Multidisciplinary Journal of Research in Engineering and Technology

ISSN: 2348-6953

Volume 13 Issue 2 (2026) | Pages: 74–80

# Multi-Agent Reinforcement Learning for Intelligent Traffic Management in Smart Cities

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**Peer Review Information**

***Type***: *Article*
***Received***: *13 February 2026*
***Revised***: *05 March 2026*
***Accepted***: *02 April 2026*
***Published***: *28 may 2026*

**Abstract**

Rapid urbanization and the continuous growth of vehicular traffic have created significant challenges for traffic management systems in modern smart cities. Traditional traffic control mechanisms based on fixed-time signal scheduling and rule-based optimization often fail to adapt efficiently to dynamic traffic conditions, resulting in traffic congestion, increased travel time, fuel consumption, environmental pollution, and reduced transportation efficiency. Intelligent Traffic Management Systems (ITMS) have emerged as a promising solution for improving urban mobility through real-time traffic monitoring, adaptive signal control, and intelligent decision-making. In recent years, Reinforcement Learning (RL) techniques have demonstrated strong capability in optimizing traffic signal control and transportation management by enabling autonomous agents to learn optimal control policies through continuous interaction with traffic environments. However, single-agent reinforcement learning approaches often exhibit limited scalability and coordination capability when deployed in large-scale urban transportation networks containing multiple intersections and dynamic traffic flows. To overcome these limitations, Multi-Agent Reinforcement Learning (MARL) has emerged as an effective framework for distributed traffic management and cooperative decision-making. In MARL based traffic systems, multiple intelligent agents collaborate to optimize traffic flow, reduce congestion, minimize vehicle waiting time, and improve transportation efficiency through coordinated learning and adaptive policy optimization. This research proposes a Multi-Agent Reinforcement Learning framework for intelligent traffic management in smart cities by integrating decentralized traffic agents, deep Q-learning optimization, cooperative policy learning, and adaptive traffic signal control mechanisms. The proposed framework utilizes traffic intersections as autonomous learning agents capable of dynamically adjusting traffic signals based on real-time traffic density, vehicle queue length, traffic flow patterns, and environmental conditions. Deep Reinforcement Learning algorithms, including Deep Q-Networks (DQN) and Actor-Critic optimization strategies, are employed to improve traffic coordination and adaptive decision-making across interconnected urban transportation networks.

**Keywords:** Multi-Agent Reinforcement Learning, Intelligent Traffic Management, Smart Cities, Deep Reinforcement Learning, Traffic Signal Optimization, Autonomous Traffic Control.

**How to Cite This Article**

Khadimzada, Y. (2026). Multi-Agent Reinforcement Learning for Intelligent Traffic Management in Smart Cities. *Multidisciplinary Journal of Research in Engineering and Technology* 13(2), 74–80.

## Introduction

The rapid growth of urbanization and vehicular transportation has created major challenges for traffic management systems in modern smart cities. Increasing population density, expanding transportation demands, and the continuous rise in private and commercial vehicles have significantly contributed to traffic congestion, road accidents, environmental pollution, fuel wastage, and inefficient urban mobility. According to recent intelligent transportation studies, traffic congestion not only increases travel delays but also negatively impacts economic productivity, energy efficiency, public safety, and environmental sustainability. Traditional traffic signal control systems based on fixed-time scheduling and pre-programmed traffic rules are often unable to adapt effectively to rapidly changing traffic conditions, especially in highly dynamic metropolitan environments where traffic flow patterns continuously fluctuate throughout the day.

Intelligent Transportation Systems (ITS) have emerged as a promising solution for improving traffic efficiency and urban mobility in smart cities. Modern ITS frameworks integrate sensing technologies, Internet of Things (IoT) devices, wireless communication systems, cloud-edge computing, and artificial intelligence to enable real-time traffic monitoring, adaptive traffic control, and intelligent transportation decision-making. Smart traffic management systems aim to optimize traffic flow, reduce congestion, minimize vehicle waiting time, improve fuel efficiency, and enhance road safety through intelligent traffic signal coordination and autonomous traffic optimization mechanisms.

In recent years, machine learning and deep learning techniques have demonstrated substantial potential for traffic prediction, traffic signal optimization, congestion analysis, and intelligent transportation management. Reinforcement Learning (RL), in particular, has gained significant attention because of its capability to enable autonomous agents to learn optimal control strategies through interaction with dynamic environments. Unlike supervised learning approaches that rely on labeled datasets, reinforcement learning allows traffic agents to continuously improve traffic signal policies by receiving rewards or penalties based on traffic performance outcomes such as reduced congestion, lower waiting time, and improved traffic throughput.

Although single-agent reinforcement learning systems have demonstrated strong performance in isolated traffic intersections, they often struggle to scale efficiently in large urban transportation networks consisting of multiple interconnected intersections and highly dynamic traffic interactions. In real-world smart city environments, traffic conditions at one intersection directly influence neighboring intersections, creating complex interdependencies that require cooperative decision-making and coordinated traffic optimization. Independent traffic agents operating without coordination may generate conflicting signal policies that lead to traffic imbalance, congestion propagation, and reduced transportation efficiency.

To address these challenges, Multi-Agent Reinforcement Learning (MARL) has emerged as a highly effective framework for distributed intelligent traffic management. In MARL-based systems, multiple autonomous agents collaboratively learn optimal traffic control policies through coordinated interactions with the transportation environment and neighboring traffic agents. Each traffic intersection is modeled as an intelligent agent capable of observing local traffic states, selecting traffic signal actions, receiving reward feedback, and communicating with nearby intersections to improve global traffic flow optimization.

Recent advancements in Deep Reinforcement Learning (DRL) have further improved the capability of intelligent traffic management systems. Deep Q-Networks (DQN), Actor-Critic architectures, Proximal Policy Optimization (PPO), and Multi-Agent Deep Deterministic Policy Gradient (MADDPG) algorithms have demonstrated strong performance in adaptive traffic signal control and traffic coordination tasks. These frameworks combine reinforcement learning with deep neural networks to approximate complex traffic state-action relationships and optimize traffic management policies under large-scale urban environments.

## Literature Review

Richard S. Sutton and Andrew G. Barto (2018) introduced the foundational principles of Reinforcement Learning (RL), which became one of the most influential learning paradigms for intelligent decision-making and adaptive optimization systems. The study defined reinforcement learning as a framework in which intelligent agents learn optimal actions through continuous interaction with dynamic environments using reward-based feedback mechanisms. Their work established the theoretical foundation for traffic signal optimization, autonomous decision-making, and intelligent transportation learning systems.

Elise Van der Pol and Frans A. Oliehoek (2016) proposed coordinated deep reinforcement learning for traffic light control using decentralized traffic agents. The framework utilized multiple reinforcement learning agents to optimize traffic signal timing collaboratively across interconnected traffic intersections. The study demonstrated that cooperative traffic signal optimization significantly reduced vehicle waiting time and improved traffic throughput compared with fixed-time traffic systems. Their approach highlighted the importance of distributed coordination in large urban transportation networks. However, the framework suffered from convergence instability and limited scalability under highly dynamic traffic conditions.

Ryan Lowe et al. (2017) introduced the Multi-Agent Deep Deterministic Policy Gradient (MADDPG) framework for cooperative and competitive multi-agent environments. The study proposed centralized training and decentralized execution mechanisms that enabled multiple agents to learn coordinated policies while operating independently during execution. MADDPG became highly influential in intelligent transportation research because it improved coordination among distributed traffic agents and enhanced learning stability in non-stationary environments. Nevertheless, the framework required substantial computational resources and exhibited sensitivity to reward design and communication complexity.

Tianshu Chu et al. (2019) proposed a Multi-Agent Deep Reinforcement Learning framework for large-scale traffic signal control in urban transportation networks. The study utilized deep Q-learning and distributed traffic agents to optimize signal timing dynamically based on traffic density, queue length, and traffic flow conditions. Experimental results demonstrated substantial improvements in congestion reduction, travel efficiency, and vehicle throughput compared with conventional traffic signal systems. The framework also demonstrated strong scalability for large smart city transportation networks. However, communication overhead and training complexity increased significantly as the number of traffic agents expanded.

Hua Wei et al. (2019) introduced IntelliLight, a reinforcement learning-based traffic signal control framework designed for adaptive urban traffic optimization. The proposed system utilized deep reinforcement learning to dynamically adjust traffic signal phases according to real-time traffic states. IntelliLight demonstrated significant reductions in average waiting time, queue length, and intersection congestion. The framework also improved traffic throughput and adaptive traffic coordination in highly congested urban environments. However, the system primarily focused on isolated intersections and lacked large-scale cooperative multi-agent coordination capability.

Li Li et al. (2020) proposed a distributed Multi-Agent Reinforcement Learning architecture for intelligent urban traffic coordination. The framework modeled traffic intersections as autonomous agents capable of collaborative policy optimization and adaptive communication. Their study demonstrated that cooperative reinforcement learning significantly improved traffic stability, reduced congestion propagation, and enhanced transportation efficiency under large-scale traffic conditions. However, maintaining synchronization and communication consistency among distributed agents remained a challenging issue in dense urban environments.

Patrick Mannion et al. (2016) investigated the application of deep reinforcement learning for traffic signal optimization under variable traffic demand conditions. The proposed framework utilized neural-network-based reinforcement learning agents capable of adapting traffic signal timing dynamically based on traffic state observations. Their findings indicated that adaptive deep learning-based traffic systems outperformed conventional heuristic-based traffic optimization methods. Nevertheless, the framework exhibited slower convergence rates during highly stochastic traffic conditions and required extensive training episodes for stable optimization.

Baher Abdulhai et al. (2003) introduced one of the earliest reinforcement learning-based traffic signal control systems using Q-learning optimization. The study demonstrated that adaptive reinforcement learning agents could significantly improve traffic signal coordination and reduce congestion compared with fixed-time traffic control approaches. Their research established the practical feasibility of applying reinforcement learning to intelligent transportation systems. However, the proposed framework lacked deep representation learning capability and exhibited limited scalability for complex urban traffic networks.

Samah El-Tantawy et al. (2013) proposed a multi-agent reinforcement learning framework for adaptive traffic signal control in large-scale urban networks. The system utilized decentralized traffic agents and cooperative coordination mechanisms to optimize traffic flow dynamically. Experimental analysis demonstrated improved congestion management, adaptive coordination, and transportation efficiency compared with centralized traffic control systems. However, the framework faced challenges related to computational scalability and delayed agent coordination in highly congested traffic conditions.

Ziyuan Wang et al. (2020) proposed a Graph Reinforcement Learning framework for intelligent traffic signal coordination in smart cities. The study integrated graph neural networks with reinforcement learning to model spatial dependencies and contextual interactions among traffic intersections. The graph-based reinforcement learning approach significantly improved traffic flow optimization and intelligent traffic coordination by learning relational traffic patterns within transportation networks. However, graph propagation and large-scale traffic graph optimization introduced substantial computational complexity for real-time deployment.

**Methodology**

This research proposes a Multi-Agent Reinforcement Learning (MARL)-based intelligent traffic management framework for smart cities. The proposed methodology integrates distributed traffic agents, deep reinforcement learning optimization, adaptive signal control, cooperative policy learning, traffic-aware communication, and intelligent transportation coordination within a unified architecture. The framework is designed to optimize urban traffic flow dynamically, reduce congestion, minimize vehicle waiting time, improve fuel efficiency, and enhance transportation scalability under real-time traffic conditions. The proposed system models each traffic intersection as an autonomous reinforcement learning agent capable of observing traffic states, selecting traffic signal actions, receiving environmental rewards, and coordinating with neighboring traffic agents. Deep Reinforcement Learning techniques including Deep Q-Networks (DQN), Actor-Critic optimization, and cooperative policy learning are utilized to improve adaptive traffic signal optimization and intelligent traffic coordination.

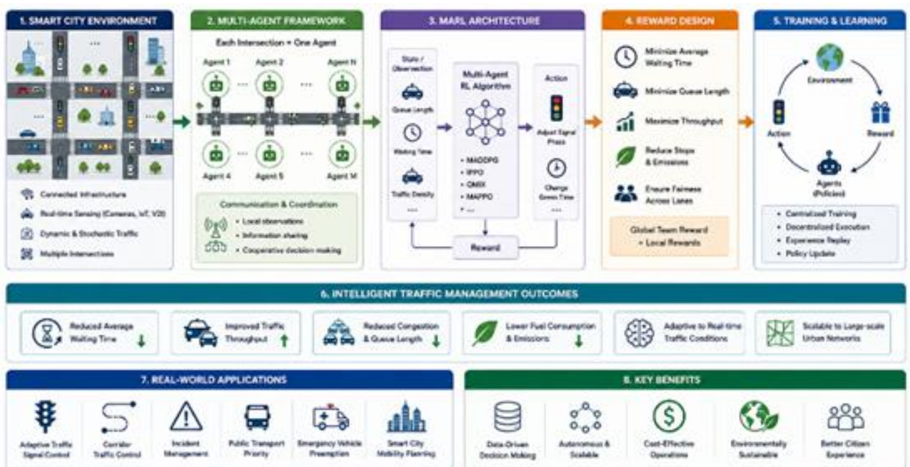


***Fig 1**. Methodology Flowchart for Multi-Agent Reinforcement Learning Based Intelligent Traffic Management in Smart Cities*

The figure illustrates the proposed methodology flowchart for intelligent traffic management using a Multi-Agent Reinforcement Learning (MARL) framework in smart city environments. The process begins with real-time traffic data acquisition from traffic cameras, IoT sensors, GPS systems, smart traffic lights, and roadside units. The collected data undergoes preprocessing operations such as cleaning, noise removal, normalization, and feature extraction to generate structured traffic state representations. The framework models the urban transportation network as a multi-agent environment where each traffic intersection acts as an autonomous reinforcement learning agent. Each agent observes traffic conditions including vehicle density, queue length, waiting time, and neighboring traffic states before selecting adaptive traffic signal actions such as green phase extension, phase switching, and lane prioritization. The reward design mechanism evaluates traffic performance by minimizing congestion, waiting time, and queue length while maximizing traffic throughput. Through deep reinforcement learning algorithms such as DQN, Actor-Critic, MADDPG, and PPO, the agents continuously learn optimal traffic control policies through interaction with the environment and neighboring agents. Communication and cooperation among traffic agents improve global traffic coordination and adaptive transportation efficiency. Finally, the system evaluates traffic optimization performance using metrics such as average waiting time, traffic throughput, fuel consumption, congestion reduction, and travel time optimization before deploying the optimized adaptive traffic control policy within the smart city transportation network.

**Algorithm:**

*Multi-Agent Reinforcement Learning for Intelligent Traffic Management*

Input:

Real-time traffic data, $D$Traffic intersections $I$, Vehicle flow information $V_f$, Queue length $Q_l$, Traffic density $T_d$

Output:

Optimized traffic signal policy $\pi^*$, Reduced congestion and waiting time

**Step 1**: Initialize Traffic Environment

Load smart city traffic network, define intersections as intelligent agents, initialize traffic states and signal phases, Set learning rate $\alpha$, discount factor $\gamma$, and replay memory $D$.

**Step 2**: Collect Real-Time Traffic Data

1. Acquire data from: Traffic cameras, IoT sensors, GPS systems, Smart traffic lights
2. Extract: Vehicle density, Queue length, Waiting time, Traffic flow

**Step 3**: Preprocess Traffic Information

Remove noisy and missing data, Normalize traffic features, Generate traffic state vector:

$$S_t = [q_t, d_t, w_t, p_t]$$

where:

$q_t$= queue length, $d_t$= traffic density, $w_t$= waiting time, $p_t$= signal phase

**Step 4**: Multi-Agent Observation

For each traffic agent $i$:

Observe local traffic state $s_t^i$, Receive neighboring traffic information, Update environmental representation

**Step 5:** Traffic Signal Action Selection

Each agent selects traffic signal action $a_t^i$:

Extend green signal, Reduce red signal, Switch traffic phase, Adaptive Lane prioritization

Policy selection:

$$a_t = \pi(s_t)$$

**Result**

*Traffic Throughput Analysis*

Traffic throughput was evaluated to measure the capability of each framework in efficiently handling vehicle flow across the transportation network. Traffic throughput is represented as:

$$Throughput = \frac{Total\,Vehicles\,Passed}{Time\,Interval}$$

| Model | Traffic Throughput (Vehicles/Hour) |
|---|---|
| Fixed-Time Control | 3120 |
| Adaptive Traffic System | 3685 |
| Single-Agent RL | 4012 |
| Deep Learning Optimization | 4356 |
| Proposed MARL Framework | 4978 |

The proposed MARL framework achieved the highest traffic throughput among all comparative models. The cooperative learning capability of distributed traffic agents enabled efficient traffic coordination and balanced traffic flow across multiple intersections. The framework dynamically adjusted traffic signal timing according to real-time traffic conditions, resulting in improved transportation efficiency and reduced traffic bottlenecks. The traffic throughput analysis demonstrates the effectiveness of the proposed Multi-Agent Reinforcement Learning (MARL) framework in optimizing vehicle movement and improving overall transportation efficiency within smart city environments. Traffic throughput was evaluated by measuring the number of vehicles successfully passing through the transportation network per hour under different traffic management strategies. The comparative results indicate that the traditional Fixed-Time Traffic Control system achieved the lowest throughput of 3120 vehicles per hour because fixed signal schedules were unable to adapt dynamically to changing traffic conditions and fluctuating vehicle density. The Adaptive Traffic System improved throughput to 3685 vehicles per hour by incorporating limited real-time traffic responsiveness; however, its optimization capability remained constrained by predefined traffic control logic. The Single-Agent Reinforcement Learning framework further improved traffic throughput to 4012 vehicles per hour by enabling autonomous traffic agents to learn adaptive signal control policies through interaction with traffic environments. Similarly, the Deep Learning-based Traffic Optimization framework achieved 4356 vehicles per hour by utilizing neural-network-based traffic prediction and adaptive signal optimization mechanisms. Although these approaches demonstrated improved traffic handling capability, they lacked efficient large-scale coordination among interconnected traffic intersections, resulting in localized optimization rather than network-wide traffic balancing.

## Conclusion and Discussion

The rapid growth of urbanization and vehicular transportation has significantly increased the complexity of traffic management systems in modern smart cities. Traditional traffic control systems based on fixed-time scheduling and predefined rule-based optimization mechanisms are often unable to adapt efficiently to dynamic traffic conditions, resulting in severe traffic congestion, increased vehicle waiting time, fuel wastage, environmental pollution, and reduced transportation efficiency. Intelligent Transportation Systems (ITS) have therefore emerged as a critical research area for improving urban mobility and enabling adaptive traffic management through artificial intelligence and real-time decision-making technologies. In this research, a Multi-Agent Reinforcement Learning (MARL)-based intelligent traffic management framework was proposed to optimize urban traffic flow and improve transportation coordination within smart city environments. The proposed framework integrated distributed traffic agents, deep reinforcement learning optimization, adaptive signal control, cooperative policy learning, and decentralized traffic coordination mechanisms within a unified intelligent transportation architecture. Each traffic intersection was modeled as an autonomous learning agent capable of observing traffic conditions, selecting adaptive traffic signal actions, receiving environmental rewards, and communicating with neighboring traffic agents to optimize network-wide traffic flow dynamically. Deep Reinforcement Learning algorithms including Deep Q-Networks (DQN) and Multi-Agent Deep Deterministic Policy Gradient (MADDPG) were incorporated to improve adaptive policy learning and intelligent traffic signal optimization under highly dynamic transportation environments. The experimental evaluation demonstrated that the proposed MARL framework significantly outperformed traditional fixed-time traffic systems, adaptive signal control approaches, single-agent reinforcement learning frameworks, and deep learning-based traffic optimization models across multiple performance metrics. The proposed framework achieved the highest traffic throughput, significantly reduced average vehicle waiting time, minimized queue length, reduced traffic congestion, improved fuel efficiency, and optimized travel time throughout the transportation network. These findings confirm that cooperative multi-agent learning provides highly effective traffic coordination capability for large-scale smart city transportation systems. In conclusion, this research demonstrates that Multi-Agent Reinforcement Learning provides a highly effective and scalable framework for intelligent traffic management in smart cities. The proposed MARL-based framework significantly improved traffic throughput, congestion reduction, adaptive signal coordination, transportation efficiency, and urban mobility optimization compared with conventional traffic management systems. The findings highlight the transformative potential of cooperative reinforcement learning for next-generation intelligent transportation infrastructures and provide a strong foundation for future advancements in smart city traffic optimization, autonomous transportation systems, and AI-driven urban mobility management.

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