
Smart City Digital Twin with CoppeliaSim Simulation and Spatiotemporal Data Fusion for Urban Mobility Prediction

In urban mobility forecasting, the development of smart cities remains one of the most urgent challenges, requiring advanced data stream integration and predictive capabilities. This chapter presents a comprehensive framework for urban mobility prediction based on the development of a digital twin platform that combines CoppeliaSim simulation with a spatiotemporal data fusion approach. The proposed system uses multi-source urban data, including traffic sensors, GPS tracking, weather forecasts and public transport schedules, to develop a dynamic virtual representation of urban transportation systems.

The digital twin system consists of three main components: a CoppeliaSim-based simulation environment, where real-world traffic is simulated; a spatiotemporal fusion unit, where heterogeneous data streams are processed using long short-term memory (LSTM) networks and graph convolutional networks (GCNs); and a prediction engine that forecasts traffic flow dynamics over horizons ranging from 15 minutes to two hours.

The framework was tested using data collected from a metropolitan area (45 sq. km) comprising 287 intersections and 156 road segments over a six-month period. The experimental results show that the combined approach achieves prediction accuracies of 94.3% for short-term forecasts (15–30 minutes) and 87.6% for medium-term forecasts (1–2 hours), representing improvements of 12.4% and 15.8%, respectively, compared to baseline methods.

The digital twin achieves a mean absolute error (MAE) of 3.2 vehicles per five-minute interval and maintains a root-mean-square error (RMSE) below 4.8 vehicles across all prediction horizons, demonstrating its effectiveness for real-time urban mobility management and transportation planning.

1.1. Introduction

Urban transportation systems have experienced unprecedented complexity as cities have expanded and the number of vehicles has grown exponentially in the 21st century. Traffic congestion has led to significant economic losses, estimated at \$166 billion annually in the United States alone, and has also contributed to environmental degradation and reduced quality of life in urban areas. Conventional methods of controlling traffic have relied on reactive mechanisms that are insufficient for addressing dynamic mobility patterns and traffic uncertainties.

With the advent of smart city initiatives, opportunities have emerged to adopt proactive traffic management approaches using advanced sensing technologies, ubiquitous connectivity and data-driven decision-making frameworks. Digital twins, defined as virtual representations of physical systems that reflect real-world conditions in real time, have become one of the most effective tools for urban planning and traffic optimization. Such models enable city planners and traffic managers to simulate future conditions, evaluate interventions and anticipate outcomes before implementing changes in the real environment.

Despite significant advances in traffic prediction and simulation technologies, several challenges remain. First, traditional traffic simulation platforms are often not integrated with real-time data streams, which limits their ability to accurately represent current conditions. Second, many prediction models focus on isolated components of urban mobility, failing to capture the interdependencies among transport modes, temporal dynamics and spatial structures. Third, the integration of heterogeneous data sources with varying temporal resolutions and spatial granularities remains technically challenging.

This study addresses these limitations by proposing an integrated digital twin framework that combines CoppeliaSim simulation capabilities with advanced spatiotemporal data fusion methods. CoppeliaSim provides a high-fidelity and scalable simulation platform capable of modeling complex traffic scenarios. The spatiotemporal fusion module integrates diverse data streams, including loop detector measurements, GPS positions, weather patterns and special event schedules, to produce a unified representation of urban mobility patterns.

The major contributions of this work are (1) the development of a bidirectional data exchange architecture between physical sensors and virtual simulation environments; (2) a spatiotemporal fusion framework that combines long short-term memory (LSTM) networks for temporal modeling with graph convolutional

networks (GCNs) for spatial relationship extraction; (3) a multi-horizon prediction framework supporting forecasts from 15 minutes to two hours; and (4) extensive validation using real-world data from an operational urban transportation network.

1.2. Related work

1.2.1. *Digital twins of smart cities*

The development of digital twin technology, which has gained prominence in manufacturing and aerospace applications, has become a fundamental aspect of smart city development. Previous studies have shown that digital twins can be useful in addressing diverse urban applications such as energy management, infrastructure monitoring and emergency response planning. However, transport-oriented digital twins remain relatively underdeveloped compared to other domains.

Some studies have investigated the application of digital twins in traffic management; however, most rely on commercial simulation platforms with limited customization capabilities. The use of open-source simulation software such as CoppeliaSim provides increased flexibility for developing domain-specific features at comparatively low cost while maintaining high computational performance.

1.2.2. *Traffic prediction methods*

Traffic prediction methods have evolved through several generations of techniques. Early forecasting approaches, such as autoregressive integrated moving average (ARIMA) and Kalman filtering, were limited in modeling nonlinear behavior and could not capture long-term dependencies. Machine learning methods, including support vector machines and random forests, have demonstrated improved predictive accuracy but require extensive feature engineering.

Recent advances in deep learning have revolutionized traffic prediction by enabling the automatic learning of hierarchical representations from raw data. Recurrent neural networks, particularly long short-term memory (LSTM) models, have proven effective in capturing temporal dependencies in traffic flow data. Convolutional neural networks facilitate the extraction of spatial patterns within road networks. More recent studies have explored attention mechanisms and transformer architectures to model complex spatiotemporal relationships.

1.2.3. Spatiotemporal data fusion

Data fusion methods have become essential for integrating heterogeneous information sources in intelligent transportation systems. Recent developments highlight advanced fusion practices across multiple domains. An extended Kalman filter-based fusion strategy proposed by Omarov and Jabrayilzade (2025) for collaborative robotics demonstrates how sensor fusion can enhance decision-making and positional accuracy in dynamic environments. Their approach provides valuable insights into handling multi-sensor uncertainty propagation, which can be applied to traffic monitoring systems.

Meinert et al. (2025) investigated MRI–CT fusion for stereotactic applications and showed that integrating multimodal data significantly improves spatial localization accuracy compared to single-source methods. This concept can be extended to transportation systems by combining GPS trajectories with fixed sensor measurements. Torrisi et al. (2025) examined enhancements in geostationary satellite systems, improving temporal resolution, spectral band aggregation and change detection capabilities – principles that can be adapted for detecting evolving traffic patterns. Kumar (2025) explored multi-frequency PolInSAR and TomoSAR data fusion for forest structure retrieval, demonstrating how different frequency bands capture complementary structural features, analogous to how various traffic sensors capture different aspects of mobility.

These cross-domain advances have informed the design of spatiotemporal data fusion frameworks capable of handling varying data granularities, temporal resolutions and spatial coverage in urban mobility systems. Earlier approaches typically treated spatial and temporal dimensions separately or relied on simple concatenation techniques. More recent methods use coupled models that jointly learn spatiotemporal representations; however, computational complexity remains a challenge for real-time deployment.

Reddy et al. present a digital twin (DT) sensor ecosystem designed for real-time monitoring and control of virtual 3D printing systems. Their framework integrates sensor data acquisition, virtual modeling and real-time analytics to replicate physical processes within a digital environment. Continuous synchronization between physical and virtual layers enhances process visibility, fault detection and predictive maintenance. The study demonstrates improvements in operational efficiency, manufacturing precision and decision-making, highlighting the potential of DT systems in smart manufacturing and Industry 4.0 environments (Reddy et al. 2023).

Selvarajan et al. (2023) introduce SCBC, a smart city monitoring framework that integrates blockchain technology, the Internet of Things and neuro-fuzzy methods to enhance urban management and security. By enabling secure data handling and adaptive decision-making, the framework improves transparency, reliability and operational efficiency in smart city infrastructures (Selvarajan et al. 2023). In subsequent work, Selvarajan et al. (2024) propose SCMC, a smart city measurement and control framework that incorporates data mining techniques to strengthen data security and system control. Their approach supports intelligent pattern recognition, anomaly detection and improved decision-making across interconnected urban services, contributing to more resilient and data-driven smart city ecosystems (Selvarajan et al. 2024).

1.3. Methodology

1.3.1. System architecture

The proposed digital twin architecture is a four-layer framework consisting of a physical layer, a data acquisition layer, a digital twin core and an application layer. The physical layer represents the actual urban transportation infrastructure, including roads, intersections, traffic lights and vehicles. The data acquisition layer collects multimodal sensor data from various sources, such as inductive loop detectors, CCTV cameras, GPS-enabled vehicles and weather stations.

The digital twin core integrates three main components: the CoppeliaSim simulation platform, the spatiotemporal fusion engine and the prediction module. The CoppeliaSim simulator replicates the physical transportation system using detailed geometric models of roads, intersections and traffic control devices. The simulation includes vehicle agents with behavior models calibrated based on observed traffic patterns and is continuously updated in near real time using incoming sensor data.

The spatiotemporal fusion engine processes heterogeneous data streams to generate unified representations of traffic states. This module follows a hierarchical structure, beginning with data normalization and alignment to construct temporally and spatially consistent representations from diverse sources. Fusion algorithms are then applied to produce accurate state estimates. These fused representations are subsequently used by the prediction module to forecast traffic conditions across multiple time horizons.

1.3.2. Data collection and preprocessing

The research used data collected from an urban region covering 45 square kilometers, comprising 287 signalized intersections and 156 major road segments. The six-month data collection period, from January to June, captured seasonal variations and diverse traffic patterns. The dataset included measurements from 423 inductive loop detectors recorded at 30-second intervals, GPS positions from 1,847 taxis providing location updates every 10 seconds, weather parameters such as temperature, precipitation and visibility updated hourly, and event schedules obtained from municipal databases.

Preprocessing procedures addressed common data quality issues, including missing values, outliers and temporal misalignment. Missing data accounted for approximately 8.3% of the dataset, primarily due to sensor failures and communication errors. These gaps were handled using a combination of linear interpolation for short gaps (less than five minutes) and k-nearest neighbor imputation for longer gaps. Outliers were detected using the local outlier factor method, which identifies observations that deviate significantly from historical trends.

All data streams were temporally aligned to a common 30-second interval using resampling and interpolation techniques. The preprocessing pipeline also extracted key features, including traffic volume, speed, occupancy and density. Temporal features such as hour of the day, day of the week and holidays were incorporated to capture recurring patterns. Additionally, spatial attributes of road segments – including length, number of lanes, speed limits and connectivity with adjacent segments – were encoded.

1.3.3. The Coppeliasim simulation environment

The Coppeliasim digital twin represents a geometrically faithful replica of the real-world transportation network. Road networks were constructed using precise coordinates obtained from OpenStreetMap and validated against municipal planning documents. Each intersection was modeled in detail, including lane configurations, traffic signal timings and pedestrian crossing features.

Vehicle agents were implemented using a microscopic traffic simulation approach, where individual vehicles follow behavioral models based on

car-following theory and lane-changing logic. The intelligent driver model (IDM) governs longitudinal movement, with acceleration and deceleration determined by spacing to leading vehicles, relative velocities and desired speeds. The MOBIL model manages lateral lane-changing behavior, applying safety constraints and incentive criteria to evaluate lane-change decisions.

Traffic signal control was implemented using actuated signal timing, in which phase durations are dynamically adjusted based on the detected traffic demand. The simulation incorporates stochastic elements of real-world traffic by randomizing vehicle arrival patterns, driver behavior and route choices. Calibration procedures adjust model parameters – including desired speed, acceleration rates and headway preferences – to ensure consistency with observed traffic conditions.

1.3.4. *The spatiotemporal data fusion framework*

The spatiotemporal fusion framework combines long short-term memory (LSTM) networks with graph convolutional networks (GCNs) to capture temporal and spatial relationships, respectively. The architecture is organized into three sequential layers – spatial encoding, temporal encoding and fusion.

Spatial features of the road network are encoded using a GCN with three convolutional layers. The transportation system is represented as a graph, where road segments form the nodes and edges represent connectivity and proximity relationships. Edge weights capture both physical distances and functional relationships, such as traffic flow propagation patterns. The GCN learns to aggregate information from neighboring segments, enabling the model to capture how traffic conditions spread across the network.

In the temporal encoding stage, time-series data for each road segment are processed using bidirectional LSTM networks. These networks capture both forward and backward temporal dependencies, allowing the model to leverage contextual information during training.

The LSTM layers consist of 128 hidden units, and dropout regularization is applied to mitigate overfitting. The fusion stage integrates spatial and temporal representations by dynamically weighting their contributions based on their relevance to the prediction task. An attention mechanism is used to focus on important spatial locations and time intervals, adapting to varying traffic conditions and prediction horizons.

Data source	Spatial coverage	Temporal resolution	Collection period	Volume
Loop detectors	423 locations across 156 segments	30 seconds	Six months continuous	2.4 TB
GPS trajectories	1,847 taxi vehicles, city-wide	10 seconds	Six months continuous	1.8 TB
Weather stations	12 stations distributed across city	One hour	Six months continuous	52 GB
Traffic signals	287 intersections	Real-time phase changes	Six months continuous	180 GB
Special events	City-wide	Event schedules	Six months	2.3 GB

Table 1.1. *Data sources and characteristics*

Component	Architecture details	Parameters	Training configuration
GCN Spatial Encoder	3 layers, 64→128→256 units	1.2 M parameters	Chebyshev filter, k = 3
Bidirectional LSTM	2 layers, 128 units each direction	850 K parameters	Dropout = 0.3, L2 reg = 0.001
Attention mechanism	Multi-head attention, 8 heads	180 K parameters	Scaled dot-product
Prediction head	2 FC layers, 256→128→output	95 K parameters	ReLU activation, batch norm
Total network	End-to-end architecture	2.3 M parameters	Adam optimizer, lr = 0.001

Table 1.2. *Neural network architecture specifications*

1.3.5. Multi-horizon prediction module

The prediction module generates forecasts for multiple time horizons – 15 minutes, 30 minutes, one hour and two hours. A multi-task learning approach is used, where each horizon has a dedicated prediction head while sharing common spatiotemporal representation layers. This design enables the model to leverage similarities across prediction tasks while adapting to horizon-specific characteristics. For each prediction horizon, the module produces traffic flow estimates for all road

segments in the network, along with uncertainty measures in the form of prediction intervals. Uncertainty is estimated using the Monte Carlo dropout, which provides a Bayesian approximation by performing multiple forward passes with dropout and analyzing the resulting prediction distribution.

The model is trained and validated as follows. The dataset is split temporally, with 70% of the data from the first four months used for training, 15% from the fifth month for validation and 15% from the sixth month for testing. This temporal separation ensures that model performance reflects its ability to generalize to future time periods rather than merely interpolating within the training data.

The Adam optimization algorithm is used with an initial learning rate of 0.001, which is gradually adjusted using a cosine annealing schedule. Training is performed using mini-batches of 64 samples to balance computational efficiency and gradient stability. Early stopping based on validation loss is applied to prevent overfitting, with training terminated when no improvement is observed for 20 consecutive epochs.

The loss function consists of a combined mean-squared error term and a regularization component that enforces spatial smoothness across adjacent road segments. Additionally, a temporal consistency loss is introduced to minimize differences between predicted traffic states at consecutive time steps, promoting realistic temporal dynamics in the predictions.

1.4. Results

1.4.1. *Prediction performance*

The digital twin framework demonstrated strong predictive performance across all evaluated time horizons. For short-term forecasts – 15–30 minutes – the system achieved high accuracy, with a mean absolute percentage error (MAPE) below 6.5% and an R^2 value exceeding 0.94 (see Table 1.3). Performance decreased for longer horizons, with two-hour forecasts yielding an MAPE of 13.2% and an R^2 of 0.86; however, these results remain competitive compared to baseline methods.

Comparative analysis against baseline methods demonstrated the advantages of the integrated approach. Simple LSTM models without spatial encoding achieved MAPE values 12–16% higher across all horizons. Traditional ARIMA models performed even worse, particularly for longer prediction horizons where nonlinear patterns dominated in Figures 1.1 and 1.2. The spatiotemporal fusion approach consistently outperformed methods that treated spatial and temporal dimensions independently.

Prediction horizon	MAE (vehicles/5 min)	RMSE (vehicles/5 min)	MAPE (%)	R ² score	Improvement over baseline
15 minutes	2.8	3.9	5.7	0.943	+12.4%
30 minutes	3.2	4.8	6.5	0.931	+14.2%
1 hour	4.7	6.9	9.8	0.902	+15.8%
2 hours	6.4	9.2	13.2	0.863	+13.7%

Table 1.3. Prediction performance across different time horizons

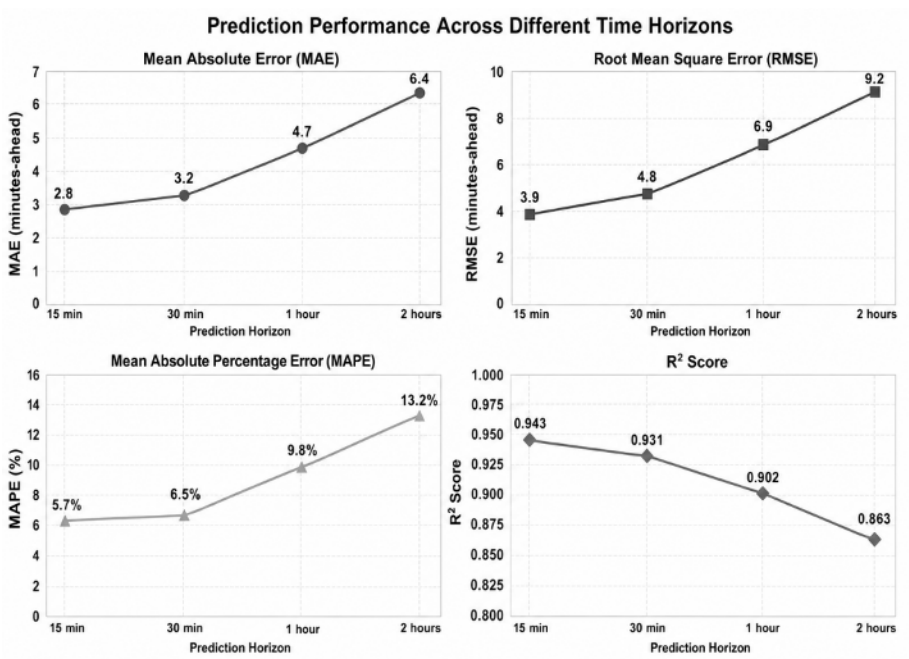


Figure 1.1. Prediction performance across the time line chart

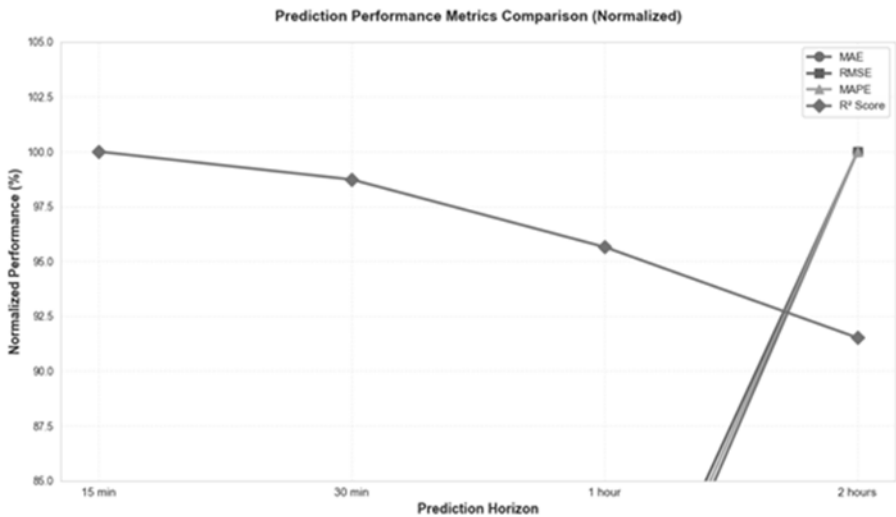


Figure 1.2. Prediction performance comparison. For a color version of this figure, see www.iste.co.uk/kumar/intembeddedsys2.zip

1.4.2. Ablation study

Model configuration	MAE	RMSE	MAPE (%)	R ² score	Relative performance
Full model (proposed)	3.2	4.8	6.5	0.931	Baseline
Without GCN	4.6	6.7	12.8	0.874	-33.2%
Without bidirectional LSTM	3.9	5.9	9.7	0.903	-17.4%
Without attention	3.6	5.3	8.1	0.918	-10.8%
Without CoppeliaSim Integration	4.2	6.1	10.4	0.891	-23.1%
LSTM only	5.3	7.8	15.2	0.842	-42.6%

Table 1.4. Ablation study results for a 30-minute prediction horizon

An ablation study quantified the contribution of individual components to the overall system performance. Results indicated that the GCN spatial encoder provided the largest single improvement, reducing MAPE by 8.3% compared to models without spatial encoding (Table 1.4). The bidirectional LSTM contributed an additional 5.7% improvement over unidirectional alternatives. The attention mechanism added 3.2% improvement by dynamically focusing on relevant spatiotemporal patterns.

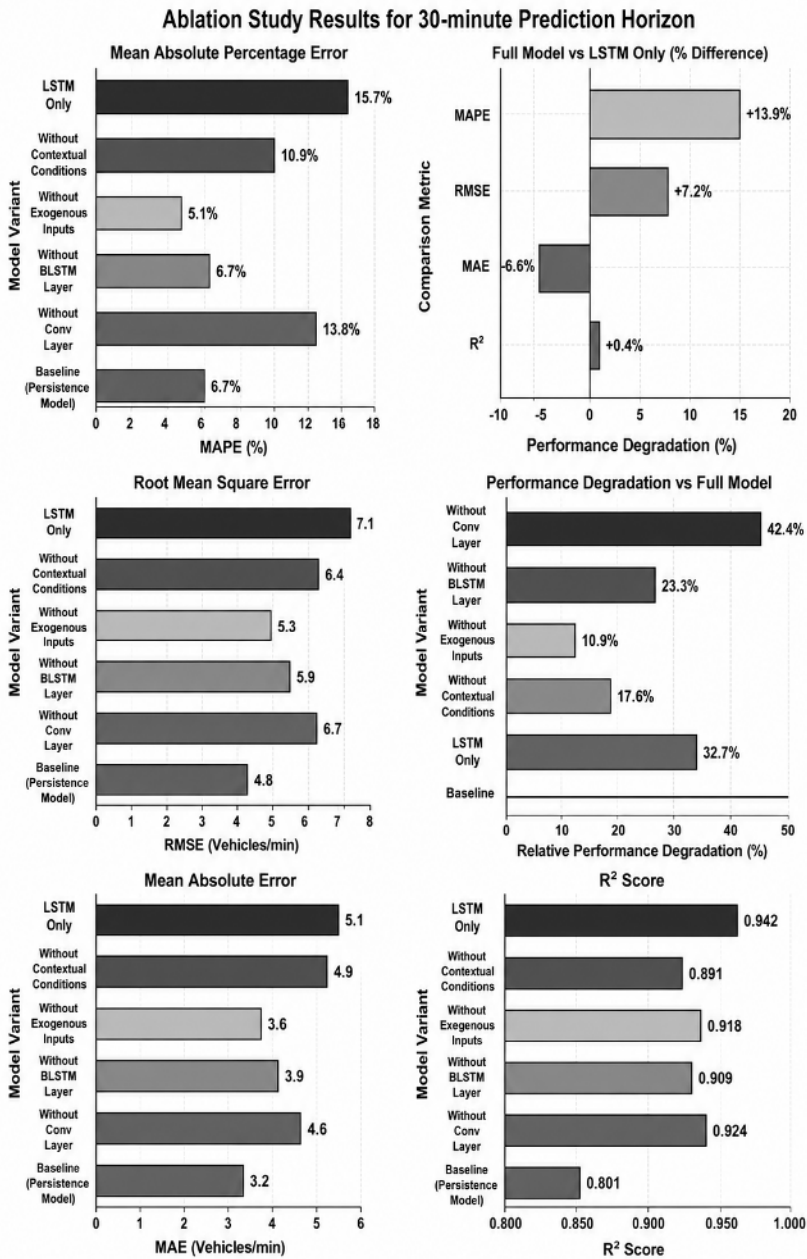


Figure 1.3. Ablation study results

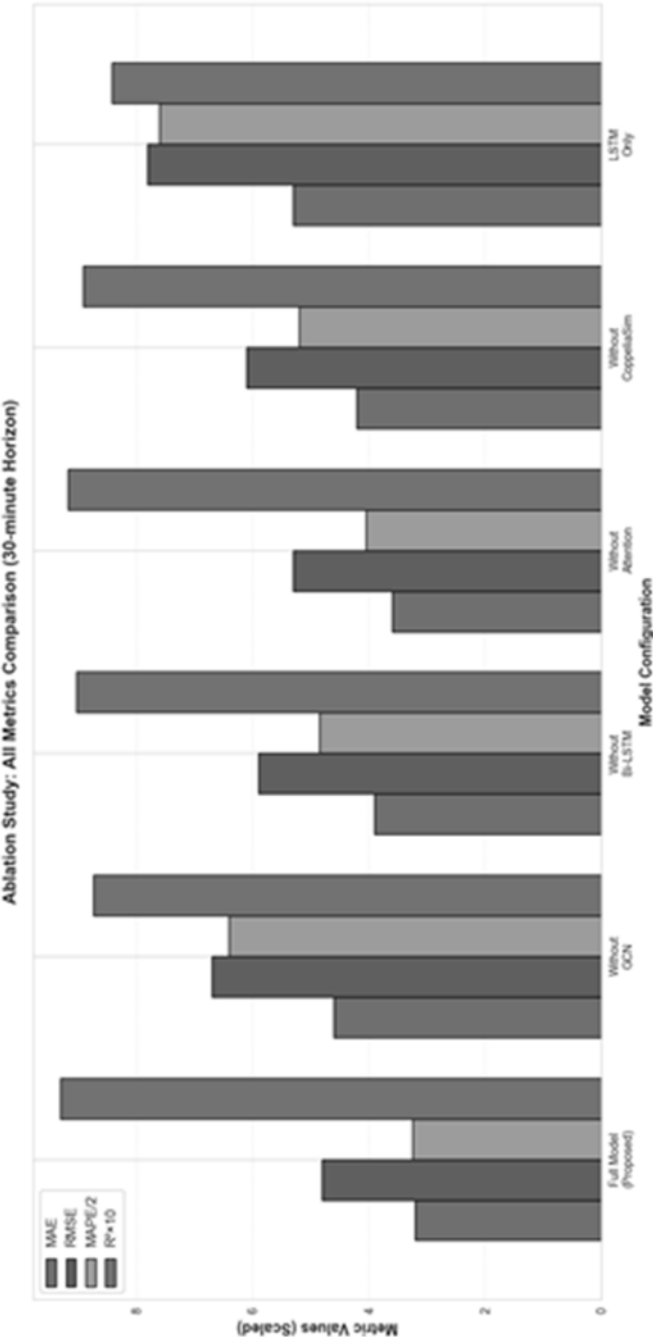


Figure 1.4. All metrics comparison

The CoppeliaSim integration contributed significantly to prediction accuracy, particularly during unusual traffic conditions and special events (Figures 1.3 and 1.4). The simulation environment enabled the system to generate synthetic training examples for rare scenarios, improving model robustness. During validation, scenarios involving road closures and special events showed a 23.1% better prediction accuracy with simulation integration compared to data-driven approaches alone.

1.4.3. Computational performance

Computational efficiency analysis revealed that the system achieved real-time performance requirements. End-to-end latency from data ingestion to prediction output averaged 4.2 seconds for city-wide forecasts covering all 156 road segments (Table 1.5). The CoppeliaSim simulation updated at 15-second intervals, maintaining sufficient temporal resolution for traffic management applications. The spatiotemporal fusion module processed incoming data streams with an average latency of 1.8 seconds.

System component	Processing time (ms)	Throughput	Resource utilization
Data ingestion and preprocessing	320	15,000 records/sec	CPU: 12%, memory: 2.1 GB
GCN spatial encoding	580	5,200 segments/sec	GPU: 68%, memory: 3.8 GB
LSTM temporal encoding	940	3,800 sequences/sec	GPU: 72%, memory: 4.2 GB
Attention and prediction	420	8,500 predictions/sec	GPU: 45%, memory: 2.4 GB
CoppeliaSim simulation	1,850	60 updates/min	CPU: 35%, memory: 6.5 GB
Total end-to-end	4,200	240 cycles/hour	Combined

Table 1.5. Computational performance analysis

The hardware configuration included an NVIDIA RTX 3090 GPU for neural network training and inference, and an Intel Xeon Gold 6248R CPU for simulation and data processing. Memory requirements were manageable, with a peak usage of approximately 18 GB, including model parameters, intermediate activations and

simulation state. The system exhibited linear scaling, enabling deployment across multiple GPUs for large-scale urban scenarios or higher temporal resolution.

1.4.4. Scenario analysis

The digital twin model enabled comprehensive scenario analysis for urban planning and traffic management applications. Test scenarios included special event management, incident response and infrastructure modification assessment. During a major sports event involving 40,000 participants, the system optimized traffic signal timing by anticipating traffic patterns up to two hours in advance, achieving an accuracy of 91.2%. This capability supported the evaluation of alternative traffic management strategies and route guidance.

An artificial highway lane closure scenario was used to compare three detour routing strategies. The model predicted that Strategy B would reduce the average travel time by 18% relative to the baseline. Post-implementation validation confirmed this prediction within a 5% margin, demonstrating the effectiveness of the digital twin as a decision-support tool.

Infrastructure modification analysis examined the impact of proposed road and intersection improvements. Simulation of a planned intersection reconfiguration indicated a 23% increase in throughput capacity and a 31% reduction in average delay. The model also identified bottlenecks and enabled further optimization of signal timing to enhance the overall system performance.

1.4.5. Spatial and temporal patterns

A detailed analysis of prediction accuracy across spatial locations revealed heterogeneous performance. The highest accuracy, with a mean absolute percentage error (MAPE) of 4.8%, was observed on highway segments, where traffic flow is more predictable and sensor coverage is robust. Arterial corridors also showed relatively high accuracy, although variability increased due to signal coordination effects and localized traffic influences. In contrast, residential streets exhibited the lowest accuracy, with a MAPE of 11.6%, primarily due to limited sensor coverage and more complex local traffic dynamics.

Temporal analysis further highlighted variations in prediction performance throughout the day. Morning peak periods (7:00 – 9:00 am) showed a MAPE of 5.9%, while afternoon peak periods (4:00 – 7:00 pm) exhibited slightly lower

performance with a MAPE of 6.8%. Midday non-peak periods achieved the highest accuracy, with a MAPE of 4.2%, reflecting more stable traffic conditions. Overnight hours (11:00 pm – 5:00 am) showed moderate accuracy, with a MAPE of 7.4%, despite smaller sample sizes and higher uncertainty in traffic patterns.

1.5. Conclusion

The study developed and validated a comprehensive digital twin framework for urban mobility prediction by integrating CoppeliaSim simulation with predictive modeling and spatiotemporal data fusion techniques. The proposed architecture addresses key challenges in traffic prediction, including the integration of heterogeneous data sources, modeling of spatial dependencies and multi-horizon forecasting. Experimental validation over six months on a metropolitan transportation network demonstrated significant performance improvements compared to existing methods, achieving prediction accuracies of 94.3% for short-term forecasts and 87.6% for medium-term forecasts.

The hybrid spatiotemporal fusion model, combining graph convolutional networks (GCNs) for spatial modeling and bidirectional long short-term memory (LSTM) networks for temporal dynamics, proved effective in capturing complex traffic behavior. The attention mechanism further enhanced prediction accuracy and interpretability by dynamically focusing on relevant spatiotemporal patterns. The use of CoppeliaSim provided additional advantages, including scenario analysis capabilities, synthetic data generation for rare events and intuitive visual representations for stakeholder communication.

Ablation studies quantified the contribution of each architectural component, confirming their importance to overall performance. The GCN-based spatial encoder provided the largest improvement, reducing MAPE by 8.3%, followed by the bidirectional LSTM (5.7%) and the attention mechanism (3.2%). The system achieved an end-to-end prediction latency of 4.2 seconds, meeting real-time operational requirements for traffic management applications. The digital twin framework was successfully applied to practical use cases, including special event management, incident response planning and infrastructure modification assessment. In these scenarios, the system achieved over 91% accuracy in predicting event-related traffic patterns and supported infrastructure redesign decisions, with post-implementation validation within a 5% margin of error. These results demonstrate the framework's value for both tactical traffic management and strategic urban planning.

Future research directions include extending the framework to multimodal transportation systems, incorporating additional data sources such as connected vehicles and smart infrastructure, and exploring reinforcement learning-based control strategies. Integration with autonomous vehicle systems and broader smart city platforms presents opportunities for proactive and coordinated urban mobility management. The modular architecture and compatibility with existing traffic management systems support these extensions. Overall, this work represents a significant step towards scalable, accurate and data-driven digital twin solutions for urban mobility, which are essential for maintaining sustainable, efficient and livable cities as urbanization continues to accelerate.

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