

AI-Based Approach for Efficient Urban Bus Transit Timetable Scheduling

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Abstract: *Urban bus systems are essential for public transport, especially in fast-growing cities. However, traditional timetable scheduling often struggles to handle real-world conditions such as traffic congestion and changing passenger demand. This leads to delays and inefficient service. Recent work has explored the use of Artificial Intelligence (AI), Machine Learning (ML), and data-driven methods to improve scheduling. Techniques like Long Short-Term Memory (LSTM) models help predict bus arrival times, while reinforcement learning and optimization methods support better scheduling decisions. Real-time data analysis also allows systems to adjust based on current conditions. This paper reviews recent developments in AI-based bus scheduling systems and compares different approaches in terms of accuracy, efficiency, and real-time performance. The findings show that these systems can reduce waiting times and improve reliability. At the same time, challenges such as system complexity, data integration, and infrastructure requirements still need attention. Future work should focus on making these systems easier to deploy and scale in real-world environments.*

Keywords: Artificial Intelligence, Smart Transportation Systems, Urban Bus Transit, LSTM Prediction Models, Reinforcement Learning, Dynamic Scheduling, Real-Time Traffic Analysis, Optimization Algorithms, Intelligent Mobility, Smart Cities

I. INTRODUCTION

Urban transportation systems are under increasing pressure as cities grow and populations rise. Public buses remain one of the most affordable and widely used transport options, but their performance often depends on how well schedules are managed.

Traditional scheduling methods are mostly fixed and do not adjust to changing conditions like traffic, road disruptions, or varying passenger demand. This results in delays, longer waiting times, and inconsistent service quality.

Advances in AI and machine learning offer new ways to address these issues. These technologies can analyze both historical and real-time data to predict traffic patterns, estimate arrival times, and improve scheduling decisions. Models such as LSTM are commonly used for time-based predictions, while reinforcement learning supports decision-making in uncertain conditions.

In addition, IoT devices and real-time data systems make it possible to monitor transport networks continuously. This allows scheduling systems to respond more effectively to current conditions. This paper focuses on how these AI-based approaches can improve urban bus scheduling and overall system performance.



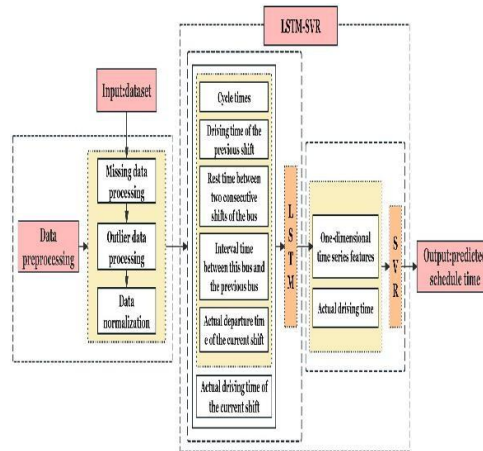


Figure 1: LSTM Model for Bus Arrival Time Prediction [9]

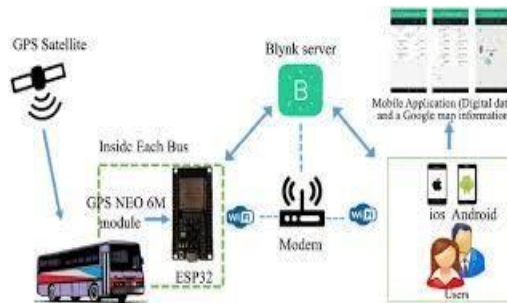


Figure 2: Architecture of AI-Based Bus Transit System [4]

How Is IoT Transforming The Traditional School Bus Tracking System



Figure 3: Real-Time Bus Tracking and Scheduling System using IoT [7]

II. LITERATURE SURVEY

Recent research shows a clear move toward using AI and data-driven methods in bus scheduling systems. With better data availability and improved computing power, more adaptive and efficient solutions are being developed. Some studies focus on automated scheduling systems that use predictive models to reduce delays and improve efficiency. While these systems perform well under stable conditions, they may struggle to adapt quickly when traffic or demand changes.



Other approaches integrate real-time tracking and ticketing using GPS and mobile applications. These systems improve transparency and user experience but depend heavily on reliable infrastructure and connectivity.

Edge-based AI models have also been introduced to process data closer to the source. This reduces delays and allows faster predictions, though limited hardware capacity can restrict scalability.

LSTM-based models are widely used for predicting bus arrival times because they can capture patterns in time-series data. They generally offer high accuracy but require large datasets and significant computing resources.

Reinforcement learning methods focus on improving scheduling decisions by learning from changing conditions. These approaches adapt well to dynamic environments but involve complex training and tuning.

Optimization techniques such as Dijkstra's algorithm and genetic algorithms are used for route planning and scheduling. While effective, they can be difficult to apply in real-time systems due to their computational demands.

IoT-based systems provide continuous data through sensors and GPS devices, helping improve decision-making. However, they require investment in infrastructure and proper data management.

Some recent work combines multiple techniques, such as integrating LSTM with reinforcement learning or using IoT data with optimization models. These hybrid approaches tend to perform better but increase system complexity.

Overall, these studies show that AI-based methods improve efficiency, reduce waiting time, and enhance passenger experience. However, issues such as cost, scalability, and system complexity still limit large-scale implementation.

Sr. No.	Author & Year	Title	Journal / Conference	Advantages	Disadvantages
1	Maurya et al., 2025	Automated Bus Scheduling and Route Management	IEEE ICCCBEA	Improves scheduling automation	Limited real-time adaptability
2	Rithik et al., 2025	AI-Based Bus Tracking & QR Ticketing	IEEE ICICIS	Enhances transparency	Infrastructure dependency
3	Ahsya et al., 2025	Edge-AI Bus Arrival Prediction	IEEE ICITCOM	Real-time prediction	Edge limitations
4	Kumar et al., 2025	Bus Arrival Time Prediction Review	IEEE TITS	Comprehensive analysis	No practical implementation
5	Anu et al., 2025	ML & Conversational AI for Transport	IEEE I2ITCON	Accurate prediction, chatbot integration	Uses static dataset
6	Shen et al., 2026	Bi-objective Bus Timetable Optimization	IET ITS	Handles disruptions effectively	High computational complexity
7	Li et al., 2026	LLM-Based Bus Scheduling	TRC Journal	Intelligent decision-making	High computational cost
8	Sun et al., 2026	AI Scheduling Overview	IEEE Magazine	Broad coverage of methods	Lack of practical validation
9	Munawar et al., 2026	AI & Fuzzy Logic Transport	CRC Press	Handles uncertainty well	Complexity in tuning
10	Li et al., 2026	Multi-Agent RL Route Optimization	IEEE TITS	Adaptive and dynamic routing	Training complexity
11	Deligiannis et al., 2026	Multimodal Transport AI	Logistics Journal	Multi-objective optimization	Implementation difficulty
12	Junejo et al., 2026	Agentic AI Optimization	VFAST Journal	Efficient optimization	Limited domain applicability
13	Yan et al., 2026	Electric Bus Scheduling (DRL)	Inventions	Energy-efficient planning	Requires large datasets
14	Lopes et al.,	AI Agents Architecture	arXiv	Scalable architecture	Not transport-



	2026				specific
15	EyeBus (2025)	Bus Detection via Computer Vision	IEEE ICCTDC	Real-time detection, accessibility	Sensitive to lighting conditions
16	Shen, W., et al. (2025)	Modular Scheduling Optimization of Intelligent Connected Buses	Sustainability Journal	Handles dynamic demand, improves passenger flow	Complex implementation, requires large datasets
17	Najafi, A., et al. (2025)	Integrated Optimization of Charging Infrastructure and Electric Bus Scheduling	Transportation Research Part D	Joint optimization, energy-efficient	Infrastructure dependency, high complexity
18	Rahman, M. H., et al. (2025)	Enhancing Underutilized Bus Routes with Semiflexible Routing	Transportation Science	Improves route utilization, flexible scheduling	Requires accurate demand prediction
19	Yu, C., et al. (2025)	Integrated Framework for Optimized Cross-Line Transit Scheduling	IEEE ITSC 2025	Reduces waiting time, improves coordination	Difficult real-time implementation
20	Guan, S., et al. (2025)	Robust Bus Schedule Adherence Using Stochastic Optimization	IEEE ITSC 2025	Handles uncertainty, improves punctuality	Requires probabilistic expertise

III. FUTURE SCOPE

Future research should focus on making AI-based bus scheduling systems more practical for real-world use. One important area is improving how real-time data is collected and used. Data from GPS, IoT devices, and traffic systems can help create more accurate predictions and allow schedules to adjust based on current conditions.

More advanced AI methods, including deep reinforcement learning and multi-agent systems, could improve decision-making in complex situations. Technologies like edge computing can reduce delays by processing data locally, while digital twin models may help simulate and test transport systems before deployment.

There is also room to improve the passenger experience through features like smart ticketing, demand prediction, and better communication through mobile applications.

At the same time, challenges such as high costs and system complexity need to be addressed. Future systems should aim to balance performance with simplicity, making them easier to deploy and maintain at scale.

IV. CONCLUSION

This paper reviewed recent approaches to improving urban bus timetable scheduling using AI-based methods. Techniques such as machine learning, reinforcement learning, and optimization algorithms have shown clear benefits in improving scheduling accuracy and reducing delays.

These systems can make public transport more reliable and efficient, leading to better passenger satisfaction. However, practical challenges such as high implementation costs, complex system design, and large data requirements still limit their widespread use.

With continued improvements in technology and system design, AI-based scheduling has strong potential to support more efficient and sustainable urban transportation in the future.

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