INTELLIGENT TRAFFIC SYSTEMS WITH REINFORCEMENT LEARNING: USING REINFORCEMENT LEARNING TO OPTIMIZE TRAFFIC FLOW AND REDUCE CONGESTION

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Abstract

Globalization, rapid industrialization, and urbanization have led to ITS as a solution to solving the world's traffic problems. Traffic management is a significant factor in addressing traffic problems, including congestion, mobility, and environmental concerns. Among them, there is Reinforcement Learning (RL), which is a field of machine learning designed for creating adaptive solutions for traffic. While traditional systems use a preprogrammed way of handling traffic signals, vehicular routes, and other transport-related issues, RL can learn from real-time data and adapt traffic flow. This characteristic makes RL a revolutionizing technology in today's transportation systems as it is capable of adapting to new conditions on the roads. This paper is aimed at discussing the use of RL in ITS with regard to some of the algorithms, including Q-Learning, DQN, and PPO, in traffic signal control, route guidance, and traffic incidents. The workings of RL are further supported by success stories, such as the decrease in waiting times by 15% in Hangzhou, China, and the enhancement of travel times by 20% in simulated Manhattan. Some issues limit the use of RL-based ITS, such as computational difficulty, sizeability, and reliability of data. The paper also considers the ways to overcome these challenges and the future perspectives of the development, such as edge computing, the use of mixed models, and the integration into the smart city environment. RL-based ITS is set to become the future of city transport, providing effective, environment-friendly, and inclusive transport systems.

Keywords: *Intelligent Traffic Systems, Reinforcement Learning, Traffic Optimization, Dynamic Traffic Signal Control, Autonomous Vehicles, Multi-Modal Transportation, Computational Complexity, Data Reliability, Smart Cities, Proximal Policy Optimization, Deep Q-Networks, Traffic Congestion Reduction.*

1. Introduction

Road traffic congestion continues to be a current and increasing problem in cities and other accessible urban areas, which affects the economy and environment as well as the welfare of road users in general (Sweet, 2011). The number of vehicles increases day by day, and the traffic pattern is dynamic, which further results in system malfunctions in traditional methods of traffic control. These methods are conventional and rely on programs that schedule times when navigation has to happen or assume situations that can only be addressed heuristically in contemporary complex and fluid traffic conditions of urban systems. Because cities continue to grow and the need for transportation infrastructure continues to increase, such solutions must be more innovative and responsive at this very stage.

Intelligent Traffic Systems (ITS) have become one of the effective instruments for overcoming traditional approaches toward traffic management. Through the integration of real-time data acquisition and automated decision-making, ITS contributes toward the real-time dynamic adjustment of flow. While other systems are fixed, ITS is dynamic and proposes concepts to eliminate congestion and enhance other factors. The problem is that most of the mentioned ITS approaches remain to leave much to predefined programming, thus not depending on multilevel decision-making ability in addressing the intricate and diverse character of urban traffic networks (Alpcan & Başar, 2010).

Another exciting branch of machine learning that has been embraced recently as a revolution in ITS is Reinforcement Learning (RL) (Sornette, 2008). RL systems communicate with their surroundings, adapting to learn how to choose from available sets of actions based on the feedback in the form of reward or penalty. The capability to modify and enhance the performance of decision-making without depending on programming makes RL more appropriate for traffic situations that are tough and volatile. Due to RL's ability to update its function according to current data input, RL applied to traffic management can effectively achieve goals not possible before (Bazzan, 2009).

Another major feature of RL is the ability to quickly and efficiently operate in large-scale and ever-changing environments. By applying learning cycles, RL agents can select the best strategies for controlling the traffic flow at single junctions, in interconnection, and in case of an unforeseen disturbance. Because of this flexibility, RL is an invaluable part of the next-generation ITS since it can solve short-term and long-term traffic problems. The integration of RL into the ITS concept is likely to change the existing concept into a more effective, scalable, and sustainable one in the urban environment.

This paper aims to review the use of RL in ITS with emphasis on the operational principles, methods of deployment, and effectiveness in real life. Based on case studies and looking at the issues, including computational and data-related ones encountered by RL-based ITS today, the discussion exposes the current functioning of RL-based ITS and its prospects. Thus, it underscores the need to persist with advances in ideas as well as partnerships to enhance the promising RL of traffic congestion in urban areas.

Figure 1: Urban Transport Challenges

2. Reinforcement Learning: A Brief Overview

2.1 Key Components of RL

Reinforcement Learning (RL) is dependent on five facets to run its function optimally. The first one is the agent, the decision maker like a traffic signal controller who learns patterns on the road (Mukherjee et al., 2010). Second is the environment, specifying the external setting that the agent is in, for instance, a traffic network. The state represents the current configuration of the environment, for example, the number of cars that are at an intersection. The action is an initiative that the agent takes to influence the decision-making process; for example, occupying authorities have to change the traffic signal timings, which is an action. Collectively all these components afford the learning of good behaviors to the agent.

The learning process is continuous and cyclic. To clarify this, the agent constantly perceives the current status, chooses an action to take, and gets a corresponding reward result from the corresponding action. This reward plays an informative role in giving feedback to the agent about the result of its decision-making. In the process, the agent aims at attaining the best sum of rewards, thus enhancing the decision-making strategy. This paper expounds that dynamism is important in RL in its application to traffic systems. Looking at the definition, RL is different from static programming in that it carries on learning throughout, thereby updating itself when the environment changes. That is, for example, if traffic volumes grow more than anticipated, the agent can change its actions in real-time to respond to such changes. That is why the RL can be particularly useful in complex and stochastic environments.

The second benefit of RL's component-based design is flexibility. All of the system's components can be configured to meet certain needs or requirements (Salehie & Tahvildari, 2009). This is specifically possible using the state representation, where reinforcement learning can scale up or down the environment right from an intersection of the road to the traffic network of an entire city. This flexibility helps to ensure that RL systems are fully operational and efficient across different contexts. One can state that RL is rather systematic but always open to changes, so it is ready to solve real-world problems of a different nature—for example, traffic jams. Through training, RL formulates and performs more sophisticated traffic interaction strategies than conventional traffic management systems.

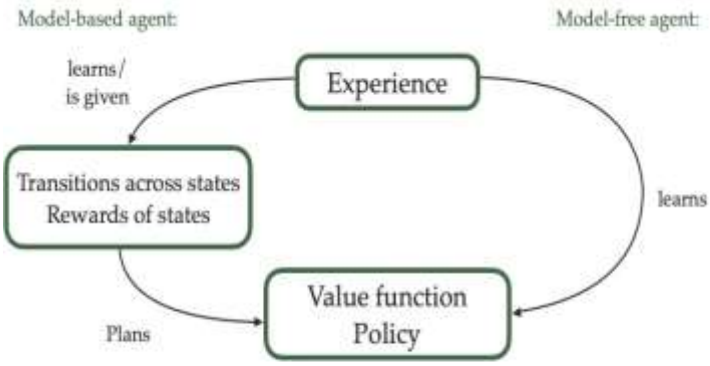

Figure 2: Basic principles of Reinforcement Learning (RL).

2.1 Key Components of RL

Table 1: Key Components of Reinforcement Learning and Their Role in ITS]

Component	Definition	Role in ITS
Agent	Decision-making entity	Controls traffic signals or dynamic routing
Environment	The external system interacting with the agent	Urban traffic network, including vehicles, pedestrians, and signals
State	Current configuration of the environment	Represents the number of vehicles, road conditions,
Action	Initiative taken by the agent	Adjusting traffic signals or rerouting vehicles
Reward	Feedback for an action taken	Minimizes congestion or optimizes travel time

2.2 Popular RL Algorithms

A number of RL algorithms have central or crucial functions in Intelligent Traffic Systems. One of the more fundamental and simple methods common in the field is Q-learning. It helps an agent understand the value of taking specified actions in provided states. This method works effectively in simple environments because it has an added weakness: scalability in complex systems (Aström et al., 2011). DQN was designed to improve Q-learning, where deep neural networks were used to handle large and continuous state actions. This innovation enables DQNs to handle the high-dimensional traffic data typical for real-world urban systems. From the defined raw traffic data, DQNs can learn directly, which makes them quite efficient in a number of decision-making cases.

Unlike what is employed in types of policies such as Q-Learning, Policy Gradient Methods directly estimate policies. It makes them especially appropriate to cases with continuous action spaces, such as fine-tuning traffic signal timings diligently. Despite the high complexity of policy gradient methods, their application for refined traffic control is justified. Among other algorithms that can be used in traffic systems is Proximal Policy Optimization (PPO). PPO significantly maintains stability and efficiency of learning by addressing the exploration and exploitation dilemma. This balance is very important in uncertainty-high conditions like traffic nets, whereby exploration to excess may lead to losses of net resources while partial exploration may cost society potential gains (Re, 2010). Multiple agents in RL techniques, like multiple intersections' traffic signals, can be implemented. These algorithms optimize decisions at the network level as opposed to the intersection level, enhancing network-wide traffic flow. The distributed structure is useful to increase the scalability and availability in the problematic traffic system.

Table 2: Comparison of RL Algorithms Used in ITS]

Algorithm	Characteristics	Scalability	Use Cases in ITS
Q-learning	Simple, learns action-value pairs	Limited	Simple traffic intersections
DQN	Uses deep neural networks for complex states	Moderate	Large-scale traffic management
Policy Gradient	Directly optimizes policy in continuous spaces	High	Fine-tuning signal timings
Proximal Policy Optimization (PPO)	Balances exploration and exploitation	High	Multi-agent systems for networks

2.3 Benefits of RL in Traffic Systems

RL provides innovative solutions that are more optimal for traffic management than conventional strategies. Requesting further differentiation from other dynamic systems, such as Static systems, RL is capable of adapting to changes taking place in real-time traffic. This ability inherently minimizes car density and underwriters' crowded scheduling to enhance uniform traffic throughput along variable conditions. One highlight of RL is its capability to deal with uncertainty. For instance, during a crash or even a road blockage, the RL systems activate or propose new routing paths. Such a responsive approach reduces interference and enhances productivity in an organization.

RL also incorporates optimal control of traffic, lights, interconnection, and routes on networks. As such, RL is able to learn traffic patterns and thus find solutions to minimize waiting times and travel distances. In these areas, Multi-agent RL improves these capabilities, making it possible to coordinate and consequently decide from intersects. RL systems always improve due to their capability of learning. They can respond to permanent shifts, including new patterns of traffic flow resulting from changes in city planning. This ensures that RL-based systems are constantly accurate and do not need frequent manual data updates as in static systems (Xu et al., 2012). RL can also improve sustainable conditions by minimizing fuel utilization and emissions. By reducing idle times and unnecessary stops, RL systems' implementation also affects the conservation of the environment along with the operational gains.

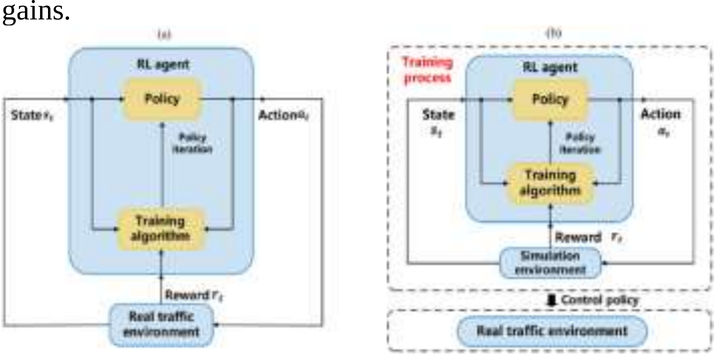

Figure 3: **Leveraging reinforcement learning for dynamic traffic control**

2.4 Scalability and Flexibility

The feature of scalability allows RL for the operation of subsequent and intricate traffic systems. In areas with complex intersection connections in high-population density areas, the coordination of traffic signals is controlled by collective RL systems at the agent level. This way, decentralization guarantees that the system's scalability does not affect its efficiency (Croman et al., 2016). The variables of RL make it convenient for handling different traffic situations. RL algorithms can be applied for simple intersection management and for the management of complex city traffic networks simultaneously. This guarantees the applicability of the findings in urban, suburban, and rural contexts.

A third advantage of RL is its scalability, which is characterized by the proper management of all resources. RL systems do not centralize control for every intersection, as opposed to traditional systems that demand integral computational tasks. This cuts down computational costs and ensures fast decision-making as a result of interaction between man and machine. Another aspect of flexibility is still related to integrating with other technologies. RL can work with IoT devices, self-driving cars, and smart City structures. This fosters effective integration between the various means of transport, making each more efficient (Suzuki et al., 2013). The possibilities of RL's usage and availability contribute to its significant influence on modern traffic systems. To this extent, RL achieves such flexibility and adaptability to accommodate various environments and technologies for effective, efficient, reliable, and sustainable traffic management.

Figure 4: The agility edge

2.5 Significance in ITS

Reinforcement Learning (RL) has triggered a paradigm shift in traffic management within urban environments. By leveraging real-time decision-making and advanced algorithms, RL-based systems minimize traffic congestion, reduce delays, and enhance road safety (Peng et al., 2012). The ability to dynamically adapt to traffic patterns is a critical improvement over static systems. For instance, RL's adaptability supports systems in responding to dynamic urbanization trends and unpredictable traffic surges, thus showcasing its potential to revolutionize urban mobility (Nyati, 2018a).

By promoting congestion cost reduction, RL-driven ITS systems enhance economic benefits. Reducing car traffic congestion results in time savings, fuel conservation, and reduced operating costs for both businesses and citizens in their business activities. Another important effect of RL-based ITS is the gain in environmental sustainability. Efficient traffic distribution decreases fuel utilization and air pollution, thus playing a role in maintaining sustainable urbanization around the world. Such systems are central to addressing climate change and sustainable urban development solutions. As the above points evidence, the flexibility inherent in RL positively contributes to public safety (Reuben & Riedl, 2013). By avoiding traffic interruptions and the consequent traffic jams, RL decreases the chances of accidents and congestion-related delays in providing emergency services. Its proactive approach guarantees safer transport systems for all stakeholders. The incorporation of RL in ITS can be seen as a breakthrough in the concept of planning in urban environments. This paper has demonstrated that through the principles of adaptability, efficiency, and sustainability, RL-based ITS systems solve the problems of modern transportation systems and provide a foundation for intelligent urban development.

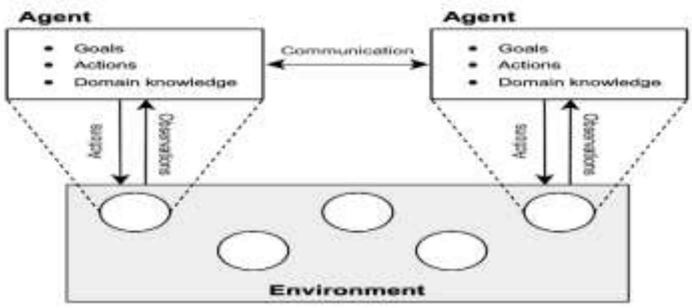

Figure 5: Multi Agent RL approach to traffic Management

3. Applications of RL in Intelligent Traffic Systems

3.1 Traffic Signal Control

The fourth one is about Traffic Signal Control, which has been improved by applied Reinforcement Learning (RL) and can then vary the traffic signal control in line with real-time traffic information. The global traffic signal is based on the preprogrammed cycle time, which has grown to be inferior when traffic flow patterns vary frequently. RL-based systems utilize actual traffic patterns to control signal phasing and timing with the intention of facilitating traffic and congestion minimization. This characteristic makes RL a much better strategy than that of managing fixed signals. Once implemented, multi-agent RL systems also supplement traffic signal control by yielding trusted results. It is like having individual actors in a framework; each traffic signal interacts with the others to maximize traffic within the network. These systems also mean that intersection control decisions produce fewer bottlenecks and guarantee consistent traffic flow across the network. This approach of decentralization enhances scalability, and the robustness of the plan is further enhanced. Among the applications of RL, one success story involves its use in Hangzhou, China. By applying the approach based on recycled machine learning using traffic signal control, the city was able to decrease the average waiting time during rush hour by 15%. In this paper, RL proves it can cater to urban intersections that receive traffic congestion, hence improving the commute and the environment.

RL systems are also capable of learning dynamic changes in traffic patterns over time. These include changes due to the development of an urban area, different seasons, or road construction (Weng, 2012). Through learning, RL guarantees that signal control strategies remain current and efficient. This capability demonstrates its value in applying the system for sustained traffic control in cities. Traffic light networks promoted by reinforcement learning reduce the time a car might be idle at an intersection. Decreased idle time accounts for savings in fuel and emissions that answer goals set for making urban settings more environmentally friendly. The twofold advantage of operation and the RL aspect make it a revolutionary optimization instrument in current traffic signal schemes.

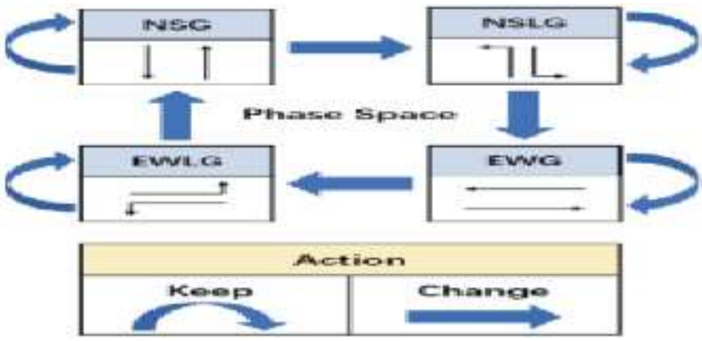

Figure 6: Large-Scale Traffic Signal Control Based on Integration of Adaptive Subgraph Reformulation and Multi-agent Deep Reinforcement Learning

3.2 Dynamic Traffic Routing

Dynamic traffic routing systems powered by RL algorithms significantly improve the efficiency of road utilization. RL systems, informed by IoT devices and real-time traffic sensor data, optimize traffic flow by distributing vehicles evenly across networks. A case study in Manhattan demonstrated a 20% reduction in travel time, reinforcing RL's role in reducing travel uncertainties and enhancing commuter experiences (Kumar, 2019). This adaptability offers measurable benefits to logistics and fleet management, aligning closely with innovations in asset tracking and efficiency (Nyati, 2018b).

RL algorithms incorporate real-time traffic sensor data as well as GPS and other temporal data, and patterns that have occurred at the time of routing. These systems find out which roads are empty and send vehicles to those roads in order to distribute traffic evenly throughout the network. This not only saves a considerable time in traveling but also eliminates overcrowding some of the routes which would lead to early fatigue of some parts of the transport system. The implementation of RL-based dynamic routing was previously demonstrated through a simulation in Manhattan. A trial showed that this system can improve average travel time by 20% by re-directing traffic away from saturated arterials. Such outcomes prove that RL can help set cities for the new traffic control system, mainly in the megacities.

Another advantage of RL in dynamic routing is that this technology adapts well to route disruptions (Qadir, 2016). Delays arising from road closures, accidents, or bad weather can be handled by redirecting traffic in real-time. This capability helps to avoid delays and makes the overall management of transport systems more reliable. RL helps enhance commuter experiences by minimizing uncertainty. The shorter and quicker routes displayed reduce variability and uncertainties associated with total travel time. This improves service reliability, particularly in logistics and freight services, where timely delivery is of the essence.

Figure 7: Traditional IoT scheme for smart agriculture.

Table 3: Benefits of RL-Based Dynamic Traffic Routing Systems]

Benefit	Description
Reduced Travel Time	RL-based routing minimizes delays by avoiding congested areas
Balanced Road Utilization	Distributes vehicles evenly across the network
Improved Fuel Efficiency	Reduces unnecessary idling and detours
Enhanced Environmental Outcomes	Decreases greenhouse gas emissions

3.3 Incident Management

The disruptions that are the outcome of an accident, construction, or emergency must be managed and rectified just as swiftly and efficiently as possible. The systems based on RL prove their superiority in handling incidents due to their ability to produce an output of responding quickly and with the best strategy. These systems alter signals, divert cars, and give way to emergencies in order to keep traffic moving even in the face of disruptions. RL systems rely on traffic information and incident data acquired from traffic sensors to identify disruptions in real-time (Abidin et al., 2015). Indeed, by defining the areas of concern and approximating the extent of congestion, RL can devise ways to ameliorate the problem. Some of the measures taken to avoid delays include changing traffic lights or guiding vehicles to other lanes.

An example of how RL was implemented was in London, where a simulation was done to operate through traffic interruptions. In any incident scenario, the RL systems proved to be most effective in reducing traffic congestion to a quarter of the usual options. This demonstrates the operational aspect of RL in scenario navigation, where it deals with difficult issues in actual-time rush traffic systems. Between them, the addition of RL to other conventional systems used for incident detection results in improved results. For example, integrating RL with artificial video analysis or IoT devices enhances the development of exact responses and faster identification of significant events. This cooperation guarantees timely interferences and eliminates disturbances. Artificial RL techniques for incident management improve public safety by handling emergencies effectively. These systems ensure faster access for emergency vehicles passing while rerouting general traffic, thus optimizing general traffic flow. These two foci of RL epitomize how RL is important for traffic management in cities.

3.4 Autonomous Vehicle Coordination

The incorporation of RL into AVs improves their cooperation within traffic systems. RL allows AVs to act and adapt to road conditions to make the best possible decisions regarding their movement, thereby helping to eliminate possible traffic jams. RL integrated with autonomous cars allows vehicles to learn from the situation, including merging on or at intersections. Another value of RL in the relative control of AVs is platooning, in which vehicles closely follow each other for better flow and fuel consumption. For speed and spacing, RL algorithms apply the best suitable space and speed that would be reasonable to apply without compromising the energy issue. It also minimizes emissions and the use of fuel, hence, it is environmentally sensitive.

Studies done before have indicated that RL models integrated with AVs can enhance the flow of traffic within roads. For example, fuel consumption was reduced by 10% when the AVs used RL to coordinate with each other. Such an improvement also indicates not only the growing efficiency of operations in civil aviation but also the possibility of reducing the costs of transporting goods and passengers. RL also assists in the assimilation of AVs into existing traffic systems. In collaboration with conventional cars and the road network, RL guarantees that AVs are integrated appropriately into mixed unstable traffic. This seamless integration avoids disruptions and enhances the deployment of autonomous solutions. RL-fashioned AVs increase resilience as they are capable of responding and mitigating possible crash-causing events. Unlike human operators who act in the aftermath of an occurrence of an incident, these systems proactively make decisions based on traffic flow data and likely incidence history. These factors include safety, productivity, and environmentalism, all of which make RL a keystone to the future of autonomous transportation.

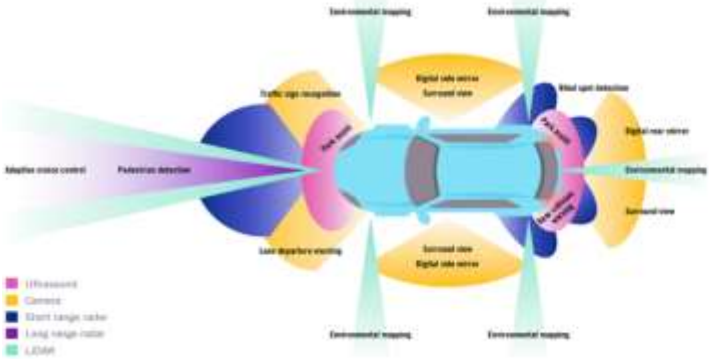

Figure 8: **Connected and Autonomous Vehicles and Infrastructures**

3.5 Multi-Modal Traffic Integration

RL does not only apply to vehicular traffic but also to transportation systems on roads for both human and goods transport, including pedestrians, cyclists, and public transport. Complimented by the gap created by the regular adjustments of traffic signals and the synchronizing of schedules, RL enhances intermodal interaction. This approach improves mobility in general across cities. To customers using pedestrian and cycle facilities, RL enhances phasing at intersection systems to minimize waiting time and enhance safety. Using data related to pedestrian traffic flow; the RL systems select crossings during times of maximum traffic. This way, the road network is balanced for citizens of any category. This focus helps improve the development of friendly environments for pedestrians more than anything else.

RL-based optimization also applies to public transit. Through operations that align traffic signals with buses and/or trams, RL contributes to improving transit reliability by managing and limiting delays. This promotes public conveyance transport, hence reducing traffic jams and protecting the environment. It also implies that RL with smart city systems further improves the proposals' intermodal coupling. For instance, through sensors in IoT, information on the locations of transit vehicles, the movement of pedestrians, and the conditions of the roads can be obtained in real-time. Behavior RL systems utilize this data to make further decisions that would facilitate the transport of all transit modes. RL has shown that it aids in the optimization of the urban population's needs as a city. Often, RL helps to optimize needs flow in transport systems, paying attention to cars, pedestrians, and public transportation at the same time. Thus, the proposed multi-modal concept allows making mobility systems in cities efficient, safe, and equally suitable for everyone.

4. Challenges and Limitations

4.1 Computational Complexity

The tasks in training RL models for city traffic systems are the huge state-action spaces, which increase computational complexities (Aslani et al., 2018). Large traffic networks include many intersections, vehicles, and uncertain events for modeling, making them a high-dimensional space. This complexity has to be worked on by RL algorithms in real-time, which presents a major challenge in terms of the actual implementation of the algorithms. Algorithms are essential in combating computational needs such as Knowledge graph construction and Reasoning Engines. For example, Hierarchical RL decomposes complex issues into several problems to reduce the number of computations made. Likewise, the number of states becomes manageable through the use of approximate methods and function approximation, such as neural networks.

They state that hardware significantly enhances the decrease of computational constraints (Wang et al., 2017). Implementing RL models with high-performance GPUs and TPUs allows training models at a much faster rate, and Edge computing helps reduce the burden on central servers. Such technological innovations are imperative to scaling RL systems to the optimum level. Another problem is the time needed for training. RL models may take significant time to reach optimal policies because of the training time in large-scale simulations. This delay slows the implementation of RL-based traffic systems, thus requiring the creation of new and faster learning algorithms. The fact that these models should be as computationally complex as needed without being too high to be applied in the real world must be taken into account. RL systems must be capable of combining the computational speed of a real-time system with adequate performance. These balances facilitate their applicability for additional large-scale implementation into urban traffic systems.

Table 4: Computational Challenges in RL-Based ITS and Solutions

Challenge	**Description**	**Proposed Solution**
Large State-Action Spaces	Urban networks involve high-dimensional data	Hierarchical RL, Neural Network Approximation
Real-Time Processing	Requires quick decisions for dynamic traffic	Edge computing, High-performance GPUs
Training Time	Prolonged training delays deployment	Transfer learning, Faster RL algorithms

4.2 Data Collection and Data Reliability

The quality of information used in RL techniques is the key to productive ITS applications. These applications require data collected in real-time from sensors, cameras, and IoT devices to assess traffic conditions and make proper decisions. However, maintaining the reliability of the data gathered is difficult. It is normal to have issues with the sensors and the readings, especially in urban areas. Environmental conditions, installations' interference, or technical difficulties may weaken the collected data's quality and, therefore, affect the RL model. These problems are solved by using fully redundant data feeds in the system and proper error-handling techniques. Delayed data transmission can also cause system inefficiency. Some capabilities can still be well supported by RL systems, provided that the data feed is as near real-time as is needed for decision-making. When receiving and processing this information is delayed, the actions taken will not be optimal, and such inefficiencies in traffic control may occur.

Another factor is the preservation of data and its confidentiality, which is an important concern. Traffic systems gather massive amounts of data, some of which may contain confidential information. While collecting and sharing information, it is important that data pass through a secure channel and be stored safely to maintain public confidence and protect systems from breaches of privacy laws. Reducing variations in data collection across multiple settings in diverse urban settings is likely to be difficult. The maturity of various cities with respect to the establishment of relevant infrastructure and the availability of corresponding measurements can substantially differ. These variations can be minimized by developing standard protocols for field data collection and integration that will allow RL systems to perform satisfactorily across different terrains.

4.3 Scalability

As much as RL approaches have proven effective and flexible in certain simulated environments, they struggle when applied to huge, realistic cities. Currently, large-scale city traffic systems involve thousands of intersections with their traffic characteristics, which poses a problem for the RL-based ITS solutions scalability issue. It is also predicted that currently developed RL models have the drawback of lack of generality when trained in one environment or a certain type of problem. RL algorithms learned on certain traffic regularities can find it difficult to perform well under different traffic dynamics, say, working in different cities or regions. For instance, transfer learning and domain adaptation are some of the modern approaches that can ensure that RL models will be generalized.

To overcome the problem of scalability, the inherent decentralized structure of multi-agent RL holds a hint of a solution. Thus, if the decision-making is decentralized among multiple and different agents, such as intersections, then the problem can be better solved at scale. Nevertheless, since these agents must work in a coordinated manner without coming to contradictory decisions, such coordination is an issue that is not easy to solve. Demand for computational resources rises with system scale, too. That is why, as the size of the traffic networks increases, the requirements for processing power and memory also increase. The scalability of the RL models and their hardware are key determinants in sustainably addressing the computational load that results from deploying large-scale RL models (Ibrahim et al., 2018). Two resources have to be taken into account when scaling up—resource utility and the performance of the system. Growing an RL system to something larger, say across a network of cities or states, should not come at the cost of real-time accurate traffic management. Maintaining this balance is critical to the implementation of RL in large, dense urban areas.

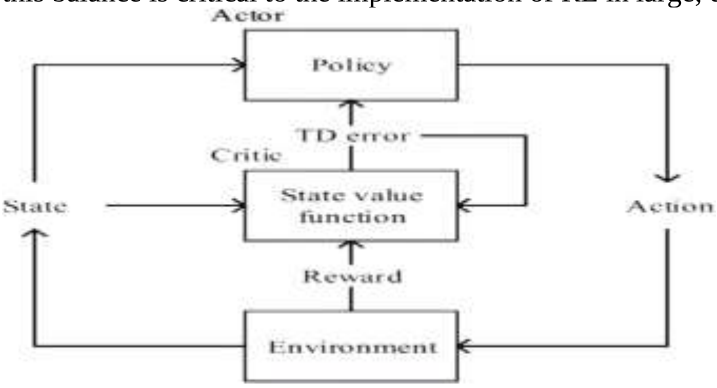

Figure 9: The framework of the actor-critic method

4.4 Safety and Testing

Safety and reliability are critical when implementing RL technologies in traffic control systems. Due to this, RL algorithms, especially in their learning exploration phase, may make strange or risky decisions. Preventing such difficulties in actual implementations requires strict performance and quality assurance. Practical settings are useful in evaluating the effectiveness of RL systems, and these are testing grounds. When real traffic data and disruptions are mimicked, a developer can assess the effectiveness and functionality of a system before it is implemented. Authentic simulations where a stimulus or situation is as close as possible to real life are especially ideal for this task.

Simulation can, therefore, be used in developing practical strategies because actual-life scenarios have to be improvised to counter any real-life experiences that may arise. However, such testing comes with certain challenges, even at the preliminary stages of operation. These risks can, however, be avoided through slow and steady introduction, such as the use of RL in managing a few intersections before scaling up to an entire city. Safety maintenance applies to system failures. There must always be circles of safety that prevent a breakdown of traffic management when the RL model is in a group, let alone when it has crashed. As part of contingencies, organizations should incorporate overlapping systems and solutions, including manual traffic control methods. Safety and reliability are the last aspects that are associated with the level of trust of the population in RL systems. Most stakeholders, including patients and healthcare providers, require assurance when it comes to the testing processes as well as the measures put in place to protect them from harm. if it is a diagnostic test, then they need to know the performance of such a test before they fully embrace it.

4.5 interfacing with other systems

Integration of the RL-based systems with currently available highway traffic management systems presents a challenge. Many traffic systems in big cities are based on old hardware and software that cannot support modern ML-based AI solutions and services, so compatibility challenges exist. The adoption of RL on legacy systems demands significant capital outlay investment. This includes changing old traffic signals, using innovative sensors, and enhancing signal communication protocols. Such upgrades are usually expensive as it may take a lot of time to upgrade the infrastructure, especially in large cities.

At the same time, stakeholders' resistance can also be a problem for integration work. This is especially so because municipal authorities, policymakers, and traffic management personnel may avoid RL for lack of acquaintance or fear that new methods will cause traffic problems. Therefore, education and pilot options are important in responding to and addressing those concerns to achieve integration. Coordinating the format of the messages that pass between RL systems and more traditional components may also help. This is possible through interfaces that integrate RL models with the existing physical infrastructure in the city to introduce AI in traffic management functions gradually without having to rip off the entire system. There's a need to ensure that the integration process is well coordinated so that it doesn't interfere much with normal process flows. A stepped approach that starts with simplified RL system applications in specific locations with high-risk levels allows cities to manage the RL systems while preserving traffic patterns and public trust.

5. Future Directions

5.1 Hybrid Models

The use of RL in conjunction with other machine learning approaches offers the potential for the development of enhanced traffic management systems. When using supervised learning, RL models could incorporate some pre-conditioned data that one wanted the system to learn during certain epochs of training. This is effective in facilitating learning as it does not let the learning rely on trial and error mode, especially in traffic scenarios within a course. They also enrich RL in terms of providing various solution strategies while functionally differing from it (Graves et al., 2016). These algorithms imitate the NS processes for choosing traffic management policies, which can be further optimized with RL. Their combination provides greater reliability and flexibility to the system, which can effectively respond to different traffic situations.

The hybrid models are quite relevant in the case of complex traffic systems that involve several separate agents. Thus, while hybrid systems combine rule-based decisions and RL, minimum performance is always guaranteed during exploratory phases. For example, if RL policies are still being trained, then traffic lights can work in a fixed manner, adhering to a certain set of rules. This is important as it overhauls the reliability of the entire system and reduces interferences. This is also true for incorporating dimensionality reduction techniques in the hybrid models to solve computational complexity (Fahimi et al., 2017). These techniques reduce large state-action spaces in RL, thus making it faster by consuming several instances of time and resources. These benefits are highly relevant for large-scale deployment in urban environments since computations are required. Traffic management is also more flexible in hybrid models as its strength. That is why, by using the principle of the integration of the Use of Multiple Para-Demographic approaches, these systems can cope with a variety of situations, from regular traffic control to emergencies. The usefulness of hybrid models in this way makes them crucial in the development of the next-generation Intelligent Traffic Systems (ITS).

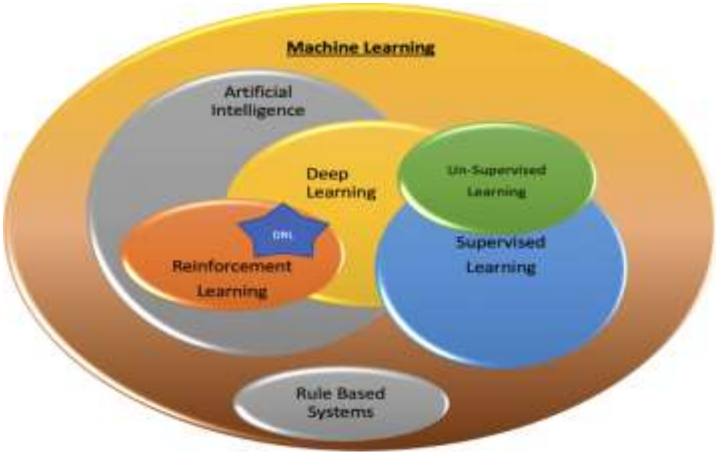

Figure 10: Relationship and overlap between DL, RL, DRL

5.2 Transfer Learning

Adopting transfer learning enhances the scalability and effectiveness of incorporating RL to optimize traffic systems (Ayesha et al., 2020). Through knowledge transfer or transfer learning, traffic management systems can operate in new environments with less training. This approach is very useful for big networks in the urban environment because training RL models are computation-intensive when done from scratch. Pre-trained models make it possible to deploy new RL systems quickly in cities with similar traffic conditions. For example, the model developed in one metropolitan location can be easily reapplied to another. This adaptability enhances implementation and reduces the cost of data collection and training.

Transfer learning also aptly solves the issue of the limited data present in less developed regions. It can be seen that through the transfer of knowledge from the models trained on traffic data-rich scenarios, the RL systems are capable of functioning optimally even in zones with limited traffic data. This capability enhances the general approach and ITS expansion to consider diverse possibilities. In addition to boosting efficiency, transfer learning also has the advantage of being able to transfer from one traffic situation to another. The learned policies from multiple environments are applied by incorporating them in pre-trained models, and they adapt well since they are developed to cope with variations in response, such as seasonal traffic, road infrastructure, or the behavior of other road users. It is always preferable to overgeneralize to strengthen the backup RL systems, as in this case. Transfer learning helps to maintain the system always improving. When new data from the deployment environment are incorporated into pre-trained models at proper intervals, traffic systems are able to change with time conditions prevailing within their environments. This makes the process of traffic flow management within urban networks permanent and highly effective.

Figure 11: **Transfer learning for smart buildings**

5.3 Edge Computing and IoT

RL applications with edge computing and the IoT allow decentralized decision-making on traffic systems in real-time. In edge computing, data analysis takes place at the edge to free up the servers from handling oppressive loads and reduce delays. This is important, particularly for RL-based ITS, since quick reactions to changing traffic signals are often required. Many physical IoT devices, such as connected sensors and vehicles, furnish the raw data required for decision-making in RL algorithms. These devices capture and relay data on the number of vehicles and pedestrians, speed, and incident occurrence to generate a traffic image. They conduct such analyses to improve traffic flow and minimize congestion in RL systems.

Distribution of the major decision-making process to the edges of the network promotes system integrity. However, in circumstances of network disruptions or server failure, the edge devices are capable of working autonomously. This is because the layers ensure that traffic continues to be managed while at the same time minimizing the risks of large-scale system failure (Bennis et al., 2018). Due to its great scalability, edge computing is applicable in large cities. This means that instead of closely relying on central servers, the management of computational tasks is distributed among these edge devices. This structure also allows for the development of local optimizations so RL systems may respond to specific traffic problems in real time (Xiao et al., 2021). Integrating RL, edge computing, and IoT enables the creation of smart city ecosystems. This means that through the proper interconnection of traffic systems in a city with other city facilities, including energy and transport systems, greater efficiency and sustainability are obtained. This synergy provides strong evidence for RL-based ITS improvement via edge computing.

Table 5: Edge Computing and IoT Integration for RL-Based ITS

Feature	Edge Computing Contribution	IoT Contribution
Real-Time Data Analysis	Decentralized processing for quick decision-making	Provides real-time traffic data via sensors
Resilience	Ensures continued operation during failures	Offers diverse data sources
Scalability	Supports large urban networks	Enables interoperability with other systems

5.4 Collaboration in Smart Cities

Integration within smart city projects helps to make the RL-based ITS work more efficiently due to increased cooperation regarding data sharing and infrastructure. Since the existing city environment is very complex, there is always an opportunity to apply traffic systems, public transit, and urban planning solutions. Data sharing is one of healthcare organizations' major collaboration tools. By absorbing information from traffic sensors, weather stations, and public transport agencies, RL systems get the big picture of urban processes. From this broader view, it is easier and more effective to manage traffic patterns.

Integrating RL-based traffic signals with public transportation timings helps in getting through traffic better. Since the RL system prioritizes buses or trams at the intersection, hoping they will cause less delay and encourage the public to use transit instead of cars, it will help decrease road congestion (Shalaby et al., 2021). Such integration is also in line with other trends for the sustainable development of urban environments. Only in cooperation with initiatives in urban planning can sustainable traffic optimization be achieved over the lifespan.

These initiatives can also help unveil the density and other characteristics of traffic that can be useful for choosing the place for infrastructure development. This results-oriented approach guarantees the development of future roadways and transit systems that respond to the growing needs of urban dwellers. Smart city collaborations also promote Innovation because they are a collective endeavor of different organizational fields. Authorities at the municipal level, technology providers, and academic institutions can come together to support RL technologies. Such partnerships define advancement and create the environment for the development of smarter and more integrated cities.

5.5 Other Species, Ethics, and Policies

Ethical considerations in RL-based ITS revolve around ensuring fairness and transparency in system design. RL systems must prioritize inclusivity, ensuring accessibility for diverse road users, including pedestrians and cyclists. Clear policy frameworks and interpretability mechanisms help in aligning RL technologies with public trust and legal compliance (Gill, 2018). Additionally, these systems must ensure data privacy and uphold ethical principles, as highlighted in innovations within real-time data systems in other domains.

Another ethical consideration is that most business organizations ought to be clearer regarding the thought processes adopted in various crucial decisions they are bound to make. RL systems should also be interpretable so that any of the stakeholders might understand how particular decisions regarding traffic management are arrived at. This makes it easy for those using the artificial intelligence systems to have faith in the systems and also makes the systems to be accountable. One of the most important criteria for using RL-based traffic systems is fairness. These systems should not contain biases that may negatively favor or hinder some communities or means of transport (Mattioli et al., 2020). For example, if the design decision prioritizes the automobile over crosswalks, it will compromise accessibility principles. Equal and efficient measures mean that all classes of road users reap the benefits from enhanced traffic flow.

These frameworks are used to facilitate RL system development and application and are, to a large extent, legal frameworks. There should be policies regarding innovation, but these policies should take into account risks and ethical issues; existing guidelines involve testing and implementation of the system, as well as its control. Through the active participation of government departments, technologies, and city administrators, it is possible to develop essential policies that are, at the same time, rational and effective. RL-based ITS requires extensive public awareness, which is possible through public education. Education of the public concerning the advantages, disadvantages, and precautions concerning those systems assists in acceptance. Multi-stakeholder approaches mean efforts are made to ensure procedural or ethical issues regarding RL systems are well addressed in order to achieve reasonable implementation.

Figure 12: **Ethical considerations associated with the use of reinforcement learning in decision-making systems.**

6. Practical Implications

Allowing ITS to incorporate Reinforcement Learning concepts provides substantial hope for increasing mobility within cities (Ghazal et al., 2021). Implementing RL-based systems results in adaptive traffic optimization, resulting in agencies with faster, delay-free movements. Because they are dynamic, these systems provide a higher level of performance compared to conventional traffic control techniques that use time—or rule-based scheduling. These occurrences improve the flexibility of transport systems in urban areas. Close cooperation between municipal authorities, technology suppliers, and urbanists has been identified as the key to the successful implementation of RL-based traffic systems. Realization entails the use of high-tech facilities such as Internet of Things sensors and high-bandwidth data transfer systems. Stakeholder cohesiveness guarantees that RL systems are well implemented to fit the needs of every city in the projection. Below are various advantages of the application of RL in ITS to the environment. As congestion is reduced and time spent stationary at traffic signals is reduced, integrated RL systems reduce fuel use and, accordingly, emissions of greenhouse gases. All these inputs are consistent with the sustainable development agenda and assist cities in transforming into sustainable cities. Also, efficient traffic patterns lower the noise level within cities as well as the general environment, making people's lives much better.

It should also be noted that there are potential economic advantages in RL-enhanced traffic systems. By reducing the time taken and improving the routing of the traveling, these systems increase productivity for the traveler and firms. Logistics and freight sectors are more likely to reap benefits that include few hindrances and high savings on operating costs. Also, throughput can reduce the maintenance costs associated with infrastructure since congestion reduces the lifespan of infrastructure. Managing RL in ITS also brings practical deployment of techniques that enhance social equity. Through efficient facilitation of multi-modal transport interfaces and enhancements of public transport components, RL systems enhance road usage for all roadway users, including walkways and bikeways. It proves the hypothesis of creating and designing inclusive and accessible modes of transportation for an inclusive urban population.

Table 6: **Advantages of RL in ITS for Environment and Economy**

Advantage	**Impact**
Environmental Sustainability	Reduces emissions and fuel consumption
Economic Benefits	Enhances productivity, lowers operational costs
Social Equity	Promotes inclusive transport systems for pedestrians and cyclists

7. Policy Recommendations

Governments and stakeholders should, therefore, focus on investments in smart infrastructure to facilitate RL-based ITS (Tuchnitz et al., 2021). Updates of the existing systems with IoT sensors, edge devices, and new-generation communication systems are needed to allow real-time data acquisition and analysis. Such commitments create the prerequisite for appropriate RL implementation and sustainable growth. Private opportunities, as well as relations with universities and AI technology suppliers, can stimulate further developments in RL technologies. The process and development of research and innovative approaches represent the cooperation between academics, businesses, and authorities to produce solutions to meet existing urban traffic conditions.

Sound regulatory frameworks are needed in this realm to facilitate the appropriate use of RL-based ITS (Rawindaran et al., 2021). These policies should include issues of safety, controlling the system's openness, and equality. Standard procedures should be followed when testing, validating, or implementing a new AI system to reduce risks and improve public acceptance of solutions for traffic management. The general public's education and, more importantly, engagement in policymaking is critical. It is established that educating the people on what RL is as an ITS, its strengths, and weaknesses goes a long way in ensuring that society accepts the technology.

Information campaigns will also help with issues of data protection and cybersecurity and promote debate between policymakers and citizens. The elements of long-term decision-making and contingency management should be integrated with the policies. New policies should be flexible to accommodate changes in Reliability technologies and the chances of new problems arising in the future (Chester & Allenby, 2019). Planned policy adoption guarantees that RL-based ITS continues to deliver envisaged results despite emerging trends within urban settings.

Figure 13: Smart cities: the role of Internet of Things and machine learning in realizing a data-centric smart environment

8. Conclusion

RL has yet to become an essential enabling technology that offers innovative solutions ITS to the prevailing problems of traffic congestion and misallocation. In contrast with conventional and heuristic traffic control strategies that employ fixed traffic schedules or manually predetermined strategies, RL is a lot more flexible and responsive to the current situation in the network. RL systems build an understanding of the environment so as to make relevant decisions that control traffic, minimize time, and optimize the system. These capabilities place RL at the center of the emerging generation of digital transport systems where flexibility and reactivity matter.

The flexibility of RL is illustrated through ITS, especially in the signalization system. The RL algorithms present here can adapt signal timings according to the traffic; this can reduce IDs and prevent congestion. This makes it possible for the RL-based systems to be superior to the more conventional fixed-schedule approaches. Another is dynamic traffic routing, where RL uses data obtained from the road to predict where congestion is likely to happen and directs vehicles to less congested areas. This approach does more than save travelers' time per trip and, at the same time, balances the fares in the network.

RL also proved useful in another important domain, which is incident management. Traffic congestion due to an accident or road blockage can be a real problem, but since the RL system redirects car movement and adapts all Traffic signals. RL is also highly effective in choreographing the motion of autonomous vehicles (AVs) to guarantee safety, fuel efficiency, and better interaction with conventional traffic streams. Literature research shows that minimizing car-to-car communication through RL-enabled AVs results in increased fuel efficiency by 10%, presenting tremendous features in the dual sense of efficiency and also sustainability. RL serves as an enabler of multi-modal transport to accommodate and engage cars, buses, bicycles, and pedestrians, hence creating sustainable urban mobility.

Taking into consideration its application in real-world ITS, it is possible to conclude that RL possesses great potential. The case studies illustrate a marked increase in the integrity of traffic, beauty of time, and elegance of fuel. For example, the traffic signal system based on the RL approach improved waiting time by 15% during rush hour in Hangzhou, China. Likewise, dynamic routing simulations resulted in a twenty percent improvement in average travel time to buildings in Manhattan. As exemplified by the works herein, RL provides the basis for addressing a wide range of traffic-related issues and offers direct benefits in terms of traffic management in urban environments.

As this paper has explained, adopting RL-based ITS is not without its challenges. Another limitation emerging here is computational complexity due to the very large state-action space common in urban traffic systems requiring substantial computational power. These demands requiring significant improvement can only be served by better algorithms like hierarchical RL besides improvements in hardware. Data acquisition and data reliability also come with their problems, as RL acts based on data collection by sensors and IoT devices. Problems like malfunctioning sensors or transmission of information can metabolize performance, hence the importance of safe and diversified systems of data gathering.

Another significant challenge is scalability. By nature, RL models are highly efficient in idealized settings, but transitioning them to complex, massive urban-scale networks is a massive task. Applying these models to different traffic conditions requires enhancing them by sophisticated methods such as transfer learning. Safety and reliability factors also exist, and their products undergo a lot of testing and validation. This means that incorporating innovative solutions into conventional systems presents difficulties in that additional resources have to be spent to adapt them to the current systems.

Solving these difficulties calls for the implementation of extensive technical, structural, and cooperative solutions. As hinted at by the concept of edge computing and the Internet of Things (IoT), more investments can lead to more real-time handling and better reaction times. Integrated learning models that incorporate RL with those of supervised or evolutionary techniques enhance reliability and flexibility. Thus, strong cooperation between governments, researchers, and industry partners is necessary to guarantee proper implementation of the plans. At the same time, the regulation that supports complete clarity and fairness greatly contributes to raising public confidence. Far from being limited to the operational side, RL has many advantages. Since emissions and fuel use decrease by enforcing RL-based ITS, environmental sustainability is relevant for the growth of green cities around the world. Further, given that RL is capable of managing multiple transportation systems, it will promote more fairness in transportation for different road users. These contributions make RL an essential tool for developing better and more viable cities.

RL avails a revolutionary model to manage traffic in cities while overcoming the drawbacks of conventional systems for practical solutions, economic viability, & social applicability. Illustrative examples of its use in traffic signal control, dynamic routing, and incident management as well as in AV cooperation demonstrate its potential to transform transport systems of metropolitan cities. That being said, current obstacles can be largely addressed, and constant evolution and cooperation are leading to the widespread integration of RL-based ITS solutions. As a result, RL helps create smarter cities to meet the existing and rising challenges in efficient, safer, and more environmentally friendly traffic systems.

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