Scalable Sliding Resource Allocation in C-V2X Mode-3 with Multi-Agent Reinforcement Learning

Moin Ali, Su Min Kim, Junsu Kim*

Department of Electronics Engineering, Tech University of Korea, Siheung, Korea {mointu12, suminkim, junsukim}@tukorea.ac.kr

Abstract—In future intelligent transportation systems (ITS), ensuring scalable and efficient resource allocation is critical for maintaining high reliability in dense vehicular environments. This paper presents a dynamic subchannel management scheme for C-V2X mode-3, leveraging Multi-Agent Reinforcement Learning (MARL) to adaptively allocate resources based on vehicle density within the coverage of Mobile Stations (MSs). Unlike conventional static or proportional slicing, the novelty of our approach lies in integrating a scalable subchannel sliding mechanism, decentralized O-learning, and sequential subframe allocation. Together, these components achieve lightweight yet effective resource adaptation, surpassing traditional proportional methods. Simulation results validate the effectiveness of the approach, achieving over 97.5% CAM delivery ratio (CDR) in high-density scenarios with up to 600 vehicles, while maintaining efficient and collision-resilient spectrum usage.

Index Terms—C-V2X mode-3, multi-agent reinforcement learning, scalability, sliding resource allocation, half-duplex problem, CAM delivery.

I. INTRODUCTION AND BACKGROUND

Cellular Vehicle-to-Everything (C-V2X) communication is a foundational component of next-generation Intelligent Transportation Systems (ITS), enabling real-time data exchange among vehicles, infrastructure, and networks to enhance road safety, traffic efficiency, and cooperative autonomous driving [1]. The 3rd Generation Partnership Project (3GPP) has defined two operational modes for C-V2X: mode-3 and mode-4. Both modes support direct vehicle-to-vehicle (V2V) communication without relying on continuous base station mediation, but they differ significantly in how resources are allocated. In mode-3, the scheduling of radio resources is handled centrally by the cellular infrastructure (e.g., eNodeB), while in mode-4, vehicles autonomously select resources through sensing-based semi-persistent scheduling (SB-SPS) [2].

Compared to mode-4, mode-3 offers superior control over interference and more efficient resource utilization due to its centralized nature. The infrastructure can leverage global knowledge of vehicle mobility, density, and topology to coordinate transmissions more effectively [3]. However, the 3GPP specifications for mode-3 do not prescribe a fixed scheduling strategy, leaving the design of efficient and adaptive resource allocation methods open for further research [4]. Existing approaches often rely on static slicing or location-based allocation, which lack scalability in dynamic urban environments and fail to manage overlapping mobile station coverage areas. Additionally, these methods rarely consider the half-duplex

transmission constraints that limit simultaneous send-receive operations, especially in dense deployments.

To overcome these limitations, this paper proposes a dynamic subchannel management scheme based on Multi-Agent Reinforcement Learning (MARL), where each Mobile Station (MS) acts as an intelligent agent that allocates subchannels and subframes in proportion to real-time vehicle density within its RSRP-based communication range. First, a scalable subchannel sliding mechanism is introduced, allowing the number of subchannels and subframes assigned to each MS to dynamically adjust according to local congestion, thereby ensuring efficient spectrum utilization. Second, each MS independently optimizes its resource selection policy through Q-learning, enabling decentralized yet coordinated decision-making that adapts to mobility and overlapping coverage areas. Third, the framework inherently mitigates half-duplex collisions by assigning sequential subframes within an MS's coverage, which preserves high CAM delivery ratio (CDR) and minimizes interference in dense vehicular scenarios. Simulation results validate the proposed approach, achieving over 97.5% PRR with balanced and interference-resilient communication across multiple overlapping MSs.

II. PROPOSED SCHEME

This work proposes a Multi-Agent Reinforcement Learning (MARL)based scalable sliding resource allocation framework, where Mobile Stations (MSs) act as intelligent agents to optimize spectral efficiency and mitigate communication constraints in vehicular networks.

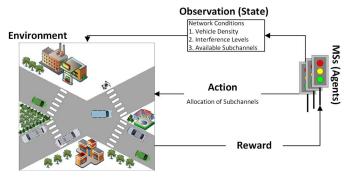


Fig. 1: MARL-based Scalable Sliding Resource Allocation.

A. Scalable Subchannel Sliding Mechanism

To address fluctuating vehicular density in dynamic traffic environments, we propose a scalable subchannel sliding mechanism in which both the number of subchannels and subframes allocated to each Mobile Station (MS) are dynamically adjusted based on the real-time vehicle count within its RSRP-based communication range. The allocation is proportional to vehicle density: high-density regions receive more subchannels and subframes, enabling increased transmission opportunities, whereas low-density regions are assigned fewer resources to avoid spectrum under-utilization. This ensures that spectrum is allocated fairly across overlapping MS coverage zones, avoids bottlenecks in congested areas, and maintains efficient utilization of radio resources in lightly loaded areas. This mechanism is designed to seamlessly adapt to temporal and spatial traffic variations, enhancing overall spectral efficiency.

B. Decentralized Resource Optimization via Q-Learning

In the proposed framework, each MS operates as an autonomous agent within a Multi-Agent Reinforcement Learning (MARL) architecture. By leveraging Q-learning, each MS learns an optimal policy for allocating subchannels and subframes without requiring constant centralized control. The O-learning process enables the MS to adapt its resource allocation strategy based on observed network conditions, including changes in vehicular mobility patterns, interference levels, and overlapping coverage scenarios. This decentralized optimization not only enhances the adaptability of the network to real-time conditions but also ensures scalability, as multiple MSs can coordinate implicitly through learned policies without direct communication. Over time, this approach converges to stable and interference-aware resource allocation patterns that maintain high communication reliability even under heterogeneous traffic loads.

In our Q-learning formulation, the state represents the local vehicular density within each MS's coverage, interference level, and available subchannels. The action corresponds to the number of subchannels and subframes to allocate (sliding adjustment). The reward is defined as the achieved CAM delivery ratio (CDR) minus a penalty for collisions or underutilization. This design ensures that the MS converges toward policies that maximize packet delivery while avoiding waste of spectrum. By combining density-proportional sliding with Q-learning updates every 10 ms, the framework guarantees sufficient resource allocation for both high- and low-density regions.

C. Sequential Subframe Allocation for Half-Duplex Mitigation

The proposed framework mitigates half-duplex transmission collisions through a sequential subframe allocation strategy that assigns different subframes to vehicles operating on the same subchannel within an MS's coverage area, ensuring they do not transmit simultaneously. This design integrates seamlessly with the scalable subchannel sliding mechanism to balance interference reduction and spectrum reuse efficiency. To further minimize inter-MS interference in overlapping

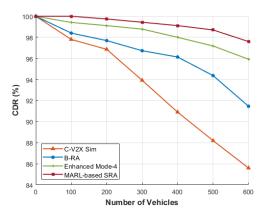


Fig. 2: CAM delivery ratio (CDR) performance with increasing vehicle density in highway topology.

coverage zones, orthogonal subchannel groups are assigned such that neighboring MSs operate on non-interfering frequency blocks—for example, MS 1 and MS 3 use subchannels 1–3, MS 2 uses subchannels 4–7, and MS 4 and MS 5 use subchannels 8–10. By coordinating subframe sequencing with orthogonal subchannel allocation, the system optimizes resource utilization, reduces collisions, and maintains high CAM delivery ratio (CDR) even in densely populated traffic scenarios.

III. PERFORMANCE EVALUATION

A. System Environment and Scenario

In this scenario, 600 vehicles traverse a 1.7 km intersection covered by five eNBs, each with a 300 m radius and 50 m overlap. Realistic traffic dynamics are modeled in SUMO using five lanes per direction, with vehicle mobility derived from urban simulation traces.

B. Performance Measurement and Analysis

1) CDR Performance analysis for crossway topology: Figure 2 presents the CAM delivery ratio (CDR) for 600 vehicles operating within overlapping multi-cell coverage under a 20 MHz bandwidth. The proposed mode-3 scheme achieves over 97.6% CDR, surpassing enhanced mode-4 [2] (96%). The balanced resource allocation (B-RA) [5] reaches about 91%, whereas the C-V2X Simulator (C-V2X Sim) [6] drops to around 85%. The improvement is driven by the proposed scalable subchannel sliding mechanism, decentralized Q-learning-based resource optimization, and sequential subframe allocation, which collectively mitigate half-duplex constraints, adapt to vehicle density, and enhance spectral efficiency in dense urban scenarios.

IV. CONCLUSION AND FUTURE WORK

This paper enhances C-V2X mode-3 by employing multiagent reinforcement learning for dynamic subchannel allocation, allowing each Mobile Station (MS) to adapt resources based on real-time vehicular density. A scalable subchannel sliding mechanism ensures proportional distribution, while sequential subframe allocation mitigates half-duplex constraints. Orthogonal RF resource management reduces inter-cell interference, improving spectral efficiency. The Q-learning-based design updates allocations every 10 ms, maintaining high reliability without centralized control. Simulations in NS-3 and MATLAB show a CAM delivery ratio exceeding 97% in dense and dynamic environments, confirming the proposed scheme's effectiveness. In addition, the Q-learning update per MS is table-based with complexity O(N), where N is the number of subchannels, making it lightweight and suitable for real-time ITS deployment. Although this work evaluates a crossway topology, the framework is generalizable to highway and large-scale mixed urban scenarios. Future work will extend the evaluation to stronger baselines such as DQN or A3C and incorporate latency analysis alongside CDR to further validate learning-based scalability.

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