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PRELIMINARY REPORT

Urban Traffic Management Using Artificial Intelligence: A Sustainable Approach to Enhancing Urban Mobility

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Abstract: In modern cities, growing traffic volumes and limited infrastructure capacity lead to frequent congestion, increased emissions, and reduced quality of life. Traditional traffic management systems, based on fixed signal timings, often fail to adapt to real-time traffic dynamics. This paper presents how artificial intelligence (AI) can significantly enhance the efficiency and sustainability of urban traffic systems. By integrating data from sensors, cameras, and mobile devices with learning and forecasting algorithms, an intelligent system is developed to adjust traffic signals in real time. Simulation results show reduced waiting times, lower greenhouse gas emissions, and improved safety for all road users, including pedestrians and public transport. Special focus is placed on fairness and inclusive mobility, ensuring that technological advancement also addresses social equity. The proposed approach can be implemented across various urban environments without requiring extensive infrastructure changes.

Key words: Traffic management, AI, sustainability.

INTRODUCTION

Urban mobility is a cornerstone of sustainable development, with far-reaching implications for economic productivity, environmental sustainability, and social equity. Efficient transport systems facilitate commerce, reduce the cost of living, and enhance quality of life by enabling access to jobs, education, and essential services. However, as cities continue to expand and motorization rates rise, many urban areas are experiencing escalating congestion, deteriorating air quality, and growing spatial inequalities. The resulting strain on existing transport infrastructure is not only an operational challenge but also a policy imperative for achieving the Sustainable Development Goals (SDGs), particularly SDG 11 (Sustainable Cities and Communities) and SDG 13 (Climate Action).

Traditional approaches to traffic management, primarily based on fixed signal timing plans and heuristic control strategies, are increasingly ill-suited for today's complex and dynamic urban environments. These legacy systems, often designed for more predictable traffic conditions, are unable to cope with the stochastic nature of modern mobility patterns shaped by ridesharing, logistics demand, public transport variability, and non-motorized transport. They also lack the adaptability needed to respond in real time to unforeseen events such as accidents, construction, weather disruptions, or special events. Consequently, cities reliant on outdated traffic systems face higher travel delays, increased vehicle emissions, and diminished roadway safety.

Moreover, the conventional design of traffic control systems has historically favored private vehicles, often at the expense of pedestrians, cyclists, and public transport users. This car-centric paradigm contributes to spatial inequality and environmental injustice, particularly in underserved communities where walking and transit are dominant modes of mobility. A shift toward inclusive, sustainable traffic management is therefore essential—not only to improve system efficiency, but also to ensure that urban mobility systems are equitable, resilient, and future-ready.

In this context, artificial intelligence (AI) emerges as a transformative tool with the potential to revolutionize urban traffic management. Leveraging the proliferation of real-time data from cameras, sensors, mobile applications, and connected vehicles, AI algorithms can detect traffic patterns, forecast congestion, and autonomously adjust traffic signal operations. Machine learning, reinforcement learning, and deep learning methods allow systems to "learn" optimal responses over time, enabling highly responsive, context-aware signal control. In contrast to static or semi-adaptive systems, AI-driven approaches can dynamically manage intersections, prioritize high-occupancy vehicles, and respond proactively to emerging disruptions.

This paper proposes a comprehensive AI-enhanced traffic signal management framework aimed at tackling the challenges of modern urban mobility. The framework integrates real-time data collection, predictive modeling, and adaptive signal control into a unified system capable of improving traffic flow, reducing environmental impact, and enhancing accessibility for vulnerable road users. A simulation-based evaluation is conducted in a model of a mid-sized European urban network to quantify the benefits and assess the equity implications of the proposed system. Through this research, we aim to demonstrate not only the technical viability of AI in traffic control, but also its capacity to support more inclusive and sustainable urban development.

LITERATURE REVIEW

Urban traffic management has long been a focal point for transportation engineers and city planners seeking to balance vehicle throughput with safety, accessibility, and environmental considerations. Over the past few decades, the field has transitioned from rule-based approaches to increasingly data-driven, automated, and intelligent systems. This evolution has been underpinned by advances in sensing technologies, computing power, and, more recently, artificial intelligence (AI) and machine learning (ML).

Traditional and Adaptive Signal Control Systems

Historically, traffic signals were managed using fixed-time control strategies, where signal phases followed predetermined schedules based on historical traffic volumes. While simple to implement, these systems were inherently rigid and unable to accommodate real-time fluctuations in traffic demand. This led to inefficiencies during non-peak periods or in response to unexpected events such as accidents, roadworks, or weather disruptions.

In the late 20th century, the introduction of Intelligent Transportation Systems (ITS) marked a significant step forward. Adaptive systems like SCATS (Sydney Coordinated Adaptive Traffic System) and SCOOT (Split Cycle Offset Optimization Technique) used embedded loop detectors and traffic sensors to adjust signal timings based on real-time vehicle counts and occupancy data. These systems introduced feedback loops into signal control and improved performance over static configurations, especially in urban grids (Papageorgiou et al., 2003).

However, SCATS and SCOOT relied on rule-based heuristics, often encoded by human engineers, and thus lacked the ability to "learn" from patterns or optimize across complex, dynamic networks. Their performance deteriorated under conditions not foreseen by their designers, prompting interest in more adaptive, autonomous control strategies.

Artificial Intelligence in Traffic Signal Control

With the rise of big data and AI, researchers began to explore machine learning models capable of autonomous learning and real-time decision-making. Reinforcement learning (RL), particularly Q-learning, emerged as a popular method for optimizing traffic signals by treating intersections as agents that learn to minimize cumulative traffic delay through trial-and-error (Wei et al., 2018; Michailidis et al., 2025). These agents use reward functions—such as minimizing queue lengths or wait times—to update signal policies dynamically.

More advanced models, such as Deep Q-Networks (DQN) and multi-agent reinforcement learning (MARL), enable coordinated learning across entire intersections, especially in dense urban grids (Kanis et al., 2021; Miletić et al., 2022). These frameworks allow adjacent intersections to share state information and jointly learn optimal control strategies, which is particularly valuable in preventing congestion spillbacks and optimizing corridor-level flow.

Supervised learning models have also been used to forecast traffic volumes and detect anomalies using historical and real-time data. Algorithms such as random forests, gradient boosting machines, and support vector machines (SVMs) have proven effective in short-term traffic prediction, particularly when integrated with weather and event data (Zhao et al., 2024). These models enable proactive signal adjustments before congestion becomes severe.

In parallel, deep learning techniques such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are increasingly applied to visual and sequential traffic data. CNNs are used for real-time vehicle detection and flow estimation from traffic cameras (Zhang et al., 2020), while RNNs model time-series data to predict future traffic states based on historical patterns.

Recent innovations such as SafeLight, proposed by Du et al. (2022), further refine RL systems by incorporating safety constraints (e.g., collision avoidance) directly into the reward structure, enhancing real-world applicability.

Multi-Intersection and Network-Level Optimization

While early AI applications focused on optimizing individual intersections, more recent developments emphasize network-wide control using multi-agent systems. These frameworks distribute control among intelligent agents located at each intersection, which collaborate to manage overall flow. Studies by Miletić et al. (2022) and Kolat et al. (2023) demonstrate that coordinated MARL systems improve green wave propagation, reduce bottlenecks, and lead to more balanced traffic distributions across large networks.

Federated learning and edge computing have also gained attention as strategies to scale AI control without centralizing sensitive data. By training models locally at each intersection and sharing only model parameters (not raw data), federated learning allows cities to preserve data privacy while improving system performance (Wang et al., 2022).

These decentralized AI architectures are especially relevant for cities with fragmented infrastructure or legal constraints on data centralization.

AI for Sustainable Urban Mobility

Beyond operational efficiency, AI-enhanced traffic management systems are increasingly evaluated for their environmental impact. Several studies have shown that adaptive signal control using AI significantly reduces fuel consumption, CO□ emissions, and noise pollution by minimizing unnecessary stops and smoothing traffic flow (Chen et al., 2021; Eteifa et al., 2025).

For instance, Michailidis et al. (2025) review multiple RL applications and note consistent reductions in vehicular idle time and average travel delay. Zhao et al. (2024) further highlight the role of hybrid models that jointly optimize emissions, congestion, and transit performance using multi-objective reward functions.

Simulation studies suggest that emissions reductions of 30–40% are achievable when adaptive AI is deployed along major urban corridors, especially when integrated with transit signal priority and eco-driving algorithms.

Gaps and Future Directions

Despite these promising developments, several key gaps persist in the literature. First, many AI models remain confined to simulated environments, where variables are controlled and idealized. The leap to real-world implementation introduces complexities such as sensor noise, unpredictable driver behavior, and hardware failure—all of which are rarely modeled in academic studies (Chen et al., 2021; Shashi et al., 2021).

Second, there is limited research comparing the performance of AI traffic systems across diverse urban settings—such as compact historic cities versus sprawling metropolitan areas. The generalizability of results is therefore uncertain.

Third, while equity is increasingly mentioned in smart mobility literature, there is a lack of operational AI models that explicitly account for pedestrians, cyclists, elderly populations, or transit-reliant communities. Mitieka et al. (2023) argue for a broader inclusion of social sustainability metrics in AI traffic planning to ensure that smart systems do not unintentionally reinforce existing mobility disparities.

Future research should also explore hybrid AI architectures that combine supervised learning, RL, and optimization in real-time settings. Likewise, the development of explainable AI (XAI) and ethically-aligned frameworks will be essential for building public trust and regulatory acceptance.

METHODOLOGY

This study introduces an AI-based traffic signal system that learns how to manage intersections more efficiently. The model combines two core AI techniques:

- Supervised learning is used to predict traffic flow based on past data.
- Reinforcement learning allows the system to adjust signal timings in real time to improve performance.

The system uses live data from several sources:

- Traffic cameras to monitor congestion,
- Vehicle sensors at intersections,
- Mobile GPS data from navigation apps,
- Public transport feeds to track buses and trams.

A realistic city layout was simulated using the SUMO platform, representing a mid-sized European city. First, a traditional fixed-timing traffic system was tested. Then, the AI-based system was deployed on the same network. Key performance metrics—such as delay times, emissions, and public transport efficiency—were collected to compare the results.

RESULTS

The simulation produced compelling evidence that AI-driven traffic signal control systems can yield significant improvements across a range of urban mobility performance indicators. The average vehicle delay per intersection—a core measure of traffic flow efficiency—was reduced by 47%, decreasing from 72 seconds in the baseline scenario to just 38 seconds under the AI-managed regime. This reduction suggests a marked improvement in intersection throughput and reduced queuing, both of which contribute to smoother traffic conditions and lower travel time variability.

Environmental benefits were equally pronounced. CO□ emissions per intersection declined by 35%, falling from 1,480 grams to 965 grams. This drop is largely attributable to the system's ability to minimize stop-and-go driving patterns, which are known to cause inefficient fuel consumption and elevated tailpipe emissions. By facilitating more continuous vehicle movement, the AI system helps reduce unnecessary acceleration and idling—both key contributors to urban air pollution and greenhouse gas output.

Pedestrian wait times at signalized crosswalks decreased by 30%, from 60 seconds to 42 seconds on average. This metric is particularly important from an inclusivity and walkability standpoint. Reducing pedestrian wait times enhances the experience of walking as a mode of transport and can encourage modal shift away from car dependency. It also has safety implications, as shorter wait times reduce the temptation for pedestrians to cross illegally or against signals.

Furthermore, bus travel time during peak hours improved by 22%, decreasing from 18 to 14 minutes across the observed network. This gain is the result of intelligent transit signal priority (TSP), which grants extended green phases or early green returns to buses approaching intersections, especially those running behind schedule. Improved bus reliability not only enhances passenger satisfaction but can also improve operational efficiency for transit agencies.

The following table summarizes the quantified improvements observed in the AI-controlled scenario:

Table 1. Quantified improvements in AI scenario

Metric	Traditional System	AI-Based System	Improvement
Vehicle Delay (s)	72	38	–47%
CO_2 Emissions (g/inter.)	1480	965	–35%
Pedestrian Wait Time (s)	60	42	–30%
Bus Travel Time (min)	18	14	–22%

In addition to these quantifiable gains, the simulation revealed meaningful equity-focused outcomes, which are often overlooked in traditional traffic performance assessments. The system was programmed to dynamically prioritize pedestrian signals in high-sensitivity zones such as school districts, hospital zones, and elderly care centers. This led to faster pedestrian clearance times in these areas, contributing to a safer and more accessible environment for vulnerable populations.

Another key feature was the prioritization of public transport equity. Buses running behind schedule were detected in real time via GPS feed integration and granted adaptive green phases at upcoming intersections. This led to fewer cumulative delays and improved on-time performance—an essential metric for retaining rider trust and encouraging public transport usage. The algorithm also considered headway restoration, helping maintain even spacing between buses to reduce bunching, a common issue in high-frequency corridors.

These outcomes underscore the AI system's ability to align operational efficiency with social goals such as accessibility, safety, and transit equity. Rather than treating efficiency and equity as trade-offs, the system demonstrates that with appropriate algorithm design, it is possible to simultaneously improve overall system performance and redistribute mobility benefits more fairly across user groups.

In conclusion, the AI-based traffic control framework outperformed the conventional system across all evaluated dimensions—mobility, emissions, safety, and fairness. These results provide a robust foundation for advocating broader implementation of intelligent traffic systems, particularly in rapidly urbanizing or transitionary cities where legacy infrastructure is under strain but major reconstruction is infeasible.

DISCUSSION

The findings of this study underscore the transformative role that artificial intelligence (AI) can play in modernizing urban traffic management systems. By enabling real-time data processing, adaptive signal control, and predictive decision-making, AI technologies offer an unprecedented ability to respond dynamically to the complexity of urban mobility. Unlike traditional systems that operate based on pre-defined schedules or historical averages, AI systems can learn continuously from current traffic conditions, adapting signal timings to reduce delays, minimize congestion, and enhance traffic flow resilience. This agility is critical in today's urban environments, where fluctuations in demand, unforeseen incidents, and changing mobility patterns render static control systems increasingly obsolete.

Importantly, this study demonstrates that AI integration need not be narrowly focused on efficiency metrics such as vehicle throughput or travel time. The inclusion of equity-aware features—such as prioritizing pedestrians, cyclists, and delayed public transport vehicles—challenges the long-standing dominance of the automobile in urban design. This shift is consistent with contemporary urban planning paradigms that emphasize multimodal accessibility, social inclusion, and environmental justice. AI, in this context, is not merely a tool for optimizing flows but a platform for rethinking whose mobility needs are prioritized and how urban space is allocated. By embedding fairness into the logic of traffic control, cities can move closer to achieving inclusive mobility systems that serve all residents, regardless of age, ability, or socioeconomic status.

Despite these promising results, several challenges must be acknowledged and addressed for AI-based traffic management systems to reach their full potential. First, the successful deployment of such systems hinges on the availability and quality of data. AI models require large volumes of high-resolution, real-time data to function effectively, including information on traffic volumes, vehicle speeds, pedestrian movements, and public transport operations. In cities lacking sufficient sensor infrastructure or where data is siloed across agencies, the performance of AI systems may be significantly constrained. Bridging this data gap requires not only technological investment but also strong institutional coordination and standardized data-sharing protocols.

Second, the integration of data from mobile phones, GPS devices, and surveillance cameras raises important ethical and legal concerns. The real-time collection and processing of location and behavioral data could infringe upon individual privacy if not carefully managed. Therefore, any city-wide implementation must be accompanied by robust data governance frameworks that ensure transparency, accountability, and data minimization. Anonymization techniques, encryption protocols, and explicit consent mechanisms should be integral components of any AI-driven mobility initiative. Moreover, public communication strategies are needed to inform citizens about how their data is used and to build trust in the system's safeguards.

Third, the so-called "black box" nature of many AI algorithms—particularly those involving deep learning or neural networks—can complicate efforts to ensure accountability and regulatory compliance. When decision-making processes are opaque or non-intuitive, it becomes difficult for operators, regulators, or the public to understand how and why certain traffic patterns are prioritized or modified. This lack of explainability can erode trust and pose challenges for post-incident evaluations or appeals. As such, there is a growing need for interpretable AI (XAI) models that offer greater transparency without compromising performance. The development and adoption of explainable machine learning tools should be a key research priority moving forward.

Fourth, the resilience of AI systems under stress conditions—such as natural disasters, cyberattacks, or sensor failures—remains a relatively underexplored area. While adaptive control can enhance flexibility under normal conditions, reliance on digital infrastructure makes the system vulnerable to disruptions. Redundancy planning, edge computing, and real-time system diagnostics must be incorporated into future AI traffic systems to ensure operational continuity and cybersecurity resilience. Pilot programs should simulate various failure scenarios to test system robustness and identify necessary safeguards.

In addition to technical and ethical considerations, social and organizational challenges must also be managed. AI traffic management systems require cross-sector collaboration between city governments, transport authorities, technology providers, and civil society. Institutional inertia, funding constraints, and lack of interdisciplinary capacity can slow adoption. Thus, capacity-building initiatives, training programs, and cross-departmental coordination mechanisms are essential for effective implementation.

Finally, the global applicability of AI traffic systems depends on their adaptability to different urban typologies. Cities vary widely in terms of traffic culture, infrastructure maturity, governance capacity, and mobility needs. What works in a densely populated European capital may not translate directly to a rapidly growing secondary city in the Global South. Contextual adaptation—guided by local data, participatory design processes, and culturally sensitive metrics—is necessary to ensure that AI systems do not reinforce existing inequalities or overlook local priorities.

In summary, while AI offers powerful tools to enhance the intelligence, efficiency, and fairness of urban traffic systems, its deployment must be thoughtfully designed and rigorously governed. The full realization of AI's potential in urban mobility hinges not only on technological innovation but also on ethical alignment, institutional readiness, and sustained public engagement.

CONCLUSION

This paper demonstrates that the integration of artificial intelligence (AI) into urban traffic signal systems can lead to transformative improvements in how cities manage mobility, sustainability, and equity. By leveraging real-time data and adaptive learning algorithms, AI systems can significantly reduce traffic delays, optimize signal phasing, and respond dynamically to unpredictable road conditions. The simulation results confirm that AI-enabled control not only enhances vehicle flow but also substantially reduces greenhouse gas emissions and improves accessibility for pedestrians and public transport users. These outcomes are critical in the broader context of urban sustainability, where transportation remains one of the most significant contributors to pollution, energy inefficiency, and social exclusion.

The proposed AI framework stands out for its ability to operate using existing infrastructure, making it a cost-effective and scalable solution suitable for cities at various stages of technological maturity. Its modular architecture allows for incremental adoption, from pilot corridors to city-wide deployments, without requiring disruptive overhauls. Moreover, the incorporation of equity-aware algorithms ensures that the benefits of improved traffic management extend beyond private vehicles to more vulnerable road users—such as pedestrians, cyclists, and transit riders—who are often underserved in traditional systems. In this way, AI-driven traffic management supports a more inclusive vision of urban development, aligned with global goals such as the UN's Sustainable Development Goal 11 (Sustainable Cities and Communities).

However, the path toward full-scale implementation is not without challenges. Ensuring the ethical use of AI in public infrastructure is paramount, particularly in terms of data privacy, algorithmic transparency, and accountability. Public trust must be cultivated through open communication, explainable AI models, and robust governance structures. Furthermore, technical limitations related to data coverage, system interoperability, and resilience in extreme traffic scenarios require further investigation and testing under real-world conditions.

Future research should prioritize large-scale, multi-jurisdictional pilot deployments that evaluate system performance in diverse urban contexts, from highly congested city centers to suburban and transitional areas. Integrating AI-based traffic systems with multimodal transport planning—encompassing walking, cycling, shared mobility, and public transit—will be essential to realize the full spectrum of sustainability benefits. Additionally, cross-disciplinary collaborations between engineers, urban planners, policymakers, and ethicists will be necessary to develop and institutionalize standards for safe, fair, and effective AI deployment in public spaces.

In conclusion, AI represents a strategic enabler for next-generation urban traffic systems. When thoughtfully implemented, it can not only optimize operational efficiency but also contribute meaningfully to the long-term resilience, inclusiveness, and ecological balance of modern cities. The convergence of AI and urban mobility is no longer a futuristic ambition—it is an urgent imperative for cities navigating the twin pressures of population growth and climate change.

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