

AI and Machine Learning for Sustainable Urban Mobility: A Systematic Review

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Abstract—Urban traffic congestion and increasing carbon emissions present growing challenges for modern cities. As AI and machine learning methods are increasingly applied to optimizing urban transport, a systematic understanding of their effectiveness across urban transport systems and real-world sustainability outcomes remains limited. This review aims to identify and evaluate the AI and machine learning methods proposed to optimize urban transport systems and assess their effectiveness in achieving sustainable mobility outcomes. Following PRISMA 2020 guidelines, a structured search of the IEEE Xplore digital library was conducted, after filtering for peer-reviewed journal publications and applying inclusion and exclusion criteria, 14 Q1 journal studies published between 2016 and 2026 were selected for the review. The findings reveal that reinforcement learning, deep Q-network variants in particular is the dominant approach, consistently outperforming fixed-time baselines, with prominent reported reductions in vehicle waiting time. The reviewed work further demonstrates a progression towards scalability and multi-agent coordination, with complementary methods such as PPO, LSTM-based prediction and federated learning extending applicability to road anomaly detection and route optimization. These results confirm the strong potential of AI for sustainable urban mobility, although a strong reliance on simulation environments in the presented papers limits conclusions about real-world transferability.

I. INTRODUCTION

Urban mobility remains one of the defining challenges of the 21st century. As cities worldwide continue to grow in population, the pressure and demands on traditional transportation infrastructure increases. One of these demands is the need to reduce the environmental impact by adopting sustainable transport solutions [1]. Through these new challenges the concept of smart cities has emerged as a response that utilizes digital technology and data driven systems in order to make urban cities efficient and sustainable to create better living conditions for the people who live there.

A key aspect of smart urban cities is the mobility outcomes. The challenge is to integrate and combine multiple different transportation modes such as vehicles, public transit, cycling and pedestrians. Coordinating all these transport modes while also keeping the goal of sustainability is a critical goal post for modern urban cities.

Artificial intelligence has become a powerful tool for tackling these challenges [2]. The adoption of AI methods such as

Machine Learning (ML) models or Reinforcement Learning (RL) agents in aspects such as traffic monitoring, mobility improvement and traffic flow predictions has offered great promises for the future. Artificial intelligence especially offers promises for tackling the growing concern of environmental challenges such as traffic congestion in modern cities [3].

This paper presents a systematic literature review examining the application of AI methods for optimizing urban transport systems and the possible sustainability effects. This review follows the guidelines established by PRISMA 2020 [4] for systematic literature reviews.

II. METHODOLOGY

This study follows a systematic literature review approach to identify and analyze research on AI and ML methods for optimizing urban transport systems.

A. Research Question

The review is guided by the following research question: What AI and machine learning methods have been proposed for optimizing urban transport systems, and how effective are they in achieving sustainable mobility outcomes?

B. Search Strategy

A structured search was conducted using the IEEE Xplore digital library. The following search string was applied:

("multimodal transport" OR "urban mobility" OR "smart city traffic") AND ("deep learning" OR "machine learning" OR "reinforcement learning") AND ("optimization" OR "sustainability")

The initial search returned 469 research papers including 371 conference papers, 78 journal articles, 7 books, 3 magazines and 10 early access articles.

C. Source Selection

To ensure consistency in quality and peer-reviews, this review focused exclusively on journal publications. Journal articles were selected as they generally undergo more extensive peer-review processes and tend to present more mature and validated research contributions compared to conference proceedings. After applying this filtering step, only journal papers were considered for further screening and analysis.

D. Screening Process

The screening process was performed in multiple stages. Titles and abstracts of all retrieved journal papers were reviewed to determine relevance. The papers not relevant to the research question or the domain of the research were excluded from further analysis.

E. Inclusion and Exclusion Criteria

Studies were included if they met all of the following criteria: (i) published in peer-reviewed journals, (ii) published between 2016 and 2026, (iii) written in English, (iv) proposed or evaluated at least one AI/ML method applied to an urban transport mode in a real or simulated environment, and (v) focused on transport optimization or mobility improvement as a primary objective.

Studies were excluded if they were purely theoretical without computational evaluation, focused exclusively on non-urban, freight or aviation transport, were not peer-reviewed, or were duplicates of already included studies.

F. Data Extraction

For each included study, data was extracted across three main areas to ensure consistency and to minimize bias toward any single paper. The three main areas are: the AI or machine learning methodology proposed, the quantitative evaluation metrics reported (such as reductions in vehicle waiting time, throughput, fuel consumption and carbon emissions) and the experimental context including transport modes and evaluation environment.

G. Study Selection

After applying the inclusion and exclusion criteria during abstract screening, the remaining studies were selected for full-text review and further analysis in the literature synthesis phase. The synthesized studies were grouped based on the methods proposed and the key objective that the studies attempted to address.

III. RESULTS

The study selection process is illustrated in Fig. 1. Out of the 469 papers returned by the initial search, 78 journal articles were carried forward for screening, of which 26 passed the title and abstract screening stage. After applying the inclusion and exclusion criteria, 14 studies were selected for final review. As shown in Table I, all 14 included studies were published in Q1 IEEE journals, indicating a high and consistent level of publication quality across the reviewed literature.

A. What AI and machine learning methods have been proposed for optimizing urban transport systems

One of the common frustrations in urban traffic is lights that follow a fixed schedule regardless of what is actually happening on the road. A light that gives the same amount of green time to a busy lane and an empty one is wasting time for everyone. To address this a Deep Reinforcement Learning agent (DRL) is used to watch an intersection and control the

traffic light cycle [5]. Rather than feeding the agent a simple count of waiting vehicles, the intersection is divided into a grid of small squares, recording whether a vehicle is present and how fast it is moving. This gives the agent a clearer picture of the situation. Later this is processed by a convolutional neural network within a Double Dueling Deep Q-Network (3DQN) framework to extract useful traffic patterns. The agent learns through trial and error in simulation, rewarded whenever total waiting time is decreased.

This approach is built on a Double Deep Q-Network (DQN). A key weakness of double DQN is that its exploration relies on epsilon-greedy action selection where actions are chosen randomly during exploration which can result in slow and inefficient learning. [6] address this directly by integrating Salp Swarm Optimization (SSO) into the exploration phase instead of relying only on random action selection, a nature-inspired algorithm that guides the agent toward more promising actions from the very start. They also broaden the state representation to include pedestrians and emergency vehicles alongside regular traffic.

Together, these two studies show a clear line of development in DQN-based signal control, where [5] establishes the framework and [6] refines the learning process.

Both studies remain limited to single intersections in simulation, which raises an obvious question: what happens when multiple intersections need to coordinate? This is addressed by introducing a Cooperative Multi-Agent Deep Q-Network (CMDQN) [7]. Each intersection runs its own agent but agents share state information with their neighbors rather than optimizing in isolation, with the focus purely on reducing waiting time across the network. The system is validated on both Simulation of Urban Mobility (SUMO) and a real world traffic network in Lahore - Pakistan.

Where [7] focus on how agents coordinate, [8] shift the question to what should actually be optimized. They compare three DRL architectures across a simulated real intersection network in Florence - Italy using real-world traffic data. The compared approaches for traffic light optimization include, a single centralized agent, independent agents per intersection, and SMART (System for Managing Actuated and Real-Time Traffic). Unlike the previous approaches SMART achieves enhanced traffic flow efficiency by dynamically adjusting traffic signals based on real time conditions. What distinguishes this work is the inclusion of trams and bus rapid transit as priority vehicles alongside regular traffic.

The approaches discussed so far treat railway infrastructure as absent from the traffic environment. [9] address this gap by building a simulation environment that includes two signalized intersections and two railroad crossings, where the open or closed state of each crossing is fed directly into the agent's state alongside regular vehicle information. Both Proximal Policy Optimization (PPO) and DQN are tested as the learning algorithms, with the system making signal decisions based on road and railway conditions simultaneously.

A concern across all these approaches is scalability to real urban networks. Most papers mentioned evaluate on simulated

intersections or small real-world patches. [10] proposes a federated architecture distributing training across edge, fog, and cloud layers, a design intended to scale to a real city.

This hierarchical federated learning approach ensures that raw sensor data remains at the local intersection for privacy, while model updates are compressed using AutoDeepCABAC before transmission to minimize communication overhead across a city-wide system. This principle of transmitting only learned parameters rather than raw data is confirmed by [11], which applies a similar federated approach within a Vehicular-Adhoc Network, where each traffic node trains locally and shares only encrypted weight updates with a central aggregation server. However, it is worth mentioning for both articles that the evaluation remains on simulation results rather than on results from real world evaluation [10] [11].

[12] proposes a hybrid framework combining a Spatio-Temporal Graph Convolutional Network with Long Short-Term Memory (STGCN-LSTM) and PPO for traffic prediction and signal optimization. The STGCN part models how roads and intersections are connected, while the LSTM part learns how traffic changes over time. Additionally it employs PPO for dynamic optimization signal control. In order to perform effectively across diverse urban scenarios the framework accounts for several factors such as weather conditions, holidays and unplanned events. The system is evaluated using the METR-LA dataset together with simulated traffic environments.

[5] and [6] mainly focus on improving DQN learning at a single intersection, [7] focuses on cooperation between intersections. [13] instead focuses on generalization and adaptability across many different intersection structures. It also relates to [12] because both use PPO while trying to handle larger urban environments, yet they still approach the problem differently. While [12] focuses on predicting traffic patterns over space and times using STGCN-LSTM before signal optimization, [13] shifts the focus on building one RL model that can adapt to many different intersection layouts using augmentation and universal training. [13] also connects to [10] and [11] because all three papers are concerned with scalability beyond small isolated intersections, although [13] does not use federated learning.

Although traffic signal control is an impactful technique that has adapted modern AI methods as presented before, these techniques have other applications beyond traffic signal control. A setback for mobility in urban environments could sometimes be the quality of the roads and keeping track of changes in quality is often essential. To address this a creative solution that makes use of sensor data collection from mobile apps then combining physics based models and a LSTM based neural network for detecting road anomalies [14]. This addresses another key issue for building sustainable smart cities which is the safety. This safety measurement could extensively be applied to emerging technologies for autonomous vehicles. [15] addresses this directly by proposing a deep reinforcement learning framework extended with a fusion algorithm for solving the task of highway ramp

merging. A critical component for the performance of these types of systems is the ability to process information in order to make well informed decisions. This is a subproblem that AI systems face in the context of transport optimization and mobility improvement. The use of unmanned aerial vehicles has proven useful for data processing, especially in edge computing systems. A critical challenge that remains within these systems is distributing compute task in an efficient way which is what [16] attempts to tackle with a Multi-Objective Simulated Annealing (MOS) approach.

[17] and [18] proposes solutions focused on optimizing routes for different transport modes. While [17] presents a framework that combines traffic flow prediction with a Reinforcement learning model using Markov decision processes (MDP) in order to prevent selfish routing and thus reduce congestion from traditional navigation systems. [18] extends this method of using reinforcement learning for route optimization by emphasizing on a multi-agent RL method that focuses on efficiency and adaptability for customized bus systems.

B. How effective are AI and machine learning methods in achieving sustainable mobility outcomes

The 3DQN model ended up reducing average delays by over 26.7% compared to fixed-time signals [5].

As presented in [6], the proposed SSO approach demonstrated reductions in total waiting time of up to 10% relative to DDQN and 12% relative to DQN under uncalibrated conditions. In the crowded scenario, these reductions increased to 10% and 18%, respectively.

[7] Proposed a CMDQN approach, which outperforms the non-cooperative DQN baseline model by 22.4% (computed from reported values) in mean waiting time and also significantly outperforming static signaling when evaluated on real world traffic scenarios. However the outlined study also recorded the highest intersection flow time for the proposed method indicating more time spent at intersections.

[9] showed enhancement for all evaluated reinforcement learning methods compared to a fixed control system. The RL-based methods outperformed the baseline method across multiple metrics such as total waiting time and mean waiting time where the top performing model proposed an enhancement of up to 42.39% and 40.00% respectively.

[10] Shows that all methods achieved similar performance under low traffic conditions (30% load). However as traffic load increased, the proposed method performed significantly better than the other approaches. At a 90% traffic load, the average waiting time decreases by more than 35% (computed from reported values) compared to the baseline FT and SOTL approaches.

The proposed method in [11] achieves a 40% improvement over fixed traffic signals, as well as a 33% increase in intersection throughput compared to fixed-time signals.

The traffic flow prediction model STGCN-LSTM presents a 28% reduction in waiting time as well as a 13% and 8% reduction in fuel consumption and carbon emission proving its

effectiveness from a sustainability point of view [12]. Similarly the paper demonstrates how the proposed PPO algorithm for traffic signal shows a 30% reduction in waiting time as well as 15% increase in throughput.

The presented approach in [13] consistently outperformed MPLight, AttendLight, MetaLight, and π -Light, reducing average vehicle waiting time by 15%, 12%, 27% and 8% respectively.

The MOSA method demonstrates an ability to impact traffic flow by reducing average vehicle waiting time during both standard load conditions as well as peak load conditions where the method achieves a 31.1% reduction in average vehicle waiting time [16].

Several of the reviewed studies achieved a common goal of reducing waiting times by optimizing traffic signal control in order to improve transportation efficiency in urban road networks. The primary aim was to improve urban mobility, while an additional benefit was the reduction of carbon emissions, contributing to a more sustainable environment.

Some of the reviewed studies do not report direct improvements in common performance metrics such as waiting time or throughput, but instead focus on proposing or describing methodological frameworks without relevant quantitative evaluations. [8] [14] [15] [17] [18].

TABLE I
QUALITY ASSESSMENT OF INCLUDED STUDIES

Paper	Journal	Publisher	Quartile
[5]	IEEE Transactions on Vehicular Technology	IEEE	Q1
[6]	IEEE Access	IEEE	Q1
[7]	IEEE Access	IEEE	Q1
[8]	IEEE Access	IEEE	Q1
[9]	IEEE Sensors Journal	IEEE	Q1
[10]	IEEE Transactions on Consumer Electronics	IEEE	Q1
[11]	IEEE Transactions on Consumer Electronics	IEEE	Q1
[12]	IEEE Access	IEEE	Q1
[13]	IEEE Transactions on Vehicular Technology	IEEE	Q1
[14]	IEEE Sensors Journal	IEEE	Q1
[15]	IEEE Transactions on Transportation Electrification	IEEE	Q1
[16]	IEEE Access	IEEE	Q1
[17]	IEEE Internet of Things Journal	IEEE	Q1
[18]	IEEE Transactions on Intelligent Transportation Systems	IEEE	Q1

The quality of the included studies was assessed based on journal reputation, publisher credibility, quartile ranking, and peer-review status. Since all included studies were published in Q1 IEEE journals, they were classified as 25% of highest impact journals in the respective field, according to the Scimago Journal & Country Rank (SJR) database.

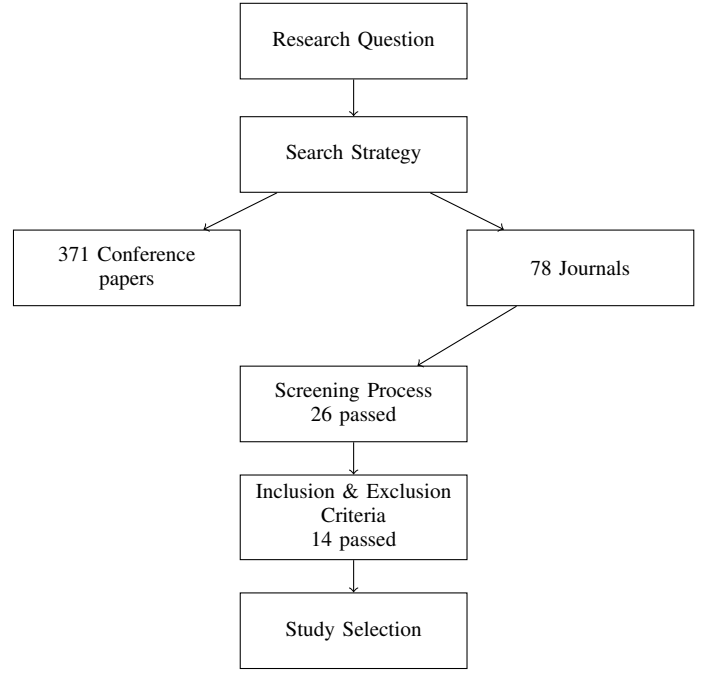


Fig. 1. Selection process used in the systematic literature review.

IV. DISCUSSION

A common theme across the reviewed studies is the use of Reinforcement learning methods for traffic signal control, deep Q-network variants in particular has shown to be the dominant approach for optimizing urban traffic systems. The result from [5] [6] [7] indicate an improved effect on reduced waiting time and traffic delay showing a positive improvement in preventing traffic congestion which has been addressed as a major objective for achieving sustainable cities. [8] and [9] also explores the possibilities of Reinforcement learning methods in traffic signal control and also introduces the integration of transportation modes such as busses, trams as well as rail road infrastructure. Introducing different types of transportation modes can be useful for the adaptability which is a recurrent limitation that the included studies often seek to improve. [9] and [6] are examples of studies that suggest this as future work.

PPO is another example of a method that has been used for optimizing urban transport systems as shown in [9], [12] and [13]. The experimental results from all three papers demonstrate improvements in waiting time, fuel consumption and throughput. The effect of PPO is particularly demonstrated in [12] where the algorithm achieved a 30% reduction in waiting time and a 15% increase in throughput.

The reviewed work however does not always limit the approaches to only one type of method. [12] for instance demonstrates how two distinct deep learning frameworks like STGCN and LSTM can be combined to one prediction model that achieves a reduction in waiting time, fuel consumption and carbon emission with 28%, 13% and 8% respectively. LSTM is also used in [14] serving as a key design choice in a

physics informed neural network for road anomaly detection. This exemplifies the flexibility of LSTM for use in both traffic control system but also in systems like road anomaly detection for improving urban mobility.

A. Research Gap

While results across these studies are promising, several recurring limitations and open challenges remain to be addressed which leaves a notable gap. The majority of studies rely exclusively on simulation environments such as SUMO, raising the question to whether the reported performance such as "reduced vehicle waiting time" or "fuel consumption" on these proposed approaches will translate to the complexity and unpredictability of live urban traffic. A substantial problem that remains unsolved is for these methods to achieve real world deployment. There are multiple challenges that must be addressed to reach the goal of real world deployment. Two of these challenges are the adaptability and scalability of these systems. These systems often rely on edge computing devices for processing information and real time decision making. Future work should explore the possibility of developing and enhancing a lightweight machine learning model for easier deployability on resource-limited edge devices. Achieving such compression would require techniques such as quantization, which reduces the numerical precision of model weights. Another suggested technique that could be explored is pruning, which eliminates redundant parameters from the model. The final suggested technique is knowledge distillation that trains a compact student model to mimic the behavior of the larger DQN or PPO-based models reviewed in this paper. Applying these methods would produce a smaller model that demands less computational power during inference. This would reduce the reliance on expensive, high-throughput hardware. This would also prevent limiting traffic optimization techniques to costly infrastructure and instead enable deployment on affordable, low-power edge devices that can be found in real-world urban traffic systems.

B. Limitations

The limitation of the outlined systematic literature review include the lack of diversity in academic literature sources. The review process used IEEE Xplore digital library as the single literature source. By collecting research from more than one academic source we would ensure a review of more diverse research material from different publishers. Another limitation is the methodological choice of limiting the review to journal papers and therefore excluding the large amount widely available conference papers. Although the argument for this is already presented it is worth noting that within fields like computer science, conference papers can often present high impact papers especially when it comes to conferences with a high academic rating. With this in mind the exclusion of conference papers in this review can be described as a limitation and a more extensive review should focus on covering those academic sources as well in order to perform a less limited systematic review.

V. CONCLUSION

This systematic literature review examined the state of the art AI and machine learning methods for optimizing urban transport systems, with a particular focus on sustainable mobility outcomes. A structured search string of the IEEE Xplore digital library yielded 14 high-quality journal publications that were selected through a thorough screening process.

The findings reveal that reinforcement learning (RL), and deep Q-network variants in particular represents the dominant methodological approach in the field. Studies consistently demonstrate that RL-based traffic signal control outperforms fixed-time baselines. The presented RL approaches report prominent improvements in vehicle waiting time. The reviewed work demonstrated a clear progression toward greater scalability and cooperation. From multi-agent coordination [7] to federated learning architectures designed for city-wide deployment [10] [11]. Complementary methods such as PPO, LSTM-based prediction, hybrid frameworks like STGCN-LSTM [12], and nature-inspired approaches such as Salp Swarm Optimization [6] further extend the scope of applicability. Road anomaly detection [14] and route optimization [17] [18] are prime examples of extensive applicability of ML and AI methods beyond traffic signal control.

A shared limitation across the reviewed studies is the reliance on simulation environments, most commonly SUMO, which raises questions about real-world transferability. Achieving deployment at scale in live urban environments remains an open challenge that demands further advances in lightweight model design for edge device compatibility and integration of the presented systems.

In summary, AI and machine learning methods show strong and growing potential for optimizing urban transport systems. Realizing the full sustainability promise of these methods will require bridging the gap between simulation-based research and real world deployment.

AUTHOR CONTRIBUTION

All authors contributed equally to all stages of this literature review, including study design, literature search and study selection, analysis and interpretation of findings, manuscript preparation and critical revision of the paper. All authors reviewed and approved the final manuscript.

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