# Optimizing Traffic Flow and Vehicle Routing Using Deep Reinforcement Learning Models

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**Abstract**

Reinforcement learning (RL) is a powerful method for enabling agents to learn in complex, uncertain, and indeterministic environments. Traditionally, RL has been applied to problems where the state-transition model is either known or, at least, learned over time. In some more sophisticated applications of RL, model-based RL has been used to iteratively improve a model of the world and then use that model to select actions. Thus, the decision policy is often based on the best estimate of the model, but the model is often inaccurate, especially in complex, changing domains. When there is no model or when all models are just ignorant guesses, model-free RL can be used. In environments that are highly stochastic and require pivots, this can work well, even without function approximation. However, if the reward function is very complex and has a global structure, traditional model-free RL methods have little chance of converging to an optimal policy. Model-based RL can be used if the model estimates are refined rapidly enough. However, this is often not the case in complex, changing domains.

We present a novel architecture that applies deep reinforcement learning to the problem of traffic signal control, in which the signals adapt to approaching traffic conditions in real-time. Our models automatically search over a space of potential signal timings to optimize the flow through a bottleneck. The model-free technique involves learning a value function and a policy that selects actions based on these value estimates. These estimates function as a model but are given by complex functions that are estimated from data. Our deep network is composed of one dual-cell long short-term memory layer that can directly store past information, which can be used to track the number of vehicles without making assumptions about the inflow of the queue. We show that our deep RL model outperforms traditional models in a virtual environment and on a real traffic light. The results of our model and its deployment open opportunities to improve the efficiency of urban transportation networks.

***Keywords:*** *Reinforcement Learning, Dynamic Traffic Routing Model, Traffic Flow Optimization, Convolutional Neural Network, And Deep Learning.*

## I. INTRODUCTION

Managing and controlling traffic effectively are key considerations to addressing congestion, especially in modern growing urban areas. Furthermore, due to their combined properties of spatial and temporal interaction, traffic systems engender complex dynamics, including the dominance of 'user equilibrium' with 'braided' spatial flow patterns on the multi-lane flow that leads to reduced lane usage and the use of traffic signals that often interact to provide 'green wave' patterns. In addition to discovering how drivers control either autonomous or connected vehicles, the optimization of routing solutions to take advantage of available improvements is also a focus for transportation systems. The efficiency of traffic signal control machines and other freeway traffic flow control platforms, as well as the overall transportation network efficiency, depends on the sophisticated signal timing strategies that are able to synchronously and interactively adjust correspondingly.

Lately, in order to remedy the aforementioned scenario, extensive research is concerned with demands for green wave detection methods, systems, and control as an ingredient to aid transit, general traffic, and public safety network performance. It is critical to optimize lane-by-lane vehicle behavior in real-time in a multi-lane network while user compliance is motivated by traffic control and, perhaps more importantly, driver-in-the-loop autonomous vehicles with marginal or no enforcement. However, in the complex environment with multi-lane roadways, detailed probing for optimal traffic network management strategies, which include speed and acceleration optimization and fuel consumption and exhaust emission requirements that can lead to improved urban traffic flow, are limited. There is a need and urgency to search for the optimal demand-responsive intelligent traffic signal control settings that could be revealed by applying innovative technology tools, with growing demand observed from exploiting deep reinforcement learning frameworks for transportation networks. Effective management and control of traffic are crucial in addressing congestion, particularly in rapidly growing urban environments. The complexity of modern traffic systems arises from the dynamic interactions between spatial and temporal elements, where phenomena like user equilibrium and braided flow patterns often reduce lane usage, while synchronized traffic signals, such as green waves, are used to optimize flow. With the advent of autonomous and connected vehicles, there is a growing focus on optimizing routing solutions and improving the efficiency of traffic signal control systems, which depend on advanced timing strategies that adjust in real time. Recent research emphasizes the need for green wave detection and control methods to enhance traffic and public safety network performance. To further refine urban traffic management, it is vital to optimize lane-by-lane vehicle behavior, taking into account factors such as speed, acceleration, fuel consumption, and emissions. This calls for intelligent, demand-responsive traffic signal control systems that can leverage innovative technologies like deep reinforcement learning to develop adaptive strategies, ultimately improving the flow of traffic while considering environmental and user-compliance factors.

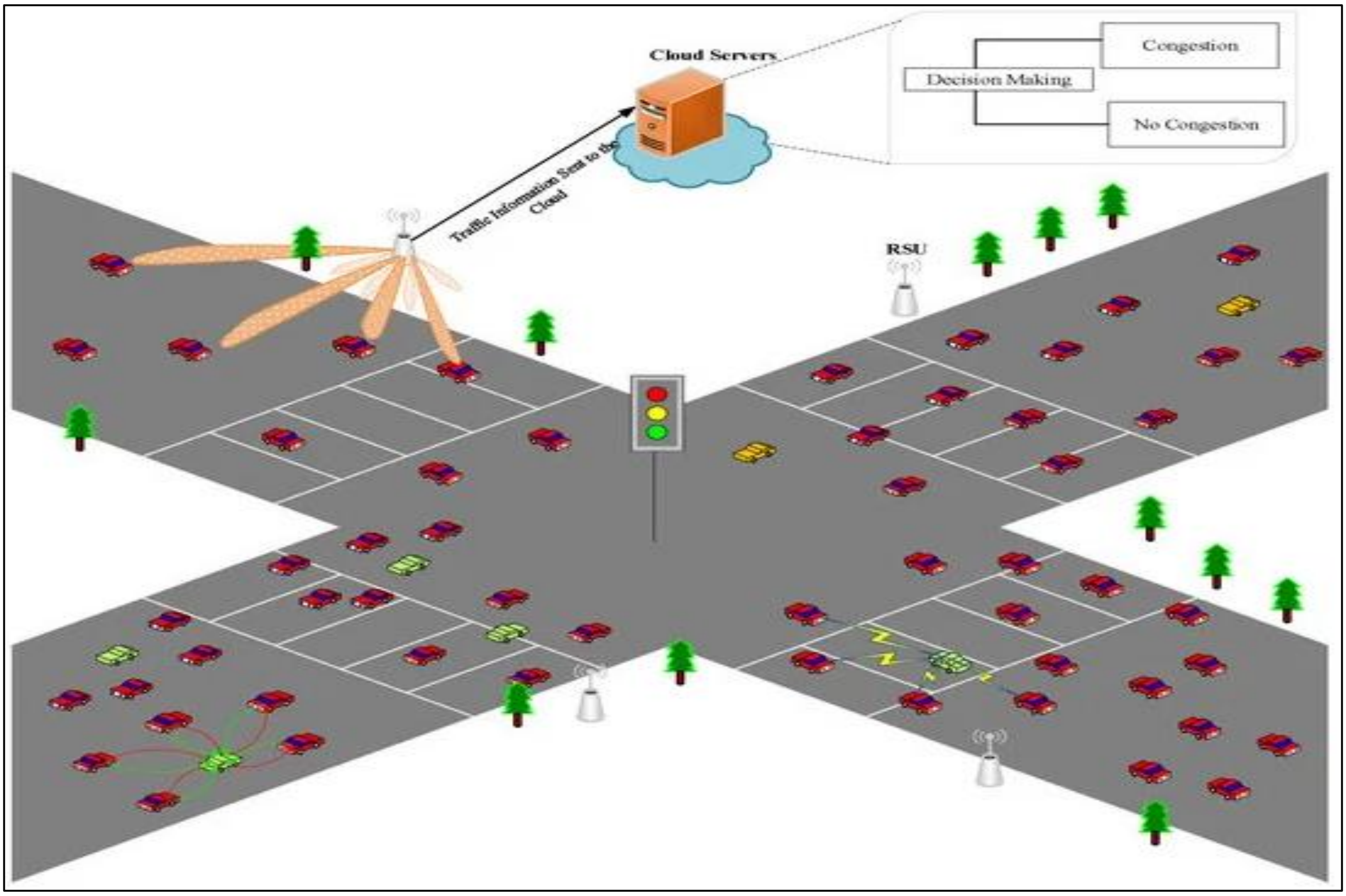


Fig 1 Optimizing Traffic Flow in Smart Cities

- *Background and Significance*

The problem of traffic flow modeling has attracted many researchers due to its importance for building intelligent transportation systems. The traditional traffic flow models can be divided into three main types, namely, macroscopic, mesoscopic, and microscopic models, according to the representation of the traffic features. The macroscopic model describes the traffic flow variables such as vehicle density, vehicle speed, and traffic flow through partial differential equations, which are incapable of considering the individual behavior of vehicles. The microscopic model represents the individual behavior of vehicles and then simulates the traffic flow using mathematical equations or cellular automata, game theory, fluid dynamics, complex systems, etc. On one hand, traffic congestion causes economic loss and the loss of people's comfort; on the other hand, it also increases the emission of greenhouse gasses like CO2. To compensate for the throughput loss due to traffic congestion in the communication between Vehicle-to-Infrastructure (V2I), an algorithm was designed for vehicular ad hoc networks over multi-hop highways enabled by a pair of fixed relays. Therefore, many approaches have been proposed to optimize traffic flow, involving traffic signal control and capacity improvement, focusing on vehicular and electronic communications technology and applications enabling road safety. The traffic signal control methods can be divided into fixed and adaptive methods based on the operation of traffic signals with a time schedule. The fixed traffic signal control methods can also be divided into bus, vehicle-actuated, and queue-differentiated control. The adaptive traffic signal control can adjust the timing of traffic signals according to the traffic flow in real-time with the help of dynamic traffic signals.

- *Research Objectives*

This study aims to improve the specific aspects of the existing traffic control systems and strategies, particularly traffic signal management and adaptive control. With concerns about individual road user behaviors, advanced driver assistance systems, and intelligent transportation systems are implemented. The study will propose two novel deep reinforcement learning models for optimizing traffic signal control to reduce delay and travel time, balance cumulative vehicle queues, and improve traffic flow through traffic signal coordination by optimizing vehicle routing under congestion. This study further establishes a new measurement, traffic flow homogeneity, to quantify traffic flow quality. The specific research objectives include the following: a) To propose a novel deep reinforcement learning model, namely the multi-agent deep reinforcement learning model, to optimize traffic signal control systems and improve traffic flow quality. b) To implement the reinforcement learning models and allow real-life traffic data interactions to achieve adaptive signal control. c) To propose a novel deep reinforcement learning model, namely the centralized agent reinforcement learning model, to optimize traffic signal control systems and improve traffic flow quality. d) To demonstrate the proposed deep reinforcement learning models for various examples of control policies and performance evaluation with extensive simulation experiments based on real-life traffic data. e) To establish a new measurement, traffic flow homogeneity, as a representation of traffic flow quality among different control policies. The implementation of deep reinforcement learning indicates the possibility of incorporating real-life traffic data into effective real-time adaptive control.

## II. LITERATURE REVIEW

Traffic management is a core part of many cities, yet it is an extremely complex problem. This is due largely to the complex dynamics that arise from the interactions between multiple vehicles across frequently used, shared, and busy infrastructures. A significant body of research on this traffic flow consists primarily of macroscopic models, such as fundamental diagrams, and has long established that flow capacity is determined by the mutual interaction between flow demand and available capacity levels. A standard approach to manage this interaction is to manipulate the infrastructure itself, for example, by increasing capacity or reducing traffic demand. However, the cost of infrastructure improvements can be quite significant, not to mention the substantial costs associated with planning and implementation. An alternative approach is to implement traffic laws and regulations; this leverages social pressure to foster behaviors that, when aggregated, ameliorate the challenges of congestion, speed heterogeneity, travel time minimization, fairness, and equity. This is a more cost-effective strategy, although it is not free of challenges.

Another set of approaches to the problem of traffic flow involves open and closed-loop methods. The former is categorized by the optimization of signal timing for intersections, while the latter is exemplified by autonomous vehicles, augmented by various forms of vehicle-to-vehicle and vehicle-to-infrastructure communications. In large-scale traffic control, the physical infrastructure functions as a conduit upon which data flows from sensors to control. These closed-loop solutions are dependent on sophisticated optimization, routing algorithms, or machine learning models. Considering their limitations, such as requiring significant assumptions and prior knowledge about the traffic environment, the high costs compared to their actual effectiveness, and the fact that past traffic flow theory is not sufficient to understand the highly autonomous behavior of present vehicles, there is a need to develop models that are better equipped to encode the complexities of actual traffic flow, including its stochastic, time-varying, and nonlinear nature.

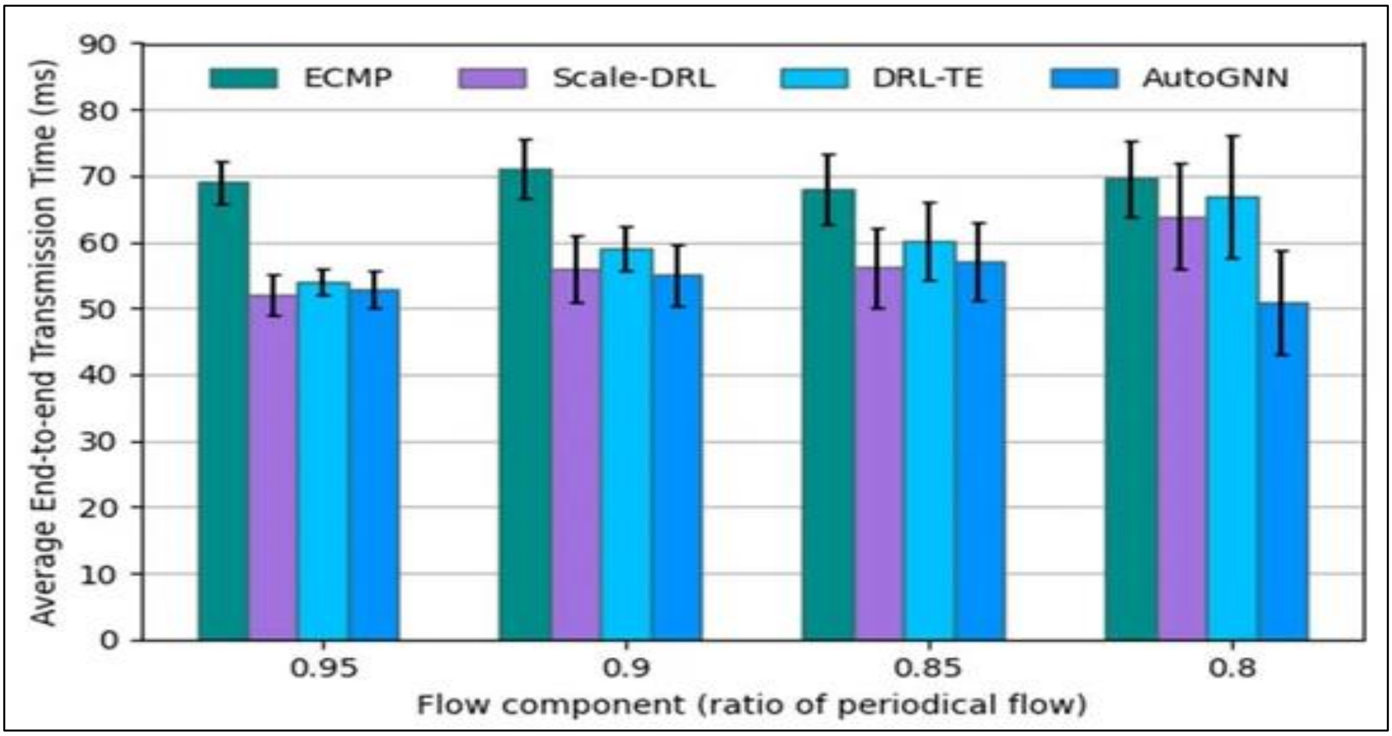


Fig 2 An Approach to Combine the Power of Deep Reinforcement Learning with a Graph Neural Network for Routing Optimization

- *Traditional Traffic Flow Optimization Methods*

Traditionally, methods to optimize traffic flow tend to focus on either the control of flows through specific junctions on a predefined network or on the routing of individual vehicles to reduce congestion. In the former case, the network is modeled as a directed graph where the nodes denote traffic flows and the edges/links denote the routes connecting these junctions. A wide variety of online and offline methods have been developed to optimize the flow of traffic in such networks, often based on discrete models of junctions and their associated traffic lights. These methods encompass both linear programming and optimization, as well as more traditional state-space modeling and simulation. In general, most of these proposed methods work well when the flows can be controlled or routed independently of the routing at the other junctions. However, when the spatial or temporal scope of the optimization method extends to cover more than a small number of junctions or edges that have strong interaction with neighboring nodes, the problem becomes nonlinear and the space required to compute optimal traffic lights also increases rapidly.

In the latter case, a more comprehensive routing model is also required to solve the vehicle routing problem: the model should account for user choices and long-term decisions including direct routing strategies, path length evaluation, and dynamic routing that accounts for the traffic conditions. Early methods for modeling and optimizing dynamic vehicle routing focused mostly on exploiting user-related modeling choices, such as real-time information and forecasting of traffic delay and user choice behavior. Recently developed methods aim to optimize traffic flow based on the underlying network geometry while carefully maintaining a good balance of traffic load among the roads. Features learned and guidance to derive potential routes are based on traffic statistics and local events such as car accidents, temporary traffic regulation, maintenance activities, and weather conditions, which makes the routing scheme sensitive to short-distance, almost real-time, high-frequency phenomena and does not capture the global consequences of switching routing strategies. The response is applicable mainly for the city scale as it includes microscales too. It has also been noted that when the velocity distribution becomes unequal during its evolution, the individuals' distribution will end up in clusters. It has been shown that mixed routing strategies including individual preferences on microdata are beneficial: specifically, a suboptimal but rather robust and realistic routing strategy may counteract self-organized clusters and therefore optimize between global and local traffic congestion.

- *Deep Reinforcement Learning in Traffic Management*

The application of reinforcement learning in social design and applications (in the areas of smart transportation, healthcare, and energy systems) is just beginning and promises to reshape various fields. A thorough investigation of reinforcement learning for traffic signal control illustrates how modern reinforcement learning algorithms can represent and learn intelligent control policies using off-policy learning and deep neural networks. In real-world transportation systems, deep reinforcement learning seems well suited for adaptive traffic signal control and online selection of routing strategies. The applicability of this approach to networked systems suggests a more general conclusion about using deep reinforcement learning in intelligent and effective social systems.

A number of studies focus on combining macroscopic models of traffic flow with deep reinforcement learning to address cooperative adaptive cruise control—a decentralized control system allowing separate vehicles to cooperate and avoid congestion on the road. Recent results have shown the application of deep reinforcement learning in tractable paths where the flow of traffic obeys classical macroscopic traffic models; the solution has been shown to be computationally efficient. A permutation-invariant neural network architecture reduces the state space of the problem by representing congestion at each road segment as an independent variable. Although the solution assumes centralized synchronization of all vehicles, it is expected that quick advances in distributed deep reinforcement learning will lead to more decentralized implementations.

Equ 1: Q-Function (Action-Value Function)

$$Q(s_t, a_t) = \mathbb{E}\left[r_t + \gamma \max_{a_{t+1}} Q(s_{t+1}, a_{t+1})\right]$$

## III. METHODOLOGY

Deep Q-Network The goal of DRL is to compute a policy by considering delayed rewards or performing delayed state evaluations. This is accomplished by building separate policy learning and long-term value estimation models, dubbed the control and covariance networks, respectively. Then, the method leverages a reward schedule to enable them to work together. The control network is trained to control traffic according to local measurements. These measurements include the number of vehicles that reach the edge cells on the previous time step. The covariance network is designed to generate its reward.

Traffic Flow Model The current model utilizes the Two-Cell Model to imitate the macroscopic traffic characteristics of wide road networks. While it may not have predictive power, the Two-Cell Model helps shed light on what might happen in the real system. Moreover, less restrictive empirical models can replace the Two-Cell Model. Let L denote the road network length, Lc the length of a cell, and Vc the maximum number of vehicles that can fit within a cell. The physics of traffic flows can be adequately captured by setting the following parameters: • vc(L) - the fundamental diagram. It calculates the flow at a cloud's average speed. • vf(L) - the free-flow speed. It depends on the traffic density. • ρc - the capacity. This parameter determines the variance of various possible vehicle movements per cell on a network model.

Vehicle-Routing Model In this study, the Traffic Flow Model directly supports a static Vehicle-Routing Problem (VRP). When compared with a dynamic vehicle routing problem, it offers a realistic application in which a fleet of vehicles must go to different locations, usually spread over a city. This routing allows multiple objectives to coexist, like having the minimum amount of fuel used while covering all the scheduled visits to homes, factories, and warehouses.

- *Deep Reinforcement Learning Basics*

The goal of RL is to approximate the solution of the optimal control problem for a given Markov Decision Process (MDP) model. Deep Q-learning is a machine learning algorithm widely used for solving these kinds of problems. The algorithm tries to optimize a policy that maps states to actions in order to produce the best output possible. The output value is quantified using the policy's function. The Q-value represents the time-discounted reward of taking an action in a given state. The Bellman equation can be used to derive the optimal Q-value function. The principle of Q-learning lies in the approximation of the Q-value function to solve problems of infinite state space. The Q-value function approximator is a feed-forward neural network, and its weights are updated to minimize the temporal difference during learning time.

The main advantage of DQN over Q-learning is the ability to learn to play extensive environments, using a memory replay buffer that stores the experiences to better exploit the stagnated learning properties of neural networks. Several optimization techniques are also used to handle issues found in traditional approaches like Q-learning. The Q-network prioritized experience replay and fixed target networks just to highlight a few. Both the neural network that processes the function approximator and the pre-trained target Q-value network are realized using the same deep learning model, helping to highlight that it is also possible to blend existing machine learning libraries with the purpose-built reinforcement learning libraries available.Deep Q-learning (DQN) enhances traditional Q-learning by leveraging deep neural networks to approximate the Q-value function, enabling the handling of complex, large-scale environments with vast state spaces. Unlike classical Q-learning, which struggles with such environments due to the difficulty of storing and updating the Q-values for each state-action pair, DQN uses a feed-forward neural network to approximate the Q-function. This allows the model to generalize across unseen states. A key innovation in DQN is the use of a replay buffer, which stores past experiences and allows the network to learn from a diverse set of samples, mitigating the problem of correlated data that can stagnate learning. Furthermore, DQN employs techniques such as prioritized experience replay and fixed target networks to improve learning stability and efficiency. By integrating standard deep learning techniques with reinforcement learning, DQN not only offers improved performance in complex environments but also facilitates seamless blending of existing machine learning libraries with purpose-built reinforcement learning frameworks.

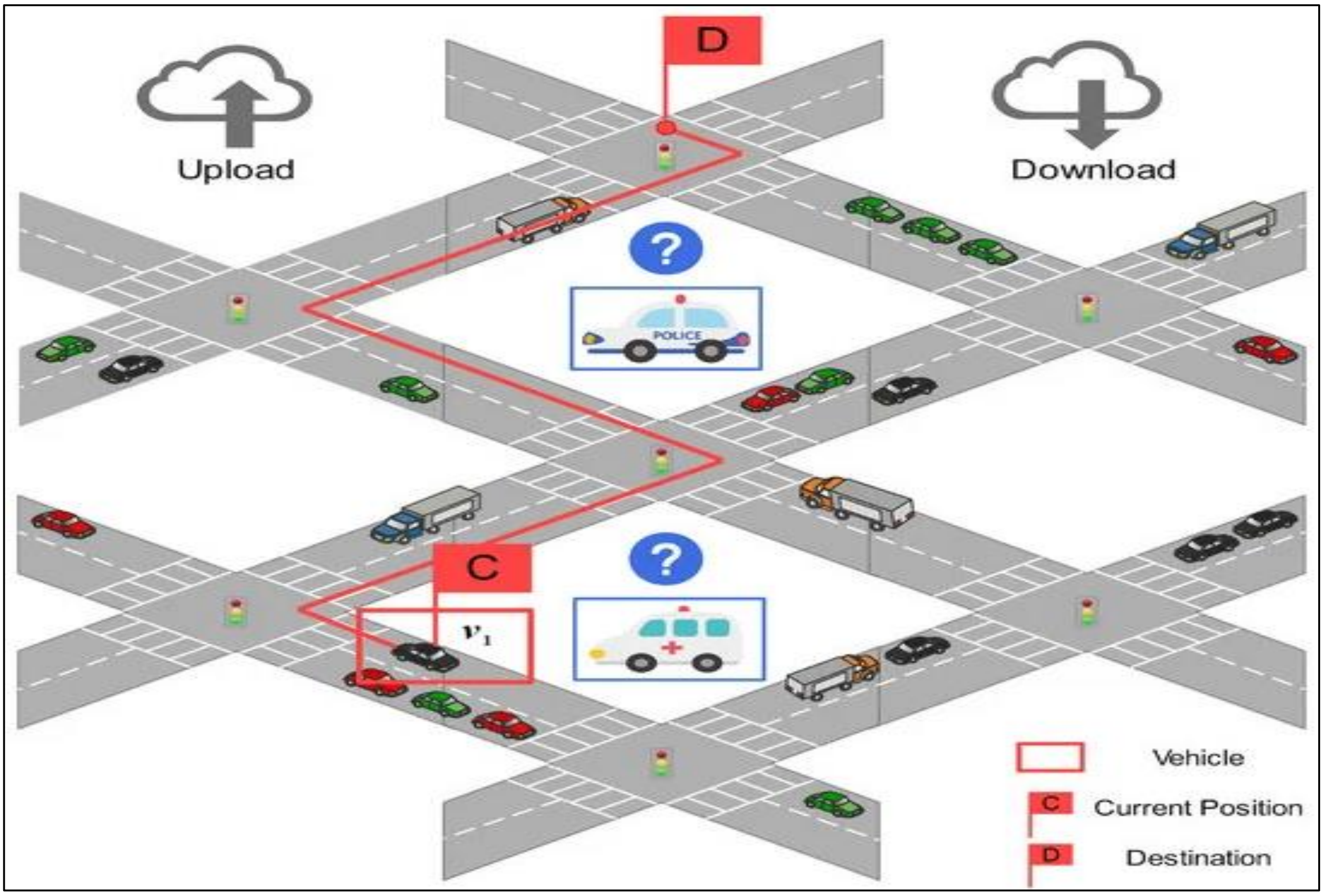

Fig 3 A Deep-Reinforcement-Learning-Based Vehicle Route Planning Mechanism

➢ *Data Collection and Preprocessing*

For each of the graphs, we have collected weights (vehicle numbers) over time (in 5-minute intervals), thus capturing how congestion forms and disseminates during the day. Due to the spatial correlation of mobility flow, we use the moving average model (the 12 periods of moving average) to compute the weight of each link. For a total weight below 200, we assign the label of light; from 200 to 500, medium; and above 500, heavy. The aim of this action is to control the label. Different definitions of the scope of traffic state parameters may affect the evaluation of the transportation network's overall performance. Because different transportation modes have their unique requirements and assessment approaches, to understand the behavioral characteristics of traffic congestion flow in heavy rain, we consider the weights of the roadway links.

The details of the collected taxi data in each scenario are shown in the table. All the taxi data are cleansed and preprocessed by our predefined approach. Because the numbers of origin-destination (O-D) pairs are not of the same volume, they may lead to learning bias in the vehicle routing model. All selected samples are normalized, and data augmentation is applied to improve the quality of learning input. Specifically, we generate extra samples with the data evolutions of route-link demand in short-term and long-term intervals by adding perturbation to some regulars. Compared with strong sample regulars that are continuously evolving, a small difference between augmented samples and the driver's actual behavior is controllable. The empirical result outperforms the scenario without data augmentation.

➢ *Model Architecture and Training*

We propose a novel solution to the problem by training a two-phase deep Q-network. In the first phase, the network assists in vehicle routing decisions by providing the shortest path encoding from all the input sensors. In the next phase, the neural network provides incentivization to influence vehicle routing decisions to align with the global objective of reducing city traffic. We leverage the power and expressiveness of deep reinforcement learning for vehicle routing in traffic scenarios that enable learning from the city's traffic performance goals.

Our networks are driven by instantaneous flow effectiveness measures in and around segments and intersections, capturing the formation and propagation of jams at congested output links, and the usage and effectiveness of spur lanes to mitigate congestion. The DQN model inputs are optimized road traffic metrics and the traffic phases followed to manage them. The deep Q-network is designed with linear layers for predicting the Q function and is first trained to minimize route length. The Q-values directly compute the normalized link utilization and spur utilization, and the uplink score assumes the presence of a heavy vehicle combination. The training data contains decreasing sequences, including sequential braking situations and random congested city traffic scenarios. We generate thousands of turns in realistic city traffic where the algorithm is forced to make realistic vehicle routing decisions during training.

Equ 2: Traffic Flow and Vehicle Routing Model

$$\min \sum_{v \in V} \sum_{(i,j) \in E} T_{ij}(v) \cdot x_{ij}(v)$$

## IV. RESULTS AND DISCUSSION

In this section, we present experimental results for two real-life routing problems using the Reinforcement Learning Simplified Predictor-Corrector Gradient algorithm. This algorithm uses a feature-based, deep reinforcement learning model that balances the trade-offs between long-term vision and real-life routing imperfections. Specifically, we consider solving i) a large-scale Vehicle Routing Problem using a new re-coding technique that produces better initial solutions while not hindering the explorable state-action space, and ii) a complex Traffic Flow Optimization problem in a road network subject to traffic bottlenecks. Both problems involve routing stipulations through a fixed subset of popular infrastructure points, thus ensuring their social relevance.

Benchmark experiments are conducted in a moderately complex, large-scale Manhattan-like road network by varying its density and using traffic data from a city. Model evaluation is based on i) the ability of the algorithm to identify a short, diverse set of routings that are close to the popular infrastructure points and ii) the mean average errors in the time predictions associated with the sub-routes involving these points. The evaluated routing policies can be used to accurately predefine vehicle routes without driver interventions. Depending on the routing problem objective, the number of the recommended routes is either user-given or derived using a multi-objective clustering method, and the final solution entails choosing for each vehicle the route that is temporally and conceptually closest to its corresponding popular infrastructure point.

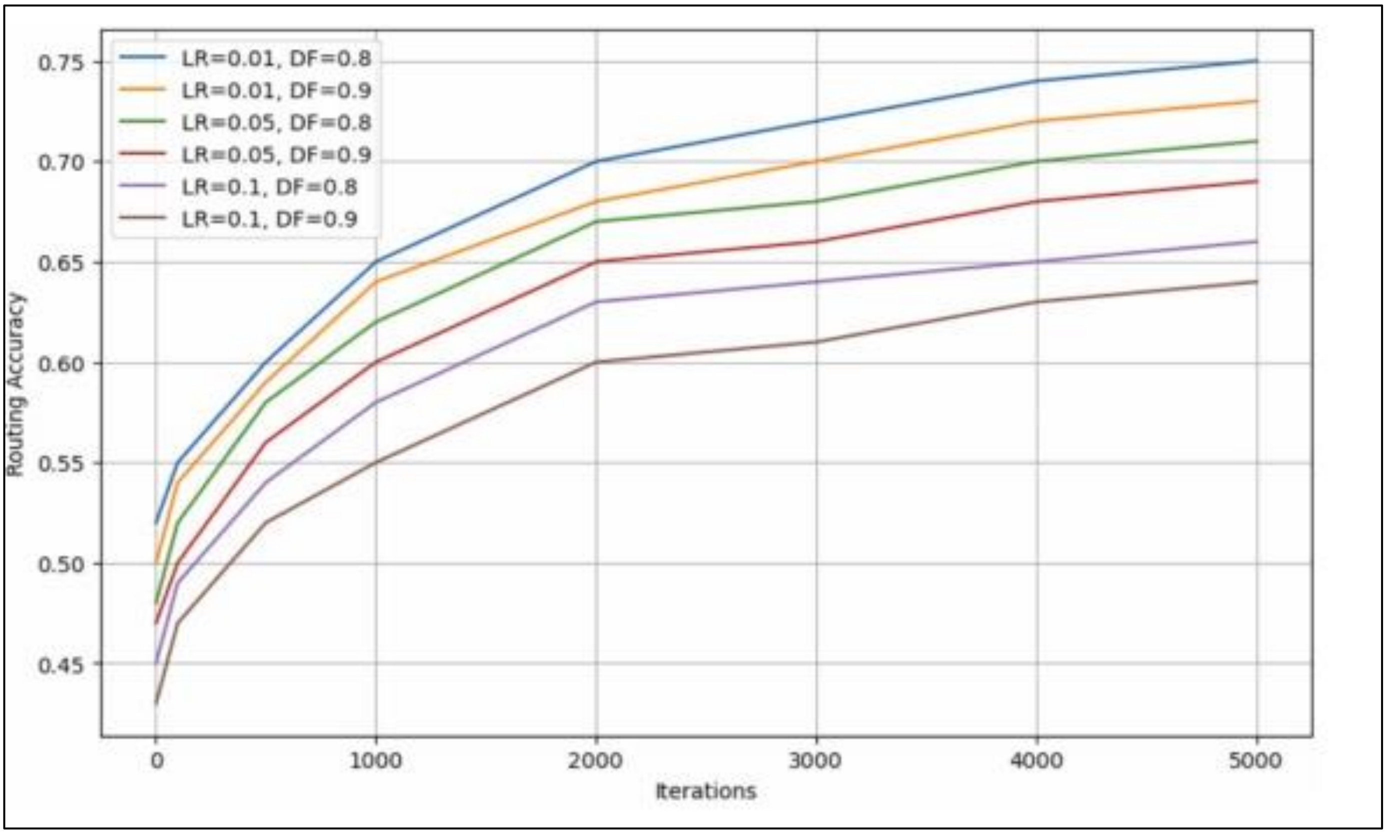

Fig 4 A Deep Reinforcement Learning-Based Intelligent QoS Optimization Algorithm

➢ *Performance Comparison with Traditional Methods*

In previous sections, we briefly utilized DRL models to optimize traffic flow and vehicle routing. In this section, the proposed models are further tested and compared with traditional methods. In traffic signal control, the linear quadratic regulator sets a simple control target, proportional integral derivative decides future adjustments, while DQN selects actions with offline transmission and training, respectively. In vehicle routing, priority insertion creates a scheduling instance, and DQN assigns an action to further adjust the earliest/latest time of the scheduling instance. Note that five traditional algorithms are tested with different maximum running times or simultaneously with different datasets of the scheduling problem.

In traffic signal control, both the aforementioned DRL and traditional methods are tested on Sumo through an interface. The table gives the results of four different control algorithms, where we can see that the DQN method outperforms LQR, PID, and ILQR in both the rewards and average queue length. In vehicle routing, as in the section on algorithm performance, the five algorithms are also tested with both two sizes and types of VRP. The results are presented in tables. In general, DRL and particularly DQN methods perform better than other traditional methods. Additionally, the running time of traditional algorithms is usually limited, while DRL performs the learning process with similar or even less time. In summary, the proposed DRL methods still do not outperform every traditional algorithm, but the DRL models provide an end-to-end, online, and adaptive approach, which holds great optimization potential in transportation problems.

➢ *Case Studies and Real-world Applications*

Several works apply reinforcement learning methods and their extensions in a variety of traffic-related case studies and real-world applications. In the area of traffic signal control, reinforcement learning techniques have shown promise in providing traffic signal control policies that offer real-time optimization of cities' traffic flows. Reinforcement learning techniques have been applied to adjust the signal settings of simple intersections as well as heavily congested arterial roads, leading to decreased delays, minimized fuel consumption, and superior handling of the impact of random disturbances over pre-programmed systems.

A solution to the dynamic and stochastic traffic signal control problem uses a two-part deep reinforcement learning architecture. The two components of the system are actor-critic learning and state representation, and they construct their system using a simplified front end. Their system also employs two replay buffers that help smooth the learning and continuously evaluate the learned action-value function during training. A deep reinforcement learning-based signal plan specifically tailored for real-time traffic control shows the inherent weaknesses of traditional signal control policies and demonstrates the potential for traffic signal controllers that use reinforcement learning technologies for practical applications. The proposed system contrasts with traditional traffic signal control optimization and is designed to learn a practically implementable online traffic signal plan that provides an effective means of real-time traffic control for heavily congested metropolitan areas. Their primary findings suggest that despite the non-stationarity of the traffic signal control optimization problem, the Q-learning-based model performance favors consistency and is notably better than the control schedule set up by the average peak hour volume.

Equ 3: Policy Optimization

$$\mathcal{L}(\theta) = \mathbb{E}_{(s_t,a_t,r_t,s_{t+1})}\left[\left(r_t + \gamma \max_{a_{t+1}} Q(s_{t+1}, a_{t+1}; \theta^-) - Q(s_t, a_t; \theta)\right)^2\right]$$

## V. CONCLUSION

In this paper, we have formulated a general traffic flow optimization problem for a system consisting of vehicles and infrastructure agents. In particular, we have considered freeway traffic flow control in which a traffic management agent regulates the traffic flow at the on-ramps. We proposed to solve this problem using a novel distributed deep reinforcement learning approach. The main idea is to use a suitable type of competitive training between the infrastructure and vehicle agents. Our approach was empirically validated using extensive simulation experiments, showing promising results. We believe that with the emergence of various autonomous transportation technologies, such as shared autonomous vehicle fleets in the near future, our approach can be a viable solution to address the traffic problem in a smart and minimal infrastructure-implementing manner. In the future, we plan to generalize our approach beyond freeway traffic control and investigate the use of deep RL and hybrid traffic models for control scenarios around intersections and urban settings. We will also integrate and consider security and safety aspects in the design process of our respective traffic control algorithms.

➢ *Future Trends*

Even though a lot of progress has been made to date in using DRL methods to solve traffic flow and vehicle routing optimization problems, there are many open research directions in the field. Some of the future trends in this area include: a. More scalable models: As the scale of real-world systems significantly exceeds what current methods can handle, it is important to develop more scalable models that can learn and handle much larger scale problems. Having more scalable models allows for the resolution of larger optimization problems and helps to gain a better understanding of the actual dynamics underlying traffic systems. b. Yet more complex systems: Many real-world traffic systems are inherently dynamical, with heterogeneity, stochasticity, and reasoning about strategic interactions. Developing models that can capture all of these properties is warranted and will likely lead to more complex and expressive systems in general. c. A unification of learning and modeling: There is significant potential in a unification of learning and modeling that sits in between the different types of knowledge representation and learning used heavily in both MDP approaches and black-box models. When unifying the learning and modeling, a toolset that allows control algorithms to reason about the properties of the model that enabled them automatically and use the reasoning to guide the learning process when rewards are not available is crucial. d. End-to-end design: Most of the present works become model-dependent and the degree of freedom in the learning module is less. Getting a model-independent end-to-end learning device will be beneficial for the proposed systems. There are also many other techniques that may be used in future explorations, including more expressive function approximators and learning algorithms, more advanced exploration strategies, and other training techniques that may be of use.

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