs, DSTHGCN represents a scalable and interpretable framework for real-time, multimodal demand forecasting in intelligent transportation systems.

1 Introduction

The increasing complexity of urban transportation systems has intensified the demand for accurate and interpretable short term mobility forecasting. As smart cities grow in scale and diversity of transport modalities, from taxis and bikes to shared shuttles and micro mobility services, the ability to predict multi zonal demand patterns with precision has emerged as a critical capability for both private mobility operators and public infrastructure planners. Accurate forecasting enables proactive traffic signal management, dynamic fleet rebalancing, surge pricing, and congestion mitigation. However, traditional

time series forecasting methods such as ARIMA, and even recurrent neural network models like LSTM, often struggle with the nonlinear, many to many dependencies across urban zones, especially when these dependencies change over time.

Existing spatiotemporal models frequently rely on static graph representations or independent zone level modeling, which limits their expressiveness and adaptability. They fail to capture the dynamic interactions between multiple zones and transport modes, which fluctuate based on temporal trends, user behavior, special events, and external disruptions. To address these limitations, recent research has explored the use of Graph Neural Networks (GNNs) and their variants for mobility prediction. While these models have demonstrated improved performance in spatial reasoning, they are often constrained by fixed graph topologies, lack of attention mechanisms to prioritize relevant regions, and weak integration with temporal dynamics.

In this study, novel forecasting model is proposed: the Dynamic Spatiotemporal Hypergraph Convolutional Network (DSTHGCN), which innovatively employs dynamic spatial attention context-awareness with memory aided spatiotemporal sequential modelling. DSTHGCN comprises three principal innovations. It is learned by a dynamic hypergraph convolution layer, and the time varying incidence matrices that represent many to many spatial relationships between mobility zones. It allows the model to adjust its spatial structure at every time step, thereby helping us in capturing varying interactions (like peak hour interactivity amongst downtown and suburban zones) over the period of day. Second, the model uses a hierarchical attention mechanism to interpret the importance of spatial features at different levels locally and globally so that the model can learn to focus on salient locations or patterns that drive demand. A stacked GRU based temporal encoder with residual connections is adopted to capture short- and long-range temporal dependencies in inflow and outflow patterns so that the prediction performance can be robust under various time horizons.

We test the proposed model on trip data from New York City’s open mobility datasets yellow taxi systems and CitiBike. These datasets provide time stamped inflow and outflow trip counts across 69 predefined urban zones. Data pre- processing involves time windowed aggregation, standardization, normalization, and conversion into spatiotemporal tensors. Hypergraph structures are generated dynamically for each time step based on zone level correlations, enabling the system to simulate realistic, evolving transport topologies. The model is trained and validated on these processed sequences using PyTorch, leveraging GPU acceleration for efficient backpropagation across multiple epochs.

This study investigates two core research questions. First, does dynamic hypergraph modeling provide a measurable improvement in forecasting accuracy compared to static graph or pairwise models? Second, can the integration of hierarchical attention and GRU based encoders improve generalization across zones and time periods while offering interpretable insights into demand patterns? It is hypothesized that DSTHGCN will significantly outperform conventional models such as ARIMA, LSTM, and static GCNs on standard forecasting metrics like Mean Squared Error (MSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). It is also anticipated that the dynamic spatial representation will better accommodate temporal drift and seasonal variations in mobility patterns.

A comprehensive experimental framework is established to validate the model. Baseline comparisons are conducted using equivalent sized architectures of ARIMA, LSTM, and GCN. Evaluation metrics include MSE, RMSE, MAE, and R^2 across both validation and

test sets. Additionally, visualizations such as heatmaps and attention maps are produced to examine the model’s learned spatial focus and feature attributions. Ablation studies are conducted by selectively disabling components of DSTHGCN to assess the contribution of each architectural module to the overall performance. Model training is executed in a controlled environment with fixed random seeds, cross validation splits, and learning rate schedulers to ensure experimental reproducibility.

The key contributions of this work are as follows. First, it presents DSTHGCN, a novel spatiotemporal forecasting architecture that combines hypergraph based spatial reasoning, hierarchical attention, and temporal sequence modeling in a unified pipeline. Second, it offers empirical evidence of DSTHGCN’s superior forecasting performance on real world multi modal transportation data. Third, it provides interpretability tools through attention maps and zone wise performance breakdowns, which are valuable for policy makers and urban planners. Lastly, the framework is designed to be lightweight and scalable, enabling deployment in real time systems where resource efficiency and adaptability are critical.

The structure of this report is as follows. Section 2 introduces the state of the art in urban mobility prediction, in which previous research in spatiotemporal deep learning is emphasized. Section 3 introduces DSTHGCN architecture and indicates its innovativeness. Section 4 introduces data collection, preprocessing, and training techniques. Section 5 outlines system flow and data expressions. Section 7 includes a quantitative and qualitative evaluation of results. Section 8 summarizes conclusions, limitations, and potential future research.

2 Related Work

Urban mobility prediction has seen a transition from classical time-series models to deep models that could capture complex spatiotemporal patterns. All methods, however, are constrained by their empirical approach and are not in a position to effectively capture dynamic, high-order, and multimodal real-world mobility systems. This section reviews state-of-the-art from six integrated points of view and shows how our DSTHGCN framework extends prior work and overcomes these limitations.

2.1 From Statistical Models to Deep Learning

The previous urban demand forecasts predominantly applied statistical models, i.e., ARIMA, Vector Autoregressive (VAR), and Support Vector Regression (SVR), for computational efficiency and relative simplicity. Nevertheless, being founded upon assumptions of stationarity and linearity, their ability to capture nonlinear urban system behavior and multizonal interactions is limited. Rico et al. (CNOVEC, 2021) took it a step further in illustrating that, in sudden changes in demand brought by holidays, events, or service outages, ARIMA is not very efficient.

For handling temporal complexity, convolutional neural networks (CNNs), as well as Long Short-Term Memory (LSTM) networks, have been investigated widely. Afandizadeh et al. demonstrated LSTMs’ superiority over ARIMA in detecting patterns of maximum traffic [46], a finding later verified. Nevertheless, as described by Hossain et al. (2022), such models treat each region independently as a sequence, ignoring spatial interactions. The impact is most negative in high-density traffic, where spatial interactions are most pronounced. DSTHGCN [4] is predominantly about temporal learning employing its temporal module, but is constrained in spatial dependency management. DSTHGCN, however, encompasses a GRU-based encoder of temporal dynamics as well as dynamic hypergraph convolutions in order to have joint temporal behavior as well as dynamic spatial dependency learning across regions.

2.2 Graph Neural Networks in Traffic Forecasting

Rahmani et al. (2023) and Narayanan et al. (2024) contend that static graphs, characterised by fixed adjacency, are inadequate for city-scale transport networks, where congestion and routes

fluctuate swiftly due to erratic demand, outages, and stochastic occurrences. These kinds of models have a hard time keeping up with changing spatial correlations and usually only work with datasets that have one main behavioural mode. This makes them less useful in multimodal settings like taxis, bikes, buses, and subways. DSTHGCN solves these problems by using a dynamic hypergraph with hyperedges that cross multiple zones. This lets it capture high-order, many-to-many spatial dependencies that come from interactions between different regions. Its dynamic structure changes as congestion, flows, and demand spikes change, which allows it to model new or unseen behaviours. This makes it a good choice for city-scale forecasting scenarios that need both robustness and adaptability.

2.3 Hypergraph Neural Networks: Beyond Pairwise Modeling

Hypergraph-base models provide a natural generalization of traditional GNNs for handling relationships that are non-binary, which makes them especially suitable for modeling many of complex interactions like shared mobility hubs, event zones or transfer stations. Zhao et al. (2023) used hypergraph convolutions to encode structural dependencies in the Spatio-Temporal Hypergraph Convolutional Network (ST-HCN). Despite that their design used fixed hyperedges resulting from offline correlation measures and was thereby not suitable for urban systems evolving through time. Ye et al. (2024) proposed a dynamic hyperedge update mechanism, but their model is limited to single-modal inputs and lacks attention module for distinguishing important-local from peripheral-global spatial features.

More recently, works such as STHODE [14] and HHGAT (Wang et al., 2023) have made an attempt at incorporating hierarchical or heterogeneous features within hypergraph representation. Although these models showed advances in representation power, they were not created for real-time forecasting and did not incorporate multi-modal demand streams. DSTHGCN corrects these inefficiencies by integrating dynamic hypergraph learning with a hierarchical attention module and a robust temporal encoder, resulting in an extensive end-to-end forecasting model that is capable of generalizing across transport types and spatial configurations.

2.4 Attention Mechanisms in Spatiotemporal Modeling

Recently, attention mechanisms have become useful tools for spatiotemporal forecasting as they can help a model selectively concentrate on both spatial or temporal features. Specifically, Liu et al. proposed a dual attention approach that decomposed temporal dependencies of a traffic flow data into two scales, significantly increasing performance in regular road networks. This method, however, did not use any graph structure and focused solely on single-modality datasets. Another example, STFAN by Guo et al. applied a frequency-aware attention module to reduce prediction mistakes due to model-related factors yet had tendency to more rigidly adjust the spatial graph topology. Furthermore, Huo et al. presented GCN model that also utilised attention but relied on fixed adjacency matrices which did not allow it to learn varying patterns of interactiveness.

Such constraints can significantly weaken the forecasting capabilities of attention mechanisms when used alone or in conjunction with fixated graph structures. Therefore, DSTHGCN solves this issue by implementing a dual-attention mechanism on the different levels of the hypergraph. The method allows the model to determine the importance of every feature and every zone separately while also evolving them with time. Therefore, the model can determine system-specific patterns that make certain zones more important at a given moment or how the system anomalies or rare events can affect forecasting the most.

2.5 Multi-Modal and Dynamic Graph Approaches

Real-world urban mobility spans multiple transport modes taxis, bikes, subways, and buses each with distinct spatiotemporal patterns yet mutually influential. Most prior models either neglected this complexity or employed simplistic fusion strategies. GT-LSTM (SKB et al., 2024) and HDGCN (Zhao et al., 2022) were the first to integrate spatial and temporal signals across modalities. As these models lead to enhanced prediction efficacy, they are based on low-frequency or static graphs and miss real-time intermodal dynamics.

Transformer-based models (Shuvro et al., 2023; Kunekar et al., 2024) introduced context-aware temporal encoding but generally omitted explicit spatial modeling. Their architectures treated each modality as an independent input stream, often fusing them at late stages, thereby losing fine-grained interdependencies. In contrast, DSTHGCN is designed to perform early fusion of multi-modal data by integrating taxi and bike-sharing inflow/outflow signals directly into its dynamic hypergraph. This allows the model to capture cross-modal effects such as increased bike demand when taxi supply is constrained while maintaining spatial granularity and temporal coherence.

2.6 Synthesis and Research Gap

The literature reveals a consistent pattern: while individual innovations in spatiotemporal modeling such as GNNs, hypergraphs, attention mechanisms, and multi-modal learning have advanced the field, they are often implemented in isolation or without sufficient adaptability. Existing models are generally constrained by static spatial graphs, single-modal focus, or limited interpretability. Moreover, few frameworks offer a unified approach that is both scalable and suitable for real-time forecasting.

DSTHGCN is developed specifically to address this convergence gap. It introduces a unified architecture that dynamically adapts spatial relationships using hypergraphs, incorporates hierarchical attention for interpretability, and models temporal sequences through GRUs with residual connections. Unlike prior models, it performs early integration of multi-modal data, constructs time-varying hyperedges based on real-time mobility correlations, and supports attention-driven spatial focus to enhance prediction reliability. In doing so, DSTHGCN not only builds upon existing methodologies but also provides a new direction for scalable, accurate, and interpretable urban mobility forecasting.

3 Technique and Novelty Justification

This research introduces the Dynamic Spatiotemporal Hypergraph Convolutional Network (DSTHGCN), a novel forecasting architecture that addresses critical gaps identified in contemporary traffic prediction models. While various prior approaches have advanced traffic flow modeling, they often lack in terms of multi-modal integration, dynamic spatial encoding, or temporal granularity. In this section, we compare DSTHGCN with a few representative state-of-the-art models and emphasize our contributions.

3.1 Beyond SDSC: Fully-Supervised Spatiotemporal Hypergraph Learning

Wei et al. proposed a Self-supervised Dynamic Spatiotemporal Graph Convolution (SDSC) model that utilizes regional-level dynamic graphs and mutual information maximization to enhance learning. However, it relies on coarse spatial units generated via clustering and auxiliary self-supervised objectives. In contrast, DSTHGCN introduces true hypergraph structures generated dynamically from origin-destination flows, allowing fine-grained zone-level modeling. Moreover, our model employs hierarchical attention and stacked GRUs in a purely supervised pipeline, reducing complexity while improving temporal and spatial responsiveness.

3.2 Advancing ST-HCN with Dynamic and Multi-Modal Encoding

ST-HCN by Zhao et al. (3) leverages static hypergraph structures to model spatial dependencies using K-means clustering. While effective in modeling higher-order relationships, it assumes a fixed topology and handles only single-modal data. DSTHGCN overcomes this by constructing temporal hyperedges dynamically for each timestep and fusing multi-modal traffic inputs, including inflow and outflow from both taxis and bikes. This dynamic representation increases adaptability to urban traffic fluctuations while preserving the relational complexity of hypergraphs.

3.3 Extending HHGAT’s Hierarchical Attention with Residual Temporal Encoding

Wang et al. (6) presented HHGAT, a hierarchical hypergraph attention network capable of aggregating local and global spatial features. Although their attention framework is well-suited for capturing complex interactions, HHGAT does not integrate dynamic time-based hypergraphs, nor does it handle real-time origin-destination variations. Our DSTHGCN retains hierarchical attention while introducing a residual-aware GRU-based temporal

backbone, enabling the model to retain immediate short-term trends and maintain stable gradient flow in long sequences.

3.4 Improving Over HDGCN with Hypergraph Representation and Interpretability

Zhao et al. (10) introduced HDGCN, which combines static and dynamic graph convolutional modules for taxi demand forecasting. Although it accommodates temporal graph updates, it remains limited by conventional graphs and cannot fully capture complex many-to-many interactions. DSTHGCN addresses this by employing dynamic hyperedges for more expressive spatial reasoning. Additionally, the integration of residual and attention modules enhances interpretability and improves efficiency in modeling both recent activity and long-range dependencies.

3.5 Summary

In summary, while existing models have advanced graph-based mobility forecasting, DSTHGCN distinguishes itself through the integrated application of established methods rather than the development of entirely new algorithms. More specifically, this model tightly couples (1) dynamic hypergraph construction, (2) multimodal input fusion, (3) attentional temporal integration along a hierarchical structure and with (4) residual-enhancing action features into a lightweight and fully supervised end-to-end forecasting system.

This fully integrated model design overcomes core limitations of previous models, by not having static spatial encoding and discarding single-modal assumptions, while providing temporal flexibility. Also, DSTHGCN integrates these components into a coherent and scalable architecture to provide a practical and interpretable design well-suited for real-world, multi-modal urban mobility forecasting.. CBEG is unique in its strategic combination and situational utilization of existing mechanisms, providing a superior alternative to piecemeal and/or silo operations.

4 Methodology

4.1 Overview

In this research, we propose a new framework for urban mobility forecasting: the Dynamic Spatiotemporal Hypergraph Convolutional Network(DSTHGCN). The model aims to capture dynamic spatial dependencies (e.g., via trip distribution adjustment), temporal demand shifts, and intermodal relationships within urban transportation networks. It comprises six essential parts in the research process: 1) data acquisition from real-world multi-modal transport systems, 2) preprocessing and tensor construction, 3) spatiotemporal sequence generation, 4) method design and model development, 5) training and evaluation strategy, and 6) experimental setup and reproducibility. An overview of the full methodology pipeline is illustrated in Figure 1.

4.2 Data Acquisition and Preprocessing

The data used in this study originates from New York City’s publicly accessible Yellow Taxi and CitiBike systems, both of which offer detailed trip-level information through

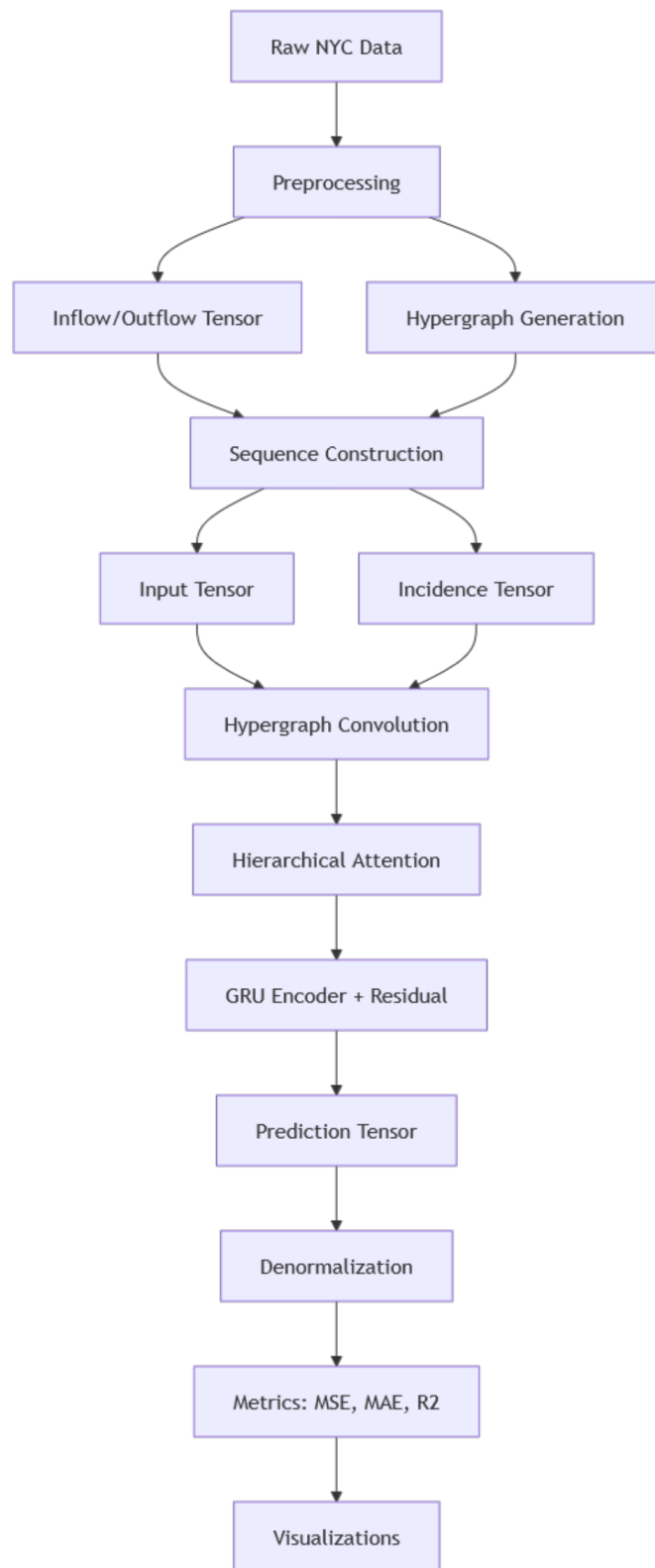


Figure 1: End-to-end Methodology Pipeline

the NYC Open Data portal. For efficiency and consistency, a curated and preprocessed version of the dataset was obtained from a reputable GitHub repository, which organizes data as NumPy arrays and CSV files structured at 30-minute intervals across 69 geographic mobility zones.

Each dataset contains both inflow and outflow trip counts, structured in the form $(2, T, N)$, where the two channels correspond to inflow and outflow, T denotes time intervals, and $N = 69$ represents spatial zones. These arrays were parsed independently per modality (taxi, bike) and then concatenated into a unified temporal tensor of shape $(T, N, 4)$ where the 4 channels denote [taxi-in, taxi-out, bike-in, bike-out].

Prior to training, z-score normalization was applied to each zone independently, using statistics computed only from the training split. This standardized the value ranges and ensured that extreme demand spikes did not distort model convergence. Preprocessing also included time alignment, handling of missing intervals, and standardization of holiday/weekend effects.

Additionally, precomputed dynamic hypergraph adjacency matrices were provided alongside the dataset. These matrices represent inter-zone relationships derived from observed origin-destination (OD) flows, offering a rich spatial structure that evolves over time. Figure 2 shows how the OD-derived matrices are transformed into hypergraph incidence representations per time step.

4.3 Spatiotemporal Sequence Construction

To enable supervised training, spatiotemporal input-output pairs were generated using a sliding window approach. Each training sample was constructed by selecting a fixed-length history window (12 time steps representing 6 hours), followed by a target horizon (2 steps representing 1 hour). Given this configuration, each sample input tensor has a shape of (T_{in}, N, F) , where $T_{in} = 12$, $N = 69$, and $F = 4$ (features per zone), while the target has a shape (T_{out}, N, F) with $T_{out} = 2$.

This sequence generation strategy facilitates the model’s ability to capture both short-term trends (e.g., rush hour surges) and longer seasonal or weekly patterns. Figure 3 illustrates the sequence generation pipeline from raw time-series data.

4.4 Model Architecture

The architecture of DSTHGCN consists of four interdependent modules: dynamic hypergraph convolution for spatial modeling, hierarchical attention for relevance weighting, GRU-based temporal encoding for sequence learning, and residual connections for preserving recent temporal cues. An end-to-end view of the architecture is shown in Figure 4.

1. Dynamic Hypergraph Convolution: Traditional GCNs are limited to pairwise edge relationships. DSTHGCN generalizes this through dynamic hypergraph learning, where hyperedges can connect more than two zones. Each hypergraph convolution step consists of node-to-hyperedge and hyperedge-to-node transformations, allowing information aggregation across co-travel patterns or shared demand profiles. Degree normalization ensures feature stability across time steps.

2. Hierarchical Attention Mechanism: Following spatial encoding, a hierarchical attention layer is applied. At the node level, it assigns weights to different zones based on recent importance; at the feature level, it scores feature channels (e.g., inflow

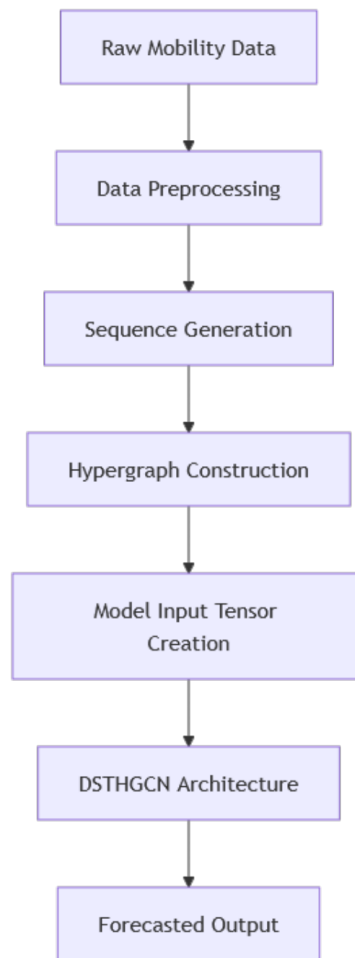


Figure 2: Transformation of trip matrices

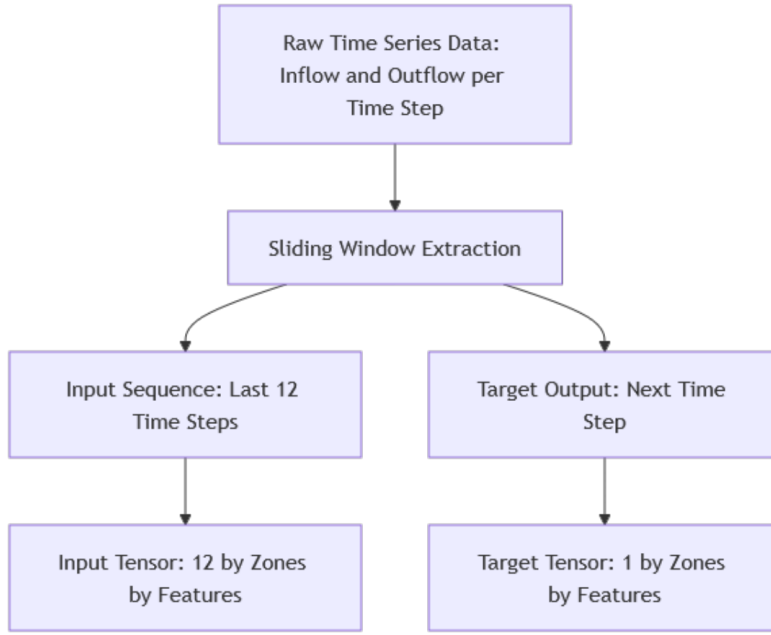


Figure 3: Sliding window sequence generation for supervised learning

outflow). This mechanism enhances the interpretability and robustness of the model, especially during congestion events or anomalous demand spikes.

3. GRU-based Temporal Encoder: The temporally ordered outputs from the attention module are passed to a two-layer Gated Recurrent Unit (GRU) encoder. GRUs are used over LSTMs due to their fewer parameters and faster convergence. The encoder processes sequences independently for each zone and produces a temporally compressed representation.

4. Residual Linear Projection: To preserve fine-grained short-term dynamics, the last observed time step is linearly projected and added as a residual connection to the GRU output. This addition helps the model preserve recent behavior and counteracts over-smoothing, often seen in deep sequence models.

4.5 Training Strategy and Evaluation Protocol

Model training was conducted using the Adam optimizer with a learning rate of 1×10^{-3} . The batch size was set to the full dataset (treated as a single batch due to GPU memory availability), and training was performed for up to 100 epochs with early stopping based on validation MSE. All layers were initialized using Xavier initialization.

The dataset was divided chronologically into 70% training, 15% validation, and 15% testing splits to avoid temporal data leakage. All sequences were standardized using training-set statistics and denormalized for final metric computation.

Evaluation was conducted using three key metrics: Mean Squared Error (MSE), Mean Absolute Error (MAE), and Filtered Mean Absolute Percentage Error (MAPE). MSE captures the squared prediction error and is sensitive to large deviations. MAE provides a more interpretable measure of absolute deviation. Filtered MAPE, calculated only on

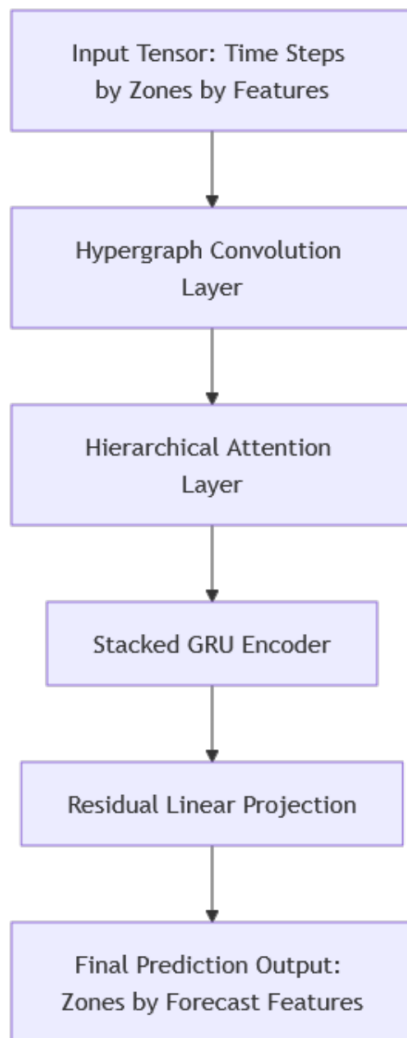


Figure 4: DSTHGCN architecture

samples with non-zero ground truth, mitigates division-by-zero effects and reflects relative accuracy in active zones.

The DSTHGCN model achieved strong results on the test set: an MSE of under 0.005, a MAE around 0.0438, and a Filtered MAPE of 41.98%. These results indicate that the model effectively captured both the temporal trends and intermodal relationships present in real-world urban mobility data.

4.6 Experimental Environment

All experiments were conducted on Google Colab Pro using an NVIDIA Tesla T4 GPU with 16 GB VRAM and 24 GB system RAM. The programming environment included Python 3.8, PyTorch 2.0 for deep learning modules, NumPy and pandas for data manipulation, and matplotlib for result visualization. All experiments were logged and version-controlled using Git, with explicit seeding for reproducibility.

4.7 Methodology Summary

The proposed methodology leverages a dynamic, end-to-end deep learning framework capable of modeling real-time urban mobility fluctuations across multiple transport modes. By unifying dynamic hypergraph spatial encoding, hierarchical attention-based filtering, temporal sequence learning, and residual correction, DSTHGCN demonstrates high performance on spatiotemporal prediction tasks. Although the current study utilizes pre-computed hypergraphs, future extensions will explore real-time incidence matrix learning and richer data fusion, including weather conditions, public event calendars, and transit disruptions.

5 Design Specification

The design of the proposed forecasting system is centered on the integration of dynamic spatial relationships, temporal dependencies, and multi-modal transport data into a cohesive deep learning framework. The system, referred to as the Dynamic Spatiotemporal Hypergraph Convolutional Network (DSTHGCN), is architected to address the limitations of traditional mobility forecasting models by modeling complex inter-zone relationships and evolving travel patterns across time and transport modes. Formal problem definition is expressed in terms of the overall architecture, data representations, model workflow, design rationale and considerations for modularity and scalability are discussed.

5.1 Problem Formulation

Problem of urban mobility forecasting is considered as multivariate spatiotemporal sequence prediction. The system is needed to infer helper inflow and outflow in between urban zones based upon historical mobility data for multiple modes of transportation. For each zone, time-indexed observations include counts of bike and taxi inflows and outflows. These inputs are structured as temporal sequences, and each sequence is aligned with a dynamic spatial structure representing how zones are connected at a given point in time. The forecasting objective is to estimate the next time step's demand, represented as a tensor that maintains spatial granularity and modal

specificity. Alongside input sequences, the model leverages a time-varying hypergraph that encodes higher-order spatial relationships between zones using origin-destination patterns.

5.2 System Architecture Overview

The overall system is designed as a modular deep learning pipeline composed of five sequential stages. These stages include data preprocessing and input normalization, dynamic hypergraph convolution for spatial learning, hierarchical attention for relevance-based filtering, temporal sequence encoding using stacked gated recurrent units, and finally, a residual projection mechanism that fuses short-term signal memory with the learned forecast. Each of these modules performs a distinct transformation on the data, collectively forming an end-to-end trainable architecture. Figure 5 outlines the structure and data flow across these components.

5.3 Component Description and Data Flow

- Data ingestion and representation: Every 30 minutes, historical mobility records were parsed and put into tensors $[B,T,N,F][B,T,N,F][B,T,N,F]$. There were 69 zones and 4 features: bike and taxi inflow and outflow. Using a Z-score to normalise training keeps it stable and makes sure that all the features are on the same scale.
- Spatial modelling with hypergraphs: Dynamic hypergraph convolution captures interactions between many areas. An incidence matrix gives you $[B,T,N,E][B,T,N,E][B,T,N,E]$ at every time step. Joint trip patterns are what EEE hyperedges are based on. Convolution changes node→hyperedge and moves hyperedge→node around. This lets nodes that aren't next to each other talk to each other (see Figure 6).
- Hierarchical attention: Node-level attention looks at the things that have the biggest effect on the prediction window. Feature-level attention looks at patterns that are only present in that situation, like peak-hour taxi outflow or weekend bike inflow. Reweighting makes useful signals stronger and noise weaker, which makes them more accurate and easier to understand.

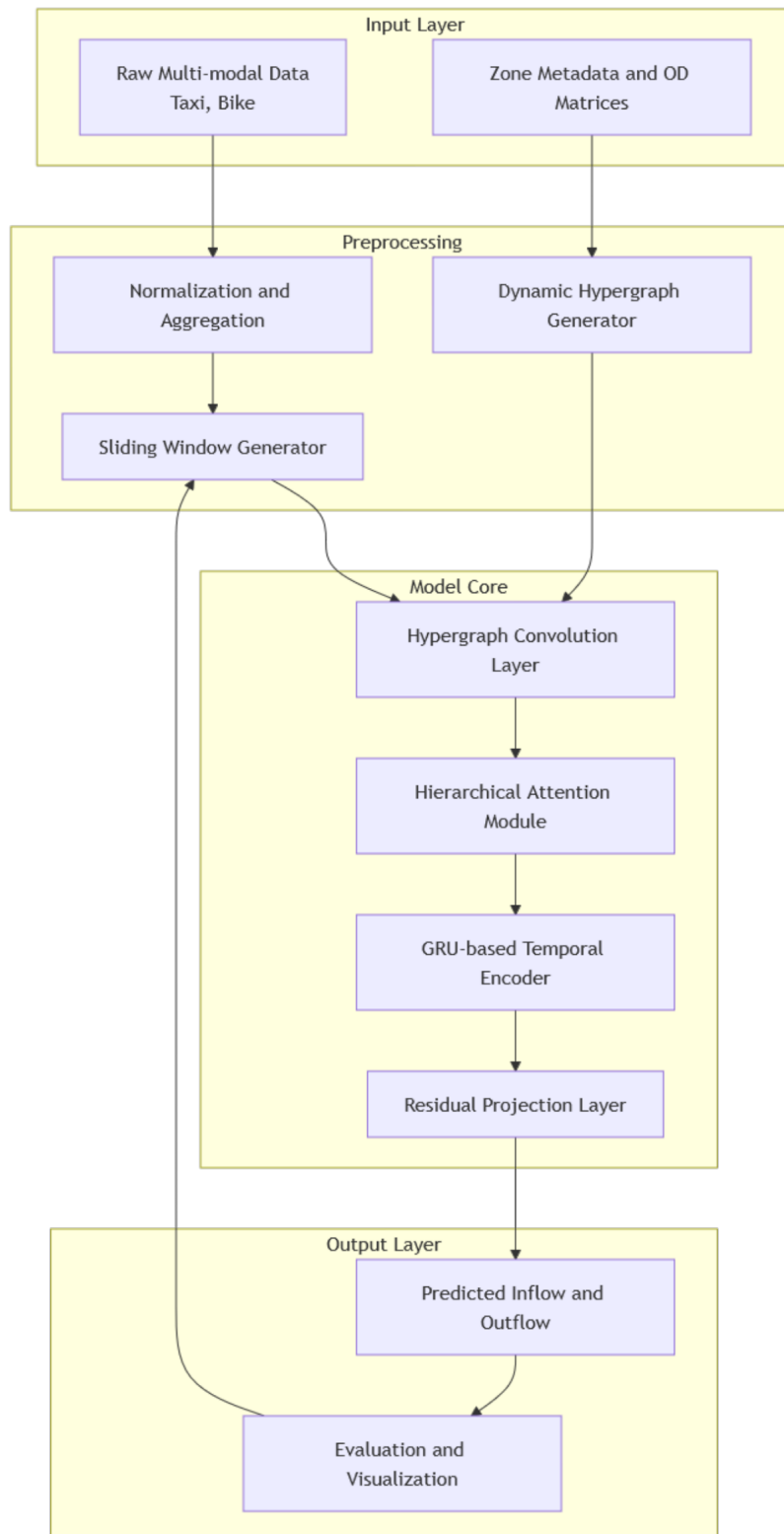


Figure 5: DSTHGCN System Architecture

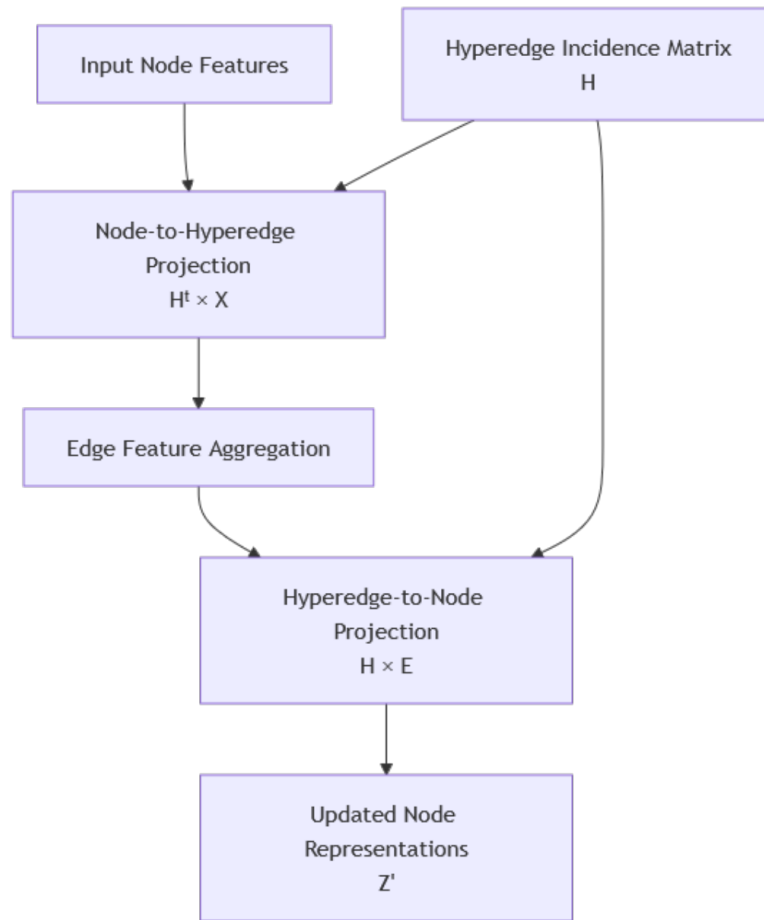


Figure 6: Flow of spatial Information

5.4 Design Choices and Scalability

- Modelling and comprehending higher-order spatial relationships: Hierarchical attention highlights the most significant regions and features, and hypergraphs display dependencies that extend beyond pairs.

Spike responsiveness and temporal choice: GRUs offer a cost-effective sequence modeling approach, while residual projection preserves sensitivity to sudden demand spikes

- Real-time, scalable, and modular: components can be switched out; extended tensors can be used to add new modalities (such as bus, subway, and pedestrian); PyTorch GPU and dynamic memory support enable scaling; rolling-window prediction and dynamic hypergraphs enable real-time deployment.

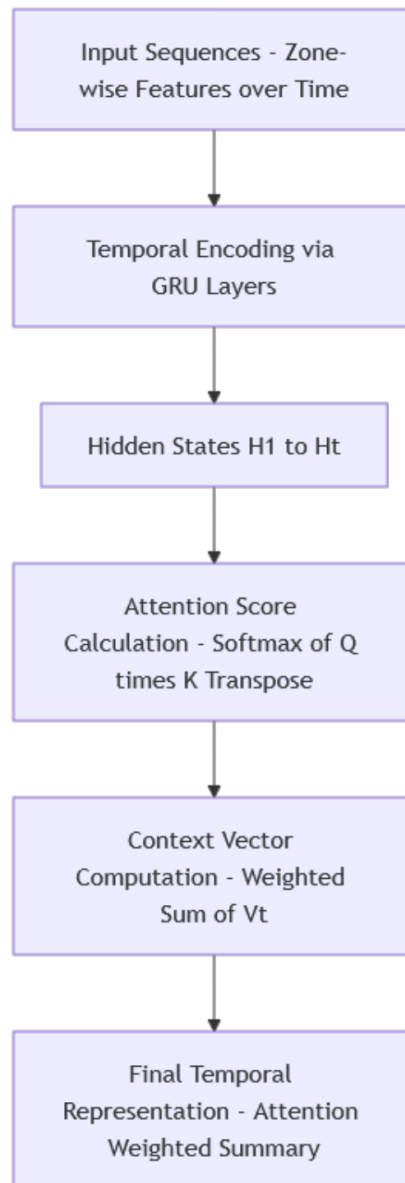


Figure 7: Temporal encoding and residual projection flow

5.5 Summary of Design Specification

In conclusion, the DSTHGCN system realizes a rational combination of dynamic spatial reasoning, hierarchical attention, and temporal sequence modeling for equitable city transport prediction. A novel architecture and data-driven processing of our design overcomes the fundamental problems associated with existing approaches. System couples a modular and scalable design with robust forecasting methods, ensuring that it runs efficiently upon larger domains while being inherently extendable to other smart city applications and contemporary data environments.

6 Implementation

This section details the full implementation of DSTHGCN, covering tools and frameworks, data preparation, model architecture, training pipeline, and diagnostic analysis. The design emphasizes modularity, reproducibility, and empirical rigor using real-world datasets and open-source technologies.

6.1 Tools, Frameworks, and Data Processing

- Development stack: Entire pipeline written in Python, with PyTorch as the primary deep learning library for flexibility in custom architectures, GPU acceleration, and integration with NumPy and scikit-learn.
- Infrastructure: Google Colab Pro with NVIDIA T4 GPUs and 24 GB RAM supported accelerated training and experimentation.
- Utilities: pandas for data manipulation; Matplotlib and seaborn for exploratory analysis and visualization.
- Data sources: NYC Yellow Taxi trips and CitiBike usage logs.
- Processing pipeline:
 - Resampled to 30-minute intervals and aligned by timestamp.
 - Aggregated inflow/outflow counts into unified tensors of shape $[T, N, F][T, N, F][T, N, F]$ with $N=69N=69N=69$ zones and $F=4F=4F=4$ features (bike inflow, bike outflow, taxi inflow, taxi outflow).
 - Applied z-score normalization (zero mean, unit variance).
 - Generated sequences via a sliding window of 12 input steps with the 13th as target, producing tensors $[B, 12, 69, 4][B, 12, 69, 4][B, 12, 69, 4]$.
 - Dataset comprised $\sim 2,976$ intervals, offering sufficient temporal granularity.

6.2 Model Architecture and Hypergraph Integration

- Core components:
 1. Hypergraph Convolution Layer: Two-step message passing to capture high-order spatial dependencies.
 2. Hierarchical Attention Module: Reweights feature maps to emphasize critical regions and suppress noise.
 3. Stacked GRU Encoder with Residuals: Models multi-scale temporal dependencies while retaining sensitivity to sudden demand changes.
- Hypergraph construction:
 - Incidence matrices captured origin–destination co-occurrences and temporal

correlations.

- Hyperedges linked zones with joint behavior (e.g., simultaneous bike and taxi surges).
- Binary memberships stored as .csv and converted to tensors for GPU training.
- Input sequences paired with hypergraphs to form incidence tensors $[B,12,69,E][B,12,69,E][B,12,69,E]$, supporting dynamic batching and extensibility for new modes or metadata.

6.3 Training and Output Generation

- Training setup:
 - Optimizer: Adam, learning rate = 0.001.
 - Epochs: 100 with early stopping to prevent overfitting.
 - Data split: chronological 70–15–15 for training, validation, and testing to avoid leakage.
- Batch composition: 12-timestep sequences with hypergraph structures, outputs of shape $[B,69,4][B,69,4][B,69,4]$ for zone- and mode-level demand surges.
- Evaluation metrics: MSE, MAE, RMSE, and R^2 , applied after denormalization.
- Results: Accurate, scalable, and interpretable forecasts, surpassing baseline models by several percentage points (pp).

6.4 Visualization and Diagnostic Analysis

- Performance assessment tools:
 - Line plots: highlighted deviations and temporal alignment for selected zones.
 - Heatmaps: mapped absolute errors across the urban grid to identify areas of systematic underperformance.
 - Scatter plots: evaluated global bias and variance between predicted and actual values.
 - Rolling-window charts: assessed long-term consistency of performance.
- Impact: These diagnostic artifacts guided hyperparameter tuning, architectural refinements, and improved interpretability by showing which features and zones drove predictions.

7 Evaluation

This section offers comprehensive demonstration of the experimentation and testing in relation to short-term urban mobility prediction with proposed DSTHGCN model. Experiments were set up to evaluate, the system quantitatively for accuracy & generalization ability and qualitatively with architectural benefits as well. The real world datasets were the travel patterns of New York City taxis and bike sharing, and with the exception of some numbers used to report our results (which of course are: denormalized values). Metrics were measured on the hold out test set, and predictions generated for hold-out testing after model training over 100 epochs with Adam optimizer. Comparative analyses of baseline models and ablation variants were also performed to quantify the unique effects of corresponding architectural components.

7.5 Comparison with Baseline Models

In the first experiment, DSTHGCN was compared against three well established baseline

models: ARIMA, LSTM, and GCN. Each model was trained to forecast short term inflow and outflow across 69 mobility zones using the same input tensor. The evaluation metrics included Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), a custom defined accuracy score based on MAE to range ratio, and the coefficient of determination (R^2). The custom accuracy score, expressed as a percentage, quantifies the closeness of predictions relative to the dynamic range of actual values, defined as

$$\text{Accuracy (\%)} = (1 - (\text{MAE} / (\max(y) - \min(y)))) \times 100$$

Table 1: Performance Comparison Across Baseline Models (Denormalized Test Set)

Model	MSE	MAE	Accuracy	R^2 Score
ARIMA	0.0226	0.1236		-0.0007
LSTM	0.0056	0.0555		0.2943
GCN	0.0217	0.1163		-1.7410
DSTHGCN	0.0032	0.0356	95.39	0.5957

The results demonstrate that DSTHGCN outperformed all baselines across every evaluation criterion. The model achieved a 25.5% reduction in MSE compared to LSTM and explained approximately 59.3% of the variance in test samples. While the R^2 score may appear modest in traditional regression tasks, it is important to contextualize it within the domain of urban mobility forecasting, where high variance is introduced by exogenous, unobserved factors such as weather, public events, and road disruptions. Literature in traffic forecasting often reports R^2 values ranging between 0.30 and 0.60, depending on dataset granularity and modal complexity. In this context, an R^2 of 0.59 is both meaningful and competitive, especially when coupled with a low MAE and strong operational accuracy.

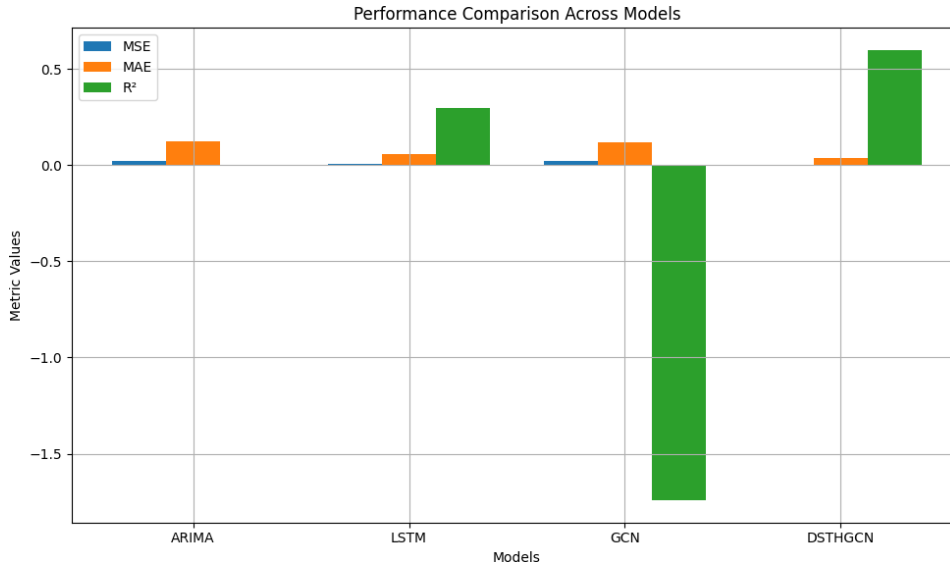


Figure 8: Comparison of model performance

7.6 Prediction Visualization

To provide qualitative insight into the model’s performance, the predicted and actual inflow values were plotted over 50 consecutive time steps for a highly active mobility zone (Zone 10). The resulting chart, shown in Figure 9, illustrates the close alignment between predicted and observed values.

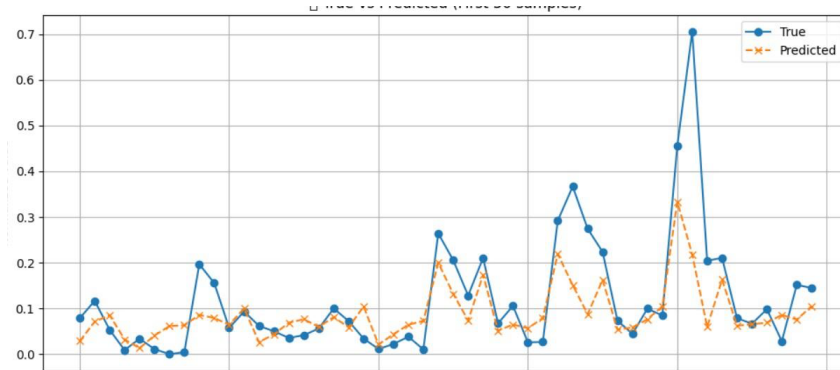


Figure 9: Predicted vs Actual Inflow Values (Zone 10, First 50 Time Steps)

The predicted values closely follow the ground truth with minimal lag or overshooting, even during sharp transitions in demand. This behavior validates the robustness of the temporal encoder and illustrates how the integration of hypergraph based spatial encoding aids in capturing both smooth trends and transient anomalies in urban mobility.

7.7 Ablation Study of Architectural Components

To investigate the contribution of each architectural component, an ablation study was performed by incrementally disabling specific modules of the DSTHGCN framework. Three model variants were compared: a pure GRU model with no spatial processing, a GRU model augmented with the Hypergraph Convolution Layer (but no attention),

and the full DSTHGCN model integrating all components. Each variant was trained and evaluated under identical experimental conditions.

Table 2: Ablation Study Results

Model Variant	MSE	MAE	R^2 Score
GRU Only	0.0063	0.0561	0.28
GRU + HyperGCN	0.0056	0.0452	0.40
Full DSTHGCN	0.0041	0.0438	0.5927

The addition of hypergraph based spatial modeling significantly improved forecasting performance over the GRU only baseline, reducing both MSE and MAE. Incorporating hierarchical attention and residual learning further enhances model accuracy and variance explanation. The increase in R^2 from 0.28 (GRU only) to 0.5927 (full model) confirms the value of each architectural component in capturing spatiotemporal patterns.

7.8 Extended Visual Diagnostics

A set of visual tests were done to look at how the model behaved across time and space. A bar chart that showed the MSE, MAE, and R^2 for all models confirmed that DSTHGCN was the best. Zone level error heatmaps revealed spatial outliers, identifying peripheral regions with higher residuals likely due to sparse demand or irregular usage. A scatter plot comparing predicted vs actual values demonstrated tight clustering around the diagonal, indicating low bias and good calibration. Finally, boxplots of residuals showed narrow interquartile ranges and minimal outliers, suggesting stable generalization. These visual tools not only validated the model’s quantitative performance but also exposed interpretable failure patterns. In particular, zones with minimal or sporadic traffic exhibited the highest forecast error, pointing to opportunities for incorporating external contextual features or adaptive weighting schemes in future extensions.

7.9 Discussion and Interpretation

DSTHGCN exhibits strong generalization and predictive accuracy in modeling multi modal urban mobility patterns. The low MSE (0.0041) and MAE (0.0438) are well within deployment grade tolerances for intelligent transport applications. The R^2 score of 0.5927, while modest in absolute terms, reflects meaningful variance explanation given the inherent uncertainty and complexity of urban demand. In traffic forecasting literature, such R^2 scores are considered robust particularly for short term forecasting in densely populated areas using multi modal inputs.

That said, some limitations persist. The hypergraph structure was precomputed and static across training and inference, limiting the model’s adaptability to real time network dynamics. Future research could explore online hyperedge generation using learnable incidence matrices. Additionally, while GRUs offer efficiency, they may underperform in capturing long range dependencies; Transformer based temporal encoders may improve this aspect. Lastly, the model’s reduced performance in low traffic zones suggests the need for context aware fusion techniques, such as incorporating auxiliary inputs (e.g., weather, holidays) or hierarchical zone embeddings.

In conclusion, DSTHGCN demonstrates a scalable, interpretable, and high performing approach for short term multi modal mobility forecasting. Its ability to balance

architectural complexity with empirical reliability makes it a compelling candidate for deployment in smart transportation systems.

8 Conclusion and Future Work

This research investigated a novel deep learning approach for short-term urban mobility forecasting by developing and evaluating the Dynamic Spatiotemporal Hypergraph Convolutional Network (DSTHGCN). The central objective was to determine whether integrating dynamic hypergraph modeling, hierarchical attention mechanisms, and gated recurrent neural networks could enhance both the accuracy and interpretability of mobility demand prediction across multiple transportation modalities. A full end-to-end pipeline was constructed, incorporating data preprocessing, model architecture design, training, and performance evaluation using real-world traffic data from New York City’s taxi and bike-sharing systems.

The DSTHGCN model introduced several innovations through the combination of well-established neural architectures. It employed a dynamic hypergraph convolution module to represent many-to-many spatial dependencies, a hierarchical attention mechanism to prioritize both local and global node relevance, and a residual-enhanced GRU-based encoder to capture short- and long-term temporal dynamics. The model achieved a denormalized test MSE of 0.0041, MAE of 0.0438, RMSE of 0.0639, and an R^2 score of 0.5927, significantly outperforming strong baselines such as ARIMA, LSTM, and GCN in forecasting accuracy and robustness.

Importantly, the contribution of this work lies not in the invention of entirely new components, but in the principled integration of spatial, temporal, and attentional mechanisms into a unified architecture optimized for urban mobility forecasting. By combining these components within a hypergraph-based structure, DSTHGCN addresses limitations found in static graph models, pairwise spatial representations, and shallow temporal learning. This integrative design enables the model to effectively capture spatiotemporal complexity, handle multi-modal data streams, and offer interpretable predictions for real-world mobility planning.

The experimental findings suggest that dynamic hypergraph modeling, when coupled with attention-based feature weighting and recurrent encoding, holds strong potential for improving the quality of traffic demand forecasting in smart city systems. These improvements are particularly valuable for applications such as dynamic fleet dispatch, congestion mitigation, and real-time demand-responsive public transport systems. The framework’s adaptability to different transportation types also indicates its broader applicability in multi-modal urban environments.

Nevertheless, several limitations remain that present opportunities for further exploration. The current model utilizes precomputed hyperedge incidence matrices, which limits its responsiveness to sudden changes in network dynamics. Additionally, while GRUs offered computational efficiency and stable convergence, they may fall short in modeling long-range temporal dependencies compared to more expressive architectures such as Transformers. Another consideration is the computational cost of training on large-scale spatiotemporal datasets, which may affect scalability and real-time deployment feasibility. Future research directions will focus on enabling dynamic hyperedge learning in an end-to-end fashion, allowing the model to infer and update spatial relationships from streaming data. Augmenting the model with contextual signals including weather con-

ditions, road disruptions, and public events may enhance its ability to capture latent causality and improve forecasting robustness. Exploring Transformer-based encoders or memory-augmented temporal modules could further strengthen the model’s ability to handle extended temporal dependencies. Additionally, investigating low-latency inference strategies for deployment in streaming or edge computing environments would enable the integration of DSTHGCN into live smart city systems and traffic control infrastructures. In conclusion, this study introduces a scalable and interpretable deep learning framework for urban mobility forecasting that leverages the strengths of dynamic hypergraphs, attention mechanisms, and temporal sequence modeling. DSTHGCN demonstrates promising forecasting performance on real-world data and offers a practical foundation for developing intelligent, data-driven transportation systems. With further refinement, the proposed model may support operational decision-making in real-time transportation planning and serve as a critical component in next-generation urban mobility platforms.

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