FCV2X-Net: Foresighted and Coordinated Vehicle-to-Everything Control for Joint Navigation and Signal Optimization

Jinwei Zeng
Department of Electronic Engineering
BNRist, Tsinghua University
Beijing, China

Hongyuan Su
Department of Electronic Engineering
BNRist, Tsinghua University
Zhongguancun Academy
Beijing, China

Jian Yuan
Department of Electronic Engineering
BNRist, Tsinghua University
Beijing, China

Yong Li
Department of Electronic Engineering
BNRist, Tsinghua University
Beijing, China

Abstract

As urban traffic networks grow more complex, seamless interaction between vehicles and infrastructure is critical, motivating Vehicle-to-Everything (V2X)-enabled intelligent transportation systems. Since vehicles are the main transport agents and traffic signals a key infrastructure component, jointly optimizing navigation and signal control is essential for sustainable V2X systems. However, existing methods often ignore long-range dependencies in road networks and lack effective large-scale vehicle coordination, limiting their ability to manage complex flows. To address this, we propose FCV2X-Net, a unified framework that enhances foresight and coordination in navigation and control. It consists of: (1) a Bayesian Graph Convolutional Network (BGCN)-based module with adaptive adjacency for modeling implicit long-range correlations; (2) a mean field-based intention propagation mechanism for scalable vehicle coordination; and (3) an intention-aware signal control module that adapts to aggregated vehicle intentions. Experiments on large-scale scenarios with $\tilde{5}0$ intersections show that FCV2X-Net increases vehicle throughput by 7.6% and reduces travel time by 7.2%, demonstrating its effectiveness for sustainable urban mobility. Codes and datasets are available at: https://github.com/JinweiZzz/FCV2X-Net.

CCS Concepts

• **Computing methodologies → Multi-agent planning**.

Keywords

Vehicle-to-Everything(V2X), Multi-agent Reinforcement Learning, Vehicle Routing, Traffic Signal Control

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1 Introduction

The rapid development of communication, sensing, and big data analytics has brought Vehicle-to-Everything (V2X) intelligent transportation systems into focus. Given the proven benefits of intelligent traffic methods in improving efficiency [10, 13], there is a growing need for scalable V2X approaches to handle complex metropolitan traffic and reduce emissions.

This study targets the joint optimization of vehicle routing and traffic signal control using reinforcement learning (RL). Existing work has explored hierarchical RL [8] and shared observations [7] as solutions, but is mostly limited to intersection-level local optimization, leading to insufficient coordination at the global scale. RL-based navigation methods [1, 6, 11] also focus on local adjacency and overlook long-range effects, often leading to avoidable congestion. Moreover, individually "optimal" choices may collectively cause congestion and worsen traffic. In conclusion, farsighted and coordinated strategies are essential and underexplored.

However, addressing the lack of foresight and coordination poses several challenges. First, modeling long-range dependencies among roads for foresighted navigation is difficult, as these relationships are implicit and diverse. Traffic states on certain roads may influence distant ones with indirect and delayed effects, which are not explicitly observable and differ across space and time. Second, for coordination, directly incorporating navigation decisions of all nearby vehicles introduces redundancy, high computational costs, and fails to anticipate the latent consequences of current decisions in dynamic and complex scenarios. Thus, effectively representing navigation intentions while accounting for their long-term impact remains challenging. In addition, joint optimization of vehicle navigation and traffic signal control requires effective interactive information between these two types of agents.

To tackle these challenges, we propose the Foresighted and Coordinated Vehicle-to-Everything (FCV2X) Control Network (**FCV2X-Net**), which jointly optimizes vehicle navigation and traffic signal control. On the vehicle side, a Bayesian Graph Convolutional Network (BGCN) with a learnable adjacency matrix captures implicit, heterogeneous long-range correlations. For large-scale coordination, a mean field-based intention propagation mechanism abstracts routing intentions and their long-range influences efficiently, avoiding redundancy. On the infrastructure side, an intention-aware signal control module adaptively responds to aggregated vehicle intentions. Together, these designs enable scalable, foresighted, and coordinated V2X optimization. Our main contributions are:

- We address the challenging problem of jointly optimizing vehicle navigation and traffic signal control in large-scale V2X systems, focusing on long-range dependency modeling and scalable coordination.
- We propose **FCV2X-Net** to tackle the joint optimization, a unified framework integrating a BGCN-based message passing module with adaptive adjacency, a mean field-based intention propagation mechanism, and an intention-aware signal control module.
- Extensive Experiments show that FCV2X-Net improves vehicle throughput by 7.6% and reduces average travel time by 7.2%, demonstrating its effectiveness, scalability, and potential for sustainable traffic management.

2 Preliminaries

2.1 Problem Formulation

We optimize the Vehicle-to-Everything (V2X) system by jointly managing vehicles and traffic signals to improve network efficiency. For signals, the task is to select the optimal green phase to maximize throughput and reduce delays. For vehicles, we model a mixed environment where some vehicles are controlled as agents and others operate independently. Each controlled vehicle chooses a turning direction at intersections to improve flow, reduce congestion and emissions, and ensure timely arrival.

2.2 Multi-Agent RL Setup

We model each traffic signal and controlled vehicle as an agent, and formulate the joint task as a Partially Observable Markov Decision Process (POMDP). Each agent has only partial observations. Here, we define the state, action, and reward for two types of agents.

- **Traffic Signal State, Action, and Reward.** S_s is the global state space; each signal agent observes $o \in O_s$, including its current phase (one-hot encoded), the number of waiting vehicles per phase, and intersection attributes (e.g., lane counts), with missing phase features padded by -1. The action space A_s is the selectable green phase index for the next control period. The reward r_s is defined as the negative total queue length, i.e., the sum of waiting vehicles across all approaches [12, 17].
- **Vehicle State, Action, and Reward.** S_v is the global state space; each vehicle agent observes

$$O_v = [D_{M \to dest}, A_{M \to dest}, L_M, T],$$

where M is the set of turning options. $D_{M \to dest}$ denotes the shortest distances to the destination, $A_{M \to dest}$ the turning angles relative to the destination direction, L_M the number of available options, and T the current timestamp. The action space A_v corresponds to possible turning directions at intersections (e.g., left, right, straight for four-phase intersections; two options for three-phase). The reward r_v is designed to reflect desired driving behaviors, as detailed in Section 4.3.

3 Method

In this section, we present our Foresighted and Coordinated Vehicle-to-Everything Control (V2X) Network **(FCV2X-Net)** designed to optimize the efficiency of V2X transport systems, with a visualization of the framework in Fig. 1. The core concept prioritizes vehicle navigation by enhancing foresight and coordination within the navigation decision-making process. The traffic signals aim to better accommodate vehicle flow based on their navigation intentions. Below, we provide detailed descriptions of each module.

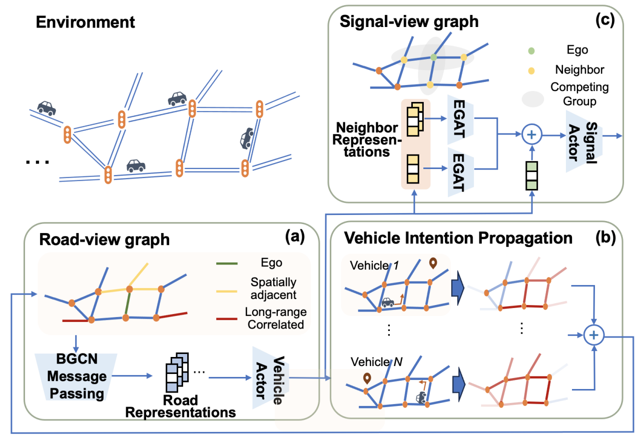

Figure 1: Overall framework of FCV2X-Net. It targets the joint optimization of vehicle navigation and traffic signal control under the V2X paradigm. FCV2X-Net consists of three major modules: (a) a BGCN-empowered module for capturing foresighted road correlation representations, (b) a mean field-based intention propagation module for vehicle coordination, and (c) a vehicle intention-guided traffic signal control module for coordinated traffic signal response.

3.1 BGCN-empowered Foresighted Road Correlation Representation

The road network contains both local adjacency effects, where nearby roads influence each other, and long-range dependencies from their co-occurrence on common routes. Although often implicit, such dependencies are crucial for navigation: awareness of congestion on future roads can guide vehicles to switch to alternatives with low cost, reducing inefficiencies. To capture these effects, we employ Bayesian Graph Convolutional Networks (BGCN) [3], which introduce a learnable adjacency matrix $\mathcal{A}$ to adaptively encode both explicit adjacency and implicit long-range correlations, instead of predefining them.

We define the adjacency matrix as

$$\mathcal{A} = \mathcal{A}_{adj} + \mathcal{A}_{imp}, \tag{1}$$

where $\mathcal{A}_{adj}$ is the fixed adjacency from road topology, and $\mathcal{A}_{imp}$ is learnable for implicit dependencies. To improve robustness, dropout is applied to obtain $\tilde{\mathcal{A}}$, used in graph convolution message passing.

Message passing is performed with an edge-featured convolutional layer that integrates connectivity information. Since the importance of correlated roads depends on vehicle destinations, we design a destination-aware edge feature. For vehicle m with destination road k, the edge feature from road i to road j is

$$E_{ij,k} = \left[\angle(i,j,k), \mathrm{Distance}(i,j)\right], \tag{2}$$

where $\angle(i,j,k)$ is the geometric angle with respect to the destination and $\mathrm{Distance}(i,j)$ is their physical distance.

Let X be the road feature matrix (defined in Section 3.2). The updated road representations are

$$\hat{X}_i = X_i + \sum_{j=1, j\neq i}^{N} \tilde{\mathcal{A}}_{ij} W H_{ij}, \tag{3}$$

where

$$H_{ij} = \mathrm{concat}\left(E_{ij,k}, X_j\right), \tag{4}$$

W is a learnable projection matrix, and N is the number of roads.

3.2 Mean Field-based Intention Propagation for Vehicle Coordination

Effective navigation requires coordination among vehicles, since individually "optimal" choices may create bottlenecks or oscillations [11]. Thus, navigation should account for both future road conditions and anticipated flows from other vehicles.

Inspired by mean-field theory [14], we model vehicle turning decisions as a distributed *intention field* over the road network. A distance-dependent radiation function propagates the effect of each decision to potentially affected roads. Given a vehicle turning into road i with destination k, its intention field on road j is defined by three factors:

- **Distance decay:**
$$\exp\left(-\frac{\mathrm{Distance}(i,j)}{\epsilon}\right),$$
where ϵ controls decay (500m in experiments).
- **Directional alignment:**
$$1 + \cos\left(\angle(i,j,k)\right),$$
encouraging smooth alignment towards the destination.
- **Directional consistency:**
$$1 + \cos\left(\angle(j,k)\right),$$
promoting continuity in heading direction.

The intention field on road j is thus:

$$Q_{i,j,k} = \exp\left(-\frac{\mathrm{Distance}(i,j)}{\epsilon}\right)\cdot\left(1+\cos(\angle(i,j,k))\right)\cdot\left(1+\cos(\angle(j,k))\right). \tag{5}$$

Aggregating $Q_{i,j,k}$ over all vehicles gives the anticipated traffic demand on road j. This aggregated intention is concatenated with road observations to form the road feature X, used in Eq. 3.

3.3 Reward and Loss Design for Vehicle Navigation Learning

With the proposed modules, we obtain intention-aware road representations capturing both explicit and implicit correlations. For each vehicle requiring a navigation decision, we concatenate the representations from Eq. 3 of all candidate outgoing roads, feed them into a two-layer MLP, and select the road with the highest score.

The reward for navigation consists of four components:

- Final reward r_f: +10 for reaching the destination, or -10 otherwise.
- Travel time r_t: negative time cost on the selected road.
- Distance reduction r_d: normalized decrease in distance to the destination, encouraging progress.
- Emission r_e: negative emissions on the road segment.

The overall reward is

$$r = r_f + w_t r_t + w_d r_d + w_e r_e, \tag{6}$$

where $w_t, w_d, w_e \geq 0$ balance the components.

To stabilize training of the adaptive adjacency matrix, we add a supervised prediction loss to the temporal-difference loss $\mathcal{L}_{\mathrm{TD}}$. Specifically, the aggregated neighbor representation from Eq. 3 is used to predict the ego road observation X_i via a linear layer:

$$X_{i,\mathrm{sup}} = W_{\mathrm{sup}}\left(\sum_{j=1,j\neq i}^{N} \tilde{\mathcal{A}}_{ij} W H_{ij}\right), \tag{7}$$

with supervised loss

$$\mathcal{L}_{\mathrm{sup}} = \|X_{i,\mathrm{sup}} - X_i\|_2^2. \tag{8}$$

The final training objective combines both terms:

$$\mathcal{L} = \mathcal{L}_{\mathrm{TD}} + \lambda \cdot \mathcal{L}_{\mathrm{sup}}, \tag{9}$$

where λ balances reinforcement and supervised learning.

3.4 Vehicle Intention-guided Coordinated Traffic Signal Control

Traffic signals regulate vehicle flows at intersections, while vehicle navigation decisions shape macroscopic traffic distribution. To achieve coordination between the two, we adapt the CityLight framework [15], which models city-scale signal control as a multi-agent coordination problem. Specifically, we directly incorporate vehicles' turning intentions into the intersection-level observations, enabling each traffic signal agent to make phase control decisions informed by anticipated vehicle flows. This design allows the signal control policy to explicitly account for user intentions while retaining the coordination mechanisms of CityLight, thereby enhancing the synergy between vehicle routing and intersection control.

4 Experiments

4.1 Dataset & Testbed

We conduct experiments on two real-world datasets, Beijing_25 and Beijing_49. Beijing_25 has 20 signals and 3210 vehicles (300 agents), while Beijing_49 has 42 signals and 4903 vehicles (500 agents). One-hour route data is used for training and evaluation. For simulation, we adopt the GPU-accelerated MObility Simulation System (MOSS)[16][1], which implements the IDM[9] and MOBIL [5] models and runs up to 100× faster than CityFlow and SUMO. Following [8], traffic signals update phases every 15s, and vehicles select turning directions at each road segment.

[1]https://moss.fiblab.net/

Table 1: Average performances in two datasets. Bold denotes the best results, and underlined denotes the second-best results. '-' denotes 'no result' due to high resource demands or expenses. TP, ATT, and E are short for throughput, average travel time, and emission.

	Beijing_25			Beijing_49		
Model	TP↑	ATT↓	E↓	TP↑	ATT↓	E↓
Fastest Route	194	**463**	**654**	270	<u>667</u>	**998**
DQN Navi [6]	167	806	2915	251	1002	4581
AN [1]	169	782	2052	266	947	3119
XRouting [11]	146	765	2330	302	985	7953
GESA [4]	<u>216</u>	638	2110	319	736	3860
MPLight [2]	198	655	2775	<u>341</u>	723	3849
NavTL [8]	205	650	2419	305	741	4020
FCV2X-Net	**235**	<u>498</u>	<u>1803</u>	**414**	**521**	<u>3000</u>
Impr. (%)	8.8%	-7.6%	-	21.4%	21.9%	-

4.2 Main Results

Comparisons between FCV2X-Net and the 7 state-of-the-art baselines over two datasets are presented in Table 1, from which we can draw these noteworthy observations:

- **Consistent superiority.** Our FCV2X-Net achieves top-tier performance in both average travel time (ATT) and throughput (TP), with average improvements of 7.2% and 7.6% across the two datasets. The Fastest Route method seems effective in reducing emissions, but this stems from severe congestion that leaves many vehicles stuck. In contrast, FCV2X-Net not only excels in ATT and TP but also outperforms all real-time navigation baselines in emission reduction, with an average gain of 8.0%.
- **Global vehicle navigation efficiency improvement.** Unlike the Fastest Route method, which only considers individual shortest paths and often causes congestion, our approach leverages real-time road states and system-wide coordination to avoid locally greedy decisions. Compared to baselines limited to short-term or local dependencies, FCV2X-Net captures long-range spatial interactions and aligns vehicle behaviors toward globally efficient outcomes, thereby dispersing traffic, reducing road competition, and significantly improving both travel time and throughput.
- **Between-intersection coordination.** By leveraging information from neighboring intersections, especially vehicle turning intentions, our method enables more informed and proactive signal control. This coordination reduces turning delays and improves local flow. In contrast, baselines that treat intersections independently cannot anticipate downstream congestion or adapt to upstream inflow, leading to phase conflicts and inefficient timing.

5 Conclusion

In this work, we propose FCV2X-Net, a unified framework that enhances foresight and coordination in V2X systems. Beyond advancing current traffic management, FCV2X-Net highlights the broader potential of integrating learning-based foresight and coordination into intelligent transportation infrastructure. Future work may extend this framework to multi-modal mobility systems (e.g., pedestrians, cyclists, and public transit) and explore its robustness under uncertain or adversarial traffic conditions. Such extensions could further strengthen the role of coordinated V2X systems in building resilient, low-carbon, and human-centric smart cities.

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