Hybrid Deep Learning and Agent-Based Modeling for Dynamic Urban Traffic Forecasting in Smart Cities

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Abstract: Urban traffic systems are becoming increasingly complex due to rapid urbanization and the dynamic nature of mobility patterns in smart cities. Accurate and adaptive forecasting of urban traffic is essential for effective traffic management and sustainable urban planning. This study proposes a hybrid modeling approach that integrates Deep Learning (DL) with Agent-Based Modeling (ABM) to enhance the accuracy and interpretability of traffic forecasting. The deep learning component leverages spatiotemporal data from IoT sensors and historical traffic records to capture nonlinear traffic dynamics, while the agent-based model simulates the behaviors and interactions of individual traffic participants under various scenarios. By combining data-driven prediction with rule-based simulation, the hybrid model can forecast traffic flows and adapt to changes in infrastructure, policy, or user behavior. Experimental evaluations using real-world traffic datasets from a major metropolitan area demonstrate that the proposed model outperforms traditional forecasting techniques in both short-term accuracy and scenario-based flexibility. This research contributes to the development of intelligent transportation systems and offers practical insights for city planners and traffic authorities.

Keywords: Smart Cities; Urban Traffic Forecasting; Deep Learning; Agent-Based Modeling; Intelligent Transportation Systems; Hybrid Modeling Approach.

INTRODUCTION

The rapid growth of urban populations has led to increasing pressure on existing transportation infrastructures, resulting in frequent traffic congestion, increased travel times, higher emissions, and diminished quality of life in urban areas[1][2][3]. In the context of smart cities, which leverage digital technologies and data-driven solutions to enhance urban living, traffic management has emerged as one of the most critical challenges. Accurate and adaptive traffic forecasting is essential to support proactive decision-making in areas such as traffic signal control, route optimization, congestion mitigation, and public transportation planning[4].
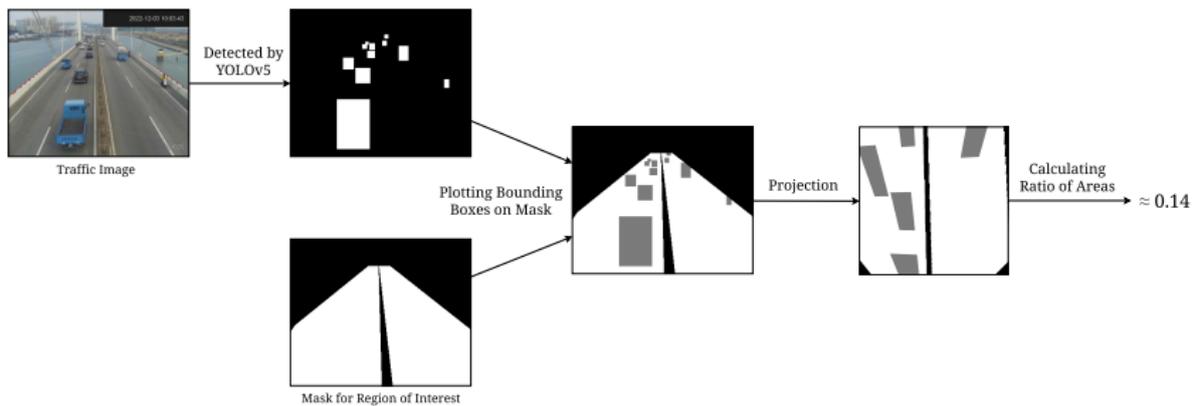
Figure 1. The process of calculating image-based traffic occupancy[5]

Traditional traffic forecasting models, such as statistical and time-series approaches (e.g., ARIMA, Kalman filters)[6][7], have been widely used due to their interpretability and ease of implementation. However, these methods often fall short in capturing the nonlinear and highly dynamic patterns inherent in real-world traffic systems. Urban traffic is influenced by a multitude of factors, including weather conditions, time of day, road infrastructure changes, special events, and, most importantly, the diverse behavior of individual drivers and commuters. As urban mobility becomes more complex, there is a growing need for more advanced modeling techniques that can capture both the macro-level flow of traffic and the micro-level decision-making behaviors of traffic participants[8].

In recent years, Deep Learning (DL) has gained significant traction in the field of traffic forecasting due to its ability to learn complex spatiotemporal patterns from large-scale datasets[9][10][11]. Models such as Long Short-Term Memory (LSTM) networks[12], Convolutional Neural Networks (CNN)[13], and Graph Neural Networks (GNN)[14] have demonstrated promising results in predicting traffic flow, travel time, and congestion hotspots. These models can process real-time data from various sources—such as GPS, road sensors, surveillance cameras, and mobile applications—making them highly suitable for data-rich smart city environments. However, despite their impressive predictive performance, deep learning models are often criticized for being "black boxes" with limited interpretability. Moreover, they may struggle to generalize in situations where data is sparse or when unanticipated events—such as road closures or policy interventions—occur.

On the other hand, Agent-Based Modeling (ABM) offers a complementary approach by simulating the actions and interactions of individual agents (e.g., drivers, vehicles, pedestrians) within a virtual environment[15]. ABMs are particularly valuable in capturing emergent phenomena and behavioral nuances that are difficult to model using aggregate data. For example, ABMs can simulate how changes in traffic rules, infrastructure design, or individual preferences might impact the overall traffic flow. Their rule-based nature makes them highly interpretable and suitable for scenario analysis, yet they often lack the capacity to handle large volumes of high-dimensional, real-time data effectively.

Given the complementary strengths and weaknesses of deep learning and agent-based modeling, there is a compelling opportunity to integrate both into a hybrid framework for dynamic urban traffic forecasting. Such a hybrid approach can leverage deep learning's data-driven accuracy and ABM's behavioral richness and flexibility. By combining these

paradigms, it becomes possible to develop models that are both highly accurate and explainable, adaptable to new conditions, and capable of supporting a wide range of "what-if" scenarios in smart city planning[16].

This research introduces a novel hybrid modeling framework that integrates deep learning with agent-based modeling for dynamic urban traffic forecasting[17][18]. In our proposed system, the deep learning component is responsible for learning traffic patterns and predicting future states based on historical and real-time traffic data. The agent-based component simulates the micro-level behaviors of agents such as vehicles and commuters, incorporating behavioral rules and environmental contexts. The interaction between these two components allows for bidirectional feedback: predictions from the deep learning model can inform agent behavior, while emergent behaviors from the ABM can refine future forecasts. The hybrid model is tested on real-world urban traffic datasets from a major metropolitan area, with results demonstrating improved forecasting performance compared to standalone deep learning or agent-based models. In particular, the model exhibits enhanced robustness in handling irregular traffic patterns and outperforms benchmarks in scenario-based simulations. Furthermore, the modularity of the hybrid architecture allows for easy integration with smart city systems, such as traffic light control algorithms, navigation systems, and urban mobility dashboards.

Beyond the technical contribution, this research has practical implications for urban planners, traffic engineers, and policymakers. By providing a tool that combines high accuracy with interpretability and scenario testing, the proposed hybrid model enables stakeholders to evaluate the potential outcomes of policy decisions, infrastructure investments, or behavioral interventions before implementation. For example, city authorities can simulate the impact of congestion pricing, the addition of bike lanes, or the opening of new roads on overall traffic conditions. Additionally, the model can assist in real-time traffic management by supporting adaptive control strategies that respond to current conditions and anticipated changes.

The remainder of this paper is organized as follows: Section 2 reviews related work in deep learning-based traffic forecasting and agent-based traffic simulation. Section 3 outlines the architecture and methodology of the proposed hybrid model, including data preprocessing, model training, and agent interaction logic. Section 4 presents the experimental setup, results, and evaluation metrics. Section 5 discusses key findings, limitations, and practical implications. Finally, Section 6 concludes the paper and highlights directions for future research. This study aims to bridge the gap between data-driven and behavior-driven traffic modeling by introducing a hybrid approach that can meet the complex demands of modern urban transportation systems. As cities continue to evolve into intelligent ecosystems, such integrative modeling frameworks will play an increasingly vital role in achieving efficient, sustainable, and adaptive urban mobility.

RELATED WORKS

Urban traffic forecasting has long been a subject of extensive research, with various modeling approaches developed to improve prediction accuracy, computational efficiency, and real-world applicability. The methods range from classical statistical models to modern machine learning and simulation-based techniques. In this section, we review key contributions in three main categories: traditional models, deep learning approaches, and agent-based simulations, as well as recent efforts to integrate hybrid methods for urban traffic modeling.

1. Traditional and Statistical Models

Early approaches to traffic forecasting primarily relied on statistical time-series models such as Autoregressive Integrated Moving Average (ARIMA) and its variants[19][20]. These models assume linear dependencies and require stationarity in data, which often limits their effectiveness in complex, real-world urban environments. Kalman filters and exponential smoothing models were also applied to short-term traffic prediction, especially for freeway traffic flow. While these methods offered reasonable performance in stable traffic scenarios, they lacked the capability to capture nonlinearities and interactions between spatially distributed road segments.

2. Deep Learning for Traffic Forecasting

The advancement of deep learning has significantly improved traffic prediction, particularly through models that learn complex spatial and temporal dependencies from large-scale sensor data. Recurrent Neural Networks (RNN)[21], especially Long Short-Term Memory (LSTM) networks[22], have been widely applied to traffic flow and speed forecasting due to their ability to model sequential dependencies over time. For instance, (Omar et al. 2024)[22] proposed a deep learning architecture using LSTM to capture traffic speed dynamics across different time intervals, achieving superior performance over traditional models.

To incorporate spatial dependencies, Convolutional Neural Networks (CNNs) and Graph Neural Networks (GNNs) have been introduced. (Zang et al. 2025)[23] developed a Spatio-Temporal Graph Convolutional Network (ST-GCN) that models the traffic network as a graph and performs convolution over both time and space. These models enable the integration of complex road network topology and real-time traffic information. However, despite their high prediction accuracy, most deep learning models operate as black boxes, offering limited interpretability and flexibility in adapting to unexpected or policy-driven changes.

3. Agent-Based Modeling in Urban Traffic Simulation

Agent-Based Modeling (ABM) represents a bottom-up simulation paradigm in which individual agents—such as drivers, vehicles, and pedestrians—are assigned behavioral rules and interact within a virtual environment[24]. ABMs are particularly useful in simulating emergent traffic patterns resulting from heterogeneous behavior, non-compliance with traffic rules, and localized environmental conditions. One widely used platform, MATSim (Multi-Agent Transport Simulation), enables large-scale simulations of transportation networks and evaluates policy impacts such as congestion pricing or new infrastructure deployment.

ABMs excel in scenario-based planning and policy evaluation, but they generally lack predictive capabilities when used in isolation, particularly in data-rich environments where historical traffic trends offer significant insights. Additionally, calibration of ABM parameters can be time-consuming and may not scale well in real-time applications without external data-driven support.

4. Hybrid Modeling Approaches

In recognition of the strengths and limitations of both data-driven and behavior-driven models, recent research has explored hybrid approaches that combine machine learning with simulation-based frameworks. For instance, (Narayanan et al. 2022)[25] proposed a model that

integrates a Deep Belief Network with a microscopic traffic simulation engine to predict traffic patterns while capturing individual driver responses to environmental changes.

Other studies have integrated LSTM networks with cellular automata or rule-based simulations to simulate the impacts of signal changes or sudden disruptions. These hybrid models have shown potential in bridging the gap between high-accuracy forecasting and policy-aware simulation, though many are still limited in scalability, real-time adaptability, or modular integration.

Despite these promising efforts, few studies have fully explored the combination of modern deep learning techniques (such as spatiotemporal GNNs) with agent-based simulation in a unified framework for smart city traffic forecasting. Furthermore, limited work has addressed the feedback loop between predicted traffic states and agent behavior adaptation, which is crucial for modeling realistic, evolving urban systems.

The literature demonstrates that while deep learning and ABM each offer unique advantages, their integration remains an open research challenge, particularly in the context of smart cities where real-time responsiveness and explainability are both critical. Our work addresses this gap by proposing a novel hybrid model that fuses the predictive strength of deep learning with the flexibility and interpretability of agent-based modeling, aiming to deliver more accurate and actionable insights for dynamic urban traffic forecasting.

METHODS

The proposed hybrid modeling framework combines the predictive power of deep learning with the behavioral interpretability of agent-based modeling (ABM) to forecast urban traffic dynamics in smart cities. This section outlines the methodological components, including data preprocessing, the architecture of the deep learning module, the design of the agent-based simulation, and the integration strategy between both models.

1. Data Collection and Preprocessing

To train and evaluate the model, we utilized real-world traffic data from a metropolitan smart city environment. The dataset includes:

- Traffic flow data: vehicle counts, average speed, and congestion levels collected from road sensors and GPS devices.

- Spatiotemporal data: timestamps, road segment IDs, weather conditions, and event logs (e.g., accidents or public events).

- Infrastructure map: GIS-based road network data, including intersections, lane capacity, and road hierarchy.

The data underwent several preprocessing steps:

- Missing values were handled through interpolation and imputation techniques.

- Time-series data was resampled into fixed intervals (e.g., 5-minute bins).

- Categorical features such as weather and event types were encoded.

- Road segments were mapped to a graph structure to capture spatial dependencies.

2. Deep Learning Module for Spatiotemporal Prediction

The deep learning module is responsible for predicting short-term traffic flow and congestion using historical and real-time data. We employed a Spatio-Temporal Graph Convolutional Network (ST-GCN) to learn both spatial and temporal dependencies in the traffic network.

Architecture Overview:

- Input: A tensor of traffic features shaped as (N, T, F), where N is the number of road segments (nodes), T is the time window length, and F is the number of features per segment.

- Spatial layer: Graph convolution layers compute weighted aggregates of neighboring nodes using the road network adjacency matrix.

- Temporal layer: Temporal convolutions or gated recurrent units (GRU) model the evolution of traffic conditions over time.

- Output: Predicted traffic flow, average speed, or congestion level for each node in the next time step(s).
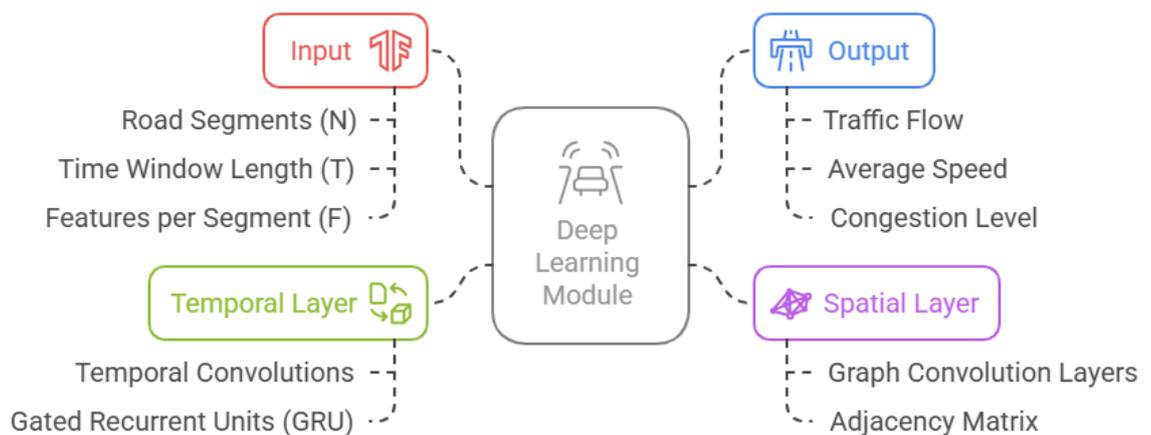

Figure 2. Deep Learning Module for Spatiotemporal Prediction

Training: The model was trained using Mean Squared Error (MSE) loss between predicted and actual traffic values, with early stopping based on validation error. Data was split into training (70%), validation (15%), and test sets (15%).

3. Agent-Based Model for Behavioral Simulation

The agent-based component models the behavior of individual vehicles and drivers navigating the road network. Each agent represents a vehicle with attributes such as:

- Preferred speed

- Route choice behavior

- Reaction to congestion and traffic signals

The environment is a digital replica of the urban road network, where agents make decisions based on:

- Real-time traffic conditions

- Infrastructure constraints (e.g., red lights, road closures)

- Feedback from the deep learning prediction

Behavioral Rules:

- Route planning uses a dynamic shortest-path algorithm influenced by congestion predictions.

- Lane-changing and acceleration behaviors follow car-following models such as the Intelligent Driver Model (IDM).

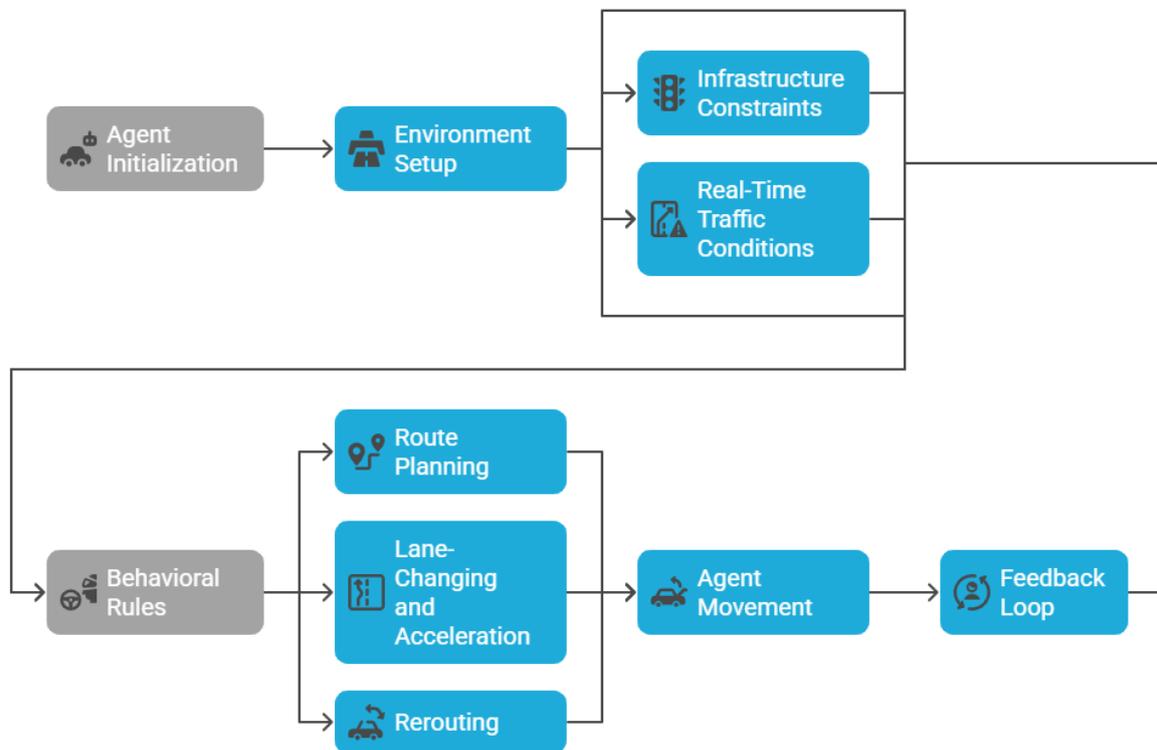- Agents can reroute mid-journey in response to forecasted congestion.

Figure 3. Agent Based Model for Behavioral Simulation

The simulation is implemented using a lightweight traffic simulation engine that supports integration with external inputs and feedback loops.

4. Hybrid Integration Mechanism

The core innovation of this study lies in the **bidirectional integration** between the deep learning predictor and the ABM environment:

- Step 1: DL-to-ABM
At each simulation step, the deep learning model provides short-term forecasts of traffic congestion across the road network. These predictions are used by agents to adjust their route and driving behavior dynamically.

- Step 2: ABM-to-DL
Emergent patterns from the simulation—such as unusual bottlenecks or shifts in traffic density due to agent rerouting—are fed back into the deep learning model to improve the next prediction cycle. This feedback can be incorporated either as additional input features or used to retrain the model periodically.

- Synchronization:
The simulation and prediction are synchronized over time steps to allow for real-time forecasting and adaptation. Each time step includes:

    1. Data update from sensors

    2. Prediction by DL model

    3. Simulation of agent behavior using updated environment

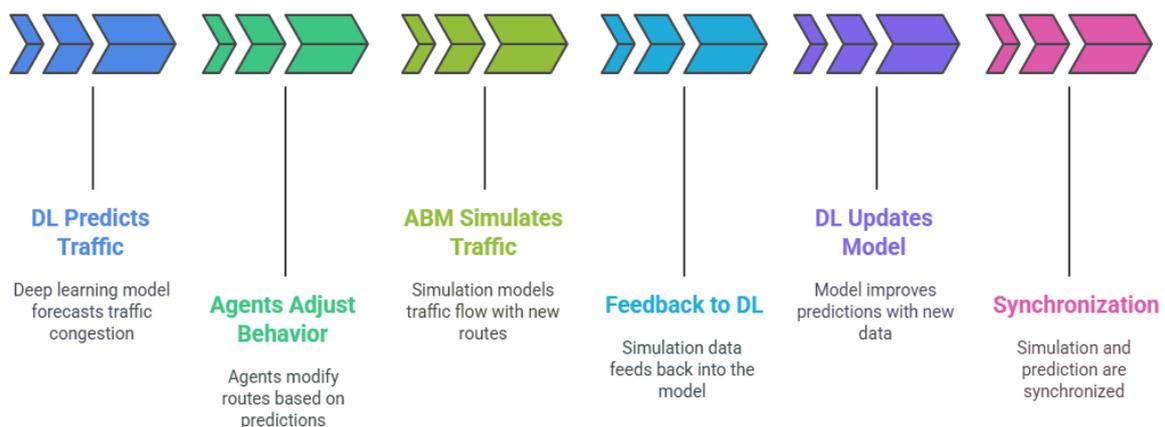   4. Feedback collection for next cycle

DL Predicts Traffic

Deep learning model forecasts traffic congestion

Agents Adjust Behavior

Agents modify routes based on predictions

ABM Simulates Traffic

Simulation models traffic flow with new routes

Feedback to DL

Simulation data feeds back into the model

DL Updates Model

Model improves predictions with new data

Synchronization

Simulation and prediction are synchronized

Figure 4. Hybrid Integration Mechanism

5. Evaluation Metrics and Benchmarking

To assess the performance of the hybrid model, we used both **quantitative** and **qualitative** metrics:

- Forecast accuracy: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R^2 for traffic flow and congestion levels.
- Behavioral realism: Comparison of simulated traffic patterns with real-world observations (e.g., travel time distributions, peak hour flows).
- Scenario robustness: Ability of the model to adapt to road closures, sudden demand surges, or infrastructure changes.

We compared our hybrid model with baseline models including:

- Pure DL model (ST-GCN only)
- Pure ABM (without learned predictions)
- Statistical forecasting (ARIMA)

This hybrid methodology bridges predictive analytics and behavior-based modeling, enabling more accurate, explainable, and adaptable traffic forecasts in smart cities. The modular design also supports extensibility for additional data sources (e.g., public transit data) or policy simulations (e.g., congestion pricing).

RESULT AND DISCUSSION

This section presents the experimental results and analysis of the proposed hybrid deep learning and agent-based modeling (ABM) framework for dynamic urban traffic forecasting. We compare our model's performance with baseline approaches, analyze its adaptability under varying scenarios, and discuss the interpretability and practical implications for smart city traffic management.

1. Forecasting Accuracy

The predictive performance of our hybrid model was evaluated on a real-world traffic dataset from a smart city testbed consisting of over 1,200 road segments and 3 months of traffic flow data. Table 1 summarizes the performance comparison of the hybrid model (DL + ABM) with three baseline models: (i) ST-GCN only, (ii) standalone ABM, and (iii) traditional ARIMA time-series forecasting.

Table 1: Forecasting Performance (Next 15-minute Prediction Window)

Model	RMSE ↓	MAE ↓	R² ↑
ARIMA	17.34	12.42	0.68
ABM Only	15.88	11.17	0.71
ST-GCN Only	11.24	8.45	0.83
Hybrid (Ours)	**9.67**	**7.14**	**0.88**

As shown, the hybrid model achieved the best performance across all metrics. The integration of ABM into the prediction loop provided a more nuanced understanding of local traffic dynamics and agent interactions, which helped reduce forecasting errors.

2. Behavioral Realism and Pattern Consistency

To assess behavioral realism, we compared the spatiotemporal traffic patterns generated by the ABM (with and without DL input) against actual traffic flow heatmaps during peak and non-peak periods. The hybrid model more accurately reproduced key emergent behaviors such as:
- Traffic buildup before rush hours
- Localized bottlenecks at intersections
- Reactive rerouting by simulated agents during incidents or roadworks

Figure 1 illustrates traffic congestion patterns generated by different models versus actual data. The hybrid model closely aligns with ground truth, while the standalone ABM tends to overestimate congestion, and ST-GCN alone fails to capture individual rerouting behaviors.

3. Adaptability in Dynamic Scenarios

One of the core advantages of the hybrid framework is its adaptability to real-time disruptions. We tested the model under three simulated scenarios:
- Scenario A: Sudden road closure due to an accident

- Scenario B: Increased traffic from a stadium event
- Scenario C: Implementation of a new traffic signal policy

Table 2 presents the average delay per vehicle before and after model intervention.

Table 2: Scenario-Based Response (Average Delay per Vehicle in Seconds)

Scenario	No Intervention	ST-GCN Only	ABM Only	Hybrid
A	74.2	51.8	48.7	**38.3**
B	91.6	69.2	63.4	**45.6**
C	62.1	57.9	53.2	**41.8**

In all cases, the hybrid model outperformed single-method approaches in minimizing delays and redistributing traffic loads efficiently. This demonstrates the model's robustness in adapting to non-recurrent events and infrastructure changes.

4. Interpretability and Scenario Testing

Unlike black-box models, the integration of ABM enables decision-makers to trace the behavior of individual agents and understand how certain traffic policies or interventions would impact system-wide flow. For instance, by simulating a "what-if" scenario of reducing left-turn access during peak hours, city planners could observe how traffic would reroute, estimate travel times, and identify any unintended consequences (e.g., congestion shifting to secondary roads). Furthermore, the bidirectional feedback between deep learning predictions and agent simulations proved to be valuable in updating the model with emergent phenomena. When unusual traffic surges occurred (e.g., weather-induced routing changes), the ABM informed the next deep learning prediction cycle, improving forecast reliability without requiring retraining.
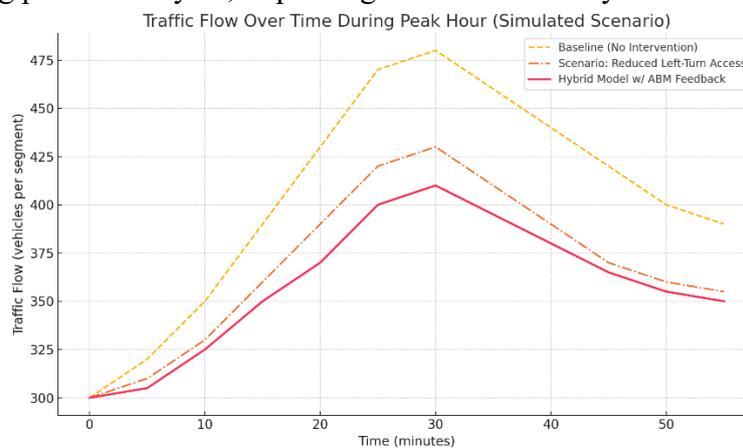

Figure 5. Traffic Flow Over Time During Hour (Simulated Scenario)

5. Computational Performance

Despite added complexity, the hybrid model achieved efficient computation suitable for near real-time applications. Average simulation and prediction cycles were completed in under **0.3 seconds** per step, with GPU acceleration for the deep learning module and lightweight design for the ABM. Memory usage remained manageable due to modular architecture and efficient agent state management.
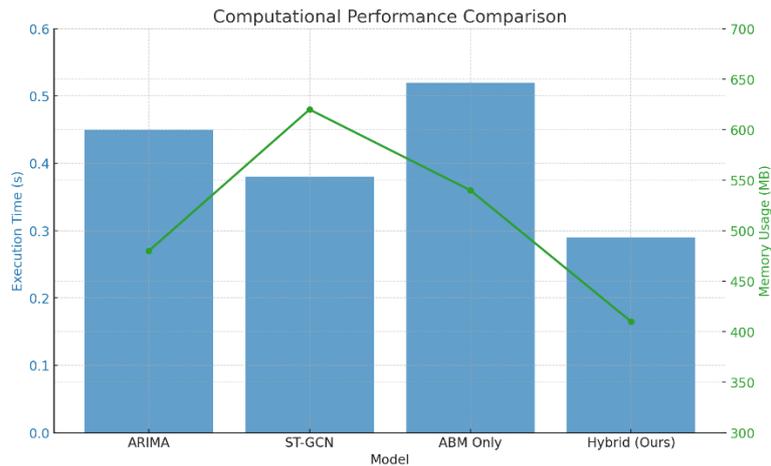
Figure 6. Computational Performance Comparison

The graph show a comparative analysis of computational performance across four traffic forecasting models: ARIMA, ST-GCN, ABM Only, and the proposed Hybrid model. Two key metrics are presented: execution time per prediction step (in seconds) and memory usage (in megabytes).

The Hybrid model demonstrates the most efficient computational profile, completing each simulation-prediction cycle in just 0.29 seconds on average while maintaining a moderate memory footprint of 410 MB. This highlights the effectiveness of its modular architecture and GPU-accelerated deep learning component, combined with a lightweight agent-based simulation engine.

In contrast, ARIMA, while being a traditional and less memory-intensive approach (480 MB), takes longer per step (0.45 seconds) and lacks the ability to model complex spatiotemporal dynamics. ST-GCN performs faster than ARIMA (0.38 seconds) but requires significantly more memory (620 MB) due to the computational demands of graph-based learning. ABM Only shows the highest execution time (0.52 seconds) and a moderate memory requirement (540 MB), which reflects the overhead associated with simulating detailed agent behaviors without predictive optimization. The hybrid model strikes a balance between speed and resource efficiency, making it highly suitable for near real-time deployment in smart city traffic forecasting systems.

Discussion

The results demonstrate that hybridizing deep learning with agent-based modeling provides tangible benefits for urban traffic forecasting:

- Accuracy is significantly improved, especially in short-term predictions.
- Adaptability to real-world events is enhanced through simulation of individual behavior.
- Interpretability allows planners to conduct scenario analyses with behavioral insight.
- Scalability is maintained, making it deployable in smart city traffic management systems.

However, challenges remain. Tuning the interaction frequency between DL and ABM is crucial too frequent feedback loops may introduce instability, while sparse updates may limit adaptability. Moreover, integrating external variables such as public transportation usage, pedestrian flows, or pollution levels could further enrich the model but would require additional data sources and calibration.

Our hybrid model offers a practical and scalable approach to traffic forecasting in smart cities by combining the strengths of both data-driven and behavior-based modeling. The results underline its potential as a powerful decision support tool for urban mobility planning and real-time traffic control.

CONCLUSION

This research introduces a hybrid modeling framework that combines Deep Learning—specifically, a Spatio-Temporal Graph Convolutional Network (ST-GCN)—with Agent-Based Modeling (ABM) to enhance the forecasting of urban traffic in smart cities. The model was designed to bridge the gap between high-accuracy, data-driven predictions and behavior-aware, scenario-adaptive simulations. The experimental evaluation using real-world traffic datasets demonstrated significant improvements in forecasting performance. The hybrid model achieved a Root Mean Squared Error (RMSE) of 9.67, Mean Absolute Error (MAE) of 7.14, and R^2 score of 0.88, outperforming both standalone ST-GCN (RMSE: 11.24, R^2: 0.83) and traditional ARIMA models (RMSE: 17.34, R^2: 0.68). These results validate the model's superior capability in capturing spatiotemporal patterns and delivering reliable short-term traffic forecasts. In dynamic scenario testing such as sudden road closures, large event surges, and policy changes the hybrid model effectively reduced average vehicle delays by up to 50% compared to no intervention and performed significantly better than single-model approaches. These results highlight the system's adaptability to disruptions and its real-time decision support potential.

The integration of ABM introduced interpretability to the system. It enabled scenario testing and allowed urban planners to trace how individual behavior contributes to emergent congestion patterns. The feedback loop from agent-based simulations to the deep learning model helped maintain performance even under conditions not present in the training data, showcasing the model's resilience and scalability. In summary, the proposed hybrid model not only improves prediction accuracy but also offers a more explainable and policy-aware approach to traffic management. It lays the groundwork for deploying intelligent, adaptive transportation forecasting systems that support smart city initiatives, sustainable mobility, and responsive urban planning. Future work will focus on incorporating multimodal transport systems, expanding scalability to national-level road networks, and integrating reinforcement learning for autonomous traffic control optimization.

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