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# LSTM NETWORKS IN TRAFFIC FORECASTING AND OPTIMIZATION: CAPABILITIES, CHALLENGES AND FUTURE PROSPECTS

*Recent advancements in traffic optimization have increasingly relied on Long Short-Term Memory (LSTM) neural networks to enhance real-time traffic flow prediction and management. LSTM-based models outperform traditional methods like AutoRegressive Integrated Moving Average (ARIMA) and Support Vector Machine (SVM), achieving over 90 % accuracy in urban traffic forecasting. These models excel at capturing temporal dependencies and spatial heterogeneity, with hybrid architectures such as GCN-LSTM (Graph Convolutional Network-LSTM) further improving spatial feature extraction in road networks. For instance, GCN-LSTM models have achieved a 95,2 % fitting degree ($R^2$) and reduced prediction errors by 30% compared to standalone models. Innovations like attention mechanisms (e.g., NTAM-LSTM) have also enhanced robustness by dynamically prioritizing critical traffic features such as flow volume and speed, reducing MAE (Mean Absolute Error) to 0,401 in network traffic datasets.*

*Beyond ground transportation, LSTM frameworks have been adapted for air traffic safety, predicting flight conflicts with less than 3 % error by integrating parameters like airspace density and velocity. Applications span dynamic route planning, traffic signal optimization, and congestion control, with LSTM-integrated systems reducing travel delays by up to 25 % during peak hours. However, challenges remain in scalability, data quality, and real-time processing, necessitating future work on edge computing and multi-modal data fusion. By synthesizing spatial-temporal dependencies and adaptive learning, LSTM networks underscore their transformative potential in addressing global transportation challenges.*

*The study highlights LSTM integration with edge computing and multi-modal data for real-time systems. Hybrid models (e.g., GCN-LSTM) reduce urban delays by 25%, outperforming standalone approaches. Future frameworks must adapt to dynamic traffic and external factors (weather, accidents), advancing sustainable, data-driven urban mobility.*

*Keywords: LSTM networks, traffic forecasting, traffic optimization, deep learning, intelligent transportation systems, spatiotemporal modeling*

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# LSTM-МЕРЕЖІ У ПРОГНОЗУВАННІ ТА ОПТИМІЗАЦІЇ ТРАФІКУ: МОЖЛИВОСТІ, ВИКЛИКИ ТА ПЕРСПЕКТИВИ РОЗВИТКУ

*Удосконалення систем оптимізації трафіку все частіше базується на нейронних мережах LSTM, які демонструють високу точність у короткостроковому прогнозуванні дорожнього руху. Завдяки здатності моделювати часові залежності та просторову неоднорідність, ці моделі суттєво перевершують традиційні підходи, такі як ARIMA та SVM. Гібридні архітектури, зокрема GCN-LSTM, а також механізми уваги (наприклад, NTAM-LSTM), підвищують точність та стійкість прогнозів, що особливо важливо для складних міських мереж. LSTM-моделі також знаходять застосування в управлінні авіатрафіком, адаптивному регулюванні світлофорів та динамічному плануванні маршрутів. Основні виклики — масштабованість, якість даних та обробка в реальному часі — потребують подальших досліджень у напрямах гібридного моделювання, edge-computing та інтеграції мультимодальних даних.*

*Ключові слова: LSTM-мережі, прогнозування трафіку, оптимізація трафіку, глибоке навчання, інтелектуальні транспортні системи, просторово-часове моделювання*

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## Introduction

Traffic congestion and inefficiencies in urban transportation systems have become pressing global issues, exacerbated by rapid urbanization and increasing vehicle numbers. Traditional traffic prediction methods, such as Autoregressive Integrated Moving Average (ARIMA) and Support Vector Machines (SVM), have struggled to capture the complex temporal and spatial dependencies inherent in traffic data [1, 2]. In recent years, Long Short-Term Memory (LSTM) neural networks have emerged as a powerful alternative, offering significant improvements in traffic flow prediction and optimization [3].

LSTM networks, a specialized form of Recurrent Neural Networks (RNNs), are uniquely designed to address the vanishing gradient problem, enabling them to retain relevant information over extended time intervals [4]. This capability makes LSTMs particularly well-suited for traffic forecasting, where patterns are often influenced by historical data over long periods [5]. Recent studies have demonstrated that LSTM-based models can achieve over 90% accuracy in predicting short-term traffic patterns, such as traffic speed, occupancy, and congestion levels, outperforming traditional methods like ARIMA and SVM [5].

LSTM models have been combined with advanced techniques like CNNs and GNNs to enhance their predictive capabilities [6]. Hybrid models like GCN-LSTM and CNN-LSTM have shown remarkable success in capturing both spatial and temporal features in traffic data, making them particularly effective in complex urban environments [6]. Additionally, the incorporation of attention mechanisms has allowed these models to dynamically prioritize critical traffic features, further improving prediction accuracy and robustness [7].

This review article aims to provide a comprehensive overview of the latest advancements in LSTM-based traffic optimization, highlighting their methodologies, applications, and challenges. We also explore future research directions, including the integration of edge computing, multi-modal data fusion, and adaptive frameworks, to address the limitations of current systems [8]. By synthesizing insights from key studies, this article underscores the transformative potential of LSTM models in tackling the complex and dynamic nature of urban traffic management.

## LSTM models in traffic prediction: methodologies and advancements

### Overview of LSTM networks

Long Short-Term Memory (LSTM) networks have emerged as powerful tools for traffic flow prediction due to their ability to capture long-range temporal dependencies [4]. A simple example of an LSTM cell is shown on Figure 1. Unlike traditional Recurrent Neural Networks (RNNs), LSTMs are designed to address the vanishing gradient problem, allowing them to retain relevant information over extended periods [4]. This capability is particularly beneficial for traffic forecasting, where patterns are often influenced by historical data over long time intervals.

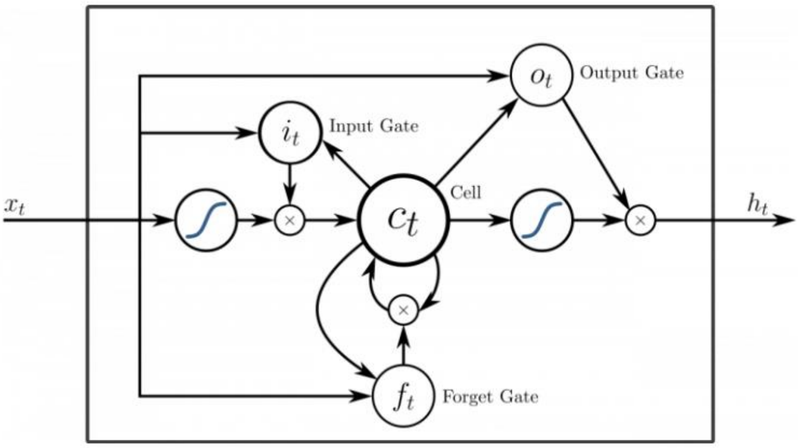


**Figure 1: Structure of LSTM cell**

Recent studies have demonstrated the efficacy of LSTMs in predicting short-term traffic patterns, such as traffic speed, occupancy, and congestion levels. For example, Abduljabbar in [1] showed that LSTM models trained on historical traffic data could achieve over 90% accuracy in forecasting real-time traffic flow in urban environments. This level of accuracy represents a significant improvement over traditional methods like ARIMA and SVM, which struggle to capture the complex temporal dependencies inherent in traffic data.

**Comparison of traditional and LSTM-based methods**

Table 1 below highlights the key differences between traditional methods and LSTM-based approaches in traffic forecasting:

Table 1

**Comparison of Traditional Methods and LSTM-based Methods in Traffic Forecasting**

| Method | Accuracy | Scalability | Data Requirements | Temporal Dependency Modeling | Spatial Dependency Modeling |
|---|---|---|---|---|---|
| ARIMA | Moderate | Low | Low | Limited | Limited |
| SVM | High | Medium | Medium | Limited | Moderate |
| LSTM-based methods | Very High | High | High | Strong | Strong |

### Hybrid models and advanced techniques

Further advancements have been made through the integration of Bidirectional LSTM (BiLSTM) networks, which process data in both forward and backward directions [6]. This bidirectional approach helps capture additional temporal dependencies, improving the model's performance in predicting traffic patterns in both the immediate and distant future. Additionally, hybrid models combining LSTM with Convolutional Neural Networks (CNNs) have been proposed to capture both spatial and temporal features in traffic data. These models have shown promise in improving the accuracy and robustness of traffic forecasting, particularly in complex urban environments where spatial heterogeneity is a major concern.

### Graph Neural Networks (GNNs) and attention mechanisms

Recent research has explored the integration of Graph Neural Networks (GNNs) with LSTM models to better capture spatial dependencies in traffic networks. For instance, Wu in [6] proposed a GCN-LSTM model that combines Graph Convolutional Networks (GCNs) with LSTM to extract both spatial and temporal features from traffic data. This hybrid model outperformed traditional CNN-LSTM models, achieving a 95.2% fitting degree ($R^2$) and reducing the Mean Absolute Error (MAE) to 5.679, showcasing its superior ability to handle irregular data structures in road networks.

Moreover, the integration of attention mechanisms with LSTM networks has significantly improved prediction accuracy by focusing on the most relevant features of the input data. Zhao and He [7] introduced the NTAM-LSTM model, which uses an attention mechanism to assign different weights to various traffic characteristics, such as packet length and flow bytes. This approach reduced prediction errors, with MAE dropping to 0.401 and RMSE to 0.637, outperforming traditional LSTM, GRU, and TCN models.

These advancements highlight the potential of combining LSTM with other deep learning techniques, such as GNNs and attention mechanisms, to further enhance traffic prediction models [6, 7]. By capturing both spatial and temporal dependencies, these hybrid models offer a more comprehensive understanding of traffic patterns, especially in dynamic and complex urban environments [6].

## Applications of LSTM models in traffic optimization

### Dynamic route planning

The adoption of LSTM-based models in intelligent traffic systems has significantly expanded the range of possibilities for optimizing urban traffic management, offering more precise and efficient solutions [8]. In general, the use of the LSTM-model for traffic optimization can be illustrated as in Figure 2. A key application of LSTMs is dynamic route planning, where traffic prediction models provide real-time updates on traffic flow, congestion levels, and disruptions. By integrating LSTM-based predictions into advanced routing algorithms, such as the A* search algorithm, it becomes possible to recommend highly optimized routes for vehicles. This capability not only helps reduce congestion but also minimizes travel times, offering a smoother driving experience for commuters.

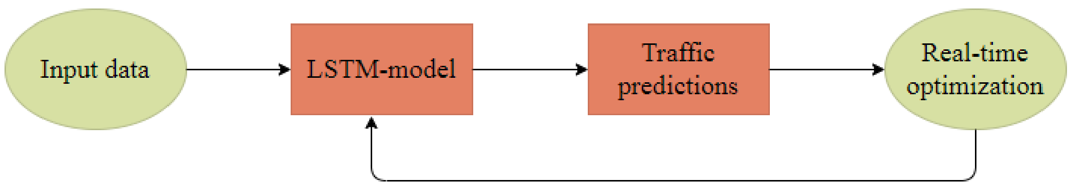


**Figure 2: Conceptual diagram of usage LSTM-model for traffic optimization**

### Air traffic management

In air traffic management, LSTM models have proven equally valuable by predicting flight conflicts and optimizing airspace usage. Lyu in [8] introduced an LSTM-based model that accurately forecasts flight conflicts in en-route airspace, with a mean error of less than 3%. This model incorporates traffic parameters, including volume, density, and velocity, with volume being identified as the most crucial factor contributing to improved prediction accuracy. The success of this application emphasizes how LSTM models can enhance the safety, reliability, and efficiency of air traffic management, especially in high-density airspace where precise predictions are vital to prevent collisions [9].

### Adaptive traffic signal control

LSTM models have also demonstrated substantial improvements when integrated with adaptive traffic signal control systems [10]. By forecasting traffic volumes at key intersections, these models enable real-time adjustments to traffic signal timings. Studies in urban areas have shown that the implementation of such LSTM-based systems led to a 25% reduction in travel delays during peak traffic hours. The ability of LSTM models to recognize complex temporal dependencies, coupled with their adaptability to fluctuating traffic patterns, makes them highly effective in dynamic traffic signal optimization, contributing to smoother and more efficient traffic flow.

In summary, LSTM-based models are transforming both urban and air traffic management, providing data-driven insights that help mitigate congestion, enhance safety, and improve overall traffic efficiency [8, 9, 10]. Their ability to forecast, adapt, and optimize in real-time ensures that these systems can handle complex, evolving transportation environments with ease.

**Challenges and limitations of LSTM models in traffic optimization**

**Scalability issues**

Despite the promising outcomes and advancements of LSTM models in traffic optimization, several persistent challenges hinder their broader application and full integration into real-time traffic management systems [11]. One primary challenge is the scalability of these systems. In large urban environments, traffic management systems handle massive volumes of data collected from an array of sources, such as sensors, GPS devices, and video feeds. The complexity of processing this vast amount of data in real-time puts immense strain on computational resources. Ensuring that these systems can generate accurate predictions promptly is a significant hurdle, as even with advanced technologies, the computational power required to handle such volumes of information may not always be sufficient.

**Data quality and availability**

Another considerable challenge lies in the quality and availability of traffic data. Traffic data, often collected from various heterogeneous sources, can be noisy, incomplete, or influenced by biases. This introduces difficulties for LSTM models in generalizing their predictions across diverse environments and traffic conditions [12]. The accuracy of these predictions is highly contingent on the integrity and quality of the input data. Poor-quality data can result in inaccurate traffic forecasts, leading to suboptimal decision-making and, in turn, less effective traffic management strategies.

**External factors**

Furthermore, external factors such as unpredictable weather conditions, road incidents, accidents, or public events can have a profound effect on traffic flow. The integration of these external variables into LSTM models remains a significant research challenge [13]. While these factors can substantially influence traffic patterns, their inherent unpredictability, along with a lack of comprehensive data, makes their incorporation into the models highly complex.

**Training data and model maintenance**

Additionally, LSTM models require extensive amounts of training data to develop reliable predictive capabilities. The need for large, high-quality datasets with accurate, labeled traffic information can raise concerns about data privacy, as well as the significant costs associated with acquiring and maintaining such datasets [14]. Moreover, traffic patterns are inherently dynamic, and as these patterns evolve over time, continuous updates and periodic retraining of the models are necessary to ensure their continued effectiveness. This introduces further complexity and resource demands, making it critical to develop adaptive models that can learn from new data without requiring an entirely new training phase.

Table 2 summarizes key challenges in LSTM-based traffic optimization — such as scalability, data quality, external factors, and real-time processing — and proposes solutions like hybrid models, enhanced data preprocessing, multi-modal data integration, and edge computing to address these limitations.

Table 2

**Challenges and Solutions in LSTM-based Traffic Optimization**

| **Challenge** | **Description** | **Proposed Solution** |
|---|---|---|
| Scalability | Handling large volumes of real-time traffic data from multiple sources. | Using hybrid models with more efficient data processing methods. |
| Data Quality | Dealing with noisy, incomplete, or biased data that affects model accuracy. | Improving data preprocessing and data collection techniques. |
| External Factors Integration | Integrating factors like weather, road incidents, and public events into models. | Integrating additional data sources and using multi-modal data. |
| Real-Time Processing | Processing large datasets in real-time for immediate decision-making. | Leveraging edge computing to process data closer to the source. |

**Future Directions and Innovations**

**Hybrid models**

To tackle the challenges faced in LSTM-based traffic optimization, several innovative research directions are emerging [15]. One promising approach involves the development of hybrid models that combine LSTMs with other advanced machine learning techniques, such as reinforcement learning or graph neural networks (GNNs). These hybrid models aim to enhance the scalability and robustness of traffic optimization systems, enabling them to handle the complexity of large-scale data more effectively. For instance, the GCN-

LSTM model proposed by Wu in [6] combines the strengths of both Graph Convolutional Networks (GCNs) and LSTMs to capture both spatial and temporal dependencies in traffic data. This approach has demonstrated improved prediction accuracy in traffic flow forecasts by leveraging GCNs' ability to model the spatial relationships between traffic nodes, while LSTMs capture the temporal dynamics of traffic patterns.

**Edge computing**

Additionally, edge computing presents a viable solution for addressing the challenge of real-time data processing. By offloading computational tasks to edge devices, traffic data can be processed closer to its source, significantly reducing latency and improving the responsiveness of traffic systems. This is particularly beneficial for applications like adaptive traffic signal control, where rapid decision-making is crucial to optimize traffic flow in real-time [15]. Edge computing enables immediate adjustments to traffic light timings based on up-to-date traffic data, thus enhancing the overall efficiency of traffic management.

**Multi-modal data integration**

Moreover, the integration of multi-modal data has the potential to significantly improve the accuracy and effectiveness of LSTM models. Incorporating data from diverse sources, such as vehicle-to-everything (V2X) communication, environmental sensors, and even social media feeds, can provide a more comprehensive understanding of the urban traffic environment. V2X communication, for example, allows for real-time information exchange between vehicles and infrastructure, while environmental data (such as weather or road conditions) can provide crucial context for predicting traffic behavior. Social media data, on the other hand, can offer insights into unexpected events or incidents that may impact traffic. The fusion of these diverse data sources enables LSTM models to generate more accurate predictions and develop better optimization strategies that account for a wide range of influencing factors.

**Adaptive frameworks**

Finally, the creation of adaptive frameworks capable of managing complex, dynamic urban traffic environments is essential for the success of LSTM-based traffic optimization systems. These frameworks must be flexible enough to integrate multiple data sources, adapt to the evolving nature of traffic patterns, and make real-time decisions that optimize the overall flow of traffic. The development of such adaptive systems will enable traffic management to respond proactively to disruptions, reducing congestion and improving the efficiency of transportation networks across cities.

By leveraging these advancements in hybrid modeling, edge computing, and multi-modal data integration, LSTM-based traffic optimization systems are poised to play a crucial role in shaping the future of urban transportation.

## Conclusions

This article has provided a comprehensive review of the latest advancements and practical applications of Long Short-Term Memory (LSTM) networks in the field of traffic optimization systems. LSTM models have demonstrated remarkable capabilities in capturing both temporal dependencies and spatial heterogeneity, making them more effective alternatives to traditional forecasting methods such as ARIMA and Support Vector Machines (SVM) [1], [2]. The review has highlighted several key areas where LSTM models have made a significant impact, including real-time route planning, adaptive traffic signal control, and predictive congestion management. These applications have been pivotal in enhancing urban mobility, reducing traffic congestion, and minimizing travel delays, all of which contribute to more efficient transportation networks [8], [9], [10].

Despite their success, several challenges remain in deploying LSTM models in real-world traffic optimization scenarios. Issues such as the scalability of systems to handle vast amounts of real-time data, the quality and availability of traffic data, and the integration of external factors like weather conditions, road incidents, and special events have been explored in depth [11], [12], [13]. To address these challenges, potential solutions have been proposed, including the development of hybrid models that combine LSTMs with other advanced machine learning techniques, the adoption of edge computing to reduce data processing latency, and the integration of multi-modal data sources such as V2X communication, environmental data, and social media feeds. These solutions aim to enhance the accuracy, scalability, and adaptability of traffic optimization systems.

Looking ahead, the future of LSTM-based traffic optimization lies in the development of adaptive frameworks capable of integrating diverse data sources and making real-time decisions to optimize traffic flow across large-scale transportation networks. By leveraging advancements in hybrid modeling, edge computing, and multi-modal data integration, LSTM models have the potential to significantly improve the efficiency and sustainability of urban transportation systems worldwide. Continued innovation in intelligent traffic optimization will be essential to address the growing complexities of urban mobility and to create smarter, more resilient cities.

## References

1. Abduljabbar, R.L., Dia, H. & Tsai, PW. (2021). Development and evaluation of bidirectional LSTM freeway traffic forecasting models using simulation data. *Sci Rep* 11, 23899. https://doi.org/10.1038/s41598-021-03282-z

2. Льовкін, В. М. (2023). Моделі прогнозування автомобільного трафіку на основі LSTM при розробці прикладних програм. *Технічна інженерія*, (2(92), 152–157. https://doi.org/10.26642/ten-2023-2(92)-152-157

3. Льовкін, В. (2024). Особливості програмування алгоритмів і структур даних при прогнозуванні автомобільного трафіку. *Herald of Khmelnytskyi National University. Technical Sciences*, *331*(1), 252-258. https://doi.org/10.31891/2307-5732-2024-331-38

4. Mihaita, Adriana-Simona & Li, Haowen & Rizoiu, Marian-Andrei. (2020). Traffic congestion anomaly detection and prediction using deep learning. 10.48550/arXiv.2006.13215.

5. Dong, Z., Zhou, Y., & Bao, X. (2024). A Short-Term Vessel Traffic Flow Prediction Based on a DBO-LSTM Model. *Sustainability*, *16*(13), 5499. https://doi.org/10.3390/su16135499

6. Wu, Zhizhu & Huang, Mingxia & Zhao, Aiping & lan, Zhixun. (2021). Traffic prediction based on GCN-LSTM model. Journal of Physics: Conference Series. 1972. 012107. 10.1088/1742-6596/1972/1/012107.

7. NTAM-LSTM models of network traffic prediction. Jihong Zhao and Xiaoyuan He. MATEC Web Conf., 355 (2022) 02007. DOI: https://doi.org/10.1051/matecconf/202235502007

8. Lyu, W., Zhang, H., Wan, J., & Yang, L. (2021). Research on Safety Prediction of Sector Traffic Operation Based on a Long Short Term Memory Model. *Applied Sciences*, *11*(11), 5141. https://doi.org/10.3390/app11115141

9. Mahajan, D., Pottigar, V. V., Suresh, C., & Fahad, A. (2025). C, Suresh & Pottigar, Vinayak & Mahajan, Divya. (2024). Implementing Real-Time Traffic Flow Prediction Using LSTM Networks for Urban Mobility Optimization. Communications on Applied Nonlinear Analysis. 32. 01-27. 10.52783/cana.v32.1705.

10. Poonia, Pregya & Jain, V.. (2020). Short-Term Traffic Flow Prediction: Using LSTM. 1-4. 10.1109/ICONC345789.2020.9117329.

11. Katambire, V. N., Musabe, R., Uwitonze, A., & Mukanyiligira, D. (2023). Forecasting the Traffic Flow by Using ARIMA and LSTM Models: Case of Muhima Junction. *Forecasting*, *5*(4), 616-628. https://doi.org/10.3390/forecast5040034

12. Lovkin, V. M., Subbotin, S. A., & Oliinyk, A. O. (2024). Method for agent-oriented traffic prediction under data and resource constraints. *Radio Electronics, Computer Science, Control*, (4), 99. https://doi.org/10.15588/1607-3274-2023-4-10

13. Zhao Z., Chen W., Wu X., Chen P. C. Y., and Liu J., LSTM network: a deep learning approach for short-term traffic forecast, *IET Intelligent Transport Systems*. (2017) 11, no. 2, 68–75, https://doi.org/10.1049/iet-its.2016.0208, 2-s2.0-85015163282.

14. Elmorshedy, R. M. E. M. (2019). Traffic Management in Residential Areas: Case Study the South District of Luxor City, Egypt. *ARCHive-SR*, *3*(2), 212–231. https://doi.org/10.21625/archive.v3i2.513

15. Fu, Rui & Zhang, Zuo & Li, Li. (2016). Using LSTM and GRU neural network methods for traffic flow prediction. 324-328. 10.1109/YAC.2016.7804912.