

“SMART TRANSPORTATION SYSTEMS: AI-BASED TRAFFIC CONTROL, SMART SIGNALS, IMPACT ON CONGESTION”

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Abstract:

Traffic congestion remains a serious issue in cities. It causes delays, higher emissions, and economic losses. This paper reviews recent advancements in data-driven methods for detecting, predicting, and reducing congestion. We examine eight recent studies that include deep-learning surveys, deep-reinforcement methods for traffic-signal control, Q-learning, and DQN approaches. We also look at trajectory-based congestion prediction and combined micro and macro state representations. We summarize common architectures, such as CNNs, LSTMs, GNNs, and multi-agent DRL. We also cover input representations, including images, probe and trajectory data, and sensor flows. Additionally, we discuss control strategies like DQN, D3QN, DDPG/KS-DDPG, and joint phase and timing control. Overall, deep learning and DRL show consistent improvements in queue length and waiting time. They also adapt better than fixed-time methods. Meanwhile, trajectory-mining methods help address sudden events that historical flow models may miss. However, challenges remain. These include ensuring reliable performance during rare events, dealing with partial observability, managing state-space explosion, improving interpretability, and deploying solutions from simulation to real-world settings. We highlight specific research gaps and suggest future directions. These include combining data from multiple sources, using hybrid model-based and learning approaches, improving scalable multi-agent coordination, and making predictions that account for uncertainty.

Keyword :- Traffic Congestion, Deep Learning, Deep Reinforcement Learning, Trajectory Mining, Traffic Signal Control, Multi-Agent, Hybrid Framework, Sustainable Transportation, Intelligent Transport System.

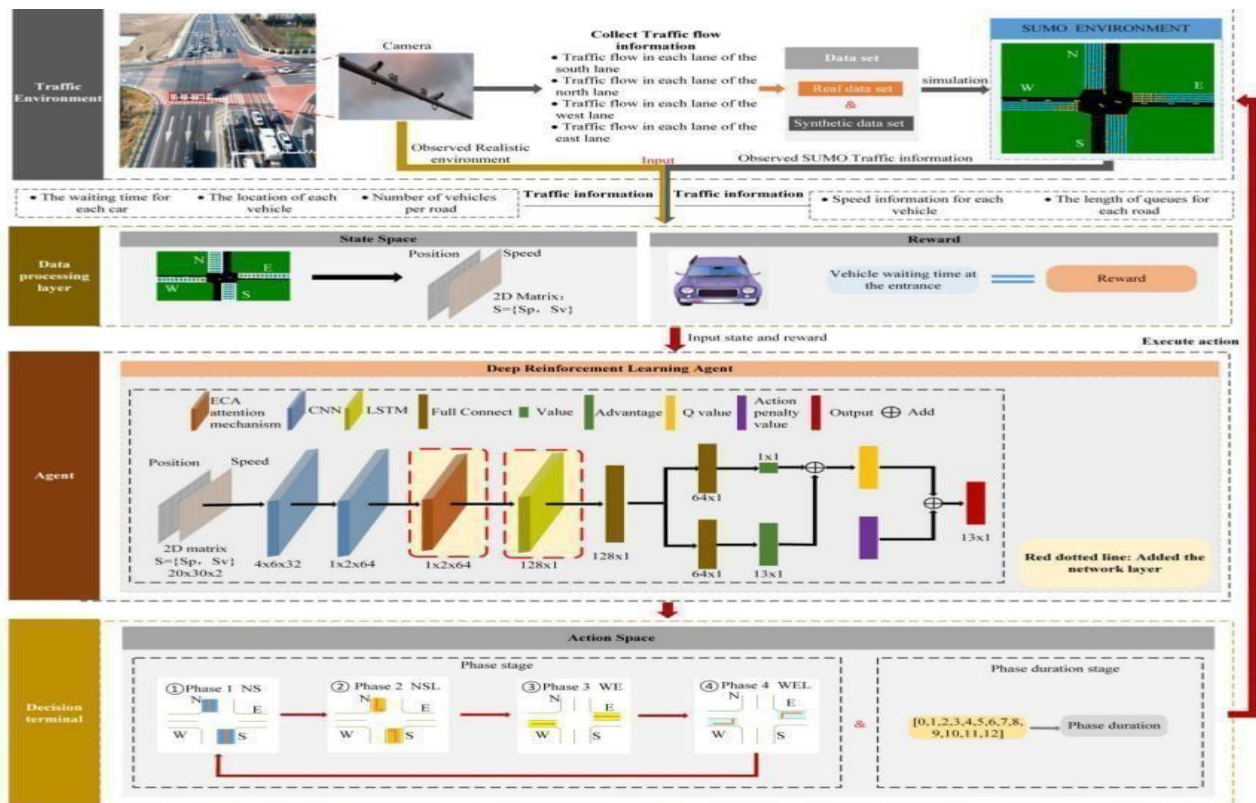
Introduction

Traffic congestion worsens mobility, increases travel time and fuel consumption, and raises greenhouse gas emissions. These issues drive the need for better forecasting and control systems for urban transportation networks. Traditional methods like fixed-time control and classical time-series forecasting (ARIMA, Kalman filters) often struggle with changing demand and unexpected events such as accidents or weather. They also do not handle high-dimensional data from sensors like cameras and probes very well.

Modern data sources and computing power allow learning-based methods to take a central role. Deep learning can detect and predict congestion from images. Spatio-temporal models, including CNNs, LSTMs, and GNNs, help forecast traffic flow. Deep reinforcement learning (DRL) improves adaptive traffic-signal control. Recent surveys and review papers summarize the landscape of AI/ML in traffic forecasting and congestion management. They point out both the opportunities and specific

challenges of the field, such as the instability of congested dynamics and the need for early warnings.

DRL-based controllers, whether single or multi-agent, have shown significant reductions in queue lengths and waiting times compared to fixed-time methods. They learn policies that adjust phase timing or manage phase sequences and durations. Attention modules and LSTM temporal encoders help simplify state-space complexity and make systems more robust during special circumstances, like traffic surges. Multi-agent strategies that enable knowledge sharing or communication scale better across networks than simple centralized policies, although they bring challenges like non-stationarity and coordination issues. Trajectory-mining methods fill gaps in flow-based predictions by forecasting the next locations of individual vehicles and estimating how many will cross a road segment in the next step. This approach can identify potential congestion from sudden events not captured in historical averages. To improve robustness, hybrid designs that combine trajectory data and aggregated flow data are recommended. In traffic control, optimizing both phase sequence and timing through DRL, using combined micro and macro state representations has shown better performance than methods that only optimize duration or sequence. However, challenges remain, such as state explosion with high-dimensional inputs, partial observability when probe data penetration is low, sim-to-real transfer, the need for interpretability, and uncertainty-aware predictions for safe decision-making in real deployments.



Source : (Wenjiao Zai , Dan Yang 2023)

Figure 1. Traffic signal control model

Literature Review

Recent research on congestion management shows the variety of AI applications in prediction, control, and optimization. Kumar and Raubal (2021) [1] examined deep learning applications for congestion prediction and detection. They made a distinction between recurring and non-recurring congestion and pointed out the importance of spatial-temporal modeling and real-time adaptability. Sayed, Abdel-Hamid, and Hefny (2023) [5] offered a related review focusing on traffic flow prediction. They identified convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) as key techniques. They also noted challenges like data variety and limited understanding.

For signal control, deep reinforcement learning has become a leading method. Zai and Yang (2023) [2] created an enhanced dueling double deep Q-network (EL_D3QN) that integrates Efficient Channel Attention (ECA) and LSTM. Their results showed reductions in waiting times, queue lengths, and CO₂ emissions. Improved phase intervals also increased robustness during traffic surges. In a similar vein, Li et al. (2021) [6] introduced KS-DDPG, a multi-agent deep deterministic policy gradient algorithm that incorporates knowledge sharing. This model improved the speed of convergence and coordination across the system, outperforming both centralized and independent methods. Sun et al. (2025) [8] built on this by optimizing the traffic signal phase sequence and duration together, resulting in more flexible intersection control.

Other approaches include lightweight reinforcement learning frameworks. Mortazavi Azad and Ramazani (2023) [3] used Q-learning with neural networks at single and paired intersections, achieving significant reductions in queue lengths compared to fixed-time systems. Communication between intersections further improved efficiency. Similarly, Kumar et al. (2024) [7] developed a sensor-based dynamic signal control system for urban areas, showing that it is practical and scalable.

In addition to signal control, congestion prediction studies have focused on trajectory data. Liu, Lei, and Jie (2025) [4] created a trajectory-mining based prediction framework that detects non-recurring congestion earlier than flow-based models. Their findings suggest that combining vehicle trajectory predictions with aggregated flow models can enhance robustness. Hybrid state-reward designs have also shown importance. Bouktif et al. (2023) [9] emphasized the need for consistent definitions of state and reward to stabilize deep reinforcement learning training. Rodrigues et al. (2019) [12] pointed out robustness issues during demand surges, sensor failures, and capacity reductions. Recent work is also looking into interpretability and new optimization methods. Liao, Mei, and Zhang (2024) [10] introduced genetic programming for traffic signal control, developing tree-based urgency functions that are more transparent than black-box deep reinforcement learning. Ren et al. (2025) [11] proposed a two-step deep reinforcement learning method that balances intersection efficiency with pedestrian safety, showing an increasing focus on inclusive traffic management.

In control systems, reinforcement learning (RL) and deep reinforcement learning (DRL) have taken the lead. Zai and Yang (2023) [2] combined Efficient Channel Attention and LSTM with a dueling Q-network. This approach showed reduced queue lengths and lower emissions. Li et al. (2021) [6] built on this by introducing KS-DDPG, a knowledge-sharing framework for multiple intersections, which led to better convergence and improved coordination across the city. Sun et al. (2025) [8] further expanded RL to optimize both phase sequence and green time together. Their findings showed that flexibility in control improves adaptability.

Lightweight RL methods are still important in limited settings. Mortazavi Azad & Ramazani (2023) [3] found that Q-learning, when boosted by communication between intersections, could surpass static systems even in small networks. Kumar et al. (2024) [7] used a sensor-based adaptive algorithm. This highlighted the ease of deployment and cost savings in urban areas. These models create practical options for real-world use where computational resources are tight.

New research also focuses on interpretability and inclusiveness. Bouktif et al. (2023) [9] addressed instability by establishing consistent state and reward representations. This improved the robustness of DRL training. Liao et al. (2024) [10] used genetic programming to create explainable urgency functions, which lessened dependence on opaque policies. Ren et al. (2025) [11] combined pedestrian safety and vehicle flow in a two-step DRL framework. This reflects a move toward solutions that are socially sustainable.

Together, these studies highlight both the potential and the challenges of AI in congestion management. Deep reinforcement learning and hybrid models frequently outperform static methods, but their scalability, robustness, and deployment in real-world scenarios still need improvement. The literature indicates a clear path toward hybrid, multi-agent, and uncertainty-aware systems that connect prediction with adaptive control.

Research Gap

- **Data Dependence & Generalization:** Many models depend on curated simulation datasets, such as SUMO and synthetic road networks. They have limited validation on real urban data. Generalization across cities and cultures has not been tested.
- **Non-Recurring Congestion:** While looked into trajectory-based events, most reinforcement learning and deep learning systems focus on recurring congestion. This limits their effectiveness in situations like accidents, emergencies, or weather changes.
- **Scalability & Coordination:** Multi-agent systems struggle in non-stationary learning environments. Here, agents can disrupt each other's learning, which affects convergence in large networks.
- **Interpretability:** Deep reinforcement learning systems are often black boxes. This limits their adoption by traffic engineers and city planners.
- **Sim-to-Real Transfer:** Most research stops at simulation and has few pilot implementations. The gap between simulated environments and real traffic conditions reduces the ability to deploy these systems.
- **Inclusive Design:** Few models effectively manage multi-modal traffic, including pedestrian, cyclist, and autonomous vehicle flows, despite the growth of mixed-traffic urban systems.

Implementations

- **Hybrid Data Fusion:** Integrate flow data, trajectories, and sensor inputs for reliable congestion prediction.
- **Federated Multi-Agent RL:** Improve KS-DDPG with federated learning to coordinate across cities without destabilizing agents.
 - **Explainable AI:** Expand genetic programming and clear reward designs for better transparency.
 - **Uncertainty-Aware Models:** Use ensemble DRL or Bayesian deep learning to handle random

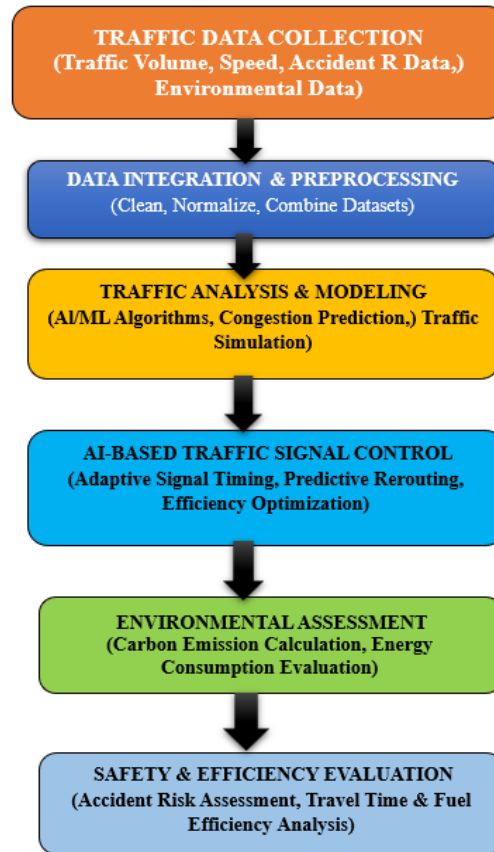


Figure 1. Flow chart of proposed for traffic data collection and implementation

The flowchart shows a systematic AI-based traffic management framework. It starts with collecting traffic volume, speed, accident records, and environmental data. Next, this data is cleaned, normalized, and integrated for further use. The processed data undergoes analysis and modeling using AI/ML algorithms for predicting congestion and simulating traffic. This process helps develop adaptive traffic signal control systems that improve signal timing, rerouting, and overall flow efficiency. After this, an environmental assessment checks carbon emissions and energy use to ensure sustainable practices. Lastly, safety and efficiency are assessed through accident risk evaluation, travel time analysis, and fuel efficiency measurement. This provides a well-rounded approach to improving traffic safety, operational efficiency, and environmental sustainability.

Future Scope

Future work should focus on uncertainty-aware DRL with predictive confidence intervals Integrating connected and autonomous vehicles (CAVs) with V2I systems could unlock real-time adaptive optimization Federated reinforcement learning and event-triggered communication can support scalability across city-wide networks Research should also move towards field validation. This means going beyond simulation and conducting pilot projects in various cities Lastly, sustainable urban mobility needs AI systems that improve not only efficiency but also reduce emissions and enhance safety. This aligns with the goals of smart cities

Conclusion

Artificial intelligence has changed how we manage traffic congestion. It allows for predictive modeling and adaptive control strategies that are more effective than traditional methods. Deep reinforcement learning and hybrid prediction frameworks clearly improve the reduction of delays, queues, and emissions. Additional innovations in interpretability, robustness, and inclusivity help ensure these systems provide not just technical performance but also support socially sustainable traffic management.

Artificial intelligence has changed how we manage traffic congestion. It allows for predictive modeling and adaptive control strategies that are more effective than traditional methods. Deep reinforcement learning and hybrid prediction frameworks clearly improve the reduction of delays, queues, and emissions. Additional innovations in interpretability, robustness, and inclusivity help ensure these systems provide not just technical performance but also support socially sustainable traffic management.

AI-driven traffic congestion management is an important advance in tackling urban mobility issues. DRL- based adaptive signal control, trajectory-based prediction, and hybrid frameworks regularly outperform traditional static models. However, problems like scalability, robustness, interpretability, and sim-to-real deployment restrict their current use. By exploring hybrid, uncertainty-aware, and interpretable methods and testing them through real-world pilots, cities can progress toward smart, sustainable traffic systems that improve mobility and lower environmental impact.

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