A Deep Reinforcement Learning Framework for Connected Vehicle Route Planning in Urban Environments

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***Abstract*—This paper introduces a deep reinforcement learning (DRL) framework for connected vehicle route planning in urban environments to optimize traffic and improve commute efficiency. The framework uses an actor-critic architecture within a simulation environment to train a policy network. This network generates optimized routes for vehicles based on both simulated and real-world traffic data, accounting for various traffic events such as accidents and road maintenance. The trained policy network then provides real-world route recommendations or commands to connected vehicles, potentially reducing congestion and improving overall urban mobility in road networks.**

***Index Terms*—Route planning, connected vehicles, deep reinforcement learning**

I. Introduction

Optimizing urban traffic is an important task to reduce city congestion states and improve traveling efficiency [1]. Urban traffic can be affected by different traffic events, such as road emergency incidents (i.e., accidents), road maintenance schedules, and temporary traffic control. Guiding vehicles to avoid moving toward those situations would greatly improve urban commute experiences. Meanwhile, vehicles equipped with a communication device (e.g., 5G network device) can share their mobility information, e.g., moving speed and directions, with an edge or cloud server [2]. By using this mobility information, a traffic optimization service located in the server can recommend better traveling routes to the connected vehicles, which may further reduce the possibility of congestion in an urban environment.

For the future connected and automated vehicles (CAVs) [3], those automated vehicles can be teleoperated to use different routes, which poses a great challenge on the vehicle route planning because the urban traffic and the planned routes of vehicles are mutually influenced. Considering the complexity of the problem, designing a reinforcement learning (RL) approach [4], [5] would be a proper way. Particularly, a deep RL method can train a policy network to generate optimized vehicle routes.

Therefore, in this paper, we introduce a deep reinforcement learning (DRL) framework for connected vehicle route planning in urban environments. Fig. 1 shows the proposed DRL framework that includes two components, such as a simulation environment and a real-world service. In the simulation environment, we design an actor-critic (AC) architecture to train a policy network that can generate optimized routes for vehicles. In the real-world service part, the trained policy network produces actions (i.e., route recommendations and commands) for vehicles by receiving the real-world traffic data. The simulation environment uses both simulated and real-world traffic data to train the policy network, so that the trained policy network can reflect both seen and unseen events for the generated actions.

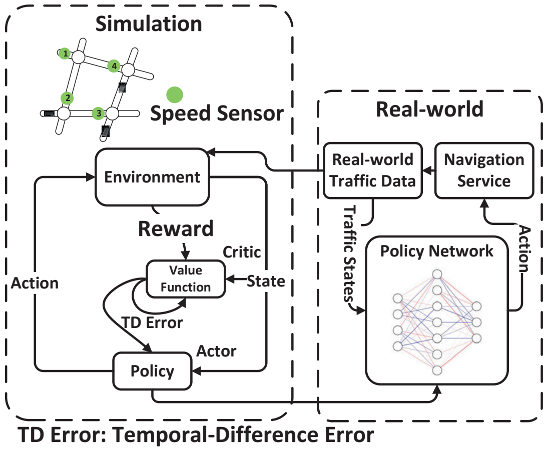

Fig. 1. The proposed DRL framework for vehicle route planning.

The remainder of this paper is organized as follows. Section II briefly introduces related work for DRL methods in vehicle route planning. Section III describes the design of the proposed framework. Section IV concludes the paper along with future work.

II. Related Work

Benefiting from the advances of DRL approaches, the neural combinatorial optimization for vehicle route planning has gained significant progresses [4], [5]. Despite recent advances, several major limitations and challenges still remain. Urban vehicle accidents and temporarily parked vehicles create unexpected anomalies that disrupt forecasting and route planning. With the emergence of CAVs, traffic rerouting to avoid con-

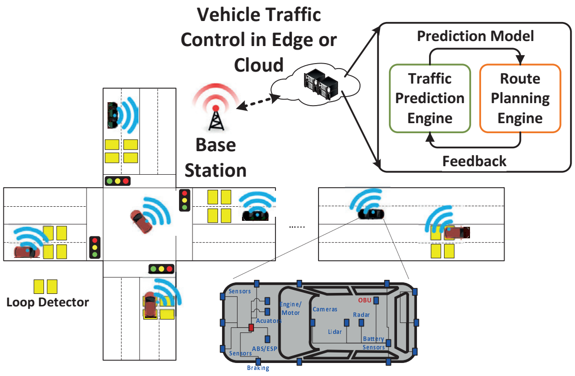

Fig. 2. The system architecture of the proposed DRL framework.

gestion may become common, undermining the reliability of existing traffic forecasts. Incorporating feedback from these altered traffic patterns into current models is difficult, as they are not designed to adapt to such dynamic changes. To tackle these problems, we propose a DRL framework to better optimize route planning in urban areas.

III. DRL Framework for Vehicle Route Planning

As shown in Fig. 1, the proposed DRL framework uses an actor-critic (AC) architecture to train a parameterized policy network that can generate optimized vehicle routes. From a system architecture point of view, the proposed framework is put into a server in either an edge or a cloud, as shown in Fig. 2. A communication-module-equipped vehicle can periodically upload mobility information (e.g., location, speed, and planned routes) to a vehicle traffic control edge or cloud (VTC) via a base station (e.g., gNodeB in 5G). Road infrastructure can also upload road traffic statistics (e.g., average speeds via loop detectors, and road throughput) to the VTC. The VTC uses this collected information to generate future traffic predictions through a traffic prediction engine (TPE). These predictions are then used by a route planning engine (RPE) to recommend optimized routes to vehicles.

A. Graph Attention Networks for Traffic Prediction

Based on our previous work [6], in the VTC, both TPE and RPE collaborate to optimize urban route planning. The proposed TPE uses a spatial-temporal graph attention (STGAT) network for urban traffic prediction. STGAT trains an autoencoder network using spatial dependency modeling, temporal embeddings, and anomaly incident features, as shown in Fig. 3. The detailed structure of the autoencoder network can be found in our previous work [6].

B. DRL-based Vehicle Route Planning

We design a DRL framework for connected vehicle route planning in urban environments. As shown in Fig. 1 and 3, the proposed DRL framework has two components: a simulation environment and a real-world service. In the simulation environment, an AC architecture trains a policy network to generate optimized vehicle routes. The trained policy network then uses real-world traffic data in the real-world service to produce route recommendations (i.e., actions) for vehicles. The

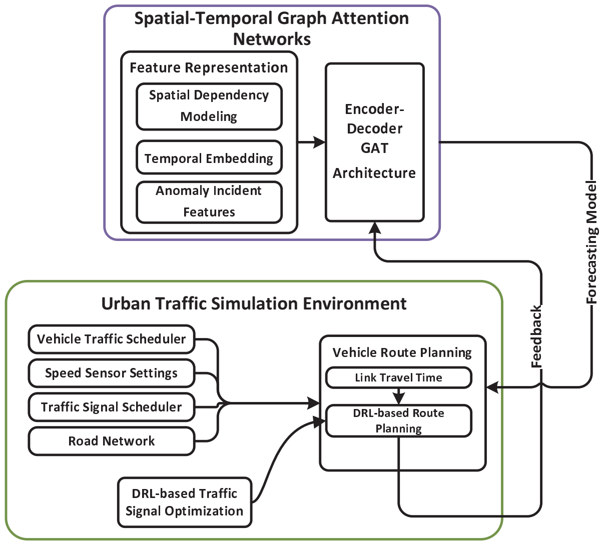

Fig. 3. DRL framework with spatial-temporal graph attention networks.

AC architecture in DRL uses both value function to learn the model and policy gradient to optimize the policy network. The temporal-difference (TD) error measures the one-step difference between any two steps.

IV. Conclusions

In this paper, we introduce a DRL framework for connected vehicle route planning in urban environments to optimize traffic and improve commute efficiency. As future work, we will try to fine-tune the reward model in the proposed framework to improve the performance in urban road networks.

Acknowledgments

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