Intelligent Adaptive Traffic Control: A Comparative Study of RNN Variants

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Abstract

This study addresses the major urban challenge of traffic congestion, causing a considerable increase in travel time, fuel consumption, air pollution, and commuter stress. With a rapidly increasing urban population in cities like the metropolitan cities of India, this problem has taken a serious turn, especially during peak hours. Traditional traffic signal systems are often static and inefficient in such situations. This paper proposes an adaptive traffic signal control system for the adjustment of traffic signal duration based on historical traffic patterns, utilizing predictive models(ARIMA, LSTM, GRU, Bi-GRU, Bi-LSTM) through the integration of simulation tools like SUMO and real-time control via TraCI. These models are evaluated based on their performance in reducing queue length, average waiting time, and overall travel time. These results demonstrate the effectiveness of adaptive traffic signals in improving urban traffic management. Bi-LSTM was found to be the best fit for the problem by 40.08% reduction in average waiting time, 43.31% reduction in queue length, and a 17.90% reduction in travel time, despite exhibiting a higher Mean Squared Error (MSE) in traffic flow prediction. A combined CO_2 reduction metric was also assessed to calculate the impact of these predictive models on environmental sustainability. Bi-LSTM achieves a CO_2 emission reduction of 33.32%, which positions it as the most effective model for traffic control.

Keywords: Adaptive Traffic control, Smart Traffic management, Environmental Sustainability

1 Introduction

The problem of traffic congestion has taken a serious turn over the years. With the increasing urban population and economic activity in Megacities like Mumbai, Delhi, Bengaluru, and Hyderabad, the number of vehicles on the road has surged dramatically. This results in complex and unpredictable traffic patterns, where traditional traffic signal systems fail to manage dynamic traffic flows, especially during peak hours, where the traffic delays can stretch to more than 2 hours. The issue has increased to a very high extent. For instance, Pune’s live traffic monitoring found ~34% of travel time lost to congestion.

Intelligent Adaptive Traffic Control represents a new era in intelligent traffic management, integrating artificial intelligence and real-time data. It is a data-driven approach that not only solves the current traffic problem but also aligns with broader sustainable urban planning objectives. It marks a significant change in modern cities' traffic management by encouraging more responsive and efficient intersections, opening the door to smarter, more resilient, and sustainable cities that improve the quality of life for their citizens [2].

This study employs a simulation-driven, data-centric methodology to address urban traffic congestion. A simulation network was generated using the Simulation Urban Mobility (SUMO) platform. SUMO is an open-source, highly portable, microscopic, and continuous multi-modal traffic simulation package designed to handle large networks and various modes of transport [3]. SUMO was integrated with the TraCI interface in Python for dynamical control and monitoring, allowing programmatic control of real-time data such as vehicle count, queue lengths and travel time.

The collected traffic data undergoes preprocessing for enhancing model performance. The cleaned and transformed dataset serves as the foundation for traffic flow forecasting and signal phase adjustments.

Five prediction algorithms are used to assess how well various forecasting methods work: BiLSTM (Bidirectional LSTM), which processes input sequences in both forward and backward directions to capture broader temporal context, improves prediction accuracy [6]; GRU & BiGRU (Gated Recurrent Units), effective substitutes for LSTM with comparable performance, including bidirectional analysis for better forecasting [7]; and ARIMA (AutoRegressive Integrated Moving Average), a traditional time-series model used for forecasting traffic flow based on historical data [4]; LSTM (Long Short-Term Memory), an RNN variant that can handle long term dependencies in sequential data, making it suitable for traffic prediction [5].

The simulation data is preprocessed and trained on the forecasting models.

The adaptive signal control mechanism is assessed using four key performance metrics: average waiting time, queue length, travel time, and lane-wise density. By comparing the predictive accuracy and practical effectiveness of each model across these metrics, the study identifies the most suitable variant for implementing real-time adaptive traffic signal control.

Furthermore, a CO_2 reduction metric was calculated adding the weighted sum of each metric to assess how our models help in improving environmental sustainability. By reducing idle time at intersections, minimizing congestion, and optimizing traffic flow, the proposed models effectively lower fuel consumption and, consequently, greenhouse gas emissions.

The key highlights addressed by this study are as follows:

- The study effectively combines the SUMO simulation platform with Python-based TraCI control to generate and manage realistic, real-time traffic scenarios for adaptive signal optimization.
- It provides a comprehensive comparison of traditional and deep learning-based traffic prediction models (ARIMA, LSTM, BiLSTM, GRU, BiGRU) to identify the most effective algorithm for real-time traffic signal control.

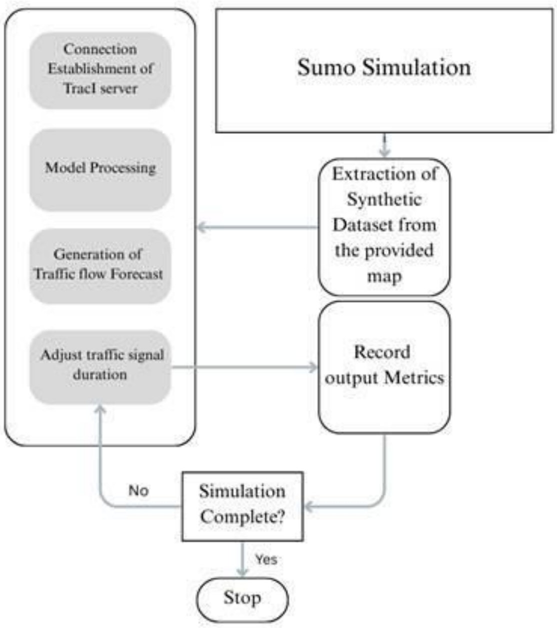

Fig 1: Framework of Traffic Flow Forecasting and Dynamic Signal Optimization Using SUMO Simulation

Fig 1 depicts a flow chart explaining the working of the traffic control module from extracting the dataset using SUMO to the connection of TracI Server and Model Processing, working and then recording the output metrics which are re-inputted to the system for further simulation steps until the simulation ends.

In this paper, further analysis of the proposed methodology is being done based on the following Research Questions (RQs);

RQ1: How do the different predictive models (ARIMA, LSTM, BiLSTM, GRU, BiGRU) compare in terms of forecasting accuracy for traffic flow?

This RQ focuses on evaluating the prediction performance of each model using metrics like Mean Squared Error (MSE). It assesses how well each algorithm can capture temporal patterns in traffic data for short-term forecasting.

RQ2: What is the impact of each model on traffic performance metrics such as average waiting time, queue length, and travel time?

This RQ looks into how the predictions generated by each model affect real-time signal control when implemented, analyzing the resulting improvements or limitations in overall traffic flow efficiency.

RQ3: How do predictive traffic models achieve environmental sustainability?

This RQ examines the environmental impact of predictive models by assessing their ability to reduce CO_2 emissions. By improving traffic flow through reduced waiting time, queue length, and travel time, these models help minimize fuel consumption and vehicle idling, thereby contributing to more sustainable and eco-friendly traffic management.

2 Related Work

In the related work section, we review several key studies that have explored adaptive intelligent traffic signal systems and their impact on modern cities traffic management. Various prediction models and methodologies have been implemented to enhance traffic flow forecasting and control, with a particular focus on machine learning techniques. Table 1 summarizes the key studies in this domain, highlighting the models which are used, their evaluation metrics, and their performance outcomes. This comparative analysis provides us a foundation for selecting the most effective approach for real-time adaptive traffic signal control systems in urban environments.

Table 1: Related Work

Paper Title	Author(s)	Dataset	Methodology Used for Prediction	Conclusion
Real-Time Adaptive Traffic Control for Smart Cities[8]	Shyam Shankaran R., Logesh Rajendran	Real-time traffic captured through camera-based systems	Adaptive Traffic Control System using Image Processing (OpenCV) for vehicle count-based dynamic signal adjustments	Successfully reduced cycle time, minimized congestion, and prioritized emergency vehicles in smart city environments
Adaptive Traffic Signal Control in a Connected Vehicle Environment: A Review[9]	Peng Jing, Hao Huang, Long Chen	Review of multiple connected vehicle systems	Comparative analysis of SCATS, SCOOT, RHODES, OPAC, MOTION, and PRODYN adaptive algorithms in connected vehicle environments	Adaptive systems leveraging connected vehicles offer significant delay reductions and traffic flow improvements

Dynamic Traffic Flow Optimization Using RL and Predictive Analytics[10]	Volodymyr N. Skoropad et al.	IoT sensor data, camera feeds, mobile data from Belgrade city	Reinforcement Learning (Deep Q-Learning, PPO) with Predictive Analytics (LSTM, ARIMA, GNN)	Achieved 33% reduction in waiting times, 16% emission cuts, and enhanced urban traffic safety
Reinforcement Learning for Adaptive Traffic Signal Control: Turn-Based and Time-Based[11]	Muhammad Tahir Rafique et al.	Simulated traffic scenarios (4 different conditions)	Turn-Based Agent and Time-Based Agent models using Deep Q-Learning focusing on queue length optimization	Both RL agents outperformed traditional fixed-time systems, achieving lower congestion and wait times
Federated Deep Reinforcement Learning-Based Traffic Control[12]	Mi Li, Xiaolong Pan, Chuhui Liu, Zirui Li	Federated learning across simulated traffic networks	Federated Proximal Policy Optimization (PPO) enabling secure, collaborative training among agents	Decreased average vehicle waiting times by 27.34% and improved model convergence speed by up to 47.69%
Adaptive Traffic Light Control Using Q-Learning and Deep Q-Networks[13]	Zhongyi Huang	Real-world road scene datasets and simulations	Markov Decision Process (MDP) combined with Q-Learning and Deep Q-Network (DQN) techniques	Improved road traffic efficiency, reduced accident incidence, and adapted effectively to complex traffic environments
Real-Time Adaptive Signal Control in CAV Environment[14]	Saeed Maadi, Sebastian Stein, Jinhyun Hong, Roderick Murray-Smith	Microscopic simulation under varying Connected and Automated Vehicle (CAV) penetrations	Reinforcement Learning-based Signal Plan Optimization combined with Vehicle Speed Guidance	Achieved significant reductions in total stop delay and queue length under high CAV penetration scenarios

Adaptive Urban Traffic Signal Control with Enhanced DRL[15]	Changjian Cai, Min Wei	Dynamic traffic simulations under varying flow conditions	Deep Reinforcement Learning model (Double Q-Learning + Dueling DQN + Prioritized Experience Replay + Noisy Networks)	Achieved faster convergence, improved traffic flow, and robust performance across different traffic demand scenarios
Multi-Intersection Signal Control Using Asynchronous Reinforcement Learning[16]	Jixiang Wang, Siqi Chen Jing Wei, Boao Wang, Haiyang Yu	Simulation-based data (SUMO simulator)	Asynchronous Advantage Actor-Critic (A3C) algorithm across multiple intersections	Enhanced learning efficiency and reduced vehicle waiting time across dense multi-intersection traffic networks

The existing literature highlights various methodologies for adaptive traffic signal control, with many focusing on reinforcement learning, predictive analytics, and simulation-based approaches. But most studies either concentrate on specific algorithms or are limited to particular urban settings and traffic scenarios. Our paper aims to fill this gap by incorporating a broader set of forecasting techniques, including ARIMA and multiple variants of Recurrent Neural Networks (RNNs), to optimize real-time adaptive traffic signal control across diverse traffic environments. Furthermore, this study emphasizes the integration of real-time traffic data with historical patterns, offering a more dynamic and scalable approach to traffic signal optimization compared to static, rule-based systems traditionally used in urban traffic control. By comparing multiple models in a simulation-driven framework, this work provides a comprehensive evaluation of their effectiveness in urban traffic management.

3 Methodology

3.1 Simulation Setup

The simulation was developed using the SUMO (Simulation of Urban Mobility) platform, focusing on the road network of Barakhamba Road, New Delhi. The SUMO Map Import Wizard was used to convert the selected map region into a traffic-ready simulation network.

To enable real-time simulation control, the TraCI (Traffic Control Interface) was integrated with a Python interface, allowing dynamic interaction and the extraction of real-time traffic metrics such as queue length, waiting time, and vehicle speeds during multiple simulation runs.

3.2 Data Collection and Preprocessing

Data Extraction: The traffic parameters collected from SUMO simulations such as queue length, waiting time, and vehicle arrival rate were retrieved through the TraCI interface for each simulation cycle.

Preprocessing for ARIMA:

- *Normalization:* Applied to ensure all features contribute equally to the forecasting models.
- *Logarithmic Transformation:* Used to reduce skewness and stabilize variance in the time-series data.

Preprocessing for RNN Models

- *Min-Max Scaling:* Normalized input features to the [0, 1] range.
- *Sequence Generation:* A sliding window approach with a window length of 10 was used to transform data into input-output sequences suitable for time-series prediction using RNNs.

3.3 Forecasting Models

ARIMA Model: The ARIMA (AutoRegressive Integrated Moving Average) model was implemented using Python's statsmodels library. Based on autocorrelation and partial autocorrelation plots, model order parameters were selected as (1,1,1). ARIMA was trained on preprocessed traffic parameters and used to forecast short-term congestion levels.

Recurrent Neural Networks (RNNs): RNNs were implemented to model temporal dependencies in traffic data. Four RNN variants were explored:

- *LSTM (Long Short-Term Memory):* Utilizes memory gates (input, forget, and output) to capture long-term dependencies and patterns in vehicle arrival and departure sequences.
- *Bi-LSTM (Bidirectional LSTM):* Extends LSTM by processing data in both forward and backward directions, thereby improving prediction accuracy using full temporal context.
- *GRU (Gated Recurrent Unit):* A more efficient alternative to LSTM, combining input and forget gates into a single update gate for faster computation.
- *Bi-GRU (Bidirectional GRU):* Combines GRU architecture with bidirectional processing, improving performance in scenarios where future context enhances decision-making.

3.4 Model Implementation

All models were implemented using TensorFlow, with the following configurations:

Table 2: Summary of Model Configuration

Model	Architecture
LSTM	32 LSTM units + 8 Dense units
BiLSTM	64 BiLSTM units + 16 Dense units
GRU	48 GRU units + 12 Dense units
BiGRU	96 BiGRU units + 24 Dense units

- Optimizer: Adam
    - Loss Function: Mean Squared Error (MSE)
    - Regularization: Early Stopping to prevent overfitting

3.5 Adaptive Signal Control Mechanism

Each model was retrained periodically during the simulation for real-time adaptability:

- LSTM: every 100 simulation steps
- BiLSTM: every 120 steps
- GRU: every 80 steps

- BiGRU: every 140 steps

Predicted traffic volumes were used to dynamically adjust green signal durations:

- High congestion→ extended green time
- Low traffic → shortened green time

All adjustments adhered to fixed upper and lower bounds for safety and feasibility.

3.6 Evaluation Metrics

To assess model performance and the effectiveness of the adaptive control, the following key performance indicators were used: Average Vehicle Waiting Time, Queue Length, Total Travel Time

The results showed substantial improvement in traffic flow and congestion reduction compared to fixed-time signal strategies and are discussed in the next section of the paper.

4 Results and Discussion

4.1 Fixed Timing Baseline Metrics

Table 3: Performance Metrics of Traditional Model Used as Baseline

Metric	Value
Average Waiting Time	10.76 seconds
Average Queue Length	5.42 seconds
Average Travel Time	58.94 seconds

RQ1:How do different predictive models (ARIMA, LSTM, BiLSTM, GRU, BiGRU) compare in terms of forecasting accuracy for traffic flow?

With reference to Table 4, deep learning models outperform the traditional ARIMA model in forecasting accuracy. GRU achieves the lowest MSE (21.53), followed closely by Bi-GRU (21.57) and LSTM (21.62), demonstrating superior predictive performance. In contrast, Bi-LSTM records the highest MSE (26.12), indicating the least accurate forecasts among the models. ARIMA also performs less effectively, with an MSE of 24.35. These results highlight the strength of RNN-based models, especially unidirectional variants like GRU and LSTM, in traffic flow prediction.

Table 4: Comparison of Prediction Accuracy Based on MSE scores

Model	ARIMA	LSTM	Bi-LSTM	GRU	Bi-GRU
MSE Score	24.35	21.62	26.12	21.53	21.57

RQ2: What is the impact of each model on key traffic performance metrics such as average waiting time, queue length, and travel time?

Table 5 presents a comparative analysis of the improvement in traffic performance metrics achieved through various prediction models. The findings reveal a discernible hierarchy in model efficacy. The Bi-LSTM model demonstrates the most substantial improvements, evidenced by the highest percentage reduction in queue length (43.31%), waiting time (40.08%), and travel time (17.90%). Conversely, the LSTM and GRU models exhibit the least significant enhancements across these metrics, registering the lowest percentage reductions in queue length (14.29%), waiting time (9.76%), and travel time (6.13%). The ARIMA model similarly indicates limited performance gains. The Bi-GRU model shows a moderate degree of improvement across the considered traffic parameters. These results underscore the superior capacity of the Bi-LSTM architecture in mitigating traffic congestion and enhancing overall traffic efficiency, warranting further investigation into its underlying mechanisms and potential for real-world deployment.

Table 5: Improvement in Performance for Different Prediction Models

Model	Waiting Time(%)	Queue Length(%)	Travel Time(%)
ARIMA	37.79	35.72	17.71
LSTM	9.76	14.29	6.13
Bi-LSTM	40.08	43.31	17.90
GRU	9.76	14.29	6.13
Bi-GRU	26.36	15.37	13.82

RQ3: How do predictive traffic models impact environmental sustainability?

CO_2 reduction was estimated using the formula:

$$CO_2 \text{ reduction } (\%) \approx 0.5 \times \text{Travel Time reduction } (\%) + 0.5 \times \text{Waiting Time reduction } (\%) + 0.1 \times \text{Queue Length reduction } (\%)$$

As presented in Table 6, Bi-LSTM (33.32%) and ARIMA (31.32%) achieved the highest CO_2 reductions, followed by Bi-GRU (21.62%). LSTM and GRU had the lowest impact (9.38%). These findings indicate that models with stronger effects on travel and waiting times tend to yield greater environmental benefits, highlighting the need to evaluate both predictive accuracy and sustainability outcomes.

Table 6: Comparison of CO2 Emission Reduction Based on Performance Metrics

Model	ARIMA	Bi-LSTM	LSTM	GRU	Bi-GRU
CO2 Reduction (%)	31.32	33.32	9.38	9.38	21.62

While the Bi-LSTM model exhibits the lowest prediction accuracy among the RNN variants, with an MSE score of 26.12, its superior performance in enhancing traffic flow—demonstrated by the most significant reductions in queue length (43.31%), waiting time (40.08%), and travel time (17.90%) —and its effectiveness in minimizing estimated CO2 emissions (33.32%), firmly establishes it as the most suitable model for optimizing adaptive traffic signal control in this study. The prioritization of real-world traffic improvement and environmental benefits over pure predictive accuracy justifies the selection of Bi-LSTM as the 'best fit' for addressing the challenges of urban traffic congestion.

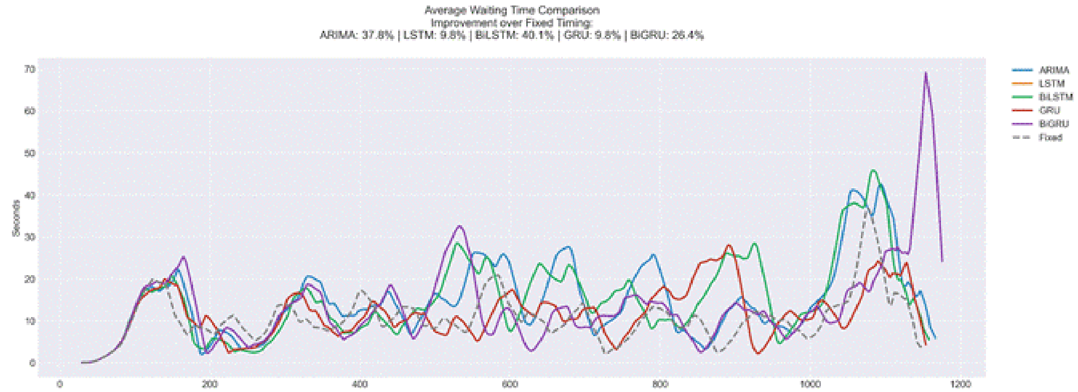

Fig 2: Comparison of Average Waiting Time for Different Forecasting Models Using 30-step Moving Average under Dynamic Signal Control

Fig 2 depicts that BiLSTM achieved the highest improvement of 40.1% over fixed-time signals, outperforming ARIMA (37.8%) and other RNN models. Its stable curve throughout the simulation demonstrates superior adaptability to dynamic traffic patterns and effective reduction in signal delays.

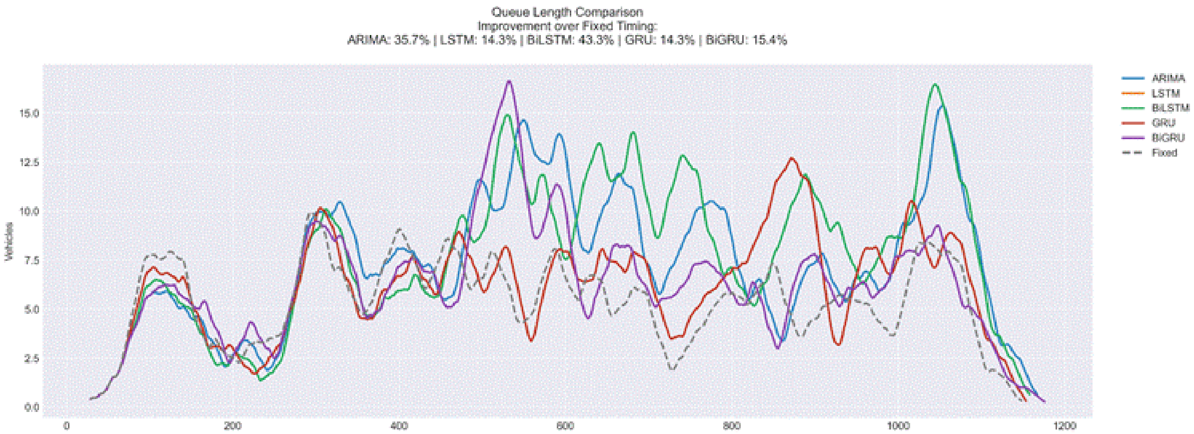

Fig 3: Queue Length Comparison Across Models Using 30-step Moving Average

As shown in Fig 3, Bi-LSTM significantly reduces queue length (43.3%) compared to other models, followed by ARIMA (35.7%) and Bi-GRU (15.4%). LSTM and GRU yield moderate improvements (14.3%). These results align with the CO_2 reduction trends, reinforcing that queue length reductions—factored into the CO_2 formula—play a crucial role in environmental impact

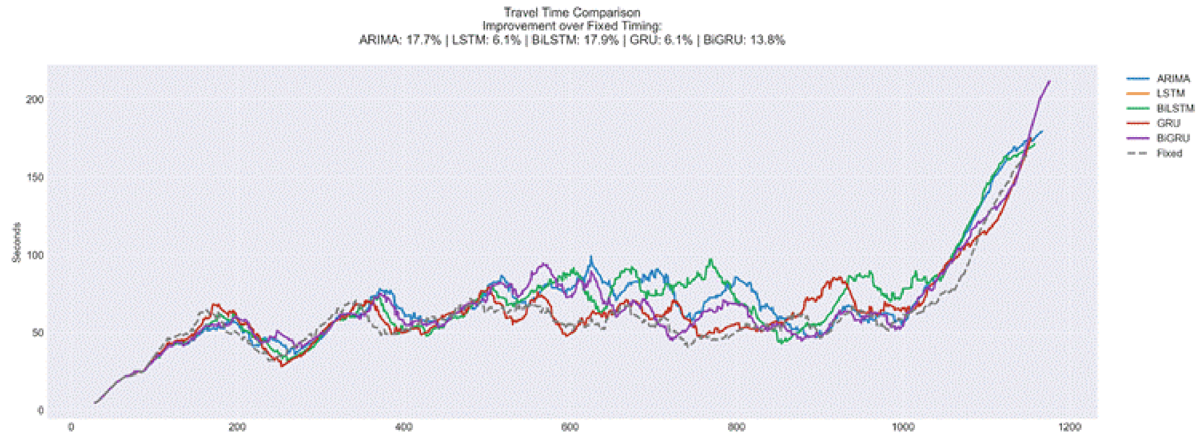

Fig 4: Travel Time Comparison of Models Using 30-step Moving Average Over Simulation Steps

With accordance to Fig 4, BiLSTM led with a 17.9% reduction in travel time, slightly more than ARIMA (17.7%). Its consistent performance indicates improved end-to-end flow and effective optimization of vehicle movement across the network.

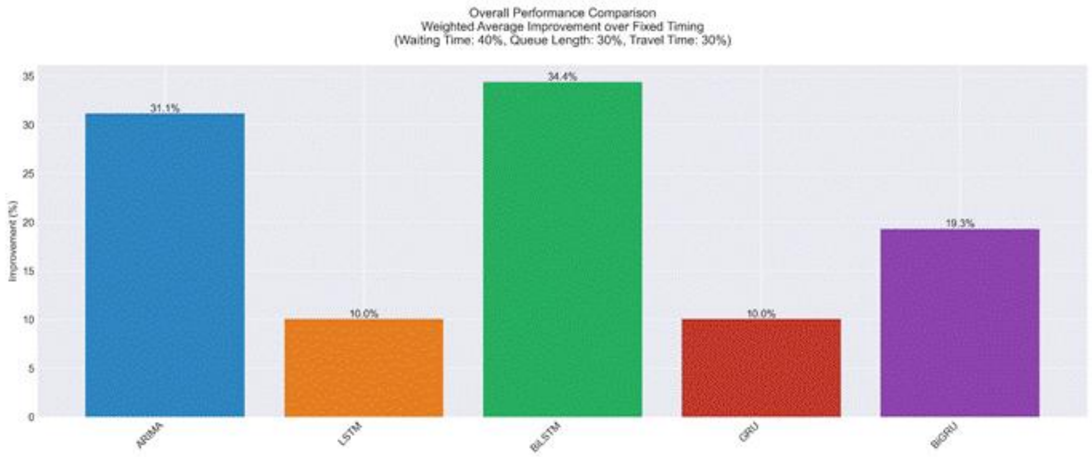

Fig 5: Weighted average performance improvement of models over fixed timing

Fig 5 helps us conclude that with a weighted improvement of 34.4%, BiLSTM demonstrated the best overall performance, driven by its superior results in all three core metrics. This establishes BiLSTM as the most effective model for adaptive traffic signal control.These results underscore the efficacy of the proposed methodology in enhancing traffic flow optimization and predictive accuracy, thereby contributing to the advancement of intelligent and adaptive traffic management frameworks.

LSTM is particularly more compatible for large and complex datasets and Bi-LSTM being a bidirectional extension LSTM, further enhances this capability by handling both past and future dependencies. This allows it to outperform other models in dynamic traffic prediction tasks.

These results underscore the efficacy of the proposed methodology in enhancing traffic flow optimization and predictive accuracy, thereby contributing to the advancement of intelligent and adaptive traffic management frameworks.

Due to hardware limitations, the RNN-models require longer simulation steps for adequate training. However, with sufficient computational resources and effective step intervals, these models can outperform traditional statistical models like ARIMA in terms of predictive power and capturing intricate patterns.

5 Conclusion

This project addresses the most critical issue of modern cities' traffic congestion by deploying an intelligent, smart and adaptive traffic signal control system. Through the integration of simulation tools like SUMO and real-time control via TraCI, a robust framework was created which predicts short-term traffic flow using machine learning models. The system incorporated five forecasting models ARIMA, LSTM, BiLSTM, GRU, and BiGRU to gauge their effectiveness in adjusting signal timings dynamically.

The comparative analysis revealed that adaptive traffic control significantly outperforms traditional fixed-time systems across all key metrics which includes waiting time, queue length, and travel time. ARIMA provided a solid baseline in predicting traffic conditions, while the RNN-based models present higher accuracy in learning complex, time-dependent patterns in traffic flow. These improvements directly contribute to smoother traffic movement, reduced idle times, and enhanced commuter experience. By using this software-based approach without relying on expensive physical infrastructure, the system offers a practical and scalable solution suitable for deployment in developing regions.

The modular design also ensures flexibility for future enhancements, such as emergency vehicle prioritization to detect and prioritize emergency vehicles, ambulances, and public transport using tools like object detection models, RFID sensors, or GPS tracking to ensure timely clearance and supports critical services without manual intervention. Integration with real-world sensor data sourced from sensors, CCTV cameras, loop detectors, or IoT-enabled counters to bridge the gap between simulation and deployment, to enable dynamic adaptation to actual road conditions and make the control system more responsive and practical for real-time use. Extension to multi-intersection coordination using decentralized, centralized, or federated learning approaches. Coordinated signal control across intersections can significantly reduce congestion propagation and improve overall network efficiency. These future enhancements underline the scalability, adaptability, and interdisciplinary potential of the proposed system. By embracing these directions, the model can evolve into a powerful tool for safer, smarter, and more sustainable urban mobility.

In essence, this work provides a meaningful step forward in the evolution of smart traffic management. It proves that with the right combination of data, simulation, and predictive intelligence, urban mobility challenges can be effectively addressed in a resource-efficient and scalable manner.

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